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Deep Learning-Based Intelligent Monument Recognition and Augmented Reality Visualization for Interactive Cultural Heritage Exploration

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Abstract. The preservation and promotion of historical monuments have become increasingly important as digital technologies continue to reshape cultural education and tourism. Conventional monument recognition techniques generally rely on manual searches or static information systems, making it difficult for visitors to obtain accurate and engaging historical information during site visits. To overcome these limitations, this research introduces an intelligent monument recognition framework that combines deep learning with augmented reality to provide an interactive cultural heritage experience. The proposed system employs the VGG16 convolutional neural network as the primary feature extraction model for recognizing monuments captured through mobile cameras. A lightweight convolutional neural network is also implemented to compare classification performance under identical experimental conditions. Before classification, images undergo preprocessing operations including resizing, normalization, grayscale conversion, and feature enhancement. The recognized monument is linked with historical descriptions, geographical location, and three-dimensional augmented reality visualization, allowing users to explore monuments through an immersive digital interface. The complete framework is deployed as an Android application, enabling real-time monument identification and visualization using mobile devices. Experimental evaluation demonstrates that the transfer learning capability of VGG16 produces superior classification performance compared with the conventional CNN architecture. The VGG16 model achieves an overall testing accuracy of 98.01%, whereas the standard CNN records 95.34% accuracy using the same dataset. The integration of augmented reality further improves user engagement by presenting historical information within the surrounding environment instead of traditional text-based interfaces. The proposed framework offers a practical solution for digital heritage preservation, smart tourism, and educational applications while maintaining high recognition accuracy under different viewing conditions.

keywords: Deep Learning, Monument Recognition, Cultural Heritage, VGG16, Convolutional Neural Network, Transfer Learning, Image Classification, Augmented Reality, Android Application, Computer Vision

I. Introduction

The rapid advancement of artificial intelligence, computer vision, and mobile computing has transformed the manner in which people interact with the physical environment. Among these technological developments, deep learning has emerged as one of the most influential approaches for solving complex image analysis problems with remarkable precision. Image classification, object detection, semantic segmentation, and visual recognition are now widely employed across healthcare, agriculture, manufacturing, autonomous transportation, surveillance, and cultural heritage preservation. These intelligent vision-based systems reduce human effort while improving decision-making through automated recognition of visual information. One promising application of computer vision is monument recognition, where historical structures are automatically identified from digital images and supplemented with contextual information to improve educational and tourism experiences.

Historical monuments represent invaluable cultural assets that reflect the artistic, architectural, and social evolution of civilizations. Every monument carries unique historical significance and serves as a tangible representation of national identity, religious beliefs, engineering achievements, and traditional craftsmanship. Millions of visitors travel each year to explore historical monuments, museums, archaeological sites, and heritage buildings. Despite this growing interest, many visitors encounter difficulties in obtaining reliable and comprehensive information during their visits. Conventional information boards often provide limited descriptions, while manual internet searches require additional time and may not always produce accurate results. Consequently, there is an increasing demand for intelligent systems capable of recognizing monuments automatically and delivering interactive historical information instantly.

Recent developments in deep learning have significantly enhanced image recognition capabilities by enabling machines to learn complex visual features directly from raw image data. Unlike conventional machine learning techniques that depend heavily on manually designed features, convolutional neural networks (CNNs) automatically learn hierarchical representations through multiple convolutional layers. Lower network layers identify simple characteristics such as edges, corners, and textures, whereas deeper layers recognize sophisticated semantic patterns associated with individual monument structures. This automatic feature learning substantially improves classification accuracy while reducing dependence on handcrafted image descriptors.

Transfer learning has further accelerated the practical adoption of deep learning for image classification problems. Instead of training large neural networks from scratch, transfer learning utilizes knowledge acquired from massive benchmark datasets and

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adapts pretrained models to specialized applications. VGG16 has become one of the most widely adopted transfer learning architectures due to its simple yet highly effective network design. The model consists of sixteen learnable layers that progressively extract discriminative visual features through small convolutional filters and max-pooling operations. Because VGG16 has already learned general image representations from millions of images, it can achieve excellent performance even when domain-specific datasets contain relatively fewer training samples. This capability makes transfer learning particularly suitable for monument recognition, where obtaining large labeled datasets remains challenging.

