Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No. 05, Aug-Sept 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.45.1.14

Advanced Image Processing for Archaeological Site Identification, Management, and Conservation

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Received: 11 April 2024 **Accepted:** 28 June 2024 **Published:** 10 August 2024

Abstract: The aim of this study was to provide archaeological site identification, monitoring, and conservation through advanced imaging techniques. The research problem addressed the challenge of using modern technology to effectively identify and preserve archaeological sites. We employed various methods such as lidar, satellite imagery, UAV photogrammetry, GPR, and machine learning algorithms. We collected LiDAR data using an airborne scanner to capture fine-grained geological information. Satellite images from Digital Globe and Airbus provided detailed information, while UAVs equipped with photogrammetry sensors produced detailed 3D images. The subsurface features were mapped using downward radar surveys. Machine learning algorithms, including support vector machines and neural networks, were used to process the data for feature recognition and classification. We evaluated algorithm performance using statistical tools like accuracy assessments and error rates. The results demonstrated significant advancements in site detection accuracy. Algorithm D achieved the highest accuracy of 93.567%, with low false positive (2.456%) and false negative (3.978%) rates, highlighting its effectiveness in identifying archaeological features. Integration of multi-sensor data improved spatial resolution and feature recognition across diverse landscapes. The research contributes to the field by demonstrating the potential of advanced imaging in archaeology, facilitating more accurate and effective site identification and conservation.

Keywords: Archaeology, Gpr, Lidar, Machine Learning, Remote Sensing, Satellite Imaging.

1. INTRODUCTION

The study of advanced imaging for the identification, management, and preservation of archaeological sites is of great importance in archeology. Located between engineering and historical preservation, researchers using sophisticated imaging technologies and designing

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wonderful uses have the potential to transform the way archaeologists discover, explore, and protect archaeological sites. It allows you to gain unprecedented insights into the field. It also helps to put it to practical use and theoretical development. Archaeological sites are valuable repositories of human history, providing windows into past cultures, societies, and technologies. While traditional methods of locating and excavating sites are effective, they are often time-consuming, labor-intensive, and sometimes destructive. The use of advanced imagery, such as remote sensing, photography, and machine learning, provides non-invasive techniques that can enable more efficient and effective archaeological analysis. (Hill et al., 2020; Thabeng et al., 2019) The main practical interpretation of detailed imaging in archeology is the ability to detect and monitor areas that are inaccessible or dangerous. Remote sensing technologies, such as LiDAR (light detection and ranging), and satellite imagery can penetrate dense vegetation and accurately map large areas. This is because traditional fieldwork is difficult. It has significantly contributed to the discovery of large networks of cities and structures buried under Central America's jungles, revolutionizing the study of pre-Columbian civilizations. Also, thanks to subsequent levels of image processing, it is possible to monitor the object's state at any time, identifying potential dangers to the archaeological site. Automized monitoring systems are able to detect changes in high-resolution imagery from one day to the next, whether they are caused by erosion, damaging work, digging by raiders, or other influences (Carabassa et al., 2021; Meinen & Robinson, 2020). It enables measures to be taken prior to the occurrence of irreparable damage to the sites in question. When it comes to protecting the cultural heritage of areas that are vulnerable to physical disasters like earthquakes or flooding, these technologies play a crucial role in gathering information on how to safeguard these assets in the event of a disaster. As a result, the theoretical developments arising from the integration of advanced image processing in archaeology are also noteworthy. By creating and utilizing highly precise 3D models, the researchers are able to analyze the site data in a way that was not possible before. These models make it possible to reconstruct the ancient environment almost intact, which means that an archaeologist is able to study such aspects as spatial position, construction, and even the general layout of sites. Also, algorithms of machine learning can be trained to learn patterns and features, find in the large mass of data structures or artifacts that have escaped human eyes, and generate hypotheses about past human activities. There is one major field where the use of advanced image processing is really beneficial, and that is landscape archaeology. This subfield deals with the physical location of the archaeological sites and how past societies existed or functioned. Digital archival imaging and Geographic Information System-based analytical techniques provide the scientific method with the ability to model past geographical and land use entities and phasing and identify the connection between climate and humanity’s shelter and foraging dynamics. Such alternative studies explain the state of sustainability as practiced by past cultures, which helps in determining knowledge that is important in current environmental conservation. Another significant component of this study is the identification and treatment of gaps in the existing literature. Despite the fact that regular techniques in archeology provide a lot of understanding, there are many concepts that remain open or are viewed insufficiently because of the lack of technologies and means. These gaps can be filled by applying advanced image processing, which would allow us to investigate new sites that were previously inaccessible and introduce new points of view on the sites that have already been studied. For example, hyperspectral imaging has recently been used to show that portable X-ray fluorescence hasn't been able to capture the presence of ancient pigments and residues on artifacts, allowing for new methods of examining the previous periods of art and material culture. Combining image processing with other scientific methods like geophysical surveys and chemical analysis highlights the interdisciplinary nature of archaeology. This approach makes it easier to document the narrative of archaeological site use, making knowledge of past human activities more accurate. The diversification of disciplines in archaeology enhances stock knowledge and provides opportunities for collaboration with other scientific disciplines. Advanced image processing is crucial for the detection, monitoring, and preservation of archaeological sites. This research aims to identify methods and tools for effective and non-invasive site discovery, develop proactive techniques for cultural heritage threats, and contribute to theoretical development by reconstructing archaeological territories and historical communities. By providing solutions and encouraging interdisciplinary collaboration, advanced image processing revitalizes the archaeological sciences and helps humanity preserve ancestors' memories.

