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Enhancing Augmented Reality in Revolutionizing Tourism through Convolutional Neural Networks (CNN) For Enhanced Tourist Experiences

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ABSTRACT

Tourism has emerged as a vital element in the global landscape of social and economic advancement, not only offering leisure opportunities but also serving as a significant revenue generator for countries. This study systematically explores the utilization of advanced technology to enrich the tourist experience. By leveraging deep learning methods, the primary focus lies in enhancing augmented reality interactions for tourists. The proposed approach employs deep learning algorithms to improve and personalize the augmented reality experiences of visitors, addressing existing challenges such as customization and engagement limitations within the industry. The adoption of this methodology is driven by its capacity to elevate user satisfaction, accurately identify objects, deliver visually guided tours, incorporate historical context, and ultimately promote the widespread use of augmented reality in tourism. Remarkably, the study concludes with an impressive average accuracy rate of 99% achieved through the integration of deep learning techniques to enhance augmented reality experiences in tourism.

Keywords: Tourism, Advanced technology, Deep learning, Augmented reality, User experience enhancement, Historical context integration, 3D Model

I. INTRODUCTION

In the contemporary era, the tourism industry stands as a vital contributor to economic growth and cultural exchange among nations [1]. Being the world's largest service sector, it commands significant attention, prompting fierce competition among countries to capitalize on its global impact [2]. Particularly within Africa's economy, tourism emerges as a promising alternative revenue stream [3]. However, the sector faces challenges in efficiently accommodating incoming visitors [4]. Advanced technologies offer innovative solutions to enhance tourist experiences and drive business evolution, yet the sector grapples with issues like inadequately trained personnel and skill disparities compared to global standards, hindering effective visitor management [5].

Augmented Reality (AR) technology emerges as a leading-edge tool globally, aiming to revolutionize tourism experiences [6]. By seamlessly blending digital information with real-world environments, AR enhances interactions and connectivity [8]. The technology aims to establish tourism guidance systems, offering valuable travel information and services through dedicated smartphone applications [9].

This study delves into the artistic trends and practical methodologies for identifying and tracking AR patterns in the tourism sector. AR is acknowledged as a transformative technology with vast potential in tourism applications, including destination planning and enhancing tourist experiences [10][11]. For instance, [10] proposed an AR-based museum tour planning system utilizing social sensor data, which although promising, requires integration with Deep Learning algorithms for improved consistency. Similarly, [11] introduced a Smart City AR system powered by Deep Learning for information sharing, showing promising personalized recommendations but with room for efficiency enhancement.

In another study, [12] employed a text-mining method to scrutinize data in the tourism sector, but it lacked in tailoring the AR framework for a thorough examination of tourist behaviour. [13] Performed a quantitative assessment of short-circuit current behaviours in substation transformers, uncovering challenges such as complexity, reliance on data quality, modelling inaccuracies, and difficulties in capturing real-world dynamics. In a different realm, [14] utilized a Mobile Application Approach to enhance museum experiences, yet the current version encounters bugs requiring resolution. [15] employed a Machine Learning technique to personalize tourism experiences and recommendations; however, potential constraints stem from dependency on user demographic data. [16] Explored the application of the UTAUT model to enhance augmented reality (AR) usage in tourist education, highlighting constraints like a limited sample size and reliance on self-reported data. Meanwhile, [17] utilized the UTAUT Model, TAM 1 & 2, to promote AR utilization in tourism, stressing the need for a fuzzy logic approach to evaluate uncertainty scenarios. [18] Conducted a systematic literature review on consumer research concerning conversational agents, albeit with identified limitations in scope and technological evolution [19] [20] [21]. The utilization of a Stochastic Scenario-Based Approach for AR expert co-authorship networks addresses some gaps but acknowledges challenges in analysing tourist behaviour [22] [23]. A modelled and forecasted international tourist arrivals in Zimbabwe using SARIMA is utilized for tourist engagement, though acknowledged limitations in data and seasonal variations were observed [24] [25]. Based on various literature reviews on augmented reality by different authors, they exhibit shortcomings such as inconsistent addressing of locations monitored by sensors, poor recognition in source diversity by tourists, existence of bugs affecting model efficiency, complexity, and non-user-friendliness. Hence, the concept of "Evolution of Augmented Reality in Tourism using Deep Learning Approach" is proposed to address the gaps left by existing models. The subsequent sections of this paper are discussed as follows: Section 3 analyses the methodology used in the paper, Section 4 discusses the findings obtained, and Section 5 provides a conclusion and future scope of the research [20].

