Indonesian Journal of Electrical Engineering and Computer Science
Vol. 34, No. 3, June 2024, pp. 2055~2064
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v34.i3.pp2055-2064

Revolutionization of augmented reality in tourism via deep learning

Yasmin Chuupa Essa, Saumya chaturvedi, Shiraz Khurana
Department of Computer Science and Engineering, Sharda University, Greater Noida, India

Article Info

Article history:

Received Dec 18, 2023
Revised Mar 1, 2024
Accepted Mar 16, 2024

Keywords:

3D model
Augmented reality
Deep learning
Improvement
Tourism

ABSTRACT

Tourism has become an integral part of social and economic development across the globe. It does not only serve as a recreational activity but also as a source of revenue for the nation. The paper systematically explores the potential enhancements in the tourist experience through cutting-edge technology. Employing deep learning methods, the study specifically concentrates on refining augmented reality encounters for visitors. The proposed approach utilizes deep learning algorithms to optimize and tailor tourists' augmented reality experiences, addressing current sectoral challenges like customization and engagement shortcomings. The methodology's selection is predicated on it is capability to elevate user experience, accurately identify objects, offer visual guided tours, integrate historical context, and ultimately propel augmented reality adoption in tourism. Notably, the investigation culminates in a noteworthy average accuracy of 99% when incorporating deep learning to enhance augmented reality in tourism.

Corresponding Author:

Yasmin Chuupa Essa
Department of Computer Science and Engineering, Sharda University
Greater Noida, India
Email: yasyessa0@gmail.com

1. INTRODUCTION

Tourism a vital tool for the world's economy, jobs creation and fostering cultural exchange. It brings in revenue through activities like accommodation, transportation, and entertainment [1], [2]. Additionally, tourism promotes understanding between different cultures and helps preserve historical sites. However, it also poses challenges such as overcrowding in popular destinations, which can strain local infrastructure [3]. Excessive tourism may dilute local cultures and harm the environment. Some places face social and economic inequalities due to tourism, and crises like the COVID-19 pandemic can hit regions heavily dependent on tourism. Balancing sustainable practices and responsible management is essential to address these challenges [4], [5].

Previous studies have identified gaps in addressing the challenges faced by the tourism industry. For instance, inadequately trained personnel and skills gaps hinder effective accommodation of foreign visitors [6]. Furthermore, existing augmented reality (AR) systems have limitations in accurately recognizing and tracking real-world objects and patterns [7]-[9]. Unlike virtual reality, AR enhances the real world by overlaying digital data in real-time, offering heightened social connectivity [10], [11].

The aim of this research is to establish an AR-based tourism guidance system through a mobile application, providing travelers with valuable information, mapping, and language translation [12]. To overcome the limitations of current AR systems, a novel deep learning approach is proposed. Deep learning algorithms are employed to analyze visual data and enhance the recognition and tracking of real-world objects [13]. This brain-inspired approach combines AR interactivity with deep learning's pattern recognition capabilities, leading to more seamless and intelligent tourism experiences [13], [14].

Several studies have explored AR applications in tourism, but they exhibit shortcomings such as lack of consistency in addressing locations monitored by sensors, poor recognition of source diversity by tourists, existence of bugs affecting model efficiency, and complicated or non-user-friendly interfaces [15], [16]. Although some approaches, like the stochastic scenario-based approach for AR expert co-authorship networks, address certain gaps, they still acknowledge challenges in tourist behavior analysis [17]. Similarly, models forecasting international tourist arrivals using SARIMA acknowledge limitations in data and seasonal variations [18]-[20]. Thus, the proposed idea of "Revolutionization of augmented reality in tourism via deep learning" aims to close the gaps left by existing models. The subsequent sections of this paper are discussed as follows: section 3 analyzes the methodology, section 4 discusses the findings, and section 5 provides the conclusion and future scope of the research.

2. METHOD

The method proposed in this research is the used of deep learning approach toward the improvement of augmented reality in tourism. The approach is analyzed using a deep learning tool in MATLAB. Figure 1 captured the detailed of the process.

The Figure 1 flowchart outlines a methodology for AR application development. The initial stage involves data collection, where images from various locations are gathered for training and testing. Subsequently, data preprocessing occurs, encompassing normalization, resizing, and rotation of image locations with labeling. The fine-tuned data is then fed into a deep learning model, such as convolutional neural network (CNN) using Surf method. Following the deep learning process, AR development is executed using MATLAB to train the model. Post-training, a real-time 2D object is employed to test the model's efficiency, displaying 3D models of recognized objects in live camera feeds. A user-friendly interface for the AR application is designed, featuring information retrieval. To enhance performance and accuracy, optimization is implemented before deploying the AR application effectively.