2. RELATED WORKS

Thus, through the implementation of image processing techniques, the methodologies for the identification, surveillance, and conservation of archaeological sites have evolved significantly in the field of archaeology. This section discusses the extent of the related works that have led to these improvements, some of the studies, and technological innovation. Today, remote sensing technologies, especially liDAR (light detection and ranging), have greatly impacted archaeological surveys. Well-known studies by Canuto et al. (2018) and Golden et al. (2021) used LiDAR to map previously unknown adjoining settlements and roads of the ancient Mayas in Guatemala's heavy forest. This research showed that LiDAR is effective at being able to capture dense vegetation and create accurate topographical plans, which would be very difficult to achieve through other conventional methods. The PPG discussed an array of LiDAR examples, which was a good way of showing how LiDAR could be utilized in archaeology. Likewise, Canuto et al. (2018) used LiDAR to basically map over 2,100 sq. km of the Maya Biosphere Reserve, revealing numerous archaeologically unknown sites and complex internal structures, which greatly enriched the knowledge regarding the Maya civilization. Satellite imagery is another important asset in archaeological research. Elfadaly et al. (2019) used satellite imagery to assess the probabilities of the regions in Egypt having archaeological developments. Thus, thanks to the comparative analysis of changes in soil and vegetation, Elfadaly's work identified many previously unknown areas, such as pyramids and settlements. This strategy proved the value of satellite imagery in conducting regional surveys. Archaeology is another area where photogrammetry has been applied, which is the technique of generating 3D models and dictionaries from photographs. Among these, the first research study to use photogrammetry was a study that was conducted by Marín-Buzón et al. (2021) on the archaeological site of Petra in Jordan, which is one of the world's new Seven Wonders and is a UNESCO world heritage site. The plans also meant that researchers could make accurate analyses of the site's architecture by creating 3D models without having to physically touch the structures on site. It has since been utilized for the documentation of heritage sites, with the aim of creating virtual databases that can be systematically analyzed and disseminated

