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Monument Recognition and Historical Era Prediction Using CNNs: A Case Study of Kusumba Mosque

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ABSTRACT

The integration of artificial intelligence (AI) into cultural heritage research presents unprecedented opportunities for the systematic documentation, analysis, and preservation of historical architecture. This study explores the application of Convolutional Neural Networks (CNNs) in automating the recognition of monument features and predicting their historical origins. Taking the Kusumba Mosque—an iconic example of Sultanate-era architecture in Bangladesh—as a case study, the research integrates traditional methods of architectural analysis with state-of-the-art deep learning techniques to classify and interpret stylistic and structural features. A custom-built deep neural network (DNN) is trained on a curated dataset encompassing a diverse range of architectural elements from multiple historical periods, including Sultanate, Mughal, and Colonial eras. The proposed model achieves a classification accuracy of 97.10%, validating its effectiveness in distinguishing intricate features such as domes, arches, inscriptions, and ornamental details. The explore engagements advanced image preprocessing and feature detection algorithms to enhance architectural feature recognition. Beyond its technical contributions, the research highlights the potential of AI in digital heritage conservation by providing a scalable and objective framework for analyzing historic monuments. This AI-powered approach not only improves classification accuracy but also enriches the interpretive framework for understanding architectural evolution, thus offering a powerful tool for historians, archaeologists, and conservationists.

1. Introduction

This study investigates the application of deep learning—specifically Convolutional Neural Networks (CNNs)—in recognizing and analyzing the historical periods of antique monuments in Bangladesh, with a primary focus on the Kusumba Mosque. The research emphasizes architectural structures from the Sultanate, Mughal, and British colonial periods. By employing computational techniques to detect distinctive architectural features, such as domes, minarets, towers, and façades, the proposed model achieves a classification accuracy of 97.10% in determining the construction eras of heritage buildings[1]. To enhance the precision of architectural style recognition, the system integrates advanced feature detection algorithms, including Canny Edge Detection, Hough Line Transform, Find Contours, and Harris Corner Detection. These techniques improve the model's ability to extract and analyze intricate design elements, thereby enabling accurate historical classification[2]. The study draws on recent advancements in artificial neural networks that have proven effective in heritage analysis—such as CNNs used for decoding ancient Maya hieroglyphs, recognizing Roman coins[3] and visualizing China's terracotta warriors. These precedents illustrate the growing impact of AI in cultural preservation, particularly when combined with technologies like photogrammetry and 3D modeling to digitally document archaeological artifacts[4]. In this context, the research introduces a CNN-based deep learning framework tailored to determine the construction period of historical buildings. By focusing on key structural features unique to the British (1858–1947), Mughal (1526–1857), and Sultanate (1206–1526, 1555–1540) eras, the model offers an AI-assisted solution for architectural era classification[5]. Centered on the Kusumba Mosque in Rajshahi, Bangladesh, this study serves as a case example of how computational vision techniques can effectively bridge traditional archaeology and modern technology. The outcomes contribute significantly to the digital preservation and academic study of South Asia's rich architectural heritage.[6]

This innovative methodology contributes in five major areas:

a. Era-Specific Monument Classification[7].
b. Design of a Specialized Deep Neural Network (DNN).
c. Improved Feature Detection Capabilities.
d. Integration of CNN with DNN Architecture[8].
e. Innovation in Archaeological Methodology[9].

2. Background Study

Artificial intelligence and computer vision, particularly through deep learning and Convolutional Neural Networks (CNNs), are revolutionizing the preservation and analysis of historical architecture. This case study on the Kusumba Mosque demonstrates how these advanced techniques can effectively identify architectural features and accurately classify historical periods, contributing to the digital preservation of South Asia's rich heritage—especially the architectural legacy of the Sultanate era.

▪ **Era-Based Architectural Classification**

Deep learning methods, particularly Convolutional Neural Networks (CNNs), enable accurate classification of architectural periods by analyzing key structural elements such as domes, minarets, and facades. This study classifies the Kusumba Mosque as a prime example of Sultanate-era architecture, providing deeper insight into its historical and cultural relevance. Architectural Feature Identification are below-

- Architectural Feature Identification
- Cultural Heritage Object Detection
- Neural Network Applications in Archaeology
- Analysis of South Asian Architecture through Deep Learning

Overall, the research underscores the transformative potential of artificial intelligence in historical analysis and heritage preservation, enhancing architectural understanding and fostering deeper appreciation of South Asia's cultural richness.

2.1 Planning and Architectural Organization of the Kusumba Mosque: A Philosophical Reflection

The Kusumba Mosque, located in Rajshahi, Bangladesh, stands as a prominent heritage monument from the Bengal Sultanate period, constructed in the 16th century. This mosque integrates spiritual symbolism, artistic expression, and functional design, reflecting a harmonious dialogue between architectural form, religious faith, and the cultural milieu of its time.

- **Site Orientation and Layout: Sacred Alignment**

In Islamic architecture, orientation holds profound spiritual significance. The Kusumba Mosque's qibla wall is precisely aligned toward Mecca, establishing a sacred directional axis for worshipers. The mosque's courtyard and surrounding spaces emphasize the concept of *ummah*—creating communal areas that foster shared reflection, prayer, and social interaction.

- **Structural Design: Geometry and Proportional Harmony**

The mosque's architectural plan exemplifies Islamic principles of geometric balance and symmetry. Its five-domed arrangement symbolizes divine order and unity. The rectangular prayer hall evokes spiritual transcendence, while the intricately terracotta-adorned mihrab serves as a focal point guiding worshippers toward divine presence. Adjacent to it, the minbar stands as a symbol of religious leadership and guidance.

