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Research Article

IoMT-Driven Non-Invasive Glucose Measurement Using Artificial Neural Networks

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Abstract – Patients with Type 1 diabetes (diabetes mellitus) must frequently monitor their blood glucose levels to control their condition. This process becomes challenging due to the difficulties and discomfort caused by traditional blood glucose testing. To make this process more convenient and less time-consuming, this study presents a non-invasive glucose monitoring system based on the Internet of Medical Things (IoMT) that offers a more user-friendly and painless alternative. The proposed system uses a light sensor connected to an ESP32 microcontroller to collect light intensity data from the user's fingertip. This data is transmitted to a remote server using FastAPI, where it is processed by a machine learning model using artificial neural networks (ANN). By analyzing the relationship between light absorption and glucose concentration, the ANN model estimates glucose levels, eliminating the need for invasive blood tests. This approach offers a pioneering alternative to traditional methods. Initial results demonstrate the system's real-time glucose monitoring capability, although challenges such as sensitivity to external factors such as finger pressure are observed. These findings demonstrate the potential of integrating IoT technologies and machine learning to improve diabetes care by enabling more continuous, comfortable, and effective glucose monitoring. The proposed system in this study is a step forward in developing accessible and patient-centered tools for diabetes management.

Keywords – Internet of Medical Things (IoMT), IoT, Diabetes Management, Non-Invasive Glucose Monitoring, Artificial Neural Networks (ANN), Smart Healthcare Systems.

I. INTRODUCTION

Diabetes mellitus is a chronic condition affecting millions worldwide, requiring patients to monitor their blood glucose levels regularly to maintain optimal health and prevent complications [1, 2]. According to the World Health Organization (WHO), the number of people with diabetes increased from 200 million in 1990 to 830 million in 2022. There is a significant risk for kidney failure, cardiovascular diseases, and neuropathy if the blood glucose levels are not in desired levels [1]. Traditional glucose monitoring methods, such as finger-prick blood tests, involve invasive procedures that can cause significant and unpleasant effects [4]. Patients perform these tests multiple times a day (at least three times a day), making long-term adherence to glucose monitoring a challenge. According to a study published in the Journal of Diabetes Nursing, frequent finger-prick testing is associated with pain and discomfort, which can lead to reduced adherence to glucose monitoring regimens [5]. Additionally, the Diabetes Care Community highlights that the pain associated with blood glucose monitoring can deter patients from testing as often as recommended. Additionally, there is a cost to the economy for every blood strip that is used, these factors impacting effective diabetes management [6]. To address these issues, advancements in technology have led to the creation of newer devices, such as continuous glucose monitors (CGMs) [7] and IoMT-enabled non-invasive systems [8-10]. These devices reduce the physical pain associated with traditional methods and alleviate the emotional burden of constant invasive testing. By providing a more comfortable and user-friendly experience, these innovations are transforming diabetes care, promoting better adherence, and improving the overall quality of life for patients. As a result, there is a growing demand for innovative, non-invasive alternatives that can improve the quality of life for individuals with diabetes.

The rapid advancement of technology, particularly in the field of the Internet of Things (IoT), has opened new possibilities for developing patient-friendly healthcare solutions. IoT allows the integration of smart devices to collect, process, and transmit real-time data, making it a powerful tool for healthcare applications.

This study presents a novel IoMT-enabled non-invasive glucose monitoring system designed to address the challenges of traditional approaches. The proposed system uses a light sensor and an ESP32 microcontroller to collect light intensity data, which is then transmitted to a remote server. The server processes this data using an artificial neural network (ANN) model to predict glucose levels with high accuracy. This approach eliminates the need for invasive procedures, offering a user-friendly and reliable alternative for managing diabetes.

The remainder of this paper is structured as follows. Section 2 reviews the related work and provides a background on IoT and ANN-based glucose monitoring technologies. Section 3 details the design and implementation of the proposed IoMT-enabled non-invasive glucose monitoring system, including its hardware components, data collection processes, and ANN-based prediction model. Section 4 presents the experimental results, evaluates the system's performance, and discusses the challenges and limitations encountered during the study. Finally, Section 5 concludes the paper by summarizing the key findings and offering recommendations for future research to further enhance the system's accuracy and applicability.

