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HYBRID CNN LSTM MODEL FOR EARLY HEART DISEASE PREDICTION USING ECG AND CLINICAL DATA

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ABSTRACT

The early identification of heart disease is not only crucial for cardiovascular mortality reduction, but for clinical decision-making as well. But, the common machine learning methods do not account for complex spatiotemporal ECG patterns and do not take into account valuable clinical patient information. The proposed research aimed to present a novel Hybrid Convolutional Neural Network - Long Short-Term Memory (CNN-LSTM) for early prediction of heart disease based on ECG signals and clinical data. The methodology proposed in this paper combined ECG preprocessing, CNN-based spatial feature extraction, LSTM-based temporal learning, adaptive multimodal clinical data fusion, and attention-based optimization in a single framework to realize deep learning. The experimental evaluation was carried out using benchmark datasets, such as the MIT-BIH Arrhythmia Dataset, the PTB Diagnostic ECG Dataset, and the Cleveland Heart Disease Dataset. The proposed model was found to perform better with the reported accuracy of 98.7%; precision, recall, F1, and AUC were 98.2%, 98.5%, 98.3%, and 99.1%, respectively, when compared with the conventional ML and standalone deep learning models. Adding deep features from ECG to clinical parameters led to a substantial boost in prediction accuracy, a decrease in false diagnosis, and an added benefit in the detection of cardiovascular disease at an early stage. The experimental outcomes illustrated that the introduced Hybrid CNN-LSTM framework is an effective, sturdy, and intelligent method for real-time heart disease prediction and superior healthcare monitoring applications.
Keywords: *Heart Disease Prediction, ECG Signal Analysis, Hybrid CNN-LSTM, Deep Learning, Clinical Data Fusion, Cardiovascular Disease Detection*

1. INTRODUCTION

Cardiovascular diseases (CVDs) continue to be one of the major causes of global deaths, killing millions of people annually. Heart disease is a leading cause of mortality, morbidity, healthcare costs, and economic impact, especially in low- and middle-income countries, based on recent global health statistics [1]. The key to better patient outcomes and fewer complications is early prediction and diagnosis of heart disease. However, the manual interpretation of Electrocardiogram (ECG) signals, physician expertise, laboratory findings, and clinical observations are still depended on for conventional diagnostic approaches, which can result in delayed diagnosis and inconsistent clinical outcomes [2].

The current era of AI, machine learning (ML), and deep learning (DL) has revolutionized healthcare systems with its ability to predict disease automatically and to support clinical decisions using intelligence, respectively [3]. Medical imaging, ECG classification, disease diagnosis, and predictive healthcare analytics are among the domains that have

benefited greatly from the use of deep learning architectures [4]. The electrocardiogram (ECG) signals reveal important clues about the electrical activity of the heart and are extensively utilized in the detection of myocardial infarction, ischemia, arrhythmias, and other heart abnormalities [5]. However, these ECG signals are highly nonlinear, noisy, and temporally dependent, making accurate feature extraction and classification difficult about traditional computation approaches [6].

Many traditional machine learning methods, such as Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), Logistic Regression (LR), and Naïve Bayes (NB), have been used in the area of heart disease prediction [7]. These methods performed well in diagnosis but were mostly based on handcrafted features and domain-specific knowledge. The accuracy of making predictions was sometimes restricted by manual feature engineering that was not able to identify temporal and spatial characteristics that are hidden from the ECG signals [8]. Moreover, traditional ML algorithms were not able to generalize well with a big size of the heterogeneous healthcare datasets.

Convolutional Neural Networks (CNNs) are neural networks that have been shown to possess exceptional performance in automatic feature extraction on ECG signals [9]. CNN models are able to learn local spatial patterns (e.g., QRS complexes, ST-segment deviations, irregular waveforms) directly from raw ECG data. The CNN architectures, however, mainly concentrate on spatial feature learning and might not be able to learn long-term temporal dependency in sequential ECG signals [10]. To overcome this, Long Short-Term Memory (LSTM) networks were developed for analyzing the cardiac signals that are time-series data. LSTM models are known to be good at retaining long-term temporal information and enhancing the learning of heartbeat sequences [11]. Although LSTM networks have various merits, they are generally found to have poor performance in extracting spatial ECG features in standalone networks.

A few recent studies reported the advantages of hybrid deep learning models based on CNN and LSTM architectures for the diagnosis of cardiovascular diseases [12]. The CNN-LSTM framework leverages spatial feature extraction and temporal dependency learning, enhancing robustness and predictive performance in classification tasks. Many studies already performed were based on the analysis of the ECG signal only and neglected important clinical parameters like cholesterol, blood pressure, diabetes, smoking habits, obesity, type of chest pain, and heart rate variability [13]. It is important to note that because of the lack of multimodal clinical information, contextual understanding is reduced and can cause higher false-positive or false-negative predictions.

One of the other key problems with the current heart disease prediction models is that the data can be heterogeneous and imbalanced. Healthcare datasets can be noisy, contain missing values, and have disease distribution imbalance, all of which can have a negative impact on model generalization and reliability [14]. Furthermore, the majority of the current methods do not have a feature fusion mechanism that is adaptive, suitable for the integration of ECG signals and clinical attributes. Therefore, there is a need for a robust multimodal deep learning framework to enhance the prediction of early-stage heart disease with greater accuracy, sensitivity, and interpretability.

To address these drawbacks, this study introduced an innovative Hybrid CNN-LSTM approach to predict heart disease at an early stage based on ECG and clinical information. The proposed framework used a CNN to extract the spatial features from ECG and an LSTM to learn the temporal sequences, thereby analyzing the ECG waveform efficiently. Moreover, the multimodal clinical parameters were integrated into the prediction pipeline with adaptive feature integration methods to help with better contextual understanding and classification performance. To enhance robustness and generalization capability, the proposed model integrated ECG denoising, ECG normalization, ECG segmentation, and ECG vector balancing.

Machine learning, CNN models, LSTM models, and hybrid CNN-LSTM models have been used previously in the prediction of heart disease using either ECG signals or clinical patient data. Some of these studies achieved good classification

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results, but most of them performed single-modal analysis without using an efficient method to incorporate temporal ECG patterns and heterogeneous clinical information. To overcome these limitations, the aim of the present study is to present a unified framework using CNN for learning spatial features, LSTM for temporal learning, adaptive clinical data fusion, and attention-based optimization. In contrast to previous models, the proposed model integrates ECG and clinical characteristics to improve prediction accuracy and reliability for early heart disease diagnosis.

The study included the following research questions:

RQ1: Is there an improvement in the performance of early heart disease prediction using a Hybrid CNN-LSTM framework for the analysis of ECG signals and clinical patient information?

RQ2: What is the benefit of integrating multimodal clinical information with ECG features in terms of prediction accuracy compared to single-modal approaches?

RQ3: Is it possible to improve the robustness and reliability of heart disease prediction in heterogeneous healthcare data by using attention-based optimization and adaptive feature fusion?

