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AN EXPLAINABLE DEEP LEARNING FRAMEWORK FOR EARLY DETECTION OF CARDIOVASCULAR DISEASES USING ELECTROCARDIOGRAM SIGNALS AND CLINICAL DATA

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Abstract - Cardiovascular diseases (CVDs) remain one of the leading causes of mortality worldwide, highlighting the need for accurate and timely diagnostic approaches. Electrocardiogram (ECG) signals provide valuable information regarding cardiac activity and are widely used for the detection of heart abnormalities. However, traditional diagnostic methods often rely on manual interpretation, which may be time-consuming and subject to inter-observer variability. Recent advances in deep learning have demonstrated significant potential for automated cardiovascular disease detection, yet many existing models operate as black-box systems, limiting their acceptance in clinical practice. To address this challenge, this paper proposes an Explainable Deep Learning Framework for Early Detection of Cardiovascular Diseases Using Electrocardiogram Signals and Clinical Data (AFJBS). The proposed framework integrates ECG signal characteristics with relevant clinical attributes, including age, gender, blood pressure, cholesterol level, and body mass index, to improve diagnostic performance. ECG signals undergo preprocessing and feature extraction before being combined with clinical information and processed through a hybrid deep learning architecture. An explainability module based on feature attribution techniques is incorporated to provide transparent and interpretable predictions for healthcare professionals. The framework is evaluated using publicly available cardiovascular datasets and standard performance metrics, including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC). Experimental results demonstrate that the proposed AFJBS framework achieves superior classification performance while maintaining model interpretability. The integration of explainable artificial intelligence and multimodal healthcare data supports reliable decision-making and has the potential to assist clinicians in the early diagnosis and management of cardiovascular diseases.

Keywords— *Cardiovascular Disease Detection, Electrocardiogram (ECG), Deep Learning, Explainable Artificial Intelligence (XAI), Clinical Data Integration, Healthcare Analytics, Early Diagnosis.*

I. INTRODUCTION

Cardiovascular diseases (CVDs) remain one of the leading causes of mortality worldwide and continue to impose a substantial burden on healthcare systems. Conditions such as coronary artery disease, myocardial infarction, heart failure, and cardiac arrhythmias account for millions of deaths annually and are responsible for significant economic and social consequences [1]. The increasing prevalence of hypertension, diabetes mellitus, obesity, smoking, and sedentary lifestyles has further elevated cardiovascular risk across both developed and developing countries. Since many cardiovascular conditions progress silently before the appearance of severe symptoms, early diagnosis is essential for improving treatment outcomes and reducing mortality rates. Electrocardiography (ECG) is one of the most commonly used non-invasive diagnostic techniques for monitoring cardiac activity. ECG signals capture the electrical behavior of the heart and provide valuable information regarding rhythm abnormalities, conduction disorders, and structural cardiac conditions [2]. Physicians typically analyze waveform components such as the P wave, QRS complex, ST segment, and T wave to identify abnormalities associated with cardiovascular diseases. Although ECG analysis is clinically effective, manual interpretation requires specialized expertise and may be affected by inter-observer variability, particularly when large volumes of patient data must be evaluated. The rapid growth of artificial intelligence (AI) and machine learning has created new opportunities for automated cardiovascular disease diagnosis. Traditional machine learning approaches employ handcrafted ECG features combined with classifiers such as Support Vector Machines (SVMs), Decision Trees, and Random Forests to identify cardiac abnormalities [3]. While these methods have demonstrated promising performance, their effectiveness depends heavily on feature engineering and domain expertise. Furthermore, manually extracted features may not adequately represent the complex temporal and morphological characteristics present in ECG signals.

