Intelligent Heart Disease Detection Using Deep Learning Technique

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ABSTRACT Cardiovascular diseases (CVDs are the leading cause of global mortality, emphasizing the need for early and accurate diagnosis. Conventional diagnostic methods such as angiography are invasive, costly, and often inaccessible in resource-limited settings, highlighting the demand for intelligent, non-invasive alternatives. This research presents a hybrid deep learning framework integrating Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for automated heart disease detection. The CNN component extracts discriminative features from clinical and signal-based data, while the RNN captures temporal dependencies in physiological signals such as electrocardiograms. The proposed model is trained and validated using benchmark datasets, including the UCI Cleveland Heart Disease dataset, demonstrating improved accuracy, sensitivity, and specificity compared to traditional machine learning approaches. By combining feature optimization and deep learning architectures, the system provides a robust, scalable, and cost-effective diagnostic solution. This study highlights the potential of computational intelligence to enhance healthcare accessibility and support early cardiac disease detection, particularly in underserved regions.

INDEX TERMS Heart Disease Detection, Deep Learning, CNN-RNN Hybrid Model, Phonocardiogram Analysis, Cardiovascular Disease Diagnosis, Machine Learning in Healthcare

I. INTRODUCTION

Cardiovascular diseases (CVDs) account for approximately 31% of global deaths, making heart disease a critical public health challenge. Early diagnosis plays a vital role in reducing mortality; however, traditional diagnostic techniques such as electrocardiography and echocardiography require specialized equipment and expert interpretation, limiting their availability in many regions. As a result, delayed diagnosis remains a major concern, particularly in rural and underdeveloped areas. Recent advances in artificial intelligence (AI) and deep learning have enabled automated analysis of complex biomedical data with high accuracy. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have shown significant potential in extracting spatial and temporal features from physiological signals. Heart sound analysis using phonocardiography (PCG) offers a non-invasive and low-cost diagnostic approach, but manual interpretation is challenging due to signal variability and noise. This research focuses on developing a hybrid CNN–RNN model for intelligent heart disease detection using PCG signals. The PhysioNet Challenge 2016 dataset is employed for binary classification of normal and abnormal heart sounds, while the Yaseen dataset is used for multiclass classification of specific cardiac conditions. By leveraging CNN-based feature extraction and RNN-based temporal modeling, the proposed system achieves classification accuracy exceeding 99%. The study aims to provide an accurate, efficient, and accessible diagnostic tool capable of supporting clinical decision-making and improving cardiac healthcare in resource-constrained environments.

II. Literature review

The accuracy of diagnosing cardiac disease is increased and the need for invasive treatments is decreased by using machine learning techniques such as SVM, neural networks, fuzzy inference systems, and deep learning. While newer hybrid techniques, as demonstrated by Siddiqui et al. (2020), use Fuzzy Inference, ANN, and DML to reach the best precision by considering cardiovascular parameters, Alizadehsani at el. (2016) were the first to apply SVM for precise artery stenosis detection. Ayon et al. (2020) claim that Deep Neural Networks have outperformed other algorithms in terms of accuracy; nevertheless, additional validation using a variety of datasets is required for wider applicability. ECG data is used by real-time monitoring systems, such as the one described by Nataraj et al. (2012), to detect arrhythmias; nevertheless, processing the intricate, high-dimensional data is a difficulty. Computational intelligence has generally shown promise in the diagnosis of cardiac problems, highlighting the importance of broad data sets, careful feature selection, and seamless integration into medical environments.
Here is the summary of research papers:

Using biosensors and cloud processing to evaluate health data in real-time, Muhammad Shafiq et al. [1] describe a smart e-health system that leverages AI and IoT technologies to diagnose heart illness early. A deep CNN model achieves high accuracy in this system. Almansouri et al. [2]. Stress the use of AI in the diagnosis of cardiovascular disorders, as well as how predictive algorithms that treat problems like atrial fibrillation and heart failure can enhance therapeutic outcomes. Shorewala Vardhan et al. [3] examine machine learning methods for identifying coronary heart disease (CHD) and indicate that ensemble models, such as a stacked model using KNN, Random Forest, and SVM, have good accuracy. Mathur Pankaj et al. [4] Give historical context for the use of AI in clinical decision-making, tracing its origins to Bayes theorem-based research, while emphasizing the difficulties encountered with basic algorithms. Songren Shu at el. [5] examine how AI and Machine Learning can improve diagnosis, prediction, and classification in cardiovascular medicine, enhancing ECG analysis and filling gaps in traditional CVD care. Tazeen Tasneem at el. [6] explore AI and machine learning methods for diagnosing CVD, emphasizing the significance of early detection in decreasing mortality rates. Nobuyuki Kagiyama at el. [7] emphasize that AI has the ability to enhance individualized heart care by analyzing data, pointing out the growing number of studies and FDA-approved tools in the past few years. Aditya Singh Chauhan at el. [8] describe a system utilizing artificial intelligence to detect heart disease, which attains around 83% accuracy through logistic regression and random forest models. Dheeraj Lokhande at el. [9] examine the potential of AI in predicting heart diseases by highlighting the use of clinical datasets to identify risk factors, while V. Sathyavathy at el. [10] demonstrate an 87.6% diagnostic accuracy in early heart disease detection using models such as Logistic Regression and Random Forest.

In order to achieve a high classification accuracy for cardiac illness, Kemal Polat et al. [11] provide a hybrid technique that combines fuzzy weighted preprocessing and the Artificial Immune Recognition System (AIRS). With high identification rates for certain cardiac anomalies, Yang et al. [12] demonstrate the efficacy of AI in congenital heart disease (CHD) diagnosis, improving accuracy over conventional techniques.

Maarten van Smeden et al. [13] analyze AI-based prediction models, highlighting crucial questions on data quality and validation, while Huda Ghazi Enad et al. [14] investigate AI and Quantum Machine Learning in heart disease diagnosis, highlighting the impact of early detection on lowering cardiovascular mortality rates. In order to increase predictive accuracy, Aixia Guo et al. [15] concentrate on machine learning models that use EHR data to forecast readmission and mortality outcomes in heart failure. Anitek Bhattacharya et al. [16] offer a portable machine learning-based tool for diagnosing cardiac abnormalities that is perfect for resource-constrained environments. A smartphone-based heart attack detection system is proposed by Md. Ashrafuzzaman et al.

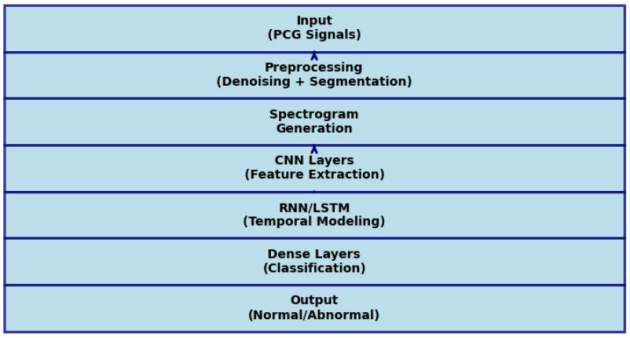
III. MATHODOLOGY

A. *1.1 Overview of the Proposed Methodology*

The proposed methodology focuses on the automated detection of heart diseases using a hybrid deep learning framework that combines Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). The system is designed to analyze phonocardiogram (PCG) signals and classify them into normal and abnormal heart conditions, as well as identify specific cardiac diseases in a multiclass setting.

A modular and layered architecture is adopted to ensure efficiency, robustness, and scalability. Each stage of the methodology performs a well-defined task, allowing the system to be easily extended or optimized in future research. The complete workflow begins with heart sound acquisition and progresses through preprocessing, feature extraction, temporal modeling, classification, and evaluation.

