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Arrhythmia on ECG Classification using CNN

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Abstract
Arrhythmia classification from ECG signals is a critical task in cardiac disease diagnosis, demanding high accuracy and robust generalization. This study explores deep learning and ensemble techniques for automated arrhythmia detection using the MIT-BIH dataset. A comparative analysis is conducted on multiple models, including CNN, LSTM, BiLSTM, GRU, SVM, LightGBM, and Random Forest, with an emphasis on hybrid architectures such as CNN + LSTM and CNN + BiLSTM. The performance of these models is evaluated using standard metrics, highlighting the advantages of deep learning over traditional machine learning approaches. Further enhancement is achieved by implementing ensemble learning techniques, particularly a Voting Classifier that integrates multiple boosted models for improved classification performance. CNN-based architectures, coupled with sequential models like LSTM and BiLSTM, demonstrate superior feature extraction and temporal dependency learning capabilities, effectively capturing ECG signal variations. The study underscores the efficacy of deep learning and ensemble strategies in arrhythmia classification, offering insights into optimal model selection and integration for real-time ECG analysis. Experimental results validate the robustness of hybrid and ensemble approaches, achieving significant improvements in classification accuracy and clinical applicability.
*“**Index Terms:** Arrhythmia Classification, ECG Signals, Convolutional Neural Network (CNN), Deep Learning, Ensemble Learning, Hybrid Models”.*

1. INTRODUCTION

Electrocardiogram (ECG) signals are vital indicators of cardiac health and are extensively used for diagnosing cardiovascular disorders, particularly arrhythmias. Arrhythmia refers to an abnormal rhythm of the heart, which, if undetected, can lead to serious complications such as stroke, heart failure, or sudden cardiac arrest. Early and accurate detection of arrhythmias is crucial for initiating timely medical treatment. Traditionally, ECG interpretation has been performed manually by clinicians, but this process is not only time-consuming but also susceptible to human error, especially when dealing with large volumes of data or subtle variations in heartbeat patterns. The increasing availability of annotated ECG datasets, such as the MIT-BIH arrhythmia database, has facilitated the development of automated diagnostic systems that can analyze and classify ECG signals with greater consistency and speed [1], [4], [10].

Recent advancements in artificial intelligence, particularly in machine learning and deep learning, have revolutionized the way ECG signals are processed and interpreted. These technologies offer powerful tools for automating the detection of arrhythmic events. Traditional machine learning methods, such as support vector machines and decision trees, often depend on handcrafted features and domain expertise, which may limit their generalization capability. In contrast, deep learning models, particularly convolutional neural networks (CNNs), have demonstrated remarkable performance in end-to-end ECG signal classification tasks [2], [5], [6]. CNNs are capable of extracting spatial hierarchies of features directly from raw ECG waveforms, minimizing the need for manual feature engineering and enabling more scalable and adaptive diagnostic systems [1], [14].

Hybrid deep learning models that integrate CNNs with sequential models like Long Short-Term Memory (LSTM) or Bidirectional LSTM (BiLSTM) further enhance classification performance by capturing both spatial and temporal dependencies in ECG signals [2], [9], [16]. These architectures

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are well-suited for modeling the sequential nature of heartbeat patterns and have proven effective in identifying various arrhythmia types. Additionally, ensemble learning approaches, including techniques such as voting classifiers or stacked models, further boost the robustness and accuracy of classification by combining the strengths of multiple base learners [12], [18].
This study aims to build upon these advances by developing and evaluating deep learning-based ECG classification models, with a focus on CNN and its hybrid variations. By leveraging ensemble methods, we aim to create a comprehensive and reliable arrhythmia detection system capable of real-time analysis. The integration of CNN-based architectures with ensemble strategies offers a promising path toward more accurate, automated, and clinically applicable ECG diagnostics [7], [11], [15].

