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THE ROLE OF GEOSPATIAL ARTIFICIAL INTELLIGENCE (GEOAI) IN SMART BUILT ENVIRONMENT MAPPING: AUTOMATIC OBJECT DETECTION OF RASTER TOPOGRAPHIC MAPS IN MALAYSIA

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Abstract

Smart built environment mapping is integrating Geospatial Artificial Intelligence (GeoAI) to enable advanced analysis, pattern recognition, and decision-making processes. This shift in understanding, planning, designing, and managing the built environment is paving the way for a smarter, more sustainable future. This commentary explores the current role of AI in enhancing technology use within the geospatial field, focusing specifically on the application of GeoAI in mapping the built environment. Additionally, the paper presents a selection of case studies related to the implementation of AI in developing automatic vectorization, particularly for geospatial mapping in built environments. This research demonstrates the effectiveness of using Convolutional Neural Network (CNN) models for sorting objects in scanned, old topographic maps of the built environment. The findings of this study are valuable for making informed decisions, devising effective strategies, and identifying opportunities for further research and exploration within the dynamic field of GeoAI in smart built environment mapping and applications.

Keywords: Built Environment, Convolutional Neural Network (CNN), Deep Learning, Geospatial Artificial Intelligence (GeoAI), Smart Mapping

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INTRODUCTION

For the past few years, geospatial technology and AI have made considerable strides together. By enabling AI models to automatically extract complex features and patterns from geographical data, deep learning techniques have transformed the industry. Automated analysis of satellite imagery and geospatial datasets is possible because of computer vision algorithms that can recognise and comprehend objects and structures in pictures and movies (Sun et al., 2020). With the integration of machine learning, computer vision, and deep learning algorithms, GeoAI combines AI methods with geospatial data to glean insightful information from vast amounts of geospatial data (Zhu et al., 2019). Gartner defines GeoAI as the application of AI techniques, such as machine learning (ML) and deep learning (DL), to generate knowledge through the analysis of spatial data and imagery.

The significance and possibilities of GeoAI are growing as a result of the expansion of geographic data availability, AI developments, and the accessibility of vast computing capacity. By automating analysis, interpretation, and decision-making, GeoAI can revolutionise conventional geospatial technology and take it to new levels of accuracy, effectiveness, and innovation. The incorporation of AI algorithms and geospatial data has facilitated the mapping and analysis of complex urban landscapes, leading to the emergence of smart built environment mapping (Jiang et al., 2020). In the context of intelligent mapping of the built environment, geospatial AI facilitates several essential functions. It automates the mapping procedure by eliminating the need for manual data collection and interpretation.

This not only saves time and resources but also allows for more consistent and frequent mapping updates. GeoAI also improves the precision and accuracy of mapping outputs by reducing human errors and biases. As the significance of AI in geospatial technology becomes evident, this study aims to explore the current role of AI in advancing technology utilisation within the geospatial field. Then the objective continued to analyse the performance of AI in object detection for historical topographic maps, using a case study as a sample. Consequently, the research presented herein sheds light on the potential of GeoAI for mapping the built environment, demonstrated through an automatic object detection case study of topographic maps in Malaysia.

LITERATURE REVIEW

Geospatial Artificial Intelligence (GeoAI)

Artificial intelligence, which involves the development of machines or computational methods, encompasses the ability to perform tasks that typically necessitate human intelligence. These tasks include reasoning, learning, and foresight, enabling the machines to operate effectively within their environment.

The first is GeoAI, which is a rapidly developing field of study that merges advancements in spatial science, artificial intelligence, and machine learning such as deep learning, data mining, and high-performance computing. Its primary objective is to extract valuable insights and knowledge from large-scale spatial data sets, often referred to as spatial big data (Boulos et al., 2019; Yakub et al., 2021).

Next is ML. This AI approach consists of a specific branch within the field of AI that relies on statistical techniques or numerical optimisation methods to construct models from data, eliminating the need for manual programming of each model parameter or computational step (Ja'afar et al., 2021). The last is DL, which refers to a particular form of machine learning that involves the utilisation of artificial neural networks and algorithms inspired by the functioning of the human brain. In this approach, large volumes of data are used to train the neural networks, enabling them to learn intricate patterns and prediction rules.

