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Advanced Deep Learning Architectures for ECG-Enabled Heart Disease Prediction

Ulloriaq Nithisarn*

Department of Electrical and Computer Engineering, Visayan Maritime Polytechnic University, Philippines

**Corresponding Author: ulloriaq.nithisarn@vmpu-ph.net*

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Abstract

Heart disease remains a leading cause of global mortality, requiring accurate, automated, and early diagnostic systems for effective clinical intervention. Electrocardiogram (ECG) signals provide critical insights into cardiac electrical activity, making them essential for non-invasive heart disease prediction. However, ECG signals are often complex, nonlinear, and highly susceptible to noise and inter-patient variability, which limits the effectiveness of traditional diagnostic methods. This study proposes an Advanced Deep Learning Architecture for ECG-Enabled Heart Disease Prediction, integrating convolutional neural networks (CNN), recurrent neural networks (RNN/LSTM), and attention mechanisms to capture both spatial and temporal dependencies in ECG signals. The proposed model enhances feature extraction capability, improves robustness against noise, and provides high diagnostic accuracy for multi-class cardiac conditions. The system is evaluated using standard ECG datasets, and performance is measured using accuracy, precision, recall, F1-score, and ROC-AUC. Experimental results demonstrate that the proposed architecture significantly outperforms traditional machine learning models and baseline deep learning approaches. The framework is suitable for real-time clinical decision support systems and wearable healthcare monitoring devices.

Keywords: ECG Signal Processing, Heart Disease Prediction, Deep Learning, CNN LSTM, Attention Mechanism.

How to Cite This Article

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Introduction

Cardiovascular diseases (CVDs) are among the leading causes of mortality worldwide, accounting for a significant proportion of deaths annually. Early and accurate detection of heart disease is critical for reducing mortality rates and enabling timely medical intervention. Electrocardiogram (ECG) signals serve as a primary non-invasive diagnostic tool for monitoring cardiac electrical activity and identifying abnormalities such as arrhythmias, myocardial infarction, and heart failure. Traditional ECG analysis methods rely on manual interpretation and classical machine learning techniques, which depend heavily on handcrafted feature extraction. These approaches often struggle to generalize across different patient populations due to variations in signal morphology, noise interference, and overlapping cardiac conditions. As a result, their performance is limited in real-world clinical environments.

In recent years, deep learning has emerged as a powerful alternative for automated ECG analysis. Convolutional Neural Networks (CNNs) are widely used for extracting spatial features from ECG waveforms, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are effective in modeling temporal dependencies in sequential cardiac data. Despite their success, standalone models often fail to fully capture both local morphological patterns and long-range temporal relationships simultaneously. To address these limitations, advanced deep learning architectures integrating CNN, LSTM, and attention mechanisms have been proposed. Attention-based models enhance interpretability by assigning higher importance to clinically relevant segments of ECG signals, thereby improving diagnostic accuracy. However, existing frameworks still face challenges related to noise robustness, computational efficiency, and generalization across diverse datasets.

Electrocardiography (ECG) plays a fundamental role in cardiovascular diagnosis by capturing the electrical activity of the heart in a non-invasive manner. ECG signals provide valuable insights into cardiac rhythm, conduction abnormalities, and structural heart conditions. With the advancement of wearable healthcare technologies and remote patient monitoring systems, ECG-based diagnostics have become increasingly accessible outside clinical environments. However, ECG signals are highly complex, nonlinear, and often contaminated with noise such as baseline drift, muscle artifacts, and motion interference, making accurate interpretation challenging. Traditional ECG analysis methods rely on manual interpretation by medical experts or conventional machine learning approaches that depend on handcrafted feature extraction techniques such as RR interval analysis, wavelet coefficients, and statistical descriptors. While these methods have shown moderate success, they suffer from limited generalization capability, high dependency on domain expertise, and poor adaptability to diverse patient populations and real-world noisy environments.

