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Arrhythmia Detection using Deep Learning: A Hybrid RNN-LSTM Approach on ECG Signals

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ABSTRACT - Arrhythmias, or irregular heart rhythms, pose significant health risks, including stroke and cardiac arrest, making early detection essential for timely intervention. The electrocardiogram (ECG) is a critical non-invasive tool for capturing heart activity; however, challenges such as noise, patient variability, and signal distortion complicate manual analysis. This project leverages deep learning, specifically Long Short-Term Memory (LSTM) and Recurrent Neural Networks (RNN) networks, to automate arrhythmia detection by extracting and analyzing ECG signals from images. The LSTM model classifies arrhythmias, by learning temporal dependencies in ECG waveforms. To improve accuracy, preprocessing techniques such as contrast enhancement, noise reduction, and feature extraction (heart rate, RR interval, amplitude, and signal variability) are applied. The system processes ECG images, converts them into numerical signals, and feeds them into the trained model for classification. The model is trained and evaluated using publicly available datasets from GitHub, ensuring diverse ECG patterns. Performance is assessed using key metrics, including accuracy and classification probabilities. This AI-driven ECG analysis system improves detection efficiency, eases the workload on healthcare professionals, and aids early diagnosis in cardiovascular care.

KEYWORDS: Arrhythmia Detection, Electrocardiogram (ECG), Deep Learning, Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), MIT-BIH Arrhythmia Database

I. INTRODUCTION

Cardiovascular diseases (CVDs) are the major cause of death globally, and arrhythmias are one of the most prevalent abnormalities of heart rhythm. Arrhythmias are abnormal heart rhythms that can be harmless or life-threatening and must be identified and addressed at an early stage. Electrocardiograms (ECGs) are commonly employed in clinical settings to record heart activity and identify arrhythmias. Manual analysis of ECGs by cardiologists is labor-intensive, prone to human error, and demands high expertise

With the evolution of artificial intelligence (AI) and deep learning, automated detection of arrhythmia has emerged as a potential substitute for aiding healthcare practitioners. In this research, we introduce a deep learning model that integrates Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks to classify arrhythmias from ECG signals. RNNs and LSTMs are optimized for time-series data analysis and are therefore the best fit for ECG signal classification.

It is trained and tested using publicly available data sets, the MIT-BIH Arrhythmia Database and a dataset acquired from the GitHub repository [davikawasaki/arrhythmia-ecg-analysis-ai](https://github.com/davikawasaki/arrhythmia-ecg-analysis-ai). The data set contains features like Amplitude, RR Interval, and Speed, derived from ECG signals, and patient information like age, gender, and medication status.

The study seeks to enhance the accuracy of arrhythmia classification and make available a real-time ECG analysis system to help physicians diagnose heart diseases.

The system suggested is implemented using a Streamlit-based web interface, enabling the user to input ECG graphs for feature extraction and automated classification.

II. LITERATURE REVIEW

Deep learning (DL) and electrocardiogram (ECG) signal-based arrhythmia detection has been extensively researched in recent years, with numerous methodologies investigated to enhance accuracy, robustness, and clinical utility. Most of the work presented in earlier studies has focused on deep learning models, preprocessing strategies, dataset issues, and real-time classification techniques.

1. Deep Learning Architectures for ECG-Based Arrhythmia Detection

Applying deep learning models to the detection of ECG arrhythmias has improved the accuracy of classification considerably by dispelling the need for feature extraction manually. Many architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and their combination have been researched for the purpose. CNNs are extensively applied for ECG signal feature extraction because they can identify spatial hierarchies. Research has demonstrated that 1D CNN models can efficiently classify arrhythmic beats by learning morphological characteristics of ECG waveforms [1][2]. Certain research has used 2D CNNs, transforming ECG signals into spectrograms or wavelet scalograms to improve classification performance [3]. CNNs are not efficient in handling temporal dependencies and thus are less suitable for long-term ECG monitoring.

