



Automated features detection in archaeology: Standardisation in the area of big data

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Session 7: From trial to triumphs: Machine Learning applications in archaeology



ARTIFICIAL INTELLIGENCE – A NEW ERA IN ARCHAEOLOGY

DIGITAL REVIEW

Machine Learning Arrives in Archaeology

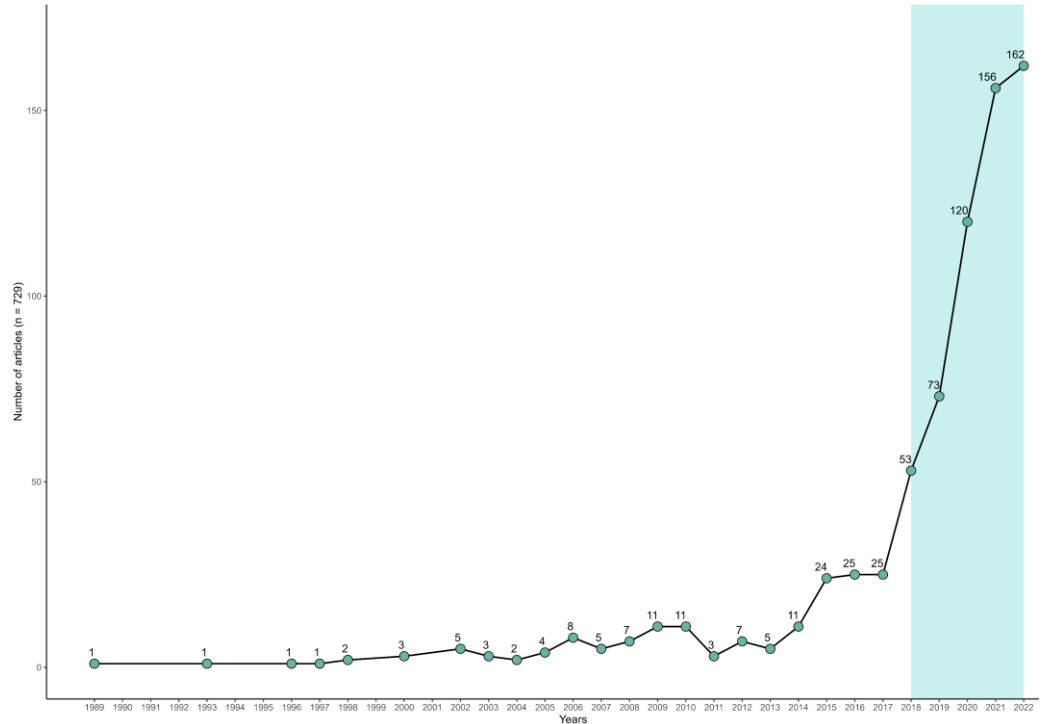
Simon H. Bickler

OVERVIEW

Machine learning (ML) is rapidly being adopted by archaeologists interested in analyzing a range of geospatial, material cultural, textual, natural, and artistic data. The algorithms are particularly suited toward rapid identification and classification of archaeological features and objects. The results of these new studies include identification of many new sites around the world, and improved classification of large archaeological datasets. ML fits well with more traditional methods used in archaeological analysis, and it remains subject to both the benefits and difficulties of those approaches. Small datasets associated with archaeological work make ML vulnerable to hidden complexity, systemic bias, and high validation costs if not managed appropriately. ML's scalability, flexibility, and rapid development, however, make it an essential part of twenty-first-century archaeological practice. This review briefly describes what ML is, how it is being used in archaeology today, and where it might be used in the future for archaeological purposes.