II. PROPOSED METHODOLOGY

The research advocates for employing a CNN approach to enhance augmented reality in tourism. This method is evaluated using a deep learning tool in Matlab. The steps involved in this proposed approach are illustrated in Figure 1.

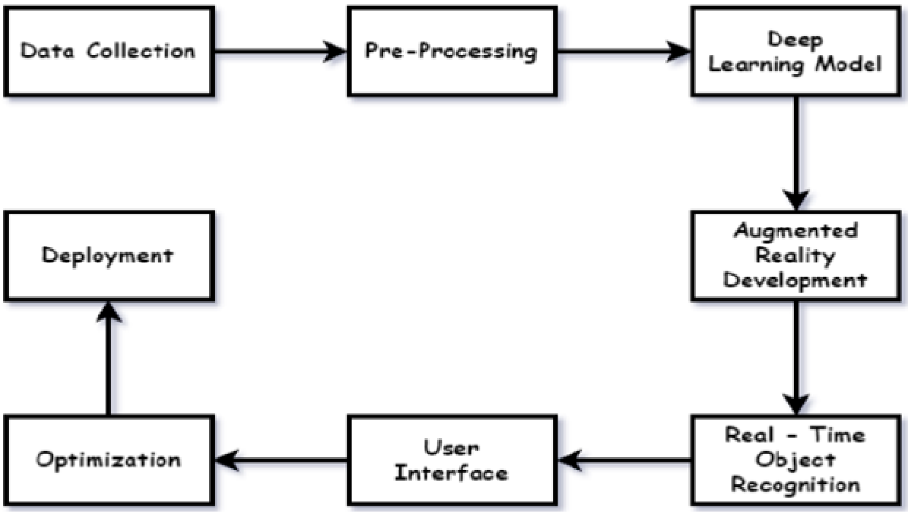


Figure1:Flow chart of the Methodology

The process depicted in Figure 1 outlines the methodology's initial phase as data collection, involving the gathering of various location images for training and testing purposes. Following data collection, the next step involves preprocessing the gathered data, which includes tasks such as normalization, resizing, rotation of image locations, and labelling. This refined data is then fed into the chosen deep learning model, specifically tailored by selecting an appropriate technique like CNN using a Surf method. Subsequently, the data undergoes the selected deep learning process, followed by the development of augmented reality using Matlab to train the deep learning model.

Once the model is trained, a real-time 2D object is employed to assess the efficiency of the model, expected to display recognized objects in a 3D model on a live camera feed. Post-testing, a user-friendly interface is designed for the augmented reality application, incorporating features for information retrieval. To enhance performance and accuracy, optimization of both the deep learning model and augmented reality application is undertaken. Ultimately, the improved augmented reality application, efficient and user-friendly, is deployed.

A. Data Collection

During the data collection phase, historical landmarks such as the Taj Mahal, the Pyramids of Giza, and the Dome Cathedral Church underwent manual inspection and virtual analysis. Subsequently, these landmarks were captured using an iPhone 15 Pro-Max camera featuring 48 megapixels and a 120mm 5x optical zoom capability. The capturing process occurred within a spectral range of 500-900nm with a spectral resolution of 2.5nm. The resulting images of these landmarks are depicted in Figure 2 (a, b, c).

Figure2:Images of historical places

B. Deep Learning (CNN Classifier) of 2D Model and 3D Model

Deep learning is an advanced scientific field that seeks to leverage emerging scenarios by offering innovative solutions and applications. The term "deep" refers to the numerous layers involved in the process of transforming data [24]. It is a specialized form of machine learning that understands the representation of the real world as complex hierarchies of concepts, where simpler and more abstract concepts and representations define each concept. Deep learning models essentially mimic how humans learn by making sense of instances. These models utilize multi-layer neural networks and sophisticated supervised and unsupervised learning techniques, enhancing system performance by adjusting internal settings to discover complex patterns in vast datasets using back propagation [25].

