Automated Ai-Driven Feature Extraction for Archaeological Site Detection in the North Peninsular Malaysia, Bujang Valley

Shairatul Akma Roslan[1], Rahinah Ibrahim[2], Normaisharah Mamat[3]

[1]Department of Landscape Architecture, Faculty of Design and Architecture, Universiti Putra Malaysia
43400 Serdang, Selangor D.E., Malaysia

[2]Department of Architecture, Faculty of Design and Architecture, Universiti Putra Malaysia
43400 Serdang, Selangor D.E., Malaysia

[3]Department of Intelligence Informatics, Faculty of Artificial Intelligence, Universiti Teknologi Malaysia Kuala Lumpur,
Jalan Sultan Yahya Petra, 54100 Kuala Lumpur, Malaysia.

***Abstract*—The comprehensive study begins by examining the current landscape of archaeological site detection, focusing on the integration of advanced technologies; and Artificial Intelligence-Remote Sensing (AI-RS) driven feature extraction. Identifying a critical issue related to the precision of archaeological site identification and the lack of interpretative frameworks poses significant challenges to archaeologists and technology makers. This research departs from traditional approaches by bridging the gap between automated detection and qualitative interpretation, specifically targeting the prominent archaeological heritage complex of the Bujang Valley in North Peninsular Malaysia. Through a case study approach, incorporating interviews and field observations, this study systematically investigates the application of AI-RS-driven methodologies, aiming to develop a more effective and innovative way to enhance archaeological feature detection and interpretation. This comprehensive study is improving the preliminary study's result from "Artificial Intelligence-Remote Sensing for Rapid Mapping of Potential Archaeological Features using Image Classification: Bag of Visual Words-based". The expected output will contribute to the field by providing new insights into identifying potential hidden archaeological areas using automated detection AI-RS. By synthesizing technical robustness with contextual understanding, the research fosters a more comprehensive understanding of archaeological environments, advancing both technological development and archaeological interpretation practices.**

Keywords: Artificial Intelligence, Remote Sensing; Feature Extraction; Archaeology; Bujang Valley

I. INTRODUCTION

There is a significant body of work exploring the application of artificial intelligence (AI) in automating the detection of archaeological sites. Lambers et al. (2019) have contributed to this discourse by demonstrating how AI techniques can effectively identify potential archaeological sites through pattern recognition and analysis. Meanwhile, Roslan et al. (2024) focus on machine learning (ML) techniques to enhance the archiving process. Their research highlights that ML algorithms when trained with geological data, can improve the prediction accuracy of site locations. Nonetheless, while both studies underscore the transformative potential of AI and ML, the integration of these technologies into current archaeological practices remains a challenge, partly due to technological limitations and the need for substantial field data to improve model training. Despite the progress made, a critical analysis of Lambers et al. (2019) and Roslan et al. (2024) reveals a gap in how these technologies are tailored to specific archaeological environments, such as the complex landscapes found in areas like Bujang Valley. While Lambers et al. (2019) focus on generalized AI models, Roslan et al. (2024) emphasize the adaptability of ML models. There is, however, a lack of consensus on which approach yields more accurate detection rates across diverse archaeological sites. This inconsistency points to the necessity for further empirical studies that directly compare both AI and ML models under controlled conditions and varied environmental scenarios.

Nevertheless, the interdisciplinary nature of these studies provides a worthwhile exploration of AI's capabilities and its limitations. Soroush et al.

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(2020) posit that the application of AI in archaeology allows researchers to uncover sites that might be overlooked due to human error or limited temporal scope. On the other hand, Hoerr et al. (2014) assert that ML's iterative learning capacities enable ongoing improvements in detection accuracy. This debate highlights the need for an integrative framework where AI and ML complement each other's strengths, providing a robust tool for archaeologists. Although these advancements, a pressing issue remains in the operationalization of these technologies in real-world scenarios. Both Huang et al. (2019) and Laugier et al. (2021) acknowledge the importance of feature extraction and its role in enhancing detection accuracy. However, there is limited discussion on the specific feature sets relevant to varied archaeological settings, which can result in underutilized or misapplied techniques. This underscores the necessity for developing standardized feature extraction processes tailored to archaeological contexts, ensuring that AI and ML applications can be more widely adopted and validated. Furthermore, ethical considerations related to data usage and site preservation have yet to be thoroughly addressed, indicating another area where future research could contribute significantly.