II. RELATED WORKS

The evolution of the IoT into the Internet of Medical Things (IoMT) represents a significant advancement, as IoMT integrates IoT principles with healthcare technologies, enabling smart, connected medical devices to enhance patient monitoring, diagnosis, and treatment outcomes. In this context, IoMT-based systems have shown promise in addressing the limitations of traditional glucose monitoring methods. By leveraging IoT, it is possible to create continuous, non-invasive glucose monitoring systems that provide real-time insights while reducing patient discomfort. Building on this potential, Tuan Nguyen Gia et al. proposed an IoT-based continuous glucose monitoring system that emphasizes energy efficiency and real-time monitoring capabilities. Their work integrates wearable sensors and RF communication protocols, enabling remote healthcare while addressing power consumption challenges [8]. Similarly, Hossain et al. explored factors influencing the adoption of continuous glucose monitoring devices, emphasizing trustworthiness and perceived value as key drivers for user acceptance. Their findings highlight the importance of user-centric designs to promote the adoption of IoT-enabled healthcare solutions [9]. Fernández-Caramés et al. expanded the scope by integrating blockchain and fog computing technologies into CGM systems, ensuring data security, real-time responses, and user incentives for data sharing [10]. These advancements [8-10] collectively showcase how IoT innovations are transforming traditional glucose monitoring into more accessible, efficient, and patient-friendly systems.

Notably, Alarcón-Paredes et al. (2019) developed an IoT-based non-invasive glucose monitoring system using a Raspberry Pi, a visible laser beam, and a camera to capture fingertip images. Their system processed the data using an ANN implemented on a Flask microservice with TensorFlow libraries, achieving a mean absolute error of 10.37% and 90.32% of estimated glucose values falling within Zone A of the Clarke Error Grid [11]. This study highlighted the potential of combining IoT and ANN for non-invasive glucose monitoring but also indicated the need for improvements in accuracy and user convenience.

Similarly, Valero et al. (2022) conducted a pilot study on a non-invasive glucose monitoring prototype using laser technology based on near-infrared spectroscopy. Their system utilized a Raspberry Pi, a portable camera, and a visible light laser to capture images when the laser passed through skin tissue. An ANN model estimated glucose concentration from the absorption and scattering of light in the skin. The prototype achieved an accuracy of 79% using finger images and 62% using ear images when compared to commercial glucometers [12]. While promising, the study acknowledged limitations such as small dataset size, the impact of external factors like skin color and thickness, and the need for improved prototype design for easier placement.

The fundamentals of ANN in processing biomedical data are introduced, showcasing how ANNs can model complex relationships between input data and glucose levels. This section highlights a gap in noninvasive glucose monitoring systems regarding the need for increased accuracy, robustness to external factors, and more user-friendly devices. This work aims to address these challenges by using a light sensor and ESP32 microcontroller for data acquisition and developing an optimized ANN model for improved performance and usability.

III. SYSTEM DESIGN AND IMPLEMENTATION

The design and implementation of the proposed IoMT-enabled non-invasive glucose monitoring system were driven by the need to address the limitations of traditional glucose monitoring methods. This section outlines the development process, which integrates principles of light absorption and advanced technologies to enhance accuracy and user convenience. The system leverages the Beer–Lambert Law to relate light absorption to glucose concentration in the blood, using a 650 nm laser light source, an ESP32 microcontroller, and a TSL2591 light sensor for precise data acquisition.

Key considerations in the design include hardware integration to ensure consistent measurement conditions and a robust data collection process that accounts for variations in finger placement and environmental conditions. Furthermore, the implementation incorporates an artificial neural network (ANN)-based model for processing collected data and predicting glucose levels. This approach combines IoT and machine learning technologies to create a reliable, non-invasive alternative for diabetes management. The following subsections detail the hardware components, data collection methodology, and ANN model development.

