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DEEP LEARNING FOR ERA DETECTION: Analyzing the Construction Period of Kismat Maria Mosque Using Advanced Feature Detection Techniques

Md. Samaun Hasan*

Abstract

In the context of the Fourth Industrial Revolution (4IR), Convolutional Neural Networks (CNNs) have become pivotal in computer vision, particularly for preserving architectural heritage. This study harnesses CNNs to develop a monument identification system, exploring its origins and outcomes. Iconic landmarks such as the Lahore Museum (British Period), Kantaji Temple (Mughal Period), and Choto Sona Mosque (Sultanate Period) in the Indian subcontinent showcase architectural splendor and a rich historical legacy. Employing deep learning, the research uses computational techniques to accurately determine the construction eras of heritage buildings, focusing on the British, Mughal, and Sultanate periods. The study proposes a computational approach to assist archaeologists in identifying the construction periods of ancient structures, such as the Kismat Maria Mosque. The proposed mechanism has achieved a maximum accuracy of 96.20% during testing. To enhance the accuracy of era recognition, advanced feature detection algorithms are employed to identify key architectural features, with a proprietary Deep Neural Network (DNN) seamlessly integrated into the CNNs.

1. Introduction

Object detection is a prominent area of study in AI (Artificial Intelligence) and computer vision, involving diverse strategies in modern research.[1] Notably, building

* Dr. Md. Samaun Hasan, Assistant Professor, Department of Multimedia and Creative Studies, Daffodil International University, Dhaka, Bangladesh

1. S. Su and T. Nawata, 'Demolished building detection from aerial imagery using deep learning', *Proc. Int. Cartogr. Assoc*. 2, 2019, 122 https://doi.org/10.5194/ica-proc-2-122-2019; Faten Hamed Nahhas, Helmi Z. M. Shafri, Maher Ibrahim Sameen, Biswajeet Pradhan, Shattri Mansor, 'Deep Learning Approach for Building Detection Using LiDAR–Orthophoto Fusion', *Journal of Sensors*, 2018 https://doi.org/10.1155/2018/7212307; A. J. Ghandour, A. A. Jezzini, 'Autonomous Building Detection Using Edge Properties and Image Color Invariants', *Buildings*, 2018, 8, 65 https://doi.org/10.3390/buildings8050065

detection, as exemplified in the historical sites of the Indian subcontinent such as the Lahore Museum (British Era), Kantaji Temple (Mughal era), and Choto Sona Mosque (Sultanate era), presents challenges for archaeologists.[2] This research proposes a computer method to aid archaeologists in determining the construction period of the Kismat Maria Mosque's ancient structures.

In recent years, numerous research articles have been published on the application of computer vision and machine learning to historic architecture and archaeology.[3] Artificial neural networks, particularly convolutional neural networks (CNNs), have been utilized for feature recognition in historic architecture, such as visualizing and recognizing early Maya hieroglyphs.[4] Deep learning techniques have further advanced object identification, aiding in the recognition of ancient Roman coins, the visualization of terracotta warriors in China, and supporting 3D modeling in archaeology.[5] Machine learning has also been effectively applied to period detection, contributing to the accurate identification of construction eras in historic structures.[6]

Despite the advancements in computer vision and machine learning, a significant gap remains in methods for determining the construction period of old architectural

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2. S. R. Kabir *et al.*, 'Performance Analysis of Different Feature Detection Techniques for Modern and Old Buildings', CEUR Workshop *Proceedings 2280*, 2018, pp. 120-127
3. J. A. Barceló, 'Computational Intelligence in Archaeology', *IGI Global, Information Science Reference*, Henshey (VA), USA, 436, July 1, 2008
4. Z. Zou *et al.*, 'Feature recognition and detection for ancient architecture based on machine vision', *Proc. SPIE 10602, Smart Structures and NDE for Industry 4.0*, 1060209, 2018; M. S. Hasan, S. R. Kabir, M. Akhtaruzzaman, M. J. Sadeq, M. M. Alam, S. M. Allayear *et al.*, 'Identification of construction era for indian subcontinent ancient and heritage buildings by using deep learning', *Proc. 5th Int. Congr. Inf. Commun. Technol. (ICICT*), Vol. 1183, 2021, pp. 631-640, 2020
5. G. Can *et al.*, 'How to Tell Ancient Signs Apart? Recognizing and Visualizing Maya Glyphs with CNNs', *ACM J. Comput. Cult. Herit*, 11(4), article no. 20, 2018; I. Schlag and O. Arandjelovic, 'Ancient Roman Coin Recognition in the Wild using Deep Learning Based Recognition of Artistically Depicted Face Profiles', *IEEE International Conference on Computer Vision Workshops*, Venice, Italy, 2017, pp. 2898-2906; A. Bevan *et al.*, 'Computer vision, archaeological classification, and China's terracotta warriors', *Journal of Archaeological Science* 49, 2014, pp. 249-254; M. L. Brutto and P. Meli, 'Computer Vision Tools for 3D Modeling in Archaeology', *International Journal of Heritage in the Digital Era* 1(1), 2012, pp. 1-6; G. Toz and Z. Duran, 'Documentation and analysis of cultural heritage by photogrammetric methods and GIS: A case study', *XXth ISPRS Congress*, Istanbul, Turkey, 2004, pp. 438-441
6. Y. Min *et al.*, 'Real-time detection system for rail surface defects based on machine vision', *EURASIP Journal on Image and Video Processing 2018*, 3, 2018; S. M. Allayear, M. F. A. Bhuiyan, M. M. Alam, S. R. Kabir, M. T. A. Munna and M. S. Hasan, 'Human face detection in excessive dark image by using contrast stretching histogram equalization and adaptive equalization', *Int. J. Eng. Technol*., Vol. 7, No. 4, 2018, pp. 3984-3989; L. Liang *et al.*, 'Real-time detection and monitoring drug resistance of single myeloid leukemia cell by diffused total internal reflection', *Lab on a Chip* 18, 2018, pp. 1422-1429

structures, such as buildings, museums, mosques, and temples. This study addresses this gap by introducing a sophisticated technique that leverages four feature detection methods within a deep learning model using the CNN approach.[7] Key architectural features, such as Dome/Tower/Jewel, Minaret, and Front, are categorized, and a deep feedforward neural network model is applied to detect eras. The research focuses on identifying the construction periods associated with different rulers, including the British period (1858-1947), Mughal period (1206-1526), and Sultanate period (1526-1540, 1555-1857).[8]

