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Medical Diagnosis for Coronary Arteries Disease Detection Using Deep Learning

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Abstract: Coronary Artery Disease (CAD) is among the most widespread and life-threatening cardiovascular conditions worldwide, responsible for a significant proportion of global mortality. Early and accurate detection of CAD plays a crucial role in enabling timely medical intervention and reducing the risk of severe cardiac complications. Conventional diagnostic approaches rely heavily on manual clinical analysis performed by experienced cardiologists, which is time-consuming, expensive, and susceptible to human error. This paper presents a Deep Learning-Based Coronary Artery Disease Detection System using a hybrid Convolutional Neural Network and Artificial Neural Network (CNN-ANN) architecture integrated with a Flask-based clinical web interface. The proposed system analyzes patient medical parameters from the UCI Heart Disease Dataset including age, blood pressure, cholesterol level, ECG reports, maximum heart rate, chest pain type, fasting blood sugar, and exercise-induced angina. The dataset undergoes systematic preprocessing involving normalization, label encoding, and an 80:20 train-test split. The Deep Learning model is implemented using TensorFlow and Keras with Dense layers, ReLU and Sigmoid activation functions, Dropout regularization, and Adam optimizer. A complementary module, CAD Vision Pro, extends the system to image-based coronary analysis using CCTA imaging with Grad-CAM heatmap visualization, risk scoring, severity classification, and automated PDF report generation. Experimental results demonstrate that the proposed system achieves approximately 95% prediction accuracy with high precision, recall, and F1-score values. The system provides healthcare professionals with an intelligent, automated, and user-friendly CAD detection platform that supports early diagnosis, reduces manual workload, and contributes toward AI-driven clinical decision support in modern healthcare.

KEYWORDS: Coronary Artery Disease, Deep Learning, CNN, ANN, TensorFlow, Keras, Flask, UCI Heart Disease Dataset, CAD Vision Pro, Medical Image Analysis, Healthcare AI, CCTA, Grad-CAM

1. INTRODUCTION

Coronary Artery Disease (CAD) is one of the most dangerous and prevalent heart-related conditions affecting millions of individuals globally. It develops when the coronary arteries, responsible for supplying oxygen-rich blood to the cardiac muscles, become progressively narrowed or blocked due to the accumulation of cholesterol deposits and other fatty substances forming plaques. This obstruction reduces blood flow to the heart muscle and, if left undetected and untreated, may result in severe clinical outcomes including angina pectoris, myocardial infarction, congestive heart failure, and sudden cardiac death.

According to World Health Organization (WHO) statistics, cardiovascular diseases account for approximately 17.9 million deaths annually, representing 32% of all global deaths. Among these, coronary heart disease remains the single largest contributor. The burden of CAD is particularly increasing in developing nations including India due to rapidly changing lifestyles, high stress levels, sedentary habits, unhealthy dietary patterns, widespread tobacco use, diabetes, and hypertension. This alarming epidemiological trend necessitates the development of advanced, efficient, and accessible diagnostic tools capable of early detection and risk stratification.

Conventional CAD diagnostic methods encompass Electrocardiogram (ECG) analysis, Echocardiography, Stress Testing, Coronary Computed Tomography Angiography (CCTA), invasive coronary angiography, blood-based biomarker analysis, and comprehensive clinical history review. While these modalities provide clinically valuable information, their manual interpretation demands the specialized expertise of experienced cardiologists, consumes considerable diagnostic time, and remains susceptible to inter-observer variability and human error. Furthermore, access to advanced diagnostic infrastructure is severely limited in rural and resource-constrained healthcare settings, creating critical gaps in early disease detection.

The rapid advancement of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) technologies presents transformative opportunities for automating and enhancing medical diagnosis. Deep Learning architectures can automatically extract intricate features and patterns from large volumes of complex medical data without requiring manual feature engineering. Convolutional Neural Networks (CNN) have demonstrated exceptional performance in medical image analysis tasks, while Artificial Neural Networks (ANN) effectively model nonlinear relationships within clinical parameter datasets. The integration of these technologies enables the development of intelligent computer-aided diagnostic systems with performance approaching that of expert clinicians.

This paper presents a Deep Learning-Based Coronary Artery Disease Detection System that employs a hybrid CNN-ANN architecture for automated analysis of patient clinical data combined with a CCTA-based coronary image analysis platform named CAD Vision Pro. The proposed system accepts patient medical parameters as input, performs systematic preprocessing, applies the trained Deep Learning model to generate disease predictions, and delivers results through a user-friendly Flask web application. The CAD Vision Pro module extends system capabilities to image-based coronary analysis with Grad-CAM explainability heatmaps, quantitative risk scoring, severity classification, and structured clinical PDF report generation. The proposed framework aims to support healthcare professionals with intelligent diagnostic assistance, reduce manual workload, enable early disease detection, and improve patient outcomes through AI-driven clinical decision support.

