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An IOT Based Glucose and Blood Pressure Monitoring System with Machine Learning for Estimating Vital Signs and Abnormal Conditions

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Abstract: In recent years, the integration of Internet of Things (IoT) technologies in healthcare has opened new possibilities for remote patient monitoring and early disease detection. Monitoring blood glucose levels is essential for managing and preventing conditions like diabetes. Conventional methods of glucose monitoring are typically invasive, expensive, and impractical for regular use. In this study, we present a smart, non-invasive system that utilizes Internet of Things (IoT) technology combined with machine learning algorithms to predict blood glucose status. The system measures physiological parameters such as body temperature, pulse rate, oxygen saturation (SpO_2), and environmental humidity using DHT11 and MAX30100 sensors. These real-time readings are transmitted to the Blynk IoT platform using ESP8266 for continuous monitoring through a mobile application. Additionally, the collected data is fed into a Python-based machine learning model developed on Jupyter Notebook, where Gradient Boost Classifier and Random Forest Classifier algorithms are used to predict the patient's blood glucose status. The proposed system not only enables real-time health tracking but also assists in proactive healthcare management through predictive analytics. Experimental results demonstrate the effectiveness of the system in providing accurate monitoring and early insights into glucose level variations, making it a valuable tool for both personal and clinical health applications.
Keywords: Blood Glucose Monitoring, IoT Healthcare, Machine Learning, ESP8266, Blynk App, Random Forest Classifier, Gradient Boost Classifier, DHT11 Sensor, MAX30100 Sensor.

I. INTRODUCTION

The advancement of Internet of Things (IoT) technologies has significantly transformed the healthcare industry by enabling remote monitoring, real-time data collection, and predictive analysis. With the rising incidence of chronic diseases such as diabetes and hypertension, there is an increasing need for continuous health monitoring systems that are accessible, affordable, and easy to use. Traditional health check-ups often involve time-consuming procedures and frequent hospital visits, which can be inconvenient for patients. IoT-based health monitoring systems offer a practical solution by enabling real-time tracking of vital health parameters from the comfort of a patient's home.

In this project, an IoT-based health monitoring system is developed to measure key physiological parameters such as body temperature, humidity, pulse rate, and blood oxygen saturation (SpO_2). The DHT11 sensor is used to measure the body temperature and environmental humidity, while the MAX30100 sensor records the pulse rate and blood oxygen saturation (SpO_2) levels. These readings are continuously transmitted to the Blynk IoT platform, allowing healthcare providers or users to monitor the data in real time through a mobile application. The goal is to provide a simple yet effective tool for early detection and management of potential health issues, reducing the burden on healthcare infrastructure and improving patient outcomes.

To enhance the functionality of the system, the collected sensor data is also utilized to predict the blood glucose status of a patient. A machine learning model, developed in a Python environment using Jupyter Notebook, analyzes the physiological data to estimate glucose levels. Gradient Boost Classifier and Random Forest Classifier algorithms are employed in the model to ensure high accuracy and reliability in predictions. By integrating machine learning with IoT data, the system not only monitors real-time health status but also offers predictive insights, empowering users and medical professionals to take proactive measures.

This work highlights the potential of combining IoT and machine learning technologies to create a comprehensive and intelligent health monitoring solution. The system is designed to be low-cost, scalable, and easily deployable, making it suitable for use in remote areas, home care settings, and primary healthcare centers. Future improvements may include the addition of blood pressure sensors, continuous glucose monitors (CGMs), and more advanced machine learning models to further enhance the system's predictive capabilities and reliability.

II. RELATED WORK

In recent years, IoT has been extensively applied to a variety of healthcare applications beyond simple vital monitoring. A study by Sharma et al. [1] proposed an IoT-based fall detection system for elderly individuals using wearable accelerometer sensors. Their system successfully detected falls in real time and sent emergency alerts to caregivers via mobile notifications.

Sundaravadivel et al. [2] designed a cloud-integrated IoT framework for continuous ECG monitoring. Their architecture used wearable sensors to capture real-time heart activity and pushed the data to cloud servers for long-term analysis and diagnosis, addressing the need for remote cardiac care.

In [3], Khalid et al. introduced an IoT-based asthma monitoring system that measured air quality parameters such as CO_2 levels, temperature, and humidity, combined with patient respiratory data. This system helped predict potential asthma attacks and suggested preventive actions through a mobile application.