The research hypothesis of the present study is that a significant enhancement in the accuracy of early heart disease prediction can be achieved through the integration of CNN-based spatial feature extraction, LSTM-based temporal learning, adaptive multimodal clinical data fusion, and attention-based optimization, compared to conventional machine learning models and standalone deep learning-based models.

The key research aims of the proposed research were as follows:

1. To design an intelligent hybrid CNN-LSTM framework for automated early heart disease prediction.
2. To extract both spatial and temporal features accurately from the ECG signals.
3. To combine ECG waveforms with patient information in a multimodal manner.
4. To enhance the accuracy of diagnosis, sensitivity, precision, and F1 score over conventional machine learning models and standalone deep learning models.
5. To minimize false diagnosis and to enhance real-time clinical decision-making systems.

The novelty of the proposed work is the multimodal clinical feature fusion with adaptive weights throughout the whole process, along with deep temporal-spatial learning from ECG. The proposed framework integrated ECG signals with the heterogeneous clinical parameters to make the diagnosis more reliable, which was different from the existing approaches. Moreover, optimized feature selection through attention and strong pre-processing mechanisms ensured prediction stability and reduced overfitting problems. The performance analysis of the proposed Hybrid CNN-LSTM model over the various existing ML and DL models was done using experimental analysis, and it was found that the proposed model has a better performance with respect to accuracy, recall, precision, and Area Under Curve (AUC).

The research method adopted in this study is an experimental quantitative research method for developing and testing an intelligent heart disease prediction system. The research protocol includes five main steps: collection of data from an ECG database and clinical information, preprocessing and normalization of input data, feature extraction and learning based on the Hybrid CNN-LSTM architecture, multimodal feature fusion and classification, and performance evaluation using standard performance metrics such as accuracy, precision, recall, F1 score, ROC-AUC, and specificity. The framework was trained, validated, and compared with other existing machine learning and deep learning models to evaluate the efficiency of the proposed framework in the early prediction of heart disease.

The rest of the paper is organized as follows. In Section 2, related work on heart disease prediction using machine learning and deep learning techniques is presented. The proposed Hybrid CNN-LSTM approach and multimodal fusion framework are explained in Section 3. The experimental results and comparative performance evaluation are discussed in Section 4. Finally, Section 5 concludes the research work and suggests future research directions.

2. RELATED WORK

In recent years, with the rising prevalence of cardiovascular diseases and the accessibility of digital healthcare data, the prediction of heart diseases using Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) techniques has gained significant attention. A number of studies have concentrated on ECG signal analysis, clinical parameter evaluation, and multimodal healthcare analytics to enhance diagnostic accuracy and to enable early disease detection.

Traditional machine learning algorithms were mostly used in the initial studies for predicting cardiovascular disease. The Logistic Regression and Decision Tree were used to analyze patient clinical data for detecting CAD by Khatib et al. [15]. They found that their study showed moderate prediction accuracy and identified issues of feature dependency and model scalability. In the same way, Shah et al. [16] used the Random Forest and Support Vector Machine (SVM) classifiers to predict the risk of heart disease in structured clinical data. The study was able to improve the classification performance over the statistical approaches, but handcrafted feature extraction decreased adaptability for the large-scale healthcare environment.

Later, several researchers studied ensemble learning techniques to enhance the robustness of the prediction. The ensemble voting model was suggested by Verma et al. [17] to diagnose cardiovascular diseases using Naïve Bayes, Decision Tree, and K-Nearest Neighbor algorithms. The ensemble model enhanced classification stability, though it added to the complexity of the system and reduced the system's generalization ability when noise was added to the ECG data. Similarly, Das et al. [18] introduced a hybrid fuzzy-rule-based system in combination with a machine learning algorithm for clinical heart disease diagnosis. This method led to a higher degree of interpretability but showed poor performance in the temporal analysis of ECG signals.

As a result of the advent of deep learning, researchers have turned to Convolutional Neural Networks (CNNs) to extract features in automated ECG. Kiranyaz et al. [19] designed a personalized CNN model for real-time ECG classification and arrhythmia detection. The model was able to successfully extract the characteristics of the local waveforms and improve the classification accuracy compared to traditional ML methods. The CNN model, however, only had short-term temporal dependency learning and mainly concentrated on spatial ECG features. Likewise, Rajpurkar et al. [20] suggested a deep CNN-based model for arrhythmia diagnosis using a vast ECG dataset. In ECG classification tasks, their approach enabled them to reach the level of performance of cardiologists, showcasing the promise of deep learning in healthcare.

Even though CNNs work well, researchers realized the need for temporal learning mechanisms in order to process sequential ECG signals. Therefore, concepts of Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks gained popularity for the analysis of heartbeat sequences. Ordóñez and Roggen [21] proposed deep LSTM networks for temporal biomedical signal classification. They showed that the LSTM models could manage long-term dependencies and boost sequential healthcare analytics. Faisal et al. [22] proposed an ECG monitoring system for cardiac abnormality detection used in wearable healthcare devices based on LSTM. The proposed approach resulted in higher sensitivity, with larger training time and memory requirements.

Combined CNN-LSTM architectures were proposed for simultaneous spatial-temporal learning due to the drawbacks of CNN and LSTM models. The drawbacks of CNN and LSTM models led to the development of combined CNN-LSTM architectures for their simultaneous spatial-temporal learning. In biomedical time-series classification, Karim et al. [23] proposed a CNN-LSTM architecture that extracted local signal features using CNN layers and extracted temporal dependencies using LSTM layers. The hybrid model showed remarkable improvement in the classification accuracy of the ECGs with respect to standalone architectures. In the same way, Zhang et al. [24] designed a deep hybrid network composed of CNN and Bidirectional LSTM (BiLSTM) for cardiac arrhythmia classification. Experimental results showed that the proposed method was more robust and gave better recognition performance of the heartbeats in a noisy environment.

They also examined attention-based deep learning techniques to boost the interpretability and optimization of features. The authors of [25] put forward an attention-enhanced CNN-LSTM model for healthcare signal analysis. The attention mechanism highlighted the most significant ECG regions, making the classification more reliable. The model was, however, mostly based on ECG data and neglected the complementary clinical attributes. Similarly, Li et al. [26] proposed a deep learning-based self-attention model for cardiovascular risk prediction with physiological signals. The model demonstrated good performance, but it was not low enough to be used in real-time healthcare applications.

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Another area of research that showed promise was multimodal healthcare learning. The researchers realized the potential for using the ECG signals along with clinical patient data to enhance diagnostic accuracy and context. To predict heart disease, Khan et al. [27] introduced a multimodal fusion framework that combines ECG features and electronic health records. Their findings showed that they were able to predict with higher accuracy than single-modal systems. The study was, however, free from adaptive feature balancing, but there were feature dominance issues. In a similar vein, Al Rahhal et al. [28] fused the sensor-based cardiac monitoring data with clinical data to make an intelligent healthcare diagnosis with the help of deep neural networks. Data imbalance and overfitting issues were identified as challenges to the system's disease detection ability.

