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OPTIMIZATION OF NON-INVASIVE GLUCOSE MONITORING ACCURACY USING AN OPTICAL SENSOR

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Abstract. *The development of non-invasive blood glucose monitoring technologies is progressing steadily, largely due to advancements in optical sensor systems. These systems assess physiological data by analyzing how light interacts with biological tissues. A common technique, near-infrared spectroscopy, typically utilizes wavelengths such as 500 nm, 970 nm, 1400 nm, and 1900 nm, selected for their enhanced responsiveness to glucose levels at varying tissue depths. In experimental settings, this method has demonstrated the ability to generate electrical signals that correlate with glucose concentrations, supporting its potential for accurate glucose tracking. The technique adheres to both detection and precision standards, particularly at higher glucose concentrations, making it a strong candidate for next-generation monitoring solutions. The study also outlines future objectives, including improving sensor accuracy, reducing device size, and enabling seamless integration with both clinical and home-based healthcare systems. Moreover, efforts to minimize interference and signal distortions are explored as part of the broader aim to refine system reliability.*

Keywords: non-invasive monitoring, glucose level, optical sensor, near-infrared spectroscopy, medical measurements

OPTYMALIZACJA DOKŁADNOŚCI NIEINWAZYJNEGO MONITOROWANIA POZIOMU GLUKOZY ZA POMOCĄ CZUJNIKA OPTYCZNEGO

Streszczenie. *Rozwój nieinwazyjnych technologii monitorowania poziomu glukozy we krwi postępuje systematycznie, głównie dzięki postępom w systemach czujników optycznych. Systemy te analizują dane fizjologiczne, badając interakcje światła z tkankami biologicznymi. Powszechnie stosowaną techniką jest spektroskopia w bliskiej podczerwieni (NIR), która zazwyczaj wykorzystuje długości fal takie jak 500 nm, 970 nm, 1400 nm i 1900 nm, wybrane ze względu na ich zwiększoną czułość na poziomy glukozy na różnych głębokościach tkanek. W warunkach eksperymentalnych metoda ta wykazała zdolność generowania sygnałów elektrycznych skorelowanych z poziomem stężenia glukozy, co potwierdza jej potencjał w zakresie dokładnego monitorowania glukozy. Technika ta spełnia zarówno wymagania dotyczące wykrywalności, jak i precyzji, szczególnie przy wyższych stężeniach glukozy, co czyni ją silnym kandydatem do zastosowania w przyszłościowych rozwiązaniach monitorujących. W badaniu określono także cele na przyszłość, w tym poprawę dokładności czujników, zmniejszenie rozmiarów urządzenia oraz umożliwienie płynnej integracji zarówno z systemami opieki klinicznej, jak i domowej. Ponadto analizowane są działania mające na celu minimalizację zakłóceń i zniekształceń sygnału, jako część szerszych starań o poprawę niezawodności systemu.*

Słowa kluczowe: monitorowanie nieinwazyjne, poziom glukozy, czujnik optyczny, spektroskopia w bliskiej podczerwieni, pomiary medyczne

Introduction

Diabetes is a chronic metabolic disorder that has emerged as a major global health concern, affecting hundreds of millions of individuals worldwide. The increasing prevalence of diabetes is largely driven by sedentary lifestyles and a global rise in obesity. Without appropriate medical management, individuals with diabetes face elevated risks of complications such as cardiovascular disease [1, 2], kidney impairment, and nerve damage, all of which can significantly reduce quality of life and increase mortality. Reliable blood glucose monitoring is a foundational aspect of effective diabetes management. According to the International Diabetes Federation, over 500 million people currently live with diabetes, with the majority residing in low- and middle-income nations. The global death toll associated with the disease reaches approximately 1.5 million people annually [15].

Traditional methods of glucose monitoring rely on invasive finger-prick testing, which involves puncturing the skin to collect small blood samples. While widely used, this method presents several challenges: it can be painful, inconvenient, and often leads to reduced patient compliance. Repeated use may also cause skin irritation and psychological stress, making frequent monitoring difficult for many patients [5].

In response to these limitations, researchers have explored various alternative methods for glucose detection. These include non-traditional approaches such as fingernail-based sensors, contact lens technologies, electromagnetic probes, and analyses using alternative biological fluids like sweat, saliva, urine, breath, and interstitial fluid [12, 20]. Although many of these techniques are still under development and supported primarily by theoretical or simulated data, they offer promising avenues for less invasive and more user-friendly monitoring systems.

