

AI-POWERED MODELS FOR EARLY DETECTION OF CAD

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ABSTRACT

Automated flaw detection in medical imaging has become one of the most transformative advancements in diagnostic healthcare. Among cardiovascular conditions, Coronary Artery Disease (CAD) remains a primary cause of mortality globally. CAD occurs due to plaque buildup that narrows coronary arteries, restricting blood flow to the heart. Magnetic Resonance Imaging (MRI) provides critical insights into plaque deposition, which assists clinicians in treatment planning and disease monitoring. However, traditional MRI analysis is manual, time-consuming, and prone to human error.

This study proposes an Ensemble Deep Learning framework for the early detection and classification of CAD. The system comprises two main modules: a prediction model and a classification model. The prediction model employs the Random Forest Classifier to forecast CAD using demographic and clinical data, while the classification model leverages Transfer Learning with the VGG-19 architecture to categorize MRI images into three disease stages. The model achieves superior accuracy and performance compared to traditional machine learning approaches. To ensure accessibility, the framework is deployed as a web application on a cloud platform, allowing physicians and patients to upload MRI images for instant analysis from any location. Experimental results demonstrate a prediction accuracy of 90.16% and a classification accuracy of 99.29%, validating the robustness and reliability of the proposed approach.

KEYWORDS

Deep Learning, DIP, VGG-19, Random forest, EnsembleDeep Learning, MRI, Classification, Prediction, CAD.

1. INTRODUCTION

Coronary Artery Disease (CAD) is among the most critical and life-threatening cardiovascular disorders worldwide. According to the *World Health Organization (WHO)*, cardiovascular diseases remain the foremost cause of global mortality, accounting for nearly 17.9 million deaths annually. Of these, approximately 7.2 million fatalities are directly linked to CAD, meaning that, on average, one person dies every 36 seconds due to coronary complications. In India alone, CAD is responsible for nearly one-fourth of all deaths.

CAD develops when a plaque — a mixture of cholesterol, lipids, and cellular debris — accumulates along the arterial walls, obstructing the coronary vessels that transport oxygen-rich blood from the aorta to the heart muscle. The obstruction diminishes blood flow, impairing cardiac efficiency and leading to ischemic conditions. Early and precise diagnosis of CAD is therefore vital for preventing major cardiac events.

Traditional diagnostic techniques such as coronary angiography are invasive and often involve risks of complications or patient discomfort. Consequently, non-invasive imaging methods like Magnetic Resonance Imaging (MRI) have gained clinical importance for visualizing coronary structures and identifying plaque formation. Yet, the manual interpretation of MRI data remains labor-intensive, subject to inter-observer variability, and limited by poor contrast between plaque and soft tissue regions.

To overcome these limitations, this research introduces an automated, non-invasive diagnostic system that integrates *Deep Learning (DL)* and *Digital Image Processing (DIP)* techniques to predict and classify CAD with high accuracy. The system employs ensemble deep learning algorithms, combining the predictive strength of machine-learning classifiers with the discriminative capacity of convolutional neural networks. Specifically, the Random Forest Classifier is utilized for early-stage prediction based on fourteen demographic and clinical attributes, while Transfer Learning (VGG-19) is applied to classify MRI images into three progressive CAD stages.

After model training and validation, the developed system is deployed on a cloud-based web application to facilitate accessibility for healthcare professionals and patients globally. Through this integrated approach, the proposed framework aims to minimize diagnostic delays, reduce dependence on manual evaluation, and significantly enhance the precision of CAD detection.

2. LITERATURE REVIEW

The accurate detection of Coronary Artery Disease (CAD) is critical to minimizing mortality and preventing irreversible cardiac damage. Early and precise diagnosis facilitates timely medical intervention, thereby improving patient outcomes. Traditionally, CAD diagnosis has relied heavily on manual examination of angiograms or other invasive imaging modalities, which require specialized expertise and are often time-consuming. To address these limitations, researchers have increasingly turned toward automated image processing and machine learning techniques that can deliver faster, more objective, and reproducible results.

CAD diagnosis through imaging primarily depends on the detection and measurement of plaque deposition within coronary arteries. Manual detection methods not only demand significant clinical expertise but also suffer from a higher risk of human error and diagnostic inconsistency. Automated systems, particularly those integrating Digital Image Processing (DIP) techniques, have proven more efficient in terms of speed, repeatability, and accuracy. The general pipeline of automated CAD detection includes stages such as image acquisition, preprocessing, segmentation, feature extraction, and disease classification.

