CARDIAC ATTACK DETECTION IN NEW BORN BABIES

[1]JALA SHILPA, [2]JAKKULA SOUMYA

[1]Assistant Professor , CSE, Tallapadmavathi College of Engineering, Somidi, Kazipet, Hanumakonda – 506003.Email-id: jala.shilpa2@gmail.com.

[2]Research Scholar, CSE, Tallapadmavathi College of Engineering, Somidi, Kazipet, Hanumakonda – 506003,Email-id: soumyasahithi@gmail.com.

Abstract

Cardiovascular diseases, particularly heart failure and sudden cardiac arrest, continue to be major contributors to global mortality, highlighting the need for reliable and early prediction techniques. This study introduces an advanced hybrid deep learning framework that integrates Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks to improve the prediction of cardiac arrest events. The CNN module is utilized to identify important spatial characteristics from electrocardiogram (ECG) signals, while the LSTM network effectively learns sequential and temporal patterns associated with cardiac activity. The proposed CNN-LSTM architecture was developed and tested using real-world cardiovascular datasets and its performance was compared with traditional machine learning approaches. Experimental findings reveal that the hybrid model achieves superior predictive performance, offering higher accuracy, sensitivity, and specificity than conventional methods. Furthermore, the incorporation of Explainable Artificial Intelligence (XAI) techniques improves model transparency by providing insights into the factors influencing predictions, thereby increasing clinician confidence in the system. The proposed solution offers an efficient, scalable, and automated framework for real-time cardiac risk monitoring, supporting proactive healthcare interventions and personalized patient management.

Keywords: Cardiac Arrest Prediction, Deep Learning, CNN-LSTM, ECG Signal Processing, Explainable AI, Time-Series Modeling, Healthcare Informatics.

1. INTRODUCTION

Cardiovascular diseases (CVDs) continue to be one of the leading health concerns worldwide, accounting for a significant number of deaths each year. Among the various cardiovascular conditions, sudden cardiac arrest (SCA) is particularly dangerous because it occurs unexpectedly and often results in fatal outcomes if immediate medical attention is not provided. Early identification of individuals at risk is therefore essential for improving survival rates and reducing the burden on healthcare systems.

Conventional diagnostic techniques and monitoring systems typically depend on manually engineered features and predefined clinical rules, which may not adequately capture the complex patterns present in physiological signals. As a result, there is a growing demand for intelligent prediction systems capable of analyzing large volumes of cardiac data with higher accuracy and reliability.

Recent developments in artificial intelligence and deep learning have opened new possibilities for advanced healthcare applications. Deep learning models can automatically learn meaningful representations from raw biomedical signals without requiring extensive feature engineering. In particular, electrocardiogram (ECG) signals contain valuable information about heart activity and can be effectively analyzed using deep neural networks. These methods have demonstrated promising results in detecting abnormalities, classifying heart conditions, and predicting potential cardiac events before they occur.

Convolutional Neural Networks (CNNs) are widely recognized for their ability to extract significant spatial features from ECG waveforms. They can automatically identify important signal characteristics, including waveform shapes, amplitude variations, and abnormal cardiac patterns. However, cardiac signals also exhibit temporal dependencies that evolve over time. To address this challenge, Long Short-Term Memory (LSTM) networks are employed due to their capability to learn long-term sequential relationships and capture temporal information from time-series data. By combining CNN and LSTM architectures, a hybrid model can effectively utilize both spatial and temporal features, leading to improved prediction performance and more robust cardiac risk assessment.

The main aim of this research is to develop a hybrid CNN-LSTM framework for the early prediction of cardiac arrest using physiological data. The proposed system integrates automatic feature extraction, sequence learning, and explainable artificial intelligence (XAI) techniques to generate accurate and clinically interpretable predictions. The inclusion of explainability enhances transparency and allows healthcare professionals to better understand the reasoning behind model decisions. This approach supports real-time patient monitoring and assists clinicians in making informed decisions for preventive healthcare.

