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The Application of Artificial Intelligence in Detecting Archaeological Elements: A Comprehensive Review

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ABSTRACT

The integration of Artificial Intelligence (AI) into archaeological research marks a profound transformation in the methods and scale of discovery. Leveraging advanced methodologies such as machine learning and computer vision, AI is revolutionizing the detection, mapping, and analysis of archaeological sites and artifacts. This review highlights the unprecedented speed, accuracy, and expansive scope that AI brings to the field, enabling researchers to process vast datasets and uncover previously undetectable features. While AI offers immense potential to accelerate discoveries and deepen our understanding of ancient civilizations, its effective deployment necessitates a strategic approach that acknowledges the critical need for human expertise, addresses inherent challenges related to data quality and computational demands, and navigates complex ethical considerations. The future of archaeological inquiry is increasingly defined by a synergistic human-AI collaboration, fostering a more comprehensive and globally interconnected narrative of our collective past.

1. Introduction

The field of archaeology, historically dependent on painstaking manual excavation and analysis, is experiencing a profound transformation with the emergence of Artificial Intelligence (AI). AI systems possess the capacity to revolutionize archaeological research by enabling the rapid and accurate analysis of extensive datasets (Antoniadou, 2025). While the earliest applications of machine learning (ML) in archaeology can be traced back to the 1970s (Bellat et al., 2025), their widespread adoption has surged dramatically in recent years, propelled by advancements in computing technology (Bellat et al., 2025). Recent reports highlight the successful collaboration between archaeologists and AI, which leverages techniques such as site pattern recognition and aerial image classification to identify new sites and facilitate artifact restoration (Antoniadou, 2025). This technological convergence is recognized as a game-changer for archaeologists dedicated to unravelling the mysteries of our past.

The integration of AI with traditional archaeological methodologies is reshaping the discipline into a dynamic, data-driven field (Parker, 2025). This convergence offers unprecedented opportunities to accelerate the pace of discovery and shed new light on centuries-old mysteries (Shine, 2024). While the application of machine learning in archaeology can be traced back to the 1970s, a marked increase in related publications since 2019 signals a pivotal turning point in the field's adoption of AI (Bellat et al., 2025). This recent surge reflects the convergence of several key developments: the advancement and maturity of AI algorithms, particularly deep learning; the growing accessibility of high-performance and affordable computing resources; and the rapid expansion of large-scale digital archaeological datasets, frequently generated through remote sensing technologies. These trends indicate that AI has evolved beyond being a novel tool to become a transformative and rapidly integrated component of archaeological research. Within the past five years, AI has shifted from experimental use to mainstream adoption, enabling a fundamentally new approach to exploration. This shift marks the dawn of a new era in archaeology, defined by enhanced analytical capacity, greater discovery potential, and deeper insights into the human past (Parker, 2025).

As archaeology evolves into a data-driven discipline, the quality, volume, and accessibility of archaeological data become fundamental to research success (Parker, 2025). The effectiveness of AI is dependent on the quality of the data it is trained on; in essence, its performance is only as strong as the data it learns from. This necessitates extensive efforts in data collection, meticulous digitization, and precise annotation, as exemplified by the multimodal dataset developed for Maya archaeology (Kokalj et al., 2025). These activities are not merely supportive but foundational prerequisites for successful AI integration. Consequently, data quality and availability emerge as critical bottlenecks, posing a significant challenge to the effective implementation of AI (Shine, 2024). This highlights an urgent need for standardized data models, robust data curation practices, and collaborative data-sharing initiatives across archaeological institutions to fully unlock AI's potential.

2. Core AI Methodologies for Archaeological Elements Detection

The application of AI in archaeology is underpinned by several core methodologies, each offering distinct capabilities for detecting and analyzing archaeological elements.

