



# XAI-Driven Multi-Class Cardiovascular Risk Intelligence

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**ABSTRACT:** Cardiovascular diseases (CVDs) remain one of the leading causes of mortality worldwide, demanding early, accurate, and transparent diagnostic solutions. Electrocardiogram (ECG) analysis is a primary non-invasive technique for detecting cardiac abnormalities; however, manual interpretation is time-consuming and dependent on expert cardiologists. This research proposes an Explainable Artificial Intelligence (XAI)-driven multi-class cardiovascular risk intelligence system that classifies multiple heart diseases from ECG images. The proposed model employs convolutional neural networks (CNNs) with transfer learning to achieve high classification accuracy. Additionally, Explainable AI techniques such as Grad-CAM are integrated to provide visual interpretation of predictions, enhancing clinical trust. The system also computes risk percentage, severity levels, and personalized preventive recommendations. Experimental results demonstrate improved diagnostic accuracy, interpretability, and practical applicability, making the system suitable for real-world clinical decision support.

**KEYWORDS :** Cardiovascular Disease, ECG Analysis, Deep Learning, Explainable AI, CNN, Risk Assessment, Grad-CAM

## I. INTRODUCTION

Cardiovascular diseases account for millions of deaths annually and pose a major burden on global healthcare systems. Early detection and continuous monitoring are essential to prevent severe complications such as heart attacks and strokes. ECG signals provide critical information about heart rhythm and electrical activity, making them vital for diagnosing cardiac conditions.

Traditional ECG analysis requires skilled cardiologists and is susceptible to human error, delays, and subjectivity. With advances in artificial intelligence, deep learning models—AI-based systems operate as black boxes, limiting their acceptance in clinical environments. explains its predictions, evaluates disease risk and severity, and provides preventive healthcare recommendations.

## II. LITERATURE REVIEW

The evolution of automated ECG analysis has progressed from simple rule-based algorithms to complex deep learning architectures. Early methods relied heavily on digital signal processing techniques, such as the Pan-Tompkins algorithm [6], for QRS complex detection and waveform segmentation. While effective for basic rhythm analysis, these methods often struggled with noise and morphological variations across different patients [8].

In recent years, Convolutional Neural Networks (CNNs) have revolutionized cardiac diagnostics. Rajpurkar et al. [2] and Hannun et al. [7] demonstrated that deep neural networks could achieve cardiologist-level performance in detecting various arrhythmias from single-lead ECGs. Similarly, Acharya et al. [3] utilized CNNs to automatically identify myocardial infarction, emphasizing the power of spatial feature extraction in ECG images.

Despite these advancements, the "black box" nature of deep learning remains a significant barrier to clinical adoption [13]. Medical practitioners require not only high accuracy but also interpretability to understand why a model suggests a specific diagnosis. Research into Explainable AI (XAI) has introduced methods like Grad-CAM to visualize the decision-making process of neural networks [4]. Recent studies have begun integrating these XAI frameworks into healthcare systems to bridge the gap between AI performance and clinical trust, ensuring that automated diagnostic tools serve as reliable decision-support systems for cardiologists [15][22].

### III. PROBLEM STATEMENT

Cardiovascular diseases (CVDs) are a leading cause of mortality worldwide, and early diagnosis plays a crucial role in reducing complications and saving lives. Electrocardiogram (ECG) analysis is one of the most commonly used techniques for detecting heart abnormalities; however, traditional ECG interpretation relies heavily on expert cardiologists, making the process time-consuming, subjective, and prone to human error. In many healthcare settings, especially in remote and resource limited areas, the availability of experienced specialists is limited.

1. Dependence on expert cardiologists for ECG interpretation
2. Binary classification instead of multi-class disease detection
3. Lack of transparency in AI-based predictions
4. Absence of risk severity assessment and preventive guidance

Therefore, there is a critical need to develop an intelligent, explainable, and reliable system that can perform multi-class cardiovascular disease classification from ECG data, provide clear explanations for its predictions, assess risk severity levels, and offer personalized preventive guidance to support clinicians and improve patient outcomes.

