AI-Driven Archaeological Site Mapping

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.Abstract

Archaeological site discovery and preservation require extensive analysis of large-scale satellite and aerial imagery, traditionally performed through manual interpretation. This process is time-intensive and susceptible to human error. This project proposes an AI-driven archaeological site mapping framework that integrates semantic segmentation, object detection, and environmental risk assessment. A U-Net-based deep learning model is used for semantic segmentation of ruins and vegetation from high-resolution satellite images, while a YOLO-based model performs archaeological artifact detection. Additionally, a machine learning-based erosion prediction model evaluates terrain stability using geospatial and environmental parameters. The integrated system provides automated inference and visualization through a dashboard interface, assisting archaeologists and researchers in decision-making. Experimental results demonstrate strong segmentation performance with a validation Dice coefficient of 0.8381 and Mean IoU of 0.7299.

I. Introduction

Archaeological exploration increasingly relies on satellite imagery and remote sensing technologies to identify and preserve historical sites. However, manual inspection of such data is inefficient for large geographic regions. Advances in deep learning, particularly convolutional neural networks (CNNs), enable automated extraction of meaningful patterns from imagery. This internship project explores the application of deep learning techniques to archaeological site mapping by combining image segmentation, artifact detection, and erosion risk prediction into a unified AI system.

II. Related Work

Project Objectives

The primary objectives of this research are:

- Automation: To reduce the manual effort required in sorting artifacts and analyzing satellite imagery.
- Precision: To utilize state-of-the-art deep learning models for high-accuracy detection and segmentation.
- Risk Assessment: To provide data-driven insights into environmental threats facing archaeological sites.
- Accessibility: To deploy complex AI models via an intuitive interface accessible to non-technical domain experts.

Literature Review

Evolution of Deep Learning in Remote Sensing

Remote sensing has evolved from simple pixel-based classification to complex deep learning approaches. Convolutional Neural Networks (CNNs) have become the standard for processing aerial imagery, enabling the automatic extraction of features such as roads, buildings, and land cover types, which is directly applicable to identifying archaeological ruins.

U-Net Architecture and Skip Connections

For semantic segmentation tasks, the U-Net architecture is a cornerstone. Originally designed for biomedical image segmentation, its encoder-decoder structure with skip connections allows the network to propagate high-resolution context information to the upsampling layers. This is crucial for archaeology, where the boundary between a "ruin" and "background" can be subtle.

YOLO: Real-time Object Detection

The "You Only Look Once" (YOLO) family of models revolutionized object detection by framing it as a single regression problem rather than a complex pipeline of region proposals. YOLOv5, specifically, offers an optimal balance between inference speed and mean Average Precision (mAP), making it suitable for field applications where artifacts need to be cataloged quickly via live camera feeds.

Gradient Boosting and XGBoost

While Deep Learning dominates image tasks, tabular environmental data is often best handled by ensemble methods. Gradient Boosting machines, such as XGBoost (eXtreme Gradient Boosting), are widely cited in literature for their efficiency in regression tasks. They build models sequentially, correcting errors of previous models. *Note: While XGBoost is a standard in the field, this project implements a Random Forest Regressor, a parallel ensemble method known for its robustness against overfitting and ease of tuning.*

System Architecture

The system follows a modular architecture:

1. Data Layer: Ingestion of images (aerial/artifact) and environmental parameters (Slope, NDVI, DEM).
2. Processing Layer:
   - YOLOv5 for bounding box detection.
   - U-Net (SMP) for pixel-wise segmentation masks.
   - Scikit-Learn Regressor for risk score calculation.
3. Application Layer: A Streamlit-based frontend that visualizes results and handles user interaction.

III. Dataset Collection and Preprocessing

A. Data Sources

High-resolution satellite images were collected from Google Earth Pro and Sentinel-2 datasets. Archaeological artifact images were sourced from publicly available datasets, including Hugging Face repositories. Environmental features such as elevation, slope, and vegetation indices were obtained from open geospatial sources.

B. Image Preprocessing

Satellite images of approximately 4920 pixels were cropped into 512 × 512 tiles to preserve spatial resolution. Corresponding segmentation masks were generated using polygon-based annotations. Standard preprocessing techniques such as normalization and resizing were applied.