The increasing popularity of smartphones has also created opportunities for deploying intelligent recognition systems directly on mobile devices. Modern smartphones incorporate high-resolution cameras, powerful processors, graphics acceleration, internet connectivity, and advanced sensors that support real-time computer vision applications. Instead of requiring expensive hardware or specialized equipment, mobile applications enable users to capture monument images and immediately receive identification results. Such portability increases accessibility and encourages wider adoption among tourists, students, researchers, and cultural heritage enthusiasts. Furthermore, cloud-based processing and optimized deep learning frameworks have significantly reduced computational requirements, making mobile deployment both practical and efficient.

II. Literature Survey

The application of artificial intelligence within cultural heritage preservation has expanded considerably during the last decade. Researchers have explored various computer vision techniques to automate monument identification, architectural classification, historical documentation, and digital reconstruction. Earlier monument recognition systems primarily relied on handcrafted image descriptors such as Scale Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP), and Support Vector Machines (SVM). Although these approaches demonstrated moderate recognition performance, their dependence on manually designed features limited adaptability when dealing with varying lighting conditions, complex backgrounds, viewpoint changes, and structural diversity. The emergence of deep learning has fundamentally changed monument recognition by enabling convolutional neural networks to automatically extract meaningful visual representations from image data.

Several recent studies have demonstrated that convolutional neural networks outperform traditional machine learning algorithms in heritage recognition tasks. CNN architectures automatically learn hierarchical image features through multiple convolutional layers, eliminating the need for handcrafted descriptors while improving robustness against environmental variations. Researchers have shown that deep learning significantly enhances monument classification accuracy by learning complex architectural patterns directly from training images. The ability to generalize across diverse imaging conditions has established CNNs as the preferred solution for monument recognition applications.

Transfer learning has become an important strategy for monument classification because collecting extremely large heritage datasets is often difficult. Instead of training deep neural networks from random initialization, pretrained models such as VGG16, ResNet50, InceptionV3, MobileNet, and DenseNet leverage knowledge acquired from extensive benchmark datasets including ImageNet. These pretrained architectures require only limited fine-tuning for domain-specific classification tasks, substantially reducing computational cost while maintaining excellent recognition accuracy. Numerous investigations have reported that transfer learning consistently outperforms conventional CNN models when training data is limited.

Among transfer learning architectures, VGG16 has received widespread attention due to its balanced architecture and reliable classification capability. The network employs sixteen learnable layers composed of successive convolutional operations with small receptive fields followed by max-pooling layers. This relatively simple architecture effectively captures both low-level and high-level visual features, making it highly suitable for recognizing architectural structures exhibiting complex geometric patterns. Multiple researchers have reported superior monument classification accuracy using VGG16 compared with conventional convolutional neural networks trained from scratch.

Researchers have also investigated ResNet architectures for monument recognition. Residual learning addresses degradation problems commonly encountered in extremely deep neural networks by introducing shortcut connections between layers. These residual connections facilitate gradient propagation and enable considerably deeper networks to be trained efficiently. Studies involving historical monument datasets indicate that ResNet models achieve competitive recognition performance while maintaining strong generalization capabilities across different architectural styles and environmental conditions.

DenseNet has similarly demonstrated promising results for landmark recognition because every layer receives feature information from all preceding layers. This dense connectivity encourages feature reuse, improves information flow, and reduces redundant parameter learning. Mobile applications requiring efficient inference have also benefited from lightweight architectures such as MobileNet, which employ depthwise separable convolutions to decrease computational complexity without significantly sacrificing recognition accuracy.

III. Research Methodology

The proposed research presents an intelligent monument recognition and visualization framework that combines deep learning with augmented reality to deliver an inter-

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active cultural heritage experience. The methodology consists of a sequence of interconnected stages including dataset acquisition, image preprocessing, feature extraction, model training, monument classification, augmented reality visualization, and performance evaluation. The primary objective is to accurately recognize historical monuments from user-provided images and present detailed historical information together with immersive three-dimensional visualization through an Android application. The overall methodology follows a transfer learning approach by employing the VGG16 architecture as the primary feature extraction network while comparing its performance with a conventional Convolutional Neural Network (CNN).