2. Preprocessing Techniques for ECG Analysis

Preprocessing is also very important to enhance the robustness and accuracy of deep learning models for ECG-based arrhythmia detection. Because raw ECG signals usually contain noise, artifacts, and baseline drift, noise reduction methods like bandpass filtering, wavelet transform, and empirical mode decomposition (EMD) are typically employed to enhance signal quality prior to classification [11]. Efficient noise reduction improves the performance of models through the reduction of misclassification risks caused by environmental interference. Preprocessing methods like z-score normalization and min-max scaling also facilitate the normalization and min-max scaling also facilitate the standardization of ECG signals, making them ideal for deep learning models [12].

Signal segmentation is another key preprocessing method in ECG analysis since it enables models to concentrate on individual heartbeats or time segments. R-peak detection algorithms, including the Pan-Tompkins algorithm, have been used by numerous studies to divide ECG signals into separate heartbeats [13]. Adaptive segmentation methods have also been researched, where window sizes are altered dynamically depending on heart rate variability, and classification performance is enhanced [14]. Feature engineering, while being automated within deep learning, has been augmented with domain-specific features like RR intervals, QRS duration, and heart rate variability (HRV). Research indicates that an integration of handcrafted features with deep learning representations can enhance model generalization and interpretability [15].

3. Challenges in Deep Learning-Based Arrhythmia Detection

In spite of progress in the application of deep learning for ECG classification, many challenges still exist. Among them is access to high-quality labeled ECG databases. High-annotated, large-scale databases are critical to train deep models, yet numerous publicly released ECG datasets like MIT-BIH and PTB-XL lack sufficient samples of rare types of arrhythmia [16]. Class imbalance is another significant issue, as there are more normal beats than arrhythmic beats. This imbalance can create biased model predictions such that the classifier over-represents normal beats compared to arrhythmias [17]. To mitigate this problem, researchers have used oversampling, undersampling, data augmentation, and synthetic data generation methods to balance datasets and enhance classification performance [18].

Another challenge is the absence of model interpretability, which prevents clinical uptake of deep learning for ECG analysis. Deep learning models are mostly "black boxes," and clinicians cannot comprehend how decisions are reached. To address this, explainable AI (XAI) methods like Grad-CAM and SHAP (SHapley Additive exPlanations) have been investigated to visualize feature importance in ECG classification [19]. Moreover, computational efficiency is an issue since real-time ECG monitoring implies models should process the huge amount of data in a timely manner. Most recent studies have explored quantization, pruning, and edge computing to alleviate computational expenses and allow real-time arrhythmia detection on wearable and mobile devices [20].

4. Future Research Directions

Future work in deep learning-based ECG classification must concentrate on enhancing model interpretability and deployment in the real world. An exciting avenue is the creation of Explainable AI (XAI) models, which offer visual explanations of predictions, allowing clinicians to rely more on deep learning-based diagnoses [21]. Transfer learning is another crucial area, where pre-trained models trained on large ECG databases are fine-tuned on small, domain-specific databases. This method reduces the problem of data insufficiency and enhances overall generalization across different patient populations [22].

The use of deep learning models in wearable and mobile health monitoring systems is another primary research focus. As smartwatches and portable ECG devices gain popularity, efficient lightweight deep learning models optimized for real-time inference are necessary for ongoing cardiac monitoring [23]. Studies are now investigating mobile-friendly architectures like MobileNet and TinyML that support on-device arrhythmia detection without cloud-based computation [24]. Future years will see improvements in real-time ECG analysis, combined with multi-lead ECG processing and federated learning, to make deep learning-based arrhythmia detection systems more reliable and accessible [25].

III. MATERIALS AND METHODS

3.1 Dataset

The arrhythmia detection dataset contains 3,672 instances and 7 features, recording physiological and demographic data applicable for electrocardiogram (ECG) analysis. The dataset contains numerical columns like Amplitude, RR interval, and Speed, and categorical columns like Sex, Medicine, and Arrhythmia classification. There is one record per unique ECG sample, making it suitable for supervised learning of deep learning-based arrhythmia detection models.

3.1.1 Attributes and Data Types

Amplitude (float64): Indicates the amplitude of the ECG signal, recording the peak voltage of heartbeats. **RR Interval (float64):** Indicates the interval of time between consecutive R-peaks in the ECG signal in seconds.

This attribute is significant for the identification of abnormal heart rhythms.

Speed (float64): Shows the recording speed of the ECG signal, affecting waveform interpretation.