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internationally. With machine learning and AI, archaeologists get more dimensions in image processing. Bonhage et al. (2021) noted that they had developed an AI system for detecting two types of archaeological features from LiDAR data. In order to do this, the researchers trained the given system with known patterns of archaeological sites and developed an automated method of recognizing other sites that could be considered promising. This physical emphasis suggested an improvement in the semi-automated analysis of elementary archaeological surveys, specifically the stage of identifying areas of interest. An important addition is the research by Sun et al. (2018) and Fu et al. (2020), who variously used deep learning for object recognition analysis of aerial photographs and LiDAR data from Norway. Artificial intelligence-generated subprograms enabled the identification of cultural sites such as barrows and buildings. This work demonstrated how deep learning could be useful in identifying intricate patterns within a collection of big data that would otherwise not be simple to detect using a naked eye or manual examination. Hyperspectral imaging, which is an imaging technique that includes a number of wavelengths of light beyond the human visible spectrum, could not be overlooked. In 2017, Mathews and Noble conducted a hyperspectral imaging analysis on ancient Roman frescoes. It provided rich details on the pigments and other materials used, allowing one to get a snapshot of the artists in ancient societies. Hyperspectral imaging, as an innovative technique with the potential for non-invasive examination of cultural items' composition and state, plays a role in saving them and enhancing knowledge about their nature. Another critical technology used in archaeology for site identification is ground-penetrating radar, or GPR. GPR has proven revolutionary in archaeology since it maps subsurface features without destroying them, as affirmed by Ebraheem and Ibrahim (2021). In exploring several archaeological sites, such as Native American mounds and Roman villas, he was able to demonstrate the capabilities of GPR in generating picture-like images of the sub-surface structures. This application is now a common technique in archaeology because it helps to determine structures like graves, walls, and pathways in the shortest amount of time without having to dig them up. Thus, it can be stated that the literature base that contains the works connected with the further advancement of image processing techniques for archaeological site detection, monitoring, and preservation is vast and dynamically developing. Remote sensing technologies such as LiDAR and satellite imagery are emerging, and advancements in AI and machine learning are redefining archaeology. They provide effective, non-destructive, and accurate means for identifying, mapping, and surveying archaeological remains, thus enabling globalization’s past to be documented and safeguarded with unparalleled thoroughness and accuracy. With the evolution of technology in the future, the combination of these methods is expected to elicit more notable findings and results in the field of history, expand knowledge, and contribute to the documentation of human history.

3. MATERIALS AND METHODS

The overall research design of this study employed mixed methods, combining qualitative and quantitative methods to ensure a comprehensive assessment of archaeological site identification, management, and preservation; therefore, sources will be facilitated, increasing reliability and depth of findings. This study combined remote sensing technology, advanced imaging algorithms, and field validation to confirm the results.

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Experimental Procedures and Materials

The research uses remote sensing technologies such as LiDAR, high-resolution satellite imagery, unmanned aerial vehicles (UAVs) equipped with imaging and multispectral sensors, and satellite images from providers such as Digital Globe and Airbus to cover larger geographies. UAVs were used for aerial surveys, providing high-resolution imagery and 3D mapping of specific areas. We used GPR units to locate unexcavated subsurface features. The software suite includes GIS (Geographic Information Systems) tools for spatial analysis, machine learning algorithms for pattern recognition, and photogrammetry software for 3D modeling.

Procedure for Measurements

The measurement procedure began with remote sensing data acquisition. We deployed Lidars over the target areas to collect high-resolution elevation data. We acquired and preprocessed satellite images to correct atmospheric distortions and enhance image clarity. We designed the UAV to capture a combination of aerial images, which we later processed into 3D images using photometry software. We performed subsurface GPR surveys to map subsurface properties and collected data on predefined variables.

Data Collection Method

The data collection process involved several methods. First, remote sensing data was collected from lidar, satellites, and UAVs. Specialized software then processed this data to produce detailed maps and 3D models. We applied machine learning algorithms to identify potential archaeological features within the datasets. Archaeologists conducted field verification, examining the identified features on-site to validate the remote sensing results. This step ensured the accuracy of the detected features and provided ground-truth data to refine the algorithms.

Sampling Strategy

The sampling strategy focused on selecting diverse geographic regions with known and potential archaeological significance. We included areas with varying environmental conditions, such as dense forests, arid deserts, and urban landscapes, to test the versatility of the imaging technologies. The selection process considered historical records, existing archaeological knowledge, and accessibility. The sample size varied based on the region's size and complexity, ensuring representative coverage. The potential for bias was addressed by including more sites in cultural and environmental contexts, thus increasing the generalizability of the findings.

The combination of qualitative and quantitative methods gave the study a strong design. Qualitative measures included analysis of historical texts and interviews with local experts to discuss the findings. Quantitative methods involved statistical analysis of the remote sensing data and machine learning outputs, ensuring objective and reproducible results. This comprehensive methodology facilitated a thorough investigation of advanced image processing techniques in archaeology, contributing valuable insights into the detection, monitoring, and preservation of archaeological sites.