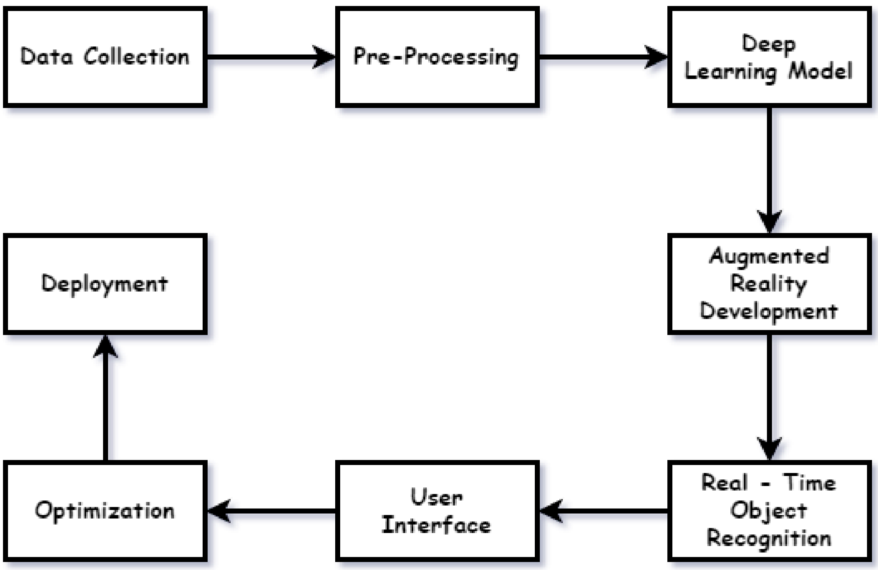


Figure 1. Methodology flow chart

2.1. Data collection

In this process, historical places such as the Taj Mahal, the Pyramids of Gaza, and the Dome Cathedral Church were manually inspected and analyzed virtually. After virtually analyzing the places, an iPhone 15 Pro-Max camera of 48 Mega Pixels with 120 mm 5× optical zoom was used for capturing the places at a range of 500-900 nm and a spectral resolution of 2.5 nm. The images of the places captured is shown in Figures 2(a)-2(c).

(a) (b) (c)

Figure 2. Iconic landmarks showcasing historical architecture of; (a) the Taj Mahal, (b) the Pyramids of Giza, and (c) the Dome Cathedral Church in Paris

2.2. Deep learning (CNN classifier) of 2D model and 3D model

Deep learning is a cutting-edge scientific domain that aims to capitalize on emerging scenarios by providing fresh solutions and applications. “Deep” denotes the numerous layers involved in the data transformation process [21], [22]. To elaborate, it is a specialized variant of machine learning that grasps the representation of the actual world as intricate hierarchies of concepts, where simpler and more abstract concepts and representations delineate each concept. Deep learning models, in essence, reproduce how humans learn by making sense of instances. Deep learning techniques are characterized by their unique use of multi-layer neural networks and advanced supervised and unsupervised learning procedures [22], [23]. There is a noticeable degree of functional versatility with these models. They improve overall system performance by adjusting internal settings for discovering complicated patterns in huge datasets using the backpropagation technique [24], [25]. Convolutional neural network marks the success of the deep learning approach. Convolutional, a mathematical concept that operate in two integral functions A(t) and B(t), that gives an output function of $(A \times B)(t)$, defines as (1),

$$(A \times B)(t) = \int_{-0}^{0} A(s)B(t+s)ds \quad (1)$$

where, A(t) and B(t) are operating input signal and convolutional kernel. In real life scenario, data are always in form of discrete and finite. The finite sum is most cases are replaced by integration. Similarly, discrete convolution is given by (2);

$$(A \times B)(t) = \sum_{\Delta t} B\,(\Delta s)A(t+\Delta t) \quad (2)$$

The significant advancement introduced by CNNs lies in the fact that the convolution kernels are not predetermined by a human expert designing the system. Instead, they are adjusted and fine-tuned by the neural network throughout the training process. Nonetheless, the human expert is still responsible for determining parameters such as the number of convolutions, their dimensions, and the overall network architecture. After processing of models using deep learning, the 2D model, and 3D model is represented in (3) and (4).

$$A_w \times B)\,(ab) = \sum_{\Delta a}\sum_{\Delta b} B\,(\Delta a, \Delta b)\,A(a+\Delta a, b+\Delta b, w) \quad (3)$$

$$(A \times B)\,(a,b,w) = \sum_{\Delta a}\sum_{\Delta b}\sum_{\Delta w} B(\Delta a, \Delta b, \Delta w)A(a+\Delta a, b+\Delta b, w+\Delta w) \quad (4)$$

A crucial factor in this network design is the dimensionality of the input, which, in part, is influenced by the shape of the input data. Figure 3 illustrates a visual depiction of 2D and 3D input data related to the specific problem at hand. The significance of employing both 2D and 3D models lies in their crucial role in enhancing the comprehension of how deep learning can enhance the augmented reality process.

2.3. Collection of data and assessment of the classifier performance

The acquired dataset was randomly split into distinct training, validation, and test sets, with proportions of 70%, 10%, and 20% of the total images, respectively. The rationale behind selecting these percentages is due to the need for a substantial proportion of test examples (20%) to ensure reliable measurements of classifier performance, given the relatively low number of samples (60 in total). Consequently, the training and validation sets are set at 70% and 10%, respectively. Table 1 displays the number of dataset samples for each class and partition. It is important to clarify that, for the 3D dataset, the numbers represent samples before applying data augmentation. In the 2D dataset, data augmentation was not applied, as each channel is treated as a sample, resulting in a sufficiently large dataset. The data augmentation techniques employed include random horizontal flip and colour jitter, and it is consistently applied to training data, not test data.

