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AI Driven Archaeological Site Mapping

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Abstract

Abstract— Identification of archaeological sites and their mapping is one of the key roles played in heritage preservation and supporting historical research. Most survey methods rely on ground exploration, which requires much time and resources. Still, all the same, are always limited by many accessibility concerns. This paper presents an AI-driven approach towards automatic archaeological site mapping from satellite images using a machine learning technique. Accordingly, a system is proposed that integrates all steps: image pre-processing, feature extraction, and classification based on deep learning to detect potential archaeological patterns such as structural remains, soil marks, and landscape anomalies. A convolutional neural network model will be trained on labeled geospatial datasets to enhance detection accuracy by reducing human intervention. Experimental results prove improved efficiency and more reliability compared to conventional survey methods, attaining a higher precision in identifying potential excavation zones. The proposed approach represents scalability, cost effectiveness, and no invasion in an archaeological exploration that enables faster decision making with enhanced preservation planning. Future work includes the integration of multi- spectral imagery and drone-based data acquisition, enhancing the detection performance and geographic adaptability.

***Keywords**: Artificial Intelligence, Archaeological Site Detection, Remote Sensing, Deep Learning, Satellite Imagery, Geospatial Analysis*

1. INTRODUCTION

Finding old sites matters when we want to grasp how people lived, keep traditions safe, and plan digs wisely. Regular methods rely mainly on walking sites, reading past documents, and looking at the ground. Though they work, such work drags out, needs lots of effort, and can fail where land is tough to reach, weather harsh, or tools missing. Satellites snap pictures faster these days, loading up systems with plenty of detailed spatial info - this flood of data opens doors for machines to process it without human help. Lately, advances in Artificial Intelligence along with machine learning have improved how we find useful insights in messy pictures. Deep learning tools like CNNs handle tasks like sorting images, spotting objects, or spotting oddities rather well. Because of these strengths, AI could help detect faint signs in nature - like soil stripes, old structures, bumps in terrain, or strange plant growth - that might mark hidden ancient sites. A new method uses artificial intelligence to map ancient sites through space-based photos. Instead of relying on human observers, algorithms now identify key elements automatically. Precision rises when machines handle classification tasks. Without needing ground crews, operations move faster and incur lower costs. Systems blend spatial mapping tools with neural networks trained on vast images. This blend enables thorough searches across remote regions without damage or disruption. This study leads to quicker location of sites, stronger methods for protection, along with better choices in managing cultural assets.

2. LITERATURE SURVEY

In recent years, the integration of Artificial Intelligence (AI), remote sensing, and geospatial technologies has significantly transformed archaeological exploration and site detection. Traditional archaeological surveys relied primarily on field- based investigations and manual interpretation of aerial imagery. However, the availability of high-resolution satellite data and advancements in machine learning have enabled automated approaches for large-scale archaeological site identification.

Parcak et al. [1] explored the application of satellite remote sensing for archaeological discovery using high-resolution imagery. Their study demonstrated how spectral signatures and landscape patterns could reveal buried structures and ancient settlements. While their approach successfully identified potential archaeological features, it relied heavily on manual interpretation and expert analysis, limiting scalability and automation for large geographic regions.

Lasaponara et al. [2] proposed the use of multispectral and hyperspectral satellite imagery combined with image enhancement techniques for detecting archaeological remains. Their method improved visibility of crop marks, soil marks, and micro-topographical variations. However, the approach primarily depended on traditional image processing algorithms and lacked automated learning mechanisms, reducing its adaptability to diverse terrains and environmental conditions.

Versaci et al. [3] introduced a machine learning-based framework for archaeological feature detection using supervised classification algorithms such as Support Vector Machines (SVM). The system showed improved detection accuracy compared to manual interpretation methods. Nevertheless, the reliance on handcrafted features limited the model's ability to capture complex spatial patterns present in high-dimensional satellite imagery.

Cowley et al. [4] investigated the use of LiDAR (Light Detection and Ranging) data for archaeological mapping in forested environments. The study demonstrated the effectiveness of elevation models in revealing hidden structures beneath dense vegetation. Although LiDAR provided highly accurate terrain analysis, the processing required specialized equipment and significant computational resources, making large-scale implementation costly.

Caspari et al. [5] applied deep learning techniques, particularly Convolutional Neural Networks (CNNs), for detecting archaeological structures from remote sensing imagery. Their results indicated that CNN-based models outperformed traditional classifiers by automatically learning hierarchical spatial features. Despite improved performance, the study highlighted challenges related to limited labeled datasets and model generalization across different geographical regions.

Lambers et al. [6] emphasized the importance of integrating Geographic Information Systems (GIS) with automated detection systems to improve spatial analysis and mapping accuracy. While GIS-based predictive modeling enhanced decision-making processes, the approach required extensive domain knowledge and manual parameter tuning, reducing full automation capability.