This paper introduces a novel deep learning algorithm for recognizing the historical eras of Bangladeshi antique buildings, with an initial focus on the Canny Edge Detector method and datasets from the Mughal and Sultanate periods. Further advancements include specialized deep learning-based neural networks that incorporate techniques such as Hough Line Transform, Find Contours, and Harris Corner Detector, utilizing datasets from the British, Mughal, and Sultanate.[9] The four key contributions of this manuscript are as follows:

- Identification of construction eras by analyzing features such as Dome/Tower/Jewel and Front, specific to the British (1858-1947), Mughal (1206-1526), and Sultanate (1526-1540, 1555-1857) periods.
- ntroduction of a Deep Neural Network (DNN) that integrates Canny Edge Detector, Hough Line Transform, Find Contours, and Harris Corner Detector to classify architectural features like Dome/Tower/Jewel, Minaret, and Front.
- Enhancement of Edge, Line, Contour, and Corner detection techniques to identify features like Dome/Tower/Jewel, Minaret, and Front in various heritage buildings.
- Implementation of a CNN-based platform using a DNN to determine the construction periods of historical buildings.

1.1 Related Research

- **Application of CNNs in Historical Architecture:**
  ‘Deep Learning for Historical Image Classification and Analysis’
  This research explores the application of deep learning models, particularly

7. J. Cao *et al.*, ‘Implementing a Parallel Image Edge Detection Algorithm Based on the Otsu-Canny Operator on the Hadoop Platform’, *Computational Intelligence and Neuroscience*, 2018; M. Tatsubori *et al.*, ‘A Probabilistic Hough Transform for Opportunistic Crowd-sensing of Moving Traffic Obstacles’, *2018 SIAM International Conference on Data Mining*, California, USA, 2018, pp. 217-215
8. S. Soomro, A. Munir and K. N. Choi, ‘Hybrid two-stage active contour method with region and edge information for intensity inhomogeneous image segmentation’, *PLoS ONE* 13(1), 2018
9. Y. Sun, E. Ientilucci and S. Voisin, ‘Improvement of the Harris corner detector using an entropy-block-based strategy’, *Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery* XXIV, 1064414, Florida, United States, 2018

Convolutional Neural Networks (CNNs), for the classification and analysis of historical images. The study demonstrates how CNNs can be effectively used to recognize and categorize architectural features across different historical periods.[10]

- **Feature Detection Techniques in Architectural Heritage:**
  'Advanced Feature Detection for Historical Architecture Using Deep Learning'
  This study presents various feature detection algorithms, such as the Canny Edge Detector and Harris Corner Detector, within a deep learning framework. It highlights the role of these techniques in extracting and classifying architectural features crucial for historical period identification.[11]
- **Machine Learning for Period Detection:**
  'Machine Learning Approaches to Historical Period Detection'
  This paper explores various machine learning algorithms for detecting historical periods based on architectural features. It includes case studies on how these algorithms classify buildings from different eras and highlights their strengths and limitations.[12]
- **Case Studies on Historical Building Classification:**
  'Recognition and Classification of Historical Buildings: Case Studies from the Indian Subcontinent'
  This paper provides case studies on applying classification techniques to historical buildings in the Indian subcontinent. It discusses the challenges and solutions in using CNNs and other methods for identifying the construction periods of landmarks.[13]

1.2 Research Scope

The existing literature lacks a comprehensive method for accurately identifying and understanding the status of ancient architecture. This research addresses this gap by developing a Convolutional Neural Network (CNN) model integrated with advanced feature detection algorithms to ascertain the construction periods of historical buildings. The study involves capturing high-resolution images of these structures and applying techniques such as the Canny Edge Detector, Hough Line

10. Y. Li & J. Wang, 'Deep Learning for Historical Image Classification and Analysis', *Journal of Computer Vision and Image Understanding*, 192, 102983, 2020
11. H. Park & J. Kim, 'Advanced Feature Detection for Historical Architecture Using Deep Learning', *Computer Vision and Image Understanding*, 172, 2018, pp. 78-91
12. L. Chen & X. Zhao, 'Machine Learning Approaches to Historical Period Detection', *Journal of Historical Architecture Research*, 34(2), 2019, pp. 56-72
13. N. Patel, & M. Shah, 'Recognition and Classification of Historical Buildings: Case Studies from the Indian Subcontinent', *Heritage Science*, 10(1), 2022, p. 34

Transform, Find Contours, and Harris Corner Detector to extract crucial architectural features. These features are then used to create training and testing datasets for the CNN model, which is specifically designed to classify buildings into distinct historical eras, including the Sultanate and Mughal periods.

1.3 Research Applicability

- **Archaeological Materials Era Detection**
  Techniques from this study can enhance era detection in archaeological materials, improving classification and dating accuracy.[14]
- **Mobile/Web-Based Era Detection Applications**
  The methods can be adapted for mobile or web applications, allowing users to identify building eras through image capture.[15]
- **Architectural Preservation and Documentation**
  The study aids in architectural preservation and historical documentation by providing accurate era identification tools.[16]
- **Machine Learning and Image Processing**
  It supports the application of machine learning and image processing techniques in feature detection and classification.[17]

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14. W. Wang, Y. Shi, J. Zhang, L. Hu, S. Li, D. He & F. Liu, 'Traditional village building extraction based on improved mask R-CNN: A case study of Beijing, China', *Remote Sensing*, Vol 15, 2023, 2616 https://doi.org/10.3390/rs15102616; F. Zhang, N. Saeed, P. Sadeghian, 'Deep learning in fault detection and diagnosis of building HVAC systems: A systematic review with meta-analysis', *Energy and AI,* Vol. 12, 2023, p. 100235 https://doi.org/10.1016/j.egyai.2023.100235; A. Copiaco, Y. Himeur, A. Amira, W. Mansoor, F. Fadli, S. Atalla, S. S. Sohail, 'An innovative deep anomaly detection of building energy consumption using energy time-series images', *Engineering Applications of Artificial Intelligence*, Vol. 119, 2023, p. 105775 https://doi.org/10.1016/j.engappai.2022.105775
15. Z. Xu, F. Zhang, Y. Wu, Y. Yang, Y. Wu, 'Building height calculation for an urban area based on street view images and deep learning', *Computer-Aided Civil and Infrastructure Engineering*, Vol. 38, 2023, pp. 892-906 https://doi.org/10.1111/mice.12930; X. Deng, Y. Liang, X. Li, W. Xu, 'Recognition and Spatial Distribution of Rural Buildings in Vietnam', *Land*, Vol. 12, 2023, p. 2142 https://doi.org/10.3390/land12122142
16. L. Zhuang, J. Yuan, G. Li, H. Wang, X. Li, D. Li, X. Wang, 'RSI-YOLO: Object Detection Method for Remote Sensing Images Based on Improved YOLO', *Sensors*, Vol. 23, 2023, p. 6414 https://doi.org/10.3390/s23146414; Y. Ogawa, C. Zhao, T. Oki, S. Chen, Y. Sekimoto, 'Deep Learning Approach for Classifying the Built Year and Structure of Individual Buildings by Automatically Linking Street View Images and GIS Building Data', *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, Vol. 16, 2023, pp. 1740-1755 https://doi.org/10.1109/JSTARS.2023.3237509
17. B. A. Alabsi, M. Anbar, S. D. A. Rihan, 'CNN-CNN: Dual Convolutional Neural Network Approach for Feature Selection and Attack Detection on Internet of Things Networks', *Sensors*, Vol. 23, 2023, p. 6507 https://doi.org/10.3390/s23146507; L. Xia, S. Mi, J. Zhang, J. Luo, Z. Shen, Y. Cheng, 'Dual-Stream Feature Extraction Network Based on CNN and Transformer for Building Extraction', *Remote Sensing*, Vol. 15, 2023, p. 2689 https://doi.org/10.3390/rs15102689