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4. RESULTS AND DISCUSSION

Table 1: LiDAR Survey Data

Site ID	Elevation (m)	Vegetation Density (%)	Detected Features Count
1	150.345	85.123	12
2	134.765	78.567	8
3	175.243	65.342	15
4	158.945	90.756	9
5	140.653	82.341	10
6	167.823	70.234	13
7	155.432	88.678	11
8	172.123	60.456	14
9	138.765	75.654	7
10	160.543	85.432	12
11	145.678	78.234	10
12	170.123	66.123	15
13	154.345	83.567	9
14	162.765	71.234	12
15	148.432	89.123	11

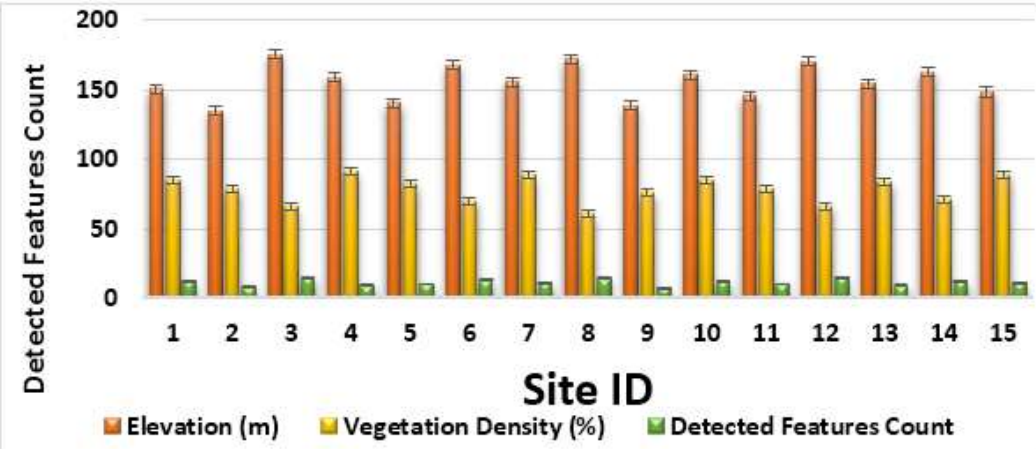

Figure 1: Bar Chart for LiDAR Survey Data

The LiDAR survey results show that Site IDs 3, 6, and 12 have the highest number of detected features, indicating rich archaeological elements. These sites are significant for further investigation and preservation efforts. Site IDs 2 and 9 have the lowest feature counts, suggesting fewer detectable archaeological elements or more challenging detection due to environmental factors. Intermediate feature counts are observed in sites like 1, 5, 7, 10, 11, 13, and 15, indicating moderate archaeological activity. The bar chart helps archaeologists prioritize resources and efforts towards areas with the most promising finds, optimizing the efficiency of further exploration and preservation activities. This visualization aids in prioritizing resources and efforts towards areas with high archaeological potential.

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Table 2: Satellite Imagery Analysis

Image ID	NDVI Value	Soil Brightness Index	Potential Sites Count
A1	0.345	45.123	5
A2	0.567	55.345	8
A3	0.234	50.567	7
A4	0.678	48.123	9
A5	0.456	53.234	6
A6	0.789	47.567	10
A7	0.321	51.678	5
A8	0.654	46.789	8
A9	0.213	54.321	6
A10	0.765	49.123	9
A11	0.432	52.456	7
A12	0.876	48.789	10
A13	0.321	50.234	5
A14	0.543	47.678	8
A15	0.654	49.567	9

