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Intelligent approaches for sustainable management and valorisation of food waste

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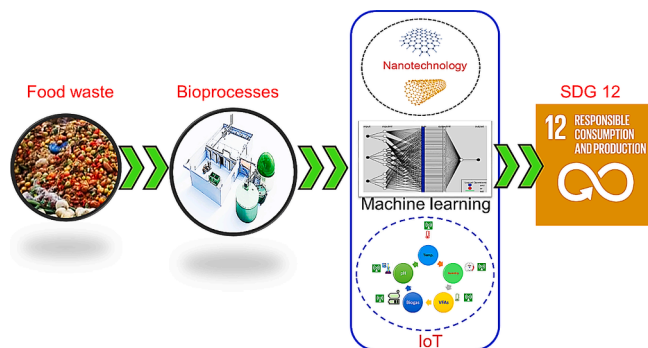
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HIGHLIGHTS

- Food waste (FW) contains potential nutrients and compounds for circular bioeconomy.
- Efficient management and valorization of FW is the most sustainable method.
- Artificial Intelligence (AI) application could help in optimizing FW supply chain.
- Machine learning (ML) can predict quite exactly the quantity and composition of FW.
- Combination of AI and ML could monitor and manage well FW-based bioprocess.

GRAPHICAL ABSTRACT



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ABSTRACT

Food waste (FW) is a severe environmental and social concern that today's civilization is facing. Therefore, it is necessary to have an efficient and sustainable solution for managing FW bioprocessing. Emerging technologies like the Internet of Things (IoT), Artificial Intelligence (AI), and Machine Learning (ML) are critical to achieving this, in which IoT sensors' data is analyzed using AI and ML techniques, enabling real-time decision-making and

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process optimization. This work describes recent developments in valorizing FW using novel tactics such as the IoT, AI, and ML. It could be concluded that combining IoT, AI, and ML approaches could enhance bioprocess monitoring and management for generating value-added products and chemicals from FW, contributing to improving environmental sustainability and food security. Generally, a comprehensive strategy of applying intelligent techniques in conjunction with government backing can minimize FW and maximize the role of FW in the circular economy toward a more sustainable future.

1. Introduction

As per the Waste Index Report, 931 MTs of food wastage were observed in 2019, with households responsible for almost 61 %, food services responsible for almost 26 %, and retail responsible for almost 13 % (UNEP, 2021). Indeed, FW is largely created from households and connected to consumer purchasing power, which is determined by national income levels (Dutta et al., 2021). In high-income nations, FW per person per day is around 307 g, which is more than double that compared to lower-placed affluent nations (Zhang et al., 2021). However, in underdeveloped nations, the majority of waste is generated at the beginning of the food supply chain due to a lack of financial and technological resources during harvesting, storage, and chilling (Chen et al., 2020)(Pinpatthanapong et al., 2022). Due to this reason, the United Nations (UN) member nations have adopted the Sustainable Development Goals 12.3 aiming to *halve global per capita food waste at the retail and consumer level by 2030, and significantly decrease food losses throughout the production and supply chains, including post-harvest losses* (Beretta and Hellweg, 2019). Furthermore, to quantify food waste and loss, the UN Environment Programme is presently developing the food waste index, which will build over the Food Loss and Waste Accounting and Reporting Standard (Ananno et al., 2021; Dalke et al., 2021). The Food Waste Initiative will calculate the amount of food waste per capita,

considering a wide range of items from preparation to consumption. The Food Loss Index, developed by the UN Food and Agricultural Organization, analyses food loss across the supply chain, including production, storage, handling, and processing (Leverenz et al., 2019).

Food waste (FW) and food loss are substantial global issues due to their negative consequences on the environment, society, and economy (Ojha et al., 2020). Food loss can be defined as a diminution in food availability and quality caused by the food chain's suppliers' choices and activities (Ottomano Palmisano et al., 2021). FW, on the other hand, is defined as a reduction in food quality and quantity due to retailer, consumer, and service provider behaviors. FW and food loss are caused mainly by the world's fast population increase and food consumption trends (O'Connor et al., 2021; Son Le et al., 2022). FW in the food chain exacerbates the ecological consequences of food production and amounts to a total of 1.3 billion tons annually, almost 33 % of all food produced for human use (Vilariño et al., 2017). As reported, pulses, cereals, vegetables and fruits, animal products, tubers, roots, and fatty acids-bearing crops are the key dietary categories that contribute to nutritional and FW or loss (Dilamian and Noroozi, 2021). The two most prevalent food types, according to food loss, are tubers, roots, and fatty acids-bearing produces (nearly 26 %) and fruits and vegetables (closely 22 %). Cereals, root crops/fruits/vegetables, and oilseeds account for 30 %, 40 %, 50 %, and 20 % of worldwide yearly FW, respectively