Ongoing research has increasingly focused on developing non-invasive blood glucose monitoring technologies, driven by the limitations of conventional invasive techniques. Among these, optical sensor technologies have emerged as particularly promising, offering light-based solutions such as near-infrared, Raman, and photoacoustic spectroscopy. These approaches enable the analysis of blood and tissue characteristics through the skin, presenting a more comfortable and user-friendly alternative to traditional monitoring procedures. Such innovations pave the way for real-time glucose tracking without the discomfort or inconvenience of skin puncture [9].

The advancement of optical sensors marks a significant technological and clinical milestone in diabetes care. Modern non-invasive systems are capable of monitoring not only blood glucose but also vital parameters such as heart rate and body temperature, contributing to a more comprehensive understanding of patient health [19]. These systems are designed to enhance treatment adherence and disease management by offering accessible and minimally disruptive monitoring options.

While non-invasive monitoring solutions show great promise, they still require validation against standard invasive methods to address concerns about occasional inaccuracies. In the present work, the study focuses specifically on optimizing the optical sensing stage of a non-invasive glucose monitoring system, including the choice of wavelength, configuration of the light source and photodetector, and the hardware architecture of the measurement circuit.

Previous studies suggest that further refinement of non-invasive glucose monitoring systems can be achieved by combining optical sensing with artificial intelligence and advanced data modelling techniques, as well as with cloud-based and IoT-based infrastructures [10, 14]. However, the present paper is deliberately restricted to the optical sensing and hardware layers, while the integration of data-driven components lies outside the scope of this study.

The main contribution of this study is the optimisation of the optical sensor configuration for non-invasive glucose monitoring. Several candidate wavelengths in the visible and near-infrared ranges are experimentally analysed, the influence

of LED operating conditions on signal stability is investigated, and a compact hardware architecture is proposed to enable reliable optical measurements suitable for future integration into advanced monitoring platforms.

1. Materials and methods

Spectroscopy provides a promising non-invasive approach for monitoring glucose levels by utilizing the interaction between light and glucose-containing solutions. In this study, the work is concentrated on the design and optimisation of the optical sensing block and its hardware implementation, rather than on advanced data-driven or machine-learning-based processing. When a beam of light passes through a transparent glucose solution, specific wavelengths are absorbed based on concentration levels, offering a method to estimate glucose accurately. Researchers have extended this principle to human skin, exploring spectral characteristics to detect glucose levels non-invasively. However, light penetration in biological tissues is limited to certain wavelengths, especially in the infrared range, and glucose does not produce highly distinctive absorption features in this spectrum. Additionally, variables such as skin composition, light scattering, and temperature sensitivity further complicate the analysis [5, 9, 12, 21].

A proposed technique involves directing infrared radiation through the earlobe and analyzing the light that emerges on the opposite side. The received signal intensity is converted into an analog voltage by infrared sensors, which corresponds to glucose levels in underlying blood vessels. This analog signal is then processed using a microcontroller platform such as the Arduino Nano [3], which facilitates the interpretation and further processing of the data. This method integrates optical sensing with low-cost embedded hardware to support real-time monitoring in a non-invasive manner [14, 16].

The architecture of the non-invasive blood glucose monitoring system is illustrated in a modular block diagram, as shown in Fig. 1. Each component – from signal acquisition to data processing – is presented through labeled blocks (A to H). The system operates on a regulated 5 V supply and uses an ATmega328p microcontroller to manage both analog and digital inputs and outputs.

As illustrated in Fig. 1a, the sensing unit is positioned at the earlobe, where tissue is placed between a light-emitting diode (LED) and an infrared (IR) receiver. The absorption and scattering of IR light by biological tissue generates a signal, as depicted in Fig. 1b. The sensor's core configuration, combining the LED and IR sensor, is shown in Fig 1c. The analog signal resulting from light-tissue interaction is delivered to the microcontroller (Fig. 1e), using raw input from Fig. 1d. The microcontroller then converts the analog input into digital data, as represented in Fig. 1f. Before further processing, the digitised signal is passed through a two-stage filtering procedure (Fig. 1g). At the hardware level, a first-order RC low-pass filter with a cut-off frequency of approximately 10–15 Hz is used to attenuate high-frequency electronic noise and motion-related artefacts while preserving slow variations associated with physiological changes. At the software level, the microcontroller applies a simple moving-average filter over a sliding window of consecutive samples to suppress residual quantisation noise and improve the stability of the estimated glucose-related signal. Final data analysis and visualization occur on a connected PC system, as shown in Fig. 1h.

