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PREDICTING CARDIOVASCULAR DISEASES THROUGH INTEGRATED DEEP LEARNING FEATURES

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ABSTRACT

This research investigates the effectiveness of various machine learning models for classifying multimodal heart signals, specifically using electrocardiogram (ECG) and phonocardiogram (PCG) data from the EPHNOGRAM and PhysioNet Cardiology 2016 datasets. The proposed architecture, particularly the hybrid (LSTM, BiLSTM) model, achieved an impressive accuracy of 92.3% on the PhysioNet dataset, surpassing existing techniques and demonstrating significant potential for clinical applications. This study evaluates several architectures, including CNN, RNN, CNN and hybrid(RNN, LSTM), BiLSTM, and hybrid(LSTM, BiLSTM). By leveraging the EPHNOGRAM dataset, which contains synchronised ECG and PCG signals, the model aims to enhance classification accuracy for various heart conditions, including normal heartbeats, arrhythmias, murmurs, and other cardiovascular diseases (CVDs). Experimental results indicate that the proposed model outperforms traditional deep learning methods, achieving superior classification accuracy. These findings underscore the promise of multimodal deep learning models in healthcare diagnostics, particularly in detecting cardiac diseases. Future research will focus on optimising hyperparameters, utilising larger datasets, and integrating additional modalities, such as cardiac imaging and demographic data, to improve cardiovascular disease classification further.

I. INTRODUCTION

Heart disease remains one of the leading causes of mortality worldwide, emphasising the importance of early detection to improve outcomes. Traditional diagnostic methods typically rely on either electrocardiogram (ECG) or phonocardiogram (PCG) signals, both of which provide vital insights into heart health. However, using only one modality limits the scope of diagnosis. ECG captures electrical activity and is effective for detecting arrhythmias, while PCG focuses on heart sounds, aiding in the diagnosis of murmurs and valve issues. Relying solely on one of these approaches can overlook complementary information[1]. Recent advances in machine learning, particularly deep learning, have opened new opportunities for analysing complex medical data, such as heart signals[2].Single-modality approaches often fail to provide a comprehensive diagnostic perspective. As highlighted by[3], multimodal methods that combine ECG and PCG signals significantly enhance diagnostic accuracy by leveraging their complementary strengths. This multimodal approach not only provides richer data but also helps reduce false positives by cross-validating information from different sources. Challenges in Multimodal Analysis Despite their benefits, the simultaneous processing of ECG and PCG signals presents challenges. Traditional machine learning models struggle to fully exploit the complex nature of multimodal data, as they require simultaneous extraction of spatial features from ECG and temporal features from PCG. Synchronisation and alignment issues between the signals further complicate this process. Standard algorithms relying on manual feature extraction are often insufficient for capturing the intricate relationships within multimodal data[4]. To address these limitations, this study proposes a hybrid deep learning model to advance heart disease diagnostics.

The model combines Convolutional Neural Networks (CNNs) to extract spatial features from ECG signals with Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM), to capture temporal sequences from PCG signals. Research by[5], demonstrates that hybrid CNN-RNN models outperform traditional approaches in multimodal contexts. By applying this strategy to ECG and PCG data, the proposed model aims to deliver more accurate and reliable diagnoses, addressing the shortcomings of single-modality systems. Research Objectives The primary goal of this research is to evaluate the effectiveness of various machine learning models in classifying multimodal heart signals, specifically focusing on ECG and PCG data. The study seeks to enhance classification accuracy for a range of heart conditions, including normal heartbeats, arrhythmias, murmurs, and other cardiovascular diseases (CVDs), using advanced deep learning architectures.

The main contributions include:

- Proposed a deep learning framework that integrates multiple architectures (CNN, RNN, LSTM, BiLSTM, and hybrid(LSTM, BiLSTM)) to classify multimodal heart signals.
- Demonstrated the effectiveness of synchronised ECG and PCG signals in enhancing classification precision.
- Improved classification capabilities for a wide range of heart conditions.
- Highlighted potential areas for future research, including optimising hyperparameters, leveraging larger datasets, and incorporating additional modalities like cardiac imaging and demographic information.

The structure of this paper is organised as follows: Section 2 presents the related work. Section 3 outlines the methodologies and techniques employed. Section 4 presents the results and discusses, and finally, Section 5 summarises the conclusions drawn from the research.

