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Toward Smart Palm Precision Agriculture: A Study on Palm Tree and Red Palm Weevil Detection

Yosra Hajjaji

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MINISTRY OF HIGHER EDUCATION AND SCIENTIFIC RESEARCH
UNIVERSITY OF MANOUBA
NATIONAL SCHOOL OF COMPUTER SCIENCE

PHD THESIS
Submitted for the degree of
Doctor in Computer Science

**Toward Smart Palm Precision Agriculture: A
Study on Palm Tree and Red Palm Weevil Detection**

Defended

By

Yosra Hajjaji

Conducted at: RIADI Laboratory, SIIVT Team



Publicly defended on December 21, 2023, in the front of the jury composed of:

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Dedication

*I dedicate this thesis with profound gratitude
To my dear parents and siblings
To my dear friends
To all the people I love
To my mentors and teachers
To all those who believe in the power of
dreams and the pursuit of excellence
And to all those who believed in me and contributed
contributed directly or indirectly to the completion of this work*

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Abstract

In the era of precision agriculture, where a 70% increase in global food production is imperative, this research unfolds as a transformative force propelled by data-driven methodologies. Focusing on the vital realm of palm cultivation, which is particularly crucial for date palm production and environmental balance, this study tackles the challenges posed by diverse and voluminous data through the integration of remote sensing big data and the Internet of Things (IoT). The central stage is deep learning, ushering in a new era of smart precision agriculture tailored for effective palm management. Three key challenges were addressed: agricultural data management, palm tree detection and counting, and pest and disease management, all with the overarching goal of fortifying resilience, productivity, and sustainability in palm production. The contributions of this research are manifested in a scalable remote sensing data management model, the introduction of a distributed architecture to handle massive, high-resolution remote sensing data, and a deep learning and UAV-based approach for efficient palm tree detection. This revolutionary approach not only accelerates data collection, reduces errors, and enhances decision-making but also contributes significantly to the sustainability of the palm industry and aligns with Sustainable Development Goals (SDGs). Additionally, this study presents an innovative solution for sustainable palm cultivation by integrating computer vision, deep learning, IoT, and geospatial data for the early detection and mapping of Red Palm Weevil (RPW) infestations. Achieving 98.8%-99.5% accuracy and detection rate with a custom DL model, this technology-driven strategy enables comprehensive mapping, monitoring, and targeted management of RPW spread, benefiting agricultural agencies, growers, and researchers.

keywords:Remote sensing big data ,Internet of Things, Big Data analytics, Deep learning, Smart palm agriculture, Remote sensing data, UAV images

Résumé

À l'ère de l'agriculture de précision, où une augmentation de 70 % de la production alimentaire mondiale est impérative, cette recherche se dévoile comme une force transformative, propulsée par des méthodologies axées sur les données. Axée sur le domaine vital de la culture du palmier, particulièrement cruciale pour la production d'huile de palme et l'équilibre environnemental, l'étude aborde les défis posés par des données diverses et volumineuses grâce à l'intégration de données massives de télédétection et de l'Internet des objets (IdO). Le protagoniste de cette scène est l'apprentissage profond, inaugurant une nouvelle ère d'agriculture de précision intelligente adaptée à une gestion efficace des palmiers. Trois défis clés sont abordés: la gestion des données agricoles, la détection et le comptage des palmiers, ainsi que la gestion des ravageurs et des maladies, le tout dans le but ultime de renforcer la résilience, la productivité et la durabilité de la production de palmiers. Les contributions de cette recherche se manifestent par un modèle évolutif de gestion des données de télédétection, introduisant une architecture distribuée pour gérer des données massives de télédétection haute résolution, et une approche basée sur l'apprentissage profond et les drones pour une détection efficace des palmiers. Cette approche révolutionnaire accélère non seulement la collecte de données, réduit les erreurs et améliore la prise de décision, mais contribue également de manière significative à la durabilité de l'industrie du palmier et s'aligne sur les objectifs de développement durable (ODD). De plus, l'étude présente une solution innovante pour une culture durable du palmier en intégrant la vision par ordinateur, l'apprentissage profond, l'IdO et les données géospatiales pour la détection précoce et la cartographie des infestations du charançon rouge du palmier (RPW). Atteignant une précision et un taux de détection de 98.8%-99.5% avec un modèle personnalisé d'apprentissage profond, cette stratégie technologique permet une cartographie complète, une surveillance et une gestion ciblée de la propagation du RPW, bénéficiant aux organismes agricoles, aux cultivateurs et aux chercheurs.

Mots-clés : Données massive de télédétection, Internet des objets, Analyse de données massives, Apprentissage profond, Agriculture intelligente des palmiers, Données de télédétection, Images UAV.

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List of Abbreviations

| | |
|---------------------|---|
| AI | Artificial Intelligence |
| ANN | Artificial Neural Networks |
| ACID | Atomicity Consistency Isolation Durability |
| AWS | Amazon Web Services |
| BD | Big Data |
| BSQ | Band Sequential |
| BPS | Balanced Placement Strategy |
| CQCC | Constant-Q Cepstral Coefficients |
| CNN | Convolutional Neural Network |
| CMR | Common Metadata Repository |
| CSDGM | Content Standard for Digital Geospatial Metadata |
| DA | Data Analytics |
| DL | Deep Learning |
| DLPT | Deep Learning-based |
| DMS | Disease Management System |
| DT | Decision Tree |
| ERS | European Remote Sensing Satellite |
| FAO | Food and Agriculture Agency |
| Fast-RCNN | Fast Region-based |
| Faster R-CNN | Faster Region-based |
| CNN | Convolutional Neural Network |
| FN | False Negative |
| FP | False Positive |
| FPS | Frames Per Second |
| Gabor Filter | Gabor Filtering |
| GDPR | General Data Protection Regulation |
| GF | Gabor Filtering |
| GIS | Geographic Information Systems |

| | |
|---------------|---|
| GridFS | Grid File System |
| GSM | Global System for Mobile Communications |
| HDFS | Hadoop Distributed File System |
| HOG | Histogram of Oriented Gradients |
| HVAC | Heating, Ventilation, and Air Conditioning |
| IoT | Internet of Things |
| IoU | Intersection over Union |
| IOTMDB | Internet of Things DataBase |
| ISO | International Organization for Standardization |
| JERS | Japanese Earth Resources Satellite |
| JPEG | Joint Photographic Experts Group |
| K-NN | K-Nearest Neighbors |
| LiDAR | Light Detection and Ranging |
| LPB | Local Binary Pattern |
| MD5 | Message-Digest Algorithm 5 |
| ML | Machine Learning |
| MLP | Multilayer Perceptron |
| mAP | Mean Average Precision |
| MODIS | Moderate Resolution Imaging Spectroradiometer |
| MQTT | Message Queue Telemetry Transport |
| NoSQL | Not Only SQL |
| NDVI | Normalized Difference Vegetation Index |
| OA | Overall Accuracy |
| OBIA | Object-Based Image Analysis |
| PA | Precision Agriculture |
| PNG | Portable Network Graphics |
| PSS | Periodic Storage Strategy |
| RAID | Redundant Array of Independent Disks |
| RB | Reflected Binary |
| R-CNN | Region-based Convolutional Neural Network |
| RS | Remote Sensing |
| RF | Radio Frequency |
| RFID | Radio Frequency Identification |
| RPW | Red Palm Weevil |
| RSBD | Remote Sensing Big Data |
| SAR | Synthetic Aperture Radar |
| SFC | Space-Filling Curve |
| SE | Squeeze-and-Excitation |
| SMF | Simple Maximum Fusion |
| SPOT | Satellite Panchromatic Observation Target |
| SQL | Structured Query Language |
| SQS | Simple Queue Service |

| | |
|----------------|---|
| SVM | S upport V ector M achine |
| SURF | S peeded-Up R obust F eatures |
| SDGs | S ustainable D evelopment G oals |
| TB | T erabytes |
| TMS | T ile M ap S ervice |
| TP | T rue P ositive |
| TSDB | T ime- S eries D atabase |
| UAVs | U nmanned A erial V ehicles |
| VGG-SSD | VGG S ingle Shot M ulti B ox D etector |
| VGGish | VGG -like model for audio feature extraction |
| Wi-Fi | W ireless F idelity |
| YOLO | Y ou O nly L ook O nce |

General Introduction

Contents

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In this chapter, we will examine the broader context that underlies our research and address the motivations that led us to conduct this study. Our goal is to illustrate why our research is not only important but essential in today’s agricultural landscape.

1.1 Context and Motivation

In recent years, precision agriculture (PA) has emerged as a breakthrough innovation in modern agriculture, ushering in a new era of farming practices. Its profound significance lies in its overarching goal to redefine agriculture by optimizing crop management, reducing resource waste, and increasing agricultural productivity [GA10; ZWW02]. With a rapidly growing global population estimated at 7.8 billion in November 2020 and expected to rise to 8.5 billion by 2030 and 9.9 billion by 2050, the world faces an unprecedented challenge [Foo19; Wis13] according to the food and agriculture agency (FAO). In practice, this means feeding nearly two billion more people than in 2020. Meeting this growing global food demand is a daunting task that will require a 70 percent increase in agricultural production, according to the Food and Agriculture Organization of the United Nations [LF17; TSR19]. The importance of PA becomes clear when we look at the staggering statistics and facts about modern agriculture. PA practices have the potential to increase crop yields by up to 70%

and offer a transformative solution to this challenge. Conventional farming practices often result in inefficient use of resources, wasting up to 50% of water and fertilizer. PA, with its precise and data-driven approach, offers a compelling solution to address these inefficiencies and steer agriculture toward a more sustainable and productive future [Roz+23; Zha16].

The cornerstone of this agricultural revolution is data, which has brought about a transformation in precision agriculture. Data-driven technologies such as remote sensing, the Internet of Things (IoT), and environmental sensors have changed the agricultural landscape [SRS20; KK19]. Currently, agriculture relies on data from multiple sources to make informed decisions. These include data from remote sensing technologies that capture critical information from satellites and drones, IoT devices strategically placed in fields, and sensors that capture environmental details. The result of an exponential increase in the amount of data promises to be disruptive but also presents challenges for managing and analyzing that data [TSR19; Mul13].

The management of palms is a particularly interesting and important area related to precision agriculture. Palms play a unique and versatile role in agriculture because of their versatility and significant economic impact. They contribute significantly to global agricultural production by providing important products such as palm oil, which is a key ingredient in the food and cosmetics industries, as well as various palm-based products used in numerous applications [GRT19]. In addition, palm trees have a significant impact on the environment, shaping landscapes and ecosystems, especially in regions where they are widely cultivated. Given their dual role in the economy and the environment, the management of palms is of utmost importance [Ten12].

Today's palm farming landscape is characterized by a mix of traditional practices and the introduction of modern technologies. Despite the long history of palm cultivation, today's demands require a shift toward precision agriculture. However, this shift is not without a number of difficulties and constraints, such as the need to control disease outbreaks, optimize resources, and ensure environmental sustainability, which requires the development of innovative solutions and the integration of advanced technologies to ensure effective palm management [El-10; SHS11; Baz+14].

In the complex landscape of palm management, two key factors stand out: remote sensing big data (RSBD) and IoT. RSBD, which comes from remote sensing technologies such as satellites and drones, and IoT data, which comes from an array of strategically placed sensors, play a critical role in shaping the future of palm management. The vast amount of data generated by these sources presents both opportunities and challenges. The challenges are many: the diversity of data in its various types and forms, the growing volume of data, the monolithic approach to service development, and the efficiency of predictive analytics. This treasure trove of data requires the application of advanced data analytics techniques to realize its full potential. Deep learning, a subfield of artificial intelligence (AI), has become a critical component in complex data analysis tasks. Its ability to autonomously learn and extract intricate patterns from data makes it a prime candidate for unlocking the multi-layered

nature of RSBD and IoT data. Ultimately, Deep Learning (DL) helps enable smart precision agriculture (SPA) for palms by extracting valuable insights from large and complex datasets.

1.2 Problem Statement

In SPPA, we face a variety of challenges that include data management, image analysis, and pests detection. The integration and analysis of large, complicated, and diverse high-resolution satellite imagery and IoT data is at the heart of these challenges. While these datasets have the potential to revolutionize palm management, there are also critical data management and utilization issues.

Effective management of Big Data from remote sensing, including high-resolution satellite imagery and data from IoT devices, is a formidable challenge. The sheer volume of information produced by these sources can strain existing systems and resources, necessitating the development of scalable distributed data management models tailored to these unique data. The implementation of such models is crucial for preventing overload, and is a prerequisite for unlocking the full potential of these valuable data sources.

The surge in IoT devices and advancements in remote sensing and satellite technology have exponentially increased data generation, making RSBD management a critical focus in SPAA. This influx of data poses a significant obstacle to efficient processing and management, potentially overwhelming the current systems. To address this, specialized approaches and careful organization of ideas are required to ensure streamlined data processing, thereby maximizing the benefits of high-resolution satellite imagery and IoT devices within the realm of the SPAA.

The challenges associated with RSBD are multi-faceted. First, the data generated by the remote sensing devices themselves are complex and require sophisticated analysis techniques to produce meaningful insights. In addition, the integration and analysis of multiple data sources from different sensors, remote sensing platforms, and IoT devices requires a comprehensive approach to obtain a coherent picture of palm management.

To address the challenges associated with the management and use of remote sensing and IoT data, there is an urgent need for the development and adoption of scalable, distributed data management models that are specifically tailored to the characteristics of these data sources. These models are essential to unlock the full potential of remote sensing and IoT data in SPPA development and to make progress in this area.

Detecting and counting palm trees in vast agricultural landscapes is a critical challenge in precision agriculture and requires innovative solutions that leverage the capabilities of DL, unmanned aerial vehicles (UAVs), and remote sensing imagery. The complexity of this task includes navigating complex visual contexts, identifying palms at different growth stages, monitoring their condition, and optimizing resource allocation. These challenges underscore the need for advanced DL algorithms capable of accurately identifying and counting palms

amidst the visual complexity of agricultural landscapes. The result not only improves palm detection efficiency but also ensures accurate counting, supports proactive, data-driven precision planting methods, and contributes to resource optimization and sustainability in palm cultivation.

Given the catastrophic impact of RPW on palm production, timely detection and mapping of this pest are of utmost importance. Early detection of RPW infestations when subtle external symptoms are present is critical. However, this task is complicated by the subtlety of the symptoms. Therefore, sophisticated detection methods must be developed to identify subtle signs of infestation and allow rapid intervention to protect the health and sustainability of palm crops. The complexity of this task lies in the need for precision and speed in identifying RPW infestations in the vast palm groves.

This research project aimed to address the complex challenges associated with palm management by introducing innovative methodologies and frameworks. Our goal was to improve the efficiency, sustainability, and precision of palm management through the use of RSBD. We plan to use advanced data analysis techniques and cutting-edge technologies to revolutionize palm cultivation, disease detection, and pest management. This initiative is guided by the recognition that effective data management and use are critical to meet the growing demand for food while ensuring the environmental sustainability of smart precision agriculture for palm.

1.3 Research Objectives

As we continue to explore the field of PA, it is becoming increasingly clear that integrating cutting-edge technologies such as remote sensing and IoT is critical to achieving our goals. When used effectively, these technologies can improve crop health, resource allocation, and decision-making in ways that were previously unattainable. This study aims to harness the potential of RSBD and IoT based on DL to usher in a new era of smart PA, with particular focus on the management of palm, an important sector of agriculture in different regions.

In this work, we mainly address three key challenges in the SPPA sector:

- **Agricultural Data Management:** effective management of large amounts of data generated by sensors and drones is essential for the implementation of smart palm agriculture. In this work, data management systems specific to the needs of palm cultivation are investigated and proposed. These systems will play an important role in organizing, storing, and processing the huge amount of data generated by PA. The systems proposed in this work will be designed to be robust, scalable, and secure to ensure efficient and reliable data management.
- **Palm Tree Detection and Counting:** accurate identification and quantification of palm trees scattered across vast agricultural landscapes is of paramount importance. This approach not only addresses the difficulties associated with palm tree detection

and counting but also introduces new methods and technologies, including the use of DL and drones, to improve and speed up these vital operations.

- **Pest and Disease Management:** in smart palm agriculture, pest and disease management is critical. Our research aims to develop innovative solutions that use technologies such as remote sensing and artificial intelligence to detect, monitor, and proactively manage pest and disease outbreaks in palm crops. Our goal was to minimize crop losses by enabling early detection and timely intervention.

By focusing our research efforts on these challenges, we strive to provide practical and meaningful solutions that improve the resilience, productivity, and sustainability of palm production in a dynamic agricultural environment.

1.4 Contributions

The growth of smart precision farming methods in agricultural innovation requires a multifaceted strategy that synergistically combines multiple technologies. The goal of this thesis is to provide a series of key contributions, each highlighting a different aspect of our overall framework. This section presents the diverse but intertwined contributions that culminate in a cohesive strategy, forming a coherent tapestry that strengthens modern agriculture.

Proposed Approach Architecture

In this section, we would like to introduce a revolutionary strategy that has the potential to change the landscape of modern agriculture. This solution leverages the interplay of modern technologies to take the notion of smart precision agriculture to new heights. This strategy is redefining the way farming systems are understood, managed, and optimized by seamlessly combining remote sensing, the Internet of Things and Deep Learning, powered by the power of Big Data technology. We set out to explore the possibilities of this synergistic solution to advance the field of precision smart agriculture.

The proposed approach represents an innovative solution divided into different levels, as visually shown in Figure 1.1. The levels of the approach are presented below:

Multi-Sources Data Acquisition Layer

The "Multi-Sources Data Acquisition Layer" is a cornerstone of our suggested approach, managing the harmonic gathering of varied data sources, including satellite images, UAV imaging, and IoT sensor data—all taken from a single geographical location.

- **Satellite Imagery:** Acquire multispectral and/or hyperspectral satellite imagery relevant to a specific agricultural problem (e.g., precision smart agriculture) from reputable sources (e.g., NASA, ESA, commercial providers). This data can provide a broad overview of the issue and help identify trends and patterns.

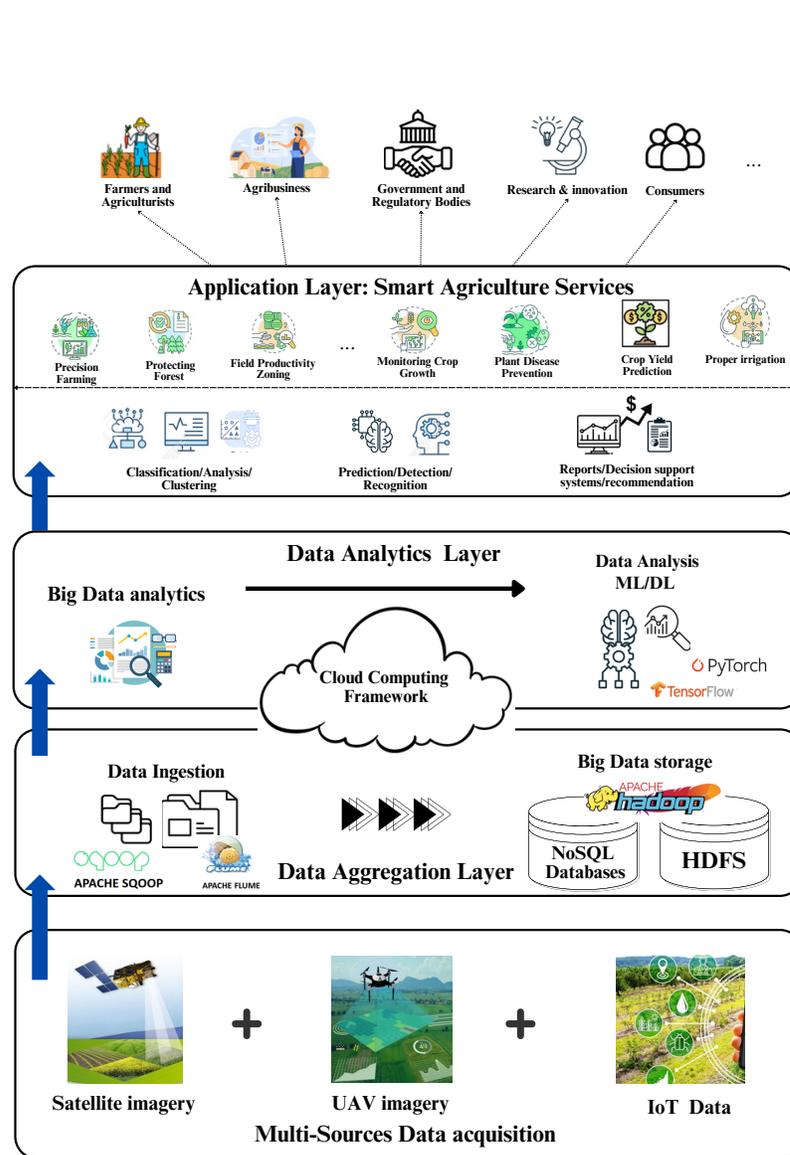


FIGURE 1.1: Overview of the smart agriculture services approach.

- **UAV imagery:** Collect high-resolution imagery using UAVs equipped with appropriate sensors to capture high-resolution images of specific areas. This data can provide detailed insights that cannot be achieved with satellite imagery alone.
- **IoT sensors:** Deploy a network of IoT sensors strategically placed in the target area to collect real-time environmental data (e.g., temperature, humidity, air quality, and soil moisture). Deploy a network of sensors to collect real-time environmental data.

This complex fusion of data sources not only provides the foundation for subsequent steps in our methodology, but also overcomes a number of challenges associated with these types of data, such as managing large data sets, different data formats, and different data collection frequencies.

Data Aggregation layer

In the data aggregation layer, we focus on two critical components: data integration and large data set management, both of which play a crucial role in the overall framework of our proposed solution.

- **Data Integration:** The main goal of this layer is to harmoniously merge data coming from many sources, such as satellite imagery, UAV data, and IoT sensor inputs. Combining these disparate data sets creates a single and complete knowledge pool, paving the way for comprehensive analysis and deep insights.
- **Massive Data Storage:** To address the challenges associated with managing Big Data, this aspect involves implementing robust storage solutions. These solutions are tailored to handle the massive amounts of data generated by satellite imagery, drone data, and IoT sensors. By integrating state-of-the-art Big Data storage frameworks (e.g., Apache Hadoop, NoSQL databases, cloud computing, etc.), we ensure efficient data organization, accessibility, and reliability. This foundational infrastructure facilitates subsequent processing and analysis steps, contributing to the smooth functioning of the entire data aggregation layer.

However, this level is not without a number of challenges. Managing and combining data from multiple sources while ensuring data quality and integrity requires significant thought. In addition, the right Big Data storage structure must be selected and implemented according to the unique requirements of our proposed solution. By overcoming these challenges, we strengthen the position of the data aggregation layer as an important intermediate link in our intelligent precision farming architecture.

Analysis layer

In the data analytics layer, we address the critical components of spatial data integration and the use of advanced machine learning and deep learning technologies for intelligent data analysis.

- **Data analysis via DL technologies** This part involves the use of DL techniques to derive relevant insights from the combined data set. These methods are useful for identifying patterns, trends, and anomalies that would otherwise remain hidden in huge databases. We equip ourselves with the ability to predict outcomes, discover critical features, and make informed decisions based on data-driven outcomes by training ML and DL models on the integrated data.

In essence, the analysis layer combines raw data with actionable insights that provide an overall understanding of the agricultural landscape and enable informed decisions for smart precision agriculture. Deep learning model construction and fine-tuning for accurate agricultural forecasting and analysis require careful consideration. By overcoming these challenges, we aim to improve the effectiveness of our data fusion and analysis layer, contributing to the advancement of intelligent precision agriculture methods.

Intelligent application level in agriculture

At the intelligent application layer, seamless integration of various functions such as classification, analysis, clustering, prediction, and detection takes place in agriculture. These interrelated processes contribute to the strong intelligence of the proposed framework. These capabilities are represented in a unified framework by symbols representing intelligent precision agriculture, crop disease detection, crop yield prediction, and more. This layer is the culmination of the integrated system's potential to provide actionable insights and decision support to a wide range of agricultural stakeholders.

- **Farmers:** Those on the front lines of agriculture can benefit significantly from these sophisticated applications. Farmers can maximize resource utilization, increase crop yields, and accelerate farming practices by making informed decisions based on real-time data analytics.
- **Government and regulatory agencies:** Government organizations responsible for overseeing agriculture can use the information gained through these applications to support policymaking, resource allocation, and sustainable land management. Such applications can help implement and enforce agricultural regulations, ensure environmental sustainability, and promote responsible agricultural practices.
- **Agribusiness:** Companies in the agribusiness industry can leverage the predictive capabilities of these applications to improve supply chain management, optimize distribution, and increase overall operational efficiency.
- **Consumers:** End consumers of agricultural products gain confidence in the quality and safety of their food as these technologies help diagnose diseases early, leading to better product quality.
- **Research and Innovation:** Researchers and innovators can use the vast amounts of data these apps provide to improve farming techniques, develop new technologies, and contribute to the overall success of the industry.
- **Environmental organizations:** Environmental organizations can use the information provided by these apps to monitor land and water use and the impact of agricultural practices on local ecosystems. This information can be used to develop plans for environmentally friendly agriculture.

The layer of smart applications empowers various stakeholders across the agricultural spectrum and paves the way for a more efficient, sustainable, and technology-driven future of agriculture. By harmoniously aligning these functions, the framework bridges the gap between raw data and actionable insights, fosters informed decision-making, and drives agricultural productivity and sustainability to new heights.

1.5 Thesis Outline

This manuscript consists of five main chapters, excluding the introductory and concluding chapters. These chapters are divided into two parts and culminate in a comprehensive general conclusion. A visual depiction of the thesis structure can be found in Figure 1.2, which offers a comprehensive overview of the organization of the work presented.

The first part presents the current state of affairs in two chapters, as follows:

- **Chapter 2** provides fundamental knowledge in our research area and covers the basics of precision agriculture for smart palms, including the principles of precision agriculture for palms, sensor technologies, Big Data analytics, and IoT sensor integration.
- **Chapter 3** provides a detailed overview of relevant work in precision agriculture for palms, highlights current trends, progress, and limitations, and identifies gaps in current research.

The second part of this manuscript consists of three chapters in which the proposed contributions are evaluated as follows:

- **Chapter 4** Chapter 4 introduces an innovative multimodal approach for efficiently managing the increasing volume of satellite data, which includes remote sensing (RS), high-resolution imagery, and Internet of Things (IoT) data. By overcoming the limitations of conventional databases, the proposed system integrates NoSQL databases, the Hadoop framework, cloud computing, and time-series databases. This streamlined approach simplifies the management of RS data, large images, and IoT data, thereby demonstrating its potential to revolutionize information handling. The inclusion of time-series databases enhances a system's ability to store, retrieve, and analyze time-dependent datasets efficiently, significantly contributing to advanced data management and analytics across a wide range of applications.
- **In Chapter 5**, we focus on increasing efficiency in the palm industry by applying DL-based object recognition and remote sensing. Specifically, we applied YOLOv5 and YOLOv8-HighAug for palm tree detection, and YOLOv8-HighAug showed the highest effectiveness. This method accelerates data collection, reduces errors, and improves palm management, which promotes sustainability and informed decision-making in the industry.

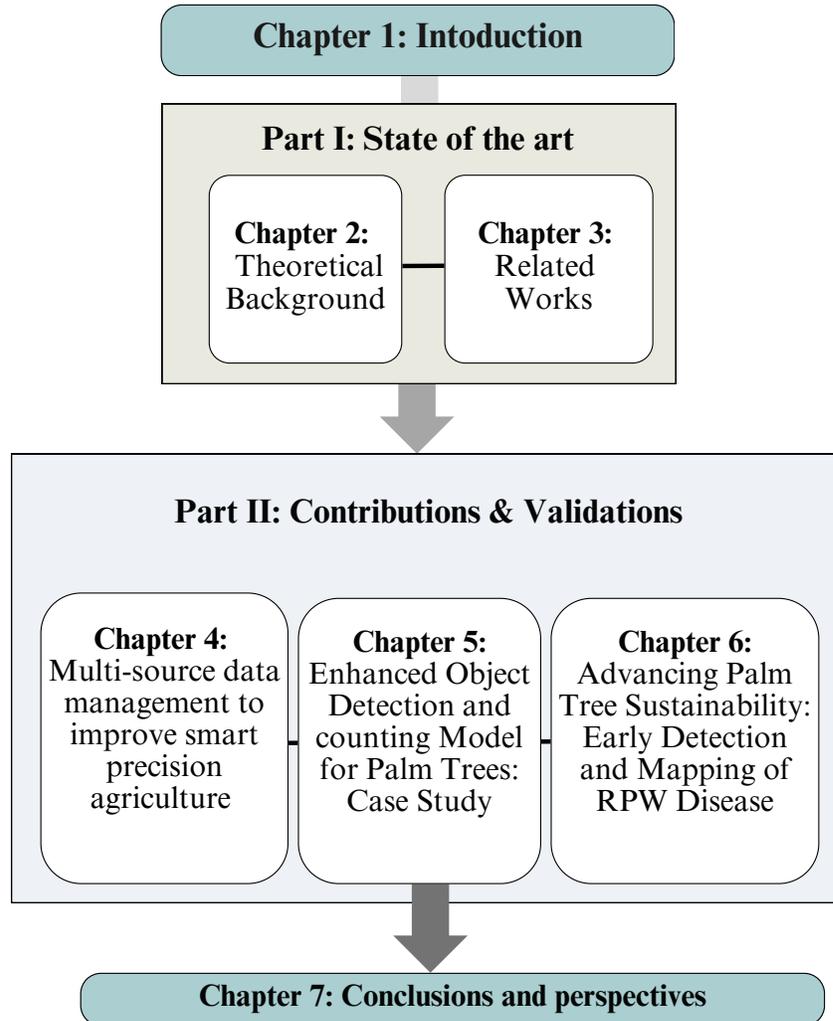


FIGURE 1.2: The thesis structure

- **In Chapter 6**, we present an innovative solution for sustainable palm cultivation that focuses on combating destructive RPW. Our approach integrates computer vision, DL, the IoT, and geographic data. We have achieved 98.8%-99.5% accuracy and detection rate in RPW infestation detection with a customized DL model. Geospatial data integration supports monitoring and targeted management. This technology-based approach benefits agricultural authorities, farmers and researchers by protecting palm plantations from RPW infestation

Chapter 1. General Introduction

Finally, in the final chapter, we offer a comprehensive summary of our proposed research contributions and outcomes, along with recognition of the limitations inherent in our proposal. In addition, we explored potential avenues for future research.

Part I

State-of-the-art

Preliminary Concepts and Theoretical Background

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2.1 Introduction

This chapter serves as the foundation for understanding the essential concepts and theoretical frameworks that underpin research on Red Palm Weevil (RPW) detection in palm tree farms. This discussion explores precision agriculture, remote sensing big data, big data management, and data analytics within the context of palm cultivation, providing innovative solutions to mitigate RPW infestations.

Structured for a comprehensive understanding, the chapter unfolds systematically. Section 2.2 delves into precision agriculture and its significance in palm cultivation. Section 2.3 examines the critical role of remote sensing big data, including satellites, Unmanned Aerial Vehicles (UAVs), Internet of Things (IoT) devices, and geographic information systems (GIS). The exploration of big data management is undertaken in Section 2.4, and Section 2.5 sheds light on various data analytics tools tailored for precision agriculture. Section 2.6 investigates the synergistic integration of IoT sensors, remote sensing imagery, and deep-learning technologies. This exploration, grounded in theoretical foundations, holds the promise of revolutionizing precision agriculture, particularly in the realm of palm cultivation, by offering innovative solutions to the challenges posed by RPW infestations. As we proceed through each section, our aim is not only to unravel the intricacies of these concepts but also to emphasize their direct relevance and contribution to our overarching goal: the development of a robust RPW detection and management system in palm tree farms.

2.2 Precision Agriculture

Agriculture is the cornerstone of economies worldwide. It employs 75% of the world’s population and is a major contributor to countries such as India, China, Brazil and Indonesia. However, as the world’s population is expected to grow to 9.6 billion by 2050, global food demand will increase by 60%, leading to challenges such as limited land availability and climate change. About 795 million people worldwide are affected by malnutrition [Foo19] [Des19].

In response to these challenges, precision-smart agriculture has emerged as a transformative solution. It combines modern technology, advanced data analytics, and digital tools to optimize crop and livestock production. Through real-time data and insights, it enables precise

decision-making and resource allocation that improve efficiency, profitability, and sustainability [Jem+23]. Innovations such as GPS, remote sensing, sensors, IoT and data analytics are driving this revolution and enabling environmentally sound agricultural practices [RI06].

Figure 2.1 illustrates the factors driving the emergence of precision agriculture, leading to transformative changes in farming techniques and ensuring sustainable agricultural production.

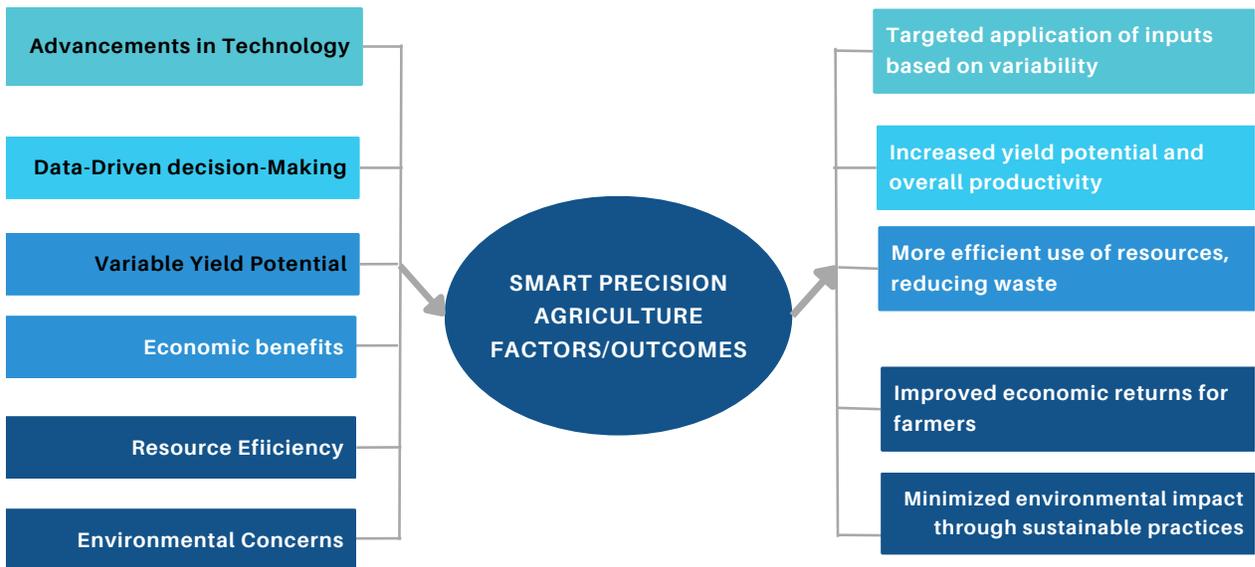


FIGURE 2.1: Key Influences on Smart Precision Agriculture

The development of smart precision agriculture is driven by influential factors that lead to the emergence of technologies that improve the efficiency and sustainability of agriculture. These influences are transforming conventional agricultural practices and underscoring the important role of smart precision agriculture in achieving sustainable and productive agricultural outcomes.

In the context of precision agriculture, smart precision agriculture represents a breakthrough solution with immense potential to transform agricultural landscapes. It enables farmers to make precise decisions and use resources efficiently, contributing to the economic and environmental sustainability of farming practices.

2.2.1 Precision Agriculture in Palm Cultivation

Although precision agriculture has the potential to revolutionize agricultural practices worldwide, it is important to recognize that its implementation is not a one-size-fits-all solution.

Different crops and farming environments require tailored approaches to take advantage of this transformative technology. In the following sections, we focus on a single but economically important crop, palm agriculture, which includes date and oil palms. These iconic agricultural pillars, most prevalent in the Middle East and North Africa, present a unique set of challenges that require specialized precision agriculture methods.

In recent years, investment in the agricultural sector has increased significantly. Palms, which comprise some 2,600 varieties from 202 different genera and can yield more than 1,000 products, have remarkable global importance [DOE22; Bou+23; Haj+23]. They are essential to the economies of many countries, especially in the Middle East, where they lead date production with over 8 million tons annually. Indonesia is the world’s leading producer of palm oil, accounting for more than 50% of global production [AE11]. The palm oil industry alone is worth about \$65 billion per year and provides livelihoods for millions of people, especially in rural areas where palm oil cultivation is a major source of income [Har+21] [Kil23].

The date palm, scientifically known as *Phoenix dactylifera* L., is of paramount importance in the Middle East and North Africa because of its great cultural, economic, and ecological significance. As one of the oldest fruit-bearing trees and vital crops, it has had a profound impact. Countries such as Egypt, Iran, Iraq, Saudi Arabia, and the United Arab Emirates play an important role, providing 67% of the world’s date production. Date palms are not only a staple food for humans and animals but are also used in industry to produce wine, oil, and fiber. [EI-98] trees contribute to the sustainability of desert ecosystems by providing shade and wildlife habitat. The nutritional benefits of dates and their numerous applications in cosmetics, construction, and papermaking underscore their versatile value [HBF22], [MES12], [EI-10].

In contrast, palm oil, scientifically known as *Elaeis guineensis*, is a global economic crop with remarkable economic importance. Today, palm oil is the world’s most important source of vegetable oil, surpassing other oilseeds such as canola, soybeans, and sunflower, accounting for a remarkable 35% of total vegetable oil consumption [Cho+17] [Sha23]. The increasing demand for vegetable oil, combined with factors such as canola, soybeans, and sunflowers, has led to the conversion of vast areas of land into palm oil plantations. This conversion not only includes existing farmland but has unfolded primarily in regions such as Indonesia and Malaysia. In this context, careful monitoring of palm oil plantations is invaluable to farmers and stakeholders as it provides an opportunity to improve plantation productivity.

2.2.2 Challenges of growing palm trees

Although palms give the impression of being low-maintenance in the landscape, they are susceptible to a number of diseases, pests, and nutrient deficiencies. Growing palms presents unique challenges that must be overcome. These include using resources efficiently, ensuring environmental sustainability, and optimizing yields. In the 2020s, palm cropping systems face

a number of pressing challenges. These include the increasing incidence of new and existing pests and diseases, notable vulnerability to changing climatic conditions, particularly in terms of higher temperatures and unpredictable rainfall patterns, and downstream issues related to supply chains and consumer attitudes [El-21] [MGP21].

Figure 2.2 illustrates the main challenges in palm cultivation. These challenges include low fruit yields, problems with fruit quality and generation time, susceptibility to pests and diseases, presence of unproductive male palms, ambiguity in distinguishing palm varieties, sensitivity to soil and water salinity, limited response to fertilizers, water quality problems, and challenges associated with the irrigation system. All of these factors highlight the complexity of palm cultivation and the need for precision agriculture to effectively address these issues.

| | | |
|-----------------------|-------------------|-----------------|
| Low yield | Quality issues | Pest & diseases |
| Non-productive plants | Variety confusion | Salinity |
| Fertilizer | Water quality | Irrigation |

FIGURE 2.2: Summary of main challenges in palm cultivation

2.2.3 Palm Cultivation opportunities

Table 2.1 summarizes the key challenges in palm cultivation and the corresponding solutions for precision agriculture to effectively address them. Precision agriculture uses real-time data, sensors, and advanced analytics to optimize resource allocation, monitor plant health, and increase overall palm productivity. These solutions aim to address issues such as low yield, fruit quality, pests, unproductive plants, varietal confusion, salinity, fertilizer management, water quality, and irrigation practices. By addressing these very challenges, precision agriculture contributes to sustainable and efficient palm production.

2.3 Multi-data sources for Palm Precision Agriculture

Several important data sources for the analysis of the agricultural process could be identified and are analyzed below:

| Challenges | Precision Agriculture Solutions |
|-----------------------|---|
| Low Yield | Optimization of resource allocation, including water and nutrients, based on real-time data. |
| Quality Issues | Continuous monitoring of fruit quality with adjustments in care and management practices. |
| Pest and Diseases | Early detection using sensors and data analytics, enabling timely intervention. |
| Non-productive Plants | Identification and removal of non-productive male palm trees through monitoring. |
| Variety Confusion | Accurate palm variety identification using data collection and management systems. |
| Salinity | Soil salinity management through precise regulation of irrigation and fertilization. |
| Fertilizer | Determination of specific fertilizer requirements for each palm to prevent overuse or underuse. |
| Water Quality | Monitoring of water quality to ensure clean and suitable irrigation water. |
| Irrigation | Optimization of irrigation practices to provide the right amount of water at the right times. |

TABLE 2.1: Precision Agriculture Solutions for Palm Cultivation Challenges

2.3.1 Satellite images and Remote Sensing

Remote sensing definition:

"Remote sensing can be broadly defined as the technology used for measuring the characteristics of an object or surface from a distance (Bird, 1991)" [Con91].

Remote sensing is based on the principle of interaction with electromagnetic radiation and enables the collection of valuable information about the Earth's surface and its properties. This method uses sensors on satellites or aircraft to detect electromagnetic radiation emitted, reflected, or absorbed by the Earth's surface in various wavelengths, including the visible range, infrared, and microwaves [Con91]. The principles of remote sensing include several important aspects:

1. **Electromagnetic radiation:** Remote sensing is based on the interaction of electromagnetic radiation with the Earth's surface. This sensor measures the emission, reflection, and absorption of electromagnetic radiation across a range of wavelengths, including visible light, infrared radiation, and microwaves, by the Earth. Satellites and aircraft sensors detect this radiation to provide images and data to characterize the Earth's properties.
2. **Energy interaction:** Electromagnetic radiation interacting with the Earth's surface

is subject to processes such as absorption, transmission, and scattering. Different materials have unique spectral fingerprints that allow remote sensing devices to distinguish between vegetation, water bodies, urban areas, and natural resources.

3. **Spectral bands:** Remote sensing device sensors detect energy in specific spectral bands, each corresponding to a range of wavelengths. Researchers have used these bands to identify land cover types, infer surface features, and detect changes over time by analyzing radiation intensity.
4. **Resolution:** Remote sensing images have different geographic, spectral, radiometric, and temporal resolutions. Spatial resolution defines the smallest detectable object on the ground, while spectral resolution refers to the ability to distinguish between wavelengths.
5. **Georeferencing:** Accurate georeferencing is critical in RS to assign geographic coordinates to each image pixel. Georeferenced data enables spatial analysis, map creation, and integration with geographic information systems (GIS).

RS data collection relies on two main types of sensors: passive and active. These sensors enable the collection of valuable information about the Earth's surface through various mechanisms. Active sensors such as synthetic aperture radar (SAR) and light detection and ranging (LiDAR) generate energy and monitor subsequent responses for imaging purposes, while passive sensors detect natural energy released or reflected from the Earth's surface [FSK21]. Images from passive sensors are classified into three categories based on their spectral bands: optical (visible and near-infrared), thermal (infrared), and microwave (longer wavelengths). Based on these different spectral ranges, the images produced by passive sensors can be divided into four main types:

1. **Panchromatic images:** These images, presented in shades of gray, are single-band images of radiation in the visible range (0.4 to 0.7 micrometers). They are characterized by high spatial resolution.
2. **Multispectral images:** These images are obtained from multiple bands with different wavelengths (usually less than ten) and provide spatial positions with unique spectral information.
3. **Hyper-spectral images:** These images are generated from numerous bands of different wavelengths (often hundreds) and provide comprehensive insights into object properties. This requires decomposing the components of each pixel to extract the material spectra.
4. **Multi-sensor images :** They are acquired from several different sensors. The goal is to use the complementarity and redundancy of continuous information in these images to develop a better interpretation. Examples of such images are optical images from passive sensors such as SPOT, LANDSAT and RADARS images from active sensors such as ERS, JERS, etc.

In summary, the synergy between passive and active sensors in precision agriculture is remarkable. Passive sensors can detect variations in plant health and water content, enriching decision-making for interventions. Active sensors, on the other hand, explore soil conditions, water dynamics, and plant structures to predict yield and distinguish between different crop species. With a solid understanding of remote sensing principles, we can now look at several platforms that facilitate the collection of invaluable data for smart precision agriculture. Each offers unique capabilities that provide farmers with real-time insights and actionable information.

Satellites : are sophisticated platforms equipped with remote sensing instruments that gracefully orbit the Earth, collecting data from the far reaches of space and providing a panoramic view of the planet’s surface [NAS14].

Satellites, powered by the intricate principles of physics and engineering, serve as remarkable tools for acquiring vital information, improving communications, protecting the environment, exploring the sky, and deepening our understanding of the complex world we inhabit and the vast cosmos that surrounds it. They serve as a linchpin in modern remote sensing, providing unparalleled benefits through their comprehensive coverage and ability to monitor dynamic changes over time [BAF17; FBF18; ABF23]. Their contribution to crop management, resource allocation, and overall agricultural efficiency is obvious, providing invaluable data and insights that accelerate breakthroughs in these areas. Figure 2.3 illustrates the many benefits of satellites in precision agriculture.

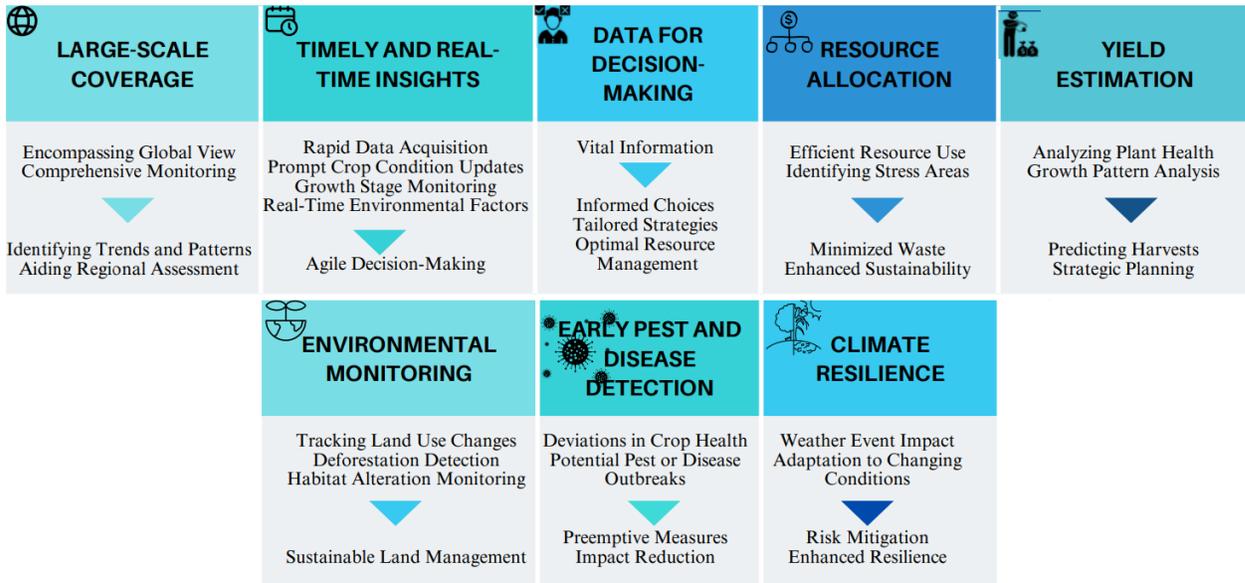


FIGURE 2.3: Key Influences of Satellites on Precision Agriculture

2.3.2 Drones and Unmanned Aerial Vehicles (UAVs)

An UAV, also known as a drone, is an aerial vehicle that operates without a human pilot or passengers on board. These vehicles, when controlled by a human operator, can range from full automation to remote control and have varying degrees of autonomy [BTK18; YA19]. UAVs are designed to perform a variety of tasks and use advanced technologies and sensors to navigate, collect data, capture imagery, and execute missions with precision. Although some UAVs are equipped with on-board intelligence that enables them to navigate and make autonomous decisions, many UAVs are controlled by human pilots who control the vehicle’s movements and operations from a remote location. The versatility of UAVs makes them indispensable for a wide range of applications, from aerial surveillance and mapping to scientific research and agricultural monitoring. In the field of precision smart agriculture, UAVs offer several advantages due to their maneuverability, flexibility, and high-resolution data capabilities [Kim+19; Mil19]. Figure 2.4 shows some of the key benefits of UAV data for smart precision agriculture.

| HIGH SPATIAL RESOLUTION | FLEXIBLE / ON-DEMAND DATA ACQUISITION | TIMELY CROP MONITORING | PRECISION APPLICATION | DATA INTEGRATION |
|---|--|---|---|--|
| Detailed Crop Observations Accurate Health Assessment | Rapid Deployment Targeted Area Coverage Real-Time Insights | | Targeted Input Delivery Fertilizers, Pesticides, Water | Comprehensive Understanding Satellite Imagery, Ground Sensors |
| Precise Growth Monitoring Effective Pest Detection Informed Local Decisions | Customized Monitoring Dynamic Decision Support | Growth Stage Assessment Planting Density Evaluation Flowering & Maturity Tracking Swift Issue Intervention | Resource Optimization Minimal Waste | Enhanced Decision-Making Improved Predictive Models |
| TOPOGRAPHIC MAPPING | EARLY DETECTION OF ISSUES | COST-EFFECTIVE | DATA CUSTOMIZATION | IMPROVED DECISION-MAKING |
| Topographic Mapping High-Resolution Maps Terrain Understanding Drainage Patterns | Subtle Vegetation Changes Pest, Disease, Nutrient Deficiency Detection | Alternative to Traditional Methods Efficient Large Area Coverage | Tailored UAV Missions Specific Goals and Requirements | Data-Driven Decisions Optimization of Inputs |
| Irrigation Optimization, Soil Erosion Prevention | Targeted Treatments Issue Prevention | Lower Data Collection Costs | Custom Monitoring and Evaluation | Increased Yield Reduced Costs Enhanced Farm Management |

FIGURE 2.4: Key Influences of UAVs on Precision Agriculture

In essence, drone data plays a critical role in improving the precision and efficiency of agricultural practices. They enable farmers to proactively manage their crops, respond to challenges, and make informed decisions that lead to improved productivity and sustainability.