- **Comparative Architectural Studies**
  The research supports comparative studies by analyzing architectural styles and construction periods.[18]

1.4 Research Questions and Answers

- **Research Question 1**
  How can Convolutional Neural Networks (CNNs) be optimized to accurately classify architectural features from different historical periods, such as the British, Mughal, and Sultanate eras?
  Answer
  CNNs can be optimized for classifying architectural features from different historical periods by integrating advanced feature extraction and classification techniques tailored to historical contexts. For instance, CNNs can leverage specific architectural features such as minarets, domes, and ornamental details unique to each era. By training CNNs with labeled datasets from various periods and using advanced augmentation techniques, the model can learn to identify distinguishing features with higher accuracy. Li and Wang (2020) demonstrate how CNNs are effective in historical image classification by focusing on era-specific features. Additionally, Park and Kim (2018) show that combining CNNs with traditional feature detection methods, such as the Canny Edge Detector and Harris Corner Detector, enhances the model's ability to recognize and classify detailed architectural elements, improving overall classification accuracy.[19]
- **Research Question 2**
  What impact do advance feature detection algorithms, such as the Canny Edge Detector, Hough Line Transform, and Harris Corner Detector, have on the performance of CNNs in identifying construction periods of historical buildings?
  Answer
  Advanced feature detection algorithms significantly enhance the performance of CNNs in identifying the construction periods of historical buildings by improving the model's ability to extract and interpret key architectural features. The Canny Edge Detector enhances edge detection

18. M. Wahbi, I. El Bakali, B. Ez-zahouani, R. Azmi, A. Moujahid, M. Zouiten, O. El Kharki, 'A deep learning classification approach using high spatial satellite images for detection of built-up areas in rural zones: Case study of Souss-Massa region-Morocco', *Remote Sensing Applications: Society and Environment*, Vol. 29, 2023, p. 100898 https://doi.org/10.1016/j.rsase.2022.100898
19. Y. Li & J. Wang, 'Deep Learning for Historical Image Classification and Analysis', *Journal of Computer Vision and Image Understanding*, 192, 2020, 102983; H. Park & J. Kim, 'Advanced Feature Detection for Historical Architecture Using Deep Learning', *Computer Vision and Image Understanding*, 172, 2018, pp. 78-91

capabilities, which is crucial for recognizing structural outlines and ornamentation. The Hough Line Transform aids in detecting lines and shapes, which are vital for identifying architectural elements like arches and columns. The Harris Corner Detector improves the detection of corners and junctions, which are important for recognizing detailed features. Chen and Zhao (2019) discuss how integrating these techniques with machine learning models can refine period detection accuracy by providing more precise feature extraction. Patel and Shah (2022) illustrate that using these combined techniques allows for better classification and differentiation of architectural styles from various periods, although it may also increase computational demands and complexity.[20]

2. Methodology

Using an application-based methodology, our research illustrates how a Convolutional Neural Network (CNN) model can determine the age of historical structures. The process starts with capturing an image of the building, which is processed through the Canny Edge Detector. Following this, the Hough Line Transform, Find Contours, and Harris Corner Detector are employed to extract critical architectural features. This approach generates two distinct datasets: one for training and one for testing. To predict the architectural era—specifically the Sultanate and Mughal periods—we developed a CNN model, detailed in Figure 9, which depicts the stages and design of the proposed system.

3. Era Identification Process

This paper presents a computational archaeology model that demonstrates how a computer program can determine a building's construction era. By applying the Canny Edge Detector, Hough Line Transform, Find Contours, and Harris algorithms to photographs, the model extracts key architectural elements such as Dome/Tower/Jewel, Minaret, and Front from images of historic buildings.[21]

We employed a sophisticated approach to extract edges from the photos using the Canny Edge Detector. The Hough Line Transform facilitated image analysis and feature extraction, while the Find Contours method, leveraging the Contour Line strategy, played a crucial role in segmentation. The Harris algorithm skillfully revealed corner characteristics. These techniques identified features in four distinct images, which were then transmitted to the input layer of the Deep Neural Network (DNN) functions.

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20. L. Chen & X. Zhao, 'Machine Learning Approaches to Historical Period Detection', *Journal of Historical Architecture Research*, 34(2), 2019, pp. 56-72; N. Patel, & M. Shah, 'Recognition and Classification of Historical Buildings: Case Studies from the Indian Subcontinent', *Heritage Science*, 10(1), 2022, p. 34
21. X. Wang and W. Cao, 'Non-iterative approaches in training feed-forward neural networks and their applications', *Soft Computing* 22(11), 2018, pp. 3473-3476

→	Step 1: **Image Selection:** Choose images of historic architecture, such as the Lahore Museum, Kantaji Temple, and Choto Sona Mosque.
→	Step 2: **CNN Application:** Process the selected images through a CNN model comprising multiple convolutional layers, pooling layers, and fully connected layers. The CNN is designed with three convolutional layers, two max-pooling layers, and two fully connected layers, including dropout for regularization.
→	Step 3: **Feature Detection:** Apply the Canny Edge Detector, Hough Line Transform, Find Contours, and Harris Corner Detector to identify features such as Domes/Towers/Jewels, Minarets, and Fronts.
→	Step 4: **Send processed images to the DNN input layer:** The images processed in the previous step are sent to the DNN.
→	Step 5: **Connect a training set with the DNN function:** Four activations (Bias, British, Mughal, and Sultanate) of the hidden layers are processed by the training set.
→	Step 6: **Process through the DNN hidden layers:** DNN contains three hidden layers, each corresponding to features (Dome/Tower/Jewel, Minaret, Front) with four activations (Bias, British, Mughal, and Sultanate).