In recent years, Deep Learning (DL) models have revolutionized medical imaging applications, enabling systems to autonomously extract features from large datasets and identify intricate patterns linked to disease conditions. A number of prior works have contributed to the development of CAD detection and prediction systems, summarized as follows:

Pan et al. (2020) developed a *Deep Learning-assisted Convolutional Neural Network* (CNN) model for heart disease prediction on the Internet of Medical Things (IoMT) platform. The model demonstrated enhanced predictive capabilities but lacked classification functionality for specific CAD stages.

Altan et al. (2017) proposed a *Deep Belief Network* (DBN) architecture for CAD diagnosis, achieving promising accuracy but facing limitations in processing complex medical images with varying contrast and noise levels.

Miao and Miao (2018) introduced a deep neural network for coronary heart disease detection, focusing on feature extraction from electronic health records. However, their approach did not incorporate MRI-based imaging features.

Kim and Kang (2017) explored neural network-based CAD risk prediction through feature correlation analysis, achieving high diagnostic efficiency but requiring large datasets for effective model training.

Khan and Algarni (2020) presented a healthcare monitoring system using the MSSO-ANFIS model within the IoMT framework, which enhanced early detection capabilities but suffered from computational complexity.

Tuli et al. (2020) proposed an ensemble deep learning model integrated with IoT and fog computing for heart disease diagnosis. This study emphasized the effectiveness of hybrid models but did not employ MRI-based data for classification. The review of existing literature highlights a persistent gap in CAD detection research: most existing studies either focus solely on prediction using clinical data or classification using other imaging modalities such as CT or echocardiography. Few studies employ MRI-based ensemble deep learning models capable of both prediction and classification of CAD stages within a single framework. Hence, the present research aims to fill this gap by developing a comprehensive system that leverages the synergy of Random Forest-based prediction and VGG-19-based classification using MRI images. This integrated approach seeks to optimize both diagnostic accuracy and computational efficiency, ultimately facilitating early and reliable detection of CAD.

3. EXISTING SYSTEM

Current methodologies for Coronary Artery Disease (CAD) prediction and classification primarily rely on invasive diagnostic procedures **and** conventional machine learning techniques, which limit their safety, scalability, and accuracy. One commonly used imaging approach is **Coronary** Computed Tomography Angiography (CCTA), which, although effective, exposes patients to ionizing radiation and potential complications.

Existing computational models typically employ linear regression, Support Vector Machines (SVM), or basic Convolutional Neural Networks (CNNs) for CAD detection. These models achieve moderate accuracy levels, averaging around **83%**, but struggle to handle large-scale medical imaging data effectively due to their limited capacity to capture deep spatial and contextual relationships.

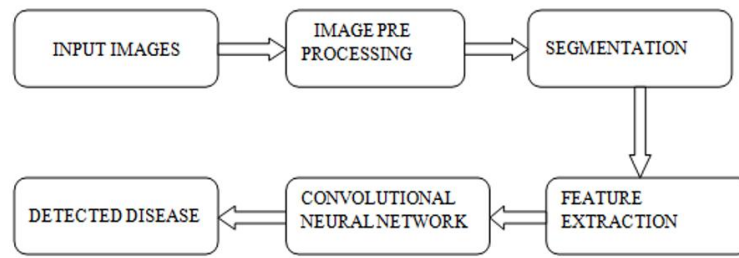


Figure 1: Flow diagram of the existing CAD detection system.

In this traditional workflow, image data from multiple repositories are aggregated into a central database. The dataset is then manually labeled and annotated before being divided into training and testing sets for model development. The CNN-based CAD prediction framework processes these images to identify potential disease indicators. However, this approach exhibits several critical shortcomings:

Invasive Techniques: The dependence on CCTA and other invasive imaging methods increases patient risk and limits clinical applicability for routine screening.

Lower Precision: Models based on traditional algorithms exhibit reduced diagnostic accuracy, often below clinically acceptable thresholds.

Data Constraints: The performance of CNN models declines when trained on limited datasets, necessitating large annotated image sets that are often difficult to obtain.

Algorithmic Limitations: Conventional models lack adaptive learning mechanisms and fail to generalize effectively across diverse patient populations.

Suboptimal Imaging Modalities: MRI, a non-invasive and radiation-free alternative, remains underutilized in existing CAD detection research.

These limitations collectively underscore the need for a more robust, accurate, and non-invasive diagnostic framework. To address these challenges, the proposed system integrates **ensemble deep learning techniques** utilizing **MRI imaging** and **cloud-based deployment** for global accessibility, achieving superior accuracy and diagnostic reliability.