II. RELATED WORK

Deep learning has transformed cardiac diagnostics using ECG and PCG signals, improving the prediction of heart conditions. CNNs capture spatial patterns, RNNs handle temporal dynamics, and hybrid models show strong potential. Multimodal approaches combining ECG and PCG enhance accuracy, though challenges like data synchronisation persist. Cheng, et al[6]. Analysed both electrocardiogram (ECG) and phonocardiogram (PCG) signals. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM), were widely used for cardiac diagnostics. CNNs demonstrated strong performance in feature extraction from ECG data due to their ability to capture spatial dependencies, while RNNs proved effective in handling the temporal nature of both ECG and PCG signals. In one study, a deep CNN combined with BiLSTM achieved notable improvements in ECG classification, reporting up to 98.7% accuracy in arrhythmia detection. According to et al[7]. Focused on PCG analysis using deep learning, which was less explored at the time but had great potential. A multimodal framework integrating both ECG and PCG signals was proposed to enhance diagnostic accuracy, especially under noisy conditions. However, challenges such as data synchronisation and feature alignment between ECG and PCG modalities persisted.

IDS Aabdalla, et al[8]. Explored ECG classification as a key approach for diagnosing heart disease, with a growing focus on prediction using machine learning techniques. The study aimed to improve cardiovascular disease classification accuracy by applying machine learning models to data from the PhysioNet database. They developed multi-class classification models to distinguish between heart failure rhythm (HFR), normal heart rhythm (NHR), and arrhythmia (ARR) using 162 ECG signals. Techniques such as frequency-time domain analysis and wavelet scattering were used for feature extraction. Their SVM model achieved a training accuracy of 97.1% and a testing accuracy of 92%, offering an efficient, accurate tool for heart disease diagnosis and a useful foundation for future research. Qiu, Yue, et al[9]. Examined multimodal learning approaches that combined multiple data types such as ECG and PCG. This direction was promising for cardiac diagnostics, as it allowed models to leverage complementary information from various physiological signals. A multimodal deep learning system was developed to integrate ECG and PCG signals for early detection of cardiovascular diseases. Despite the advancements, issues like data alignment, signal noise, and computational complexity limited the practical application of these multimodal systems, particularly in real-time scenarios like wearable and home-based monitoring systems.

Rai, Hari Mohan[10]. Demonstrated that hybrid architectures combining CNNs with RNNs were highly successful in analysing time-series data like ECG and PCG signals. For instance, a hybrid CNN-LSTM model proposed for ECG-based arrhythmia detection achieved an accuracy of 99.5% in recognising five types of arrhythmias. Another hybrid model combining CNN with BiLSTM showed superior performance by capturing both spatial and temporal patterns in ECG data, improving generalisation, and reducing overfitting across datasets. Islam, Md Shofiqul, et al. [11].Introduced the HARDC model, which used a dilated CNN and a bidirectional recurrent neural network (BiGRU-BiLSTM) architecture. By incorporating local and global feature information, alongside an attention mechanism, the model achieved a classification accuracy of 99.60%, with high F1 scores, precision, and recall. This approach also demonstrated reduced computation time, making it an innovative and cost-effective strategy for ECG signal compression and recognition. Negin, et al[12]. Developed a lightweight deep learning approach for detecting eight different cardiac arrhythmias and normal rhythms, achieving a diagnostic accuracy of 98.24%.

They used resampling and baseline wander removal techniques to preprocess ECG signals. The model, combining CNN and LSTM layers, was applied to ECG data from PhysioNet databases, demonstrating higher accuracy compared to previous methods. Rajakumar[13]. Proposed a novel approach for predicting fetal arrhythmias from cardiotocographic (CTG) signals using an Ensemble Feature Extraction (EFE) model. This model tackled the variability in CTG signals through sophisticated feature extraction methods and classification using the XGBoost algorithm. The model achieved an accuracy of 96.34%, precision of 96.7%, and recall of 97.3%, providing valuable insights into improving signal classification accuracy. Baharoon[14]. Enhanced multimodal deep learning systems by combining fundus images with demographic data (age and gender). Their model, HyMNet, outperformed other multimodal frameworks, achieving an AUC of 0.791 for heart disease prediction by fusing features from multiple sources, showcasing the potential of combining imaging with other data types in cardiac diagnostics.

