JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

REAL-TIME ECG SIGNAL MONITORING AND CLOUD-BASED ANALYSIS USING ESP32 AND AWS

[1]Ms.Jyoti Sachin Kamble,[2]Mrs. Neeta R. Kadam,[3]Dr. Manisha P. Hajare

[1]Student,[2]Assistant Professor,[3]Assistant Professor
[1]Department of Electronics & Telecommunication,
[1]JSPM NTC, Pune, India

Abstract : The advancement of Internet of Things (IoT) technologies has enabled real-time health monitoring systems to become more efficient and accessible. This paper presents a low-cost, real-time Electrocardiogram (ECG) data monitoring and analysis system using the ESP32 microcontroller and AWS Cloud services. An AD8232 ECG sensor is interfaced with the ESP32 to capture raw ECG signals from the human body. The data is transmitted wirelessly to AWS IoT Core over Wi-Fi, where it is processed and stored. AWS Lambda functions are used to route the data to AWS SageMaker, which hosts a pre-trained machine learning model for signal classification and anomaly detection. The results are visualized through a cloud-based dashboard, enabling remote monitoring of cardiac health. This system demonstrates an effective integration of embedded systems and cloud computing for remote patient care and health diagnostics. The implementation is scalable, energy-efficient, and can be extended to other biomedical signals in the future.

***Keywords* - ECG Monitoring, ESP32, AWS IoT Core, Machine Learning.**

I. INTRODUCTION

The rapid advancement of Internet of Things (IoT) technologies has revolutionized the healthcare sector by enabling real-time, remote monitoring of patients' vital signs. Among the various health parameters, the Electrocardiogram (ECG) is one of the most essential diagnostic tools for evaluating heart function. Traditional ECG systems are typically used in hospitals or clinics and require dedicated equipment and medical professionals for continuous monitoring. This limitation often prevents continuous monitoring, especially for patients with chronic conditions who need regular heart health assessments.

To address this gap, this paper proposes a cost-effective and efficient real-time ECG data monitoring system based on the ESP32 microcontroller and AWS Cloud services. The AD8232 ECG sensor is used to capture the electrical signals generated by the heart. This sensor interfaces with the ESP32 microcontroller, which is responsible for collecting, processing, and transmitting the data over Wi-Fi to the AWS Cloud. By leveraging the power of cloud computing, the system allows remote monitoring of ECG data, enabling healthcare providers to track patient health from any location.

Once the ECG data is transmitted to the cloud, it is processed using AWS IoT Core, AWS Lambda, and a machine learning (ML) model hosted on AWS SageMaker. The Lambda function routes the data to the ML model, which classifies the ECG signals, detects potential anomalies, and provides actionable insights. The processed data is visualized on a cloud-based dashboard, allowing real-time health monitoring for both patients and healthcare professionals.

This system integrates embedded systems (ESP32) with cloud-based computing (AWS), providing a scalable, flexible, and energy-efficient solution for continuous health monitoring. The use of IoT for transmitting real-time ECG data enhances accessibility to healthcare, especially for patients in remote or underserved areas. Furthermore, the ability to apply machine learning to analyze ECG signals offers the potential for early detection of cardiac conditions, thereby improving patient outcomes and reducing the need for immediate medical intervention.

By incorporating these advanced technologies, this system demonstrates a significant step toward the development of affordable, accessible, and efficient health monitoring systems. It not only facilitates continuous ECG monitoring but also helps in the early detection of heart-related diseases, which can lead to better management of chronic conditions and improved healthcare delivery.

II. LITERATURE SURVEY

Heart Disease is the main cause of Population Death. The World Health Organization survey says that heart ailment is the common cause of population death in the world. Most of the time, a cardiac arrest results in abrupt death before the patients get any consideration from a medical professional. This paper proposes an Electrocardiogram (ECG) monitoring system, which detects the heart problem using IoT (Internet of Things) applications [1]. using an IOT based integrated healthcare system to ensure quality patient care. Sensors are used to track vital parameters, and the data collected by the sensors is sent to the cloud via a WiFi module.

A wireless healthcare monitoring system has created that can provide real time online information about a patients conditions. The system is made up of sensors, a data acquisition unit, a microcontroller (i.e. ESP32) and software [2]. ESP32 microcontroller is low power consumption, built-in wireless functionality and broad support from a large developer community. It can considerably serve as an excellent candidate for a wearable gadget that demands continuous battery use and smooth communication with other systems.