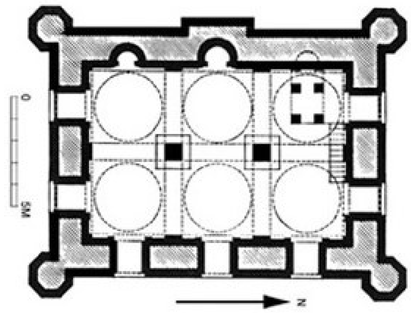


Figure 1. Florplan of Kusumba Mosque

- **Architectural Features: Symbolism in Design**
- Key structural components convey rich symbolic meanings, intertwining material form with spiritual intent:
  • Domes and roof structures expressing cosmic harmony
  • Minarets emphasizing verticality and spiritual aspiration
  • Arches and openings framing sacred spaces and light
- **Materiality and Ornamentation: Expressions of Aesthetic Spirituality**

The Kusumba Mosque's terracotta decoration manifests divine order and artistic refinement. The use of locally sourced bricks represents *khilafah*—the stewardship of earth—while Arabic calligraphy imbues the structure with profound spiritual resonance.

- **Courtyard and Ablution Area: Philosophical Transition Spaces**

Serving as a threshold between the secular and sacred, the mosque's courtyard encourages communal engagement and personal contemplation. The ablution area symbolizes purification and spiritual renewal, essential practices before prayer.

- **Climatic Adaptation: Harmonizing with Nature**

Reflecting the Islamic concept of *fitrah*—natural harmony—the Kusumba Mosque seamlessly integrates aesthetic beauty with functional design, responding to the regional climate. This balance preserves historical integrity while inspiring reflection on the interconnectedness of architecture, nature, and human spirituality.

2.2. A Critical Examination of the Indoor and Outdoor Environments of the Kusumba Mosque: A Philosophical Reflection

The Kusumba Mosque in Rajshahi, Bangladesh, exemplifies Islamic architectural mastery, where the seamless harmony between indoor and outdoor spaces embodies spirituality, nature, and community. This study leverages deep learning techniques to analyze and digitally preserve the mosque's architectural design and historical significance.

Indoor Spaces: A Sanctuary of Divine Oneness

The mosque's interior reflects the concept of *tawhid* (divine oneness). CNN-based feature detection identifies key elements such as arches, domes, and the mihrab, enriching the understanding of its design vocabulary and historical context.

Figure 2. Indoor Environs: The Sanctuary of Transcendence

- **The Interplay of Light and Space**

Utilizing CNN-driven object recognition, the analysis highlights how natural light enters through carefully positioned windows and arches, creating an ethereal ambiance that symbolizes divine presence. The model captures how light animates the spiritual atmosphere within the prayer hall.

Geometric Patterns and Ornamental Design

Deep learning models detect intricate geometric motifs and floral patterns characteristic of Islamic abstraction. These elements guide attention from the physical form toward metaphysical symbolism, unveiling the profound spiritual meanings embedded in the mosque's ornamentation.

Acoustic Resonance: A Philosophical Exploration of Sound and Divine Harmony

By combining 3D modeling with deep learning-based acoustic simulations, the study explores the mosque's soundscape. It examines how Quranic recitations resonate through the dome and vaulted ceilings, amplifying the worshippers' spiritual experience within the sacred space.

- **Outdoor Spaces: Bridging Nature and Community**

The Kusumba Mosque's exterior environment acts as a transitional space bridging the sacred interior with the surrounding community. Deep learning models identify architectural features such as courtyards, pathways, and adjacent structures, illustrating the Islamic ideal of harmonious coexistence between sacred spaces and communal life.

Figure 3. Outdoor Environs: The Interface with Nature and Community

- **The Courtyard: A Space for Community and Reflection**

Object recognition tools analyze the courtyard's spatial organization, emphasizing its role in promoting social interaction and reinforcing the Islamic principle of *ummah* (community).

- **Harmonizing with Nature: Architectural Integration**

Deep learning analysis reveals how the mosque's design integrates with its tropical environment. Features like natural ventilation and raised platforms reflect sustainable building practices aligned with Islamic principles of balance and respect for nature.

- **The Pathways: Journeying Towards the Sacred**

The study uses object detection to examine the mosque's pathways, symbolizing the spiritual progression from the temporal world to divine engagement. The serene layout of these pathways prepares visitors for contemplative and sacred experiences.

3. Review of Existing Literature

- Kemal et al. conducted a study on building collapses caused by the recent earthquakes in Türkiye. Using satellite imagery, they employed U-Net, LinkNet, FPN, and PSPNet models for detection. The research focused on the 7.7 Pazarcık and 7.6 Elbistan earthquakes and achieved an accuracy of 96%[10].
- Zhonghua et al. evaluated monument damage through rapid fine-grained analysis. They applied the HRSSES method for collapse detection and employed 3D reconstruction strategies that provided an eight-fold enhancement. The study identified floor collapse defects from AS images using a dataset of 48,092 samples collected from 361 houses, achieving an accuracy of 93.22%[11].

- Claudio et al. utilized machine learning models for image recognition, distinguishing between graphical and semantic information. Their empirical evaluation achieved an average accuracy of 80%[12].
- Jose et al. carried out image classification for damage recognition using a Fujifilm IS-Pro digital single-lens camera. The researchers employed spectral information, achieving 92% accuracy and a Kappa score of 85.71[13].
- Lingfei et al. developed object detection strategies for identifying damaged buildings, applying YOLOv4 to aerial imagery. The study incorporated CSPDarkNet-53 and the Focal EIoU loss function, achieving accuracy rates ranging from 88.23% to 93.26%[14].
- Jaemin et al. conducted object identification for construction sites using synthetic images to represent hazardous conditions. By applying superimposed imagery techniques, the study achieved an accuracy of 88.6%[15].
- Jie et al. carried out ground and object identification using YOLOv5. The researchers applied feature fusion on remote sensing images and employed EfficientDet with the DIOR dataset, achieving 80.5% accuracy—2% higher than the baseline[16].

4. Scope of the Study

This study investigates the Indo-Saracenic architecture of the Kusumba Mosque, highlighting its fusion of Mughal and Sultanate elements. It analyzes the mosque's spatial organization, including the use of natural light within the prayer hall and the tranquil design of its courtyards. The research further examines ongoing conservation challenges and explores the application of modern technologies—such as mobile applications[17], 3D scanning, and machine learning—in safeguarding the site. Ultimately, the study underscores the mosque's significance as a vital symbol of cultural heritage and identity.

