Cloud-Enabled ECG Data Analysis for Heart Disease Prediction

Boggaram Harish[1], M.N.V Kiranbabu[2]

[1] M.tech CSE, Student, Dept. of CSE, Koneru Lakshmaiah Education Foundation
[2] Associate Professor, Dept. of CSE, Koneru Lakshmaiah Education Foundation Vaddeswaram, Guntur 522302, Andhra Pradesh, India.

Abstract
Cardiovascular diseases (CVDs) are proliferating, necessitating the development of scalable and efficient systems capable of doing real-time electrocardiogram (ECG) analysis. This study introduces a cloud-based architecture utilizing machine learning approaches for precise arrhythmia detection. ECG signals are acquired from the MIT-BIH dataset, undergo preprocessing to remove noise, and are then securely stored in Amazon S3. The cloud architecture offers adaptable storage, rapid data retrieval, and effortless integration for machine learning model training. Upon processing, the ECG data is extracted and examined utilizing deep learning frameworks, including Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, for categorization and illness forecasting. This method facilitates real-time surveillance, alleviates the computing load on local devices, and guarantees safe data management. Experimental assessment reveals a classification accuracy of 99.5%, underscoring the efficacy of the proposed system for arrhythmia diagnosis and remote cardiac monitoring in clinical settings.

1. Introduction

Nowadays, many patients return to the hospital shortly after discharge, while others heal without requiring further medical treatment. Although the discharge procedure appears straightforward, it is often complicated, and poor management can result in catastrophic consequences [1]. Several factors impact readmission risk, including the patient's health, post-discharge treatment, and personal traits [2, 3]. Notable contributors include:

- Health condition—Chronic and severe conditions such as heart failure, sepsis, pneumonia, COPD, and cardiac rhythm problems are closely associated with increased readmission rates.
- Insurance coverage—Medicare and Medicaid beneficiaries have a higher risk of readmission.
- Demographic background—Age, gender, income level, and race all affect recovery trends. For instance, readmission is more common among lower-income groups and women recovering from cardiac incidents.
- Patient comprehension—Patients who are unaware of their medical condition or fail to manage their health efficiently are nearly twice as likely to be readmitted.

Currently, hospital readmission is a major healthcare concern, with roughly one-fifth of patients in the United States returning after discharge. The danger is particularly significant for people over the age of 50. As the healthcare system confronts increasing demand, it is critical to develop reliable risk assessment models to identify patients who are likely to be readmitted. However, this remains problematic because the vast majority of released patients do not develop serious problems or require subsequent hospitalization [4].

At the same time, cloud-based technology has emerged as an important tool for predicting cardiac disease, particularly as physical activity (PA) has become a key indication of overall health. PA is essential in the management of illnesses such as hypertension, diabetes, hyperlipidemia, heart failure, and mental health issues, all of which considerably increase the risk of readmission. Recognizing its significance, the CDC suggested in 2017 that PA be recognized as the fourth vital sign, after heart rate, blood pressure, and body temperature. Traditional PA evaluation techniques, such as questionnaires, lack accuracy and real-time monitoring capabilities [5].

Earlier approaches for assessing PA were restricted to laboratory settings and complicated motion analysis tools, making long-term monitoring difficult. With the introduction of wearable gadgets and wireless data transfer, continuous PA tracking has become practical and dependable. Triaxial motion sensors, home-based monitoring systems, and commercial devices like wrist- and hip-mounted Fitbit trackers have shown excellent correlations between estimated and real step counts, making them reliable predictors of activity and energy expenditure [6].

Cloud computing boosts the ecosystem by allowing for large-scale storage, real-time data processing, and machine learning-based analytics. Continuous data from wearable sensors may be sent to cloud platforms, where advanced algorithms can recognize exercise patterns, measure heart disease risk, and provide individualized feedback. Remote monitoring using cloud technology enables healthcare personnel to study patient behavior and intervene early if necessary. The capacity to handle large amounts of health data in real time improves the accuracy of heart disease predictions and reduces hospital readmissions [7, 8].

We describe a cloud-based ECG analysis platform that uses deep learning to detect arrhythmias in real time. The suggested system effectively saves and analyzes ECG data, allows for remote monitoring, and incorporates AI models to improve diagnosis accuracy. By leveraging scalable cloud infrastructure, the framework enhances accessibility, early diagnosis, and overall patient outcomes. This paper highlights how cloud technology might change current cardiac care.