The system also integrates data storage and analysis features, allowing medical practitioners to observe with trends of patient's health as well as detects abnormalities in real time. In addition, it allows for quicker intervention and better patient care [3]. The Wi-Fi module sends the data to the cloud. The sensors are connected to the ESP32 processor. If the patient desires, he or she is free to move. The data collected by the sensors is analyzed by the processor, and the processed data is sent to the cloud via a Wi-Fi module. On a computer or a mobile device [2]. An electrocardiogram (ECG) is a vital diagnostic tool used to identify various heart conditions. Through the identification of specific abnormalities in the heart's electrical activity [1]. using the dataset of ECG images of cardiac patients, and can be performed on a single CPU, overcoming the limitation of computational power.

In addition, the classification accuracy has significantly improved after applying the proposed method as a feature extraction tool for traditional machine learning algorithms. Thus, this method could be integrated into the IoT ecosystem in healthcare. This will encourage other AI researchers to explore other methods for cardiovascular disease detection [4]. An electrocardiogram (ECG) is a signal that measures the electric activity of the heart. The proposed approach is implemented using ML The key challenge in ECG classification is to handle the irregularities in the ECG signals which is very important to detect the patient status.

Therefore, we have proposed an efficient approach to classify ECG signals with high accuracy Each heartbeat is a combination of action impulse waveforms produced by different specialized cardiac heart tissues. Heartbeats classification faces some difficulties because these waveforms differ from person to another, they are described by some features. These features are the inputs of machine learning algorithm [5]. Amazon Simple Storage Service (Amazon S3) is storage for the Internet. It's a simple storage service that offers software developers a highly-scalable, reliable, and low-latency data storage infrastructure at very low costs. Amazon S3 provides a simple web services interface that can be used to store and retrieve any amount of data, at any time, from within Amazon Elastic Compute Cloud (Amazon EC2) or from anywhere on the web. You can write, read, and delete objects containing from 1 byte to 5 terabytes of data each. The number of objects you can store in an Amazon S3 bucket is virtually unlimited. Amazon S3 is also highly secure, supporting encryption at rest, and providing multiple mechanisms to provide fine-grained control of access to Amazon S3 resources [6]. AWS architecture that processes live electrocardiogram (ECG) feeds from common wearable devices, analyzes the data, provides near-real-time information via a web dashboard. The ECG analysis to detect if anomalies are present is based on the classification of spectrograms generated from 1-minute-long ECG trace strides.

To accomplish this classification job, we use Recognition Custom Labels to train a model capable of identifying different cardiac pathologies found in spectrograms generated from ECG traces of people with various cardiac conditions [7].

III. SYSTEM OVERVIEW

The system captures ECG signals using an AD8232 sensor and transmits them via ESP32 to AWS IoT Core. AWS Lambda processes the data, and Amazon SageMaker classifies the heartbeats as normal or abnormal. The results are visualized for real-time monitoring. Fig. 1 illustrates the functional block diagram of the system, which is divided into six primary layers:

A. Data Acquisition:

The ECG data is acquired using an AD8232 ECG sensor, which records electrical signals from the human body. These analog signals are sent to an Arduino Uno, which performs initial processing and digitization. The data is then forwarded to an ESP32 microcontroller that features Wi-Fi capabilities for wireless data transmission. For real-time monitoring during data collection, the ECG waveforms are visualized using the Serial Plotter. As shown in Fig. 1

B. Core Processing:

The ESP32 is programmed to handle serial communication with the Arduino, format the incoming data, and transmit it securely to the cloud using the MQTT protocol. The microcontroller connects to AWS IoT Core, where it publishes the data to a specified MQTT topic. This enables a secure, continuous data flow from the local device to the AWS cloud environment.

C. Cloud Infrastructure:

Once the ECG data is transmitted, AWS IoT Core serves as the gateway for receiving, managing, and forwarding the incoming signals. The data can be optionally stored in cloud storage services such as Amazon S3 or DynamoDB, creating a repository for historical ECG signals. This forms the foundation for long-term analysis and training of machine learning models.

