

Portable Health Monitoring and Prediction System Based on Machine Learning

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Abstract- It is essential to regularly examine bodily indicators to maintain good health. This study suggests a small, reasonably priced tool for regular health examinations. This tool is designed to measure blood oxygen levels and body temperature using two ESP32 microcontrollers one SpO2 sensor (MAX30102) and a temperature sensor (DS18B20). The device can do initial health check-ups on its own using a machine learning algorithm. This technique is very helpful for senior citizen living alone at home, people living in isolated areas, places where accidents happen, security guards working in difficult terrain, and anyone dealing with unexpected emergencies. IoT cloud technology was used to send health-related data to medical professionals, guaranteeing prompt and effective medical care.

Keywords- health monitoring, sensor, IoT, machine learning

Introduction

Traditional health monitoring devices are often bulky, expensive, and not easily accessible to individuals in rural or underdeveloped regions. With the advancement of technology, there has been a growing interest in developing portable and affordable health monitoring systems that can be used beyond traditional healthcare settings. These devices are especially useful in contexts with low resources or in remote locations where access to medical services is restricted. The goal of this project was to create a portable health monitoring system that measures vital signs including body temperature and SpO2 (blood oxygen saturation) by integrating many sensors. The system is designed using ESP32 microcontrollers, which enabled wireless data transmission to a central server for real-time monitoring and analysis. This system utilized the MAX30102 pulse oximeter sensor, DS18B20 temperature sensor to measure SpO2 and Body Temperature simultaneously. This system forecasted the patient's health status and issued early warnings for any medical emergencies by utilizing machine learning techniques. The results of this study are useful in the field of telemedicine and could enhance the provision of healthcare in underserved and rural areas.

CURRENT MEDICAL FIELD HEALTH MONITORING SYSTEM

Numerous health monitoring technologies have greatly enhanced patient care in the medical industry. Vital indications like blood oxygen levels and temperatures are tracked by wearable health monitors like the Fitbit and Apple Watch, which promote proactive health management. Telemedicine platforms, such as Teladoc and Amwell, facilitated remote consultations, enhancing access to healthcare, especially for patients in rural areas. Home health devices, such as blood pressure monitors from Omron, empower patients to manage their health independently. Mobile health applications like My-FitnessPal provided personalized insights to help users maintain healthy habits. Data from these technologies was examined by Clinical Decision Support Systems (CDSS) to help medical practitioners make well-informed decisions.

Literature Review

In a study by David Naranjo-Hernandez *et al.* in 2017 [1] a smart shirt was designed with the purpose of gathering physiological data from the wearer. A variety of sensors, including ECG, temperature, blood pressure, blood glucose, heart rate, and oxygen saturation sensors, are integrated into this shirt in the appropriate locations. Wireless Body Sensor Networks (WBSNs) have been widely used to evaluate people's physiological parameters, especially for illness monitoring, prevention, and therapy, according to another study by Fang and Yie Leu in 2017 [2]. In this paper, they proposed the Mobile Physiological Sensor System (MoPSS), a smart phone-based WBSN that uses body sensors. Besides, Miad Faezipour *et al.* in 2020 reported that telemedicine may be essential in the disruptive and rapidly spreading new corona virus illness (COVID-19) pandemic on a global scale [3]. Additional research work was done with Wearable sensors that collect physiological parameters like body temperature, heart rate, ECG, oxygen level, etc. by Suparna Biswas *et al.* in 2021 [4]. The sensors are then sent to a medical cloud via a smartphone, where the cloud systems can handle several functions like data cleaning, data storage, and data analysis.

System Architecture

The System architecture includes two main sections.

- Hardware architecture
- Software architecture.

Hardware Architecture

1)ESP32, developed by Espressif Systems, is a powerful and versatile microcontroller, succeeding the ESP8266. The ESP32 can be programmed using the Arduino IDE or the ESP-IDF framework. Its applications span IoT devices, wearables, consumer electronics, and industrial automation.