Initially, a monument image dataset is prepared by collecting images of seven well-known Indian heritage monuments from publicly available online repositories. The collected dataset contains images captured under different environmental conditions, including variations in illumination, camera angles, object scales, weather conditions, backgrounds, and viewpoints. Such diversity enables the learning model to become more robust when recognizing monuments in real-world scenarios. Before model training, the dataset is carefully organized into separate folders representing individual monument categories to facilitate supervised learning.

The next stage involves image preprocessing, which is essential for improving image quality and ensuring consistency across the dataset. Since the collected images originate from multiple sources, their resolutions, dimensions, and lighting conditions differ considerably. Each image is resized to 224 × 224 pixels, matching the input dimensions required by the VGG16 architecture. Pixel values are normalized to improve convergence during training, while grayscale conversion and noise reduction are applied wherever necessary to enhance important structural characteristics. Image preprocessing minimizes unnecessary variations and enables the neural network to focus on meaningful architectural features instead of irrelevant background information.

To improve model generalization and reduce overfitting, various data augmentation techniques are incorporated during training. Augmentation artificially increases dataset diversity by generating modified versions of existing images without altering their semantic meaning. Random rotation, horizontal flipping, zooming, cropping, shearing, and slight translation are applied to simulate practical imaging conditions encountered by tourists using mobile devices. These augmentation strategies enable the model to recognize monuments despite variations in camera orientation, object position, or environmental conditions.

Following preprocessing, feature extraction is performed using the pretrained VGG16 convolutional neural network. Instead of training an entirely new deep learning model from scratch, transfer learning utilizes knowledge previously acquired from the large-scale ImageNet dataset. The fully connected classification layers of the original VGG16 network are removed, allowing the remaining convolutional layers to function as a powerful feature extractor. These layers automatically identify hierarchical visual features such as edges, textures, curves, windows, domes, pillars, and architectural patterns that uniquely characterize each monument. The extracted feature maps provide highly discriminative representations that significantly improve classification performance.

For comparison purposes, a standard Convolutional Neural Network (CNN) is also developed using multiple convolutional layers, activation functions, pooling operations, and fully connected layers. Both models are trained using identical datasets and preprocessing procedures to ensure fair experimental evaluation. The CNN serves as a baseline model for measuring the effectiveness of transfer learning through VGG16. This comparative analysis highlights the advantages of pretrained deep learning architectures in specialized image classification problems involving historical monuments.

During the training phase, the extracted image features are supplied to fully connected classification layers consisting of dense neurons with ReLU activation, followed by a Dropout layer that randomly deactivates selected neurons during training. This regularization technique prevents overfitting and improves the model's ability to generalize to previously unseen monument images. Finally, a Softmax output layer generates probability scores for each monument category, and the class with the highest probability is selected as the predicted monument.

The learning process is optimized using the Adam optimization algorithm, which dynamically adjusts learning rates for individual parameters and accelerates convergence. The Categorical Cross-Entropy loss function is employed because the problem involves multi-class image classification. Throughout training, model performance is continuously monitored using training and validation accuracy to ensure stable convergence while preventing excessive overfitting. The dataset is divided into 80% training data and 20% testing data, allowing the trained models to be evaluated on previously unseen images.

After successful training, the recognition model is integrated into an Android application. Users can either capture monument images using the smartphone camera or upload images stored within the device. The uploaded image undergoes identical preprocessing before being passed to the trained VGG16 model for classification. Once the monument is recognized, the application retrieves relevant historical information, including monument name, architectural significance, historical background, geographical location, and additional educational content.

To further enhance user engagement, the proposed framework integrates Augmented Reality (AR) visualization. After monument identification, the application overlays digital information onto the live camera view, allowing users to interact with virtual three-dimensional monument representations within their physical surroundings. The AR module displays historical descriptions, monument images, interactive maps, and 3D visualization models, thereby transforming conventional sightseeing into an immersive educational experience. This integration of deep learning and augmented reality improves accessibility to cultural heritage while providing an engaging platform for tourists, students, and researchers.