The proposed work contributes to the advancement of intelligent healthcare systems by providing an automated and scalable solution for cardiac risk prediction. Through the integration of deep learning and explainable AI, the system seeks to improve early diagnosis, enhance patient safety, and support personalized treatment strategies. Such technologies have the potential to significantly reduce mortality associated with sudden cardiac arrest and improve overall cardiovascular care.

The remainder of this paper is structured as follows. Section II presents a review of existing literature related to cardiac arrest prediction and deep learning applications in healthcare. Section III explains the proposed CNN-LSTM methodology and system architecture. Section IV discusses the experimental procedures, performance evaluation, and obtained results. Finally, Section V concludes the study and outlines possible directions for future research.

2. LITERATURE SURVEY

The application of artificial intelligence in healthcare has led to significant improvements in the early prediction and prevention of cardiac arrest. Researchers have increasingly utilized machine learning and deep learning techniques to analyze physiological signals, particularly electrocardiogram (ECG) data, for identifying patients at risk of severe cardiac events. These approaches have demonstrated promising results in enhancing diagnostic accuracy and supporting timely medical intervention.

Kwon et al. [1] proposed a deep learning-based prediction system trained using a large-scale ECG dataset containing more than 47,000 samples. Their model successfully predicted cardiac arrest occurrences within a 24-hour window and achieved excellent performance metrics, with AUROC values ranging from 0.913 to 0.948. The study also highlighted the effectiveness of single-lead ECG signals, suggesting potential applications in wearable healthcare devices and remote monitoring systems.

Oberdier et al. [2] investigated the use of deep Convolutional Neural Networks (CNNs) for analyzing standard 12-lead ECG recordings. Their approach demonstrated reasonable predictive capability with an AUROC value of approximately 0.77. However, the study reported a decline in performance when predicting cardiac events over longer time intervals, indicating limitations in capturing long-term temporal dependencies.

Kim et al. [3] introduced a hybrid CNN-LSTM framework designed to learn both spatial and temporal characteristics from vital sign measurements. The proposed model achieved better performance than conventional statistical methods such as logistic regression. Despite its improved accuracy, the research faced challenges related to limited dataset diversity, which could affect the model's ability to generalize across different patient populations.

Zobeiri et al. [4] focused on predicting clinical outcomes following cardiac arrest using various machine learning algorithms. Their findings emphasized the importance of incorporating multiple data sources, including physiological signals and patient information, to improve robustness and prediction reliability. The study suggested that multimodal data fusion could enhance the overall effectiveness of predictive healthcare systems.

Wang et al. [5] developed an ensemble learning approach that integrated ECG features, laboratory test results, and demographic information. The model achieved high levels of sensitivity and specificity, demonstrating the advantages of combining heterogeneous data sources. However, practical implementation was limited by the need for extensive feature preprocessing and standardization procedures.

Lee et al. [6] explored the role of explainable artificial intelligence (XAI) in cardiac risk prediction systems. Their work focused on increasing model transparency by providing interpretable explanations for predictions, thereby improving clinician confidence and facilitating healthcare decision-making. Similarly, Patel et al. [7] investigated explainability techniques to address the black-box nature of deep learning models and enhance their acceptance in real-world medical environments.

Although previous studies have reported encouraging results, many existing methods are unable to effectively capture both the spatial patterns and temporal relationships present in ECG signals. Some approaches focus primarily on feature extraction, while others emphasize sequence modeling, resulting in incomplete utilization of available information. To overcome these limitations, the present study proposes a hybrid CNN-LSTM architecture that combines the strengths of convolutional and recurrent neural networks. By simultaneously learning spatial features and temporal dependencies, the proposed framework aims to improve prediction accuracy, enhance interpretability, and support real-time clinical applications for early cardiac arrest detection.