IV. Semantic Segmentation Model

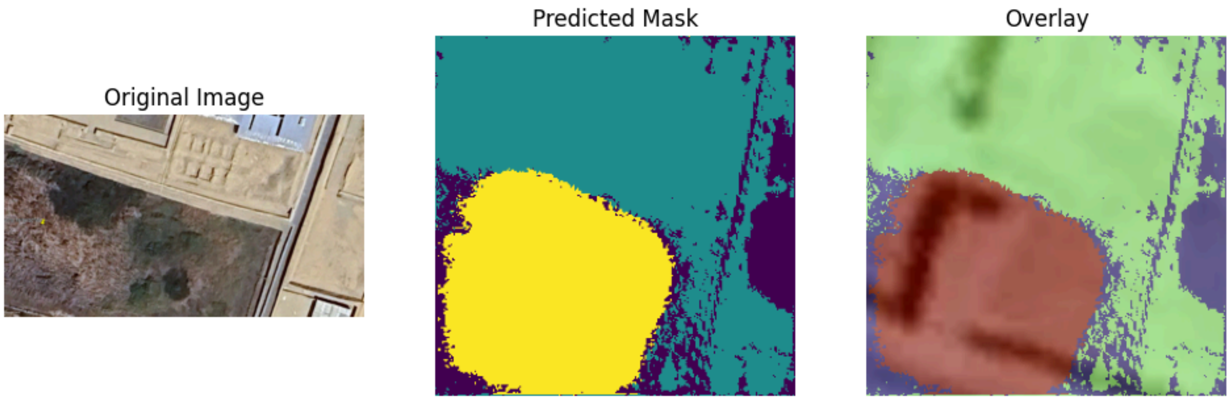
A U-Net architecture with a ResNet-34 encoder pretrained on ImageNet was employed for semantic segmentation. The model was trained using Dice Loss and Focal Loss to address class imbalance. Training was conducted for 50 epochs using the AdamW optimizer.

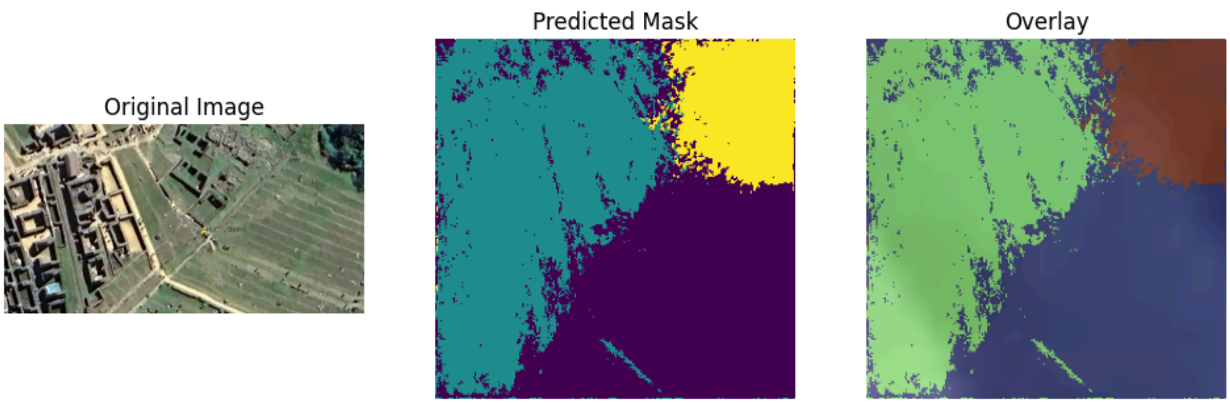
A. Evaluation Metrics

The segmentation performance was evaluated using Accuracy, Dice Coefficient, and Intersection over Union (IoU).

B. Results

The model achieved a validation accuracy of 0.8836, a Dice coefficient of 0.8381, and a Mean IoU of 0.7299, indicating effective segmentation of ruins and vegetation.





V. Artifact Detection Using YOLO

A YOLO-based object detection model was trained using transfer learning to identify archaeological artifacts such as coins, pottery, sculptures, and tools. The model achieved the following performance metrics:

- **Precision:** 0.909
- **Recall:** 0.0749
- **mAP@0.5:** 0.103

VI. Terrain Erosion Prediction

A machine learning model using environmental features such as NDVI, slope, and elevation was developed to predict soil erosion risk. The output was categorized into low, medium, and high erosion risk levels. The model achieved an R^2 score of 1.0, indicating high predictive accuracy on the validation dataset.