In examining the field of artifact recognition, Remote Sensing (RS) plays a pivotal role in refining the accuracy of identification and classification processes, as elaborated by Khan et al. (2018). Their research illustrates how modern sensor arrays can capture detailed data, effectively supporting AI-driven recognition systems. However, the integration of these RS sensors with existing AI algorithms to enhance accuracy remains underexplored, pointing to a potential research gap. A collaborative approach merging sensor advancements with AI could bridge this gap, improving the nuance in artifact recognition. As Khan et al. (2018) have elucidated, the sensors employed exhibit high precision in collecting data pertinent to artifact characteristics. Nevertheless, the processing of this data through currently available AI models often overlooks the unique attributes of certain artefactual categories. This suggests a need for more specialized AI models that can accommodate the intricacies of data produced by advanced sensors, which current literature, including Khan's, does not fully address.

Notwithstanding these challenges, the potential synergy between RS sensor technology and AI in artifact recognition is a promising avenue. Opitz et al. (2018) emphasize the importance of real-time data collection and processing, which could radically transform how artifacts are identified in the field. Yet, the literature does not sufficiently discuss the constraints of RS sensor technologies, such as data overload and the environmental factors affecting sensor accuracy. Addressing these issues through targeted research could unveil new methodologies that optimize both AI and sensor capability. An emerging discourse among researchers like Khan et al. (2018) centers on the refinement of recognition accuracy, which remains paramount in archaeological digitization efforts. While sensor technology adds a layer of depth to AI's analytical power, the development of context-aware algorithms is still in its infancy. This points to an important gap, as the integration of contextual data could potentially elevate the precision of artifact recognition and classification. As the fields of sensor technology and AI continue to evolve, so too must our approach to leveraging these advancements, ensuring that archaeology as a discipline can fully harness the possibilities they offer.

II. BACKGROUND STUDY

The integration of Artificial Intelligence (AI) and Remote Sensing in archaeology has unlocked new potentials in automated detection and feature extraction, particularly in analyzing archaeological sites. Roslan et al. (2024) advanced this field by focusing on the use of satellite imagery to auto-detect archaeological features, which underscores a significant leap toward more efficient and accurate analyses of large sites. Despite this progress, the study emphasizes that while AI offers precision and efficiency, there remains a critical gap in addressing the contextual understanding of these findings. Technology can identify potential archaeological features, but the historical and cultural context must still be interpreted by experts to ensure accurate insights. Moreover, Sharafi, et al. (2016) delve into the potential of artificial intelligence to automate the detection of archaeological features within satellite imagery. Their investigation highlights the capability of AI-based applications to analyze and extract features with minimal human oversight, thus addressing some of the limitations noted by Tapete (2018). Despite this, there is an inherent complexity in ensuring the precision and reliability of such automated systems. The implementation of AI could lead to a paradigm shift in feature extraction; nevertheless, the blend of qualitative insights remains indispensable for contextual understanding in archaeological research. Costa et al. (2018) introduced the Bag of Visual Words (BOVW) method focusing on automated detection and feature extraction, a significant aspect in the development of Artificial Intelligence applications.

Nevertheless, there are important historical and heritage considerations requiring attention, as highlighted by Pavlidis (2019). The research underlines the value of heritage in preserving cultural narratives, asserting that technology, while a boon in managing vast datasets and mapping sites, cannot replace the nuanced understanding that

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human researchers bring to the fold. Despite the promising capabilities of AI in identifying physical features, Pavlidis draws attention to the ongoing necessity of human interpretation to validate and contextualize these discoveries within the broader spectrum of heritage studies. Pavlidis (2019) also underscores the importance of situating technological advancements within the broader context of cultural heritage. While acknowledging the transformative potential of tools like AI in archaeology, Pavlidis suggests that the humanistic implications of these technologies must be carefully considered. There is an opportunity to not only automate archaeological processes but to also deepen the understanding of cultural legacies. Therefore, as automated systems become more prevalent, incorporating expert knowledge into their design and implementation becomes crucial.

In the realm of archaeology, automated methods like AI-driven feature extraction can identify site features with precision. Nevertheless, interpretation as discussed by Santos et al. (2013) remains crucial in contextualizing these detected features within the broader historical and cultural narratives. This dichotomy highlights a shortfall in current literature, where the application of automated detection technologies often lacks the depth brought by qualitative interpretative frameworks. The data will be analyzed using content analysis. This approach involves systematically examining the data to extract themes related to automated feature extraction and archaeological site detection. Content analysis is suitable for this study because it allows for the identification and categorization of patterns that are crucial for understanding AI applications in archaeology. The analysis will include coding textual and visual data, identifying recurrent themes, and interpreting these concerning the AI-RS-driven methodologies and archaeological contexts.

