

ARM Based AI Module for Ectopic Beat Detection

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Abstract

Cardiovascular diseases are among the leading causes of death worldwide, and early detection of cardiac arrhythmias is essential for effective healthcare monitoring and treatment. This paper presents an ARM-based intelligent healthcare monitoring system for real-time ECG arrhythmia detection using deep learning and Internet of Things (IoT) technologies. The proposed system integrates ECG signal acquisition, physiological parameter monitoring, signal preprocessing, feature extraction, and automated arrhythmia classification using a Raspberry Pi platform. The ECG signal is acquired using an ECG sensor and digitized using the ADS1115 analog-to-digital converter. Signal preprocessing techniques such as bandpass filtering, notch filtering, normalization, and smoothing are applied to improve signal quality and remove noise. R-peak detection and heartbeat segmentation are performed for accurate analysis. Continuous Wavelet Transform (CWT) is used to convert ECG signals into time-frequency representations, which are then provided as input to a lightweight Convolutional Neural Network (CNN) model for automatic arrhythmia classification. In addition to ECG monitoring, the system continuously monitors physiological parameters such as heart rate (BPM), blood oxygen saturation (SpO₂), body temperature, and fall detection using MAX30102, DHT11, and MPU6050 sensors. The processed data and classification results are transmitted to a cloud-connected Flask-based web dashboard for real-time remote healthcare monitoring and visualization. The system also generates alert notifications during abnormal conditions. The proposed system provides a low-cost, portable, and efficient solution for continuous patient monitoring and early arrhythmia detection. Experimental results demonstrate that the integration of embedded systems, deep learning, and IoT technologies improves healthcare accessibility, real-time diagnosis, and remote patient supervision.

Keywords— Arrhythmia Classification, Continuous Wavelet Transform, Convolutional Neural Network, ECG Monitoring, Internet of Things, Raspberry Pi, Healthcare Monitoring.

I. INTRODUCTION

Cardiovascular diseases are among the leading causes of death worldwide, and cardiac arrhythmias significantly contribute to severe heart-related complications and sudden cardiac arrest. Arrhythmias are abnormal heart rhythms caused by irregular

electrical activity in the heart, which may lead to stroke, heart failure, or other life-threatening conditions if not detected at an early stage [1]. Electrocardiogram (ECG) monitoring is one of

the most widely used techniques for analyzing the electrical activity of the heart and identifying various cardiac abnormalities [2]. However, traditional ECG monitoring systems generally require continuous hospital supervision and manual interpretation by medical professionals, making long-term monitoring difficult, time-consuming, and expensive [3].

Recent advancements in artificial intelligence (AI), Internet of Things (IoT), and embedded healthcare systems have enabled the development of intelligent real-time healthcare monitoring solutions [4]. Deep learning models, especially Convolutional Neural Networks (CNNs), have demonstrated remarkable performance in automated ECG classification and arrhythmia detection applications [5]. CNN-based approaches can automatically extract meaningful features from ECG signals without requiring manual feature engineering, thereby improving diagnostic accuracy and reducing computational complexity [6].

Several researchers have proposed wearable and IoT-based healthcare monitoring systems for continuous patient supervision. Kiranyaz et al. [7] developed a real-time patient-specific ECG classification system using one-dimensional CNN architecture for arrhythmia analysis. Acharya et al. [8] proposed an automated arrhythmia identification system using deep CNN models for ECG signal classification. Similarly, Yildirim [9] introduced a wavelet transform and deep learning-based approach for ECG analysis, demonstrating improved classification performance for cardiac abnormality detection.

Although significant progress has been achieved in ECG monitoring and classification systems, several limitations still exist. Many existing systems focus only on ECG monitoring without integrating additional physiological parameters such as body temperature, blood oxygen saturation (SpO₂), and fall detection [10]. Some systems also suffer from high computational complexity, lack of portability, limited real-time processing capability, and poor remote healthcare accessibility [11]. Furthermore, many healthcare monitoring systems do not provide efficient cloud-based visualization and remote monitoring support for healthcare professionals [12].