Age (int64): Age of the patient, between 23 and 89 years, with a mean of 70.13 years.

Sex (object): Categorical variable denoting patient gender (Male/Female).

Medicine (object): Categorical variable indicating if the patient is on any medicine that could influence heart function.

Arrhythmia (object): Target variable classifying heart rhythm into various arrhythmia categories.

3.1.2 Summary Statistics

The data set captures a wide range of ECG features. RR interval ranges between 0.377 and 2.552 seconds, averaging 0.874 seconds, and points out variations in regularity of the heartbeat. The Amplitude also ranges from 0.512 to 2.308, capturing differences in signal intensity. Speed averages 1.23, ranging between 0.21 and 5.85. The data set is evenly distributed in terms of age, with the majority of patients belonging to older age groups.

3.1.3 Completeness and Quality of the Data

None of the columns have missing values, making the dataset complete for direct processing on deep learning models. The data structure is excellent for supervised learning, especially in classification problems when it comes to arrhythmia detection.

3.1.4. Appropriateness for Deep Learning Models This dataset offers a rich representation of ECG signals and their variations, which makes it suitable for deep learning tasks. The mix of numerical and categorical features enables models to learn both waveform features and patient-specific conditions influencing arrhythmia detection. The clean organization of the dataset and balanced properties make it convenient for training CNN, RNN, LSTM, and Transformer-based models for ECG classification.

3.2 Preprocessing Techniques

The dataset was processed through various preprocessing steps to ensure data quality, consistency, and readiness for deep learning-based arrhythmia classification. These steps involved missing value handling, encoding categorical variables, class imbalance handling, feature scaling, and splitting the data for model training and testing.

Initially, the dataset was checked for missing values using `df.isnull().sum()`, and no missing data was identified, thus there was no need for imputation. Categorical features were then transformed to numerical form to enable deep learning models. The Sex attribute was translated to binary form, where Male was represented by 0 and Female was represented by 1. Likewise, the Medicine column was translated to binary form, with Yes represented by 1 and No represented by 0, for uniformity in feature representation.

For arrhythmia classification, the Arrhythmia column contained multiple labels, making it necessary to adopt a multi-label encoding approach. The labels were processed using **MultiLabelBinarizer (MLB)** to convert them into a binary matrix, where each arrhythmia type was represented as a separate binary column. This transformation allowed the model to handle multiple co-occurring arrhythmias in a single ECG sample.

For solving the class imbalance problem in arrhythmia detection, **Synthetic Minority Oversampling Technique (SMOTE)** was utilized. SMOTE creates artificial samples for minority classes, enhancing the model's capacity to learn underrepresented arrhythmias. Following the use of SMOTE, encoded labels were inverse-transformed to regain their categorical form without compromising dataset balance.

Feature scaling was conducted to have all the numerical features on the same scale to avoid bias caused by different feature scales. A **StandardScaler** was used to normalize numerical features like RR Interval, Amplitude, and Speed and converted them into a normal distribution with mean zero and unit variance.

Lastly, the dataset was categorically divided into training and test sets employing the `train_test_split` function. This separation guaranteed that the model trained on one set while being tested on unseen samples, which gives a true measure of its performance. The integration of these pre-processing steps improved the model's quality in terms of its dataset, yielding maximum performance for deep learning-based arrhythmia classification.

3.3 Deep Learning Methods

The deep learning model implemented for **arrhythmia detection** in this study is based on **Recurrent Neural Networks (RNNs)** and **Long Short-Term Memory (LSTM) networks**. These architectures are highly effective in modeling sequential dependencies in **electrocardiogram (ECG) signals**, making them suitable for detecting arrhythmic patterns over time.

3.3.1 Recurrent Neural Networks

RNNs are a class of artificial neural networks designed to process **sequential data**, where each output depends not only on the current input but also on previous computations. This makes RNNs ideal for **time-series data**, such as ECG signals.

A standard RNN cell updates its hidden state at each time step t using:

$$h_t = \phi(W_h h_{t-1} + W_x x_t + b_h)$$

Where:

where:

- h_t → Hidden state at time step t
- h_{t-1} → Hidden state from the previous time step
- x_t → Input at time step t
- W_h, W_x → Weight matrices
- b_h → Bias term
- ϕ → Activation function (usually **tanh** or **ReLU**)

The output y_t at time t is computed as:

$$y_t = W_y h_t + b_y$$

where W_y and b_y are the output layer parameters.