The Beer–Lambert Law relates the absorption of light to the properties of the material through which the light is traveling. It states that the absorbance of a material is directly proportional to its concentration the c, the path length l, and the molar absorptivity ε:

$$A = \varepsilon \times c \times l \tag{1}$$

In the context of this system, the laser light passing through the fingertip is absorbed by glucose molecules in the blood. By measuring the intensity of transmitted light I, and knowing the incident light intensity I_0, the absorbance can be calculated:

$$A = \log_{10}\left(\frac{I_0}{I}\right) \tag{2}$$

By applying the Beer–Lambert Law, changes in glucose concentration can be inferred from variations in light absorption.

A. Hardware Components

Figure 1 illustrates the system architecture of the proposed IoMT-enabled non-invasive glucose monitoring system. The proposed IoMT-enabled non-invasive glucose monitoring system employs three primary hardware components to ensure accurate and reliable data acquisition. The 650 nm 5 mW laser light source acts as the primary light source, emitting a focused red laser beam that effectively penetrates skin tissue. This wavelength is selected for its sensitivity to glucose concentration, enabling precise measurements of light absorption. The ESP32 microcontroller, a low-cost and low-power system-on-chip with integrated Wi-Fi and Bluetooth capabilities, serves as the central processing unit. It handles data acquisition from the light sensor and facilitates communication with the remote server. The TSL2591 light sensor, known for its high dynamic range and exceptional sensitivity, measures both infrared (IR) and visible light to detect transmitted light intensity variations caused by blood glucose levels. These components are integrated in a configuration optimized for consistent measurements, where the laser light source is mounted in a setup resembling a fingerprint scanner, and the TSL2591 sensor is positioned beneath the fingertip to capture transmitted light. The ESP32 microcontroller processes the collected data and transmits it to a remote server via FastAPI for further analysis. This integrated hardware system forms the foundation of the glucose monitoring solution, ensuring accurate and user-friendly operation.

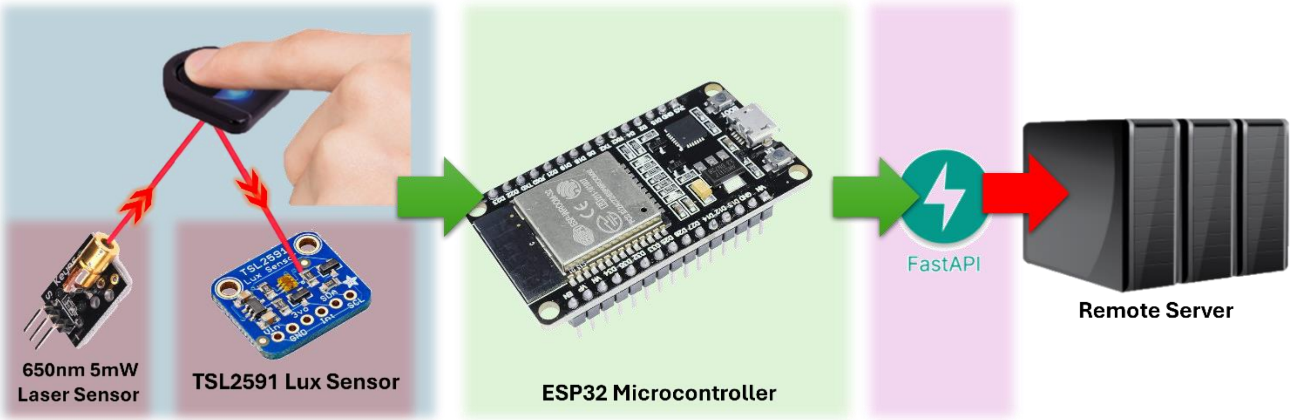

Figure 1: System architecture for IoMT-enabled non-invasive glucose monitoring

B. Data Collection

The data collection period took 1 week. Multiple measurement sessions were performed at various times throughout the day to capture fluctuations in glucose levels. To account for variability and minimize systematic errors, the patient's finger was pressed on the reader at different angles and pressures. Additionally, measurements were taken under varying ambient light conditions to assess the system's robustness against environmental interferences. In total, 100 tests were conducted, each involving a 10-minute measurement period aligned with blood strip tests for reference glucose level determination.