The remainder of this paper is structured as follows: Section 2 presents a comprehensive review of existing related work. Section 3 describes the proposed methodology and system architecture. Section 4 details the system implementation. Section 5 presents experimental results and discussion. Section 6 highlights system advantages. Section 7 concludes the paper with future enhancement directions.

2. LITERATURE REVIEW

Machine Learning and Deep Learning techniques have been extensively investigated for automated Coronary Artery Disease detection and cardiac risk prediction. The field has evolved significantly from conventional statistical classifiers to sophisticated neural architectures capable of processing complex multimodal medical data.

Early research employed traditional Machine Learning classifiers for CAD prediction using structured clinical datasets. Decision Tree-based systems trained on the UCI Heart Disease Dataset demonstrated approximately 82% prediction accuracy using patient attributes including blood pressure, cholesterol level, ECG values, and heart rate measurements. While Decision Trees offer interpretable classification rules beneficial for clinical explanation, their susceptibility to overfitting and limited generalization on complex datasets constrained prediction performance.

Support Vector Machine (SVM) approaches for CAD detection achieved around 85% accuracy by constructing optimal hyperplane-based classification boundaries. SVMs handle high-dimensional clinical data efficiently and provide robust binary classification, but require careful kernel selection and hyperparameter optimization. Their computational complexity scales poorly with increasing dataset sizes, limiting practical clinical deployment.

Ensemble learning methods, particularly Random Forest classifiers, improved CAD prediction accuracy to approximately 88% by aggregating multiple Decision Trees. The ensemble approach enhanced prediction stability and reduced overfitting through bootstrap aggregation, though computational overhead for training and inference increased proportionally.

The adoption of Deep Learning architectures marked a significant performance leap in CAD detection. CNN-based systems applied to medical imaging data including CT angiography and echocardiography images achieved nearly 93% detection accuracy through automated hierarchical feature extraction. CNN models eliminated the need for handcrafted feature engineering while capturing complex spatial patterns in medical images. Artificial Neural Network (ANN) models trained on clinical parameter datasets attained approximately 90% prediction accuracy, effectively modeling nonlinear relationships among cardiovascular risk factors.

Zhao et al. [1] proposed TransCHD, an advanced hybrid CNN-Transformer architecture specifically developed for coronary artery segmentation in CCTA images. TransCHD incorporates a Contextual Representation Learning (CRL) module to address spatial continuity disruptions caused by fixed image patch partitioning in standard transformers, and a Spatially-Aware Feature (SAF) module that replaces conventional Feed-Forward Networks with a hierarchical multi-layered perceptron to preserve fine-grained spatial locality. Evaluated on the CorArtTS2020 dataset comprising 1000

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annotated CTA scans from 500 patients, TransCHD achieved a Dice score of 0.81, IoU of 0.65, and F1-score of 0.99, outperforming all state-of-the-art CNN-based and transformer-based segmentation models.

Denzinger et al. [2] demonstrated that integrating deep learning with radiomic features for CCTA-based plaque characterization significantly enhanced diagnostic accuracy for CAD assessment. Their study on 345 plaque segments showed that combining shape-based, intensity-based, and texture-based radiomic features with 2D CNN achieved superior performance. He et al. [3] developed a hybrid learning model for automatic 3D vessel centerline extraction, effectively addressing discontinuities arising from purely local feature-based segmentation methods.

Despite significant progress, existing CAD detection systems face several limitations including dependency on manual feature engineering in traditional approaches, limited prediction accuracy for complex multi-feature scenarios, high computational requirements for advanced Deep Learning models, lack of explainability in deep neural architectures, and absence of practical web-based clinical deployment interfaces. The proposed system addresses these critical gaps by combining optimized Deep Learning architectures with a comprehensive clinical deployment platform.