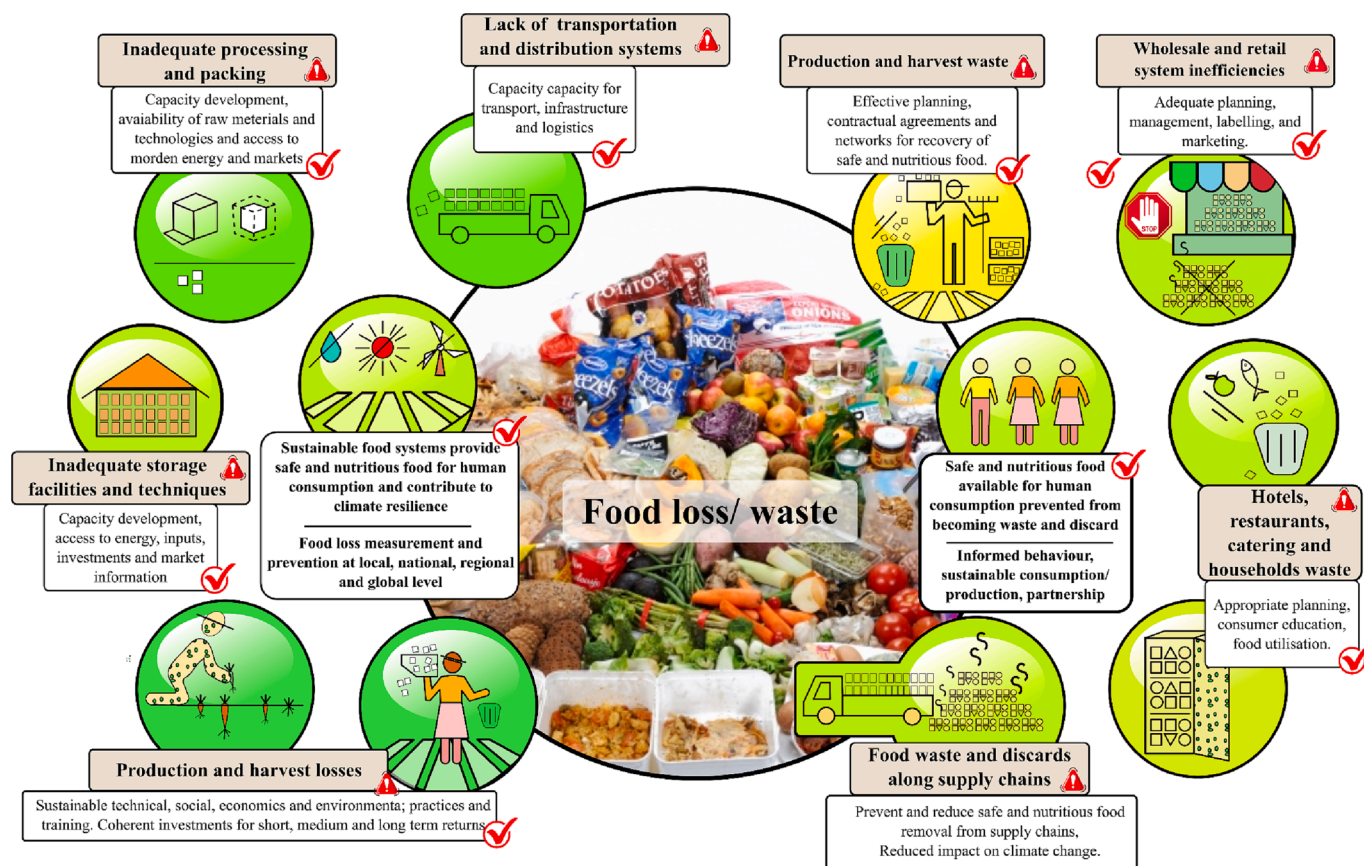


Fig. 1. Various food waste sources, showing complex issues in control and management (Natalie Marchant, 2021).

(Capanoglu et al., 2022). In general, FW and food loss are considered complex matters and they could come from various sources as depicted in Fig. 1, showing the difficulties in managing FW and food loss.

Facing the ever-increasing FW, FW management has been a worldwide concern owing to the rising populace causing intense demand for food. Currently, incineration and landfill are the primary methods of FW disposal, but economic and environmental sustainability have been a concern (Slorach et al., 2019; Talan et al., 2021a). As a result, biological approaches for recovering nutrients and energy through FW valorisation have been investigated (Chausali et al., 2022; Govarthan et al., 2022). However, these biological techniques have limitations and cannot provide a full answer for FW control. In this context, several sustainable technologies using smart approaches like zero-solid waste discharge, anaerobic digestion, bio-fermentation, etc., are being considered for resource and energy recovery (Hyun Chung and Ranjan Dhar, 2021)(Narisetty et al., 2022). Due to the sheer organic matter, availability, and high nutritional content of FW, it may be regarded as a low-cost and suitable feedstock to produce value-added materials like biohydrogen, biomethane, biodiesel, biogas, biomethane, and fertilizers (Engelberth, 2020; Sirohi et al., 2023). Composting, bioethanol synthesis, feed fermentation, anaerobic digestion (AD), and other bioprocesses are researched for resource recovery and energy from FW (Idris et al., 2021; Kharisma et al., 2022; Närvänen et al., 2020; Talan et al., 2021b). These processes for turning FW into value-added goods, though, have certain drawbacks, such as a shortage of skilled hands, high operating costs, and post-processing of solid residues (Demichelis et al., 2018; Sharma et al., 2021). In such a case, a technique for effective FW management toward simultaneous energy and nutrients recovery with low operating costs, and little solid residue discharge is needed in the global FW market (Kamal et al., 2023).

According to the literature assessment, efforts to minimize FW will fail to produce the envisioned sustainability and suppleness co-benefits unless the infrastructural systems that compose food supply chains are strengthened. The infrastructural systems that create, supply, and manage food and associated waste; the human infrastructure, which includes employees; and the use of modern technologies for plan execution, coordination, monitoring, and simulation necessitate new investigations and solutions. Positive governance, institutions, and information infrastructure are all likely to increase coordination and management. While there are several review studies accessible on the issue of FW valorisation, there are nearly no review studies available in the open literature on smart ways available such as artificial intelligence (AI), machine learning (ML), and the internet of things (IoT) to increase the efficiency and sustainability of FW valorisation. The fact shows that these smart approaches have improved the quality of life across the board, beginning with IoT-enabled smart homes and offices, and complex problem resolution and model prediction with AI and ML. As a result, the goal of this work is a new review study on the application of smart approaches like AI, ML, and IoT to efficient management and sustainable valorisation of FW aiming to fill the research gaps. Indeed, this current work focuses on the application of AI, ML, and IoT techniques to analyse the role of FW, as well as to manage FW as these techniques pertain to bioprocesses objectively, and it provides an in-depth examination of major algorithms and their applications in model prediction of FW. This paper has the potential to be a ready-to-use reference guide on smart ways for sustainable FW valorisation. In addition, this paper also addresses some of the difficulties and views surrounding AI and ML, as well as future research directions.

The present review is structured in a way that the first section discusses the global issue of FW and food loss. The second section presents various ways to use FW and the role of FW in circular economy, like turning it into bioenergy in detail. The third section talks about using machine learning to improve the process of using food waste. The fourth section talks about IoT technology that can help monitor and control the process in real time. The fifth section discusses the challenges associated with using modern approaches in FW bioprocessing. Finally, the

conclusion summarizes the whole article.

2. Role of FW in circular bioenergy

A significant portion of food and household waste is biodegradable and may be used as a bioresource to recover value-added products like biochemicals, bioplastics, biofuels, enzymes, etc., via bioprocessing techniques such as AD, microbes-based fermentation, and bioprocess based electrochemical systems (Tamasiga et al., 2022). Bioprocessing of urban waste is the most cost-effective waste management alternative today, given the possibility and development of non-toxic substances (Imam et al., 2021). Bacteria used in waste bioprocessing have been shown to have a high potential for organic waste fraction breakdown (Banerjee and Arora, 2021; Bhurat et al., 2023). Furthermore, bioprocessing technology might be used with other waste treatment processes to increase waste management efficiency. These technologies, however, can only be properly implemented if national and local governments support them (Usmani et al., 2021).

