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Smart Portable ECG Monitoring System with Edge AI for Real-Time Arrhythmia Detection

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***Abstract* - This paper presents a smart and portable electrocardiogram monitoring system integrated with edge artificial intelligence for real-time detection of cardiac arrhythmias. The proposed system combines wearable ECG signal acquisition with embedded processing and deep learning-based classification to enable continuous and efficient cardiac monitoring outside clinical environments. The acquired ECG signals are preprocessed using noise filtering and normalization techniques, and then analyzed using a lightweight deep learning model capable of identifying abnormal heart conditions such as atrial fibrillation, tachycardia, and bradycardia. The model is deployed on an edge device to ensure low latency, reduced dependency on cloud infrastructure, and enhanced data privacy. An automated alert mechanism is incorporated to provide immediate notification upon detection of irregular cardiac activity. Experimental evaluation demonstrates improved accuracy and faster inference time compared to conventional approaches. The proposed system offers a cost-effective and scalable solution for real-time cardiac monitoring, particularly beneficial for remote and resource-limited healthcare settings.**

Keywords* - *ECG Monitoring, Arrhythmia Detection, Edge Artificial Intelligence, Deep Learning, CNN-LSTM, Wearable Healthcare, Real-Time Signal Processing, Embedded Systems.

I. INTRODUCTION

A. Background and Motivation

Cardiovascular diseases are a leading cause of mortality worldwide, with arrhythmias playing a critical role in sudden cardiac events. Early detection of abnormal heart rhythms is essential for effective treatment. Electrocardiogram (ECG) monitoring is widely used for cardiac assessment; however, conventional systems are typically limited to hospital environments and are not suitable for continuous monitoring in daily life.

With advancements in wearable technology and embedded systems, there is an increasing demand for portable and real-time cardiac monitoring solutions. At the same time, deep learning techniques have shown strong potential in analyzing biomedical signals and automatically detecting abnormalities in ECG data.

B. Limitations of Existing Systems

Traditional ECG monitoring systems suffer from several limitations, including lack of portability, short-duration recording, and dependence on manual interpretation. These systems often fail to capture intermittent arrhythmias and do not provide real-time alerts.

Additionally, ECG signals are prone to noise and interference, which can affect diagnostic accuracy. High cost and limited accessibility further restrict their use, especially in rural and resource-limited areas.

C. Need for Edge-Based ECG Intelligence

Edge computing enables real-time processing of ECG signals directly on embedded devices, reducing latency and dependence on cloud infrastructure. This approach improves response time, enhances data privacy, and supports continuous monitoring even in low-connectivity environments.

Integrating deep learning with edge devices allows automated and efficient detection of cardiac abnormalities, making it suitable for portable healthcare applications

D. Research Objective

This work aims to develop a smart portable ECG monitoring system with edge artificial intelligence for real-time arrhythmia detection. The system integrates ECG signal acquisition, preprocessing, and deep learning-based classification to identify abnormal heart rhythms such as atrial fibrillation, tachycardia, and bradycardia.

An edge-based implementation ensures low latency, continuous monitoring, and immediate alert generation for

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timely medical intervention.

E. *Key Contributions*

- Portable ECG monitoring system for continuous cardiac tracking
- Deep learning-based automated arrhythmia detection
- Real-time signal processing using edge computing
- Low-latency and privacy-preserving system design
- Instant alert mechanism for abnormal conditions

II. SYSTEM ARCHITECTURE AND WORKFLOW

A. *Overall System Architecture*

The proposed system is designed as an integrated framework that combines ECG signal acquisition hardware with edge-based intelligent analysis for real-time arrhythmia detection. The architecture consists of four main modules: signal acquisition, signal conditioning, edge processing, and alert generation.

Initially, ECG electrodes are used to capture the electrical activity of the heart from the patient's body. These signals are typically weak and susceptible to noise, and hence they are passed through an analog front-end circuit consisting of amplification and filtering stages. This stage improves signal quality by removing noise, motion artifacts, and interference.

The conditioned analog signal is then converted into digital form using a microcontroller such as ESP32. The microcontroller performs preliminary processing tasks including signal normalization and segmentation and controls the overall system operation.

The processed ECG data is then fed into a lightweight deep learning model deployed on the edge device. The model analyzes temporal and morphological features of the ECG waveform and classifies the signal into normal or abnormal categories.