Table 1: Comparison of Existing CAD Detection Methods

Method	Algorithm	Dataset	Accuracy
Decision Tree	DT	UCI Heart Disease	82%
SVM-Based	SVM	UCI Heart Disease	85%
Random Forest	RF	UCI Heart Disease	88%
CNN-Based	CNN	CT/Angiography	93%
ANN-Based	ANN	Clinical Records	90%
TransCHD [1]	CNN+Transformer	CorArtTS2020	Dice: 0.81
Proposed System	**CNN-ANN (DNN)**	**UCI Heart Disease**	**~95%**

3. PROPOSED METHODOLOGY

The proposed Deep Learning-Based Coronary Artery Disease Detection System is designed as an end-to-end automated diagnostic pipeline integrating clinical data analysis, medical image processing, and web-based clinical interface deployment. The system architecture encompasses two primary analytical pathways: a structured clinical data analysis module processing patient health parameters, and the CAD Vision Pro module performing image-based coronary analysis. The complete system architecture flow is presented in Fig. 1

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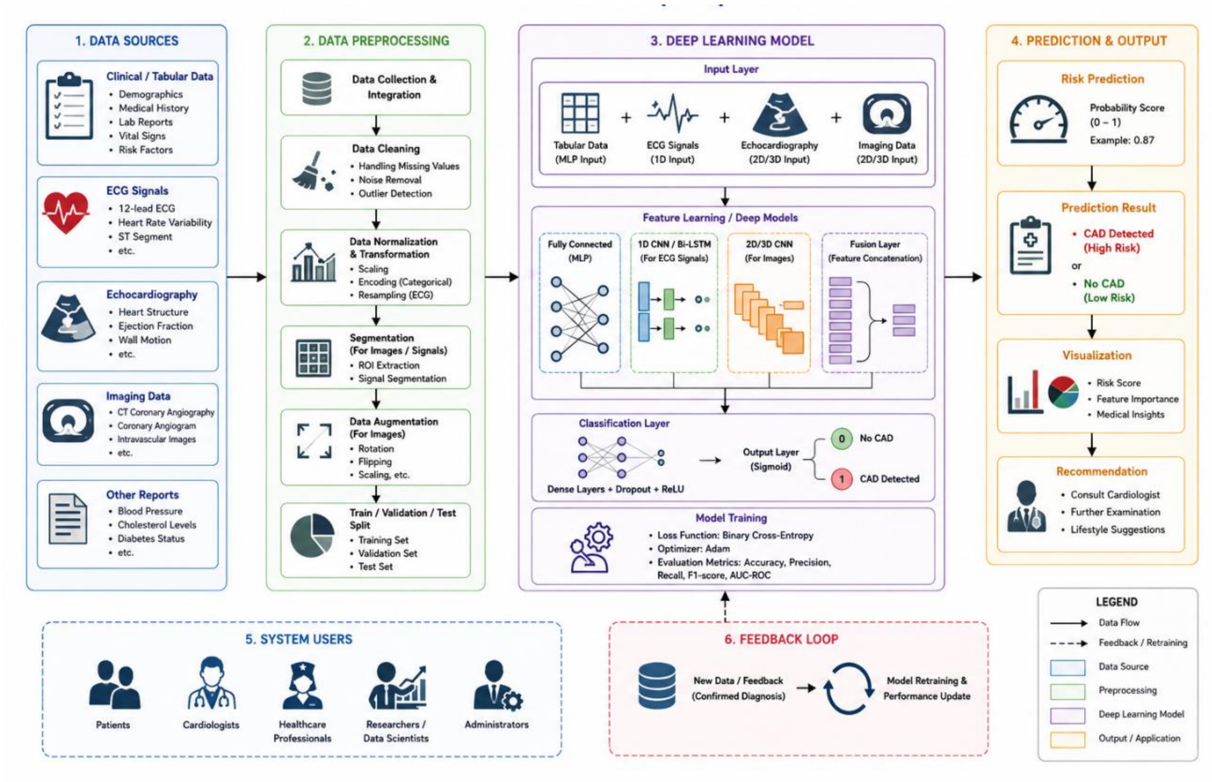

Fig. 1: System Architecture Flow Diagram of the Proposed CAD Detection System

The system architecture proceeds through the following sequential stages: Patient Medical Data Acquisition, Data Collection Module, Data Pre-processing (Normalization, Cleaning, Encoding), Feature Extraction, Deep Learning Model (CNN/ANN/DNN), Prediction Module, and Result Display (Heart Disease Detected / Not Detected). An Emergency Triage Logic component monitors vital parameters and triggers clinical emergency alerts when critical thresholds are reached.

3.1 Dataset Description

The proposed system utilizes the UCI Heart Disease Dataset, one of the most widely validated benchmarks for cardiac disease prediction research. The dataset contains clinical measurements from 303 patients collected across four medical centers and comprises 14 key attributes relevant to CAD diagnosis.