Keywords: machine learning, transfer learning, heritage management, classification, neural networks

“Machine Learning Arrives in Archaeology”, S. Bickler, 2021,
Advance in Archaeological Practice

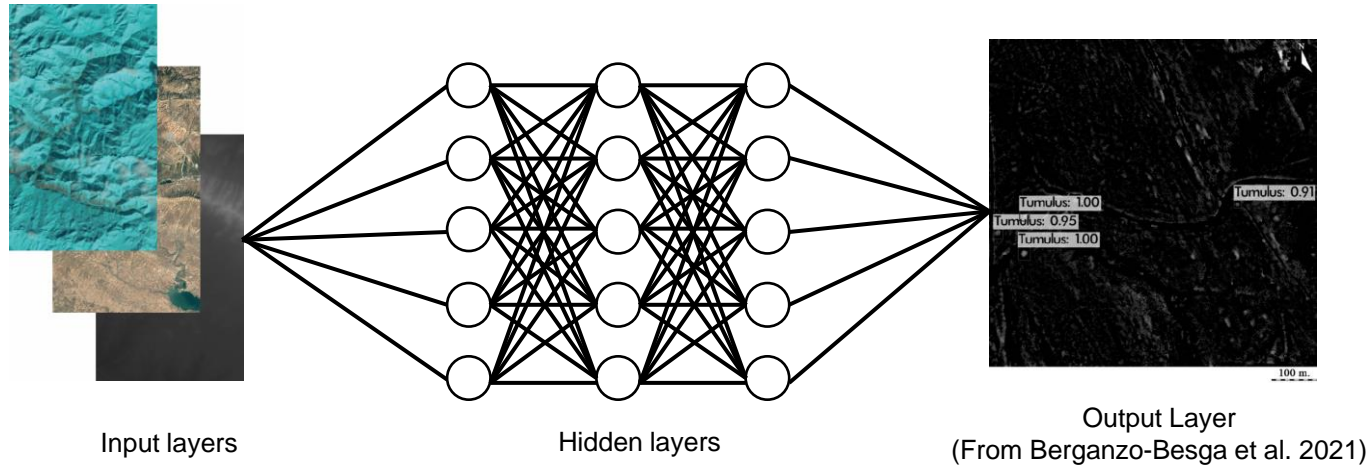


Archaeological papers related to machine learning (Bellat, et al, submitted)



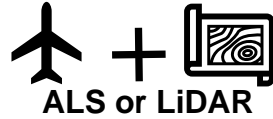
Automatic Structures Detection or Geographic Object-Based Image Analysis (e.g. GEOBIA)

Combination of morphometric and
spectroscopic parameters from Remote Sensing





TIMELINE OF INNOVATIONS

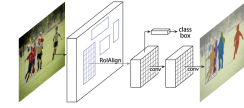


Automatic Detection of Pit Structures in Airborne Laser Scanning Data
ØIVIND DUE TRIER^{1*} AND LARS HOLGER PILO²



Review

Object-based image analysis: a review of developments and future directions of automated feature detection in landscape archaeology
Dylan S. Davis



Mask R-CNN

Semantic Segmentation of Airborne LiDAR Data in Maya Archaeology
Marek Bundzel^{1,*}, Miroslav Jaškur¹, Milan Kováč², Tibor Lieskovský³, Peter Siničák¹ and Tomáš Tkáčik¹

2006

Detection of Ancient Settlement Mounds: Archaeological Survey Based on the SRTM Terrain Model

B.H. Menze, J.A. Ur, and A.G. Sherratt

Beginning of automatic structures detection



2012

Semi-Automatic Mapping of Charcoal Kilns from Airborne Laser Scanning Data Using Deep Learning

Øivind Due Trier¹, Arnt-Børre Salberg², and Lars Holger Pilø²

Deep learning models



2016

2018

2019

Automated segmentation of archaeo-geophysical images by convolutional neural networks

Melda Küçükdemirci^{1,2}, Apostolos Sarris^{1,3}

Ground penetrating radar (GPR)



2020



What are the homogeneities of practices among the automatic archaeological structures detection community?



WHICH METHODS ARE USED?

Methods	Number of uses
Artificial Neural Network	29
Ensemble Learning*	9
Unsupervised Learning and Clustering	3
Linear Classifier	2
Bayesian Classifier	1
Nearest Neighbour Classifier	1

Total of papers screened = 1460
Total of papers on automatic detection = 27

* including Random Forest which is regarded as decision trees and rule induction models



WHICH MODELS ARE USED?