Fig. 1 ESP32 DEV. KIT V-1

2)MAX30102 is a compact optical biosensor from Maxim Integrated, designed to monitor blood oxygen saturation (SpO₂). With low-noise signal processing and I2C communication, it's easy to integrate into portable devices. Maxim Integrated offers documentation and open-source libraries for development with platforms like Arduino.



Fig.2 MAX30102

3) DS18B20 is a digital temperature sensor from Maxim Integrated, known for its accuracy and ease of use. Key features include high accuracy ($\pm 0.5^{\circ}\text{C}$) over a wide range (-55°C to $+125^{\circ}\text{C}$) and selectable resolution (9 to 12 bits). The sensor operates by converting analog temperature signals to digital format for transmission.

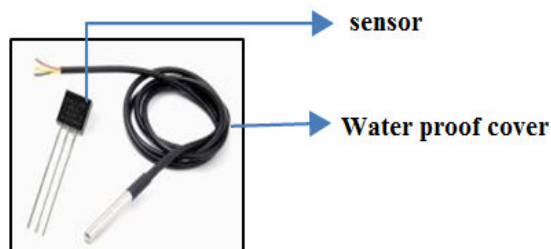


Fig. 3 DS18B20

Software Architecture

1) ThingsBoard is an open-source IoT platform for collecting, storing, visualizing, and analyzing data from IoT devices. It supports integration with other systems and provides robust security features. ThingsBoard Cloud can be deployed as a fully managed service or on-premises for more control. Used cases include industrial IoT, smart cities, smart agriculture, and connected healthcare.



Fig.4 ThingBoard

2) **Arduino Integrated Development Environment (IDE)** is an open-source software platform for programming Arduino boards, available on Windows, macOS, and Linux. The IDE includes a serial monitor for debugging and offers example sketches and tutorials for beginners. The active Arduino community provides extensive resources, while users can extend the IDE's functionality with third-party tools and integrations.



Fig.5 Arduino IDE

3) **Google Colab** is a cloud-based platform that allows users to write and execute Python code in a collaborative environment. It provides free access to powerful computing resources, including GPUs and TPUs, making it ideal for machine learning and data analysis tasks. Because of its accessibility and ease of use, Colab is frequently utilized by researchers, educators, and data scientists.



Fig.6 Google Colab for Machine Learning Environment

Block Diagram and Circuit Diagram

The block and circuit diagram illustrated in Fig. 7 has shown an IoT-based health monitoring system. It integrates multiple sensors and a cloud platform for real-time data collection and analysis:

- Temperature Sensor (DS18B20) and SpO2 Sensor (MAX30102) collect body temperature and blood oxygen (SpO2) data, respectively.
- The sensors are connected to ESP32 microcontrollers. One ESP32 handles the temperature data, while another handles SpO2 data.
- Both ESP32 units transmit the data to Things Board Cloud, which stores and visualize the information.
- The data is then processed by a Machine Learning Model, which analyzed the readings and sent results to a computer screen for monitoring.

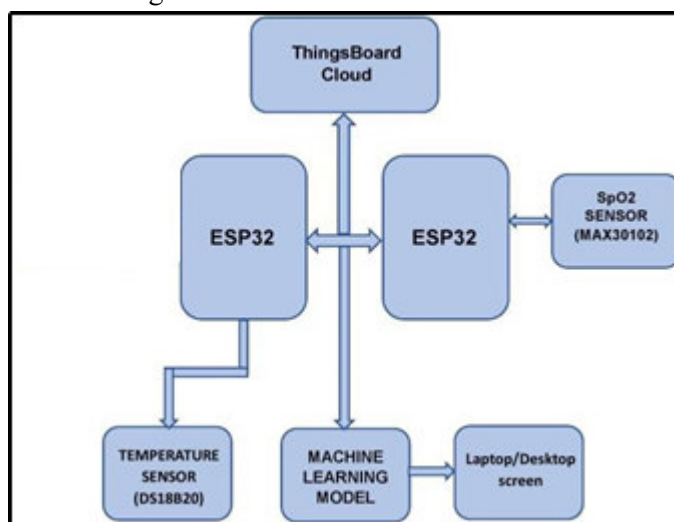


Fig.7 Block diagram of Portable IoT-Based Health Monitoring and Prediction System with Machine Learning.