2.1. Machine Learning and Deep Learning

Machine learning (ML) algorithms enable computers to analyze data and identify complex patterns without being explicitly programmed for each specific task, allowing them to make autonomous predictions and decisions (Saiwa, 2025). Formally, ML involves programming computers to optimize a performance criterion by leveraging example data or past experience (Bellat et al., 2025). Deep Learning (DL), a subset of ML, has gained significant traction among archaeologists due to its exceptional capabilities in pattern recognition, predictive analysis, and image processing. Convolutional Neural Networks (CNNs) and other DL models are widely employed, particularly in conjunction with aerial and satellite imagery (Antoniadou, 2025). Artificial Neural Networks and ensemble learning collectively constitute two-thirds of the models utilized in recent archaeological ML researches (Bellat et al., 2025).

ML approaches can be broadly categorized as:

(i) Supervised Learning: This method is applied when input data is paired with annotated instances, allowing the algorithm to learn from labeled datasets in which each input corresponds to a known output. By identifying patterns in these input-output pairs, the model develops the capability to generalize and make accurate predictions on previously unseen data (Shine, 2024). Supervised learning is typically categorized into two main types: Classification, which predicts categorical outcomes (e.g., identifying the type of artifact in an image), and Regression, which estimates continuous numerical values (e.g., predicting the age or dimensions of an archaeological object based on its features).

(ii) Unsupervised Learning: This method involves training models using unlabeled datasets, allowing them to independently analyze and process data to uncover hidden patterns, connections, or clusters. Clustering, which groups comparable data points based on intrinsic attributes, and Dimensionality Reduction, which reduces the number of features while preserving essential information, are common techniques (Shine, 2024).

(iii) Reinforcement Learning: This technique centers on how an agent improves its decision-making over time by interacting with an environment. The agent receives feedback in the form of rewards or penalties based on its actions and seeks to maximize cumulative rewards by learning from these interactions and adjusting its behavior accordingly (Shine, 2024). These algorithms can assist archaeologists in optimizing excavation strategies by learning to explore sites efficiently based on the likelihood of discovering valuable elements, thereby conserving time and resources (Shine, 2024).

A notable observation is that clustering and unsupervised methods are underrepresented compared to supervised models (Bellat et al., 2025). This observation has direct implications for data collection and annotation efforts in archaeology. Supervised learning, while powerful, requires large, labeled datasets for training (Kokalj et al., 2025). This requirement explains the recurring challenge of data quality and availability and the inherent difficulty in creating extensive labeled datasets for training ML models within the archaeological domain. It also underscores the critical need for expert human annotation and highlights the value of initiatives like crowdsourcing for 3D data to generate the necessary training material (Qingli, 2025). Furthermore, this heavy reliance on supervised methods might inadvertently limit the discovery of truly novel or unexpected patterns that unsupervised methods are inherently better suited to identify, suggesting a crucial area for future methodological development and research in archaeological AI.

2.2. Computer Vision Techniques

Computer Vision (CV), a subfield of artificial intelligence, equips computers with the ability to perceive, interpret, and analyze visual information, enabling the processing of images at a scale and speed far beyond human capability (Saiwa, 2025). This powerful capability supports the automated analysis of various visual data sources, including aerial photographs, satellite imagery, and 3D reconstructions. In archaeological applications, CV allows researchers to detect subtle features often hidden beneath vegetation or soil, generate precise site maps, and monitor these locations over time for changes due to looting, erosion, or other environmental impacts (Saiwa, 2025). Object detection techniques commonly built on convolutional neural networks (CNNs) and DL models are frequently employed to pinpoint potential archaeological sites (Antoniadou, 2025). One prominent example is Ultralytics YOLOv8, a cutting-edge computer vision model utilized for object detection in vision-based archaeological site mapping (Vina, 2024).

2.3. Remote Sensing

Remote Sensing (RS) has become an indispensable tool in the global effort to document, protect, and study archaeological and cultural heritage. Its ability to conduct rapid surveys, analyze extensive spatial datasets across multiple scales, and monitor changes in archaeological sites over time has significantly advanced archaeological research. The fusion of RS technologies with AI, particularly ML and DL, has further expanded the scope and precision of archaeological investigations. These integrated systems enable the automated detection, classification, and interpretation of subtle landscape features and buried structures that are otherwise undetectable through traditional field methods (Antoniadou, 2025).

