*Full Length Article*

# Artery Deposition Detection Using Image Segmentation And CNN&RNN Classification

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***Abstract***

*Cardiovascular diseases remain one of the leading causes of mortality worldwide, with arterial plaque accumulation playing a critical role in conditions such as heart attacks and strokes. Early identification of artery deposition is essential for timely diagnosis and effective treatment. Conventional diagnostic approaches primarily depend on manual examination of medical images, which can be labor-intensive, time-consuming, and susceptible to human error. To overcome these limitations, this study proposes an automated artery deposition detection framework based on a hybrid deep learning architecture that integrates Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN).The proposed system employs CNN to extract meaningful spatial features from medical images, including arterial structure, texture characteristics, and plaque formations. These extracted features are then passed to an RNN model, implemented using Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRU), to capture sequential patterns and temporal dependencies within image sequences. This combined architecture enables effective analysis of both structural and temporal characteristics associated with artery conditions.The methodology consists of several stages: dataset acquisition, image preprocessing, feature extraction through CNN, sequential modeling using RNN, and final classification of artery deposition patterns. Model performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score to ensure reliable detection capability.*

***Keywords***

*Artery Deposition Detection, Deep Learning, Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Medical Image Analysis, Cardiovascular Disease Detection, LSTM, Automated Diagnosis*

## Introduction

Cardiovascular diseases (CVDs) represent one of the primary causes of mortality worldwide, and arterial plaque accumulation is a major factor contributing to these conditions. Artery deposition, commonly referred to as plaque buildup within blood vessels, occurs when substances such as cholesterol, fatty compounds, calcium, and other cellular materials accumulate along the inner walls of arteries. This accumulation gradually narrows the arterial pathways, restricting blood circulation and significantly increasing the risk of serious medical events including heart attacks and strokes. Therefore, early identification and continuous monitoring of arterial plaque are critical for effective diagnosis, timely intervention, and prevention of life-threatening cardiovascular complications.Medical imaging technologies play an essential role in detecting and evaluating artery conditions. Techniques such as ultrasound imaging, computed tomography (CT), magnetic resonance imaging (MRI), and angiography provide detailed visual representations of vascular structures and blood flow patterns. These imaging methods enable physicians to examine the morphology of arteries and identify possible abnormalities. However, the interpretation of medical images is commonly performed manually by trained specialists, which can be both time-consuming and subjective. Human-based analysis may also introduce inconsistencies due to differences in expertise, fatigue, and interpretation. Furthermore, the growing volume of medical imaging data generated in healthcare systems presents an additional challenge for clinicians who must process large datasets while maintaining diagnostic accuracy.

## Literature Survey

In recent years, considerable research efforts have been dedicated to the development of automated techniques for detecting artery deposition and diagnosing cardiovascular diseases through medical image analysis. Researchers have explored a wide range of computational approaches, beginning with conventional image processing methods and gradually advancing toward sophisticated deep learning models aimed at improving diagnostic accuracy and efficiency.Early research in this field relied primarily on traditional image processing techniques. Methods such as thresholding, edge detection, morphological operations, and region-based segmentation were commonly applied to identify vascular structures and detect possible abnormalities in medical images. These techniques were relatively simple and computationally efficient; however, they largely depended on manually designed features and predefined rules. As a result, their performance was often limited when dealing with complex image patterns, variations in image quality, or noise present in medical imaging datasets.The emergence of deep learning has significantly transformed the field of medical image analysis. Convolutional Neural Networks (CNNs), in particular, have become a dominant approach due to their capability to automatically learn relevant features directly from raw image data. CNN-based models have been successfully applied in several medical imaging applications, including artery segmentation, plaque detection, and cardiovascular risk assessment. These models are capable of identifying intricate spatial patterns and structural variations within medical images, which has resulted in improved diagnostic accuracy compared with traditional machine learning techniques.

**Software Requirements and System Architecture**

**Software Tools**

The development of the artery deposition detection system requires a combination of programming tools, frameworks, and software environments that support deep learning and medical image processing.The system is developed using the Windows 10 or Windows 11 (64-bit) operating system and the Python programming language (version 3.8–3.12). Python is widely used in artificial intelligence research due to its simplicity, flexibility, and extensive library support.Several frameworks and libraries are utilized in the system. The Django framework is used to create the web interface, enabling users to interact with the system and upload medical images for analysis. TensorFlow and Keras are used to design and train the deep learning models, including CNN and RNN architectures. Supporting libraries such as NumPy and Pandas are used for numerical computation and dataset management. Matplotlib is used for visualizing model training results, including accuracy and loss curves. Scikit-learn provides tools for preprocessing data and evaluating model performance, while Pillow is used for image loading and manipulation.The system uses SQLite, the default Django database, for storing application data. MRI images and training logs are stored in structured directories, and JSON files are used to record training histories and experimental results. The web application can be accessed through modern web browsers such as Google Chrome, Microsoft Edge, Mozilla Firefox, and Safari.