5. Relevance of the Study

- **Cultural Heritage Preservation**: The application of deep learning, particularly Convolutional Neural Networks (CNNs), significantly improves the digital documentation and classification of historical architecture. This study contributes to the preservation of the Kusumba Mosque by accurately identifying its Sultanate-era features and promoting conservation efforts[18].
- **Architectural Restoration**: AI-driven models assist in preserving historical authenticity by recognizing and reconstructing original architectural elements. This ensures that restoration work on monuments like the Kusumba Mosque remains faithful to their historical origins[19].
- **Archaeological Research Advancement**: The integration of automated era prediction supports archaeologists in efficiently dating and interpreting architectural components, enhancing research methodologies and facilitating more accurate digital records of heritage sites[20].
- **Tourism and Visitor Experience**: The use of AI-based applications and augmented reality (AR) tools can elevate the visitor experience by offering real-time, interactive insights into the Kusumba Mosque's historical context and architectural significance[21].
- **Education and Research**: Deep learning technologies empower educators, researchers, and students with advanced tools for analyzing architectural heritage. This fosters academic engagement, supports interdisciplinary research, and strengthens awareness of South Asia's cultural legacy through the lens of the Kusumba Mosque[22].

6. Research Questions and Answers

Research Question 1: How can Convolutional Neural Networks (CNNs) be optimized for monument recognition and historical era prediction of the Kusumba Mosque?

Answer: To optimize CNNs for monument recognition and historical era prediction of the Kusumba Mosque, the model should be trained on datasets highlighting key architectural features distinctive to the Bengal Sultanate period, including terracotta ornamentation, domes, arches, and façade patterns. Employing transfer learning from pre-trained models, applying data augmentation to expand training samples, and fine-tuning hyperparameters enhances the CNN's capability to accurately classify architectural styles and predict the mosque's historical era. This optimization supports precise monument identification and aids in heritage documentation and preservation efforts.

Research Question 2: How do advanced feature extraction techniques enhance CNN-based historical era recognition for the Kusumba Mosque?

Answer: Advanced feature extraction methods such as the Canny Edge Detector, Hough Line Transform, and Harris Corner Detector enhance CNN performance by highlighting distinctive architectural details like terracotta brick patterns, ornamental motifs, and structural edges unique to the Kusumba Mosque. By emphasizing these subtle yet critical features, these techniques improve the CNN's capacity to discern fine stylistic differences, leading to more precise era classification and supporting accurate documentation and preservation of the mosque's historical legacy.[23]

7. Research Approach

This research adopts an application-driven approach utilizing a Convolutional Neural Network (CNN) to predict the historical era of monuments, with a specific focus on the Kusumba Mosque. High-resolution images of the mosque are processed using advanced feature extraction techniques such as the Canny Edge Detector, Hough Line Transform, and Harris Corner Detector to capture key architectural elements. Two datasets are prepared—one for training and one for testing the model. The CNN is designed to classify architectural styles primarily from the Sultanate and Mughal periods. After training on the curated dataset, the model's performance is evaluated on the test set, demonstrating the effective integration of CNNs with classical feature detection methods for accurate era prediction of historic monuments like the Kusumba Mosque.

8. Process of Era Classification

This study employs deep learning and computer vision techniques to identify the historical era of the Kusumba Mosque. The Canny Edge Detector is used to delineate the mosque's structural outline, the Hough Line Transform extracts key geometric features, Find Contours isolates distinct architectural components, and Harris Corner Detection refines feature extraction for detailed analysis. These computational methods produce four processed images emphasizing critical architectural elements, which are then analyzed by a Deep Neural Network (DNN) equipped with multiple hidden layers and activation functions to classify features corresponding to the Bengal Sultanate, Mughal, and British colonial periods. This framework facilitates accurate classification of the mosque's construction era based on its visual and structural characteristics.

By integrating deep learning with classical feature extraction, this identification system improves the precision of historical era classification for the Kusumba Mosque, supporting enhanced documentation, conservation efforts, and educational initiatives centered on its architectural heritage.

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

Step1 ▼	**Image Selection** ▪ Capture an image of the Kusumba Mosque focusing on distinctive architectural elements such as domes, minarets, and façades.
Step2 ▼	**CNN Architecture Development** Convolutional Neural Network (CNN) is designed with: ▪ **3 Convolution Layers**: Extracting detailed architectural features. ▪ **2 Max-Pooling Layers**: Reducing spatial dimensions while retaining key features. ▪ **2 Fully Connected Layers**: Integrating extracted features for classification. ▪ **Dropout Layer**: Preventing overfitting during training.

Step 3 ▼	**Feature Extraction using Computer Vision** Apply advanced computer vision techniques to extract architectural features. ▪ **Canny Edge Detector**: Identifies structural edges. ▪ **Hough Line Transform**: Detects linear patterns in architectural design. ▪ **Find Contours**: Segments and isolates important shapes. ▪ **Harris Corner Detection**: Identifies intricate architectural corners and motifs.
Step 4 ▼	**Input to DNN** The extracted feature images are passed to a Deep Neural Network (DNN) for classification.
Step 5 ▼	**Training with Historical Data** The DNN is trained on a dataset tailored to architectural styles from different historical periods, including the Bengal Sultanate, Mughal, and British colonial eras.
Step 6 ▼	**DNN Structure and Classification** The network consists of three hidden layers: ▪ **First Hidden Layer:** Analyzes domes and arches. ▪ **Second Hidden Layer:** Focuses on minaret structures. ▪ **Third Hidden Layer:** Classifies façade details. The activations in the final layer determine the most probable historical period.

