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# IoT-Based Remote Health Monitoring System for Real-Time Patient Data

**Abstract:** - This project presents an IoT-based solution to assist and enhance patient care by empowering medical professionals with a tool that enables timely, proactive and necessary medical intervention. Our project encompasses multidisciplinary research spanning across various fields. The system includes various biosensors to monitor critical vital signs such as body temperature, heart rate, oxygen level, and ECG continuously. The readings are sent through a Wi-Fi microcontroller to a secure hospital server, providing real-time data retrieval for healthcare professionals. A machine learning model utilizes real-time ECG data to identify abnormalities early. A React-built web application provides an easy-to-use interface to create real-time visualizations for clinicians, track trends, and receive emergency notifications. It provides a cloud-based deployment that provides security, reliability, and healthcare standard compliance. Its versatility allows it to be applied to a wide range of applications - telemedicine, ambulance-to-hospital workflow, and large scale remote monitoring of health. It can also be considered an essential tool in many cases such as in a pandemic world, emergency medicine and rural health. This AI-based solution introduces general healthcare practices to a new world where it bridges the gap between precise health monitoring and modern predictive tools. It promises the potential of transforming contemporary patient care with reliable real-time insights, early and prioritized interventions and improved clinical outcomes.

**Keywords:** Emergency Response System, Internet of Things (IoT), Remote Patient Monitoring, Early Detection

## I. Introduction

In this era of massive population spurts and the dire need for excellent medical care, catering to every person's health needs becomes a top priority. Contemporary healthcare facilities, especially in terms of general or recovery wards, require a healthcare professional to manually examine the health of every patient.

Continuous monitoring like this is not just labor-intensive but also highly dependent on the professional's availability and the intervals to measure the vitals. There can be many scenarios where the nurse to patient ratio may not be good enough to meet each patient's need, leading to missed critical events and delayed rounds. These shortcomings hint at a need for a tool to help prioritise and continuously monitor patient vitals. These can significantly reduce human errors while simultaneously aid nurses to organise their duties well.

If we move further to beyond in-hospital situations like remotely located patients, especially in the absence of a nurse round the clock, a continuous monitoring tool with an early detection system and an alert mechanism can come in handy to take immediate action and avoid any delayed crisis.

The COVID-19 outbreak in 2019-2020 also raised an urgent need to minimize in-person contacts and increase telehealth consultations and home-based monitoring solutions.

To address these aforementioned situations, our work proposes a vital sign monitoring tool. Its objectives are to (1) Design a cost-efficient sensor machine with robust connectivity and a patient friendly look; (2) Integrate an early detection algorithm to alert for any signs of upcoming arrhythmia in the patient; and (3) evaluate the system's performance through simulations and pilot deployments. Thus, our solution aims to enhance patient safety, optimize clinical resources and build a framework for resilient healthcare delivery.

## II. Proposed Solution

We aim to design a Real-Time Vital-Sign Monitoring Framework that includes:

i) A patient-friendly collection of IoT sensors to continuously capture data.

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ii) Edge-gateway nodes like ESP8266 for local collection of data, preprocessing and encryption.

iii) Cloud-based analytics platform on ThinkSpeak for scalability and hosting these clinical dashboards.

iv) A deep learning model to detect early signs of arrhythmia.

Overall, the goal is to build a seamless, real time monitoring tool with minimal latency and high predictive accuracy.

## III. System Components

### *3.1. NodeMCU ESP8266*

A Wi-Fi-enabled microcontroller that collects vital sign data from the sensors and uploads it to the cloud. It's compact, low-power, and easy to program using Arduino IDE.

### *3.2. Pulse Sensor*

An optical sensor that uses light to detect pulse rate from the changes in blood flow. Useful for real-time pulse monitoring.

### *3.3. MAX30102*

A sensor that measures heart rate and $SpO_2$ using red and IR LEDs. It offers accurate readings and works well for continuous monitoring.

### *3.4. AD8232*

An ECG module that records the electrical activity of the heart. It helps in detecting irregular heart rhythms and cardiac health.