Remote sensing platforms provide multi-source data, including spectral, spatial, and temporal dimensions, which are crucial for identifying anthropogenic patterns. AI algorithms are trained to recognize specific indicators of archaeological interest such as vegetation anomalies, soil disturbances, or microtopographical shifts by learning from annotated datasets and historical patterns. This allows for scalable and efficient analysis across vast and inaccessible regions. Key remote sensing technologies integrated with AI include:

(i) Light Detection and Ranging (LiDAR): Airborne Laser Scanning (ALS) using LiDAR has revolutionized archaeological surveys, particularly in forested or vegetatively dense environments. LiDAR emits laser pulses from aerial platforms to generate high-resolution, three-dimensional maps of terrain (Opitz & Cowley, 2013). One of its key advantages is the ability to pierce through dense forest canopies by capturing ground elevations beneath vegetation layers. This has revealed hidden landscape features such as ancient road networks, platforms, water reservoirs, and settlement grids that were otherwise obscured (Parker, 2025). These capabilities have dramatically expanded the geographical reach of archaeological discovery, reducing the time and effort required for ground surveys.

(ii) Satellite Imagery: High-resolution satellite imagery, collected from systems such as WorldView-2, WorldView-3, Sentinel-1 (SAR), and Sentinel-2 (optical) has become a cornerstone of remote archaeological investigations. Machine learning algorithms applied to these datasets can detect subtle variations in terrain characteristics, including soil coloration, shadow patterns, moisture gradients, and vegetation signatures that hint at sub-surface features or man-made structures (Parker, 2025). This method is particularly effective for large-scale regional analysis, enabling archaeologists to prioritize high-potential areas for further exploration.

(iii) Synthetic Aperture Radar (SAR): SAR is a radar-based technology that can operate under all weather conditions, day or night, and can penetrate surface obstructions such as sand dunes or vegetation layers. When integrated with ML algorithms, SAR data provides detailed subsurface images that allow for the detection of buried archaeological features with exceptional accuracy (Pylessons, 2025). This technology offers a non-invasive means of exploring ancient landscapes, dramatically increasing the efficiency and safety of archaeological discovery.

The demonstrated success of combining different remote sensing data types—such as Airborne Laser Scanning (ALS), Synthetic Aperture Radar (SAR), and optical satellite imagery—in archaeological detection points to a crucial strategy for overcoming environmental limitations (Kokalj et al., 2025). Traditional archaeological survey methods, or even single-sensor remote sensing approaches, are often severely limited by environmental factors like dense forest canopies or vast, shifting sand dunes. The unique capabilities of SAR to penetrate sand and LiDAR to effectively see through forest vegetation mean that previously invisible or inaccessible sites (Pylessons, 2025). can now be detected. This multi-modal data fusion approach is not merely about accumulating more data; it is about leveraging complementary data sources that collectively overcome specific environmental obscurities (Kokalj et al., 2025). This capability has directly facilitated significant breakthroughs in difficult environments, as demonstrated by discoveries in Dubai and the Maya region (Parker, 2025). This establishes a clear relationship where advanced data fusion techniques directly lead to unprecedented archaeological discoveries in previously intractable landscapes. Table 1 provides an overview of the AI methodologies employed in the detection of archaeological elements, outlining key techniques and their applications within the field.

Poorly defined requirements and caveats of the ML methods used within archaeological contexts points to a critical challenge regarding the interpretability of AI models (Bellat et al., 2025). This observation indicates a significant gap in understanding between AI specialists who develop these models and archaeologists who apply them. For AI to be effectively and ethically integrated into archaeological practice, archaeologists need to comprehend not just what an AI model can achieve, but how it arrives at its conclusions, its inherent limitations, and the assumptions embedded within its algorithms. Without sufficient interpretability and explainability, archaeologists might either blindly trust AI results or, conversely, dismiss valuable insights due to a lack of transparency. This directly hinders the validation of results and the integration of domain expertise into the analytical process (Shine, 2024). Therefore, there is a pressing need to enhance AI model training and develop clearer, more transparent workflows tailored for archaeological applications (Bellat et al., 2025).