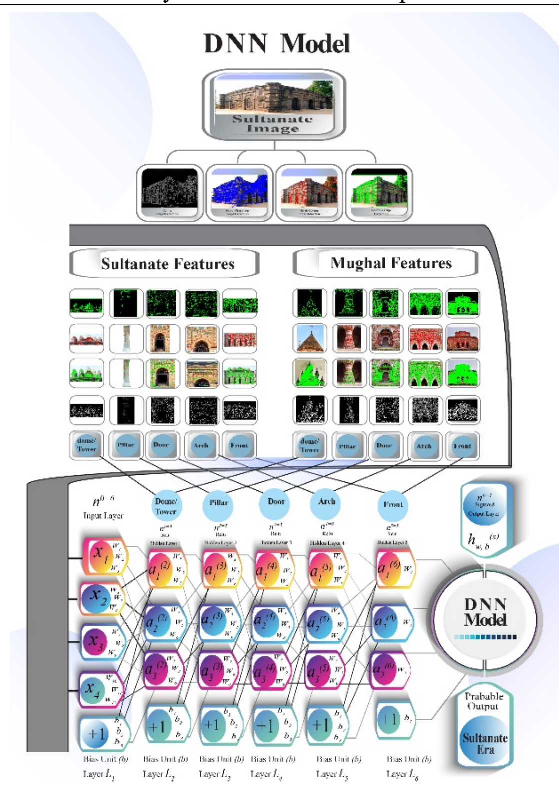


Figure 4 Architecture and process of the era identification model for Indian subcontinent old and heritage buildings.

We extracted edges from the photo, using Hough Line Transform for analysis, Find Contours[24], for segmentation, and the Harris algorithm for corner detection. These techniques generated four images, which were processed by a Deep Neural Network (DNN) with hidden layers and activations for the British, Sultanate, and Mughal periods. This DNN function enables the software to classify architectural periods based on visual patterns[25]. Figures 4. vividly illustrate the design and process of the period identification model.

9. Experimental Approaches

Several computer techniques are employed to identify a building's features and traits, with a specific experiment showcasing the detection of damaged areas in a historic structure[26]. Within the image processing domain of computer vision, various patterns, including edges, corners, points, and more, serve as viewpoints for feature detection[27,28]. In this study, a range of methods, such as the Harris Corner Detector, Canny Edge Detector, Hough Line Transform, and Find Contours, were utilized to compile structural characteristics from buildings spanning the British, Sultanate, and Mughal periods, forming the comprehensive training dataset.

9.1 Canny Edge Detection Technique

Edge recognition, using the Canny edge detection method, calculates intensity gradients in horizontal (Gx) and vertical (Gy) directions to identify pixel borders. The gradient is perpendicular to edges and rounded to represent vertical, horizontal, and diagonal directions[29].(see Figure 5)

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

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

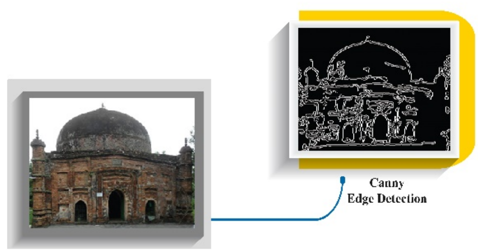


Figure 5 Feature detection of The Sadi Mosque (Mughal) by using the Canny Edge detection method.

9.2 Hough Line Transform Technique

The Hough Line Transform method is used for feature extraction in image processing, efficiently identifying lines, including arbitrary shapes, using Polar and Cartesian coordinates. Historic structures' lines were precisely located with this technique, represented as y = mx + b or r = x cos θ + y sin θ[30,31]. The probabilistic Hough Line Transform methodology, shown in Fig. 6, was applied to derive the line equation for the image.

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

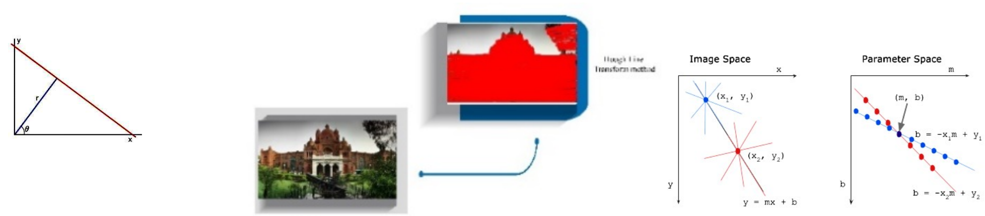


Figure 6. Feature detection of the Lahore Museum (British) by using the Hough Line Transform method.

9.3 Contour Detection Method

Contours, representing continuous points of the same color along boundaries, are essential for object detection and form analysis. Using the Image Moment approach, contours of antique buildings were precisely located. The spatial structure moment, denoted by mij, compares various shapes to identify features of historic buildings[32]. (see Fig. 7)

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

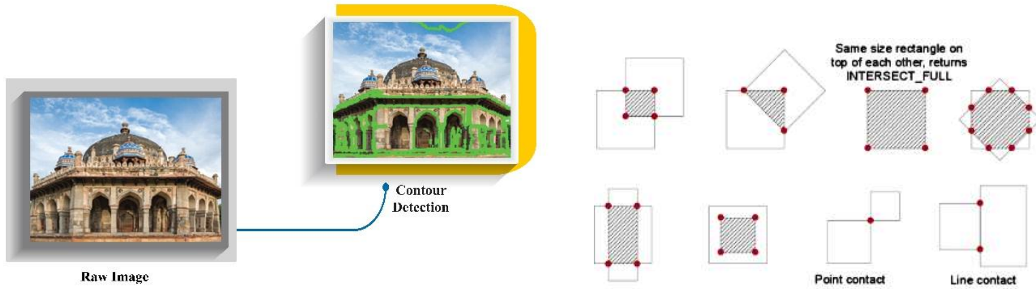


Figure 7. Feature detection of the Tomb of Isa Khan (Mughal) by using the Find Counter detection method.

9.4 Harris Corner Detection Technique

Corner detection is a method used to identify distinct features in an image. The Harris corner detection technique locates corners by analyzing the direction of edges around a point. It uses a Gaussian window to assign weights to pixels and calculates image intensity differences during displacement across x and y[33,34]. The Harris algorithm, applied in this experiment, helps extract corners from images, as shown in Figure 8.

