ARCHAEOLOGICAL SURFACE CERAMICS DETECTION USING LOW ALTITUDE IMAGES BASED ON WEAK LEARNERS

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Introduction

In recent years, the field of remote sensing science has seen significant advancements, particularly in its application to support archaeological research [1,2]. These technological innovations, including the improvements of space-based sensors in terms of their spatial and spectral resolution, and the adoption of open access and free distribution of satellite datasets (such as Landsat and Sentinel products), have opened up exciting new possibilities for space-based remote sensing applications [3]. The democratization of low-altitude systems, with drones now available at relatively low costs, has further expanded the scope of archaeological research, particularly for documentation purposes [4]. At the same time, there has been a notable shift in archaeological computational approaches from desktop-based applications to cloud-based approaches, often integrated with advanced AI algorithms [5]. These changes, occurring in a relatively short period, suggest that we are at the dawn of a new era in what can be termed “remote sensing archaeology”. In 2019, Orengo and Garcia-Molsosa [5] demonstrated the great potential of the Google Earth Engine big data cloud platform in detecting archaeological potsherds. Their pioneering work, the first of its kind, aimed to advance low altitude technologies with remote sensing methodologies for archaeological surface detection. The purpose of our research is to delve into the potential of Artificial Intelligence (AI) algorithms in classifying and detecting archaeological surface ceramics using low-altitude sensor cameras. We aim to demonstrate how an interdisciplinary approach between Remote Sensing and Artificial Intelligence can effectively overcome the 'accuracy paradox' phenomenon of working with imbalanced remote sensing data implementing weak learners.

Methodology

This research uses Artificial Intelligence (AI) algorithms to classify archaeological ceramic surfaces. Images are captured using low-altitude sensor cameras mounted on two drones. Computational processing is done using ArcGIS Pro software's Image Analyst tools. The process involves creating a training model with three classes(Ceramics, Soil and Crops) and applying four supervised classifiers to the data (K-Nearest Neighbour (KNN), Random Forest (RF), Support Vector Machine (SVM), and the Maximum Likelihood algorithm). The accuracy is assessed by comparing the classification to detailed images and evaluating the results using a confusion matrix per classifier The methodology is illustrated in the figure 1 below.

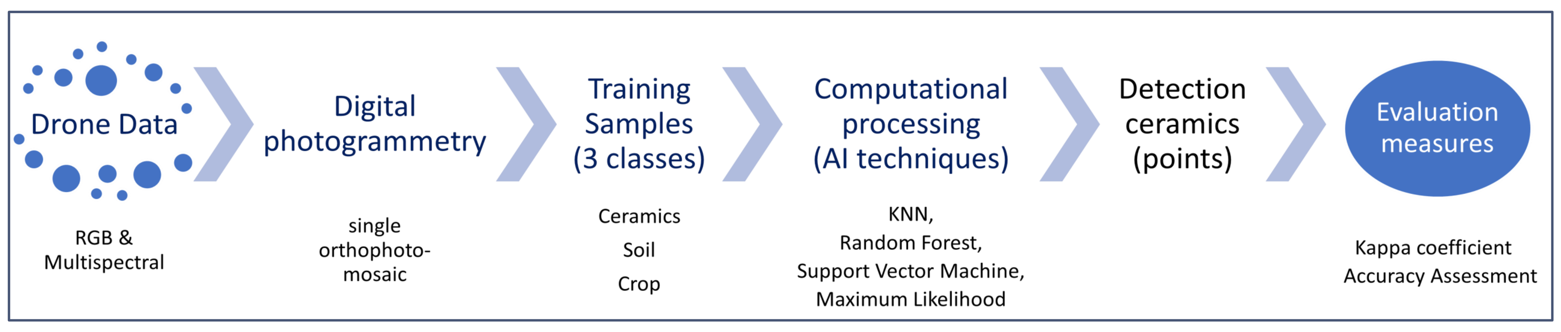


Figure 1. Research methodology.