To validate the system, simulations were conducted using mathematical modeling software, as depicted in Fig. 2. The results confirmed that the 970 nm wavelength emitted by the LED corresponds well with the optical transmission window of biological tissue, allowing for effective signal detection. Planck's law was applied (1) to describe the spectral energy distribution of electromagnetic radiation under thermal equilibrium at temperature T, highlighting the quantitative relationship between frequency and radiation energy. This theoretical foundation supports the design principles used in the system [17].

$$E = h \cdot f \tag{1}$$

where h is a Planck's constant; f – the frequency of the LED emission.

By utilizing a device that emits optical radiation and captures data after the light passes through human tissue, we were able to assess the transmitted light intensity. As light propagates through biological material, it interacts with various structures, leading to phenomena such as absorption, scattering, reflection, and refraction. These effects arise from the heterogeneous nature of tissues, including cells and interstitial fluids, and can affect the uniformity of light distribution [4, 8].

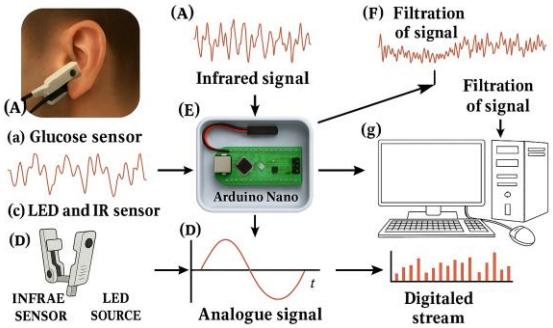

Fig. 1. Architecture of the non-invasive blood glucose monitoring system; (a) glucose sensor, (b) wavelength–radiation dependency, (c) LED and IR sensor, (d) analog signal, (e) microcontroller, (f) digital signal, (g) signal filtering, (h) personal computer

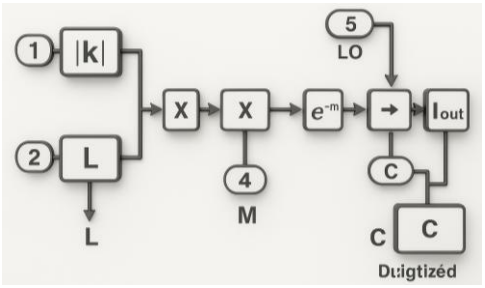

Fig. 2. Mathematical model for data calculation

To model this interaction, the Beer – Lambert law provides a useful framework, stating that light absorption is influenced by both the concentration of absorbing molecules and the distance the light travels through the medium. Although ideal conditions assume stable signal levels, real-world fluctuations in glucose concentration introduce slight variations in the detected output, reflecting physiological changes in tissue composition.

$$I_{out} = I_0 \cdot \exp\left(-k \cdot c \cdot L \cdot m\right) \tag{2}$$

where I_{out} is the intensity of the LED emitting a white light wave at a nominal voltage of 3.4 V; I_0 – the initial light intensity after transmission through the skin; L – the thickness of the measured biological layer (in this case, human skin); k – the absorption coefficient; c – the spectral range coefficient; m – the surface condition coefficient, used to eliminate noise and stabilize median values during the measurement period.

For practical operation, the optical measurement channel was calibrated against reference invasive glucose measurements. During the calibration procedure, pairs of data points were collected, consisting of the photodetector output voltage and the corresponding capillary blood glucose value obtained using a commercially available glucometer. On the basis of these paired measurements, a linear regression model was fitted to derive a calibration curve that relates the measured voltage to the estimated glucose concentration. The resulting calibration coefficients were then used in subsequent measurements to convert the non-invasive optical signal into glucose-equivalent units.

Following calibration, fluctuations in the detected signal – used to estimate blood glucose levels – are primarily influenced by voltage variations resulting from changes in light intensity after tissue absorption [7]. The internal layout of the infrared sensor is depicted in Fig. 3, which highlights the key hardware components integrated into the system.

The main circuit board includes:

- A microcontroller for signal processing and control
- Power management and protection integrated circuits (ICs)
- A USB interface to support wired data communication
- A Bluetooth module enabling wireless data transmission to external devices.