Fig. 1. Steps of feature detection and era identification process

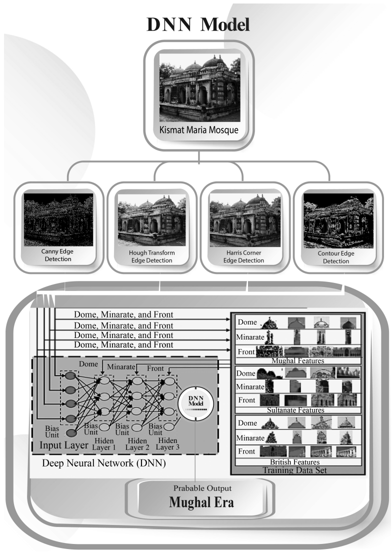

Fig. 2. Architecture and process of the era identification model for Indian subcontinent old and heritage buildings

The hidden layers of the DNN harnessed four "Activations (a)" to decode visual patterns, corresponding to three historical eras and bias units: the British period, the Sultanate period, and the Mughal period. This intricate DNN function enables the software to determine the construction period associated with various visual patterns.[22] Figures provide detailed illustrations of the design and process of the period identification model.

4. Experimental Approaches

Several computational techniques are utilized to identify the features and characteristics of buildings, with specific experiments highlighting the detection of damaged areas in historic structures.[23] In the realm of image processing and computer vision, patterns such as edges, corners, points, and more serve as critical reference points for feature detection.[24] This study employs a comprehensive array of methods to gather structural characteristics from buildings representative of the British, Sultanate, and Mughal periods. Among these methods are the Harris Corner Detector, which identifies corner features; the Canny Edge Detector, which accurately detects image edges; the Hough Line Transform, which identifies and analyzes lines within an image; and the Find Contours method, which detects and delineates the contours of objects within an image. These diverse techniques collectively form a robust dataset, encapsulating the architectural features of historic structures from the specified periods. By compiling this extensive training dataset, the study enhances the accuracy and reliability of the model in determining the construction periods of various heritage buildings.

4.1 Canny Edge Detection

Edge recognition, a critical mathematical operation, efficiently identifies key points within an image. By employing the Canny edge detection method, we accurately pinpoint and measure features. This is achieved by calculating the intensity gradient of the image, filtering it in both horizontal (Gx) and vertical (Gy) directions, and determining the gradient and orientation of the pixel borders.[25]

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22. S. Li, 'A review of feature detection and match algorithms for localization and mapping', *IOP Conference Series: Materials Science and Engineering* 231(1), 012003, 2017
23. E. Napoles and M. Berber, 'Precise formula for volume computations using contours method', *Bulletin of Geodetic Sciences* 24(1), 2018, pp. 18-27
24. C. Affonso *et al.*, 'Deep learning for biological image classification', *Expert Systems with Applications* 85(C), 2017, pp. 114-122; C. Crespo *at al.*, 'Damage detection on historical buildings using unsupervised classification techniques', *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences* XXXVIII, Part 5 Commission V Symposium, Newcastle upon Tyne, UK, 2010, pp. 184-188
25. P. Ghosh, A. Pandey and U. C. Pati, 'Comparison of Different Feature Detection Techniques for Image Mosaicking', *ACCENTS Transactions on Image Processing and Computer Vision* 1(1), 2015, pp. 1-7

$$Edge\_Gradient(G) = \sqrt{G_x^2 + G_y^2} \qquad (1)$$

$$Angel(\theta) = \tan^{-1}\left(\frac{G_y}{G_x}\right) \qquad (2)$$

Using the Canny edge detection technique, the gradient consistently oriented perpendicularly to the edges, and was adjusted to align with the necessary angles for vertical, horizontal, and diagonal directions. Figure 3 illustrates the outcomes achieved with the Canny approach.

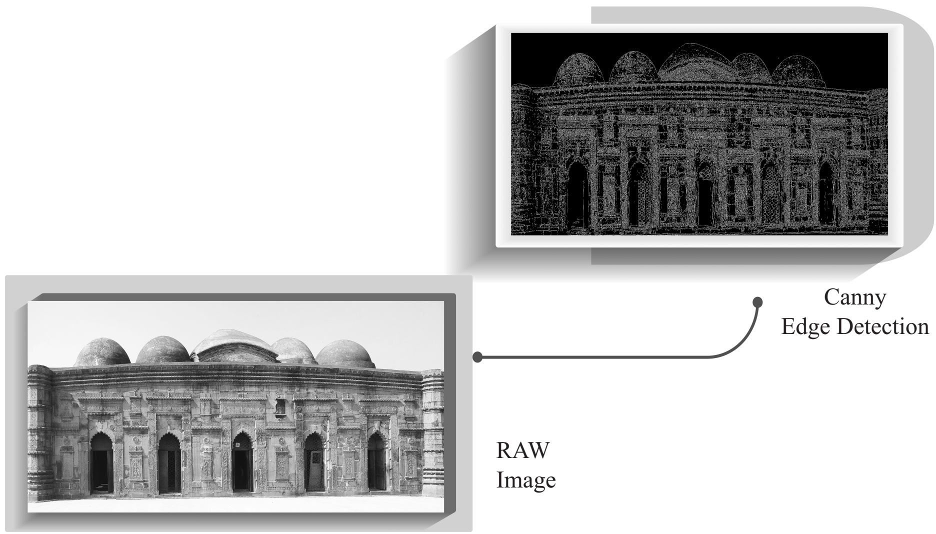


Fig. 3. Canny edge detection of the Choto Sona Mosque (Sultanate)

4.2 Hough Line Transform

The Hough line transform method was used for feature extraction, efficiently identifying lines in images. This technique utilizes the Polar coordinate system (r) and Cartesian coordinates (m, b) to detect lines, including arbitrary shapes.[26] Lines were represented parametrically as $r = x \cos\theta + y \sin\theta$ or in Cartesian form as $y = mx + b$. The probabilistic Hough Line Transform was also applied, as shown in Fig. 4, to determine line equations in historic structures.

$$y = \left(-\frac{\cos\theta}{\sin\theta}\right)x + \left(\frac{r}{\sin\theta}\right) \qquad (3)$$