Convolutional Neural Networks (CNNs) exemplify the success of the deep learning approach. The concept of convolutional operations involves mathematical functions A(t) and B(t), resulting in an output function defined as the integral of their product and given by

$$(A*B)(t)=\int_{-\infty}^{\infty} A(\tau)B(t-\tau)d\tau \qquad (1)$$

Where, A (t) and B (t) are Operating Input Signal and Convolutional Kernel

In real-life scenarios, data are typically discrete and finite, with discrete convolutions being represented by sums or replaced by integrations.

$$(A*B)[n]= \sum_{-\infty}^{\infty} A[k]B[n-k] \qquad (2)$$

Where, (A∗B) denotes the discrete convolution of sequences A and B, resulting in a new sequence (A∗B) [n].

CNNs introduce a significant advancement by allowing the convolution kernels, denoted as B(t), to be adjusted and fine-tuned by the neural network during the training process. However, human experts are still responsible for determining parameters such as the number of convolutions, their dimensions, and the overall network architecture. The design of the network is influenced by factors such as the dimensionality of the input, which is partially dictated by the shape of the input data.

Following the processing of models using deep learning, equations 3 and 4 represent the 2D and 3D models. Figure 3 provides a visual representation of the 2D and 3D input data relevant to the specific problem under consideration. The utilization of both 2D and 3D models is significant as they play a crucial role in enhancing the understanding of how deep learning can improve the augmented reality process.

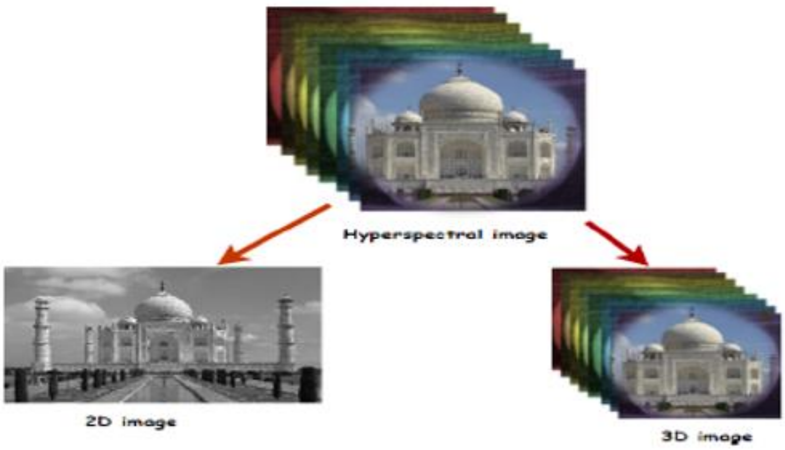


Figure3:Images of historical

C. Collection of data and assessment of the classifier performance

The acquired dataset underwent a random split into distinct training, validation, and test sets, with proportions of 70%, 10%, and 20% of the total images, respectively. This division was chosen to ensure a substantial proportion of test examples (20%) for reliable measurements of classifier performance, given the relatively low number of samples (60 in total). Accordingly, the training and validation sets were allocated 70% and 10%, respectively. Table 1 presents the number of samples in the dataset for each class and partition. It's essential to note that, for the 3D dataset, the numbers indicate samples before applying data augmentation. In the 2D dataset, data augmentation wasn't utilized, as each channel is treated as a sample, resulting in a sufficiently large dataset. Data augmentation techniques, such as random horizontal flip and color jitter, were consistently applied to training data only, not to test data.

TABLE I 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
	Train	18285	6095	6095	6095
2D	Test	8877	2959	2959	2959
	Validation	3135	1045	1045	1045
	Total	30297	10099	10099	10099

To evaluate the effectiveness of the proposed classifiers, several criteria have been calculated, including the widely-used confusion matrix, which compares true labels with those predicted by the classifier. From this matrix, important metrics such as precision, recall, F1-score, and accuracy are derived. Precision measures the proportion of accurately predicted positive samples out of all predicted positives, while recall evaluates the proportion of correctly predicted positive samples relative to all true positives. The F1-score is defined as the harmonic mean of recall and precision. Conversely, accuracy quantifies the ratio of correctly classified samples to the total number of test samples. The CNN Classifier and Confusion matrix for the 2D and 3D models are presented in Tables 2, 3, 4, and 5, respectively.