2.3.3 Ground Sensors and IoT Devices

Ground Sensors

Ground sensors, a key component in agricultural IoT systems, function as integrated IoT devices. These devices consist of multiple modules and are critical for collecting, transmitting and monitoring Big Data in agriculture. Basically, IoT technology connects everyday objects and devices to the Internet, enabling effortless data collection, transmission and exchange without the need for direct human intervention. The concept of IoT is illustrated in Figure 2.5 [Kho+15a]. Sensors equipped with computing power are strategically positioned in regions with Internet connectivity. These sensors operate within a network that enables seamless communication between devices and objects regardless of their location [GDR16; Kha+22; Dri+21]. Specialized systems help collect data by locating and transmitting information across a range of communication devices within an IoT architecture. Linking devices through various access networks, including radio frequency identification (RFID) and wireless sensor devices [Saf+20b] [Saf+20a], is enabled by communication solutions such as Wi-Fi, ZigBee, Bluetooth and GSM. This comprehensive overview connects the context, evolution, and applications of IoT in precision agriculture and offers insights into its operating mechanisms and potential [BTK17].

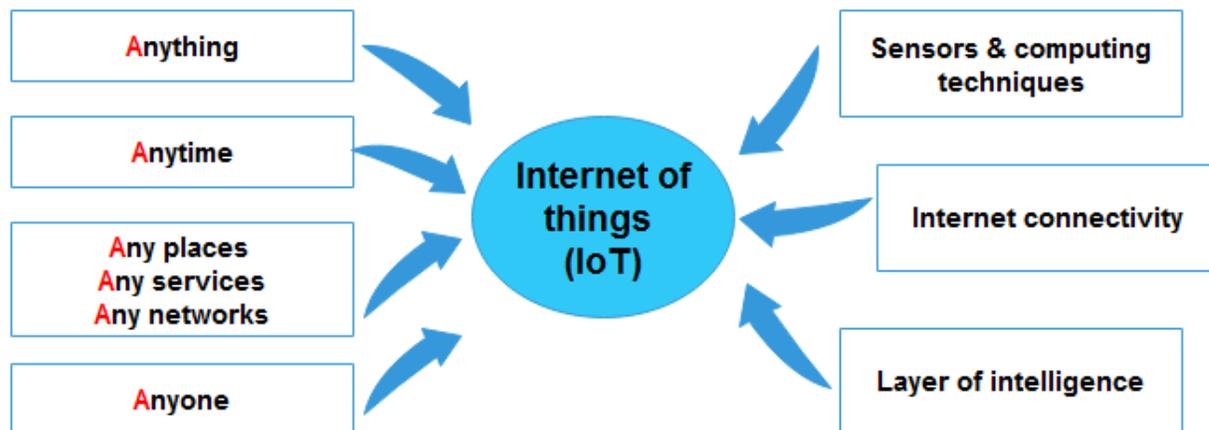


FIGURE 2.5: Concept of the Internet of Things [Haj+21]

In precision agriculture, this connectivity has sparked a revolution in data-driven farming practices [SP16; Sto+16]. By integrating IoT sensors into agricultural processes, farmers can monitor, analyze, and act on insights in their fields in real time. This integration ushers in an era of informed decision-making that can optimize resource use, increase yields, and ensure environmental sustainability. This section discusses the applications, benefits, and challenges of IoT in precision agriculture and highlights its central role in transforming today's agricultural practices [Far+19; FA21].

IoT Sensors

Sensors are devices that detect and respond to various inputs, such as light, motion, pressure, heat, and humidity. They convert these inputs into signals that can be interpreted by humans, making them valuable for analysis and processing. These sensors are used in a variety of applications, from security systems that detect motion to HVAC systems that measure temperature. They are also being integrated into everyday objects such as smartphones, vehicles and home appliances. Sensors work by detecting physical or chemical changes in the environment and converting them into electrical signals. The type of sensor used depends on the change it is intended to detect (see Figure 2.6). A temperature sensor, for example, detects temperature changes and transmits them as electrical signals for evaluation [Haj+21; Ati+20].

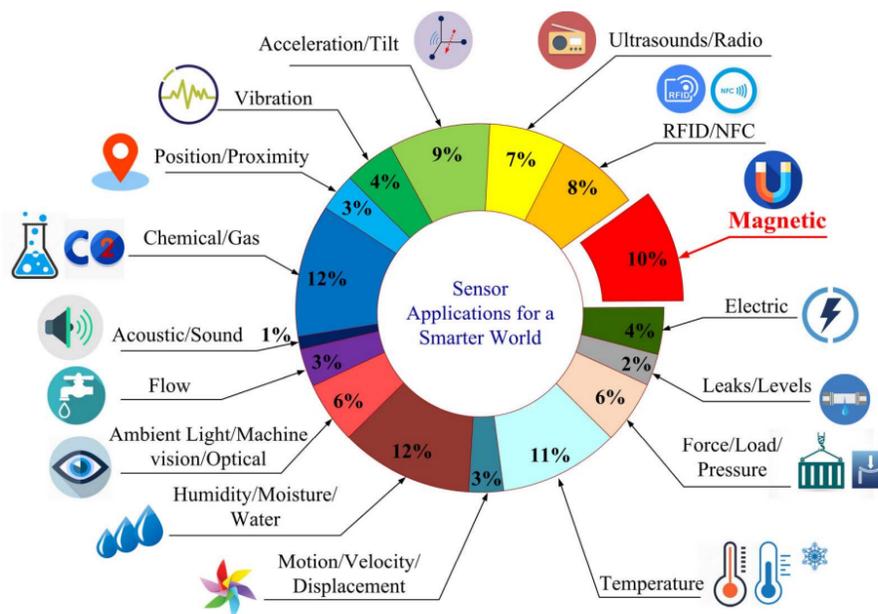


FIGURE 2.6: Common sensor categories in IoT applications.

In precision smart agriculture, IoT sensors play a transformative role. They offer important insights into ecological and agricultural aspects. Each sensor, developed in different shapes and sizes, captures specific data that is important for making informed decisions. These sensors are widely used in agriculture to collect and transmit real-time data about environmental and crop conditions. IoT-driven precision agriculture uses sensors to monitor fields and automate irrigation based on variables such as temperature, light, humidity, and soil moisture. These applications reduce manual labor and increase farming efficiency. Farmers can monitor their fields remotely, enabling precise resource use for greater sustainability and productivity [Liu+19; GK16]. So, integrating IoT technologies into precision agriculture enables data-driven decision-making and promises significant improvements in agricultural practices and resource management.

2.3.4 Geographic Information System (GIS)

Geographic information systems are playing a central role in the advancement of smart precision agriculture, revolutionizing the way farmers manage and optimize their land. By integrating spatial data and technologies, GIS offers a multifaceted approach to agricultural decision-making. These systems enable farmers to map, analyze and understand the geographic differences in their fields by incorporating multiple layers of data such as soil types, topography, weather patterns and crop health. By integrating real-time sensor data with historical information, farmers can use GIS to make informed decisions about irrigation, fertilization and crop management. GIS-based mapping tools help determine optimal cropping patterns and analyze yield variability, enabling precision farming techniques that maximize productivity while minimizing resource use. In addition, GIS helps monitor the spread of pests, diseases, and weeds, enabling targeted interventions and the implementation of effective control measures. Overall, GIS is a cornerstone of smart precision agriculture, facilitating data-driven decisions and increasing operational efficiency through the use of spatial information and analysis [EG21].

2.4 Big Data Management for Precision Agriculture

2.4.1 Big data characteristics

The use of big data in palm agriculture presents several unique features and difficulties, as shown in Figure 2.7. These challenges are intrinsically linked to broader big data challenges, including those related to data volume, variety, and velocity [Ous+18]:

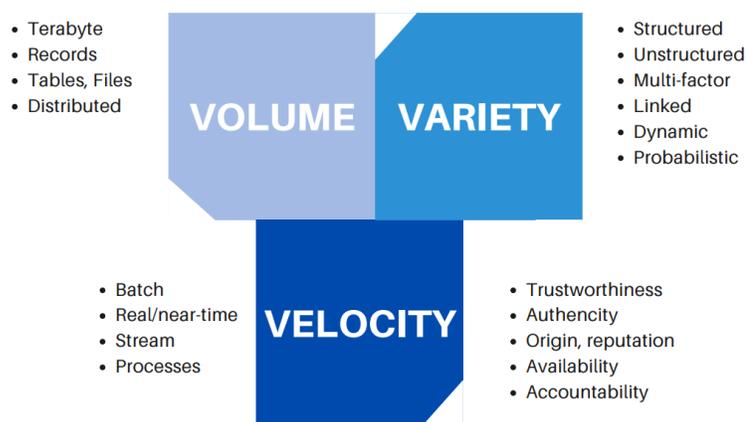


FIGURE 2.7: Big data challenges

Volume: this is related to the sheer volume of data. At PA, data is being generated on an unprecedented scale. Farmers are collecting data from a variety of sources, including IoT sensors, remote sensing imagery, and equipment sensors. This includes information on soil

conditions, weather patterns, crop health, etc. Managing and analyzing such large amounts of data using traditional methods can be challenging.

Variety: refers to the different structural nature of a data set. At PA, you can find data in various forms and formats, including structured data (e.g., sensor readings), unstructured data (e.g., images captured by drones), and semi-structured data (e.g., weather forecasts). In addition, the data can have different formats, such as text, images, time series data, and geospatial data. Managing this diversity is a fundamental challenge in Big Data analytics for agriculture and specifically for PA.

Velocity: concerns the speed at which data must be generated, analyzed, and processed. At PA, real-time data is critical for timely decision-making. IoT sensors, for example, provide constant updates on soil moisture or weather conditions, allowing farmers to make immediate adjustments, such as irrigation or fertilization. The speed of data is crucial for optimizing farming operations and responding immediately to changing conditions.

2.4.2 Distributed Computing

Distributed computing is a vital technology in precision agriculture that facilitates the processing of vast amounts of data generated from various sources. This involves utilizing multiple networked computers to perform computational tasks collaboratively. In precision agriculture, where data is generated from sources such as satellite imaging, drones, ground sensors, and IoT devices, distributed computing plays a critical role in managing these data volumes. This approach allows for parallel processing and analysis of extensive datasets, accelerates data processing, and enables timely decision-making. Distributing tasks across multiple computing nodes significantly reduces the computational load on individual systems, leading to faster data analysis, which is crucial for real-time decision support in agricultural practices. Additionally, distributed computing enhances fault tolerance and scalability by spreading the workload across a network of interconnected devices, providing a robust framework for managing growing data requirements in precision agriculture.

2.4.3 Big data technologies

Apache Hadoop

an essential component of Big Data infrastructure, is an open source project launched by the Apache Foundation. As opposed to running a specialized data center, the architecture is designed for the distributed storage and processing of enormous amounts of data on computer clusters made of commodity hardware. Structured, semi-structured, and unstructured data can be processed by many frameworks and tools that are part of the Hadoop ecosystem [Ber+16; EJK21]. The main components of Apache Hadoop are the Hadoop Distributed File System (HDFS) for storage and MapReduce for processing. When faced with a large task, Hadoop splits it into multiple task chunks and distributes them to different nodes within a cluster [Sha+19].

HDFS

HDFS is a scalable and distributed file system inspired by the Google File System (GFS) to address the challenges posed by the increasing amount of data that cannot be accommodated on a single machine. HDFS is a distributed file system that utilizes commodity hardware. Although it shares similarities with other distributed file systems, it is distinct in its design for low-cost hardware and high fault tolerance. HDFS allows for rapid access to application data and is well suited for applications that handle large data collections.

Built on a master/slave architecture, the HDFS cluster consists of a single Name Node serving as the master server responsible for managing the file system namespace and controlling client access to files. The slaves in the cluster are a group of Data Nodes, typically one for each node in the cluster, and they handle storage linked to the nodes on which they operate. NameNode oversees file system namespace activities, such as opening, closing, and renaming files and directories. It also influences the mapping of blocks to DataNodes. The DataNodes, on the NameNode's command, handle read and write requests from the file system's clients, as well as block creation, deletion, and replication. Figure 2.8 describes the HDFS architecture.

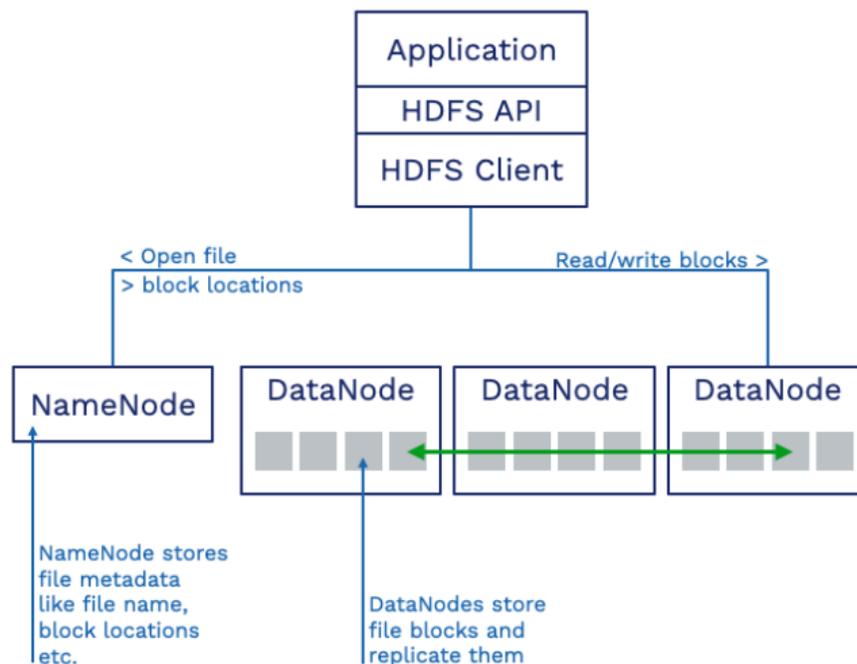


FIGURE 2.8: HDFS Architecture

NoSQL databases

The name of this technology not only alludes to the SQL database [WB13]. Unlike traditional relational databases, which are unsuitable for managing large amounts of unstructured and

semi-structured data, NoSQL databases can perfectly manage large amounts of unstructured and semi-structured data. In other words, they are managed by a non-relational DMS and do not require a fixed schema (i.e., schema-less) [HF18]. NoSQL databases offer four alternative data model storage options (key value model, column data model, document data model, and graph data model), each with its own advantages and disadvantages [Cor+17]. There is no one solution that can be considered far superior to the others; however, some databases are better suited to addressing particular problems.

Time-Series Database

A time-series database (TSDB) is a specialized database designed for the efficient management of time-series or time-stamped data, such as metrics, events, or measurements recorded over time. Unlike conventional databases, TSDB are optimized for queries and analyses that focus on changes over time. The key features of TSDBs include data co-location to enhance query performance, support for fast and simple range queries, high write performance to accommodate rapid data recording, efficient data compression techniques, and scalability to manage the substantial growth of time-series data. TSDBs are particularly critical in the context of the IoT, where the proliferation of connected devices generates vast amounts of timestamped data. The popularity of TSDBs has increased with the increased adoption of IoT technologies because these databases offer efficient storage solutions for time-stamped data from sensors and devices. Common applications of TSDBs include IoT data storage, DevOps monitoring, and real-time data analysis, demonstrating their versatility and significance in contemporary data-management scenarios [NYZ17].

Cloud Computing

Cloud computing refers to the delivery of computing services—such as storage, processing power, databases, and software—over the internet. In the context of precision agriculture, cloud computing plays a pivotal role in handling and processing the enormous amounts of data generated from various sources, like IoT devices, drones, satellites, and other sensors deployed in fields. Rather than processing programs on local or personal computers, this type of computing relies on shared, remote servers made available over the Internet for data management, storage, and processing [Dup+]. Since many smart environment applications need to analyze large amounts of streaming and historical data with low latency for data processing, it makes sense to propose cloud computing technologies to increase the speed of data analysis [Yan+19].

The use of cloud computing in modern agriculture is a critical aspect of managing the vast amounts of data generated by IoT devices. This technology allows farmers to access shared computing resources through personal computers and the Internet, eliminating the need for physical infrastructure ownership. Cloud computing is organized into three layers—System, Platform, and Application—and offers various services such as Infrastructure as a Service (IaaS), Platform as a Service (PaaS), and Software as a Service (SaaS). These services are

delivered over the Internet and can be deployed through public, private, community, or hybrid cloud models [EJK21].

The effective management of IoT big data in smart agriculture is essential for realizing the full potential of data-driven farming. By leveraging cloud computing, farmers and stakeholders in the agricultural sector can make informed decisions, enhance productivity, optimize resource utilization, and contribute to the sustainability and efficiency of modern agricultural practices.

2.5 Data Analytics For Precision Agriculture

2.5.1 The data analytics process

Data analytics is about systematically exploring, interpreting, and transforming large data sets to extract meaningful insights and valuable information. Through the use of various analytical techniques, statistical methods, and technological tools, data analysis uncovers patterns, trends, and correlations in structured and unstructured data. This process enables organizations to make informed, data-driven decisions, predict future trends, and optimize operations [SC19]. Whether in business, science, healthcare or agriculture, data analytics plays a central role in transforming raw data into actionable knowledge. It enables companies and professionals to gain valuable insights, increase efficiency, and gain a competitive advantage in their respective fields [Ahm+17].

The process of data analysis involves five main phases, which are illustrated in Figure 2.9. The first phase is about gathering requirements, i.e., identifying the problem, understanding the needs of the business, and determining the purpose of the data analysis. Although this phase can be time-consuming and demanding, it lays the foundation for the subsequent steps [Ahm+17]. Once the requirements are identified, the next phase is about data collection. This phase is about collecting data, which is then cleaned, filtered and sorted to ensure accuracy and improve the efficiency of the analysis. Then the appropriate analytical techniques are used to process and analyze the data. Finally, in the last phase, the results and outcomes of the analysis process are interpreted and evaluated [Doj23].

2.5.2 Methods for data analysis

The method has delineated four principal categories of data analytics, as depicted in Figure 2.10: descriptive, diagnostic, predictive, and prescriptive analytics [Mar+17]. Below are concise descriptions of each of these four types of data analytics:

- **Descriptive Analysis:** categorizes data to reveal emergent patterns, employing techniques like data aggregation and statistical measures for frequency, dispersion, and central tendencies.

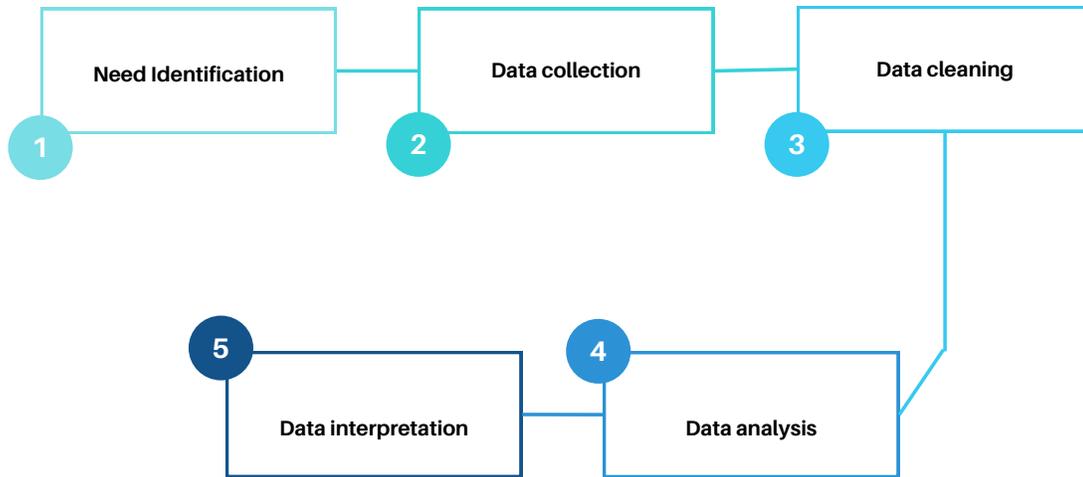


FIGURE 2.9: Data analytics process

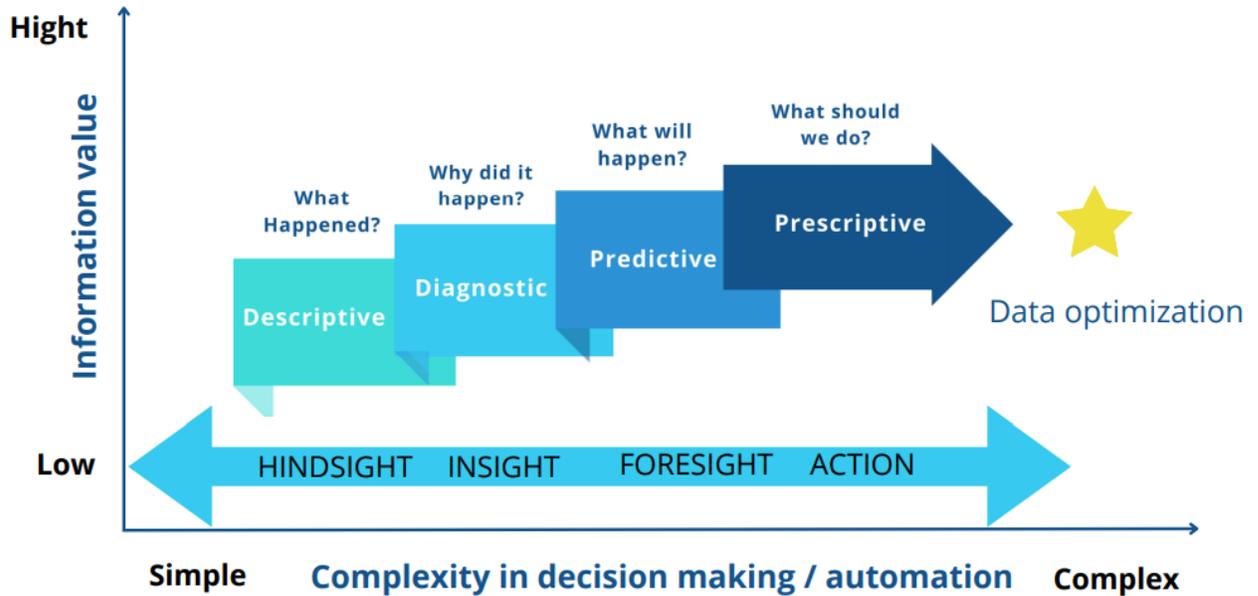


FIGURE 2.10: Data analysis methods

- **Exploratory Analysis:** This approach explores diverse datasets to uncover potential relationships or driving patterns, aiding in framing hypotheses for further investigation, such as in data mining for hypothesis generation.

- **Diagnostic Analysis:** aims to discern why certain patterns exist, employing methods like hypothesis testing and distinguishing between correlation and causation to understand root causes.
- **Predictive Analysis:** focuses on forecasting future events, guiding decisions about product features or market performance, and utilizing machine learning and AI alongside prior analytic results.
- **Prescriptive Analysis:** determines the most effective strategies for implementing decisions, utilizing machine learning algorithms to analyze vast datasets and provide actionable recommendations across business functions.

2.5.3 Analytical Functions

Various analytical techniques have been recommended to handle distinct analytical tasks. These methods encompass:

- **Classification:** Utilizing classification algorithms to identify the class of a new observation from a set of categories based on acquired knowledge from the input data widely used in Machine Learning, it finds applications in fields such as image recognition, sentiment analysis, and spam filtering.
- **Clustering:** Involves using clustering methods to group similar items based on specific characteristic qualities. Valuable for unveiling patterns in data, it's commonly employed in market segmentation, social network analysis, and image segmentation.
- **Recognition:** trains machines to identify and categorize events, objects, places, or individuals from images or video data. Mainly utilized in computer vision, it applies to areas like facial recognition and handwriting identification.
- **Detection:** Analyzing photos and videos to detect items or situations is widely used in surveillance systems, medical imaging, and quality control in manufacturing.
- **Prediction:** An advanced analytics system uncovering trends related to future occurrences and proposes necessary actions. Applied in predictive maintenance, demand forecasting, and fraud detection.
- **Analysis:** involves cleaning and processing data to extract relevant information supporting decision-making. A crucial step in data analytics, it finds use in fields such as business intelligence, customer profiling, and social media analysis.
- **Recommendation:** Uses data mining techniques to offer clients product suggestions and appropriate courses of action. Commonly employed in recommendation systems, personalized marketing, and e-commerce.

2.5.4 Data Analytics Techniques

In this section, we examine various Data Analytics techniques, including computer vision, machine learning, and deep learning, and how they interrelate. These technologies are fundamental to extracting insights from complex data, as illustrated in Figure 2.11. We explore the intricacies of these methodologies and their interdependencies to highlight their crucial role in data analysis. It is important to note that these techniques play pivotal roles, facilitating advancements in precision agriculture, crop monitoring, environmental sensing, and the development of smart ecosystems. These technologies are instrumental in optimizing resource management, enhancing crop yield predictions, and fostering sustainable practices within smart agricultural and environmental settings.

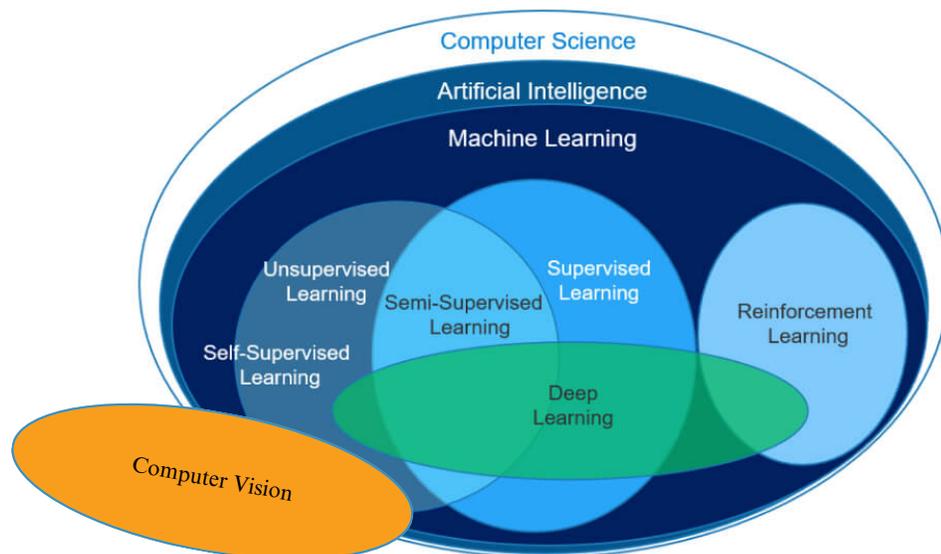


FIGURE 2.11: Data analysis techniques

Computer vision

Computer vision is an area of artificial intelligence that allows machines to perceive and understand visual data such as images and videos. This technology involves systems that are capable of extracting significant information, identifying objects, and comprehending visual content similar to human vision. Computer vision has numerous applications in multiple industries, including healthcare, automotive, security, and agriculture. Its applications include object recognition, image analysis, video understanding, facial recognition, autonomous vehicle navigation, and quality control in manufacturing processes.

Computer vision involves several basic tasks, such as image classification, object detection/recognition, semantic segmentation and instance segmentation as illustrated in Figure 2.12. The implementation of these tasks is crucial for progress in the field of computer vision and the improvement of its practical application.

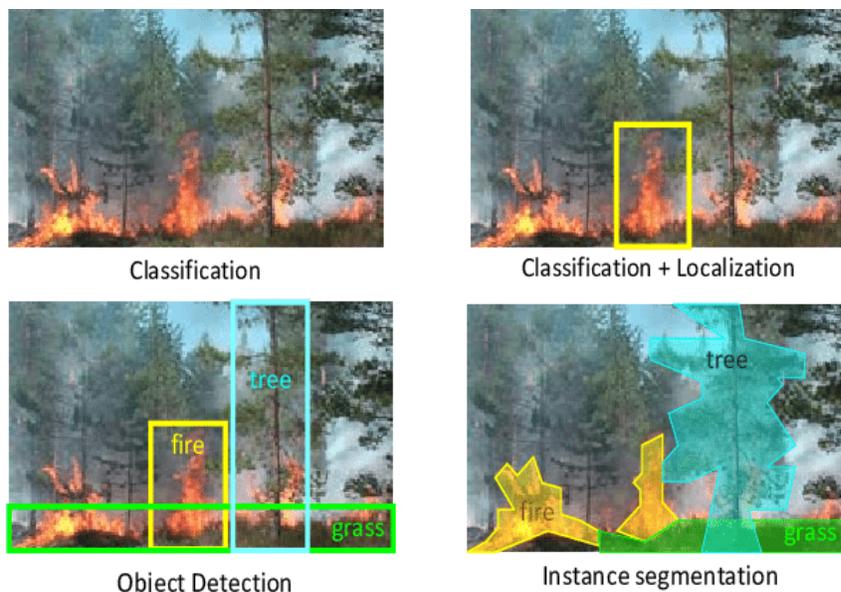


FIGURE 2.12: Computer vision tasks

Object detection

Object detection techniques are the foundation for the artificial intelligence field. It involves developing models capable of identifying object instances within an image and accurately assigning appropriate class labels to these instances. To achieve this, the instances are encompassed by bounding boxes that define the smallest rectangle spatially containing the objects. This spatial delimitation allows for precise localization of the objects in the image. Figure 2.13 depicts the progression of object detection techniques, illustrating the transition from traditional machine-learning-based methods for object detection to more advanced deep-learning-based approaches.

Machine learning-based methods utilize image-based feature extraction techniques, such as Speeded-Up Robust Features (SURF), Histogram of Oriented Gradients (HOG), and Local Binary Pattern (LPB), followed by a classification algorithm to generate the final results. Conversely, deep learning-based methods such as R-CNN and YOLO automatically extract features using deep learning algorithms, specifically CNNs. Some object detection models are further modified to produce pixel-wise predictions, which enable the achievement of the instance segmentation task and will be presented in the subsequent section.

Advancements in ML and DL have significantly accelerated the integration of Artificial Intelligence (AI) across diverse domains, fundamentally transforming pivotal operations [Qiu+16]. Within this scope, AI empowers computers to perform tasks that traditionally require human intelligence, including image recognition, speech-to-text conversion, language translation, and, notably, computer vision. The evolution of AI capabilities, particularly in the

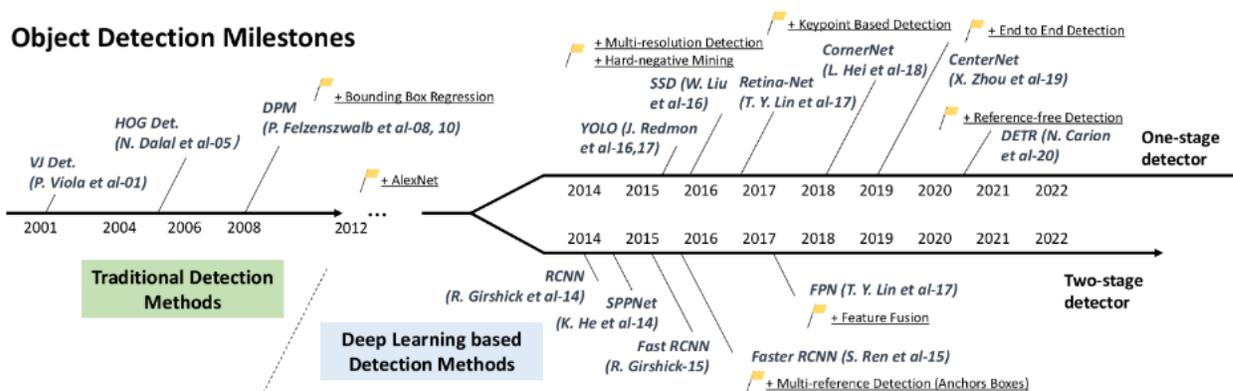


FIGURE 2.13: A road map of object detection [Liu+20]

realm of computer vision, has shown remarkable progress over the years.

Machine Learning

ML, a subfield of AI, allows computer systems to learn and improve their behavior by training on specific data sets. Once trained, the model acquires the ability to make decisions without explicit programming. This is a key property that underlines the efficiency and adaptability of AI systems in various applications [AJK23].

ML is a pivotal technique that aids in unraveling patterns within datasets and offers descriptive, predictive, and prescriptive insights. Selecting appropriate data for constructing ML models is paramount and requires careful consideration. Figure 2.14 illustrates various machine-learning techniques. Supervised learning utilizes labeled data to train models and employs various algorithms such as logistic regression, support vector machines (SVM), decision trees (DT), random forests (RF), naive Bayes, and artificial neural networks (ANN) for classification. In contrast, unsupervised learning identifies data patterns without classification labels and employs techniques such as clustering and grouping to discern trends within datasets. Semi-supervised learning incorporates both labeled and unlabeled data, necessitating the establishment of relationships among the data distributions. Reinforcement learning (RL) guides decision-making in uncertain environments by rewarding desired behaviors and employing models such as Markov decision processes (MDP) and Q-learning for sequential decision-making [MCM13].

2.5.5 Deep Learning for object detection

Deep learning is a type of machine learning and artificial intelligence that draws inspiration from the structure and functionality of the human brain's neural networks. It employs advanced, multilayered neural networks to process and learn from vast amounts of data.

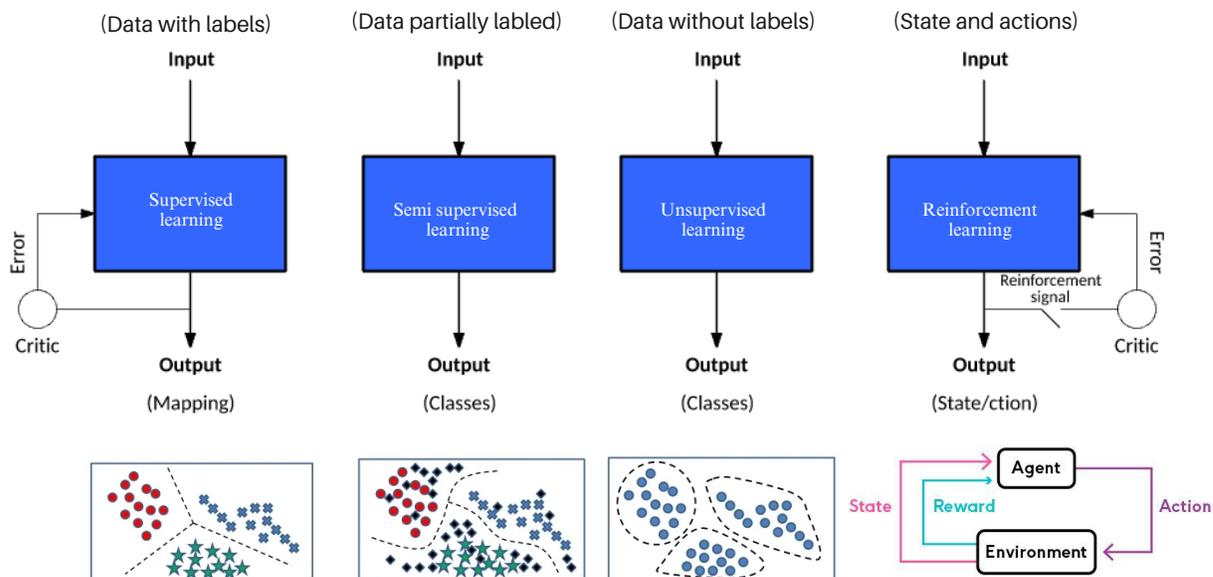


FIGURE 2.14: Machine learning types

The fundamental principle underlying deep learning involves creating intricate hierarchical representations of data to derive high-level abstractions, patterns, and features.

The primary goal of deep learning is to automatically uncover intricate patterns and representations within data. Rather than depending on features or rules crafted by humans, deep learning algorithms learn to recognize patterns from the data itself through multiple layers of interconnected nodes, referred to as neurons. These multiple layers enable the system to progressively extract higher-level features and abstractions from raw data inputs.

Deep learning, characterized by its multilayered approach, constructs computational models that represent complex data abstractions. Integral to this advancement are key enabling algorithms in deep learning, such as generative adversarial networks, convolutional neural networks, and model transfers, which fundamentally transform our comprehension of information processing.

Deep learning, commonly referred to as DL, has assumed an increasingly significant role in various aspects of our lives. Its profound impact is evident in critical domains such as cancer diagnosis, precision medicine, self-driving vehicles, predictive analytics, and speech recognition. Unlike the labor-intensive process of crafting features in traditional learning, classification, and pattern recognition systems, which struggle to scale for larger datasets, deep-learning algorithms excel. In many scenarios, especially with intricate problems, deep

learning surpasses the constraints of earlier shallow networks, which hinders the efficient training and extraction of hierarchical representations from multidimensional data. Deep neural networks (DNNs) employ multiple layers with highly optimized algorithms and architectures to process and understand data at intricate levels [GGM23].

Artificial Neural Networks

Artificial Neural Networks (ANNs) are algorithms designed to simulate the functions of neurons in the human brain. An ANN is structured akin to a neuron (Figure 2.15 (a)) and typically consists of three primary layers: the input, hidden, and output layers, as illustrated in Figure 2.15 (b). These layers serve as the fundamental computational units that receive input, process it, and transmit output to the subsequent layer, collectively forming a network. This interconnected structure involves neurons in one layer being linked to neurons in the following layer. ANNs are employed to discern and extract intricate patterns and trends that might pose challenges for other computational methods or human perception

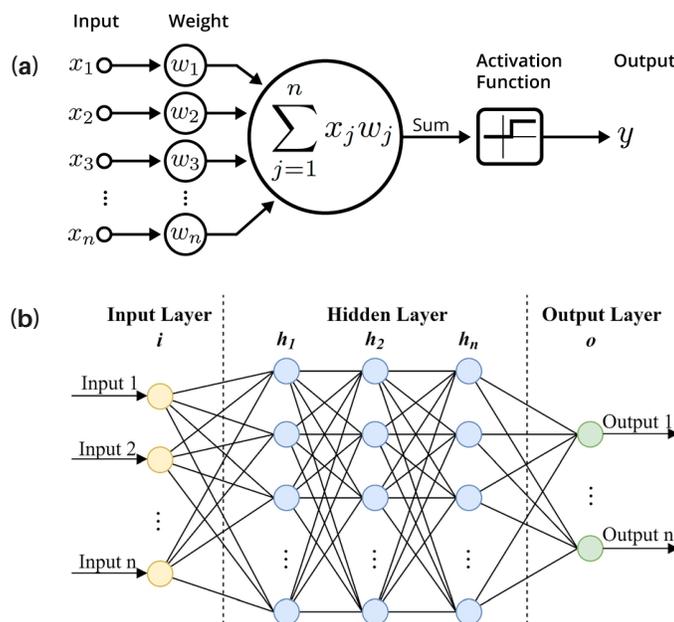


FIGURE 2.15: Neuron Network (a), Artificial Neural Network Architecture (b)

Convolutional Neural Networks

Convolutional Neural Networks (CNN) are very similar to traditional neural networks; the main difference is that the CNNs assume that the input is an image, which reduces the number of learning parameters and takes into consideration the arrangement of pixels and the relationship between them in an image. The CNN architecture, shown in Figure 14, consists of 3 types of layers: convolutional, pooling, and fully connected layers.

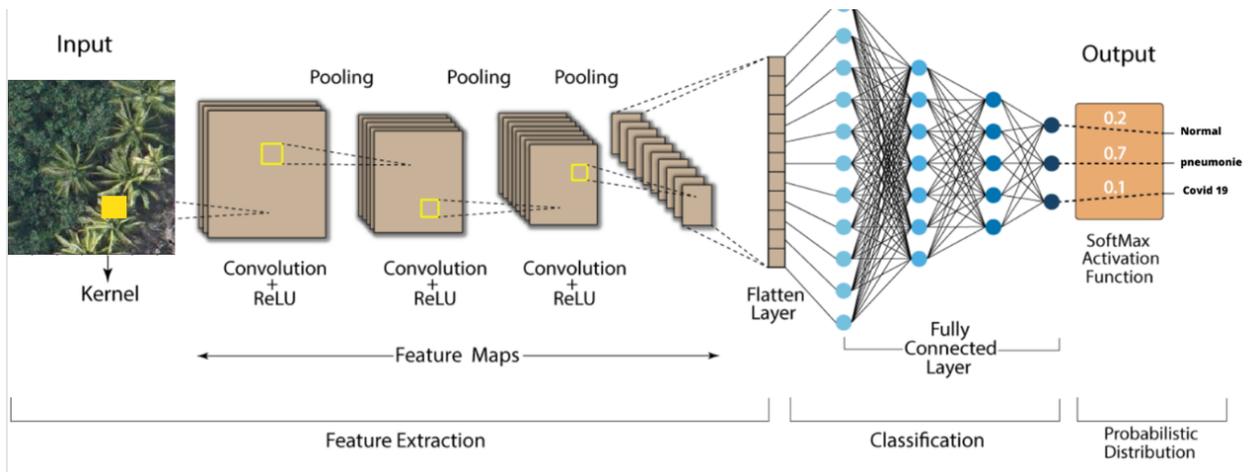


FIGURE 2.16: Conventional Neural Network Architecture

- **Convolutional Layer:**

- Convolution Operation: In this layer, a set of learnable filters or kernels convolves across the input image to extract various features.
- Feature Maps: The output of this layer comprises feature maps that represent specific learned features (edges, textures) from different parts of the input image.

- **Pooling Layer:**

- Downsampling: This layer reduces the spatial dimensions (width and height) of the previous layer’s output, decreasing the number of parameters and controlling overfitting.
- Types of Pooling: Max pooling or average pooling are common methods used in CNNs.

- **Fully Connected Layer:**

- Neural Network Structure: Similar to a traditional neural network, these layers contain neurons connecting to all neurons in the preceding layer, helping to make predictions.
- Classification/Output: The final layers map the extracted features to the desired output (e.g., classification into different categories).

CNNs, through the arrangement and interaction of these layers, can automatically learn hierarchical representations of features from the input data. This ability to detect features at different levels of abstraction makes CNNs highly effective in image recognition and other visual tasks.

One-stage detectors vs Two-stage detectors

Based on the speed-accuracy trade-off and the method followed to perform feature extraction, we can differentiate between two types of object detectors using deep learning: two-stage detectors and one-stage detectors. Figure 2.17. illustrates the distinct steps incorporated within the architecture of one-stage detectors (a) and two-stage detectors (b), respectively.

Two-stage detectors are region proposal-based detection systems. Models like R-CNN, Fast R-CNN [Gir15], Faster R-CNN [Ren+15], and FPN [Lin+17] utilize region-based Convolutional Neural Networks (CNNs). Initially, the region-based CNN identifies various regions in the image where object instances might be located, known as Regions of Interest (ROIs). Subsequently, the features extracted from each proposed region are passed through several fully connected layers, which generate the classes and a confidence score used as a ranking criterion for the region proposals. Generally, these models are more accurate than one-stage detectors, albeit at a slower speed [DZW20].

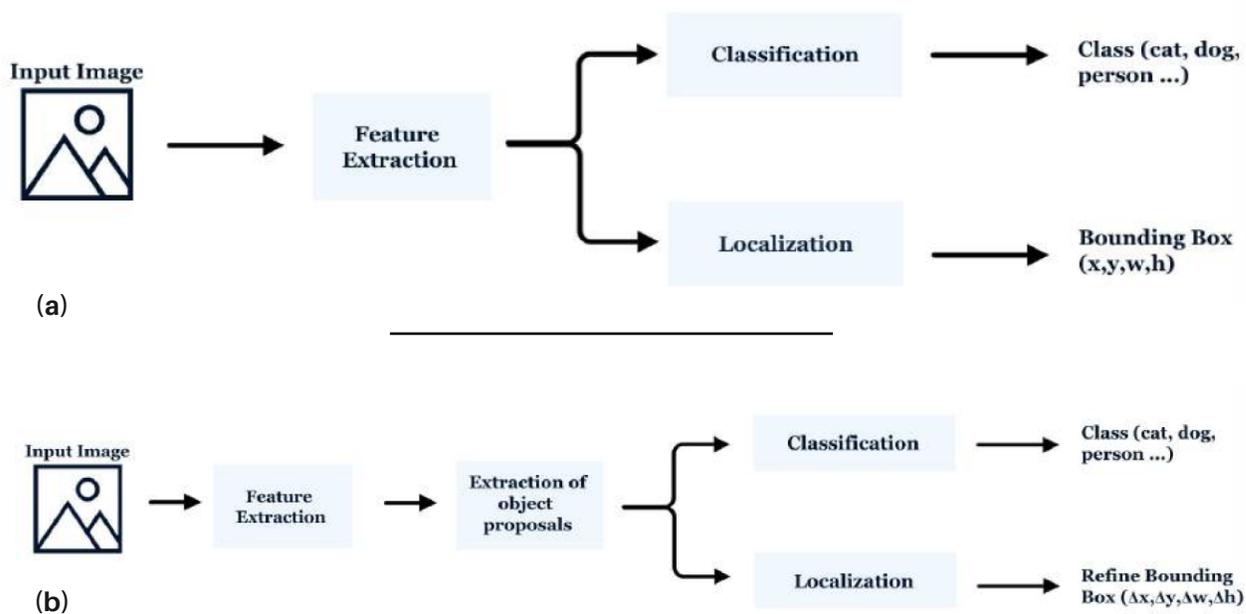


FIGURE 2.17: (a) one-stage detectors, (b) two-stage detectors

One-stage detectors are regression-based detection systems that employ a feed-forward Convolutional Neural Network (CNN) to ascertain the position of the object instances in an image, namely determining the coordinates defining the bounding box surrounding the object. Widely used one-stage detectors include YOLO (You Only Look Once) [Jia+22; Red+16], SSD (Single Shot MultiBox Detector) [Liu+16], and RetinaNet. While one-stage

detectors are appreciated for their simplicity and speed, they exhibit lesser accuracy in tasks such as identifying small objects and generating masks.

2.5.6 The evaluation metrics

This method involves the use of quantitative metrics such as Precision, Recall, and Intersection over Union (IoU), etc., to impartially evaluate the performance of the selected models, Yolov8 and Yolov5. Our goal is to find out which model performs best in accurate palm recognition by quantitatively comparing the models. Furthermore, this approach allows us to identify areas of lower effectiveness in the model that can be improved to increase the overall quality of the object recognition system.

Precision: a measure of the accuracy of a prediction or classification model. It was calculated by dividing the number of true positive predictions by the total number of positive predictions. The formula for accuracy is as follows:

$$Precision = \frac{TP}{TP + FP} = \frac{TP}{\text{All detections}} \quad (2.1)$$

where true positive (TP) denotes the cases where the model correctly recognizes a date palm in an image. False positive (FP) is when the model incorrectly classifies an object as a date palm when it is not, while false negative (FN) means that the model does not recognize a true date palm in the image.