26. M. Thareja and A. Goyal, 'Performance Analysis of Edges, Corners and the genres: A Subjective Estimation', *IOSR Journal of Electronics and Communication Engineering 1*, 2016, pp. 98-104; A. Mordvintsev and A. K. Revision, 'Canny Edge Detection', *OpenCV-Python Tutorials*, 2013

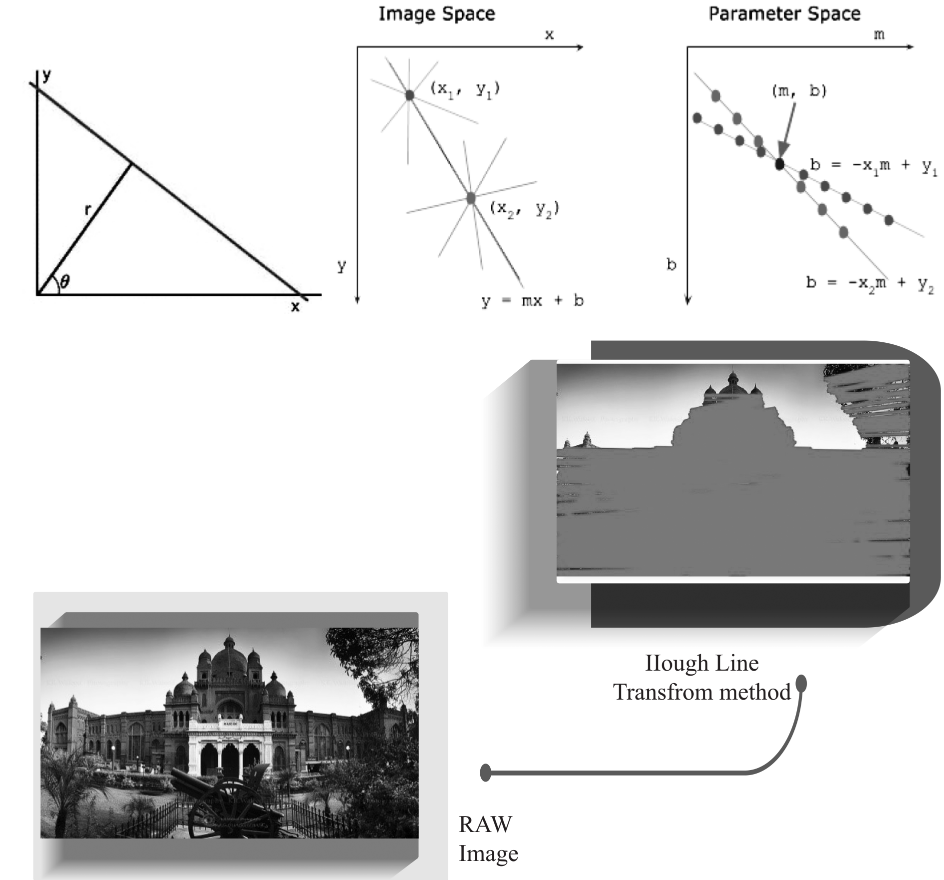


Fig. 4. Feature detection of the Lahore Museum (British) by using the Hough Line Transform method

4.3 Method of Find Contours

Contours, forming continuous curves or paths that connect points of the same color along boundaries, are crucial for object detection and shape analysis. In this study, the Image Moment approach was employed to accurately locate contours of antique buildings in images.[27] The spatial structure moments, denoted as *mij*, are calculated using nested loops for orders i and j. This method, which involves comparing different shapes, effectively identified various features of historic buildings.

$$m_{ij} = \sum_{x,y} \left(array(x, y).x^{j}.y^{i} \right) \qquad (4)$$

27. Hough Line Transform, *OpenCV*, 2017

Figure 5 illustrates the different contour-detection methods employed in our experiment. It highlights how the Find Contours approach was utilized to detect structural features of an old mosque.

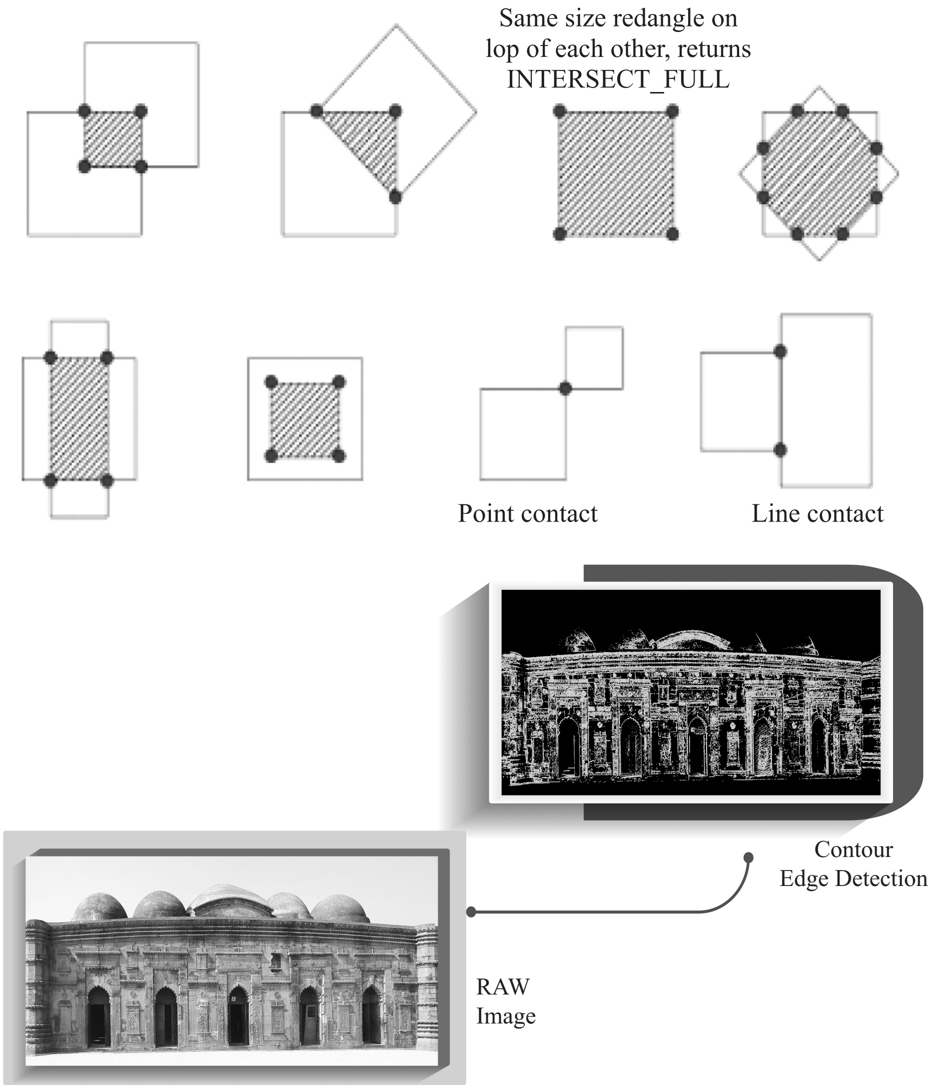


Fig. 5. Feature detection of Choto Sona Mosque (Sultanate) by using the Find Counter detection method