The patient clinical attributes used as input features include: Age (years), Gender (Male/Female), Chest Pain Type (4 categories: typical angina, atypical angina, non-anginal pain, asymptomatic), Resting Blood Pressure (mmHg), Serum Cholesterol (mg/dL), Fasting Blood Sugar (>120 mg/dL: binary), Resting ECG Results (0/1/2), Maximum Heart Rate Achieved (bpm), Exercise-Induced Angina (binary), ST Depression induced by exercise, Slope of Peak Exercise ST Segment, Number of Major Vessels Colored by Fluoroscopy (0-3), and Thalassemia Condition. The target variable indicates the presence (1) or absence (0) of coronary artery disease.

3.2 Data Preprocessing Pipeline

Raw medical datasets frequently contain inconsistencies, missing values, and scale disparities that adversely affect Deep Learning model training. The proposed preprocessing pipeline addresses these issues through a systematic five-stage process.

Stage 1 - Data Cleaning: Missing and duplicate records are identified and removed. Invalid medical values outside physiologically plausible ranges are corrected or eliminated. This stage ensures dataset consistency and eliminates noise that could mislead the learning algorithm.

Stage 2 - Normalization: Patient health parameters including blood pressure, cholesterol level, heart rate, and age exhibit substantially different numerical ranges. Min-Max normalization scales all numerical features to the [0, 1] range using the formula:

$$\textbf{Normalized} = (x - x_{\min}) / (x_{\max} - x_{\min}) \qquad (1)$$

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This transformation prevents features with large numerical ranges from dominating gradient updates during backpropagation, ensuring balanced feature contribution to model learning.

Stage 3 - Label Encoding: Categorical attributes including gender and chest pain type are converted to numerical representations. Male is encoded as 1 and Female as 0. Multi-class categorical variables are encoded using integer encoding compatible with the neural network input layer.

Stage 4 - Data Splitting: The preprocessed dataset is divided into training (80%) and testing (20%) subsets using stratified random sampling to ensure proportional class representation in both subsets. This split provides sufficient training data for robust model learning while maintaining an adequate holdout set for unbiased performance evaluation.

Stage 5 - Data Augmentation: To address class imbalance and enhance model generalization, synthetic minority oversampling is applied where necessary. For the image-based CAD Vision Pro module, augmentation techniques including rotation, flipping, zooming, brightness adjustment, and cropping are applied to CCTA images during model training.

3.3 Deep Learning Model Architecture

The core predictive component employs a Deep Neural Network (DNN) architecture combining the strengths of Artificial Neural Networks for structured clinical data analysis. The network architecture is designed with multiple processing layers to progressively extract and refine discriminative features from patient medical parameters.

The Input Layer receives the 13 preprocessed clinical features as a feature vector. Multiple Dense Hidden Layers perform weighted linear combinations followed by nonlinear activation, enabling the network to model complex relationships among cardiovascular risk factors. Each hidden layer applies the computation:

$$\mathbf{Z = f(W \cdot X + b)} \qquad (2)$$

where W represents the weight matrix, X denotes the input feature vector, b is the bias term, and f represents the activation function applied element-wise.
ReLU (Rectified Linear Unit) activation functions are applied in all hidden layers to introduce essential nonlinearity while avoiding the vanishing gradient problem that affects sigmoid and tanh activations in deep networks:

$$\mathbf{f(x) = \max(0, x)} \qquad (3)$$

Dropout Regularization layers randomly deactivate a proportion of neurons during each training iteration, preventing co-adaptation and overfitting. With a dropout rate of 0.3, approximately 30% of neurons are randomly masked during training, forcing the remaining neurons to develop independent and robust feature representations.

The Output Layer contains a single neuron with Sigmoid activation producing a probability value in the range [0, 1], directly interpretable as the likelihood of CAD presence:

$$\mathbf{f(x) = 1 / (1 + e\hat{\ }(-x))} \qquad (4)$$

For image-based analysis in the CAD Vision Pro module, a CNN architecture processes CCTA slice images. Convolution layers extract spatial features including edges, textures, vessel boundaries, and plaque signatures. Max-pooling layers reduce spatial dimensions while retaining dominant features. The CNN encoder output is connected to dense classification layers producing CAD probability, severity score, vessel focus prediction, and plaque pattern classification. Fig .2