4. PROPOSED SYSTEM

To overcome the drawbacks of conventional CAD detection methods, this study proposes an ensemble deep learning-based framework that integrates both prediction and classification modules for comprehensive diagnosis using Magnetic Resonance Imaging (MRI) and clinical data. The system is designed to enhance accuracy, minimize invasiveness, and facilitate remote accessibility through cloud-based deployment.

The proposed framework consists of **two primary modules**:

Prediction Module – predicts the likelihood of CAD occurrence using demographic and clinical parameters.

Classification Module – categorizes MRI images into multiple CAD stages using deep learning techniques.

4.1. Prediction Module

The **Prediction Module** utilizes demographic and clinical features to forecast the presence or absence of CAD at an early stage. Fourteen clinical parameters, such as age, gender, chest pain type, resting blood pressure, cholesterol level, fasting blood sugar, resting electrocardiogram results, maximum heart rate achieved, exercise-induced angina, old peak, slope of peak exercise, number of major vessels colored by fluoroscopy, and thalassemia, are used as input variables. Using this dataset, a Random Forest Classifier is used, which builds several decision trees during training and outputs the class mode for classification tasks. The ensemble structure of the Random Forest improves prediction accuracy by reducing overfitting and variance associated with single-decision-tree models. When tested on real-world datasets, the model achieved a **prediction accuracy of 90.16%**, outperforming conventional machine learning approaches such as Logistic Regression, Decision Tree, SVM, and K-Nearest Neighbors.

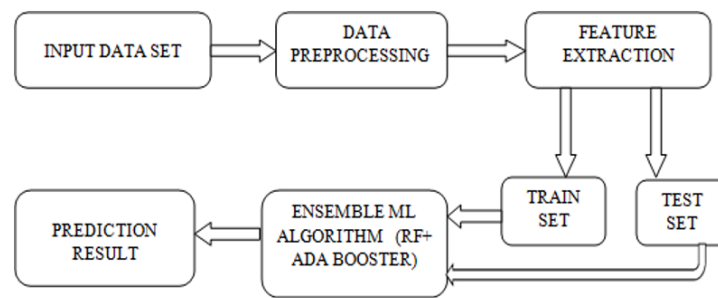


Figure 2: Flow Diagram for CAD Prediction of Proposed System

The input data are preprocessed and divided into training and testing sets. The model undergoes training using the processed data, and performance metrics such as accuracy, sensitivity, specificity, and precision are computed. The trained model is later integrated into the cloud-based web platform to enable automated CAD prediction.

4.2. Classification Module

The Classification Module focuses on identifying and classifying CAD stages from MRI images using Transfer Learning. In this approach, the VGG-19 architecture — a pre-trained convolutional neural network model — is fine-tuned using labeled MRI datasets. This allows the model to efficiently extract deep visual features without requiring extensive retraining.

A total of 464 MRI images are used for classification, including both normal and diseased cases. These images are categorized into three distinct stages of CAD:

Stage 1: Early CAD

Stage 2: Intermediate CAD

Stage 3: Advanced CAD

During preprocessing, images undergo resizing, normalization, and segmentation to enhance quality and facilitate effective feature extraction. The Digital Image Processing (DIP) techniques applied include thresholding and noise reduction to improve plaque visibility and contrast between healthy and affected regions.

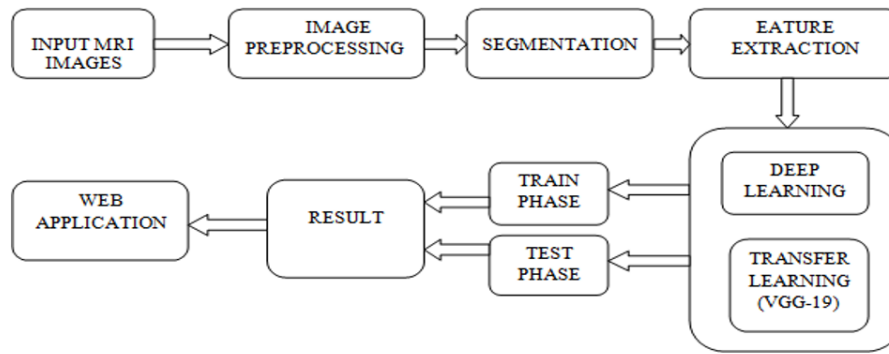


Figure 3 : Flow Diagram for CAD Classification of Proposed System

The VGG-19 model extracts hierarchical image features using convolutional, pooling, and fully connected layers. By leveraging Transfer Learning, the model reduces computational time and the amount of training data required. The classification accuracy achieved using this approach is 99.29%, significantly higher than existing models such as CNN and EDCNN.