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

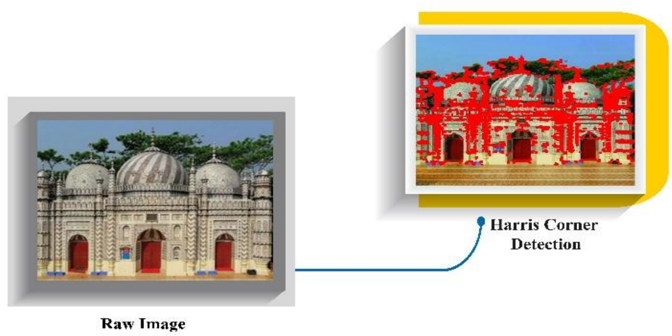
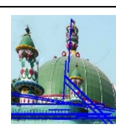
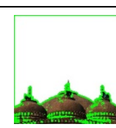
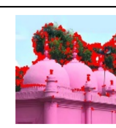
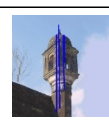
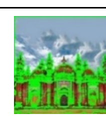
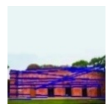
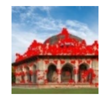
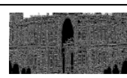
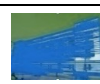
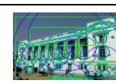


Figure 8. Feature detection of the Bajra Shahi Mosque (Mughal) by using the Harris corner detection method.

9.5 Dataset Preparation and Classification

Table 2. Training dataset and classification of Mughal, Sultanate, and British eras.

Feature	***Sultanate Era (1206-1526)***			
	Canny Edge Detection	*Hough Line Transform*	*Find Countours Techniques*	*Haris Corner Dectection*
Dome				
Minatare				
Front				

Feature	***Mughal Era (1206-1526)***			
	Canny Edge Detection	*Hough Line Transform*	*Find Countours Techniques*	*Haris Corner Dectection*
Dome				
Minatare				
Front				
Feature	***British Era (1206-1526)***			
	Canny Edge Detection	*Hough Line Transform*	*Find Countours Techniques*	*Haris Corner Dectection*
Dome				
Minatare				
Front				

To determine the construction era, we applied feature detection techniques and built a Decision Tree for classification into Sultanate, Mughal, and British periods. The tree structure refines "if-then" rules, learned through training data. Table 2 shows the classification of features (Dome/Tower/Jewel, Minaret, Front) for each era (Mughal, Sultanate, and British) using four methods: Canny Edge Detector, Hough Line Transform, Find Contours, and Harris Corner Detector.

9.6 Deep Neural Network (DNN) Architecture

The programming technique of artificial neural networks empowers a computer to learn from data observations. Deep learning, a valuable method leveraging neural networks, is applied in this experiment through a Deep Neural Network (DNN). The input layer consists of five nodes (x1, x2, x3, x4, and bias unit), as illustrated in Table 3, Fig. 5, Fig. 6, Fig. 7, and Fig. 8. Figure. 9 portrays the mathematical structure[35] of the node in the neural network, where "a" represents activation, "b" denotes bias, and "W" signifies the input layer's weight. A bias unit[36] facilitates successful learning by adjusting the activation left or right. Fig. 9 provides a comprehensive view of the entire DNN model.[37]

Table 3. Input and inputs of DNN.

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

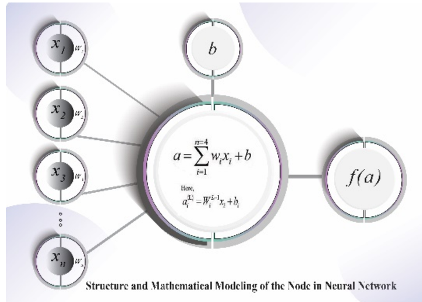


Figure 9. Structure and Mathematical Modeling of the Node in Neural Network

Fig. 9. Mathematical formation of DNN where a is Activation, L is the layer, b is Bias Unit and W is the Weight of the layer. From Fig. 9, the equation for each activation node (a) is as follows:

For hidden layer 1:

$$a_i^{(L)} = f(W_i^{(L-1)} x_i + b_1^{(L-1)} \qquad (6)$$

After hidden layer 1:

$$a_i^{(L)} = f(W_i^{(L-1)} a_i^{(L-1)} + b_1^{(L-1)} \qquad (7)$$

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

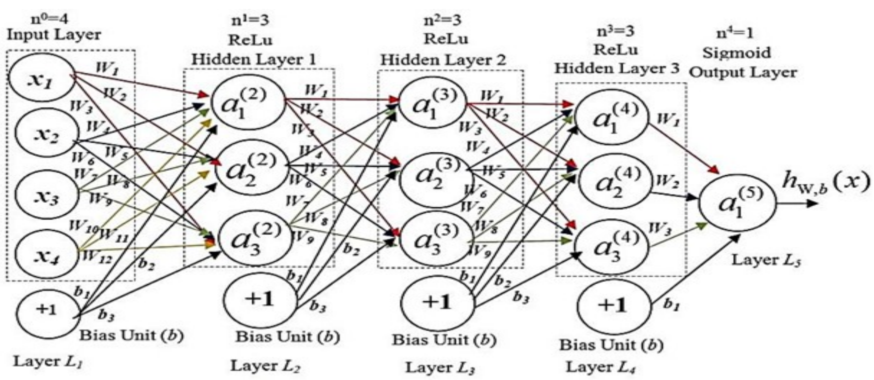


Figure 10. Deep Neural Network (DNN) for construction era identification.

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

Layer, L = 2 (Hidden Layer 1):

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

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

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

Layer, L = 3 (Hidden Layer 2):

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

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

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

Layer, L = 4 (Hidden Layer 3):

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

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

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

Layer, L = 5 (Output Layer):

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

In Figure 10, the network inputs are depicted as nodes. The nodes labeled "+1" represent bias units, corresponding to intercepts. Designating ni as the number of nodes in a neural network (without a bias unit), Weight Wi(L-1) represents the parameter linked to the relationship between the i unit in layer L and the weight originating from layer L-1 before it. Bias units consistently provide a value of +1, and no inputs or linkages go into the bias units. The activation ai(L) of unit i in layer L is specified, where ai(L)= xi for the i-th input when L=1. The hypothesis hw, b(x), defined by parameters W and b, produces a real number.