Through this topic, leveraging the advancements in geospatial data and AI capabilities, GeoAI offers substantial advantages for urban planning, enabling more effective environmental administration and management in the built environment. Integration of technologies in various fields can benefit from revolutionised planning, design, and management processes, leading to the development of more sustainable and efficient mapping. With automated object detection on topographic maps, GeoAI contributes significantly to enhancing the accuracy and speed of mapping initiatives, facilitating better-informed decisions and smarter urban development strategies in the country.

Smart Built Environment: Enhancing Decision-Making, Efficiency, and Sustainability

In the built environment, GeoAI has become a potent technology that offers revolutionary capabilities in several planning, design, and management-related areas. The built environment encompasses several key concepts, each vital to shaping and managing urban areas effectively. Urban planning involves the design and organisation of cities, towns, and other urban spaces to optimise their liveability, functionality, and sustainability. Its architecture combines the art and science of planning and constructing buildings and structures while adhering to standards for usability, aesthetics, and environmental impact. Additionally, the infrastructure is the backbone of its civilisation, encompassing essential transportation networks, water supply systems, energy systems, and communication networks.

Sustainable development focuses on addressing present needs without compromising the ability of future generations to meet their own needs, necessitating consideration of economic, social, and environmental factors in built environment planning and design. Land use planning in the development process entails selecting the most suitable use for a piece of land, taking into account zoning laws, environmental concerns, and local requirements. The term "environmental impact" refers to how human actions influence the environment, such as pollution, resource depletion, and climate change. The built environment has a significant impact on adverse environmental effects, which are what sustainable design concepts aim to mitigate. Lastly, community development involves enhancing the well-being of a community through various efforts, including the construction of public spaces, housing, and infrastructure, thereby fostering social, economic, and cultural growth.

All these key concepts provide a foundation for understanding the various aspects and considerations involved in planning, designing, and managing the built environment. The built environment could also be understood to study the potential for enhancing numerous aspects of the built environment that surround humans. To make decisions that contribute to the overall growth and management of the built environment, it focuses on improving decision-making processes linked to urban planning, resource allocation, and policy creation. In addition, it looks at how to use resources more effectively, create less waste, and produce more with fewer negative environmental effects.

GeoAI integration in smart-built settings improves urban life quality by enhancing infrastructure effectiveness and productivity, promoting sustainable development, and enhancing spatial understanding. It aids in informed decision-making, resulting in more flexible, resilient, and sustainable cities. This technology uses AI to analyse geospatial data, leading to intelligent urban planning, improved infrastructure management, environmental sustainability, and increased catastrophe resilience as applied in built environment studies (Mustapha et al., 2023; Mohd Rasu et al., 2023; Adnan et al., 2023; Mohd Zubir et al., 2022; Ridzuan et al., 2021; Omar et al., 2021; Rasam et al., 2017; Abdul Rasam et al., 2016).

Smart Mapping: Transforming GeoAI Automation in Built Environment Applications

In the context of GeoAI and the built environment, smart mapping extends traditional mapping techniques by leveraging the capabilities of AI and geospatial technology to generate interactive, dynamic, and insightful visualisations of spatial data. With the exponential development of available data, smart mapping techniques facilitate the management, analysis, and visualisation of data (Sun et al., 2020). AI algorithms can be used to autonomously extract complex features and patterns from geospatial data, enabling more accurate and comprehensive representations of the built environment (Yuan et al., 2021).

In addition, smart mapping facilitates the integration of diverse data sources and formats, such as satellite imagery, sensor data, social media feeds, and textual reports. By combining diverse datasets, smart mapping enables decision-makers to obtain valuable insights for urban planning, infrastructure management, and environmental monitoring (Zhu et al., 2019). Other than that, smart mapping's dynamic nature allows real-time updates and interactive exploration of geospatial data. It facilitates the visualisation of changes and trends over time, thereby facilitating proactive decision-making and prompt responses to emergent challenges or opportunities. For instance, smart mapping's real-time monitoring of infrastructure assets can detect anomalies and initiate immediate actions to prevent failures or ensure prompt maintenance (Banihashemi et al., 2021). Moreover, smart planning improves communication and collaboration among built environment stakeholders. It provides user-friendly and intuitive interfaces that facilitate effective knowledge exchange, data interpretation, and collaborative decision-making. Hence, various disciplines, including urban planning, architecture, and environmental management, can interact with the mapped data, nurturing interdisciplinary collaborations and promoting holistic approaches to addressing complex challenges (Lu et al., 2021).