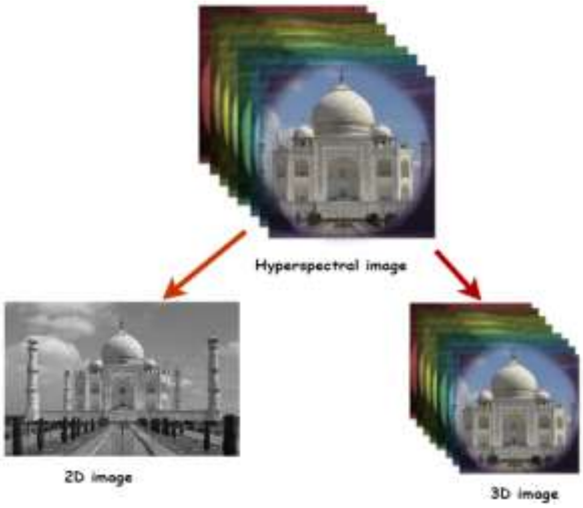


Figure 3. Hyperspectral images of 2D and 3D images of Taj Mahal

Table 1. Sample of dataset used for training, testing and validation

Model	Name of dataset	Samples	Classes		
			0	1	2
3D	Train	120	40	40	40
	Test	54	18	18	18
	Validation	27	9	9	9
	Total	201	167	167	167
2D	Train	1,8285	6,095	6,095	6,095
	Test	8,877	2,959	2,959	2,959
	Validation	3,135	1,045	1,045	1,045
	Total	30,297	10,099	10,099	10,099

To assess the efficacy of the proposed classifiers, various criteria have been computed, including the widely used confusion matrix, which juxtaposes true labels against those predicted by the classifier. Derived from this matrix are key metrics such as precision, recall, and F1-score. The CNN classifier and confusion matrix for the 2D model and 3D model are detailed in Tables 2-5.

Table 2. 2D CNN classifiers confusion matrices

Approach	Real class	Class One	Class Two	Class Three	Total
2D-CNN-18	Class 0	2,872	1	80	2,961
	Class 1	277	2,005	679	2,961
	Class 2	442	221	2,298	2,961
2D-CNN-7	Class 0	2,341	427	193	2,961
	Class 1	36	2,770	155	2,961
	Class 2	372	314	2,275	2,961

Table 3. Criteria for the performance of 2D model using CNN classifier

Approach	Class	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
2D-CNN-18	Class 0	81	98	89	
	Class 1	91	69	78	81.2
	Class 2	77	79	75	
2D-CNN-7	Class 0	86	78	83	
	Class 1	80	93	87	84.3
	Class 2	89	78	83	

Table 4. 3D CNN classifiers confusion matrices

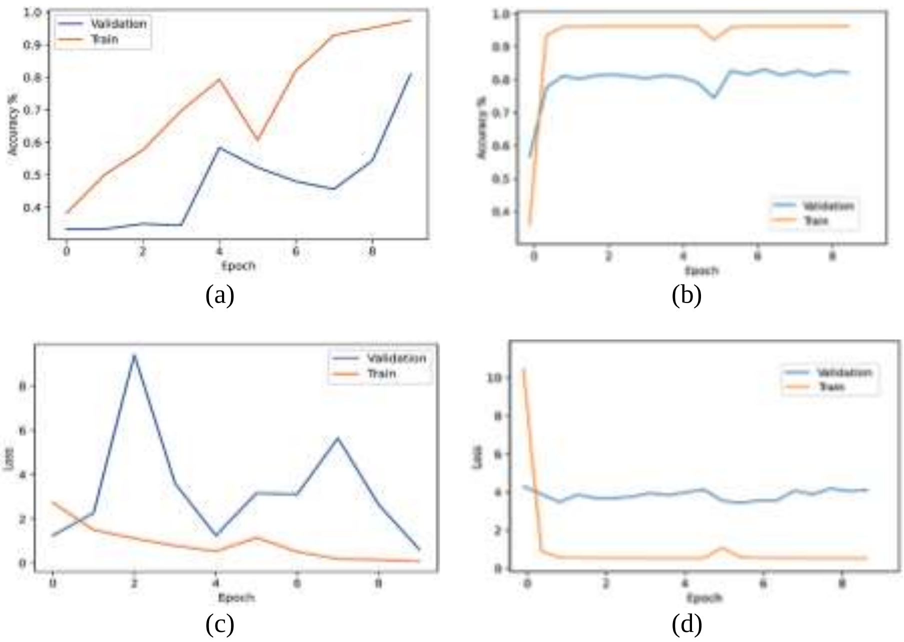
Approach	Real class	Class 0	Class 1	Class 2	Total
3D-CNN-18	Class 0	16.0	1.0	0.0	17.0
	Class 1	0.0	17.0	0.0	17.0
	Class 2	0.0	2.0	15.0	17.0
3D-CNN-7	Class 0	14.0	1.0	2.0	17.0
	Class 1	0.0	16.0	1.0	17.0
	Class 2	1.0	0.0	16.0	17.0