10. Results and Analysis

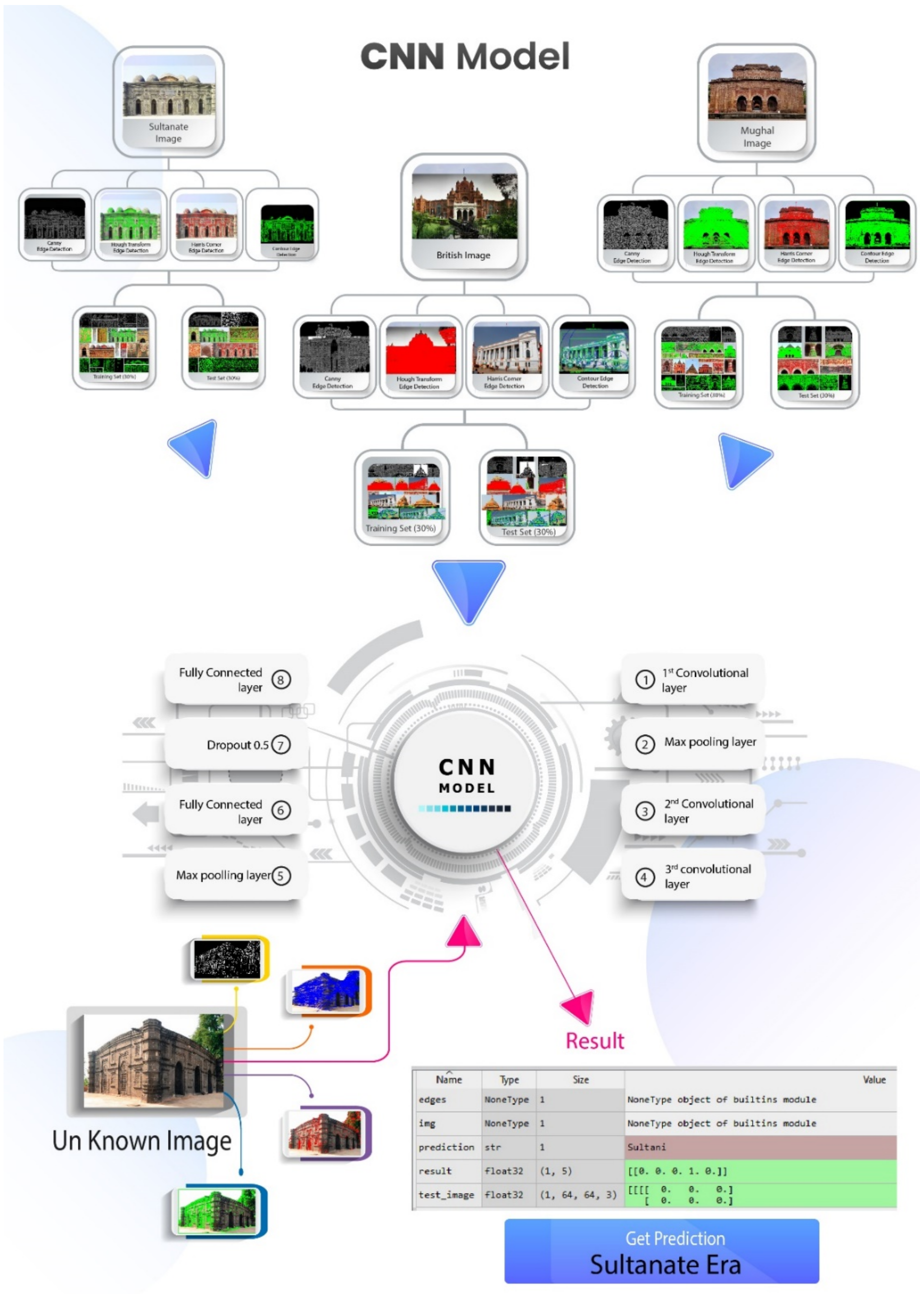


Figure 11. CNN model for era identification of the old building.

The model accurately determines the construction era by analyzing architectural features such as the façade, dome, and minaret through a computational algorithm. Its performance is assessed using confusion matrices, and the CNN model—trained on an optimized dataset—effectively classifies the era, as shown in Fig. 11. The results of construction era identification for the Sultanate period using the CNN model are presented in Fig. 12.

Name	Type	Size	Value
edges	NoneType	1	NoneType object of builtins module
img	NoneType	1	NoneType object of builtins module
prediction	str	1	Sultani
result	float32	(1, 5)	[[0. 0. 0. 1. 0.]]
test_image	float32	(1, 64, 64, 3)	[[[[0. 0. 0.] [0. 0. 0.]

Figure12. Results of construction era identification of Sultanate period by using the CNN model.

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

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

Where,

TP = True Positive; FP = False Positive;

TN = True Negative; FN = False Negative

In this research, a total tested 500 images data has been used. The Sultanate building contains 270 data, Mughal building 130, and British building 100 data. We get, TP = 254, TN = 227, FP = 3, FN =16. Following the above equation 18 for the raw data, 97.10% accuracy was achieved from this research. This research achieved much better accuracy than the recent previous work. In the previous work, the researchers got 92.33% by using only the Canny Edge Detector method for Mughal and Sultanate periods.

11. Performance Evaluation: Training and Validation Insights

The effectiveness of the model is assessed through training accuracy vs. validation accuracy, illustrated in Figure 12. The left plot demonstrates accuracy over 20 epochs, with initial rapid improvement followed by fluctuations—suggesting instability due to overfitting or learning rate issues. Interestingly, validation accuracy occasionally surpasses training accuracy, likely due to dropout or regularization techniques stabilizing learning.