Specifically, smart mapping enables decision-makers in the built environment to obtain meaningful insights, make informed decisions, and promote sustainable development through these developments. To help urban planners make well-informed decisions, AI systems can process and evaluate enormous amounts of geographical data. By anticipating patterns of urban development and enhancing transit networks, GeoAI enables planners to create more liveable, sustainable cities (Kopec et al., 2018).

METHODOLOGY

Case Study of GeoAI Implementation: Automatic Object Detection and Classification of an Archived Topographic Map

This section showcases a sample of a case study and the practical application of GeoAI in the context of smart built environment mapping. It demonstrates the potential to revolutionise how geospatial data is analysed, interpreted, and utilised for creating more intelligent and efficient urban landscapes. The case study aims to automate the process of vectorization to achieve smart mapping, realising the immediate benefits in time and cost savings as well as improving the accuracy of the data. This study uses the Historical Topographic Hardcopy Map as the domain of datasets. Figure 1 below shows an example of the dataset.

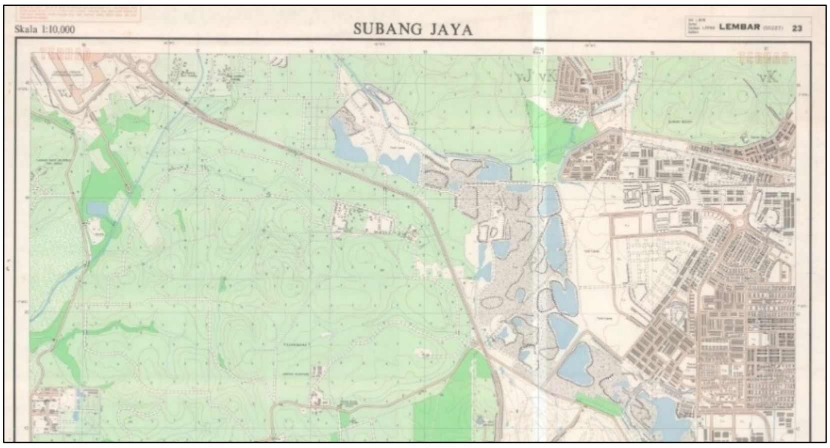

Figure 1: Sample of Historic Topographic Scanned Hardcopy Map
Source: Mapping Section, PTAR 1 UiTM Shah Alam (Yusof, 2021)

In the context of geospatial data processing, an automatic vectorization model provides several important benefits. Utilising a GeoAI deep learning model enables the completely digitised vectorization process to be carried out using automated procedures. This digitalisation process not only saves considerable time but also improves accuracy, providing direct benefits to library institutions, particularly their cartography departments. A specific application of vectorization is used to prepare maps for smart mapping by transforming geospatial views into vectorized data that is ready for use. Library institutions normally deal with numerous obstacles, such as a lack of mapping expertise, limited human resources, and digitization time constraints. To overcome these obstacles, a geospatial domain-specific automated system is devised using artificial intelligence. Using AI techniques, this system seeks to streamline the digitization process and increase productivity (Anuar, 2021).

Research Framework

The method of this study is described in Figure 2 below. A general review of selected papers was conducted to examine the roles of GeoAI for smart built environment applications. The data collection process then involved obtaining scanned historical topographic hardcopy maps from the mapping section of Perpustakkan Tun Abdul Razak (PTAR) UiTM Shah Alam. The collected images were in pdf format.

Images from scanned maps were then cropped using Adobe Photoshop to a size of 244 x 244 inches. From the cropped images, four objects were classified in the study: buildings, water bodies, land use, and roads. These objects were then subjected to data preprocessing, which included image enhancement of colour, clarity, and augmentation. The procedure then continued with the implementation of CNN through training and testing for two methods: CNN standard architecture and lightweight. During the data training and validation stage, several software tools and libraries were utilised to facilitate the processing.