The increasing demand for portable, low-cost, intelligent, and real-

time healthcare systems motivates the development of an integrated healthcare monitoring platform capable of continuous ECG analysis and remote patient supervision. This paper presents an ARM-based intelligent healthcare monitoring system for real-time ECG arrhythmia classification using deep learning and IoT technologies. The proposed system utilizes a Raspberry Pi platform integrated with ECG sensors, pulse oximeter sensors, temperature sensors, and accelerometer modules for comprehensive physiological monitoring.

The acquired ECG signals undergo preprocessing operations such as filtering, normalization, smoothing, and R-peak detection to improve signal quality and remove noise artifacts [13]. Continuous Wavelet Transform (CWT) is then applied to convert the ECG waveform into a time-frequency representation suitable for deep learning analysis [14]. The transformed ECG images are provided as input to a lightweight CNN model for automatic classification of arrhythmia categories such as Normal, Supraventricular, Ventricular, Fusion, and Unknown.

In addition to ECG monitoring, the system continuously measures heart rate, blood oxygen saturation, body temperature, and body movement for fall detection using MAX30102, DHT11, and MPU6050 sensors. The processed data and classification results are transmitted to a Flask-based web dashboard through IoT communication for real-time monitoring and remote healthcare supervision [15]. Alert notifications are generated whenever abnormal physiological conditions are detected.

The major contributions of this work include:

- Development of an ARM-based embedded healthcare monitoring platform for real-time physiological-monitoring.
- Integration of Continuous Wavelet Transform and CNN for intelligent ECG arrhythmia classification.
- Implementation of multi-parameter health monitoring including ECG, BPM, SpO₂, temperature, and fall detection.
- Development of a cloud-connected IoT dashboard for remote healthcare monitoring and alert generation.

The remainder of this paper is organized as follows: Section II presents the literature survey related to ECG monitoring and arrhythmia classification systems. Section III describes the proposed methodology and system architecture. Section IV discusses the experimental results and system performance. Section V concludes the paper and outlines future research directions.

II. LITERATURE SURVEY

This literature survey reviews recent advancements in ECG monitoring, arrhythmia classification, deep learning techniques, and IoT-based healthcare systems. The survey highlights the evolution of intelligent healthcare monitoring technologies and identifies the limitations of existing systems that motivate the development of the proposed work.

Xie et al. [1] proposed an ARM-based AI module for ectopic beat classification using a lightweight CNN model. Their work demonstrated the effectiveness of embedded AI systems for real-time ECG classification while maintaining low computational complexity suitable for portable healthcare devices. Morshed et al. [2] developed an on-chip AI classifier for wearable ECG systems capable of real-time arrhythmia detection. Their system emphasized energy-efficient hardware implementation for continuous patient monitoring applications. Zhang et al. [3] introduced a lightweight CNN architecture for ECG arrhythmia classification on wearable healthcare devices. The proposed model achieved high classification accuracy while reducing memory requirements and computational overhead. Raj et al. [4] presented an energy-efficient embedded CNN system for ECG monitoring using ARM processors. Their work demonstrated that embedded deep learning models can provide reliable ECG analysis in low-power healthcare applications.

Neumann and Tejedor [5] implemented CNN-based ECG signal processing on ARM Cortex-M4 embedded systems. Their study focused on optimizing CNN models for real-time execution in resource-constrained embedded hardware platforms. Rajpurkar et al. [6] developed a deep learning model capable of cardiologist-level arrhythmia detection using large-scale ECG datasets. Their CNN-based approach significantly improved automatic arrhythmia classification accuracy and reduced dependence on manual ECG interpretation.

Kiranyaz et al. [7] proposed a real-time patient-specific ECG classification system using one-dimensional Convolutional Neural Networks. Their system automatically extracted ECG features and demonstrated efficient arrhythmia classification for continuous healthcare monitoring. LeCun et al. [8] provided foundational research on deep learning techniques and highlighted the effectiveness of Convolutional Neural Networks in pattern recognition and biomedical signal analysis applications.

Ince et al. [9] developed a robust automated ECG classification system for patient-specific arrhythmia detection. Their work demonstrated the importance of personalized ECG analysis for improving diagnostic performance. Pan and Tompkins [10] introduced a real-time QRS detection algorithm that became one of the most widely used ECG signal preprocessing methods for R-peak detection and heartbeat segmentation.