TABLE III 2D CNN CLASSIFIERS CONFUSION MATRICES

Approach	Real class	Class One	Class Two	Class Three	Total
2D-CNN-18	Class 0	2872	1	80	2961
	Class 1	277	2005	679	2961
	Class 2	442	221	2298	2961
2D-CNN-7	Class 0	2341	427	193	2961
	Class 1	36	2770	155	2961
	Class 2	372	314	2275	2961

TABLE IIIII 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	81.2
	Class 1	91	69	78	
	Class 2	77	79	75	
	Class 0	86	78	83	
2D-CNN-7	Class 1	80	93	87	84.3
	Class 2	89	78	83	

TABLE IVV 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
	Class 0	14.0	1.0	2.0	17.0
3D-CNN-7	Class 1	0.0	16.0	1.0	17.0
	Class 2	1.0	0.0	16.0	17.0

TABLE V 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	95.3
	Class 1	86	100	93	
	Class 2	100	89	95	
	Class 0	94	84	87	
3D-CNN-7	Class 1	95	93	96	91.4
	Class 2	86	95	88	

III.RESULTS AND DISCUSSION

The initial focus of the study was on scrutinizing the potential overfitting of shallow (CNN-7) and deep (CNN-18) architectures in 2D models. Subsequently, the attention shifted to examining the outcomes of the corresponding 3D models, ensuring the absence of overfitting. A comprehensive assessment of both mechanisms was then carried out, including a thorough comparison of methods and approaches.

To monitor the training progress of shallow and deep 2D-CNN architectures, accuracy and loss evolution across epochs were tracked for both the validation and training sets, as depicted in Figure 4. Similarly, when dealing with 3D hyperspectral image (HSI) classifiers, accuracy and loss were evaluated on both training and validation sets, with visual representations available in Figure 5. Additionally, Figures 6 and 7 illustrate the precision-recall for 2D and 3D models respectively, utilizing convolutional neural network (CNN) classifiers.