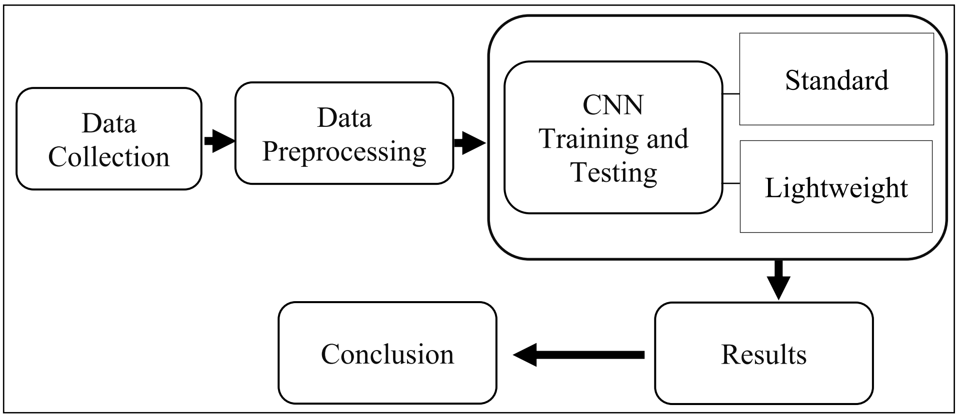

Figure 2: Methodology of Study

These include Anaconda, Jupyter Notebook, and a variety of deep learning packages and libraries such as Keras, TensorFlow, and PyTorch. Additionally, Python served as the primary programming language for implementation, while Matplotlib was used for visualisation purposes to analyse the model's performance and results effectively. Finally, a conclusion was highlighted at the end of the results comparison, highlighting the significance of the technique and its future potential in further developing this method. The methodological approach combined qualitative and quantitative methods.

Multiple criteria were used to assess the accuracy of the model's performance. First, using graph interpretation, the accuracy of training and validation was examined. It was possible to see how the model was learning, how well it could generalise, and whether it was overfitting or underfitting by plotting the accuracy over epochs. Second, the shape of the loss graph for the model was looked at. Plotting the loss function over time allowed researchers to track learning progress, identify over- or underfitting, and evaluate convergence. The loss function quantifies the difference between predicted and expected outputs. Thirdly, to identify prediction mistakes and evaluate accuracy, the confusion matrix was used to compile the model's predictions and actual labels. Lastly, the classification report used assessment measures to assess how well the model predicted accurate class labels, including accuracy, precision, recall, and F1 score.

RESULT AND DISCUSSION

The Roles of GeoAI for Smart Built Environments: A Review

The function of AI in the built environment and its possible benefits are examined in this article. It investigates how AI approaches and GIS technology improves decision-making processes, increase efficiency, enable predictive analytics, support infrastructure management, build catastrophe resilience, and promote sustainable development by analysing pertinent literature and case studies. Consequently, urban planning, infrastructure development, and environmental management can all benefit from better decision-making thanks to the integration of AI with GIS technologies (Chen et al., 2020). Huge amounts of geographical data can be processed and analysed by AI algorithms to yield valuable insights that aid professionals in making data-driven decisions (Li et al., 2019).

Particularly, AI improves efficiency and resource allocation by automating the analysis and interpretation of geographical data (Bao et al., 2019). AI increases consistency and precision in decision-making and resource allocation by minimising manual labour and time-consuming procedures (Zhang et al., 2021). Another important addition of AI to the built environment is predictive analytics. AI can predict future trends, patterns, and repercussions by using historical geographical data and machine learning algorithms (Wang et al., 2020). This skill facilitates proactive decision-making and increases readiness for upcoming difficulties (Zhang et al., 2021). Without a doubt, AI is extremely important for managing and maintaining infrastructure.

Next, by combining AI algorithms with geographical data, real-time monitoring, evaluation, and proactive maintenance of infrastructure assets are made possible (Li et al., 2020). It enhances the lifecycle management of assets by identifying maintenance needs, spotting anomalies, and forecasting possible breakdowns (Wang et al., 2019). AI also helps the built environment be more resilient and disaster-ready, as well as assists in assessing damage, identifying affected locations, and coordinating emergency response operations by analysing real-time geospatial data from a variety of sources (Chen et al., 2020). It makes planning for evacuations, resource mobilisation, and recovery measures easier (Wang et al., 2020).