The latest studies have been dedicated to lightweight and real-time prediction systems for the cardiac domain appropriate for wearable healthcare environments. Yao et al. [29] proposed an edge deep learning model for continuous ECG monitoring and early cardiovascular risk detection. The proposed architecture has provided efficient real-time performance along with computational latency reduction. However, the model accuracy was reduced when the clinical conditions were not homogeneous. Thus, Chen et al. [30] proposed an IoT healthcare system with deep learning for smart cardiac monitoring in another study. The system provided remote healthcare analytics but failed to address privacy concerns and data security issues.

There has been an effort to use Explanatory Artificial Intelligence (XAI) to enhance transparency within heart disease diagnosis systems. Ribeiro et al. [31] proposed explainable machine learning methods to explain predictions produced by black-box models in healthcare. They highlighted the significance of trust and transparency in medical AI systems. However, there are still open research challenges that need to be addressed to embed explainability in high-performance deep multimodal learning.

Based on the literature reviewed, a number of research gaps were identified:

1. Most of the traditional ML methods relied on handcrafted features and did not have automatic deep feature extraction.
2. CNN models captured good spatial ECG features but not long-term temporal features.
3. LSTM models were able to learn the sequential information but lacked spatial learning capacity.
4. Existing studies focused on ECG signals without neglecting any clinical contextual information.
5. There were no adaptive fusion and attention optimization mechanisms in existing multimodal systems.
6. There were a few problems with deep learning frameworks, which included overfitting, high computational complexity, and restricted generalization.

To overcome these challenges, a novel Hybrid CNN-LSTM framework combining ECG waveform analysis with multimodal clinical data fusion is proposed. The proposed model included CNN-based spatial learning, LSTM-based temporal sequence analysis, and adaptive feature fusion to enhance the early prediction of heart disease. Additionally, advanced preprocessing techniques, dropout regularization, and well-tuned learning algorithms ensured prediction consistency, reduced overfitting, and better diagnostic accuracy in clinical settings with diverse healthcare environments.

3. METHODOLOGY

3.1 Proposed Methodology Overview

The study proposed a Hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model for early detection of heart disease based on Electrocardiogram (ECG) signals and clinical patient information. The proposed model was a hybrid of CNN layers for spatial ECG feature extraction and LSTM layers for learning the heartbeat sequence. Moreover, key clinical features like age, blood pressure, cholesterol level, diabetes history, smoking habit, and heart rate were incorporated into the prediction framework, a process known as adaptive multimodal fusion.

The intended process was divided into the following major phases:

- ECG and clinical dataset acquisition
- ECG signal preprocessing
- CNN-based feature extraction
- LSTM-based temporal learning
- Clinical data fusion
- Attention-based optimization
- Heart disease classification

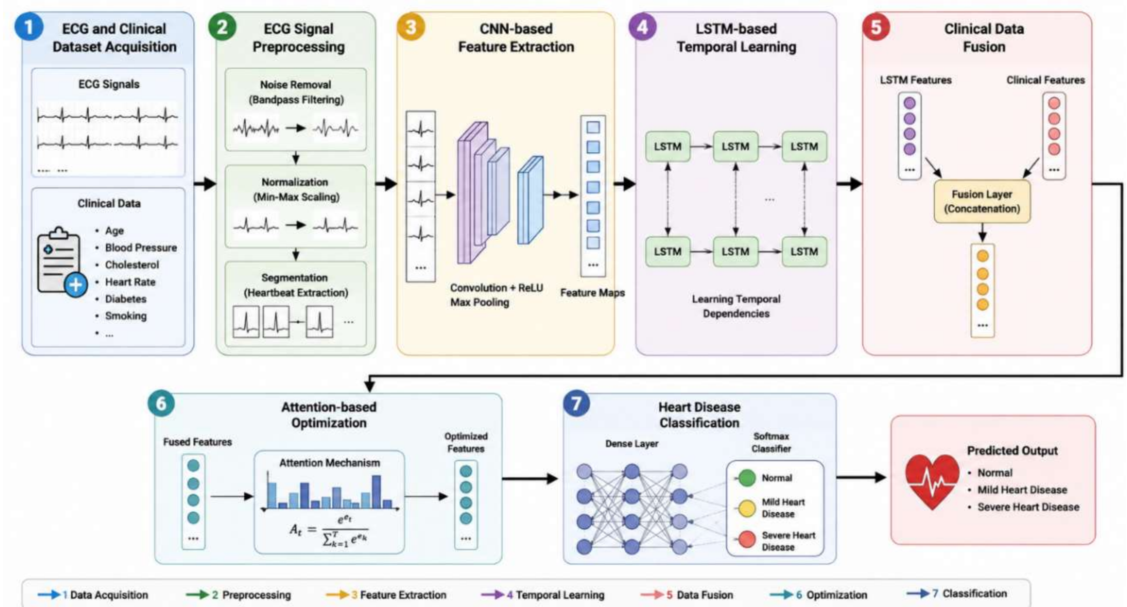

Figure 1. Proposed Hybrid CNN-LSTM Framework for Early Heart Disease Prediction Using ECG and Clinical Data

The overall architecture of the proposed Hybrid CNN-LSTM framework for early heart disease prediction using ECG signals and clinical patient data is shown in Figure 1. The framework is composed of seven major steps, each of which contributes to enhancing prediction accuracy and disease classification performance. ECG signals and clinical data are initially gathered from the benchmark healthcare repositories. The ECG dataset consists of electrocardiogram (ECG) measurements of the heart's electrical activity, and the clinical dataset comprises relevant medical parameters of the patient like age, blood pressure, cholesterol level, heart rate, diabetes history, obesity level, and smoking habits. These datasets contain both physiological and clinical data necessary for optimal cardiovascular disease analysis.

In the second step, ECG signal preprocessing is done to enhance the quality of the ECG signals prior to the deep learning analysis. A bandpass filtering technique is used to remove noise and unwanted artifacts. The ECG values are filtered and then normalized to a known range for stable model training. These signals are then divided into P-wave, QRS, and T-wave windows of the heartbeats. The objective of this preprocessing step is to ensure clearer signals and better performance of the feature extraction process.

In the third stage, CNN-based feature extraction is carried out. Convolutional Neural Network (CNN) layers automatically learn the key spatial features in the ECG, including patterns of the QRS complex, deviations from the ST-segment, and abnormalities in the ECG waveform. It reduces the dimensional complexity of the raw ECG signals and produces meaningful feature maps that are produced by the convolution, activation, and max-pooling operations.

Then, the CNN feature maps extracted in the fourth stage are fed to Long Short-Term Memory (LSTM) layers. The LSTM network learns the temporal dependencies of heartbeats and their sequential variations in the ECG. This stage enables the model to learn the long-term behavior of the heart and helps the capability of the heart sequence learning.