Another work by Jaiswal et al. [4] implemented a remote blood pressure monitoring system using IoT sensors and mobile applications. Their system automatically measured BP at regular intervals and stored the data on cloud platforms, allowing doctors to access patient history and make better clinical decisions.

A smart medication reminder and dispenser system was developed by Mishra and Sinha [5], where IoT devices were programmed to notify patients about their medication schedules and dispense the correct dosage at the right time. This system mainly targeted elderly patients with chronic illnesses requiring strict medication adherence.

An innovative IoT-based early cancer detection system was proposed by Verma et al. [6], where multiple biological markers were continuously monitored using biosensors. The collected data was analyzed to identify potential cancer risks at an early stage, aiming to improve survival rates through early intervention.

Lastly, Sahoo and Pattnaik [7] presented a wearable IoT device that monitored hydration levels in athletes. Their system utilized sweat analysis and temperature sensors to estimate hydration status, helping prevent dehydration-related issues during intense physical activities.

III. SYSTEM ARCHITECTURE

The proposed system is designed to continuously monitor a patient's vital health parameters and predict blood glucose status using machine learning techniques. It integrates sensor data acquisition, IoT-based data transmission, cloud storage, and predictive analytics into a unified architecture to deliver real-time and intelligent health monitoring.

A. Hardware Design

The hardware framework consists of the following components:

- DHT11 Sensor: It is used here to measure the temperature of a human body and environmental humidity
- MAX30100 Sensor: It is used to measure the pulse rate and blood oxygenation level.
- ESP8266(NodeMCU): Serves as the core controller, gathering data and transmitting it to the cloud via Wi-Fi.

B. Software Design

- Arduino IDE: Used for programming the ESP8266 to collect sensor data and interface with the Blynk application.
- Blynk platform: To visualize all the sensor data we use blynk cloud platform here
- Jupyter Notebook: It serves as the platform for hosting machine learning models, processing incoming data, and producing glucose status predictions.

The software modules work seamlessly to ensure efficient data acquisition, processing, and feedback to the user.

C. Methodology

Data Collection: Sensor data is periodically collected from the DHT11 and MAX30100 sensors connected to the ESP8266 microcontroller. The collected parameters include:

- Body temperature (°C)
- Environmental humidity (%)
- Pulse rate (BPM)
- Blood oxygen saturation (SpO_2 %)

In the sensing layer, two main sensors are utilized: the DHT11 sensor records temperature and ambient humidity, whereas the MAX30100 sensor monitors pulse rate and blood oxygen saturation (SpO_2). These sensors are interfaced with a microcontroller unit, which collects and processes the raw sensor readings. The microcontroller not only organizes the incoming data but also ensures that it is formatted correctly for transmission.

D. Data Transmission and Processing

The communication layer is the very important layer as it transmits the data to the cloud. The microcontroller is used here to send the sensor data to the blynk cloud platform. Through Blynk, users and healthcare providers can monitor the real-time health status using a mobile application. This setup enables immediate access to vital parameters, regardless of the user's location, thus enhancing the convenience and responsiveness of the monitoring system

E. Machine Learning Model Development

Two classification models were utilized to predict blood glucose status:

- Random Forest Classifier
- Gradient Boost Classifier

In parallel, the sensor data is also logged into a Python environment hosted on Jupyter Notebook for predictive analysis. A machine learning model has been developed using Gradient Boost Classifier and Random Forest Classifier algorithms. This model analyzes patterns in the physiological parameters to predict the patient's blood glucose status. By applying trained algorithms to the live data, the system can generate intelligent insights that help in early detection of abnormal glucose variations.