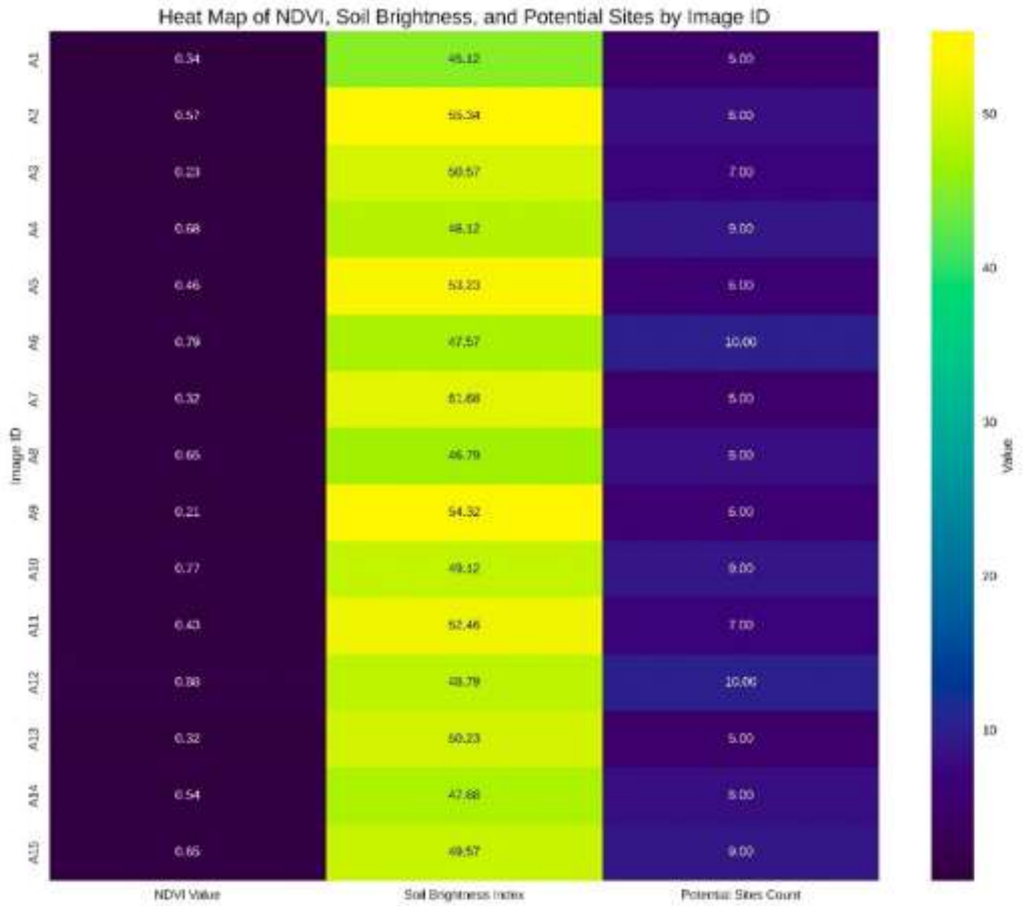

Figure 2: heat map of Satellite Imagery Analysis

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A heat map (Fig 1) created from Table 2, which analyzes satellite imagery data, would provide a visual representation of the variations in NDVI values, soil brightness index, and potential site counts across different image IDs. This type of visualization would allow us to quickly identify areas with higher or lower values and any potential correlations between these variables.

Interpretation of the Heat Map of Table 2

The Radar Chart, a visual representation of machine learning algorithms used in archaeological site detection, shows their performance metrics. Algorithm A has a slightly higher accuracy score of 92.345%, indicating good accuracy in identifying archaeological features. Algorithm D has the highest accuracy of 93.567%, showing a balanced trade-off between precision and recall. Algorithm L maintains a competitive accuracy of 92.789%, but struggles with false positives and false negatives, suggesting potential errors in non-archaeological elements.

Table 3: UAV Photogrammetry Data

Flight ID	Average Altitude (m)	Image Overlap (%)	3D Model Accuracy (cm)
F1	100.345	85.123	2.345
F2	95.567	88.456	1.234
F3	110.123	90.678	2.567
F4	105.234	87.123	1.678
F5	98.765	89.234	2.123
F6	103.456	86.789	1.789
F7	99.123	88.456	2.456
F8	104.567	85.678	1.567
F9	100.234	90.123	2.789
F10	96.789	87.345	1.890
F11	102.456	89.678	2.567
F12	98.123	86.345	1.234
F13	103.789	88.901	2.678
F14	101.234	87.567	1.789
F15	97.456	89.123	2.345