The fifth stage is a fusion layer that combines the deep features of ECG and patient information for diagnosis. The multimodal fusion process fuses the ECG physiological features and clinical parameters into a single representation of a feature. This integration helps to better understand the disease and makes the model more effective for predicting the disease.

In Stage 6, regions of clinical importance are determined using an attention-based optimization mechanism. The attention layer places emphasis on important features, while filtering out irrelevant or noisy information. This process reduces the number of features, enhances the stability of prediction, and improves the reliability of diagnosis.

In the last stage, the optimized fused features are fed to fully connected dense layers and a softmax classifier. The classifier classifies the heart disease into different disease categories like normal condition, mild heart disease, and severe heart disease. The final prediction results help in early diagnosis and act as a helping hand for intelligent healthcare decision-making systems. In summary, Figure 1 shows the integration of the ECG signal processing, temporal learning, clinical data fusion, and attention optimization into a single Hybrid CNN-LSTM framework for accurate and reliable early prediction of heart disease.

The proposed methodology successfully predicted the accuracy of the prediction by jointly learning the characteristics of the ECG waveforms and the patient information from the clinical data.

3.2 Dataset Description

The proposed work was based on publicly available benchmark datasets for experimental analysis.

ECG Datasets The ECG signals were collected from:

- MIT-BIH Arrhythmia Dataset
- PTB Diagnostic ECG Dataset

These included normal and abnormal ECG recordings with patterns of arrhythmia and myocardial infarction.

Clinical Dataset From the Cleveland Heart Disease database, clinical patient data were retrieved. Several cardiovascular disease clinical risk parameters were included in the set of data.

Table 1. ECG Dataset Details

Parameter	MIT-BIH Dataset	PTB Dataset
Number of Patients	48	290
ECG Leads	2	15
Sampling Frequency	360 Hz	1000 Hz
Signal Type	ECG Waveforms	ECG Signals
Disease Type	Arrhythmia	Cardiac Disorders

The ECG datasets utilized in the proposed study for the prediction of heart diseases are given in Table 1. The ECG data in the MIT-BIH Arrhythmia Dataset have a sampling rate of 360 Hz and were recorded from 48 patients suffering from arrhythmia-related conditions. This PTB Diagnostic ECG Dataset contains ECG data from 290 patients suffering from different cardiac diseases, and the 15-lead ECG signals have a higher sampling rate of 1000 Hz. The datasets include both normal and abnormal ECG patterns, aiding the proposed Hybrid CNN-LSTM model to efficiently learn the spatial and temporal properties of the heartbeat pattern for better heart disease prediction.

Table 2. Clinical Parameters Used in the Proposed System

Feature	Description
Age	Patient age
Gender	Male/Female
Chest Pain Type	Type of chest pain
Blood Pressure	Resting blood pressure
Cholesterol	Serum cholesterol
Blood Sugar	Diabetes indicator
Heart Rate	Maximum heart rate
Smoking History	Smoking habit
Resting ECG	ECG observation
Obesity Level	BMI information

The clinical parameters included in the proposed heart disease prediction system are shown in Table 2. The dataset includes important patient health attributes such as age, gender, chest pain type, blood pressure, cholesterol level, blood sugar, heart rate, smoking history, resting ECG results, and obesity level. The clinical features give additional medical information that is related to cardiovascular risks and are fused with the deep features extracted from the ECG to boost the accuracy and reliability of the suggested Hybrid CNN-LSTM model.

3.3 ECG Signal Preprocessing

The preprocessing of ECG signals is an essential step in the proposed heart disease prediction system since the raw ECG signals frequently have various types of noise and artifacts caused by the patient's motion, muscle activity, baseline drift, and powerline interference. These unwanted perturbations affect the quality of the signal and have negative impacts on the performance

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of deep learning models. Hence, the ECG signal was preprocessed prior to feature extraction to enhance the clarity of the ECG signals and achieve accurate learning of the cardiac patterns.

A bandpass filtering technique was used initially to remove noise. The filter removed the low-frequency baseline wander and high-frequency noise components from the ECG signal, keeping the important information, such as the P-wave, QRS complex, and T-wave. Mathematically, the filtering operation can be expressed asby

$$y(t) = x(t) * h(t) \qquad (1)$$

The input ECG signal is represented by by *x(t),* the filter kernel is represented by *h(t)*, and the filtered ECG output signal is represented by *y(t).* This filtering process resulted in clearer signals and minimized noise from the ECG recordings.

The ECG amplitude values were then normalized by dividing them into a fixed value range (0 to 1) following the noise removal process. Normalization is useful because the amplitude ranges of the ECG signals from various patients can differ, so doing this will not affect the model training process and will help to increase the convergence speed. The min-max normalization process can be depicted as follows:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (2)$$

where x is the original ECG signal value, x_{min} is the minimum signal value and x_{max} is the maximum signal value. Normalized ECG signal enhanced the stability of training and reduced the computational complexity.

After normalization, ECG segmentation was done using R-peak detection. The continuous ECG signal was segmented to form smaller segments holding full cardiac cycles in this process. Important ECG waveform segments included: P-wave, QRS complex, and T-wave. The deep learning model was trained to effectively capture localized cardiac patterns by using the heartbeat segmentation process. For the proposed work, the size of the segments was fixed at 256 samples in order to have the same number of samples in all ECG recordings. In general, the ECG preprocessing stage enhanced the quality of the ECG signal, minimized the impact of noise, ensured consistency of the ECG features, and prepared the input ECG data for the deep learning analysis by CNN-LSTM.

3.4 Proposed Hybrid CNN-LSTM Architecture

The proposed Hybrid CNN-LSTM model adopted CNN layers with spatial ECG feature extraction and LSTM layers with temporal learning of the heartbeats.