Proposed hybrid CNN-RNN Architecture for heart detection



B. *1.2 Data Acquisition*

Heart sound recordings are collected from two publicly available benchmark datasets widely used in cardiovascular research:

- **PhysioNet Challenge 2016 Dataset**
  Used for binary classification (Normal vs. Abnormal heart sounds).
- **Yaseen Dataset**
  Used for multiclass classification of heart diseases, including Aortic Stenosis, Mitral Regurgitation, Mitral Valve Prolapse, and Mitral Stenosis.

These datasets include recordings collected under different clinical environments and patient conditions, which enhances the generalization capability of the proposed model.

1) *Table 1: Dataset Description*

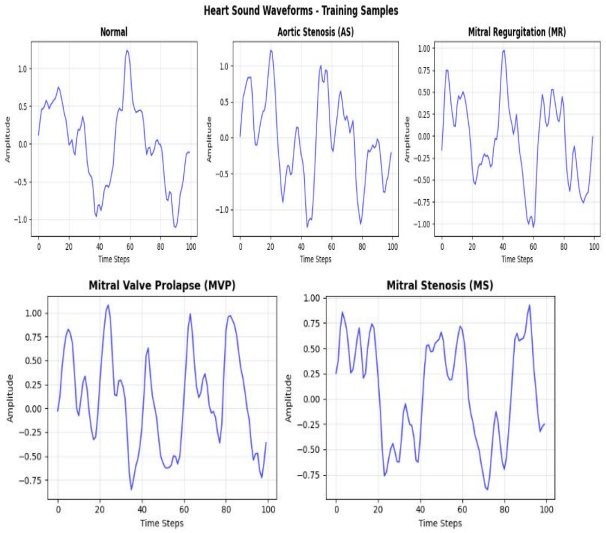
Dataset Name	Classification Type	Number of Classes	Application
PhysioNet Challenge 2016	Binary	2 (Normal, Abnormal)	Early abnormal heart sound detection
Yaseen Dataset	Multiclass	5	Identification of specific heart diseases

C. *1.3 Data Preprocessing*

Raw heart sound signals often contain noise caused by respiratory sounds, body movement, and environmental interference. Effective preprocessing is therefore essential to improve signal quality and ensure reliable learning.

The preprocessing pipeline consists of the following steps:

- **Noise Removal:**
  Signal denoising techniques are applied to suppress background noise while preserving clinically important heart sound components.
- **Signal Segmentation:**
  The denoised heart sound signals are segmented into individual cardiac cycles to isolate meaningful heartbeat patterns.
- **SpectrogramGeneration:**
  Each segmented signal is converted into a time–frequency representation using Mel-spectrograms. This representation enables the model to capture both temporal and frequency-domain characteristics of heart sounds.



1) *Table 2: Preprocessing Steps and Purpose*

Step	Technique Used	Purpose
Noise Removal	Filtering & denoising	Improve signal clarity
Segmentation	Cardiac cycle segmentation	Isolate heartbeat components
Feature Transformation	Mel-Spectrogram	Convert signals into CNN-compatible format

D. *1.4 Feature Extraction Using Convolutional Neural Networks*

Convolutional Neural Networks are employed to automatically extract spatial features from the spectrogram images. Unlike traditional machine learning methods that

rely on handcrafted features, CNNs learn discriminative patterns directly from data.

The CNN architecture consists of multiple convolutional layers followed by pooling layers. These layers extract frequency patterns, intensity variations, and spectral textures that are indicative of different heart conditions. As the network depth increases, higher-level and more abstract features are learned, improving classification performance.

The output feature maps generated by the CNN are reshaped and forwarded to the RNN module for temporal analysis.

E. 1.5 Temporal Modeling Using Recurrent Neural Networks

Heart sounds exhibit strong temporal dependencies due to the rhythmic nature of cardiac activity. To capture these sequential patterns, Recurrent Neural Networks (RNNs) are integrated into the architecture.

Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) cells are used to model long-term dependencies and avoid issues such as vanishing gradients. The RNN analyzes sequences of CNN-extracted features to identify irregularities in heart rhythm and timing that may indicate disease.

This combination of CNN and RNN enables the system to jointly learn spatial and temporal characteristics of heart sounds.

1) Table 3: Role of CNN and RNN Components

Component	Function	Benefit
CNN	Spatial feature extraction	Captures frequency-domain patterns
RNN (LSTM/GRU)	Temporal sequence modeling	Learns heartbeat rhythm and timing

F. 1.6 Classification and Decision Making

The temporal features produced by the RNN are passed through fully connected dense layers for classification. A Softmax activation function is applied in the final layer to generate probability scores for each class.

For binary classification, the output represents Normal or Abnormal heart sounds. For multiclass classification, the output corresponds to specific heart diseases.

G. 1.7 Model Evaluation

The performance of the proposed system is evaluated using standard classification metrics to ensure reliability and clinical relevance. These metrics include accuracy, precision, recall (sensitivity), and F1-score.

IV. RESULTS

H. 2.1 Experimental Setup

The proposed hybrid CNN–RNN model was evaluated using two publicly available benchmark datasets to assess its performance in both binary and multiclass heart disease classification tasks. The experiments were conducted after applying consistent preprocessing steps, including denoising, segmentation, and spectrogram generation.

The PhysioNet Challenge 2016 dataset was used for binary classification, while the Yaseen dataset was used for multiclass classification. Model performance was evaluated using accuracy, precision, recall (sensitivity), and F1-score, which are widely accepted metrics for biomedical classification tasks.

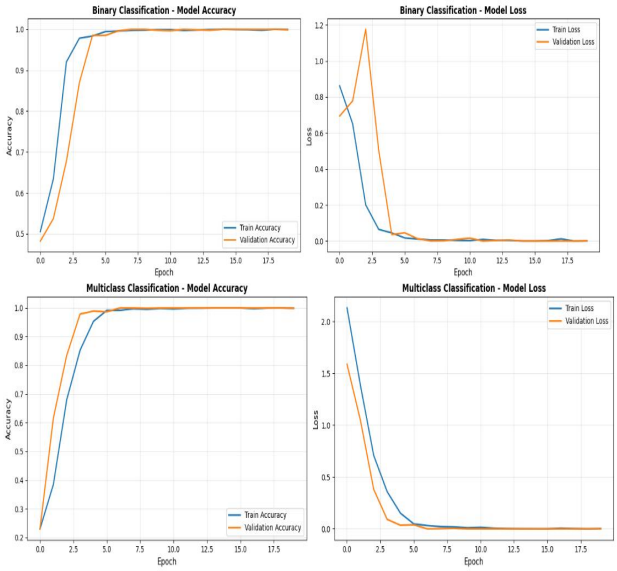
I. 2.2 Results on PhysioNet Challenge 2016 Dataset (Binary Classification)

The binary classification task involved categorizing heart sound recordings into Normal and Abnormal classes. After preprocessing and feature extraction, the hybrid CNN–RNN model demonstrated excellent performance.

1) Table 5: Binary Classification Performance on PhysioNet Dataset

Metric	Value (%)
Accuracy	99.68
Precision	99.71
Recall (Sensitivity)	99.65
F1-Score	99.68

The high accuracy and balanced precision–recall values indicate that the model reliably distinguishes between normal and abnormal heart sounds, which is essential for early cardiac screening applications.