The field of standard classifier learning algorithms encounters challenges when faced with imbalanced data sets, where the proportion of classes is skewed. This can affect the accuracy of minority class modeling. Issues such as small sample sizes, separability, and sub-concepts influence the effectiveness of the models. To address this, solutions such as resampling data or modifying learning algorithms can be employed. Boosting algorithms like AdaBoost can help enhance predictions in machine learning by assigning higher weights to incorrectly classified points during the training process. (See next diagram)

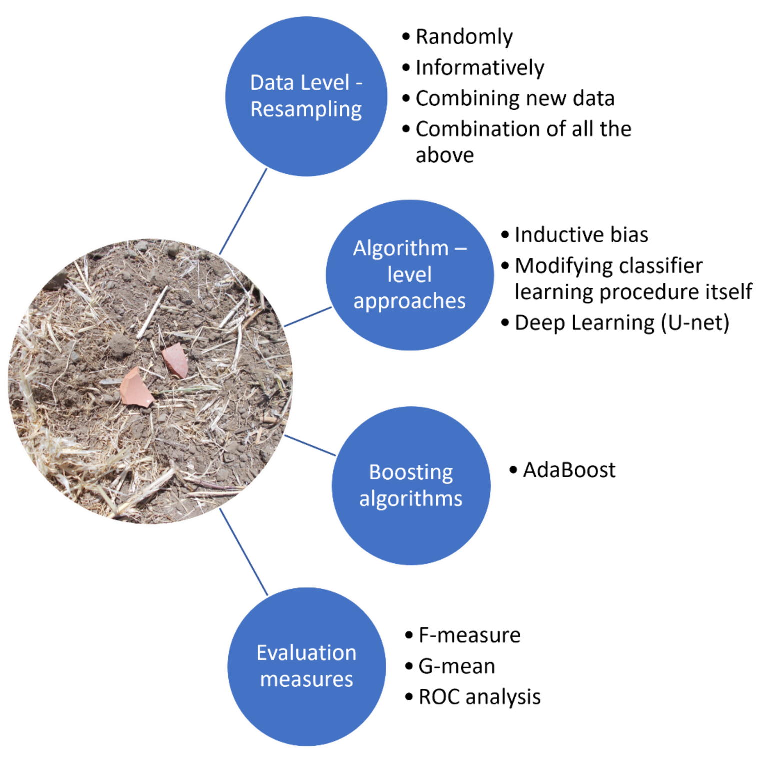
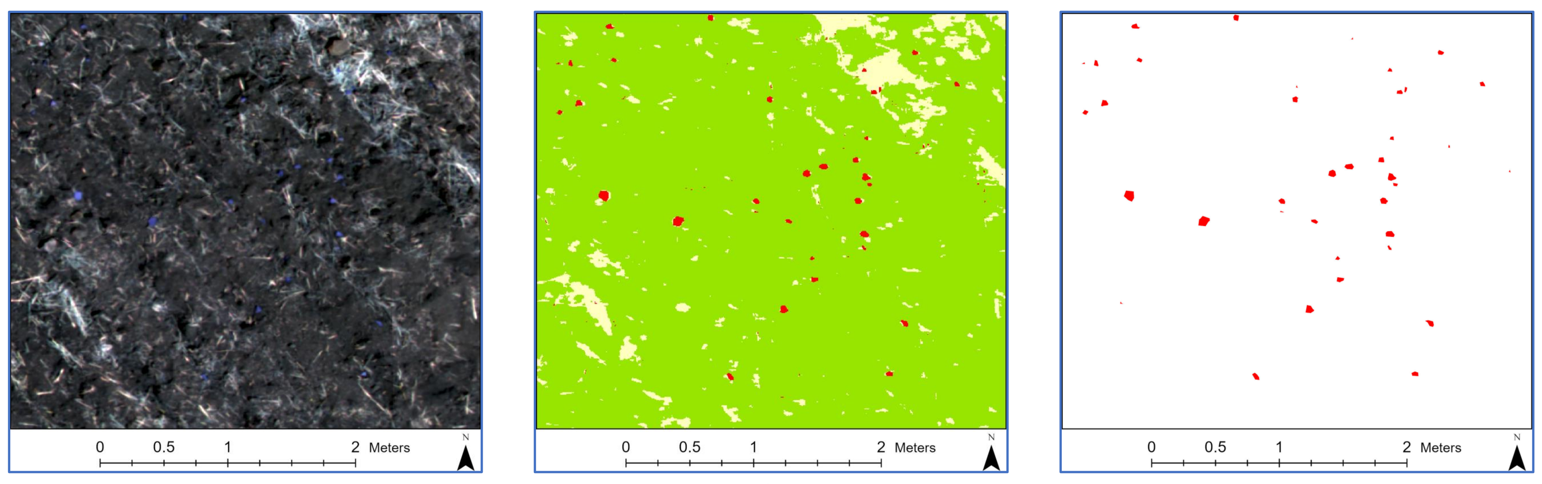


Diagram: Further analysis methodology and tools to treat imbalanced data.