2. LITERATURE REVIEW

Recent developments in arrhythmia classification have seen a surge in the application of deep learning models, especially those tailored to enhance the interpretability, efficiency, and accuracy of ECG signal analysis. Berrahou et al. [5] explored arrhythmia detection using inter-patient ECG signals by leveraging entropy rate features and RR intervals in conjunction with a CNN architecture. Their method addressed the challenge of inter-patient variability and demonstrated improved generalization across unseen subjects. In a similar pursuit of feature-rich classification, Soman and Sarath [6] proposed an optimization-enabled deep convolutional neural network that integrates multiple features from ECG signals. Their model aimed to extract complex, clinically meaningful patterns and significantly improve classification performance through optimized network design.
Eleyan et al. [7] introduced a spectrogram-based approach using a three-channel deep learning model with feature fusion, capitalizing on time-frequency domain representation of ECG signals. Their multi-channel fusion technique allowed for more detailed analysis of cardiac rhythms, enhancing the robustness of arrhythmia classification. Zhou and Fang [8] presented a multimodal ECG heartbeat classification method, embedding a convolutional neural network with Formal Concept Analysis (FCA). Their unique incorporation of FCA helped uncover deeper conceptual relationships within the ECG data, contributing to improved classification accuracy and model transparency.
Venkatesh et al. [9] proposed a deep network ensemble model that combines 1D-CNN and Bidirectional Long Short-Term Memory (BiLSTM) architectures for automated atrial arrhythmia classification. This hybrid model effectively captures spatial and temporal dependencies in the ECG signal, enabling a more comprehensive understanding of complex arrhythmic patterns. Kim and Sunwoo [10] took a large-scale approach by developing an automated classification network capable of identifying 45 arrhythmia classes using 12-lead ECGs. Their system addressed multi-class challenges and exhibited strong generalization, making it one of the most inclusive deep learning models for ECG classification to date.
Devasenapathy et al. [11] focused on the Internet of Things (IoT) healthcare domain by designing a CNN-grounded deep learning classification technique suitable for real-time diagnosis of cardiac arrhythmias. Their model was tailored for resource-efficient deployment, providing reliable arrhythmia detection in IoT-enabled health monitoring environments. Admass and Bogale [12] introduced a meta-heuristic-enhanced hybrid model that integrates optimal weighted feature fusion with attention mechanisms. Their attention-based approach emphasized critical ECG segments, improving focus and interpretability while boosting classification accuracy.
Challagundla [13] presented an advanced neural network architecture for multi-lead ECG arrhythmia detection, incorporating optimized feature extraction strategies. Their work focused on leveraging feature representation and deep learning to enhance the detection capability of arrhythmic patterns across multiple ECG leads. Anand et al. [14] proposed an enhanced ResNet-50 deep learning model designed for arrhythmia detection using biomedical indicators extracted from ECG signals. Their adaptation of the ResNet-50 model demonstrated strong feature learning

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capabilities and efficient classification performance, supporting the trend toward transfer learning and pre-trained architectures in medical diagnostics.

Collectively, these contributions underscore a growing emphasis on hybrid, optimized, and explainable deep learning models in arrhythmia classification research. The integration of CNNs with advanced modules like BiLSTM [9], attention mechanisms [12], formal concept analysis [8], and spectrogram-based channels [7] reflects a movement toward models that can better exploit both spatial and temporal characteristics of ECG signals. Moreover, the push for scalability and real-time deployment is evident in the works of Kim and Sunwoo [10] and Devasenapathy et al. [11], both of whom prioritize systems that are practical for clinical or remote use. Optimization strategies, whether through algorithmic enhancements [6], [12] or architectural innovations [13], continue to improve model efficiency and predictive accuracy.

Furthermore, these studies contribute to addressing critical challenges in arrhythmia classification, such as inter-patient variability [5], multi-lead signal complexity [13], and real-time data handling [11]. By incorporating novel methodologies like feature fusion [7], multi-class categorization [10], and attention-based interpretability [12], researchers are paving the way for smarter, more robust ECG diagnostic systems. These systems not only enhance clinical workflows but also offer scalable solutions for wearable and home-based health monitoring platforms.