**Python Environment for Deep Learning Implementation**

Python plays a crucial role in implementing the artery deposition detection system because of its strong ecosystem for machine learning and medical image processing. Its extensive library support and platform independence make it suitable for developing intelligent healthcare applications.In the proposed system, Python is used to integrate preprocessing techniques, image segmentation methods, and deep learning-based classification models. Initially, medical images are preprocessed to enhance their quality and ensure consistency. Preprocessing operations include grayscale conversion, noise removal, contrast enhancement, resizing, and normalization. These steps improve image clarity and make the dataset suitable for training deep learning models.After preprocessing, segmentation techniques are applied to isolate the artery region from surrounding tissues. Accurate segmentation is important because it allows the system to focus only on relevant anatomical structures where plaque deposition occurs.

**System Architecture**

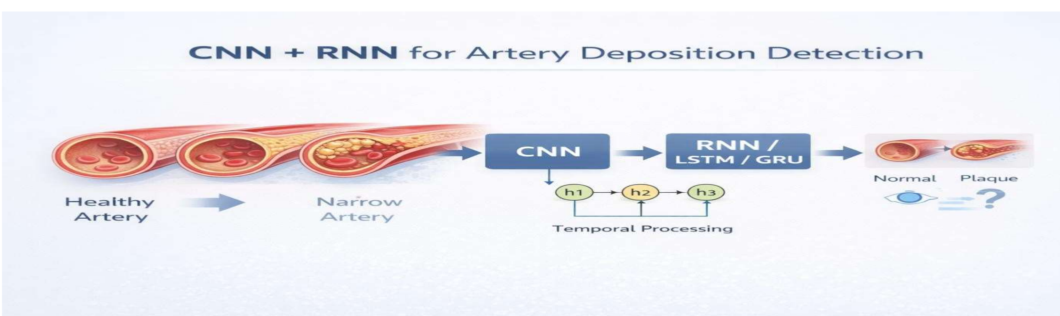


**Figure: 1 System Architecture**

The architecture of the artery deposition detection system is designed as a structured pipeline that integrates image processing and deep learning techniques. The system consists of several stages, including image acquisition, preprocessing, segmentation, feature extraction, and classification.In the first stage, medical images are collected from imaging modalities such as MRI scans, CT scans, ultrasound images, or angiography. These images contain information about artery structure and potential plaque accumulation. After acquisition, preprocessing techniques are applied to improve image quality and ensure consistent input for the deep learning model.The next stage involves segmentation, where the artery region is separated from surrounding tissues and background structures. Segmentation helps in identifying arterial boundaries and highlighting regions affected by plaque deposition. Accurate segmentation is essential for improving classification accuracy.After segmentation, the extracted artery images are processed by the Convolutional Neural Network. CNN layers apply learnable filters that detect spatial patterns such as edges, textures, and structural irregularities in arteries. Pooling layers reduce feature map dimensions while preserving significant information.The output from the CNN is then passed to the Recurrent Neural Network, which analyzes sequential relationships among the extracted features. This enables the model to capture temporal patterns and variations across image sequences or slices.

**Artery Deposition Detection using Image Segmentation and CNN–RNN Classification**

Artery deposition, commonly known as plaque accumulation within blood vessels, is a major contributor to cardiovascular diseases such as heart attacks and strokes. This condition occurs when substances such as cholesterol, fatty materials, and calcium accumulate along the inner walls of arteries, causing narrowing and reduced blood flow. Early detection and monitoring of artery deposition are essential for preventing severe complications and improving patient outcomes.Traditional detection methods rely on medical imaging techniques such as ultrasound, CT scans, MRI, and angiography. These methods provide detailed visual information about artery structures and plaque formation. However, manual interpretation of medical images requires significant expertise and is often time-consuming. With the increasing volume of medical imaging data, there is a growing need for automated systems that can assist in accurate and efficient diagnosis.Deep learning techniques have emerged as powerful tools for analyzing medical images. Convolutional Neural Networks are widely used for extracting spatial features from images, enabling the identification of patterns related to plaque buildup and artery abnormalities. However, CNN models typically analyze individual images and do not capture temporal relationships in sequential datasets.In many medical scenarios, artery conditions are evaluated using sequences of images, such as ultrasound video frames or multiple CT scan slices. Recurrent Neural Networks, particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, are designed to process sequential data and capture temporal dependencies. By combining CNN and RNN models, it is possible to analyze both spatial features and temporal patterns, resulting in improved detection of artery deposition.