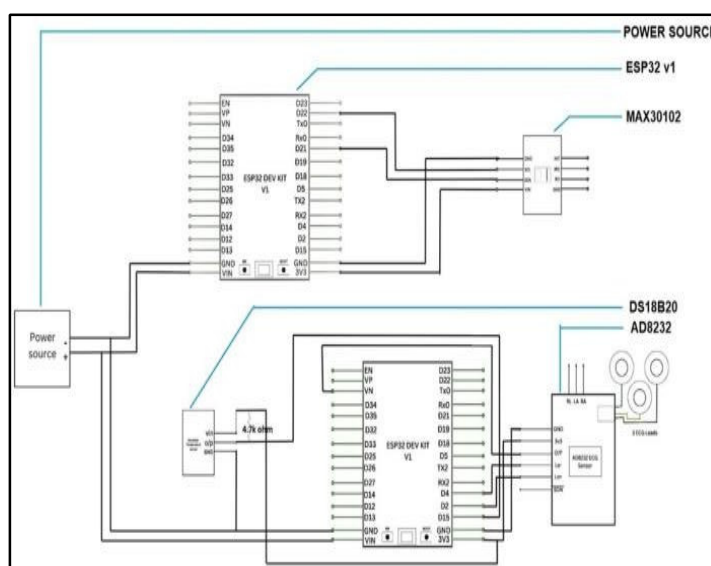


Fig. 8 Circuit diagram of Portable IoT-Based Health Monitoring and Prediction System with Machine Learning.

Experimental Setup

The experimental setup for the IoT-based health monitoring system integrates multiple sensors and a cloud platform for real-time data collection and analysis. The portable health monitoring system developed in these project measures body temperature using a temperature sensor (DS18B20) and blood oxygen levels by a SpO2 sensor (MAX30102). These sensors are interfaced with ESP32 microcontrollers, with one handling the temperature data and the other focusing on SpO2 readings. Data from both ESP32 units is transmitted to the Things Board Cloud, where it is stored and visualized for easy access. Subsequently, a machine learning model processed the data, analyzing the readings and sending the results to a computer screen for real-time monitoring.