Table 5. Criteria for the performance of 3D- model using CNN classifier

Approach	Class	Precision (%)	Recall (%)	F1-score (%)	Accuracy (%)
3D-CNN-18	Class 0	100	95	98	
	Class 1	86	100	93	95.3
	Class 2	100	89	95	
3D-CNN-7	Class 0	94	84	87	
	Class 1	95	93	96	91.4
	Class 2	86	95	88	

3. RESULTS AND DISCUSSION

The study employs shallow (CNN-7) and deep architectures (CNN-18) in 2D and 3D models, examining potential overfitting. Evaluation involves tracking training progress using accuracy and loss curves across epochs for both validation and training sets. Figure 4 displays results for 2D models, it is depicted through the accuracy and loss metrics on both training (orange) and validation (blue) sets, specifically: Figure 4(a) accuracy for 2D-CNN-18, Figure 4(b) accuracy for 2D-CNN-7, Figure 4(c) loss for 2D-CNN-18, Figure 4(d) loss for 2D-CNN-7. Figure 5 illustrates progress in 3D hyperspectral image classifiers. The assessment compares efficacy and methods between the two architectures, emphasizing the absence of overfitting in 3D models. It is illustrated in terms of accuracy and loss across the training (orange) and validation (blue) sets for two architectures: Figure 5(a) 3D-CNN-18 accuracy, Figure 5(b) 3D-CNN-7 accuracy, Figure 5(c) 3D-CNN-18 loss, and Figure 5(d) 3D-CNN-7 loss. Also, the precision-recall for both 2D and 3D as shown in Figure 6 models using CNN classifiers is shown in Figures 6(a) and 6(b), respectively. This study thoroughly evaluates the performance of shallow and deep CNN architectures on both 2D and 3D hyperspectral image classification tasks. The absence of overfitting in 3D models is a noteworthy finding, indicating the robustness of these architectures for processing higher-dimensional data. The inclusion of precision-recall metrics provides further insights into the classifiers' performance, complementing the accuracy and loss measurements.



(a) (b) (c) (d)

Figure 4. The progression of training procedures for 2D-convolutional neural network (CNN) classifiers; (a) accuracy for 2D-CNN-18, (b) accuracy for 2D-CNN-7, (c) loss for 2D-CNN-18, and (d) loss for 2D-CNN-7

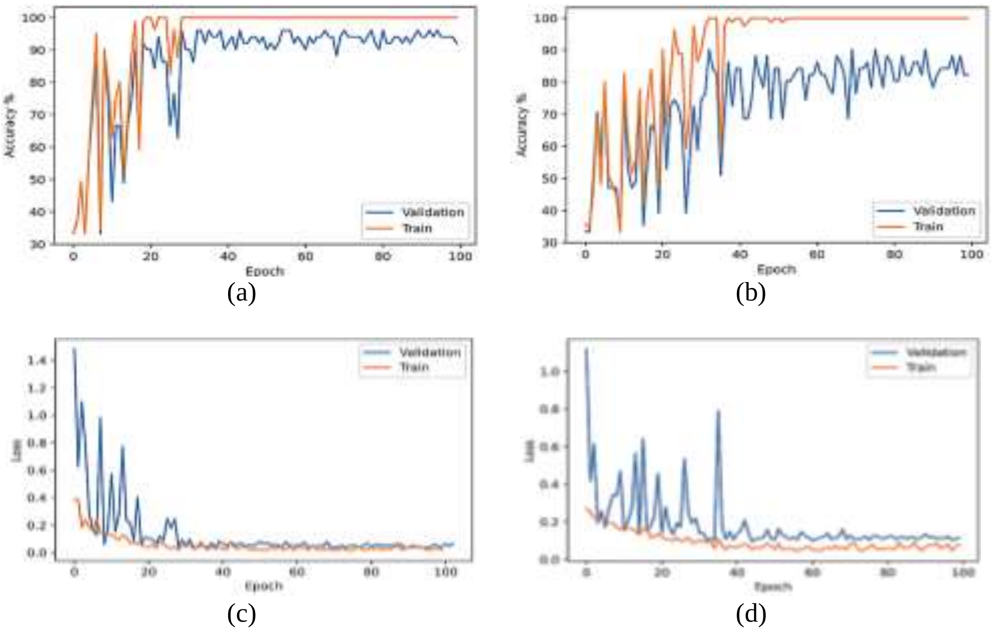
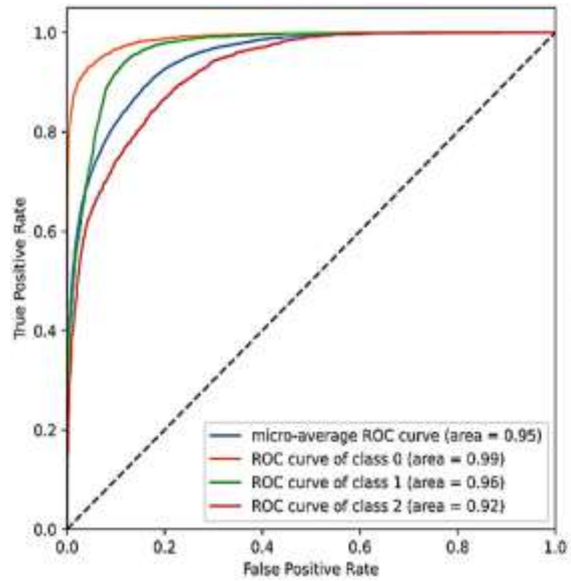