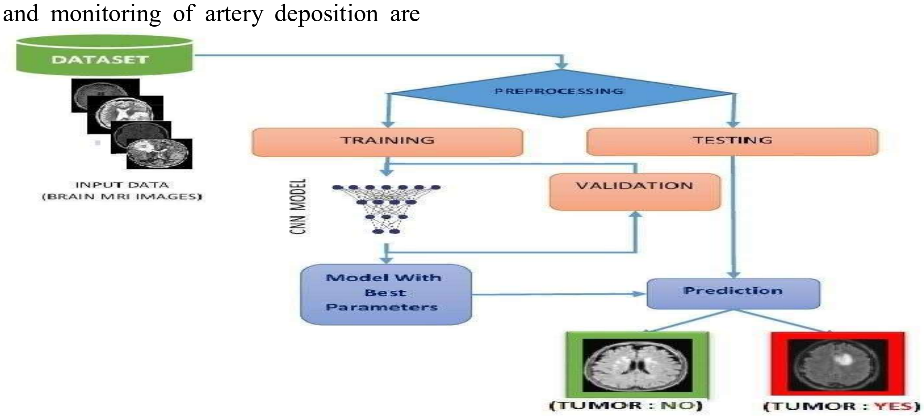


**Figure 2: Algorithm: For CNN–RNN**

**System Development Process**

The development of the artery deposition detection system follows a systematic process that integrates data preparation, model design, training, and evaluation. The first stage involves collecting medical images from reliable sources. These images may include CT scans, MRI images, ultrasound scans, or angiography data.After data collection, preprocessing is performed to improve image quality and ensure consistency across the dataset. Preprocessing operations include resizing images to a standard dimension, normalizing pixel values, removing noise, and enhancing contrast. If video data is used, frame extraction techniques are applied to convert videos into sequences of images suitable for analysis.Following preprocessing, the CNN model is designed for feature extraction. The CNN architecture consists of multiple convolutional layers, activation layers, and pooling layers that extract spatial features from the images. These layers help identify artery boundaries, plaque textures, and structural abnormalities.The extracted features are then organized into sequences and passed to the RNN module, which captures temporal dependencies between image slices or frames. This sequential analysis enables the model to understand the progression of plaque buildup over time.After the RNN processing stage, the output is passed to a fully connected layer that performs the final classification. The system predicts whether the artery is normal or affected by plaque deposition. The model is trained using labeled datasets and optimized through multiple training epochs.