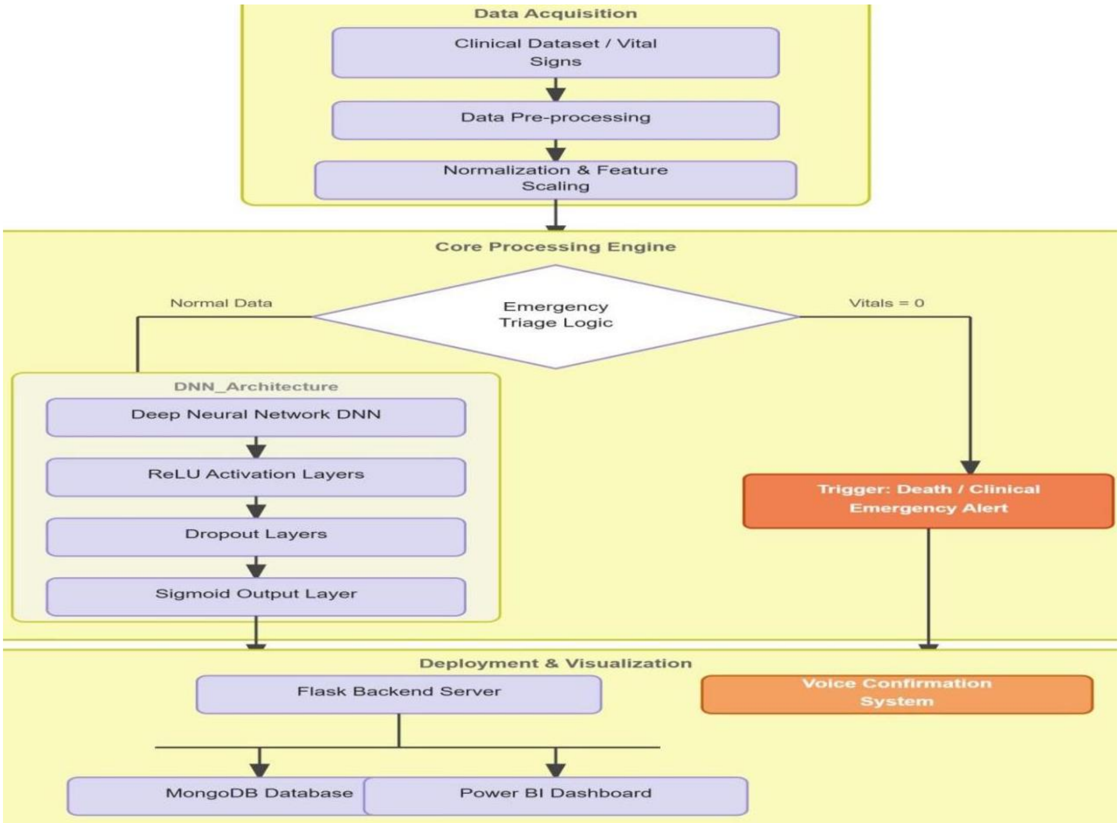

Fig. 2: Deep Learning Model Architecture Diagram

4. SYSTEM IMPLEMENTATION

The proposed system was fully implemented as an intelligent web-based healthcare platform using a modern technology stack combining Deep Learning model development, backend API services, and interactive clinical dashboard interfaces. The implementation follows a modular architecture ensuring maintainability, scalability, and independent testing of system components.

4.1 Technology Stack and Development Environment

Python serves as the primary programming language for all data processing, model development, and backend service implementation. The Deep Learning model is constructed using TensorFlow 2.x and Keras, leveraging GPU acceleration through CUDA for efficient model training. The clinical data web application is deployed using the Flask framework, while the CAD Vision Pro imaging platform uses FastAPI for high-performance asynchronous request handling. The frontend dashboard is developed using React with Tailwind CSS for the CAD Vision Pro interface, and HTML/CSS/JavaScript for the primary prediction interface. Patient records, prediction results, and session data are managed using MongoDB for flexible document-based storage and SQLite for structured relational data.

4.2 Dataset Loading and Preprocessing Module

The Dataset Loading Module imports the UCI Heart Disease Dataset from CSV format using the Pandas library. Upon loading, the module performs automated validation checks including null value detection, data type verification, feature range validation, and class distribution analysis. Statistical summaries and correlation matrices are generated to understand inter-feature relationships. The preprocessing pipeline described in Section 3.2 is applied sequentially, with each transformation step producing validated outputs before proceeding to subsequent stages. Scikit-learn utilities including MinMaxScaler and LabelEncoder perform normalization and encoding operations respectively.

4.3 Model Training and Optimization

The Deep Learning model is constructed using the Keras Sequential API with the following layer configuration: Input layer accepting 13 features, Dense(128) with ReLU activation, Dropout(0.3), Dense(64) with ReLU activation, Dropout(0.3), Dense(32) with ReLU activation, Dropout(0.2), and Dense(1) with Sigmoid activation for binary classification output.