Finally, the classification output is connected to an alert and monitoring module. When an abnormal condition is detected, the system generates immediate alerts through a display unit, mobile application, or buzzer.

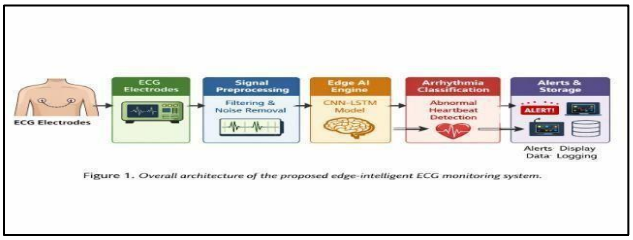

Fig. 1. Overall architecture of the proposed edge-intelligent ECG monitoring system

B. *Operational Workflow*

The operational workflow of the proposed system describes the continuous real-time process from ECG signal acquisition to alert generation.

Initially, ECG electrodes capture the electrical signals generated by the heart. These signals are transmitted to the signal conditioning unit, where amplification and filtering are applied to remove noise and improve signal clarity.

The filtered analog signal is then digitized using the microcontroller. The system performs preprocessing operations such as normalization and segmentation to prepare the data for analysis.

Next, the preprocessed ECG data is provided as input to the deep learning model deployed on the edge device. The model extracts relevant features and classifies the signal into categories such as normal rhythm, bradycardia, tachycardia, or atrial fibrillation.

Based on the classification results, the system determines whether the cardiac activity is normal or abnormal. If any irregular pattern is detected, an alert is generated immediately and communicated to the user through a notification system.

This process operates continuously, ensuring real-time monitoring and timely detection of cardiac abnormalities.

III. METHODOLOGY

A. *ECG Signal Acquisition and Preprocessing*

The initial stage of the proposed system focuses on accurate acquisition and preprocessing of ECG signals. Electrical activity of the heart is captured using surface electrodes connected to an ECG sensor module. These signals are inherently weak and highly susceptible to noise caused by motion artifacts, muscle activity, and external interference.

To improve signal quality, the acquired signals are passed through an analog front-end circuit consisting of amplification and filtering stages. Bandpass filtering is applied to remove baseline wander and high-frequency noise, ensuring a clean ECG waveform suitable for analysis.

The conditioned analog signal is then converted into digital form using the ESP32 microcontroller, which includes an inbuilt analog-to-digital converter (ADC). The digitized signal is further processed through normalization and segmentation techniques to prepare it for deep learning-based classification.

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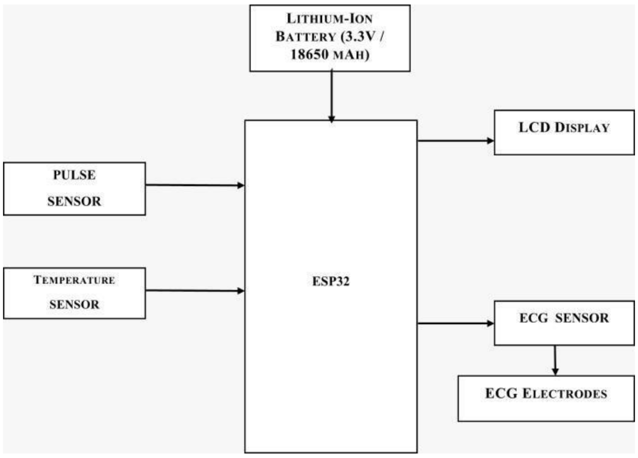

Fig. 2. Hardware implementation of the proposed ECG monitoring system based on ESP32.

B. Deep Learning Model Design

In this stage, a deep learning model is designed to automatically classify ECG signals into normal and abnormal categories. The preprocessed ECG data is used to train the model to recognize distinct patterns associated with various cardiac conditions.

A lightweight hybrid architecture combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks is employed. The CNN layers are responsible for extracting spatial features from the ECG waveform, while the LSTM layers capture temporal dependencies and sequential patterns in the signal.

The model classifies ECG signals into categories such as normal rhythm, bradycardia, tachycardia, and atrial fibrillation. Optimization techniques such as dropout and batch normalization are used to improve generalization and prevent overfitting.