AI also aids in sustainable development by integrating AI methods with geospatial data (Zhang et al., 2021). It makes it possible to plan for land use, evaluate environmental effects, and find potential for green infrastructure (Li et al., 2019). AI improves sustainable urban planning and development, lowers environmental footprints, and optimises energy use (Bao et al., 2019). The application of geospatial and AI in the built environment has broad ramifications. AI boosts infrastructure management, raises catastrophe resilience, increases efficiency, enables predictive analytics, and encourages sustainable growth. As a result, the built environment is now understood, planned, designed, and managed differently as a result of these developments, opening the door to a smarter, more sustainable future.

AI-Based Automatic Object Detection and Classification: Result of Testing Using the Standard Architecture of CNN

Based on Figure 3 below, the study observed a consistent increase in training accuracy, which suggests that the model was capturing the patterns and features presented in the training dataset, allowing it to make better predictions based on the data it had seen during training. On the other hand, the validation accuracy, which measures the model's performance on unseen data, followed a similar trend of improvement but with some fluctuations. Through observation, the loss function quantified the disparity between the model's predicted output and the expected output, intending to minimise this difference during training. Plotting the loss over epochs provided valuable information about the model's learning progress and convergence. The significance of the loss graph and its interpretation monitored the model's learning progress, with decreasing or plateauing losses indicating effective learning.

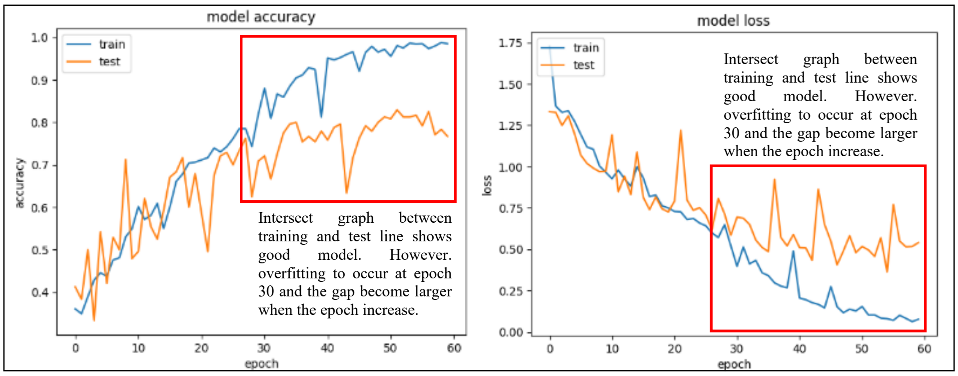

Figure 3: Graph of Model Accuracy-Loss for Training and Validation

The analysis of the training then continued with the classification report. Based on the results in Figure 4 below, the F1 scores reflected a balance between precision and recall for each class. Classes 0, 2, and 3 demonstrated relatively high F1 scores, indicating a harmonious trade-off between precision and recall, while class 1 has a slightly lower F1 score of 0.73. This implies that the model might encounter challenges in achieving a balanced performance for class 1. Considering the overall performance, the model exhibited an accuracy of 82%, indicating its ability to correctly predict the class labels for a majority of instances. The macro averages for precision, recall, and F1-score were 0.86, 0.83, and 0.83, respectively, indicating an acceptable overall performance across all classes. The weighted averages, which were considered the support for each class, yielded similar values, with precision at 0.86, recall at 0.82, and F1-score at 0.83.

Classification report :

	precision	recall	f1-score	support
0	0.96	0.83	0.89	30
1	0.61	0.90	0.73	30
2	0.93	0.83	0.88	30
3	0.96	0.73	0.83	30
accuracy			0.82	120
macro avg	0.86	0.83	0.83	120
weighted avg	0.86	0.82	0.83	120

Figure 4: Classification Report for Dataset Training and Validation

Result of Testing Using an Advanced Lightweight Model

Lightweight Convolutional Neural Networks (CNNs) have gained significant attention in the field of computer vision. It is specifically designed to provide efficient and accurate feature recognition on resource-constrained devices, such as mobile phones or embedded systems.

The lightweight CNN architecture incorporates depth-wise separable convolutions, which decompose the standard convolution operation into depth-wise convolutions and point-wise convolutions. This factor significantly reduces the computational complexity of the network while maintaining a good level of recognition accuracy (Howard et al., 2017). By utilising MobileNet, lightweight models based on MobileNet have demonstrated their effectiveness in automating feature extraction, aiding applications such as road extraction (Wang et al., 2019) and building footprint recognition (Zhang et al., 2022) on hardcopy maps. The relationship between MobileNet and lightweight CNNs highlights the impact and versatility of MobileNet's design principles in addressing the challenges of resource-constrained environments and specific application domains like hardcopy map feature recognition.