Goldberger et al. [11] developed PhysioNet and PhysioBank databases, which provide publicly available physiological signal datasets widely used for ECG analysis and biomedical research. Acharya et al. [12] proposed an automated arrhythmia identification system using CNN models and demonstrated improved ECG classification performance for different cardiac abnormalities.

Yildirim [13] introduced a wavelet transform and deep Bidirectional Long Short-Term Memory (BiLSTM) network for ECG signal classification. Their study showed that wavelet-based time-frequency analysis improves deep learning feature extraction

capability. Oh et al. [14] combined CNN and LSTM techniques for automated arrhythmia diagnosis using variable-length ECG signals, achieving improved classification accuracy for cardiac disorder detection.

Shashikumar et al. [15] proposed a wearable deep learning-based system for atrial fibrillation monitoring using portable healthcare devices. Their work demonstrated the importance of wearable technologies in continuous healthcare monitoring applications. Yang et al. [16] developed a multi-feature fusion and CNN-based arrhythmia recognition system that improved classification accuracy through effective ECG feature integration.

Sarkar et al. [17] implemented ECG classification using Continuous Wavelet Transform and Convolutional Neural Networks. Their approach demonstrated that time-frequency ECG representations significantly improve arrhythmia classification performance. Raspberry Pi Foundation [18] provided technical specifications and documentation for Raspberry Pi embedded systems, which are widely used in IoT and healthcare applications due to their portability, low cost, and processing capability.

TensorFlow Developers [19] introduced TensorFlow as an open-source machine learning framework for implementing deep learning models in healthcare applications. TensorFlow supports efficient CNN model training, deployment, and real-time inference for biomedical signal analysis. Flask Documentation Team [20] developed the Flask web framework for lightweight web application development and IoT dashboard implementation in real-time healthcare monitoring systems.

The literature survey indicates that deep learning, IoT communication, and embedded healthcare systems have significantly improved ECG monitoring and arrhythmia classification technologies. However, many existing systems still face challenges related to computational complexity, portability, multi-parameter integration, and real-time remote monitoring. Most systems focus primarily on ECG analysis without integrating additional physiological parameters such as blood oxygen saturation, body temperature, and fall detection into a single healthcare platform.

The proposed work aims to address these limitations by developing an ARM-based intelligent healthcare monitoring system integrating ECG analysis, CNN-based arrhythmia classification, multi-parameter monitoring, and IoT-enabled remote healthcare supervision into a unified embedded healthcare platform.

TABLE I. COMPARISON OF EXISTING HEALTHCARE MONITORING SYSTEMS

Aspect	Our Work	Existing Work
Primary Processing Unit	Uses Raspberry Pi ARM-based embedded	Most systems use desktop-based processing or single-purpose

	platform for real-time healthcare monitoring	wearable devices [1], [4]
ECG Classification Technique	Uses Continuous Wavelet Transform (CWT) and CNN for automatic arrhythmia classification	Existing systems mainly use traditional machine learning or basic CNN architectures [6], [12]
Multi-Parameter Monitoring	Integrates ECG, BPM, SpO ₂ , temperature, and fall detection in a single platform	Many systems focus only on ECG monitoring without additional physiological parameters [10], [15]
Real-Time Processing	Provides real-time ECG analysis and arrhythmia classification	Some existing systems have higher computational latency and offline processing [3], [5]
IoT Connectivity	Uses Flask-based IoT dashboard for cloud-connected healthcare monitoring	Several systems provide limited or no remote monitoring support [14], [20]
Alert Generation	Generates automatic alerts during abnormal cardiac conditions and fall events	Existing systems mainly focus on monitoring without intelligent alert mechanisms [2], [16]
Embedded AI Integration	Implements lightweight CNN suitable for ARM-based embedded systems	Many deep learning models require high computational resources [6], [8]
Portability	Compact and portable healthcare monitoring device suitable for remote usage	Existing hospital-based systems are bulky and less portable [3], [11]
Data Visualization	Real-time ECG waveform and health parameter visualization through web dashboard	Several systems provide limited graphical visualization [14], [20]
Healthcare Accessibility	Supports remote patient monitoring and telemedicine applications	Existing systems often require continuous hospital supervision [1], [9]
Cost Effectiveness	Low-cost implementation using	Traditional ECG monitoring systems are expensive and