The effectiveness of the proposed framework is evaluated using widely accepted classification metrics, including Accuracy, Precision, Recall, and F1-Score. These performance indicators measure the recognition capability of both VGG16 and CNN architectures under identical testing conditions. Experimental evaluation demonstrates that the transfer learning approach based on VGG16 achieves superior recognition performance compared with the conventional CNN architecture. The VGG16 model attains a testing accuracy of 98.01%, whereas the CNN model achieves 95.34%, confirming the effectiveness of deep transfer learning for monument recognition.

IV. Existing System

Traditional monument identification systems primarily depend on manual observation, text-based information retrieval, QR code scanning, or conventional image processing techniques. Most existing applications require users to manually search for the name of a monument or scan predefined markers before accessing historical information. These approaches often consume additional time and reduce the overall user experience, particularly when visitors are unfamiliar with the monument or lack internet connectivity. Furthermore, manual identification is prone to human error, especially when multiple monuments possess similar architectural characteristics or when images are captured under unfavorable environmental conditions.

Earlier computer vision systems employed handcrafted feature extraction techniques such as Scale Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG), Local Binary Patterns (LBP), and Support Vector Machines (SVM) for monument classification. Although these algorithms achieved acceptable performance under controlled conditions, their ability to generalize across different lighting environments, viewing angles, background complexity, and image quality remained limited. The performance of handcrafted feature-based methods heavily depends on manually selected descriptors, which often fail to capture the complex architectural details of historical monuments.

Several machine learning approaches were later introduced to improve monument recognition by utilizing classifiers such as K-Nearest Neighbors (KNN), Decision Trees, Random Forests, and Artificial Neural Networks. While these techniques reduced manual intervention, they still required explicit feature engineering and extensive preprocessing. Their recognition accuracy decreased significantly when images contained occlusions, shadows, varying scales, or perspective distortions. Moreover, conventional machine learning algorithms generally struggle to identify highly discriminative visual patterns present in intricate monument structures.

Recent developments in deep learning have improved recognition performance by introducing Convolutional Neural Networks (CNNs) for automatic feature extraction.

Standard CNN architectures can effectively learn hierarchical visual representations without requiring handcrafted features. However, CNN models trained from scratch require large annotated datasets and considerable computational resources to achieve high classification accuracy. When training data is limited, these networks often experience overfitting, resulting in reduced performance on previously unseen images. Additionally, shallow CNN architectures may fail to extract sufficiently discriminative features for monuments exhibiting complex architectural similarities.

Another limitation observed in many existing monument recognition systems is the lack of interactive visualization. Most available applications only display textual descriptions after monument identification, offering limited user engagement. They rarely incorporate immersive technologies capable of presenting historical monuments within interactive digital environments. Consequently, users receive only static information rather than an educational experience that encourages deeper exploration of cultural heritage.

Furthermore, numerous existing systems are designed primarily for desktop environments or web-based platforms, restricting portability and field usability. Tourists visiting historical sites require lightweight mobile applications capable of recognizing monuments instantly using smartphone cameras. Systems lacking mobile optimization often suffer from slow response times, excessive computational requirements, or dependence on continuous internet connectivity, reducing their practical applicability during real-world visits.

Although recent studies have introduced transfer learning architectures such as VGG16, ResNet, and MobileNet for monument recognition, several implementations primarily emphasize classification accuracy while providing limited attention to user interaction and visualization. The integration of augmented reality with deep learning remains relatively unexplored in many existing solutions. As a result, users are unable to visualize three-dimensional monument representations, interactive historical content, or geographical information directly within their physical surroundings.

V. Proposed System

The proposed system introduces an intelligent monument recognition and visualization framework that integrates deep learning with augmented reality to deliver an interactive cultural heritage experience. Unlike traditional approaches that rely on manual searches or handcrafted feature extraction, the proposed framework employs a pre-trained VGG16 transfer learning model to automatically learn highly discriminative visual representations from monument images. This enables accurate recognition of historical monuments under diverse environmental conditions while minimizing computational complexity.