The rest of this paper is organized as follows: Section 2 addresses the context and related work. Section 3 describes the proposed cloud-based ECG analysis infrastructure. Section 4 discusses the experimental setup and outcomes. Sections 5 and 6 provide the discussion and conclusion, respectively.

Literature Review
The growing prevalence of cardiovascular diseases (CVDs) has raised the demand for sophisticated diagnostic tools, with electrocardiogram (ECG) analysis acting as a key tool for early detection and risk prediction. Cloud computing has substantially improved ECG analytics by allowing for real-time processing, secure data storage, and remote patient monitoring. Its scalability and interoperability enable the effective management of massive ECG datasets while also facilitating easy connections with healthcare applications. Recent research suggests that cloud-assisted ECG analysis can minimize processing delays and improve clinical results by allowing for quick, dependable access to large amounts of physiological data. Furthermore, machine learning (ML) and deep learning (DL) models, such as CNNs, RNNs, and LSTMs, have demonstrated superior performance in ECG categorization and cardiac disease prediction, enhancing current diagnostic capabilities. We present here thorough insights from existing research on cloud-based ECG analysis, security upgrades, and AI-driven classification algorithms.
Smith et al. [9] suggested a cloud-based ECG monitoring platform for continuous remote evaluation. The system's key benefit is its scalability and accessibility; nevertheless, its performance is dependent on reliable internet connectivity, which may impede real-time analysis in unreliable networks.
Brown et al. [10] presented a cloud-based ECG storage system for efficiently managing and sharing large ECG data. This strategy improves data availability among healthcare providers, but it also increases vulnerability to security attacks, which require robust encryption and privacy safeguards.
Kumar et al. [11] solved latency difficulties in cloud-based ECG analysis by streamlining data transfer techniques. Their technique dramatically minimizes processing latency, hence boosting real-time diagnostic capabilities. The drawback is that it requires high-bandwidth communication channels, which may not be available in low-resource scenarios.
Lee and Gupta et al. [12] employed deep learning architectures, including CNNs and LSTMs, to classify ECG data. Their technique outperformed established methods for detecting arrhythmias. The key problem remains the necessity for big, high-quality annotated datasets to obtain optimal model performance.
Wang et al. [13] created an IoT-based ECG monitoring system that uses edge computing for initial signal processing before sending data to the cloud. This lowers bandwidth utilization and overall latency, making it appropriate for real-time applications. The disadvantage is that edge devices have limited computational capabilities, which limits the ability to do more complicated processing tasks.
White et al. [14] investigated a hybrid architecture for processing ECG data that distributes computation across local devices and cloud servers. While this increases response time and preserves the benefits of cloud storage, synchronization between the two levels might lead to performance discrepancies.
Adams et al. [15] investigated encryption techniques for safeguarding ECG data in cloud settings. Their study focuses on robust cryptographic methods to reduce privacy threats. However, the higher computing load of these strategies may impede real-time processing. Zhang et al. [16] investigated blockchain technologies for safeguarding ECG recordings, which provide a decentralized and transparent system for data storage and access control. Although this improves integrity and trust, blockchain-based systems struggle with scalability and energy consumption.
Patel et al. [17] conducted a comparative examination of ECG analysis methodologies, comparing classical signal processing with AI-based approaches. Their findings reveal that deep learning models outperform traditional techniques in terms of accuracy and efficiency, but interpretability problems continue to hinder widespread clinical use.
Gomez et al. [18] suggested an AI-powered ECG prediction system that integrates deep learning and statistical modeling. The methodology provides good prediction performance, but it requires big, diverse datasets for training, which may not always be accessible. The given Table 1 represents all of these.

