# Wearable Non-Invasive Glucose Monitoring System Using Optical Sensing

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***Abstract-*** *Non-invasive glucose monitoring remains a critical challenge in biomedical engineering due to the complex interaction of light with biological tissues and the weak specificity of glucose-related optical signals. This paper presents the design and implementation of a wearable non-invasive glucose monitoring system based on Near-Infrared (NIR) optical sensing. The proposed system utilizes a 940 nm NIR light source, selected within the optical window that minimizes water absorption while ensuring adequate penetration into the skin. The sensing principle is based on the Beer–Lambert law, where the attenuation of light intensity is related to the absorption coefficient of the medium, which is influenced by glucose concentration. A photodiode detects the diffusely reflected light, and the resulting signal is amplified, filtered, and digitized using an ESP32 microcontroller. Signal preprocessing techniques are applied to reduce noise and improve measurement stability. The processed data is transmitted wirelessly to a mobile application via Bluetooth Low Energy (BLE) for real-time monitoring. Due to the presence of significant optical scattering, physiological variability, and dominant water absorption, the extracted signal represents a composite response rather than a glucose-specific measurement. Therefore, the current system focuses on demonstrating feasibility rather than achieving clinical-grade accuracy. Experimental results confirm successful signal acquisition and wireless transmission, validating the system architecture. Future work will involve multi-wavelength sensing, advanced signal processing, and machine learning-based calibration models to improve accuracy and robustness. This study contributes toward the development of practical, wearable, and non-invasive glucose monitoring technologies.*

***Keywords:*** Non-invasive glucose monitoring, Near-Infrared (NIR), Optical sensing, Wearable device, ESP32, Bluetooth Low Energy (BLE), Beer–Lambert law.

## I. INTRODUCTION

Diabetes mellitus is a chronic metabolic disorder that results in high blood glucose levels because of problems with the production of insulin or how the body uses insulin. It is one of the global health challenges that need to be consistently monitored to avoid serious complications like cardiovascular diseases, neuropathy and kidney failure. Accurate and frequent glucose monitoring is crucial for successful diabetes management and improved patient outcomes.

Traditional glucose monitoring techniques, including fingerprick methods, are invasive, painful and inconvenient, often leading to poor patient compliance. Continuous Glucose Monitoring (CGM) systems enable real-time monitoring but are still semi-invasive, requiring a sensor to be inserted under the skin.

Moreover, these systems are relatively expensive and may not be suitable for all users.

Optical sensing methods have been receiving much focus in recent times because of their potential applications in noninvasive biomedical systems. One of these optical sensing approaches that have garnered interest is NIR (Near-Infrared) Spectroscopy, which has proven effective in interacting with various molecular components within biological tissues, such as glucose. In this regard, light attenuation in biological tissues is based on the Beer-Lambert Law, which is determined by the concentration of absorbers in relation to the distance of travel of light in the tissues.

The use of NIR for the measurement of glucose concentration, however, has proven to be quite difficult due to the complex nature of the optical properties of human tissue.

In this paper, a wearable, non-invasive glucose monitoring system using NIR optical sensors is introduced. This system includes an NIR light-emitting diode operating at 940 nm, a photodiode to detect the reflected light, and an ESP32 module for data processing and wireless transmission of the signal by Bluetooth Low Energy (BLE).

The main achievement of this study is proving the concept of building a wearable, non-invasive device capable of detecting blood glucose levels using an integrated optical sensor, an embedded system, and wireless transmission capabilities. Although this prototype cannot ensure clinical accuracy, it can serve as a foundation for further enhancements in multichannel analysis, signal processing algorithms, and machine learning algorithms for calibration.

## II. LITERATURE REVIEW

*A. Existing Sign Language Recognition Systems*

There have been many studies on non-invasive glucose monitoring to overcome traditional invasive systems. The biggest problem is to extract the glucose-related information out of the highly complex physiological signal data that is affected by many physiological parameters. Various techniques like optical, electromagnetic, and electrochemical measurement methods have been suggested.

In their paper published in 2009, Caduff et al. proposed a multisensing approach using both dielectric and optical sensors for monitoring glucose concentration in Type 1 diabetic patients. Their study showed that the combination of different kinds of sensors could enhance the performance of prediction since each sensor technique has some weakness. Nevertheless, their proposed system is too complicated in terms of hardware design. In their study, Tura et al. (2007) undertook an extensive evaluation of the non-invasive methods of glucose sensing, which included NIR spectroscopy, Raman spectroscopy, and reverse iontophoresis. The authors' conclusion was that these techniques have not achieved enough accuracy to make them clinically reliable since they suffer from interference of the biological environment and external variables.

