An IoT-Based Wireless Wearable Health Monitoring System Using ESP32 with Machine Learning-Driven Cloud Visualization

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How to cite this article: Mahalakshmi A, Shalini S, Vencilaus Licy Booban A, Keerthika V, Saumya Sri R P. An IoT-Based Wireless Wearable Health Monitoring System Using ESP32 with Machine Learning-Driven Cloud Visualization. Int J Drug Deliv Technol. 2026;16(37s): 110-118. DOI: 10.25258/ijddt.16.37s.17

***Abstract*—** In this paper, a compact wearable health monitoring system using an IoT platform is proposed. The proposed system is designed and developed using a 3D-printed smartwatch design. The hardware design is made up of an ESP32 microcontroller, which comes with a MAX30102 photoplethysmography sensor and an LM35 temperature sensor for physiological signal acquisition with real-time processing. Signal processing and feature extraction, which are performed using Pulse Transit Time (PTT) estimation, are carried out to obtain the value parameters for non-invasive blood glucose and blood pressure estimation. A Random Forest regression algorithm is used to model the nonlinear relationship between the extracted features and the reference values. The proposed system is stable and powered by a rechargeable lithium-ion battery with a charging C-type pin, which is used for mobile charging and switching circuitry. The acquired data are transmitted through Wi-Fi to the Blynk IoT platform and a Python-based web interface for remote visualization and monitoring. The proposed system also shows the abnormal range of the measured value with a standard value. Experimental results using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) show that the proposed system has a satisfactory prediction capability, which supports the feasibility of the proposed intelligent wearable healthcare solution.

***Keywords*—** *Internet of Things (IoT), Wearable Health Monitoring System, ESP32 Microcontroller, MAX30102 Sensor, LM35 Temperature Sensor, Photoplethysmography (PPG), Random Forest Regression, Non-invasive Monitoring, Blynk IoT Platform, Remote Patient Monitoring, Machine Learning, Smartwatch-based Healthcare*

I. INRODUCTION

Wearable healthcare devices have received considerable attention because of their capability to offer continuous physiological monitoring and early health risk detection. Currently available commercial devices are mainly focused on the measurement of basic physiological parameters like heart rate and blood oxygen saturation levels, while blood glucose and blood pressure measurements are often done using invasive or cuff-based approaches. Recent studies have investigated the use of photoplethysmography (PPG) techniques for non-invasive cardiovascular monitoring, but many of these studies are not based on machine learning models for enhanced prediction or rely on expensive hardware platforms. There are also some IoT-based monitoring systems that are only focused on data transmission without using intelligent signal processing and predictive analysis. To overcome these challenges, this paper presents a compact IoT-enabled wearable health monitoring smartwatch designed using a 3D-printed case. The proposed system combines an ESP32 microcontroller with MAX30102 and LM35 sensors for real-time processing of physiological signals. Unlike previous works, the proposed framework includes Pulse Transit Time (PTT) feature extraction and a Random Forest regression model for improving the accuracy of non-invasive blood glucose and blood pressure level estimation. The proposed system is designed to be battery-operated using a rechargeable lithium-ion battery with power management and Wi-Fi connectivity for smooth data transfer to the Blynk IoT platform and Python-based web interface. Performance analysis using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) analysis shows improved predictive accuracy over traditional sensor-based systems. The proposed system provides a cost-effective, portable, and intelligent solution for continuous remote health monitoring.

II. LITERATURE SURVEY

1) Mohammed, Mazin Abed, Mohd Khanapi Abd Ghani, Sajida Memon, Abdullah Lakhan, Haydar Abdulameer Marhoon, Ahmed Dheyaa Radhi, Lukas Danys, and Radek Martinek. "Secure IoMT smartwatch-based blood glucose monitoring using multimodal activity and nutrition data with transfer learning." Scientific Reports (2026). The proposed system utilizes an ESP32 microcontroller and biomedical sensors to monitor patients and transmit data to a web-based system through Wi-Fi connectivity.

The system is considered to be more advanced compared to other health monitoring systems because it incorporates machine learning to predict heart diseases based on collected health parameters.