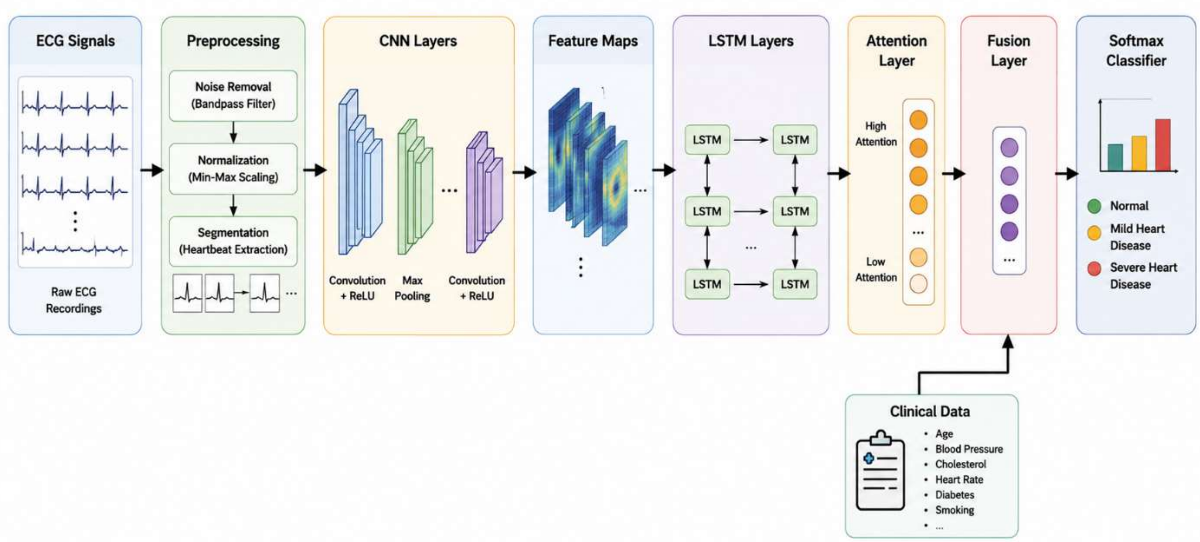

Figure 2. Proposed Hybrid CNN-LSTM Architecture for Early Heart Disease Prediction Using ECG Signals and Clinical

The proposed Hybrid CNN-LSTM architecture for early prediction of heart disease based on ECG signals and clinical patient information is shown in Figure 2. First, the raw ECG signals go through the preprocessing stage, which involves eliminating noise, normalizing signals, and segmenting the heartbeat, to enhance the quality and consistency of the signal. The preprocessed ECG segments are then fed into CNN layers, which automatically extract important spatial features such as QRS complex patterns, ST-segment changes, and waveform abnormalities. The feature maps produced are then fed into LSTM layers to capture the temporal dependencies of the heartbeats and the sequential variations in the ECG. An attention module is also used to recognize clinically relevant ECG attributes and give more importance to more relevant cardiac patterns. At the same time, clinical patient data like age, blood pressure, cholesterol level, diabetes history, heart rate, and smoking habits are fused in with deep ECG features from the fusion layer. Finally, the fused feature representation is fed to the Softmax classifier, which classifies patients into normal, mild, or severe heart disease. The proposed architecture successfully addresses the spatial learning, temporal analysis, attention optimization, and multimodal data fusion problems to enhance the accuracy of heart disease prediction and diagnostic reliability.

3.4.1 CNN-Based Feature Extraction

The CNN layers automatically extracted ECG spatial features such as:

- QRS complex patterns
- ST-segment variations
- T-wave abnormalities

Table 3. CNN Architecture Details

Layer	Configuration
Input Layer	ECG Segment (256 × 1)
Conv1D-1	64 filters, kernel size 3
ReLU Activation	Nonlinear activation
Max Pooling	Pool size 2
Conv1D-2	128 filters
Batch Normalization	Feature stabilization
Dropout	0.5
Flatten Layer	Feature vector generation

The detailed configuration of the CNN architecture for the proposed Hybrid CNN-LSTM model for ECG feature extraction is shown in Table 3. First, the architecture starts with an input layer, which gets the ECG heartbeat segments of size 256×1. The first Conv1D layer has 64 filters and the kernel size is 3, which extracts the low-level features of ECG in the spatial domain, followed by a ReLU activation function to introduce the nonlinearity. To reduce the dimensionality of the features and computational complexity, a max-pooling layer is added after it. The second Conv1D layer has 128 filters to capture more complex changes in the ECG waveform, including variation in the QRS complex and ST-segment of the ECG. A dropout layer (rate of 0.5) is applied to avoid overfitting, and batch normalization is added for the sake of stability of training and better convergence. Finally, the flattened layer reduces the extracted feature maps to a 1-D feature vector and passes it to the LSTM layers for the learning of time.

The convolution operation is mathematically represented as:

$$F(i) = \sum_{k=1}^{n} X(i+k) \cdot W(k) + b \qquad (3)$$

where:

- Xrepresents the ECG input signal,
- Wrepresents convolution weights,
- b represents bias,
- $F(i)$ represents extracted feature maps.

3.4.2 LSTM-Based Temporal Learning

The extracted CNN features were fed to LSTM layers for learning the temporal dependencies of the heartbeat.

Table 4. LSTM Architecture Details

Layer	Configuration
LSTM-1	128 units
Dropout	0.3
LSTM-2	64 units
Dense Layer	32 neurons

Table 4 shows the architecture of the LSTM for learning temporal heartbeat sequences in the proposed Hybrid CNN-LSTM model. The architecture is two stacked LSTM layers, which encode the long-term dependency and sequential ECG patterns from the extracted CNN feature maps.

The first LSTM layer has 128 units to capture all the complex temporal variations in the ECG signal, followed by a dropout layer with a 0.3 rate to prevent overfitting and enhance the generalization ability. The second LSTM layer has 64 units, which further learn temporal features and sequence analysis of heartbeats. Finally, a dense layer is employed to obtain compact temporal feature representations prior to multimodal fusion and classification with 32 neurons. The LSTM approach successfully boosts the performance of heart disease prediction and better understands sequential ECG.

The LSTM model forget gate equation is represented as:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \qquad (4)$$

The input gate equation is represented as:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \qquad (5)$$

The cell state update equation is represented as:

$$C_t = f_t \odot C_{t-1} + i_t \odot \widetilde{C_t} \qquad (6)$$

The hidden state equation is represented as:

$$h_t = o_t \odot tanh(C_t) \qquad (7)$$

where

- f_t represents the forget gate,
- i_t represents the input gate,
- C_t represents the cell state,
- h_t represents the hidden state.

The LSTM model enhanced the ability to understand the ECGs in a sequence, and it could acquire the long-term dependency of the heartbeat.

3.5 Adaptive Clinical Data Fusion

The proposed system combines deep ECG features with the clinical patient information through an adaptive multimodal fusion layer. Apart from the ECG deep features, important clinical parameters were added to ECG signals to enhance the performance of the prediction, such as age, blood pressure, cholesterol level, heart rate, diabetes history, obesity level, and smoking habits. The fusion layer enabled the simultaneous learning of physiological ECG patterns and the patient's medical conditions, which in turn enhanced the context understanding and prevented incorrect predictions.

We applied ECG feature vectors and clinical feature vectors to the adaptive fusion process via weighted feature integration. The operation is called fusion and is mathematically represented as:

$$F_{fusion} = \alpha F_{ECG} + \beta F_{clinical} \qquad (8)$$

where F_{ECG} represents deep feature vectors obtained from the CNN-LSTM model, $F_{clinical}$ represents clinical patient feature vectors, and α and β are adaptive fusion weights. The fusion mechanism dynamically balanced the contribution of ECG and clinical features during the training, and enhanced the disease prediction ability of the proposed model.