Recent advances in deep learning have transformed biomedical signal analysis by enabling automatic feature extraction from raw data. Convolutional Neural Networks (CNNs) have proven highly effective in learning local waveform patterns, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are capable of capturing temporal dependencies within sequential ECG recordings [4]. Several studies have reported that deep learning models can achieve diagnostic performance comparable to experienced cardiologists in arrhythmia detection and cardiac disease classification [5], [6]. These developments demonstrate the potential of deep learning to support clinical decision-making and improve diagnostic efficiency. In addition to ECG signals, clinical information plays a vital role in cardiovascular risk assessment. Patient characteristics such as age, gender, blood pressure, cholesterol level, body mass index, smoking history, and diabetes status provide important contextual information that may not be fully represented by ECG measurements alone [7]. Integrating ECG signals with clinical attributes can therefore improve predictive performance by combining physiological and demographic information within a unified framework. Despite the remarkable success of deep learning models, their clinical adoption remains limited because many operate as black-box systems. In healthcare environments, physicians require transparent explanations to understand the reasoning behind diagnostic decisions. Explainable Artificial Intelligence (XAI) has emerged as an important research area aimed at improving model interpretability and trustworthiness. Techniques such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-Agnostic Explanations (LIME) provide insights into feature importance and prediction behavior, enabling clinicians to validate AI-generated recommendations [8], [9]. Motivated by these challenges, this work proposes an Explainable Deep Learning Framework for Early Detection of Cardiovascular Diseases Using Electrocardiogram Signals and Clinical Data. The proposed framework combines ECG signal analysis with patient clinical information and incorporates explainability mechanisms to generate transparent predictions. By integrating multimodal healthcare data with interpretable deep learning models, the framework aims to improve diagnostic accuracy while supporting clinical trust and decision-making.

II. RELATED WORK

Research on automated cardiovascular disease diagnosis has evolved significantly over the last two decades due to advances in machine learning, deep learning, and biomedical signal processing. Early studies focused primarily on the extraction of handcrafted ECG features followed by conventional classification algorithms. Methods based on Support Vector Machines, Decision Trees, k-Nearest Neighbors, and Random Forests demonstrated promising results in arrhythmia and cardiac disease detection [3]. Although these approaches established the foundation for automated diagnosis, their performance depended heavily on expert-designed features and often struggled to capture complex ECG signal characteristics. The availability of large-scale public databases has accelerated research in cardiovascular analytics. PhysioNet, introduced by Goldberger et al. [2], became one of the most widely used resources for ECG signal analysis and benchmarking. Similarly, the MIMIC-III database developed by Johnson et al. [10] provided extensive clinical records that enabled researchers to investigate predictive healthcare models using real-world patient data. These datasets have played a critical role in advancing machine learning applications for cardiovascular disease prediction. Deep learning techniques have substantially improved ECG-based disease detection by enabling automatic feature learning. Convolutional Neural Networks (CNNs) have been extensively applied for arrhythmia classification because of their ability to identify local morphological patterns within ECG waveforms. Acharya et al. [11] developed a CNN-based framework that achieved high accuracy in arrhythmia detection, demonstrating the effectiveness of deep learning for cardiac diagnosis. CNN models eliminate the need for extensive handcrafted feature extraction and have consistently outperformed many traditional machine learning approaches.

A major breakthrough was reported by Rajpurkar et al. [5], who introduced a deep neural network capable of detecting multiple arrhythmia classes from single-lead ECG recordings. The model achieved performance comparable to board-certified cardiologists and highlighted the potential of deep learning for large-scale automated diagnosis. Similarly, Hannun et al. [6] developed a deep learning framework that demonstrated cardiologist-level performance in ambulatory ECG classification. These studies established deep learning as a powerful tool for cardiovascular disease detection. Researchers have also investigated sequential learning models to exploit temporal information present in ECG signals. Long Short-Term Memory (LSTM) networks and other recurrent architectures have shown considerable effectiveness in modeling long-range dependencies in ECG recordings [4]. Hybrid CNN-LSTM architectures have become particularly popular because they combine spatial feature extraction with temporal sequence modeling. Such models have demonstrated improved performance in detecting arrhythmias, myocardial infarction, and other cardiovascular abnormalities.