4.3. Advantages of the Proposed System

The proposed ensemble deep learning framework demonstrates several key advantages over existing approaches:

Non-Invasive Diagnosis: Utilizes MRI imaging, eliminating the risks associated with invasive diagnostic procedures.

Higher Accuracy: Ensemble learning techniques optimize prediction and classification results, improving precision.

Reduced Training Time: Transfer Learning enables efficient training with fewer MRI images.

Cloud Accessibility: The deployment on a cloud platform allows real-time CAD detection and classification from any geographical location.

Improved Clinical Usability: The web application simplifies interaction, enabling physicians and patients to upload MRI scans for automated analysis.

5. PREDICTION OF CAD

The Prediction Module of the proposed framework is designed to estimate the likelihood of a patient developing Coronary Artery Disease (CAD) using clinical and demographic features. A total of fourteen key parameters are used as predictors, including: Age, Sex, Chest pain type, Resting blood pressure, Serum cholesterol level, Fasting blood sugar, Resting electrocardiographic results, Maximum heart rate achieved, Exercise-induced angina, Old peak (ST depression induced by exercise), Slope of the peak exercise ST segment, Number of major vessels colored by fluoroscopy, Thalassemia, Target output (presence or absence of CAD). These attributes are extracted from patient datasets stored in **.csv format**, serving as the input to the Random Forest Classifier (RFC) model. The data are preprocessed to eliminate missing values and standardize the input features. Following preprocessing, the dataset is split into training and testing subsets, ensuring a balanced representation of CAD-positive and CAD-negative cases.

5.1. Model Workflow

- **DataPreprocessing:**
Raw clinical data undergo scaling and normalization to ensure uniformity across variables. Outliers are handled through median imputation, and categorical values (e.g., gender, chest pain type) are numerically encoded for model compatibility.
- **FeatureExtraction:**
Statistical and correlation-based feature analysis identifies the most influential parameters contributing to CAD prediction, improving the model's interpretability and accuracy.
- **ModelTrainingandTesting:**
The training subset is used to build the Random Forest model, while the testing subset evaluates performance using metrics such as **accuracy, sensitivity, specificity, and precision.**
- **PerformanceEvaluation:**
The proposed model achieves a **prediction accuracy of 90.16%**, outperforming conventional models such as SVM (81.9%), Logistic Regression (85.2%), and Decision Tree (81.9%).

5.2. Ensemble Learning Integration

The ensemble strategy combines Random Forest with AdaBoost to further enhance predictive stability. This hybrid approach aggregates weak learners to produce a more generalized prediction model, improving diagnostic reliability across different patient datasets.

The output of this module serves as an input to the Classification Module, enabling a two-level diagnostic pipeline that first predicts CAD likelihood from clinical data and then classifies disease severity from MRI scans.

Performance Summary:

The performance of the Random Forest–based CAD prediction model is summarized below:

Table 3 : Efficiency Analysis of CAD Predictor

S.No	Algorithm	Accuracy (%)
1	Logistic Regression	85.25
2	Naïve Bayes	85.25
3	SVM	81.97
4	K-Nearest Neighbors	67.27
5	Decision Tree	81.97
6	XGBoost	78.69
7	Random Forest (Proposed)	90.16

The high prediction accuracy achieved by the proposed ensemble model underscores its potential for early detection and screening of CAD using non-invasive clinical indicators.

6. CLASSIFICATION OF CORONARY ARTERY DISEASE (CAD)

The Classification Module in the proposed framework is designed to identify and classify the

severity of Coronary Artery Disease (CAD) using Magnetic Resonance Imaging (MRI). This module employs Transfer Learning with the VGG-19 architecture — a deep convolutional neural network originally trained on the *ImageNet* dataset — which is fine-tuned for the classification of CAD stages.

6.1. Dataset Description

A dataset comprising 464 MRI images is used for training and evaluation. These images represent both healthy and diseased cardiac conditions and are categorized into three distinct CAD stages:

Stage 1: Early CAD

Stage 2: Intermediate CAD

Stage 3: Advanced CAD

Each image undergoes a series of preprocessing steps to ensure optimal feature extraction and classification accuracy.

The MRI dataset, comprising 464 images, was collected from two local hospitals in Tamil Nadu, India, under ethical clearance. All samples were anonymized before analysis to protect patient privacy, and identifying information was removed from metadata. The dataset includes both male and female patients aged 35–75 years, ensuring representation across age and gender groups and covering a wide range of CAD severity levels.