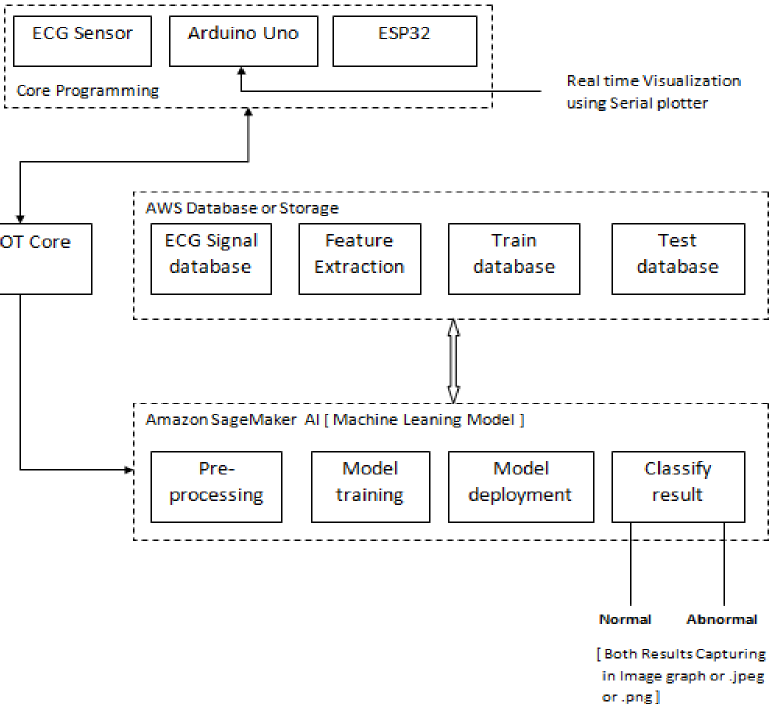


Fig. 1

D. Data Processing Pipeline:

The collected ECG signals undergo feature extraction, where vital characteristics like peak intervals and waveform shapes are identified. This step transforms raw data into meaningful features. The data is then split into training and testing datasets, which are fed into machine learning workflows.

E. Machine Learning System:

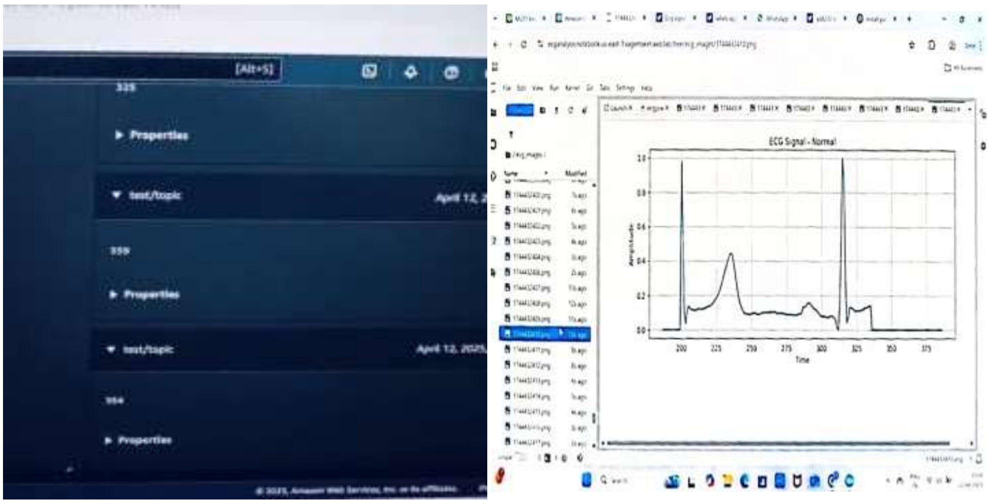
Amazon SageMaker is used to build and train a classification model using the preprocessed ECG features. The system supports model training, validation, and deployment. Algorithms such as support vector machines or neural networks are employed to distinguish between normal and abnormal heartbeats. AWS Lambda is used to trigger real-time inference by the trained model whenever new ECG data arrives.

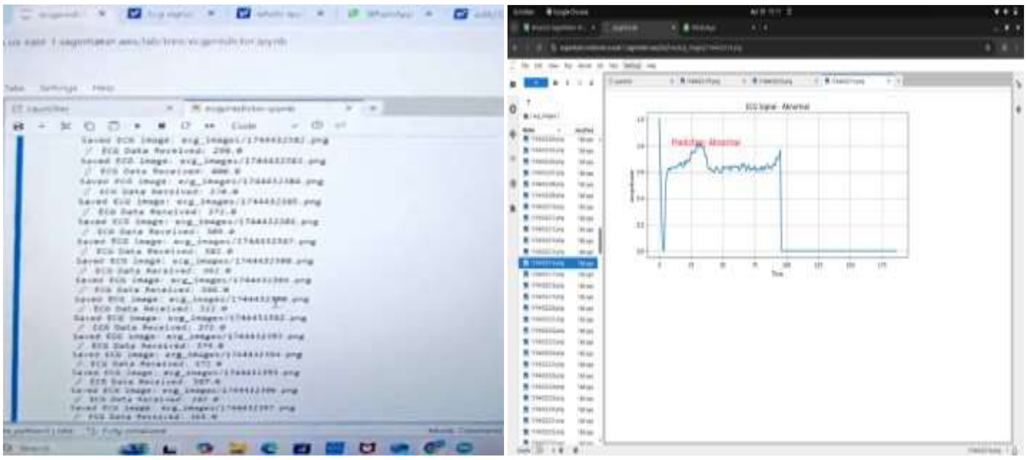
F. Output Visualization:

The results from the SageMaker model are classified into normal or abnormal signals. These outcomes are paired with ECG waveform images (e.g., in JPEG or PNG format) and stored or displayed via a cloud dashboard. This allows for effective visualization and review by medical practitioners, enabling timely diagnosis and remote patient monitoring.

IV. RESULT ANALYSIS

The proposed ECG monitoring and classification system was tested using real-time data from hardware and a publicly available dataset from Kaggle. This evaluation aimed to assess the system's ability to accurately classify ECG signals using AWS-based machine learning infrastructure





A. Training and Testing

The dataset used for model training and testing was obtained from Kaggle and contained labeled ECG images representing six heartbeat classes. The dataset included 3,120 images for training and 900 images for testing. After preprocessing, these images were fed into the machine learning pipeline hosted on Amazon SageMaker, where the classification model was trained using extracted features. The trained model was then evaluated using the test set to validate its performance.

B. Results

The system demonstrated effective classification of ECG signals into normal and abnormal categories as shown in Fig. 2 Visual results in the form of ECG waveform graphs were generated and stored for medical review. The model performed consistently during testing, confirming that the integration of IoT, cloud services, and machine learning can provide a reliable and scalable solution for ECG analysis.

V. CONCLUSION AND FUTURE WORK

This project successfully demonstrated an IoT-based ECG monitoring and classification system using the ESP32 microcontroller, AWS IoT Core, and Amazon SageMaker. The system enabled real-time ECG signal acquisition, cloud-based storage, and machine learning-based classification into normal or abnormal conditions. Integration with AWS services facilitated efficient data transmission, processing, and visualization, making the solution scalable and practical for remote health monitoring.

In the future, the system can be enhanced by integrating advanced deep learning models for more precise classification, supporting multi-class detection of cardiac conditions. Additionally, implementing real-time alerts, mobile app integration, and expanding compatibility with wearable sensors can improve usability and clinical relevance.

REFERENCES

[1] D. K. Ravish and K. P. K., "Recording of ECG for Detection of Heart Abnormalities Using ESP32 and Ubidots," *Int. J. Enhanced Res. Sci. Technol. Eng.*, vol. 13, no. 5, pp. 45–49, May 2024.

[2] S. K. Sangeethalakshmi, S. Preethi Angel, U. Preethi, S. Pavithra, and V. Shanmuga Priya, "Patient health monitoring system using IoT," *Mater. Today Proc.*, Jun. 2021. [Online]. Available: https://doi.org/10.1016/j.matpr.2021.06.188

[3] M. I. Castillo, "Wireless Based Wearable Patient Health Monitoring System Using ESP32," B.Eng. thesis, Dept. Ind. Electron. Autom. Eng.[Institution Name], Jan. 2024.

[4] Abubaker, Mohammed B., and Bilal Babayigit. "Detection of cardiovascular diseases in ECG images using machine learning and deep learning methods." IEEE Transactions on Artificial Intelligence 4, no. 2 (2022): 373-382.

[5] Alarsan, Fajr Ibrahem, and Mamoon Younes. "Analysis and classification of heart diseases using heartbeat features and machine learning algorithms." Journal of big data 6, no. 1 (2019): 1-15.

[6] M. M. Firdhous, "Storage options in the AWS cloud,"*Academia.edu*,Available: https://www.academia.edu/download/62020653/storage_options_in_the_aws_cloud_020200206-75635-320zzw.pdf

[7] S. Kandpal and A. Kalidindi, "AWS Cloud technology for near-real-time cardiac anomaly detection using data from wearable devices," *AWS Machine Learning Blog*, Nov. 11, 2020.. Available: https://aws.amazon.com/blogs/machine-learning/aws-cloud-technology-for-near-real-time-cardiac-anomaly-detection-using-data-from-wearable-devices/