Table 1: Overview of AI Methodologies used in Archaeological Elements Detection

AI Methodology		Core Principle	Primary Application in Archaeology
Machine Learning	Supervised Learning	Involves training on labeled input-output pairs, enabling the model to learn the relationship between inputs and outputs and make accurate predictions on unseen data.	Classification (e.g., artifact typology), Regression (e.g., dating)
	Unsupervised Learning	Analyzes unlabeled data to uncover hidden patterns, clusters, or relationships.	Grouping similar artifacts, Exploratory data analysis, Dimensionality reduction
	Reinforcement Learning	Agent learns optimal actions through trial and error, maximizing cumulative rewards from environmental interactions.	Planning optimal excavation strategies
Deep Learning		Utilizes multi-layered (deep) neural networks to detect, learn, and process intricate patterns in data, enabling high-	Image Processing, Predictive Analysis, Pattern Recognition, 3D reconstruction

		level tasks such as image recognition, object detection	
AI Methodology		**Core Principle**	**Primary Application in Archaeology**
Remote Sensing	LiDAR	Utilizes laser pulses to generate high-resolution 3D maps of terrain, with the ability to scan through vegetation and reveal underlying surface features.	Advancing site distribution knowledge, Uncovering hidden structures beneath forests
	Satellite Imagery	Captures high-resolution images from space; analyzed for subtle surface indicators.	Predicting undiscovered ruins, Site detection and mapping
	SAR	Active remote sensing that penetrates obstacles like sand and dense vegetation.	Detecting subsurface structures, Non-invasive exploration
Computer Vision		Enables computers to perceive and interpret visual information from images/videos.	Automated analysis of visual data, Feature identification, Mapping, 3D Reconstruction
Natural Language Processing		Empowers machines to comprehend, analyze, and generate human language, facilitating tasks such as text analysis, information	Deciphering ancient languages, Text analysis of historical records

	extraction, and automated translation.	

3. Applications in Archaeological Element Detection

The transformative capabilities of AI extend across numerous facets of archaeological research, from initial discovery to detailed interpretation.

3.1. Site Discovery and Mapping

AI is revolutionizing the detection of new archaeological sites through techniques such as aerial image classification and site pattern recognition (Antoniadou, 2025). ML algorithms, trained on known archaeological sites, meticulously analyze high-resolution satellite images, including those from DigitalGlobe's WorldView constellations, Sentinel-1 SAR, and Sentinel-2 optical data, to predict where undiscovered ruins might lie (Parker, 2025). These algorithms consider subtle indicators such as topography, soil discoloration, distinct vegetation patterns, and even micro-shadowing effects to highlight regions of interest. (Castiello, 2022) presented a ML approach using the Random Forest algorithm to address archaeological challenges such as site detection and locational preferences. It analyzes data from six Swiss regions, demonstrating how the method handles heterogeneous and incomplete archaeological datasets.

For subsurface detection, ALS surveys have proven crucial for advancing knowledge in archaeological site distribution, particularly in heavily forested regions, by significantly accelerating and expanding traditional archaeological landscape surveys (Kokalj et al., 2025). Similarly, SAR technology, when combined with ML, can penetrate layers of sand and dense vegetation to detect subsurface structures with exceptional precision (Pylessons, 2025).

Archaeological Predictive Models (APMs) leverage ML to forecast the likelihood or distribution of archaeological sites by analyzing variables such as topography, soil composition, vegetation cover, and proximity to water sources (Shine, 2024). This data-driven, proactive approach enables archaeologists to allocate resources more efficiently, concentrating fieldwork in areas with the highest potential for significant discoveries. Computer vision models like Ultralytics YOLOv8 can be trained to detect subtle landscape changes such as slight variations in soil color, vegetation growth, or ground texture that may indicate the presence of buried archaeological structures (Vina, 2024).

3.2. Artifact Classification and Analysis

ML algorithms are especially effective for the fast identification and classification of archaeological features and artifacts (Bickler, 2021). DL models have extensively been applied to archaeological datasets for artifact classification. For instance, (Resler et al., 2021) developed a CNN model to analyze a diverse dataset spanning over a million years of South Levantine material culture.