### *3.5. MLX90614*

A non-contact infrared sensor that accurately measures body temperature. Ideal for hygienic and fast temperature checks.

### *3.6. Custom 3D Designed Case*

A protective case that holds all components securely. It ensures portability, durability, and ease of use.

## IV. System Architecture

### *4.1. Physical Architecture*

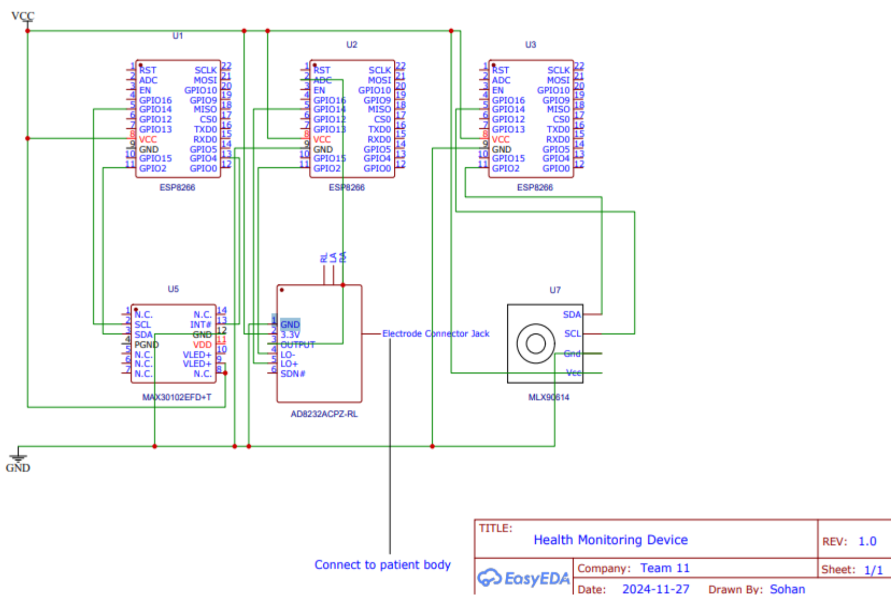


**Fig. 4.1**. Circuit Design depicting the Hardware Architecture

The physical architecture consists of multiple ESP8266 modules connected to biomedical sensors for real-time health monitoring. The system integrates the following components:

**i) ESP8266 Modules (U1, U2, U3):** Serve as the main microcontrollers for gathering sensor data and facilitating Wi-Fi wireless connectivity.

**ii) MAX30102 (U5):** Connected via I2C (SDA, SCL), this sensor captures heart rate and $SpO_2$ data.

**iii) AD8232 ECG Sensor (RL):** Connected to one of the ESP8266s, it detects the heart's electrical signals through an electrode connector jack placed on the patient's body.

**iv) MLX90614 (U7):** An infrared temperature sensor interfaced via I2C, used to measure non-contact body temperature.

**v) Power Supply:** All components are powered using a common VCC and GND rail to maintain voltage consistency and proper grounding.

*4.2. Software Architecture*

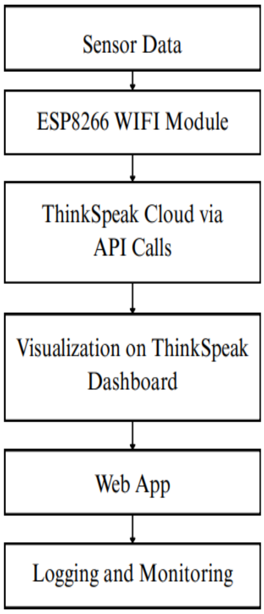


**Fig 4.2**. Software Architecture

**i) Sensor Data:** The system starts with real-time data acquisition from biomedical sensors. These readings include pulse, temperature, oxygen level and ECG.