Number of models used:

- Total = 45
- Different = 24

Models	Number of uses (2 >)
Random Forest	7
MR-CNN	7
U-Net	3
FR-CNN, R-CNN and CNN	5 (2/1/2)
ResNet	3

CNN = Convolutional Neural Network

R-CNN = Region Based CNN

FR-CNN = Faster R-CNN

MR-CNN = Mask R-CNN



WHAT DATA ARE USED?

Data	Pre-treatment images (Yes/No)	Number of uses
LiDAR (4 ALS)	5/8	13
Satellite images	2/4	6
GPR	0/2	2
UAVs images	2/1	3
Others	1/2	3



PRE-TRAINING DATA SET

Recurrent use of **Transfer Learning**

No Data set from Remote Sensing

Data set	Number of uses
<i>ImageNet</i>	4
<i>COCO</i>	3
Others	3

RESULTS AND METRICS

Best F1 score reach **98.2** with ResNet (Yang et al. 2022)

Best accuracy reach **99.7 ± 0.4** with RF (Monna et al. 2020)



GOOD PRACTICES ALREADY EXISTING 1/3

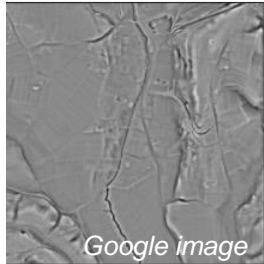
Data pre-process

DEM/DSM

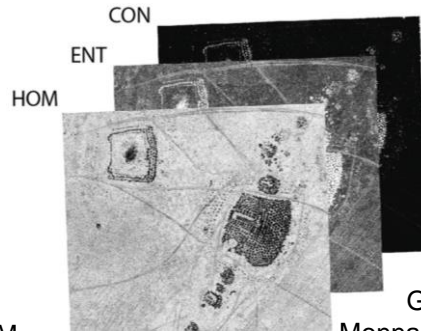
- Simple Local Relief Model (SLRM)
- Red Relief Image Map (RRIM)

RGB

- Grey level co-occurrence matrix (GLCM)
- HSV colors



SLRM



GLCM

Monna et al. 2020



PCA

Multi-label



Structures

- Round shape ✓
- Circular shape ✓
- Triangle shape ✗

Roads

- Stone pavement ✗
- Track ✓



GOOD PRACTICES ALREADY EXISTING 2/3

Pre-training

MillionAID (Object detection)
941,631 images; 51 labels



An Empirical Study of Remote Sensing Pretraining

Di Wang, Jing Zhang, Bo Du, Senior Member, IEEE, Gui-Song Xia, Senior Member, IEEE, and Dacheng Tao, Fellow, IEEE

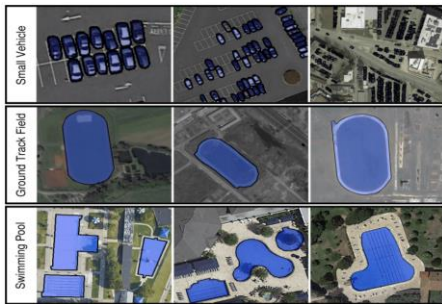
Abstract—Deep learning has largely reshaped remote sensing (RS) research for aerial image understanding and made a great success. Nevertheless, most of the existing deep models are initialized with the ImageNet pretrained weights. Since natural images inevitably present a large domain gap relative to aerial images, probably limiting the fine-tuning performance on downstream aerial scene tasks. This issue motivates us to conduct an empirical study of remote sensing pretraining (RSP) on aerial images. To this end, we train different networks from scratch with the help of the largest RS scene recognition dataset up to now — MillionAID, to obtain a series of RS pretrained backbones, including both convolutional neural networks (CNN) and vision transformers such as Swin and ViTAE, which have shown promising performance on computer vision tasks. Then, we investigate the impact of RSP on representative downstream tasks including scene recognition, semantic segmentation, object detection, and change detection using these CNN and vision transformer backbones. Empirical study shows that RSP can help deliver distinctive performances in scene recognition tasks and in perceiving RS related semantics such as “Bridge” and “Airplane”. We also find that, although RSP mitigates the data discrepancies of traditional ImageNet pretraining on RS images, it may still suffer from task discrepancies, where downstream tasks require different representations from scene recognition tasks. These findings call for further research efforts on both large-scale pretraining datasets and effective pretraining methods. The codes and pretrained models will be released at <https://github.com/VITAE-Transformer-RSP>.