FW is especially appealing to researchers of renewable energy due to its lignocellulosic composition, which contains high cellulose and lignin levels. It has been proven that different FW such as apple pomace, bagasse, sugarcane vinasse, and brewers' leftover grain could be used for converting into biofuels (Bigdeloo et al., 2021; Santagata et al., 2021; Singh et al., 2021). Enzyme-assisted cellulose and hemicellulose biodegradation and biotransformation provide free xylose and glucose (Liu et al., 2020), which fermentative microorganisms may turn into fuel ethanol. Furthermore, the lignin molecule may create hydrogen and methane during pyrolysis and anaerobic digestion, showing that FW looks to be a highly renewable energy resource and a reservoir of several added-value compounds (Chalima et al., 2019; Raizada and Yadav, 2022). However, it was recently discovered that making bulk chemicals from biowaste is almost four times cheaper than converting them to biofuels (Shukla et al., 2020).

Bio-refinery is an emerging idea in the area of waste processing that aims to transform all sorts of waste-derived material into different types of energy, biofuels, chemicals, and materials via a sequence of economically feasible and low-impact technical processes (Goswami et al., 2019). The bio-refinery idea promotes cooperation among scientists/researchers from many domains such as biochemistry, economics, environmental/material sciences, and chemical engineering to transition to a bio-based business that uses renewable resources for better profitability (Caldeira et al., 2020; Maina et al., 2017). Indeed, the idea of a circular type economy is well suited to the sustainability of FW valorization in the long term. It is the right push needed to pull more investment and awareness among the masses. It is regenerative and restorative, with the reuse of existing resources and components as a fundamental notion (Usmani et al., 2022). It is thought to extend their worth, reduce waste creation, and shut loops. To enable the enactment of a circularity-based economy and the closure of loops, technical, financial, and societal transformations are necessary (Dangol et al., 2022). The European chemical industry may be able to use waste flow as feed for bio-based polymer and chemical production, reducing the need to import fossil-based raw materials. The use of indigenous feedstock will also result in the deployment of innovative techniques, that will increase productivity and provide new job opportunities (Majava et al., 2022; Omran and Baek, 2022). A summary of research works undertaken by researchers depicting sustainable FW valorization/bioprocesses for useful products is given in Table 1.

As massive FW is becoming a global misfortune, sustainable treatments are the most attractive solution. The FW may be utilized as a possible feedstock in biological processes to generate a variety of bio-based products, as well as for cleanup. FW valorization can be enabled by bioprocesses such as fermentation, the genesis of acids, the production of biomethane, the oleaginous process, and most important biofuels. FW can be converted to biofertilizers, animal feed, platform chemicals, bioelectricity, animal feed, etc. Integrating these

Table 1
Summary of sustainable FW valorization/bioprocesses.

Theme	Approach	Main outcomes	Reference
Sustainable FW management in Bangladesh	Analysis of waste management	According to the research, FW may create 481.6 MW of electricity per year	(Ananno et al., 2021)
FW in the aviation sector	Material flow analysis	Considerable reduction in FW	(Thamagasorn and Pharino, 2019)
FW management at Hong Kong International airport	Life cycle cost-benefit analysis	Developed model can be implemented globally	(Lam et al., 2018)
Analysis of Italian plant for FW composting	Circular bio-economy	Substitution of natural gas with biomethane	(Le Pera et al., 2022)
Sustainable food system framework	Fuzzy-Delphi method for qualitative information	Production evaluation, transport, and preservation result in technological innovation	(Tseng et al., 2022)
Bio-refinery for sustainable FW valorization	FW to biodiesel	248.21 g of biodiesel per kg of FW	(Patel et al., 2019)
Solid biofuel from FW	Hydrothermal carbonization	Production of solid biofuel towards sustainable FW valorization	(Wang et al., 2021)

FW: food waste.

bioprocesses improves process efficiency and resource recovery over time (Usmani et al., 2021). An integrated approach to biorefinery strategy may lead to establishing a circular bio-economy. The waste biorefinery strategy for FW necessitates optimizing the cascade of distinct bioprocesses to transition from a wastage-laden economy to a circular bio-economy (Dahiya et al., 2018). Indeed, the circular economy idea based on FW necessitates a paradigm change throughout all manufacturing chains, from giant processors to medium/small producers (Osorio et al., 2021). It will impact not just sellers of products and services, but also all areas of modern society, including the press, communication services, academia, and governance (Hosseinzadeh-Bandbafha et al., 2022; Santeramo, 2021).

3. Machine learning for bioprocesses

Machine learning (ML) is a promising technique that is rapidly evolving owing to its capability to handle a wide range of issues in fields such as engineering, information technology, medicine, mining, gaming, and many others. Using ML increases the power of modeling complex systems with non-linear input–output relationships, especially when the number of inputs, outputs, or decision scenarios is large. ML models, like many other data-driven techniques, do not need physical knowledge of the system, but they may nevertheless predict physical occurrences if properly trained and adequate data for model training is available (Singh et al., 2023). The application of ML techniques in the domain of FW valorisation was observed mainly in three categories e.g., model-prediction, optimization, and the hybrid approach of prediction-optimization (Malefors et al., 2022). Several ML methods have been used to simulate the non-linear and complicated interactions of the several bioprocesses, including artificial neural network (ANN) (Shenbagaraj et al., 2021), random forest (Cheng et al., 2022), support vector machine (SVM) (Andrade Cruz et al., 2022; Sarlaki et al., 2021), adaptive neuro-fuzzy inference system (ANFIS) (Olatunji et al., 2022; Primaz et al., 2021), decision trees, boosted regression tree and also Bayesian optimized ML methods. In the case of optimization, several heuristic methods and evolutionary methods are being used such as particle swarm optimization, genetic algorithm, grey wolf optimizer, artificial

bee colony, bat algorithm, black hole optimization, cat swarm optimizer, etc. Recently, hybrid approaches to connecting ML with optimization methods to improve precision are being implemented such as ANN- particle swarm optimization, ANFIS-grey wolf optimizer, bat algorithm-ANN, etc. The following section discusses these methods as applicable to FW valorisation.

Bioprocesses are frequently used to remediate various organic wastes while also producing sustainable energy and nutrient-rich digestate. However, the bioprocess is unstable, which hurts the output. Significant efforts have been made to create techniques for controlling the different bioprocesses to preserve process firmness and forecast the performance of bioprocess (Sinner et al., 2021). Amongst various methodologies, ML has received a lot of attention in recent times for bioprocess optimization, predicting unknown parameters, detecting trepidations, and real-time observation (Peter et al., 2023; Wan et al., 2022). In ML, inductive interpretation is used to broaden the scope of relationships between datasets, which is then utilized to make informed conclusions in new situations (Andrade Cruz et al., 2022; Sharma and Sharma, 2021). A typical flow process depicting ML application for anaerobic digestion of FW is depicted in Fig. 2.