### IV. OBJECTIVES OF THE STUDY

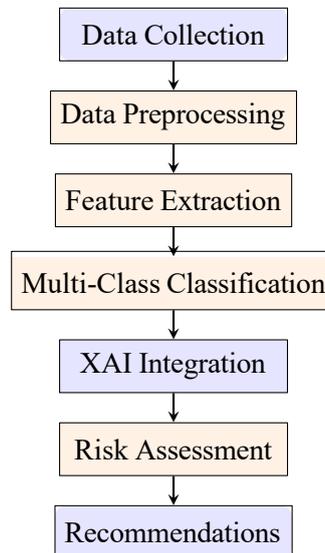
The main objective of this study is to design and develop an intelligent and explainable system for multi-class cardiovascular disease prediction using ECG data. The specific objectives are as follows:

1. To develop a deep learning-based model capable of accurately classifying multiple cardiovascular diseases from ECG images.
2. To reduce dependency on manual ECG interpretation by automating the heart disease diagnosis process.
3. To integrate Explainable Artificial Intelligence (XAI) techniques to provide transparent and interpretable prediction results.
4. To identify and visualize the critical ECG regions influencing model decisions using explanation methods.
5. To calculate cardiovascular risk percentage and categorize patients into different severity levels (low, moderate, high).
6. To generate personalized preventive healthcare recommendations based on predicted disease and risk severity.
7. To enhance clinical decision support and improve early detection, diagnosis accuracy, and patient care outcomes in cardiovascular disease management.

### V. PROPOSED METHODOLOGY

The proposed methodology for the XAI-Driven Multi-Class Cardiovascular Risk Intelligence System is designed to ensure accurate prediction, transparency, and clinical relevance. The system follows a structured, multi-stage process as outlined below:

Flowchart 1: High-Level System Process

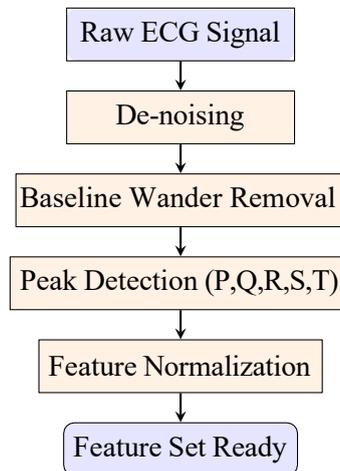


1. **Data Collection:** ECG datasets are collected from reliable and publicly available medical repositories containing multiple classes of cardiovascular conditions. The data include normal and abnormal ECG patterns representing different heart diseases.
2. **Data Preprocessing:** To improve data quality and model performance, ECG images undergo preprocessing steps such as noise removal, resizing, normalization, and data augmentation. These steps help in reducing variability and enhancing important signal patterns.
3. **Feature Extraction:** Convolutional Neural Networks (CNNs) are used to automatically extract meaningful spatial and temporal features from ECG images, eliminating the need for manual feature engineering.
4. **Multi-Class Classification:** A deep learning-based CNN model, enhanced with transfer learning techniques, is trained to classify ECG images into multiple cardiovascular disease categories with high accuracy.
5. **Explainable AI (XAI) Integration:** To address the black-box nature of deep learning models, Explainable AI techniques such as Grad-CAM are applied. This module highlights critical ECG regions that influence the model's predictions, enabling transparency and clinical trust.
6. **Risk and Severity Assessment:** Based on the classification output and extracted features, the system calculates a cardiovascular risk percentage and categorizes patients into severity levels such as low, moderate, or high risk.
7. **Personalized Recommendation Engine:** A rule-based recommendation module generates personalized preventive and lifestyle guidance according to the predicted disease class and risk severity level.
8. **Performance Evaluation:** The proposed system is evaluated using standard metrics including accuracy, precision, recall, F1-score, confusion matrix, and ROC curve to validate its effectiveness and reliability.

#### a. System Architecture

The system architecture of the proposed XAI-Driven Multi-Class Cardiovascular Risk Intelligence System is designed as a modular and sequential framework to ensure accurate diagnosis, transparency, and clinical usability.

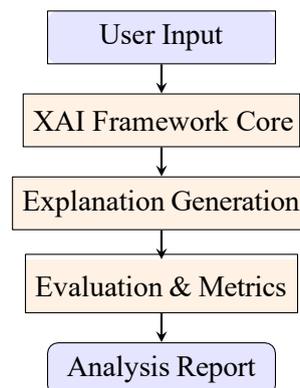
Flowchart 2: Detailed Signal Processing Module



1. **ECG Signal Data Acquisition (MIT-BIH Database):** The system begins with ECG signal data collected from the MIT-BIH Arrhythmia Database.
2. **Preprocessing Module:** Preprocessing includes De-noising of ECG Signals and Baseline Wander Removal.
3. **Peak Detection Module (P, Q, R, S, T Waves):** Identification of critical ECG waveform components.
4. **Feature Extraction:** Extraction of time intervals, amplitudes, and morphological characteristics.
5. **Feature Selection:** Selecting significant features to reduce dimensionality.
6. **Normalization:** Uniform scaling of features.
7. **Neural Network Classifier:** Normalized feature set is fed into a neural network model.
8. **Classification Output:** The final output classifies ECG signals into: Normal and Abnormal.