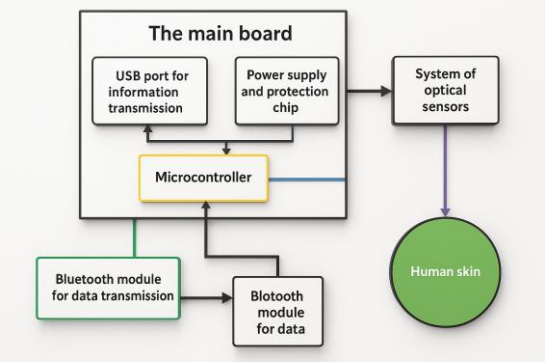

Fig. 3. Block diagram of the infrared sensor

The system operates through the integration of a microcontroller and an Optical Detection System (ODS). When the ODS comes into contact with the skin, it captures optical signals related to tissue properties and sends the resulting data to the microcontroller. This raw signal is then processed and converted into interpretable data, which can be transmitted via USB or Bluetooth for external evaluation and storage.

The core sensing mechanism utilizes a photoelectric sensor positioned alongside a near-infrared light source to perform spectrometric analysis of glucose concentration. As the earlobe is placed within the optical path, subtle light reflections from blood vessels are detected, while the test environment minimizes external light interference to ensure signal accuracy [11, 13].

A photodetector generates an electrical response upon receiving the reflected light, producing a voltage signal proportional to the optical interaction. This voltage is processed by the Arduino Nano, which applies signal processing algorithms to estimate glucose concentration based on non-invasive data interpretation techniques. The final glucose readings are displayed in real-time via an LCD interface. In order to assess whether the analogue-to-digital conversion stage provides sufficient resolution, the dynamic range of the photodetector output was evaluated. Under typical operating conditions of the developed measurement system, the analogue voltage at the sensor output varies approximately between 0.3 V and 2.5 V, depending on tissue optical properties and glucose concentration. The Arduino Nano microcontroller employs a 10-bit ADC with a reference voltage of 5 V, corresponding to a quantisation step of about 4.88 mV. Experimentally observed signal changes associated with variations in glucose concentration typically exceed 20–80 mV. Consequently, the quantisation step is significantly smaller than the useful signal variations, confirming that the ADC resolution and dynamic range are fully sufficient for reliable detection of glucose-related optical signal fluctuations. The complete circuit design for this NIR-based glucose monitoring system is illustrated in Fig. 4.

The system receives electrical power from a 9 V direct current (DC) source. To provide a consistent 5 V supply required by the LED and the Arduino Nano microcontroller, a voltage regulator (LM7805) is implemented. A current-limiting resistor is connected in series with the LED to maintain a steady current and ensure uniform light emission during operation [6]. This 5 V rail also serves as the main supply for the Arduino Nano and the optical sensor front-end, ensuring a consistent operating point for the entire measurement channel.

To stabilize the optical power of the LED and reduce temporal drift of the emitted radiation, the LED driving regime was configured to operate in a quasi-constant current mode using carefully selected current-limiting resistors. This ensured that the working point of the LED remained within a narrow operating range, minimizing variations in optical output caused by supply voltage fluctuations or thermal effects. Such stabilization is essential for improving the repeatability and accuracy of optical measurements in non-invasive glucose monitoring systems.

Experimental testing confirmed that the combination of the Arduino Nano and a conventional 5 mm photodiode delivers a sufficient level of accuracy for detecting signal variations [18] related to glucose measurement. This configuration proved reliable for collecting consistent data, as illustrated in Fig. 5.

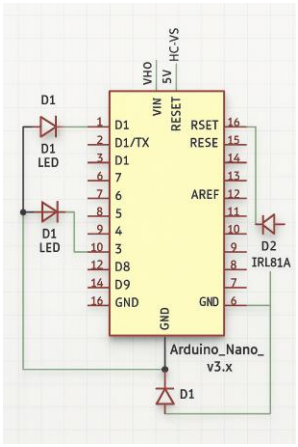

Fig. 4. Circuit diagram of the NIR-based blood glucose detector

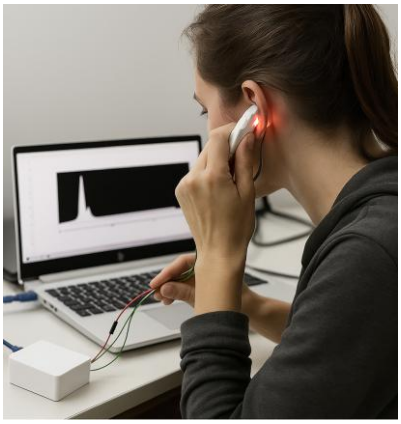

Fig. 5. Non-invasive device for measuring blood glucose levels

Fig. 5 demonstrates the fully assembled prototype of the developed non-invasive blood glucose monitoring system. The compact arrangement of optical and electronic components confirms the feasibility of integrating near-infrared sensing with low-cost embedded hardware into a portable device. The demonstrated structure supports stable optical coupling between the LED emitter and photodetector through biological tissue, enabling reliable acquisition of glucose-related signal variations under practical operating conditions.