ML has developed as a data-driven approach that is uninfluenced by the complicated linkages used in mathematical models (Al-Waeli et al., 2019; Said et al., 2022a). This technique is wholly dependent on the data that is publicly accessible or from historical events like experiments. A training and testing technique using a training data set is used in ML to enable the model to discover previously unknown patterns in the data (Tercan and Meisen, 2022). The model is validated using a separate data set to enhance the model's predictive performance by hyperparameter optimization (Nguyen et al., 2021). Following that, model testing is used with a new set of data to assess the accuracy of the model. Although ML algorithms are capable of handling intricate multivariate data, can forecast non-linear correlations, and manage outliers and missing values, choosing the correct approach for a specific assignment is vital to attaining optimal results (Jamei and Ahmadianfar, 2020; Shenbagaraj et al., 2021).

3.1. Artificial neural networks (ANN)

ANNs are modern computational techniques that can be used to efficiently model engineering processes where, due to unidentified interrelationships and feedback complexity among different processes at different scales, classical-type regression methods produce inadequate results. In such instances, an ANN trained merely on an observational set of input–output data may create the data processing structure necessary to effectively correlate the set of inputs and associated outputs (Fajobi et al., 2022). Thereafter can be used to indicate latent patterns of interrelationships by themselves. One model structure, referred to as a universal approximator, may handle complicated multiple inputs into multiple output data concurrently by correctly adjusting the weights of interneuron connections and neuron bias values during controlled training. Furthermore, no preceding assumptions about the choice of a correlating template are required. The models can be tested on statistical indices to measure the model's robustness.

In multilayer perceptron type ANN, each layer is made up of neurons that are linked to the neurons in the preceding and succeeding levels through connection weights (W_{ij}). These weights are modified based on the trained network's mapping capacity. An extra bias term (b_j) is included to create a threshold for neuron activity. The input data (X_i) are supplied to the network via the input layer, and the weights are then transmitted to the hidden layer. The weighted output (X_iW_{ij}) is then added to a threshold to generate the neuron input (N_j) in the output layer. This neuron input is processed by an activation function $f(N_j)$ to get the desired output Y_j . The log-sigmoid function that has the form; serves as the most widely employed activation function.

Biogas production, for example, has been efficiently forecasted using

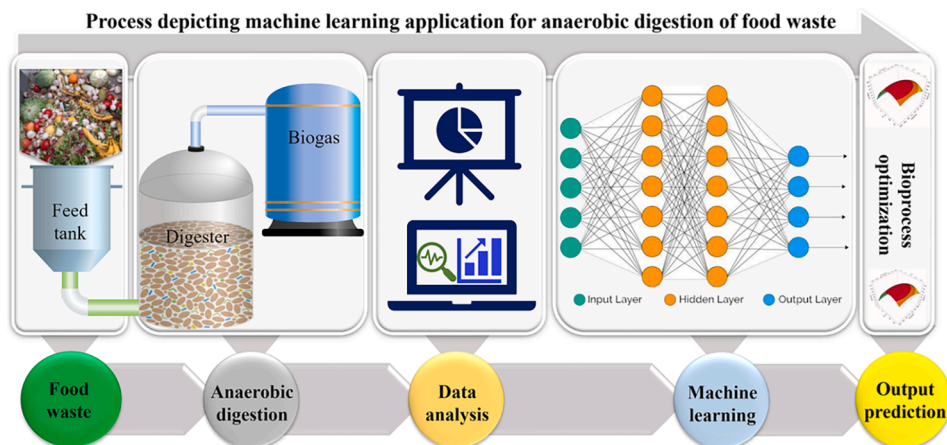


Fig. 2. Flow diagram of typical bioprocesses using machine learning.

ANN models in controlled laboratory-scale tests (Gonçalves Neto et al., 2021). Özarslan et al. (2021) employed ANN to simulate and model the co-digestion performance of tea waste mixed with a co-substrate of spent tea. The peak cumulative yield of methane during co-digestion was modeled as 468.43 mL CH₄/g volatile solids in the case of the ratio of spent tea waste and tea factory was 35 % and 65 % w/w volatile solids, correspondingly. Co-substrates had a 183 % greater anticipated methane output than mono-substrates. Quashie et al (2021) simulated the process of biogas production from FW employing an ANN. The research focuses on the impacts of numerous parameters on biogas generation, including removal of chemical oxygen demand, effluent pH, oxidation decreasing potential, organic loading rate, volatile type fatty acids, influent pH, and influent ammonium. The Levenberg Marquardt back-propagation method was selected as the model's algorithm from a seven-benchmark comparison. The determination coefficient and fractional variance employed for the exactitude of the optimum ANN model were 0.9414 and 0.0484. ANN in this study could emulate the modeling of process parameter interactions with high precision (Barik and Murgan, 2015). Several other researchers employed ANN with different configurations and also in a hybrid setting with different optimization techniques. The literature in this domain shows that ANN is the most used model prediction for food valorization processes (Kapoor et al., 2020; Sharma and Sahoo, 2022).

3.2. Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS, employs a fuzzy logic cum neural network-based hybrid learning approach, to achieve excellent learning in quantity and modeling. ANFIS surpasses the ANN model in terms of lower residuals and peak flow prediction accuracy. Complex issues may be solved using the ANFIS model with fuzzy inputs and a neural network. The ANFIS model employs back-propagation to optimize the member function parameters (fuzzy rules). Fuzzification, which describes inputs that aren't unique, makes the neural network's responsibility more accessible, leading to a more resilient overall model. ANFIS governs several set rules that can learn non-linear equations. The directional linkages are connected via nodes. Each node serves a distinct purpose and is comprised of set parameters. A Takagi-Sugeno-type fuzzy system is crucial since it holds IF-THEN rules and is the most accurate as well as widely used fuzzy modeling algorithm.