Exploring specific regional applications with AI advancements, Naizatul et al. (2018) discuss the significance of leveraging modern technological tools in heritage sites such as Bujang Valley. They argue that the incorporation of AI-driven applications in archaeological research at Bujang Valley highlights both the potential and the limitations of reliance on automated detection systems. Although these systems enhance feature extraction, the researchers emphasize that without qualitative expertise in cultural preservation and interpretation, the data's relevance to heritage conservation may be compromised. In contrast, Roslan et al. (2024) and Tapete (2019), technological advancements can provide robust tools for data collection and preliminary analysis, and the synthesis of these findings into meaningful heritage conservation strategies requires a nuanced human touch. However, there is still a need to bridge the technological potential with the intricate narratives and interpretations that human experts can provide. Pavlidis (2019) also underscores the importance of situating technological advancements within the broader context of cultural heritage. While acknowledging the transformative potential of tools like AI in archaeology, Pavlidis posits that the humanistic implications of these technologies must be carefully considered. There is an opportunity to not only automate archaeological processes but to also deepen the understanding of cultural legacies. Therefore, as automated systems become more prevalent, incorporating expert knowledge into their design and implementation becomes crucial. Bridging the technological with the interpretive not only addresses existing gaps but also enriches the understanding of archaeological environments, thus paving the way for the development of advanced applications that are both technically robust and contextually informed.

Therefore, in this study, the integration of AI-RS applications presents transformative tools for archaeology, particularly in feature extraction and heritage preservation. It is essential to maintain a balance between technological efficiency and qualitative depth. The effectiveness of such technologies relies not only on their technological sophistication but also on the collaboration with archaeologists and heritage experts to interpret the data meaningfully. As technological applications continue to evolve, connecting these gaps necessitates a balanced approach that values both machine efficiency and human expertise, ensuring that cultural heritage is preserved with depth and precision. The field of archaeology has long benefited from advancements in technology, with recent developments highlighting the pivotal role of satellite imagery for the detection and analysis of archaeological sites which can reveal previously undetected features on the earth's surface. However, while this approach provides a macroscopic view of potential sites, a significant challenge remains in accurately interpreting these images without substantial human intervention. This gap opens the door for the integration of artificial intelligence into remote sensing, promising to transform how archaeological features are detected.

III. STUDY AREA

The Civilization of *Kedah Tua*, Bujang Valley, Malaysia.

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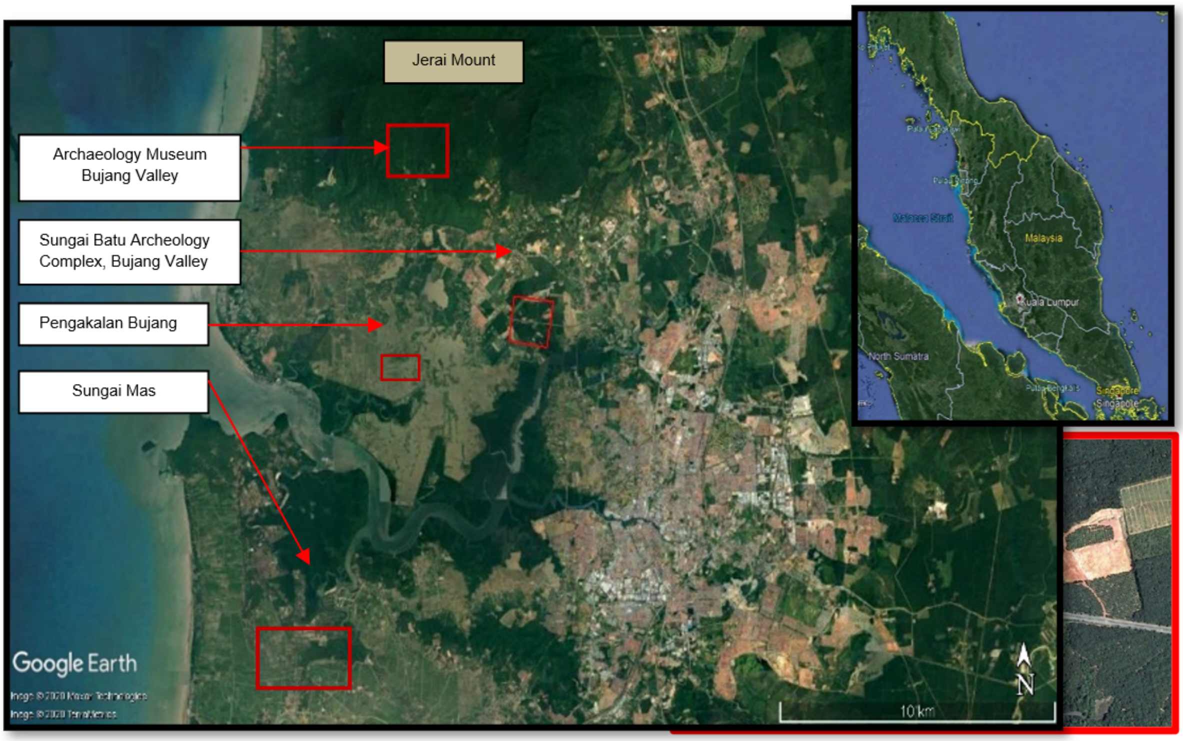

Figure 1. Key Map of Peninsular Malaysia and the four-spotted locations of archaeology areas in Bujang Valley, Kedah region (Source: Google Earth Pro).