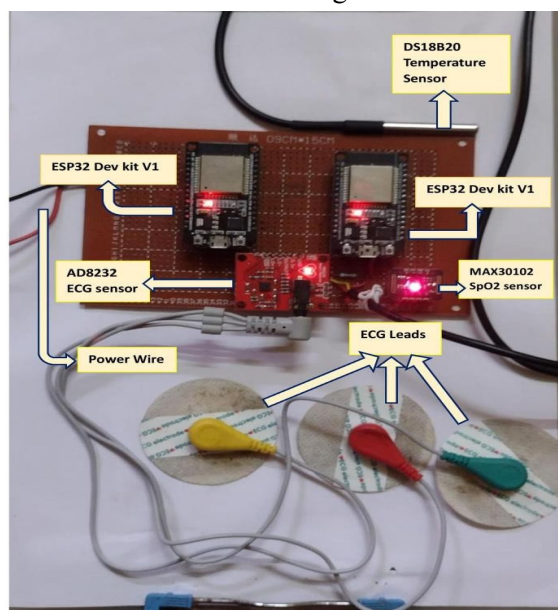


Fig.9 Experimental Setup of Portable IoT-Based Health Monitoring system

Fig. 10 Shows the result of regression analysis graph for calibrating the SpO2 (MAX30102) sensor, result: Slope (m):28.01 and Intercept (c): 64.40; this gives the equation for the relationship between the R-values and the calibrated SpO2 values as: $SpO2 = 28.01 \times R + 64.40$. Fig.11 shows the calibrated SpO2 and Heart-Rate output demonstrated enhanced accuracy, effectively reflecting the user's oxygen saturation levels and Heart-Rate in Arduino serial monitor. Figure 12 presents a comprehensive dashboard from the Things Board Cloud Platform, displayed on a ESP32 Monitor. This dashboard effectively showcased various health metrics in real-time, including SpO2 (Oxygen Saturation) at 93 percentage, Heart Rate at 14bpm (notably influenced by motion artifacts), and Body Temperature measured at 35°C (96°F). These parameters are critical for assessing the user's health status, particularly in settings where rapid changes can occur. The integration of these diverse metrics provides a holistic view of the user's health, enabling more informed decisions regarding care and intervention. Logistic Regression was employed as a key machine learning algorithm, resulting in an accuracy of 93.88 percent.

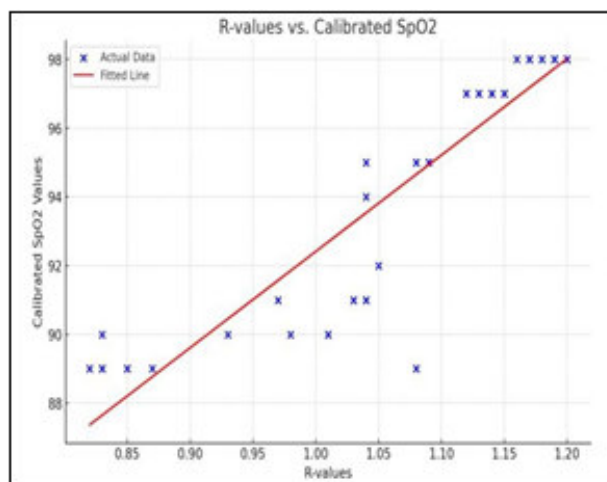


Fig.10 Regression analysis graph.

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Not Connected Select a board and a port to connect automatically.
SpO2 (current, %): 98.29
Time (ms): 171564
Heart Rate (current, bpm): 74
R-Value (current): 1.19
SpO2 (current, %): 97.69
Time (ms): 172363
Heart Rate (current, bpm): 75
R-Value (current): 1.19
SpO2 (current, %): 97.66
Time (ms): 173137
Heart Rate (current, bpm): 77
R-Value (current): 1.20
SpO2 (current, %): 97.98
Time (ms): 173943
Heart Rate (current, bpm): 74
R-Value (current): 1.18
SpO2 (current, %): 97.44
Time (ms): 174742
Heart Rate (current, bpm): 74
R-Value (current): 1.18
SpO2 (current, %): 97.52
Time (ms): 175441
    
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Fig.11 Calibrated SpO2 values.

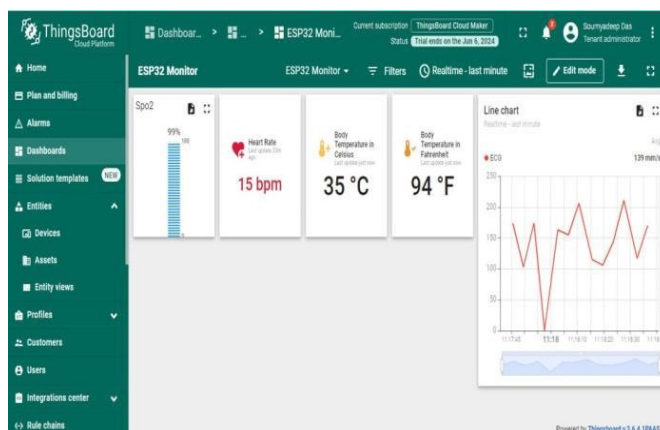


Fig.12 ThingsBoard Cloud Platform

Conclusion

The measurement of two significant health indicators like body temperature and SpO2 using two sensors DS18B20, MAX30102 and machine learning techniques have been observed in this project. Regression analysis was used to effectively calibrate the measurements, improving their accuracy. Machine learning

model exhibits prediction skills; implementation of a real-time dashboard on the Things Board Cloud Platform enables prompt interventions. The possibility of integrating sensor technologies and data analytics to enhance patient outcomes in remote health monitoring is highlighted by this work.

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