The excellent prediction abilities and availability of suitable algorithms have resulted in the extensive use of ANFIS in the domain of FW valorization. Yang et al. (2021) employed the ANFIS to predict biogas yield from several kinds of FW. The results of the proposed models show that they are quite capable of forecasting biogas generation. The mean squared error (MSE) and mean relative error (MRE) values determined for ANFIS were 0.0039 and 29.318, respectively indicating that the

model had a greater capacity to forecast the target data. You et al. (2017) compared the prediction efficiency of ANN, random forest, ANFIS, and SVM for investigating the higher calorific value of waste burning in a circulating-type fluidized bed reactor. To assess the prediction efficiency of the models, a complete comparative study was conducted. The results show that the ANFIS outperformed the other three models, with the random forest model coming in second and the ANN model coming in last.

3.3. Support vector regression (SVR)

In 1995, Vapnik's statistical learning model laid the groundwork for the support vector machine (SVM). Since its conception, SVM has found various applications across a wide range of study areas. SVM was primarily created for classification problems, but it was subsequently expanded to include regression applications. When used for classification or prediction, it is referred to as support vector classification or support vector regression (SVR). SVR has special enticing properties like a tractable global optimal solution with great repeatability and consistency (Quan et al., 2022). Furthermore, SVR is less prone to overfitting problems, enabling it to generalize successfully in the face of smaller datasets. Finally, SVR may explain complex non-linear decision boundaries. The purpose of simple regression is to reduce the error rate, whereas the goal of SVR is to accommodate the error inside a certain threshold, which suggests that the job of SVR is to estimate the best value within such a specified margin known as ρ -tube. A generalized representation of SVR with bioprocesses can be seen in Fig. 3a.

The SVR approach finds a function that imitates the expected and observed response values using a precision value ' ρ ', where errors less than ' ρ ', are regarded insignificant. SVR finds a line or a hyperplane in a higher dimension that fits the data. Kernel (φ) is utilized to search the hyperplane in a greater dimension than incurring extra processing overhead. When the size of the data grows, so does the computational cost (Awad and Khanna, 2015). Several researchers reported the use of SVR for model prediction of FW valorization. The least squares support vector regression was utilized to optimize the pretreatment process parameters to increase the production and efficiency of biogas generated from the anaerobic fermentation of maize stalk by Dong et al. (2019). The experimental parameters of orthogonal experimental design were the weight of the corn stalk, alkali pretreatment, ultrasonic duration time, and single/dual-frequency ultrasound. The results showed least squares support vector regression as an effective optimization method for process characteristics. Cinar et al. (2022) employed SVR for temperature management in an AD process. Models were built to predict biogas generation under various feeding intensities and temperature fluctuations. This model can be used to forecast the influence of temperature changes on process efficiency, allowing for real-time control

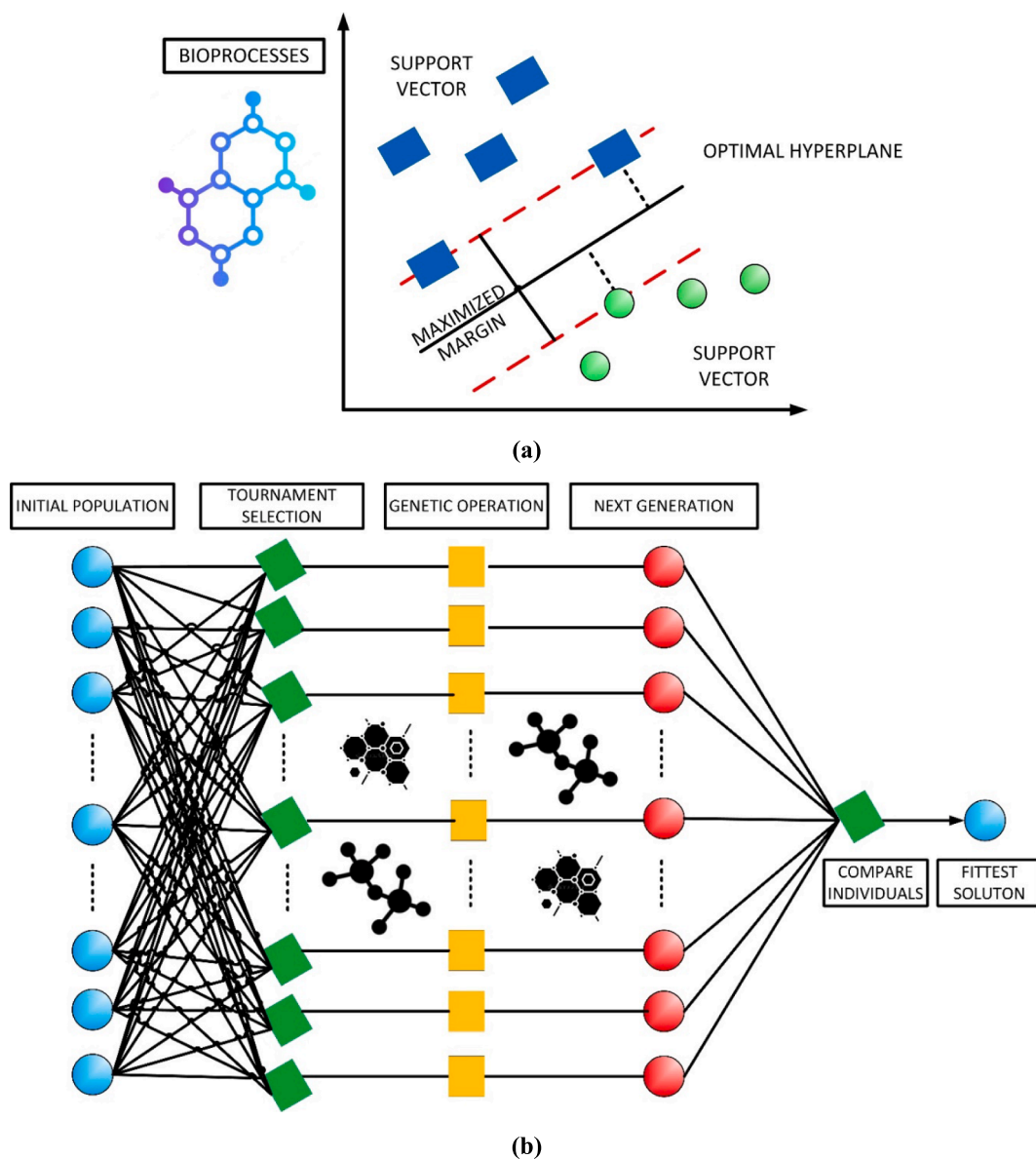


Fig. 3. A generalized representation towards bioprocesses; (a) Support vector regression (SVR) and (b) Gene expression programming (GEP).