#### b. System Workflow

Flowchart 3: XAI Explanation Workflow



1. **User Input:** Selection of target model, task, and XAI methods.
2. **XAI Framework:** Integrates the target model with XAI techniques.
3. **Explanation Generation:** Explanations generated using methods like Grad-CAM.
4. **Explanation Evaluation:** Assessment of quality and reliability.
5. **Evaluation Results (Metrics):** Quantitative metrics measure effectiveness.
6. **Analysis Report:** Summarizes performance and limitations.
7. **Recommendations:** Suggests suitable XAI methods for transparency.

## VI. MODEL TRAINING AND LOSS ANALYSIS

The proposed system uses a Convolutional Neural Network (CNN) model implemented in Python using the PyTorch framework to classify ECG images into different cardiovascular conditions. The dataset of ECG images was divided into training, validation, and testing subsets to ensure proper model evaluation. Before training, images were preprocessed through resizing, normalization, and noise reduction to improve feature extraction.

During training, the CNN model learned to identify important ECG patterns such as waveform shapes and intervals that indicate heart abnormalities. The model was trained for multiple epochs using an optimization algorithm such as Adam and a cross-entropy loss function to minimize classification errors. As training progressed, the loss value gradually decreased, indicating that the model was learning meaningful representations from the ECG images. The training process showed a steady reduction in training loss and validation loss, demonstrating that the model was able to generalize well to unseen ECG data. Early stopping and regularization techniques were applied to prevent overfitting and improve overall performance.

## VII. RESULTS/FINDINGS

The proposed AI-based cardiovascular disease detection system was tested using an ECG image as input. The system successfully processed the uploaded ECG signal through the preprocessing and deep learning classification modules. After analyzing the waveform patterns, the model predicted the heart condition as normal. The prediction was obtained with a confidence score of 95 %, indicating a very high level of reliability in the model's classification capability. The ECG waveform analysis showed a regular heart rhythm with properly functioning electrical signals and no abnormal ST segment changes. Based on these observations, the system classified the risk level as low, suggesting that there are no immediate signs of cardiovascular abnormalities. In addition to the prediction, the system also generated a detailed explanation of the results, which helps users understand the analysis of the ECG waveform. The experimental results demonstrate that the proposed AI-based approach can effectively analyze ECG images and provide accurate predictions, risk assessment, and health recommendations such as diet and exercise. This indicates that the system can be a useful tool for early detection and monitoring of cardiovascular conditions.