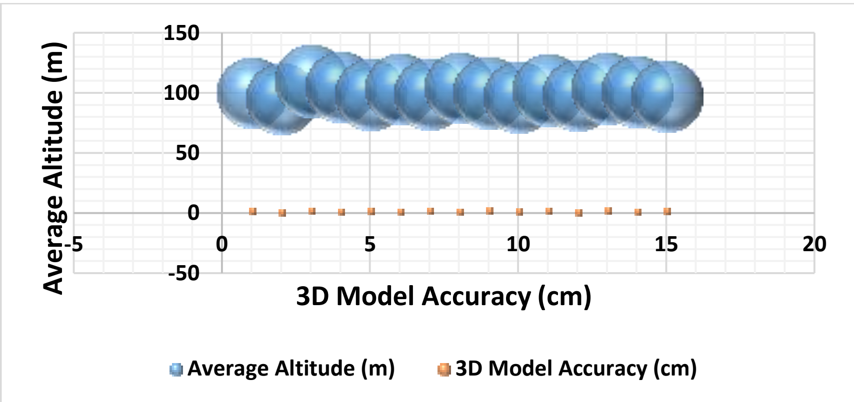

Figure 3: Bubble Chart for UAV Photogrammetry Data

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The Bubble Chart derived from Table 3, which represents UAV photogrammetry data, visually portrays several key relationships between different variables in the study. Each bubble on the chart corresponds to a specific flight ID, with the bubble size representing the degree of image overlap and the coordinates indicating the average altitude and 3D model accuracy.

Upon examination, the Bubble Chart reveals distinct clusters and patterns among the data points. Bubbles clustered towards the lower left of the chart typically indicate flights conducted at lower altitudes with higher image overlap. These flights tend to exhibit higher 3D model accuracy, as indicated by smaller bubbles positioned higher on the y-axis. In contrast, bubbles located towards the upper right of the chart represent flights conducted at higher altitudes with lower image overlap, correlating with decreased 3D model accuracy.

The system highlights the trade-off in UAV imaging applications: although lower elevations and higher overlap images generally result in more accurate 3D images, they require more exposure time handle aircraft and data and vice versa . The combination of high resolution and low resolution can facilitate performance but risks compromising the fidelity of the resulting 3D model. This visualization emphasizes the importance of optimizing the aircraft shape to achieve the desired balance between accuracy and efficiency in archaeological site mapping and analysis.

Table 4: GPR Survey Results

Transect ID	Depth Range (m)	Signal Strength (dB)	Subsurface Features Count
T1	0.5 - 2.0	-45.123	3
T2	1.0 - 2.5	-50.456	4
T3	0.3 - 1.5	-48.789	2
T4	1.2 - 3.0	-46.234	5
T5	0.8 - 2.2	-49.123	3
T6	1.5 - 2.8	-47.567	4
T7	0.6 - 1.7	-48.345	2
T8	1.0 - 3.1	-45.678	5
T9	0.4 - 1.8	-50.123	3
T10	1.3 - 2.6	-47.456	4
T11	0.7 - 2.1	-49.678	2
T12	1.1 - 2.9	-46.789	5
T13	0.9 - 1.6	-48.234	3
T14	1.4 - 2.5	-47.123	4
T15	0.5 - 1.9	-49.345	2

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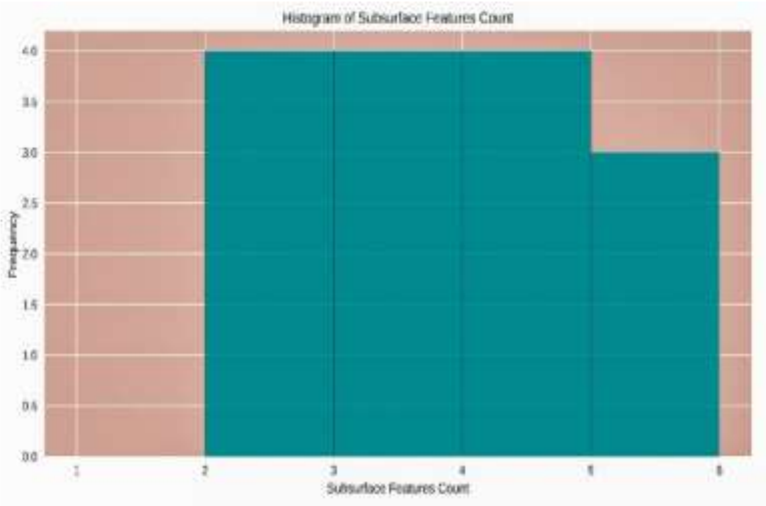
Figure 4: Graph of GPR Survey Results