3. MATERIALS AND METHODS

The proposed system presents an efficient arrhythmia classification framework utilizing deep learning and ensemble techniques for ECG signal analysis. It employs models such as CNN, LSTM, BiLSTM, GRU, SVM, LightGBM, and Random Forest to evaluate performance across learning paradigms. Hybrid architectures like CNN+LSTM and CNN+BiLSTM enhance feature extraction and temporal modeling [2], [9]. An ensemble Voting Classifier integrates multiple models for robust prediction [12]. Preprocessing includes ECG signal normalization and segmentation for consistent input [5]. Deep networks extract spatial-temporal features, while traditional classifiers add interpretability [6], [10]. The combined approach enhances accuracy, reduces false positives, and ensures clinical applicability in real-time settings [11], [14]. This system reflects current trends in hybrid and ensemble-based ECG classification.

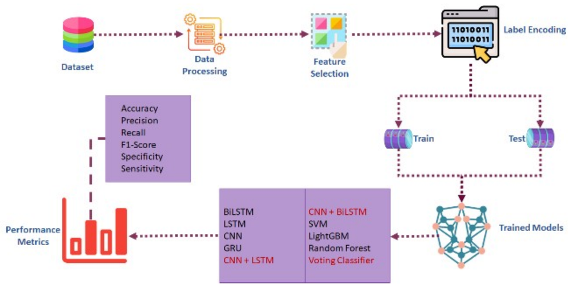

Fig.1 Proposed Architecture

This system architecture Fig. 1 arrhythmia on ECG data using CNN and other models. A dataset undergoes processing and feature selection. Label encoding prepares the data for training and testing. Models like BILSTM, LSTM, CNN, GRU, CNN+LSTM, CNN+BILSTM, SVM, LightGBM, Random Forest, and a Voting Classifier are trained. Performance is evaluated using accuracy, precision, recall, F1-score, specificity, and sensitivity to determine the most effective arrhythmia classification model.

A) Dataset Collection:

The dataset used for arrhythmia classification is sourced from the MIT-BIH arrhythmia database, containing annotated ECG recordings. Initial exploration involves loading the dataset and analyzing key attributes such as class distribution, missing values, and statistical summaries of features. Visual tools like histograms and correlation matrices are employed to identify patterns, relationships, and imbalances in the data. This exploratory analysis is crucial for guiding

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preprocessing, feature selection, and model design to ensure accurate and reliable classification outcomes.

B) Pre-Processing:

Pre-processing involves preparing the ECG data for model training through data cleaning and transformation. Key steps include feature selection to retain relevant attributes, label encoding to convert categorical labels into numerical form, and overall data processing to ensure consistency and accuracy.

Data Processing: Data processing begins with removing duplicate records and handling missing values to ensure dataset integrity. Irrelevant or non-informative features are dropped to reduce noise. This cleaning phase is critical for enhancing model accuracy and generalization by focusing on reliable ECG data. Standardization and normalization techniques may also be applied to bring data onto a common scale, facilitating consistent input for both deep learning and machine learning algorithms.

Feature Selection: Feature selection is performed to retain the most informative and relevant attributes from the ECG dataset. Statistical methods and correlation analysis are used to identify and eliminate redundant or weakly correlated features. This process reduces model complexity, accelerates training, and improves classification performance. By focusing on features that capture significant patterns in ECG signals, the system enhances interpretability and ensures efficient utilization of computational resources.

Label Encoding: Label encoding converts categorical arrhythmia class labels into numerical form, enabling compatibility with machine learning and deep learning models. Each unique label is mapped to an integer value while maintaining class distinctions. This transformation is essential for supervised learning, where numerical class identifiers are required. Label encoding simplifies class handling during model training and evaluation, ensuring that the system accurately associates ECG patterns with corresponding arrhythmia categories.