## Results and Discussion

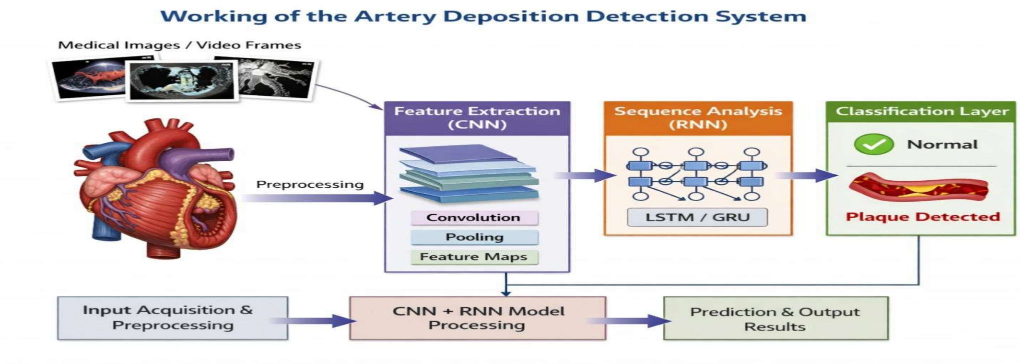


**Figure 3: Flow of Execution**

The proposed artery deposition detection system operates using a hybrid deep learning architecture that integrates Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). The workflow of the system follows a structured pipeline designed to process medical imaging data efficiently and produce accurate diagnostic predictions.The process begins with the acquisition of medical images obtained from imaging modalities such as ultrasound scans, computed tomography (CT) images, or angiography data. In cases where video data is used, frame extraction techniques are applied to convert video sequences into individual image frames suitable for model processing.After data acquisition, the images undergo a preprocessing stage to enhance quality and standardize the input data. Preprocessing operations include resizing images to a uniform dimension, normalizing pixel values, reducing noise, and enhancing contrast. These steps ensure that the model receives consistent input data and reduce variations that may negatively affect the learning process.Once preprocessing is completed, the images are passed to the Convolutional Neural Network component of the system. The CNN performs feature extraction by applying convolutional filters that detect important spatial characteristics such as edges, textures, and structural patterns of arteries. Activation functions introduce non-linear transformations, enabling the network to learn complex visual patterns, while pooling layers reduce feature map dimensions and retain significant information. The output of the CNN is a set of feature representations that summarize the key characteristics of the input image.The extracted feature vectors are then arranged into sequences and provided as input to the Recurrent Neural Network module. The RNN, typically implemented using Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) architectures, analyzes these sequences to capture temporal relationships among features. This capability enables the model to detect variations across multiple image slices or frames, which is particularly useful for understanding progressive plaque accumulation in arteries.