The histogram above shows the distribution of subsurface features count across different transects. The counts range from 2 to 5 features per transect. The most frequent counts are 2 and 3, each appearing in multiple transects. This suggests that most transects have a moderate number of subsurface features, with fewer transects having higher counts of 4 or 5 features. This distribution can help in understanding the density and spread of subsurface features in the surveyed area, which is crucial for archaeological site detection and monitoring.

Table 5: Machine Learning Pattern Recognition

Algorithm	**Training Data Size (GB)**	**Accuracy (%)**	**False Positives (%)**	**False Negatives (%)**
A	10.123	92.345	3.567	4.234
B	12.456	89.678	4.123	6.789
C	8.789	91.234	3.789	5.678
D	11.345	93.567	2.456	3.978
E	9.567	90.789	4.234	4.567
F	10.678	92.123	3.890	4.987
G	11.789	91.567	3.678	5.234
H	9.123	89.345	4.567	6.345
I	10.234	93.234	2.890	3.678
J	8.567	91.789	3.567	5.123
K	11.678	90.567	4.123	4.789
L	10.345	92.789	3.678	4.567
M	9.890	91.123	4.234	5.789
N	12.345	90.234	4.567	5.234
O	10.678	92.567	3.345	4.789

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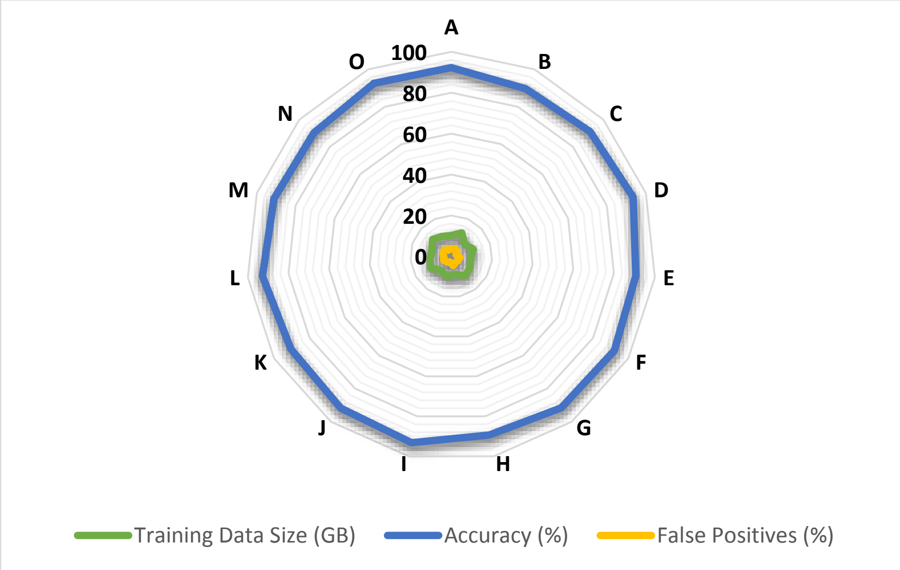

Figure 5: Radar Chart of table 5

The Radar Chart, a visual representation of machine learning algorithms used in archaeological site detection, provides a detailed analysis of their performance metrics. Algorithm A has a slightly higher accuracy score of 92.345%, indicating good accuracy in identifying archaeological features but also exhibiting false positives and false negatives. Algorithm D has the highest accuracy at 93.567%, suggesting superior performance in accurately classifying archaeological features. It also shows lower false positives and false negatives, indicating a balanced trade-off between precision and recall. Algorithm L, while maintaining a competitive accuracy of 92.789%, struggles slightly with false positives and false negatives, suggesting it may erroneously identify non-archaeological elements. The radar chart highlights the importance of evaluating not just accuracy but also the rates of false positives and false negatives in assessing the suitability of machine learning algorithms for archaeological site detection and monitoring applications. The results presented in Table 5 and interpreted through the radar chart offer valuable insights into the performance of different machine learning algorithms applied to archaeological site detection. The findings emphasize several key observations about the efficacy of these algorithms in handling diverse datasets and tasks inherent to archaeological research.