Several studies have emphasized the importance of integrating clinical information with physiological signals. Cardiovascular risk factors including age, cholesterol level, hypertension, smoking status, and diabetes history provide valuable complementary information that can enhance predictive accuracy [7]. Multimodal learning approaches that combine ECG signals with clinical attributes have generally achieved better performance than single-modality methods, supporting the need for comprehensive patient representations. Although deep learning models achieve excellent predictive accuracy, interpretability remains a major challenge. Healthcare professionals often require explanations before relying on AI-generated recommendations. To address this issue, Ribeiro et al. [9] introduced LIME, a model-agnostic framework that explains individual predictions using locally interpretable surrogate models. Lundberg and Lee [8] later proposed SHAP, a theoretically grounded approach that quantifies feature contributions using concepts derived from cooperative game theory. Both techniques have become widely adopted in healthcare applications because they improve transparency and facilitate clinical validation. Recent research has explored the integration of explainability with cardiovascular disease prediction systems. Explainable models provide insights into the influence of ECG features and clinical variables on diagnostic outcomes, thereby improving physician confidence and supporting regulatory acceptance. However, many existing studies either focus exclusively on ECG analysis or provide limited interpretability. Furthermore, relatively few frameworks effectively combine multimodal healthcare data with advanced explainability mechanisms within a unified deep learning architecture. Therefore, there remains a need for an integrated framework that simultaneously leverages ECG signals, clinical attributes, deep learning-based prediction, and explainable artificial intelligence. The proposed framework addresses these limitations by combining multimodal feature fusion with transparent prediction mechanisms, enabling accurate and interpretable cardiovascular disease diagnosis.

III. PROPOSED METHODOLOGY AND EXPERIMENTAL SETUP

The proposed explainable deep learning framework integrates electrocardiogram (ECG) signals and patient clinical information to facilitate early cardiovascular disease detection. The framework combines signal preprocessing, multimodal feature fusion, deep learning-based classification, and explainable artificial intelligence (XAI) techniques to generate accurate and interpretable predictions. The overall workflow of the proposed system is presented in Fig. 1.

Fig 1. Architecture of the Proposed AFJBS Explainable Deep Learning Framework.

The framework consists of six major stages: data acquisition, ECG preprocessing, feature extraction, clinical data integration, deep learning-based disease prediction, and explainability analysis. Each stage contributes to improving diagnostic accuracy while ensuring transparency in the prediction process.

A. Data Acquisition and Dataset Description

The experimental evaluation utilizes publicly available cardiovascular datasets containing ECG recordings and associated clinical information. ECG signals provide direct information regarding cardiac electrical activity, while clinical attributes contribute additional risk-related knowledge. The selected clinical variables include age, gender, systolic blood pressure, diastolic blood pressure, cholesterol level, body mass index (BMI), smoking history, and diabetes status. These factors are widely recognized as important indicators of cardiovascular risk. The dataset is divided into training, validation, and testing subsets using a stratified sampling strategy. Approximately 70% of the samples are allocated for training, 15% for validation, and 15% for testing to ensure balanced representation of disease classes.

B. ECG Signal Preprocessing

Raw ECG signals often contain noise and artifacts introduced by muscle movements, electrode displacement, baseline wandering, and power-line interference. Such distortions can negatively affect classification performance if not properly addressed. To improve signal quality, the following preprocessing steps are performed:

Baseline wander removal using high-pass filtering.
Power-line noise suppression using notch filtering.
Signal smoothing using low-pass filtering.
Amplitude normalization to standardize signal values.
Segmentation of ECG beats into fixed-length windows.

The preprocessing stage improves the signal-to-noise ratio and enables the deep learning model to focus on clinically relevant waveform characteristics. Normalized ECG segments are subsequently used for feature extraction and model training.