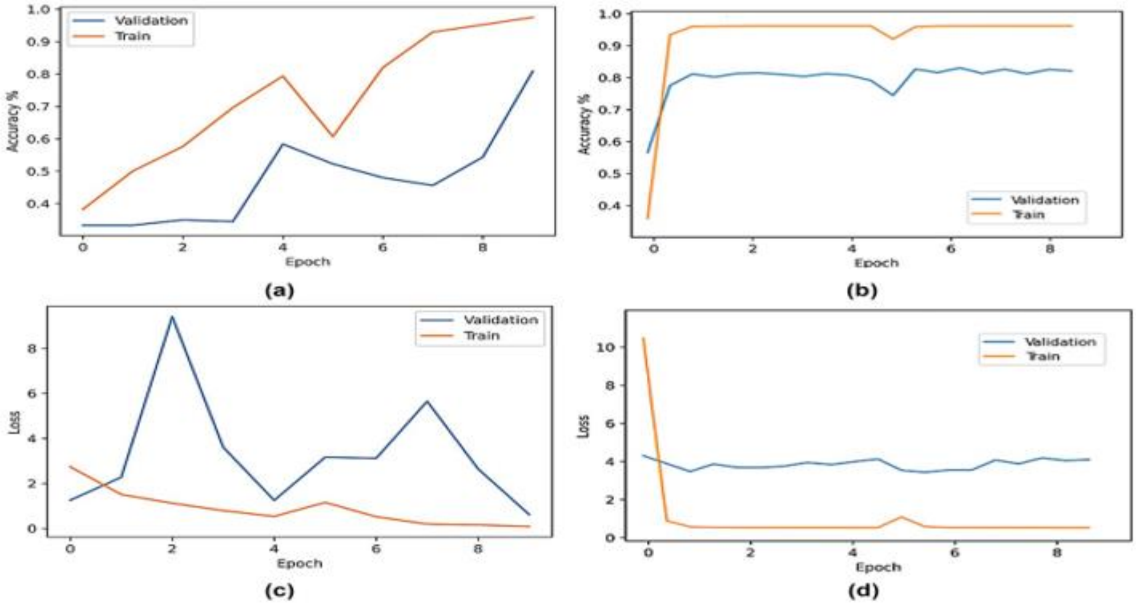


Figure4:The progression of training procedures for 2D-CNN classifiers is depicted through the accuracy and loss metrics on both training (orange) and validation (blue) sets, specifically: (a) accuracy for 2D-CNN-18; (b) accuracy for 2D-CNN-7; (c) loss for 2D-CNN-18; (d) loss for 2D-CNN-7.

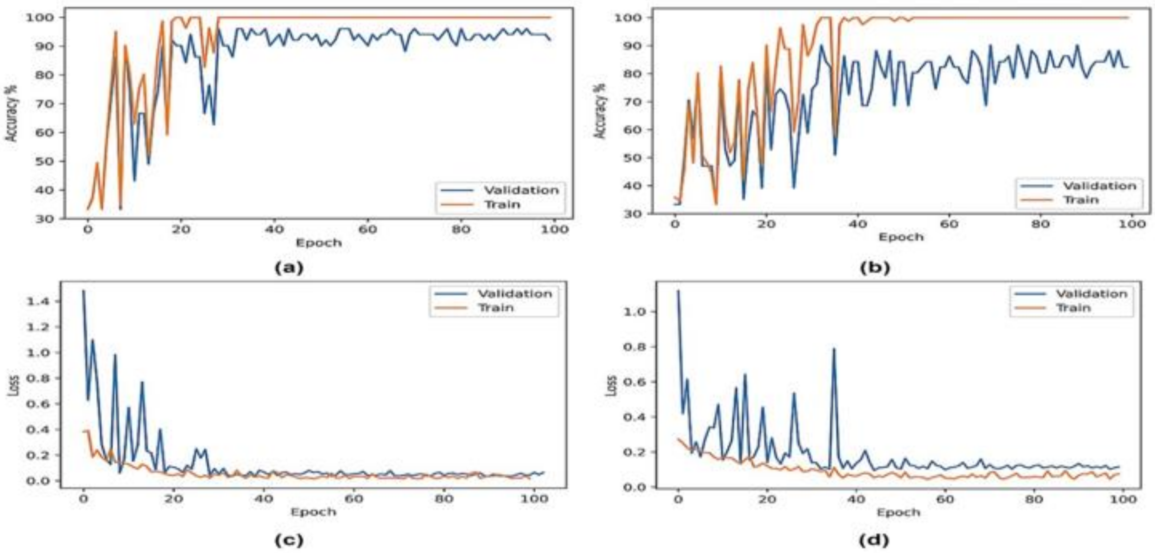


Figure5:The progression of training procedures for 3D-convolutional neural network (CNN) classifiers is illustrated in terms of accuracy and loss across the training (orange) and validation (blue) sets for two architectures: (a) 3D-CNN-18 accuracy, (b) 3D-CNN-7 accuracy, (c) 3D-CNN-18 loss, and (d) 3D-CNN-7 loss