**ii) ESP8266 WiFi Module:** The NodeMCU ESP8266 acts as the main processing and communication unit.

**iii) ThinkSpeak Cloud:** ThingSpeak serves as a cloud-based IoT analytics platform. ESP8266 pushes data to ThinkSpeak using API keys and endpoints.

**iv) Visualization on ThinkSpeak Dashboard:** ThingSpeak provides built-in visualization tools such as line charts, bar graphs, and gauges to display ECG, SpO2, temperature readings using time-stamped logs.

**v) Web App:** A custom React-based web application interfaces with the cloud platform. It displays live and historical data from ThinkSpeak using REST APIs or via backend server fetches. Shows alerts based on ML-based arrhythmia detection models.

**vi) Logging and Monitoring:** All incoming data is logged with timestamps. This is used for medical analysis and notifications for medical abnormalities.

*4.3. Machine Learning Model Architecture*

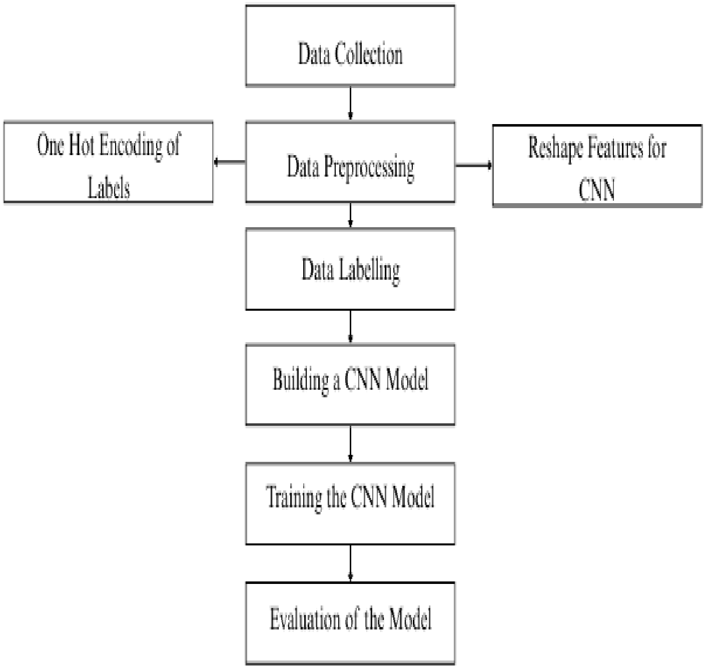


**Fig 4.3.** Machine Learning Model Architecture

The machine learning model is built to detect arrhythmia from the ECG readings obtained from the AD8232 module. The architecture contains the following stages:

**i) Data Collection:** ECG is collected from the dataset.

**ii) Data Preprocessing:** The raw ECG data is filtered, reducing noise and features are reshaped to match the CNN model.

**iii) Data Labeling:** Each ECG is labeled as an irregular ECG or a regular ECG reading.

**iv) Building the CNN model:** The model is trained with the pre-processed and labeled ECG data to learn patterns associated with arrhythmic events.

**v) Evaluation:** The trained model is tested with the unseen ECG data to evaluate its performance using metrics like accuracy, F1-score, and sensitivity.

This pipeline enables real-time, automated arrhythmia detection, improving the speed and accuracy of early identification of arrhythmia.

## V. METHODOLOGY

### *5.1. Sensor Integration*

Biomedical sensors were selected based on their reliability and compatibility with the microcontroller. Accurate voltage levels and steady signal readings were guaranteed by the precise GPIO pins that each sensor was interfaced with.

### *5.2. Hardware Setup*

All the components are housed in a 3D-printed device. The case was designed to fit the patient's palm in such a way that the readings are true.

### *5.3. Data Acquisition and Transmission*

The continuously gathered data is transmitted to ThinkSpeak, a cloud-based IoT platform.

### *5.4. Model Development*

A Convolutional Neural Network (CNN) was developed for arrhythmia detection using ECG data. The model includes noise filtering, feature scaling, reshaping data and one-hot encoding. It was also optimized for maximum accuracy.