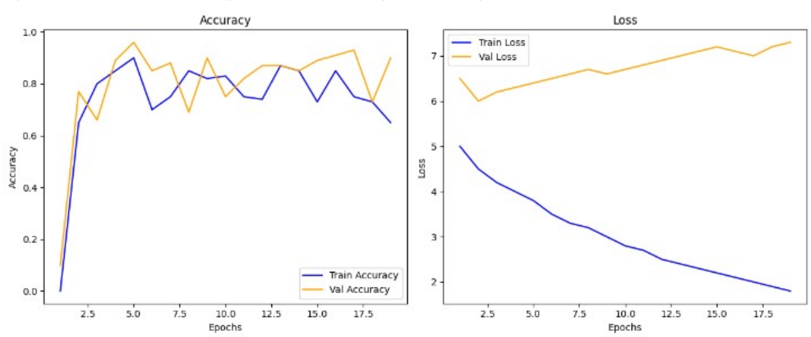


Figure 13. The Results on Train Accuracy VS Validation Accuracy

The right plot tracks loss over epochs, where increasing validation loss indicates overfitting—a common deep learning challenge. To counteract this, strategies such as:

- Regularization (L1/L2 and dropout)
- Early stopping
- Data augmentation
- Hyperparameter tuning can be employed to enhance model generalization and prevent excessive memorization of training data.
- Comparison with Existing Research

Table 4. Literature review represented

References	Implementation	Accuracy
Kenal et al.	Satellite imagery was processed using U-Net, LinkNet, FPN, and PSPNet.	96%
Zhonghua et al.	The HRSSES approach was employed for collapse detection and integrated with 3D reconstruction techniques to achieve an eight-fold improvement.	93.22%
Claudio et al.	The study distinguished between graphical and semantic information.	80%
Jose et al.	A Fujifilm IS-Pro digital single-lens camera was used, and the researchers employed spectral data.	92%
Lingfei et al.	Incorporated CSPDarkNet-53 and the Focal EoU loss function.	93.26%
Jaemin et al.	This research employed synthetic images to analyze hazardous construction sites.	88.6%
Jie et al.	Remote sensing images were used, and feature fusion was performed.	80.5%
Proposed Approach	**By combining convolutional neural networks (CNNs) with specialized feature detection techniques—including edge, line, and corner detection—this research introduces a novel method for accurately identifying architectural eras.**	**97.10%**

A comparative study with seven prior implementations (Table 4) highlights the effectiveness of this approach. While existing methods such as U-Net, spectral analysis, and CSP-DankNet 53 achieve impressive accuracy (ranging from 80% to 98%), the proposed CNN-based model—integrating specialized feature detection techniques like edge, line, and corner analysis—achieves a breakthrough accuracy of 97.10%.

12. Conclusion

This study illustrates the application of artificial neural networks combined with advanced feature extraction techniques to predict the construction era of historic monuments, focusing on the Kusumba Mosque. Utilizing algorithms such as the Canny Edge Detector, Hough Line Transform, Find Contours, and Harris Corner Detector enhances the model's accuracy in classifying architectural styles from the Sultanate, Mughal, and British periods. Despite these advancements, challenges persist, particularly when processing low-resolution or distorted images, which can reduce predictive reliability. Future work will aim to refine the model's robustness, improving its capability to accurately identify architectural features even in suboptimal image conditions.

References

[1] Zhanga, J., Zhangb, X., & Jic, X. (2024). Application of Convolutional Neural Networks in High Score Remote Sensing Image Classification. Academic Journal of Computing & Information Science, 7(2), 79-84.

[2] Jing, J., Liu, S., Wang, G., Zhang, W., & Sun, C. (2022). Recent advances on image edge detection: A comprehensive review. Neurocomputing, 503, 259-271.

[3] Singh, M. R., Ganaraj, K., & Sable, P. D. (2020). Surface mediated Ca-phosphate biomineralization and characterization of the historic lime mortar, Janjira Sea Fort, India. Journal of Cultural Heritage, 44, 110-119.

[4] Kasapakis, V., Gavalas, D., & Dzardanova, E. (2024). Mixed reality. In Encyclopedia of Computer Graphics and Games (pp. 1139-1142). Cham: Springer International Publishing.

[5] Hasan, M. S., Kabir, S. R., Akhtaruzzaman, M., Sadeq, M. J., Alam, M. M., Allayear, S. M., ... & Ali, M. (2020, February). Identification of construction era for Indian subcontinent ancient and heritage buildings by using deep learning. In International Congress on Information and Communication Technology (pp. 631-640). Singapore: Springer Singapore.

[6] Shao, Z., Tang, P., Wang, Z., Saleem, N., Yam, S., & Sommai, C. (2020). BRRNet: A fully convolutional neural network for automatic building extraction from high-resolution remote sensing images. Remote Sensing, 12(6), 1050.

[7] Wang, X., Li, J., Tao, J., Wu, L., Mou, C., Bai, W., ... & Deng, Z. (2022). A recognition method of ancient architectures based on the improved inception v3 model. Symmetry, 14(12), 2679.

[8] Arun, P. V., & Porwal, A. (2019). Spatial-spectral feature based approach towards convolutional sparse coding of hyperspectral images. Computer Vision and Image Understanding, 188, 102797.

[9] Casillo, M., Colace, F., Gupta, B. B., Lorusso, A., Marongiu, F., & Santaniello, D. (2022, June). A deep learning approach to protecting cultural heritage buildings through IoT-based systems. In 2022 IEEE International Conference on Smart Computing (SMARTCOMP) (pp. 252-256). IEEE.

[10] Hacıefendioğlu, K., Başağa, H. B., Kahya, V., Özgan, K., & Altunışık, A. C. (2024). Automatic detection of collapsed buildings after the 6 February 2023 Türkiye earthquakes using post-disaster satellite images with deep learning-based semantic segmentation models. Buildings, 14(3), 582.

[11] Gu, J., Xie, Z., Zhang, J., & He, X. (2024). Advances in rapid damage identification methods for post-disaster regional buildings based on remote sensing images: A survey. Buildings, 14(4), 898.