	Raspberry Pi and embedded sensors	infrastructure dependent [4], [18]
Scalability	Easily expandable for cloud healthcare and wearable applications	Scalability is limited in many standalone monitoring systems [5], [13]

The comparison table highlights the advantages and limitations of existing healthcare monitoring systems and demonstrates the effectiveness of the proposed ARM-based intelligent healthcare monitoring system for real-time ECG arrhythmia classification and remote patient monitoring.

III. PROPOSED METHODOLOGY

The proposed healthcare monitoring system is designed to provide real-time ECG arrhythmia classification and physiological parameter monitoring using embedded systems, deep learning, and Internet of Things (IoT) technologies. The system integrates ECG signal acquisition, preprocessing, feature extraction, Convolutional Neural Network (CNN)-based arrhythmia classification, multi-parameter health monitoring, cloud communication, and web-based visualization into a unified intelligent healthcare platform.

The proposed system utilizes a Raspberry Pi ARM-based embedded platform as the central processing and control unit. Multiple biomedical sensors are interfaced with the Raspberry Pi to continuously acquire ECG signals and other physiological parameters such as heart rate, blood oxygen saturation (SpO_2), body temperature, and body movement for fall detection. The collected data is processed in real time and transmitted to a cloud-connected web dashboard for remote healthcare monitoring.

The ECG signal acquisition process is performed using ECG electrodes connected to the ADS1115 analog-to-digital converter. Since ECG signals are low-amplitude biomedical signals highly affected by noise and interference, signal preprocessing is necessary before analysis. The preprocessing stage includes bandpass filtering, notch filtering, normalization, smoothing, and R-peak detection to improve signal quality and remove unwanted noise components [10].

After preprocessing, heartbeat segmentation is performed based on the detected R-peaks. Each segmented heartbeat is transformed into a two-dimensional time-frequency representation using Continuous Wavelet Transform (CWT). The CWT technique provides detailed temporal and frequency information of ECG signals, improving feature extraction capability for deep learning-based classification [17].

The generated CWT images are provided as input to the Convolutional Neural Network (CNN) model. The CNN architecture automatically extracts important ECG features such as waveform morphology, frequency variations, and heartbeat patterns without requiring manual feature engineering. The CNN

model consists of convolution layers, Rectified Linear Unit (ReLU) activation functions, max pooling layers, flatten layers, fully connected dense layers, and a Softmax output layer for arrhythmia classification [6].

The CNN model classifies ECG signals into different arrhythmia categories such as: Normal, Supraventricular, Ventricular, Fusion, Unknown. In addition to ECG monitoring, the proposed system continuously monitors heart rate and blood oxygen saturation using the MAX30102 pulse oximeter sensor. Body temperature is monitored using the DHT11 temperature sensor, while body movement and fall detection are performed using the MPU6050 accelerometer sensor. These additional physiological parameters provide comprehensive healthcare monitoring and improve patient safety during emergency situations.

The Raspberry Pi processes all acquired sensor data and communicates with a Flask-based IoT dashboard through WiFi connectivity. The web dashboard displays real-time ECG waveforms, classification results, physiological parameters, historical records, and alert notifications. Users and healthcare professionals can remotely access the dashboard for continuous patient monitoring and healthcare analysis [20].

The proposed system also incorporates an alert generation mechanism using a buzzer and dashboard notifications. Whenever abnormal ECG patterns, low oxygen saturation, high temperature, or fall events are detected, the system immediately generates alerts to provide early medical assistance and improve emergency response capability.

The proposed methodology integrates embedded systems, biomedical signal processing, deep learning, and IoT communication into a low-cost and portable healthcare solution. The integration of Continuous Wavelet Transform and CNN-based arrhythmia classification improves diagnostic accuracy and enables intelligent real-time healthcare monitoring suitable for telemedicine, elderly care, home healthcare, and remote patient supervision applications.

