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Cardio Disease Analysis
(IoT – Deep Learning)

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Abstract

Cardiovascular diseases (CVDs) are among the leading causes of mortality worldwide, emphasizing the need for early diagnosis and continuous monitoring. In this study, we propose an IoT-based electrocardiogram (ECG) monitoring system using ESP32 and the AD8232 sensor (1-lead) to acquire real-time heart signals. The collected ECG data is analyzed using a deep learning model that classifies the heartbeat as normal or abnormal based on an existing ECG dataset. The system integrates IoT technology for remote patient monitoring and deep learning algorithms, including 1D Convolutional Neural Networks (1D-CNNs) and Long Short-Term Memory (LSTM) networks, to enhance the accuracy of arrhythmia detection. The results demonstrate the feasibility of using low-cost, portable devices for early cardiac abnormality detection, providing an effective solution for telemedicine and healthcare in resource-constrained areas.

Keywords

ECG Monitoring, IoT, AD8232, ESP32, Deep Learning, Cardio Vascular Diseases, Arrhythmia Detection, Machine Learning, Convolutional Neural Networks, Long Short-Term Memory, Telemedicine.

INTRODUCTION

Cardiovascular diseases (CVDs) are a growing global health concern, accounting for a significant number of deaths annually. Traditional ECG monitoring systems rely on specialized medical equipment and frequent hospital visits, making them impractical and inaccessible for individuals in remote or underdeveloped regions. The emergence of Internet of Things (IoT) technologies, combined with biomedical sensors, has revolutionized healthcare by enabling real-time and remote monitoring of vital parameters—significantly reducing the strain on healthcare infrastructure.

This project proposes an IoT-based ECG monitoring system utilizing the AD8232 sensor (1-lead) and the ESP32 microcontroller for real-time acquisition of heart signals. The collected ECG data is transmitted over the internet to a local server for processing and analysis. To accurately classify heartbeats as normal or abnormal, the system employs a deep learning-based classification model built using a hybrid 1D-Convolutional Neural Network (1D-CNN) and Long Short-Term Memory (LSTM) architecture. The 1D-CNN component effectively learns spatial features such as QRS complexes, P-waves, and T-waves, while the LSTM component captures temporal dependencies across the ECG signal, improving arrhythmia detection performance.

By integrating IoT-driven data acquisition with deep learning classification, the system offers a portable, low-cost, and scalable solution for continuous cardiac

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monitoring. This approach addresses major limitations of conventional ECG machines—such as high cost, limited portability, and the need for clinical supervision—making it especially beneficial for telemedicine applications and underserved communities. Ultimately, this project aims to enhance early diagnosis and timely intervention in cardiovascular care, improving patient outcomes through smarter, more accessible technology.

Objective

The primary objectives of this project are:

A. To develop an IoT-enabled ECG monitoring system using ESP32 + AD8232 (1-lead) for real-time heart signal acquisition.
B. To implement a 1D-CNN + LSTM deep learning model to analyze ECG signals and classify heart conditions as Normal or Abnormal.
C. To provide a user-friendly desktop GUI for real-time ECG visualization and deep learning-based health status feedback.
D. To enable real-time data transfer from the ESP32 to the local system using HTTP communication.
E. To display deep learning analysis results instantly within the GUI

Proposed Idea

The proposed system leverages IoT components such as the ESP32 microcontroller and AD8232 ECG sensor (1-lead), which are responsible for capturing and transmitting real-time heart signals. The ESP32 provides WIFI connectivity, allowing seamless data transmission to the server, while the AD8232 sensor ensures accurate ECG signal acquisition.

This combination allows for low-cost, continuous heart monitoring, making healthcare more accessible to remote and underdeveloped areas. On the Deep Learning side, the system employs a Hybrid 1D-CNN + LSTM model to analyze ECG signals. 1D-CNN layers extract spatial patterns from ECG waveforms, while LSTM layers capture sequential dependencies, ensuring accurate classification of heartbeats as normal or abnormal.

The combination of 1D-CNN and LSTM enables precise arrhythmia detection by leveraging both spatial and temporal characteristics of ECG signals, significantly improving diagnostic accuracy. By integrating IoT-based data acquisition with deep learning-driven analysis, this project provides a cost-effective and scalable solution for real-time ECG monitoring. The system allows patients to receive early diagnosis and timely medical intervention, reducing the risk of severe cardiac conditions. This fusion of IoT and AI-driven healthcare represents a significant advancement in telemedicine and remote patient monitoring, making cardiac health management more efficient and accessible.