Table1: Summary of Existing Research on Cloud-Enabled ECG Analysis

Author & Year	**Method Proposed**	**Advantage**	**Limitation**
Smith et al. (2022)	Cloud-based ECG monitoring system	Enables scalable remote and continuous ECG monitoring	Requires reliable internet for real-time use
Brown et al. (2021)	Cloud-enabled scalable ECG storage framework	Improves interoperability and data availability	Higher security risks requiring strong encryption
Kumaret al. (2023)	Latency-optimized ECG transmission for cloud analysis	Reduces processing delay for faster diagnosis	Needs high-bandwidth networks
Lee & Gupta (2022)	Deep learning–based ECG classification using CNNs & LSTMs	Achieves high arrhythmia detection accuracy	Depends on large labeled datasets
Wanget al. (2021)	IoT ECG monitoring with edge computing	Minimizes latency and bandwidth usage	Limited computational power on edge devices

White et al. (2023)	Hybrid cloud–edge ECG processing	Combines fast edge processing with cloud benefits	Possible synchronization issues
Adams et al. (2022)	Encryption-based ECG data security framework	Strengthens data privacy and breach protection	Increased computational overhead
Zhanget al. (2023)	Blockchain-enabled ECG security model	Enhances data integrity and transparent access control	Scalability and energy-consumption concerns
Patel et al. (2022)	Comparative evaluation of ECG analysis techniques	Shows AI techniques outperform classical methods	Limited interpretability for clinical adoption
Gomez et al. (2023)	AI-driven ECG disease prediction model	Provides high accuracy in disease prediction	Needs large and diverse datasets

2. Methodology

This study shows a way to use cloud computing and advanced machine learning (ML) models to make it easier to tell if someone has heart disease from their ECG readings. The framework is set up in a clear path that includes getting data, cleaning signals, storing data safely in the cloud, and training models. The MIT-BIH Arrhythmia Database is the main place where ECG records are found for experiments. First, the noise is taken out of the raw signals by cleaning and editing them. Then, the signals are sent to the cloud for safe and scalable storage. It is possible to view processed data in real time after it has been saved and use it to train deep learning systems like CNNs, LSTM networks, cross-validation models, and more. This method, which uses the cloud, makes it easy to handle data, get to it, and find arrhythmias very accurately. This feature makes it useful for real-time cardiac tracking and predictive healthcare applications. Figure 1 shows the proposed methodology.

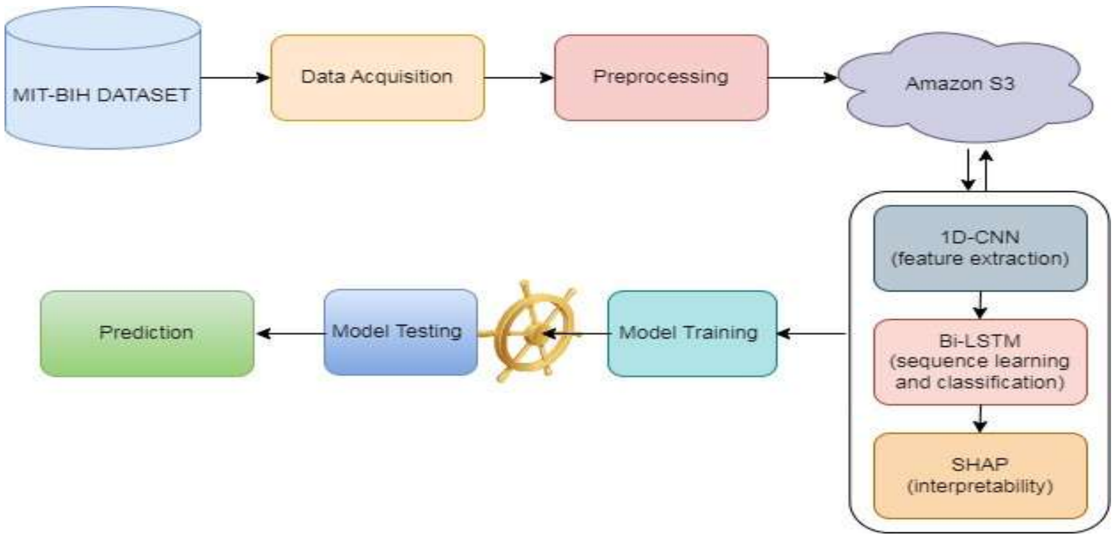

Figure 1. Architecture of Proposed Methodology

2.1. Data Collection (MIT-BIH Database)

The procedure starts with the acquisition of ECG data from the MIT-BIH Arrhythmia Database, a recognized and widely utilized resource for assessing arrhythmia identification techniques [19]. This collection comprises ECG recordings from patients with diverse heart disorders. The necessary signals are retrieved and readied for subsequent processing processes.