The Bujang Valley, located in Merbok, Kedah, Malaysia, is a historically archaeological complex recognized for its role as an ancient Southeast Asian hub for trade, industry, and settlement, dating back to the 6th century BCE. Known as the kingdom of *Kedah Tua* (Ancient Kedah), the valley spans 144 square miles, bounded by Bukit Choras in the north, the Muda River in the south, the Straits of Malacca to the east, and the North-South Expressway to the west (refer Figure 1). The site includes prominent archaeological areas such as Sungai Batu Archaeological Complex, Archaeology Museum Bujang Valley, Pengkalan Bujang, and Sungai Mas, which have yielded abundant artifacts through extensive investigations. Historically, the valley served as a key center for black iron production, a temporary stopover for sailors navigating between the Bay of Bengal, the Straits of Malacca, and regions as far as India, the Middle East, and China. Geophysical studies reveal that parts of the valley were submerged during the 1st and 2nd centuries, with significant changes in the Muda River's flow and sea levels from the 9th to 15th centuries. Mount Jerai, a landmark at 1,300 meters above sea level, was a vital navigational point and held spiritual significance. Today, the valley, characterized by mountainous terrain, river valleys, and beaches, features a landscape dominated by oil palm trees and shrub vegetation. Its cultural and historical value is further underscored by its inclusion in the UNESCO World Heritage list and its representation in the Bujang Valley Archaeology Museum. Therefore, this study focused only on the area of Sungai Batu, Bujang Valley concurrently with the preliminary study of identifying hidden archaeology in the area of Museum Archaeology Bujang Valley (Roslan et al., 2024).

IV. METHOD AND RESULT

The comprehensive study employed a case study approach to investigate automated AI-RS-driven feature extraction for archaeological site detection in the specific site in Bujang Valley. Two different locations were tested shown in the red boxes in Figure 2. The previous study area is an Archaeology Museum at Bujang Valley that has been experimenting during preliminary study (Roslan et al., 2024), and the current location is the area of Sungai Batu (Batu River) near the location of the Archaeology Museum. Both areas have evidence of archaeological monuments. However, the investigation has been stopped at the museum area, fortunately, the area of Sungai Batu is still under the excavation phase and investigation. Even though there are existing archaeological monuments, it was believed by researchers that there, yet many hidden archaeological features that are still unrevealed. Thus, this study objective is appropriate because it provides an in-depth exploration and prediction of how Artificial Intelligence can be applied within real-world archaeological contexts. It allows for a

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comprehensive analysis of the application of automated detection techniques, aligning with understanding the integration of AI-RS in archaeological and feature extraction practices. Thus, Figure 3 illustrates a schematic workflow for the overall study. This schematic workflow graph is the extension methodology from the preliminary study starting from image extraction and image interpretation. Subsequently, image analysis was divided into five (3) components to strengthen processes. image extraction and interpretation techniques such as i) Different Gaussians ii) Pixel-range-based iii) Green Leave Index (GLI), and iv) Feature Matching analyses v) Region-Based Segmentation. Python and Global Mapper software were used for data analysis and processing. The software offers comprehensive qualitative analysis capabilities, which facilitate detailed examination of feature extraction and interpretation