Recall: The recognition score is used to evaluate the model's ability to recognize and identify date palms. The proportion of TP, correctly recognized by a classifier or model was measured by the recall value. It is defined as TP divided by the total numbers TP and FN. The recall formula is as follows:

$$Recall = \frac{TP}{TP + FN} = \frac{TP}{\text{All ground truth}} \quad (2.2)$$

F1-score: The F1 score serves as a valuable metric in binary classification tasks because it provides a single value that effectively reconciles the relationship between precision and recall. It is determined as the harmonic mean of accuracy and recall:

$$F_1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (2.3)$$

Intersection over Union: To evaluate the accuracy of the predicted position of the bounding box for detection purposes, the average IoU must be calculated. This statistic evaluates the degree of overlap between the expected and actual bounding boxes in many images. A higher average IoU means that the model is more accurately locating objects within the images, while a lower value indicates that the model's performance could be improved. The

IoU is a measure of data overlap that is often used to evaluate object recognition systems. The area of overlap between the two bounding boxes was divided by the area of their union. The IoU formula is as follows:

$$IoU = \frac{Bp \cap Bgt}{Bp \cup Bgt} = \frac{\text{Area of Intersection}}{\text{Area of Union}} \quad (2.4)$$

Where: Bp is the predicted bounding box and Bgt is the ground truth bounding box. The operator \cap denotes the intersection of the two bounding boxes and \cup the union. As shown in Figure 2.18.

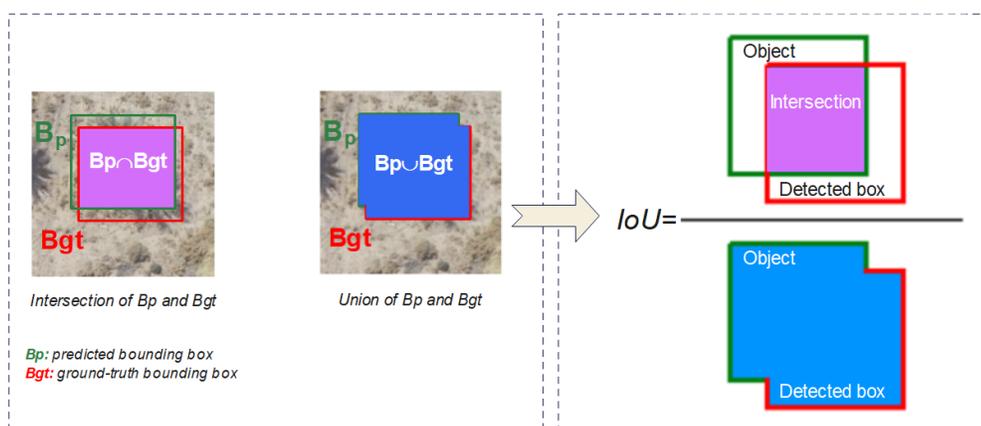


FIGURE 2.18: Visualizing the process of IoU computation between the predicted and true bounding boxes provides insight into the accuracy of the model in locating objects in image recognition tasks

Average Precision is a measure of the overall performance of a classification model over all possible values of a threshold parameter. It was determined by taking the average of the precision values at all recall values. The formula AP is as follows:

$$AP = \frac{1}{n} \sum_{r \in R} \text{precision}(r) \quad (2.5)$$

Where: R is the set of all possible recall values.

AP is the average precision of a given class. It corresponds approximately to the area under the curve (AUC) between precision and recall. AP was evaluated at four different IoU thresholds (0.5, 0.7, 0.8, and 0.9).

Mean Average Precision: is a measure of the overall performance of a classification model across multiple classes. It was calculated as the average AP score for each class. The formula for mAP is as follows:

$$mAP = \frac{1}{c} \sum_{i=1}^c AP_i \quad (2.6)$$

Where: c is the total number of classes. AP_i is the AP in the i th class, and N is the total number of classes to be evaluated.

Average Inference Time per image: This metric indicates the average time required by the YOLOv8 model to process a single image during the inference phase. This statistic provides useful information about the model's efficiency in real-time situations, where the inference speed is critical.

$$AverageInferenceTime(ms) = \frac{\text{Total Inference Time (ms)}}{\text{Number of Images}} \quad (2.7)$$

Where: Total inference time (ms) is the total time required by the YOLOv8 model during inference to process all images in the dataset, measured in milliseconds. Number of images: indicates the total number of images in your dataset.

2.6 Synergistic Integration of Big Data, Deep Learning, and IoT in Precision Agriculture for smart Palm Tree Management

The synergistic relationship between big data, deep learning, IoT, and precision agriculture, particularly in the context of palm tree management, is of utmost importance for the advancement of agricultural practices. The integration of IoT devices, such as ground sensors, weather stations, drones, and automated machinery, into precision agriculture allows for the collection of real-time localized data. These data are continuously monitored to provide a comprehensive understanding of the agricultural environment.

The combination of IoT-generated data with remote sensing data further enriches the big data ecosystem, providing detailed insights at a localized level. For palm tree management, IoT devices provide critical information regarding the specific conditions required for optimal palm growth, such as variations in soil moisture, temperature fluctuations, and the presence of pests.

The fusion of IoT data with advanced deep-learning techniques enables the development of intelligent models that can process real-time, high-resolution data to recognize complex patterns, predict disease outbreaks, optimize irrigation schedules, and precisely identify regions requiring targeted agricultural interventions.

The integration of IoT-generated data with remote sensing information and the application of deep learning techniques significantly strengthen precision agriculture strategies for palm

tree management. This comprehensive approach, which combines big data analytics, real-time IoT-generated data, and deep learning applications, fosters informed decision-making and more efficient agricultural practices.

2.7 Conclusion

In conclusion, this chapter serves as a strategic foundation for our project, highlighting the crucial role of precision agriculture in revolutionizing palm cultivation. By examining the challenges and opportunities of growing palm trees, precision agriculture emerged as a critical enabler, offering targeted solutions for increased efficiency and sustainability. The exploration of remote sensing big data underscores the importance of multi-source data in precision agriculture, emphasizing the diverse range of information from satellites, drones, ground sensors, and GIS. This multifaceted data approach is integral to our project, ensuring a comprehensive understanding of palm ecosystems and enabling nuanced decision-making.

Moreover, insights into big data management, including distributed computing, NoSQL databases, and cloud computing, lay the groundwork for handling the vast datasets inherent in precision agriculture. The ability to efficiently manage and process data is essential to the success of our project, ensuring the seamless integration of information from various sources. The subsequent discussion of data analytics, encompassing methods, functions, and techniques, places our project at the forefront of technological innovation. The incorporation of deep learning for object detection aligns with cutting-edge advancements in the field and promises enhanced precision in analyzing palm tree ecosystems.

Ultimately, this chapter underscores the transformative potential of our project in the realm of smart palm tree management through the synergy of big data, deep learning, and the IoT. Our objective is to create cutting-edge solutions that facilitate data-driven, precise decision-making in the cultivation of palm trees. By focusing on key aspects of precision agriculture, our research positions itself as a pioneer in innovation, significantly contributing to the sustainable stewardship of palm ecosystems.

In the following chapter, we undertake an extensive examination of the relevant literature and projects, offering a comprehensive perspective on the progress made in precision agriculture and its implementation in palm cultivation.

Chapter 3

Related Works

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3.1 Introduction

This chapter is divided into three major sections and serves as a compendium of current knowledge and innovative advances. The first section (3.2.2) is devoted to challenges and breakthroughs in agricultural data management and addresses the complexities of dealing with Big Data from remote sensing and efficient storage of IoT-generated data. The second section (3.3) focuses on the latest approaches to palm tree detection and counting, with an emphasis on developing methods to address these important needs. Finally, the third section (3.4) focuses on recent advances in early detection and mapping of RPW diseases. The goal is to provide growers with modern tools for proactive management.

There are a wealth of solutions in this research area that provide invaluable insights. However, the primary focus in all sections of this chapter is on the latest research findings. This strategic focus includes a comprehensive analysis and comparison of these solutions to highlight their profound importance. Each section dealing with agricultural data management, palm detection, and RPW disease detection is devoted to an in-depth examination and evaluation of the latest advances. This comprehensive approach ensures a thorough comparative analysis, highlighting the respective merits and contributions in the field.

3.2 Approaches for Multi-sources Data Management

3.2.1 Concerns and Challenges

3.2.1.1 RSBD Storage Challenges

The increasing volume of remote sensing data now reaching the petabyte, exabyte, and zettabyte domains poses substantial challenges in raster data storage. Traditionally, file formats like HDF (MODIS), GeoTIFF (Landsat), and JP2000 (Sentinel-2) have been employed, accommodating datasets ranging from megabytes to terabytes. Cloud-based platforms, recognizing the surge in data, adopt innovative storage approaches, often utilizing lightweight formats, such as PNG and JPEG, organized as tiles for efficient visualization and online processing. These platforms can also leverage Discrete Global Grid Systems (DGGS).

Figure 3.1 offers an in-depth exploration of the evolution of remote sensing instruments across three crucial sensor characteristics: spectral, spatial, and temporal resolutions. These advancements have resulted in an escalation of volume, velocity, and variety in remote sensing data products, presenting challenges in management and processing, while unlocking avenues for new applications. For instance, improvements in temporal resolution enable daily biomass monitoring, whereas enhanced spatial resolution facilitates fine-grained classification (such as settlement types), damage assessments, and the monitoring of critical infrastructure, including nuclear proliferation.

Although the 3Vs (volume, velocity, and variety) effectively characterize big data, it is not necessary for remote sensing big data to satisfy all three dimensions. In this context, a big

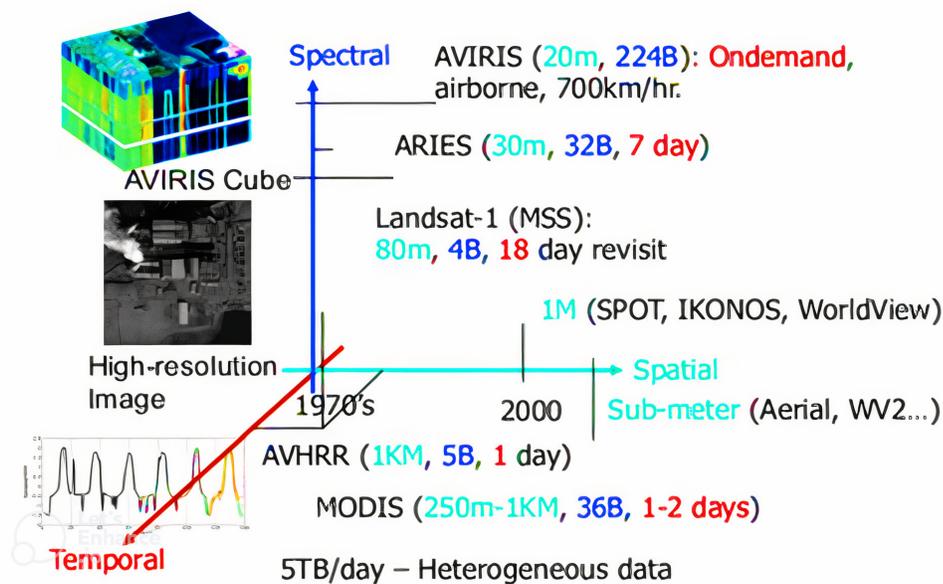


FIGURE 3.1: Advances in remote sensing data products [Vat+12]

data problem can be defined by any combination of volume and velocity, volume and variety, or variety and velocity. Beyond these common challenges, remote sensing applications face additional hurdles, including the extensibility of integrating disparate management systems for different satellites within a remote sensing data center. Of particular significance is the intrinsic value concealed within the data, a crucial quality of big data. By utilizing data processing methods, this concealed value can be revealed, allowing for the practical realization of the significance of big data in remote sensing applications.

However, the sheer scale of remote sensing data now surpasses the capacities of conventional standalone storage hardware, such as block storage or redundant arrays of independent disks (RAID). Distributed storage systems (DFS) have emerged as a viable solution because of their ability to handle petabytes of data. Nevertheless, the associated costs can be prohibitively high, thus impacting both individuals and government entities. Notably, considerations of charging for access to popular remote sensing data sources such as Landsat have been contemplated by entities such as the USGS to recover expenses.

Furthermore, the retrieval of array data in remote sensing introduces unique challenges stemming from the intricacies of the data structures. This results in decreased input/output (I/O) efficiency and heightened access latency, a facet often overlooked by existing big data technologies. For instance, in time-series analysis, remote sensing data are distributed across multiple files or objects, leading to numerous random-access operations and incurring costs during the extract-transform-load processes.

Effectively addressing these challenges necessitates the development of advanced data storage

schemes aligned with big data storage technologies tailored to the specificities of remote sensing data. This includes optimizing storage systems for the efficient handling of diverse file formats, managing distributed data, and mitigating the financial barriers associated with large-scale storage solutions.

3.2.1.2 IoT Data Storage Challenges

One of the key challenges in managing IoT data is selecting an appropriate type of database. This task can be complex owing to the diverse nature of the IoT environment. When selecting a database for IoT applications, several factors must be considered, including scalability, speed, flexible schema, compatibility with various analytical tools, security, and cost. While RDBMS can be used to address IoT, they have limitations that can become barriers to realizing the full potential of IoT data. On the other hand, NoSQL databases offer the flexibility necessary to store different types of data and adapt to changing business needs. While RDBMS systems may continue to play a role in managing structured data from business IT systems, IoT requires databases that can handle a wide range of data from a large number of sensors, devices, and gateways with varying data structures and are potentially connected and integrated over many years.

The IoT relies heavily on the vast amounts of data generated by applications. This presents a number of challenges for the database management system of an application, particularly in terms of scalability and the ability to quickly ingest data. IoT data are often highly diverse; therefore, the ability to manage rapidly changing data is crucial for storing these data. The frequency with which a database can handle these demands is influenced by several factors. Scalability is primarily determined by the sharding and replication techniques used for partitioning and distributing data in a cluster as well as the volume of data produced. The overall throughput of a database system is dependent on several factors, including scalability, consistency requirements, data model complexity, index utilization, and fundamental systems (such as storage engines and programming languages), as well as hardware. It is essential that the database designed to power an IoT request considers these variables to meet the requirements without compromising performance.

3.2.2 Efficient Massive Data Storage Solutions

In this subsection, we examine the current state-of-the-art solutions for storing massive amounts of satellite and UAV image data, as well as extensive IoT data. The focus is on advanced technologies and methodologies that exhibit efficiency, scalability, and parallel processing capabilities. By emphasizing the specific requirements of satellite and UAV image data as well as IoT data within the context of smart palm agriculture, we will explore breakthroughs in NoSQL databases and cloud computing. These technologies are crucial for achieving scalable and parallel data storage, catering to the evolving demands of remote sensing and IoT applications in the realm of smart-palm agriculture.

3.2.2.1 RSBD Storage Solutions

The storage of remote sensing data on a large scale comprises both remote sensing data and metadata storage. In the realm of storing remote-sensing raster data, a plethora of technologies and methods have been developed to address the challenges posed by the rapidly increasing volume of data. A thorough examination of these solutions is provided in Table 3.1, this comprehensive breakdown aims to elucidate the diverse landscape of solutions available for the storage of remote sensing data, considering their distinct advantages and potential limitations. Concurrently, both NoSQL and RDBMS have proven their effectiveness in handling complex metadata associated with remote sensing datasets. As depicted in Figure 3.2, a visual representation succinctly summarizes the unique characteristics of the four NoSQL databases, excluding the Array database Management Systems (Array DBMS). For RDBMS raster storage in cloud-based solutions, Object Storage System (OSS) is the preferred choice for open data sharing, whereas DFS assume a pivotal role in RSBD platforms. The cost-effective nature of public cloud-based OSS services alleviates the financial burden of RSBD management, thereby making OSS the preferred option in recent RSBD systems. Despite their potential, NoSQL and Array DBMSs have limitations, particularly in terms of cost.

The decision-making process between NoSQL and the RDBMS for cloud-based RSBD metadata storage depends on the specific application scenario. NoSQL demonstrates strength in managing the complete archive of remote sensing data, which is challenging for an RDBMS. Studies of Wang et al [Wan+19] and Cheng et al [CZW20] supported this assertion, highlighting the superior functionality of NoSQL, particularly in large RSBD systems. Conversely, the RDBMS exhibits commendable cost performance in scenarios involving small to medium volumes of RSBD management. Ultimately, the choice between NoSQL and RDBMS is contextual, with NoSQL emerging as a robust solution for large-scale RSBD applications, underscoring its viability and prowess in raster data storage.

The range of options available for storing remote-sensing data highlights the complexity of managing such data. No single solution is suitable for all situations, and the selection of a storage system must consider specific data characteristics, access patterns, and collaborative requirements. The emergence of new technologies, such as cloud-optimized formats and NoSQL DBMSs, suggests that the landscape is constantly evolving, presenting opportunities for further research and advancements in remote-sensing data storage. Future endeavors should concentrate on overcoming the challenges that have been identified and examining the potential for synergies between different storage solutions to develop more resilient and versatile systems.

| Storage Solution | Description | Advantages | Disadvantages |
|------------------------------|--|---|---|
| Cloud-Optimized Data Formats | Formats like Zarr and Cloud Optimized GeoTiff (COG) optimized for cloud storage. | <ul style="list-style-type: none"> • On-demand access to specific portions without downloading the entire dataset (COG). | <ul style="list-style-type: none"> • Limited support for certain cloud services. |
| OSS | Commonly used by major cloud providers (e.g., Amazon, Microsoft, Google). | <ul style="list-style-type: none"> • Facilitates open sharing of data. | <ul style="list-style-type: none"> • Lack of direct data sharing capabilities. High redundant overhead costs in some scenarios. |
| DFS | Mature big data storage technology, dominant in RSBD platforms. | <ul style="list-style-type: none"> • Advantageous functions like appending writes and modifications. | <ul style="list-style-type: none"> • Not as easily shareable as OSS. Clear need for functions like append write and random read. |
| NoSQL Databases | Wide-column, In-memory key-value, and Document NoSQL databases. | <ul style="list-style-type: none"> • Supports storage of large amounts of unstructured RSBD raster data. | <ul style="list-style-type: none"> • Wide-column NoSQL may lack spatial indexing. In-memory key-value may have limited capacity. |
| Array DBMSs | storing and manipulating remote sensing data as arrays. | <ul style="list-style-type: none"> • High-level array manipulation for storage, metadata, and indexing. | <ul style="list-style-type: none"> • In early stages for RSBD data management. Challenges in incorporating data into NoSQL. |

TABLE 3.1: Summary of Remote Sensing Raster Data Storage Solutions.

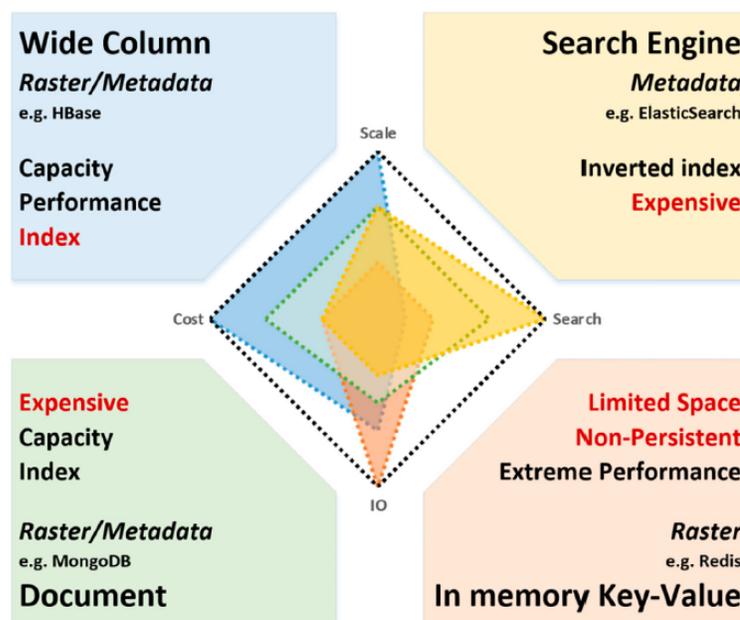


FIGURE 3.2: The advantages and disadvantages of the four distinct types of NoSQL databases will be examined, along with an assessment of their respective costs, search capabilities, and input/output performance (illustrated through a radar chart in the center).

State-of-art in RSBD storage and metatada management

In this subsection, we provide an outline of existing research that addresses the question of how to effectively manage large amounts of massive remote sensing data. Our focus is on the architectures, subdivision models, index structures, and tools and methods used in these studies. We also considered the impact of spatial correlation and metadata standardization on the management of such data. The table 3.2 provides a comprehensive overview of existing solutions for RSBD storage and metadata management technologies.

In 2013, Liu et al. [Liu+13], proposed a novel approach to efficiently manage massive RS data, as traditional methods have reached their limits in terms of cost and extendability. The authors designed a method based on pyramid maps, Hbase, and MapReduce for data storage

and processing, which was found to increase the data import and processing speed as the Hbase cluster increased. However, further testing in an optimal experimental environment and a good understanding of Hadoop parameters are required to fully assess performance.

In 2016, Li et al. [Li+16], presented a method for RS data integration and management based on the geosot subdivision model, which was found to improve storage management and query speed. This approach requires testing in a distributed environment to improve accuracy.

In 2017, Yang et al. [Li+16], implemented a method for massive RS image storage using a spark-based pyramid model. The authors demonstrated the efficiency of this method in terms of image storage and construction performance compared with MapReduce and Hadoop. Further exploration is required, including practical applications such as image retrieval, image detection, and image classification.

In 2018, Jing and Dongxue [JT18] and Yosra et al. [HF18] designed a storage model for remote sensing (RS) image data based on open-source big data technology and a pyramid map for image data subdivision, with the aim of improving the low efficiency and scalability of traditional processing models. The results of their methods showed that they improved both data writing and query speed, as well as high scalability. Additionally, the improved index used in [HF18] had high spatial proximity in the Hbase table.

In 2019, Wang et al. [Wan+19] presented a distributed storage and access method for large RS data based on the GridFS mechanism to improve I/O speed, horizontal expansion, and low-query performance in massive RS data management. This approach was scalable and had random access performance owing to sharing technology. However, it is necessary to study the influence of the number of data nodes on the performance of distributed systems.

In 2020, Cheng et al. [Xu+20] proposed ScienceEarth, a framework for large-scale RS data storage, management, and processing in cluster computing in a cloud environment. According to their test results, the availability and computation of the RS data proved that their approach was efficient in retrieving and processing RS data. However, efficiency can be affected by the workload situation in the cloud, and the ScienceGeoIndex needs to be optimized to provide standard map services. The platform needs to support vector data and include ML and DL frameworks.

TABLE 3.2: Overview of existing solutions of the RSBD storage and metadata management technologies

| Ref. | Storage Architecture | Subdivision Model | Spatial Correlation | Index Structure | Metadata Standardization | Tools & Methods |
|----------|----------------------------------|---------------------------------------|---------------------|--|--------------------------|--|
| [Liu+13] | Distributed | Pyramid Map | Yes | Hbase (Key-Value) | No | Hadoop, Hbase, MapReduce |
| [Li+16] | Local Server | GeoSOT (2^n -tree) | Yes | Inverted Index | Yes | Kingbase Enterprise Server, Oracle Platform |
| [YMY+17] | Single/Distributed Storage | Pyramid Map/TMS (Tile Map Service) | Yes | Hbase (Key-Value) | No | Hadoop, HDFS, Hbase, Spark RDD |
| [JT18] | Distributed | Image Pyramid + Uniform Grid Division | Yes | Grid Index+ Hilbert Curve | No | Hbase, MapReduce, MRHbase, MySQL |
| [HF18] | Distributed | Pyramid Map | Yes | Hbase (Key-Value) | No | Hbase, Cassandra, MongoDB |
| [Wan+19] | Distributed Cluster Architecture | GridFS Mechanism | — | MD5 | No | MongoDB, PostgreSQL, WiredTiger Engine |
| [Xu+20] | Distributed Cluster Architecture | Quad Tree | Yes | Hbase (Key-Value based on Quad Tree + Hilbert Curve) | Yes | Hadoop, Hbase, HDFS, Spark, Open-Stack Cloud |
| [WWZ20] | Distributed Cluster Architecture | Google S2 | Yes | Hbase (Key-Value based on Hilbert Curve) | No | Hadoop, Zookeeper, Hbase |
| [Yan+20] | Distributed Storage | Google S2 | Yes | Hbase (Key-Value) | + Yes | Hbase, Zookeeper, Hive, Kylin |

—: Not mentioned

In the same year, Wang et al. [Wan+20] and Yang et al. [Yan+20] proposed methods for storing RS image data using Google S2 and Hbase. The proposed method aims to improve tile storage and query efficiency, resolve data organization and sharing issues caused by the use of various spatial object formats, and has potential applications in other distributed databases, data retrieval, data analysis, and lost-tile reconstruction. Furthermore, it can be used for mining fine-grained RS data.

3.2.2.2 IoT Data Storage Solutions

In this section, we provide an overview of related work that is considered significant for the advancement of our own research.

In 2012, Tingli Li et al [Li+12] introduces IOTMDB, a NoSQL-based solution designed to address the challenges of managing extensive and diverse data generated by the IoT. IOTMDB is specifically tailored to the characteristics of IoT data, ensuring efficient storage and seamless data sharing through integration with the RNS platform and ontology-based data abstraction. The proposed storage strategies, including pre-processing mechanisms and unified data expression forms, are aimed at enhancing cluster performance and optimizing data storage. This study further presents a set of NoSQL-based query syntaxes to accommodate various types of IoT queries. Future work will involve the implementation of a NoSQL-based database model for IOTMDB as well as the exploration of techniques for processing and analyzing massive IoT data to maximize its value.

In 2019, the paper authored by Mohammad Nasar and Mohammad Abu Kausar [NK19] delves into the pivotal role of databases in the effective management of vast amounts of data generated by IoT devices. Recognizing the constraints of traditional relational databases in handling the magnitude and complexity of IoT data, the authors focused on NoSQL databases, specifically time-series databases. This study presents and examines five prominent time-series databases—InfluxDB, Kdb+, Graphite, Prometheus, and RRDtool—to assess their suitability for efficiently managing diverse and extensive IoT datasets. This research highlights the unique characteristics of IoT data, emphasizes the growing significance of NoSQL databases, and provides a comprehensive comparison to aid researchers and practitioners in making well-informed choices for IoT data management.

In 2020, Giacobbe, Maurizio and Chaouch [Gia+20] presents a case study that concentrates

on the implementation of InfluxDB, a time-series database, with the goal of optimizing monitoring and analytics in distributed IoT environments. The primary objective of this implementation is to streamline data management and enable efficient IoT-as-a-Service in geo-distributed smart ecosystems. The authors aimed to create new opportunities for various stakeholders, including individuals, PAs, academia, and industries, to collaboratively define and explore innovative synergies.

Recently in 2023, The paper authored by Sandra Włostowska et al, [WŁO+23] significantly contributes to the state-of-the-art database systems for smart buildings and smart metering applications. The authors conducted a comprehensive comparison of NoSQL, TSDB, and relational (SQL) databases with a focus on practical applications, integration with industry standards, and communication protocols. This study evaluates open-source databases such as PostgreSQL, MongoDB, and InfluxDB, examining installation, configuration methods, and interfaces in popular programming languages. Empirical findings regarding access times and disk space usage provide valuable insights. The paper's conclusion presents the results and offers recommendations for potential applications in the discussed fields, adding to the current knowledge base in database technology for smart environments.

The table 3.3 presents a comprehensive comparison of storage solutions for managing IoT data. The evaluation of attributes, such as advantages, disadvantages, cost, and security measures, aims to identify the most suitable technology for storing time-series data associated with RPW sound data and metadata.

NoSQL for Iot data storage As previously discussed in Section 3.2.1.2, the primary requirements for databases in IoT applications are scalability and capacity to rapidly ingest data. NoSQL systems are well suited for these applications owing to their inherent design for substantial horizontal scalability. Another notable characteristic of NoSQL databases is their efficient utilization of in-memory data storage, which offers significant advantages in terms of the write throughput and latency. In contrast, traditional RDBMS systems have limitations in handling the volume and velocity of data generated by the IoT, and their schemas may become cumbersome when dealing with rapidly changing information from IoT applications.

The flexibility of NoSQL databases is evident in their ability to easily configure schemas by introducing new fields to a database or adding unique column groups to a table. This flexibility facilitates the management of information from IoT applications that undergo rapid changes. With the storage of vast and rapidly expanding unstructured data, NoSQL database solutions have gained popularity, surpassing the efficiency and scalability constraints of rigid relational databases. This prompts a re-evaluation of traditional relational models. Relational databases adhere to normalization laws, organizing information into field records and tables, and NoSQL databases, with their focus on scalability and flexibility, continue to provide a robust alternative for modern, large-scale data processing needs [Li+12].

| Storage Solution | Advantages | Disadvantages | Cost |
|----------------------------|---|---|---------------|
| Time-SeriesDB [NK19] | <ul style="list-style-type: none"> • Optimized for time-series data. • Efficient handling of timestamped IoT information. | <ul style="list-style-type: none"> • Specialized for time-series data, may have limitations with other data types. | Varies |
| NoSQL-Databases [Li+12] | <ul style="list-style-type: none"> • Designed for large volumes of unstructured data. • Suitable for diverse IoT data types. | <ul style="list-style-type: none"> • Some solutions may lack complex querying capabilities. | Varies |
| Distributed Databases | <ul style="list-style-type: none"> • Scalability and performance benefits. • Distributes load across multiple servers. | <ul style="list-style-type: none"> • Implementation complexity. | Varies |
| Cloud-Storage [Bru+18] | <ul style="list-style-type: none"> • Cost-effective and scalable. • Provides durable storage for IoT data. | <ul style="list-style-type: none"> • Potential latency in data retrieval. | Pay-as-you-go |
| Data Lakes | <ul style="list-style-type: none"> • Stores raw, unstructured data. • Enables processing with technologies like Apache Hadoop. | <ul style="list-style-type: none"> • Requires careful data governance. | Varies |
| Edge Storage | <ul style="list-style-type: none"> • Low-latency storage at the edge. • Reduces the need for immediate centralized data transmission. | <ul style="list-style-type: none"> • Limited storage capacity at the edge. | Varies |

TABLE 3.3: Comparison of Storage Solutions for Massive IoT Data.

Time-Series Databases for Iot data storage The assessment of storage alternatives for coping with extensive IoT data reveals a range of options, each presenting its own unique benefits and challenges. TSDB proved to be the most suitable option for situations with a heavy reliance on timestamped data, as they provide specialized optimization for time-series information. NoSQL databases, on the other hand, offer a flexible solution for accommodating large volumes of unstructured data, making them well-suited for a variety of IoT data types. Distributed databases provide advantages in terms of scalability and performance but have increased complexity in implementation. Cloud storage offers a cost-effective and scalable solution; however, it is important to consider potential latency issues in data retrieval. Data Lakes, with their focus on storing raw and unstructured data, offer opportunities for processing using technologies like Apache Hadoop, but demand careful data governance. Edge storage, with its emphasis on low-latency storage at the edge, reduces the need for immediate centralized data transmission but faces limitations in storage capacity at the edge. The selection of a storage solution depends on the specific characteristics of the IoT data, processing requirements, scalability needs, and budget considerations. In some cases, a hybrid approach incorporating multiple solutions may provide a comprehensive strategy for addressing the intricacies associated with storing massive amounts of IoT data depending on the nuances of the IoT system architecture [NK19],[Gia+20].

3.2.3 Discussion

Upon conducting a thorough examination of existing solutions for RSBD storage and metadata management technologies, it is crucial to acknowledge inherent limitations and challenges associated with the approaches presented in these studies. A predominant limitation evident across multiple references is the absence of standardization in metadata. The standardization of metadata is vital for ensuring interoperability and seamless data integration. The lack of standardization in the majority of studies could pose obstacles to data exchange and collaboration among different systems.

Moreover, the selected storage architecture varies significantly among studies, with some opting for distributed systems, while others prefer local servers or distributed cluster architectures. This diversity in storage architecture introduces challenges when attempting to compare or integrate solutions across platforms, hindering cross-system compatibility.

Spatial correlation, although acknowledged in all solutions, is addressed using different methods that may vary. Effectively handling spatial correlation is critical for the accurate analysis and interpretation of remote sensing data. The nuanced approaches observed could impact the overall efficacy of the storage solution.

A notable limitation highlighted in the table is the diversity of index structures utilized across studies. While some employ advanced spatial indexing techniques like the Hilbert Curve, others rely on simpler structures such as key-value pairs. The choice of the index structure has implications for query performance and data retrieval efficiency, reflecting the absence of a standardized or optimized approach in the field.

Furthermore, the tools and methods exhibit significant variation, ranging from Hadoop and MapReduce to specific databases like Hbase, Cassandra, and MongoDB. The lack of a standardized toolkit or methodology may pose challenges for researchers and practitioners aiming to adopt or replicate these solutions in different environments.

In conclusion, while the table 3.2 provides a comprehensive compilation of existing RSBD storage and metadata management solutions, the lack of metadata standardization, diverse storage architectures, varied treatment of spatial correlation, differences in index structures, and the absence of a standardized toolkit underscore the current challenges and limitations in this field. Addressing these limitations in future research is crucial for developing more robust and interoperable solutions for handling large-scale remote-sensing data.

On the other side of the analysis, it is evident that TSDBs are indispensable for the continuous monitoring of RPW sound data. The demand for an optimized storage solution to handle timestamped information makes TSDBs essential. Their distributed and scalable architecture aligns well with the dynamic characteristics of RPW IoT data, ensuring efficient storage and retrieval. The table serves as a guide for selecting the optimal storage technology to accommodate the large volume of time-series data generated by RPW monitoring devices, facilitating accurate analysis for early disease detection.

Going forward, our primary objective is the development of a multi Data Model that addresses the challenges we have identified. This model enables the integration of diverse data types from various sources, providing a standardized and adaptable representation that facilitates seamless analysis. At present, there appears to be a dearth of literature focusing on the management of multisource data for the specific purpose of storing and managing remote sensing big data and IoT data in the context of smart palm agriculture services. Future research in this area is crucial for bridging this gap and advancing the field of smart agriculture practices.

3.3 Approaches for Palm Tree Detection and Counting

In the field of precision agriculture, effective management of palm trees has become increasingly important in the face of rising global demand for palm products. Data analytics plays a

critical role in revolutionizing the monitoring, management, and conservation of these important agricultural commodities. Advanced data analytics provide valuable insights into palm health, growth patterns, and potential threats. This data-driven approach enables growers and agriculture professionals to make informed decisions, optimize resource allocation, and increase crop yields. By harnessing the power of data analytics, precision agriculture not only ensures sustainable palm growth but also makes an important contribution to global food security and the efficient use of natural resources. This section discusses the methods, technologies, and applications of data analytics tailored to the specific needs of palm agriculture and highlights their indispensable role in modern agriculture.

3.3.1 Palm Tree Detection and Recognition

Accurate identification and determination of palms is of paramount importance as it is a fundamental element for effective management, biodiversity conservation, and promotion of the date palm industry in various sectors such as agriculture, forestry, and environmental protection. A comprehensive study of palms, including their census and spatial analysis, plays a key role in predicting production capacity and improving plantation monitoring. However, collecting accurate data is challenging, highlighting the need to integrate state-of-the-art agricultural technologies. Therefore, it is imperative to develop an efficient, cost-effective, and accurate approach for analyzing individual palms (IPTs) to promote smart palm management. This effort becomes even more urgent when considering how laborious, resource-intensive, and financially burdensome existing methods are. However, it is not always possible to produce accurate statistics [WNG00]. Therefore, the combination of modern technology and agriculture is crucial for effective palm management.

Studies on tree canopy classification and recognition algorithms can be divided into three main categories: classical image processing, traditional ML, and DL methods. In addition, it is worth noting that the following findings were discovered after extensive and thorough research in the literature, as summarized in Figure 3.3:

3.3.1.1 Classical Tree detection Techniques

Classic image processing techniques include template matching [KQ11], [Dos+17], [Mur+19], local maximum filter [WNG00], [Pou+02], [Kho+15b], [Wan+16], [Li+19], image binarization [Pit01], [Dal+09], image segmentation [Fer+16], [Wag+18], [Ava+18], etc. These traditional tree canopy detection methods are based on tree canopy morphology and use feature extraction algorithms such as shape, edge, and color [GMD18], [Cam+20]. One of the main advantages of these methods is their relative simplicity and the ability to use existing tools or software such as eCognition and ArcGIS without the need to laboriously collect baseline data or manually label samples (with the exception of template matching) [Dos+17], [ZSB14]. Many studies have attempted to detect and outline tree canopies in images, with average accuracy rates ranging from 75% to 95% [MŽ15],[Dos+17], [SHS11].

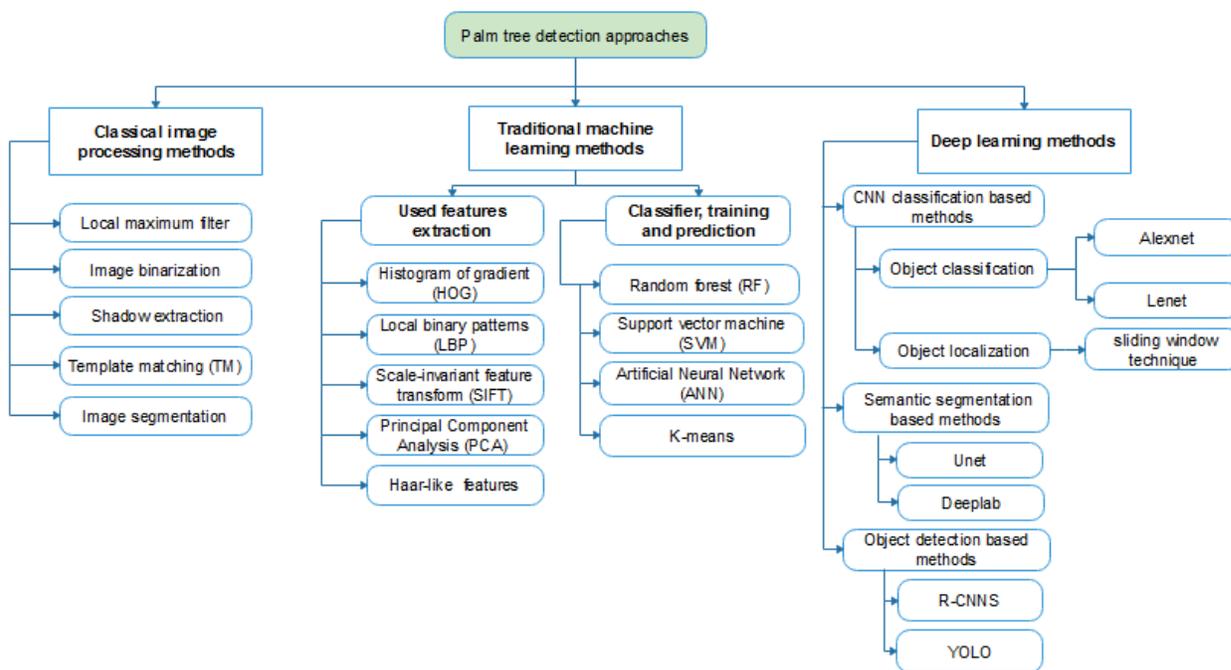


FIGURE 3.3: Taxonomy of palm tree detection relevant methods

3.3.1.2 Classical ML Techniques For Tree Detection

Based on traditional machine learning, canopy detection involves two main steps: feature extraction for detection and classification and training and predicting classifiers to segment oil palm images into individual canopies. The feature extraction step is important for the second step and often involves handcrafted techniques, such as HOG [WZW19], LBP [Mal+14], SIFT [Mal+14; Nam+16], PCA [SDM19], and ELM [Mal+14]. The extracted features can contain different types of information such as spectral indices and shadow information [Joh+20; ÖÜ20]. To recognize tree canopies, traditional machine learning methods usually rely on annotations and supervised classifiers such as RF [Wei+17; Blo+17], SVM [Riz+18; Dai+18], ANN [Nev+17], and OBIA [Riz+18]. Some studies have used unsupervised ML algorithms such as K-means to detect individual trees [Riz+18; Ma+20]. Traditional machine learning methods for tree canopy detection tend to be more efficient and accurate than classical image processing methods, particularly in complex regions. Refer to Table 3.4 for a comprehensive summary of key outcomes from the examined studies, presenting insights into palm tree detection using various ML algorithms.

| Refs | Method | Dataset | Results | Objective(s) |
|----------|-------------------|------------|----------------------------------|-----------------------------|
| [Kal+17] | SVM, TM, TM + OBA | UAV Images | OA: 87% (TM+OBA), 71% (TM) | Counting oil palm inventory |

| | | | | |
|----------|---|--|---|--|
| [WZW19] | HOG-SVM,SVM | UAV Images | OA: 99.21% | Automatic detection and enumeration of individual oil palm trees |
| [Al+18] | RF, SVM, K-NN | Aerial remote sensing images | OA: 91.88% and 87.03%, | Date palm tree Detection and mapping |
| [Riz+18] | SVM of OBIA, FR + GIS | WorldView-3 satellite, LiDAR airborne imagery. | OA: 98,80% for counting and 84.91% for age estimation | Counting and age estimation of the oil palm tree. |
| [Tag+19] | Image processing + GIS functionalities, RF, SVMR, RP, k-NN. | UAV Images + ground data | Best OA: 85% for RF with 0.82 kappa index | Identification and quantification of palm trees |

TABLE 3.4: Overview of the main results in considered studies based on ML algorithms for palm tree detection

However, although these methods can also identify tree species [WZW19; Tag+19] and do not require manual selection of tree-planting plots. For some complicated feature extraction and tree classification methods such as those proposed in [Nev+17; Mal+14; Lóp+16] (for example, DT, RF, K-NN, MLP, SIFT, LBP, and ELM). However, image data are required for certain types of imagery, such as hyperspectral and thermal imagery, very high-resolution drone imagery, point cloud data, and hyperspectral imagery. Because of these requirements, large-scale palm detection is subject to additional limitations. According to [AKA18], the final results differ from one to another depending on the type of feature extraction. The bottleneck of ML methods is that they rely heavily on handcrafted features. This means that when new data are added, new handcrafted features are needed for this new data, which can be expensive. Subsequently, an extraction method was applied to the new features. This process is lengthy and requires sophisticated feature design during feature extraction and fine-tuning of the parameters during training [Fas+16].

3.3.1.3 DL Techniques For Tree Detection

The remote sensing community has shown a willingness to develop new methods to improve preprocessing, classification, and segmentation techniques [LW07; Ali+23; Bou+22a]. Deep learning, a type of machine learning that uses artificial neural networks modeled after the human brain, has proven successful in various applications, such as computer vision and medical applications. Due to its ability to learn from data and extract features in a hierarchical manner, it has become a popular topic in research. Since 2012, DL has been applied in numerous fields, including image and handwriting recognition, and has been particularly successful in medical and healthcare [Ben+22a; Ben+22b; Bou+22b]. More recently, it has

also been used for canopy recognition, particularly in agriculture, to increase efficiency and reduce costs. Convolutional neural networks have also been used in remote sensing since 2014, with many studies achieving good results in tasks such as tree canopy detection and plant type classification in large and complex areas from remote sensing images for early warning and disease detection systems [HK20].

Overall, these approaches can be divided into three types: first, CNN classification methods; second, semantic segmentation-based methods; and third, object recognition-based methods, which are presented below:

CNN Classification Methods The latest Deep Learning-based methods for tree canopy detection are based on the CNN classification method combined with the sliding window technique [Don+19]. Typically, they divide the entire image into numerous image patches of a given window size and then classify them as background or tree canopy using different CNN architectures, such as AlexNet ([LFY17; Li+18; CCT17]), LeNet ([CCT17; Mub+19]), VGG ([Bon+20; Li+18]), ResNet ([Gui+17; Zhe+21a]), etc. Although the CNN methods perform better than the previous two methods (i.e., the image processing and ML methods), especially in regions with crowded and overlapping trees, they almost adopted the sliding window approach to complete the final detection, which suffers from low computational performance due to the relatively large number of detected candidates of different sizes, such as the aforementioned approaches in [LFY17; Li+18]. These methods are ineffective and do not detect trees with different crown sizes because the size of the patch must be predefined based on our prior knowledge [Mub+19]. Furthermore, these methods require not only annotation of tree canopy samples, but also additional annotation efforts for other species such as background, other plants, etc.

Semantic Segmentation methods Another approach to tree canopy detection is semantic segmentation. In this method, a continuous algorithm is used to label each pixel of an image as part of a tree canopy or not, without the need for the time-consuming sliding window technique used in some CNN classification-based methods. Semantic segmentation aims to create a dense, detailed label for the entire image rather than a single label for each patch or window, as in CNN classification. These methods can be more efficient than CNN classification methods because they can detect multiple trees in a single image at once. Several state-of-the-art semantic segmentation models, such as U-Net, FCN, and DeepLab v3+, have been used in tree canopy detection and have achieved impressive results. In general, the semantic segmentation approach to tree canopy detection is more efficient than the CNN classification method because it can detect multiple trees in a single image at once. Some examples of work in which these models have been used for tree canopy detection include [Fre+19; Wag+20; Rhi+21; XQH20; ZSB14].

Semantic segmentation methods are suitable for mapping tree species that do not require counting trees. In areas with overlapping trees, these methods tend to perform poorly because they may detect only one tree and not multiple overlapping or touching trees. The output of

the semantic segmentation methods is a probability map or confidence map indicating how likely it is that a pixel belongs to a tree canopy. These methods require additional post-processing steps (e.g., detection of local maxima) to produce the final contours of each tree [Osc+20]. In addition, semantic segmentation-based methods may not be the most accurate for determining tree canopy size because they primarily focus on detecting and counting tree crowns. Therefore, semantic segmentation-based methods are not the best choice for identifying individual tree crowns.

Object detection-based methods In recent years, numerous methods have been developed to detect various spatial objects in high-resolution remote sensing images, including palm crowns [Li+20a; ABF21; Aya+22]. Table 3.5 describes the latest relevant approaches to palm/tree crown detection based on object detection methods that have shown promising results.

These methods can be divided into two categories: two-stage object recognition methods such as Fast-RCNN ([CLL20]), Faster R-CNN [Zhe+21b; Zhe+21a], Mask R-CNN [Oce+20; G B+20], and One-stage object recognition methods such as YOLO v2/v3/v4 [AKB21; Xia+19], RetinaNet [CDV20; Wei+19; Sel+20] and VGG-SSD [Xia+19].

Overall, the goal is to develop models that can accurately locate and recognize palms in new images, even under complex and changing environmental conditions. Some studies have compared the accuracy and efficiency of these approaches to canopy detection [Xia+19; San+19] and found that two-stage object detection methods tend to have higher accuracy compared to single-stage methods, but that single-stage algorithms can significantly improve the speed of canopy detection [CLL20]. However, the existing studies on palm tree detection based on object recognition methods have some limitations. Among these limitations is the fact that these types of algorithms require large amounts of annotated training data, which can be time-consuming and expensive to obtain for palm crowns. The performance of object recognition algorithms can be affected by varying lighting conditions and the presence of shadows, which can be particularly challenging for palmate crowns due to their large and often complex structure, while other algorithms may have difficulty detecting small or partially occluded palmate crowns. Some object detection algorithms also have problems detecting palm crowns in dense forests or in areas with a large number of overlapping crowns [CDV20]. The accuracy of object detection algorithms can depend on the specific parameters chosen for the model, and it can be challenging to find the optimal set of parameters for a given data set of palm crowns.

The study in question evaluated its models on only one type of satellite imagery, which calls into question their generalizability to other imagery types or contexts. [Zhe+19] models were trained and evaluated on a limited dataset, which may limit their applicability to other locations or conditions. These approaches often focus only on the detection of one tree species and do not distinguish between different subcategories. Although some researchers have treated mature and young oil palm separately, the method required previously defined mature

oil palm regions and young oil palm regions using different sliding window sizes [Mub+19; CLL20]. The method proposed by Adel et al. [AKB21] is a promising approach for automated palm census and geolocation, but it requires large amounts of high-quality training data and is sensitive to the quality of input images and geolocation data. Implementing this method requires a large amount of high-quality training data, which can be challenging, especially for large-scale operations and in remote regions. The quality of the input data plays a critical role in determining the performance of the model. If the input data is of inferior quality, the accuracy of the model may be compromised. Furthermore, if the imagery used for training is not accurate enough, it can lead to inaccuracies in palm tree detection and localization.

In contrast, there can be a tradeoff between the speed and accuracy of object recognition algorithms, with faster algorithms often having lower accuracy and vice versa. This can be particularly important in palm crown detection, where the algorithm may need to process a large number of images in a short time.