(a) (b)

Figure 2: Proposed hardware setup - (a) General view of the system and (b) Finger placement for data collection

Figure 2 gives an overview of the proposed hardware setup for the IoMT-enabled non-invasive glucose monitoring system, including the general configuration (Figure 2(a)) and the finger placement process for data collection (Figure 2(b)). The system is designed to capture light absorption data effectively, which correlates with glucose concentration in the blood. In Figure 2(a), the general view of the hardware shows the placement of the key components: the 650 nm laser light source and the TSL2591 light sensor. The laser source emits a focused red beam at a wavelength of 650 nm, which passes through the user's fingertip. The light sensor, positioned directly beneath the finger, measures the transmitted light intensity, capturing variations in both visible and infrared light. This configuration ensures precise and consistent data acquisition, which is critical for accurate glucose level prediction. Figure 2(b) illustrates the finger placement process during data acquisition. The user places their fingertip directly over the laser light path, ensuring the light beam passes through the tissue. The sensor detects the transmitted light intensity, which varies based on the blood's optical properties influenced by glucose concentration. Proper finger placement is essential to minimize external factors, such as inconsistent pressure or alignment, which could affect the sensor readings.

The data collection process consists of three steps. First, during lux measurement, the laser was directed through the fingertip, and the TSL2591 sensor recorded the intensity of the transmitted visible and infrared (IR) light. At the same time, blood glucose levels were measured using a standard glucometer (blood strip test) to obtain accurate reference values. Finally, the ESP32 microcontroller logged the sensor readings along with timestamps and transmitted the collected data to a remote server via FastAPI. Figure 3 illustrates the data flow in the IoT-enabled non-invasive glucose monitoring system, showcasing the interaction between the system's components and the progression of data from input to prediction. The process begins with finger placement on the device, where a 650 nm laser light source emits a focused beam through the fingertip. This light beam interacts with the tissue and blood, and the transmitted light is captured by the TSL2591 light sensor, which processes the light and records its intensity. The processed light data is then transmitted to the ESP32 microcontroller, which acts as the central unit for data collection and communication. The ESP32 formats and forwards the light intensity data wirelessly to the FastAPI server. On the server side, this data is analyzed and processed using a trained artificial neural network (ANN) model to predict the blood glucose levels.

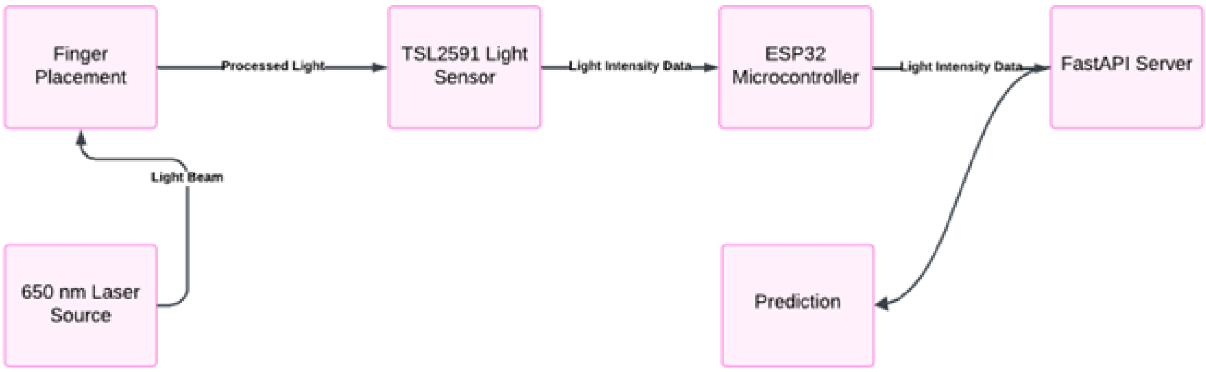

Figure 3: Data flow diagram of the IoMT-enabled non-invasive glucose monitoring system

Table 1 provides an example of the data collected from the proposed glucose monitoring system during measurement sessions. This table includes three key variables: visible light intensity, infrared (IR) light intensity, and the corresponding blood glucose levels (measured in mg/dL). This table showcases the raw data collected from the sensor, illustrating how visible and infrared light intensities are correlated with reference glucose levels to enable machine learning-based glucose prediction.