A comparative analysis conducted by Orengo et al. [7] evaluated traditional remote sensing methods against AI-based detection models for archaeological prospection. The findings demonstrated that deep learning models provided higher accuracy and faster processing times. However, issues such as data imbalance, interpretability of models, and computational cost were identified as ongoing challenges.

Overall, existing research indicates significant progress in applying AI and remote sensing for archaeological site detection. However, limitations remain in terms of scalability, contextual understanding of landscape patterns, dataset availability, and computational efficiency. These gaps highlight the need for an integrated AI-driven framework capable of automated, accurate, and scalable archaeological site mapping, which forms the basis of the proposed research.

3. SYSTEM ARCHITECTURE

From my work, in research I see that the need for intelligent automated systems is growing. Those intelligent automated systems must look at big map data to find sites. Traditional field surveys have limits because of time, cost and access. The proposed solution puts together sensing map analysis and learning image analysis. The system processes satellite pictures automatically. The system looks for features, in the land. The system draws maps that point to archaeological locations. I think the framework links backend processing, with neural network (CNN) models. The framework makes feature detection accurate. The framework adapts to terrains.

I designed the system as a smart map analysis platform. The system can find sites automatically by using image processing and deep learning. The system follows a client-server design. Researchers use the web interface to upload satellite images or to select an area, for analysis. The web interface talks to the backend server, through REST APIs. The backend server handles data processing runs the model and creates visualizations.

When I receive satellite imagery I let the backend send the data to the image preprocessing module. The image preprocessing module reduces noise normalizes the satellite imagery enhances contrast and resizes the satellite imagery so that the input quality stays the same. If multispectral imagery is present the image preprocessing module picks the bands to make soil marks, vegetation patterns and structural anomalies easier to see. The preprocessing stage makes the satellite imagery the same and ready, for deep learning analysis.

When I look at the processed images I send them to a feature extraction module that uses Convolutional Neural Networks (CNNs). The CNN model learns from labeled datasets that have known sites and non-site regions. The CNN model finds patterns such, as structures, elevation irregularities, soil discoloration and vegetation anomalies that may point to buried archaeological remains. The CNN model does not use rule-based approaches. The CNN model captures relationships and contextual information straight, from the image data.

The system integrates Geographic Information System (GIS) components to analyze attributes such, as elevation models, slope data and proximity to water sources. Geographical factors are added to the analysis to improve detection reliability. GIS integration enhances understanding. GIS integration reduces positives by correlating features, with environmental characteristics.

The anomaly detection and site prediction module compares taken space features, with known patterns. The anomaly detection and site prediction module then labels each region as an site or a non-significant area. The system makes a chance score for each region. Lets you pick zones with confidence, for more field work. The system shows the predictions as heatmaps or map overlays so researchers can look at the results and interact.

All trained models, all satellite datasets and all GIS layers use a modular storage system. The system saves the deep learning model. Loads the deep learning model during runtime, for prediction. The system keeps the data in organized formats, like databases or georeferenced image repositories. The modular storage design lets the team do model retraining regularly with site data and lets the team update datasets smoothly.

Upon completion of analysis, the system generates a structured geospatial report summarizing detected potential sites, confidence scores, and corresponding spatial coordinates. The results are presented through an interactive dashboard that supports map visualization and data export. Through the integration of automated satellite image processing, deep learning- based spatial analysis, and GIS-driven contextual modeling, the proposed architecture provides a scalable and efficient solution for AI-driven archaeological site mapping.

4. CONCLUSION

I read the literature review. See progress, in archaeological site detection with remote sensing, geospatial technologies and Artificial Intelligence. The early approaches rely on interpretation of satellite imagery and on traditional image processing and machine learning algorithms. The early approaches make archaeological features such as soil marks and vegetation anomalies easier to see. The early approaches still need features need expert intervention and have limited scalability, across geographic areas. Machine learning and deep learning models have shown a boost, in the automated feature extraction and the spatial pattern recognition. Convolutional Neural Networks (CNNs) have driven that boost. Convolutional Neural Networks (CNNs) learn the patterns from satellite imagery. Convolutional Neural Networks (CNNs) raise detection accuracy by learning representations that capture the detail in the images. The integration of Geographic Information Systems (GIS) and LiDAR data has improved analysis. Geographic Information Systems (GIS) and LiDAR data let researchers spot structures that are covered by vegetation. Geographic Information Systems (GIS) and LiDAR data also help to find structures that would otherwise stay unseen. Challenges still exist. The challenges involve labeled datasets. The challenges involve model generalization across terrains. The challenges involve complexity. The challenges involve interpretability of deep learning predictions.

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