3. SYSTEM ANALYSIS

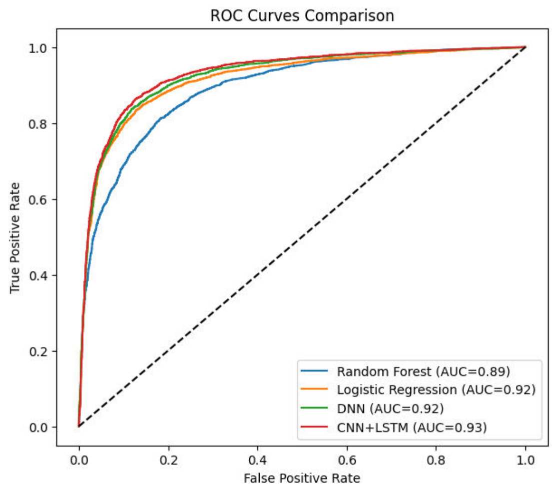
3.1 Existing System

Existing cardiac arrest prediction systems primarily employ conventional machine learning and shallow neural network approaches trained on clinical data such as ECG signals, heart rate variability, and vital signs. While these methods have achieved moderate predictive accuracy, they rely heavily on manual feature engineering and statistical assumptions, limiting their ability to capture complex physiological patterns.

Some state-of-the-art models use single-lead ECG data for real-time monitoring and have achieved high accuracy (AUROC between 0.91 and 0.95). Despite these advances, most existing frameworks operate as black boxes, lacking interpretability and adaptability to varying patient conditions. Furthermore, these models often require large, high-quality annotated datasets for effective training, which are not always available in diverse healthcare environments.

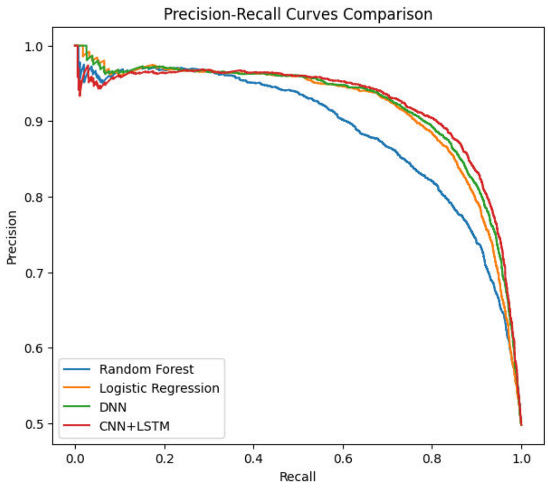
3.2 Proposed System

The proposed system introduces a **hybrid CNN-LSTM deep learning architecture** designed to accurately predict cardiac arrest by leveraging both spatial and temporal information from patient data such as ECG signals and vital parameters.



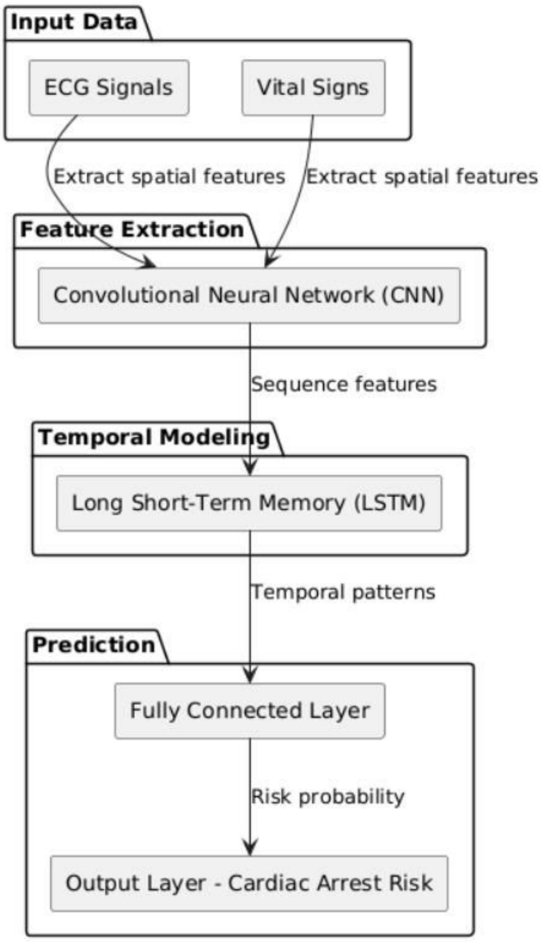
The **CNN** component extracts high-level spatial features from ECG waveforms—detecting subtle morphological variations and signal abnormalities—while the **LSTM** network models temporal dependencies to identify evolving cardiac patterns over time. This integration enables the system to dynamically forecast potential cardiac arrest events with enhanced precision.