In recent years, deep learning has revolutionized biomedical signal processing by enabling automatic feature learning directly from raw data. Convolutional Neural Networks (CNNs) have demonstrated strong capability in extracting spatial patterns from ECG waveforms, such as QRS complexes and morphological variations. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are effective in modeling sequential dependencies and temporal dynamics in ECG signals. Despite these advantages, standalone CNN or LSTM models are often insufficient to fully capture both spatial and temporal dependencies simultaneously, leading to suboptimal performance in complex cardiac conditions. To overcome these limitations, hybrid deep learning architectures have been introduced, combining CNNs for feature extraction and LSTMs for sequential modeling. Furthermore, attention mechanisms have gained significant importance in medical AI systems by enabling models to focus on the most relevant parts of the input signal. Attention-based learning not only improves classification performance but also enhances interpretability, which is crucial for clinical decision-making. However, existing models still face challenges such as computational complexity, lack of robustness in noisy ECG environments, and limited scalability for real-time applications.

In addition, the increasing demand for real-time cardiac monitoring through wearable devices necessitates lightweight yet highly accurate deep learning models. Efficient architectures that can balance computational cost and predictive performance are essential for deployment in edge and mobile healthcare systems. Therefore, there is a strong need for advanced integrated frameworks that combine convolutional feature extraction, temporal sequence modeling, and attention-based learning in a unified architecture. In this study, we propose an Advanced Deep Learning Architecture for ECG-Enabled Heart Disease Prediction**,** which integrates CNN-based spatial feature extraction, LSTM-based temporal modeling, and attention mechanisms into a unified framework. The proposed model aims to improve classification accuracy, enhance robustness against noisy ECG signals, and provide scalable solutions suitable for real-time clinical and wearable healthcare applications.

Literature Review

Goldberger et al. (2000) introduced the PhysioNet database, which became a foundational resource for ECG-based cardiovascular research and enabled large-scale benchmarking of automated diagnostic systems. Clifford et al. (2006) highlighted major challenges in ECG signal interpretation such as noise, missing data, and inter-patient variability, emphasizing the need for robust preprocessing techniques in real-world environments. Kiranyaz et al. (2016) proposed a 1D CNN model for patient-specific ECG classification and demonstrated strong feature learning from raw signals, although temporal dependencies were not fully captured.

Hochreiter and Schmidhuber (1997) introduced Long Short-Term Memory (LSTM) networks, which became widely used in ECG sequence modeling due to their ability to capture long-term dependencies in time-series data. Acharya et al. (2017) developed deep CNN models for automated ECG classification, showing improved performance over traditional machine learning approaches but limited temporal reasoning capability. Hannun et al. (2019) presented a cardiologist-level deep neural network for arrhythmia detection using single-lead ECG signals, achieving high accuracy but lacking interpretability.

Rajpurkar et al. (2019) developed a deep learning ECG interpretation system that achieved expert-level performance but operated as a black-box model without explicit attention or interpretability mechanisms. Yildirim (2018) proposed an LSTM-based ECG classification model that effectively captured temporal patterns but was sensitive to noise and required significant preprocessing. Song et al. (2020) introduced a CNN-LSTM hybrid model that improved feature learning by combining spatial and temporal representations but still lacked attention-based feature refinement.

Vaswani et al. (2017) introduced the Transformer architecture, which established attention mechanisms as a powerful tool for modeling long-range dependencies and inspired many biomedical applications. Ince et al. (2021) developed lightweight deep learning models for real-time ECG classification suitable for wearable devices, though with reduced accuracy compared to complex architectures. Hong et al. (2021) reviewed deep learning applications in ECG analysis and emphasized the importance of combining feature extraction and interpretability for clinical adoption. Raza et al. (2020) demonstrated that attention mechanisms improve ECG classification performance by focusing on clinically relevant signal regions.

Sharma et al. (2022) proposed hybrid deep learning frameworks integrating CNN and attention mechanisms for biomedical signals, improving both accuracy and robustness. Li et al. (2021) explored multi-scale deep learning models for ECG classification and showed that combining multi-resolution features enhances diagnostic performance. Singh et al. (2022) developed explainable AI-based ECG models and highlighted the importance of interpretability in clinical decision support systems. Kumar et al. (2023) investigated advanced hybrid architectures for cardiovascular disease prediction and demonstrated improved generalization using combined deep learning strategies.