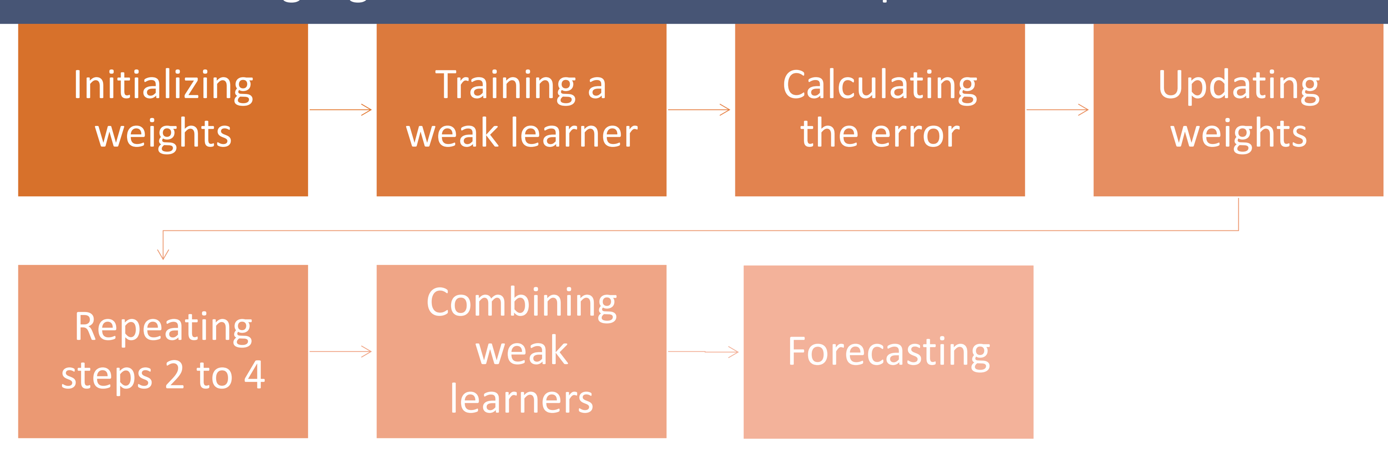


(a) (b) (c)

Example of a zoom area: (a) Input multispectral image, (b) Classification using Support Vector Machine indicating with red colour the ceramics, (c) Detected ceramics.

Accuracy Improvements

To address this issue of misclassifying minority classes our research suggests a methodology for detecting surface ceramics using low-altitude multispectral and RGB cameras based on weak learners. In 1995, researchers [8] and [9] developed the AdaBoost algorithm to improve the classification performance of other learning algorithms. It adjusts its parameters based on data performance by re-weighting data and computing weights for final aggregation iteratively. Using AdaBoost in our decision-making framework has significantly improved prediction accuracy compared to using only a decision tree. The boosting algorithm involves several steps:



Results

The study utilized classifiers trained on image samples for three categories: 'ceramics', 'soil', and 'crops'. Overall accuracy was determined by using randomly distributed testing pixels. Accuracy was calculated as the proportion of correctly predicted samples in the test set divided by the total predictions made.

Accuracy = Correct Predictions / Total Predictions

In our study, we found that the accuracy for soil and crop classification was around 80%, while it was lower for ceramics. Concerns were raised about the number of testing pixels needed to reliably estimate accuracy. Referring to [7], we determined that 225 samples were required for 90% accuracy, and 119 testing pixels were needed for 95% accuracy. These figures assume that the classes follow a normal distribution. When we used 225 testing samples, we re-evaluated the accuracy of all classifiers. Results illustrated in Table 1 below.

	KNN	MAX Likelihood	SVM	RF
RGB	13%	12%	24%	15%
Multispectral	23%	52%	61%	31%

Table 1. Ceramics Accuracy after supervised classification

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Conclusion

Our research focused on using AI to detect archaeological ceramics from high-resolution images captured by UAVs. We employed supervised machine learning algorithms using RGB and multispectral images. The classifiers employed in the study could predict majority classes (soil and crops) with high accuracy but could not accurately predict minority classes (surface ceramics). A new methodology has been proposed to improve the accuracy of detecting surface ceramics using drone images. This approach involves a boosting technique for weak learners and utilizes RGB and multispectral images. The resulting method provides more reliable and precise results, significantly improving the previous technique.. We plan to expand our research to include different types of ceramics and spectral behaviors in the same area and conduct drone surveys for algorithm training and outcome assessment.

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