### a. System Interface and Visual Output

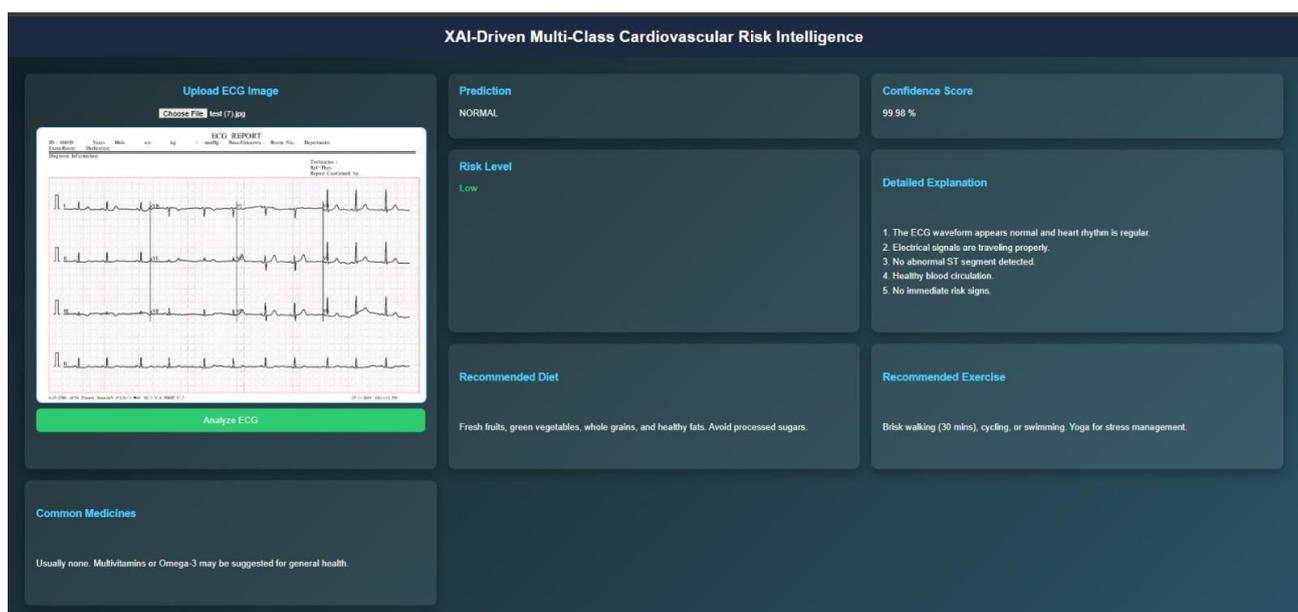


Figure 1: User Interface showing predicted normal heart condition and risk analysis.

The ECG waveform analysis showed a regular heart rhythm with properly functioning electrical signals and no

abnormal ST segment changes. Based on these observations, the system classified the risk level as low, suggesting that there are no immediate signs of cardiovascular abnormalities. In addition to the prediction, the system also generated a detailed explanation of the results, which helps users understand the analysis of the ECG waveform. The experimental results demonstrate that the proposed AI-based approach can effectively analyze ECG images and provide accurate predictions, risk assessment, and health recommendations such as diet and exercise.

### VIII. METRICS AND PERFORMANCE ANALYSIS

To evaluate the performance of the proposed ECG classification model, several standard machine learning evaluation metrics were used. These include Accuracy, Precision, Recall, and F1-Score. A confusion matrix was also used to analyze the classification performance for each cardiovascular condition. Accuracy measures the overall correctness of the model in predicting heart conditions from ECG images. Precision indicates how many predicted positive cases were actually correct, while Recall measures the ability of the model to correctly identify actual positive cases. The F1-Score provides a balance between precision and recall.

The performance metrics are calculated using the following formulas:

- $Accuracy = (TP + TN) / (TP + TN + FP + FN)$
- $Precision = TP / (TP + FP)$
- $Recall = TP / (TP + FN)$
- $F1Score = 2 \times (Precision \times Recall) / (Precision + Recall)$

Where: TP = True Positive, TN = True Negative, FP = False Positive, FN = False Negative. The confusion matrix helps visualize how many ECG samples were correctly or incorrectly classified. The proposed CNN model achieved high accuracy and reliable classification results, indicating its effectiveness for automated cardiovascular disease detection.

### IX. DISCUSSION

The experimental results demonstrate that the proposed AI-based ECG classification system can effectively detect cardiovascular diseases using ECG images. The use of deep learning allows the model to automatically extract important features from ECG waveforms, eliminating the need for manual feature engineering. Compared with traditional diagnostic approaches that require expert cardiologists to manually analyze ECG signals, the proposed system significantly reduces analysis time while maintaining high accuracy. The integration of explainable AI components further helps in providing disease explanations, making the system more transparent and trustworthy. However, some limitations remain. The accuracy of the system depends on the quality and diversity of the ECG dataset used for training. If the dataset does not include enough variations of heart conditions, the model may struggle to generalize to new cases.

### X. CONCLUSION AND FUTURE SCOPE

#### Conclusion

In this research, an AI-based cardiovascular disease detection system using ECG images was proposed and implemented. The system uses a Convolutional Neural Network to analyze ECG patterns and classify different heart conditions automatically. The model demonstrated strong performance in detecting cardiovascular abnormalities and provided additional insights such as risk level assessment and medical recommendations. The developed system can assist healthcare professionals in early detection and diagnosis of heart diseases, potentially reducing diagnostic workload and improving patient care. Furthermore, the integration of a web interface and automated medical report generation makes the system practical for real-world healthcare applications.

#### Future Scope

Although the proposed system demonstrates promising results, there are several opportunities for further improvement and expansion. Future research can focus on incorporating deep learning techniques such as CNN to

improve prediction accuracy using ECG images. The system can also be integrated with real-time healthcare monitoring devices and wearable sensors to continuously monitor patient health conditions. Additionally, the use of larger and more diverse datasets from multiple hospitals can improve the generalization capability of the model. Cloud-based deployment and mobile health applications can also be developed to make the system accessible to doctors and patients remotely.

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