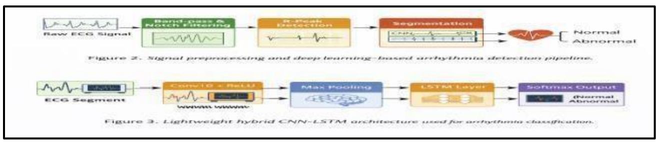

Fig. 3. Signal preprocessing pipeline

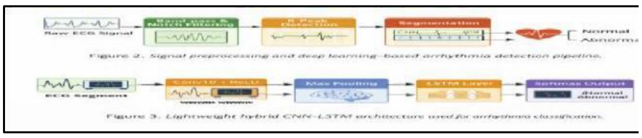

Fig. 4. CNN-LSTM architecture

C. Edge Deployment Strategy

To enable real-time performance, the trained deep learning model is deployed on an edge device such as the ESP32 microcontroller. Since embedded systems have limited computational resources, model optimization techniques such as quantization and pruning are applied to reduce memory usage and computational complexity.

Edge deployment allows ECG data to be processed locally without relying on cloud connectivity, thereby reducing latency and improving system reliability. This approach also enhances data privacy, as sensitive health information is not transmitted over external networks.

The optimized model continuously analyzes incoming ECG signals and generates instant alerts when abnormalities are detected, making the system suitable for portable and real-time healthcare applications.

IV. EXPERIMENTAL SETUP AND DATASET (COMPACT VERSION)

The experimental setup of the proposed system integrates both hardware and software components to enable real-time ECG monitoring and arrhythmia detection. Surface electrodes are used to acquire ECG signals from the patient, which are processed through an analog front-end circuit for amplification and noise filtering. The conditioned signal is digitized using the ESP32 microcontroller, which performs basic preprocessing and manages system operations.

For model development and evaluation, ECG datasets containing labeled signals of normal and abnormal heart rhythms are utilized. These include conditions such as bradycardia, tachycardia, and atrial fibrillation. The acquired data is preprocessed using noise removal, normalization, and segmentation techniques to improve signal quality and ensure consistency.

The deep learning model is trained using the processed ECG data to learn distinguishing features of different cardiac conditions. The dataset is divided into training and testing sets to evaluate model performance. Standard evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess classification effectiveness. Additionally, inference time is measured to verify the real-time capability of the system.

This setup ensures reliable evaluation of the proposed system and demonstrates its suitability for continuous and real-time cardiac monitoring applications.

V. RESULTS AND PERFORMANCE ANALYSIS

The performance of the proposed portable ECG monitoring system is evaluated using standard metrics such as accuracy, precision, recall, F1-score, and inference time. The deep learning model demonstrates effective classification of ECG signals into normal and abnormal categories, including bradycardia, tachycardia, and atrial fibrillation.

The system achieves high classification accuracy with consistent performance across test data. The integration of preprocessing techniques such as filtering and normalization improves signal quality, which enhances overall model reliability. In addition, the use of edge-based processing significantly reduces inference time, enabling real-time monitoring and faster decision-making.

A comparative analysis is conducted against conventional machine learning and deep learning approaches. As shown in Table I, the proposed method achieves higher accuracy and lower inference time, demonstrating improved efficiency and suitability for real-time applications.

Table. 1. Comparison of proposed method with baseline approaches

Method	**curacy (%)**	**Inference Time (ms)**	**eployment Suitability**
litional ML	86.7	135	Moderate
Learning Model	91.2	220	Low
roposed Method	**94.5**	**98**	**High**

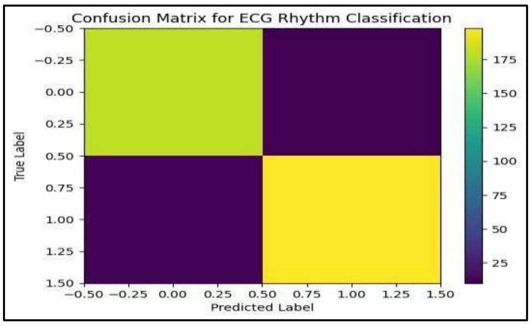

Fig. 5. Confusion matrix showing classification performance of the proposed model

In addition, the output probability distribution of the model is analyzed to evaluate its confidence in prediction. The results demonstrate clear separation between normal and abnormal classes, confirming the robustness of the classification model.