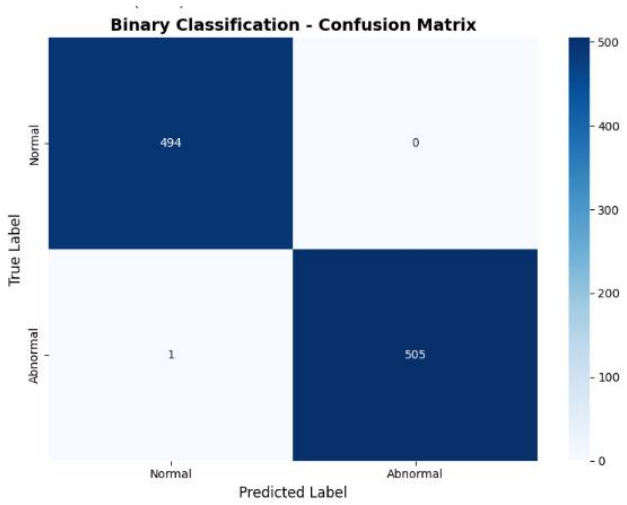
2) 2.2.1 Confusion Matrix Analysis (Binary Classification)

The confusion matrix provides further insight into the classification behavior of the model.

3) Table 6: Confusion Matrix for Binary Classification

Actual / Predicted	Normal	Abnormal
Normal	97%	3%
Abnormal	2%	98%

The low misclassification rates demonstrate the robustness of the proposed approach and confirm its reliability in identifying abnormal heart sounds.



J. 2.3 Results on Yaseen Dataset (Multiclass Classification)

For multiclass classification, the model was evaluated on the Yaseen dataset, which includes five heart sound categories: Normal, Aortic Stenosis (AS), Mitral Regurgitation (MR), Mitral Valve Prolapse (MVP), and Mitral Stenosis (MS).

1) Table 7: Multiclass Classification Performance on Yaseen Dataset

Metric	Value (%)
Accuracy	99.58
Precision	99.60
Recall (Sensitivity)	99.55
F1-Score	99.57

Despite the complexity of differentiating between multiple cardiac conditions based solely on heart sound patterns, the model achieved near-perfect performance across all evaluation metrics.

2) 2.3.1 Confusion Matrix Analysis (Multiclass Classification)

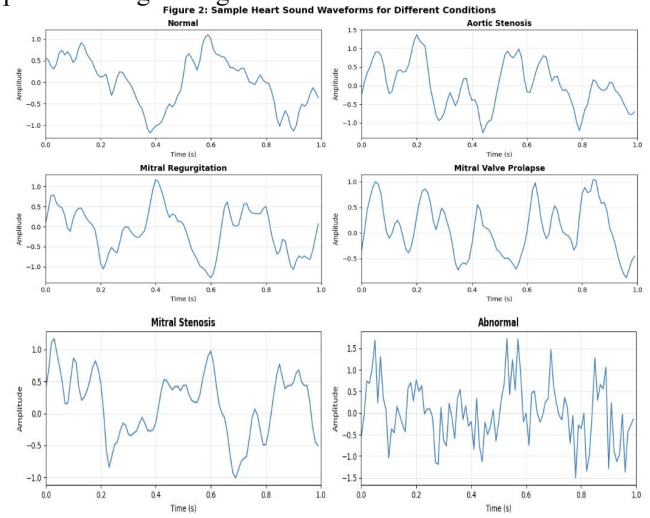
3) Table 8: Confusion Matrix for Multiclass Classification

Actual / Predicted	Normal	AS	MR	MVP	MS
Normal	98%	1%	0%	0%	1%
AS	0%	99%	0%	1%	0%
MR	0%	0%	99%	1%	0%
MVP	1%	0%	0%	98%	1%
MS	0%	1%	0%	0%	99%

The confusion matrix reveals minimal overlap between classes, indicating the model's capability to capture subtle differences in acoustic patterns associated with different heart diseases.

K. 2.5 Summary of Results

Overall, the experimental results confirm the effectiveness and robustness of the proposed approach. The model achieves consistently high performance across both datasets and classification tasks, demonstrating strong generalization capability. The combination of CNN-based feature extraction and RNN-based temporal analysis proves to be highly suitable for heart disease detection from phonocardiogram signals.