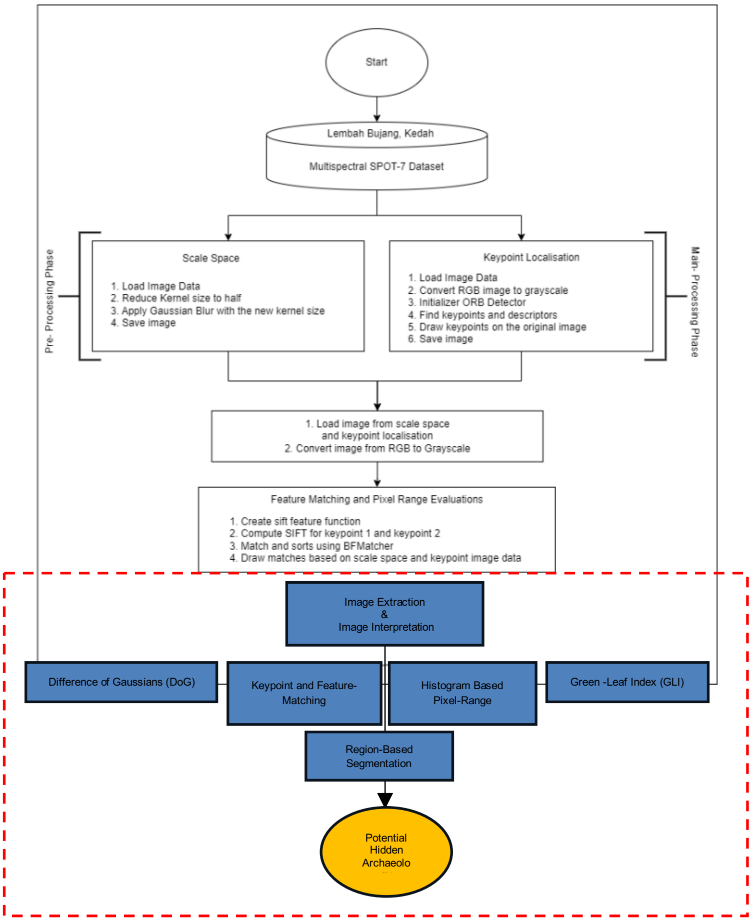

Figure 3. Schematic workflow to identify potential archaeology features using the integration of AI-RS applications.

i) Difference of Gaussians (DoG)

In this study, the Difference of Gaussians (DoG) was used for image processing to detect boundaries and extract features for early image interpretation. The algorithm involves comparing two images that have undergone Gaussian blurring with different standard deviations. Denoising the image was considered before applying DoG. The different σ1 and σ2 were applied to adjust the sensitivity of object/feature edges at various scales. Figure 4 shows the results of DoG in differences σ1 and σ2 values in two different locations. Noticeably the images highlight regions of rapid intensity are changes according to σ1 and σ2 values. The result illustrates that the archaeological monuments' edges and intensity value at the test Study Area1, Archeology Museum Bujang Valley is more obvious if the sigma values are (b) σ = *(0,0); (0,0)* and (c) σ = *(1,0); (0,1)*. For the focus area at Study Area1A, it is approximately clear if using (f) *σ = (0,0); (0,0).* (g) *σ = (1,0); (1,0).* Meanwhile, the area of Sungai Batu shows, that the DoG image highlights the feature's edges and image intensity when applied the value of (n) *σ = (1,0); (1,0).*

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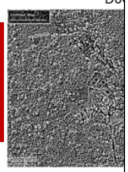
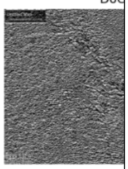
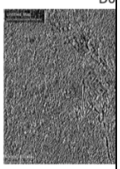
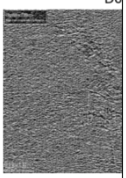
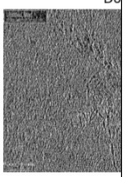
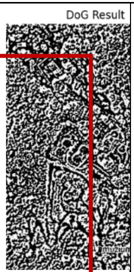
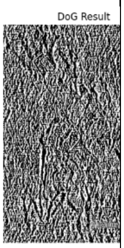
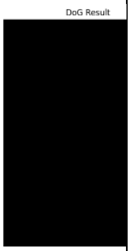
STUDY AREA1:
ARCHEOLOGY MUSEUM OF BUJANG VALLEY

 (a) Greyscale Image	 (b) sigma (0,0); (0,0)	 (b) sigma (1,0); (1,0)	 (c) sigma (0,1); (0,1)
 (c) sigma (0,1); (1,0)	 (c) sigma (1,0); (0,1)	 (d) sigma (1,1); (1,1)	

STUDY AREA1A:
FOCUS AREA OF ARCHEOLOGY MUSEUM, BUJANG VALLEY

 (e) Image Greyscale	 (f) sigma (0,0); (0,0)	 (g) sigma (1,0); (1,0)	 (h) sigma (0,1); (0,1)
 (i) sigma (0,1); (1,0)	 (j) sigma (1,0); (0,1)	 (k) sigma (1,1); (1,1)	

STUDY AREA 2:
SUNGAI BATU, BUJANG VALLEY

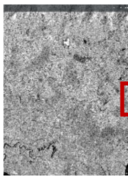
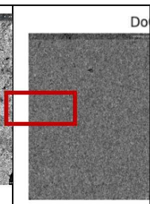
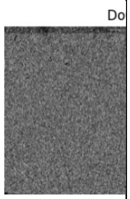
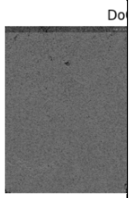
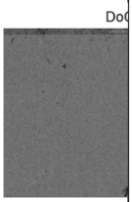
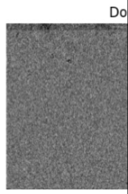
 (l) Greyscale Image	 (m) sigma (0,0); (0,0)	 (n) sigma (1,0); (1,0)	 (o) sigma (0,1); (0,1)
 (p) sigma (0,1); (1,0)	 (q) sigma (1,0); (0,1)		

Figure 4. DoG images in differences in sigma ($\sigma1$ and $\sigma2$) values at Bujang Valley.