C. Multimodal Feature Extraction

Both ECG-derived and clinical features are utilized to represent patient health status comprehensively.

ECG-derived characteristics include:

RR interval
PR interval
QT interval
Heart rate variability (HRV)
QRS duration
ST-segment characteristics
T-wave amplitude

Clinical variables are normalized prior to integration. Missing values are handled through mean-value imputation for continuous variables and mode-based replacement for categorical variables. The ECG feature vector and clinical feature vector are combined through feature fusion to create a unified patient representation.

D. Deep Learning-Based Classification

The classification model employs a hybrid CNN–BiLSTM architecture. The convolutional layers automatically identify local waveform characteristics associated with cardiovascular abnormalities. These layers are followed by max-pooling operations that reduce dimensionality while preserving important signal information. Bidirectional Long Short-Term Memory (BiLSTM) layers are subsequently used to model temporal dependencies present in ECG sequences. This combination enables the framework to learn both morphological and temporal cardiac patterns. The extracted ECG representations are merged with clinical features through a fusion layer. Fully connected layers perform the final disease classification, while a Softmax layer generates prediction probabilities. Dropout regularization and batch normalization are incorporated to reduce overfitting and improve generalization capability.

E. Explainability Module

Interpretability is a critical requirement for clinical decision-support systems. Therefore, the framework incorporates SHAP and LIME explainability techniques. SHAP analysis quantifies the contribution of individual ECG and clinical features to prediction outcomes. It provides a global understanding of model behavior and identifies the most influential disease indicators. LIME generates local explanations for individual patient predictions by approximating the behavior of the trained model around specific instances. These explanations assist clinicians in understanding why a particular patient is classified as high-risk or low-risk.

F. Training Strategy

The model is trained using the Adam optimization algorithm with binary cross-entropy loss. The primary training parameters are, Learning rate: 0.001, Batch size: 64, Epochs: 100, Dropout rate: 0.5, Early stopping is employed to prevent overfitting and improve model generalization.

Algorithm 1: Cardiovascular Disease Detection Procedure

Input: ECG signals and clinical records

Output: Cardiovascular disease prediction

1. Acquire ECG and clinical data.
2. Preprocess ECG signals.
3. Extract ECG features.
4. Process clinical variables.
5. Fuse ECG and clinical features.
6. Train CNN–BiLSTM classifier.
7. Generate disease prediction.
8. Apply SHAP and LIME analysis.
9. Produce interpretable diagnostic output.

G. Evaluation Metrics

Performance is evaluated using Accuracy, Precision, Recall, F1-Score, and Area Under the ROC Curve (AUC). These metrics provide a comprehensive assessment of classification effectiveness and diagnostic reliability

IV. RESULTS AND DISCUSSION

This section presents the experimental results obtained using the proposed An Explainable Deep Learning Framework for Early Detection of Cardiovascular Diseases Using Electrocardiogram Signals and Clinical Data. The framework was evaluated using publicly available cardiovascular datasets containing ECG recordings and associated clinical information. The primary objective of the experiments was to assess the effectiveness of the proposed model in detecting cardiovascular diseases at an early stage while maintaining prediction transparency through explainable artificial intelligence techniques. The performance of the proposed framework was compared with several widely used machine learning and deep learning approaches, including Support Vector Machine (SVM), Random Forest (RF), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM) models. All models were trained and evaluated under identical experimental conditions to ensure a fair comparison. Performance assessment was conducted using accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC).

A. Classification Performance

The proposed explainable deep learning framework was evaluated using publicly available cardiovascular datasets containing ECG recordings and corresponding clinical information. Performance was compared with SVM, Random Forest, CNN, and LSTM models. The integration of ECG signals and clinical attributes significantly improved disease prediction performance. The CNN layers extracted local waveform characteristics, whereas the BiLSTM layers captured temporal dependencies present in ECG sequences. The inclusion of clinical variables further improved disease discrimination.