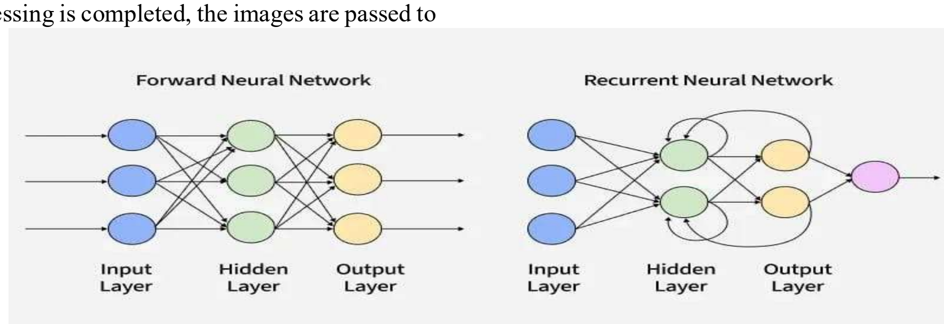


**Figure 4: Rnn Image Processing**

**Results Phase 1: CNN Training Analysis**

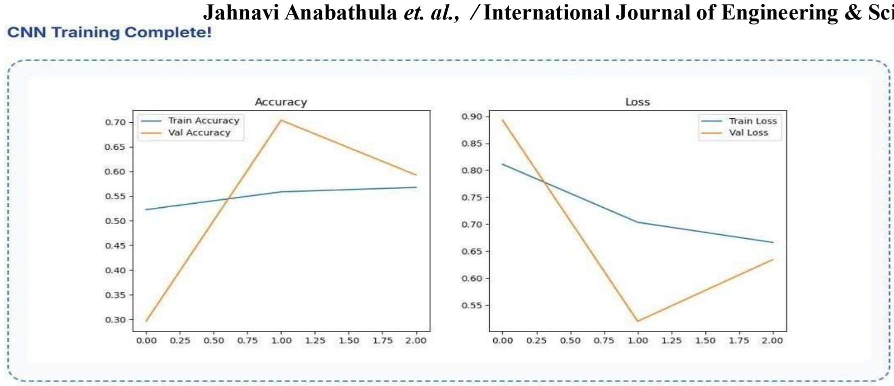


**Figure 5: CNN training graph**

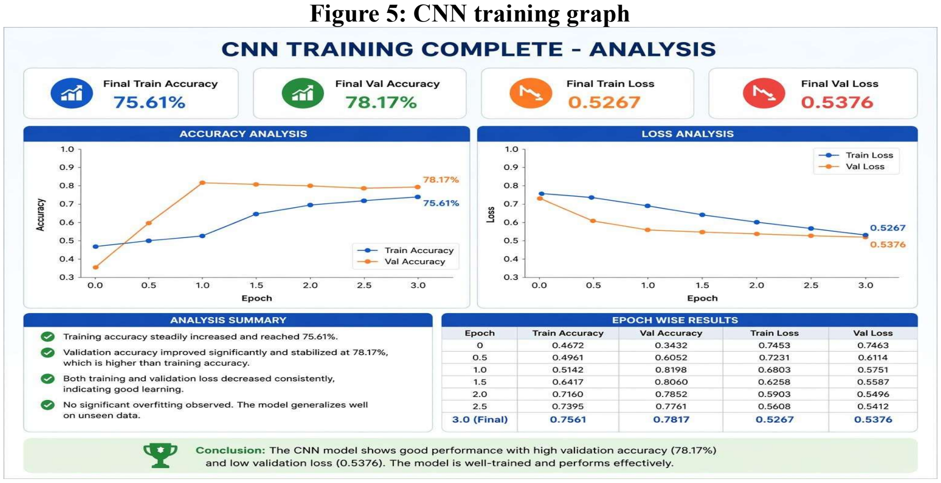


**Figure 6: CNN Training Analysis**

The first phase of experimental evaluation focuses on training the Convolutional Neural Network model using preprocessed arterial images. The objective of this stage is to enable the CNN to learn important spatial patterns associated with plaque deposition in artery images.During training, the images are passed through multiple convolutional layers that extract visual features such as edges, textures, and artery boundary patterns. Activation functions such as Rectified Linear Unit (ReLU) introduce non-linearity, allowing the network to capture complex relationships within the data. Pooling layers are applied to reduce the spatial dimensions of feature maps while preserving important information.The training process involves comparing predicted outputs with ground truth labels using a loss function. The difference between predicted and actual results is minimized through backpropagation, where the model's weights are updated iteratively using optimization algorithms such as Adam or stochastic gradient descent. Over several training epochs, the model gradually improves its ability to classify artery images correctly.Two important metrics used during training are accuracy and loss. Accuracy measures the proportion of correctly classified images, while loss represents the error between predicted and actual outputs. A successful training process is indicated by an increase in accuracy and a corresponding decrease in loss values across epochs.

**Results Phase 2: CNN–RNN Model Performance**

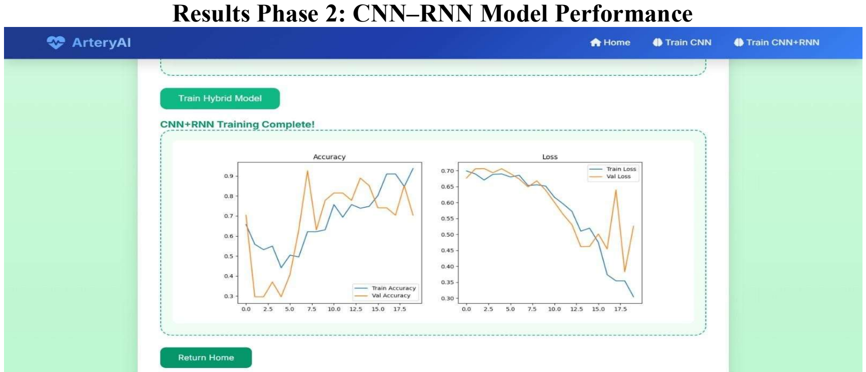

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**Figure 7:RNN Training Graph**