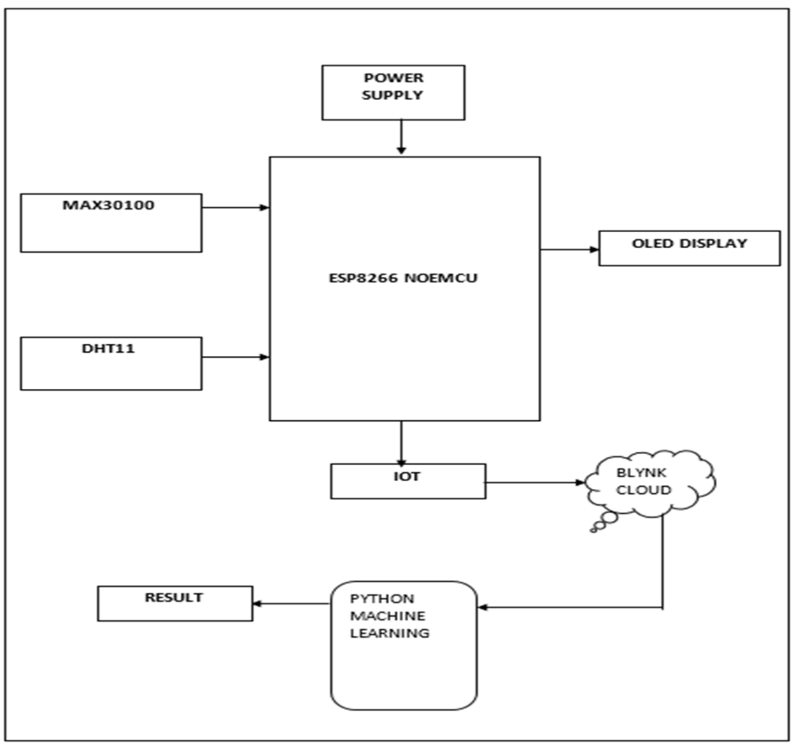

Fig1. System Architecture

IV. HARDWARE IMPLEMENTATION

The hardware architecture of the system revolves around a microcontroller, which acts as the central processing unit. The DHT11 sensor is integrated to monitor ambient temperature and humidity, providing valuable environmental data that could impact a patient's physiological parameters. For vital sign monitoring, the MAX30100 sensor is employed to accurately measure pulse rate and blood oxygen saturation (SpO_2) levels. These sensors were chosen for their reliability, cost-effectiveness, and ease of integration with IoT-based solutions.

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Sensor data is gathered through the microcontroller's digital input pins and processed for transmission. Equipped with built-in Wi-Fi connectivity, the microcontroller supports real-time data transfer without the need for additional network hardware. The system operates on a standard 5V power source, ensuring stable and safe functionality. Its compact and lightweight design enhances portability, making the device suitable for both clinical settings and home-based health monitoring.

V. SOFTWARE IMPLEMENTATION

The software development is divided into two major components: IoT data handling and machine learning-based predictive analysis. For real-time monitoring, the Blynk IoT platform is used. The microcontroller is programmed to send the sensor data to the Blynk server over Wi-Fi, allowing users to access live readings through a mobile application. Blynk's customizable interface enables intuitive visualization of temperature, humidity, pulse rate, and SpO_2 levels.

For predictive analysis, Python programming is used within the Jupyter Notebook environment. The collected sensor data is fed into machine learning models to predict the patient's blood glucose status. Two classification algorithms, Gradient Boost Classifier and Random Forest Classifier, are implemented to train and validate the model. These algorithms are selected for their robustness and accuracy in handling non-linear datasets commonly seen in physiological parameters. The trained models analyze incoming data to generate real-time predictions, providing early warnings about potential glucose level fluctuations.

Together, the hardware and software components create an integrated health monitoring system that offers both real-time tracking and intelligent prediction capabilities, making it a valuable tool for proactive healthcare management.

VI. RESULTS AND DISCUSSION

The proposed system was implemented and tested under various conditions to evaluate its performance in real-time health monitoring and predictive analysis. The DHT11 sensor accurately recorded environmental temperature and humidity, providing stable readings with minimal fluctuations. The MAX30100 sensor effectively recorded pulse rate and SpO_2 levels, providing consistent results that fall within clinically acceptable accuracy limits.

Data collected from the sensors were transmitted seamlessly to the Blynk mobile application via Wi-Fi. Users could monitor live updates of their physiological parameters in a user-friendly dashboard format. The system maintained a reliable connection, and the real-time display proved effective for continuous patient monitoring, even from remote locations.