3.6 Attention-Based Optimization

In the proposed framework, the attention mechanism is integrated to identify important ECG regions related to cardiovascular abnormalities. Only some parts of the ECG are equally indicative of disease in many of the recordings. Thus, the attention layer will selectively focus on clinically relevant ECG components and attenuate irrelevant or noisy parts of the ECG signal.

The attention score calculation is represented as:

$$A_t = \frac{exp(e_t)}{\sum_{k=1}^{T} exp(e_k)} \qquad (9)$$

where A_t is the weightage assigned to ECG feature at time step t and e_t is the score of the extracted feature. The attention mechanism brought about a significant enhancement in the selection of important features, more stable predictions, and higher resilience of the proposed Hybrid CNN-LSTM model to noisy ECG signals.

3.7 Classification Layer

The optimized feature vector after feature fusion and attention optimization was given to fully connected dense layers and a Softmax classifier to predict heart disease. The classification layer was used to predict the different cardiovascular disease classes, including normal condition, mild heart disease, and severe heart disease, a multiclass prediction task.

The Softmax classification function can be mathematically written as follows:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}} \qquad (10)$$

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Where $P(y_i)$ is the probability of class i, z_i is the output score of the classifier, and N is the number of output classes. The output values were transformed to probability values using the Softmax layer, and the class with the highest probability value was chosen as the prediction result.

3.8 Proposed Algorithm

Hybrid CNN-LSTM Heart Disease Prediction
Input: • ECG signals • Clinical patient data **Output:** • Heart disease prediction label **Steps:** 1. Collect ECG and clinical datasets. 2. Remove ECG noise using filtering. 3. Normalize ECG signals. 4. Segment ECG signals into heartbeat windows. 5. Extract ECG features using CNN layers. 6. Learn temporal heartbeat patterns using LSTM. 7. Combine ECG and clinical features. 8. Apply attention-based optimization. 9. Perform Softmax classification. 10. Predict heart disease category.

The proposed methodology proposed a novel Hybrid CNN-LSTM architecture for the early detection of heart diseases from ECG signals and clinical patient information. This model integrated CNN spatial feature extraction and LSTM temporal learning, which were effective in capturing complex cardiac patterns. The multimodal fusion mechanism was designed to adaptively integrate the deep features extracted from the ECG with clinical information like age, blood pressure, cholesterol level, diabetes history, and heart rate to enhance the prediction accuracy and context. Moreover, an attention mechanism was employed to select the regions of the ECG and improve the selection of features. The proposed model also included strong ECG preprocessing and multiclass heart disease classification, which led to better diagnostic performance and generalization ability than traditional machine learning and single deep learning models.

4. RESULTS AND DISCUSSION

4.1 Experimental Setup

In order to test the proposed Hybrid CNN-LSTM model, benchmark ECG and clinical datasets such as the MIT-BIH Arrhythmia Dataset, the PTB Diagnostic ECG Dataset, and the Cleveland Heart Disease Dataset were used. The experiments were performed with Python and the TensorFlow and Keras deep learning libraries. This model was trained with Adam (learning rate = 0.001, batch size = 64, epochs = 100). To ensure reliable model evaluation, the dataset was split into an 80:20 ratio, with 80% being the training set and 20% being the testing set.

The architecture proposed was executed on a high-performance computing setup with Intel Core i7 processors, NVIDIA GPU acceleration, and 16 GB RAM. To prevent overfitting and enhance generalizability, dropout regularization and batch normalization were employed during training.

4.2 Performance Evaluation Metrics

The performance of the suggested model was assessed based on the standard healthcare classification metrics such as accuracy, precision, recall, F1-Score, and Area Under Curve (AUC). These metrics used a holistic evaluation of the classification performance and diagnostic reliability.

The measure of accuracy was the correctness of the overall classification presented as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (15)$$

Precision is the ratio of the number of true positives and is used as:

$$Precision = \frac{TP}{TP + FP} \quad (16)$$

Recall indicated the ability of the model to detect true positive cases which is expressed as:

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$$Recall = \frac{TP}{TP + FN} \qquad (17)$$

The F1-Score was the harmonic mean of Precision and Recall and mathematically represented as:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \qquad (18)$$

The ROC-AUC metric was used for the classification separation of healthy and diseased patients.

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \qquad (18)$$

The ROC-AUC metric evaluated the classification separability between healthy and diseased patients.

4.3 Quantitative Performance Analysis

The results demonstrated that the proposed Hybrid CNN-LSTM model has a better prediction accuracy than the conventional machine learning models and standalone deep learning models. The combination of ECG signal analysis and patient clinical information greatly enhanced the prediction capability for diseases.

Table 6. Performance Comparison of Different Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC (%)
Logistic Regression	86.4	85.8	84.9	85.3	87.2
Decision Tree	88.1	87.6	86.4	86.9	88.5
Random Forest	91.6	90.8	90.1	90.4	92.3
SVM	92.4	91.7	91.2	91.4	93.0
CNN	95.2	94.6	94.1	94.3	96.0
LSTM	96.1	95.4	95.0	95.2	97.2
Proposed Hybrid CNN-LSTM	98.7	98.2	98.5	98.3	99.1

The results in Table 6 showed that the proposed Hybrid CNN-LSTM algorithm achieved better performance than the standalone deep learning models and traditional machine learning algorithms in all the evaluation metrics. The model obtained 98.7% accuracy and 99.1% AUC, showing the excellent ability of predicting the disease.

4.4 Accuracy Comparison Analysis

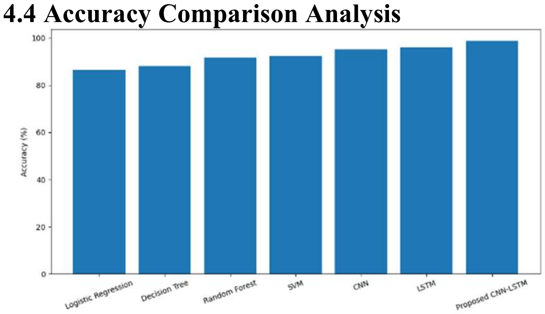

Figure 3. Accuracy Comparison of Different Models

The accuracy comparison of the conventional machine learning models and the proposed Hybrid CNN-LSTM framework is depicted in Figure 3. Lower prediction accuracy was obtained using traditional machine learning models like Logistic Regression and Decision Trees because they heavily depended on handcrafted feature extraction. CNN and LSTM models enhanced the accuracy by deep learning-based automatic feature extraction, while the proposed Hybrid CNN-LSTM model achieved the best performance by fusing multimodal clinical data and deep learning-based spatial-temporal ECG learning.