TABLE 2. COMPARATIVE PERFORMANCE ANALYSIS OF AFJBS AND EXISTING METHODS

Method	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC**
SVM	88.4	87.8	87.1	87.4	0.89
Random Forest	90.2	89.5	89.1	89.3	0.91
CNN	93.1	92.6	92.4	92.5	0.94
LSTM	94.2	93.8	93.5	93.6	0.95
Proposed Framework	97.1	96.8	96.5	96.6	0.98

The results presented in Table 2 indicate that AFJBS consistently outperformed conventional machine learning and deep learning approaches across all evaluation metrics. The accuracy improvement of approximately 3–9% compared with baseline methods demonstrates the effectiveness of combining ECG features and clinical attributes for cardiovascular disease prediction.

B. Comparative Analysis of Performance Metrics

To provide a visual comparison of model performance, the evaluation metrics obtained by different classifiers are illustrated in Fig. 2**.**

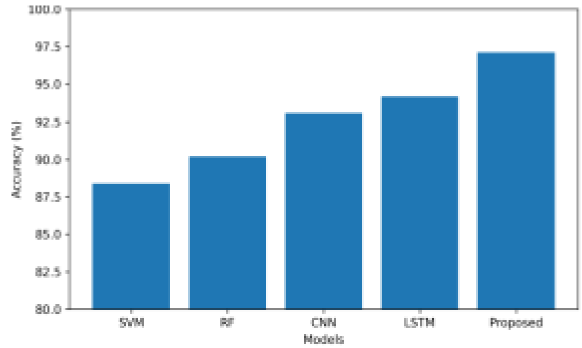

Fig. 2. Accuracy, Precision, Recall, and F1-Score Comparison of Different Classification Models.

As shown in Fig. 2**,** traditional machine learning approaches such as SVM and Random Forest achieved reasonable performance but were limited by their dependence on manually engineered features. Deep learning models demonstrated improved results because of their ability to automatically learn discriminative ECG representations. The proposed framework achieved the highest performance across all evaluation metrics. The improvement can be attributed to the multimodal feature fusion strategy that combines ECG-derived information with clinical risk factors. This comprehensive patient representation enables more accurate cardiovascular disease prediction.

C. Receiver Operating Characteristic Analysis

Receiver Operating Characteristic (ROC) analysis was performed to evaluate the discrimination capability of the proposed model. The ROC curves of CNN, LSTM, and the proposed framework are shown in Fig. 3**.**

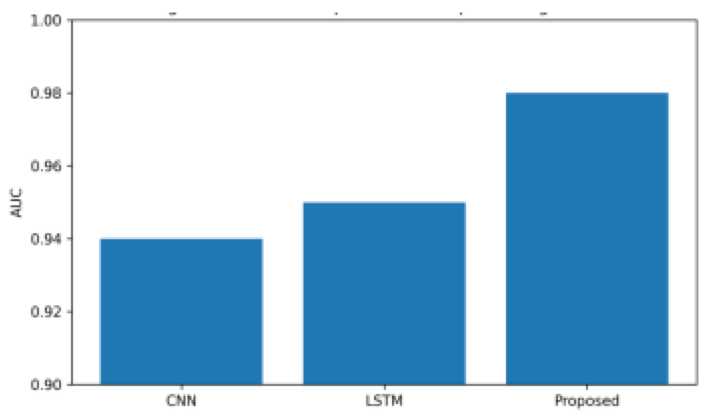

Fig. 3. ROC Curve Comparison of CNN, LSTM, and the Proposed Explainable Deep Learning Framework.