The Fig 1 illustrates the block diagram of the proposed healthcare monitoring system illustrates the overall architecture and functional flow of the system. The Raspberry Pi acts as the central processing unit and interfaces with multiple biomedical sensors for continuous physiological monitoring. The ECG sensor acquires cardiac electrical activity signals, which are converted into digital form using the ADS1115 analog-to-digital converter. Additional physiological parameters such as heart rate, blood oxygen saturation (SpO_2), body temperature, and body movement are monitored using MAX30102, DHT11, and MPU6050 sensors respectively.

The acquired ECG signals undergo preprocessing operations including filtering, normalization, smoothing, and R-peak detection to remove noise and improve signal quality. The preprocessed ECG signal is segmented into individual heartbeats and transformed into time-frequency representations using Continuous Wavelet Transform (CWT). These CWT images are

provided as input to the Convolutional Neural Network (CNN) model for automatic arrhythmia classification.

The CNN model extracts important ECG features and classifies the heartbeat into different arrhythmia categories such as Normal, Supraventricular, Ventricular, Fusion, and Unknown. The Raspberry Pi continuously processes the classification results and sensor data in real time.

The processed physiological parameters and classification outputs are transmitted to the Flask-based IoT web dashboard through WiFi connectivity. The dashboard enables real-time visualization of ECG waveforms, health parameters, alert notifications, and historical health records for remote healthcare monitoring.

continuous acquisition of physiological signals. The ECG sensor acquires the electrical activity of the heart, while the ADS1115 analog-to-digital converter converts the analog ECG signal into digital form for further processing. Additional physiological parameters such as heart rate and blood oxygen saturation are monitored using the MAX30102 pulse oximeter sensor. Body temperature monitoring is performed using the DHT11 temperature sensor, and fall detection is achieved using the MPU6050 accelerometer and gyroscope sensor.

The acquired ECG signal undergoes several preprocessing operations including filtering, normalization, smoothing, baseline wander removal, and R-peak detection to improve signal quality and eliminate noise artifacts. After preprocessing, heartbeat segmentation is performed to isolate individual cardiac cycles for analysis.

Continuous Wavelet Transform (CWT) is applied to the segmented ECG signals to generate two-dimensional time-frequency representations. These transformed ECG images are then provided as input to the Convolutional Neural Network (CNN) model for automatic arrhythmia classification. The CNN model extracts important ECG features and classifies heartbeats into different arrhythmia categories such as Normal, Supraventricular, Ventricular, Fusion, and Unknown.

The Raspberry Pi continuously processes sensor data, classification results, and alert conditions in real time. The processed information is transmitted to a Flask-based IoT web dashboard through WiFi connectivity. The dashboard provides real-time visualization of ECG waveforms, physiological parameters, arrhythmia classification results, historical health records, and alert notifications. Healthcare professionals and users can remotely monitor patient health conditions through internet connectivity.

proposed architecture also includes an alert generation mechanism using a buzzer and dashboard notifications. Whenever abnormal ECG patterns, abnormal SpO₂ levels, elevated body temperature, or fall events are detected, the system immediately generates alerts to improve emergency healthcare response and patient safety.

The integration of embedded systems, biomedical signal processing, deep learning, and IoT communication enables the proposed system to provide a low-cost, portable, scalable, and intelligent healthcare monitoring solution suitable for telemedicine, elderly care, home healthcare, and remote patient monitoring applications.

IV. RESULTS AND DISCUSSIONS

The proposed ARM-based intelligent healthcare monitoring system was successfully implemented and tested for real-time ECG arrhythmia classification and physiological parameter monitoring. The system integrates ECG signal acquisition, preprocessing, Continuous Wavelet Transform (CWT)-based feature extraction, Convolutional Neural Network (CNN)-based