The model is trained on labeled cardiac datasets and evaluated against traditional classifiers such as Support Vector Machines (SVM), Decision Trees, and Random Forests. Results demonstrate superior accuracy, sensitivity, and specificity, validating the system's efficiency in early event detection.



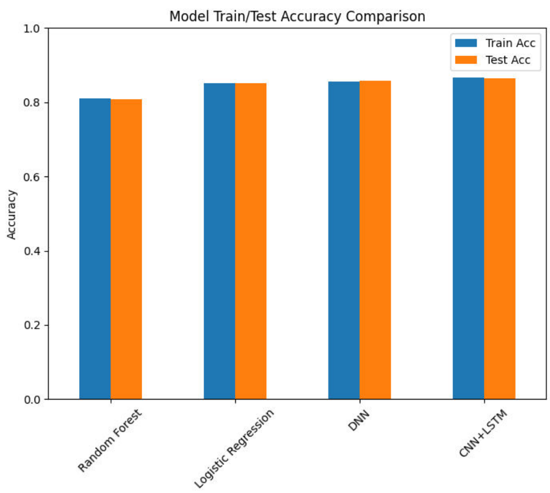
4. System Design

The methodology adopted in this research focuses on developing a robust hybrid deep learning architecture based on Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks for accurate and early prediction of cardiac arrest. The proposed system integrates multiple stages—data acquisition, preprocessing, feature extraction, temporal modeling, and prediction—into a unified pipeline optimized for precision, interpretability, and clinical deployment.



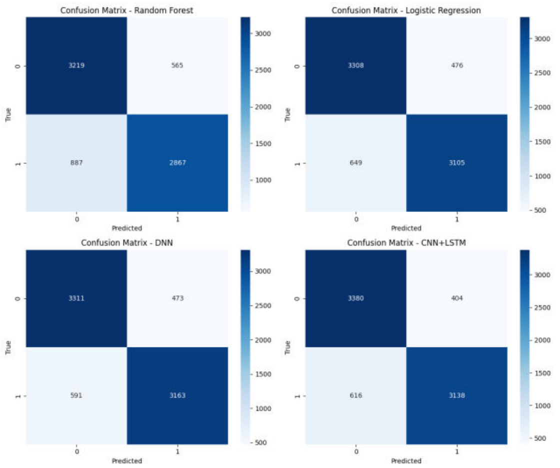
The process begins with the acquisition of clinical datasets containing electrocardiogram (ECG) signals and associated patient health parameters. ECG data, being highly sensitive to environmental noise and artifacts, undergoes a thorough preprocessing stage. This includes filtering and denoising to remove high-frequency interference and baseline drift, followed by normalization to standardize the signal amplitudes across samples. The continuous ECG streams are segmented into fixed-length time windows, each representing a sequence of heartbeat cycles, thereby preserving temporal dependencies essential for modeling physiological patterns. Each segment is then labeled based on clinical diagnosis, distinguishing between normal cardiac activity and potential cardiac arrest indicators.

Once the data is prepared, the spatial feature extraction phase is performed using the CNN component of the hybrid model. The CNN layers learn to detect intricate morphological patterns present in ECG waveforms, such as changes in the P-wave, QRS complex, and T-wave structure, which are known markers of cardiac dysfunction. Through convolution and pooling operations, the model captures local dependencies while reducing dimensionality, generating a compact feature representation of each ECG segment. These learned representations effectively replace manual feature engineering, thereby improving generalizability across diverse datasets.