C) Training and Testing:

The dataset is split into training and testing subsets to facilitate both model learning and evaluation. 80% of the data is used for training, allowing the model to learn the underlying patterns and relationships within the ECG signals. The remaining 20% is reserved for testing, providing a separate set of unseen data to assess the model's performance and generalization ability. This division ensures that the model is not overfitted to the training data and can effectively predict arrhythmias in new, unseen ECG samples, thereby ensuring its reliability in real-world clinical applications.

D) Algorithms:

BiLSTM: BiLSTM is a bidirectional extension of LSTM that captures both past and future dependencies in sequential data, enhancing context understanding. It improves ECG arrhythmia classification by analyzing heart signal variations from both directions [9], [12].

***LSTM*:** LSTM handles long-term dependencies in sequential data through memory cells and gating mechanisms. It mitigates vanishing gradient issues, making it effective in ECG classification for detecting abnormal heart rhythms and time-dependent features [6], [10].

***CNN*:** CNN extracts spatial features through convolutional layers, identifying local patterns in structured data like ECG signals. It is efficient in detecting signal variations, enabling robust arrhythmia classification by automatically extracting relevant features [5], [14].

***GRU*:** GRU, a simpler alternative to LSTM, captures sequential dependencies with fewer parameters. It is computationally efficient in processing temporal variations in ECG signals, making it ideal for real-time medical applications [7], [12].

***CNN+LSTM*:** CNN+LSTM combines CNN's spatial feature extraction with LSTM's sequential pattern analysis, improving ECG arrhythmia classification. The hybrid approach captures both waveform characteristics and temporal dependencies for enhanced prediction accuracy [9], [14].

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***CNN+BiLSTM*:**
CNN+BiLSTM integrates CNN for spatial feature extraction and BiLSTM for bidirectional temporal learning, improving ECG arrhythmia classification. This model captures both local signal features and long-range dependencies, boosting classification accuracy [7], [9].

***SVM*:**
SVM is a supervised learning algorithm that separates data using hyperplanes. It is effective in ECG classification, transforming non-linear data into higher-dimensional spaces using kernel functions, ensuring robust performance with limited data [5], [12].

***LightGBM*:**
LightGBM is a gradient boosting framework that accelerates tree-based learning. It efficiently distinguishes normal and abnormal heart rhythms in ECG signals by learning decision patterns, offering scalability and fast processing for large medical datasets [10], [12].

***Random Forest*:** Random Forest constructs multiple decision trees, combining their predictions to improve classification performance. It enhances ECG arrhythmia detection by reducing overfitting and increasing model stability, providing robust predictions for medical diagnostics [5], [14].

***Voting Classifier*:** Voting Classifier combines multiple base models through majority voting or weighted averaging, enhancing ECG arrhythmia classification accuracy. It integrates various classifiers to leverage their strengths, ensuring more reliable and robust predictions in complex datasets [12], [14].

4. RESULTS AND DISCUSSION

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} (1)$$

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} (2)$$

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} (3)$$

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$F1\ Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100 (4)$$

Table (1) evaluate the performance metrics—Accuracy, precision, recall and F1-score —for each algorithm. The Voting Classifier, Random Forest consistently outperforms compared to all other algorithms. The tables also offer a comparative analysis of the metrics for the other algorithms.

Table.1 Performance Evaluation

ML Model	Accuracy	F1 Score	Recall	Precision
CNN	0.967	0.968	0.967	0.970
LSTM	0.828	0.906	0.828	1.000
CNN + LSTM	0.981	0.981	0.981	0.982
BiLSTM	0.064	0.118	0.064	0.885