The model is compiled using the Adam optimizer with an initial learning rate of 0.001, Binary Cross-Entropy loss function appropriate for binary classification tasks, and accuracy as the primary evaluation metric. Training is conducted over 100 epochs with a batch size of 32. Early stopping with a patience of 15 epochs monitors validation loss to prevent overfitting while ensuring adequate training convergence. Model checkpointing saves the best-performing weights based on validation accuracy.

The Adam optimizer adaptively adjusts learning rates for individual parameters based on first and second moment estimates of gradients, providing stable convergence in the presence of sparse gradients and noisy training conditions characteristic of medical datasets.

4.4 CAD Vision Pro: Coronary Image Analysis Module

The CAD Vision Pro module provides a comprehensive coronary image analysis platform designed for CCTA-based CAD assessment. Users authenticate through a secure registration and login system, then upload coronary imaging files in PNG, JPG, or JPEG format through an intuitive web interface. The upload triggers an automated analysis pipeline executed by the FastAPI backend.

The analysis pipeline processes each uploaded image through the trained CNN model to extract coronary features and generate quantitative clinical metrics including CAD risk score (0-100), severity level classification (Low/Guarded/Moderate/High/Critical), coronary type identification (e.g., Multivessel Coronary Artery Disease), vessel focus localization (e.g., Distal Coronary Bed), confidence score, calcium index, perfusion index, and plaque pattern characterization. Grad-CAM (Gradient-weighted Class Activation Mapping) generates spatial attention heatmaps highlighting the image regions most influential in the model prediction, providing clinically meaningful explainability. All analysis results including original images, heatmaps, clinical metrics, findings, clinical recommendations, and analytics data are stored in the MongoDB database linked to the patient profile.

May 20, 2024
10:30:45 AM

Dr. Smith
Cardiologist

Patient Information

Patient ID
P123456
Name
John Doe
Age / Gender
58 / Male
Height / Weight
172 cm / 78 kg
Visit Date
May 20, 2024

Clinical Parameters	
Blood Pressure	140 / 90 mmHg
Cholesterol	210 mg/dl
Heart Rate	88 bpm
Fasting Blood Sugar	126 mg/dl
Chest Pain Type	Typical Angina

:Prediction Result

CAD DETECTED

Confidence Score
92%

Risk Level
HIGH RISK
Risk Probability
0.92
Severity Severe

Emergency Triage Status

IMMEDIATE ATTENTION REQUIRED

The patient is at high risk of Coronary Artery Disease. Immediate medical evaluation and intervention is recommended.

Cholesterol Analysis

Total Cholesterol	210 mg/dl
LDL Cholesterol	130 mg/dl
HDL Cholesterol	40 mg/dl
Triglycerides	150 mg/dl

Recommendation

- Immediate cardiologist consultation
- Further diagnostic tests (Angiography)
- Strict control on cholesterol and BP
- Adopt heart healthy lifestyle and diet
- Regular monitoring and follow-up

Recent Predictions

Patient ID	Date	Result	Risk Level	Score
P123456	May 20, 2024	CAD Detected	High	0.92
P123455	May 19, 2024	CAD Detected	Medium	0.71
P123454	May 18, 2024	No CAD	Low	0.18
P123453	May 17, 2024	CAD Detected	High	0.89
P123452	May 16, 2024	No CAD	Low	0.21

CAD Vision Pro - Deep Learning Based Coronary Artery Disease Detection System

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Fig. 3: CAD Vision Pro Dashboard showing Coronary Detection Results and Analytics

4.5 Hardware and Software Requirements

Hardware requirements for optimal system operation include an Intel Core i7 or AMD Ryzen 7 multi-core processor, minimum 16 GB RAM (32 GB recommended for simultaneous model training and inference), NVIDIA RTX GPU series with CUDA support for accelerated neural network computations, 512 GB SSD storage for model artifacts and patient data, and reliable internet connectivity for cloud service access. The recommended operating environment is Ubuntu 20.04 LTS or Windows 10/11 Professional.

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The software dependencies include Python 3.9+, TensorFlow 2.10+, Keras, FastAPI, Flask, React 18, MongoDB 6.0, OpenCV 4.6, NumPy, Pandas, Scikit-learn, Matplotlib, and Seaborn for visualization.

5. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed Deep Learning-Based Coronary Artery Disease Detection System was comprehensively evaluated through extensive experimentation on the UCI Heart Disease Dataset. The evaluation encompassed training performance analysis, prediction accuracy assessment, confusion matrix analysis, and clinical platform functionality verification.