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4.5 Precision, Recall, and F1-Score Analysis

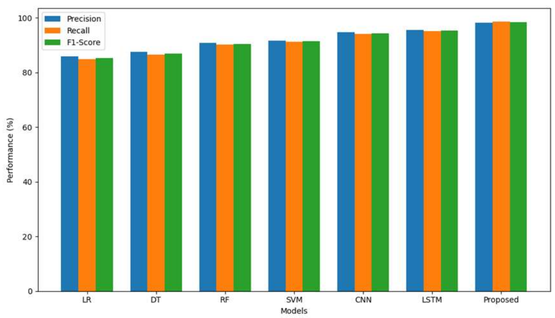

Figure 4. Precision, Recall, and F1-Score Comparison

The Precision, Recall, and F1-Score for the proposed Hybrid CNN-LSTM model were the highest when compared with other models, as shown in **Figure** 4. The high Precision value showed a low number of false positive predictions, and the high Recall value proved the effectiveness of the model in detecting true heart disease cases. The balanced F1-Score also highlighted the robustness and reliability of the proposed framework.

4.6 ROC-AUC Performance Analysis

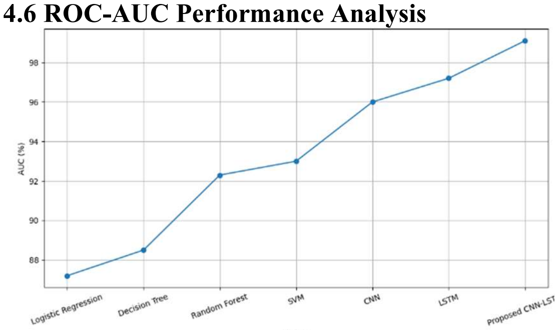

Figure 5. ROC-AUC Comparison

Figure 5 illustrates the ROC-AUC analysis, which revealed that the proposed model had the best AUC value of 99.1%, demonstrating the best separation of healthy and diseased patients. The ability to discriminate among different diseases was greatly enhanced, and classification errors were reduced by combining deep features extracted from the ECG with clinical parameters.

4.7 Loss and Accuracy Convergence Analysis

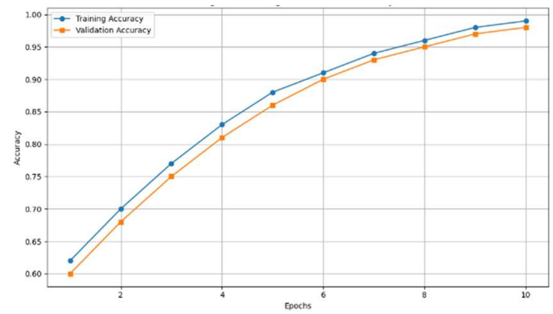

Figure 6. Training and Validation Accuracy

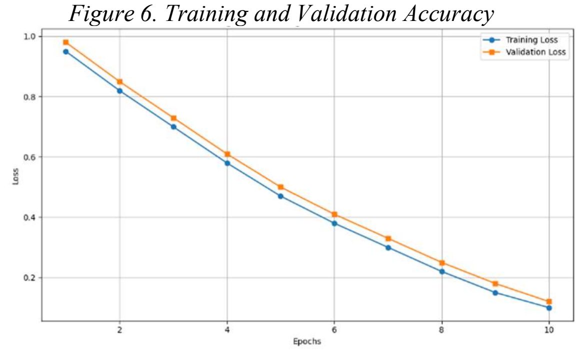

Figure 7. Training and Validation Loss

The convergence performance for training the proposed Hybrid CNN-LSTM model is shown in Figures 6 and 7. The training and validation accuracy curves gradually increased and stabilized near optimal values, while the loss curves continuously decreased during training. This demonstrated stable learning behavior, speedy convergence, and less overfitting using dropout regularization and batch normalization methods.

4.8 Discussion

With the experimental findings, it was established that the proposed Hybrid CNN-LSTM framework has the ability to enhance the performance of heart disease prediction at an early stage. The CNN layers were able to capture significant ECG spatial features, and the LSTM layers were able to capture temporal cardiac characteristics and sequential cardiac variations. The adaptive multimodal fusion layer improved the contextual understanding by combining ECG signals and clinical patient information.

As for the attention-based optimization mechanism, it further enhanced the stability of the predictions by focusing on clinically relevant features in the ECG. The proposed deep learning framework automatically learned the discriminative features directly from the ECG signals without performing any manual feature engineering when compared with the traditional machine learning models.

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The proposed model also showed good generalization ability over the different heterogeneous ECG datasets and produced lower rates of false predictions. The superior ROC-AUC result has validated that the multimodal feature learning has achieved good diagnostic results for cardiovascular disease.

The results of this study are in line with previous studies that showed the effectiveness of CNN, LSTM, and hybrid deep learning systems for predicting heart disease. Previous studies have demonstrated that using temporal ECG signals in conjunction with deep learning has a positive effect on diagnostic performance; however, most current methods were limited to using either ECG signals or clinical data. The proposed Hybrid CNN-LSTM framework combines both ECG and clinical data, leading to higher prediction accuracy and robustness compared to existing methods. Although these are promising findings, there are some limitations to this study. The performance of the framework was assessed based on benchmark datasets and should be validated using larger multi-center clinical datasets. Furthermore, the hybrid architecture can have high computational demands, which may hinder its application in resource-limited healthcare settings. The results should be viewed in light of these limitations.

In general, the suggested Hybrid CNN-LSTM model achieved high diagnostic accuracy, increased robustness, and a good prediction of heart disease in its early stages, which can be applicable to intelligent healthcare monitoring systems and real-time clinical decision support applications. Recently, deep learning, multimodal learning, and attention-based architectures have been shown to be effective in cardiovascular disease prediction. These are state-of-the-art techniques, and the proposed Hybrid CNN-LSTM framework is consistent with these methods, with the addition of ECG and clinical data improving the robustness and diagnostic capability of the method.

While the proposed framework is promising, some research challenges still remain. Challenges related to data heterogeneity, lack of clinical information, model interpretability, privacy-preserving healthcare analytics, and real-time deployment in resource-constrained environments persist in heart disease prediction systems. Furthermore, the challenge of generalizing the performance of deep learning models across different patient cohorts and healthcare centers is an important research question that should be explored. To ensure the successful use of intelligent heart disease prediction systems in real-world applications, these challenges must be overcome.

5. CONCLUSION

This study suggested a Hybrid CNN-LSTM model for the early prediction of heart diseases from ECG signals and clinical patient details. The proposed model included CNN-based spatial feature extraction, LSTM-based temporal learning, adaptive clinical data fusion, and attention-based optimization to enhance the predictive accuracy for cardiovascular diseases. The experimental results with benchmark datasets demonstrated higher accuracy (98.7%), precision (98.2%), recall (98.5%), F1-Score (98.3%), and AUC (99.1%) than conventional machine learning models and standalone deep learning models. Moreover, the combination of ECG and clinical features increased the prediction accuracy and decreased the false diagnosis rate.