As far as optical techniques are concerned, NIR spectroscopy has been of much interest because of its capability to penetrate into biological tissues and interact with the molecules of glucose, water, and hemoglobin. It has been found that glucose is poorly absorbing in the NIR range of the spectrum. However, the molecule of water, which is predominant in the biological tissue, is highly absorbing. Raman spectroscopy has been suggested as an alternative approach to optical sensing, based on its capacity to produce molecularspecific signals for glucose. But, the application of the Raman sensing system is restricted due to low sensitivity, high noise interference, and high cost, thus rendering this technology not appropriate for inexpensive wearable applications.

Microwave sensors have also been considered as an alternative sensing approach for measuring blood glucose levels non-invasively. This method exploits the variation in the dielectric constant of the biological medium caused by changes in glucose concentration. In contrast to optical approaches, microwave systems are affected by fluctuations in temperature and tissue inhomogeneity. Reverse iontophoresis-based devices utilize an electric charge to draw ISF from the body. Despite the fact that reverse iontophoresis does not involve taking samples of blood directly, some problems, such as skin irritation, low speed, and unreliability, have been observed.

The current trend in research is to integrate machine learning and data-driven models with sensor technology. These solutions seek to establish a correlation between measured values and the glucose level. Nevertheless, these methods are associated with significant computation costs, need large training sets, and necessitate considerable calibration efforts.

## III. RELATED WORK

A variety of methods have been suggested for non-invasive or minimally invasive glucose monitoring, with different degrees of success and practical limitations.

A system based on multiple sensors was developed by Caduff et al. (2009) to estimate the glucose level, combining dielectric and optical measurements. Their results indicated that the prediction performance can be improved with the combination of multiple sensing modalities. But the system demands extensive calibration and increases hardware complexity, making it less ideal for compact wearable implementations.

Tura et al. (2007) have reviewed in detail the non-invasive glucose monitoring techniques such as optical spectroscopy, reverse iontophoresis and electromagnetic methods. So far, no one technique has demonstrated consistent clinical reliability, they found, largely due to interference from biological variability and environmental conditions.

Optical methods, especially Near-Infrared (NIR) spectroscopy have been extensively studied because of their noninvasive characteristics and their suitability for wearable systems. It has been shown that NIR light can penetrate biological tissue and generate measurable signals associated with glucose concentration. However, the signal from glucose absorption is relatively weak compared to stronger absorbers such as water, leading to low specificity and less accurate results.

Because of the ability to provide molecular level information, Raman spectroscopy has been studied as a more specific alternative. It is more specific than NIR but its use is limited by low signal intensity, high sensitivity to noise and expensive instrumentation, making it unsuitable for portable devices.

The sensing techniques based on microwaves have also been proposed , exploiting the dielectric property changes of tissue due to the glucose concentration .

The first wearable devices are based on reverse iontophoresis systems that try to draw interstitial fluid (ISF) using a low electric current. This method does not require blood sampling but has disadvantages of skin irritations, slow response and inconsistent accuracy, which hinder its long-term use.

Recent progress has been made toward integrating sensing techniques with machine learning algorithms to model the complex relationship between physiological signals and glucose concentration. Although these approaches are promising in improving prediction accuracy, they require a large dataset and extensive calibration which is difficult to implement in real-time wearable systems.

## IV. PROPOSED METHODOLOGY

The methodology under development involves a portable, non-invasive glucose measurement technique utilizing nearinfrared (NIR) optical detection, embedded processing, and wireless communication. It aims to measure the optical signals from the skin, process the information, and calculate changes in blood glucose level in real-time.

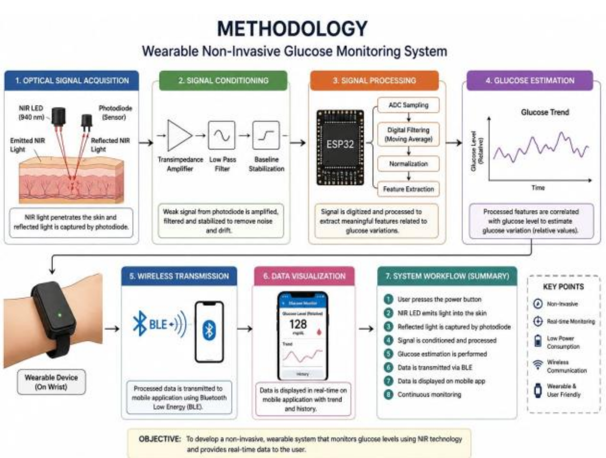


Fig. 1. proposed methodology

*A. System Overview*

The procedure comprises four main phases:

1. Optical Signal Capture
2. Signal Conditioning and Processing
3. Estimation of Glucose Content
4. Wireless Transmission of Data and Visualization

The design uses a 940-nm NIR LED light source, photodiode detector, and ESP32 microcontroller module featuring BLE communication capability.