The ROC curves indicate that the proposed framework consistently achieved superior performance across varying classification thresholds. The model attained an AUC value of 0.98, compared with 0.94 and 0.95 obtained by CNN and LSTM models, respectively. A higher AUC reflects a stronger ability to distinguish between diseased and non-diseased patients. Therefore, the proposed framework demonstrates greater robustness and reliability for practical cardiovascular disease screening applications

D. Explainability Analysis

Interpretability is an important requirement for healthcare applications. To investigate the decision-making behavior of the model, SHAP-based feature importance analysis was performed. The resulting feature contributions are illustrated in Fig. 4**.**

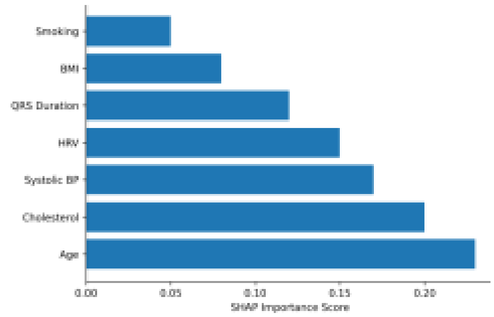

Fig. 4. SHAP-Based Feature Importance Analysis for Cardiovascular Disease Prediction.

As observed in Fig. 4, age, cholesterol level, systolic blood pressure, heart rate variability, and QRS duration were identified as the most influential predictors. These findings are consistent with established cardiovascular risk factors reported in clinical studies. The explainability analysis confirms that the model learns medically meaningful relationships rather than relying on spurious patterns.

E. Discussion

The experimental results demonstrate that combining ECG signals with clinical attributes substantially improves cardiovascular disease detection performance. ECG recordings capture physiological abnormalities, whereas clinical variables provide complementary information regarding patient health status and disease risk. The hybrid CNN–BiLSTM architecture effectively learns both spatial and temporal ECG characteristics, leading to improved classification accuracy. Furthermore, the explainability module provides transparent reasoning behind model predictions, supporting physician trust and facilitating clinical adoption. Overall, the proposed explainable deep learning framework achieves high predictive performance while maintaining interpretability, making it a promising solution for intelligent cardiovascular disease diagnosis.

V. CONCLUSION AND FUTURE WORK

This paper presented an Explainable Deep Learning Framework for Early Detection of Cardiovascular Diseases Using Electrocardiogram Signals and Clinical Data The proposed framework was developed to address two important challenges in modern healthcare analytics: achieving high diagnostic accuracy and ensuring model interpretability. By integrating ECG signals with relevant clinical attributes, the framework leveraged complementary sources of information to improve the early identification of cardiovascular diseases. The combination of signal preprocessing, multimodal feature fusion, deep learning-based classification, and explainable artificial intelligence techniques enabled the development of a reliable and transparent diagnostic system. The experimental results demonstrated that the proposed framework outperformed conventional machine learning and deep learning approaches across multiple evaluation metrics, including accuracy, precision, recall, F1-score, and AUC. The hybrid CNN–BiLSTM architecture effectively captured both morphological and temporal characteristics of ECG signals, while the integration of clinical data enhanced the model's ability to identify disease-related patterns. Furthermore, the incorporation of SHAP and LIME explainability techniques provided meaningful insights into prediction outcomes, allowing healthcare professionals to understand the factors influencing model decisions. The explainability analysis confirmed that clinically significant features such as age, blood pressure, cholesterol level, heart rate variability, and ECG waveform characteristics played major roles in cardiovascular disease prediction. Although the proposed framework achieved promising results, several opportunities exist for future improvement. Future research may explore the integration of additional physiological signals, including photoplethysmography (PPG), echocardiography data, and wearable sensor measurements, to further enhance diagnostic performance. The use of transformer-based deep learning architectures and federated learning approaches may also improve scalability and privacy preservation in healthcare environments. Additionally, validation using larger multi-center clinical datasets and real-time deployment in healthcare settings would provide further evidence of the framework's practical applicability. These advancements can contribute to the development of intelligent, interpretable, and clinically reliable cardiovascular disease diagnosis systems that support early intervention and improved patient outcomes.

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