Zeeshan, et al[15]. Presented two multimodal fusion frameworks, MIF and MFF, for ECG heartbeat classification by converting ECG signals into images and using deep learning techniques for feature extraction. These approaches significantly improved the detection of arrhythmias and myocardial infarctions, outperforming traditional methods by integrating diverse representations.
Suliman, I. D., & Vasumathi, D[2]. Highlighted the critical role of the heart in circulating blood throughout the body and addressed the global impact of cardiac disease (CD) as a leading cause of death. Detecting and predicting heart diseases remains challenging for healthcare professionals, given common but nonspecific symptoms such as rapid heartbeats, chest pain, and breathing difficulties. Early detection of CD can help individuals take preventive actions before the disease progresses. The study aimed to apply and compare various classification models, including K-Nearest Neighbours (KNN), Decision Trees (DT), Naive Bayes (NB), Logistic Regression (LR), and Random Forest (RF), using five cardiac disease datasets. The models were implemented in Anaconda Jupyter Notebook, utilising its robust libraries for greater accuracy.

After ten iterations, Logistic Regression (LR) achieved the highest accuracy of 96.67% on the Cleveland dataset, outperforming existing algorithms. Hemaxi, et al[16]. Explored deep learning models like Gated Recurrent Unit (GRU), LSTM, and CNN for cardiovascular disease classification using ECG data. Their research, using the PTB-XL dataset, found that 1D ECG representations were more effective in capturing temporal patterns essential for classification compared to 2D image-based approaches, particularly for GRU models, which exhibited superior sensitivity and specificity. Azemi[17]. Addressed the challenge of classifying heart sound recordings (PCGs) as normal, abnormal, or uncertain. The PhysioNet Challenge 2016 facilitated the development of algorithms for PCG classification, and top models used techniques like CNNs, AdaBoost, and SVMs, with sensitivity reaching 0.94 and specificity 0.78, providing valuable data for future research in heart sound classification. Zhou, F., & Fang[18]. Applied a fusion of image representations from ECG signals for arrhythmia classification, achieving an accuracy of 99.6%. Their method used recurrence plots (RP), Gramian angular fields (GAF), and Markov transition fields (MTF) to improve recognition accuracy, demonstrating the efficacy of image-based models in ECG classification.

Mohamed, et al[19]. Reviewed lightweight deep learning approaches, such as LSTMs and wavelet transforms, to enhance ECG signal classification efficiency. Their study proposed a simplified multimodal deep fusion model that reduced computational complexity while maintaining high accuracy (98.80%), particularly beneficial for small datasets. Shao, Zhe[20].Presented an Image Fusion Model (IFM) for ECG heartbeat classification. This model converted heartbeats into three distinct image types—GAF, RP, and MTF—merging them into a single modality. Using AlexNet for feature extraction, the model achieved high accuracy, precision, and recall, surpassing earlier approaches on the PhysioNet MIT-BIH and PTB datasets. While significant advancements have been achieved in deep learning-based cardiac diagnostics, especially concerning ECG data, there remains a critical need for further research in PCG analysis. Our studies have focused on various types of feature extraction, utilising different datasets and exploring diverse deep learning approaches.

III. METHODOLOGY

The proposed framework combines a CNN for spatial feature extraction and an RNN (specifically LSTM/BiLSTM) for capturing temporal dependencies from ECG and PCG signals. This hybrid model processes the data in two stages: first, it extracts key morphological patterns with CNN layers and then learning the sequential relationships between heartbeats through RNN layers. This integrated approach is designed to improve heart condition classification by leveraging both spatial and temporal features effectively.