3.4 Approaches for RPW Disease early detection

The early detection of diseases in palm trees is vital for preserving their health and productivity, as these plants are susceptible to various diseases that can significantly harm their growth and yield. Timely and accurate disease detection is crucial for implementing effective disease management and control measures. In this section, we discuss the challenges associated with disease detection in palms, the methods and technologies used for this purpose, and the importance of early diagnosis for preserving palm tree populations and the agricultural industries they support.

3.4.1 Palm Tree Diseases

Palm trees are susceptible to various diseases because they are exposed to different environmental factors. Although some palm diseases have visible symptoms that facilitate their detection, others pose a more hidden threat. Bayoud disease, for example, caused by *Fusarium oxysporum* var. *albedinis*, is a serious disease of date palm that is widespread in Morocco and Algeria. Inflorescence blight, known as Khamedj, is caused by *Mauginiella scaettae* and poses a significant risk to date palms in Iraq, Libya, Morocco, Tunisia, and Saudi Arabia [Tan+96]. Leaf spots due to *Helminthosporium* spp. and *Alternaria* spp. were reported from the Al-Qassim region of Saudi Arabia [ALJ10]. Figure 3.4 illustrates some different palm diseases affecting these iconic trees.

Chapter 3. Related Works

| Ref. | Method | Backbone | Dataset | Results | Objective(s) |
|-----------|--|---|--|--|--|
| [Zhe+19] | The proposed method: sample pre-processing tailored RPN of Faster-RCNN + a post-processing method based on empirical planting rules + data augmentation Compared with: CNN, Two-Stage CNN by [LFY17], Faster-RCNN | VGG16 | QuickBird satellite images | F1-score of 94.99% | Large-scale detection of oil palm trees |
| [Liu+21] | The proposed method: Faster-RCNN Compared with: SVM, ANN | VGG-16 + softmax | UAV Images | OA: 97.06%, 96.58%, and 97.79% in 3 different sites | Automatic Detection of Oil Palm Tree |
| [Xia+19] | The proposed method: VGG-SSD + overlapping partition method Compared with: Faster-RCNN, YOLO-V3, Retina-net, Mobilenet-SSD | Resnet-50 | UAV Images | VGG-SSD: best accuracy of 90.91% | Fast and robust detection of oil palm in large scale |
| [CDV20] | The proposed method: RetinaNet + Transfer learning + data augmentation | Resnet-50 | Aerial remote sensing imagery and a palm map | mAP: 0.861 | Detection of Palm Tree; Tree Inventory in large scale |
| [CLL20] | The proposed method: Fast RCNN + SMF-driven DMS + data fusion (local maximum) filtering Compared with: Faster-RCNN, YOLOV2 | VGG-16, Alexnet | UAV Images: Optical and 3D Data | A: 99.8%, 100% and 91.4% in young, mature and mixed vegetation areas | Detection of Palm Tree in mixed study areas |
| [Zhe+21a] | The proposed method: MOPAD Based on Faster RCNN, + RPF module + RPN + hybrid class-balanced loss module + Sliding window technique Compared with: RF, SVM, CNN (ResNet-101), Grid R-CNN, GA Faster R-CNN, Cascade R-CNN, Libra Faster R-CNN | ResNet-101 | UAV Images | Average F1-score 72.83% and 70.57% for two sites | Both accurate detection of oil palm trees and monitoring of their growing status |
| [Yar+21] | The proposed method: Faster R-CNN | Resnet-50, VGG-16 | UAV images with RGB bands | P with Resnet-50 and VGG-16 respectively 96.34%, 95.15% | Oil Palm Tree Detection and Health Classification |
| [AKB21] | The proposed method: Faster R-CNN, YOLOv3, YOLOv4, and EfficientDet-D5 Compared with: [LFY17] (Alexnet) | Resnet-50, Darknet-53, CSPDarknet-53, EfficientNet-B5 | UAV Images | mAP: 99% of YOLO V4 and EfficientDet FPS: 7.4 | Automated counting and geolocation of palm trees |

| | | | | | |
|----------|--|---|--------------------------------------|--|--|
| [PW23] | The proposed method: YOLOv3 | Darknet-53 | VHR Satellite imagery and UAV images | F1-Score of up to 91.05% | Automatic detection and counting of oil palm trees |
| [JEE22a] | The proposed method: the sub-versions of YOLOv5 Compared with: Yolov3, Yolov4, SSD300 (Single-Shot-MultiBox-Detector) | CSPDarknet-slim, Darknet-53, CSPDarknet53 | UAV images | mAP of 92.34% with YOLO-V5m (medium depth) model | Date palm tree detection in drone imagery |
| [Wib+22] | The proposed method: YOLOv3, YOLOv4, and YOLOv5m | Darknet-53, CSPDarknet53, CSPDarknet-slim | UAV images and aircraft images | F1-scores of 97.28%, 97.74%, and 94.94% | Large-Scale Oil Palm Tree Detection using High-Resolution Remote Sensing |

TABLE 3.5: Overview of the main results in considered studies based on object-detection algorithms for palm tree detection

The red palm weevil, known as *Rhynchophorus Ferrugineus* and *Rhynchophorus Vulneratus*, is the most dangerous pest that has threatened palm trees in the last two decades. This threat has remained stubbornly hidden but continues to pose a significant threat to the health of these trees [Kou+20; Ibr+23; Ibr+23]. This destructive pest has been detected in over 60 countries, including France, Greece, Italy, Spain, and various regions of the Mediterranean and Latin America. It was first discovered on the Arabian Peninsula in the 1980s and spread rapidly westward. It reached the United Arab Emirates in 1986, Saudi Arabia in 1987, and Iran in 1992. Since then, it has spread across the Red Sea to North Africa, particularly to Egypt's Sharqiya governorate, where it infects date palms. Initially, RPW infections showed no visible symptoms, making early detection difficult. By the time symptoms appear, the palms are often already severely damaged and at risk of death. RPW is a formidable flyer that can travel distances of up to 9007 m, so it can infect different parts of palms, especially along the base of the trunk (70%) in date palms and near the apical bud (80-90%) in other palm species [EF20].

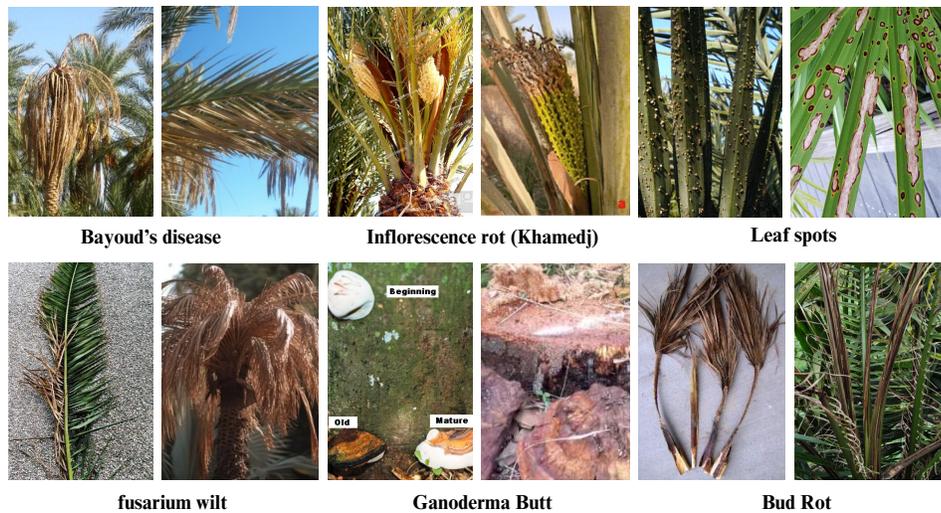


FIGURE 3.4: Most common palm tree diseases.

It is estimated that the beetles can spread up to 50 kilometers per day, resulting in rapid

geographic dispersal and posing a significant threat to trees in widespread locations. According to EPPO (European and Mediterranean Plant Protection Organization), RPW has now spread to 85 countries and regions worldwide [Smi+09]. Constant monitoring of the situation is essential to prevent further spread. The financial implications of the extensive damage to palms are significant, especially for date and coconut producers. The number of date palms affected by RPW is high; in Saudi Arabia, an estimated 80,000 palms are affected, and this number is increasing daily [Muk+11].

In terms of the economic impact of this pest, it is estimated that losses to the date palm industry in the Middle East region from the eradication of infested palms alone amount to approximately eight million dollars annually. This does not include the additional administrative costs to governments and crop losses. In addition, the Food and Agriculture Organization of the United Nations has projected that the cost of pest control and replacement of damaged palms in Spain and Italy alone will amount to 200 million euros in 2023 [Foo20]. On the other hand, the RPW threat not only poses a financial risk but also has the potential to cause physical harm to people and property. Widespread infestations of RPW have caused severe damage to growers, homeowners, and governments and pose a persistent and significant threat to palm health.

The RPW has a unique reddish-brown coloration and measures about 4 cm in length and 1 cm in width. It is distinguished by the presence of black dots on its pectoral ring. Adult weevils are remarkably large, especially in terms of their snout, which is equipped with biting jaws. These specialized jaws help female weevils penetrate palms to lay their eggs. The male weevil has a distinctive feature on its snout—a tuft of soft, reddish-brown hairs—that is not present on the female weevil, as shown in Figure 3.5. It is known to colonize various vulnerable areas of palms, including wounds in the crown, leaf axils, and areas where offshoots have been removed. This pest has a relatively short life expectancy of about 3 months but can cause extensive damage during its life cycle, as shown in figure 3.6. The infection process of this beetle involves egg laying in palms, from which larvae develop. It is during the larval stage that the palm tree is most at risk, as this is considered the most dangerous stage in the weevil’s life cycle. The larvae of the weevil feed on the soft fibers of the palms and form tunnels in the trunk and holes in the stems and fronds. These tunnels weaken the structure of the tree and cause significant damage, decay and possibly breakage [NM21].

The severity of RPW infestation on palms is divided into three different stages. *First and second* limited and superficial areas of infestation that do not penetrate the thigh depth, and fronds remain green and normal. *Third-degree infestation* is considered an advanced infestation characterized by easy removal of offshoots and fronds and the shedding of sawdust. The fronds become wizened and yellow with a little green, and the palm may collapse and fall over. *Fourth-degree*, a foul-smelling resinous liquid oozes out, and the palm eventually collapses and loses its fronds.



FIGURE 3.5: Male weevil (left), Female weevil (right).

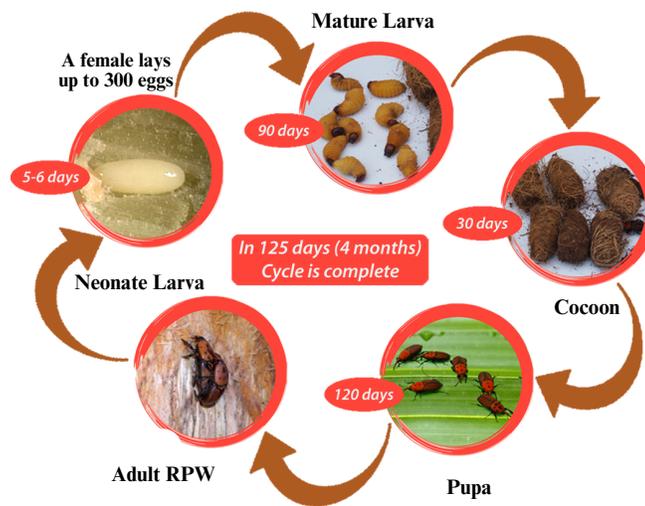


FIGURE 3.6: RPW Life Cycle illustration.

3.4.1.1 Challenges in RPW early detection

Early detection of red palm weevil infestations is critical because it allows for timely intervention and potentially saves trees from irreversible damage and the need for removal. Therefore, early detection plays a critical role in controlling the spread of RPW and minimizing the economic damage it causes. In addition, monitoring and early detection facilitate the implementation of measures such as isolation or treatment of infected trees. However, one of the biggest challenges is figuring out how to efficiently detect RPW insects in the early stages of infestation, since there are few external indicators of palm infestation?

Detecting the devastating RPW weevil in the first two to three weeks of the weevil larval stage is similar to detecting late-stage cancer in humans; visible signs do not appear until it is already dangerous (see Figure 3.4), making it difficult to save the tree once it is infested. By this time, the trees may have already fallen and other insects have already invaded, making treatment more difficult. When palms show clear signs of stress, it usually means that the

infestation is well advanced; at that point, the tree cannot be saved. The biggest challenge is detecting RPW early, and different tree species require tailored detection methods. Although several methods have been investigated, none have proven reliable in treating RPW-infested palms. Consequently, these palms remain at risk if not detected at an early stage. Despite extensive research, no reliable method for early detection has yet been found.

3.4.1.2 RPW Detection Methods

In the past, RPW infestations were primarily detected through visual inspections conducted by local officials or tree owners [KAF21]. However, this approach has its limitations, and a more reliable and efficient method is needed to address the widespread problem of RPW infestation [Sor+13]. Alternative methods such as acoustic detection [HSC16], [Sir+10], [Pin+08], chemical detection [Sch12], thermal remote sensing [AIH19] [AIH19], [Coh+12], [Coh+10], [Ots79] [Gol+15], and hyperspectral [BME17] [Yon+14] are listed in table 3.6. Each method has its own advantages and disadvantages in the search for improved RPW detection techniques.

However, despite intensive efforts to develop techniques for detecting RPW, these methods are still far from being practical or feasible, so detection depends mainly on visible symptoms, which may only become apparent at later stages of infestation and are subjective and dependent on the experience of the observer. In addition, they can only detect the presence of adult weevils and can be invasive, potentially damaging trees during manual removal. These limitations can lead to late detection, allowing infestations to progress and potentially requiring drastic measures such as tree removal [Ahm20]. Palm trees produce significant amounts of woody debris, about 25–35 kg per palm, and can thrive for over a century. Unlike many forest trees, which have a shorter life span and do not yield annual wood products, palms offer the unique advantage of producing 2.5–3.5 tons of wood per palm during their long lives. This special feature distinguishes palms because they contribute continuously to wood production, whereas other tree species provide wood mainly at the end of their life cycle and often in much smaller quantities than palms [TDH23]. Therefore, the removal of palms represents an actual loss. Accurate identification of pests is crucial for effective pest control and the use of pesticides. However, relying solely on manual identification can lead to inefficiency and high labor costs. To overcome this challenge, agricultural pest control strategies need to be put in place. Therefore, there is an urgent need to develop a novel model for early detection of RPW. Currently, an optimal solution requires the integration of different methods and technologies [Sor+13].

3.4.1.3 Advancements in RPW early Detection Approach's

The literature on palm diseases describes various methods and technologies for monitoring and detecting RPW pests. Recently, computer vision systems and image recognition technologies have become significant areas of research worldwide and have attracted the attention of researchers. In the early detection of canola glossy beetles, these technologies have made

significant advances in agricultural pest control by reducing the cost of detection while greatly increasing speed and efficiency. Convolutional neural networks (CNNs) have proven to be exceptionally accurate and efficient in the automatic detection of crop pests. This capability enables precise identification of pest species and facilitates the accurate application of pesticides, which is hugely important for increasing grain production capacity and food security. In addition, the characteristic acoustic features of RPWs play a crucial role in training machines and deep-learning models, enabling early detection of RPWs before they damage palms.

Integrating machine learning with acoustic features provides a powerful tool for effective pest management and offers a comprehensive approach to the RPW challenge. At the same time, IoT and sensor technologies have proven to be valuable tools for collecting data and developing practical applications for identifying and detecting agricultural pests and insects using artificial intelligence techniques, as highlighted in recent studies [NA22], [Ste+20]. Overall, these methods range from image processing algorithms ([AIH19; Eld+20]) to acoustic and optical detection and processing approaches ([Ash+22; Mao+21]).

Furthermore, there is a striking inconsistency in the evaluation metrics used in these studies. Interchangeable metrics such as accuracy, precision, detection and F1 score make direct comparison of the methods difficult. The use of standardized assessment measures would lead to a more direct evaluation of the methods.

Critically, the use of small samples in some studies may affect the statistical significance of their results, leading to questions about the reliability of the results. Clear and transparent documentation is essential to establish credibility, especially when concerns arise about the assumptions and limitations of certain methods. While transfer learning is widely [SVA21; TDH23; Kar+21], critics may argue that the use of pre-trained models is not always appropriate for RPW detection and that tailored approaches specifically designed for pest detection may provide more accurate results.

Recently, the application of contemporary agricultural methodologies has demonstrated notable efficacy in various agricultural domains [BW19; Yan+21]. Within the purview of our investigation, our focus was on examining the utilization of modern technologies, particularly in the domain of early disease detection, which is a pivotal concern for agricultural stakeholders. Early detection is of substantial significance, as it ensures the maintenance of healthy farms and the cultivation of high-quality crops. The literature has delineated multiple endeavors directed towards employing modern technologies to achieve the prompt identification of plant infestations [HTR23; Mal+23; Zhu+23]. Nonetheless, this specific domain of research, especially concerning palm trees, remains an area that requires further and in-depth exploration [Fer+21]. In this research, we have conducted a review of previous studies that are pertinent to our investigation into the early detection of RPW infestations utilizing acoustic signals.

In a study conducted by Mufleh et al. [AH11], an efficient RPW detection system was

| Method | Pros | Cons |
|------------------------|---|---|
| Visual Inspection | <ul style="list-style-type: none"> • Non-invasive. • Low-cost method. • Detects trunk holes and brown liquid. | <ul style="list-style-type: none"> • Training required. • Not highly accurate. • Detection occurs after significant damage. |
| Visual/Thermal Imaging | <ul style="list-style-type: none"> • Cost-effective. • Does not harm palm trees. • Promising for early detection. • Detects tree temperature rise. • Applies via aerial imaging for large areas. | <ul style="list-style-type: none"> • Detects water stress, not necessarily RPW-related. • Equipment can be expensive. • Limited to detecting temperature changes. • Still in the initial stages of development. |
| Chemical Detection | <ul style="list-style-type: none"> • Promising early detection method. • Dogs can locate infested trees by scent. • Canines trained to detect RPW-infested trees. | <ul style="list-style-type: none"> • Requires trained dogs. • Limited to detecting infested trees, not specific locations. |
| Traps | <ul style="list-style-type: none"> • Relatively simple and cost-effective. | <ul style="list-style-type: none"> • Provides only a general area of infestation. |
| Acoustic | <ul style="list-style-type: none"> • Does not harm palm trees. • Offers very high accuracy. • Portable devices are available. • Can detect RPW in its early stages. | <ul style="list-style-type: none"> • Accuracy may vary. • Requires operator training. • Primarily tested in labs, not widely implemented. |
| Hyperspectral | <ul style="list-style-type: none"> • Does not harm palm trees. • Provides very high accuracy. • Can detect RPW in its early stages. • Applicable over large areas using RS. | <ul style="list-style-type: none"> • Complex, involving remote sensing satellites. • Needs fast computers and ample storage. |

TABLE 3.6: RPW Detection Methods: Pros and Cons

developed using image processing and ANNs. The research identified the Conjugate Gradient (CG) with Powell/Beale Restarts Algorithm as the most effective due to its quick training time and high accuracy in a 3-layer ANN configuration. The study signifies the potential of this automated solution for RPW detection and pest management in palm tree cultivation, setting aside specific accuracy results. Further research could focus on refining the ANN's structure or exploring advanced image processing techniques. However, challenges might arise in scaling the solution for real-time field applications or adapting to diverse environmental conditions.

Alaa et al. [Ala+20] aimed to detect palm tree diseases using image processing and machine learning techniques. Specifically, researchers captured normal and thermal images to identify three types of diseases: leaf spots, bright spots, and red palm weevils. To achieve this, they employed CNN and SVM algorithms, with the VGG CNN achieving a 97.9% success rate in detecting leaves and bright spots and the SVM achieving a 92.8% success rate in identifying RPW using thermal images. This study highlights the potential of thermal imaging for RPW detection and proposes future explorations of aerial thermal imaging and hyperspectral imaging. Furthermore, the study suggests utilizing swarm intelligence algorithms to optimize the performance of the CNN and SVM models.

In the work of Anis Koubaa et al. [Kou+20], a framework for the early detection of red palm weevils using IoT technology was presented. The proposed framework utilizes smart agriculture sensors to detect the presence of red palm weevils using accelerometers. Signal processing and probability methods were developed to analyze the data collected by these sensors and accurately identify the activity of the red palm weevil.

The study was headed by Heba Kurdiet et al. [Kur+21] and centered on the early detection of Red Palm Weevil (RPW) infestation utilizing data mining classification algorithms. The investigation evaluated the performance of ten advanced classification algorithms, including Naive Bayes, KSTAR, bagging, PART, J48 Decision Tree, MLP, SVM, random forest, logistic regression and AdaBoost, by employing plant size and temperature measurements to predict RPW infestation in its initial stages. The results demonstrated an accuracy of up to 93%, with temperature and circumference being the most critical features for predicting infestation. However, the study stresses the need for further data collection to refine the findings and advocates exploring untapped data-mining techniques to enhance RPW prediction accuracy.

The research conducted by Kagan et al. [KAF21] focused on the application of DL and aerial street view image analysis to automate the detection and monitoring of RPW infestations. This study scrutinized more than 47,000 aerial and 61,000 street-level images to identify and verify infested palm trees using cutting-edge DL algorithms. The framework, employing transfer learning with Faster R-CNN ResNet-50 FPN pre-trained on COCO and incorporating data augmentation, demonstrated the feasibility of large-scale infestation detection and monitoring utilizing publicly available online data, underscoring the potential to transform existing monitoring practices. However, this study acknowledged several limitations, including the absence of timely updates in images and the scarcity of varied infestation stages,

which affected the accuracy of the classifier.

The research conducted by Wang et al. [Wan+21] focused on leveraging fiber-optic distributed acoustic sensing (DAS) and machine learning for early RPW detection in large palm tree farms. Through controlled simulations, an ANN and CNN were trained using temporal and spectral data obtained from the fiber-optic DAS system. The ANN achieved an impressive 99.9% classification accuracy with temporal data, whereas the CNN showed a high 99.7% accuracy with spectral data in controlled noise conditions, demonstrating the efficacy of this approach. This study addressed practical challenges in deploying the system in real farm settings, highlighting considerations such as the system's range, cost, and protective measures for the optical fiber in challenging farm environments. This study emphasizes the potential of this innovative approach for efficient and cost-effective RPW monitoring on large-scale open-air farms. Table 3.7 provides an overview of these relevant prior works.

Karar et al.[Kar+21] presented an IoT-based framework for detecting RPWs in their early stages by using TreeVibes sensors and a cloud-based DL model. The proposed system utilized the InceptionResNet-V2 classifier, achieving a high accuracy of 97.18% in differentiating between clean and infested trees. This study discusses the significance of IoT technology in monitoring RPW infestation and the potential utility of DL models for accurate classification, comparing InceptionResNet-V2 to other transfer learning models (e.g., Resnet-50, MobileNet, Densenet-121, EfficientNetB0, and Xception), and demonstrating the superiority of the former. Although the classifier's large size is noted as a limitation, this study suggests cloud computing services as a viable solution. Additionally, this study emphasizes the importance of considering security protocols and subsystems for secure IoT-based agricultural systems in future research.

Piyush Singh et al. [SVA21] introduced a deep learning-based framework to detect diseases and pest infections in coconut trees using hand-collected images and various CNN models (i.e., VGG16, VGG19, InceptionV3, DenseNet201, MobileNet, Xception, InceptionResNetV2, NASNetMobile). It identified effective segmentation methods and fine-tuned models, achieving 96.94% validation accuracy with the custom CNN model and 82.10% with MobileNet. The optimized CNN and MobileNet models were deployed in a web application for automated detection. This research emphasizes the need for larger datasets, explores advanced segmentation techniques, and plans to include severity levels in future investigations.

The study introduced by Karar et al. [Kar+22] presented an IoT-based sound detection model to identify RPW larvae in date palm trees, employing a modified mixed depthwise convolutional network (MixConvNet). Utilizing the TreeVibes dataset, the proposed MixConvNet classifier demonstrated superiority over other deep learning models, achieving a high accuracy score of 97.38. Additionally, the classifier showcased precise identification of RPW infestation cases with an accuracy value of $95.90\% \pm 1.46$ using 10-fold cross-validation. The future focus involves the practical implementation of the IoT-based sound detection system for RPW larvae in date palm trees, exploring edge computing integration and addressing security and privacy aspects in open communication networks for audio signal analysis in

| Ref. | Year | Algorithms | Method Steps | Dataset | Accuracy |
|----------|------|--|---|---|---------------------------------|
| [AH11] | 2011 | ANN, SGC, CG | <ul style="list-style-type: none"> • Apply image processing to captured images • Use ANN for RPW identification • Test various ANN sizes and algorithms | 319 images of RPW and additional 93 images of other Insects | 99.5% |
| [Ala+20] | 2020 | SVM | <ul style="list-style-type: none"> • Capture normal and thermal images of palms • Gather datasets for RPW-infected palms • Evaluate classification performance | 2400 thermal images | 92.8% |
| [Kur+21] | 2021 | Data mining classification algorithms | <ul style="list-style-type: none"> • Collect and prepare data from trees • Train ten algorithms to predict RPW • Assess algorithm performance by various metrics | 1200 records | Accuracy: 82.58%- 93.8% |
| [KAF21] | 2021 | CNN, faster R-CNN ResNet-50 FPN, XResNet | <ul style="list-style-type: none"> • Collect and process data from trees • Use ten algorithms for early RPW prediction • Assess algorithms with performance metrics • Map the necessary data for effective analysis | over 100,000 aerial and street view images | - |
| [Wan+21] | 2021 | ANN, CNN | <ul style="list-style-type: none"> • Install fiber optic DAS system on palm trees • Capture audio signals for analysis • Train ANN and CNN with DAS data • Deploy DAS system in large farms | Spectrogram | ANN: 99.9%, CNN: 99.7% |

TABLE 3.7: Comparative Analysis of RPW Detection Methods in chronological order (Continued).

| Ref. | Year | Algorithm | Method steps | Dataset | Accuracy |
|----------|------|---|--|---------------------------------|---|
| [Kar+21] | 2021 | CNN, Inception-ResNet | <ul style="list-style-type: none"> Acquire spectral features Transform features into images Train MixConvNet model Compare performance against other models | TreeVibes dataset | 94.53% \pm 1.69 using 10-fold cross-validation |
| [SVA21] | 2021 | CNN, Customized CNN model | <ul style="list-style-type: none"> Segment tree images with various algorithms Train a 2D-CNN for disease identification Adapt pre-trained CNN models for image classification Deploy automated detection in a web app | Hand-collected image sets | 82.10%, 96.94% |
| [Kar+22] | 2022 | Modified mixed-depth-wise CNN (Mix-ConvNet) | <ul style="list-style-type: none"> Create an IoT-based RPW larvae sound detection model Test the model with the RPW sound dataset Use MixConvNet for RPW detection Compare MixConvNet with other classifiers | TreeVibes dataset | 95.90% \pm 1.46, using 10-fold cross-validation |
| [SE22] | 2022 | ANN | <ul style="list-style-type: none"> Process images for enhancement and segmentation. Extract texture and color features Employ ANN for classification. | 448 RPW images and ants' images | 92.22% |
| [Als+22] | 2022 | Faster R-CNN, Inceptionv2 | <ul style="list-style-type: none"> Use R-CNN to locate RPW in images via bounding boxes Employ CNN to extract features within these boxes Analyze features for RPW identification and coordinate location | 300 RPW images from Google | 99% |

Comparative Analysis of RPW Detection Methods in chronological order (Continued).

| Ref. | Year | Algorithm | Method steps | Dataset | Accuracy |
|----------|------|-----------------------------|---|---|-----------------|
| [Ash+22] | 2022 | CNN | <ul style="list-style-type: none"> • Use R-CNN to detect RPW locations with bounding boxes in images. • Employ CNN to extract features within these boxes. • Analyze features for RPW identification and coordinates. | Acoustic signals, RPW larvae, and tree infestation | ~97% |
| [Alb+23] | 2023 | Mask RCNN, MobileNetv2, GTO | <ul style="list-style-type: none"> • Pre-process images using Gabor filtering (GF). • Utilize Mask RCNN with MobileNetv2 for RPW identification. • Utilize the GTO algorithm for optimized RPW detection. | RPW samples images | 99.27%. |
| [TDH23] | 2023 | Transfer learning, ML, DL | <ul style="list-style-type: none"> • Apply transfer learning using the VGGish model. • Train the model to identify RPW pest sounds. • Validate using RPW dataset with healthy and infested samples. • Compare VGGish model with other traditional and DL models. | Acoustic data; 2485 audio samples from RPW public benchmarked | Accuracy: 94.5% |
| [Wu+23] | 2023 | YOLOv5 | <ul style="list-style-type: none"> • Train YOLOv5 with added layers for better detection. • Implement SE and CBAM mechanisms for feature enhancement. • Collect 2600 RPW images and segment them into sets. • Validate model performance and precision through experiments. | 2600 images using the rear camera of a phone | Accuracy: 93.8% |

Comparative Analysis of RPW Detection Methods in chronological order.

farms.

Karar et al. [Kar+22] introduced an IoT-based sound detection model for identifying RPW larvae in date palm trees utilizing a modified mixed depthwise convolutional network (MixConvNet). The proposed model, MixConvNet, demonstrated superior performance compared with other deep learning models, achieving a high accuracy score of 97.38% using the TreeVibes dataset. The model also demonstrated precision in identifying RPW infestation cases, with an accuracy value of $95.90\% \pm 1.46$ using 10-fold cross-validation. In the future, the focus will be on implementing an IoT-based sound detection system in practical settings, exploring the integration of edge computing, addressing security and privacy concerns in open communication networks for audio signal analysis, and managing the data generated by the system.

Saleh et al. [SE22] presented an image-based machine learning model that is designed to identify the RPW within palm tree habitats. The model incorporates various image processing techniques (image enhancement and segmentation using Otsu's thresholding) to distinguish RPW from other insects. Using a dataset of 913 images that included RPW and ant images, the model achieved an accuracy of 92.22% through ten-fold cross-validation. This study offers a practical solution to mitigate the economic losses resulting from RPW-inflicted tree damage and demonstrates its potential for real-world applications. The authors plan to enhance the model's accuracy by expanding the dataset and exploring the use of deep learning techniques, such as CNNs, which could potentially result in a 95% accuracy rate.

Al-Sanea et al. [Als+22] developed a deep-learning model that can detect the Red Palm Weevil (RPW) in real-time and locate it with precision. This study aimed to provide early identification and accurate classification of RPW to prevent infestations, particularly in the Al-Qassim region. This study achieved 100% accuracy in detecting early stage RPW infestations. A comparative analysis of the proposed model with conventional algorithms, including SVM, MLP, AdaBoost, Random Forest, and Naïve Bayes, revealed that the conventional algorithms had an accuracy of 93.08% in RPW detection, whereas Naïve Bayes achieved 82.58%. However, the proposed faster R-CNN model demonstrated a substantially higher accuracy of 99% for classifying and localizing RPW cases. The significance of this research lies in offering an efficient and cost-effective solution for RPW detection in palm trees, ensuring their survival, and highlighting the importance of effective early infestation detection. Future work could explore the use of alternative deep learning models, such as YOLO, for enhanced detection of various tree species.

Ashry et al. [Ash+22] proposed a novel approach for the early detection of RPWs in extensive farming areas using an optical fiber DAS system and a CNN. This study utilized temporal and spectral acoustic signals captured by the DAS system within a 100–800 Hz filter range to train the CNN models. These models were able to distinguish between "infested" and "healthy" signals with classification accuracies of 97.0% and 97.1%, respectively. By merging the classification outcomes from the temporal and spectral CNN models, the system

achieved a notable reduction in the false-alarm performance metric of the sensor by approximately 20%. The system demonstrated proficiency in identifying infested and healthy trees, both in a controlled environment and on an outdoor farm, particularly when wind speeds were below 9 mph. The primary advantage of this sensor is its ability to provide continuous monitoring across vast farming areas using a single optical fiber cable. However, the performance of the system in high wind conditions outdoors requires further enhancement for optimal functionality.

Albraikan et al. [Alb+23] developed a novel method, termed Red Palm Weevil Detection using Gorilla Troops Optimizer with DL (RPWD-GTODL), which aims to automate the accurate detection of the RPW, a pest that impacts palm trees. This approach integrates CV, DL, and parameter optimization to enhance date tree productivity. The RPWD-GTODL method utilizes GF for image pre-processing and employs Mask RCNN with MobileNetv2 as the backbone network for RPW detection. The method achieved an accuracy of 99.27% for RPW identification, demonstrating its superiority over other DL models for precise real-time RPW detection. This study highlights the potential of the RPWD-GTODL method for future applications in insect classification, thermal UAV imagery, large-scale dataset testing, computational complexity analysis, and the use of advanced DL models for improved detection outcomes.

The study by Torkey et al. [TDH23] employs transfer learning with the VGGish deep learning model to identify RPW based on acoustic features. With RPW infestations posing a significant threat to palm cultivation and early detection challenges due to limited visible signs, the proposed model, trained on an RPW dataset, achieves 94.5% accuracy. It outperforms both traditional (SVM, DT, NB, LR) and deep learning models (InceptionResV3, ResNet50, DenseNet121, EfficientNetB0, Xception) in recognizing RPW sounds. The research highlights acoustic data's potential for early RPW detection, suggesting exploration of additional features for training deep learning models. This study advances early RPW detection using acoustic data, addressing a crucial gap in pest detection solutions.

Wu et al. [Wu+23] presents an enhanced YOLOv5 object detection algorithm that is tailored for efficient RPW management, addressing the limitations of manual counting and enhancing agricultural monitoring. By integrating attention mechanisms, such as squeeze-and-excitation (SE) and Convolutional Block Attention Module (CBAM), the model improves feature extraction, achieving a high accuracy of 93.8% precision and an average of 90.1% precision on the RPW image dataset. The practical application of this algorithm is emphasized for its real-time detection capabilities, aiding in prompt pest control measures, and its scalability for broader pest predetection systems. Future research should focus on expanding the dataset and leveraging additional modal information to enhance insect classification and detection accuracy.

3.4.2 Discussion

Research on the early detection of RPW has revealed a multitude of methodologies, underscoring the importance of developing effective detection systems. A range of technologies has been employed in various studies, such as image processing, machine learning, deep learning models, acoustic feature recognition, and IoT-based systems, to address the challenge of RPW detection. For example, Mufleh et al. [AH11] demonstrated the high accuracy of Artificial Neural Networks (ANNs) in identifying RPWs, whereas Wang et al. [Wan+21] achieved notable results by integrating fiber-optic distributed acoustic sensing with machine learning.

Notwithstanding these encouraging outcomes, it is essential to address certain limitations associated with these solutions. These include concerns regarding the scalability of these solutions for real-time field applications and their adaptability to diverse environmental conditions. Studies such as that by Al-Sanea et al. [Als+22] have underscored the need for alternative deep-learning models to improve detection in various tree species.

Several studies have suggested the urgency of expanding datasets, utilizing more data, exploring advanced segmentation techniques, and including severity levels to provide more comprehensive insights into pest infestations. Moreover, the implementation of cloud computing, edge computing, and IoT technologies is highly recommended to overcome limitations related to the scalability and applicability of these systems. However, practical challenges persist in real-world applications, particularly regarding scalability and accuracy. To address these challenges, interdisciplinary collaboration among agricultural science, data science, and engineering is crucial for developing robust and practical RPW detection systems.

Notable limitations include the relatively limited variety of datasets used in certain studies (Al et al. [AH11], Alaa et al. [Ala+20], Kurdi et al. [Kur+21]), potentially affecting the generalizability of developed models to broader scenarios. Moreover, the lack of comprehensive testing under real-world conditions (e.g., Ashry et al. [Ash+22]) raises questions regarding the practicality and robustness of these methods.

The evaluation metrics used in these studies are inconsistent, rendering comparisons of the methods difficult. Standardized assessment measures are necessary to facilitate a more reliable evaluation. Additionally, the small sample sizes might have affected the statistical significance of the results, thereby compromising the reliability of these findings.

High accuracy levels reported in some studies, such as 99% (e.g., [Wan+21; Als+22; Alb+23]), might raise suspicion, especially in controversial contexts, given the impact of real-world environmental factors on accuracy.

Discussions should focus on the effectiveness and scalability of IoT-based solutions in agriculture, ethical concerns related to privacy and environmental impacts, and the specialization of AI models for pest detection versus broader agricultural challenges. Despite these gaps and controversies, the integration of IoT technologies for RPW detection and mapping remains

limited in the presented studies.

By addressing the identified gaps and fostering discussions on these controversies, the development and acceptance of RPW detection methods, particularly in the context of IoT and mapping applications, can be significantly advanced.

3.5 Conclusion

This chapter has undertaken a comprehensive exploration of the current landscape and recent advancements in smart precision agriculture, with a specific focus on palm tree management and early detection of RPW diseases. The discussion was organized into three primary sections, each delving into the challenges and progress in the management of massive agricultural data, innovative techniques for palm tree detection and counting, and recent strides in RPW disease detection.

The examination highlighted the intricate aspects of handling Big Data sourced from remote sensing and efficient storage of IoT-generated data within the agricultural context. The investigation of palm tree detection methods underscored the importance of addressing fundamental needs in the palm industry, emphasizing the development of modern tools for effective management. Additionally, the exploration of RPW disease detection has showcased cutting-edge solutions for early identification and mapping, which are critical for safeguarding palm plantations.

In this section, a diverse array of solutions and research findings is presented, offering invaluable insights into the dynamic domain of smart precision agriculture. By strategically focusing on the latest research, a thorough analysis and comparison of these solutions were conducted, highlighting their significance in advancing the field. The knowledge synthesized in this chapter establishes a robust foundation for subsequent chapters, setting the stage for the implementation and integration of smart technologies in palm cultivation practices.

Looking ahead, the insights garnered from the examination of remote sensing big data and IoT management in the context of smart precision agriculture contribute significantly to the state-of-the-art. The synthesis of these advancements provides a nuanced understanding of the challenges and opportunities of handling agricultural data, paving the way for sustainable and efficient palm agriculture practices in the future.

Part II

Contributions and Validations

Multi-modal data management for enhanced smart palm trees precision agriculture

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4.1 Introduction and motivation

The effective utilization of diverse data sources has become indispensable in the rapidly evolving field of precision agriculture. This chapter focuses on multi-source data management, concentrating on integrating massive remote sensing data, UAV observations, and the intricate network of IoT sensor data. Our primary objective was to explore the challenges and opportunities in efficiently managing these datasets, driving the advancement of smart precision agriculture, particularly in Smart Palm Agriculture (SPA).

Satellite remote-sensing technologies significantly enhance our capacity to monitor agricultural landscapes; however, the resulting data volume, surpassing 1TB per day, poses challenges in storage and management. The motivations for managing RS data in smart precision agriculture are multifaceted. Satellite imagery, with high resolution, optimizes palm agriculture by offering detailed insights and enabling interventions, such as precision irrigation and pest management. Essential features such as the Normalized Difference Vegetation Index (NDVI) from satellite imagery, which provides a quantitative measure of vegetation health, are invaluable in smart palm precision agriculture. Variations in vegetation health can be discerned by analyzing NDVI values, allowing tailored interventions.

UAVs offer real-time, high-resolution perspectives in agricultural fields and provide valuable insights for precision analysis. The integration of massive amounts of UAV data is motivated by their unique contributions, capturing detailed information to address time-sensitive challenges. In the era of interconnected devices, IoT sensors play a crucial role in capturing detailed information regarding agricultural environments. The motivation for incorporating massive amounts of IoT data arises from its potential to provide real-time, context-aware information that is vital for precision farming.

One of the key challenges in advancing smart-precision agriculture is the effective management and storage of massive datasets. Our motivation, rooted in the pursuit of comprehensive and scalable solutions, drives us to explore this chapter’s focus on managing the integration of satellites, UAV, and IoT data, specifically addressing pressing storage issues. By addressing these challenges, our objective is to accelerate the progress of smart-precision agriculture, envisioning a future in which data-driven insights empower informed, optimized decisions. These applications align perfectly with the main objective of our thesis, which is to demonstrate the practical value and transformative implications of multi-source data in enhancing

agricultural practices. Significantly, this chapter aims to directly respond to the purpose and objective of our first thesis by exploring the obstacles and prospects associated with the integration of massive remote sensing data, UAV observations, and IoT sensor data.

In the context of my thesis on massive multisource data management, these challenges underscore the critical need for innovative solutions to handle and exploit RSBD effectively. Overcoming these obstacles will unlock the full potential of RSBD for applications such as precision agriculture and environmental monitoring, thus facilitating sustainable and impactful research in the field.

4.2 Background

4.2.1 Multi-resolution pyramid model

The multi-resolution pyramid model is a suitable way for managing and organizing both large-scale and high-resolution RS image data. This model's structure is easy to manage and functions as a kernel data structure for many virtual globe systems, such as Google Earth. The pyramid image is a block-oriented image decomposition that depicts a large-scale RS image at several Levels Of Detail (LOD) in accordance with the image resolution, working from the highest to the lowest level (Figure 4.1).

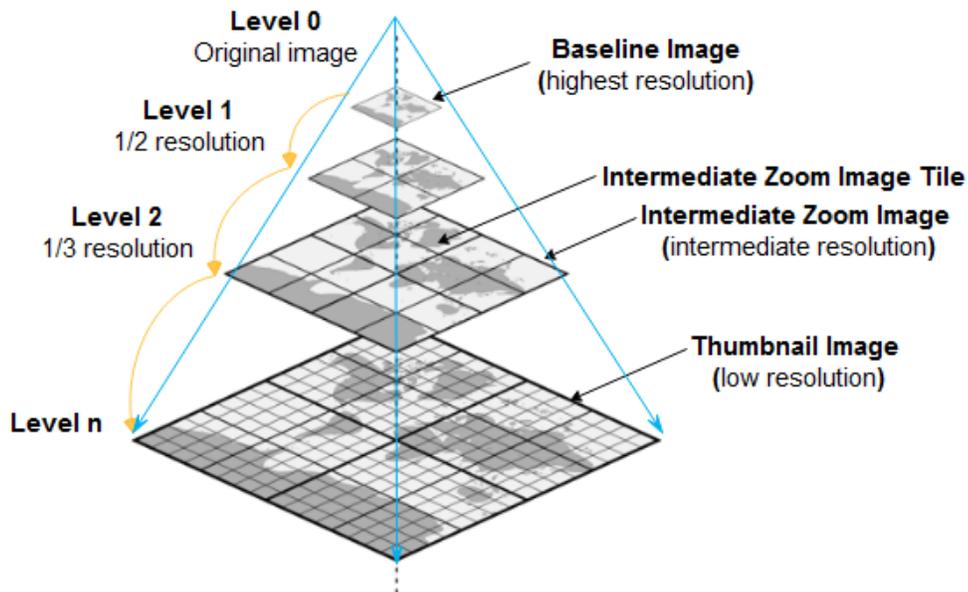


FIGURE 4.1: Four levels RS image tiled pyramid.

Figure 4.1 shows a four-level pyramid in action. The number of higher image quality levels produced during the pyramid's creation is referred to as the pyramid level. We obtain additional layers of the pyramid as the image's resolution increases. The original image is

at the base of the pyramid. Consider a image at the base of the pyramid with a resolution of 1024*1024 pixels. The resolutions quickly dropped to 512*512, 256*256, and 128*128 by resampling the original image as the pyramid layers grew.

4.2.2 Hbase

HBase, a freely accessible distributed database that operates on the Hadoop Distributed File System (HDFS), stands out as a notable example in this domain. It facilitates fault-tolerant data storage and provides random, consistent, and real-time access to big data. HBase organizes data into tables based on rows and columns, with each unit of data comprising several rows and specific columns referred to as an element. Elements retain multiple variations of similar data recorded at different timestamps. In the HBase table, a column family consists of a set of logically related columns, determined before table use, with columns dynamically generated during utilization. Data in HBase are stored in a dictionary according to the order of row keys. Each row key is unique, serving as both the sole identifier for the table files and the primary key for data retrieval. These logical components are presented in the Figure 4.2 bellow.

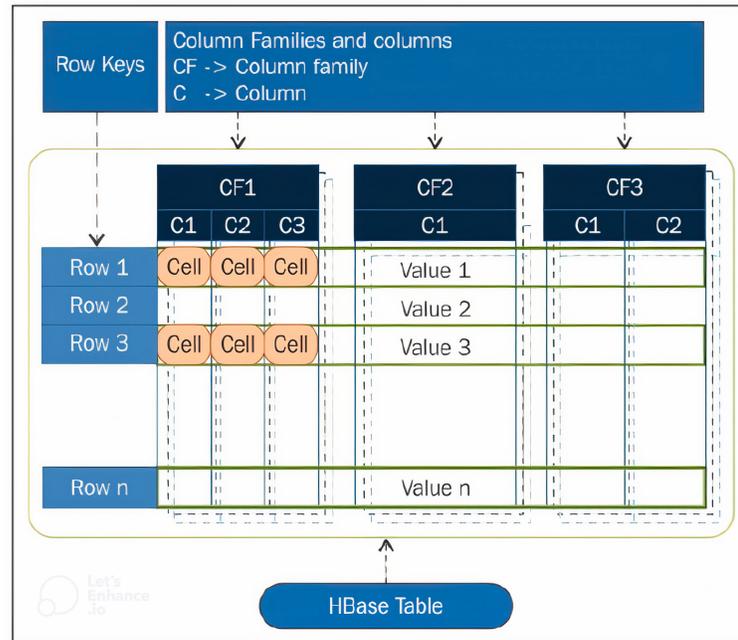


FIGURE 4.2: Hbase Model

Physically [Liu+13], HBase is composed of:

- **HBase Master:** Responsible for region assignment to HRegion servers, handling DLL operations (Create, delete tables), and monitoring the health of each region server.

- **HRegion Server:** Runs on the Hadoop Distributed File System (HDFS) DataNode. It communicates with HBase Master to get the list of regions to be served and informs the Master that it is live.
- **HBase Client:** Responsible for discovering HRegion servers that are serving the particular row range of interest.
- **HFile:** The most basic element of HBase, achieving the fundamental function of fast and efficient storage of Big Table data.
- **Zookeeper:** The coordinator used by HBase as a distributed coordination service. Zookeeper maintains server health in the cluster.

The relationship between these components and how they work together is shown in Figure 4.3 below.

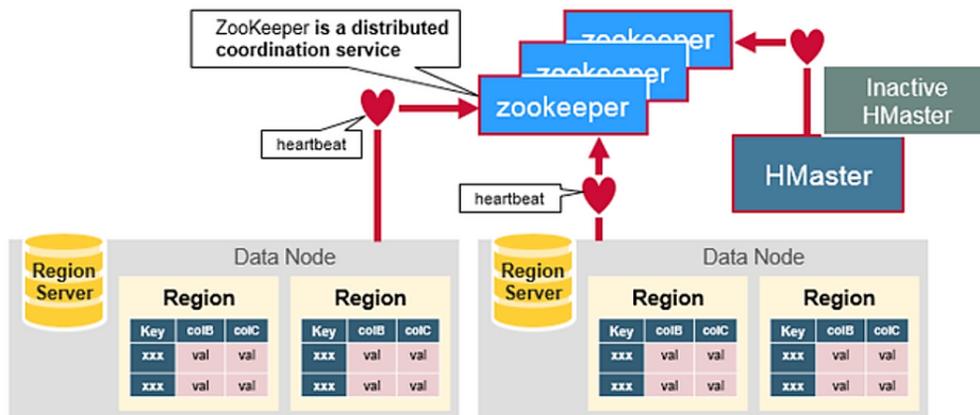


FIGURE 4.3: Hbase Architecture

4.2.3 InfluxDB

InfluxDB, a product of InfluxData developed using the Go programming language, is a schemaless open-source time-series database that can be enhanced with optional proprietary components. This database is designed for optimal performance when handling time-series data, and offers an SQL-like query language. The open-source version of InfluxDB, known as the TICK Stack (refer to Image 4.4), constitutes a comprehensive time-series database platform that includes a range of services, such as the InfluxDB core, and can be deployed on both cloud and on-premises infrastructures, even on a single node. InfluxData provides two proprietary versions of InfluxDB: InfluxEnterprise (IE) and InfluxCloud (IC). These versions offer additional features, including high availability, scalability, backup, and restoration and can be deployed on premises with InfluxEnterprise or cloud infrastructure with InfluxCloud.