and monitoring of biogas systems. In this study, some different ML algorithms - linear and logistic regression, k -nearest neighbors, decision trees, random forest, SVR, and extreme gradient boosting - were compared to field test results to model-predict the effects of fluctuations in temperature on process stability. According to the metric precision of the models generated using the confusion matrix, SVR delivered the highest accuracy of 93 %. Kazemi et al. (2021) employed SVR for fault detection in the AD process using FW and wastewater. AD process is complex, and monitoring such processes is critical to ensuring optimal functioning and preventing breakdowns and catastrophic repercussions during plant operation. To accomplish this aim, a realistic data-driven framework for fault identification in AD is provided and verified using a simulated data set collected using the International Water Association's benchmark simulation model No.2. Before soft-sensor design, the most acceptable subset of input variables was identified using the feature selection approach. The optimal selection of input variables was chosen to be ammonia concentration, pH, pressure, and CO₂ mole fraction. Each soft sensor was tested for fault robustness, and it was discovered that although an ensemble of neural networks and extreme learning machine approaches have demonstrated great accuracy in

predicting volatile fatty acids under normal operating circumstances, they cannot be utilized successfully for fault detection since they are not robust enough.

3.4. Gene expression programming (GEP)

Ferreira suggested gene expression programming (GEP) as a subset of genetic programming. With minimal modifications, most operations of genetic programming are employed in GEP (Ferreira, 2006). In general, numerous processes may be mimicked and assessed by connecting different terminals and functions in an expression tree. The genetic algorithm looks through the available data for a function that predicts the response, while genes carry out genetic variations. In GEP model construction, the roulette wheel technique is used to choose data repeated simultaneously by genetic operators. The function set, the terminal set, the function of fitness, the controlling parameters, and the closure criteria are the five chief components of the GEP. A genome or chromosome is a fixed-length linear symbolic string that contains one or more genes in GEP. By weighting their linkages, GEP learns about correlations between variables in data sets. The algebraic expression may

be shown using phenotype and genotype. Increasing the number of genes leads to more intricate GEP expression while increasing the number of chromosomes is time-consuming. The number of constants utilized in each gene's mathematical equation is determined by the user. Trial and error were employed to calculate the count of chromosomes, genes, and head size.

Despite being a robust model prediction method for complex engineering problems, the researchers have not sufficiently utilized the GEP. There are few studies reported in the domain of biofuel-powered engines, nanofluids, and concrete design by [Sharma \(2020\)](#) and [Sharma et al. \(2021\)](#). The forecasting capacity of GEP in the calculation of CH₄ production and effluent substrate generated by two anaerobic filters was investigated by [Seckin et al. \(2011\)](#). The observed data from both upflow anaerobic filters - one being mesophilic (35 °C) and the other thermophilic (55 °C) - were employed for the valorization of waste under various organic loadings used in the modeling investigation. The GEP-based model included three control factors: duration of hydraulic retention, rate of organic loading, and influent substrate (Si), as well as one output, methane yield. When compared to the more traditional Stover-Kincannon approach the findings justify the use of the GEP methodology (with R² = 0.786) as an alternative to more traditional techniques in estimating methane yield. [Abdulsalam et al. \(2020\)](#) employed GEP to predict the physiochemical properties of waste-derived biochar, such as mass, energy yield, and higher heating value. The ability of the GEP approach to forecasting hydrochar characteristics based on input parameters was determined to be adequate in this study. A generalized representation of GEP with bioprocesses can be seen in [Fig. 3b](#).

3.5. Gaussian process regression (GPR)

The ML-based GPR technique is a supervised but non-parametric method that uses the observed data to prognosticate a dependent variable. GPR, as opposed to least-square regression, could be a more robust tool for coping with chaotic and complex data. The detailed procedure of GPR can be accessed in the literature ([Lee et al., 2020](#); [Said et al., 2022b](#); [Yuan et al., 2008](#)).

In comparison to ANN and ANFIS, the GPR technique is relatively less used despite being a highly efficient technique. [Xiao et al. \(2021\)](#) employed a novel generic data-driven two-stage model, hybrid neural networks, which was first created to estimate CH₄ generation from in-situ biogas upgrading in bio-cathode MECs through direct electron transfer. The developed model was compared with the GPR-based model. Compared to the traditional one-stage model, the new ML-based modeling technique could improve the applicability and versatility by recording substantial transitional variables and anticipating CH₄ production via direct electron transfer with an impressive performance as R² was observed as 0.918 while the mean squared error was 0.0065. [Yapıcı et al. \(2022\)](#) used SVM and GPR to model-predict the biogas yield. The Gaussian Kernel Function performed well for SVR prediction (0.0011 RMSE and 0.89 R², whereas the Exponential Kernel Function performed best for GPR (0.0011 RMSE and 0.93 R²). The eccentricities in the SVM-based model with linear type kernel fluctuate throughout a vast range of 0.25 % to 80.85 %, but the deviations in the GPR model employing exponential type kernel were well within 0.06 % to 03.91 %, of each other.

Although methane output from an industrial facility has been forecasted regularly utilizing random forest and extreme gradient boosting ([Chiu et al., 2022](#); [De Clercq et al., 2020](#)). Likewise, biogas output from the maize straw co-digested with cow manure was projected and maximized using an ANFIS model in pilot-scale research. Furthermore, ML web-based applications and waste modeling can improve the analytical skills, strategic planning, and scheduling of biogas plant operators ([Spyridonidis et al., 2020](#); [Zareei and Khodaei, 2017](#)). [Long et al. \(2021\)](#) effectively used ML in conjunction with genomic data to model-predict anaerobic digestion performance. To anticipate reactor

performance, classification, and regression models were built. Using genetic data, high prediction accuracy was attained. Microbial species and critical operating factors were discovered. The model can give advanced warning and process management recommendations. A summary of works depicting the application of ML for improving the FW valorization is given in [Table 2](#).

To accomplish forecasting, the ANN attempts to build a direct correlation between observed input data and output forecasted data. However, due to a lack of time-based correlation establishment among data sequences, the ANN-based model fails to define the relationship between time and data, restraining its applicability in time series-based prognostic approaches ([Sharma et al., 2022](#)). As a result, the recurrent neural network is proposed as a resolution to this issue. The recurrent neural network may create a sequential type mapping between observation and forecasted values by creating cyclical connections to neurons. As a result, the outcome of each time-based step is impacted by the input of the previous time step. A recurrent neural network achieves the stored characteristic as a consequence. The recurrent neural network training technique includes a backward and forward step. A recurrent neural network's forward pass is analogous to a mono-hidden layer of a multilayer perceptron ([Hajjabotorabi et al., 2019](#); [Wang et al., 2020](#)). The stimulations from both the present external input and the hidden layer responses from past time steps occur at the hidden layer. The distinction is that the initiation of the hidden layer affects the loss function for recurrent neural networks both from its influence on the output layer and the hidden layer in the succeeding phase ([Wang and Zhang, 2018](#)).