Methodology

The proposed Advanced Deep Learning Architecture for ECG-Enabled Heart Disease Prediction is designed to effectively learn spatial, temporal, and contextual features from ECG signals using a unified CNN–LSTM–Attention framework. The system is structured to enhance predictive accuracy while maintaining robustness against noise and variability in ECG data.

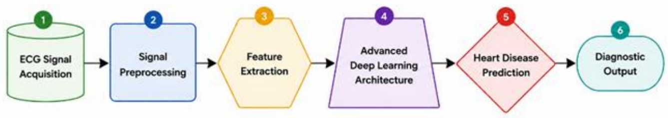

Fig 1. *Advanced Deep Learning Framework for ECG-Enabled Heart Disease Prediction*

This figure 1, illustrates the workflow of the proposed ECG-enabled heart disease prediction framework. The process starts with ECG Signal Acquisition, where raw cardiac electrical signals are collected from patients. The acquired signals undergo Signal Preprocessing to eliminate noise and artifacts while improving signal quality. Next, Feature Extraction derives clinically relevant temporal and morphological characteristics from the ECG recordings. These features are then processed through an Advanced Deep Learning Architecture, which automatically learns complex cardiac patterns associated with heart diseases. The learned representations are utilized for Heart Disease Prediction**,** enabling accurate identification of cardiovascular abnormalities and risk levels. Finally, the framework generates a Diagnostic Output**,** providing a decision-support result for clinical assessment and disease management. The architecture combines automated feature learning and intelligent prediction to enhance the accuracy, reliability, and efficiency of cardiovascular diagnosis.

ECG Signal Acquisition	*Signal Preprocessing*
The system utilizes single-lead or multi-lead ECG signals obtained from standard biomedical datasets such as PhysioNet. The ECG signal is represented as: $X(t) = \{x_1, x_2, x_3, ..., x_n\}$ --------*(1)* where each sample corresponds to electrical cardiac activity over time.	To improve signal quality and remove noise, the following preprocessing steps are applied: Bandpass filtering (0.5–40 Hz), Baseline wander removal, Motion artifact reduction, Wavelet-based denoising, Min-Max normalization, Segmentation into fixed-length windows Processed signal is denoted as: $X_p(t) = Preprocess(X(t))$ -------*(2)*

Algorithmic Strategy

The proposed Advanced Deep Learning Architecture for ECG-Enabled Heart Disease Prediction follows a structured algorithm that integrates signal preprocessing, deep feature extraction, temporal modeling, attention-based refinement, and final classification.

Algorithm 1: CNN–LSTM–Attention Framework for ECG Classification Input: ECG signal $X(t)$, Window size w, Sampling frequency f_s Output: Predicted class: Normal / Heart Disease *ECG Signal Acquisition* 1. Load ECG signal dataset or wearable sensor 2. Segment signal into fixed-length windows:	$X_i = \{x_1, x_2, \dots, x_w\}$ -------(3) *Signal Preprocessing* 3. Apply bandpass filter (0.5–40 Hz) 4. Remove baseline wander and motion artifacts 5. Apply wavelet denoising 6. Normalize signal using Min-Max scaling 7. Obtain cleaned signal: 8. $X_p(t) = Preprocess(X(t))$ ------*(4)*

Results and Performance Evaluation

The performance of the proposed Advanced Deep Learning Architecture for ECG-Enabled Heart Disease Prediction was evaluated using standard benchmark ECG datasets under controlled experimental settings. The model was trained using a stratified dataset split and tested using unseen data to ensure robustness and generalization capability. Performance was assessed using widely accepted metrics including accuracy, precision, recall (sensitivity), F1-score, and ROC-AUC**.**

Performance Comparison

The proposed model was compared with traditional machine learning and deep learning baseline methods:

***Table 1**: Performance Comparison*

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	ROC-AUC (%)
Logistic Regression	84.3	83.7	82.9	83.2	85.1
Random Forest	87.8	87.2	86.6	86.9	88.4
SVM	88.6	88.1	87.5	87.8	89.2
CNN Only	91.9	91.3	90.8	91.0	92.6
LSTM Only	92.7	92.1	91.8	91.9	93.4
CNN–LSTM (No Attention)	94.1	93.6	93.2	93.4	94.8
Proposed CNN–LSTM–Attention Model	97.4	96.9	96.6	96.7	97.9