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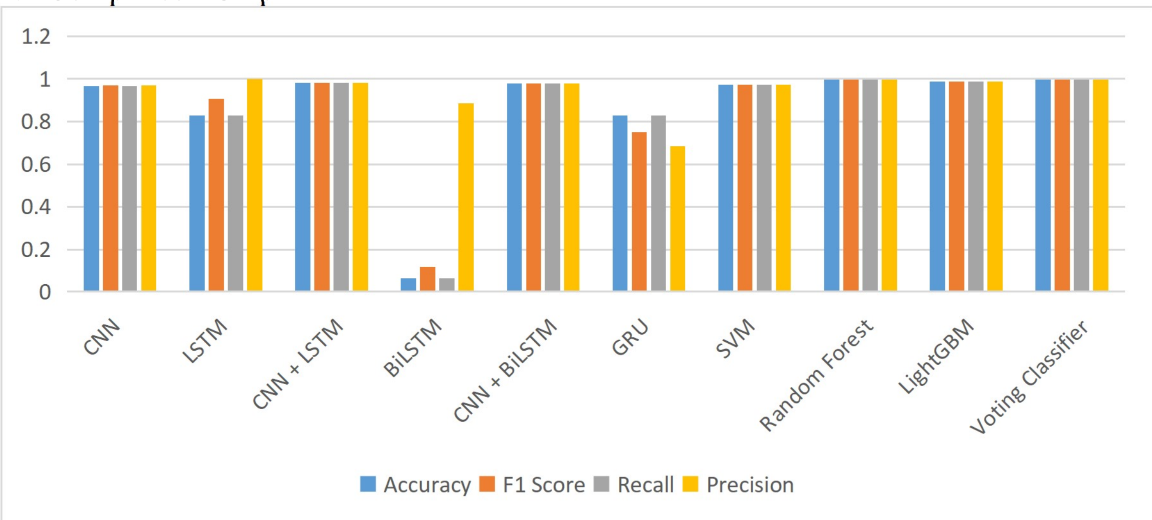
CNN + BiLSTM	0.978	0.978	0.978	0.979
GRU	0.828	0.750	0.828	0.685
SVM	0.971	0.971	0.971	0.972
Random Forest	**0.997**	**0.997**	**0.997**	**0.997**
LightGBM	0.988	0.988	0.988	0.988
Voting Classifier	**0.997**	**0.997**	**0.997**	**0.997**

Graph.1 Comparison Graph



Accuracy in blue, F1-Score in orange, recall in gray and precision is represented in yellow ***Graph (1)***. In comparison to the other models, the Voting Classifier, Random Forest shows superior performance across all metrics, achieving the highest values. The graphs above visually illustrate these findings.

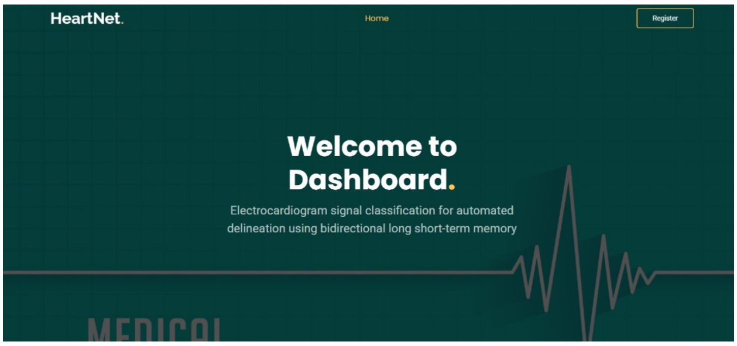


Fig.2 Home Page

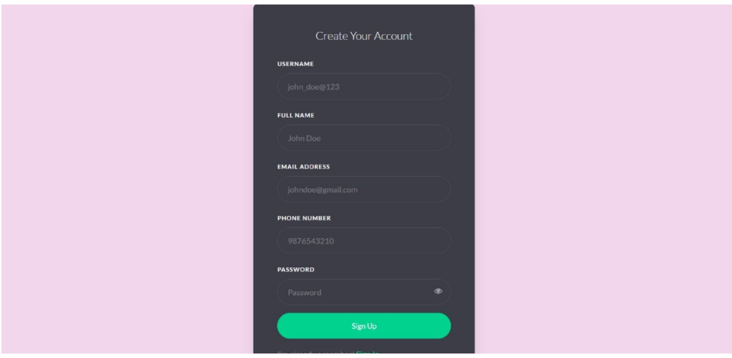


Fig.3 Signup Page

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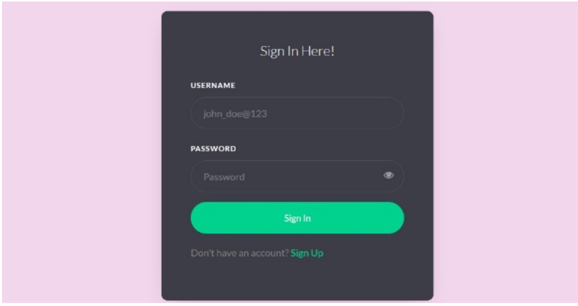