Another major aspect of the proposed system is that it emphasizes the use of real-time monitoring and prediction for better diagnosis and treatment of health conditions. The use of web-based systems is considered to be effective for better management and reporting of health parameters. However, the proposed system is considered to be less effective because it utilizes fewer sensors and is not integrated with mobile-based IoT systems.

In addition, the system shows how predictive models can help in the identification of health risks that might occur in the future, which can improve the decision-making process in healthcare services by predicting the risks based on the results of the data analysis. The accuracy of the predictive model relies on the dataset used, which implies the need to update the data for better results.

2) Farouk, Mariam, Anwer S. Abd El-Hameed, Angie R. Eldamak, and Dalia N. Elsheakh. "Noninvasive blood glucose monitoring using a dual band microwave sensor with machine learning." Scientific Reports 15, no. 1 (2025): 16271. In the proposed system, the vital parameters are monitored using multiple sensors. The sensors used in the system are a pulse sensor to monitor heart rates, an LM35 temperature sensor to measure body temperature, and an SpO_2 sensor to measure oxygen saturation levels. These sensors are connected to the microcontroller and send the parameters to the cloud platform using Wi-Fi connectivity.

The system uses the Blynk IoT platform to display real-time parameters using a mobile. This helps patients and medical professionals understand the health conditions and monitor the parameters continuously. The importance of IoT in continuously monitoring vital parameters and avoiding hospital visits is also discussed in the paper. This helps patients and medical professionals understand the health conditions using the user-friendly interface of the Blynk application.

Furthermore, there is an alert system that is incorporated to ensure that patients are alerted in case of any abnormalities. The research highlights the efficiency of integrating an embedded system with an IoT platform for developing cost-effective and portable solutions for healthcare applications. ESP32 is used to ensure that the system can operate efficiently because of its Wi-Fi capability and its ability to consume less power.

3) Refaie, Amr Khaled, and Mostafa Abdelaziz. "Non-Invasive Glucose Monitoring Using PPG, AI, and IoT-Driven Mobile Integration for Real-Time Diabetes Management." The paper was presented at the 2024 International Conference on Computer and Applications (ICCA), pages 1-5. IEEE, 2024. Traditional invasive methods for glucose measurement cause discomfort and limitations. so, in this paper they gave full attention on non-invasive glucose monitoring. Photoplethysmography (PPG), an optical technique, is being experimented to estimate glucose levels based on blood volume changes. Applied machine learning to PPG data, using models like SVM, decision trees, and regression techniques etc. but polynomial regression is used due to its less MSE. However, accuracy is not assured due to motion, skin variability, and ambient light. Integrating IoT enables real-time data transmission and remote vital health monitoring. The current study uses the MAX30102 PPG sensor and ESP32 microcontroller for a wearable glucose monitoring setup. Various ML models were tested, with polynomial regression showing the best performance. A mobile app developed in Flutter displays real-time glucose trends. This system supports continuous, painless, and remote diabetes management. Future work aims to develop a smartwatch-based solution for improved usability and adoption.

4) Okubanjo, Ayodeji Akinsoji, Okandeji Alexander, Odeyinka Olumide, Akinloye Benjamin, and Oluyemi Oluwatoyin. "Development of a low-cost IoT-based e-health monitoring system for diabetic patients." Journal of Electrical Systems and Information Technology 11, no. 1 (2024): 54. This paper describes an working of IoT-based e-health system for continual monitoring of diabetic patients who are suffering. The e-health system includes glucose sensors (Dexcom G6), heart rate and SpO_2 (MAX30100) sensors, and temperature (LM35) sensors connected with an Arduino Nano and NodeMCU for processing data and transmission. Real-time displayed on LCD and supplied, cloud hosted in Blynk and cloud served is the access to downloaded data in smartphone connection to the user. Alerts via SMS or email are sent out when critical values are encountered. The costing of the e-health system is about ~$16 which is continued to have less than 2% error as compared to clinical devices. The e-health system will work in rural and underprivileged areas.