I. Keypoint Localization

Algorithm Scale-Invariant Feature Transform (SIFT) was used to analyze the image. The intention is to highlight the areas of interest such as patterns, or structures resembling ancient ruins which help identify features or monuments that might indicate buried structures. As the result illustrated in Figure 5, the larger circle represents potential large features or patterns with coarser and low-frequency details of detection, while smaller circles show that the potential of small features and the key points were identified in finer and high-frequency details. In fact, the larger circles indicate features with greater significance, such as stronger edges, corners, or textures. Therefore, this study was selected and highlighted the larger circle only and will be compared to other proposed techniques as mentioned. In addition, the radius of the boundary has been set from Study Area 2 to limit the identification analyses.

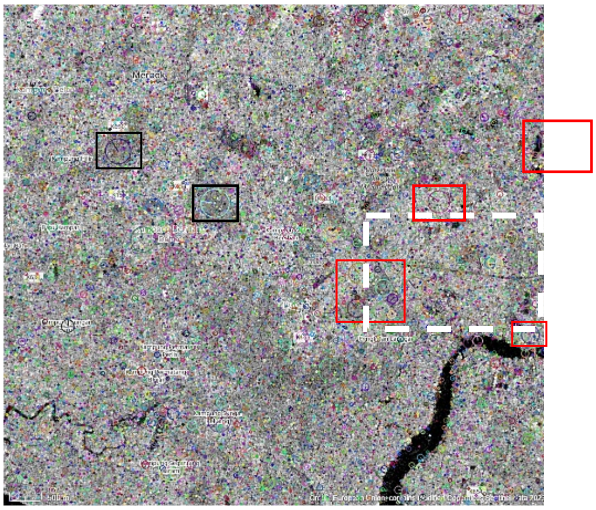


Figure 5. Image with keypoint detection over Study Area 2, Sungai Batu, Bujang Valley.

II. **Feature Matching.**

Feature matching is crucial at this stage in order to recognize and match features between two images. Study Area 2 and the corresponding *Candi* image (image training) were employed. The image of *Candi* has been chosen because there is a good chance that another *Candi* will be revealed, and the shape of Candi is unique and not typical of other built-up buildings in the vicinity. For this image analysis, the Brute Force Matching approach was used to directly compare descriptors. Additionally, the experiment ratio test is applied to determine the threshold values in the feature-matching ratio. Figure 6 indicated that only 2373 of the approximately 31423 total matches defined between the two images were rectified. Given that prior research has conducted comparison analysis over threshold tests, the ratio test threshold is {m.distance < 0.8 * n.distance} (Roslan et al., 2024). Following the application of the ratio test, the matching score is 1.0, which is the ratio of correct matches to total matches. This proves the accuracy of every match that passed the ratio test. The fact that this matching score persists at 1.0 means that every match that straightens the threshold of the adjusted ratio test is accurate for the corresponding image.

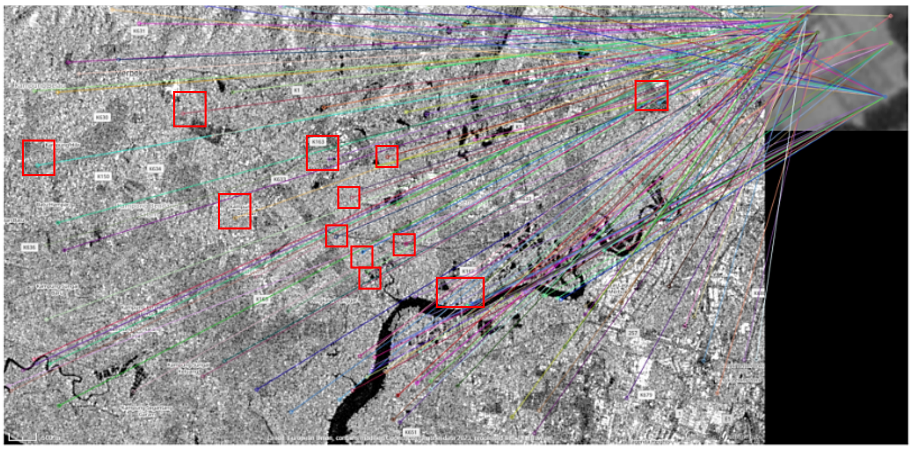


Figure 6. Image applied with feature matching over Sungai Batu, Bujang Valley.

III. **Histogram-Based – Pixel Range**

The histogram graph shows the minimum value of the image pixel is 30 and the maximum value is 170. The output illustrates the range of pixels between 90 to 170 were approximated determining the potential archaeological features in the Study Area2 of Sungai Batu. However, the range of pixels between 30 and 80 defined the water bodies, streams, or rivers. Accordingly, the range of pixels was tested based on a histogram graph generated from the images that have been analyzed. Figure 7.