The radial basis function neural network is also popular owing to its benefits, such as simple construction, additional estimate features, and a fast-learning process. Radial basis function networks consist of three layers, in which the input layer serves just to link the network to its surroundings ([Hemmati-Sarapardeh et al., 2018](#)). The hidden layer consists of multiple nodes that employ a non-linear change to the control factors (input) employing a radial basis function, like a thin plate spline function or Gaussian function. The output layer is a linear summation unit. In the usual training procedure, the configuration of the radial basis function network is chosen via trial and error. Parameters of the radial basis function are estimated in two phases: The centers of the

Table 2
Notable studies on machine learning for improving FW valorization.

FW/biomass	Machine learning technique	Main outcomes	Reference
Corn stalk	Least squares-support vector machine	Optimization helped in improving the biogas yield.	(Dong and Chen, 2019)
Pawpaw fruit	Response surface methodology	26.5 % increase in yield of biogas	(Dahunsi et al., 2017)
FW water and sewage	Time series and Pearson's correlation analysis	Improved bioavailability of waste mixture	(Choi et al., 2021)
Karanja seed cake and cattle dung	Genetic algorithm and ANN	Robust prediction model with a R close to one.	(Barik and Murugan, 2015)
FW	Recurrent neural network	Robust prognostic model developed	(Seo et al., 2021)
Vegetable, food, and fruit waste	ANN	Model-based predictions were more than 85 % correct.	(Gonçalves Neto et al., 2021)
Fresh fish waste	Random forest, ANN, Long short-term memory networks, and SVM	Long short-term memory networks provided the best results with root-mean-square error as low as 27.82.	(Miguéis et al., 2022)
Pumpkin peel waste	ANN and response surface methodology	ANN outperformed the response surface methodology	(Chouaibi et al., 2020)

FW: food waste; ANN: artificial neural network; SVM: Support vector machine.

hidden layer nodes are found in the first step using the k-means clustering approach. In the second stage, simple linear regression is used to construct the link weights (Sohani et al., 2022).

The ML approaches outlined in previous sub-sections were mostly published in the literature on FW valorization and anaerobic digestion applications. Such ML techniques may be used with the desirability approach, particle swarm optimization, genetic algorithms, and imperialist competitive algorithms to improve forecast accuracy and processing efficiency. An interdisciplinary technique that may drastically cut down on the amount of high-quality food that is thrown away combines ML with the sustainable valorization of FW. Beneficial applications of ML may be found in the following steps of the process: selection of potentially high-value FW, quality identification, odor-based categorization, supply chain management, and ultimate disposal. The effects of ML are connected to various problems, and the approaches to resolving those problems may give rise to a new revolution in the fields of waste reduction, food security, and environmental concerns. However, the widespread use of ML is being hampered by several obstacles, one of which is the demand for highly qualified individuals to solve issues and build new systems.

4. Internet of things for bioprocesses

Controlling numerous components influencing bioprocesses precisely is critical for meeting growing research and production demands. These factors include nourishment and metabolite concentrations (like lactate and glucose), cell density, pH, oxygen level, humidity, and temperature (EA et al., 2021). The real-time measurement of bioprocess

parameters such as cellular elements, metabolites, and nutrients is significantly more complex. The UV-visible, mid-infrared, near-infrared, fluorescence, and Raman spectroscopic methods show potential for real-time monitoring of a variety of parameters. The employment of the spectroscopy technique, however, does suffer from poor discernment, chemometrics skill, and multivariate data processing ability. Consequently, there is still a desire for durable sensor systems, low in cost, small in size, and constantly running with greater selectivity (Rusli et al., 2021). To monitor these key characteristics, many analytical approaches have been used. The Internet of things (IoT) is one most promising technology with immense prospects (Chau et al., 2021; Hasoun et al., 2022). It has the necessary qualities of real-time monitoring systems, which can be extensively used for parameters such as humidity, temperature, pH, pressure, and oxygen level monitoring (Cruz et al., 2021). The IoT has been enhanced by the use of microfabrication techniques, enabling downsizing and the creation of innovative multi-parametric electrochemical sensors (Van et al., 2022a). Sensors that could respond to a wide range of chemical, biological, and physical stimuli are often required for IoT applications. Normally, these small sensors must be joined together (Gopikumar et al., 2021a). Researchers would want to assemble many small sensors on single substrate applications that need high performance in a tiny size, low energy usage, and expenditure (Melikoglu, 2020). In general, a typical arrangement of IoT-based FW valorisation systems is shown in Fig. 4.

Kazemi et al. (2020) suggested a methodology for real-time monitoring that combines recent ML approaches with digital monitoring. This device used the internet to monitor volatile fatty acids in the process of anaerobic digestion in real time. The different models' predicting and



Fig. 4. The Internet of things-based system for managing the food waste valorization process.

generalization skills were also assessed. According to this comparison, the soft sensor based on genetic programming is more precise than the other soft sensors. The findings of the study by [Shan et al. \(2021\)](#) show that the innovative multi-sensor approach coupled with IoT can give insight into silage aerobic microbial respiration and hence provide more specific information to guide silage management than earlier assessments of aerobic stability. [Logan et al. \(2019\)](#) studied a pilot-size decentralized biogas reactor having a capacity of 675 L. It was conceived, constructed, and deployed to treat FW produced by the university campus community. The reactor was run in anaerobic, mesophilic, and wet conditions, using feedstock containing 10 % total solids. At organic loading rates of 1, 2, and 3 kg volatile solids/m³.d, the average decrease in total solids was 70.7, 66.5, and 54.98 %. The IoT provided real-time remote monitoring and supported the centralized operator in improving process performance, resulting in improved maintenance and operation of the decentralized anaerobic digestion systems. [Gopikumar et al. \(2021b\)](#) employed an Arduino microcontroller with a mechanical trash segregator to recognize the kind of trash and separate it. The regular and real-time surveillance of process control is based on plasma controlled remotely and onsite using the IoT cloud. The devices are linked to the process of mathematical calculation, which plays an important role in transforming the objects, and are used to examine turbidity, suspended solids, dissolved oxygen, and chemical oxygen demand using sensing devices, thus also managing the effluent. [Nath et al. \(2021\)](#) conducted studies on tiny energy-generating devices, namely cost-effective microfluidic paper-based microbial fuel cells. Several bacterial-based research was conducted to determine the most suited ideal bacterial settings, including growth curve studies, volumetric ratios, and incubation duration. IoT-based hardware has been created and combined with the microfluidic paper-based microbial fuel cells platform to monitor real-time device performance, resulting in the platform's long-term potential to run miniature microelectronics detectors and portable devices. A summary of research works undertaken by researchers depicting IoT's application in the FW valorization/Bioprocesses is given in [Table 3](#).