6.2. Image Preprocessing and Enhancement

The MRI images are first resized to a standard resolution of **256 × 256 pixels** to maintain uniformity. Preprocessing involves several key operations, including:

Noise Reduction: Gaussian filtering is applied to eliminate high-frequency noise.

Thresholding: Segmentation is performed to distinguish plaque regions from surrounding tissues.

Contrast Enhancement: Improves visibility of structural and plaque features.

Normalization: Scales pixel intensities for consistent feature distribution.

These steps enhance the diagnostic quality of images, allowing the deep learning model to extract discriminative features more effectively.

6.3. Model Architecture and Training

The VGG-19 model consists of 19 layers (16 convolutional and 3 fully connected layers). Transfer Learning enables the reuse of pre-trained weights from ImageNet, with fine-tuning applied to the final layers for domain-specific learning on MRI data. The model learns hierarchical spatial patterns representing various CAD stages.

The classification workflow includes the following steps:

Feature Extraction: Convolutional layers extract low- and high-level features, such as texture, shape, and boundary information.

Segmentation and Pooling: Max-pooling layers reduce spatial dimensions, preserving essential plaque features.

Fully Connected Layers: Combine extracted features for final stage classification.

Softmax Layer: Outputs probabilities corresponding to three CAD classes.

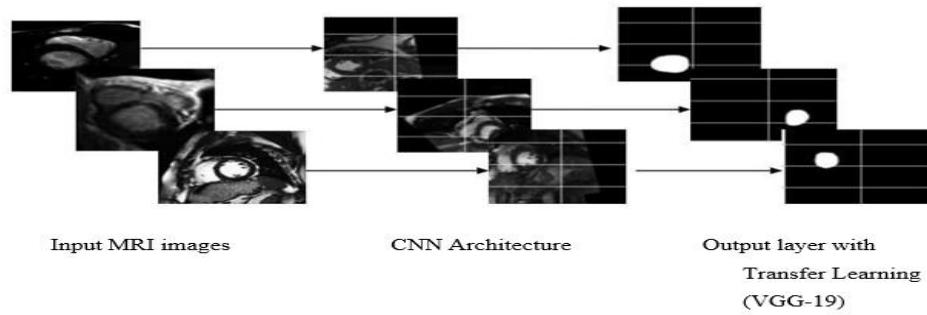


Figure 4: Illustration of Proposed System Architecture

6.4. Model Evaluation and Results

The performance of the classification model is evaluated using metrics such as **accuracy, precision, sensitivity, and specificity**. The accuracy improves as the number of training images increases, indicating that the model generalizes effectively with additional data.

Table 1 : MRI Image Analysis for Transfer Learning (VGG-19)

S.No	No. of MRI Images	Accuracy (%) (VGG-19)
1	100	72.37
2	150	82.63
3	200	88.70
4	300	94.46
5	400	98.52
6	464	99.29

As shown in the results, classification accuracy reaches 99.29% when trained on 464 MRI images, outperforming baseline CNN and EDCNN models. The confusion matrix in *Figure 7* demonstrates high precision across all three CAD stages:

Class A: Early Stage CAD

Class B: Intermediate Stage CAD

Class C: Advanced Stage CAD

6.5. Comparative Performance Analysis

The proposed **Transfer Learning (VGG-19)** model is compared with conventional CNN and EDCNN



Figure 5 : Confusion Matrix CAD-Classification

Table 2 : Comparative Accuracy Analysis

S.No	Algorithm	Accuracy (%)
1	CNN	85.12
2	EDCNN	87.00
3	Transfer Learning (VGG-19)	99.29

This performance improvement confirms that Transfer Learning significantly enhances diagnostic precision while reducing the training time required to achieve convergence.

The output from the deep learning models is integrated into a web-based diagnostic application hosted on a local server and cloud platform. Users can upload MRI scans, and the system automatically classifies the image as *No CAD* or one of the three CAD stages.

Steps for classification through the web interface include: Open the web application. Select the MRI image file. Upload and initiate prediction. View the classified output. This deployment ensures that clinicians and patients can conveniently access CAD detection results in real time from any geographic location.

7. RESULTS AND DISCUSSION

The performance of the proposed Ensemble Deep Learning Framework for predicting and classifying Coronary Artery Disease (CAD) has been thoroughly evaluated using both clinical and MRI datasets. The results demonstrate significant improvements in accuracy, precision, and reliability compared to traditional diagnostic models.