4.4 Method of Harris Corner Detection

Corner detection is a technique used to identify the corner features within an image. In computer vision, a corner is defined as a point where two distinct edge directions converge. The Harris corner detection method is employed to locate these corners by analyzing image characteristics. It systematically examines various directions for displacement (u, v) across multiple image intensities. This approach utilizes a Gaussian window function to apply weights to pixels in the vicinity, refining the detection of corners. The mathematical formulation of the Harris algorithm,[28] which was applied in this experiment, is detailed below.

$$E(u,v) = \sum_{x,y} w(x,y)[I(x+u,y+v) - I(x,y)]^2 \quad (5)$$

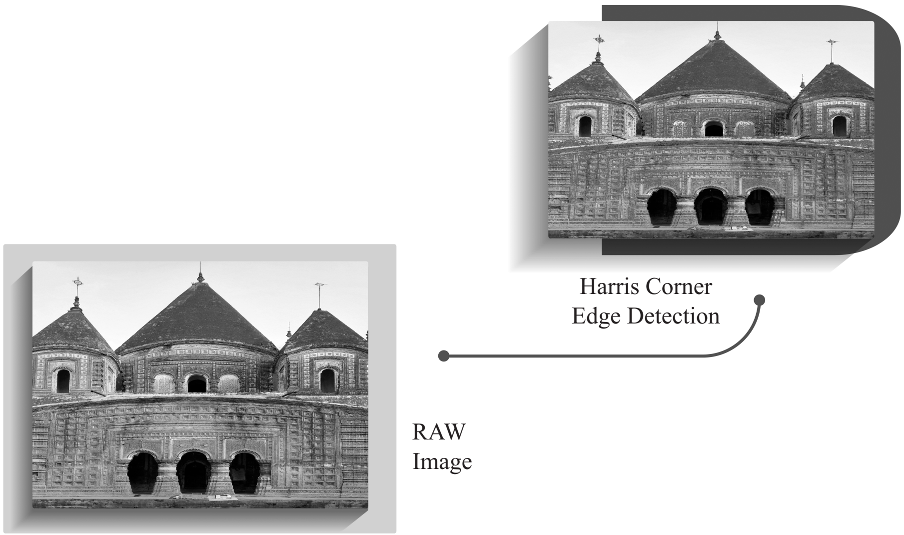


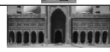
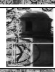
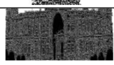
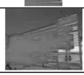
Fig. 6. Feature detection of The Gobinda Temple (Mughal) by using the Harris corner detection method

In Equation 5, E represents the difference between the original and the shifted windows. The window's displacement in the *x* and *y* directions is denoted by *u* and *v*, respectively. The window function *w* (*x, y*) is centered at position (*x, y*), with the image intensity given by *I* (*x, y*). The intensity after displacement is *I* (*x+u, y+v*). A Gaussian function is used as the window function *w* (*x, y*). The Harris corner detection function in OpenCV, cv2.cornerHarris, was utilized for this analysis. The results of the improved Harris corner detection approach are shown in Fig. 6.

28. J. Alakuijala *et al.*, 'Image transformation from polar to Cartesian coordinates simplifies the segmentation of brain images', *14th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Paris, France, 1992, pp. 1918-1919; Y. Zhang *et al.*, 'Pathological brain detection based on wavelet entropy and Hu moment invariants', *Bio-Medical Materials and Engineering* 26(1), 2015, pp. S1283-S1290

4.5 Training Dataset and Classification

Table 1. Training dataset and classification of Mughal, Sultanate and British eras.

Features	Canny Edge Detection	Hough Line Transform	Find Contours Techniques	Harris Corner Detector
	Mughal Era(1526–1540, 1555–1857)			
Dome				
Minaret				
Front				
	Sultanate Era(1206–1526)			
Features	Canny Edge Detection	Hough Line Transform	Find Contours Techniques	Harris Corner Detector
Dome				
Minaret				
Front				
	British Era (1858–1947)			
Features	Canny Edge Detection	Hough Line Transform	Find Contours Techniques	Harris Corner Detector
Dome				
Minaret				
Front				

To identify the construction era, we established three classifications corresponding to the Sultanate, Mughal, and British periods. Using feature detection techniques, we developed a Decision Tree[29] based on the results of these methods. This Decision Tree employs an "if-then" rule set organized in a tree-like structure, with rules learned from the training data. Table 1 displays the classification of data within the training dataset, segmented into three historical periods (Mughal, Sultanate, and British). Each period is associated with three specific features (Dome/Tower/Jewel, Minaret, Front), which were detected using four methods: Canny Edge Detector, Hough Line Transform, Find Contours, and Harris Corner Detector.

5. Deep Neural Network (DNN) Model

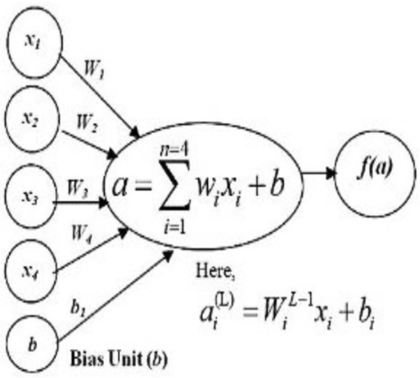
Artificial neural networks enable computers to learn from data by recognizing patterns and making predictions. In this study, deep learning is implemented using

29. Structural Analysis and Shape Descriptors. *OpenCV* (2014); F. Nelli, 'OpenCV & Python – Harris Corner Detection – a method to detect corners in an image', *Meccanismo Complesso*, 2017

a Deep Neural Network (DNN). The input layer of the DNN comprises five nodes: x1, x2, x3, x4, and a bias unit, as shown in Table 2 and Figures 1, 2, and 7. Figure 7 illustrates the mathematical structure[30] of each node, where "a" denotes activation, "b" represents the bias,[31] and "W" indicates the weights of the input layer. The bias unit helps optimize learning by adjusting the activation values. Figure 7 provides a detailed overview of the DNN architecture.[32]