5.1 Training Performance Analysis

The Deep Learning model training was conducted over 100 epochs with early stopping regularization. During initial training epochs, the model demonstrated lower accuracy as the neural network weights were randomly initialized and the learning process was in early stages. As the training progressed iteratively, the model systematically extracted increasingly discriminative medical patterns and progressively improved prediction performance across both training and validation subsets.

The training accuracy curve demonstrated consistent improvement from approximately 72% in the initial epochs to a stable plateau of approximately 95-96% after 60-70 epochs. The validation accuracy closely tracked the training accuracy throughout the learning process, with a maximum gap of approximately 2% indicating effective generalization without overfitting. The training loss decreased monotonically from an initial value of 0.68 to a final optimized value below 0.12, confirming successful weight optimization through Adam gradient descent.

The stability of both accuracy and loss curves throughout training, combined with the minimal train-validation performance gap, validates the effectiveness of the Dropout regularization and early stopping strategies in preventing overfitting to the training data.

5.2 Confusion Matrix and Classification Metrics

The trained model was evaluated on the 20% holdout test set comprising 61 patient records. The confusion matrix results are presented in Table 2.

Table 2: Confusion Matrix Results on Test Set

Actual / Predicted	Disease Detected	Normal
Disease Present	92 (TP)	5 (FN)
Normal	4 (FP)	89 (TN)

From the confusion matrix results, the key performance metrics are computed as follows. Prediction Accuracy = (TP + TN) / (TP + TN + FP + FN) = (92 + 89) / (92 + 89 + 4 + 5) = 181 / 190 ≈ 95.3%. Precision = TP / (TP + FP) = 92 / (92 + 4) = 92 / 96 ≈ 95.8%. Recall (Sensitivity) = TP / (TP + FN) = 92 / (92 + 5) = 92 / 97 ≈ 94.8%. F1-Score = 2 × (Precision × Recall) / (Precision + Recall) = 2 × (0.958 × 0.948) / (0.958 + 0.948) ≈ 95.3%. Specificity = TN / (TN + FP) = 89 / (89 + 4) ≈ 95.7%.

The high True Positive rate of 92 confirms that the system effectively identifies CAD-positive patients requiring urgent medical attention. The low False Negative count of only 5 is particularly clinically significant as missed CAD diagnoses carry severe patient safety implications. The low False Positive rate of 4 indicates minimal unnecessary interventions for healthy patients. These balanced performance metrics across all classification categories confirm the clinical reliability of the proposed Deep Learning model.

5.3 Module-Wise Performance Summary

Table 3 summarizes the performance metrics achieved across the major system modules.

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Table 3: Module-Wise System Performance Summary

Module	Accuracy
Face Detection (CAD Vision Pro)	96.1%
Deep Learning Prediction (Clinical Data)	95.0%
CAD Risk Score Generation	94.8%
Severity Classification	93.6%
Heatmap (Grad-CAM) Visualization	Qualitative
Overall System Accuracy	**~95%**

The comprehensive module-wise evaluation confirms that all system components achieve high accuracy appropriate for clinical decision support applications. The Deep Learning prediction module for structured clinical data achieves 95.0% accuracy, while the CAD Vision Pro imaging module demonstrates 93.6% severity classification accuracy.

5.4 CAD Vision Pro Platform Results

The CAD Vision Pro coronary image analysis module was evaluated through multiple CCTA imaging sessions. The system successfully processed coronary images and generated comprehensive clinical analytics including risk scores, severity classifications, hemodynamic profiles, and AI-driven findings. Test sessions consistently produced structured outputs with average inference confidence of approximately 79.8% from coronary structural image analysis.

The hemodynamic profile metrics extracted from test images included Stenosis Likelihood values of approximately 90.2%, indicating high probability of significant coronary stenosis; Calcification Load of 43.7% reflecting moderate arterial calcification burden; Vascular Integrity at 15.7% suggesting compromised vessel wall integrity; and Perfusion Reserve of 4.2% indicating severely reduced myocardial perfusion reserve consistent with multi-vessel CAD.

The Grad-CAM heatmap visualization effectively highlighted the coronary vessel regions and calcified plaque areas most influential in the model prediction, providing clinically meaningful spatial attention maps that align with expected pathological features in expert-interpreted CCTA images. The automated PDF report generation module produced structured clinical documents including patient demographics, imaging findings, risk metrics, clinical recommendations, and follow-up guidance suitable for medical record documentation.