Through the results in Figure 5 below, the accuracy metric measured the model's performance in terms of correctly classified samples, with higher values indicating better accuracy. Looking at the accuracy values, there was an increasing trend over the epochs. The model's accuracy started at 0.4800 and reached a peak of 0.9974 at almost every epoch. Similarly, the validation accuracy started at 0.2500 and reached a peak of 0.990 at epoch 185.

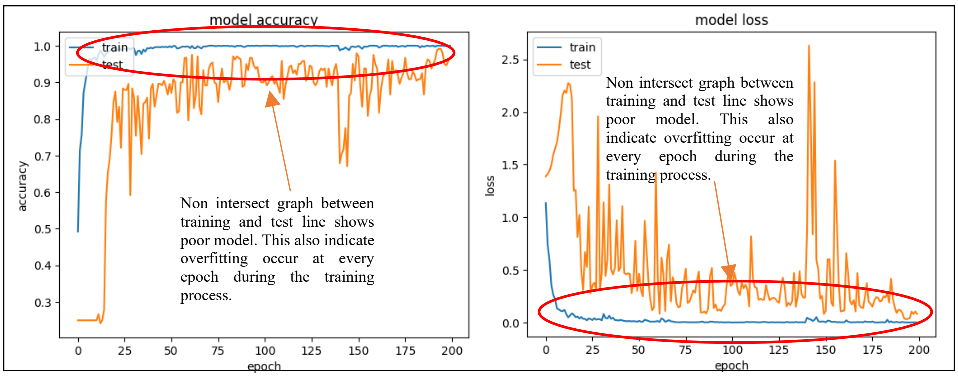

Figure 5: Graph of Model Accuracy-Loss for Training and Validation

This improvement in accuracy suggests that the model is learning and making better predictions as the training progresses. Based on the model loss graph, the loss metric represented the model's error during training, where lower values indicated better performance. The accuracy metric measured the model's performance in terms of correctly classified samples, with higher values indicating better accuracy. The loss on the training data decreased from 1.2365 to almost 0 throughout the training data. As well as the testing, the graph pattern shows a uniform decrease of almost 0 loss over the epoch, indicating that the model is learning and improving its predictions.

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Classification report :
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        30
           1       0.83      0.97      0.89        30
           2       1.00      0.87      0.93        30
           3       0.97      0.94      0.95        31

    accuracy                           0.94       121
   macro avg       0.95      0.94      0.94       121
weighted avg       0.95      0.94      0.94       121
```

Figure 6: Classification Report for Dataset Training and Validation

Based on the above Figure 6 experiment results, the classification report shows classes 0, 1, 2, and 3 demonstrated relatively high F1-scores, indicating a high prediction percentage with an average of 90% successful prediction. This indicates that a significant proportion of instances predicted by these classes are correct. The results also achieved a training accuracy of almost perfectly 99.99% and a validation accuracy above 90% on epoch 200 with several trained datasets of 1320 images. Overall, the lightweight CNN model demonstrated successful performance in accurately identifying objects in topographic hardcopy map datasets, exhibiting high accuracy levels on both training and validation data.

CONCLUSION

This paper has demonstrated the effectiveness of employing Convolutional Neural Network (CNN) models for object classification in scanned historical topographic maps. The use of AI has revolutionised the way geospatial data is collected, analysed, and interpreted. Moreover, the study underscores the significance of leveraging Geospatial AI technologies to facilitate informed decision-making and foster responsible urban development. By adopting innovative methods such as automated object detection in topographic maps, planners and policymakers are better equipped to tackle critical issues related to land use management, infrastructure planning, and environmental conservation. This, in turn, promotes the development of a more resilient and sustainable built environment for future generations. Looking ahead, this paper outlines several recommendations for future research and potential industry applications. A key area for further investigation involves the integration of advanced deep learning techniques, such as transfer learning or ensemble methods, to improve the accuracy and efficiency of object classification. Additionally, examining the scalability of the developed methodology to larger datasets or different geographical regions could offer valuable insights into its broader applicability.

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