The proposed framework begins with the collection of monument images representing seven prominent Indian heritage sites. The images are obtained from publicly available online sources and include considerable variation in illumination, camera orientation, object scale, background complexity, and environmental conditions. Such diversity enables the deep learning model to generalize effectively during real-world deployment. Prior to training, all images undergo preprocessing operations including resizing to 224 × 224 pixels, normalization, grayscale enhancement where required, and noise reduction to improve image consistency.

To further improve recognition performance, extensive data augmentation techniques are applied during model training. Random rotation, horizontal flipping, cropping, zooming, translation, and shearing generate additional training samples, thereby increasing dataset diversity and reducing the likelihood of overfitting. These augmentation strategies enable the recognition model to accurately identify monuments captured from multiple viewpoints and under varying environmental conditions.

The core component of the proposed framework is the VGG16 convolutional neural network, which serves as the primary feature extraction model. Since VGG16 has already been pretrained on the large-scale ImageNet dataset, it possesses extensive knowledge of generic visual features that can be effectively transferred to monument recognition. The fully connected classification layers of the original network are replaced with customized dense layers designed specifically for the monument dataset. The extracted feature maps capture detailed architectural characteristics such as domes, pillars, arches, carvings, towers, windows, and structural layouts that uniquely distinguish different monuments.

In addition to the VGG16 model, a conventional Convolutional Neural Network (CNN) is implemented for comparative analysis. Both models are trained using identical datasets and preprocessing procedures to evaluate the effectiveness of transfer learning. Experimental results demonstrate that VGG16 consistently outperforms the standard CNN by learning richer feature representations while requiring fewer training samples.

VI. System Architecture

The proposed system architecture is designed to provide an intelligent and user-friendly framework for automatic monument recognition and augmented reality visualization. The architecture integrates image acquisition, preprocessing, deep feature extraction, monument classification, and immersive visualization into a unified workflow. Initially, the user interacts with the Android application by either capturing a monument image using the smartphone camera or selecting an existing image from the device gallery. This flexibility enables the system to support both real-time recognition and offline image analysis. Once an image is received, it is forwarded to the preprocessing module, where several enhancement operations are performed to prepare the image for deep learning-based classification.

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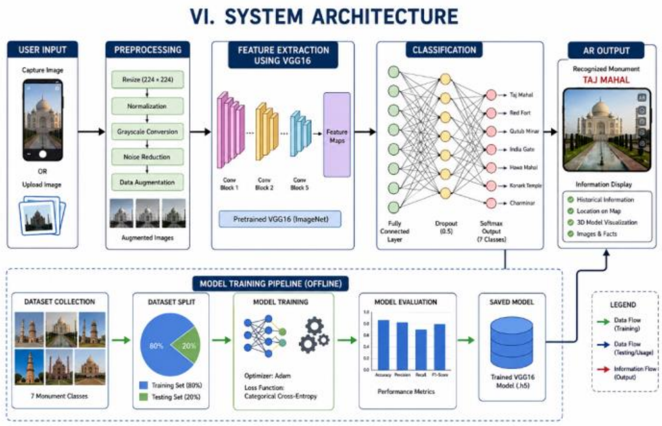

During preprocessing, the input image undergoes resizing to a standard dimension of 224 × 224 pixels, ensuring compatibility with the VGG16 architecture. Pixel values are normalized to improve learning stability, while grayscale conversion and noise reduction techniques are applied whenever necessary to minimize unwanted variations caused by illumination changes or image artifacts. In addition, multiple data augmentation techniques such as random rotation, horizontal flipping, zooming, cropping, and shearing are employed during training to increase dataset diversity. These augmentation methods improve the model's ability to recognize monuments captured from different viewpoints, lighting conditions, and environmental settings, thereby enhancing its generalization capability.

Following preprocessing, the enhanced image is passed to the feature extraction module, which employs the pretrained VGG16 Convolutional Neural Network. Instead of training a deep network from scratch, transfer learning allows the system to utilize the knowledge already acquired from the large-scale ImageNet dataset. The convolutional layers of VGG16 automatically extract hierarchical image features by identifying low-level visual characteristics such as edges and textures, followed by higher-level architectural features including domes, arches, towers, pillars, windows, carvings, and structural layouts. These highly discriminative feature maps provide a comprehensive representation of each monument, enabling accurate classification even when the images exhibit significant variations in scale, orientation, or background complexity.