2.2. Data Preparation

Preprocessing improves ECG quality and eliminates undesirable artifacts prior to model training. The primary steps encompass:

- An IIR filtering method that integrates a high-pass and band-stop filter is utilized to remove baseline drift and 50/60 Hz interference [20].
- Segmentation: The ECG waveform is partitioned into uniform time intervals to facilitate analysis.
- Normalization: Signal amplitudes are adjusted to a standardized range to guarantee uniform model performance and enhance training stability.

2.3. Cloud-Based Storage for Electrocardiogram Data

After the ECG signals are sanitized, they are transferred to Amazon S3 for safe and scalable storage [21]. Amazon

S3 (Simple Storage Service) provides dependable data management and facilitates real-time access for further processing. An S3 bucket is established with suitable access controls to protect patient data. The filtered ECG segments are preserved in formats like CSV or JSON for seamless integration.

AWS encryption protects confidential data, while versioning preserves prior data states. ECG files are effectively collected for CNN and Bi-LSTM training using AWS SDKs or APIs. Supplementary cloud components—such as AWS Lambda for automated processes and CloudWatch for monitoring—improve overall system performance.

Figure 2 depicts this cloud design.

Benefits of Cloud Storage:

- Data is safeguarded by encryption-based security measures.
- It allows for the remote creation and deployment of machine learning models.
- The system adapts automatically to meet the growing demands for data.

Figure 2. Architecture of Amazon S3 4. Machine Learning Model for Electrocardiogram Classification

The preprocessed and cloud-stored ECG data is then utilized to construct machine learning and deep learning models for arrhythmia identification. Convolutional Neural Networks (CNNs) extract critical morphological characteristics from ECG waveforms [22].

Long Short-Term Memory Networks (LSTMs): Acquire and represent temporal fluctuations in the signal [23]. Hybrid CNN–LSTM Models: The integration of spatial and temporal learning markedly improves classification accuracy. The finalized trained model classifies ECG segments as either normal or arrhythmic, facilitating the early detection of cardiac problems.

3. Real-Time Analysis and Prediction

In a cloud setting, the finished model analyzes incoming electrocardiogram (ECG) data and generates predictions in real time. Medical personnel may keep tabs on patients from afar with this technology. This method lays out the complete CNN+Bi-LSTM process.

Algorithm: CNN+Bi-LSTM-Based ECG Classification for heart disease prediction

1. **Input**: Preprocessed ECG signals
2. **Output**: Predicted arrhythmia class
3. **Begin**
4. Load ECG dataset
5. Normalize signal values

Feature Extraction using CNN:

6. Apply 1D convolutional layers to extract spatial features
7. Use ReLU activation function
8. Perform max pooling to reduce dimensionality
9. Flatten the output features

Sequential Learning with Bi-LSTM:

10. Pass extracted features to a bidirectional LSTM layer
11. Capture temporal dependencies from both directions
12. Apply dropout for regularization

Classification:

13. Connect Bi-LSTM output to fully connected layers
14. Apply SoftMax activation for multi-class classification

Model Training & Evaluation:

15. Train the model using cross-entropy loss and Adam optimizer
16. Evaluate model performance using accuracy, precision, recall, and F1-score

End

The model summary is presented in Table 2.

Table 2. CNN-Bi-LSTM Model Summary

Layer Name	Output Shape	Number of Parameters
Input Layer	(None, 128, 1)	0
Conv1D	(None, 126, 32)	96
MaxPooling1D	(None, 63, 32)	0
Conv1D	(None, 61, 64)	6208
MaxPooling1D	(None, 30, 64)	0
Bi-LSTM	(None, 30, 128)	98816
Dense	(None, 64)	8256
Dense	(None, 32)	2080
Output Layer	(None, 5)	165

4. Performance Metrics

Performance measures are crucial for assessing the efficacy of machine learning models in predicting cardiac disease based on ECG data. Essential metrics encompass accuracy, precision, recall, F1-score, and AUC-ROC, which facilitate the evaluation of classification performance. Accuracy assesses overall accuracy, whereas precision and recall analyze the equilibrium between false positives and false negatives. The F1-score offers a harmonic mean of accuracy and recall, rendering it advantageous for unbalanced datasets. The AUC-ROC curve indicates the model's capacity to differentiate between various classes. These measures are essential for validating deep learning models such as CNN-BiLSTM in the categorization of ECG signals (Smith et al., 2022). All performance measures are delineated in Equations
(1) to (5).