Figure 5. The progression of training procedures for 3D-convolutional neural network (CNN) classifiers; (a) 3D-CNN-18 accuracy, (b) 3D-CNN-7 accuracy, (c) 3D-CNN-18 loss, and (d) 3D-CNN-7 loss

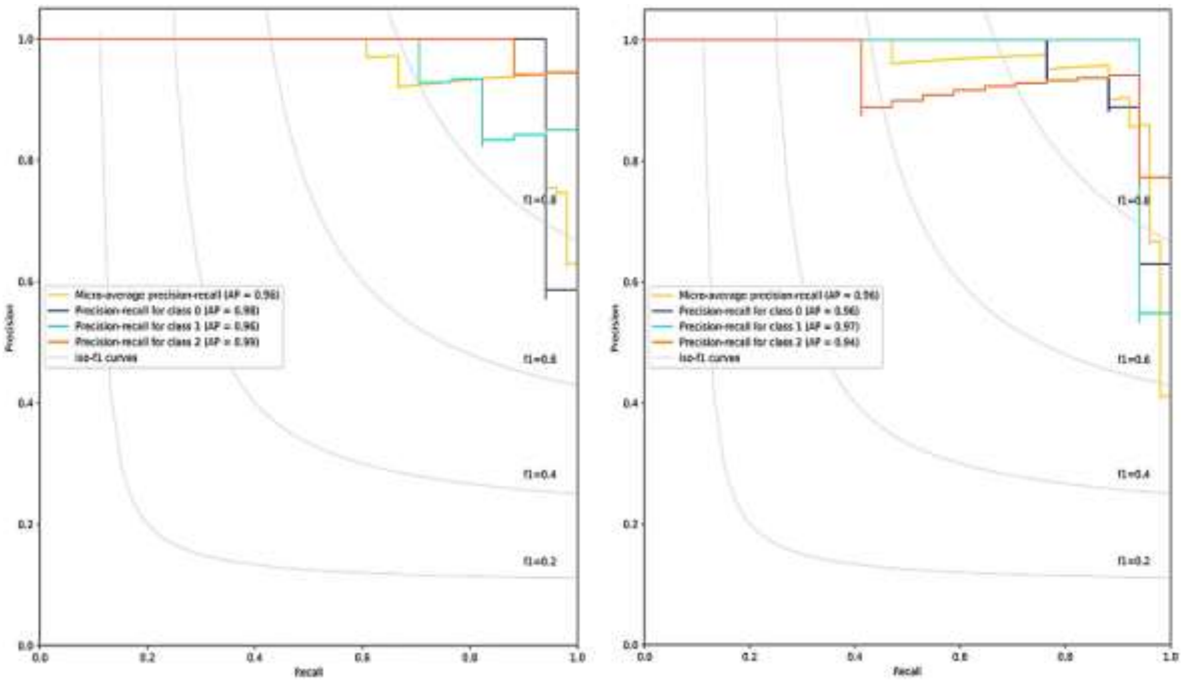
Based on the comparison of the 2 and 3-D models, the deep learning process shows in Figures 7 Display picture of Taj Mahal, Figure 7(a) Captured at initial stage, Figure 7(b) fine-tuned using CNN Figure 7(c) in an Augmented Reality form, Figure 8 Preprocessing of the pyramids of Giza images Figure 8(a) Original capture 8(b) Enhanced through Convolutional neural network refinement 8(c) Presented in augmented reality format and Figure 9. Preprocessing steps applied to the pyramids of Giza images, from Figure 8(a) original capture to Figure 8(b) enhanced refinement using CNN Figure 8(c) presentation in augmented reality format. How it improves the augmented reality toward tourism. In Figure 7(a), the image captured displays a historical building (Taj Mahal). The image is then preprocessed and trained using a deep learning (surf) speeded-up robust feature approach as shown in Figure 7(b). Similarly, after fine-tuning and extraction of unwanted noise using the deep learning approach, the image is finally navigated using the 3D model for the augmented reality processes as captured in Figure 7(c). These steps demonstrate the application of deep learning techniques and 3D modeling for augmented reality experiences involving historical structures like the Taj Mahal. Similarly, in Figure 8(a), a photograph of a historical building, the Pyramids of Giza, is depicted. This image undergoes pre-processing and training using a deep learning technique known as the speeded-up robust feature approach, illustrated in Figure 8(b). Following fine-tuning and removal of unwanted noise through deep learning, the image is further processed using a 3D model for augmented reality applications, as demonstrated in Figure 8(c). The same pipeline is applied to another historical site, the Pyramids of Giza, showcasing the versatility of the proposed approach.