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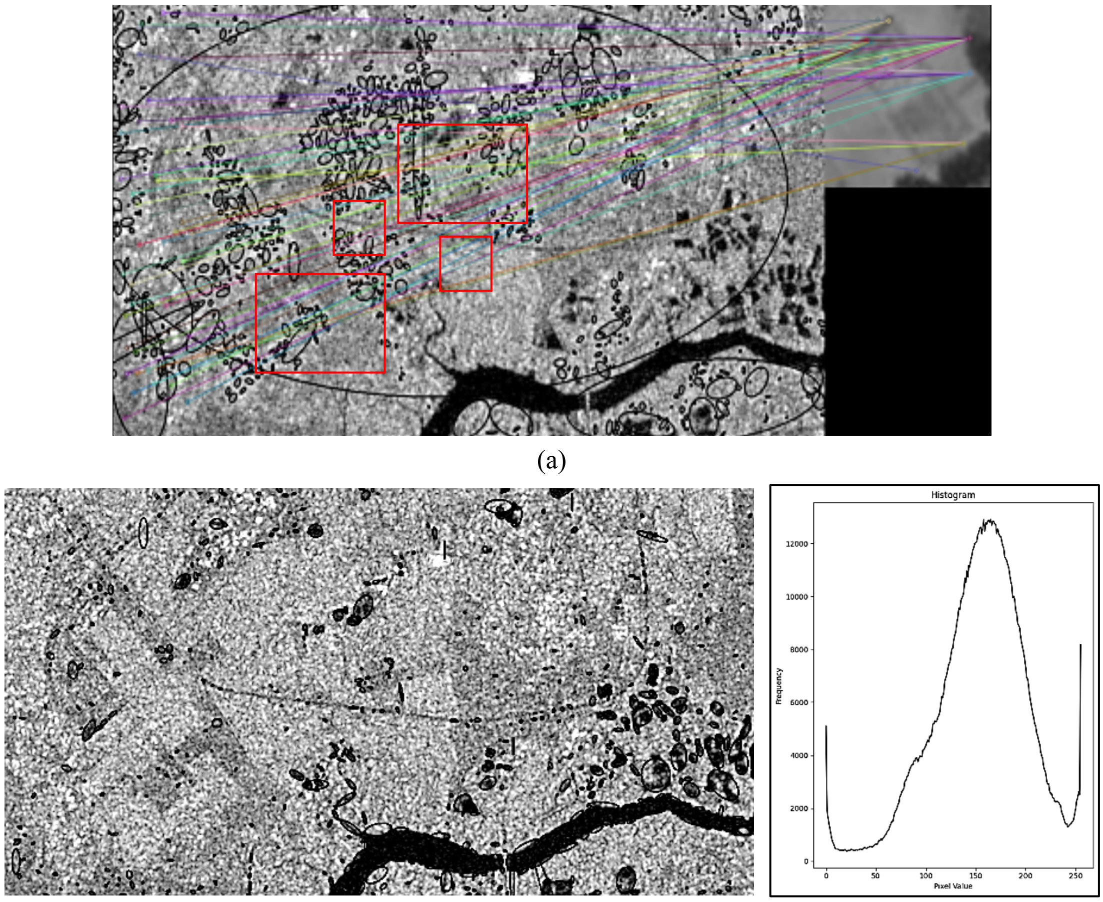

(a)

(b) (c)

Figure 7. (a) Zoom image over Sungai Batu and the range of pixels between 90-170 defined the area of potential hidden features with the image Matches overlapped to Pixel Range analyses image. (b) The range of pixels between 30 and 80 defined the water bodies/rivers. (c) The histogram graph shows the min and max of the image pixel value against image frequency.

IV. Green-Leaf Index (GLI)

GLI takes advantage of changes in plant vigor and growth, which can subtly highlight subtle surface and subsurface irregularities brought on by ancient landscapes, buried structures, or changed soil characteristics. Figure 8 demonstrates that the green color can be defined as vegetation cover, while the white color defines a water body elements such as stream or swampy area and other potential features/monuments according to the potential areas in the bounding boxes near the location of Archaeological Complex of Sungai Batu, Bujang Valley.