5) Yadav, Balkrishna Rasiklal. "Smart RFID and IoT-Based Patient Monitoring Systems in Modern Healthcare." International Journal of Engineering and Management Research 14, no. 5 (2024): 89-93. In recent years, the combination of RFID and IoT technologies for the use of improving operational efficiencies and patient outcomes in healthcare settings has been mentioned by numerous studies. RFID technology provides reliable, accurate, and timely wirelessly identified tracking of patients and medical devices to enrich workflows and enhance asset management. IoT technology provides continuous monitoring via transmitting all vital signs, such as temperature, blood pressure, and oxygen saturation, to cloud platforms for review and assessment. The system design often includes sensor modules, microcontrollers (for example, popular designs include Arduino and NodeMCU), cloud storage, and access to control units in real time. All of these technologies facilitate remote care, which reduces human error relating to patient identification and enables timely medical intervention. RFID-based asset tracking also improves avoidance of lost equipment and effective use of resources. Many issues must still be resolved before these technologies can be reliably implemented, including privacy of data, interconnectivity of devices, and staff training for DI and IoT systems.

However, RFID-IoT technologies have great potential to radically transform health care delivery.

III. MATERIALS AND METHODS

A. Microcontroller Unit (ESP32)

The ESP32 microcontroller is the computational core of the proposed biomedical monitoring system and is tasked with controlling all the sensing, processing, and output functions. The microcontroller is a 32-bit dual-core processor that is capable of running at high clock speeds with optimized power consumption, making it ideal for real-time biomedical health monitoring. The microcontroller has a variety of integrated peripheral interfaces such as analog-to-digital converters (ADC), digital communication interfaces such as I^2C and SPI, general-purpose input/output (GPIO) interfaces, and wireless communication modules.

In the designed system, the ESP32 initializes all the connected peripherals during system startup, sets the sampling rates for optical sensing, and sets up I^2C communication with the heart rate/SpO_2 sensor and the OLED display. The analog output of the temperature sensor is continuously sampled using the internal ADC with the necessary resolution to ensure accurate digitization of the signal. After acquiring the physiological signals, the microcontroller performs signal preprocessing operations such as smoothing, noise reduction, and baseline removal. The microcontroller also performs computational operations such as peak detection for pulse measurement and ratio processing for oxygen saturation computation.

B. Heart Rate Sensor

The heart rate sensing module works on the principle of an optical sensing technique that senses the dynamic changes in the blood volume in the peripheral tissues. When a finger is placed on the sensing area, an LED light embedded in the sensor emits light into the skin. As the blood flows through the arteries with each heartbeat, the amount of blood in the tissue changes. This causes the intensity of the reflected light to change, which is then detected by a photodiode. This electrical signal takes the form of a pulsatile waveform, which is called a photoplethysmographic (PPG) waveform, indicating cardiac activity.

In the system, this analog signal is processed to convert it into a digital signal, which is then sent to the microcontroller. The signal has both a pulsatile part that corresponds to the arterial blood flow and a baseline part that is affected by the surrounding tissues and environmental factors. The ESP32 microcontroller then processes this signal to pick out the pulsatile peaks that correspond to each heartbeat. Based on the time difference between the peaks and the pulses per minute, the heart rate is calculated in beats per minute (BPM). For improving the accuracy of measurement, digital filtering processes like moving average filtering or low-pass filtering are employed. Continuous monitoring enables the system to recognize irregularities in heartbeats, such as tachycardia or bradycardia. If the calculated heart rate goes beyond the predefined limits of physiological values, the alert system is triggered to notify the user immediately.

C. SpO_2 Sensor

The SpO_2 sensing function is incorporated into the optical sensing module, which uses the principle of dual-wavelength light absorption analysis. The sensor uses the emission of two different wavelengths of light, usually in the red and infrared parts of the spectrum, which then travel through or are reflected from the fingertip. Oxygenated hemoglobin and deoxygenated hemoglobin have different absorption properties for these wavelengths. As the arterial blood pulses through the tissue, the changes in oxygen content cause a detectable change in the intensity of the reflected light.

The signal from the sensor is made up of alternating current (AC) signals that are pulsatile and associated with arterial blood and direct current (DC) signals that are associated with non-pulsatile tissues and venous blood. The microcontroller picks these signals and calculates a ratio of the normalized red and infrared signals. This ratio is then mathematically linked to the arterial oxygen saturation percentage. The calculated SpO_2 is then displayed on the OLED module and continuously monitored against safety limits. When the oxygen saturation levels drop below normal physiological levels, the system produces an auditory signal through the buzzer.