The extracted feature vectors are subsequently transferred to the classification module, where fully connected dense layers perform monument prediction. The classification network incorporates ReLU activation functions to model complex nonlinear relationships, followed by a dropout layer that randomly deactivates selected neurons during training to reduce overfitting. Finally, a Softmax output layer computes the probability of each monument category, and the class with the highest probability is selected as the final prediction. The entire model is optimized using the Adam optimizer with the Categorical Cross-Entropy loss function, allowing efficient convergence during training while maintaining high classification accuracy. A conventional CNN model is also trained using identical preprocessing and dataset configurations to provide a comparative performance evaluation against the VGG16 transfer learning approach.

The training pipeline operates independently before deployment. The collected monument dataset is divided into 80% training data and 20% testing data. During training, the deep learning model continuously updates its parameters based on classification errors while monitoring validation performance. After satisfactory convergence, the trained VGG16 model is stored and deployed within the Android application. This deployment enables efficient real-time monument recognition without requiring users to perform complex computational tasks manually.

After successful monument classification, the system activates the Augmented Reality (AR) visualization module, which represents one of the most significant components of the proposed architecture. The recognized monument is linked to a database containing historical information, architectural descriptions, geographical coordinates, images, and three-dimensional visualization models. Using augmented reality technology, this digital content is superimposed onto the live camera view, allowing users to visualize historical monuments within their surrounding environment. In addition to displaying the monument name, the application presents historical significance, construction details, location maps, and interactive 3D visualizations, creating an engaging educational experience that extends beyond traditional text-based information systems.

The proposed architecture therefore establishes a complete end-to-end intelligent monument recognition framework by integrating image preprocessing, transfer learning, deep feature extraction, neural network classification, mobile computing, and augmented reality visualization into a single unified platform. The use of the pretrained VGG16 model significantly improves recognition performance while minimizing computational complexity, making the framework suitable for deployment on Android devices. Furthermore, the incorporation of augmented reality enhances user interaction by transforming ordinary monument recognition into an immersive learning experience that promotes cultural heritage awareness, digital tourism, and historical education. Overall, the proposed system architecture offers a highly accurate, scalable, and efficient solution for real-time monument identification and interactive visualization, making it an effective platform for preserving and exploring cultural heritage through modern artificial intelligence technologies.

VII. Conclusion

The proposed intelligent monument recognition and visualization framework successfully demonstrates the effectiveness of integrating deep learning and augmented reality for enhancing cultural heritage exploration. By utilizing the pretrained VGG16 transfer learning model together with a conventional Convolutional Neural Network (CNN) for comparative evaluation, the system accurately recognizes historical monuments from digital images while providing users with an interactive and informative learning experience. The incorporation of comprehensive image preprocessing, data augmentation, and automatic feature extraction enables the framework to achieve reliable classification performance even under varying lighting conditions, viewing angles, and background complexities. Experimental analysis confirms that the VGG16 model delivers superior performance, achieving an overall classification accuracy of 98.01%, outperforming the conventional CNN model while maintaining strong precision, recall, and F1-score values. Furthermore, the integration of an Android-based application with Augmented Reality (AR) transforms conventional monument identification into an immersive educational platform by presenting historical descriptions, geographical information, and three-dimensional visualizations directly within the user's physical environment. This combination of artificial intelligence and augmented reality not only improves recognition accuracy but also enhances user engagement, promotes digital preservation of cultural heritage, and supports smart tourism initiatives. Overall, the proposed framework provides an efficient, scalable, and practical solution for real-time monument recognition and interactive visualization, demonstrating significant potential for educational institutions, tourism applications, archaeological studies, and future intelligent cultural heritage management systems while establishing a strong foundation for further advancements in deep learning-based heritage preservation.