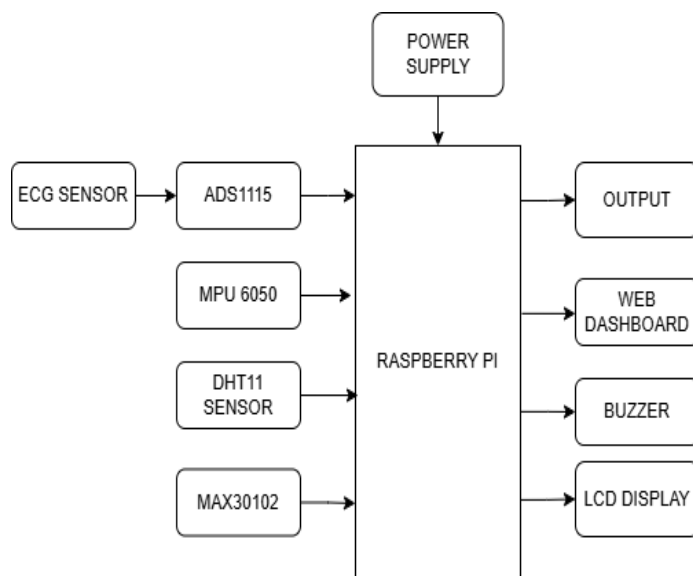


Fig.1: Block Diagram of Proposed System

Whenever abnormal physiological conditions or fall events are detected, the system generates alerts using a buzzer and dashboard notifications to improve emergency medical response and patient safety.

System Architecture

The system architecture of the proposed healthcare monitoring system is designed to provide real-time ECG arrhythmia classification, physiological parameter monitoring, and remote healthcare supervision using embedded systems, deep learning, and Internet of Things (IoT) technologies. The architecture integrates biomedical sensors, signal processing modules, deep learning models, cloud communication, and a web-based healthcare dashboard into a unified intelligent healthcare platform.

The Raspberry Pi ARM-based embedded platform acts as the central processing and control unit of the system. Multiple biomedical sensors are interfaced with the Raspberry Pi for

arrhythmia classification, and IoT-enabled remote healthcare monitoring using a Raspberry Pi embedded platform.

The ECG signal acquisition module successfully captured cardiac electrical activity using ECG electrodes interfaced through the ADS1115 analog-to-digital converter. The acquired ECG signals initially contained noise components such as baseline wander, motion artifacts, and power-line interference. Signal preprocessing operations including filtering, normalization, smoothing, and R-peak detection effectively improved signal quality and enabled accurate heartbeat segmentation.

Fig. 2 shows the R-peak detection process performed on the acquired ECG signal. The detected peaks are marked accurately for heartbeat segmentation and preprocessing operations. The R-peak detection algorithm successfully identified the QRS complexes from the ECG waveform, enabling precise segmentation of individual heartbeats for further analysis.

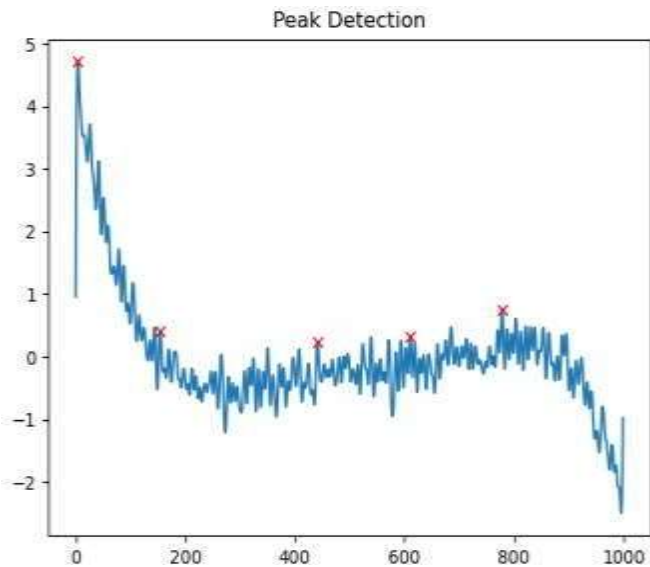


Fig. 2: R-Peak Detection from ECG Signal

After preprocessing, heartbeat segmentation was performed based on the detected R-peaks. The segmented ECG signals were then transformed into time-frequency representations using Continuous Wavelet Transform (CWT).

Fig. 3 shows the segmented ECG beat extracted from the pre-processed ECG signal using R-peak detection. The segmented heartbeat contains important cardiac waveform characteristics required for arrhythmia analysis.