D. Temperature Sensor

The measurement of body temperature is done through the use of a semiconductor-based analog temperature sensor. The sensor gives a voltage output that is proportional to the temperature. The sensor works on the principle of giving a voltage output that varies linearly with changes in temperature. This makes it easy to convert the output to physical units. The sensor is capable of detecting thermal changes that are associated with body heat when it is in direct contact with the skin. The voltage output is then sent to the analog input channel of the ESP32, which is then converted to a digital output.

The digital output is then calibrated using the calibration factor of the sensor to determine the temperature in degrees Celsius. The output is linear, which makes it easy to calibrate without using complex calibration circuits. The continuous measurement of temperature ensures that the body temperature increase is accurately measured. The microcontroller then compares the temperature with threshold values that define normal and fever temperatures.

E. OLED Display Module

The OLED display module is added to enable immediate and clear visualization of the measured physiological parameters. The OLED display technology uses organic electroluminescent layers that emit light when electrically stimulated, without the need for a separate backlight source. This feature leads to lower power consumption, a higher contrast ratio, and improved readability in ambient light. The display is connected to the ESP32 microcontroller using the I²C communication interface, which allows efficient data transfer with only a few microcontroller pins.

In the system, the microcontroller processes the physiological data into readable text and graphic form before sending it to the display module. The display continuously updates the values of heart rate, oxygen saturation, and body temperature in real time. Apart from displaying numerical values, the system can also indicate abnormal values using blinking indicators or warning messages. The OLED display module improves the usability of the system by providing immediate feedback without the need for external monitoring devices.

F. Lithium-Ion Battery

A Lithium-Ion Battery will be employed as a power source in the wearable health monitoring system. This is because a Lithium-Ion Battery is efficient, compact, and rechargeable. This property makes a Lithium-Ion Battery suitable for use in a smartwatch-based health monitoring system, which is a wearable technology. A Lithium-Ion Battery has a nominal voltage of 3.7V. This voltage is enough to power a low-voltage system. A Lithium-Ion Battery will power all major components in the smartwatch-based health monitoring system. This includes an ESP32 Microcontroller, a MAX30102 Sensor, an LM35 Sensor, an OLED Display, etc. A Lithium-Ion Battery will ensure uninterrupted power supply to all components. This will ensure uninterrupted monitoring of all vital health parameters such as heart rate, oxygen saturation, etc.

Another significant advantage of using a lithium-ion battery is that it has a low self-discharge rate and a long cycle life, i.e., it can be recharged many times without compromising its performance. This is advantageous for the healthcare monitoring system, as it is expected to operate every day. Furthermore, the battery is connected to a charging module, i.e., TP4056, to ensure that it is safely charged and protected from overcharging, over-discharging, and short circuits. Therefore, the use of a lithium-ion battery makes the wearable health monitoring system more portable, efficient, and convenient to use.

G. TP4056 Charging Module

This charging module utilizes a constant current and constant voltage (CC/CV) charging technique to charge the lithium-ion battery efficiently and safely, without any potential damage to the battery.

In this proposed system, a TP4056 charging module is utilized to connect between the USB Type-C connector and the lithium-ion battery. When a voltage supply is provided to the system via the USB Type-C connector, this charging module regulates the charging current and gradually starts charging the lithium-ion battery until it is fully charged to a voltage of 4.2 volts, which is the maximum voltage of a lithium-ion battery.

In addition, this TP4056 charging module utilized in this project is integrated with an inbuilt protection circuit, which is usually integrated with a protection IC known as a DW01, to avoid overcharge, overdischarge, and short-circuit conditions in the lithium-ion battery. The compact design and low price of the TP4056 module make it very suitable for incorporation in a small-scale embedded system, such as the proposed smartwatch design. As such, it is very crucial in ensuring efficient power management and durability of the system.

H. USB Type-C Port

The Type-C connector is capable of providing higher current, unlike the micro-USB connector, allowing faster charging. The implementation of the Type-C connector provides ease of use and makes the project more convenient to use. Additionally, the connector is robust and can withstand more wear and tear, allowing it to be employed for frequent usage in wearable devices. In general, the USB Type-C port plays a significant role in enhancing the convenience, efficiency, and user-friendliness of the proposed health monitoring system.