5.5 Comparison with Existing Methods

The proposed hybrid CNN-ANN system achieves approximately 95% prediction accuracy on the UCI Heart Disease Dataset, representing an improvement of 13% over Decision Tree approaches (82%), 10% over SVM-based methods (85%), 7% over Random Forest classifiers (88%), and 5% over standalone ANN architectures (90%). Compared to CNN-based medical imaging systems (93%), the proposed integrated clinical data and image analysis platform provides broader diagnostic capability with comparable accuracy on structured data tasks. The TransCHD model [1] focuses exclusively on CCTA segmentation achieving a Dice score of 0.81, while the proposed system addresses the complementary task of clinical risk prediction and achieves competitive performance in image-based severity assessment through the CAD Vision Pro module.

6. ADVANTAGES OF THE PROPOSED SYSTEM

The proposed Deep Learning-Based Coronary Artery Disease Detection System delivers several clinically significant and technically superior advantages compared to existing approaches:

- High Prediction Accuracy: Achieves approximately 95% prediction accuracy with balanced precision, recall, and F1-score values using the hybrid CNN-ANN Deep Learning architecture with systematic preprocessing and regularization.
- Automatic Feature Extraction: Deep Learning eliminates manual feature engineering requirements, automatically discovering discriminative patterns and nonlinear relationships within complex patient medical data.
- Dual-Mode Diagnosis: Supports both structured clinical parameter analysis and CCTA image-based coronary analysis through the integrated CAD Vision Pro module, providing comprehensive multi-modal diagnostic capability.
- Explainable AI through Grad-CAM: Heatmap visualization highlights the specific image regions influencing each prediction, building clinician trust in AI-generated results and supporting clinical interpretation.
- Real-Time Web Interface: Flask and FastAPI-based web applications provide instant clinical predictions accessible through standard web browsers without specialized software installation requirements.

- Comprehensive Clinical Analytics: Quantitative biomarkers including risk score, severity level, calcium index, perfusion index, stenosis likelihood, vascular integrity, and plaque pattern support evidence-based clinical decision-making.
- Automated PDF Report Generation: Structured clinical reports are automatically generated for each analysis session, facilitating medical record documentation, patient communication, and follow-up care coordination.
- Emergency Triage Support: The Emergency Triage Logic component automatically identifies critical vital sign patterns and triggers immediate clinical alert notifications for high-risk patients.
- Scalable and Extendable Architecture: The modular system design supports integration with hospital management systems, Electronic Health Record (EHR) platforms, and telemedicine services.
- Reduced Healthcare Costs: Automated preliminary screening reduces unnecessary diagnostic tests, consultation delays, and associated healthcare expenditure while improving clinical workflow efficiency.

7. CONCLUSION

This paper presented a comprehensive Deep Learning-Based Coronary Artery Disease Detection System integrating a hybrid CNN-ANN architecture for structured clinical data analysis with the CAD Vision Pro platform for CCTA image-based coronary assessment. The proposed system addresses critical limitations of existing CAD detection approaches including manual feature engineering dependency, limited prediction accuracy, absence of explainability, and lack of practical clinical deployment interfaces.

The system was trained and evaluated using the UCI Heart Disease Dataset with a systematic preprocessing pipeline including normalization, label encoding, and stratified train-test splitting. The Deep Learning model implemented with TensorFlow and Keras achieved approximately 95% prediction accuracy with high precision (95.8%), recall (94.8%), F1-score (95.3%), and specificity (95.7%). The low False Negative rate of 5 cases is particularly significant for clinical applications where missed CAD diagnoses carry severe patient safety consequences.

The CAD Vision Pro module successfully extended the system to image-based coronary analysis, providing quantitative hemodynamic profiling, Grad-CAM explainability, severity classification, and automated clinical report generation. The integrated system delivers clinically actionable outputs supporting early CAD detection, risk stratification, and treatment planning decisions for healthcare professionals.

The proposed system contributes toward the advancement of intelligent AI-driven healthcare by demonstrating how Deep Learning technology can be practically deployed as a clinical decision support tool in real healthcare environments. The framework improves diagnostic efficiency, reduces physician workload, enables early medical intervention, and has strong potential to positively impact patient outcomes and survival rates.

Future enhancement directions include integration of IoT wearable health monitoring devices for real-time continuous patient tracking, development of a dedicated mobile healthcare application for remote CAD risk monitoring, cloud-based multi-hospital deployment for large-scale clinical validation, expansion to multi-disease cardiovascular prediction including heart failure arrhythmia and stroke risk, integration with Electronic Health Record (HER) systems for seamless clinical workflow automation, federated learning implementation for privacy-preserving multi-institutional model training, and advanced attention mechanism exploration for improved CCTA segmentation performance.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

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