[12] Mirarchi, C., Gholamzadehmir, M., Daniotti, B., & Pavan, A. (2024). Semantic enrichment of BIM: the role of machine learning-based image recognition. Buildings, 14(4), 1122.

[13] Meroño, J. E., Perea, A. J., Aguilera, M. J., & Laguna, A. M. (2015). Recognition of materials and damage on historical buildings using digital image classification. South African Journal of Science, 111(1-2), 01-09.

[14] Shi, L., Zhang, F., Xia, J., Xie, J., Zhang, Z., Du, Z., & Liu, R. (2021). Identifying damaged buildings in aerial images using the object detection method. Remote Sensing, 13(21), 4213.

[15] Kim, J., Wang, I., & Yu, J. (2024). Experimental study on using synthetic images as a portion of training dataset for object recognition in construction site. Buildings, 14(5), 1454.

[16] Xue, J., Zheng, Y., Dong-Ye, C., Wang, P., & Yasir, M. (2022). Improved YOLOv5 network method for remote sensing image-based ground objects recognition. Soft Computing, 26(20), 10879-10889.

[17] Hasan, M. S., Uddin, M. S., Hasan, K. J., Rahman, M., & Ali, M. (2025). Deep Learning for Cultural Heritage: A Mobile App for Monument Recognition Using Convolutional Neural Networks. International Journal of Interactive Mobile Technologies, 19(3).

[18] Nilson, T., & Thorell, K. (2018). Cultural heritage preservation: The past, the present and the future.

[19] Liu, Y. J., Li, W., Li, Y. H., & Li, S. J. (2021, June). Application Research of BIM Technology in Ancient Architecture Restoration. In IOP Conference Series: Earth and Environmental Science (Vol. 787, No. 1, p. 012163). IOP Publishing.

[20] Moullou, D., Vital, R., Sylaiou, S., & Ragia, L. (2023). Digital tools for data acquisition and heritage management in archaeology and their impact on archaeological practices. Heritage, 7(1), 107-121.

[21] Sharma, V., & Srivastav, D. (2023). A Study of the Experiences of First-Time and Repeat Tourists during 56 Bhog Offerings in Mathura, India. Int. J. Sci. Res. in Multidisciplinary Studies Vol, 9(12).

[22] Llamas, J., Lerones, P. M., Zalama, E., & Gómez-García-Bermejo, J. (2016, October). Applying deep learning techniques to cultural heritage images within the INCEPTION project. In Euro-Mediterranean Conference (pp. 25-32). Cham: Springer International Publishing.

[23] Kabir, S. R., Akhtaruzzaman, M., & Haque, R. (2018, December). Performance Analysis of Different Feature Detection Techniques for Modern and Old Buildings. In RTA-CSIT (pp. 120-127).

[24] Hasan, M. S., Ali, M., Rahman, M., Arju, H. A., Alam, M. M., Uddin, M. S., & Allayear, S. M. (2019, September). Heritage building era detection using CNN. In IOP Conference Series: Materials Science and Engineering (Vol. 617, No. 1, p. 012016). IOP Publishing.

[25] Li, S. (2017, September). A review of feature detection and match algorithms for localization and mapping. In IOP Conference Series: Materials Science and Engineering (Vol. 231, No. 1, p. 012003). IOP Publishing.

[26] Napoles, E., & Berber, M. (2018). Precise formula for volume computations using contours method. Boletim de Ciências Geodésicas, 24(1), 18-27.

[27] Affonso, C., Rossi, A. L. D., Vieira, F. H. A., & de Leon Ferreira, A. C. P. (2017). Deep learning for biological image classification. Expert systems with applications, 85, 114-122.

[28] Crespo, C., Armesto, J., González-Aguilera, D., & Arias, P. (2010). Damage detection on historical buildings using unsupervised classification techniques. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 38(5), 184-188.

[29] Ghosh, P., Pandey, A. and Pati, U. C.: Comparison of Different Feature Detection Techniques for Image Mosaicing. *ACCENTS Transactions on Image Processing and Computer Vision* 1(1), pp. 1–7 (2015).

[30] Thareja, M. and Goyal, A.: Performance Analysis of Edges, Corners and the genres: *A Subjective Estimation. IOSR Journal of Electronics and Communication Engineering 1*, Conf.15010, pp. 98–104 (2016).

[31] Mordvintsev, A. and Revision, A. K.: Canny Edge Detection. *OpenCV-Python Tutorials* (2013).

[32] Teplyakov, L., Kaymakov, K., Shvets, E., & Nikolaev, D. (2021, January). Line detection via a lightweight CNN with a Hough layer. In Thirteenth International Conference on Machine Vision (Vol. 11605, pp. 376-385). SPIE.

[33] Alakuijala, J., Oikarinen, J., Louhisalmi, Y., Ying, X., & Koivukangas, J. (1992, October). Image transformation from polar to Cartesian coordinates simplifies the segmentation of brain images. In 1992 14th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (Vol. 5, pp. 1918-1919). IEEE.

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[34] Zhang, Y., Wang, S., Sun, P., & Phillips, P. (2015). Pathological brain detection based on wavelet entropy and Hu moment invariants. Bio-medical materials and engineering, 26(1_suppl), S1283-S1290.

[35] Mesarić, J., & Šebalj, D. (2016). Decision trees for predicting the academic success of students. Croatian Operational Research Review, 7(2), 367-388.

[36] Song, Y.Y. and Lu, Y.: Decision tree methods: *applications for classification and prediction. Shanghai Archives of Psychiatry* 27(2), pp. 130–135 (2015). Song, Y. Y., & Lu, Y. (2015). Decision tree methods: applications for classification and prediction. Shanghai archives of psychiatry.

[37] Yoon, J. H., Nguyen, M. N., Lee, H. S., Youn, J. W., Kim, D. J., Lee, D. W., & Ahn, K. K. (2016). Optimization of Design Parameters of a EPPR Valve Solenoid using Artificial Neural Network. Journal of Drive and Control, 13(2), 34-41.