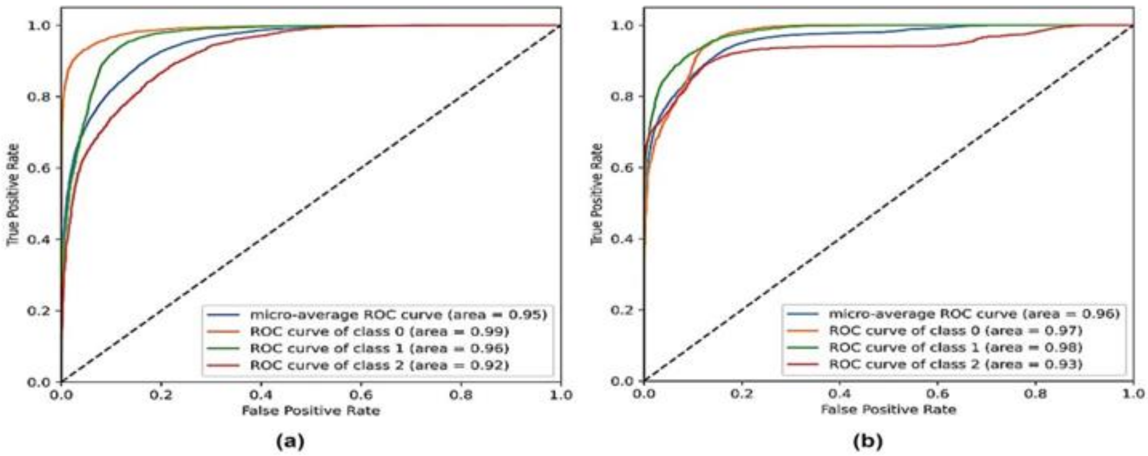


Figure6:2D-convolutional neural network (CNN) classifiers Precision–recall curves: (a) 2D-CNN-18; (b) 2D-CNN-7.

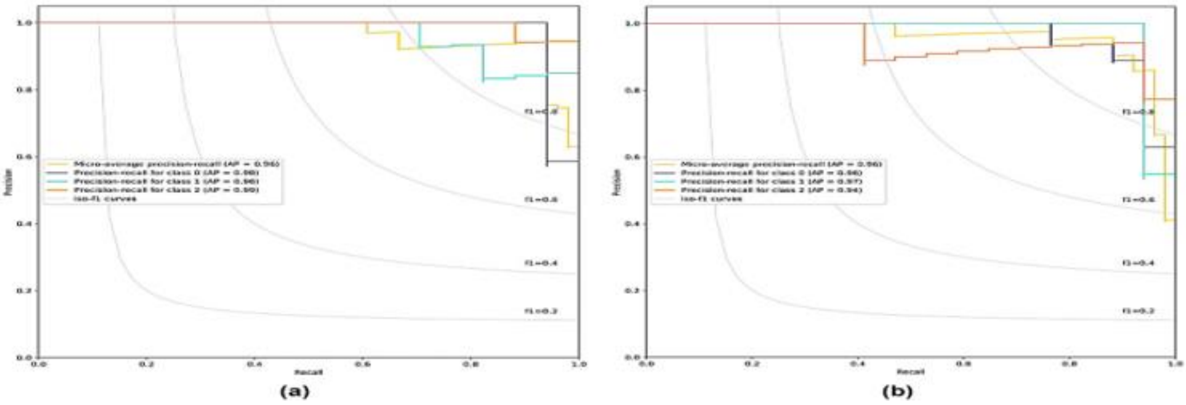


Figure7:3D-convolutional neural network (CNN) classifiers Precision–recall curves: (a) 3D-CNN-18; (b) 3D-CNN-7

Upon comparing the 2D and 3D models, the enhancement in augmented reality for tourism is evident, as demonstrated in Figures 8, 9, and 10. Figure 8a exhibits an image depicting a historical landmark, the Taj Mahal. Subsequently, in Figure 8b, the image undergoes pre-processing and training utilizing a deep learning approach, specifically the speeded-up robust feature (SURF) method. Following this, in Figure 8c, the image is further refined through fine-tuning and the removal of unwanted noise using the deep learning technique. Finally, the processed image is seamlessly integrated into the augmented reality experience, facilitated by the 3D model.