Systematically Implementation

1. IoT-Based ECG Data Collection

Connect ESP32 and AD8232 (1-lead configuration) to capture real-time ECG signals. The ESP32 microcontroller is responsible for wirelessly transmitting ECG data from the AD8232 sensor to the backend for further processing. The AD8232 acts as an analog signal amplifier and conditioning circuit to obtain clean ECG waveforms from the patient.

AD8232 pins	Pin Functions	ESP32 Connection
GND	Ground	GND
3.3v	Power supply	3.3v
OUTPUT	Output signal	G34

Apply signal filtering techniques to remove noise from the ECG signal:

- High-Pass Filter (HPF): Used to eliminate low-frequency baseline wander noise.
- Python Libraries (NumPy, SciPy, wfdb, tensorflow): Implemented for real-time signal processing and feature extraction before sending the data to the deep learning model.

3. Deep Learning Model for ECG Classification

A hybrid CNN + LSTM model was developed and trained using 1-lead ECG signals from the MIT-BIH Arrhythmia Database (for abnormal cases) and the

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MIT-BIH Normal Sinus Rhythm Database (for normal cases). This model follows a two-stage architecture:

1D-CNN (1-Dimensional Convolutional Neural Network): Learns spatial features from 1D ECG waveforms, such as the QRS complex, P-wave, and T-wave, enabling the detection of key morphological patterns across time-series data.

LSTM (Long Short-Term Memory): Captures the temporal dynamics and sequential dependencies in ECG signals, which is critical for accurate arrhythmia classification.

This combination allows the model to effectively analyze both the shape and time-based progression of ECG signals, improving classification accuracy between Normal and Abnormal heart rhythms.

Formula for Hybrid 1D-CNN + LSTM Model:

❖ **1D-CNN Feature Extraction:**

1. **Convolution**: $x_{(l+1)} = f\,(w_l * x_l + b_l)$

- where f is the ReLU activation function, w_l are the convolution filters, and b_l is the bias.

2. **Pooling:** $x_{pooled} = \max(x_{(l+1)})$

- max pooling is applied with a pool size of 2.

❖ **LSTM Temporal Processing:**

Forget Gate:

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

Input Gate:

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

Cell Candidate:

$$\tilde{c}_t = \tanh\,(W_C \cdot [h_{(t-1)}, x_t] + b_C)$$

Cell State Update:

$$C_t = f_t \odot C_{(t-1)} + i_t \odot \tilde{c}_t$$

Output Gate:

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

Hidden State Update:

$$h_t = o_t \odot \tanh\,(C_t)$$

❖ **Dense Layers for Classification**

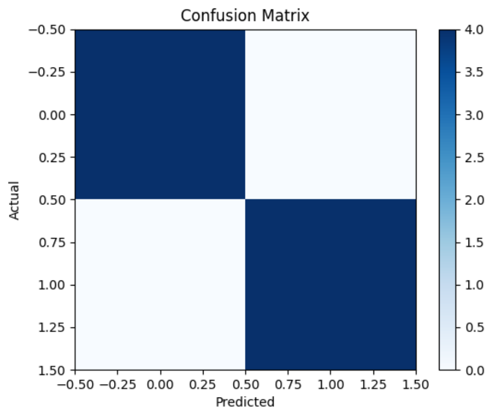
Dense (Fully Connected) Layer:

$$z = \mathrm{ReLU}\,(W_d \cdot h_T + b_d)$$

Output Layer (Binary Classification):

$$\hat{y} = \sigma\,(W_y \cdot z + b_y)$$

Model Evolution :



The trained 1D-CNN and LSTM model was evaluated using a test set derived from the MIT-BIH Arrhythmia and Normal Sinus Rhythm datasets. The confusion matrix indicates that the model achieved perfect binary classification performance on the test data. All normal and abnormal ECG samples were correctly identified, demonstrating the model's strong ability to distinguish between healthy and arrhythmic heart conditions.