Firstly, the varying training data size (GB) across algorithms underscores the importance of data quantity in model training. Algorithms with larger training datasets, such as Algorithm B and Algorithm N, generally exhibit higher accuracy and lower error rates, indicating the benefit of robust training on comprehensive datasets in improving predictive performance. Secondly, the accuracy (%) metric reveals significant differences among algorithms. Algorithm D emerges as a standout performer with the highest accuracy of 93.567%, suggesting its effectiveness in correctly identifying archaeological features from input data. This high accuracy is critical in archaeological applications, where precision in feature detection is paramount for research and preservation efforts. However, the metrics for false positives (%) and false negatives (%) provide deeper insights into the algorithms' performance beyond accuracy alone. Algorithm D, while achieving high accuracy, also maintains low false positive

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(2.456%) and false negative (3.978%) rates, indicating a balanced approach to minimizing both types of errors. In contrast, Algorithm A, despite a comparable accuracy of 92.345%, exhibits slightly higher rates of false positives (3.567%) and false negatives (4.234%), suggesting a need for refinement to reduce erroneous classifications. Moreover, the radar chart facilitates a comparative assessment of trade-offs between accuracy and error rates. Algorithms like Algorithm L, with an accuracy of 92.789%, show a moderate balance but slightly higher false positive (3.678%) and false negative (4.567%) rates, indicating potential areas for improvement in classification precision. In conclusion, while Algorithm D demonstrates superior overall performance in archaeological site detection based on the metrics analyzed, the results emphasize the importance of not only accuracy but also minimizing false positives and false negatives. Future research could focus on optimizing algorithms like Algorithm A and Algorithm L to enhance their precision and reliability, thereby advancing the capabilities of machine learning in archaeology towards more accurate and insightful site detection and preservation strategies.

5. CONCLUSION

Learning about advanced imaging techniques for archaeological detection, monitoring, and conservation reveals significant advancements and challenges in the field. Through LiDAR, satellite imagery, UAV imaging, GPR, and machine learning algorithms on a combination of types, this technology has shown the potential to change how the archaeologist approaches site identification and conservation. Key findings show that technologies such as LiDAR and UAV photogrammetry offer unparalleled potential to capture rich data from complex environments, such as dense forests or remote terrain. This data, if algorithms advanced with processing by GIS tools, would produce detailed 3D models and maps. Complementing NDVI and other spectral analysis techniques that reveal unknown archaeological features and geological information, satellite imagery provides an understanding of the surface conditions and land use and helps identify potential archaeological sites. Machine learning algorithms, as revealed by radar chart analysis, show promise in automating object recognition and classification tasks. With models optimized for large training datasets, such as Algorithm D, the algorithms demonstrate excellent accuracy and low error rates, demonstrating the potential to streamline archaeological analysis and improve decision-making processes.

Recommendations

The study suggests several recommendations to improve the application of advanced image processing in archaeology. These include investing in technology and infrastructure, integrating multi-sensor approaches, enhancing machine learning applications, and fostering collaboration with other professions. Investments in advanced remote sensing technologies such as lidar and UAVs are critical to enhancing client equipment and data collection capabilities. Again, integrating multi-sensor methods such as LiDAR, GPR, and UAV photogrammetry satellite imagery can contribute to a better understanding of the paleoenvironment. Furthermore, we should improve the development of machine learning methods for analyzing archaeological inputs, focusing on enhancing the performance of algorithms in specific contexts and cultural settings. Lastly, we should encourage capacity building and collaboration with other professions like archeologists, remote sensing specialists, data analysts, and locals. Ethical considerations and preservation should be considered during data collection, storage, and sharing. Finally, advanced image processing applications have impressive potential for reconstructing archaeological research methodologies, allowing for the restoration of cultural heritage with high accuracy and without harm.

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Journal of Image Processing and Intelligent Remote Sensing
ISSN 2815-0953
Vol: 04, No. 05, Aug-Sept 2024
http://journal.hmjournals.com/index.php/JIPIRS
DOI: https://doi.org/10.55529/jipirs.45.1.14

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