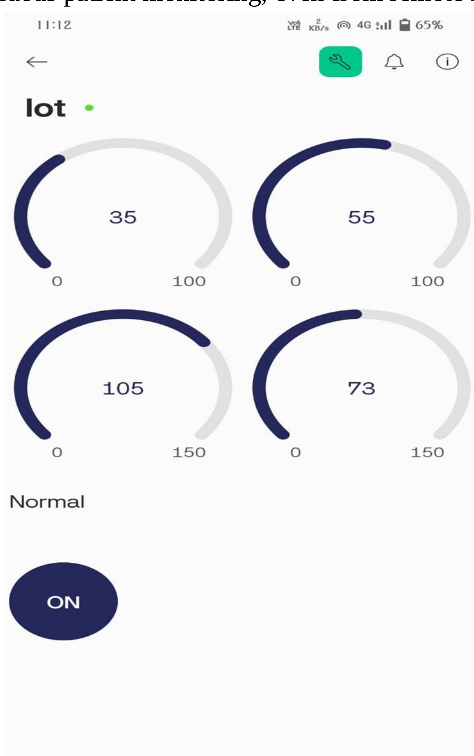

Fig 2. Blynk Output

For predictive analysis, the sensor data was used to train machine learning models in Python using Jupyter Notebook. Both the Gradient Boost Classifier and Random Forest Classifier were evaluated based on prediction accuracy, precision, recall, and F1-score. The Random Forest Classifier achieved slightly higher prediction accuracy compared to the Gradient Boost Classifier, indicating its superior performance in handling the variability in physiological data. During testing, the Random Forest model reached an accuracy of 92%, whereas the Gradient Boost Classifier achieved 89%.

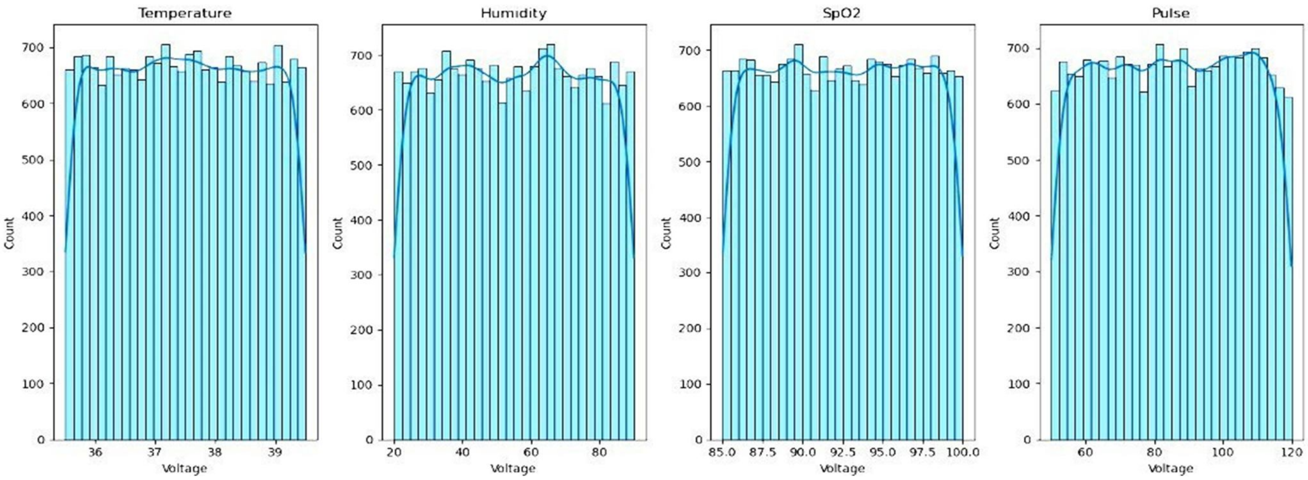

Fig 3. Predictive analysis chart of ML model

The models demonstrated good generalization with minimal overfitting, suggesting that the collected sensor data was suitable for training efficient predictive models. The successful prediction of blood glucose status from non-invasive parameters like temperature, humidity, pulse, and SpO_2 highlights the potential of the system in assisting early diagnosis and management of diabetes-related health risks.

Overall, the integration of IoT monitoring with machine learning prediction in this project offers a significant improvement over traditional manual health tracking method. The system provides both continuous monitoring and proactive insights, enabling better health outcomes through timely interventions. Future work could focus on expanding the dataset, including more advanced sensors, and optimizing the machine learning models to further enhance prediction accuracy.

VI. CONCLUSION

In this work, an IoT-based health monitoring system has been successfully developed to continuously track vital parameters such as temperature, humidity, pulse rate, and SpO_2 levels. The integration of sensors with real-time data visualization through the Blynk platform enables easy and immediate access to critical health information for both patients and caregivers. Beyond simple monitoring, the system leverages machine learning models — specifically Gradient Boost Classifier and Random Forest Classifier — to predict the patient's blood glucose status, enhancing its capability as a proactive healthcare solution.