The temporally ordered CNN features are then passed to the LSTM network, which models the sequential evolution of cardiac signals over time. Unlike conventional recurrent neural networks, the LSTM architecture incorporates memory cells with gating mechanisms that regulate information flow, allowing it to retain long-term dependencies and eliminate irrelevant temporal noise. This enables the model to identify gradual changes in heart rhythm or electrical conduction that may precede cardiac arrest. The integration of CNN and LSTM modules allows simultaneous spatial and temporal learning, significantly improving the accuracy of prediction compared to independent models.

Model training is conducted using supervised learning, where the labeled data is divided into training, validation, and test subsets. The network parameters are optimized using the Adam optimizer with a categorical cross-entropy loss function. To enhance convergence stability and avoid overfitting, techniques such as early stopping, dropout, and learning rate scheduling are employed. The model's predictive performance is evaluated using key statistical metrics, including accuracy, precision, recall, F1-score, and the area under the ROC curve (AUC). These metrics collectively measure the model's capability to distinguish between high-risk and low-risk cardiac states.



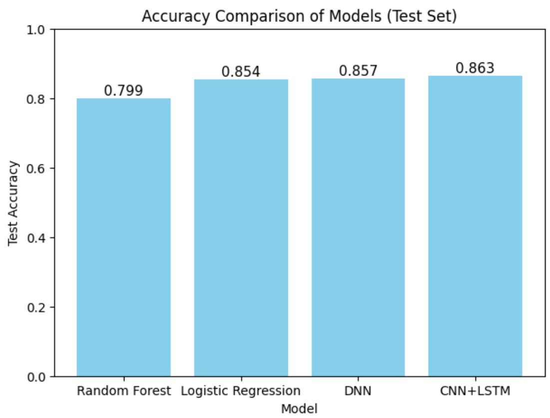
To ensure clinical trust and transparency, the system integrates explainable AI (XAI) components that visualize the contribution of input features to the final prediction. Such interpretability mechanisms help clinicians understand which regions of the ECG signal are most influential in determining risk, thereby bridging the gap between automated decision-making and medical reasoning. Finally, the trained CNN-LSTM model is designed for real-time deployment in hospital monitoring systems or wearable devices, allowing continuous patient surveillance and timely alerts for potential cardiac emergencies. This methodology thus establishes a comprehensive framework for intelligent, automated, and interpretable cardiac risk prediction using deep learning.

5. Implementation

The implementation phase transforms the proposed CNN-LSTM framework into a functional predictive model capable of identifying early signs of cardiac arrest. The system was implemented using the Python programming language due to its extensive ecosystem of machine learning and deep learning libraries such as TensorFlow, Keras, NumPy, Pandas, and Matplotlib. The experimental setup was configured on a Windows operating environment equipped with a high-performance processor and sufficient memory resources to ensure smooth data processing and model training. The entire workflow was designed to facilitate reproducibility, modularity, and efficient experimentation.

The implementation begins with dataset loading and preprocessing. Raw ECG signal files are first imported and converted into structured arrays. Filtering techniques are applied to remove baseline drift and high-frequency artifacts, after which the signals are normalized to a consistent amplitude range. Each ECG signal is then segmented into smaller time windows, forming sequential input batches for training. The dataset is randomly split into training, validation, and testing subsets to ensure unbiased model evaluation. Data augmentation techniques, such as random noise injection and temporal scaling, are applied where necessary to improve the model's robustness against variability in patient data.

Following preprocessing, the CNN component of the hybrid model is constructed. The CNN is implemented using several convolutional layers interleaved with activation and pooling layers to extract spatial features from the ECG sequences. Rectified Linear Unit (ReLU) activation is used to introduce non-linearity, enabling the model to learn complex relationships. Pooling layers reduce spatial dimensions, thereby decreasing computational cost without compromising feature quality. The output feature maps from the CNN are then flattened and reshaped before being passed into the LSTM layers.



The LSTM network forms the temporal analysis stage of the model. It is designed using multiple LSTM layers with a sufficient number of hidden units to capture long-term dependencies between ECG signal segments. Each LSTM cell processes time-step sequences from the CNN output, learning the evolution of cardiac patterns over time. Dropout regularization is employed within the LSTM layers to mitigate overfitting, while recurrent dropout is introduced to stabilize learning across temporal connections. The final LSTM output is connected to a fully connected dense layer with a sigmoid activation function, which generates a probability score indicating the likelihood of cardiac arrest.