I. Power Switch

It provides control to the user to turn the system ON/OFF as per requirement. It has been connected between the battery output and the input of the circuit. When the power switch is turned ON, the circuit gets completed, and the current flows to the ESP32 microcontroller and other connected devices in the system. When the power switch is turned OFF, the circuit gets disconnected, and the power supply to the system gets cut off.

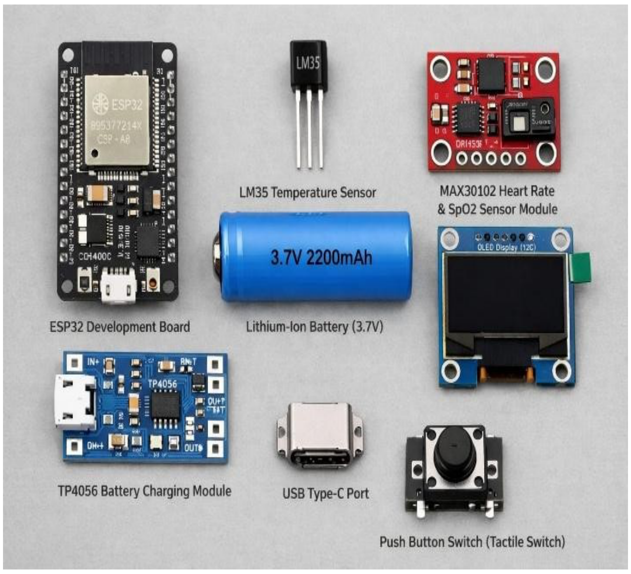


Image 1: Components

J. Blynk IoT Application and Working Procedure

The Blynk IoT application has been employed in the project to provide a cloud-based solution for real-time monitoring, visualization, and access of health parameters measured by the wearable device. Communication between the ESP32 board and the Blynk IoT server takes place through internet protocol like HTTP or MQTT.

IV. PROPOSED SYSTEM

The proposed wearable health monitoring system is a low-cost, IoT-enabled model designed to monitor vital physiological parameters such as heart rate, oxygen saturation (SpO_2), and body temperature in real time. The system integrates biomedical sensors with an ESP32 microcontroller and uses Wi-Fi connectivity to transmit the collected data to the Blynk IoT cloud platform for remote monitoring through a mobile application.

The system consists of input sensors, a processing unit (ESP32), power management components, and a user interface for data visualization. It enables continuous health tracking and provides alerts for abnormal readings, thereby supporting early detection and timely intervention. The compact and wearable design makes it suitable for both home-based and clinical monitoring applications.

A. 3D Printing

The design for the smartwatch casing was created by using computer-aided design (CAD) software to develop a compact and ergonomic smartwatch to facilitate continuous health monitoring. The design for the smartwatch casing was created to include the microcontroller, sensors, battery, and display within a single casing. Spaces for the temperature sensor and optical sensor were included to efficiently monitor physiological parameters. The smartwatch casing design was created by using polylactic acid (PLA), which is a lightweight yet strong material for prototyping. The process for creating the smartwatch involved fused deposition modeling (FDM) 3D printing technology to develop a 3D model from a computer-aided design. This technology helped to efficiently develop and modify the design for the smartwatch. A Velcro strap was included with the smartwatch to ensure a snug fit on the wrist. The entire process took a few hours to develop a lightweight yet efficient smartwatch. The final prototype provides a robust and light wearable device that will accommodate the wearable health monitoring system. The printing and assembly process of the final prototype took approximately 4-6 hours to produce a wearable device.

Features	**Dimensions(cm)**
Housing	L=6, B=4, H= 4.5
Strap	L=13, B= 3
Display window	L=2.5, B=1.5
Temperature sensor recess	L=0.6, B=0.6
MAX30102 sensor recess	L=1, B= 0.5
Charging port	L=1, B = 0.5
Switch port	D=1