Table 1: Sample Data Collected from Sensor Measurements

Visible Light Intensity	**IR Light Intensity**	**Blood Glucose (mg/dL)**
6179.0950	31708.8739	120
6186.5002	31701.4696	150
…	…	…

C. ANN-Based Prediction Model

Figure 4 demonstrates the artificial neural network (ANN) architecture used in the proposed IoMT-enabled non-invasive glucose monitoring system for predicting blood glucose levels. The model of our glucose predictor ANN is made up of three primary layers: the input layer, a single hidden layer, and the output layer. The Input Layer comprises two nodes, representing the two prediction features: visible light intensity and infrared (IR) light intensity. These features are derived from the transmitted light measurements obtained by the TSL2591 light sensor after the 650 nm laser beam reflects from the patient's finger. The Hidden Layer contains ten neurons with activation functions that model the non-linear relationships between the input features and the glucose levels. This layer is designed to extract patterns and correlations in the light absorption data, enabling the ANN to process complex relationships effectively. The Output Layer contains a single neuron that generates the predicted blood glucose level as its output. The ANN is trained using supervised learning techniques, where the actual glucose levels obtained from blood strip tests are used as ground truth during the training process. The ANN architecture depicted in Figure 4 demonstrates a streamlined approach to glucose prediction, balancing complexity and computational efficiency. By utilizing light intensity data and advanced neural network techniques, the system provides an accurate and non-invasive alternative to conventional glucose monitoring methods.

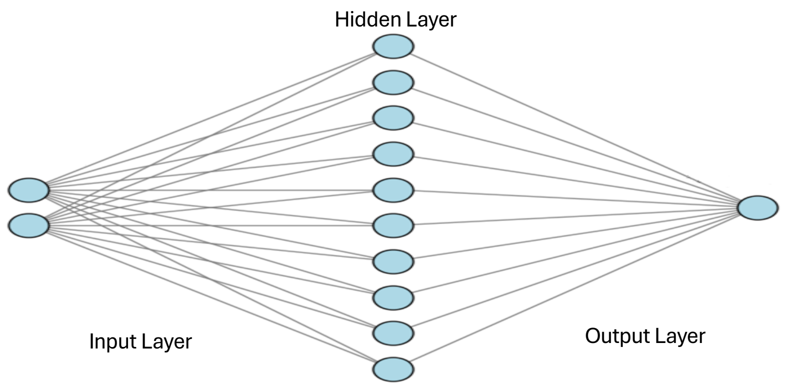

Figure 4: Artificial neural network (ANN) architecture for glucose level prediction

An artificial neural network (ANN) model was developed using PyTorch libraries to predict blood glucose levels based on the collected light intensity data. The model, encapsulated within a custom class named Glucose Predictor, comprises an input layer that accepts two features: visible light intensity and infrared (IR) light intensity. These inputs are processed by a hidden layer consisting of ten neurons equipped with activation functions to capture nonlinear relationships within the data. Finally, the output layer generates the predicted glucose level. This architecture enables the ANN to effectively learn and model the complex relationship between light absorption measurements and blood glucose concentrations, thereby providing accurate and reliable glucose level estimations.

The model training process is designed with several key steps to ensure optimal performance and accurate predictions. Initially, data preprocessing is performed, where the input features (visible and infrared light intensities) and target values (blood glucose levels) are normalized to improve the convergence rate during training. The dataset is divided into training and validation sets to evaluate the model's performance and to prevent overfitting. During training, the model is optimized over several epochs using the mean squared error (MSE) as the loss function, and weights are updated with the Adam optimizer. Finally, the model's performance is assessed on the validation set using metrics such as MSE to quantify prediction accuracy and correlation coefficients to measure the relationship between predicted and actual glucose levels.