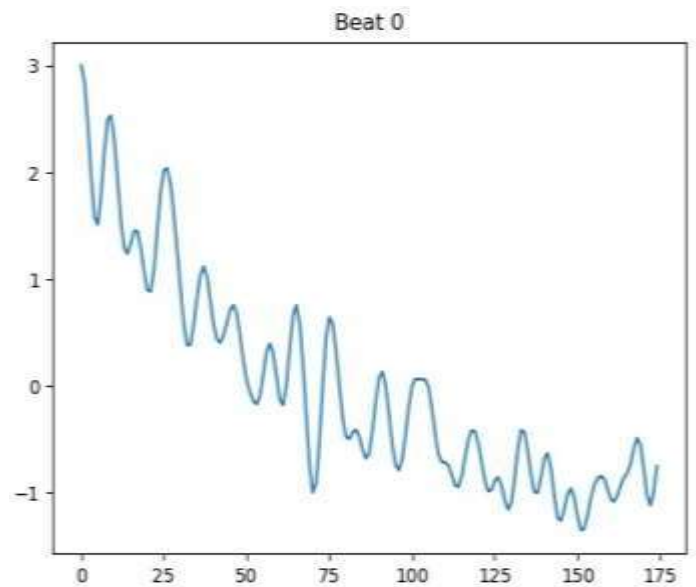


Fig. 3: Segmented ECG Beat Signal

The generated CWT images effectively captured both temporal and frequency information of ECG signals, improving feature extraction capability for deep learning-based classification

Fig. 3 shows the segmented ECG beat extracted from the pre-processed ECG signal using R-peak detection. The segmented heartbeat contains important cardiac waveform characteristics required for arrhythmia analysis.

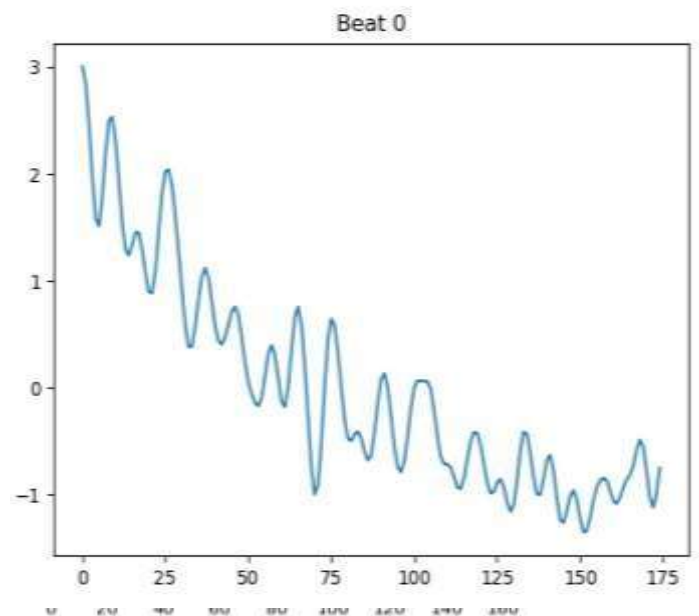


Fig. 4 shows the Continuous Wavelet Transform (CWT) representation of the segmented ECG signal. The CWT image provides detailed time-frequency information of the ECG

waveform, which improves feature extraction capability for CNN-based arrhythmia classification.

Fig.4: Continuous Wavelet Transform Representation of ECG Signal

The generated CWT images were provided as input to the Convolutional Neural Network (CNN) model. The CNN architecture automatically extracted significant ECG features such as waveform morphology, heartbeat patterns, and frequency variations without requiring manual feature engineering. Experimental observations showed that the integration of CWT and CNN significantly improved classification accuracy and enabled efficient arrhythmia detection in real-time healthcare monitoring applications.

The CNN model successfully classified ECG signals into different arrhythmia categories such as Normal, Supraventricular, Ventricular, Fusion, and Unknown. The classification process demonstrated stable performance and reliable arrhythmia prediction during real-time testing.