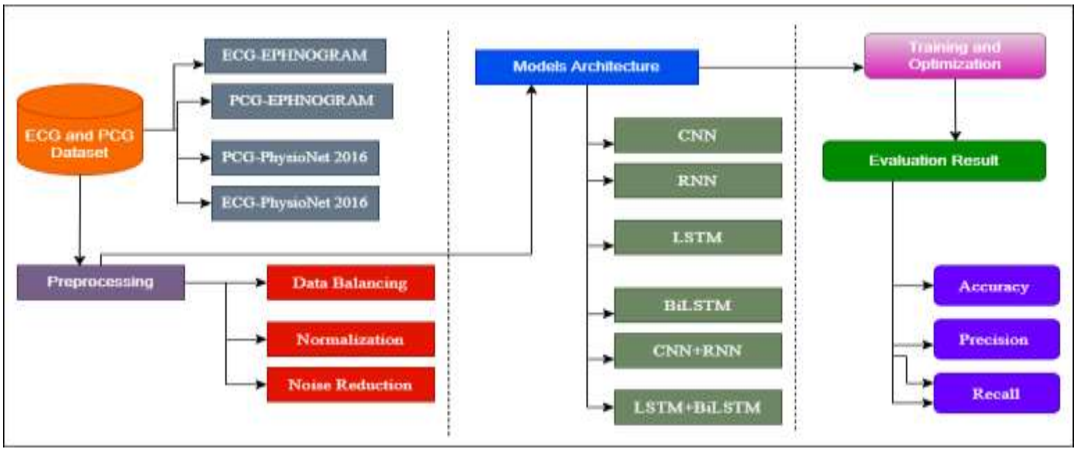

Figure 1: Overview of the Deep Learning Framework for ECG and PCG Analysis.
Source: Authors, (2026).

Dataset

The PhysioNet/Computing in Cardiology 2016 dataset contains over 3,100 recordings of ECG and PCG signals, which help in classifying heartbeats as normal, abnormal, uncertain, or artefact. These recordings span various durations and provide synchronised data crucial for multimodal analysis in heart disease detection[21]. The EPHNOGRAM dataset includes synchronised ECG and PCG signals from over 200 patients, capturing both the electrical activity of the heart (ECG) and its mechanical functions (PCG). It features a multimodal approach, which enhances classification performance for various cardiovascular conditions like arrhythmias and murmurs. The dataset is significant for its high sampling rate (typically 1,000 Hz) and the complementary nature of the data, making it highly valuable for detecting intricate heart conditions that may be missed using a single modality[21].

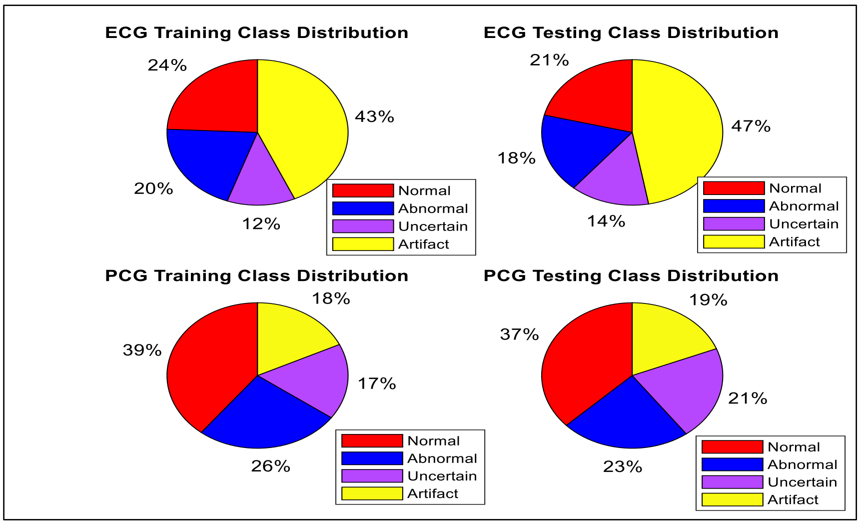

Figure 2: PhysioNet Cardiology 2016 Dataset.
Source: Authors, (2026).

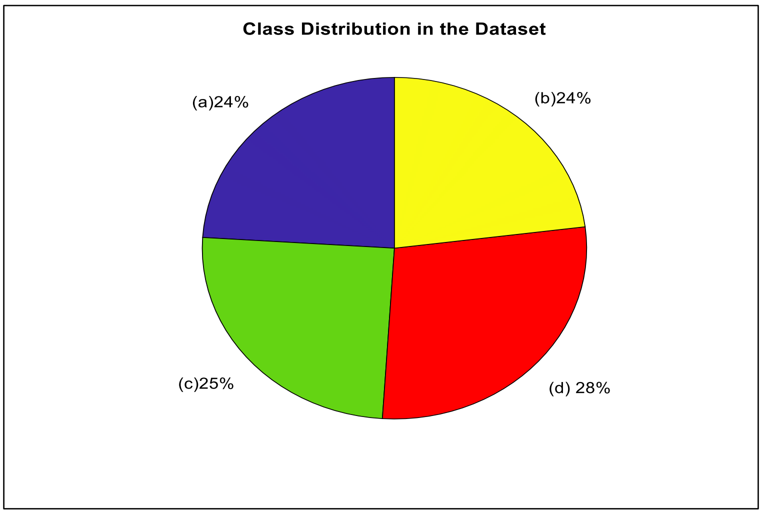

Figure 3: EPHNOGRAM Dataset.
Source: Authors, (2026).