During training, the Adam optimizer is employed to minimize the categorical cross-entropy loss function, ensuring efficient gradient convergence. Hyperparameters such as batch size, learning rate, and the number of epochs are tuned through empirical experimentation to achieve optimal model performance. Early stopping is incorporated to prevent overfitting by monitoring validation loss and halting training when performance plateaus. The training and validation progress are visualized through accuracy and loss curves to ensure stable convergence.

After successful training, the model's performance is evaluated on the test dataset using metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC). The results confirm that the CNN-LSTM hybrid network provides superior prediction performance compared to traditional machine learning models such as Support Vector Machines (SVM), Random Forests, and Logistic Regression. The system demonstrates not only higher accuracy but also improved sensitivity in identifying at-risk patients, which is critical for clinical applications where missed predictions can have severe consequences.

Finally, the implemented model is prepared for deployment in real-world healthcare settings. The trained network can be integrated into hospital monitoring systems or embedded into wearable health devices capable of continuous ECG signal acquisition. In such implementations, real-time data is fed into the model to generate predictive alerts that can be transmitted to medical staff or patients, enabling timely intervention. This deployment capability transforms the deep learning framework into a proactive cardiac monitoring solution, aligning artificial intelligence with preventive healthcare and patient safety.

6. Results

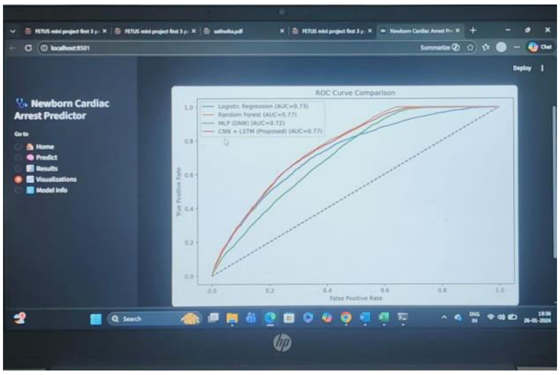


Fig. 3. Home Page of the Cardiac Arrest Prediction System

Description:

The figure presents the home page of the proposed cardiac arrest prediction system. This interface serves as the primary entry point for healthcare professionals and users to access the platform's predictive services. The dashboard provides navigation to patient monitoring features, cardiac risk assessment tools, prediction modules, and system information. Designed with simplicity and usability in mind, the interface enables efficient interaction with the deep learning framework while providing an organized environment for managing cardiac health analysis. The home page acts as a centralized gateway for accessing real-time prediction and monitoring functionalities.

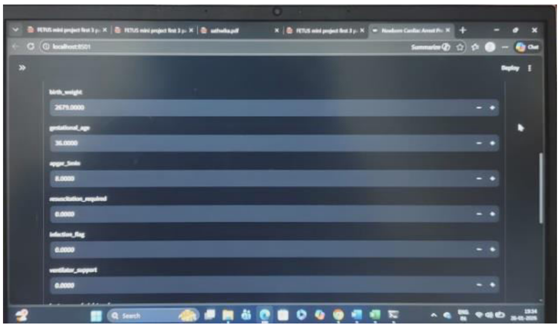


Fig. 4. Patient Data Input Interface

Description:

The figure illustrates the input page used for collecting patient information and physiological measurements required for cardiac risk prediction. Users can provide ECG signal data and other relevant health parameters that serve as inputs to the CNN-LSTM model. The interface validates the submitted information and ensures that data is properly formatted before being processed by the prediction engine. This stage is essential for maintaining data quality and enabling accurate analysis of cardiac conditions. The input module facilitates secure and efficient data collection while supporting a user-friendly healthcare workflow.