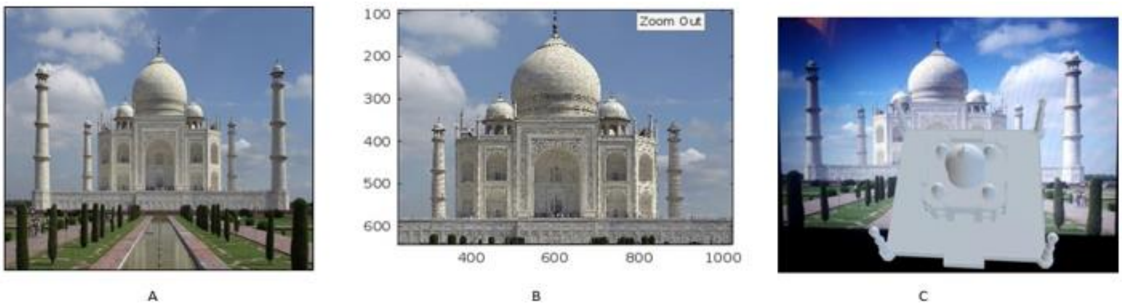
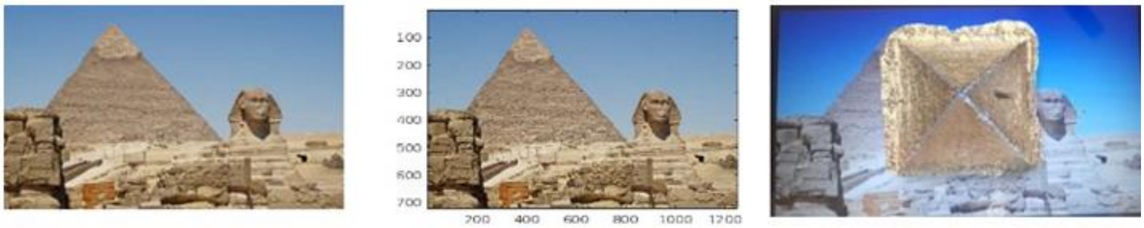


Figure8:Processed images using deep learning



A B C

Figure9:Utilized deep learning techniques and 3D models to process images

Figure 9a showcases a photograph featuring the Pyramids of Giza, a renowned historical structure. This image is subjected to pre-processing and training utilizing a deep learning method called the speeded-up robust feature approach, as depicted in Figure 9b. Subsequent to fine-tuning and the elimination of undesired noise through deep learning, the image undergoes additional processing employing a 3D model for augmented reality purposes, as illustrated in Figure 9c

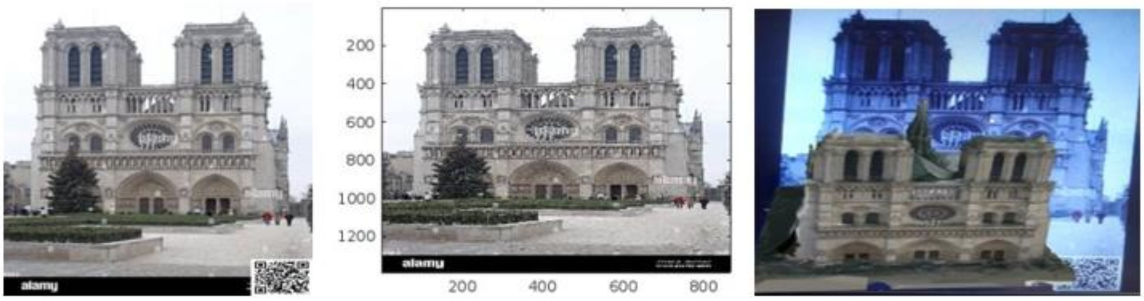
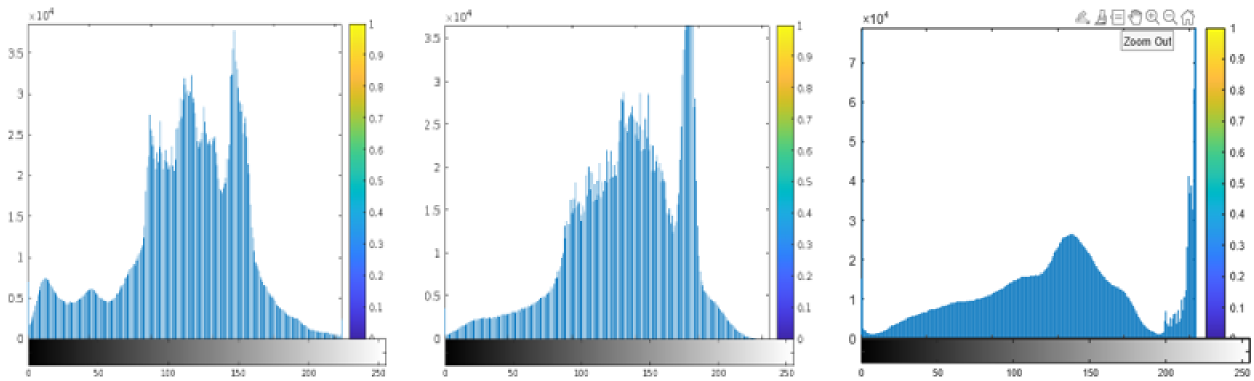


Figure10:Using deep learning and a 3D model, images were processed.