Preprocessing

Data Balancing

Both the PhysioNet Challenge 2016 and EPHNOGRAM datasets exhibit class imbalance, with conditions like normal rhythms being more common than arrhythmias. This imbalance can lead to biased model predictions. To address this, oversampling techniques like SMOTE were used to enhance minority class representation, while undersampling was applied to reduce the size of the majority class. Data augmentation, including time-shifting, noise addition, and random cropping, was employed to increase the diversity of ECG and PCG signals while maintaining their physiological characteristics.

Signal Normalization

ECG and PCG signals from both datasets were collected from various devices, resulting in differences in amplitude and baseline drift. To standardise these signals, Min-Max normalisation scaled them to a [0, 1] range, while Z-score normalisation stabilised their distribution by adjusting for mean and standard deviation variations.

Noise Reduction

Noise in ECG and PCG signals, often due to muscle activity or stethoscope artefacts, was minimised using bandpass filtering. For ECG signals, frequencies between 0.5 Hz and 50 Hz were retained, while for PCG signals, a range of 20 Hz to 200 Hz was applied to preserve critical heart sound information and reduce unwanted noise.

Model Architecture

CNN for Feature Extraction:

CNNs are employed to extract spatial features from both ECG and PCG signals. The architecture consists of convolutional layers followed by ReLU activation and max-pooling layers, which downsample the data while preserving key features. This process reduces the input dimensionality and helps identify patterns in heart signals crucial for classification.

RNN for Temporal Learning:

After CNNs extract spatial features, RNNs, particularly Long Short-Term Memory (LSTM) or Bidirectional LSTM (BiLSTM), are used to capture the temporal relationships in the heart signals. These models are essential for processing sequential data like heartbeats, where dependencies between past and future information significantly influence the classification of heart conditions.

CNN+RNN Hybrid Model:

The hybrid CNN+RNN model leverages the spatial feature extraction capabilities of CNN and the temporal learning strength of RNN. This architecture efficiently captures both spatial patterns in the heart signals and the sequential dependencies over time, making it highly effective for analysing ECG and PCG data.

III.3 LSTM AND BILSTM MODELS:

LSTM captures long-term dependencies in ECG and PCG data by retaining key information from previous heartbeats, improving signal pattern analysis. BiLSTM extends this by processing data in both forward and backward directions, offering a deeper understanding of temporal dynamics. The LSTM+BiLSTM hybrid model combines both strengths, excelling at identifying complex patterns in ECG and PCG signals.

III.4 TRAINING AND EVALUATION

The training of the model was conducted using a cross-entropy loss function, which is commonly used for classification tasks. This loss function measures the performance of the classification model by comparing the predicted probability distribution to the actual class labels, penalising incorrect predictions.

Optimizer: The Adam optimiser was employed for training. Adam (Adaptive Moment Estimation) is popular because it combines the benefits of both the AdaGrad and RMSProp optimisers, using adaptive learning rates for each parameter to speed up convergence while maintaining stability.
Learning Rate: A fixed learning rate of 0.001 was used throughout training. This learning rate was chosen as a balance between training speed and model performance, allowing the model to converge without overshooting the optimal point.
The model parameters were updated iteratively based on the gradients calculated from the loss function, and training was conducted for multiple epochs to ensure that the model learned both spatial and temporal features effectively.
Evaluation Metrics:
The model's performance was evaluated using metrics, including:
Accuracy: The percentage of correctly predicted labels out of the total number of predictions. This metric indicates how well the model performs, but it may be less effective when classes are imbalanced.
Precision: The proportion of true positive predictions (correctly predicted positive class) out of all predicted positives. Precision is crucial for determining how well the model identifies true positives without mistakenly labeling negatives as positives.
Recall: The proportion of true positives out of the actual positives. It measures the model's ability to identify all relevant instances of the positive class.
F1-Score: The harmonic mean of precision and recall, providing a single metric that balances both. The F1-score is useful when the dataset has an imbalance between classes, since it penalises extreme values of either precision or recall.