Table 1: Measurements of 3D Model Watch

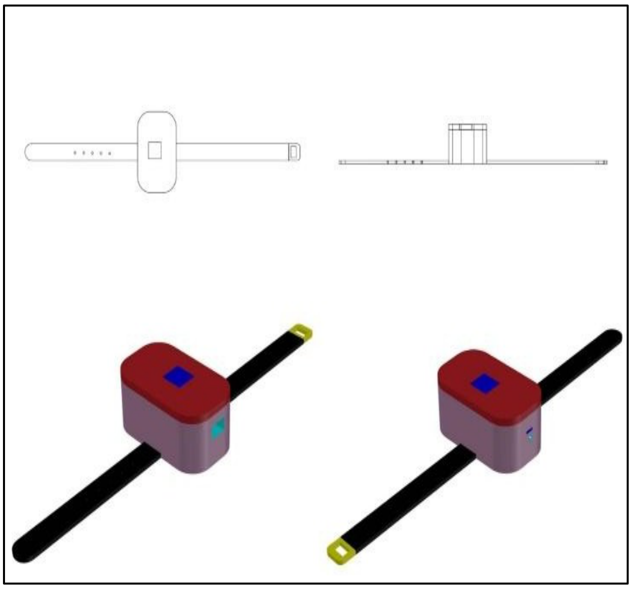


Image 2: Layout of 3D Model Watch

B. Datasets

The dataset used in this project was collected from the publicly available platform Kaggle, which provides a wide range of real-world data for research and development. A total of "729 data records" were taken for analysis. The dataset includes important physiological parameters such as heart rate, oxygen saturation (SpO_2), and body temperature, along with additional details like age and gender to improve the quality of prediction. It also contains corresponding values of systolic and diastolic blood pressure and blood glucose levels, which are considered as target outputs.

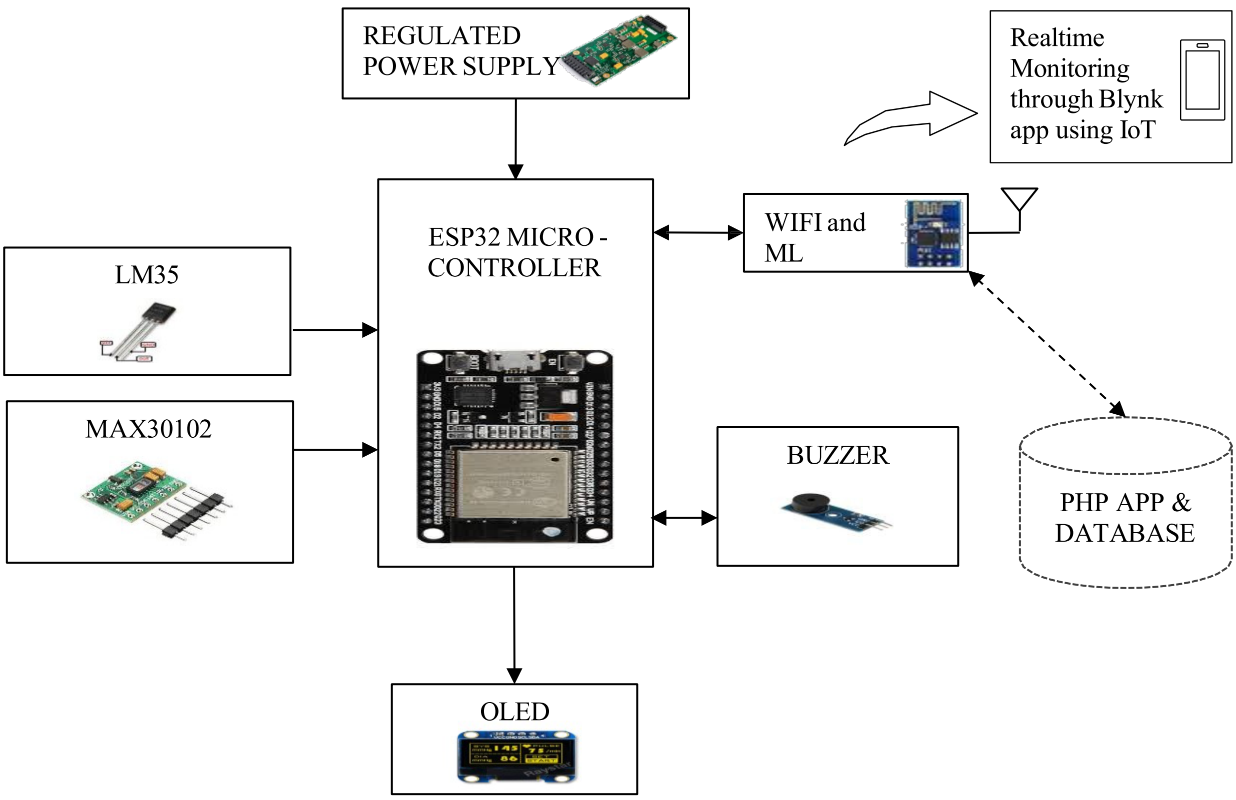
S. N	**G**	**Age**	**GLU**	**BP**	**HR**	**SpO2**	**Temp**
1	M	25	95	72	72	98	36.5
2	F	45	140	66	85	96	37.0
3	M	60	180	64	90	95	37.2
4	F	35	110	40	78	97	36.8