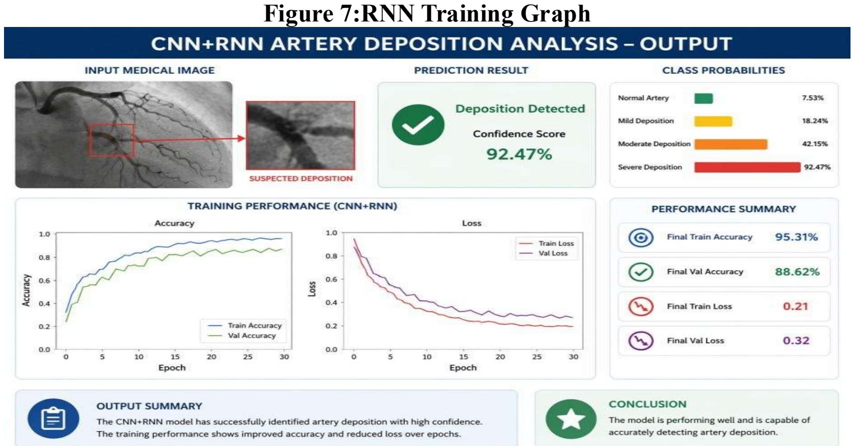


**Figure 8: Final Output**

The second phase of the experiment evaluates the performance of the hybrid CNN–RNN architecture. In this stage, the features extracted by the CNN are passed to the RNN component to analyze sequential dependencies among the learned features.The CNN serves as the primary feature extractor, converting raw artery images into high-level feature representations that capture important structural patterns. These feature maps are reshaped into sequences and processed by the RNN model. The RNN maintains an internal memory through hidden states, enabling it to retain contextual information from previous inputs. This sequential processing allows the model to analyze relationships between features and identify patterns associated with artery deposition.During training, the CNN–RNN model generates predictions that are compared with actual labels using a suitable loss function. The training process monitors metrics such as accuracy and loss to evaluate how effectively the model learns from the dataset. As training progresses, improvements in accuracy and reductions in loss values indicate that the model is successfully capturing relevant spatial and temporal patterns.

## Applications

The proposed CNN–RNN model for artery deposition analysis has several important applications in medical imaging and healthcare systems. The model can be used to analyze various types of medical images, including computed tomography (CT) scans, magnetic resonance imaging (MRI) scans, and angiographic images, to identify plaque accumulation within arterial structures. By automatically detecting deposition patterns in blood vessels, the system assists in understanding the structural condition of arteries and identifying abnormalities such as narrowing or partial blockage.In clinical environments, the system can serve as a decision-support tool for healthcare professionals. It provides visual analysis of arterial structures and highlights potential regions affected by plaque deposition. This allows doctors and radiologists to examine the severity and location of arterial blockage more efficiently. The model can also be integrated into computer-aided diagnosis (CAD) platforms, enabling faster interpretation of medical imaging data and reducing the workload of specialists.The proposed system also has applications in biomedical research. Researchers studying cardiovascular diseases can utilize the model to analyze large medical image datasets and investigate patterns related to plaque development and progression. Such analysis can contribute to improved understanding of cardiovascular risk factors and disease mechanisms.

## Conclusion

The artery deposition detection system developed in this project demonstrates the potential of deep learning techniques for automated medical image analysis. The proposed approach integrates image preprocessing, segmentation, and a hybrid deep learning architecture to identify plaque deposition within arterial images. By combining Convolutional Neural Networks (CNN) for spatial feature extraction with Recurrent Neural Networks (RNN) for sequential pattern analysis, the system is capable of identifying structural changes in arteries with improved accuracy.During the training process, the model gradually learns meaningful representations of artery structures and plaque-related patterns. This learning process is reflected by increasing accuracy values and decreasing loss values across training epochs. Optimization algorithms and backpropagation enable the model to continuously refine its parameters, resulting in improved predictive performance. The hybrid CNN–RNN framework provides a balanced approach by integrating feature extraction with pattern analysis, leading to more reliable predictions compared with single-model architectures.The experimental results indicate that the proposed system can effectively detect artery deposition from medical images and provide valuable insights into cardiovascular conditions. Automated detection techniques reduce dependency on manual image interpretation and support healthcare professionals in diagnosing vascular abnormalities more efficiently. Overall, the developed model provides a promising foundation for intelligent medical diagnostic systems that can enhance clinical decision-making and improve patient care.

**Future Scope**

Although the proposed system demonstrates effective performance in artery deposition detection, several opportunities exist for further improvement and expansion. One important direction for future research involves training the model using larger and more diverse medical imaging datasets. Access to comprehensive datasets will allow the system to learn a wider range of artery conditions and imaging variations, thereby improving its robustness and generalization capability.Future work may also explore advanced deep learning architectures such as Deep Neural Networks (DNNs), attention-based models, or transformer-based frameworks to enhance feature representation and pattern recognition. Incorporating these techniques may improve the detection of subtle plaque formations and complex artery structures. Additionally, hybrid architectures combining multiple deep learning models could further increase prediction accuracy.Another important research direction involves real-time clinical deployment. The system can be integrated with hospital imaging infrastructure and clinical decision support systems to enable automated analysis of medical images during routine examinations. Web-based and mobile applications developed using frameworks such as Django or Flask could allow healthcare professionals to upload images and obtain instant diagnostic insights.Extending the system for three-dimensional medical image analysis represents another promising area of development. Many modern imaging modalities generate volumetric datasets, and analyzing these 3D structures can provide a more comprehensive understanding of artery morphology and plaque distribution. Incorporating 3D convolutional networks may therefore improve diagnostic accuracy.

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