IV.RESULT AND DISCUSSION

In our evaluation of the heart disease classification models using the PhysioNet Cardiology 2016 and EPHNOGRAM datasets, the hybrid LSTM+BiLSTM model achieved the highest performance, with an accuracy of 92.3%, precision of 91.9%, recall of 91.5%, and an F1-score of 91.7%. This suggests that combining long short-term memory networks with bidirectional LSTMs effectively captures temporal dependencies in the data. For the PhysioNet dataset, models based on CNN outperformed RNNs, highlighting the importance of convolutional feature extraction. In contrast, the performance of models on the EPHNOGRAM dataset was slightly lower overall, with the RNN+CNN model achieving a notable accuracy of 90.1%.

Table 3: Comparison of Model Performance DATASET 1.

DATASET	Models	Accuracy	Precision	Recall	F1-score
ECG and PCG PhysioNet Cardiology 2016	CNN	85.2	84.1	83.8	83.9
	RNN	88.5	87.9	88.1	88
	CNN	89.7	89.1	88.9	89
	RNN+CNN	90.4	90	89.8	89.9
	LSTM	91.1	91	90.7	90.8
	BiLSTM	92.3	91.9	91.5	91.7
ECG and PCG EPHNOGRAM	LSTM+BiLSTM	85.4	84.9	86.7	85.3
	RNN	88.2	87.5	89.1	88.3
	CNN	90.1	89.4	90.5	89.9
	RNN+CNN	84.7	83.5	85.2	84.3
	LSTM	86.9	86.2	87.1	86.6
	BiLSTM	89.4	88.8	89.9	89.3

Source: Authors, (2026).

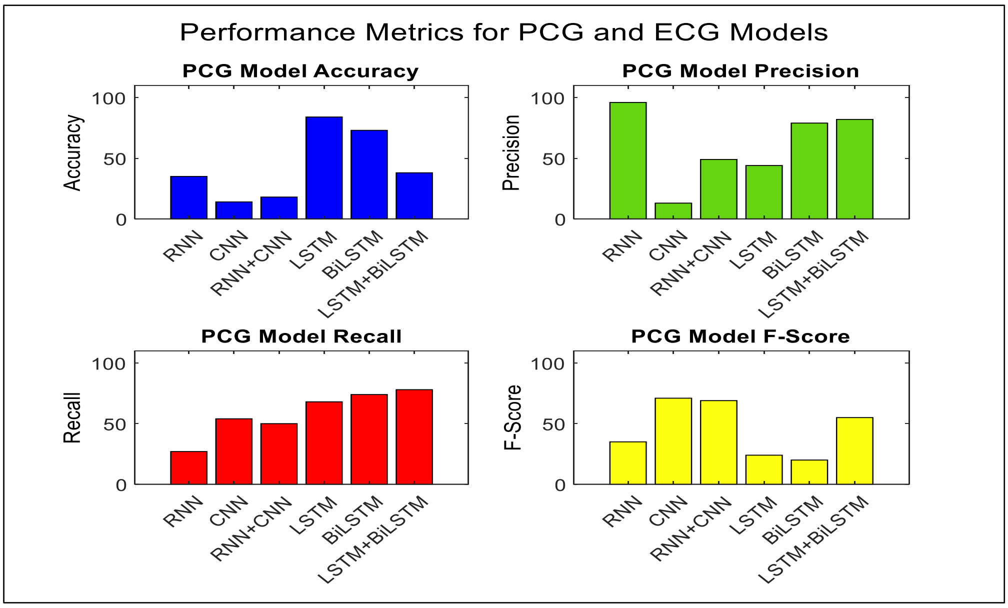

Figure 3: Performance Metrics of CVD Classification Models on the PhysioNet Cardiology 2016 Dataset.
Source: Authors, (2026).