*5.5. Web Interface and Visualisation*

A web application was built using React with components that are easy to use by non- technical professionals like medical staff. This interface displays dynamic charts, status indicators and a notification system triggered by the sensors.

*5.6. Testing and Evaluation*

The system was tested to verify its accuracy, connectivity, and real-time performance. Evaluation metrics such as accuracy, sensitivity, and latency were calculated.

## VI. Implementation

*6.1. Sensor Integration:* Sensors are connected to the NodeMCU to collect ECG, pulse, and temperature data.

*6.2. Data Transmission:* ESP8266 transmits sensor readings to ThingSpeak using Wi-Fi and API calls.

*6.3. Cloud Visualisation:* ThinkSpeak provides an IoT dashboard with multiple graphs.

*6.4. Machine Learning Implementation:* A trained CNN model for early detection of arrhythmia based on incoming ECG data collected by the sensors.

Model: "sequential"

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv1d (Conv1D) | (None, 254, 32) | 128 |
| batch_normalization (BatchNormalization) | (None, 254, 32) | 128 |
| max_pooling1d (MaxPooling1D) | (None, 127, 32) | 0 |
| conv1d_1 (Conv1D) | (None, 125, 64) | 6,208 |
| batch_normalization_1 (BatchNormalization) | (None, 125, 64) | 256 |
| max_pooling1d_1 (MaxPooling1D) | (None, 62, 64) | 0 |
| flatten (Flatten) | (None, 3968) | 0 |
| dense (Dense) | (None, 128) | 508,032 |
| dropout (Dropout) | (None, 128) | 0 |
| dense_1 (Dense) | (None, 2) | 258 |
| dense_1 (Dense) | (None, 2) | 258 |
| dense_1 (Dense) | (None, 2) | 258 |

Total params: 515,010 (1.96 MB)
Trainable params: 514,818 (1.96 MB)
Non-trainable params: 192 (768.00 B)

**Fig. 6.5.** CNN Layers of the Model

*6.5. Web Application:* A react-app to display the graphs and metrics along with a notification system for the healthcare providers.

*6.6. Device Assembly:* All components are enclosed in a compact, patient-friendly casing. The case is a 3D-printed device that is user-friendly and provides reliable readings.

## VII. Results And Analysis

*7.1. Sensor Accuracy:* Vital signs like heart rate, temperature, and ECG were captured accurately by sensors (e.g., MAX30102, AD8232) with stable readings under various conditions.

*7.2. Data Transmission Performance:* ESP8266 modules successfully transmitted real-time data to the ThinkSpeak cloud with minimal delay (<2s average latency).

*7.3. Visualisation Output:* Data was clearly visualized on ThinkSpeak dashboards and mirrored effectively on the web app for remote monitoring.