Computer vision automates the traditionally time-consuming task of identifying and cataloging thousands of fragments such as pottery, bones, and other materials discovered during excavations. For example, the Arch-I-Scan project at the University of Leicester employs ML and image recognition techniques to automatically identify and document pottery fragments by analyzing their size, shape, design, and texture (Vina, 2024). AI systems, trained on extensive databases of artifacts, can identify specific styles, shapes, and even artist signatures that would be almost impossible for a non-specialist to spot, as demonstrated with Roman and Greek pottery (Parker, 2025). Additionally, AI aids in the classification of ancient butchery marks found on bones (Shaw, 2025). AI demonstrates outstanding performance in classification, clustering, and multimodal analysis for artifacts, exemplified by its application to Neolithic Baodun Culture pottery fragments (Qingli, 2025). Furthermore, AI-based reassembly techniques have successfully recovered many complete pottery objects from fragmented remains at sites like Daxinzhuang in China, significantly improving classification efficiency (Qingli, 2025).

3.3. 3D Reconstruction and Digital Preservation

AI-driven 3D modeling technologies demonstrate exceptional precision in reconstructing missing or damaged components of archaeological artifacts, even when working with incomplete inputs such as fragmented statues or partially preserved murals (Opitz & Cowley, 2013). These tools significantly outperform traditional manual reconstruction methods in terms of speed and efficiency, dramatically reducing the time required for artifact restoration (Vina, 2024). By generating high-fidelity digital models, AI algorithms can analyze fragment geometry, surface textures, and stylistic features to accurately reassemble the original objects. This not only enables precise measurement and structural interpretation but also offers deeper insights into the technological practices, artistic conventions, and cultural contexts of the civilizations that produced them (Vina, 2024). AI is instrumental in digital preservation efforts, enabling ancient murals, inscriptions, and relics that are too fragile to move to be digitally archived and recreated using AI-enhanced imaging (Parker, 2025). Combining 3D modeling with artifact analysis techniques allows for digital restoration and the recreation of ancient production processes (Qingli, 2025).

3.4. Settlement Pattern Analysis

Machine learning significantly aids archaeologists in identifying and interpreting ancient human settlement patterns (Saiwa, 2025). AI enhances the precision of archaeological discoveries, providing deeper insights into landscape usage, settlement dynamics, and cultural development over time (Amazouz, 2025). Classification techniques play a crucial role in analyzing settlement patterns (Qingli, 2025).

3.5. Deciphering Ancient Languages

AI is being employed to crack linguistic codes of lost or poorly understood languages, a task that traditionally required decades of scholarship. DL models can analyze character patterns and compare them with known languages, as recently applied to Linear B, an early Greek script (Parker, 2025). Natural Language Processing (NLP) techniques can decipher and translate ancient languages, extract key information from historical texts (such as ancient inscriptions or historical records), and identify patterns and potential linguistic connections (Shine, 2024). PYTHIA, for example, is a software developed for reconstructing texts and epigraphs using deep neural networks (Shine, 2024).

The diverse range of AI applications, extending from initial site detection to detailed artifact classification and even the decipherment of ancient languages, indicates that AI is moving far beyond mere detection to facilitating a deeper comprehension of ancient mysteries. Initially, AI's primary value in archaeology was perceived as identifying where archaeological elements are located. However, its successful application in automated artifact classification, precise 3D reconstruction, and particularly in the complex task of language decipherment signifies a profound progression (Parker, 2025). This means AI is not solely a discovery tool but an increasingly sophisticated interpretive aid, empowering archaeologists to construct a more comprehensive narrative of our collective heritage (Shine, 2024).

AI's inherent ability to process enormous quantities of data at lightning speed has a direct and transformative impact on the types of archaeological problems that can now be effectively tackled (Amazouz, 2025). Archaeological challenges such as systematically surveying vast, often inaccessible regions or meticulously reassembling thousands of fragmented pottery pieces were previously considered daunting and time-consuming or even nearly impossible when relying solely on traditional manual methods (Amazouz, 2025). AI’s exceptional speed and scalability have revolutionized the way archaeologists tackle challenges once considered intractable. These capabilities have enabled groundbreaking discoveries, such as the detection of over 60,000 previously unknown Maya structures (Parker, 2025) and the identification of more than 300 new Nazca geoglyphs in a significantly shorter timeframe that traditional methods would require (Amazouz, 2025).This demonstrates that AI is not merely performing existing tasks faster; it is enabling entirely new scales of research and discovery, fundamentally expanding the scope of archaeological inquiry.