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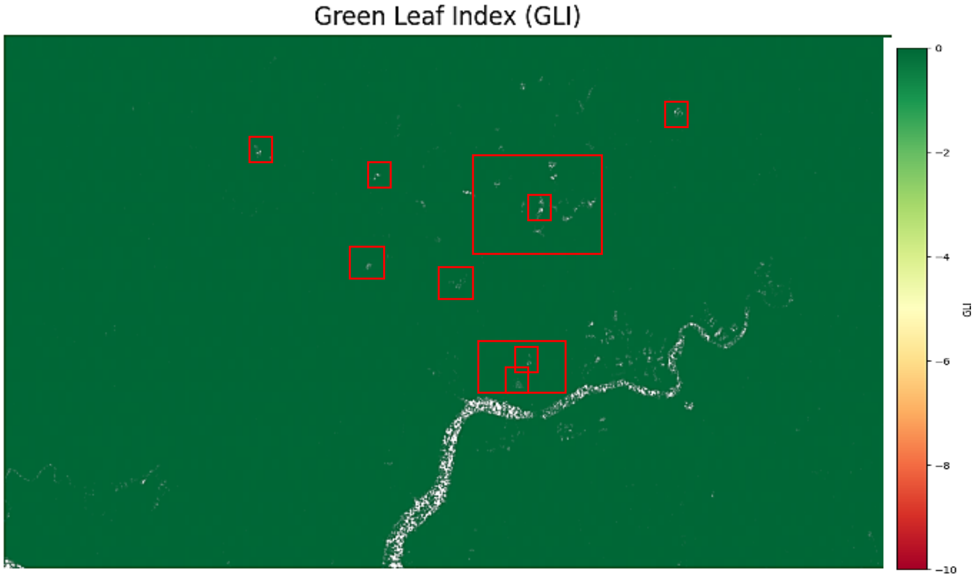

Figure 8. GLI image of Sungai Batu, Bujang Valley. Green color defined the vegetation cover, white color defined the built-up, potential archaeological features, and water bodies elements.

V. STUDY SIGNIFICANCE

The practical contributions of this research will directly benefit several key stakeholders such as archaeologists and research which provides an automated application that significantly reduces the time and labor involved in identifying archaeological sites in the Bujang Valley. This tool will enhance the accuracy and efficiency of their excavations, allowing them to focus on deeper analysis and interpretation of findings. Besides, the outcome of this study will equip local government and policymakers with data-driven insights to better preserve and manage archaeological resources in the region. By using the automated detection system, they can make informed decisions about land development and heritage conservation, balancing modern needs with the protection of cultural history. The second vital player's roles are Cultural Heritage Organizations. It is beneficial in improving resource allocation and strategic planning when protecting cultural sites. The insights gained from the application can guide the creation of effective preservation policies and public education campaigns, raising awareness about the Bujang Valley's historical importance. Lastly, universities and research centers can integrate the developed application into their curricula to train future archaeologists and developers on cutting-edge, AI-driven technologies in heritage detection. This exposure to practical, advanced tools enhances students' learning experiences and prepares them for real-world challenges in archaeology.

VI. STUDY CONTRIBUTION AND CONCLUSION

This research will make significant contributions to the body of knowledge in the field of archaeology and artificial intelligence. The study addresses the current lack of automated systems specifically tailored for archaeological site detection in the Bujang Valley. By providing new insights into the application of AI-RS-driven feature extraction, it will offer a systematic approach to detecting and documenting archaeological sites, which are currently under-researched. The study experimented with AI-RS-driven feature extraction tailored to the archaeological context of the Bujang Valley. This framework contributes to the theoretical understanding of how AI-RS can be applied to archaeological site detection, integrating both domain-specific knowledge and advanced machine learning techniques. By combining qualitative methodologies with AI applications, the research extends current theories related to archaeological site detection by considering the spatial and cultural factors unique to the North Peninsular Malaysia region. This extension provides a deeper understanding of how modern technology can be adapted to respect and enhance archaeological practices. However, the findings will lay the groundwork for future studies in the site study serving as a reference point for similar applications in other geographic and cultural settings. This study demonstrates the potential for AI to revolutionize archaeological practices and will encourage further interdisciplinary research, promoting comparative studies and extending automated detection methods to diverse archaeological terrains.

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In conclusion, this study tackles the challenge of detecting archaeological sites in the Bujang Valley of North Peninsular Malaysia using artificial intelligence-remote sensing for automated feature extraction. By adopting a qualitative methodology in developing an application, this research aims to improve the efficiency and accuracy of identifying potential archaeological sites. The anticipated results include the successful creation of an AI-RS-driven tool that enhances the precision of site detection and reduces the time and resources typically required for archaeological surveys. Moreover, this study approach allows the study to bridge the gap between theoretical advancements and field application, ensuring that the insights gained can be directly applied in real-world scenarios. Ultimately, it will contribute to academic knowledge by advancing methodologies in feature extraction and site detection within the context of archaeology in Malaysia. Additionally, it has significant implications for the real world, as it enhances the capabilities of archaeologists and conservators in preserving cultural heritage more effectively and efficiently. This study not only propels academic discussions in AI-RS applications but also provides a valuable tool for archaeology, benefitting both scholars and practitioners in the field.

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