Fig. 1. The challenges of aerial scene recognition. (a) and (b) are the natural image and aerial image belonging to the “park” category. (c) and (d) are two aerial images from the “school” category. Despite the distinct view difference between (a) and (b), (b) contains the playground that is unusual in the park scenes but usually exists in the school scenes like (d). On the other hand, (c) and (d) show different colors as well as significantly different spatial distributions of land objects like the playground and swimming pool. Here, (a) is obtained from http://travel.qatar.com/q24486613-sawahill_country_park by searching “park” on internet, while (b), (c), and (d) are the aerial images from the AID dataset.

Index Terms—Remote Sensing Pretraining, CNN, Vision Transformer, Classification, Detection, Semantic Segmentation.

large scope of land uses and land covers. The obtained aerial scene is usually difficult to be interpreted since the interference



iSAID (Segmentation)
2,806 images; 15 labels

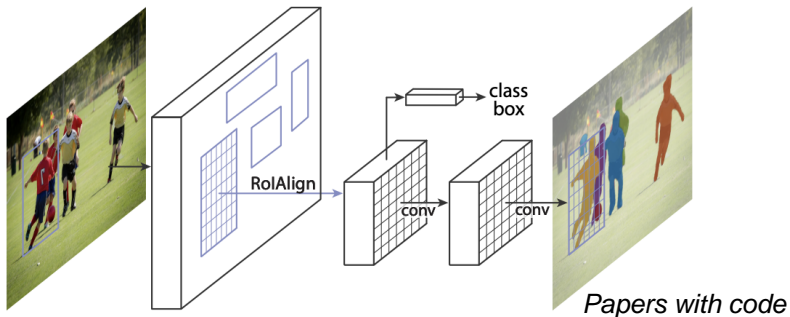


Github Wang et al. 2022



GOOD PRACTICES ALREADY EXISTING 3/3

Model



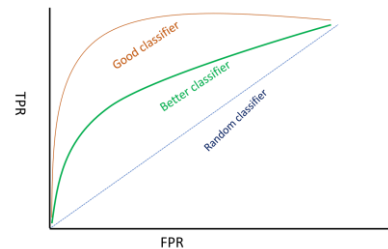
Masked Region based Convolutional Neural Network (**MR-CNN**)