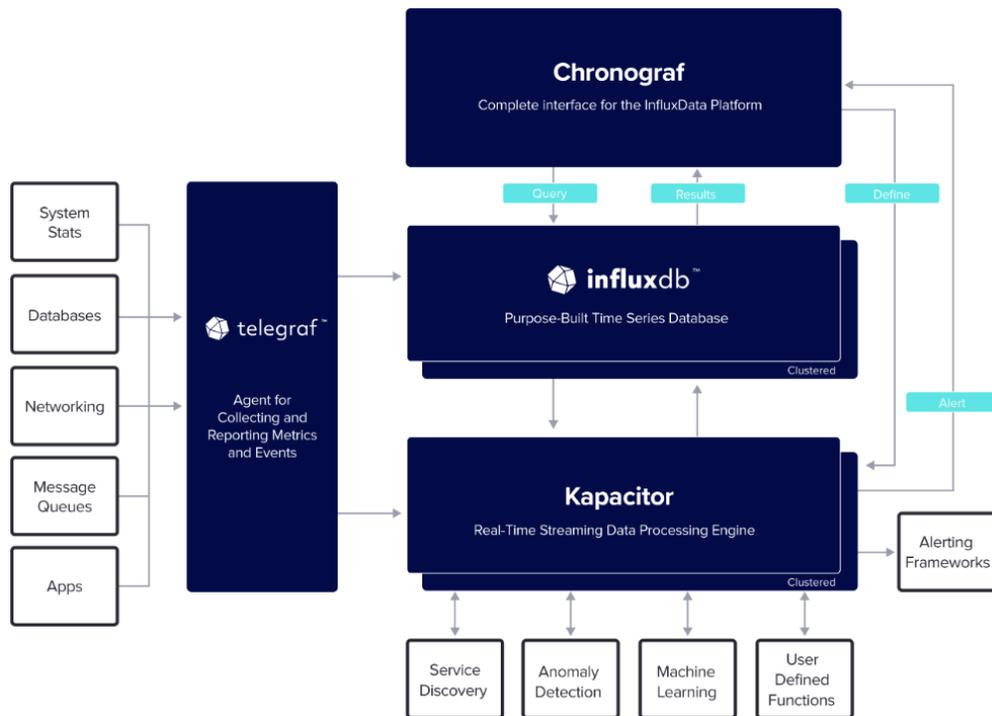


FIGURE 4.4: Influxdb Architecture

The decision to utilize InfluxDB for storing IoT data, with a specific focus on red palm weevil-related information for early detection, is strategic. InfluxDB, developed in Go as a specialized time-series database, stands out for its efficiency. Its compilation into a single binary file without reliance on external dependencies makes it an ideal choice for scenarios involving timestamped big data, such as those encountered in IoT applications.

The repository [3] includes benchmarking code that evaluates InfluxDB against various databases, including Elasticsearch, Cassandra, MongoDB, and OpenTSDB. This is particularly relevant for IoT applications because of its ability to mimic operations in scenarios involving hundreds or thousands of virtual machines. The testing methodology was transparent and carried an MIT license.

In practical IoT implementations, InfluxDB demonstrates an advantage with its high-performance HTTP/S API for both write and query operations. It supports plugins, such as Telegraf and Graphite, for data ingestion, enhancing its adaptability. The automatic expiration and deletion of data, based on defined retention policies, ensures effective data management over time. SQL-like Continuous Queries (CQ) facilitate interactions with data by enabling automatic downsampling and expiring data, aligning well with the needs of IoT environments.

The open-source characteristics of InfluxDB enable effortless integration into cloud-based

platforms, thereby facilitating the transmission of time-series data between controlled intelligent environments. In a typical configuration, a software agent situated at the gateway oversees data flow within the smart environment.

In conclusion, InfluxDB is a suitable option for IoT applications, equipped with the necessary functionalities for efficient data storage, retrieval, and administration, which are vital for detecting early warning signs associated with red palm weevils [NK19].

4.3 Proposed approach for multi-modal data management

Databases are among the best ways to store data overall. However, they face challenges in handling the rapid growth of geographical data, which leads to storage inefficiencies and performance bottlenecks. To tackle this, we propose a distributed paradigm tailored for managing extensive remote sensing image data efficiently. Our innovative Hbase model, built on a tile pyramid image data structure, improves both storage and access through attribute indexing. This system offers a clear method to effectively manage large-scale geographical datasets across diverse sources.

The illustration of our multi-modal data management strategy in Figure 4.5 demonstrates the harmonious blending of massive satellite, UAV, and IoT data, resulting in a cohesive and expandable solution for effective storage and access of information. This innovative approach consists of two distinct models, each specifically designed to address the unique challenges and characteristics of remote sensing data and massive IoT data. These models are described as follow:

4.3.1 RS Data Management Model

To guarantee the efficient storage of high-resolution remote sensing imagery, we have developed a HBase model based on a tile pyramid image data structure for distributed storage. By indexing the metadata that characterizes the remote sensing data, we have significantly enhanced both storage and access capabilities.

4.3.1.1 Pyramid model for image division

Typically, satellite images are larger than 300 MB. The image is divided, and then the data volume is increased by one-third. As a result, according [CT14] and [LJW19], the amount of mosaic tile data can approach 10 GB or 100 GB. [WCS09] The pyramid model based on image block technology aids in the effective storage and access of RS data. Building up a hierarchical, multiscale pyramid model with a global sub-division grid image is the most popular way to arrange image data blocks. The image blocks of specified geographical regions and resolution levels may thus be easily accessed by end users as needed, [CZW20]. RS images often consist of many bands. In this study, we discuss multi-band, high-resolution satellite photos (i.g., multi-spectral images). Every band is a combination of various pyramid

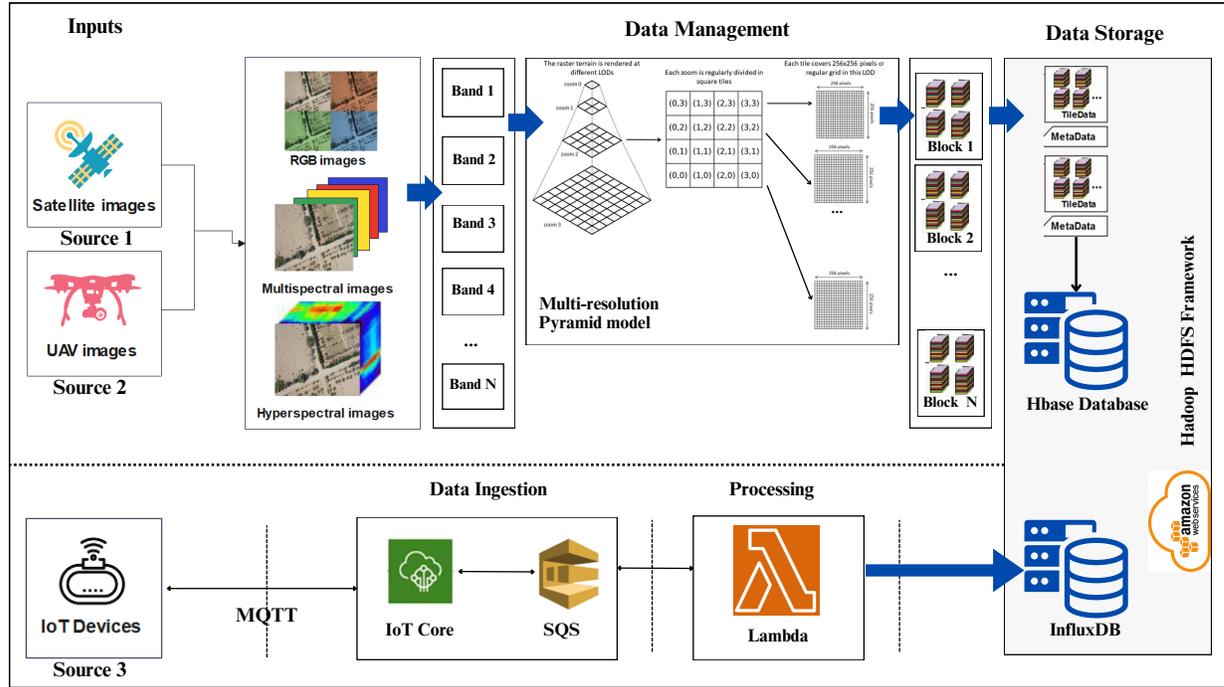


FIGURE 4.5: Multi-modal data management approach: (above) RS data management model, (below) IoT data management model.

layers, where a pyramid layer may offer a variety of blocks. Initially, the original image serves as the foundation, situated at the apex of the pyramid, which is referred to as "level 0" (the highest level of data). Subsequently, the pyramid was partitioned into equal segments. An image pyramid is shown in Figure 4.6(a). Each partition is referred to as a tile. A tile is characterized by its level, row, and column. These distinctions dictate how tile data are encoded. The encoding procedure is illustrated in Figure 4.6(a).

The procedure for dividing an image is as follows: first, the high-resolution satellite image must be split into several zoom levels based on the multi-resolution pyramid model (Figure 4.1). The pyramid model's images will then be separated into layers and rectangular tiles with the same pixel size, as explained in the theory of partition. For instance, the tile size in ArcSDE (SDE for Spatial Database Engine) is 128×128 while the tile size in Oracle GeoRaster is 256×256 [XXR07]. In the suggested system, the block size is set at 256×256 dollars by default [LCG11]. Second, the row and column numbers (row_{nu} , col_{nu}) of a block in the pyramid layer may be used to identify it. With a given longitude λ and latitude φ , the following equations may be used to get the corresponding values at pyramid level κ :

$$row_{nu} = [((\varphi + 90)/(180/2^{\kappa})) \bmod 2^{\kappa}] \quad (4.1)$$

$$col_{nu} = [((\varphi + 180)/(180/2^{\kappa})) \bmod 2^{\kappa+1}] \quad (4.2)$$

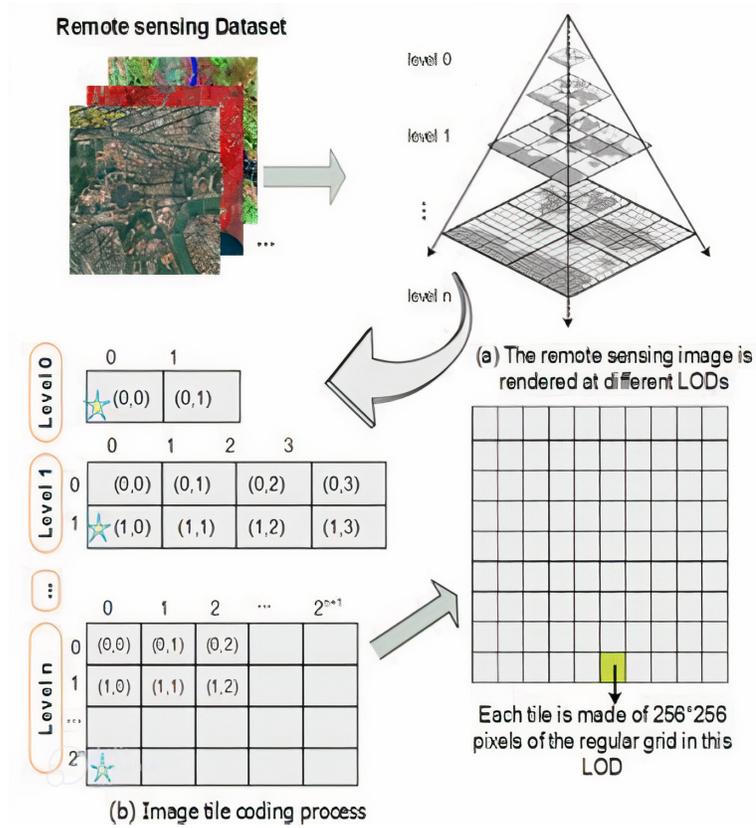


FIGURE 4.6: Pyramid model of bloc image.

Additionally, the $(rownu, colnu)$ numbers and the pyramid level k might be used to denote the geographic area of a tile as follows:

$$west = ((rownu \bmod 2^{k+1}) \times 180/2^k) - 180 \quad (4.3)$$

$$east = west + 180/2^k \quad (4.4)$$

$$south = ((colnu \bmod 2^k) \times 180/2^k) - 90 \quad (4.5)$$

$$north = south + 180/2^k \quad (4.6)$$

4.3.1.2 Image Data Storage Model

To effectively manage high-resolution remote sensing (RS) images, numerous researchers have employed image-based structures for data division, as demonstrated in previous studies (e.g., [YMY+17]). Building on these findings, we designed a novel model that utilizes Hbase and HDFS to store and access image data, leveraging the benefits of distributed databases.

Figure 4.7 depicts an overview of the suggested approach for the storage of image data. A collection of RS image data makes up the recommended system's entry. In our context,

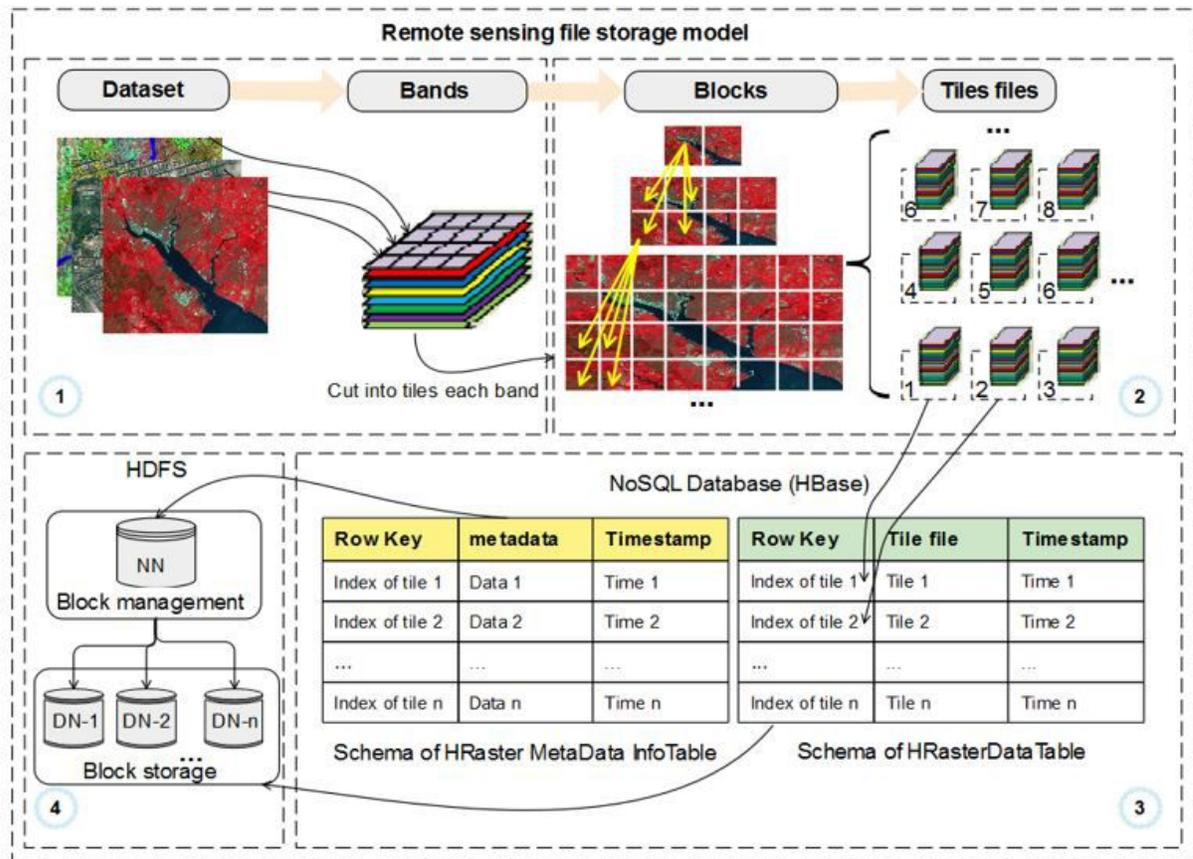


FIGURE 4.7: RS data system with HDFS and Hbase.

high-resolution (spatial, spectral, and temporal) images—such as multi-spectral and hyper-spectral images—as well as high-spatial- and high-temporal-resolution images—are at issue.

Each of these images has many bands, as seen in Figure 4.7 (1)). Each band is divided into many levels and blocks in accordance with the steps involved in constructing the pyramid model (see the first section). So, for each band, a collection of pyramids is created. We employed the band sequential format (BSQ) to store all data of the same position, from all bands, in the same block in order to reduce the amount of data transmitted across the worker nodes (Figure 4.7 (2)). The blocks are then removed from each pyramid and put in the Hbase database. Based on Hbase and HDFS, we created a tile-based, scalable, high-resolution data storage system. The metadata and RS image data blocks are kept in separate tables, referred to as HRaster MetaDataInfoTable and HRasterDataTable, respectively. The metadata column in the HRaster MetaDataInfoTable table is used to record the metadata of each layer of the image in order to speed up data retrieval queries. When a new RS image is imported, a new RasterDataTable table is created to store the tile file portions and a new file of metadata is added to the HRaster MetaDataInfoTable (Figure 4.7 (3)).

To improve the load balancing and security features provided by HDFS, we have implemented a Hbase database on top of it. Hbase allows us to store vast amounts of data and enables fast data queries based on row keys. This integration provides a scalable and efficient solution for managing and accessing RS data.

In Figure 4.7 (4), we illustrate the master/slave architecture of HDFS. The DataNodes are responsible for storing the actual block data, while the NameNodes oversee the file system and metadata of the entire RS data. This distributed architecture ensures high availability and fault tolerance for the RS data. By leveraging the combined capabilities of HDFS and Hbase, we can effectively manage and process large-scale RS data while benefiting from load balancing, security features, and fast data retrieval.

We applied the balanced placement strategy (BPS) and periodic storage strategy (PSS) suggested in [WWZ20] to increase the effectiveness of the distributed database. The tiles will first be distributed evenly across the nodes in accordance with the BPS approach (Figure 4.8). Since the tiles will be kept together based on their spatial correlation, this method helps to prevent data skew and hot-spotting and enhances query performance. Second, when storing tiles of the same image, the PSS technique aggregates the tile according to the period to save data blocks. As a result, the suggested technique enhances not only the efficiency of data administration and access but also the temporal interaction inside data blocks.

4.3.1.3 RS tile data index

The space-filling curve (SFC) has several definitions that are based on various mapping possibilities (such as Morton, Peano, and Gray); see [Sag12] [BCM18] for examples. The Hilbert SFC appears to be superior and more stable when compared to other linearization curves. Therefore, we suggest using the Hilbert SFC technique to index each tile and fill the grid of each image [BCM18]. This approach, which converts two-dimensional spatial locations into one-dimensional space and assigns cells unique codes, guarantees the data's great spatial closeness [WWZ20]. As a result, tiles with matching Hilbert codes are preserved together.

The production of the four order Hilbert curves (H1, H2, H3, and H4) for both 1D and 3D data is shown in Figure 4.9, which is based on step-wise geometric recursion. We develop the concept of tile indexation and row keys for each tile in the database in accordance with the design of the pyramid model and the Hilbert curve indexation model.

For tile data made up of four main sections, we utilized a sample from a row-key model (see Figure 4.10). RasterID is stored in bits from 0 to 15, pyramid level number is stored in bits from 15 to 16, image band number is stored in bits from 16 to 32, and the final 32 bits of the row-key are used for the Hilbert code, which identifies the tile's spatial placement within the image. We can quickly run particular queries thanks to RS data indexation. Additionally, we can quickly retrieve RS data stored in the database for data processing and analysis thanks to the RS tile data index.

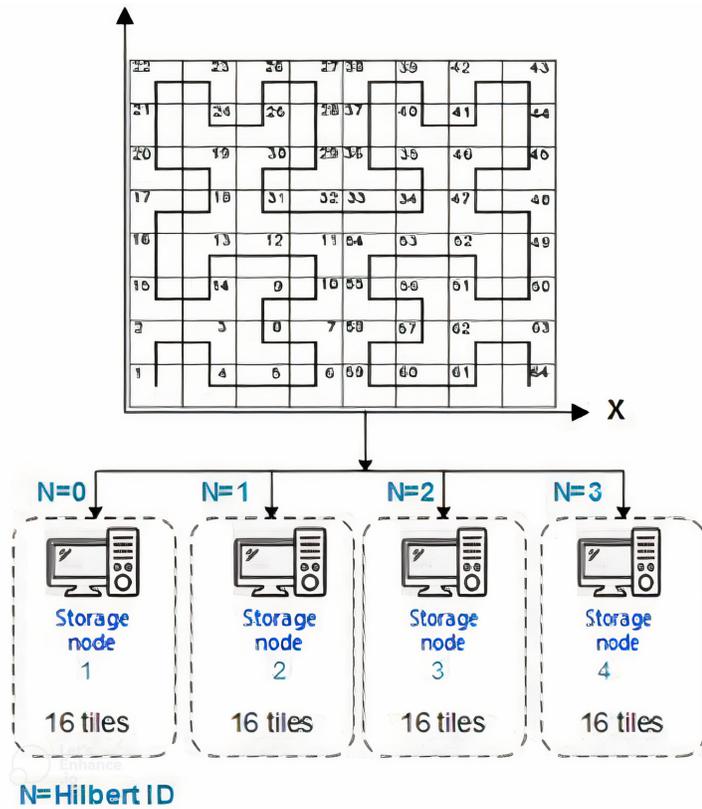


FIGURE 4.8: Tiles distribution using BPS.

The proposed model initiates with the introduction of a unified metadata file model, foundational for standardizing metadata across diverse distributed data centers, facilitating seamless importation and integration of data. This is followed by the implementation of two data organization models– the pyramid model and the Hilbert-SFC-based data-indexing mechanism, strategically enhancing the efficiency of querying and accessing remote-sensing images. For robust data management, the integration of the NoSQL database management system Hbase ensures the efficient distribution of stored data across multiple nodes, enhancing scalability and accessibility. Additionally, the utilization of the Hadoop framework plays a pivotal role in managing and processing remote sensing big data. This comprehensive system, encompassing unified metadata modeling, advanced classification models, and distributed database and processing frameworks, forms an integrated solution for multi-source remote sensing data management and storage.

4.3.1.4 Standardizing the Archival Model for RS Metadata

The role of RS metadata is pivotal in facilitating complementary studies on Earth observations. Efficient management of these metadata can streamline the application and exchange of RS knowledge. In this study, RS metadata refer to the descriptive information associated

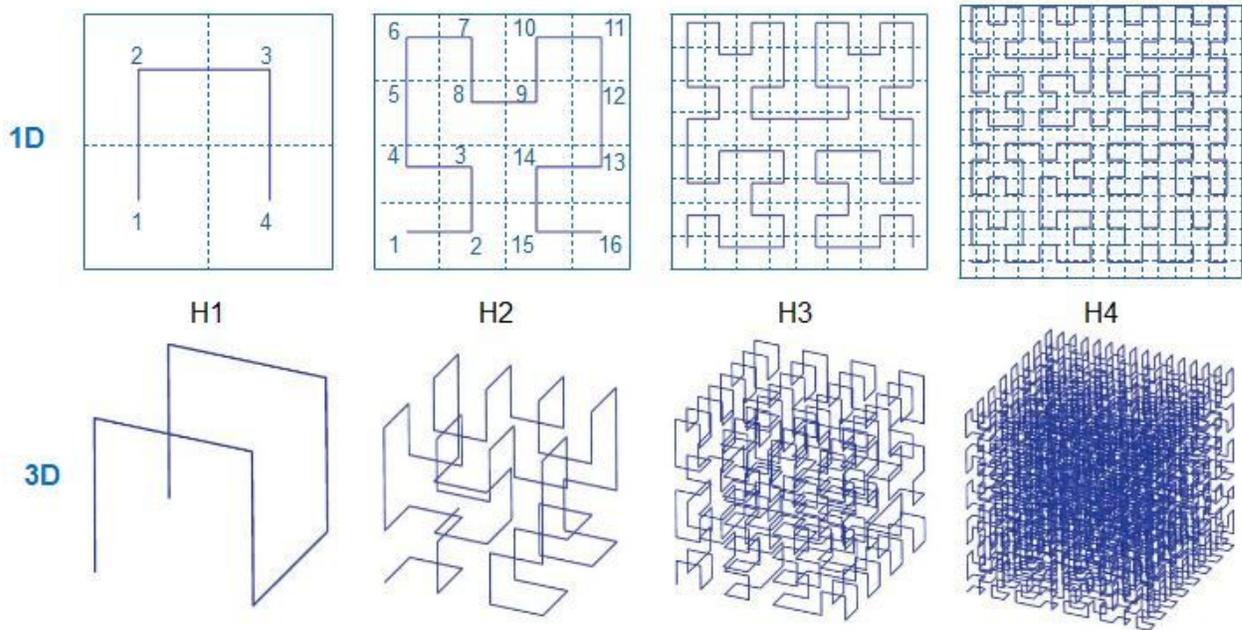


FIGURE 4.9: The filling process of the Hilbert curve for tiles data index.



FIGURE 4.10: Hbase key value structure

with satellite image data, where these metadata are generated to store attribute information. However, the components of metadata files are diverse, introducing complexities in the unified management of RS metadata. For instance, in the ZY-3 metadata file, the fields "Satellite-ID" and "Sensor-ID" correspond, whereas in the Landsat 8 metadata file, the fields "SENSOR-ID" and "SPACECRAFT-ID" serve as the sensor identifiers in the satellite and the satellite identifier of the image, respectively. Therefore, it is imperative to establish a unified archiving model for RS data management.

Unified Satellite Image Metadata In this study, we adopted the ISO 19115-2:2009 standard for geo-information metadata, which is the second section of ISO 19115 and an extension of the image and grid data. This standard has been incorporated into the global metadata warehouse Common Metadata Repository (CMR), becoming a standard for data sharing, integration, and recovery between geo-data centers and international geographic information organizations. We employed a uniform standard format model for archiving the RS metadata; its defined fields are listed in Table 4.1. This standard is established based on a comprehensive survey and investigation of existing metadata standards, including the

ISO 19115 geographical information metadata standard, and CSDGM (Content Standard for Digital Geospatial Metadata) ISO 19115:2003 cor.1:2003, along with the metadata structure of various RS data resources.

Unified UAV Image Metadata A comprehensive and robust model for the metadata of UAV images was developed in conjunction with the standardization of satellite image metadata. This model, which is detailed in Table 4.2, encompasses the essential fields for organizing and describing UAV-captured images. The 'ImageInfo' section includes key information such as the 'ImageName,' 'UAV-ID,' and 'Camera-ID' for the purpose of unique identification. The temporal aspects of the images are covered by 'CaptureTime,' while the spatial dimensions are encapsulated in 'GPS-Latitude,' 'GPS-Longitude,' and 'Altitude.' Information about the UAV's orientation, the specific sensor used ('SensorInfo'), image resolution, and the flight path taken during capture ('FlightPath') contributed to the richness of this metadata model. Furthermore, insights into prevailing weather conditions during image capture enhance the contextual understanding of the data. 'DataLink,' 'DataProvider,' and 'DataOwner' facilitate seamless data-retrieval 'and' ownership attribution. Overall, this UAV Image Metadata Model adheres to a unified structure for consistent and organized archival UAV image data, thereby enabling cohesive analysis and interlinking with other geospatial datasets.

4.3.2 Massive IoT data storage

In the second model, we shifted our focus to IoT devices and their integration into AWS infrastructure. AWS provides a comprehensive suite of services, each serving a specific purpose in our data processing pipeline.

4.3.2.1 Data Transmission: MQTT Protocol

The message queue telemetry transport (MQTT) protocol serves as the foundation for an effective IoT data transmission. This adaptable and streamlined messaging system streamlines communication between IoT devices and the extensive AWS ecosystem. Designed to function optimally in resource-limited settings, MQTT guarantees prompt and dependable transmission of data, making it an ideal choice for managing the red palm weevil dataset and similar applications that require real-time data exchange. The following Equation represents the efficiency calculation:

$$\text{Efficiency} = \frac{\text{Data Successfully Transmitted}}{\text{Total Data Sent}} \quad (4.7)$$

4.3.2.2 Data Ingestion: AWS IoT Core and SQS

The AWS IoT Core is a crucial element in the domain of data ingestion, acting as a central hub for coordinating and processing substantial volumes of data originating from IoT

TABLE 4.1: Standard archival model for RS metadata

| Classification | Field name | Description |
|-----------------------|----------------------|-------------------------------------|
| MetadataInfo | Creation | Time of metadata creation |
| | Last update | Time of last update |
| ImageInfo | ImageName | Image data name |
| | Tilescodes | |
| | Level | |
| | Satallite-ID | Satellite identifier |
| | Sensor-ID | Sensor identifier |
| | ReceiveTime | Time of data reception |
| | Satallite-ID | Satellite identifier |
| | ReferencesysitemID | Reference coordinate system |
| | Time-beginposition | Start time |
| | Time-endposition | Stop time |
| | ProductLevel | Product level |
| | ProductFormat | Product format |
| | Time-endposition | Stop time |
| | SpatialResolution | Spatial resolution |
| | Time-endposition | Stop time |
| | ProcessingLevel | Pprocessing level |
| | Centerlongtude | Center point longitude |
| | Centerlatitude | Center point latitude |
| | TopLeftLatitude | Latitude in the upper-left corner |
| | TopLeftLongitude | Longitude in the upper-left corner |
| | TopRightLatitude | latitude in the upper-right corner |
| | TopRightLongitude | Longitude in the upper-right corner |
| | BottomRightLatitude | Latitude in the lower-right corner |
| | BottomRightLongitude | Longitude in the lower-right corner |
| | BottomLeftLatitude | Latitude in the lower-left corner |
| | BottomLeftLongitude | Longitude in the lower-left corner |
| FilePath | Path | |
| SceneRow | Row | |
| CloudPercent | Cloud cover volume | |
| DataLink | Data download URL | |
| DataProvider | Data provider | |
| DataOwner | Data owner | |

TABLE 4.2: Standard UAV Image Metadata Model

| Classification | Field name | Description |
|----------------|-------------------|--|
| MetadataInfo | Creation | Time of metadata creation |
| | Last update | Time of last update |
| ImageInfo | ImageName | Image data name |
| | UAV-ID | UAV identifier |
| | Camera-ID | Camera identifier |
| | CaptureTime | Time of image capture |
| | GPS-Latitude | Latitude of UAV at capture |
| | GPS-Longitude | Longitude of UAV at capture |
| | Altitude | Altitude of UAV at capture |
| | Orientation | UAV orientation |
| | SensorInfo | Information about the camera/sensor used |
| | Resolution | Image resolution |
| | FlightPath | Path followed during the UAV flight |
| | WeatherConditions | Conditions during image capture |
| | DataLink | Data download URL |
| DataProvider | Data provider | |
| DataOwner | Data owner | |

devices. This robust service is dedicated to providing secure, scalable, and low-latency communication, which is of utmost importance when dealing with massive IoT datasets such as those associated with red palm weevil monitoring. To optimize data flow, the AWS utilizes a Simple Queue Service (SQS) as an intermediary, effectively queuing incoming IoT data. This not only increases efficiency, but also paves the way for subsequent processing that is specifically tailored to the nuances of the red palm weevil dataset. The following Equation represents the optimization calculation:

$$\text{Optimization} = \frac{\text{SQS Queued Data}}{\text{Total Incoming Data}} \quad (4.8)$$

4.3.2.3 Processing: AWS Lambda Functions

Understanding the intricate task of managing the red palm weevil dataset requires a robust processing mechanism. AWS Lambda functions, with their serverless architecture, serve as critical components in executing vital operations, such as effortlessly inserting data into databases. This serverless approach imbues flexibility and scalability, enabling seamless adaptation to fluctuating workloads inherent in red palm weevil monitoring. Be it real-time data processing or periodic analysis, AWS Lambda functions are poised to fulfill the unique requirements of red palm weevil dataset management, thereby fostering an agile and responsive system. The following Equation represents the flexibility calculation:

$$\text{Flexibility} = \frac{\text{Serverless Operations}}{\text{Total Operations}} \quad (4.9)$$

4.3.2.4 InfluxDB for IoT Data Storage

InfluxDB, a database management system renowned for its expertise in handling time-series data, plays a pivotal role as the ultimate storage solution in architecture. The data, transmitted through the MQTT pipeline, are seamlessly integrated with the AWS IoT Core and are efficiently buffered via SQS before determining its ultimate destination in InfluxDB. The architecture of the database was meticulously optimized to meet the specific demands of handling massive IoT datasets, making it a scalable, high-performance, and well-organized repository. This level of optimization is crucial for managing the red palm weevil dataset. In the context of RPW IoT data, InfluxDB is a critical component offering an ideal solution. As data undergo transmission, integration, and buffering, the specialization of InfluxDB in handling time-series data becomes evident. Its scalability ensures adaptability to increasing data volumes and provides a sustainable solution for the continuous monitoring of red palm weevils. The database's exceptional performance facilitates real-time insights, whereas its organized repository management enables logical categorization and indexing, ensuring the ease of data retrieval. In summary, InfluxDB emerged as a tailored and finely tuned solution perfectly aligned with the complexities of the red palm weevil dataset.

In the context of RPW monitoring, InfluxDB provides a robust solution for efficiently managing both metadata and sensor data:

Metadata Data Management in InfluxDB

The metadata, containing information about monitoring stations, is organized in a measurement called `metadata`. Each monitoring station is uniquely identified by a `station_id` tag and additional fields such as `location`, `latitude`, and `longitude` offer valuable contextual information. An example is shown in Figure 4.11.

```
metadata, station_id=001 location="Farm A",latitude=12.345,longitude=67.890
metadata, station_id=002 location="Farm B",latitude=13.567,longitude=68.901
metadata, station_id=003 location="Farm C",latitude=14.789,longitude=69.012
...
```

FIGURE 4.11: Metadata Data Management in InfluxDB

RPW Sensor Data Management in InfluxDB

For RPW sensor data, a measurement named `rpw_sensor` is employed. This measurement includes fields like `temperature`, `humidity`, and `status`. The `station_id` tag associates each

data point with a specific monitoring station, facilitating organized retrieval and analysis. An example is shown in Figure 4.12.

```
rpw_sensor,station_id=001 temperature=28.5,humidity=65,status="healthy" 1627992000000
rpw_sensor,station_id=002 temperature=27.8,humidity=63,status="infested" 1627992100000
rpw_sensor,station_id=003 temperature=29.3,humidity=68,status="healthy" 1627992200000
...
```

FIGURE 4.12: RPW Sensor Data Management in InfluxDB

This structured approach enables seamless queries to extract insights from both metadata and sensor readings. Leveraging InfluxDB’s flexibility, this model ensures efficient data storage, retrieval, and analysis for comprehensive RPW monitoring.

4.4 Experimental and results

In this section, we focus on evaluating the effectiveness of remote sensing image data model of storage. We deliberately excluded any tests related to the IoT data storage model, as numerous comprehensive studies have already conducted extensive comparisons between our chosen database, InfluxDB, and other databases. These studies have assessed its performance and benchmarked its effectiveness across diverse contexts and scenarios [NK19; Gia+20; HKK; WŁO+23]. The collective results of these studies emphasize the strong justifications for selecting InfluxDB as our preferred database solution for storing massive Iot data.

4.4.1 Dataset collection

The experimental dataset comprised an extensive and varied collection of high-resolution remote sensing (RS) images sourced from multiple satellite platforms and sources. These include Spot-6 and Spot-7, which provide multispectral data with four bands at resolutions of 1.5 meters and 6 meters, respectively; QuickBird, which offers multispectral data with four bands at resolutions of 0.65 meters and 2.4 meters; and unmanned aerial vehicles (UAVs) that capture RGB images with resolutions varying based on the platform.

Additionally, data from Copernicus (Sentinel-2) contributed to 13 bands with resolutions ranging from 10 m to 60 m, while Sentinel-3 (OLCI) provided 21 bands with resolutions ranging from 300 m to 1 km. WorldView-3 delivers eight multispectral and eight shortwave infrared bands at a high resolution of 1.24 meters, whereas Landsat 8 contributes 11 bands with resolutions of 15, 30, and 100 m. Hypersat supplies hyperspectral data with up to 448 bands and WorldView-2 features eight multispectral and eight coastal blue bands at a resolution of 1.84 meters.

This diverse dataset, with its multispectral and hyperspectral characteristics, offers a broad spectrum of information and is a valuable resource for conducting comprehensive experiments and analyses in remote sensing and environmental applications.

The dataset was meticulously organized into several groups, each of which represents a distinct data size. This arrangement enables testing and experimentation across a range of resource intensities. The sizes of these categories ranged from 20GB to 40GB, with the possibility of expansion up to 100GB. They have been tailored to specific characteristics, providing flexibility for evaluating performance on various scales. The dataset comprises a diverse array of sources, high resolutions, and multispectral and hyperspectral layers, reflecting a comprehensive effort to enhance the effectiveness of our proposed method in remote sensing and environmental applications.

TABLE 4.3: RS images data details

| Data source | Number of Bands | Resolutions |
|-------------------------|---|---|
| Spot-6 | 4 | 1.5 m, 6 m |
| Spot-7 | 4 | 1.5 m, 6 m |
| QuickBird | 4 | 0.65 m, 2.4 m |
| UAVs (RGB) | 3 (Red, Green, Blue) | Varies by UAV platform |
| Copernicus (Sentinel-2) | 13 | 10 m, 20 m, 60 m (depending on band) |
| Sentinel-3 (OLCI) | 21 | 300 m - 1 km (depending on band) |
| WorldView-3 | 8 (Multispectral), 8 (Shortwave Infrared) | 1.24 m |
| Landsat 8 | 11 | 15 m, 30 m, 100 m |
| Hypersat | Up to 448 | Varies by band (e.g., 2.5 m, 5 m, 10 m) |
| WorldView-2 | 8 (Multispectral), 8 (Coastal Blue) | 1.84 m |

OLCI: Ocean and Land Color Instrument

4.4.2 Evaluation metrics

Four measurements were used for the evaluations: speedup, efficiency, scaleup, and sizeup. The following sub-sections discuss these measurements and the results obtained.

In evaluating a parallel system, two performance measures of particular interest are speedup and efficiency

Speedup

Speedup is a metric used to evaluate the potential improvement in the execution time that can be achieved through parallelism. It is calculated as the ratio of the sequential execution

time to the parallel execution time and is expressed as follows:

$$\text{Speedup } (S_m) = \frac{T(1)}{T(m)} \quad (4.10)$$

Where the execution time of a task on one computing node is represented by $T(1)$, while the execution time of a parallel task utilizing m computing nodes is represented by $T(m)$. A perfect parallelism results in a linear speedup, where a system with m times the number of computing nodes achieves a speedup of m . However, achieving linear speedup is challenging due to the increasing communication costs associated with an increase in the number of computing nodes. According to [EZL89], processes with an efficiency of greater than 0.5 (50%) are considered to have achieved good performance.

Efficiency

Efficiency is defined as the average utilization of n allocated processors. Ignoring the I/O, the efficiency of the single-processor system was 1. The speedup in this case was, of course, 1. In general, the relationship between efficiency (E) and speedup (S) is given by

$$\mathbf{E}(\mathbf{n}) = \frac{S(n)}{n} \quad (4.11)$$

If the efficiency remains at 1 as processors are added, we have a linear speedup. Technically, for linear speedup, only $S(n) = C \cdot n$ for some constant C , where $0 < C \leq 1$. We use a stricter definition $C = 1$ throughout. This is the ideal case, as improvements in speedup can be obtained at no cost in terms of efficiency. In general, linear speedup is not achievable because of contention for shared resources, the time required to communicate between processors and between processes, and the inability to structure the software such that an arbitrary number of processors can be kept busy.

Eager, Derek L and Zahorjan [EZL89] noted evidence that the “typical” speedup has the form:

$$\text{Speedup}(\mathbf{S}(\mathbf{n})) = \log n \quad (4.12)$$

Other studies have provided evidence that much larger “typical” speedups can be attained.

Scaleup

In the context of parallel computing, the term "scaleup" refers to the capability of a parallel system or application to manage larger workloads or datasets as the system's resources, such as processors, memory, or storage, are increased or scaled. Scaleup is often evaluated by assessing the performance of a system as the complexity of the problem being solved increases. Scaleup is closely associated with the concept of "scalability," which encompasses a system's ability to handle increased amounts of work by adding more resources. Scaleup

specifically pertains to the enhancement in performance or efficiency as the system scales, typically by adding more parallel processing units.

In a parallel system, achieving good scale-up implies that as the system size or complexity increases, computational performance improves or remains consistent. This is a crucial consideration in the design and evaluation of parallel algorithms and architectures, as it directly affects the system’s ability to handle computationally demanding tasks efficiently. The scale-up of a parallel system can be mathematically expressed as follows:

$$\mathbf{Scaleup}(m) = \frac{T(1, D)}{T(m, mD)} \quad (4.13)$$

where m is the number of computing nodes, $T(1, D)$ is the execution time of the tasks on 1 computing node with a data size of D , and $T(m, mD)$ is the execution time of the parallel tasks with m computing nodes and a data size m times D . Perfect parallelism demonstrates a constant scaleup.

Sizeup

Sizeup evaluates the ability of parallelism to handle growth, measuring the execution time of parallel tasks as the data size increases. It assesses how much longer it takes to execute parallel tasks when the data size is n -times larger than the original datasets. Sizeup analysis maintains the number of computing nodes constant and grows the size of the datasets by the factor n . Sizeup can be expressed as follows:

$$\mathbf{Sizeup}(m, n) = \frac{T(m, nD)}{T(m, D)} \quad (4.14)$$

where m is the number of computing nodes, n is the incremental factor of the data size, $T(m, D)$ is the execution time of parallel tasks with m computing nodes and data size D , and $T(m, nD)$ is the execution time of parallel tasks with m computing nodes and data size n times D .

4.4.3 Experimental Setup

The Our experimental methodology relies on the use of virtual machines that have been carefully designed within the Amazon Web Services (AWS) cloud platform. AWS provides a comprehensive suite of analytics management services based on open-source principles. This environment seamlessly supports well-known open-source frameworks including Apache Hadoop, Apache Hive, Apache Kafka, Apache Spark, and Apache Storm [JMK23].

The detailed specifications of the cluster nodes, as outlined in Table 4.4, provide a comprehensive overview of the essential attributes that drive the experimental setup. Notably,

the deployment included instances of Hbase version 1.4.13, ZooKeeper version 3.4.14, and Hadoop version 2.7.3 across all instance machines.

This carefully controlled environment underscores the robustness and reliability of our experimental studies, enabling us to assess our proposed approaches within the dynamic landscape of cloud-based analytics on an AWS platform.

TABLE 4.4: AWS EC2 Instances Node Description

| Node type | Head Node | Worker node |
|---------------|------------------|------------------|
| Instance | m5.large | m4.large |
| Node size | 2 vCPUs, 8GB RAM | 2 vCPUs, 8GB RAM |
| OS | Linux | Linux |
| Hourly Price | \$0.096 | \$0.032 |
| AWS EC2 Price | \$0.064/hour | \$0.064/hour |
| Total Price | \$0.16/hour | \$0.096/hour |

4.4.4 Experimental results and discussion

4.4.4.1 Experiment A: Parameter Optimization of tile size:

In this experiment, two different parameters, the tile size, and the data size were selected to compare the slice time per response time. As measures for the performance comparison, we took into account two storage models at various sizes as well as time storage.

Figure 4.13 shows that when the tile size increases, the reaction time also increases and vice versa. Additionally, we see that the division time is growing at the same rate as the RS data size. We must carefully select the value of the tile size option if we want to meet the quick query response time criterion. Additionally, when the RS image data size is huge, image processing effectiveness may be increased. In this situation, an equilibrium parameter value must be chosen to satisfy the needs of both users for quick data access and image processing.

4.4.4.2 Experiment B: Scalability on cluster and data size

In this experiment, we examine how effectively the recommended distributed management architecture handles large quantities of high-resolution photos. First, the database’s ingestion performance is evaluated to measure the impact of the cluster’s data node count at the moment of data writing. For comparison, the suggested Hbase model is combined with the conventional Oracle geographical database. As a result, while the number of data nodes rose from 1 to 12, the overall size of the data was maintained.

Second, the performance of ingestion for each group of nodes is examined while the dataset size is increased in order to quantify the impact of data size. Each of the compute nodes uses seven sets of images with varying volume sizes ranging from 20GB to 100GB. The photos are

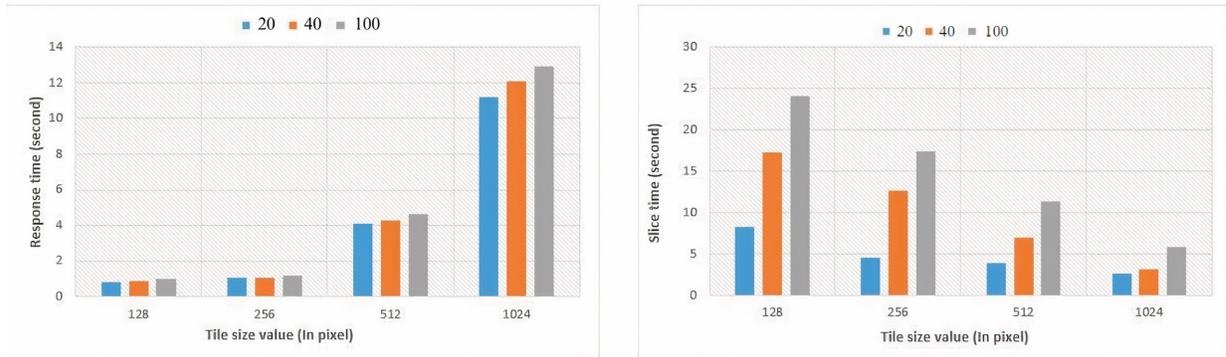


FIGURE 4.13: Response time and slice time of 4 construction methods with different tile size value and data size respectively

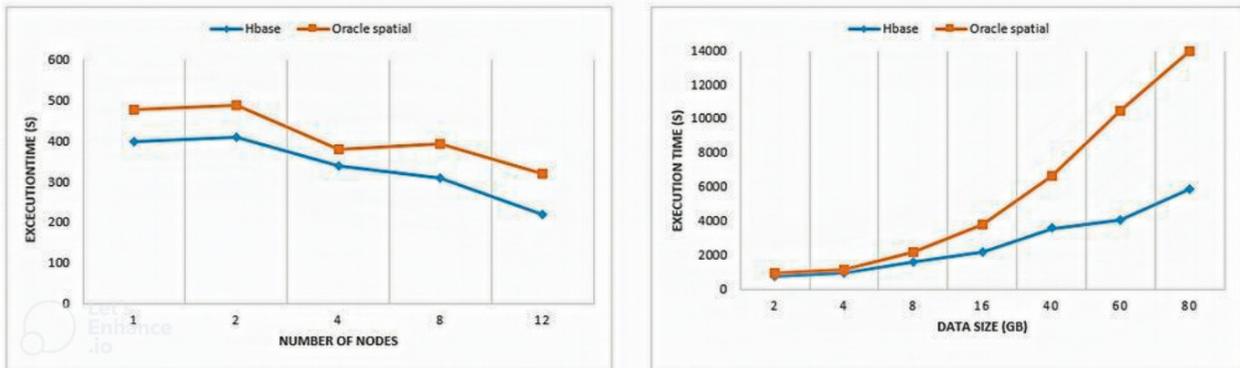


FIGURE 4.14: (a) Data ingestion time of different worker nodes, (b) Write time for different data size

separated into blocks and then stored in each of the 12 nodes. from Reference 4.14.a, For both Hbase and Oracle Spatial databases, it is apparent that the amount of time required for data import decreases as the number of worker nodes in the cluster rises. The storage performance of the suggested approach with Hbase is comparatively more stable, despite the fact that both databases scale well. This finding leads us to the conclusion that performance may be improved by adding more worker node instances to the cluster, especially when there is a strong network connection between the data nodes. Figure 4.14.b illustrates it from the other side.b) that the time needed to insert the RS data image initially varies very slightly across the two types of databases before increasing proportionally as the size of the RS image data rises.

The suggested model's data importation performance is comparatively steady, and the differences between the two databases are clear. The suggested tile-based distributed management approach of huge, high-resolution satellite images has thus been refined in light of the testing results.

4.5 Conclusion

The proposed multimodal system serves as a foundational framework for addressing critical tasks in precision agriculture, particularly in the context of palm tree management and pest detection. In anticipation of our forthcoming contributions, our primary focus will be on employing this system for efficient palm tree detection and counting, as well as for the early detection of the RPW.