5	M	50	200	74	88	94	37.5
6	F	28	90	50	70	99	36.4

Table 2: Dataset values From Clinical Web

After downloading the dataset in CSV format, it was processed using Python to remove inconsistencies and handle missing values. The cleaned dataset was then divided into training and testing sets for model development and evaluation. A supervised machine learning approach was applied to analyze the relationship between the input parameters and the predicted health values. This dataset plays a key role in enabling the system to estimate blood pressure and glucose levels, thereby supporting continuous health monitoring and early detection of possible health risks.

C. Block Diagram



D. Analysis of Blood Glucose and Blood Pressure

A dataset containing physiological parameters was utilized for the purpose of understanding the relationship between vital health indicators and for training the machine learning model. The dataset includes parameters such as heart rates, oxygen saturation (SpO2), body temperature, blood glucose level, and blood pressure. Multiple health observations were recorded, where each observation represents a collection of parameters measured from people with varying health conditions.

Initially, statistical analysis was conducted for understanding the correlation between the parameters. Correlation analysis was carried out for understanding the level of influence of parameters such as heart rates, oxygen level, and temperature on blood glucose and blood pressure. Parameters that show a level of correlation were selected as the input parameters for the prediction model.

A regression-based machine learning model was trained for learning the correlation between the input physiological parameters and the health parameters. During the training phase, the model learned the level of influence of parameters such as heart rates, oxygen level, and temperature on blood glucose and blood pressure. The model learned the coefficients that describe the influence of heart rates, oxygen level, and temperature on blood glucose and blood pressure. Data pre-processing techniques like normalization were also used to improve the performance of the model and achieve the same prediction accuracy.

Once the training process is completed, the model is saved and integrated into the health monitoring system. When real-time data is sent from the sensors through the ESP32 and the IoT platform, the model uses the learned relationships from the data to estimate the glucose and blood pressure levels. This is how the prediction of health parameters is done automatically through the machine learning algorithm without the need for any extra sensors.

Image 3: Analysis of Health Observation

E. Machine Learning Based Health Monitoring System

The proposed health monitoring system uses the Internet of Things and machine learning for the analysis of vital health parameters. Physiological health parameters such as heart rate, oxygen saturation, blood glucose level, blood pressure, and body temperature are monitored using sensors connected with the ESP32 microcontroller. The data obtained by the sensors is sent to the application using the Blynk IoT platform. The system uses a pre-trained supervised machine learning classification model for the prediction of the health condition of the user as normal or abnormal.

Before passing the input parameters to the machine learning model for prediction, the feature scaling technique is applied for the normalization of the input parameters. Then the input parameters are passed to the machine learning model stored in the file “health_model.pkl” for prediction.

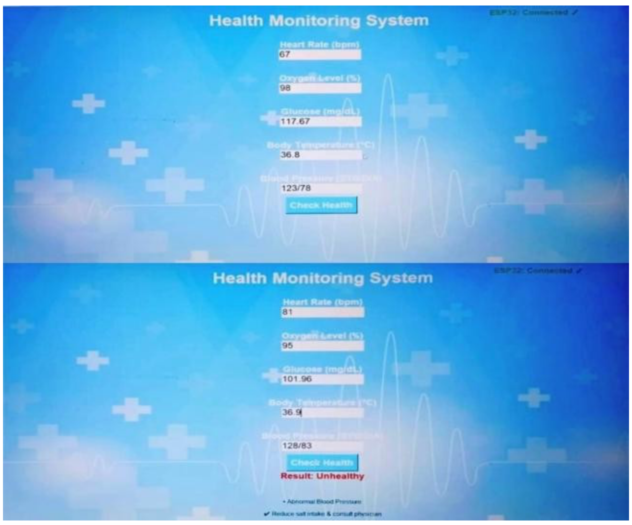


Image 3: Health Monitoring System

Machine learning assists in recognizing abnormal patterns in various vital parameters such as high glucose levels, abnormal blood pressure, abnormal heart rate, and abnormal body temperature. According to these machine learning predictions, the system displays the status and suggests simple medical advice using a graphical user interface. This allows automated health assessment and detection of potential health issues in a remote monitoring system.