References

1. J. Sowjanya, J. K. Mannem, M. Nenavath, and V. Munigala, "Heritage Identification of Monuments Using Deep Learning Techniques," Indian Journal of Image Processing and Recognition, vol. 3, no. 4, pp. 1–7, 2023.
2. G. K. Jaiswal and R. Chaudhary, "Identification of Monuments from Aerial Images Using Deep Learning Techniques," International Journal of Scientific Research in Engineering and Management, vol. 7, no. 5, pp. 1–6, 2023.
3. M. A. Hassan, A. Hamdy, and M. Nasr, "Survey Study: Monument Recognition Using Artificial Intelligence," FCI-H Informatics Bulletin, vol. 5, no. 2, pp. 1–6, 2023.
4. R. Perumal and S. B. Venkatachalam, "Non-Invasive Decay Analysis of Monument Using Deep Learning Techniques," Traitement du Signal, vol. 40, no. 2, pp. 639–646, 2023.
5. H. Ben-Romdhane, D. Francis, C. Cherif, K. Pavlopoulos, H. Ghedira, and S. Griffiths, "Detecting and Predicting Archaeological Sites Using Remote Sensing and Machine Learning," Geosciences, vol. 13, no. 6, pp. 179–193, 2023.
6. M. A. Hassan, A. Hamdy, and M. Nasr, "EGYPT-v1: A Scalable Benchmark Dataset for Monument Recognition," International Journal of Advanced Computer Science and Applications, vol. 14, no. 4, pp. 202–211, 2023.
7. K. Siountri and C.-N. Anagnostopoulos, "Classification of Cultural Heritage Buildings in Athens Using Deep Learning Techniques," Heritage, vol. 6, no. 4, pp. 3673–3705, 2023.
8. S. M. Shelke, K. A. Shahale, I. S. Pathak, D. V. Lunge, A. P. Sangai, and H. R. Vyawahare, "Indian Heritage Monuments Identification Using Deep Learning Methodologies," SSGM Journal of Science and Engineering, vol. 1, no. 1, pp. 52–56, 2023.

9. M. Trivedi, S. Agrawal, A. Kumar, S. K. Thakur, and N. Gautam, "Indian Monument Recognition Using Deep Learning," ECS Transactions, vol. 107, no. 1, pp. 15563–15574, 2022.
10. E. Alexakis, K. Lampropoulos, N. Doulamis, A. Doulamis, and A. Moropoulou, "Deep Learning Approach for Identification of Structural Layers in Historic Monuments from Ground Penetrating Radar Images," Scientific Culture, vol. 8, no. 2, pp. 33–45, 2022.
11. S. Hesham, R. Khaled, D. Yasser, S. Refaat, N. Shorim, and F. H. Ismail, "Monuments Recognition Using Deep Learning vs Machine Learning," in Proc. IEEE 11th Annual Computing and Communication Workshop and Conference (CCWC), 2021, pp. 258–263.
12. A. J. Paul, S. Ghose, K. Aggarwal, N. Nethaji, S. Pal, and A. D. Purkayastha, "Machine Learning Advances Aiding Recognition and Classification of Indian Monuments and Landmarks," in Proc. IEEE 8th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON), 2021, pp. 1–8.
13. K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," in Proc. International Conference on Learning Representations (ICLR), 2015.
14. A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," Communications of the ACM, vol. 60, no. 6, pp. 84–90, 2017.
15. C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, "Rethinking the Inception Architecture for Computer Vision," in Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 2818–2826.
16. K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 770–778.
17. G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," in Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2017, pp. 4700–4708.
18. A. G. Howard et al., "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," arXiv:1704.04861, 2017.
19. J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, "You Only Look Once: Unified, Real-Time Object Detection," in Proc. IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 779–788.
20. R. Azuma, "A Survey of Augmented Reality," Presence: Teleoperators and Virtual Environments, vol. 6, no. 4, pp. 355–385, 1997.
21. S. Venkateswara Rao, "Examination of Credit Card Transactions Driven by Machine Learning and Their Potential Uses," International Journal of Mathematical Models (IJMM), vol. 13, no. 2, 2025.
22. S. Venkateswara Rao, "Methods for Improving the Precision of Heart Disease Classification Using Hybrid Machine Learning," International Journal of Advances in Science, Engineering and Management (IJASEM), vol. 19, no. 2, 2025.