Our upcoming contribution, "Efficient Palm Tree Detection Using Deep Learning and UAV Imagery," builds upon the fundamental principles of our multi-modal approach. By seamlessly integrating deep learning techniques with UAV imagery within our unified system, we aim to improve the precision and efficiency of palm tree detection and counting, ultimately contributing to the advancement of state-of-the-art methodologies in precision agriculture.

Our second contribution focuses on the early detection of the Red Palm Weevil, a destructive pest in palm cultivation. By harnessing the capabilities of our multimodal system, we strive to deliver a robust and timely solution for identifying the signs of RPW infestations. Early detection is crucial for implementing effective pest control measures, thereby promoting sustainable management of palm plantations.

The versatility of our proposed multimodal system enabled us to address distinct challenges in both palm-tree management and pest detection. The success of these contributions will further validate the adaptability and efficacy of our system across various agricultural domains, making significant strides in the application of advanced technologies for sustainable and precision farming practices.

Enhanced Object Detection and counting Model for Palm Trees

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5.1 Introduction and motivation

Building on our earlier approach to multi-source agriculture management, we now consider this an equally important aspect of our overall plan. This chapter describes our novel method

for efficiently detecting palm trees using DL and UAV imagery. We chose this method for two reasons: first, it presents a major challenge in precision agriculture, and second, it fits effortlessly into our second goal of smart palm agriculture applications.

Palms are economically and environmentally important in a variety of agricultural areas and require accurate detection and continuous monitoring for optimal land management. However, the complexity of palm tree detection encompasses a variety of problems, such as the varying appearance of trees, occlusions, and changing environmental conditions. To address these multiple difficulties, we leverage the power of state-of-the-art deep learning algorithms combined with high-resolution data collected by UAVs. This comprehensive methodology overcomes the limitations of conventional approaches and enables accurate palm tree detection, counting, and monitoring.

UAV imagery has proven to be extremely effective for monitoring palm plantations. These techniques support several applications, including land cover classification, tree detection and counting, yield estimation, age determination, and pest and disease detection. Remote sensing provides valuable temporal and multimodal data that improves palm plantation productivity.

High-resolution imagery RS, especially very high-resolution (VHR) satellite imagery, provides a cost-effective solution for automatic canopy detection and allows accurate palm detection and counting. Aircraft equipped with infrared, LiDAR, and multispectral sensors also contribute to this process. However, budget constraints often limit the use of space and airborne platforms, especially for small and medium enterprises.

In this context, UAVs offer a cost-effective and flexible alternative for palm detection and monitoring. They capture high-resolution images at customizable altitudes and speeds, providing detailed and accurate information. Compared to other platforms, UAVs also offer better accessibility and maneuverability. Consequently, drone imagery has become the preferred data source for palm plantation monitoring, offering cost savings, comprehensive coverage, and access to remote areas [WW12; BCM12; AM14].

In the last decade, remarkable advances in computer hardware and the rapid development of AI technology have opened new avenues for object recognition and feature extraction in remote sensing imagery. CNNs, a key component of AI, have driven these developments. There are several CNN architectures for object recognition in computer vision and image analysis, which can be divided into two main categories: two-stage and single-stage models. An influential milestone in the field is the two-stage object recognition model called R-CNN, introduced in 2013 by Girshick et al. [Gir+14] This model has significantly advanced the field.

Our research addresses the use of the YOLOv8 a one single stage DL model in conjunction with UAV imagery for automatic palm tree detection and counting. Our goal is to evaluate the performance of this approach by comparing it to the YOLOv5 and YOLOv4 models used in a previous study that provided the dataset for our experiments. This study aims to

provide more accurate and timely plantation statistics that will benefit stakeholders involved in palm management.

In summary, the main contributions will be presented in this chapter can be described as follows:

- **New YOLOv8-based detection method:** We present a unique YOLOv8-based model tailored for date palm detection and counting. This model was trained on UAV imagery to provide accurate date palm identification and counting.
- **Performance comparison:** We evaluate the effectiveness and efficiency of our approach by comparing it to other innovative methods, including YOLOv5. We analyze the accuracy and computational efficiency.
- **Real-World Dataset Testing:** Our experiments include real-world datasets and demonstrate the versatility and effectiveness of our method in different scenarios and environments.
- **Quantitative Results:** We provide quantitative measurements comparing our approach to six leading deep object detection models. This demonstrates the superior performance of our method in palm tree detection.
- **Qualitative Results:** The effectiveness of our model's performance is demonstrated through visually appealing examples, which highlight its capacity to accurately detect palm trees in a range of situations. This qualitative analysis complements the quantitative results, offering a comprehensive insight into the resilience and versatility of our proposed method.

5.2 Methodology

The primary objective of this project was to identify the presence of palm trees in images by utilizing the capabilities of a pre-trained CNN known as YOLOv8. Although YOLOv8 is not specifically designed for palm-tree classification, its strength lies in its ability to extract features from images, allowing it to mathematically describe the geometries or objects present in an image.

The proposed methodology employs the YOLOv8 framework for object identification with the aim of achieving accurate and efficient detection of date palms. The process, illustrated in Figure 5.1, unfolds in two distinct phases: "Offline" and "Online." The offline phase commences with the UAV image database serving as the input dataset. Through region selection, rectangles were drawn around areas of interest potentially containing date palm plants, narrowing the focus for future training. Bounding boxes are then created around the date palm instances at specified locations, generating truthful annotations for the training data.

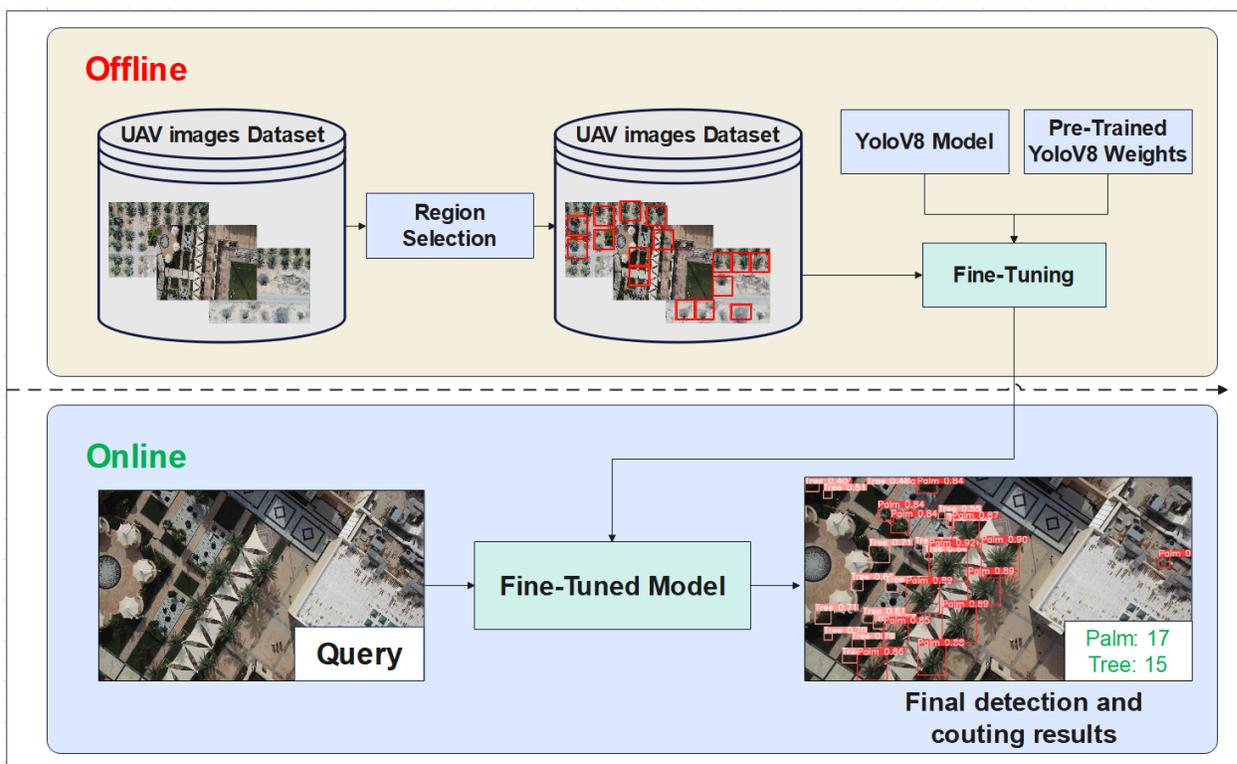


FIGURE 5.1: Flowchart of the proposed method for detection of date palm trees.

This annotated dataset was subsequently integrated into the UAV dataset to facilitate fine tuning. The YOLOv8 model, which is a state-of-the-art object recognition method, was fine-tuned using weights from a general object recognition task. This approach enabled the model to specialize in reliable date palm recognition. In the online phase, users can input image queries depicting the environments with potential date palms. The fine-tuned YOLOv8 model evaluates these queries by providing bounding boxes for detected date palms. In addition, the system offers real-time information on the count of date palms in the image, thereby enhancing its practical utility.

The dataset used for training consisted of two classifications: palms and trees. These labeled data are employed to train CNNs within the YOLOv8 framework, with the aim of achieving binary classification to differentiate palm trees from other tree species. In the classification process, the detected palms and trees are enclosed within rectangles to account for variables such as size variations, potential overlap or occlusion with other objects, and diverse backgrounds such as sand or buildings. Addressing these variations within rectangular image pixels is essential for effective CNN training, ensuring that the trained models can accurately distinguish palm trees from other trees.

To prepare the dataset for YOLOv8 model training, a preprocessing stage was implemented.

This includes creating bounding boxes, cropping and saving images, and converting the data to the YOLO format. These steps are critical for ensuring that the dataset is appropriately structured and ready for model training. The iterative nature of this comprehensive approach, encompassing dataset preparation and YOLOv8 model training, establishes a robust foundation for precise and reliable palm-tree detection in UAV images.

5.2.1 Data-preprocessing

We used a two-step technique to increase palm detection accuracy and training efficiency. First, we created the largest bounding boxes that could enclose the palms in the images. This was done by developing a customized algorithm. The method iterated over a list of bounding boxes to determine the coordinates of the largest bounding box that contained all the smaller boxes. The resulting largest bounding boxes provided a more comprehensive representation of the palm regions of interest. Details can be found below:

We then cropped and saved the images based on the largest bounding boxes generated. Each image in the dataset was cropped based on the coordinates of the matching largest bounding box. This technique eliminates the specific focus area of the palm tree and disregards the background. This technique eliminates irrelevant background information and focuses on the occurrence of the palm tree. We provide targeted and relevant information to improve the accuracy of palm identification algorithms by identifying palm zones of interest.

Images were then cropped using the largest bounding boxes to ensure that analysis and model training focused on the most valuable and representative parts. This strategy ensured that the most informative parts of the images were used for future analysis and model training. The cropped images served as the basis for developing and testing our YOLOv8-based palm recognition algorithm.

5.2.2 Yolo for palm recognition

While Faster R-CNN belongs to the family of two-stage object detectors, YOLO belongs to the class of one-stage object detectors. This is a novel approach to real-time object detection in images or videos. The key idea behind YOLO is to perform object detection in a single pass rather than using the traditional two-stage approach of applying a classifier to regions of interest. YOLO employs a single CNN to predict the bounding boxes and class probabilities directly from full images in one evaluation. The development of the first version of YOLO was initiated in 2016 by Redmon et al. [Red+16]. Since then, it has been considered one of the most attractive state-of-the-art models for object detection. In the years following the release of the original YOLO algorithm, various updated versions and variations of YOLO have been developed, such as YOLOv2 and YOLOv3 by Joseph Redmon and Farhadi [RF17] [RF18], each delivering substantial improvements in both performance and efficiency. In 2020, Bochkovskiy et al. [BWL20] and Jocher [Joc22] developed the YOLOv4 and YOLOv5, respectively.

Algorithm 1: Generating Largest Bounding Boxes and Cropping Images

Data: List of bounding boxes $bboxes$

Result: Cropped images based on the largest bounding boxes

```
1 Initialize  $largest\_box\_xmin$  to  $\infty$ ;  
2 Initialize  $largest\_box\_ymin$  to  $\infty$ ;  
3 Initialize  $largest\_box\_xmax$  to  $-\infty$ ;  
4 Initialize  $largest\_box\_ymax$  to  $-\infty$ ;  
5 Initialize empty list  $cropped\_images$ ;  
6 for each bounding box  $bbox$  in  $bboxes$  do  
7   Retrieve  $xmin, ymin, xmax, ymax$  from  $bbox$ ;  
8   if  $xmin < largest\_box\_xmin$  then  
9     |  $largest\_box\_xmin \leftarrow xmin$ ;  
10  end  
11  if  $ymin < largest\_box\_ymin$  then  
12    |  $largest\_box\_ymin \leftarrow ymin$ ;  
13  end  
14  if  $xmax > largest\_box\_xmax$  then  
15    |  $largest\_box\_xmax \leftarrow xmax$ ;  
16  end  
17  if  $ymax > largest\_box\_ymax$  then  
18    |  $largest\_box\_ymax \leftarrow ymax$ ;  
19  end  
20 end  
21 for each image in the dataset do  
22   Crop the image based on  
    [ $largest\_box\_xmin, largest\_box\_ymin, largest\_box\_xmax, largest\_box\_ymax$ ];  
23   Save the cropped image in a separate directory;  
24   Add the cropped image to  $cropped\_images$ ;  
25 end
```

The YOLO algorithm is fast and accurate, making it well suited for real-time applications such as video surveillance, self-driving cars, and video games. They also have the potential to be used in various applications related to analyzing palm crops as well as for identifying and counting palm trees in images or videos. The real-time processing capabilities and object detection efficiency of YOLO make it a highly efficient solution for tasks such as counting palm trees. The implementation of CNNs in YOLO further enhances the accuracy of palm tree detection. This automated tree counting process can offer reliable data for researchers and planners. Moreover, YOLO proves valuable in detecting pest infestations in palm tree plantations, enabling timely intervention to protect the trees. YOLO's capacity to survey and monitor large areas makes it a versatile tool for assessing tree health, identifying instances of illegal cutting, and facilitating plantation planning.

In conclusion, YOLO demonstrates promising results for palm tree detection and serves as a valuable tool for automating the mapping and monitoring of palm tree populations in diverse environments. However, it's essential to acknowledge that YOLO, like other object detection algorithms, may exhibit sensitivity to variations in training data and could require careful tuning for optimal performance.

5.2.2.1 YOLOV5-YOLOV8

This section delineates the most notable algorithms of recent times and provides an exhaustive summary of the critical elements of this paper that concentrate on enhancing YOLOv8. YOLO, a highly respected real-time object detector, has gained broad recognition owing to its lightweight network architecture, effective feature fusion methods, and improved detection accuracy. At present, YOLOv5 and YOLOv7 are the two most prevalent algorithms in use.

YOLOv5 is a one-stage target detection algorithm that utilizes a network structure comprising inputs, trunks, necks, and outputs. The algorithm offers four distinct models - YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x - each increasing in network depth and weight file size. To optimize computational efficiency and minimize network complexity, the YOLOv5s model was selected for experimental training, with a particular focus on real-time detection performance. The network architecture of the YOLOv5s model is shown in Figure 5.2.

YOLOv5, developed by Ultralytics in 2022 [Boe23], brings substantial enhancements compared to its predecessor, YOLOv4. These improvements encompass faster detection speed, increased accuracy, expanded support for object classes, a streamlined architecture, enhanced resilience to image-level noise, adaptability to different resolutions and aspect ratios, improved memory usage, and various other features. Additionally, the model undergoes training using a multi-scale strategy to enhance its capability to detect objects of varying sizes. In YOLOv5, the overall loss function is a composite of multiple individual loss functions, each addressing different aspects of the object detection task. Key loss functions employed in YOLOv5 include classification loss, localization loss, confidence loss, and focal loss. The training of YOLOv5 involves optimizing this combination of loss functions to achieve robust object detection performance.

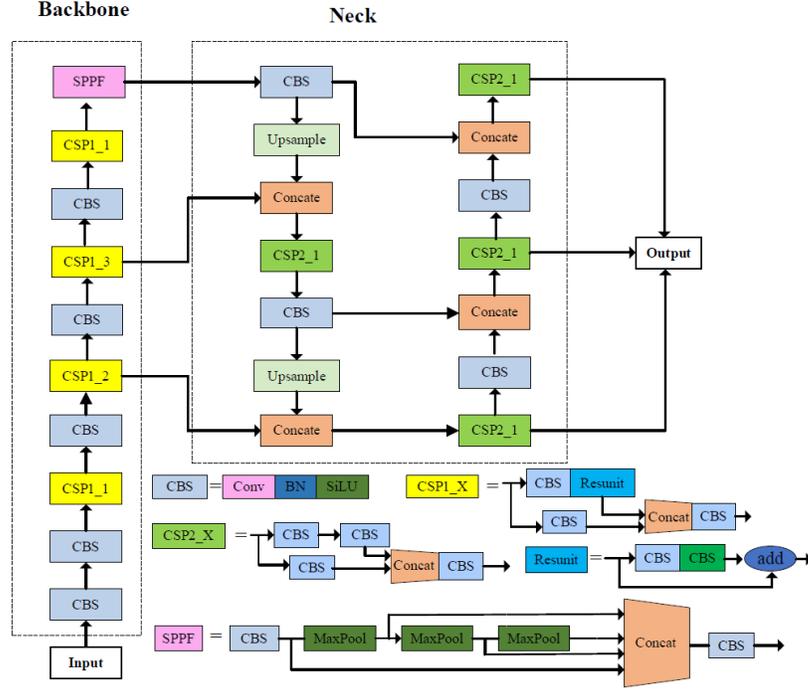


FIGURE 5.2: The network structure of yolov5.

The final loss function can be written as:

$$L = w_c * L_{cls} + w_l * L_{loc} + w_{obj} * L_{obj} + w_{focal} * L_{focal} \quad (5.1)$$

where :

- L is the total loss.
- w_c , w_l , w_{obj} , and w_{focal} are weighting factors.
- L_{cls} , L_{loc} , L_{obj} , and L_{focal} are different components of the loss function.

The loss function is used to train the object detection model, and the weighting factors are used to adjust the relative importance of each component of the loss function.

YOLOv8, launched on January 10, 2023, represents a significant improvement over its predecessor, including YOLOv5, and it marks the latest pinnacle in real-time object detection and segmentation. This model, considered the most advanced in the YOLO series to date, has set new benchmarks and established itself as a standard-setting solution in the field of AI. According to Glenn Jocher [Boe23], YOLOv8's exceptional performance has broadened the scope of possibilities for straightforward and efficient AI applications, offering superior capabilities for innovative applications.

In the comparison between Ultralytics YOLOv8 and YOLOv5, notable differences emerged in their architecture and capabilities. YOLOv8 adopts a hybrid backbone architecture that

incorporates the strengths of YOLOv5 and EfficientDet. In contrast, YOLOv5 exclusively utilized the CSPDarknet53 backbone. YOLOv8 surpassed YOLOv5 in terms of accuracy and speed, establishing it as a more advanced and versatile model. Additionally, YOLOv8 exhibits capabilities beyond YOLOv5, handling tasks such as object detection, instance segmentation, and panoptic segmentation, whereas YOLOv5 is primarily designed for object detection. Both models are suitable for various object detection applications and are characterized by high precision and adaptability. The choice between them depends on the specific requirements and constraints of a given task. Figure 5.3 shows the network structure of YOLOv8, illustrating its hybrid backbone architecture that combines the strengths of YOLOv5 and EfficientDet. Adapted from Ultralytics.

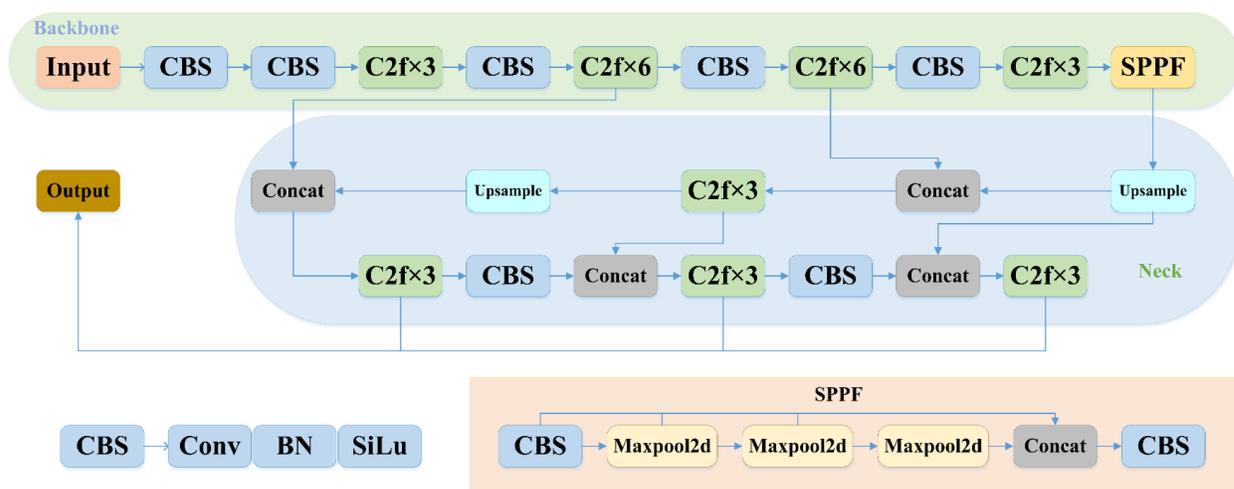


FIGURE 5.3: The network structure of yolov8.

Ultralytics YOLOv8 employs a combination of different loss functions for effective object-detection model training. The primary loss functions include the localization loss, confidence loss, and class loss, each contributing uniquely to the overall loss. The localization loss is computed as the mean squared error between the predicted and ground-truth bounding box coordinates, while the confidence loss is calculated as the binary cross-entropy between the predicted and ground-truth objectness scores. The class loss is determined as the categorical cross-entropy between the predicted and ground-truth class probabilities. In addition, YOLOv8 incorporates a focal loss function, assigning greater importance to misclassified samples for a more robust and stable training process. These loss functions are combined into a weighted sum, with weights empirically set to prioritize the most significant components.

The resulting combined loss function is optimized during training using backpropagation and stochastic gradient descent (SGD) to enhance the performance of the model in object detection and segmentation.

The final loss function can be written as:

$$L = \lambda_{coord} * L_{coord} + \lambda_{obj} * L_{obj} + \lambda_{cls} * L_{cls} + \lambda_{focal} * L_{focal} \quad (5.2)$$

where:

- L_{coord} represent the localization loss.
- L_{obj} confidence loss.
- L_{cls} class loss.
- L_{focal} focal loss.

The weights assigned to each loss function are represented by λ_{coord} , λ_{obj} , λ_{cls} , and λ_{focal} . The objective of training YOLOv8 is to minimize this combined loss function, which is achieved through backpropagation and gradient descent techniques.

Overall, Ultralytics YOLOv8 and YOLOv5 represent significant advances in object detection, and their continued development and improvement will have a major impact on the field of AI and computer vision.

5.2.2.2 Training the network

Several data augmentation strategies were used in training the YOLOv8 model for palm recognition, including modifications (hue, saturation, and value), random rotation, translation, scaling, shear transformation, and vertical or horizontal flipping of the image. These strategies allow the model to learn and recognize objects from different angles and orientations and to account for differences in lighting, color, and contrast. In addition, the mixup extension was used to generate more training cases by combining labels and pixels to minimize overfitting and improve generalization [Zha+17]. The mosaic augmentation approach generates mosaic images by integrating numerous images and labels into a single training example, adding a mix of elements from different scenarios, and improving the resilience of the model [JEE22b]. These data augmentation strategies are critical to increasing the performance and reliability of the YOLOv8 model for palm tree detection. By combining these strategies and associated parameter values, the model becomes more robust, can tolerate a wide range of environmental variables, and can be generalized to new data while minimizing overfitting. Tables 5.1 and 5.2 provide a comprehensive representation of these data expansion parameters as well as other important parameters of the training process, such as model weights, dataset configuration, number of epochs, image size, batch size, and early stopping criteria. Prior to training, the starting weights of the YOLOv8 model are determined. This training procedure allows the network to learn and recognize objects with great accuracy and robustness, including date palms.

A validation procedure was used to verify the performance of the model using the specified mode. The recognition performance of the model was evaluated using a validation dataset

TABLE 5.1: Data Augmentation Parameters

| Parameter | Description | Value |
|-------------|-------------------------------|-------|
| hsv_h | Hue adjustment | 0.015 |
| hsv_s | Saturation adjustment | 0.7 |
| hsv_v | Value (brightness) adjustment | 0.4 |
| degrees | Random rotation | 10 |
| translate | Translation (shift) | 0.1 |
| scale | Scaling | 0.9 |
| shear | Shear transformation | 0.3 |
| perspective | Perspective distortion | 0.0 |
| flipud | Vertical flipping | 0.5 |
| fliplr | Horizontal flipping | 0.5 |
| mixup | Mixup augmentation | 1.0 |
| mosaic | Mosaic effect | 0.1 |

| Parameter | Value |
|-----------------------|--------------------|
| Epochs | 60 |
| Batch Size | 3 |
| patience | 20 |
| Optimizer | SGD |
| NMS IoU | 0.7 |
| Initial Learning Rate | 1×10^{-2} |
| Final Learning Rate | 1×10^{-2} |
| Momentum | 0.937 |
| Weight-Decay | 5×10^{-4} |
| Image Scale | 0.9 |
| Image Flip Left-Right | 0.5 |
| Mosaic | 1.0 |
| Image Translation | 0.1 |
| Mixup | 0.1 |

TABLE 5.2: Parameter Setup

with images scaled to 1024×1024 pixels. This evaluation determines the ability of the model to recognize objects in the provided dataset. In addition, the validation procedure was performed for different intersection over union (IoU) thresholds such as 0.5, 0.7, 0.8, and 0.9 to evaluate the model’s resilience and detection accuracy with increasing overlap between the predicted bounding box and the actual bounding box.

To properly train the object recognition model in YOLOv8, a mixture of loss functions was used throughout the training phase. Localization loss, confidence loss, class loss, and

focus loss are examples of loss functions. The mean square error between the expected and actual bounding box coordinates is measured as localization loss. The binary cross-entropy between the predicted and actual objectivity values was calculated using confidence loss. The categorical cross entropy between the predicted and actual class probabilities was used to calculate the class loss. In addition, YOLOv8 has a focused loss function that assigns more weight to misclassified data, making the training process more robust and stable.

The final loss function of YOLOv8 can be written as follows:

$$L = \lambda_{coord} * L_{coord} + \lambda_{obj} * L_{obj} + \lambda_{cls} * L_{cls} + \lambda_{focal} * L_{focal} \quad (5.3)$$

where:

- L_{coord} : Localization loss.
- L_{obj} : Confidence loss.
- L_{cls} : Class loss.
- L_{focal} : Focal loss.

The weights assigned to each loss function are denoted by λ_{coord} , λ_{obj} , λ_{cls} , and λ_{focal} . The goal of training YOLOv8 was to minimize this combined loss function. This is achieved through backpropagation and gradient descent techniques that optimize the parameters of the model to improve its accuracy in date palm detection.

Input images of size 4096×2160 pixels were reduced to a standard size of 1280×1280 pixels during the training phase of the network. The numerous hyperparameters described above were used to fit the YOLOv8 model. The dataset was split into many folds to enable successful training using a proprietary stratified k-fold cross-validation approach. The training images and labels were split into different folders based on the folding and class labels. The dataset configuration file was updated to reflect the two classes and their names ('Palm' and 'Tree'). For training, the Ultralytics library was used, which provides a high-level API for training object recognition models.

The YOLOv8 network learns to recognize date palms with high accuracy and resilience by applying multiple training procedures, fine-tuning hyperparameters, and adding relevant inputs.

5.2.2.3 Palm Tree Counting and Identification

The algorithm 2 describes the process of palm detection and counting from a collection of drone images using the YOLOv8 model. Below is a breakdown of the main steps of the algorithm. The method starts with the configuration of the relevant hyperparameters 5.1. Preprocessing the drone image involves preparing it for input to the YOLOv8 model by performing transformations and other necessary preprocessing (explained in Section 5.2.1).

Algorithm 2: Palm Tree Identification and Counting with YOLOv8 on UAV Dataset

Data: Input UAV images dataset I , Model M , Grid size S , Number of bounding boxes per grid cell B , Number of object classes N , Confidence threshold T_c , IoU threshold T_{iou}

Result: Bounding boxes B and corresponding scores S

1 **Set Algorithm Hyperparameters:**

2 Image size: 1280, Batch size: 3, Number of epochs: 60, Weights file: "yolov8l.pt",
Optimizer: "SGD", Random seed: 45, Device: "cuda" if available, else "cpu".

3 **for** each UAV image I_i in the dataset **do**

4 **Preprocess the UAV image;**

5 $P_I \leftarrow \text{preprocess_image}(I_i)$;

6 **Convert image to tensor and add batch dimension;**

7 $I_{\text{tensor}} \leftarrow \text{torch.from_numpy}(P_I).\text{unsqueeze}(0).\text{to}(M.\text{device})$;

8 **Forward pass through the model;**

9 $P \leftarrow M(I_{\text{tensor}})$;

10 **Extract bounding boxes from predictions;**

11 $B \leftarrow \text{calculate_bounding_boxes}(P, S)$;

12 **Calculate scores for each bounding box;**

13 $S \leftarrow \text{calculate_scores}(P, N)$;

14 **Remove bounding boxes with low confidence scores;**

15 $B_f, S_f \leftarrow \text{remove_low_confidence_boxes}(B, S, T_c)$;

16 **Apply non-maximum suppression;**

17 $B_n, S_n \leftarrow \text{apply_non_max_suppression}(B_f, S_f, T_{iou})$;

18 **Translate the bounding boxes B_i back to the original image coordinates;**

19 $B_i \leftarrow \text{translate_bounding_boxes}(B_n)$;

20 **Count the number of remaining palm tree bounding boxes;**

21 $C_i \leftarrow \text{count_palm_trees}(B_i)$;

22 **Store the detected palm trees, their bounding boxes B_i , and the count for
the current UAV image;**

23 $\text{store_result}(I_i, B_i, C_i)$;

24 **end**

25 **Return** Detected palm trees with their bounding boxes and counts for each
image in the dataset;

The following steps were performed for each drone image in the dataset. The preprocessed image is converted into a tensor and sent to the YOLOv8 model, which generates predictions. These predictions provide information about the bounding boxes and the associated confidence values. The bounding boxes are retrieved from the model predictions, taking into account the given grid size and the number of bounding boxes per grid cell.

Each bounding box was assigned a value reflecting the probability of the presence of an object (palm trees in this example). This data set determines the number of object classes. Bounding boxes with low confidence levels were deleted, leaving only the boxes with higher confidence levels. Non-maximal suppression is used to remove overlapping bounding boxes that are redundant, leaving only the most important ones. The remaining bounding boxes are reset to their original positions in the image.

This method counts the number of bounding boxes of palms and stores the identified palms, the associated bounding boxes, and the current number of UAV images.

5.3 Experimental results

5.3.1 Data-sets Description

In this experimental phase, we looked at the dataset from the study by Adel et al. [AKB21]. This dataset includes 258 aerial images taken at a palm plantation near Kharj, Saudi Arabia, and an additional set of 91 images taken at the Prince Sultan University (PSU) campus.

Kharj is a city in the central region of Saudi Arabia, about 80 kilometers southeast of the capital city of Riyadh. With an average temperature of about 90 °F (32 °C) and extreme temperatures ranging from 57 °F (14 °C) to 104 °F (40 °C), the city has a distinct hot desert climate with low humidity. With an average annual precipitation of about 50 mm, Kharj's climate perfectly fits its classification as a hot desert climate. The region is known for its agricultural activities, especially the cultivation of palm trees, and has encouraged the growth of date palms, which are not only famous for their succulent fruits but also play an important role in local agriculture. The palm groves are an important economic factor, underscoring their importance in the economic fabric of the region.

Aerial imagery was carefully captured using two different drone platforms: the DJI Phantom 4 Pro equipped with a DJI FC6310 camera providing 4864*3648 and 4096*2160 resolution, and the DJI Mavic Pro equipped with a DJI FC220 camera providing 4000*3000 resolution. Figure 5.5 shows the DJI Phantom 4 Pro drone compared to the DJI Mavic Pro drone. Detailed information about these drones and their cameras can be found in the table below 5.3 respectively. This diverse dataset contains 13,071 instances of palms and various other tree species that were carefully classified manually using the labelbox platform.

A compelling aspect of this dataset is its representation of a range of real-world challenges encountered in practical scenarios. The palms in this dataset exhibit a spectrum of characteristics, including varying diameters, uneven distribution across the images, and their



FIGURE 5.4: saudi-arabia-map-al-kharj



FIGURE 5.5: DJI Phantom 4 Pro vs. mavic-pro

coexistence with a variety of tree species. It is worth noting that the composition of the dataset is clearly dominated by date palms, with other tree species predominating (11,150 palms versus 1921 other plants).

In addition, it is important to recognize that the image quality in this dataset reflects the typical conditions encountered in outdoor UAV imagery. These images reflect the inherent challenges of outdoor UAV imagery and provide an authentic representation of such scenarios.

Figure 5.6 shows two exemplary examples of raw images captured by the drone. These examples include a mix of date palms, agricultural land, and other tree species and illustrate the versatility of the dataset. This dataset is a useful resource to support the development and evaluation of deep neural network-based techniques for date palm detection and counting while providing a realistic representation of the problems encountered, including the particular phenomenon of date palm dominance.

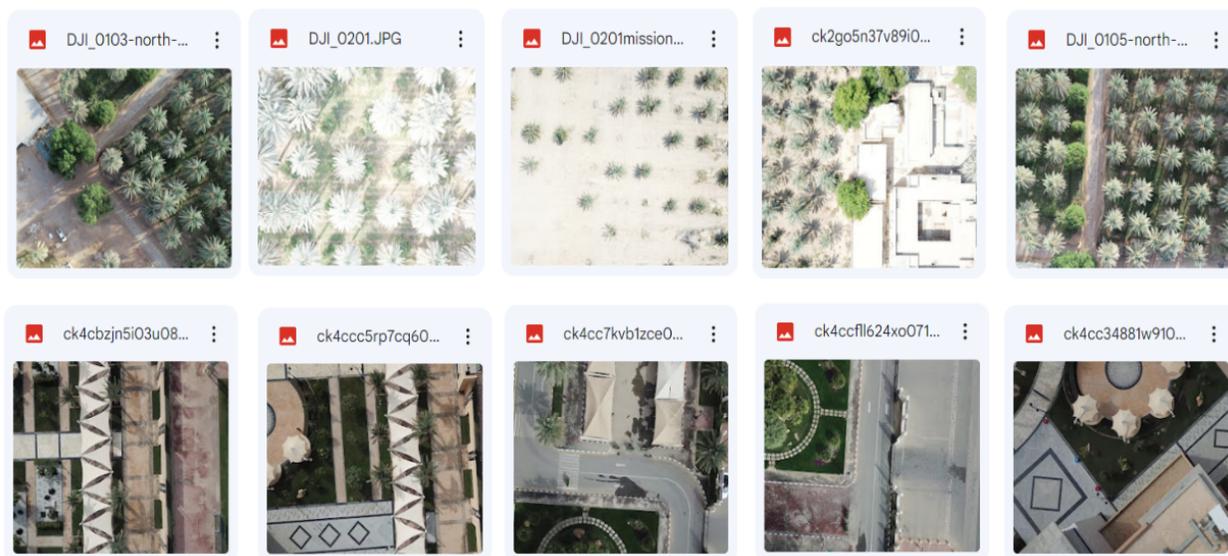


FIGURE 5.6: Examples of the captured drone images from a farm in Al-Kharj and from PSU campus, respectively.

5.3.2 Experimental Setup

We used the computing capabilities of Google Colab, which is a strong cloud-based platform, to run the tests. The studies were conducted on an NVIDIA Tesla T4 GPU, which is well known for its high performance. The GPU was outfitted with the most recent driver version 525.85.12 and CUDA version 12.0, ensuring compatibility and efficiency during the trials.

TABLE 5.3: Specifications of DJI Phantom 4 Pro and DJI Mavic Pro Drones

| Drone Model | DJI Phantom 4 Pro | DJI Mavic Pro |
|-------------------------|--|--|
| Camera Model | DJI FC6310 | DJI FC220 |
| Camera Specs | <ul style="list-style-type: none"> - Image Sensor: 1-inch CMOS sensor - Maximum Resolution: 20 Megapixels - Image Size: 5472 x 3648 pixels - Image Size: 4864 x 3648 pixels - Image Size: 5472 x 3078 pixels - Image Size: 4000 x 3000 pixels - Video Resolution: 4K at 60fps - Lens: Fixed lens with a 24mm focal length and f/2.8 aperture - ISO Range: 100 - 12800 - Shutter Speed: 8s to 1/2000s - Gimbal Stabilization: 3-axis gimbal - Supported SD Cards: Micro SD - Max Capacity: 128GB - Write Speed: $\geq 15\text{MB/s}$ - Rating: Class 10 or UHS-1 required | <ul style="list-style-type: none"> - Image Sensor: 1/2.3-inch CMOS - Max Resolution: 12.35 MP - Image Size: 4000 x 3000 pixels (4:3) - Image Size: 4000 x 2250 pixels (16:9) - Image Size: 4000 x 3000 pixels (4:3) - Video Resolution: 4K at 30fps - Lens: 28mm, f/2.2 - ISO Range: 100 - 1600 (auto) - Shutter Speed: 8s to 1/8000s - Gimbal: 3-axis |
| Image Type | Optical (RGB) | Optical (RGB) |
| Flight Time | Up to 30 minutes | Up to 27 minutes |
| Maximum Speed | 72 km/h (45 mph) in Sport mode | 65 km/h (40 mph) |
| Obstacle Sensing | Equipped with obstacle sensors on all sides | Forward and downward sensors |
| Features | ActiveTrack 2.0, TapFly, Return to Home, Vision Positioning System, etc. | ActiveTrack, TapFly, Gesture Mode, Return to Home, Vision Positioning, etc. |

5.3.3 Palm Tree Detection And Counting Results

In this section, we evaluate the performance of the proposed YOLOV8-based strategy (YOLOv8, YOLO-HighAug) for date palm detection with approaches based on YOLOV5 (YOLOv5-6l, YOLOv5-L, YOLOv5-L-HighAug). Each approach was trained on the same training dataset mentioned above. The same YOLO pre-trained weights and hyperparameters were used in the construction of the YOLO-V8 networks. The networks were trained until their validation loss did not change and were then evaluated on identical test data sets. The performances were compared numerically and subjectively.

5.3.3.1 Quantitative results

We applied a quantitative performance comparison method as described in [PND20] and [JEE22b] to evaluate object recognition performance metrics in the context of date palm plant recognition. This method involves an objective evaluation of the effectiveness of the selected models, Yolov8 and Yolov5, using numerical measures such as accuracy, precision, and recognition. We hope to determine whether the model performs better in date palm detection and identification through a quantitative comparison of performance. In addition, this method will allow us to discover areas where the less effective model can be improved and increase the overall quality of the object identification system.

Confusion Matrices In this section, we provide a formal evaluation of the performance of various YOLO models in palm tree detection. The confusion matrices for YOLOv5, YOLOv5-6L, YOLOv8, and YOLOv8 with high augmentations offer a detailed breakdown of true positives, false positives, true negatives, and false negatives, respectively. These visualizations provide valuable insights into the precision and recall of each YOLO model in the context of palm-tree detection, offering a comprehensive analysis of their capabilities.

To evaluate the performance of four distinct models, YOLOv5-highaug, YOLOv5-6L, YOLOv8-highaug, and YOLOv8-L, in the context of palm tree detection, several key insights emerge. YOLOv5-highaug demonstrated notable effectiveness, achieving a high true-positive rate for palm detection at 95%, while maintaining a relatively low false-positive rate for trees at 5%. However, the model faces a considerable challenge with a substantial false negative rate for palms of 53%, indicating potential areas for improvement in enhancing palm detection. YOLOv5-6L exhibited commendable performance, boasting high true positive rates for both palms (95%) and trees (83%). However, similar to YOLOv5-highaug, it grapples with a significant false negative rate for palms of 53%, underscoring the need for refinement in palm detection. YOLOv8-highaug stands out with the highest true positive rate for palm detection at 97%, but this accomplishment is accompanied by a notable false-negative rate of 56%. Finally, YOLOv8-L is effective in detecting both palm and tree instances, achieving high true positive rates; however, it faces a moderate false negative rate for palm detection at 51%. Overall, YOLOv8-highaug emerged as a leading contender, showing superior palm-detection capabilities. Nevertheless, addressing the imbalanced data and optimizing each

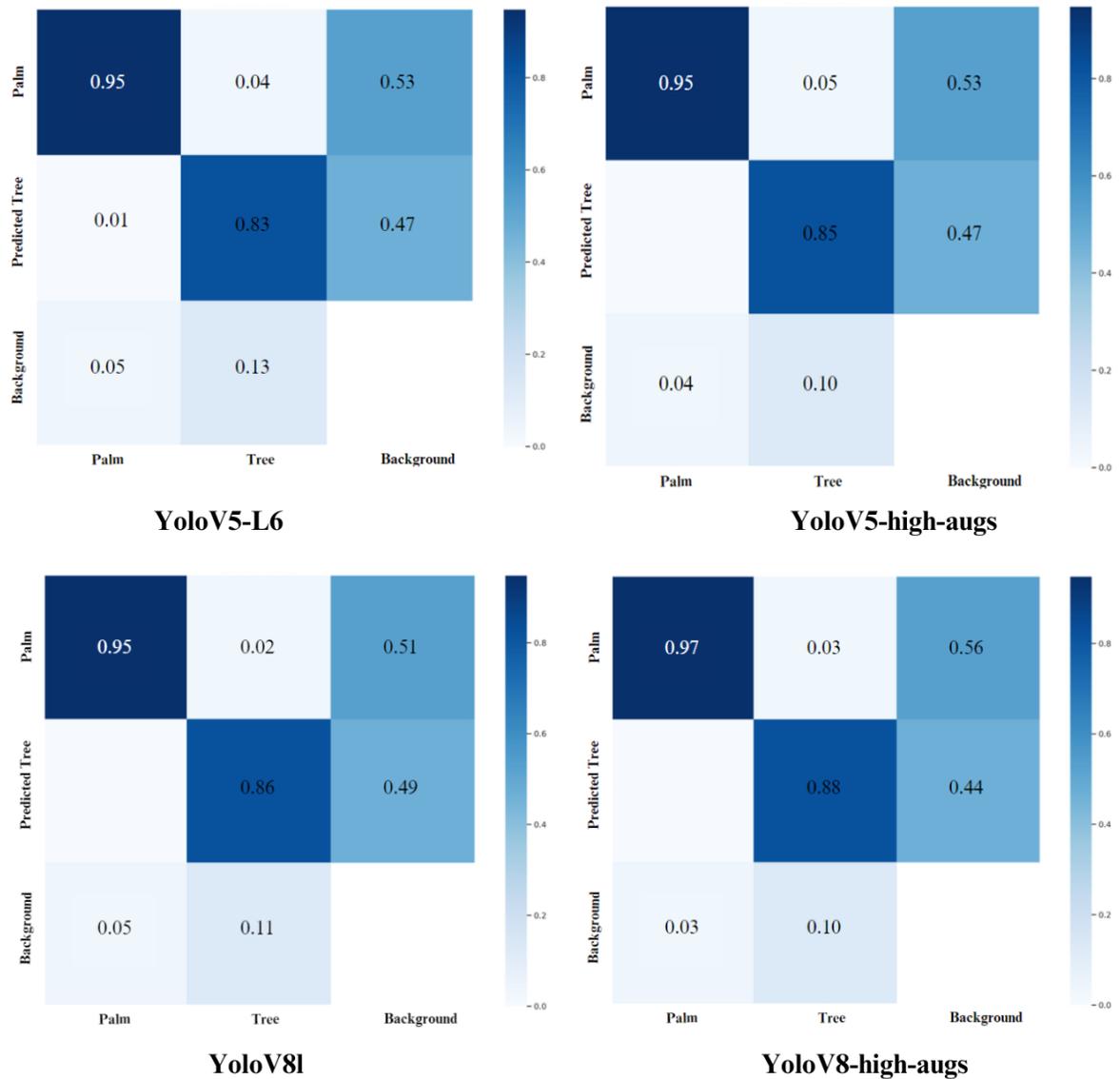


FIGURE 5.7: Confusion matrices for palm tree detection using YOLOv5, YOLOv5-6L, YOLOv8, and YOLOv8 with high augmentations, highlighting model performance in true positives, false positives, true negatives, and false negatives..

model to mitigate false negatives remains a crucial consideration for further enhancing palm tree detection accuracy.

Epoch-wise Performance Metrics Analysis In this section, we present a comprehensive analysis of the quantitative results obtained by testing five distinct object identification

models: YOLOv5-6L, YOLOv5-L, YOLOv5-L-HighAug, YOLOv8, and YOLOv8-HighAug. Specifically, we delve into epoch-wise performance metrics, exploring critical parameters such as accuracy, recall, F1 score, average accuracy (AP), and AP@50 to provide a detailed insight into the evolving capabilities of the models over numerous training epochs.

Figure 5.8 presents a detailed summary of the quantitative data collected during the evaluation of the object identification models. Over multiple training epochs, the plots illustrate crucial performance parameters, including the accuracy, recognition, average precision (AP), and AP@50. The precision plot (Figure 5.8 (A)) showcases the precision achieved by each model across different epochs. Notably, at epoch 8, YOLOv5-6L achieved the highest accuracy of 0.97, while YOLOv8 and YOLOv8-HighAug achieved Precisions of 0.86 and 0.85, respectively. The recall plot (Figure 5.8 (B)) displays the best recall values for each model, with YOLOv5-6L achieving the highest recall value of 0.87 at epoch 35. Additionally, other models, such as YOLOv8 and YOLOv8-HighAug, demonstrated excellent recall performances. The fifth plot (Figure 5.8) illustrates the F1 score, which represents a trade-off between precision and recall.

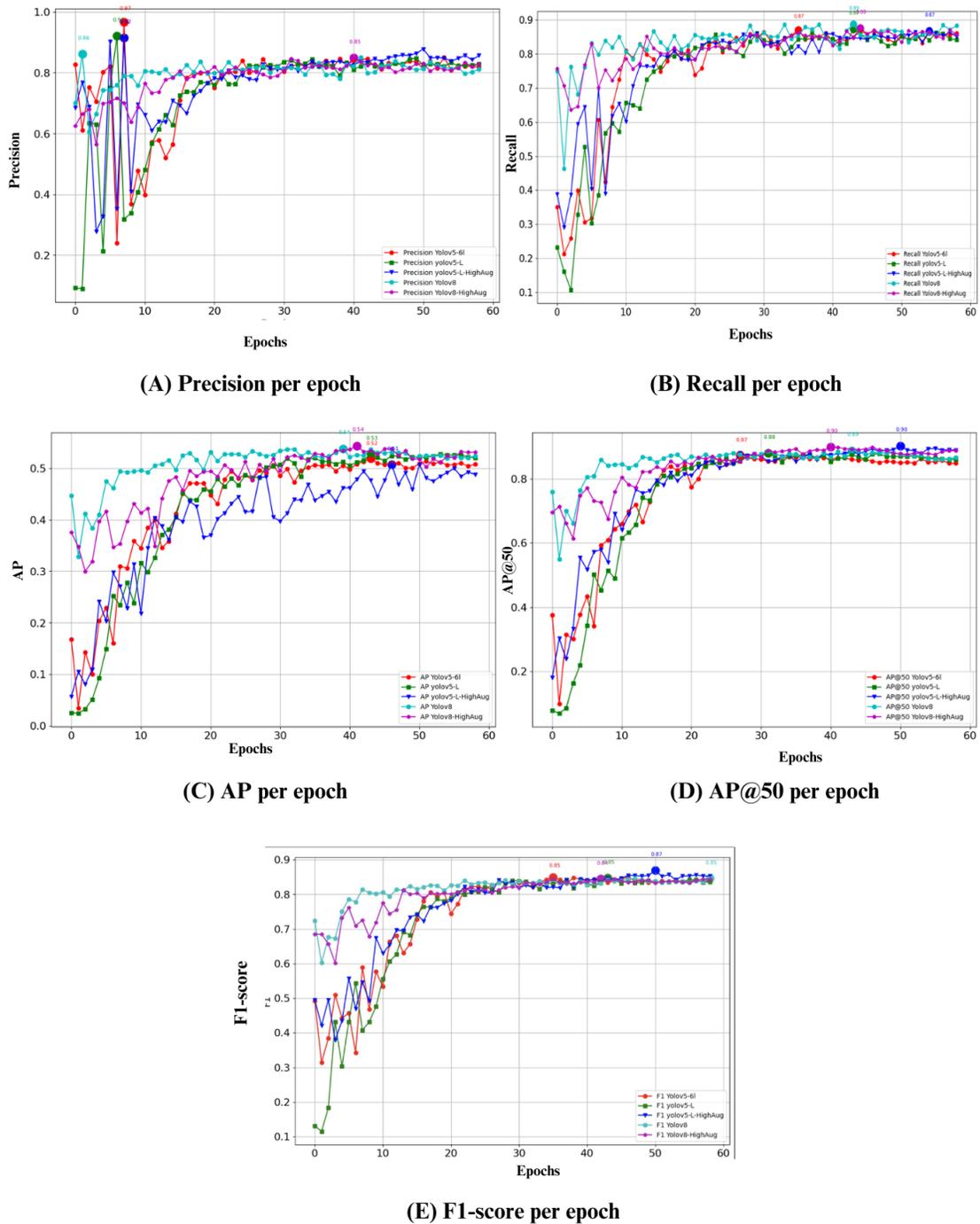


FIGURE 5.8: Precision, Recall, AP, AP@50 and F1-score per epoch history of the five specific models (YOLOv5-6l, YOLOv5-L, YOLOv5-L-HighAug, YOLOv8 and YOLOv8-HighAug)

At epoch 8, YOLOv5-6L had the highest F1 score (0.919), signifying excellent overall performance. YOLOv8 and YOLOv5-L-HighAug achieved F1 scores of 0.874 and 0.893, respectively. The best AP values produced by each model in certain epochs are highlighted in the sixth graph (Figure 5.8 (C)). At epoch 39, YOLOv8 had the highest AP (0.54). Meanwhile, YOLOv5-L-HighAug performed admirably, with an excellent AP@50 of 0.9 at epoch 50. These findings demonstrate that YOLOv5-L-HighAug excels in recognizing objects with more accuracy when a tighter IoU threshold is used. Overall, the study highlights the strengths and flaws of each model, assisting in the selection of the best model for date palm tree recognition. The top-performing model in terms of accuracy, recall was YOLOv5-6L, whereas YOLOv5-L-HighAug outperformed AP@50 (Figure 5.8 (D)), which is critical for specialized applications requiring accurate localization. YOLOv8, however, exhibits competitive performance across several parameters, making it a strong contender for object detection tasks. When making a final selection, it is critical to consider the model requirements as well as individual application demands.