The increasing emphasis on AI-assisted 3D reconstruction of archaeological sites and artifacts highlights AI's crucial role in proactive cultural heritage preservation. Beyond its role in discovery, AI significantly contributes to safeguarding cultural heritage against various threats, including the ravages of time, war, or climate change (Parker, 2025). The ability to create durable digital records of vulnerable sites ensures that even if physical artifacts or sites are damaged or lost, their invaluable information and historical context are meticulously preserved (Parker, 2025). This adds a critical layer of resilience and long-term security to global cultural heritage management efforts. Several case studies of AI-Assisted archaeological discovery in recent years have been presented in Table 2.

4. Challenges and Ethical Considerations

Despite the significant advantages offered by AI in archaeological detection, several challenges and ethical considerations must be addressed for its responsible and effective integration.

4.1. Data Quality, Availability, and Annotation Requirements

Archaeological data is inherently diverse, encompassing excavation records, field surveys, remote sensing data, museum collections, and historical documents, and its quality and availability can vary significantly, posing substantial challenges for AI applications (Shine, 2024). Advanced DL models require a large number of labeled samples for training but easily accessible, archaeologically labeled datasets are extremely rare (Kokalj et al., 2025). The process of labeling archaeological data is often subjective and demands specialized expert knowledge, making the creation of large-scale, high-quality labeled datasets difficult (Shine, 2024). Unlike many other scientific disciplines that might benefit from readily available, standardized, and massive datasets, archaeological data is often inherently fragmented, incomplete, and collected under a wide array of varying methodologies (Bellat et al., 2025). This means that any biases, inaccuracies, or inconsistencies present in the initial, often manually curated, training data will not only be propagated but potentially amplified by AI models, leading to systemic errors in detection, classification, or interpretation.

Table 2: Case Studies in AI-Assisted Archaeological Discovery

Case Study	Location	AI Technology Used	Archaeological Elements Detected	Outcome/Discovery
Nazca Lines (Shaw, 2025)	Southern Peru, Nazca Pampa desert	AI models, IBM AI analytical program, Drone imagery, CNNs	Geoglyphs (mysterious desert designs)	Discovery of 303 new geoglyphs has expanded the known catalog by 40%. Due to AI's sensitivity which is 20 times greater than the human eye, these features were identified much faster than traditional methods.
Maya Structures (Parker, 2025)	Guatemala/Yucatan Peninsula (e.g., Chactún)	LiDAR (ALS), AI, Deep CNNs, Multimodal annotated dataset (ALS, SAR, optical satellite)	Ancient Maya structures (e.g., buildings, platforms)	Over 60,000 previously unknown Maya structures uncovered; reshaped understanding of Maya civilization scale; up to 95% accuracy in object classification
Dubai Ancient Civilization (Pylessons, 2025)	Dubai desert, Rub' al Khali	AI, Synthetic Aperture Radar (SAR), Machine learning algorithms	5,000-year-old ancient settlements, urban planning, trade routes, structures	Uncovered hidden civilization non-invasively; challenged previous beliefs about Arabian Peninsula habitation; rapid data analysis
Case Study	**Location**	**AI Technology Used**	**Archaeological**	**Outcome/Discovery**

			Elements Detected	
GeoPACHA Project (Zimmer-Dauphinee, VanValkenburgh, & Wernke, 2024)	Andes region (e.g., Arequipa to Cuzco)	GeoPACHA web app, DeepAndesArch AI model, Satellite imagery (WorldView 2/3), Human-machine teaming	Archaeological loci (discrete remains)	Detected over 1 million archaeological loci in <5% of area; emphasizes human validation and iterative AI refinement
Automated Pottery Analysis (Qingli, 2025)	University of Leicester, Daxinzhuang site (China)	Image recognition, Machine learning, AI-based reassembly techniques	Pottery fragments, complete pottery objects	Automated identification and recording of pottery details; recovered many complete pottery objects from fragments; improved classification efficiency

4.2. Computational Demands and Technological Constraints

Advanced DL models require significant computational resources that archaeological institutions or individual researchers may lack (Shine, 2024). Practical considerations include the need to reduce computational storage and processing requirements, optimizing DL models for effective detection with small datasets remains a key challenge in automated archaeological detection (Kramer, 2021).