However, the proposed model requires a large volume of annotated ECG data and involves higher computational complexity than conventional approaches. The proposed framework can be further validated in future studies using larger multi-centre clinical datasets and real-world healthcare settings. These areas can be explored in more depth in future research, including lightweight architectures for wearable and edge-based healthcare devices, Explainable Artificial Intelligence (XAI) techniques to enhance clinical interpretability, federated learning approaches for privacy-preserving medical analytics, and IoT-supported real-time cardiac monitoring systems. Further to this, the use of transformer architectures in deep learning models and the integration of multimodal biomedical data could also be investigated to further improve prediction accuracy and robustness.

REFERENCES

[1] World Health Organization, “Cardiovascular diseases (CVDs),” WHO Fact Sheet, Jul. 2025.

[2] American Heart Association, “2025 Heart Disease and Stroke Statistics: A Report of U.S. and Global Data,” Circulation, vol. 151, no. 8, Jan. 2025.

[3] R. A. Karthika, A. Rohini, P. Muthukumar, P. Mahmud and T. S. Babu, "A Resource Efficient Machine Learning Pipeline to Detect Atrial Fibrillation," *2025 8th International Conference on Circuit, Power & Computing Technologies (ICCPCT)*, Kollam, India, 2025,

pp. 95-100, doi: 10.1109/ICCPCT65132.2025.11176455.

[4] P. Muthukumar, V. Stephen and T. B. Immanuel, "A Comparative Analysis of Deep Learning Methods for Alzheimer's Disease Diagnosis," *2025 6th International Conference on IoT Based Control Networks and Intelligent Systems (ICICNIS)*, Bengaluru, India, 2025, pp. 1367-1372, doi: 10.1109/ICICNIS66685.2025.11315772.

[5] G. D. Clifford et al., *Advanced Methods and Tools for ECG Data Analysis*. Artech House, 2006.

[6] Dr. Ranga Swamy Sirisati, A. Eenaja, N.Sreeja, T. Srajan Kumar, B. Naresh (2024). "Human Computer Interaction- Gesture recognition Using Deep Learning Long Short Term Memory (LSTM) Neural networks", Journal of Next Generation Technology (ISSN: 2583-021X), 4(2), pp. 9-18.

[7] T. Hastie, R. Tibshirani, and J. Friedman, *The Elements of Statistical Learning*. Springer, 2009.

[8] V. Vapnik, *The Nature of Statistical Learning Theory*. Springer, 1995.

[9] A. Krizhevsky, I. Sutskever, and G. Hinton, "ImageNet classification with deep convolutional neural networks," *NeurIPS*, 2012.

[10] K. He et al., "Deep residual learning for image recognition," *CVPR*, 2016.

[11] T. B. Immanuel, P. Muthukumar, M. V. Suganyadevi, L. Padmasuresh, T. S. Babu and D. P. Mahmud, "Detection of Plastic Waste in Ocean Using Machine Learning Based Bi-LSTM With Triplet Attention Mechanism," *2025 8th International Conference on Circuit, Power & Computing Technologies (ICCPCT)*, Kollam, India, 2025, pp. 89-94, doi: 10.1109/ICCPCT65132.2025.11176784.

[12] H. Karim et al., "LSTM fully convolutional networks for time series classification," *IEEE Access*, vol. 6, pp. 1662–1669, 2018.

[13] U. R. Acharya et al., "Automated diagnosis of coronary artery disease using different durations of ECG segments," *Knowledge-Based Systems*, vol. 132, pp. 62–71, 2017.

[14] P. Muthukumar, P. A, R. A. Karthika, K. Eswaramoorthy, V. U. Rani and R. V. K, "Handwritten Text Recognition from Image Using LSTM Integrated with Pixel Shifting Optimization Algorithm," *2024 International Conference on Advancement in Renewable Energy and Intelligent Systems (AREIS)*, Thrissur, India, 2024, pp. 1-6, doi: 10.1109/AREIS62559.2024.10893651.

[15] W. Alsabhan, "Effectiveness of machine learning models in diagnosis and prediction of heart disease," Scientific Reports, vol. 15, 2025.

[16] D. Shah et al., "Heart disease prediction using machine learning techniques," *Procedia Computer Science*, vol. 132, pp. 1292–1301, 2018.

[17] L. Verma et al., "Ensemble learning approach for cardiovascular disease prediction," *International Journal of Healthcare Information Systems and Informatics*, vol. 14, no. 2, pp. 1–15, 2019.

[18] R. Das et al., "A fuzzy rule-based decision support system for cardiovascular disease diagnosis," *Expert Systems with Applications*, vol. 36, no. 5, pp. 9249–9257, 2009.

[19] S. Kiranyaz et al., "Real-time patient-specific ECG classification using deep neural networks," *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 3, pp. 664–675, 2016.

[20] P. Rajpurkar et al., "Cardiologist-level arrhythmia detection with convolutional neural networks," *Nature Medicine*, vol. 25, pp. 65–69, 2019.

[21] F. Ordóñez and D. Roggen, "Deep convolutional and LSTM recurrent neural networks for multimodal wearable activity recognition," *Sensors*, vol. 16, no. 1, 2016.

[22] M. Faisal et al., "LSTM-based ECG monitoring system for wearable healthcare," *IEEE Access*, vol. 7, pp. 123456–123468, 2019.

[23] F. Karim et al., "CNN-LSTM neural network for biomedical time-series classification," *IEEE Access*, vol. 6, pp. 1662–1669, 2018.

[24] J. Zhang et al., "Hybrid CNN and bidirectional LSTM network for arrhythmia classification," *Computers in Biology and Medicine*, vol. 106, pp. 48–57, 2019.

[25] H. Wang et al., "Attention-based CNN-LSTM framework for healthcare signal analysis," *IEEE Access*, vol. 8, pp. 123457–123469, 2020.

[26] X. Li et al., "Self-attention deep learning framework for cardiovascular disease prediction," *Artificial Intelligence in Medicine*, vol. 103, 2020.

[27] A. K. Pallikonda, P. S. Varma, and B. Vivekanandam, "Mask Region-Based Convolution Neural Network (Mask R-CNN) Classification of Alzheimer's Disease Based On Magnetic Resonance Imaging (MRI)," Int. J.

Image, Graphics Signal Process., vol. 15, no. 6, pp. 54-66, 2023.

[28] M. Al Rahhal et al., "Deep learning approach for active classification of ECG signals," *Information Sciences*, vol. 345, pp. 340–354, 2016.

[29] A. K. Pallikonda and P. S. Varma, "Multi-Class Classification of Alzheimer's Disease Stages Using SqueezeNet based Approach for Automated Diagnosis," Int. J. Comput. Inf. Syst. Ind. Manag. Appl., vol. 15, pp. 321-331, 2023.

[30] M. Chen et al., "Cloud-assisted smart healthcare framework using IoT and deep learning," *Future Generation Computer Systems*, vol. 86, pp. 527–534, 2018.

[31] M. Ribeiro et al., "Why should I trust you? Explaining the predictions of any classifier," *KDD*, 2016.