AI-DRIVEN ARCHAEOLOGICAL SITE ANALYSIS

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OVERVIEW

This project introduces an AI-driven system designed to automate archaeological site analysis, addressing the limitations of manual interpretation which is often time-consuming and prone to human error . By leveraging deep learning and computer vision techniques specifically U-Net for semantic segmentation and YOLO for object detection the system analyzes aerial and satellite imagery to identify archaeological structures and vegetation patterns . Additionally, it incorporates machine learning to predict terrain erosion risks, ultimately aiming to streamline site mapping and improve data accuracy for preservation efforts .

INTRODUCTION

Conventional methods for analyzing archaeological sites using satellite and drone imagery rely heavily on manual interpretation, a process that is both prone to human error and time-intensive. Furthermore, handling massive amounts of geospatial data creates difficulties regarding efficiency and accuracy. To address this, the project employs Artificial Intelligence (AI), specifically Computer Vision and Machine Learning, to automate the mapping of these sites. The solution utilizes deep learning models specifically U-Net for semantic segmentation and YOLO for object detection alongside machine learning algorithms to identify erosion risks, vegetation patterns, and archaeological structures.

PROBLEM STATEMENT

Identifying and monitoring archaeological sites is currently a labor-intensive and complex task. Manual analysis requires specialized expertise, takes a significant amount of time, and often results in inconsistencies. Moreover, current methods lack the ability to simultaneously analyze land cover, detect structures, and assess erosion risks. The absence of an automated, integrated system hinders effective risk assessment and preservation planning.

SOLUTION STATEMENT

The goal of this initiative is to create an AI-driven system that maps archaeological sites using satellite and aerial imagery. This system integrates object detection, semantic segmentation, and erosion prediction to automatically recognize erosion-prone zones, vegetation, and archaeological features. By merging machine learning with deep learning, the solution aims to decrease manual workload, enhance accuracy, and assist archaeologists in preserving sites.

OBJECTIVES

- Develop an AI-based system to automate archaeological analysis.
- Use U-Net to perform semantic segmentation for identifying vegetation and ruins.
- Employ YOLO to detect archaeological artifacts.
- Utilize machine learning models to predict terrain erosion risks.
- Combine all these modules into a single interactive application.

SYSTEM ARCHITECTURE

The proposed platform automates the assessment and identification of archaeological regions. It consists of three primary components:

1. **Semantic Segmentation:** Uses U-Net to classify pixels as background, vegetation, or ruins.
2. **Object Detection**: Uses YOLO to locate structures and artifacts.
3. **Erosion Prediction**: Uses machine learning to evaluate risk based on terrain features. These components are unified in a single interface where users can upload images and view all analytical results.

METHODOLOGY

- **Data Collection:** The project gathered aerial and satellite imagery depicting ruins, terrain, and vegetation.
- **Preparation**: Data was annotated with bounding boxes (for YOLO) and pixel-level masks (for segmentation), then normalized and resized.
- **Model Training:** A U-Net model with a ResNet34 encoder was trained to segment ruins and vegetation. A YOLO model was trained to identify structures via bounding boxes. A machine learning model was employed to classify terrain stability using features like slope scores and vegetation ratios.
- **Integration:** The models were deployed using Streamlit to create an interactive visualization pipeline.

WORKFLOW

1. Input: Users upload satellite or aerial images.
2. Preprocessing: Images are normalized and resized.
3. Segmentation: U-Net classifies regions into ruins or vegetation.
4. Detection: YOLO localizes artifacts and structures.
5. Feature Extraction: The system extracts terrain data, such as slope score and vegetation ratio.
6. Prediction: The ML model determines if the area is stable or prone to erosion.
7. Output: A dashboard displays the segmentation maps, erosion risks, and detected objects.

TECHNOLOGIES USED

- Languages & Platforms: Python, Google Colab, local environments.
- AI & CV: Deep Learning, Machine Learning, OpenCV.
- Models: U-Net (ResNet34 encoder), YOLO, Random Forest/Regression.
- Libraries: PyTorch, Segmentation Models PyTorch, Ultralytics YOLO, NumPy, Pandas, Matplotlib.
- Deployment: Streamlit.

PERFORMANCE

- Segmentation (U-Net): Evaluated using Intersection over Union (IoU) and Dice Score.
- Object Detection (YOLO): Evaluated using Precision, Recall, and Mean Average Precision (mAP@0.5).
- Erosion Prediction: Evaluated using R^{2} Score and Root Mean Square Error (RMSE).