4.3. Interpretability and Explainability of AI Models

For AI models to be effectively adopted and in archaeology, they must offer interpretability and explainability to enable rigorous validation of their results (Kamath & Liu , 2021). Researchers need to understand which features or patterns the AI is prioritizing, validate its hypotheses, and establish transparency in the analysis and interpretation process (Adadi & Berrada, 2020).

4.4. Combining AI with Traditional Fieldwork and Expert Knowledge

Despite AI's advancements, human expertise remains necessary, and AI is best viewed as a complementary tool (Shine, 2024). Overdependence on technology could inadvertently reduce the critical thinking and creative problem-solving that human expertise brings to archaeology (Vina, 2024). AI can initially produce a high number of false positives, requiring significant human effort for validation, as seen in the Nazca project where researchers scrutinized an average of 36 AI-generated suggestions to find one valid geoglyph (Falde, 2024). As AI increasingly handles routine detection, classification, and initial data processing tasks, the core role of the human archaeologist is shifting. It transitions from primary data collection and initial identification to higher-level analysis, rigorous critical validation of AI outputs, and crucial ethical oversight. This implies that future archaeologists will require a hybrid skillset, combining profound traditional field knowledge and interpretive expertise with robust data science proficiency, to effectively harness AI tools while safeguarding the cultural and scientific integrity of the discipline.

4.5. Ethical Implications

Concerns have emerged that increased automation in archaeology may reduce the need for traditional field roles. AI-generated digital reproductions and 3D reconstructions raise complex questions about cultural ownership, especially regarding artifacts from colonized or indigenous communities (Parker, 2025). Issues of privacy, data ownership, and responsible use must be addressed (Davis & Sanger, 2021). A key ethical concern is AI's potential to learn biases from training data, leading to skewed interpretations (Amazouz, 2025). If archaeologists cannot understand or validate AI predictions, the scientific credibility of findings is undermined. Opaque or unverified AI decision-making risks misrepresenting the past, with lasting consequences for historical narratives and cultural identity (Tenzer et al., 2024). This underscores the urgent need for ethical frameworks, transparent algorithm design, and rigorous validation protocols to ensure accountability, build trust, and preserve the integrity of AI-assisted archaeological research.

5. Conclusion

Artificial Intelligence has profoundly transformed archaeological detection, enabling discoveries at unprecedented speed and scale, particularly through advanced remote sensing and image analysis techniques. Its applications have expanded significantly, spanning initial site discovery, detailed artifact classification, precise 3D reconstruction, and even the complex decipherment of ancient languages, effectively moving beyond mere detection to facilitate deeper historical and cultural interpretation. The field is undergoing rapid evolution, evidenced by a significant increase in AI-related publications and the adoption of diverse methodological applications across various archaeological subfields. The most effective and sustainable approach for integrating AI in archaeology is a human-machine teaming model, where AI performs initial feature detection and data processing, while human archaeologists provide essential validation and refine models through feedback, ensuring continuous improvement. This iterative process, coupled with adherence to well-defined methodologies, makes AI an indispensable fixture in archaeology, given its impact on efficiency and discovery rates. This necessitates a strategic shift for the archaeological community: from debating AI's use to responsibly and ethically implementing it. AI's capacity for large-scale remote sensing fundamentally alters the geographical and conceptual scope of research, enabling macro-level understanding of human settlement patterns and cultural interactions across vast, previously inaccessible landscapes, as seen with Maya structures and the Dubai desert civilization. This advancement holds the promise of fostering a more interconnected global archaeological narrative, thereby enriching our collective understanding of history.

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