F. Blynk App

The health monitoring system proposed in this paper uses a Blynk app as a tool to transmit health parameters in real time. The system uses an ESP32 microcontroller to collect data from sensors such as heart rate, SpO2, and body temperature. This data is then sent to a cloud server through an internet connection. In Blynk, a microcontroller communicates with a mobile application through a “Virtual Pin” concept, which acts as a bridge between hardware and a mobile application to communicate data.

In this system, “V0 represents heart rate, V1 represents SpO2, V2 represents glucose levels, V3 represents body temperature, V4 represents systolic blood pressure, and V5 represents diastolic blood pressure”. The microcontroller updates this data to a cloud server through an internet connection, which can be accessed remotely through a Blynk application installed on a mobile device. This application uses widgets to display health parameters to a patient in real time.

The user has to log in to the Blynk mobile application with the “administrator username and password” in order to access the monitoring dashboard. After the login process is completed, the user interface displays the updated health parameters sent by the cloud server. The Python application for the monitoring system receives the same health parameters and processes the data with the help of the machine learning model.

The machine learning model processes the physiological parameters and predicts the health condition of the user. The output of the health condition is displayed on the user interface and the Blynk mobile application. If all the health parameters are within the normal limits, the system displays the health condition as “Healthy”. If the health parameters are not within the normal limits, the system displays the health condition as “Unhealthy” along with health suggestions.

V. RESULT AND DISCUSSION

The IoT-based wearable health monitoring system designed and developed in this project can measure and display various health parameters in real time. The system can integrate various sensors with the ESP32 microcontroller to continuously monitor and track heart rate, SpO_2 levels, blood glucose levels, blood pressure, and body temperature. The data can be processed and displayed on the OLED screen.

The system can run continuously with proper wireless connectivity and communicate health data to a mobile app via Wi-Fi connectivity. This indicates proper functionality and stability of the system. This feature will be helpful for remote health monitoring and can be used for both personal and professional purposes.

The power management module also indicates proper functionality and stability of the system. This indicates that the system can be used for health monitoring and tracking purposes. The system can be said to be a success in achieving its objectives and can be used to track health conditions and detect abnormal conditions in real time.

Image 4: Final Result Outputs

VI. FUTURE WORK

Future work of this project focuses on improving both hardware design and data accuracy. A double-layer PCB can be implemented to reduce circuit size and enhance system reliability. This will also help in better component arrangement and reduced noise in signal transmission. Further improvements can be made by integrating onboard data storage for continuous monitoring. The system can be enhanced to collect and store patient data over a period of one week. By calculating the average values of physiological parameters, more stable and reliable predictions can be obtained. This approach helps to reduce sudden fluctuations in readings and improves overall accuracy. In addition, long-term data analysis can support better understanding of patient health trends. The device can also be upgraded with improved sensors for higher precision. These enhancements will make the system more suitable for real-time and long-term health monitoring applications.

VII. CONCLUSION

The current project deals with an IoT-based health monitoring system using a machine learning approach for the constant observation of vital health parameters. The system is able to sense physiological parameters such as heart rate, oxygen level, and body temperature using sensors connected to the ESP32 module, as well as blood glucose and blood pressure using a machine learning approach. These parameters are sent to the cloud using the Blynk IoT platform with the help of virtual pins. A machine learning approach is used to predict the health of the user based on the parameters sensed by the system. The results are displayed on the desktop as well as the mobile application, allowing for the supervision of health from a distant location. This approach can be useful for the observation of health and can also provide suggestions for health when abnormalities are sensed. This is an effective use of IoT and machine learning for an intelligent health system.

VIII. REFERENCE

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