*B. Optical sensing mechanism*

A 940 nm near-infrared light source is utilized for illumination of the skin. It falls within the optical window (700-1100 nm) because at these wavelengths, the light penetrates well, while the absorption by water is minimal when compared to larger wavelengths.

As NIR light is passed through the skin, it experiences:

Absorption by various chromophores including glucose, water, and hemoglobin

Scattering due to heterogeneous tissues
Reflection to the skin surface

This reflected light is detected using a photodiode that generates an electrical output based on the intensity of the reflected light.

*C. Theoretical model*

The proposed system is based on the principle that light interaction with biological tissue varies according to the composition of that tissue, including the presence of glucose. When Near-Infrared (NIR) light is directed onto the skin, it penetrates the outer layers and interacts with various components such as blood, interstitial fluid (ISF), water, and glucose molecules.

As the light travels through the tissue, a portion of it is absorbed, while the rest is scattered and reflected back toward the surface. The amount of light absorbed depends on the concentration of absorbing substances present within the tissue. Since glucose is one of these substances, changes in glucose levels influence the overall light absorption characteristics, although its effect is relatively small compared to dominant absorbers like water.

The reflected light is detected by a photodiode, which converts it into an electrical signal. This signal represents a combined response of multiple physiological factors, including glucose concentration, blood flow, tissue structure, and hydration levels. Therefore, the detected signal is not purely glucosespecific but rather a composite optical signal. To extract meaningful information, the system analyzes variations in the detected signal over time. These variations are correlated with changes in glucose levels using signal processing techniques. However, due to the complex nature of light-tissue interaction, factors such as scattering, skin thickness, pigmentation, and environmental conditions also influence the signal.

As a result, the theoretical model assumes that glucose estimation is achieved through indirect correlation rather than direct measurement. The system focuses on identifying patterns and trends in the optical signal that correspond to glucose variations, rather than determining exact glucose concentration.

This model highlights the fundamental challenge of noninvasive glucose monitoring: the need to isolate glucoserelated information from a signal that is significantly affected by other biological and environmental factors.

*D. Signal conditioning*

The electrical signal received through the photodiode is faint and prone to noise interference. As such, a signal conditioning process is done, which consists of:

Transimpedance amplifier (TIA) – converts the current into voltage

Low-pass filter – eliminates high-frequency noise
Baseline stabilization – minimizes signal drift This guarantees that the signal can be processed digitally.

*E. Digital signal processing*

The conditioned signal is converted to digital form using the ADC of the ESP32 microcontroller. The following signal processing methods are implemented:

Moving average filter for smoothing variations
Normalization for minimizing variation
Feature extraction from signal amplitude and variations
As the signal under measurement depends on various factors, the system concentrates on the detection of relative variations rather than the exact glucose value.

*F. Glucose estimation approach*

The problem with directly estimating the glucose level by measuring optical signals lies in the following reasons:

The dominant absorption of water
The scattering effect on tissue
Variability of physiological parameters

For this reason, a correlation-based technique has been adopted where changes in signal intensity correspond to fluctuations in glucose levels.

*G. Wireless communication and Mobile Interface*

The analyzed data is sent via the BLE technology from the ESP32 to the mobile application. BLE technology is chosen because of the following features:
Energy-saving
Wearable-friendly
Real-time data transfer The mobile application includes:

Information related to glucose
Data archive
Basic visualizationhash

*H. System Workflow*

The complete operation of the system is as follows:

1. User activates the device using a push button
2. NIR LED emits light into the skin
3. Photodiode captures reflected light
4. Signal is amplified and filtered
5. ESP32 processes the signal
6. Glucose estimation is performed
7. Data is transmitted via BLE
8. Mobile app displays results

*I. Design consideration*

Choice of 940 nm wavelength to avoid water effect
Low power consumption for wearable devices
Minimizing noise and motion artifacts
Compact and ergonomic hardware design

*J. Limitations*

Optical Signal Does Not Identify Glucose
Accuracy Requires Calibration
Vulnerable to Environmental and Physiological Changes Optical Signal Does Not Identify Glucose

## V. PERFORMANCE METRICS

The performance of the developed non-invasive glucose monitoring device is assessed based on a number of parameters that include aspects of signal quality, efficiency, and ease of use. As the technology being developed is still a prototype, the emphasis will be placed more on practicality rather than clinical precision.