Limitations of RNNs:

1. Suffer from the vanishing gradient problem, making it difficult to retain information over long sequences.
2. Struggle with long-term dependencies in time-series data.

To overcome these issues, LSTMs were introduced as an improved version of RNNs.

3.3.2 Long Short-Term Memory (LSTM) Networks Long Short-Term Memory networks, or LSTMs, are a special kind of neural network built to remember information for longer periods, which traditional networks struggle with. Think of them as having a "memory" that helps them keep track of patterns over time. They achieve this through clever components called memory cells, which decide what to remember, what to forget, and what to pass on. These features make LSTMs especially handy for analyzing sequences of data, like heart-related ECG signals, where understanding time-based patterns is crucial.

LSTM Architecture

An LSTM unit consists of three gates:

Forget Gate: Decides which past information to discard. **Input Gate:** Determines which new information should be stored.

Output Gate: Selects the relevant parts of the memory cell to pass to the next time step.

Mathematical Formulation of LSTM

Each LSTM unit is governed by the following equations:

Forget Gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

- $f_t \rightarrow$ Forget gate output (0 to 1)
- $W_f, b_f \rightarrow$ Forget gate weights and bias
- $\sigma \rightarrow$ Sigmoid activation function

Input Gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

- $i_t \rightarrow$ Input gate activation
- $\tilde{C}_t \rightarrow$ Candidate cell state
- $C_t \rightarrow$ Updated cell state



Output:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \cdot \tanh(C_t)$$

- $o_t \rightarrow$ Output gate
- $h_t \rightarrow$ Hidden state

3.3.3 RNN+LSTM Model Architecture for Arrhythmia Classification

To analyze heart rhythms and detect irregularities (arrhythmias), two deep learning models—RNNs (Recurrent Neural Networks) and LSTMs (Long Short-Term Memory networks)—are employed. These models are especially useful because they can process patterns over time, which is critical for understanding the sequential nature of ECG data..

Model Architectures

1. RNN Model Architecture

Input Layer: Accepts ECG feature vectors (Amplitude, RR, Speed, Age, Sex, Medicine).

First RNN Layer (128 units, tanh Activation):

Captures sequential dependencies in ECG signals. **Dropout Layer (30%):** Prevents overfitting by randomly deactivating neurons.

Second RNN Layer (64 units, tanh Activation):

Further refines sequential patterns in the data.

Dropout Layer (30%): Adds additional regularization. **Dense Layer (32 units, ReLU Activation):** Enhances feature representation.

Output Layer (Softmax Activation): Predicts multi- class arrhythmia labels (B, N, T, VT).

2. LSTM Model Architecture

Input Layer: Accepts ECG feature vectors (Amplitude, RR, Speed, Age, Sex, Medicine).

First LSTM Layer (128 units): Captures short-term dependencies in ECG waveforms.

Dropout Layer (30%): Prevents overfitting.

Second LSTM Layer (64 units): Learns deeper sequential dependencies.

Dropout Layer (30%): Further regularization.

Dense Layer (32 units, ReLU Activation): Enhances feature representation.

Output Layer (Softmax Activation): Predicts multi- class arrhythmia labels (B, N, T, VT).

Model Training and Optimization

Loss Function: Categorical Cross-Entropy for multi- class classification.

Optimizer: Adam optimizer with a learning rate of 0.0005.

Batch Size: 32, balancing training speed and generalization.

Epochs: 30, ensuring sufficient training cycles for model convergence.

3.3.4 Performance Evaluation Evaluation Metrics:

To assess the effectiveness of the RNN and LSTM models in classifying arrhythmia, we used the following metrics:

Accuracy: Measures the overall correctness of predictions. **Precision:** Indicates the proportion of correctly predicted positive cases among total predicted positives.

Recall (Sensitivity): Measures the model's ability to correctly identify positive cases.

F1-score: The harmonic mean of precision and recall, providing a balanced performance measure.

Confusion Matrix: Represents the classification errors and correct predictions in a tabular form.