In Figure 9(a), the photograph showcases the Dome Cathedral Church in Paris, a historical building. This image is subjected to preprocessing and training using a deep learning technique called the speeded-up robust feature approach, as depicted in Figure 9(b). After fine-tuning and removal of unwanted noise through deep learning methods, the image undergoes additional processing utilizing a 3D model for augmented reality applications, as demonstrated in Figure 9(c). The inclusion of a third historical site, the Dome Cathedral Church, further highlights the generalizability of the proposed methodology across diverse architectural structures. This study presents a comprehensive pipeline for augmented reality experiences involving historical buildings. By leveraging deep learning techniques for feature extraction and noise removal, coupled with 3D modeling, the researchers demonstrate the applicability of their approach to iconic structures like the Taj Mahal, Pyramids of Giza, and the Dome Cathedral Church. This versatility underscores the potential for extending the proposed methodology to other historical sites and augmented reality applications.

Figure 10 displays the enhanced 3D model images obtained through a deep learning approach, with histograms in Figures 10(a)-(c) illustrating intensity variations. The histograms depict gradual increases with broader shades, spanning a wide range of intensities. Image 1 exhibits a gradual intensity rise, image 2 displays surpassing concentrations, and image 3 features a prominent peak at coordinates (x=249, y=41,276), highlighting distinct characteristics. This analysis confirms the images' high quality, validating the effectiveness of the deep learning approach. The inclusion of Figure 10, along with the detailed descriptions, provides a visual representation of the improvements. The histograms offer insights into intensity distributions, and the specific features of each image contribute to a comprehensive understanding of the enhanced 3D model images resulting from the proposed methodology.



(a)



(b)

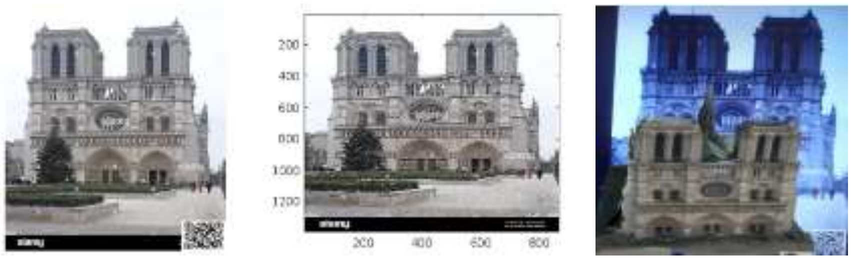
Figure 6. Evaluation of shallow and deep CNN architectures on 2D and 3D hyperspectral image classification tasks (a) precision-recall curves for 2D CNN classifiers and (b) precision-recall curves for 3D CNN classifiers

(a) (b) (c)

Figure 7. Display picture of Taj Mahal; (a) captured at initial stage, (b) fine-tuned using CNN, and (c) in an augmented reality form

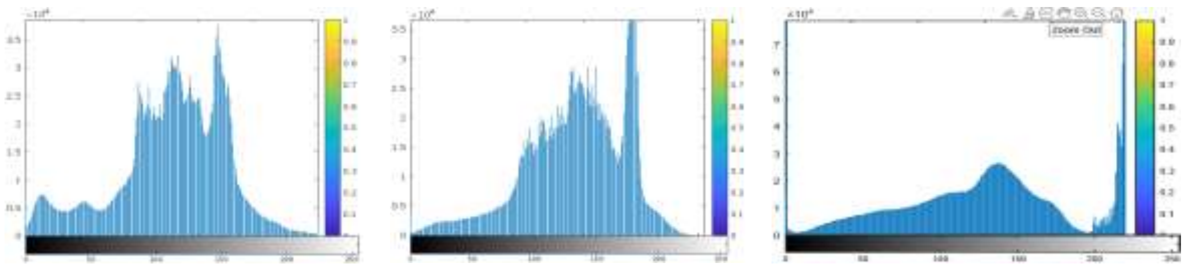
(a) (b) (c)

Figure 8. Preprocessing of the pyramids of Giza images; (a) original capture, (b) enhanced through convolutional neural network refinement, and (c) presented in augmented reality format



(a) (b) (c)

Figure 9. Preprocessing steps applied to the pyramids of Giza images, from; (a) original capture to, (b) enhanced refinement using convolutional neural network, and (c) presentation in augmented reality format



(a) (b) (c)

Figure 10. Enhanced 3D model images via deep learning, with histograms illustrating intensity; (a) gradual increases with broader shades variations, (b) surpassing concentrations variations, and (c) a prominent peak at coordinates (x=249, y=41,276) revealing distinct characteristics variations

Based on the proposed methodology, Table 6 captured the accuracy of the deep learning approach toward the improvement of 2-D and 3-D images respectively. Table 6, shows the real-world representation of the Taj Mahal, Pyramids of Giza and Dome Cathedral. Through the use of a deep learning approach (2D CNN 7, 18 and 3DCNN 7, 18), the accuracy for 2D images was 84.3%. Also, by improving the 2D images to 3D models, the accuracy of the images was 95.3%, underscoring the profound influence of deep learning on the enhancement process.