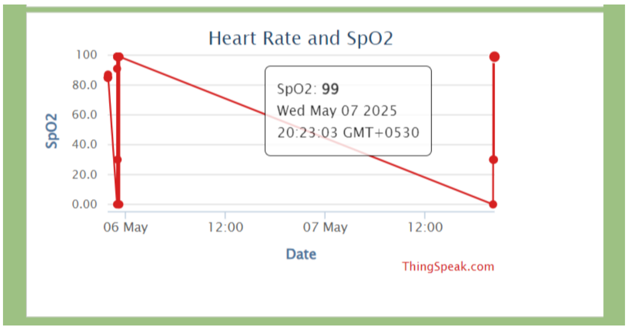


**Fig. 7.1.** SpO2 visualisation from ThinkSpeak

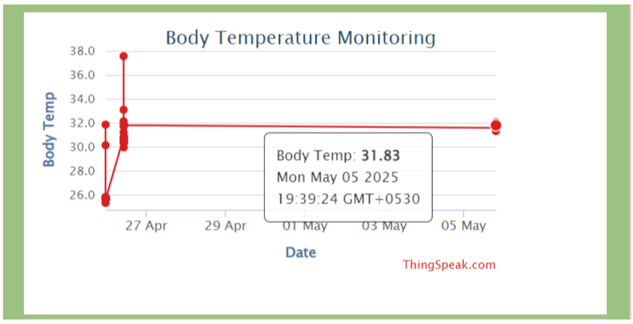


**Fig 7.2.** Temperature reading visualisation from ThinkSpeak

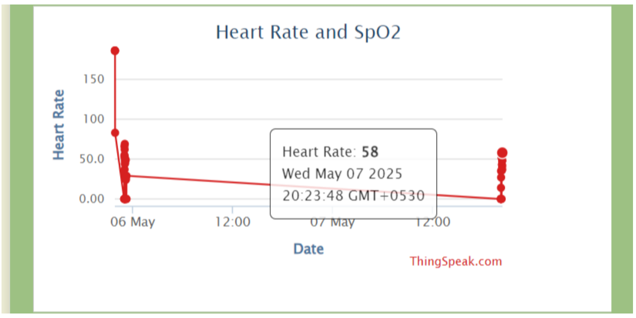


**Fig. 7.3.** Heart Rate visualisation from ThinkSpeak

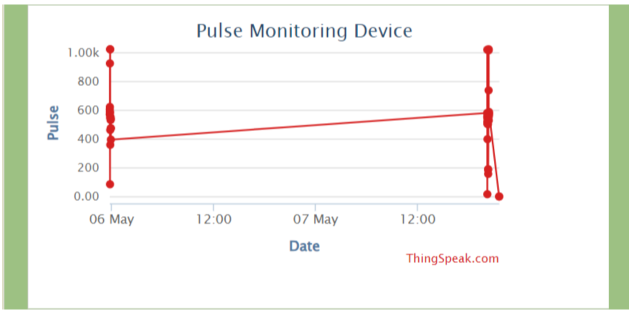


**Fig 7.4.** Pulse reading visualisation from ThinkSpeak


**Fig. 7.5.** Visualisations on the React App

*7.4. ML Model Performance:* The CNN model achieved 96.87% accuracy in detecting arrhythmic patterns from ECG signals, validated against labeled data.


Fig.7.1. Model Accuracy

*7.5. Device Comfort & Usability:* The custom 3D-designed case provided a compact platform while taking the patient's comfort into account.

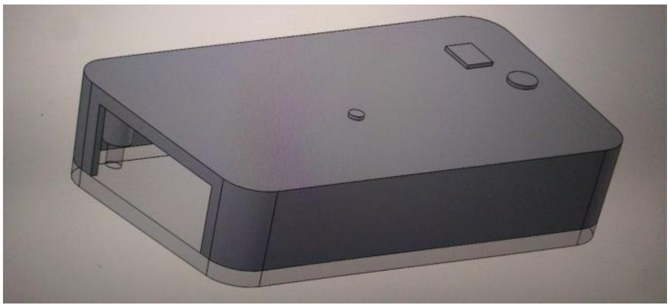

**Fig.7.6(a)** 3D model of the Device (1)

**Fig.7.6(b)** 3D model of the Device (2)

*7.6. System Reliability:* Continuous testing showed the system performed reliably over extended periods without major data loss or hardware failure.

## VIII. CONCLUSION

This project successfully delivers a IoT device that is capable of real-time monitoring of a patient's vitals. By using ThinkSpeak platform, it ensures accurate monitoring and timely data transmission It contains a notification architecture to notify professionals about any abnormal readings. The project also integrates an ML model to provide diagnostic support for arrhythmia. Overall, the project presents itself with a strong potential to revolutionize healthcare.

## IX. Future Scope

Future enhancements may include expansion of the sensors to include a larger number of vital sign monitoring to make it more robust. It can include enhancing the data privacy by using secure healthcare platforms. It may also include a larger and more diverse Machine Learning model with more readings and better accuracy. The project also demonstrates a potential to be used in a wider range of applications like telemedicine, room for virtual consultations and real-time capabilities make it suitable for elderly care, postoperative monitoring, and emergency response systems.

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