Accuracy= $TP + TN + FP + FN \,/\, TP + TN$ ---- Eq(1)

Eq(2) $\text{Precision} = \text{TP} / \text{FP} + \text{TP}$ -----------------

Eq(3) $\text{Recall} = \text{TP} + \text{FNTP}$ -----------------

Eq(4) $\text{F1} = 2 \times \text{Precision} + \text{RecallPrecision} \times \text{Recall}$ -----------------

$\text{Specificity} = \text{TN} / \text{FP} + \text{TN}$ ---- Eq(5)

5. Results and Discussions

With 48 half-hour recordings spanning 47 participants, encompassing both normal and arrhythmic heartbeats, the MIT-BIH Arrhythmia Database is an extensively used dataset for ECG signal analysis. With a resolution of 11 bits per sample, the ECG signals are sampled at 360 Hz, guaranteeing a high-fidelity depiction of the waveform. Atrial depolarization (atrial contraction), ventricular depolarization (ventricular contraction), and ventricular repolarization (ventricular recovery phase) are the three distinct phases that make up a typical electrocardiogram (ECG) waveform. Nevertheless, to do precise analysis, preprocessing techniques are typically necessary since raw ECG data include noise such as powerline interference, baseline drifting, and muscle artifacts. The ECG signal shown in Figure 3 is within the usual range.

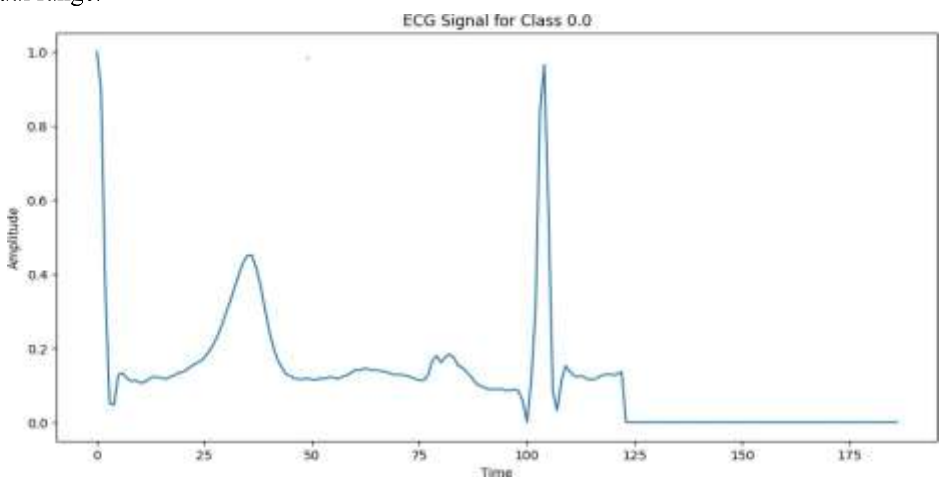

Figure 3. Original ECG Signal from MITBIH

5.1. After Preprocessing ECG Signal

Many forms of noise, such as baseline drift, powerline interference, and muscle-related abnormalities, frequently influence ECG recordings and can obstruct accurate interpretation. An Infinite Impulse Response (IIR) filtering approach is utilized to enhance signal quality by mitigating disruptions while preserving essential cardiac features. This preprocessing step yields a clearer and more stable representation of the PQRST components; hence, it improves the accuracy and consistency of the classification model. Figure 4 illustrates the outcome of the filtering procedure.