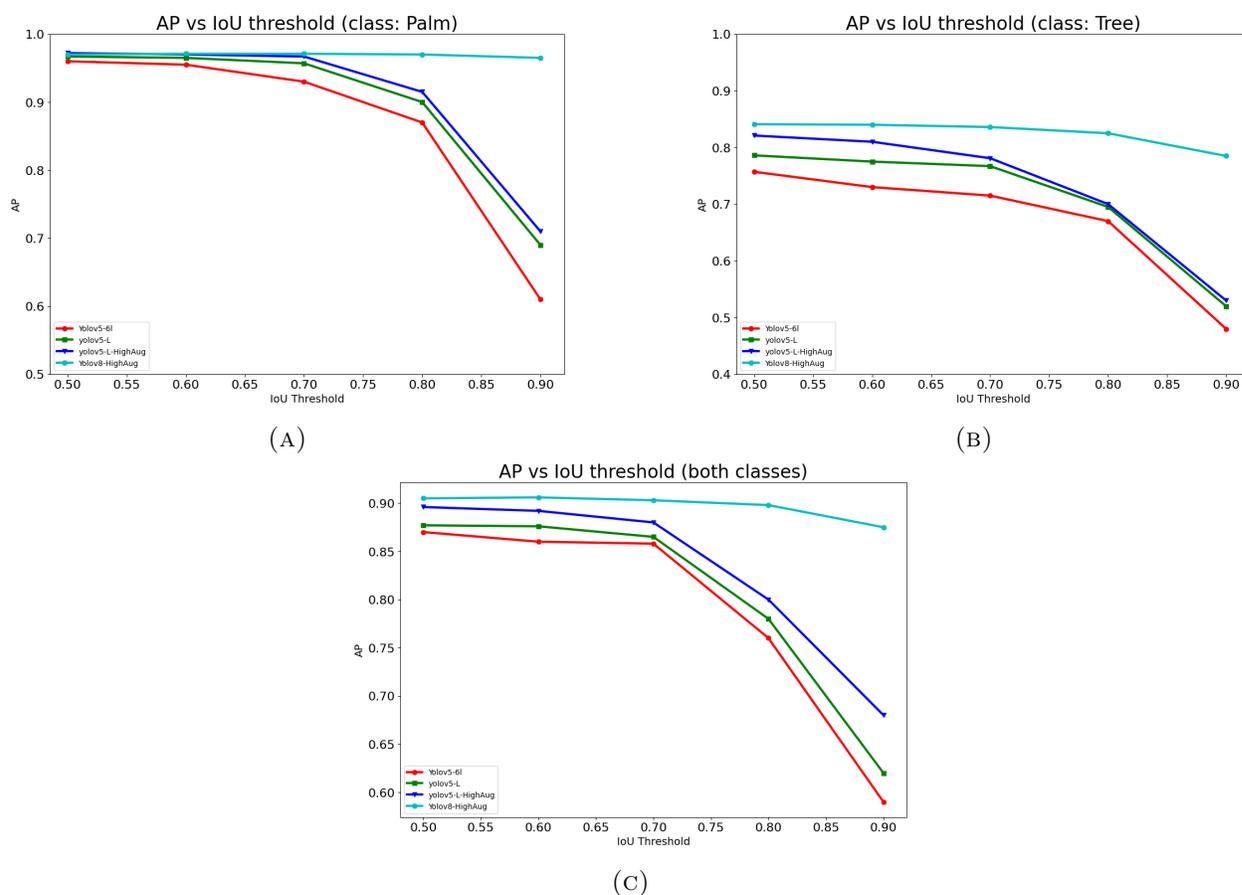


FIGURE 5.9: The average precision (AP) values for each of the two categories, Palm and Other trees, as well as the mean average precision (AP) for both categories on the testing dataset at various IoU threshold levels.

The average accuracy (AP) of the four tested object detectors at different intersection over union (IoU) thresholds for each of the two classes (palm and tree) and the AP for both classes are shown in Figure 5.9. The reported results provide helpful insights into the performance of each method for different IoU thresholds, both for specific classes (palm and tree) and in general (all instances). Most notably, Yolov8-HighAug consistently yields higher average precision values across a range of IoU thresholds (AP), proving to be the superior approach in this study. These results show that Yolov8-HighAug performs well in detecting objects with varying degrees of spatial overlap, making it an interesting option for accurate and trustworthy object identification applications.

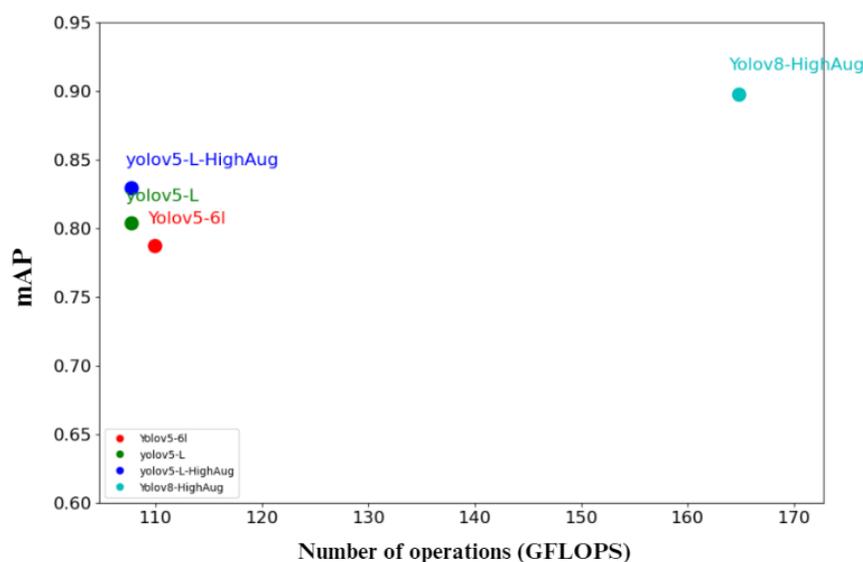


FIGURE 5.10: Comparison of the four algorithms in terms of mAP (averaged for IoU values between 0.5 and 0.9 by step of 0.1) and inference time.

In Figures 5.10 and 5.11, we use the mAP metric to examine the accuracy of each model at different IoU thresholds (0.5, 0.7, 0.8, and 0.9). We also measured the computational power of the models in GFLOPS, indicating inference time and resource utilization. The results of these experiments provided important insights into the performance of the models considered. Figure 5.10 shows the computational efficiency of the recognition process, which was obtained by measuring the inference time for each model. The results of these studies show that among the models studied, YOLOv8-HighAug achieves exceptional accuracy with an average accuracy (mAP) of 0.92 and an average inference time of 92 ms, demonstrating its superior ability to recognize palms. YOLOv8-HighAug is an interesting option for applications where precise detection of palms is important, especially under conditions where precision is critical. In particular, YOLOv5-L achieved a competitive mAP value of 0.81, while the mAP values of YOLOv5-L-HighAug and YOLOv5-6l were slightly lower at 0.84 and 0.78, respectively.

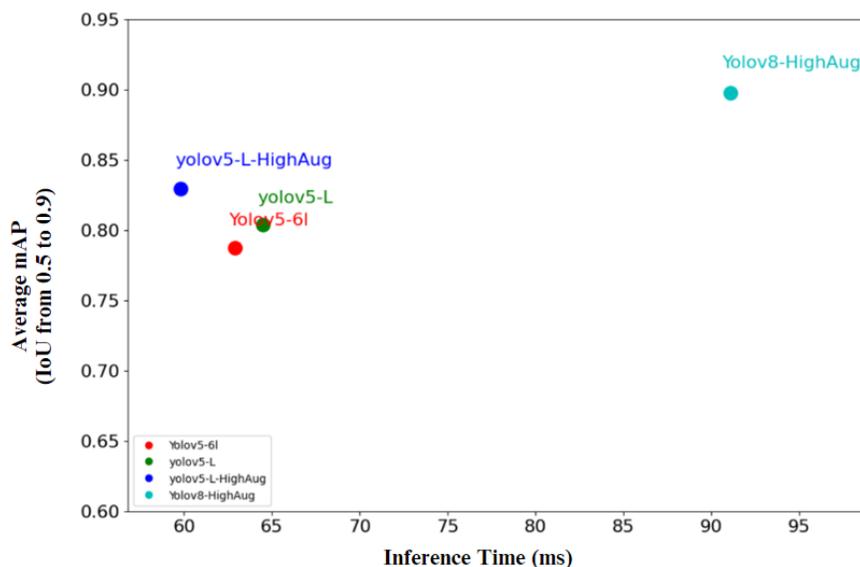


FIGURE 5.11: mAP vs. Number of Operations

Computational Efficiency and Practical Implications In this subsection, we evaluate the computational efficiency of various object identification models by considering metrics such as GFLOPS and inference times and examine their practical implications for the realm of smart agriculture. In terms of computational efficiency, YOLOv5-L-HighAug required the fewest resources, with only 106 GFLOPS, as shown in Figure 5.11. YOLOv5-L was second with 107 GFLOPS, while YOLOv5-6l required 110 GFLOPS. YOLOv8-HighAug had a higher mAP, but also a higher computational cost of 165 GFLOPS. Given the importance of these assessments for smart agriculture applications for farmers and stakeholders, inference time and number of operations are critical. Efficient models with shorter inference times can help farmers make real-time decisions about crop management, insect detection, and resource optimization. Reducing the number of operations (e.g., GFLOPS) enables more effective use of computational resources, allowing these models to be used in resource-constrained contexts. YOLOv8, with its consistently high accuracy and excellent values from AP, can accurately and reliably identify objects in smart agriculture applications. At the same time, the exceptional performance of YOLOv5-L-HighAug in AP @50 demonstrates its applicability for accurate detection tasks essential for identifying important problems such as pest infestations or agricultural diseases. The balanced trade-off between accuracy and detection of YOLOv5-6L can provide a suitable compromise for common agricultural activities.

Finally, analysis of the performance of these models and their impact on smart agriculture applications demonstrates the importance of accurate and efficient object identification in providing useful information to farmers and stakeholders. The results in Figure 5.8 highlight the importance of selecting the most appropriate model based on individual application needs to enable the integration of new technologies into current agricultural practices to increase productivity and sustainability.

5.3.3.2 Qualitative results

This section presents a visual representation of the performance of our model in detecting palm and tree objects within images, as illustrated in Figure 5.12. The chosen examples demonstrate the versatility of our model by showcasing images captured from a farm at varying angles, as well as images from the campus environment.

Our model displays commendable precision in accurately identifying both palm and tree instances, even when dealing with smaller specimens. Visual examples underscore the robustness of our approach across diverse scenarios and highlight its ability to adapt to different environmental challenges.

It is essential to acknowledge that, while our model excels in certain challenges, external factors such as variations in lighting conditions, occlusions, or complex backgrounds may influence its performance. The presented visual examples serve as valuable qualitative assessments, providing insights into the strengths and potential limitations of our model in real-world scenarios.

5.3.4 Discussion

In this part, we compare the performance of the object recognition models used in this study, including Yolov5-L, Yolov5-6L, Yolov5-L-HighAug, and Yolov8-HighAug, with other models from [AKB21], in particular Faster-RCNN, Yolov3, Yolov4, and EfficientDet. We tested these models using the "all", "palm", and "tree" classes on the dataset and examined their average precision values (AP) on various intersection over union (IoU) criteria.

The results showed that our models obtained competitive AP results for all three classes at different IoU levels. However, Yolov8-HighAug routinely outperformed them, with larger AP values. This outstanding result demonstrates the superiority and robustness of Yolov8-HighAug in object recognition tasks.

As for the results of the Adel and all. study [AKB21], Faster-RCNN had modest AP values for the "all", "palm", and "tree" classes, but was outperformed by Yolov8-HighAug in terms of overall recognition accuracy. Yolov3 had good AP values, indicating reasonable recognition accuracy, but fell short of the better performance of Yolov8-HighAug. Yolov4 had exceptional AP values for the "all" class at IoU thresholds of 0.5 and 0.6, but a slight drop in performance for the "palm" and "tree" classes. Yolov8-HighAug had better AP scores, indicating its better object detection capabilities. EfficientDet performed well, especially for the "palm" class, but like Yolov4, was outperformed by Yolov8-HighAug in all classes and for all IoU thresholds.

In terms of mAP values and inference times, Yolov8-HighAug outperformed all other models with the highest average mAP of 0.88, indicating higher accuracy in object detection. Yolov5-L-HighAug came in second with a mAP of 0.83, while Faster-RCNN achieved the lowest mAP of 0.57, indicating that it may be less accurate than the other models. Yolov5-L-HighAug

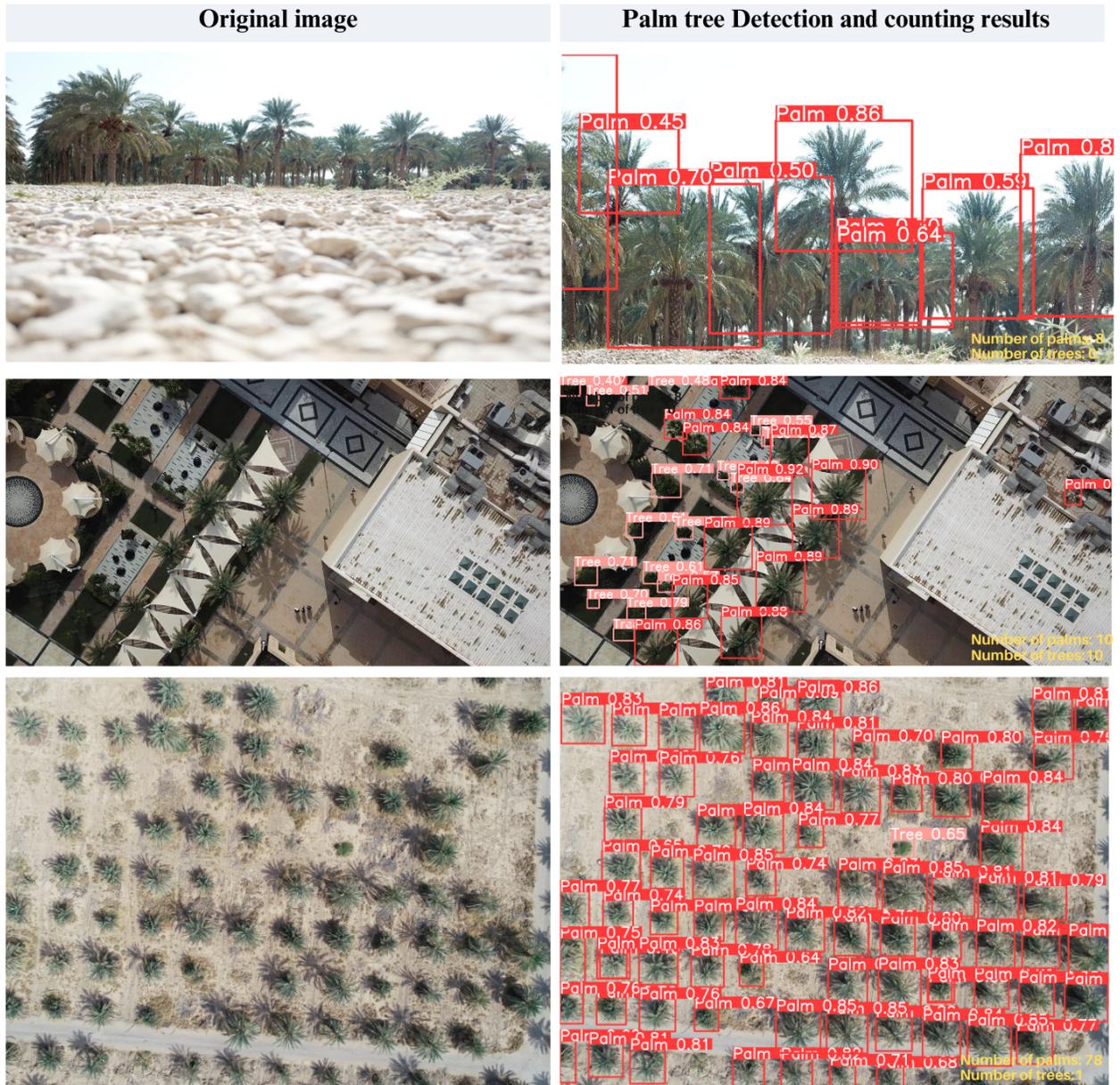


FIGURE 5.12: Qualitative Results of Palm and Tree Object Detection

also had the shortest inference time of 59 milliseconds, making it interesting for real-time applications. Compared to the best model, Yolov8-HighAug and Yolov5-L-HighAug had a slightly lower mAP of about 5.68%, while the other models had mAP decreases between 8% and 35.23%.

In terms of computational efficiency evaluated in GFLOPS (GigaFLOPS), Yolov8-HighAug proved to be the best performing model, with the highest average mAP of 0.88 and higher object identification accuracy than the other models. Its high mAP made it the standard for calculating percent improvements. Faster-RCNN and Yolov3 had lower mAP values of 0.56 and 0.54, respectively, resulting in significant negative percent improvements of approximately -36.36% and -38.64% compared to Yolov8-HighAug. Yolov4 had an mAP of 0.79, resulting in a negative percent improvement of approximately -10.23%. Both EfficientDet and Yolov5-L had slightly lower mAP values of 0.81, resulting in a negative percent improvement of approximately -8.00%. Yolov5-6L had an mAP value of 0.78, resulting in a negative percent improvement of -11.36%. Interestingly, Yolov5-L-HighAug achieved the lowest negative percent improvement of approximately -5.68%, which is similar to the mAP value of Yolov5-L while requiring comparable processing resources.

The comparison of mAP scores with inference times and GFLOPS revealed important information about the strengths and limitations of each model. Yolov8-HighAug had higher accuracy but required more processing resources, while Yolov5-L-HighAug had an excellent combination of accuracy and efficiency. These results can help researchers make informed decisions based on their individual requirements and select the best model for their object identification tasks.

Finally, both our study and [AKB21] show that Yolov8-HighAug consistently outperforms the other models and emerges as the best model for object identification tasks. Its ability to achieve higher AP values across multiple IoU thresholds suggests that it can detect objects with varying degrees of spatial overlap. As with any model evaluation, the architecture, training data, and hyperparameters should be considered. In addition, practical variables such as data processing efficiency and implementation simplicity may influence the best model for real-world applications.

Overall, the results show that Yolov8-HighAug is a powerful model for object recognition that demonstrates its potential for accurate and robust recognition tasks for different object classes and IoU thresholds. Future studies could address the aspects that contribute to the dominance of Yolov8-HighAug, as well as possible refinements to improve the overall performance of object recognition models.

5.4 Conclusion

This chapter focuses on the application of different YOLO models, including YOLOv8-HighAug, YOLOv5-L, YOLOv5-6L, and YOLOv5-L-HighAug, for the detection of date palms in drone images. Experiments were performed on a dataset of 349 images acquired by a fixed-wing drone, presenting several challenges, including varying palm sizes, occlusions, overlaps, and complex backgrounds on a farm or campus in Saudi Arabia. In summary, this study demonstrates the effectiveness of YOLOv8-HighAug and other proposed models in accurately detecting date palms in the complex world of drone imagery. These results provide

valuable insights into the practical applications of YOLOv5-L, YOLOv5-6L, YOLOv5-L-HighAug, and YOLOv8-HighAug for object detection tasks, particularly in agriculture and environmental monitoring.

In essence, our innovative approach that leverages DL and UAV data for efficient palm detection has the potential to revolutionize precision agriculture. By combining state-of-the-art Deep Learning algorithms with UAV-generated imagery, we successfully overcame the difficulties of palm detection, including visual diversity, occlusions, and changing environmental conditions. This breakthrough technology not only raises the standard for palm detection and counting but also paves the way for groundbreaking developments in agriculture. These advances include predictive yield modeling, disease detection, and comprehensive environmental monitoring. Our method represents a significant advance in the field of precision agriculture, combining technical capabilities with agricultural challenges to promote more informed, efficient, and sustainable practices.

In the next chapter, we address a critical problem in palm cultivation. Red palm weevils pose a significant threat to date palms. In this chapter, we explore how the integration of IoT technology and multimodal data can enable the early detection and mapping of this destructive pest. By leveraging data from multiple sources and IoT sensors, we aimed to develop proactive strategies to protect date palms, increase crop yields, and promote sustainable agricultural practices. This chapter continues our commitment to merge technology and agriculture to find more informed, efficient, and environmentally sustainable solutions.

Chapter 6

Early Detection and Mapping of Red Palm Weevil Disease

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6.1 Introduction and motivation

Palm trees, with over 2,500 species, play a vital role in the global culture and economy. In regions such as the Middle East and Indonesia, where the palm industry thrives, these trees contribute significantly to date production and palm oil production. However, the industry faces challenges, particularly the Red Palm Weevil (RPW), which causes economic and ecological repercussions. The ability of the RPW to remain hidden within palm trunks makes early detection crucial.

IoT devices play a critical role in providing real-time data from palm farms, enabling proactive monitoring, early detection of diseases and pests, and rapid response. This collected sonic data is used to identify palm species and assess their health. In addition, the integration of palm detection with RPW mapping enables the identification and tracking of RPW-infested palms, facilitating targeted actions to control this destructive pest [Els+19; JEE22b].

DL algorithms analyze various acoustic signals produced by RPW larvae and their feeding behavior. To develop an effective palm disease and pest control strategy, DL classifications based on sound data from IoT devices, palm identification, and RPW mapping are integrated. This technology, using IoT sensors and DL algorithms, provides efficient and data-driven management solutions that improve the health and productivity of palm farms [HBF22; Gha+22; Haj+21].

By seamlessly integrating IoT sensors with multimodal data, this approach establishes a comprehensive strategy for the early identification and mapping of RPW. Grounded in state-of-the-art DL algorithms and leveraging the capabilities of IoT sensor networks, our methodology excels in detecting, categorizing, and mapping palms infested by RPW. This innovative strategy builds on the foundation laid in Chapter 5, which focuses on advanced palm identification techniques.

In essence, our approach amalgamates cutting-edge DL algorithms with the robust capabilities of IoT sensor networks, ensuring the efficient detection, categorization, and mapping of RPW-infested palms while minimizing redundancy. It is crucial to note that this chapter’s methodology is intricately connected to the groundwork laid out in Chapter 4, which introduced a multimodal data storage system. We presume that our data are already stored within this system, emphasizing the seamless integration of data management processes across chapters. This interconnected framework establishes a cohesive and efficient workflow, streamlining the application of advanced technologies in smart palm precision agriculture.

This chapter pertains to the third thesis objective: pest and disease management in smart palm agriculture. With the aid of remote sensing and artificial intelligence, the objective is to detect, monitor, and proactively manage pest and disease outbreaks in palm crops, thereby minimizing crop loss and preserving palm populations. This chapter is divided into three sections: The first section, outlined in Section 6.2, provides a comprehensive overview of the three key phases: DL Health Classification, Palm Tree Detection using YOLOv8, and RPW Map Generation. These phases constitute the core of the IoT and multimodal data approach for the early detection and mapping of red palm weevils. The second section, presented in Section 6.3, includes an experimental study that details the dataset used, assessment metrics, experimental design, and conclusions with key findings, implications, and recommendations for future research.

6.2 Proposed Method

Figure 6.1 illustrates the workflow of the proposed approach, which is divided into three main phases: DL classification based on sound data from IoT devices, palm detection, and RPW assignment. In the following sections, each of these phases is described in detail. By fusing cutting-edge technologies and data-driven methods, the proposed methodology aims to successfully monitor and maintain palm health and productivity.

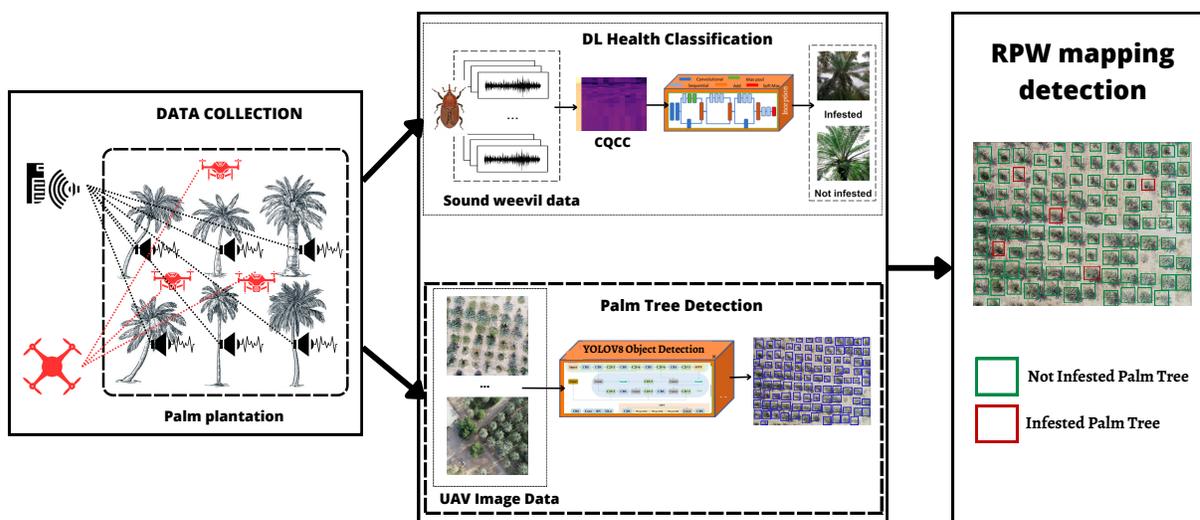


FIGURE 6.1: Overview of our proposed approach to palm tree detection, counting, and health classification based on integrated UAV remote sensing and sound RPW sound data.

Our methodology can be described as follows:

1. We captured remote sensing imagery with a drone and recorded Arduino-based acoustic sensor measurements for RPW noise.

2. We created a dataset consisting of Palm Tree Image Samples (PTIS) and Sound Weevil data.
3. The health status of DL palms was classified using sound weevil data and an InceptionV3 model.
4. The selected YOLOv8 models were trained, validated, and tested to detect and count palms using PTIS as a reference.
5. Analyzed the precision and efficiency of the best YOLOv8-based model for palm tree detection;
6. We created a map showing the location and distribution of healthy and unhealthy palms using both palm classification results and object detection techniques.

6.2.1 Palm Health Classification from sound Weevil

6.2.1.1 Weevil Sound Dataset Feature Extraction

In a study conducted by Boulila et al. [Bou+23] a range of deep learning techniques was employed using nine backbone models, including MobileNetV2, ResNet50V2, ResNet152V2, VGG16, VGG19, DenseNet121, DenseNet201, Xception, and InceptionV3. The aim of this investigation was to evaluate the performance of various deep learning techniques in detecting RPW infestations using sound features extracted from the Weevil Sound dataset.

Their presented results show the accuracy and loss values for the classification experiments using these models. Notably, the Constant-Q Cepstral Coefficients (CQCC) feature set consistently demonstrated superior performance across various CNN architectures. The models trained on the CQCC feature set, particularly the DenseNet121 model, achieved a remarkable accuracy of 98.8%-99.5%. This robust performance underscores the efficacy of the CQCC feature in accurately identifying and classifying RPW infestations.

It is worth noting that the choice of CQCC was motivated by its exceptional individual performance, surpassing other single-feature extraction algorithms such as LFCC, MFCC, Chroma, GFCC, BFCC, Mel Spectro, and Spectral Centroid. This evidence supports the decision to incorporate the CQCC feature in our study as it consistently demonstrated the highest accuracy levels across various deep learning models, providing a strong foundation for reliable and accurate RPW detection.

We utilized the CQCC feature to convert sound files into images. Extracting valuable features from recorded sound data is essential for training DL models. Various features have been explored in existing literature [Li+20b]. These include the conversion of a waveform into a spectrogram that provides a visual representation. Our selection of the CQCC feature aligns with its proven effectiveness in the context of RPW detection, as demonstrated by its superior performance compared with other features in our experimental evaluations.

Constant-Q Cepstral Coefficients (CQCC) The CQCC feature extraction algorithm is a robust technique that is frequently employed in audio signal processing tasks such as voice recognition, sound categorization, and music analysis. This algorithm effectively captures both the spectral and temporal properties of audio signals, making it a versatile representation for a wide range of audio-based applications. In this section, we delve into the CQCC algorithm in detail, including its major phases and equations. The extraction of the CQCC features is illustrated in Figure 6.2.

1. **Constant-Q Transform:** The Constant-Q Transform (CQT) of the input audio signal is calculated as the first step of the CQCC method. The CQT is similar to the well-known Short-Time Fourier Transform (STFT), but uses logarithmically subdivided frequency bins to more closely approximate human auditory perception. This is defined by the following equation:

$$X[n, k] = \sum_{m=0}^{M-1} x[n + m]w[m]e^{-j2\pi kQm/M} \quad (6.1)$$

where $X[n, k]$ represents the CQT coefficients at time frame n and the frequency bin k . $x[n]$ denotes the input audio signal, $w[m]$ is a windowing function (e.g., a Hamming window), Q is the Q-factor that determines the number of frequency bins per octave, and M is the window length.

2. **Log-compression and Power Normalization:** To improve the perceptual representation of the audio signal, log compression is performed after the calculation of the CQT coefficients. It is advantageous to compress the components with greater amplitude while emphasizing the components with lower amplitude. The log-compressed coefficients, denoted by $X_{\log}[n, k]$, are obtained using the following equation:

$$X_{\log}[n, k] = \log(1 + \mu|X[n, k]|) \quad (6.2)$$

where μ is a small positive constant that avoids the logarithm of zero and controls compression. A power normalization process was performed to normalize the power across several frequency bins. It attempts to guarantee that the features produced are resistant to changes in signal amplitude. The power-normalized coefficients, denoted by $X_{\text{norm}}[n, k]$, are computed as follows:

$$X_{\text{norm}}[n, k] = \frac{X_{\log}[n, k] - \bar{X}_k}{\sigma_k} \quad (6.3)$$

where \bar{X}_k and σ_k represent the mean and standard deviation, respectively, of the CQT coefficients within each frequency bin k .

3. **Cepstral Coefficients:** Next, the Cepstral Coefficients are obtained by applying the discrete cosine transform (DCT) to the power-normalized coefficients. DCT correlates

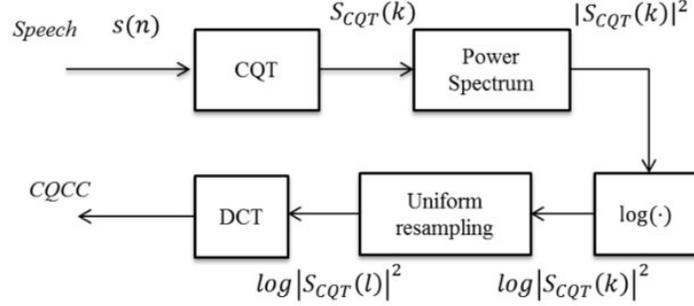


FIGURE 6.2: CQCC feature extraction process [Oo+19]

the coefficients and retains the most relevant information. The resulting cepstral coefficients, denoted as $C[n, k]$, are given by the following equation:

$$C[n, k] = \sum_{m=0}^{M-1} X_{\text{norm}}[n, k] \cos\left(\frac{\pi k(m + 0.5)}{M}\right) \quad (6.4)$$

4. **CQCC Features:** Finally, the cepstral coefficients are concatenated over several time frames to obtain the CQCC features. Thus, the audio signal is represented in a concise and discriminative manner suitable for further processing and analysis.

6.2.1.2 DL Health Classification from sound Weevil

We utilized various deep learning techniques, including InceptionV3, Inception-ResNetV2, and Mixconvnet on the RPW dataset generated for our study. The training of these transfer learning models, which were implemented using TensorFlow and Keras frameworks, was conducted over 200 epochs with a learning rate of 0.0001 and an RMSprop optimizer [BKK20]. To avoid overfitting, the dataset was divided into training (80%), validation (10%), and testing (10%) sets. The weights of these models have been fine-tuned for ImageNet [Rus+15] data classification. ImageNet is a comprehensive dataset comprising 15 million high-resolution images distributed across 22,000 categories, with 4,400 classes specifically dedicated to plant, flora, and plant life classification.

Our study on health classification from weevil sounds involved a deliberate consideration of the aforementioned deep learning models based on their demonstrated efficacy in diverse applications. InceptionV3, known for his utilization of inception modules and multi-scale convolutions, respectively, has shown excellent ability to capture intricate features, making them well suited for our audio classification task. Inception-ResNetV2, amalgamating the strengths of Inception and ResNet, offers improved training efficiency and performance

through its residual connections. Mixconvnet, leveraging mixed depth-wise separable convolutions, was incorporated for its capacity to enhance model expressiveness. The ensemble of these models aimed to exploit a spectrum of architectural characteristics, allowing for a comprehensive exploration of their individual and collective effectiveness in health classification from weevil sounds.

The use of the RMSprop optimizer in all training experiments was a result of its well-suited nature for training deep neural networks with a large number of parameters. This range of CNNs underscores the versatility and applicability of our proposed approach to diverse audio classification tasks by utilizing various CNN architectures. The utilization of CQCC in conjunction with various CNNs enables the extraction of diverse audio characteristics, leading to improved performance across a range of audio classification scenarios. The combination of feature extraction techniques and CNN architectures enhances the robustness and adaptability of the proposed approach.

6.2.1.3 Transfer learning classifiers

This section gives an overview of the proposed transfer learning models for identifying the health status of palm trees, as follows. First, different version architectures of Inception models are described, highlighting the main features of each transfer learning model.

Inception models Figure 6.3 illustrates the primary architectures for the two iterations of the inception model. The initial inception classifier introduced by Szegedy et al. [Sze+15] aims to surpass existing classifiers in the ImageNet Large-Scale Visual Recognition Challenge 2014 (ILSVRC14). Inception-V1 enhanced the detection and classification accuracy by augmenting the depth and width of the CNN model while maintaining a consistent computational cost. The optimized architecture of Inception-V1 adhered to the Hebbian principle and incorporated multi-scale processing. Notably, Inception-V1, featuring a 22-layer CNN with dimension reduction, is commonly referred to as GoogleNet, as shown in Figure 6.3 a.

In 2016, Szegedy et al. [Sze+16] introduced Inception-V2 and V3, as illustrated in Figure 6.3b. These upgraded versions feature a modification in the 5×5 convolution module of Inception-V1, replacing it with two 3×3 convolutions. However, Inception-V3 incorporates additional enhancements into its network architecture. It employs factorized 7×7 convolutions and an RMSProp optimizer. In addition, the auxiliary classifiers underwent batch normalization, and label smoothing was introduced to mitigate overfitting in the deep network. Inception V3 utilizes softmax classifiers for prediction, global average pooling for aggregation of geographic inputs, and auxiliary classifiers for additional monitoring. Owing to its effective multiscale feature extraction and computational efficiency, Inception V3 achieves the highest performance on a wide range of computer vision tasks after being trained on large datasets [Al +22].

Inception V3 has demonstrated versatility in various image-related tasks, including object detection, image segmentation, and video classification. The use of factorized convolutions

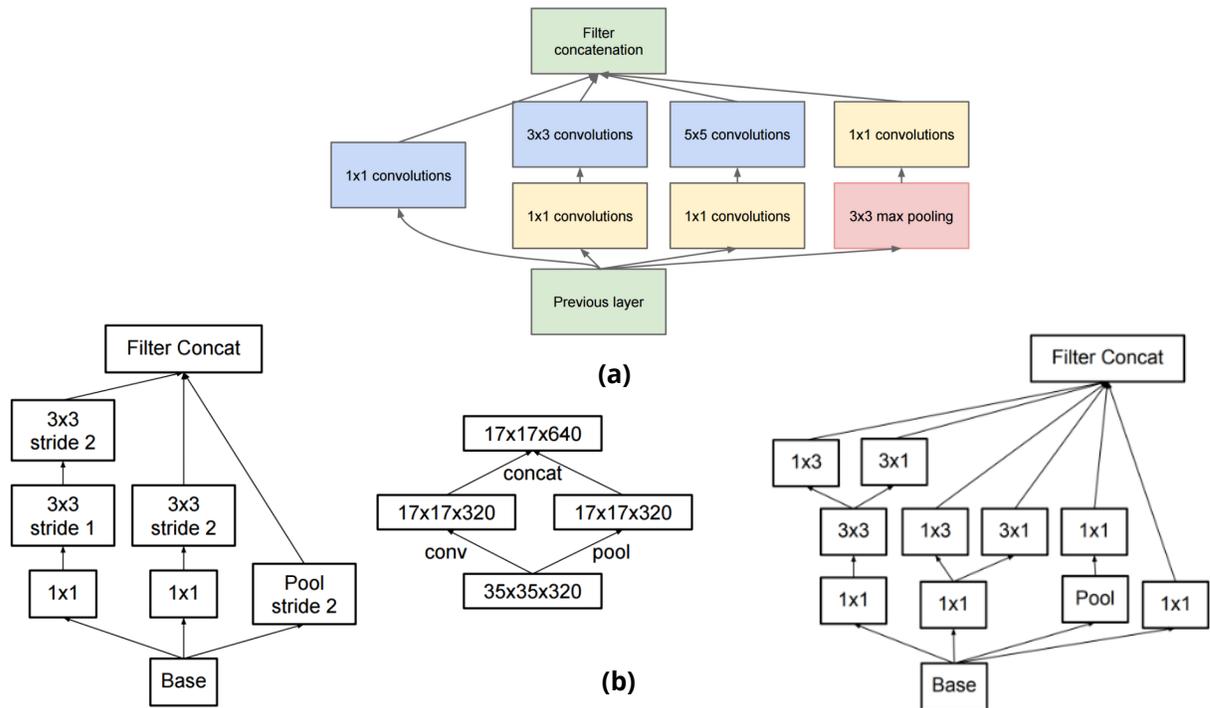


FIGURE 6.3: Inception-v3 architecture

and inception modules contributes to efficiency and accuracy. Pre-training on ImageNet enhances its adaptability, making it suitable for diverse applications with impressive accuracy [Al +22]. The architectural design of Inception V3, boasting approximately four million parameters, distinguishes it as a more compact model compared to other models such as VGG. Inception V3 excludes fully connected layers and relies solely on a pooling layer, thereby accelerating its computational capabilities [Wir21].

To gain further insight into its development, Google implemented Inception V3 with parallel convolutional layers of different filter widths and inception modules to effectively capture information at various scales. Using softmax classifiers for prediction, global average pooling for geographic input aggregation, and auxiliary classifiers for additional monitoring, Inception V3 achieved the best performance across a range of computer vision tasks [Al +22]. Upon thorough examination of various deep learning models for the purpose of RPW detection utilizing sound features, we have opted to employ the InceptionV3 architecture for a number of compelling reasons. InceptionV3 has demonstrated exceptional performance across a diverse range of computer vision tasks, thus gaining considerable traction within the deep learning community.

Initially, InceptionV3 is acclaimed for its capacity to discern intricate hierarchical structures in data through the utilization of its inception modules. These modules facilitate efficient learning and representation of features at various scales, which is of particular importance when working with intricate datasets such as the sound features extracted from the Weevil

Sound dataset. Accurate detection of RPWs necessitates the identification of subtle patterns, making InceptionV3’s hierarchical learning capability a highly valuable asset.

Furthermore, InceptionV3 boasts a relatively lightweight architecture when compared to certain other deep learning models, thereby striking a favorable balance between model size and computational efficiency. This is of particular significance for practical applications, as it allows for efficient deployment and inference across a wide range of computing platforms, including resource-constrained environments.

Moreover, the InceptionV3 model has been extensively adopted and fine-tuned in a variety of domains, showcasing its versatility and adaptability. The availability of pre-trained weights on substantial datasets, such as ImageNet, serves as a valuable starting point for transfer learning, enabling effective training on our particular RPW sound dataset using a relatively modest amount of labeled data.

In conclusion, our decision to employ the InceptionV3 architecture for our RPW detection study is rooted in its established ability to capture intricate patterns, its efficient design, and its extensive success in various computer vision applications. We are confident that these qualities make InceptionV3 a suitable and effective choice for achieving precise and reliable RPW detection from sound features in our study.

InceptionResNet-V2 Inception-ResNetV2, a highly sophisticated convolutional neural network architecture that has been developed for the recognition of images, has demonstrated exceptional effectiveness in a variety of applications. First proposed by He et al. [He+16], this architecture combines key elements from both the Inception and ResNet architectures to achieve superior performance. Specifically, the inception module, which is known for its ability to capture multi-scale features, is enhanced with residual connections inspired by ResNet. This integration is designed to leverage the strengths of both architectures, facilitating efficient feature extraction and mitigating the vanishing gradient problem in deep networks. The resulting model comprises stacked inception-residual blocks, each of which incorporates inception modules with residual connections. Batch normalization is employed to ensure stable training, and a global average pooling layer is utilized for spatial dimension reduction prior to the final classification layer. Inception-ResNetV2 is noteworthy for its exceptional accuracy and efficiency in diverse computer vision tasks, which makes it particularly well-suited for image classification and feature extraction. The InceptionResNet-V2 model architecture is shown in Figure 6.4 (a).

Mixconvnet MixConvNet, a novel CNN architecture introduced by Zhang et al. [ZHW22] in 2022, represents a significant advancement in the field of deep learning for image-classification tasks. The architecture incorporates a distinctive mixed-depthwise convolutional operation, aiming to strike a balance between computational efficiency and expressive power. The model builds on the efficiency of depthwise separable convolutions by introducing a mixed convolution operation that combines depthwise and standard convolutions. This innovation allows

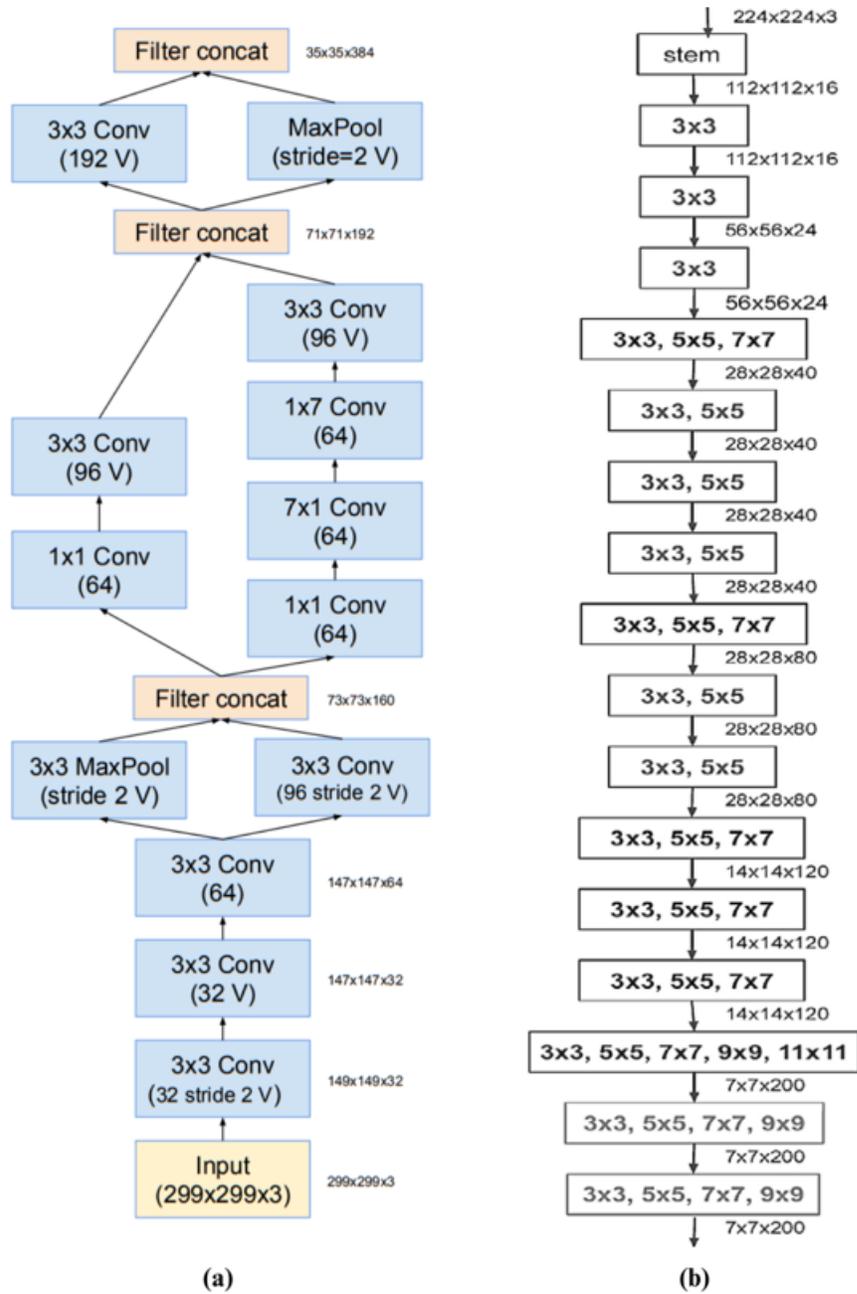


FIGURE 6.4: (a).InceptionResNet-V2 Model Architecture- (b).MixConv-S Model Architecture

the network to capture intricate features while maintaining its computational efficiency. The architecture consists of multiple blocks of mixed-depth-wise convolutions, followed by batch normalization and nonlinear activation functions. MixConvNet achieves competitive accuracy with reduced computational costs, making it a promising choice for applications with

resource constraints. This model is a noteworthy advancement in CNNs architectures, showcasing the ongoing evolution towards improved efficiency and performance. The Mixconvnet model architecture is shown in Figure 6.4 (b).

6.2.2 Palm tree detection using YOLOv8

Building on the foundation of our previous method for efficiently detecting palm trees using DL and UAV imagery (see 5 section), we now focus on the complexity of palm tree detection itself. The YOLOv8 model, known for its powerful object recognition capabilities, is key to our comprehensive solution for early detection and mapping of the red palm weevil (RPW).