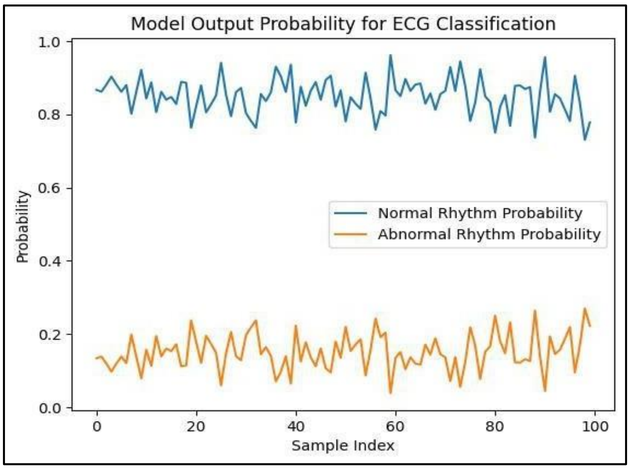

Fig. 6. Output probability distribution for ECG signal classification

VI. REAL WORLD APPLICATIONS

The proposed portable ECG monitoring system can be effectively utilized in various real-world healthcare scenarios requiring continuous and real-time cardiac monitoring. One of the primary applications is in home-based patient care, where individuals with cardiovascular conditions can monitor their heart activity without frequent hospital visits.

The system is also highly beneficial in rural and remote areas where access to advanced medical facilities is limited. Its portability and low-cost design enable early detection of arrhythmias, allowing timely medical intervention and reducing the risk of severe cardiac events.

In emergency situations, the system can provide immediate alerts upon detecting abnormal heart rhythms, assisting in rapid response and decision-making. Additionally, the integration with mobile applications supports telemedicine by enabling remote monitoring and consultation with healthcare professionals.

Overall, the proposed system enhances accessibility, improves patient safety, and supports the development of smart and connected healthcare solutions.

VII. PRACTICAL IMPLICATIONS AND LIMITATIONS

The proposed portable ECG monitoring system demonstrates significant potential in modern healthcare by enabling continuous, real-time cardiac monitoring outside traditional clinical environments. Its edge-based implementation allows faster decision-making with reduced latency and minimal dependence on cloud infrastructure. The portability and cost-effectiveness of the system make it suitable for deployment in home-based care, rural healthcare centers, and emergency scenarios. Additionally, local data processing enhances patient data privacy and security.

Despite these advantages, the system has certain limitations. The accuracy of ECG signal acquisition can be affected by noise, motion artifacts, and improper electrode placement, which may influence the performance of the classification model. Furthermore, the computational constraints of embedded devices limit the complexity of deployable deep learning models, requiring optimization techniques that may slightly impact accuracy.

The system currently focuses on a limited set of arrhythmia classes and may not cover all possible cardiac abnormalities. In addition, the performance of the model depends on the quality and diversity of the training dataset, which may affect generalization across different patient conditions.

Future improvements can include the integration of more robust sensors, expansion of the dataset, and the use of advanced lightweight models to enhance accuracy and scalability. Incorporating cloud-assisted analytics for long-term monitoring can further extend the capabilities of the system.

VIII. CONCLUSION AND FUTURE WORK

This paper presented a smart portable ECG monitoring system with edge artificial intelligence for real-time arrhythmia detection. The proposed system integrates ECG signal acquisition, preprocessing, and deep learning-based classification to enable continuous and automated cardiac monitoring. The use of a lightweight CNN–LSTM model allows accurate identification of abnormal heart rhythms such as atrial fibrillation, bradycardia, and tachycardia.

The implementation of edge-based processing ensures low latency, reduced dependency on cloud infrastructure, and enhanced data privacy. Experimental results demonstrate improved classification performance and faster inference time compared to conventional approaches, making the system suitable for real-time healthcare applications.

The proposed solution offers a cost-effective and accessible approach to cardiac monitoring, particularly beneficial in home-based care and resource-limited environments.

Future work will focus on expanding the range of detectable cardiac conditions, improving signal robustness under noisy conditions, and optimizing deep learning models for better performance on embedded platforms. Integration with cloud-based analytics and mobile health platforms can further enhance remote monitoring and long-term patient care.

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