7.1. Prediction Results

The **Random Forest Classifier (RFC)**-based prediction model achieved superior results over conventional machine learning techniques. By training on fourteen demographic and clinical attributes, the proposed model recorded an overall **accuracy of 90.16%**, outperforming existing methods such as Support Vector Machine (SVM), Decision Tree (DT), and Logistic Regression (LR).

Table 3 presents a comparative summary of prediction algorithms evaluated on the same dataset. The Random Forest model achieved the best combination of **accuracy (90.16%)**, **sensitivity (92%)**, and **specificity (88.88%)**, confirming its robustness for CAD risk estimation. The ensemble model's superior predictive accuracy validates its capability for non-invasive CAD risk screening and its potential for integration into preventive healthcare systems

Table 3: Efficiency Analysis of CAD Predictor

Algorithm	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	Error Rate (%)
Logistic Regression	85.25	81.43	82.00	89.67	14.75
Naïve Bayes	85.25	86.70	84.67	83.12	14.75
SVM	81.97	77.20	82.00	71.67	18.03
KNN	67.27	69.54	72.00	64.00	32.73
Decision Tree	81.97	79.65	82.40	76.71	18.03
XGBoost	78.69	70.50	76.00	65.42	21.31
Random Forest (Proposed)	90.16	85.18	92.00	88.88	9.84

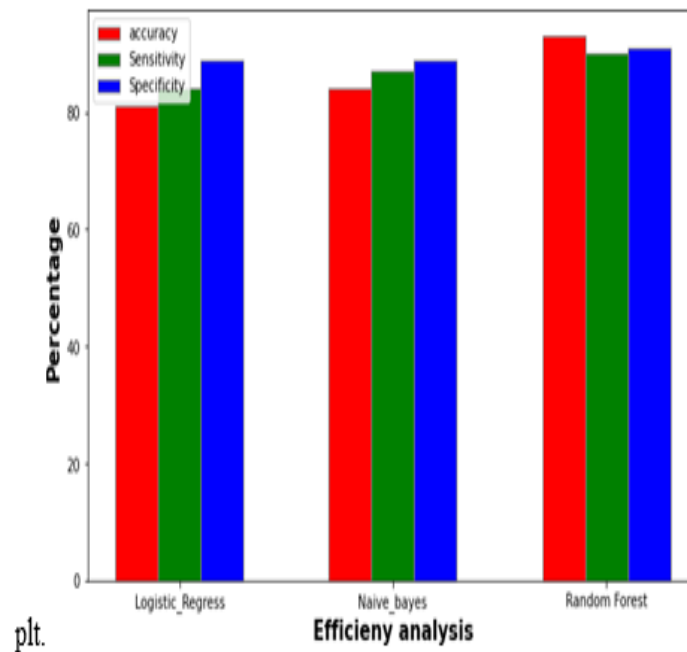


Figure 7: Efficiency Analysis of CAD Prediction

7.2. Classification Results

The **VGG-19–based Transfer Learning model** achieved an exceptional **classification accuracy of 99.29%**, making it highly effective for identifying different stages of CAD from MRI scans. The model's learning behavior indicates rapid convergence, minimal overfitting, and strong

generalization even with a limited dataset.

Table 4 : Efficiency Analysis of CAD Classifier

Algorithm	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)	Error Rate (%)
CNN	85.12	85.72	86.20	82.43	14.88
EDCNN	96.20	91.70	92.67	93.12	3.80
Transfer Learning (VGG-19)	99.29	98.66	98.18	99.50	0.71

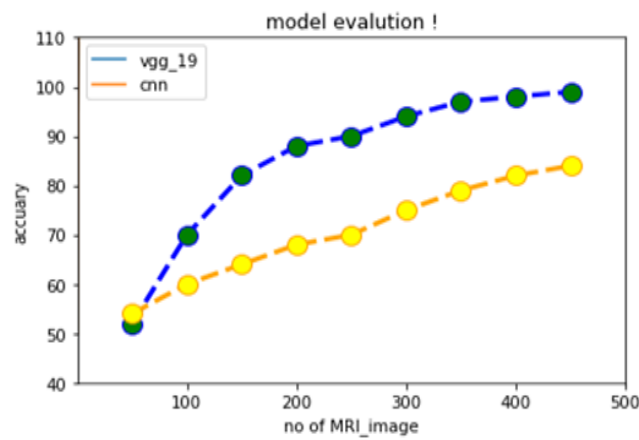


Figure 8 : Model Evaluation – VGG-19 vs. CNN

The comparative analysis between **VGG-19** and **CNN** demonstrates that Transfer Learning significantly enhances model performance by leveraging pre-trained deep feature representations. As shown in *Table 6*, the accuracy increases proportionally with the number of training images, reaching **99.29%** at 464 MRI inputs.