Table 2. Input and inputs of DNN

Input Layer	Input Image
x1	Canny Edge Detection Image
x2	Hough Line Transform Image
x3	Find Counter Image
x4	Harris Corner Detection Image
Bias Unit (b)	+1



Mathematical formation of DNN where a is Activation, L is the layer, b is Bias Unit and W is the Weight of the layer

30. J. Mesarić and D. Šebalj, 'Decision trees for predicting the academic success of students', *Croatian Operational Research Review* 7(2), 2016, pp. 367-388
31. Y.Y. Song and Y. Lu, 'Decision tree methods: applications for classification and prediction', *Shanghai Archives of Psychiatry* 27(2), 2015, pp. 130-135
32. J. H. Yoon *et al.*, 'Optimization of Design Parameters of an EPPR Valve Solenoid using Artificial Neural Network', *Journal of Drive and Control* 13(6), 2016, pp. 34-41

From the figure, the equation for each activation node (a) is as follows:

For hidden layer 1:

$$a_i^{(L)} = f(W_i^{(L-1)}\, x_i + b_1^{(L-1)} \quad \text{……… …………………………………….… (6)}$$

After hidden layer 1:

$$a_i^{(L)} = f(W_i^{(L-1)}\, a_i^{(L-1)} + b_1^{(L-1)} \quad \text{…………………………........................ ……………………..……. (7)}$$

Here, Index = i; Activation = a; Current Layer = L; Previous Layer = L-1; Input node = x; Bias Unit = b

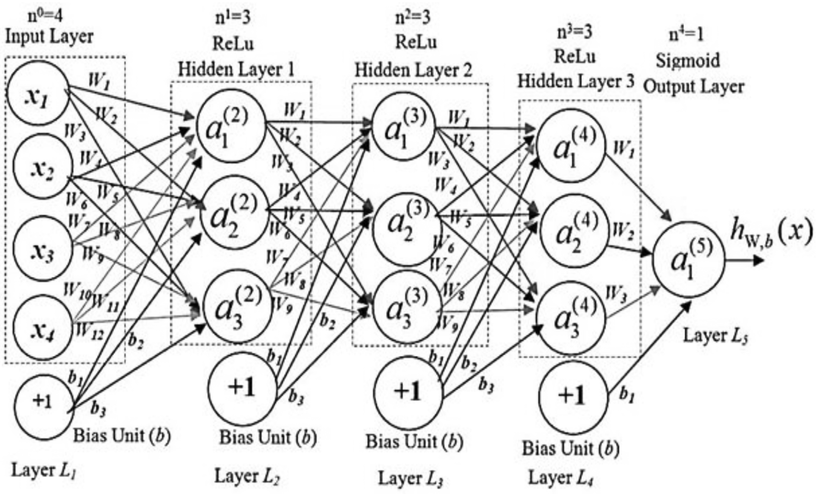


Fig. 7. Deep Neural Network (DNN) for construction era identification

The computational algorithm of the developed DNN is represented as follows:

Layer, L = 2 (Hidden Layer 1):

$$a_1^{(2)} = f(W_1^{(1)}x_1 + W_4^{(1)}x_2 + W_7^{(1)}x_3 + W_{10}^{(1)}x_4 + b_1^{(1)}) \quad (8)$$

$$a_2^{(2)} = f(W_2^{(1)}x_1 + W_5^{(1)}x_2 + W_8^{(1)}x_3 + W_{11}^{(1)}x_4 + b_2^{(1)}) \quad (9)$$

$$a_3^{(2)} = f(W_3^{(1)}x_1 + W_6^{(1)}x_2 + W_9^{(1)}x_3 + W_{12}^{(1)}x_4 + b_3^{(1)}) \quad (10)$$

Layer, L = 3 (Hidden Layer 2) :

$$a_1^{(3)} = f(\mathrm{W}_1^{(2)} a_1^{(2)} + \mathrm{W}_4^{(2)} a_2^{(2)} + \mathrm{W}_7^{(2)} a_3^{(2)} + b_1^{(2)}) \quad (11)$$

$$a_2^{(3)} = f(W_2^{(2)} a_1^{(2)} + W_5^{(2)} a_2^{(2)} + W_8^{(2)} a_3^{(2)} + b_2^{(2)}) \quad (12)$$

$$a_3^{(3)} = f(W_3^{(2)} a_1^{(2)} + W_6^{(2)} a_2^{(2)} + W_9^{(2)} a_3^{(2)} + b_3^{(2)}) \quad (13)$$

Layer, L = 4 (Hidden Layer 3) :

$$a_1^{(4)} = f(W_1^{(3)} a_1^{(3)} + W_4^{(3)} a_2^{(3)} + W_7^{(3)} a_3^{(3)} + b_1^{(3)}) \quad (14)$$

$$a_2^{(4)} = f(W_2^{(3)} a_1^{(3)} + W_5^{(3)} a_2^{(3)} + W_8^{(3)} a_3^{(3)} + b_2^{(3)}) \quad (15)$$

$$a_3^{(4)} = f(W_3^{(3)} a_1^{(3)} + W_6^{(3)} a_2^{(3)} + W_9^{(3)} a_3^{(3)} + b_3^{(3)}) \quad (16)$$

Layer, L = 5 (Output Layer) :

$$h_{W,b}(x) = a_1^{(5)} = f(W_1^{(4)} a_1^{(4)} + W_2^{(4)} a_2^{(4)} + W_3^{(4)} a_3^{(4)} + b_1^{(4)}) \quad (17)$$