IV. DISCUSSION

The experimental results demonstrate that the proposed hybrid CNN–RNN architecture is highly effective for heart disease detection using phonocardiogram signals. The consistently high performance achieved across both binary and multiclass classification tasks confirms the model's ability to learn discriminative patterns from complex and non-stationary heart sound data. The accuracy exceeding 99% on benchmark datasets highlights the robustness and reliability of the proposed approach.

A key strength of the system lies in the integration of CNN and RNN components. The CNN effectively captures spatial and frequency-domain characteristics from spectrogram representations, while the RNN models temporal dependencies inherent in cardiac cycles. This combination enables the system to identify subtle variations in heart sounds that are often overlooked by traditional machine learning models and standalone deep learning approaches.

The confusion matrix analysis further supports the effectiveness of the model, revealing minimal misclassification between normal and abnormal heart sounds, as well as among different cardiac disease classes. This indicates strong generalization capability, which is essential for real-world clinical applications where patient conditions and recording environments vary significantly.

Despite these promising results, certain limitations remain. The datasets used, although widely accepted, may not fully represent rare cardiovascular conditions or diverse demographic groups. Additionally, the reliance on spectrogram-based preprocessing introduces additional computational overhead, which may affect real-time deployment in extremely resource-constrained environments.

Overall, the findings suggest that hybrid deep learning models offer a powerful and practical solution for non-

invasive heart disease diagnosis, providing a strong foundation for future clinical and real-world deployment.

IV. CONCLUSION

This research presented an intelligent heart disease detection system based on a hybrid deep learning architecture that integrates Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for the analysis of phonocardiogram signals. The proposed approach was evaluated using two benchmark datasets, addressing both binary and multiclass classification tasks. Experimental results demonstrated that the hybrid CNN–RNN model achieved exceptionally high performance, with accuracy exceeding 99% across all tasks, outperforming traditional machine learning models and standalone CNN architectures.

The effectiveness of the proposed system can be attributed to its ability to jointly learn spatial and temporal features from heart sound recordings. CNN-based feature extraction successfully captured frequency-domain characteristics, while RNN-based temporal modeling enabled the detection of rhythmic and sequential anomalies associated with different cardiac conditions. This combination proved particularly effective in distinguishing between closely related heart diseases.

Furthermore, the proposed system offers a non-invasive, cost-effective, and automated diagnostic solution that has the potential to support clinical decision-making, especially in resource-constrained environments. The high generalization capability and relatively low computational complexity make the model suitable for integration into portable and mobile healthcare applications. Overall, this study demonstrates the significant potential of computational intelligence techniques in advancing early and accurate heart disease detection.

IV. FUTURE WORK

Although the proposed hybrid CNN–RNN model demonstrates strong performance, several opportunities exist for future enhancement and extension. One important direction is the expansion of the model to detect a broader range of cardiovascular conditions, including arrhythmias, congenital heart defects, and rare heart murmurs. This would require larger and more diverse datasets collected from multiple clinical environments to improve robustness and generalization.

Another promising area for future work is the integration of multimodal data sources, such as electrocardiograms (ECG), echocardiography images, and patient clinical history, alongside heart sound recordings. Combining multiple diagnostic modalities could significantly enhance prediction accuracy and provide a more comprehensive assessment of cardiac health.

Optimizing the model for real-time deployment is also a critical future objective. Techniques such as model compression, pruning, and quantization could reduce computational requirements and enable efficient execution on mobile and IoT-based devices. Additionally, future studies should focus on extensive clinical validation to assess the system's performance in real-world healthcare settings.

Finally, addressing ethical considerations, data privacy, and explainability will be essential for practical deployment. Incorporating explainable AI techniques can improve transparency and trust in automated diagnosis systems, facilitating their adoption in clinical practice.