IV. EXPERIMENTAL RESULTS AND SYSTEM EVALUATION

The model's performance was initially intended to be assessed using three primary metrics: Mean Squared Error (MSE), Correlation Coefficient (R), and Bland-Altman Analysis. MSE measures the average squared difference between the predicted and actual glucose levels, providing insight into the model's prediction accuracy. The Correlation Coefficient (R) indicates the strength and direction of the linear relationship between the predicted and actual glucose values, reflecting the model's ability to capture trends in the data. Bland-Altman Analysis was planned to assess the agreement between the ANN predictions and the reference glucose measurements by analyzing the differences versus the averages of the two methods.

During the system validation phase, significant challenges emerged that hindered the effective evaluation of the ANN model's performance. The model output demonstrates high sensitivity to finger placement variations, leading to substantial inconsistencies in absorbance measurements. These variations made it difficult to obtain reliable and consistent data, thereby impeding the model's ability to learn and generalize the relationship between light absorption and glucose concentration accurately. Environmental factors, such as fluctuating ambient light conditions, further complicated the calculation of absorbance, introducing additional noise into the measurements. The ANN model did not achieve the desired predictive performance, as evidenced by elevated MSE values and low correlation coefficients between predicted and actual glucose levels. The variability in sensor outputs due to finger placement and other light conditions made it clear that the system's current configuration was inadequate for reliable glucose prediction.

Several challenges and limitations were identified throughout the study, which impacted the system's performance and reliability. The system showed high sensitivity to finger placement, where variations in angles and pressures introduced significant inconsistencies in absorbance measurements, leading to unreliable glucose predictions. The dataset used for model training, sourced from a single Type 1 diabetic patient over one week, lacked diversity, limiting the ANN model's ability to generalize across different finger placements and environmental conditions. Additionally, the TSL2591 sensor demonstrated high sensitivity to slight changes in finger pressure and positioning, resulting in measurement noise that compromised data accuracy. Environmental interferences, such as fluctuations in ambient light conditions, further complicated absorbance calculations and introduced additional errors. Finally, the ANN model struggled to effectively learn from the noisy and inconsistent data, leading to poor predictive performance and low correlation with actual glucose levels. These challenges highlight the need for improved sensor stability, more controlled measurement conditions, and a more diverse and extensive dataset to enhance the system's accuracy and reliability in non-invasive glucose monitoring.

V. CONCLUSION AND FUTURE WORK

The proposed IoMT-enabled non-invasive glucose monitoring system applies the Beer–Lambert Law to estimate glucose concentration by measuring light absorption through the fingertip. The study involved collecting data from a Type 1 diabetic patient over one week, resulting in 100 tests under varying conditions. While initial results were inconclusive due to sensor sensitivity, limited dataset diversity, and measurement inconsistencies, the integration of a Kalman filter demonstrated potential for enhancing prediction accuracy by minimizing errors and providing more reliable glucose level estimations with a one-minute waiting time.

To improve the proposed system, several future enhancements are recommended. Expanding the dataset is critical, which includes increasing the participant pool to collect data from a more diverse group of patients and extending the data collection period to capture a wider range of glucose level fluctuations for improved model generalization. Hardware improvements could affect the efficiency of the system, such as redesigning the finger placement mechanism to ensure consistent positioning and pressure through ergonomic fixtures, as well as incorporating shielding or enclosures to minimize ambient light interference and maintain consistent measurements. Sensor optimization should be explored by identifying alternative sensors or wavelength combinations that are less sensitive to external factors and more specific to glucose absorption. On the modeling side, advanced artificial neural network (ANN) architectures, such as convolutional neural networks or ensemble methods, can be implemented to better capture complex patterns in the data. Additional features, such as temperature or heart rate, could be incorporated to improve prediction accuracy, and Kalman filter parameters can be optimized for better noise reduction. Finally, extensive clinical trials are necessary to validate the system's efficacy and robustness across diverse conditions and populations. Addressing these aspects will enhance the reliability and practicality of non-invasive glucose monitoring solutions, contributing significantly to improved diabetes management.

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