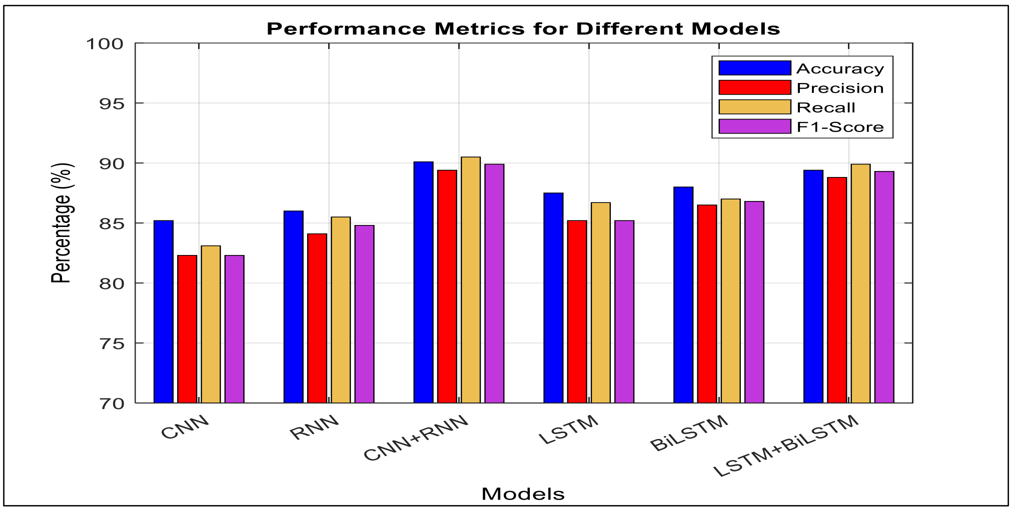

Figure 4: Performance Metrics of CVD Classification Models on the EPHNOGRAM Dataset
Source: Authors, (2026).

The table4 compares the performance of various models for classification tasks, highlighting accuracy, precision, recall, and F1-score. For instance, Diker et al.'s CNN achieved an accuracy of 83.82% with a precision of 82%, while Pengpai Li et al.'s LSTM+GA model excelled with an accuracy of 93.6%. Zeng et al.'s Bi-GRU model also performed well, achieving an F1 score of 93.27%. Our proposed LSTM+BiLSTM model achieved competitive results with an accuracy of 92.3%, a precision of 91.9%, and a recall of 91.5%. These results indicate its strength in handling time-series data, comparable to state-of-the-art methods like Zeng's Bi-GRU and Pengpai's LSTM+GA.

Table 4: Performance Comparison of Different Studies with Existing Work

Reference	Model	Accuracy	Precision	Recall	F1-score
A. Diker et al[1]	**CNN**	83.82	82	95	88.02
C. Pang et al[2]	**RF-RESNET**	87.2	88.8	79.5	83.9
Pengpai Li et al[3]	**LSTMs + GA**	93.6	90.3	84.5	87.4
Wajid Aziz et al[4]	**Ensemble Models**	81.9	89	83	85.8
Zeng, et al[5]	**Bi-GRU**	93.27	93.34	93.27	93.27
Ours	**LSTM+BiLSTM**	**92.3**	**91.9**	**91.5**	**91.7**

Source: Authors, (2026).

V.CONCLUSION

This research has demonstrated the effectiveness of various machine learning models for classifying multimodal heart signals, specifically using ECG and PCG data from the EPHNOGRAM and PhysioNet Cardiology 2016 datasets. The proposed architecture, particularly the LSTM+BiLSTM model, achieved a notable accuracy of 92.3% on the PhysioNet dataset, surpassing existing techniques and highlighting its potential for clinical use. Future research will optimise hyperparameters, leverage larger datasets, and incorporate modalities such as cardiac imaging and demographics for the classification of cardiovascular disease.

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Discussion of results: Islam D. S. Aabdalla, D.Vasumathi.
Writing – Original Draft: Islam D. S. Aabdalla, D.Vasumathi.
Writing – Review and Editing: Islam D. S. Aabdalla, D.Vasumathi.
Resources: Islam D. S. Aabdalla, D.Vasumathi.
Supervision: Mohammed Islam D. S. Aabdalla, D.Vasumathi.
Approval of the final text: Islam D. S. Aabdalla, D.Vasumathi.

VIII. REFERENCES

[1] H. Han, M. Xiang, C. Lian, D. Liu, and Z. Zeng, "A Multimodal Deep Neural Network for ECG and PCG Classification With Multimodal Fusion," in 2023 13th International Conference on Information Science and Technology (ICIST), 2023: IEEE, pp. 124-128.

[2] I. D. Suliman and D. Vasumathi, "Prediction of Heart Disease Using Machine Learning Algorithms," in 2023 14th International Conference on Computing Communication and Networking Technologies (ICCCNT), 2023: IEEE, pp. 1-12.

[3] K. Yan, T. Li, J. A. L. Marques, J. Gao, and S. J. Fong, "A review on multimodal machine learning in medical diagnostics," Math. Biosci. Eng, vol. 20, no. 5, pp. 8708-8726, 2023.

[4] N. Neelima, K. Jegdic, and A. Nagarwal, "Integrated Fusion Approach for Multi-Class HeartDisease Classification through ECG and PCG Signalswith Deep Hybrid Neural Networks," 2024.