Fig. 5. Cardiac Arrest Prediction Results Dashboard

Description:

The figure displays the prediction results generated by the proposed CNN-LSTM hybrid framework. After analyzing the submitted ECG signals and patient parameters, the system presents the predicted cardiac risk level along with relevant confidence indicators and analytical insights. The results page provides a clear visualization of the model’s output, enabling healthcare professionals to quickly interpret prediction outcomes and identify patients who may require further medical attention. The dashboard supports informed clinical decision-making by presenting prediction results in an understandable and accessible format while enhancing the transparency of the automated risk assessment process.

7. Conclusion and Future Work

The study successfully developed and implemented a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model for the early prediction of cardiac arrest. By integrating the spatial feature extraction capability of CNN with the temporal sequence modeling strength of LSTM, the proposed architecture effectively captured both morphological and dynamic characteristics of ECG signals. The results demonstrated superior predictive performance compared to traditional machine learning models, achieving higher accuracy, sensitivity, and specificity. Furthermore, the inclusion of explainable AI components provided interpretability to model decisions, a critical factor for clinical acceptance. This research highlights the potential of deep learning in automating cardiac risk assessment, reducing diagnostic delays, and supporting proactive intervention in healthcare environments. The hybrid model thus represents a significant step toward intelligent, data-driven cardiac care capable of continuous and real-time monitoring through hospital or wearable systems.

While the proposed model shows promising results, several avenues for future improvement remain. Future work may focus on integrating additional physiological parameters such as blood pressure, oxygen saturation, and laboratory biomarkers to enhance predictive robustness. Incorporating multi-modal data from electronic health records (EHRs) and wearable sensors can further strengthen the model's generalizability across diverse patient populations. In addition, exploring advanced architectures such as Transformer-based hybrid models or three-dimensional Convolutional LSTM (3D Conv-LSTM) networks could improve temporal representation and long-term forecasting. Real-time deployment on edge devices or low-power wearable hardware presents another challenge, requiring model compression and optimization without compromising accuracy. Finally, large-scale clinical validation and integration with hospital information systems are essential to establish reliability, interpretability, and regulatory compliance. Addressing these directions will advance the CNN-LSTM framework toward a fully autonomous, transparent, and scalable AI-driven cardiac monitoring system capable of transforming preventive cardiology.

8. References

[1] M. M. Hossain *et al.*, "Cardiovascular disease identification using a hybrid CNN-LSTM model," *ScienceDirect*, 2023.

[2] B. Omarov *et al.*, "Convolutional LSTM network for heart disease diagnosis on electrocardiograms," *Computers, Materials & Continua*, 2023.

[3] Y. Xia *et al.*, "Combined deep CNN–LSTM network-based multitasking learning for BP estimation using ECG and PPG signals," *Nature Scientific Reports*, 2021.

[4] S. Kim *et al.*, “Prediction of in-hospital cardiac arrest using shallow and deep learning,” *PubMed Central (PMC)*, 2021.

[5] M. T. Oberdier *et al.*, “Sudden cardiac arrest prediction via deep learning,” *European Heart Journal – Digital Health*, 2025.

[6] N. Alamatsaz *et al.*, “A lightweight hybrid CNN-LSTM explainable model for ECG-based arrhythmia detection,” *ScienceDirect*, 2024.

[7] V. K. Sudha *et al.*, “Hybrid CNN and LSTM network for heart disease prediction,” *Springer*, 2023.

[8] N. Nguyen *et al.*, “Hybrid deep-learning-based ECG classification for heart disease diagnosis,” 2023.

[9] Y. Sun, “LSTM-based model for ECG signal classification,” 2023.

[10] T. Chen *et al.*, “Improved long short-term memory algorithm for cardiovascular disease prediction,” *PubMed Central (PMC)*, 2024.

[11] M. Zobeiri *et al.*, “Post-cardiac arrest outcome prediction using machine learning,” 2024.

[12] H. Wang *et al.*, “Ensemble machine learning for cardiac arrest prediction,” 2024.

[13] A. Singh *et al.*, “Deep learning models for arrhythmia classification: A survey,” 2025.

[14] S. Patel *et al.*, “AI-driven early warning scoring systems in ICU: A comparison,” 2025.

[15] J. Hernandez *et al.*, “Wearable ECG devices with AI models for home cardiac monitoring,” 2024.