The designed system emphasizes low-cost hardware, user-friendly mobile interfaces, and intelligent predictive analytics, making it highly suitable for both personal use and remote healthcare applications. By combining real-time monitoring with predictive modeling, the solution not only tracks current health status but also provides early warnings, enabling timely intervention and better management of chronic conditions.

Overall, this project demonstrates how IoT and machine learning technologies can be effectively integrated to create smarter, more responsive healthcare systems. Future enhancements could include the addition of more physiological sensors, implementation of advanced deep learning models, and secure cloud-based data storage to further strengthen the system’s accuracy, scalability, and security.

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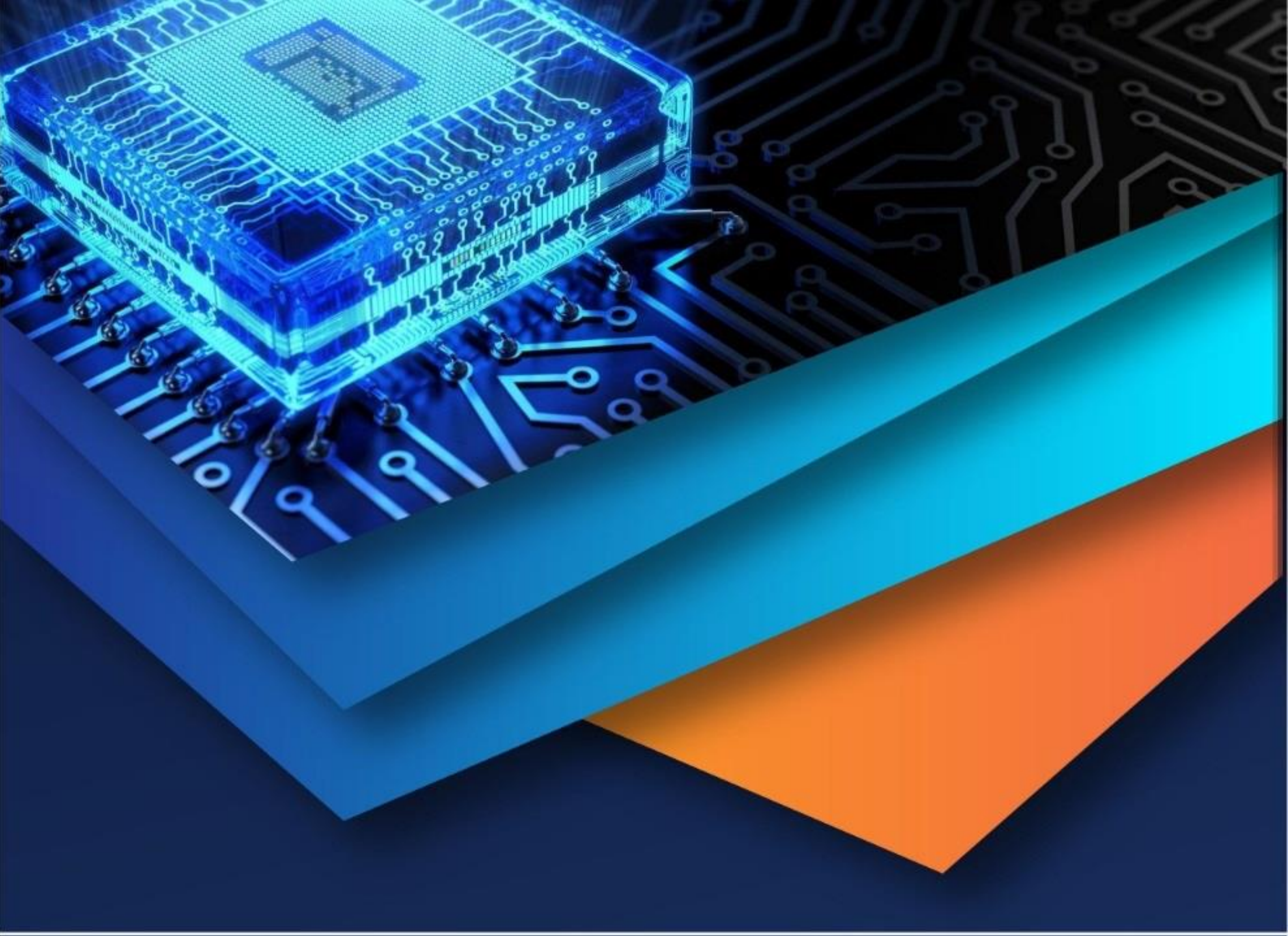

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