Metrics

$$F1 = \frac{2 * P * R}{P + R}$$

$$\text{Average Precision} = \sum_n (R_n - R_{n-1}) P_n$$

ROC Curve



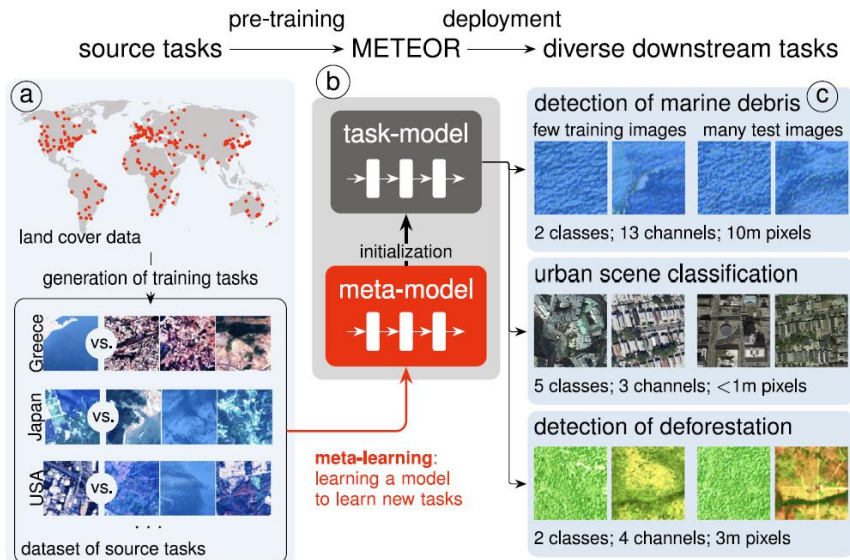
Segmentation task

$$\text{Intersection over Union (A,B)} = \frac{|A \cap B|}{|A \cup B|}$$

$$\text{Pixel Accuracy} = \frac{TP + TN}{TP + TN + FN + FP}$$



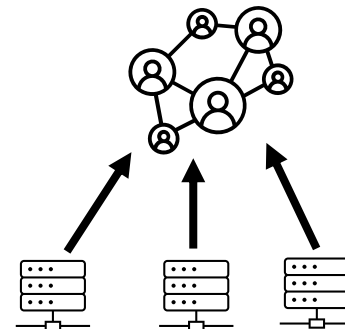
PRACTICES TO IMPLEMENT



Rußwurm et al. 2024

Meta-learning

Common data set



Standardised protocol



ArcheolDA (Berganzo-Besga 2023)



THINK BROADER



Review

Detection of Archaeological Looting from Space: Methods, Achievements and Challenges

Deodato Tapete ^{*} and Francesca Cigna ^{*}

Italian Space Agency (ASI), Via del Politecnico snc, 00133 Rome, Italy; francesca.cigna@asi.it

* Correspondence: deodato.tapete@asi.it

Received: 5 September 2019; Accepted: 5 October 2019; Published: 15 October 2019



CAA2023 Session 34

VHR satellite imagery-based detection of archaeological sites looting in desertic regions via Deep Learning approaches

Authors: Arianna Traviglia, Maria Cristina Salvi, Marco Fiorucci,
Gregory Sech, Ayesha Anwar, Riccardo Giovanelli, Michela De
Bernardin



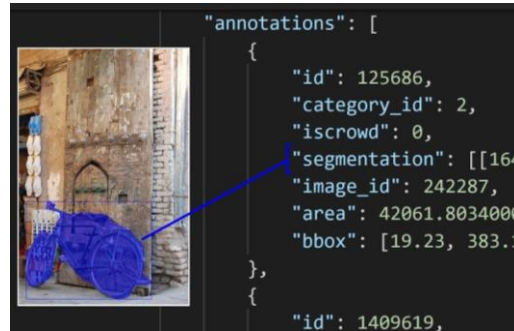
TANGIBLE NEXT STEPS

Special Interest Groups

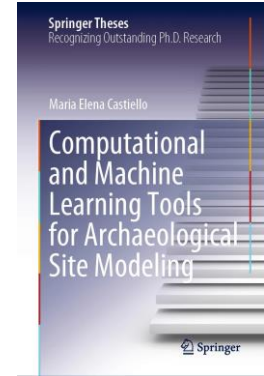
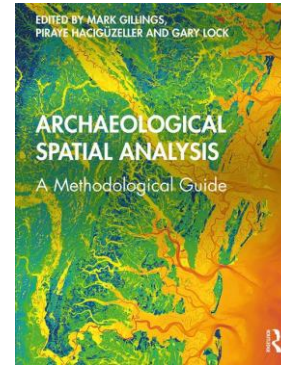
The Special Interest Group (SIG) initiative was introduced at the 2001 Conference.

- Complex Systems Simulation
- Computer Programs for Archaeologists
- [Mobile GIS](#)
- [3D spatial analysis](#)
- [Scientific Scripting Languages in Archaeology \(SIG-SSLA\)](#)
- [Semantics and LOUD in Archaeology \(SIG Data-Dragon\)](#)
- [Archaeological Practices and Knowledge Work \(SIG ARKWORK\)](#)
- [Computationally Modeling Water-based Movement \(SIG CMWM\)](#)

CAA Special Interest Group



Common data base



Toolbook



Thank you for
your attention



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