The goal of this part is to accurately and effectively detect date palm trees by utilizing the YOLOv8 object detection framework. The real-time object detector YOLOv8, which was introduced in 2023 under the name, is the result of numerous real-time object detectors' technological developments. It combines the advantages of many models to provide a complete answer for object detection tasks, such as palm tree detection. Our decision to use YOLOv8 was driven by its capacity to combine the greatest features and improvements from several methodologies, producing improved performance and accuracy. Modern backbone and neck architectures (i.e., YOLOv5) are incorporated into YOLOv8, which enhances feature extraction and enables accurate palm tree detection.

The network uses a sigmoid activation function to determine the likelihood that a palm tree will be detected in each instance of detection, as shown in Equation (6.5), where σ represents the sigmoid function and net denotes the input to the sigmoid.

$$\text{Output} = \sigma(\text{net}) \tag{6.5}$$

In contrast to the Anchor-Based technique utilized in earlier versions, YOLOv8 adds the Anchor-Free approach. Additionally, YOLOv8's matching approach uses the dynamic Task Aligned Assigner. Equation 6.6 is used to calculate the alignment degree at the Anchor level for each instance, where "s" stands for the classification score, "u" for the IOU value, and "alpha" and "beta" for the weight hyperparameters. The remaining anchors are regarded as negative samples, and "m" anchors with maximum value "t" are chosen to represent positive samples. The loss function is then used to train the model. Because of these improvements, YOLOv8 has the highest accuracy of any object detector to date, with a 1% improvement over YOLOv5.

$$t = s^\alpha \cdot u^\beta \tag{6.6}$$

Equation (6.7) illustrates how YOLOv8 uses a complete loss function that combines classification loss, localization loss, and confidence loss among other components to enhance the performance of the model. Each term contributes to different parts of the detection task, and the loss function is intended to direct the training process and enhance detection performance by penalizing inaccurate predictions and promoting accurate detections.

$$\text{Loss} = \text{Classification Loss} + \text{Localization Loss} + \text{Confidence Loss} \quad (6.7)$$

YOLOv8 is the best option for real-time palm tree detection in applications like environmental monitoring, urban planning, and agriculture because to its excellent balance between accuracy and speed. Additionally, YOLOv8 offers a range of pre-trained models that are adapted to various performance needs. These models provide a comfortable place to start by utilizing the knowledge and optimizations that are already there in YOLOv8. This expedites implementation and saves time and money when creating a reliable palm tree detecting system. As a result, YOLOv8 was selected as the reference version and the starting point for our work.

6.2.2.1 Network architecture

The Focus, CBL, SPP, and CSP modules, among others, are shared by YOLOv8 and YOLOv5. Similar functions and goals are served by these modules in YOLOv8 as they were in YOLOv5. The CBL module is used by the Focus module to create feature maps after splitting the input image into four parallel slices. Convolution operations are carried out using the CBL module with batch normalization and leaky-ReLU activation for feature extraction. Similar to YOLOv5, the CSP module in YOLOv8 is built on CSPNet and comprises of CSP1 and CSP2 modules. These modules are used to partition the input feature map, fuse cross-level features, and establish the depth of the architecture in the network backbone and neck parts of YOLOv8. In order to capture spatial information, the SPP module, which is also featured in YOLOv5, downsamples input features using max pooling layers and then mixes them with the beginning features. The fundamental ideas and purposes of these modules are the same in both YOLOv8 and YOLOv5, despite possible differences in architectural components and configurations. The preparation of the dataset, training, validation, and testing procedures are covered in the following subsections.

6.2.2.2 Network training

With precise labeling that distinguished between palm trees and other types of trees, the training dataset had two classes: palm and tree. The recognized palm trees and trees were contained within rectangular bounding boxes that took into account size variations, overlap, occlusion, and various backdrops. Techniques for data augmentation, such as scaling, cropping, rotation, and color space modifications, were used to enhance the training dataset. For additional augmentation, mosaicking, a method that combines numerous images to produce a composite image, was employed to introduce differences in scene composition and context. The number of training images for each class was greatly boosted by this enlarged dataset, which improved the model's capacity for generalization and precise date palm tree detection. To enhance the training procedure, a number of hyperparameters were changed, including the SGD optimizer with a momentum value of 0.9 and a decay rate of 0.0005. For consistency, a random seed of 45 was chosen, and the training process was tracked with model

saving every 10 epochs. To avoid overfitting, early stopping with a patience of 20 epochs was implemented. These setup options made sure that the YOLO-V8 model was trained consistently and successfully for precise palm tree detection.

6.2.2.3 Palm tree detection

We scaled the test images to 1280x1280 pixels after training the YOLO-V8 network in order to keep the aspect ratio constant. This size was selected because it found a good compromise between maintaining details and lightening the computing burden. The trained network was then fed the resized images to produce 80x80, 40x40, and 20x20-scale feature maps. In YOLO-V8, three bounding boxes, each comprising data on the coordinates, size, confidence level, and class probability, were generated for each prediction scale. Low confidence boxes were eliminated, and redundant detections were suppressed by defining a threshold and using Non-Maximum Suppression (NMS). Finally, to precisely pinpoint the palm trees, the bounding boxes were rescaled to the original image size. This procedure enhanced the system's overall performance and made it possible to detect palm trees of all sizes efficiently and accurately.

6.2.3 RPW map generation

The main objective of creating an RPW map is to locate the presence of RPW on UAV images and identify RPW infestations on palms. This requires a coordinated strategy using UAV imagery, palm object detection algorithms, and recording devices attached to the palms. The location of each recording device is first stored in a cloud database before it is carefully placed and attached to specific palm trees. The sounds of the palms are recorded by these devices and then subjected to sound analysis. Key spectral and temporal features are captured by extracting CQCC features from the recorded sounds.

During the training of the InceptionNetV3 model, the TreeVibes dataset was employed to process the CQCC features. However, it's crucial to note that for the generation of the RPW map, a private dataset from the same geographic zone as the drone images was utilized. This private dataset contributed to the accurate mapping and categorization of RPW-infested palms within the targeted region. The model, through sound analysis, determined the RPW infestation status of each palm. To establish a connection between infestation status and location, the results of the categorization process were stored alongside the coordinates of each palm. Concurrently, drones equipped with cameras captured high-quality images of the farm, with a focus on the areas of interest containing the palm groves. These drone-captured images provided a comprehensive overview of the entire farm.

The final step is to apply palm object detection techniques, such as YOLOv8, to the UAV images. These techniques locate palm trees in photographs and determine their locations by returning bounding box coordinates for each palm tree found.

Now begins the crucial process of coordinate matching and visualization. The coordinates of the palms detected in the object detection phase are compared to the coordinates of the

palms detected by the corresponding recording devices. This matching helps to establish a link between the category of RPW infection and the palms found.

Once the matching is complete, the RPW map visualization is created. Depending on the level of RPW infection, the bounding boxes of the identified palms are colored. If a palm is infested with RPW, the corresponding bounding box is highlighted in red to indicate the presence of an infestation. The bounding box of a palm that has not been found to be infested is shown in blue, indicating a healthy palm.

6.3 Experimental Study

This study employed Python code programming with the TensorFlow and Keras packages [GKP19] to implement the proposed InceptionV3 classifier and other models of transfer learning. All experiments were conducted on an HP Victus laptop running Windows 11 Home Single Language Edition version 22H2. The device features a 12th-generation Intel Core i7-12700H processor operating at a base frequency of 2.30 GHz. It has 24.0 GB of installed RAM. The system was a 64-bit operating system based on an x64 processor. Additionally, the laptop was equipped with Disque 1 SSD M.2 storage and included an Nvidia GeForce graphics card for enhanced graphical processing capabilities.

6.3.1 Data-sets Collection

6.3.1.1 The TreeVibes Dataset

In our scholarly endeavor, we availed ourselves of the extensive TreeVibes dataset, which encompasses over 54,000 ten-second audio samples. This dataset, described in detail by Rigakis et al. [Rig+21], serves as a vital resource for delving into the acoustic attributes of trees, with a particular focus on wood-boring insects, such as *Rhynchophorus ferrugineus* (RPW) and other pests. It is worth mentioning that our objective was to utilize this dataset for training and comparison with other studies, as several models proposed in the literature have employed the same dataset for similar objectives.

The TreeVibes dataset covers a diverse range of tree species, recorded at various times throughout the year. Each audio sample was associated with comprehensive metadata, including descriptors for tree species, geographic location, season, weather conditions, and timestamps. These metadata include vital information, such as GPS coordinates, date and time of recording, temperature, humidity, and barometric pressure. The dataset encompasses different tree species from various continents, which facilitates the study of sound variations associated with seasonal and weather-related changes. Table 6.1 provides a comprehensive overview of the contents of the dataset can be found in Table 6.1. This table provides detailed information regarding the number of audio samples, tree species diversity, and other relevant metadata.

| Label | Number of records |
|--------------|-------------------|
| Not infested | 967 |
| Infested | 53676 |

TABLE 6.1: Number of records in TreeVibes dataset

A distinctive feature of the TreeVibes dataset is its innovative data-collection approach. As shown in Figure 6.5, the dataset was obtained using a remotely controlled device equipped with a piezoelectric transducer, which was distinct from conventional microphones. This transducer records vibrations inside trees generated by wood-boring insects, such as RPWs, using a drill or a metallic waveguide as a sound coupler. The recorded data were compressed in Ogg format, transmitted to a cloud server, and subsequently decompressed, logged, and classified. The design of the dataset allows remote access to recordings, enabling the application of automatic classification methods for early pest detection. The TreeVibes device operates self-sufficiently and is powered by a built-in solar panel, eliminating the need for recharging and enabling prolonged use on trees. Its global coverage through an SIM map, combined with GPS tracking, facilitates seamless communication between the trees and the server.

Despite the richness of the dataset, there are challenges in collecting and tagging the data on infested trees. Devices must be placed on trees with visible signs of infestation, or recordings must be made of felled trees while adhering to the required permits. Expanding on the specifics of the device, as described by the authors, the TreeVibes sensing device employs an embedded piezoelectric crystal as a microphone to capture vibrations in the infested trees. The acquired sounds, including those of RPWs and other borers, were converted to audio signals. These signals are then stored or wirelessly transferred via the proposed IoT network to a cloud server for further signal processing and analysis.

It is important to note that the TreeVibes device can detect the feeding and movement of RPW larvae but cannot count them or precisely define their location inside the trunk of the palms. Proper placement of the sensing device on the trunk is crucial for successfully detecting suspected sounds of RPWs and other borers within a spherical region with a radius of 1.5 to 2.0 meters.

The TreeVibes dataset includes annotated audio recordings of RPWs and other insect pests such as *Xylotrechus chinensis* and *Aromia bungii* (red-necked longicorn). This open-access database, available for download at <http://www.kaggle.com/potamitis/treevibes>, contains 35 annotated folders with 2485 audio recordings. In this study, we utilized this dataset for the early detection of wood-boring insects and for pest management. In this study, we assumed that audio recordings featuring sounds of feeding and movement from pests were exclusively attributed to the larvae of the RPW.

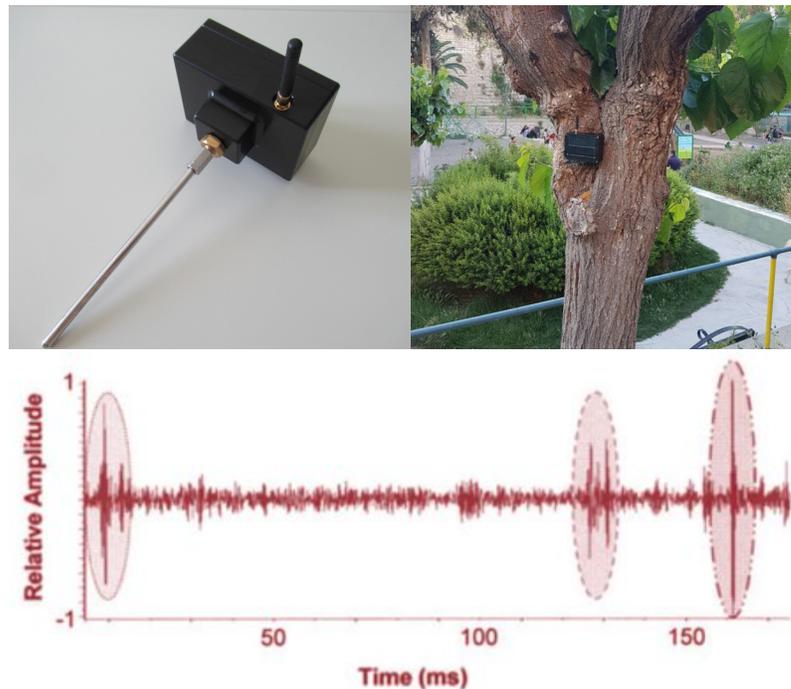


FIGURE 6.5: (upper) Piezoelectric Transducer Inside the Tree for Acquiring RPW Sounds. (lower) mean spectral sound profile of three different RPWs

6.3.1.2 Private Acoustic Dataset

The Al-kharj region was chosen as the focal point for a case study, aiming to assess the efficacy of the proposed approach. This deliberate choice builds upon the familiarity and groundwork established in the previous section (see section 5.3.1 in Chapter 5) , providing a seamless transition for evaluating the effectiveness of our methodology in a region already studied and characterized.

The study utilized a dataset comprising recordings obtained through remote vibro-acoustic surveillance of date palm trees placed in the Al-kharj region. Recordings were captured using a device attached to the tree trunk, and it is noteworthy that this device aligns with the equipment used in the TreeVibes dataset 6.5 (for more details about the device, refer to <https://www.insectronics.net/>). The use of consistent instrumentation in our approach guarantees comparable methodology across different datasets, which facilitates meaningful comparisons and strengthens the reliability of our method. Furthermore, we deliberately selected a dataset from the same geographical zone where the drone images were captured to ensure spatial synchronization during the map generation process.

To ensure precise reading points, markings were carefully placed on each date palm trunk, exactly one meter above the ground level. Next, drill holes were meticulously created at a 30-degree angle using a drill machine equipped with an 8-mm diameter. The brad-point drill

bit reached a depth of 35 cm within the palm tree. A single hole was carefully drilled at the designated location on the trunk, and an acoustic device was installed around the tree to enhance the detection of RPW sounds.

The acoustic device, designed for optimal sound data collection, features a probe or waveguide measuring 35 cm in length. This specialized component was carefully inserted into the tree and embedded in a recording machine. The waveguide was positioned within a previously drilled hole in the date palm trunk, establishing a direct connection to the recording machine. The recording machine is equipped with headphones, allowing users to assess the intricate sound signals produced by RPW activities. This comprehensive device architecture facilitates seamless data transmission between the device and a central server or cloud system. The RPW device boasts a sound signal detection radius within the date palm tree of approximately 1.5–2 meters. In this study, specific parameters were configured, including a five-minute repeat period and a recording duration of 20 s. Each daily tree recording captured 20 seconds of sound data. This rigorous recording protocol was diligently executed across the entire spectrum of date palm trees, accompanied by precise timestamps for each recording. Table 6.2 presents a comprehensive overview of the number of recordings per class, with the aim of facilitating a more profound comprehension of the dataset.

| Label | Number of records |
|--------------|-------------------|
| Not infested | 531 |
| Infested | 571 |

TABLE 6.2: Number of records in our Private Dataset

6.3.1.3 UAV images data

As mentioned in the previous chapter 5, we used the same dataset for this study. This dataset, as described earlier, includes a total of 349 collected images consisting of aerial photographs from two different locations. Two drones were used to capture the images. The first drone was a DJI Phantom 4 Pro, which was equipped with a DJI FC6310 camera with resolutions of 4864×3648 and 4096×2160 . The second drone was a DJI Mavic Pro equipped with a DJI FC220 camera with a resolution of 4000×3000 pixels. Figure 6.6 shows UAV examples captured by drones. To analyze and classify the images, the dataset was manually labeled using the Labelbox platform. A total of 13,071 instances were labeled, with 11,150 instances identified as palm trees and 1,921 instances identified as other trees.

6.3.2 Evaluation metrics

Mean Validation Accuracy: MVA represents the average accuracy of a model in a validation dataset. It is a measure of how well the model correctly classifies the data in the validation data set. Typically, the average validation accuracy is calculated by averaging the

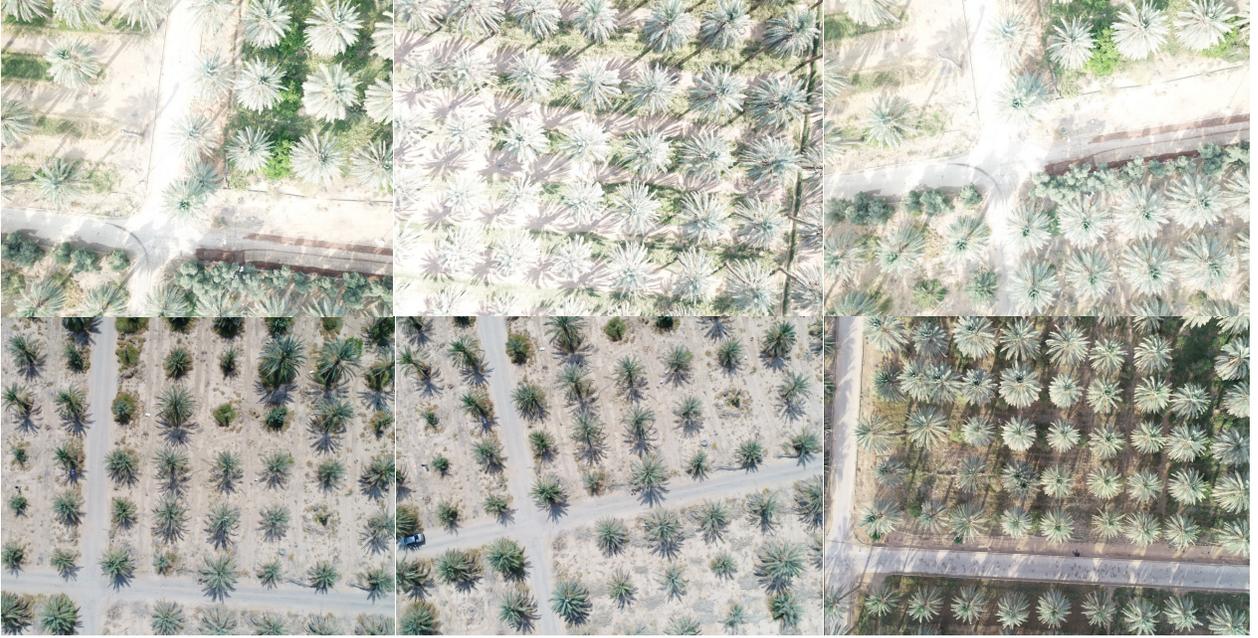


FIGURE 6.6: UAV images examples

accuracy values obtained during validation for different stacks or validation folds. If you have accuracy values A_1, A_2, \dots, A_n for n validation runs, the mean validation accuracy (MVA) can be calculated as follows:

$$MVA = \frac{1}{n} \sum_{i=1}^n A_i$$

Mean Validation Loss: MVL represents the average loss (e.g., cross-entropy loss or mean squared error) of a model in a validation dataset. It quantifies the dissimilarity between the predicted values and the true values in the validation set. Similar to the mean validation accuracy, the mean validation loss is calculated by averaging the loss values obtained during validation for different stacks or validation folds. If you have loss values L_1, L_2, \dots, L_n for n validation runs, the mean validation loss (MVL) can be calculated as follows:

$$MVL = \frac{1}{n} \sum_{i=1}^n L_i$$

In our analysis, we also use a number of well-known evaluation benchmarks to comprehensively investigate the performance of our model. These benchmarks, which include Precision,

Recall, and mAP, have already been examined in detail in the previous chapter (section 2.5.6).

Precision measures the accuracy of our model in detecting positive instances and guarantees that an expected infection is indeed a positive case. Recall evaluates the model's ability to detect all positive instances and highlights its accuracy in detecting all infections. As mentioned earlier, the mAP provides a useful overview of the model's performance at various confidence levels. Together, these criteria provide a solid evaluation framework for assessing the effectiveness of our strategy in detecting and controlling wood-boring insect infestations.

6.3.3 Results and discussion

6.3.3.1 RPW classification based on sound data

Using the CQCC feature extraction technique, we converted the dataset of the red palm weevil audio recordings into visual representations. As illustrated in Figure 6.7, the technique was applied to a dataset of audio files labeled as either "infested" or "not infested." The figure shows four samples from each class, and the outputs of the feature extraction techniques are shown for each sample.

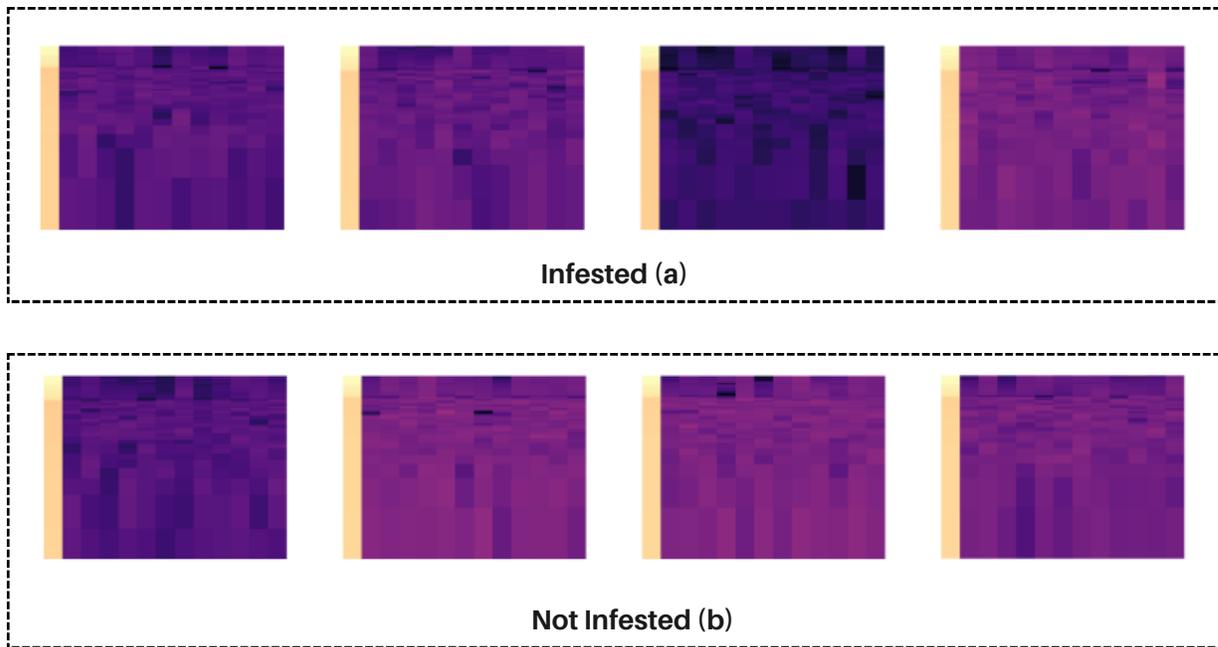


FIGURE 6.7: The images obtained for each class (Infested and not-infested palms).

Using ratios of 0.8, 0.1, and 0.1, the image dataset was divided into training, validation, and test sets. The DL model used was InceptionV3, trained with a batch size of 16, a learning

rate of 0.0001, and 200 iterations. Both the binary cross-entropy loss function and the Adam optimizer were used. The test data set was used to evaluate the trained InceptionV3 model, and the results were very encouraging. The results were very encouraging. The model performed well, scoring 98.8% on accuracy. Different iterations allowed visualization of validation accuracy and loss, as shown in Figures 6.8, 6.9. The plots show a decreasing trend in the loss function and a constant increase in accuracy during training.

Performance comparison

For the RPW classification task, we employed the CQCC feature extraction technique to transform a dataset of red palm weevil audio recordings into visual representations. Figure 6.7 showcases the application of this technique to a labeled dataset, distinguishing between "infested" and "not infested" audio files. The figure displays four samples from each class, presenting the outputs of the feature extraction technique for each sample.

First, our objective was to evaluate our methodology by applying a range of machine-learning algorithms including; support vector machines (SVM), Logistic Regression (LR), Random Forest (RF) and Decision Tree (DT), to our private dataset. The results are consolidated in Table 6.3. Although the outcomes were encouraging, it is essential to emphasize that our long-term objective was to achieve perfect accuracy. The early detection of Red Palm Weevil is of paramount significance, and we remain committed to exploring avenues that can improve the accuracy of our method.

TABLE 6.3: Performance of ML algorithms on our private Dataset

| ML Algorithms | SVM | LR | RF | DT | Our Proposed Method |
|-----------------|-----|-------|-----|-----|---------------------|
| <i>Accuracy</i> | 98% | 99,2% | 98% | 99% | 99.8% |

Second, our objective was to assess the robustness of our approach by applying it to various deep-learning algorithms, particularly focusing on the most recent and highest-performing results highlighted in the literature review. The methodologies and achievements outlined by Karar et al. in 2021 and 2022 are particularly influential in guiding our comparative analysis [Kar+21; Kar+22]. The dataset was split into training, validation, and test sets with ratios of 0.8, 0.1, and 0.1, respectively. We utilized the InceptionV3 deep learning model, with a batch size of 16, a learning rate of 0.0001, and 200 iterations. The training employed the binary cross-entropy loss function and the Adam optimizer. The performance evaluation on the test dataset yielded highly encouraging results, with the model achieving 98.8% accuracy, precision, recall, and F1 score.

Different iterations enabled the visualization of validation accuracy and loss, as depicted in Figures 6.8 and 6.9. These plots illustrate a decreasing trend in the loss function and a consistent increase in accuracy during the training process.

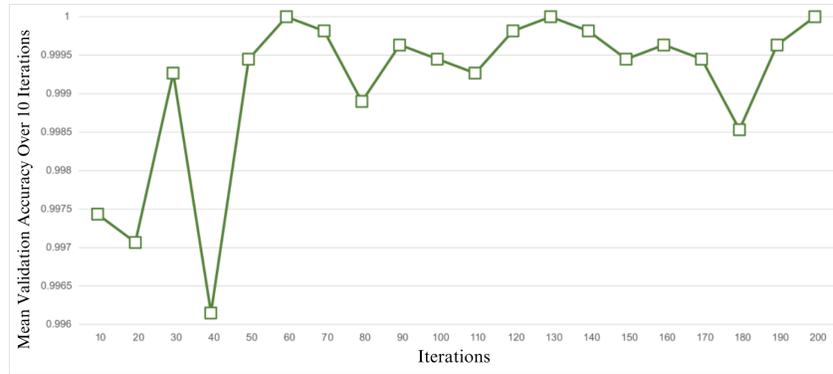


FIGURE 6.8: Mean validation accuracy over 10 iterations.

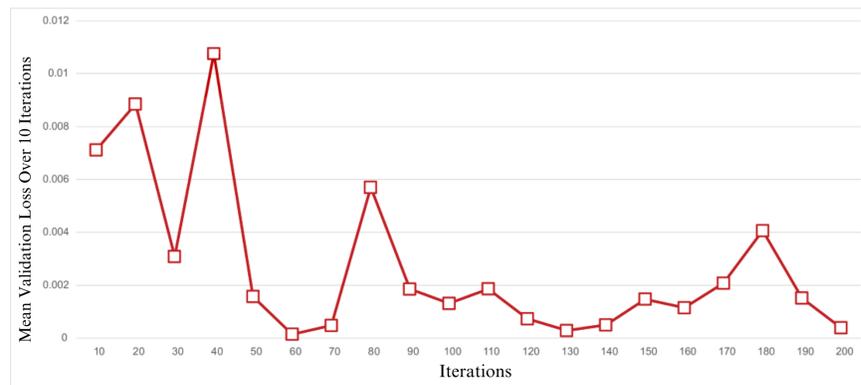


FIGURE 6.9: Mean validation loss over 10 iterations.

The outcomes presented in Table 6.4 serve as a robust validation of the efficacy of our approach assessed on the Treevibes dataset. Notably, the InceptionV3 model surpasses other classifiers, exhibiting exceptional performance across all evaluation metrics and attaining perfect precision, recall, and F1-score scores. The model consistently achieved an accuracy rate of 98.8%, underscoring its resilience in accurately categorizing instances as infested or non-infested.

These results substantiate the success of our proposed methodology for the classification of red palm weevils and establish a foundation for reliable and precise pest detection. It is imperative to note that the performance on our private dataset surpassed these outcomes, achieving an impressive 99.5% accuracy.

TABLE 6.4: Transfer learning classifier performance tested on Treevibes Dataset

| Classifier | Class | P | R | F1-score | A (%) | Loss |
|--|--------------|--------------|--------------|------------|--------------|-----------|
| <i>InceptionResnet,</i> <i>[Kar+21]</i> | Infested | 0.99 | 0.92 | 0.95 | 97.18 | 2.82% |
| | Not infested | 0.97 | 0.99 | 0.98 | | |
| <i>MixConvNet,</i> <i>[Kar+22]</i> | Infested | 0.99 | 0.93 | 0.96 | 97.38 | 2.62% |
| | Not infested | 0.94 | 1 | 0.97 | | |
| <i>Our proposed method:</i> <i>InceptionV3 + CQCC</i> | Infested | 99.5% | 98.5% | 99% | 98.8% | 1% |
| | Not infested | 98.8% | 99.2% | 99% | | |

P: precision, R: recall, A: accuracy

6.3.3.2 YoloV8 for palm tree detection

Using a carefully selected palm recognition dataset, we trained the YOLOv8 object recognition model. Our goal was to develop an accurate and reliable model that can recognize palms in a variety of environments. A 1280x1280 image with 60 training epochs was used with the large YOLOv8 model architecture. The efficiency of our trained YOLOv8 model for palm tree detection was demonstrated by the evaluation results. With a precision of 0.841, palms were correctly detected 84.1% of the time. With a recall value of 0.865, 86.5% of the actual palm plants in the dataset were successfully identified. To evaluate the overall accuracy, we measured the mean accuracy (mAP). At a confidence level of 50%, the mAP@50 result was 0.899, indicating high accuracy. At a wider range of confidence thresholds, performance was less effective, as indicated by the mAP@50-95 value of 0.541. The training progress for the palm object recognition matrix is shown in Figure 6.10.

Our YOLOv8 model achieved exceptional results that were significantly bolstered by the strategic integration of data from red palm weevils, accompanied by precise GPS coordinates. The supplementary dataset proved to be a game changer, playing a pivotal role in improving the performance of our model.

The red palm weevil dataset introduced real-world variations and challenges encountered in palm tree environments, which introduced a unique dimension to the training process. The inclusion of GPS coordinates facilitates a nuanced understanding of the spatial distribution of palm trees and their corresponding infestation patterns. This additional layer of information enables our model to adapt more effectively to diverse geographical conditions.

By incorporating this enriched dataset, we observed impressive enhancements in several key performance metrics. The precision of our YOLOv8 model experienced a noteworthy boost, reaching an ameliorated value of 0.871, representing an increase from the initial value of

0.841. This signifies that the model achieved even greater accuracy in correctly identifying palms, now standing at an impressive 87.1

Similarly, the recall value saw a substantial improvement, reaching an improved value of 0.895, up from the initial 0.865. This signifies an increased capability of our model to successfully identify a greater proportion (89.5%) of actual palm plants within the dataset.

The mean accuracy (mAP) at a confidence level of 50% also increased, reaching an ameliorated value of 0.918. This highlights a further refinement in accuracy, solidifying the model's proficiency in palm-tree detection.

In summary, the incorporation of red palm weevil data, coupled with GPS coordinates, has not only enriched the training process but has also led to substantial improvements in precision, recall, and overall accuracy. These improved values underscore the model's heightened effectiveness in recognizing palms across diverse environments, showcasing its robustness and adaptability.

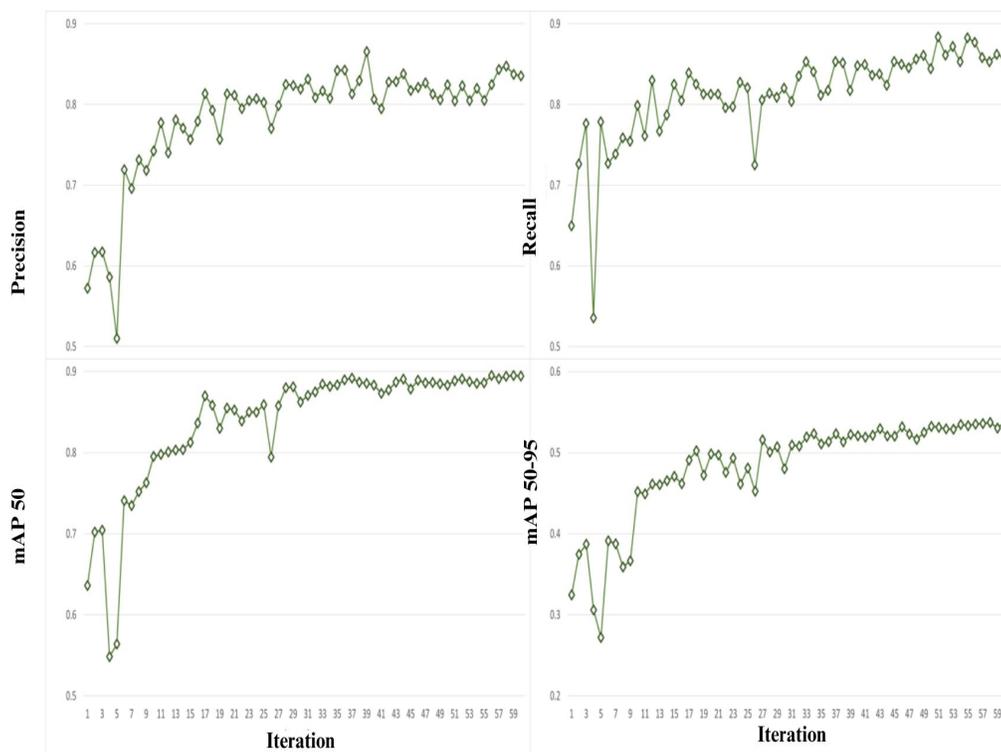


FIGURE 6.10: Precision, Recall, mAP50, and mAp50-95 history.

6.3.3.3 Spatial Synchronization for RPW Detection

This section describes the spatial synchronization method employed to combine data from two primary sources: acoustic sensors embedded within palm trees to detect RPW activity, and

aerial imagery obtained via drones. The integration of these datasets is critical to accurately assessing the health status of palm trees.

Each palm tree in the study area was equipped with an acoustic sensor designed to detect RPW sounds, which served as a distinctive indicator of their presence and activity. These sensors, geotagged with precise latitude and longitude coordinates, facilitated the precise matching of the sensor and its location on the ground.

Deployed drones equipped with high-resolution cameras captured comprehensive aerial images of the farm, including metadata with exact latitude and longitude coordinates corresponding to the ground-level sensor locations.

The object detection algorithms were calibrated to identify individual palm trees in aerial photographs, ensuring accurate identification based on distinctive palm tree features. Our method relies on spatial synchronization, which involves aligning the geographic coordinates from sensors with drone metadata. This precise matching ensured that each palm tree identified in the aerial image was correctly associated with its respective sensor data. After synchronization, the health status derived from the acoustic sensor data was visually represented on aerial images. Trees without RPW activity are encircled in green, while those with RPW presence are marked in red, facilitating easy identification and management of infested trees.

The spatial synchronization process is crucial for reliable data fusion, reducing the potential for misidentification and errors in determining tree health. This precision significantly enhanced the accuracy of our pest detection system.

The spatial synchronization of acoustic sensor data with aerial imagery has emerged as a key element, enabling the precise identification and visualization of palm tree health. This approach not only enhanced the accuracy of our pest detection system but also presented a scalable solution for monitoring agricultural areas for pest activity.

6.3.3.4 RPW map generation

The RPW mapping method has produced encouraging results in identifying and visualizing RPW infestations on palm farms. Effective management techniques can be supported by the results, which provide useful insights into the distribution of palms infested with RPW. Figure 6.11 shows the RPW map with the UAV image and bounding boxes for infested and non-infested palms.

Discussion

Acoustic-based detection systems play a vital role in supplementing image-based techniques to identify plant diseases and infestations, particularly when external symptoms are not readily apparent. Despite the susceptibility of sound to background noise in various environmental conditions, DL techniques, such as CNNs, have emerged as a powerful solution, showing



FIGURE 6.11: RPW Map Visualizing Infested and Not Infested Palm Trees.

exceptional proficiency in detecting the RPW, even in challenging acoustic environments.

DL's strength lies in its capacity to learn and distinguish the unique characteristics of the RPW's acoustic signature from the surrounding noise. The distinctive features of RPW acoustic signals, including their unique frequency range, waveform pattern, and duration, enable CNNs to effectively discern RPW signals from other environmental sounds. However, the implementation of this solution in a real-world scenario requires acknowledgment of certain limitations.

The outstanding success in achieving 98.8% accuracy in RPW classification can be primarily attributed to the diligent efforts made to acquire an impeccable dataset. By ensuring pristine-ness of the dataset, we effectively attenuated the deleterious consequences of ambient noise on the performance of the model. To ensure the reliability and robustness of the classification model, stringent data preprocessing measures were implemented, including the application of advanced filtering techniques, such as bandpass and high-pass filters, to reduce noise, as

well as the selection of relevant features, such as CQCC and various spectral features.

Moreover, the proposed method exhibited enhanced effectiveness when the YOLOv8 model was integrated for palm tree detection in UAV images and RPW mapping. Farm managers seeking to take targeted actions to protect the health and production of palm ecosystems can greatly benefit from the information provided by the newly created RPW distribution map.

However, it is essential to acknowledge that implementing the proposed strategy on a larger scale, particularly on commercial palm farms, has both advantages and disadvantages. The accuracy of palm detection in UAV images may be influenced by geographic variables such as variations in vegetation density or topography. Therefore, these aspects must be adequately considered in the development and implementation of a system to ensure robust performance under diverse environmental conditions.

In light of the pressing need for cost-effective alternatives, particularly those designed to meet the requirements of small-scale farmers, we advocate the creation of affordable and user-friendly devices. Our dedication to making this advanced technology accessible to a wider audience goes beyond the focus on achieving high levels of accuracy. It encompasses a commitment to fostering inclusivity and providing solutions that empower a wide range of farmers to adopt sophisticated pest management techniques.

In proposing these alternatives, we envision a future in which the advantages of advanced pest detection technologies are not limited to large-scale agricultural operations but are accessible to farmers of varying scales. This democratization of technology not only promotes the sustainability of palm agriculture but also contributes to the overall resilience and prosperity of diverse farming communities.

6.4 Conclusion

Timely identification of RPW infestations is important for mitigating the adverse effects of this pest on palm trees and the industries dependent on them. Early detection serves as a crucial factor in limiting the propagation of infestations and enabling swift interventions to contain and manage the population. Proactive measures to prevent the spread of the red weevil to adjacent trees contribute to preserving the overall health of the palm population while also being cost-effective control measures. Addressing this issue before substantial damage occurs may necessitate less extensive and more economical control methods, ultimately minimizing the economic impact of red weevil infestations on the palm industry.

Our research advocates the adoption of a DL approach for the proactive detection and mapping of RPW infestations in palm farms. Our innovative methodology seamlessly integrates computer vision, DL, the IoT, and geospatial data to accurately identify and classify palm trees affected by RPW, contributing to a comprehensive RPW management system.

Overall, our proposed technique for early identification and mapping of the RPW represents

a significant stride towards sustainable palm ecosystem management. By leveraging the synergistic potential of IoT devices, DL algorithms, and multimodal data, we've established a pathway for proactive monitoring and targeted intervention. The resulting RPW map serves as a visual tool for identifying and locating RPW-infested palms, providing actionable information for strategic treatments. This method has the transformative potential to redefine how palm stands are protected, showcasing the power of technological innovation in conserving natural resources and ensuring agricultural sustainability. Potential avenues for enhancing and extending our system include the following: Seamless integration with existing farm management tools to automate pest control and monitoring, streamlining the RPW management process. Exploration of advanced DL techniques, such as reinforcement learning or generative models, to refine the detection system's performance, predict infestation severity, and assess potential tree damage Conducting comprehensive field trials in diverse settings, geographical locations, and varying climatic conditions involving different palm tree species and background noise These trials aimed to provide deeper insights into the system's performance across real-world conditions.

Conclusion and perspectives

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7.1 Summary of contributions

Precision agriculture has emerged as a transformative paradigm in the contemporary quest for sustainable and efficient food production. In this era, where a 70% increase in global food production is not just a goal but a necessity, the integration of data-driven methodologies becomes imperative. This research, titled "Toward Smart Palm Precision Agriculture: A Study on Palm Tree and Red Palm Weevil Detection," seeks to harness the power of technology to address critical challenges in the cultivation of palm trees, particularly focusing on date palm production and environmental balance.

The cultivation of palms is of great significance for both global food security and environmental equilibrium. This endeavor is further emphasized by its alignment with the Sustainable Development Goals (SDGs). In response to the pressing need for increased productivity and resilience in palm production, this study employs a multifaceted approach that leverages remote sensing big data and the Internet of Things (IoT).

The primary focus of our investigation was the application of deep learning, which ushers in a new era of smart precision agriculture specifically designed for effective palm management. This convergence of technologies not only addresses the current challenges in palm cultivation but also supports global initiatives aimed at achieving sustainable and responsible agricultural practices.

Our multifaceted approach, which integrates remote sensing big data and IoT, is poised to contribute significantly to the realization of SDGs related to food security, environmental sustainability, and innovation in agriculture. The adoption of deep learning serves as a cornerstone, facilitating a transformative shift toward smart precision agriculture.

In integrating these advanced technologies, our research aims to harmonize their potential, creating a synergy that enhances productivity while fostering resilience in the face of changing agricultural demands. The resulting framework aspires to meet the immediate needs of the present, while establishing a strong foundation for a sustainable and technologically driven future in palm management.

Contributory Approaches: An Overview

In the context of this thesis, the following contributions have been realized:

- **We propose a scalable, multimodal distributed management model for massive, high-resolution remote sensing data and IoT data [C1]**

The proposed solution addresses the challenges posed by vast amounts of satellite remote sensing (RS) data and the diverse nature of Internet of Things (IoT) data. This innovative approach surpasses the limitations of traditional databases in handling high-resolution RS Big Data and IoT datasets. The proposed multimodal distributed architecture includes a unified metadata file, pyramid model, and Hilbert Curve for effective data organization. The use of NoSQL databases within a Hadoop-based framework on the Amazon Web Services (AWS) cloud platform enables the parallel and distributed management of both RS and IoT data. The integration of time-series databases enhances the multimodal approach, allowing for the efficient storage, retrieval, and analysis of time-dependent IoT datasets. The experimental results demonstrate the significant potential of the proposed approach in overcoming traditional constraints. The proposed solution not only transforms the RS data management landscape but also presents an integrated solution for storing massive high-resolution image data and time-dependent IoT datasets.

- **We proposed a Deep Learning and UAV-based approach for efficient palm tree detection to support precision agriculture for palm trees [P2]**

We investigated current methods for automatic palm tree detection and counting. Based on the results, we propose an approach that aims to increase the efficiency of the palm tree industry by using Deep learning-based object detection and remote sensing. We focus on the efficient detection and localization of palm trees using UAVs equipped with deep Learning algorithms. This approach is revolutionizing the palm industry by reducing errors, accelerating data collection, and accurately detecting and managing palms. The use of DL-based object recognition increases efficiency and sustainability in the palm industry and improves decision-making, resource optimization, and the achievement of the SDGs.

- **We proposed an IoT and Multi-Modal Data for Early Detection and Mapping of Red Palm Weevil in Sustainable Palm Tree Farming [C3]**

In this section, we present an innovative solution for sustainable palm cultivation to control the destructive weevil. By integrating computer vision, DL, the IoT, and geographic data, our approach detects and classifies RPW-infested palms. Our custom DL model achieved 98.8%-99.5% accuracy and detection rate in detecting the infestation. Geospatial data integration enables comprehensive RPW spread mapping, monitoring, and targeted management. This technology-based strategy benefits agricultural agencies, growers, and researchers by protecting palm plantations and productivity from RPW infestations.

Together, these diverse but interrelated contributions form a comprehensive approach that demonstrates the versatility and potential of data-driven solutions in modern precision agriculture. Each individual contribution is examined, evaluated, and contextualized in the following sections to highlight its importance within the larger tapestry of our work. This complex web of contributions illustrates our commitment to advancing the field of smart precision agriculture and defining the future landscape of sustainable agricultural practices through novel approaches.

7.2 Future work and research directions

Our work lays the groundwork for a diverse range of future research initiatives, encompassing both methodological advancements and practical applications.

Scalable, Distributed Management Model for Remote Sensing Data

Perspectives: The scalable, distributed management model for remote sensing data presents an opportunity for further exploration in the realm of edge computing. Integrating edge computing technologies can enhance the real-time processing capabilities of the system, ensuring timely analysis of high-resolution remote sensing data directly at the source. Additionally, considering the potential application of machine learning algorithms to dynamically adapt and optimize the distributed model based on changing data characteristics would usher in a more intelligent and responsive data management framework.

Future Ideas: The evolution of hybrid architectures is a promising avenue for future development. By combining cloud-based processing with edge computing, we can create a flexible and responsive system that leverages the strengths of both approaches. Dynamic scaling mechanisms, capable of adjusting resources in real-time to meet varying data processing demands, represent a cutting-edge area for research. These advancements aim to propel the distributed management model to new heights of efficiency and adaptability in handling massive high-resolution image data.

Deep Learning and UAV-Based Palm Tree Detection for Precision Agriculture

Perspectives: Looking ahead, continuous model training emerges as a key perspective for the deep learning and UAV-based palm tree detection approach. Enabling the algorithm to adapt to evolving environmental conditions ensures its effectiveness over time. Additionally, exploring the integration of multi-sensor fusion, such as incorporating infrared or hyperspectral sensors on UAVs, holds promise for enhancing the accuracy and robustness of palm tree detection, particularly in diverse agricultural landscapes.

Future Ideas: The concept of autonomous UAVs opens avenues for future research, where UAVs equipped with autonomous capabilities can operate efficiently in large-scale palm plantations without constant human intervention. Transfer learning techniques represent another promising area, potentially reducing the need for extensive labeled data by leveraging pre-trained models on related tasks. These future ideas aim to advance the efficiency and adaptability of palm tree detection, contributing to the evolution of precision agriculture practices.

IoT and Multi-Modal Data for Early Detection of Red Palm Weevil

Perspectives: The IoT and multi-modal data approach for early detection of Red Palm Weevil infestations opens up the prospect of developing real-time monitoring systems. Strengthening the IoT infrastructure to enable continuous surveillance allows for prompt detection and intervention. Additionally, considering the integration of predictive modeling into the system could lead to the creation of disease prediction models, offering insights into potential infestation risks based on historical data and environmental factors.

Future Ideas: Exploring the development of automated intervention systems represents an exciting future direction. These systems could be designed to automatically deploy targeted treatments upon early detection of Red Palm Weevil infestations or alert agricultural agencies for swift and effective action. Furthermore, investigating the cross-domain applications of the IoT and multi-modal data approach to detect and manage other agricultural pests and diseases could contribute to the creation of a comprehensive and adaptive agricultural ecosystem.

List of publications

My PhD and research collaboration resulted in several worldwide papers, which are listed below:

Journal Publications

[P1] HAJJAJI, Yosra, BOULILA, Wadii, FARAH, Imed Riadh, Imed Romdhani and Amir Hussain. (2021). Big data and IoT-based applications in smart environments: A systematic review. *Computer Science Review*, 39, 100318. (Quartile: Q1, Impact Factor: 8.75) [Accepted on 14/11/2020]

Conference Publications

[C1] Hajjaji, Yosra, Wadii Boulila, and Imed Riadh Farah. "An Improved Tile-Based Scalable Distributed Management Model of Massive High-Resolution Satellite Images," in 25th International Conference on Knowledge Based and Intelligent Information and Engineering Systems (KES2022), 2022. (Rank: B, Publisher: Elsevier)

[C2] Hajjaji, Yosra, Wadii Boulila, and Imed Riadh Farah. "Leveraging Artificial Intelligence Techniques for Smart Palm Tree Detection: A Decade Systematic Review," in 25th International Conference on Knowledge Based and Intelligent Information and Engineering Systems (KES2022), 2022. (Rank: B, Publisher: Elsevier)

[C3] HAJJAJI, Yosra, ALZAHM, Ayyub, BOULILA, Wadii and Anis KOUBAA. "Sustainable Palm Tree Farming: Leveraging IoT and Multi-Modal Data for Early Detection and Mapping of Red Palm Weevil," in 26th International Conference on Knowledge Based and Intelligent Information and Engineering Systems (KES2023), 2023. (Rank: B, Publisher: Elsevier)

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