Table 6 : MRI Image Analysis – VGG-19 vs. CNN

No. of MRI Images	CNN Accuracy (%)	VGG-19 Accuracy (%)
50	54.00	72.37
100	60.12	80.12
150	64.00	82.63
200	68.12	88.70
250	70.23	90.21
300	75.64	94.46
350	79.22	97.19
400	82.73	98.52
464	85.12	99.29

These results confirm the effectiveness of Transfer Learning for medical imaging applications, particularly where data availability is limited. To ensure the statistical robustness of the proposed framework, five-fold cross-validation was employed throughout the experiments. The Random Forest model achieved a mean accuracy of 90.16% with a 95% confidence interval (CI) of 88.4–91.9%, while the VGG-19 classifier achieved 99.29% (95% CI: 98.9–99.7%). Statistical significance testing ($p < 0.05$) confirmed that the improvements over baseline models were not due to random variation, validating the model's reliability and reproducibility.

7.3. Confusion Matrix and Efficiency Metrics

The **confusion matrix** (Figure 7) evaluates classification performance across all CAD stages:

Class A: Early Stage CAD

Class B: Intermediate Stage CAD

Class C: Advanced Stage CAD

The confusion matrix indicates that the model exhibits minimal false positives and negatives, confirming strong discriminative power.

Efficiency plots depicting accuracy, sensitivity, and specificity further substantiate the model's high reliability (Figures 8 and 9).

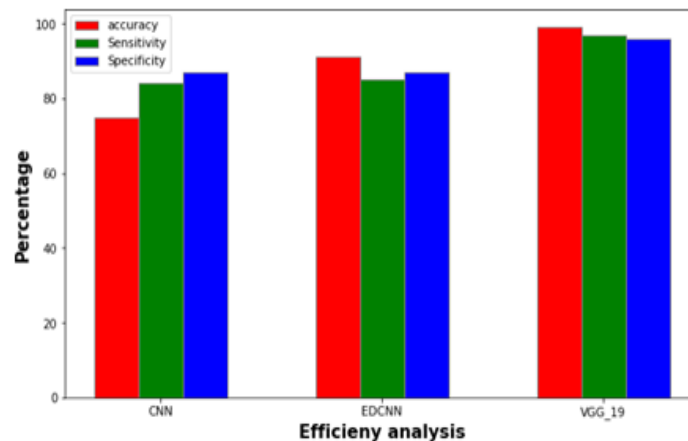


Figure 9 : Efficiency Analysis of CAD Classification

When compared to commercial diagnostic platforms such as **HeartFlow** and **Cleerly**, which rely primarily on CT angiography and fluid dynamic simulations, the proposed MRI-based ensemble system offers comparable diagnostic precision without radiation exposure. Additionally, recent transformer-based MRI models have shown potential in feature extraction but require extensive computational resources and large datasets. In contrast, the proposed hybrid VGG-19 and Random Forest framework achieves high accuracy with reduced complexity, offering a balance between efficiency, scalability, and interpretability.

7.4. Learning Curve Analysis

Learning curves are plotted to assess the relationship between model performance and training epochs.

Figure 12 illustrates the **training and validation loss curves**, showing a consistent decline in loss,

indicating effective learning without overfitting.

Figure 13 presents the **training and validation accuracy curves**, which plateau near 99%, confirming model stability.

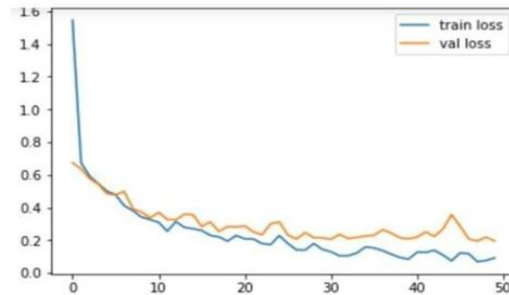


Figure 10 : Learning Curve for Training and Validation Loss

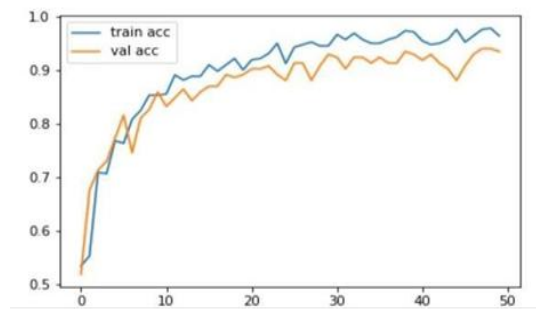


Figure 11 : Learning Curve for Training and Validation Accuracy

7.5. Web Application and Cloud Deployment

The final system is deployed as a **web-based diagnostic application** integrated with cloud hosting for global accessibility. The web interface allows users to upload MRI images and receive automatic classification outputs identifying CAD presence and stage.