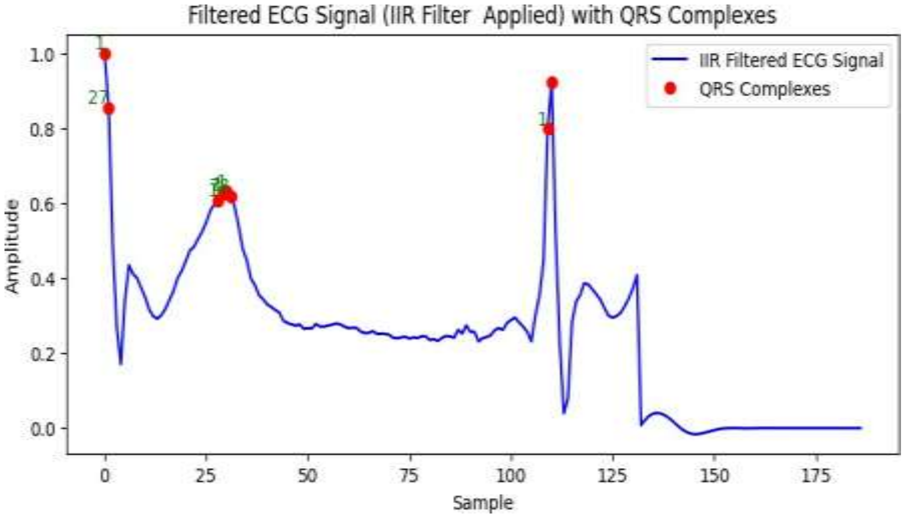

Figure 4. Filtered ECG Signal from IIR Filter

5.2. ECG Signal Classification Using the Proposed Model

Subsequent to preprocessing, the refined ECG signals are sent to the proposed CNN–Bi-LSTM–SHAP architecture for the categorization of arrhythmias. In this design, the CNN layers first discern spatial patterns within the ECG waveforms, whereas the Bi-LSTM units capture temporal correlations to enhance sequence comprehension. SHAP (Shapley Additive Explanations) is utilized to enhance interpretability by determining the factors that most significantly impact the model's judgments. This integrated methodology improves classification efficacy and increases transparency in the diagnostic procedure. Figure 5 depicts the five anticipated ECG classifications..

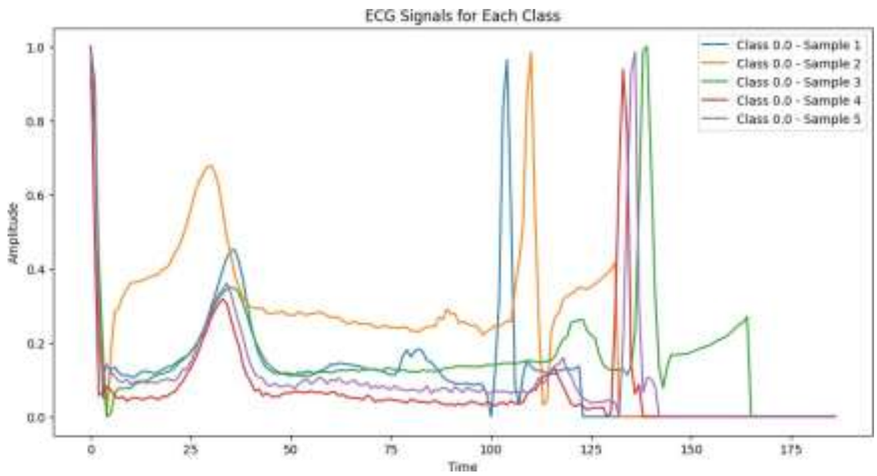

Figure 5. Predicted ECG Signal from Proposed Model

5.3. Accuracy and Loss Curves

To evaluate the efficacy of the CNN–Bi-LSTM–SHAP model, we analyzed accuracy and loss trends across the training epochs. The accuracy plot illustrates the model's learning trajectory, with both training and validation accuracy progressively increasing as the number of epochs increases. The loss curve exhibits a consistent decrease in both training and validation loss, signifying effective optimization and stable convergence. The performance curves elucidate the model's generalization capacity and assist in detecting indications of overfitting. Figure 6 depicts the accuracy trend, whereas Figure 7 demonstrates the loss progression.