[5] D. G. GONGADA, "MULTIMODAL SIGNAL ANALYSIS FOR DEPRESSION AND ANXIETY PREDICTION: A HYBRID CNN-RNN APPROACH," Journal of Theoretical and Applied Information Technology, vol. 101, no. 24, 2023.

[6] J. Cheng, Q. Zou, and Y. Zhao, "ECG signal classification based on deep CNN and BiLSTM," BMC medical informatics and decision making, vol. 21, pp. 1-12, 2021.

[7] S. A. L. Mary, S. Sivasubramanian, R. Palanisamy, and T. Thamizh Thentral, "An effective hybrid optimal deep learning approach using BI-LSTM and restricted Boltzmann machines whale optimization to detect arrhythmia," Multiscale and Multidisciplinary Modeling, Experiments and Design, pp. 1-19, 2024.

[8] I. D. Aabdalla and D. Vasumathi, "WAVELET SCATTERING TRANSFORM FOR ECG CARDIOVASCULAR DISEASE CLASSIFICATION."

[9] Y. Qiu et al., "Deep learning-based multimodal fusion of the surface ECG and clinical features in prediction of atrial fibrillation recurrence following catheter ablation," BMC Medical Informatics and Decision Making, vol. 24, no. 1, p. 225, 2024.

[10] H. M. Rai, K. Chatterjee, and C. Mukherjee, "Hybrid CNN-LSTM model for automatic prediction of cardiac arrhythmias from ECG big data," in 2020 IEEE 7th Uttar Pradesh section international conference on electrical, electronics and computer engineering (UPCON), 2020: IEEE, pp. 1-6.

[11] M. S. Islam, K. F. Hasan, S. Sultana, S. Uddin, J. M. Quinn, and M. A. Moni, "HARDC: A novel ECG-based heartbeat classification method to detect arrhythmia using hierarchical attention based dual structured RNN with dilated CNN," Neural Networks, vol. 162, pp. 271-287, 2023.

[12] N. Alamatsaz, L. Tabatabaei, M. Yazdchi, H. Payan, N. Alamatsaz, and F. Nasimi, "A lightweight hybrid CNN-LSTM explainable model for ECG-based arrhythmia detection," Biomedical Signal Processing and Control, vol. 90, p. 105884, 2024.

[13] S. Magesh and P. Rajakumar, "Ensemble feature extraction-based prediction of fetal arrhythmia using cardiotocographic signals," Measurement: Sensors, vol. 25, p. 100631, 2023.

[14] M. Baharoon et al., "HyMNet: a Multimodal Deep Learning System for Hypertension Classification using Fundus Photographs and Cardiometabolic Risk Factors," arXiv preprint arXiv:2310.01099, 2023.

[15] Z. Ahmad, A. Tabassum, L. Guan, and N. M. Khan, "ECG heartbeat classification using multimodal fusion," IEEE Access, vol. 9, pp. 100615-100626, 2021.

[16] H. Narotamo, M. Dias, R. Santos, A. V. Carreiro, H. Gamboa, and M. Silveira, "Deep learning for ECG classification: A comparative study of 1D and 2D representations and multimodal fusion approaches," Biomedical Signal Processing and Control, vol. 93, p. 106141, 2024.

[17] H. Hazeri, P. Zarjam, and G. Azemi, "Classification of normal/abnormal PCG recordings using a time–frequency approach," Analog Integrated Circuits and Signal Processing, vol. 109, no. 2, pp. 459-465, 2021.

[18] F. Zhou and D. Fang, "Multimodal ECG heartbeat classification method based on a convolutional neural network embedded with FCA," Scientific Reports, vol. 14, no. 1, p. 8804, 2024.

[19] M. Hammad, S. Meshoul, P. Dziwiński, P. Pławiak, and I. A. Elgendy, "Efficient lightweight multimodel deep fusion based on ECG for arrhythmia classification," Sensors, vol. 22, no. 23, p. 9347, 2022.

[20] Z. Shao, "Deep Atrial Fibrillation Classification Based on Multi-modal Attention Network," in Proceedings of the 2022 14th International Conference on Machine Learning and Computing, 2022, pp. 512-518.

[21] M. A. Reyna et al., "Heart murmur detection from phonocardiogram recordings: The george b. moody physionet challenge 2022," PLOS Digital Health, vol. 2, no. 9, p. e0000324, 2023.