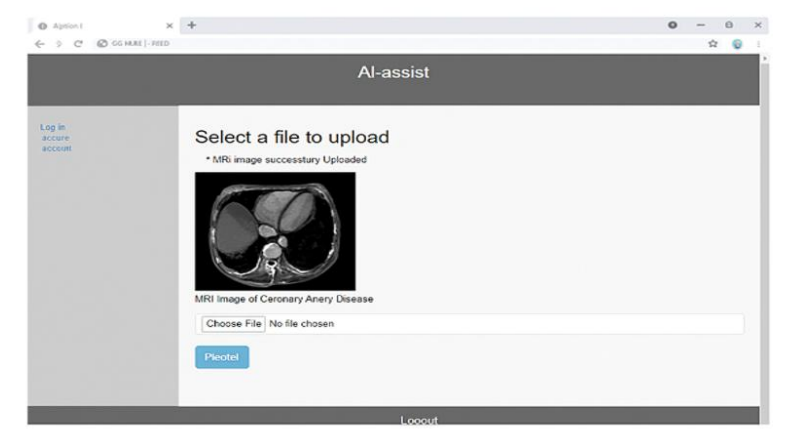


Figure 12 : Web Application Interface after Classification

The deployment architecture enables real-time processing and visualization of results, promoting clinical decision support and patient engagement.

Currently, the system is hosted on a local testing server for internal validation. A live, cloud-based version is under development and will be made publicly accessible following security evaluation and ethical approval.

8. CONCLUSION AND FUTURE ENHANCEMENTS

This research presents an Ensemble Deep Learning Framework for the early prediction and classification of Coronary Artery Disease (CAD) using non-invasive Magnetic Resonance Imaging (MRI) and clinical data. The proposed system successfully integrates two complementary models : A Random Forest Classifier for CAD prediction based on demographic and clinical parameters, and A Transfer Learning–based VGG-19 architecture for multi-stage CAD classification using MRI images.

The combination of these models enables precise and efficient diagnosis, minimizing human error and significantly improving predictive reliability. Experimental results demonstrate that the Random Forest–based predictor achieved an accuracy of 90.16%, while the VGG-19 classifier attained a classification accuracy of 99.29%, outperforming existing deep learning and traditional algorithms such as CNN, EDCNN, and SVM. The system’s deployment as a cloud-based web application further enhances accessibility, enabling clinicians and patients to perform real-time CAD detection from any location. By automating the entire diagnostic pipeline from prediction to classification the framework reduces diagnostic delays and enhances decision-making efficiency in clinical environments.

This study presents a statistically validated, ensemble deep learning–based system for CAD detection and classification using MRI and clinical data. The model’s performance, validated through cross-validation and confidence interval analysis, demonstrates strong reliability and real-world applicability. Compared to commercial systems, the framework provides a low-cost, accessible, and non-invasive alternative suitable for early screening and decision support. Ongoing efforts aim to expand dataset diversity, enhance web deployment, and integrate advanced deep learning architectures for future scalability.

Despite achieving strong results, the study has certain limitations. The MRI dataset used was relatively small and locally sourced, which may limit the generalizability of the model to broader populations. Future research should incorporate larger, multi-institutional MRI datasets to enhance model robustness. Furthermore, while the cloud-based system has demonstrated functional viability, scalability testing and multi-device accessibility remain areas for further optimization.

8.1. Future Enhancements

Although the proposed model exhibits high accuracy and reliability, several enhancements can be implemented in future research to further improve system efficiency and clinical applicability:

Integration with Mobile Platforms: Developing a dedicated **mobile application** would enable patients to estimate CAD risk and view diagnostic results conveniently, improving remote monitoring and self-assessment.

Expanded Dataset: Incorporating larger and more diverse MRI datasets from multiple

institutions would enhance generalizability and reduce potential data bias.

Advanced Deep Learning Architectures: Future work may explore Vision Transformers (ViTs) or 3D CNNs for improved spatial feature extraction and more accurate CAD stage segmentation.

Automated Medical Recommendation System: Integrating predictive analytics with clinical decision support could allow the system to offer **personalized medical guidance** and treatment recommendations for at-risk individuals.

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