In general, the IoT makes it easier to monitor and manage the

Table 3
Notable researches on IoT for food and biomass waste valorization.

Food and biomass waste	IoT framework	Main outcomes	Reference
Waste sludge and wastewater	Geographic information system based monitoring	Improved monitoring for planning and implementation	(Gopikumar et al., 2021b)
Restaurant FW	Radio frequency identification tag, surveillance camera coupled with geographic information system	Net positive impact on all the stakeholders	(Wen et al., 2018)
Soybean protein	Monitoring sensors for temperature	Long term preservation of fruits and vegetables	(Niu and Jiang, 2022)
Household FW	Sensors, relay, and mobile applications	Important parameters be measured with IoT network	(Van et al., 2022b)
FW in restaurants and home	Radio frequency identification based sensors and display	Reduction in FW	(Kodan et al., 2020)
Food sector waste	Data collection with sensors and uploading to local cloud	Effective monitoring of FW, water, and energy	(Jagtap et al., 2021)
University campus FW	Programmable logic controller connected with IoT network	Centralized monitoring of remote operations in real-time	(Logan et al., 2019)

FW: food waste; IoT: Internet of things.

bioprocesses that are used to transform waste food into usable products, such as biofertilizers, biofuel, solvents, medicinal compounds, flavoring agents, biosurfactants, and so on. To make optimal use of an IoT-based system, one of the main criteria is the optimization of the physical architecture of the sensors, radio frequency identification, and data networks. However, the uneven network and hardware, the need to often replace radio frequency identification tags for waste food bins, measurement inaccuracy sensors, the potential of data leakage, and disagreements between government bodies over how to correctly construe the data from the IoT system are all unfavorable effects.

5. Challenges and prospective

The development of green, creative, safe, and sustainable procedures supports the viability of adopting sustainable technologies to convert FW into useful goods and energy. The modern approaches comprising IoT, sensors, ML, and nanotechnology are proving to be a positive catalyst for sustainable FW valorization and circular economy ([Lin et al., 2022](#)). However, scaling up these procedures to industrial/mass scale is limited by operational problems such as high FW collecting costs, selection of appropriate ML techniques, the optimized layout of sensors installation, availability of a strong internet network, a skilled hand, chemical characterization, and process compatibility ([Babbitt et al., 2022](#); [Culaba et al., 2022](#)).

The availability of data for model building continues to be a key barrier. Experimenting may be costly and time-demanding, and constructing ML-based models generally needs training data. Many research gathered experimental data from the literature; however, variations in data citation might make this procedure complex and subsequent comparison problematic ([Ascher et al., 2022](#)). Furthermore, the kind of training data utilized affects the trade-off between the generalization and predictive performance of the model. Using extremely homogenous experimental data from, for example, just one kind of valorization method leads to a model with superior prognostic accuracy for modeling the process of the specific type of FW. This, though, indicates that the model is appropriate for the specific sort of training dataset employed. Developing more varied models with inferior but still acceptable prediction efficiency would be beneficial. Furthermore, the quantity of training data necessary would rise since the data would be needed to represent a greater range of parameters. Furthermore, since there are several concerns in the network setup, sensor layout design, and operations optimization, the cost of establishing bio-refineries is significant ([Andrade Cruz et al., 2022](#)). ML combined with sustainable FW valorization is a multidisciplinary strategy that may significantly reduce the waste of high-quality food. ML is beneficial when selecting potentially high-value FW, quality identification, odor-based classification, supply chain management, and final disposal. ML impacts are related to various issues, and solutions to those challenges may emerge as a new revolution in waste reduction, food security, and environmental concerns. However, several limitations are hindering the rollout of ML, such as the requirement for highly skilled hands to deal with problems and design new programs.

IoT improves the supervision and control of bioprocesses that convert FW to useful products such as biofertilizers, biofuel, solvents, pharmaceutical ingredients, flavoring agents, biosurfactants, etc. An optimized layout of sensors, radio frequency identifications, and data networks are essential for effectively utilizing IoT-based systems. Negative outcomes include the inconsistent network/hardware, the requirement to often renew radio frequency identification tags for waste food bins, measurement error sensors, data leakage threats, and differences among government agencies over how to appropriately interpret data from the IoT system. Aside from the scaling-up obstacles and infrastructural setup, all of the valorization strategies also have certain difficulties. For example, the anaerobic digestion process is heavily reliant on the proper development of bacterial populations, and their degrading behavior is impacted by a variety of parameters such as

substrate type, competition with local bacterial communities, ambient temperature, and operating pH (Roopnarain et al., 2021; Yadav et al., 2022). The optimized maintenance of degradation conditions and fine-tuning of these operating parameters vary greatly depending on the kind of FW being processed. There is also a dearth of skilled manpower and apt knowledge of the degradation routes, which makes adjusting the bioprocess for FW valorization difficult. As a result, further study is needed to uncover these interactions, smart approaches, and metabolic pathways to improve pretreatment and valorization approaches (Chilakamarry et al., 2022).

6. Conclusion

A scientific and smart strategy using IoT, AI, and ML to value and manage food waste toward sustainability was scrutinized in this paper. The most effective way to manage food waste and turn it into something useful is to combine two methods: collecting data via IoT technology and analyzing the data using real-time ML algorithms and AI technology. This method can assist the researchers in better understanding and controlling the complex process of food waste valorization. However, developing unique and robust modeling frameworks should be further enhanced to accelerate prognostic research for food waste valorisation and reduction toward sustainable development.

CRediT authorship contribution statement

Zafar Said: Conceptualization, Methodology, Writing – original draft. **Prabhakar Sharma:** Conceptualization, Methodology, Writing – review & editing. **Quach Thi Bich Nhuong:** Writing – review & editing. **Bhaskor J Bora:** Writing – review & editing. **Eric Lichtfouse:** Conceptualization, Writing – review & editing. **Haris M. Khalid:** Writing – review & editing. **Rafael Luque:** Writing – review & editing. **Xuan Phuong Nguyen:** Writing – review & editing. **Anh Tuan Hoang:** Conceptualization, Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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