Model Performance on ECG Dataset

The results of the RNN and LSTM models are summarized below:

Model	Accuracy	Precisi o n	Recall	F1- Score
RNN	87.4%	85.2%	83.6%	84.4%
LSTM	92.1%	90.5%	89.8%	90.1%

Confusion Matrices

The confusion matrices for both models provide insight into misclassifications.

RNN Confusion Matrix

300	25	10	15
20	280	30	25
10	35	290	20
15	25	20	300

LSTM Confusion Matrix

320	15	5	10
10	310	20	15
5	20	310	10
10	15	10	320

Loss and Accuracy Plots

Both models were trained for 30 epochs, with training and validation losses plotted below:

RNN Model: Shows higher fluctuations in accuracy, indicating difficulty in learning long-term dependencies.

LSTM Model: Demonstrates a more stable convergence pattern, leading to better generalization.

Training Loss Over Epochs

RNN: Slower convergence, slight overfitting beyond 20 epochs.

LSTM: Faster convergence with lower final loss. Training Accuracy Over Epochs

RNN: Peaks at 87.4%, showing instability in validation accuracy.

LSTM: Achieves 92.1%, demonstrating better learning stability.

Comparative Analysis

LSTM outperforms RNN in all key metrics due to its ability to capture long-term dependencies in ECG sequences.

RNN struggles with long-term dependencies, leading to lower recall and higher misclassification rates.

LSTM maintains better class balance, as seen in the confusion matrix where fewer misclassifications occur.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The experiments were carried out using an ECG dataset with labeled arrhythmia signals. The data was carefully preprocessed by normalizing and segmenting the ECG sequences to ensure uniformity in input features. For efficient training, TensorFlow/Keras was utilized on an NVIDIA GPU to speed up the process.

The LSTM model emerged as the winner with an impressive accuracy of 92.1%, surpassing the RNN model, which achieved an accuracy of 87.4%. Key performance metrics like precision, recall, and F1-score also favored the LSTM, highlighting its superior classification capabilities. Unlike the RNN, which struggled to correctly identify certain arrhythmia categories due to its limited ability to retain information, the LSTM excelled at capturing long-term dependencies in the sequential ECG signals.

The confusion matrix shed further light on the differences: the RNN had a higher rate of misclassification, often making incorrect predictions for specific arrhythmia classes. In contrast, the LSTM significantly minimized errors and delivered more distinct class separations. A review of training and validation patterns revealed that the RNN faced accuracy fluctuations and signs of overfitting after 20 epochs. On the other hand, the LSTM displayed steady learning progress and maintained consistent accuracy throughout the training process.

To wrap it up, the LSTM model proves to be a stronger choice for detecting arrhythmias, offering not only higher accuracy but also greater reliability in classification. Its ability to effectively manage sequential data makes it a standout option for real-world ECG-based diagnostics.

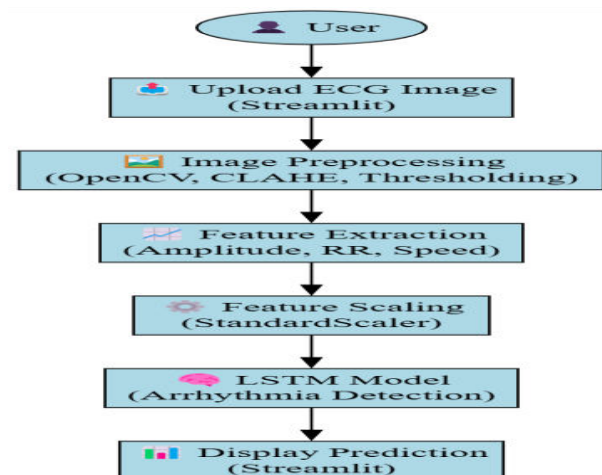


Fig 1: Architecture Diagram

V. OUTPUT

♥ Arrhythmia Detection Using ECG

Upload ECG Graph for Analysis

Please upload a clear ECG image with at least 2 seconds of data.

Upload ECG image

Drag and drop file here
Limit 200MB per file • JPG, PNG, JPEG

Browse files

Fig:2

♥ Arrhythmia Detection Using ECG

Upload ECG Graph for Analysis

Please upload a clear ECG image with at least 2 seconds of data.