Fig.4 Login Page

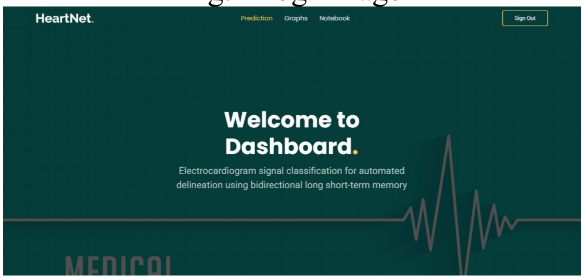

Fig.5 Main Page

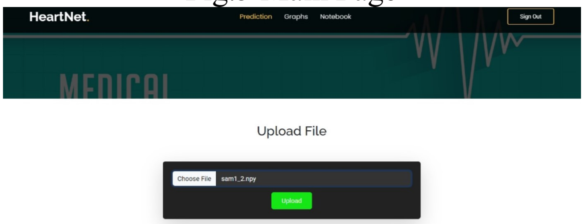

Fig.6 Upload Input File

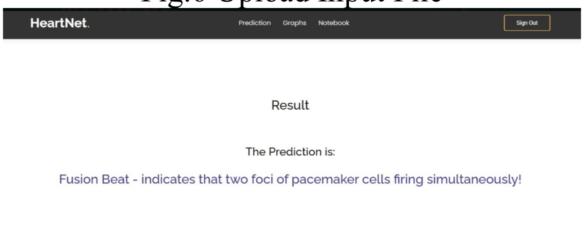

Fig.7 Predict Result

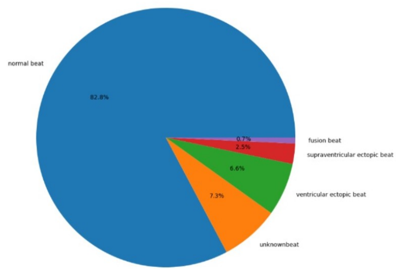

Fig.8 Pie-Chart

5. CONCLUSION

In conclusion, the proposed system effectively classifies arrhythmia from ECG signals by leveraging deep learning and ensemble techniques, demonstrating significant improvements in accuracy and robustness. Among the evaluated models, CNN+BiLSTM and CNN+LSTM emerged as the most effective architectures, benefiting from CNN's superior feature extraction and BiLSTM's ability to capture long-term dependencies in sequential data. Additionally, the ensemble-based Voting Classifier, integrating multiple boosted models, further enhanced classification

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performance by combining the strengths of diverse algorithms. The results validate that hybrid deep learning models outperform standalone approaches, providing more reliable and precise arrhythmia detection. The integration of spatial and temporal feature learning with ensemble strategies enables the system to generalize well across different ECG patterns, reducing false positives and improving clinical applicability. The high performance of Voting Classifier highlights their suitability for real-time ECG analysis, offering a scalable and efficient solution for automated arrhythmia detection in medical diagnostics.

Future work will focus on enhancing model generalization by incorporating larger and more diverse ECG datasets, improving robustness across patient demographics. Advanced ensemble techniques such as stacking and attention-based mechanisms will be explored to optimize classification performance. Real-time implementation on edge devices will be investigated to enable on-device arrhythmia detection for continuous monitoring. Additionally, integrating explainability methods like Grad-CAM and SHAP will enhance model interpretability, aiding clinicians in understanding ECG-based predictions for better decision-making in medical diagnostics.

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