Table 6. Comparison of accuracy using CNN between 2D and 3D Models

Image	2D CNN 18	3D CNN 18	2D CNN 7	2D CNN 18
Taj Mahal	81.2%	95.3%	84.3%	91.4%
Pyramids of Giza	81.2%	95.3%	84.3%	91.4%
Dome Cathedral	81.2%	95.3%	84.3%	91.4%

4. CONCLUSION

Recent observations suggest that integrating deep learning techniques with augmented reality can significantly enhance the accuracy of object and pattern recognition in tourism applications. Our findings provide conclusive evidence that this approach, modeled after the human brain, is associated with substantial improvements in image accuracy, as demonstrated by the 95.3% accuracy achieved for 3D models of iconic tourist attractions like the Taj Mahal, the Pyramids of Giza, and the Dome. This phenomenon is not due to elevated numbers of traditional pattern recognition methods but rather a result of the deep learning algorithms' ability to analyze and identify patterns effectively.

Furthermore, our study demonstrates that the proposed deep learning-based augmented reality system is more resilient than conventional approaches in accurately interpreting and interacting with real-world environments. This has significant implications for the tourism industry, as it can make historical sites and artifacts more attractive and engaging for tourists, fostering greater interest and appreciation. Looking ahead, future studies may explore the fusion of augmented reality with blockchain technology, enabling secure and transparent transactions within tourism while ensuring the authenticity of historical sites and artifacts. This convergence has the potential to redefine tourist experiences, providing a secure, immersive, and personalized journey for travelers, thereby reshaping the tourism landscape significantly.

REFERENCES

[1] E. E. Cranmer, M. C. T. Dieck, and P. Fountoulaki, "Exploring the value of augmented reality for tourism," *Tourism Management Perspectives*, vol. 35, 2020, doi: 10.1016/j.tmp.2020.100672.

[2] I. Cibilić, V. Poslončec-Petrić, and K. Tominić, "Implementing augmented reality in tourism," *Proceedings of the ICA*, vol. 4, pp. 1–5, Dec. 2021, doi: 10.5194/ica-proc-4-21-2021.

[3] B. A. Dapshima, R. Mishra, and P. Tyagi, "Transformer faults identification via fuzzy logic approach," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 33, no. 3, pp. 1327–1335, Mar. 2024, doi: 10.11591/ijeecs.v33.i3.pp1327-1335.

[4] D. Ariansyah, B. Pardamean, E. Barbaro, and J. A. Erkoyuncu, "Augmented reality training for improved learnability," *CIRP Journal of Manufacturing Science and Technology*, vol. 48, pp. 19–27, Feb. 2024, doi: 10.1016/j.cirpj.2023.11.003.

[5] Y. Essa, A. Usman, T. Garg, and M. K. Singh, "Predicting the song popularity using machine learning algorithm," *International Journal of Scientific Research and Engineering Trends*, vol. 8, no. 2, pp. 1054–1062, 2022.

[6] A. Lakshmanarao, A. Srisaila, T. S. R. Kiran, K. V. Kumar, and C. S. Koppireddy, "An efficient smart grid stability prediction system based on machine learning and deep learning fusion model," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 33, no. 2, pp. 1293–1301, Feb. 2024, doi: 10.11591/ijeecs.v33.i2.pp1293-1301.

[7] W. M. Lim, K. M. Jasim, and M. Das, "Augmented and virtual reality in hotels: Impact on tourist satisfaction and intention to stay and return," *International Journal of Hospitality Management*, vol. 116, Jan. 2024, doi: 10.1016/j.ijhm.2023.103631.

[8] P. Peeters, E. Çakmak, and J. Guiver, "Current issues in tourism: Mitigating climate change in sustainable tourism research," *Tourism Management*, vol. 100, Feb. 2024, doi: 10.1016/j.tourman.2023.104820.

[9] C. D. Schultz and H. Kumar, "ARvolution: Decoding consumer motivation and value dimensions in augmented reality," *Journal of Retailing and Consumer Services*, vol. 78, May 2024, doi: 10.1016/j.jretconser.2023.103701.

[10] B. Bhattarai, R. Subedi, R. R. Gaire, E. Vazquez, and D. Stoyanov, "Histogram of oriented gradients meet deep learning: A novel multi-task deep network for 2D surgical image semantic segmentation," *Medical Image Analysis*, vol. 85, p. 102747, Apr. 2023, doi: 10.1016/j.media.2023.102747.

[11] P. Liu, H. Zhang, and K. B. Eom, "Active deep learning for classification of hyperspectral images," *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 10, no. 2, pp. 712–724, Feb. 2017, doi: 10.1109/JSTARS.2016.2598859.

[12] D. Wu *et al.*, "Computer vision-based intelligent elevator information system for efficient demand-based operation and optimization," *Journal of Building Engineering*, vol. 81, 2024, doi: 10.1016/j.jobe.2023.108126.