OUTPUT

🏛 Archaeological Site Analysis System

Models loaded successfully

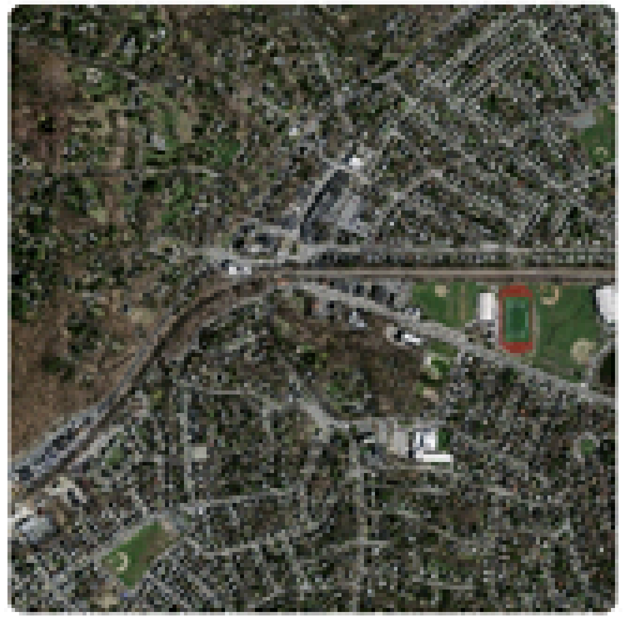
Upload an archaeological image

Drag and drop file here
Limit 200MB per file • JPG, PNG, JPEG

Browse files

22679050_15.png 5.1MB

Input Image



OUTPUT

Model Outputs

U-Net Segmentation

YOLO Object Detection

Terrain Analysis

Vegetation Ratio

0.3041

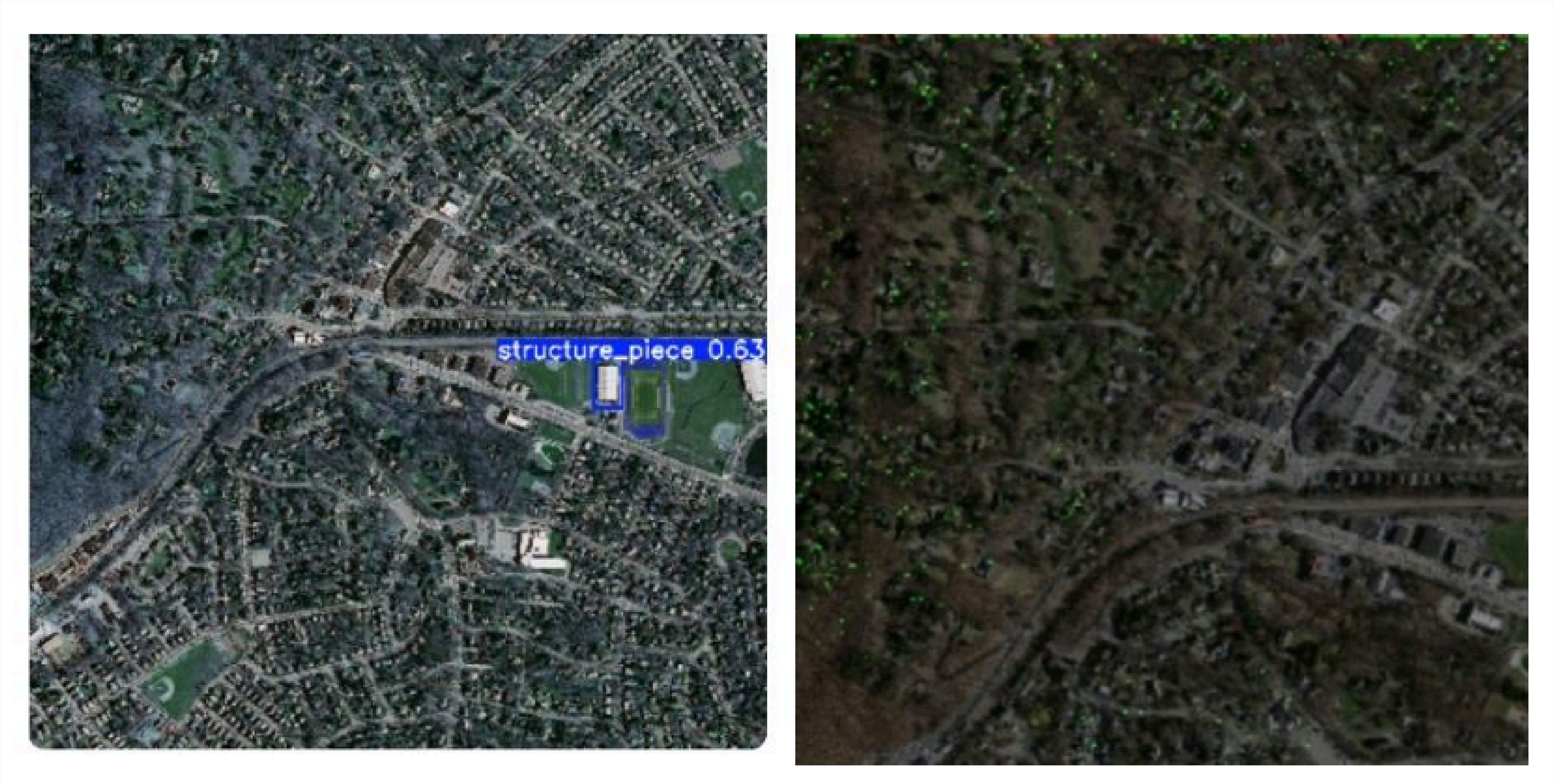
Slope Score

123.17

Erosion Risk

Stable

OUTPUT



RESULTS

- Successfully implemented AI-based semantic segmentation, object detection, and terrain erosion prediction.
- U-Net accurately segmented ruins and vegetation from aerial imagery.
- YOLO effectively detected archaeological structures using bounding boxes.
- The terrain erosion module classified regions as erosion-prone or stable based on extracted terrain features.
- All outputs were visualized through an interactive dashboard.

FUTURE WORK

- Integrating NDVI and DEM data for better analysis.
- Using diverse, larger datasets to improve accuracy.
- Deploying to the cloud for real-time usage.
- Implementing temporal monitoring to track changes over time.

CONCLUSION

The project successfully implemented and visualized all three AI modules. U-Net accurately segmented vegetation and ruins, while YOLO effectively detected structures. The project concludes that this integrated AI approach improves consistency, reduces manual effort, and supports heritage conservation.

THANK YOU