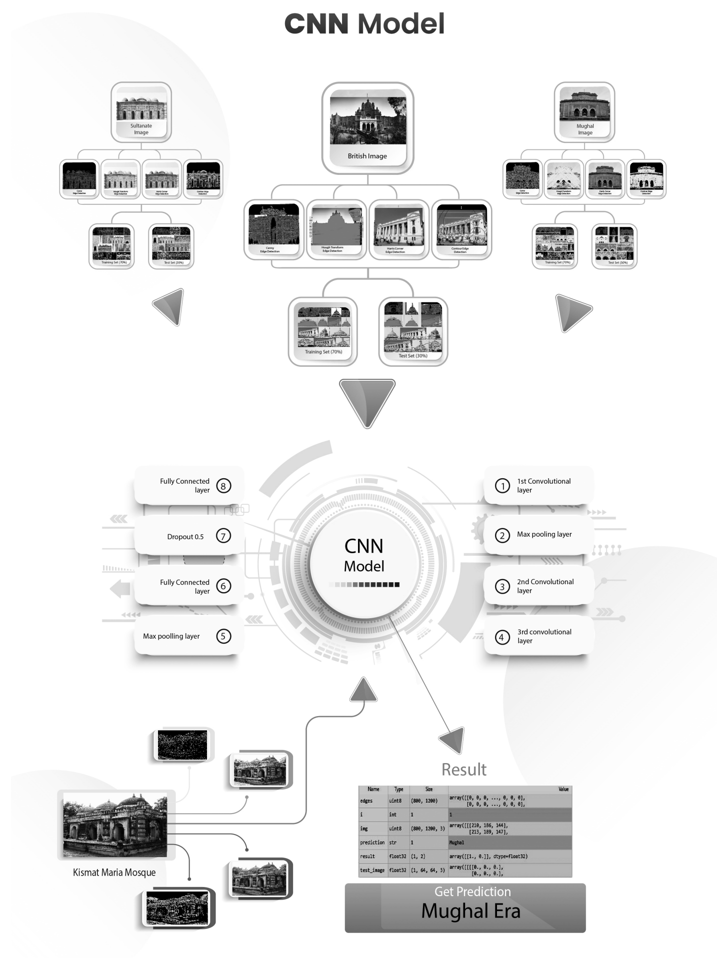


Fig. 8. CNN model for era identification of the old building

In Figure 7, network inputs are represented as nodes. Nodes labeled "+ *1*" indicate bias units, which act as intercepts. The notation *ni* refers to the number of nodes in a neural network layer excluding the bias unit. The weight $W_i^{(L-1)}$ denotes the parameter connecting the *i*-th unit in layer *L* to the weight from layer *L*−1. Bias units always have a value of +1 and do not receive inputs or connections. The activation $a_i^{(L)}$ of the *i*-th unit in layer *L* is defined as $a_i^{(L)}=x_i$ for the *i*-th input when *L*=1. The hypothesis $h_{W,b}(x)$, determined by parameters *W* and *b*, generates a real number output.

6. Convolution Neural Network (CNN) Model

A Convolutional Neural Network (CNN) was designed based on a Deep Neural Network (DNN) model, incorporating three convolutional layers, two max-pooling layers, two fully connected layers, and dropout. The CNN handles 64x64 pixel input images with a single channel that captures features such as edges, corners, and points. It utilizes the Canny Edge Detector, Hough Line Transform, Find Contours, and Harris Corner Detector algorithms. After applying these algorithms, two datasets were created: *a* training set and a test set. The CNN model then generated historical predictions based on these datasets.

7. Results and Analysis

The model efficiently identifies the construction era by analyzing features such as front, dome, and minaret using a computer algorithm. Performance is assessed using confusion matrices, and the CNN model, trained with the adjusted dataset, accurately determines the era, as shown in figure 9.

Name	Type	Size	Value
edges	uint8	(800, 1200)	array([[0, 0, 0, ..., 0, 0, 0], [0, 0, 0, ..., 0, 0, 0],
i	int	1	1
img	uint8	(800, 1200, 3)	array([[[210, 186, 144], [213, 189, 147],
prediction	str	1	Mughal
result	float32	(1, 2)	array([[1., 0.]], dtype=float32)
test_image	float32	(1, 64, 64, 3)	array([[[[0., 0., 0.], [0., 0., 0.],

Fig. 9. Results of construction era identification of Mughal period by using the CNN model

Accuracy is also used as *a* statistical grade for the test calculations. The law for calculating accuracy is:

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + TN + FP + FN)} \times 100\% \quad (18)$$

Where,

TP = True Positive; FP = False Positive;

TN = True Negative; FN = False Negative

This research used a dataset of 500 images, including 270 of Sultanate buildings, 130 of Mughal buildings, and 100 of British buildings. The results are as follows: TP = 264, TN = 217, FP = 13, and FN = 6. Based on these values, the model achieved an accuracy of 96.20%, as calculated using Equation 18.

This accuracy surpasses that of recent previous work, which achieved 92.33% using only the Canny Edge Detector method for Mughal and Sultanate periods.[33]

8. Performance Evaluation: Training and Validation Insights

Model effectiveness is evaluated through training and validation accuracy in Fig. 10.

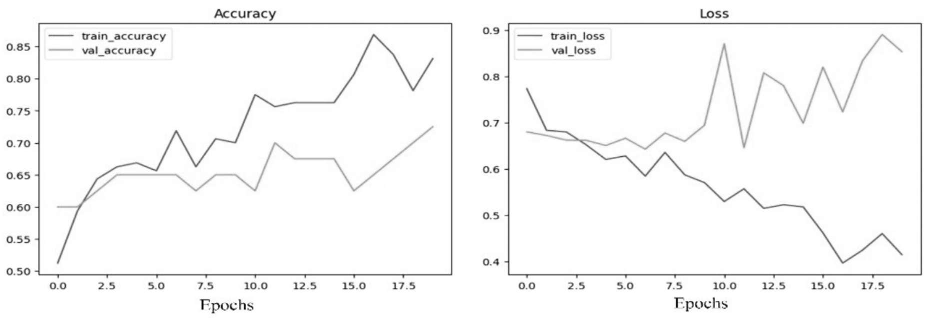


Fig. 10. Training vs. Validation Accuracy

The left plot shows accuracy trends over 20 epochs, with rapid initial improvement followed by fluctuations, indicating possible overfitting or learning rate issues. Validation accuracy sometimes exceeds training accuracy, likely due to regularization stabilizing learning.

The right plot tracks loss, where increasing validation loss suggests overfitting. To improve generalization, strategies such as regularization (L1/L2, dropout), early stopping, data augmentation, and hyperparameter tuning can be applied.

9. Conclusion

This study presents an advanced program that leverages artificial neural networks and feature identification techniques to accurately determine the construction era

33. M. S. Hasan *et al.*, 'Heritage Building Era Detection using CNN', IOP Conference Series: *Materials Science and Engineering* 617(1), 2019

of historic buildings. By analyzing heritage structures from the Mughal, Sultanate, and British periods, it integrates four feature identification algorithms—Canny Edge Detector, Hough Line Transform, Find Contours, and Harris Corner Detector—achieving notable accuracy improvements over previous methods. However, challenges remain, particularly with low-resolution or distorted images that impact predictive accuracy. Future research aims to overcome these limitations, enhancing the model's ability to identify architectural features across diverse image conditions.