The MAX30102 sensor successfully monitored heart rate and blood oxygen saturation (SpO₂) levels continuously. The DHT11 sensor accurately measured body temperature, while the MPU6050 accelerometer effectively detected sudden body movements and fall events. The integration of multiple physiological parameters improved overall healthcare monitoring capability and enhanced patient safety during emergency conditions.

The Flask-based IoT dashboard successfully displayed real-time ECG waveforms, physiological parameters, arrhythmia classification results, historical records, and alert notifications through WiFi communication. The dashboard enabled remote healthcare monitoring and allowed healthcare professionals to continuously monitor patient health conditions from remote locations.

Whenever abnormal ECG patterns, low SpO₂ levels, high temperature, or fall events were detected, the system generated alert notifications through the buzzer and web dashboard. This alert mechanism improved emergency response capability and enabled timely medical assistance.

The hardware prototype demonstrated stable performance and reliable sensor integration during continuous monitoring operations. The Raspberry Pi platform successfully handled biomedical signal acquisition, deep learning inference, sensor interfacing, and IoT communication simultaneously without significant delay.

The proposed healthcare monitoring system provides several advantages over traditional healthcare monitoring methods,

including portability, low cost, intelligent arrhythmia classification, remote healthcare accessibility, and real-time physiological monitoring. The integration of embedded systems, deep learning, and IoT technologies enables efficient and scalable healthcare monitoring suitable for telemedicine, elderly care, home healthcare, and remote patient supervision applications.

Although the proposed system demonstrated effective performance, certain limitations still exist. The classification accuracy may vary depending on ECG signal quality and motion artifacts during signal acquisition. The system also requires stable internet connectivity for continuous IoT dashboard communication. Future improvements may include implementation of advanced deep learning architectures, wearable sensor integration, cloud-based data analytics, and enhanced cybersecurity mechanisms for secure healthcare communication.

Overall, the experimental results demonstrate that the proposed ARM-based intelligent healthcare monitoring system successfully performs real-time ECG arrhythmia classification and physiological parameter monitoring, providing an effective solution for next-generation smart healthcare applications.

V. CONCLUSION

This paper presented an ARM-based intelligent healthcare monitoring system for real-time ECG arrhythmia classification using deep learning and Internet of Things (IoT) technologies. The proposed system successfully integrated ECG signal acquisition, physiological parameter monitoring, signal preprocessing, Continuous Wavelet Transform (CWT)-based feature extraction, Convolutional Neural Network (CNN)-based arrhythmia classification, and IoT-enabled remote healthcare monitoring into a unified embedded healthcare platform.

The Raspberry Pi ARM-based embedded system effectively interfaced with multiple biomedical sensors including ECG electrodes, MAX30102 pulse oximeter sensor, DHT11 temperature sensor, and MPU6050 accelerometer sensor for continuous physiological monitoring. Signal preprocessing techniques such as filtering, normalization, smoothing, and R-peak detection improved ECG signal quality and enabled accurate heartbeat segmentation for arrhythmia analysis.

The application of Continuous Wavelet Transform provided detailed time-frequency representations of ECG signals, improving feature extraction capability for deep learning analysis. The CNN model successfully classified ECG signals into different arrhythmia categories such as Normal, Supraventricular, Ventricular, Fusion, and Unknown. Experimental results demonstrated that the integration of CWT and CNN significantly improved classification efficiency and enabled reliable real-time arrhythmia detection.

The Flask-based IoT dashboard successfully enabled remote healthcare monitoring by displaying ECG waveforms, physiological parameters, arrhythmia classification results, historical health records, and alert notifications through internet

connectivity. The system also generated emergency alerts during abnormal physiological conditions and fall events, improving patient safety and emergency healthcare response capability.

The proposed system provides several advantages including portability, low implementation cost, intelligent ECG analysis, remote healthcare accessibility, and real-time physiological monitoring. The integration of embedded systems, biomedical signal processing, deep learning, and IoT communication demonstrates an efficient approach for next-generation smart healthcare applications suitable for telemedicine, elderly care, home healthcare, and continuous patient supervision.

Future enhancements may include implementation of advanced deep learning architectures, cloud-based healthcare analytics, wearable healthcare integration, improved cybersecurity mechanisms, and large-scale clinical validation for enhanced diagnostic performance and healthcare reliability.

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