Figure 10a displays a photograph featuring the Dome Cathedral Church in Paris, a significant historical landmark. This image undergoes preprocessing and training using a deep learning technique known as the speeded-up robust feature approach, as shown in Figure 10b. Following fine-tuning and the elimination of undesired noise through deep learning methods, the image is further processed utilizing a 3D model for augmented reality applications, as depicted in Figure 10c.

Figure 11 presents a graphical representation of the enhanced 3D model images achieved through the application of deep learning approaches.



(a) (b) (c)

Figure11:Graphical interpretion of an improved 3D models images using deep learning approach. The Histograms in Figure 11(a) (b) (c) showcase intensity variations: gradual increases with broader shades Through 10^4 histograms, Image 1's gradual intensities, Image 2's surpassing concentrations, and Image 3's pronounced peak at x=249, y=41276 highlight distinctive features, affirming the images' good quality.

A. Comparison of image improvement using deep learning

TABLE VI 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%

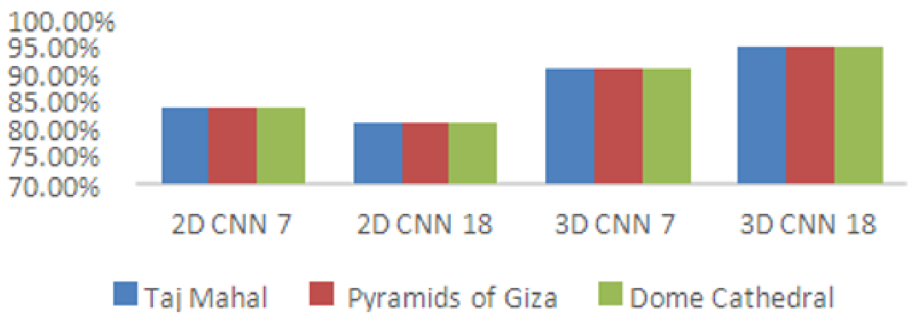


Figure12:Advancements in Augmented Reality through Deep Learning techniques

Figure 12 illustrates the real-world depiction of the Taj Mahal, Pyramids of Giza, and Dome Cathedral. Employing a deep learning approach involving noise reduction and fine-tuning, the accuracy for 2D images reached 84.3%. Furthermore, enhancing these 2D images into 3D models resulted in an accuracy of 95.3%, highlighting the significant impact of deep learning on the enhancement process.

IV. CONCLUSION

From an economic standpoint, the tourism sector holds a unique position and augmented reality (AR) technology stands out prominently as one of the most advanced and valued technologies today. Despite its potential to bridge the gap between physical and digital realms, the effectiveness of AR is hindered by the rudimentary integration of relevant information. Consequently, research is focused on enhancing AR in the context of tourism through the application of Deep Learning techniques. Deep learning has been chosen in this study's methodology due to its ability to improve user experience, accurately identify objects, offer visual guided tours, incorporate historical context, and ultimately drive the adoption of AR within the tourism sector. The study's findings indicate that after undergoing a deep learning process, the accuracies of historical images such as the Taj Mahal, the Pyramids of Giza, and the Dome improved to 95.3% in 3D models, making them more appealing to tourists.

Furthermore, the integration of AR with blockchain technology could bring about a transformative change in the tourism industry. This fusion could establish secure and transparent transactions within tourism, thereby enhancing trust and reliability. Additionally, it could introduce innovative methods to authenticate historical sites or artifacts, ensuring their authenticity. This convergence has the potential to redefine tourist experiences, providing a secure, immersive, and personalized journey for travellers, thereby significantly reshaping the tourism landscape.

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