[13] K. Malek, A. Mohammadkhorasani, and F. Moreu, "Methodology to integrate augmented reality and pattern recognition for crack detection," *Computer-Aided Civil and Infrastructure Engineering*, vol. 38, no. 8, pp. 1000–1019, 2023, doi: 10.1111/mice.12932.

[14] K. Prabu and P. Sudhakar, "A hybrid deep learning approach for enhanced network intrusion detection," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 33, no. 3, pp. 1915–1923, 2024, doi: 10.11591/ijeecs.v33.i3.pp1915-1923.

[15] M. Younesi Heravi, Y. Jang, I. Jeong, and S. Sarkar, "Deep learning-based activity-aware 3D human motion trajectory prediction in construction," *Expert Systems with Applications*, vol. 239, 2024, doi: 10.1016/j.eswa.2023.122423.

[16] Q. Cheng, S. Zhang, S. Bo, D. Chen, and H. Zhang, "Augmented reality dynamic image recognition technology based on deep learning algorithm," *IEEE Access*, vol. 8, pp. 137370–137384, 2020, doi: 10.1109/ACCESS.2020.3012130.
[17] S. Minaee, Y. Boykov, F. Porikli, A. Plaza, N. Kehtarnavaz, and D. Terzopoulos, "Image segmentation using deep learning: A survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 44, no. 7, pp. 3523–3542, 2022, doi: 10.1109/TPAMI.2021.3059968.
[18] O. M. Saad, S. Fomel, R. Abma, and Y. Chen, "Unsupervised deep learning for 3D interpolation of highly incomplete data," *Geophysics*, vol. 88, no. 1, pp. WA189-W200, 2023, doi: 10.1190/geo2022-0232.1.
[19] K. Zhang, J. Wang, J. Zhang, Y. Wang, and Y. Zeng, "Exploring the impact of location-based augmented reality on tourists' spatial behavior, experience, and intention through a field experiment," *Tourism Management*, vol. 102, Jun. 2024, doi: 10.1016/j.tourman.2024.104886.
[20] S. Nasir, M. N. Zahid, T. A. Khan, K. Kadir, and S. Khan, "Augmented reality an economical solution for engineers and designers," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 17, no. 2, pp. 833–844, 2019, doi: 10.11591/ijeecs.v17.i2.pp834-844.
[21] R. Chaurasiya and D. Ganotra, "Deep dilated CNN based image denoising," *International Journal of Information Technology*, vol. 15, no. 1, pp. 137–148, Jan. 2023, doi: 10.1007/s41870-022-01125-2.
[22] S. Wang, S. A. Zargar, and F.-G. Yuan, "Augmented reality for enhanced visual inspection through knowledge-based deep learning," *Structural Health Monitoring*, vol. 20, no. 1, pp. 426–442, Jan. 2021, doi: 10.1177/1475921720976986.
[23] C. Kannan, R. Muthusamy, V. Srinivasan, V. Chidambaram, and K. Karunakaran, "Machine learning based detection of DDoS attacks in software defined network," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 32, no. 3, pp. 1503–1511, 2023, doi: 10.11591/ijeecs.v32.i3.pp1503-1511.
[24] G. Lampropoulos, E. Keramopoulos, and K. Diamantaras, "Enhancing the functionality of augmented reality using deep learning, semantic web and knowledge graphs: A review," *Visual Informatics*, vol. 4, no. 1, pp. 32–42, 2020, doi: 10.1016/j.visinf.2020.01.001.
[25] M. A. Khan, S. Israr, A. S Almogren, I. U. Din, A. Almogren, and J. J. P. C. Rodrigues, "Using augmented reality and deep learning to enhance Taxila Museum experience," *Journal of Real-Time Image Processing*, vol. 18, no. 2, pp. 321–332, 2021, doi: 10.1007/s11554-020-01038-y.

BIOGRAPHIES OF AUTHORS

Yasmin Chuupa Essa is currently pursuing a M. Tech in Software Engineering at Sharda University. She holds a B.Tech in Information Technology from the same institution. She can be contacted at email: Yasyessa0@gmail.com.

Saumya Chaturvedi is a accomplished Computer Science professional, is currently an Associate Professor at Sharda University's School of Engineering and Technology. Holding a Ph.D. in artificial intelligence and machine learning, an M. Tech from MNNIT, and a B.Tech from Uttar Pradesh Technical University, she boasts 12+ years of teaching and research experience. Dr. Chaturvedi has 20+ publications in Scopus and UGC indexed journals, 4 patents, and authored a book. Actively engaged in reviewing for Scopus Indexed Journals Computing. She can be contacted at email: saumyanmishra5@gmail.com.

Shiraz Khurana as an Associate Professor in the Department of Computer Science and Engineering at Sharda University's School of Engineering and Technology, he brings over 11 years of distinguished teaching experience in India and abroad. Proficient in Python and Java programming, he has mentored projects for global corporations, boasting a portfolio with 10 research papers, 3 patents, and participation in 10 expert lectures. He can be contacted at email: shiraz.khurana@sharda.ac.in.