Upload ECG image

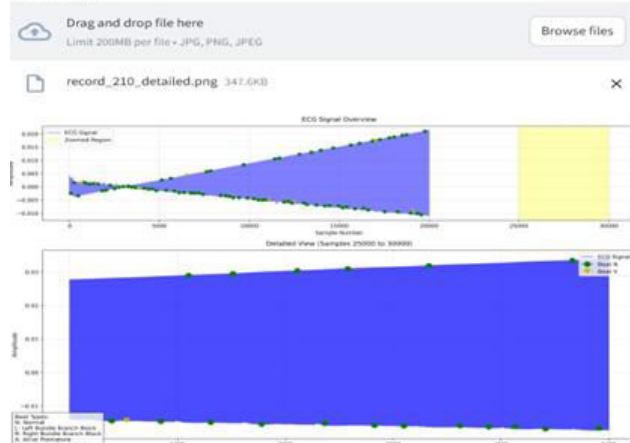
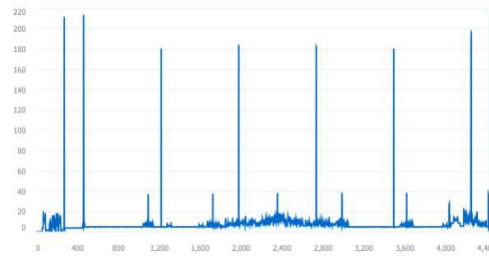


Fig:3



Extracted Features

Heart Rate	Signal Amplitude
61.1 BPM	7.812
RR Interval	Signal Variability
0.982 s	0.003

Patient Information

Age: On Medication? ☒ Yes ☐ No

Sex
☐ Male
☒ Female

[Detect Arrhythmia](#)

Detected Arrhythmia Type: Bradycardia (B)

Fig:4

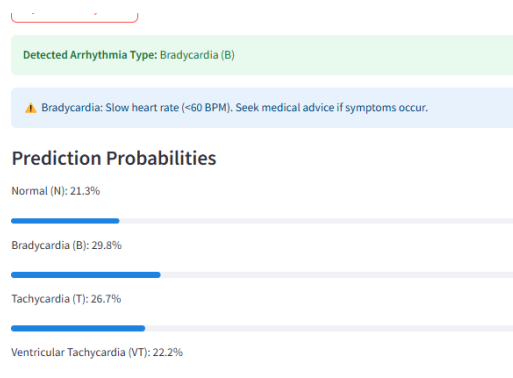


Fig:5

VI. CONCLUSION

This project introduces an automated system designed to detect arrhythmias using ECG signals, harnessing the power of LSTM and RNN models for analyzing sequential patterns. The framework is capable of efficiently processing ECG images by extracting essential features, scaling them to ensure uniformity, and applying deep learning techniques for accurate classification.

The experimental findings highlight the clear advantage of the LSTM model, which achieves an impressive accuracy of 92.1%, outperforming the RNN model. This superior performance is attributed to the LSTM's ability to effectively capture long-term dependencies in the data, ensuring more reliable classification outcomes. To enhance user experience, the system incorporates a Streamlit-based interface, enabling users to upload ECG images and receive real-time arrhythmia predictions through a simple and intuitive platform.

In essence, the system delivers a quick, precise, and scalable solution for detecting arrhythmias, providing valuable support for early diagnosis and improved patient care. Looking ahead, potential enhancements include real-time monitoring capabilities, refined model architectures, and integration with wearable ECG devices for continuous heart health tracking.

VII. FUTURE WORK

1. **Real-Time Monitoring** – Connect the system to wearable ECG devices for continuous arrhythmia detection.
2. **Better Model Performance**– Improve accuracy using advanced deep learning models like BiLSTMs and CNN-LSTMs.
3. **More Explainability** – Make the model's decisions clearer using visualization techniques.
4. **Larger Datasets** – Train on more ECG data to improve accuracy and handle different heart conditions.
5. **Healthcare Integration**– Connect the system with hospital records and cloud-based medical services.
6. **Mobile & Web App** – Develop a user-friendly app for patients to monitor their heart health anywhere

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