This result reflects the effectiveness of combining spatial feature extraction (CNN) and temporal sequence learning (LSTM) for ECG signal classification

4. GUI Application Development

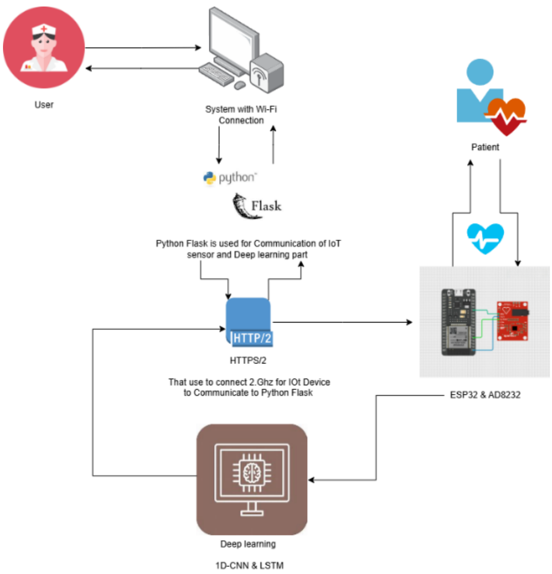
Develop a user-friendly desktop GUI using Python for real-time visualization of ECG signals and deep learning-based classification results. The GUI displays live ECG waveforms and indicates whether the heart condition is Normal or Abnormal based on the model's output.

Implement Flask as the backend:

Flask is used as a lightweight backend server to handle real-time ECG data sent from the ESP32 via HTTP POST requests. The backend performs the following tasks:

- Receives ECG signal data and accumulates it until 2000 samples are collected.
- Applies preprocessing (normalization) to match the model's training setup.
- Uses a trained 1D-CNN+ LSTM deep learning model to classify the ECG signal as **Normal** or **Abnormal**.
- Sends the prediction result to the desktop GUI for live display and user feedback.

This setup ensures seamless integration of IoT-based ECG acquisition, real-time deep learning inference, and an interactive GUI for immediate result visualization — all within a single local application environment.



System Diagram

Application Areas of the Proposed System

Healthcare & Telemedicine

The system facilitates remote cardiac monitoring, early disease detection, and emergency response. By integrating AI-powered multi-modal ECG analysis with explainable AI (XAI), it enhances diagnosis accuracy, making telemedicine services more reliable, especially for remote and underserved areas.

Sports & Fitness

It ensures real-time cardiovascular monitoring for athletes, detecting irregular heart rhythms and arrhythmias during high-intensity training. By analyzing ECG trends over time, the system helps in optimizing workouts, reducing health risks, and preventing sudden cardiac arrests.

Wearable Technology

Integrated into smart wearables, the system offers continuous real-time ECG monitoring with blockchain-secured medical records. Users receive instant AI-driven heart health insights, ensuring early intervention for individuals with heart disease risk factors.

Military & Defence

By providing continuous heart health tracking for soldiers in extreme environments, such as high-altitude or combat zones, the system ensures timely medical alerts and emergency response, preventing sudden cardiac failures in the field.

Medical Research and AI Training

The hybrid AI model (1D-CNN+ LSTM + Transformer) enables cutting-edge research on cardiac health patterns. The system contributes to personalized heart disease prediction, refining future AI-driven diagnostics with real-world ECG data, making it valuable for hospitals and research institutions.

Preventive & Personalized Healthcare

Unlike traditional ECG systems, this project predicts future heart disease risks by analyzing lifestyle factors, genetic history, and ECG patterns over time. Patients receive personalized heart health recommendations, promoting preventive healthcare rather than reactive treatments.

CONCLUSION

This project successfully integrates IoT technology and deep learning to provide a real-time ECG monitoring and analysis system. The combination of ESP32 with AD8232 (1-lead) enables continuous ECG data acquisition, which is processed using a Hybrid 1D-CNN+ LSTM model for accurate cardiac anomaly detection. By enabling real-time monitoring through local communication, the system supports early disease detection and timely medical attention — critical for preventing severe cardiac events.

A user-friendly desktop GUI is developed to visualize live ECG signals and display deep learning-based predictions in real time. The system uses a Flask backend to handle incoming ECG data from the ESP32, apply preprocessing, and perform inference using the trained model. This localized setup eliminates the need for internet connectivity, database storage, or automated reporting, focusing instead on simplicity, speed, and immediate user feedback.

This project has meaningful social impact, especially in areas such as telemedicine, wearable tech prototyping, and resource-limited environments. It addresses key limitations of traditional ECG systems — such as cost, bulkiness, and reliance on clinical infrastructure — by offering a portable, low-cost, and easily deployable solution for real-time cardiac monitoring.

However, certain limitations exist, including the use of a single-lead ECG setup and the absence of multi-user support or long-term data storage. Future improvements could include adding multi-lead ECG capability, cloud-based data syncing, and real-time alerting mechanisms for enhanced reliability and scalability.

In conclusion, this project bridges IoT-based ECG acquisition with deep learning-powered analysis in a lightweight and accessible way. With further enhancements in hardware integration and model optimization, it holds strong potential for broader application in smart healthcare and personalized medical solutions.

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