*A. Signal Stability*

Signal stability can be defined as the reliability of the signal collected through the photodiode over time. Consistent readings mean consistent sensor readings, Taken from multiple trials performed in the same location By looking at variations in signal strength.

*B. Signal-to-Noise Ratio (SNR))*

SNR is a measure of how good the recorded signal is compared to the background noise. More SNR → Better and more reliable signal Sources of noise: Ambient light Motion artifacts

*C. Respond time*

Response time refers to the time spent by the system in: Capturing the signal Processing it Displaying its output in the mobile application

*D. Power comsumption*

Efficiency of energy is vital for wearable gadgets. Determining by: ESP32 functioning LED light utilization BLE connectivity

*E. Sensitivity*

Sensitivity can be defined as the capability of the system to detect small optical signal variations caused by physiological factors. Key to measuring glucose-related tendencies Restricted by interference from water, tissues, etc.

## VI. RESULT AND DISCUSSION

*A. Experimental Setup*

The design for the non-invasive glucose monitoring wearable system was realized through the use of a 940 nm NearInfrared (NIR) LED, a photodiode detector, and an ESP32 microcontroller featuring built-in BLE technology. Testing of the system was conducted indoors to limit any possible outside influences like sunlight and motion artifacts. The sensor was attached to the wrist, and readings were taken several times under consistent conditions.

*B. Result*

From the results of the experiment, it can be noted that: The optical signal was successfully captured from the reflected signal from the skin. Photodiode provided fluctuations in the signal intensity consistently during several trials. Signal conditioning circuit successfully increased weak signals and suppressed noise levels. The signal was processed by the ESP32 and was successfully sent using BLE technology. The data received by the mobile application was displayed instantly on the screen. A trend graph for one measurement shows gradual fluctuations in the signal strength.

*C. Signal Analysis*

The acquired signal is the result of a combined response caused by: Concentration of glucose Water in biological tissue Changes in blood flow Skin properties Given the significant amount of water in tissue, the role of glucose is minimal compared to the other factors. Consequently, the main factor measured by the system is relative changes in intensity.

*D. Performance Evaluation*

The following criteria were used to evaluate the effectiveness of the system: Stability of Signal: Readings were stable through controlled experiments. Repeatability: Consistent pattern was noted during multiple trials. Response Time: The data was analyzed and displayed in real time. Communication Efficiency: BLE communication was stable and low-latency. This validates that the system operates effectively as a prototype.

*E. Discussion of Findings.*

The results demonstrate that the proposed system is capable of capturing and processing optical signals from biological tissues in a non-invasive manner. The integration of optical sensing with embedded processing and wireless communication was successfully achieved in a compact wearable form.

However, the study also highlights the fundamental challenge of non-invasive glucose monitoring: the difficulty in isolating glucose-specific information from a signal dominated by water absorption and tissue scattering. This confirms observations from existing literature that optical-based glucose sensing requires advanced calibration and signal processing techniques.

The current implementation serves as a proof-of-concept system, demonstrating feasibility rather than clinical applicability. Future improvements, such as multi-wavelength sensing and machine learning-based models, are necessary to enhance accuracy and reliability.

## VII. CONCLUSION

This work presented the design and development of a wearable non-invasive glucose monitoring system based on Near-Infrared (NIR) optical sensing. The proposed system integrates an optical sensing module, signal conditioning circuitry, an ESP32 microcontroller, and Bluetooth Low Energy (BLE) communication to enable real-time data acquisition and visualization through a mobile application.

The system successfully demonstrates the feasibility of using NIR light to capture physiological variations from biological tissues in a non-invasive manner. Experimental observations confirm that the device is capable of acquiring stable optical signals and transmitting processed data wirelessly with low latency. The compact and low-power design makes it suitable for wearable applications, providing a user-friendly alternative to traditional invasive glucose monitoring methods.

However, due to the complex nature of light interaction with biological tissues, the measured signal is influenced by multiple factors such as water absorption, tissue scattering, and physiological variability, which limit the accuracy of glucose estimation. As a result, the current implementation focuses on demonstrating system architecture and feasibility rather than achieving clinical-grade performance.

Future work will focus on improving system accuracy through multi-wavelength sensing, advanced signal processing techniques, and machine learning-based calibration models. Additionally, further research involving controlled clinical data and optimized sensor design is required to enhance reliability and enable practical deployment.

In conclusion, this study provides a foundational framework for non-invasive glucose monitoring using wearable optical sensing, contributing to the advancement of next-generation healthcare technologies aimed at improving patient comfort and accessibility.

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