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Root Mean Squared Error (RMSE): 0.0024

R-squared (R² Score): 1.0000
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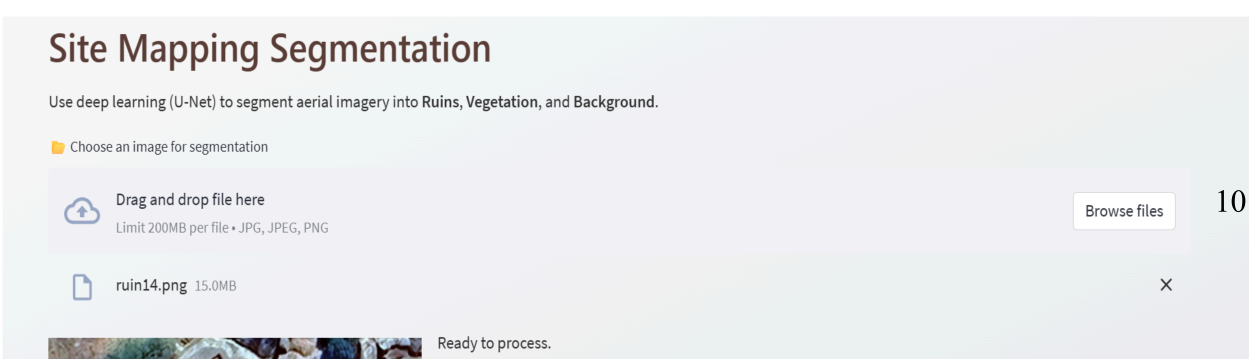
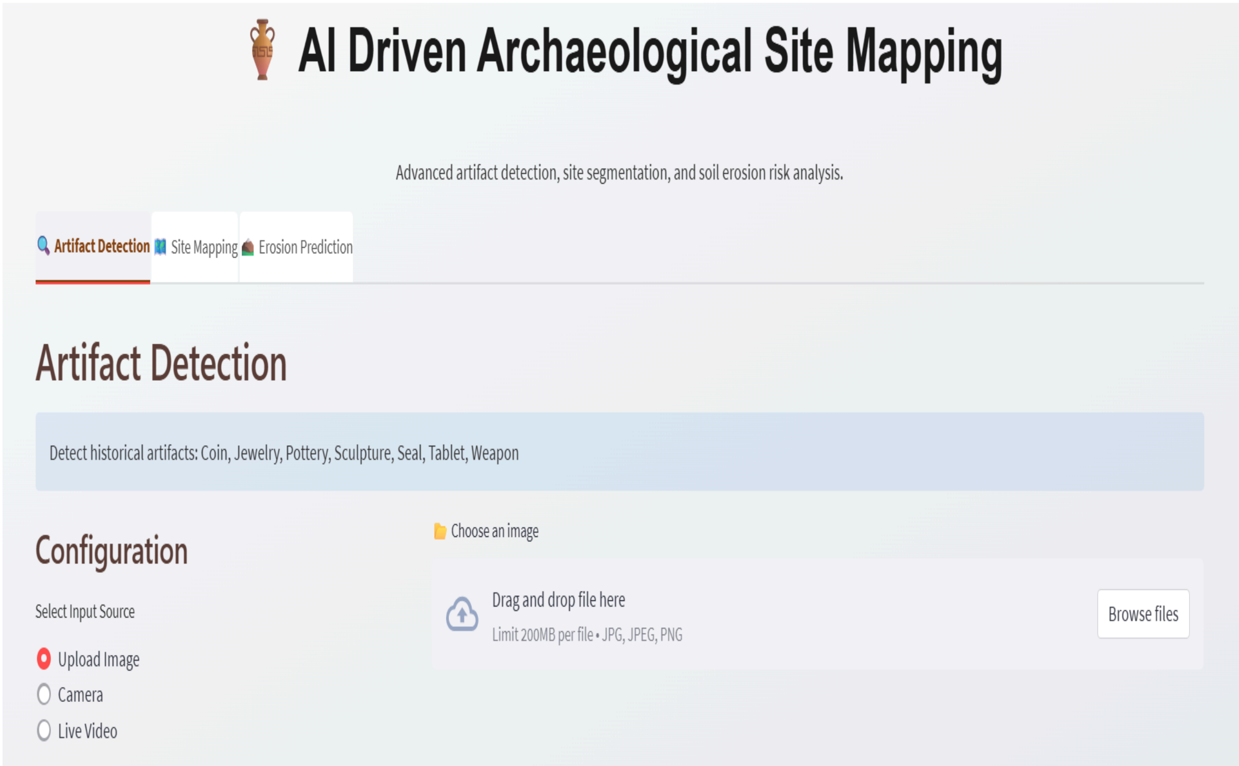
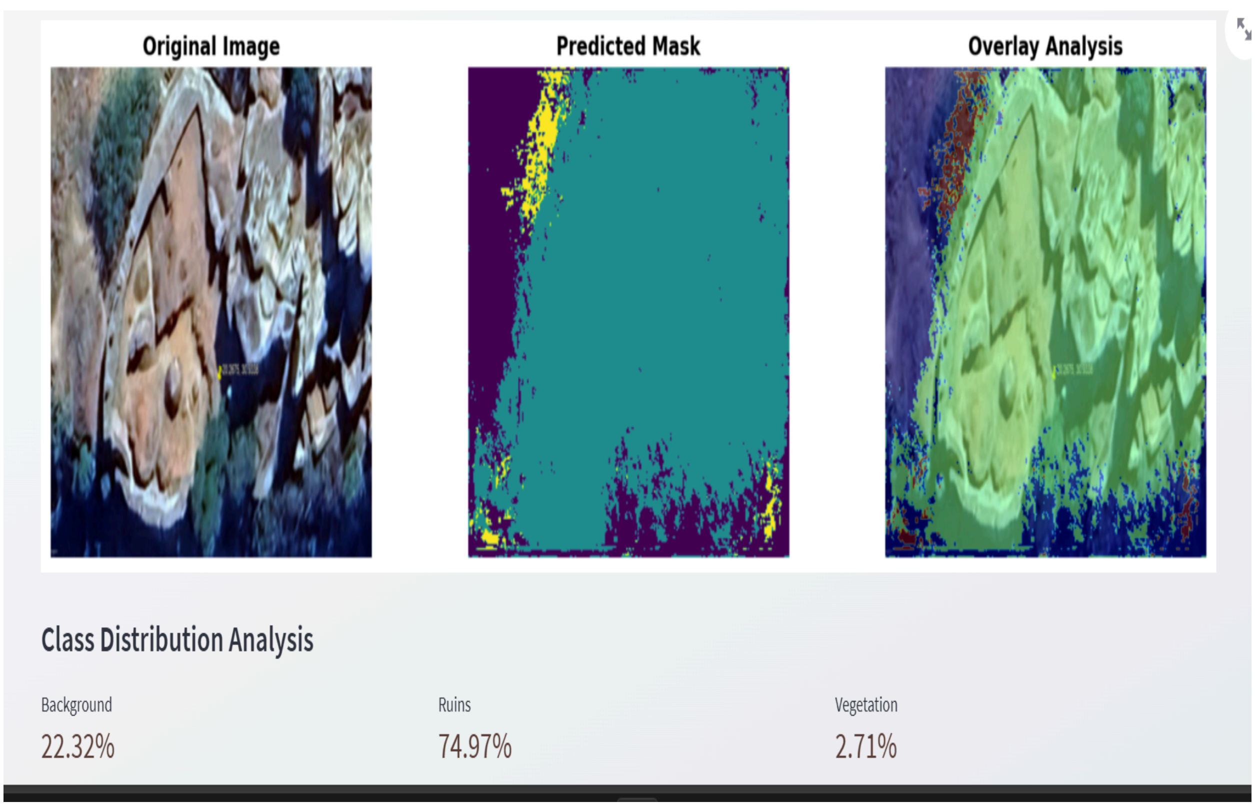
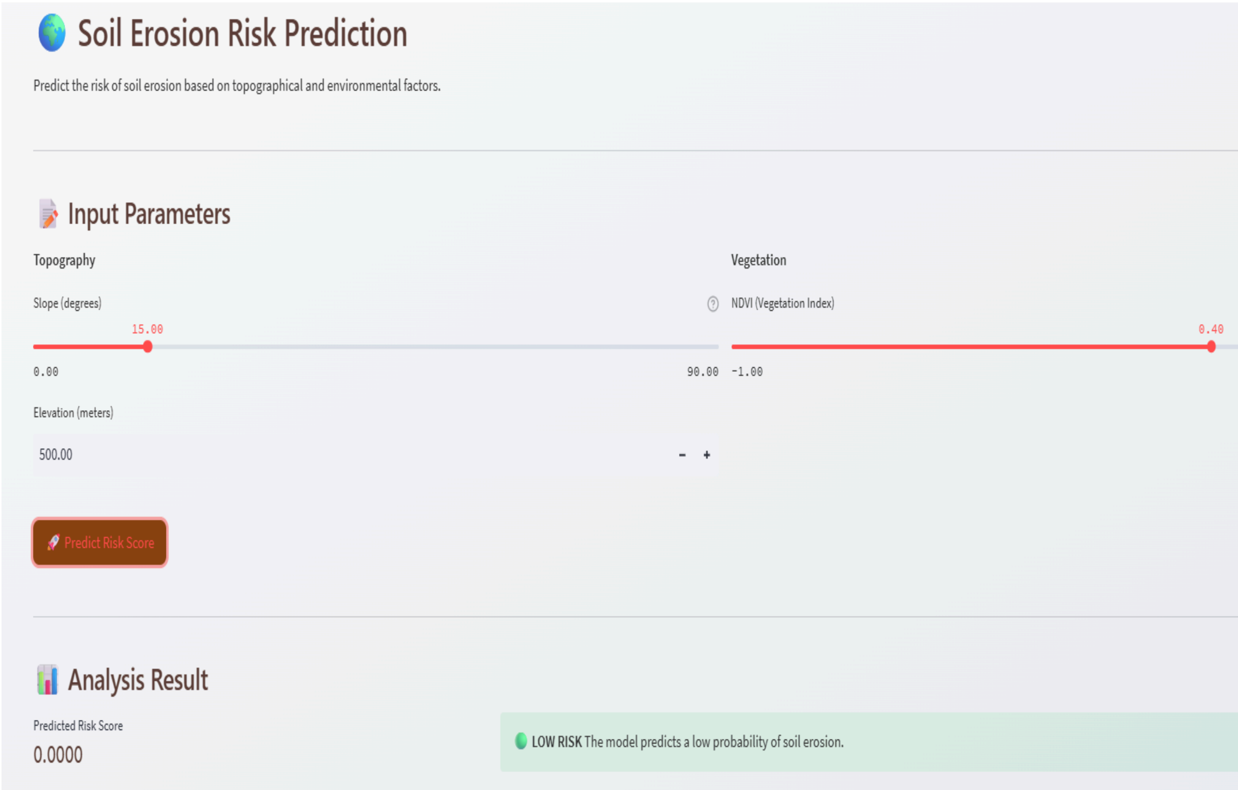
VII. System Integration and Dashboard

All trained models were integrated into a unified inference pipeline with a Streamlit-based dashboard. The dashboard provides separate modules for segmentation, artifact detection, and erosion risk prediction, enabling interactive visualization and analysis.




AI Driven Archaeological Site Mapping
Advanced artifact detection, site segmentation, and soil erosion risk analysis.
Artifact Detection
Site Mapping
Erosion Prediction
Artifact Detection
Detect historical artifacts: Coin, Jewelry, Pottery, Sculpture, Seal, Tablet, Weapon
Configuration
Select Input Source
Upload Image
Camera
Live Video
Choose an image
Drag and drop file here
Limit 200MB per file • JPG, JPEG, PNG
Browse files


Original Image
Predicted Mask
Overlay Analysis
Class Distribution Analysis
Background
22.32%
Ruins
74.97%
Vegetation
2.71%



VIII. Conclusion and Future Work

This project demonstrates the feasibility of applying deep learning techniques to archaeological site mapping. The integrated system automates image analysis and environmental assessment, reducing manual effort and improving accuracy. Future work includes expanding the dataset, incorporating temporal analysis, and integrating GIS-based visualization tools.

References

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