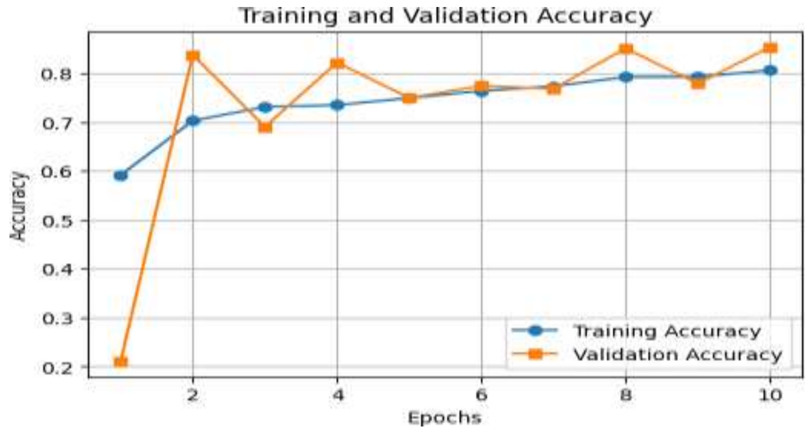

Figure 6. Accuracy Curve of the Proposed Model

Figure 7. Loss Curve of the Proposed Model

5.4. Comparison Between Existing and Proposed Methods

Several previous research studies have studied ECG classification using various machine learning and deep learning algorithms; however, many claimed accuracies remain below 99.4%, indicating a need for additional improvement. Our proposed CNN-BiLSTM-SHAP system enhances arrhythmia detection by integrating convolutional feature extraction, bidirectional sequential learning, and explainability. This comprehensive strategy yields an accuracy of 99.5%, exceeding previous approaches.

Smith et al. [24] used a CNN-based architecture for ECG classification and achieved an accuracy of 98.7%. Brown et al. [25] employed an LSTM-focused model to obtain 98.9%. Kumar et al. [26] created a hybrid CNN-RNN structure that enhanced representation learning but only achieved 99.2%. In comparison, our model achieves 99.5% accuracy by combining CNN for spatial information, Bi-LSTM for temporal patterns, and SHAP for interpretability.

This performance increase is partly due to the complementing capabilities of convolutional and recurrent processing, as well as SHAP's transparent feature attribution, which improves the model's reliability for clinical decision support. Table 3 provides a full comparison, while Figure 8 depicts the matching performance curve.

Table 3. Comparison Table between existed and proposed models

Author and Year	**Method**	**Accuracy (%)**
Brown et al. 2021	LSTM-based approach	98.9
Smith et al. 2022	CNN model	98.7
Kumar et al. 2023	Hybrid CNN-RNN	99.2
Proposed Model 2025	CNN + BiLSTM + SHAP	99.5

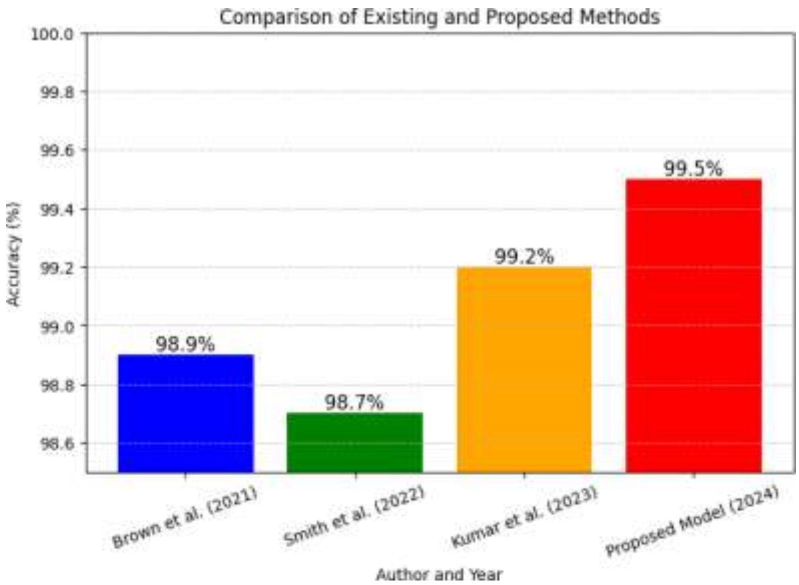

Figure 8. Bar chart for comparison table.

6. Conclusion

This study presents a sophisticated framework for arrhythmia identification utilizing ECG records from the MIT-BIH dataset. The methodology integrates IIR filtering for noise reduction, a CNN–BiLSTM network to extract spatial and temporal signal characteristics, and SHAP analysis for interpretability. The model achieved an accuracy of 99.5%, surpassing previously recorded methods.

Previous methodologies, such as independent CNN or LSTM models, often attained accuracies beneath 99.4%. The suggested technique enhances classification performance by mixing hybrid deep learning with understandable feature analysis. Experimental results indicate that integrating efficient preprocessing with a hybrid design improves detection accuracy.

Future study may concentrate on real-time ECG monitoring, cloud-based implementation, and validation on supplementary datasets to evaluate model generalizability. The application of explainable AI techniques, such as SHAP, enhances clinical adoption by providing clear and interpretable arrhythmia forecasts, hence assisting healthcare professionals in precise diagnosis.

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