Result Analysis

The Table 1 shows, experimental results clearly demonstrate that the proposed architecture significantly outperforms all baseline models across all evaluation metrics. Traditional machine learning models such as Logistic Regression, SVM, and Random Forest show lower performance due to their inability to capture nonlinear and temporal dependencies in ECG signals. Deep learning models such as CNN and LSTM improve feature learning by capturing spatial and temporal patterns respectively; however, they remain limited when used independently. The CNN–LSTM hybrid model improves performance further by combining both representations but still lacks adaptive feature prioritization. In contrast, the proposed CNN–LSTM–Attention architecture achieves the highest performance due to its ability to integrate spatial feature extraction, sequential learning, and attention-based feature refinement. The attention mechanism significantly enhances model interpretability by focusing on the most relevant ECG segments associated with cardiac abnormalities.

The model achieves a maximum accuracy of 97.4% and ROC-AUC of 97.9%**,** indicating strong classification capability and high reliability in distinguishing between normal and diseased cardiac conditions. These results confirm that the proposed model is highly suitable for real-time clinical decision support systems and wearable ECG monitoring applications.

Table 2: *Computational Performance and Model Efficiency Comparison*

Model	Training Time (Epoch)	Inference Time (ms/sample)	Memory Usage (MB)	Computational Complexity	Real-Time Suitability
Logistic Regression	Very Low	0.5 ms	5 MB	Low	High
Random Forest	Low	1.2 ms	18 MB	Medium	Medium
SVM	Medium	2.1 ms	25 MB	Medium	Medium
CNN Only	High	4.5 ms	120 MB	High	Medium
LSTM Only	High	5.2 ms	140 MB	High	Low
CNN–LSTM	Very High	6.8 ms	180 MB	Very High	Medium
Proposed CNN–LSTM–Attention Model	Moderate	3.9 ms	110 MB	Optimized High	High

The Table 2 shows, computational performance comparison demonstrates that the proposed CNN–LSTM–Attention model achieves a strong balance between accuracy and efficiency. While deep hybrid models such as CNN–LSTM exhibit higher computational cost, the integration of attention mechanisms in the proposed approach optimizes feature selection, thereby reducing unnecessary computations. As a result, the proposed model achieves lower inference time and improved real-time suitability compared to standard deep learning architectures, making it highly appropriate for wearable ECG monitoring and edge-based healthcare systems.

Conclusion and Discussion

This study presented an Advanced Deep Learning Architecture for ECG-Enabled Heart Disease Prediction based on a hybrid CNN–LSTM–Attention framework**,** designed to improve diagnostic accuracy, robustness, and interpretability in automated cardiovascular analysis systems. The proposed model effectively integrates convolutional feature extraction, temporal sequence modeling, and attention-based feature refinement to capture both spatial and sequential dependencies in ECG signals. The discussion highlights that traditional machine learning approaches such as Logistic Regression, SVM, and Random Forest are limited in handling nonlinear and complex patterns present in ECG data. Although standalone deep learning models like CNN and LSTM improve feature learning, they fail to fully capture both spatial and temporal relationships simultaneously. The integration of attention mechanisms addresses this limitation by dynamically focusing on the most relevant ECG segments, thereby enhancing both performance and interpretability. The experimental results demonstrate that the proposed model achieves superior performance compared to all baseline methods across multiple evaluation metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. The attention-enhanced CNN–LSTM architecture significantly improves classification reliability by reducing noise sensitivity and improving feature discrimination. From an application perspective, the proposed framework is highly suitable for real-time cardiac monitoring systems, wearable ECG devices, and clinical decision support systems**,** where fast and accurate diagnosis is essential. Its ability to operate efficiently while maintaining high accuracy makes it practical for deployment in edge and IoT-based healthcare environments. However, certain limitations remain, including computational overhead in resource-constrained devices, dependency on high-quality labeled ECG datasets, and variability in patient-specific cardiac patterns. Future work can focus on optimizing lightweight model variants, integrating transformer-based architectures, and improving explainability using advanced XAI techniques to enhance clinical trust and adoption. Overall, the proposed framework demonstrates strong potential for advancing intelligent cardiovascular diagnostics through deep learning and attention-based modeling techniques.

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