2. Experiment and results

The development of non-invasive blood glucose monitoring technologies continues to advance, driven by innovations in optical sensing methods. These systems analyze physiological information by observing how light interacts with biological tissues across specific wavelengths. In this system, four key wavelengths – 500 nm, 970 nm, 1400 nm, and 1900 nm – were

selected based on their relevance to glucose absorption and tissue penetration efficiency.

Experimental testing confirmed that these wavelengths offer strong sensitivity to glucose concentration variations while minimizing interference from skin pigmentation, water content, and other tissue components. Among them, 970 nm demonstrated particularly favorable characteristics for signal stability and tissue compatibility, making it a strong candidate for continuous glucose tracking.

To implement this, the device uses light-emitting diodes (LEDs) and photodetectors aligned with these wavelengths. Each NIR channel is tuned to detect specific spectral responses, enabling more accurate monitoring through wavelength-specific signal differentiation. Fig. 6 illustrates the parallel configuration of LEDs and sensors across the selected spectrum. Fig. 7 displays the relationship between LED operating temperature and optical power output, showing how thermal conditions influence brightness and energy consumption. The red-spectrum LED used in the system delivers the highest initial optical power upon activation, supporting high-precision optical measurement. Fig. 8 visualizes the correlation between electrical current and LED brightness, underscoring the need for optimized power management in wearable sensing devices.

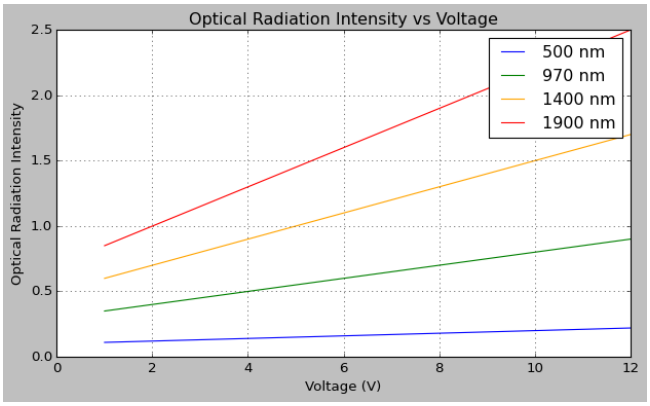

Fig. 6. Graphs plotted using sensors at wavelengths of 500, 970, 1400, and 1900 nm

Fig. 6 illustrates the relationship between optical radiation intensity and voltage for four different wavelengths: 500 nm, 970 nm, 1400 nm, and 1900 nm. As observed, all wavelengths demonstrate a linear increase in optical radiation intensity with rising voltage. However, the rate of increase varies significantly among them. The red line, representing 1900 nm, shows the steepest slope, indicating that this wavelength yields the highest optical output per unit of voltage. In contrast, the 500 nm wavelength displays the lowest intensity response, with minimal change across the voltage range. The intermediate wavelengths, 970 nm and 1400 nm, show moderate increases. This trend suggests that longer wavelengths are more responsive to voltage changes in terms of emitted radiation, which is critical when selecting optimal wavelengths for sensor calibration and power efficiency in non-invasive glucose monitoring systems.

Fig. 7 illustrates the relationship between LED emission power and correlated color temperature for various LED types, including red, green, blue, warm, and cold light sources. The graph shows that the red LED exhibits a steady linear decrease in relative power as the color temperature increases, indicating that red LEDs perform best at lower luminous temperatures. In contrast, blue and cold LEDs display a strong positive correlation, with power increasing sharply as temperature rises, suggesting higher efficiency at elevated temperatures. The green and warm LEDs demonstrate non-linear behavior, with noticeable dips and peaks across the temperature range, indicating fluctuating efficiency depending on the color temperature. These results highlight that LED spectral performance is highly dependent on temperature conditions, and proper wavelength selection must consider thermal stability when designing optical systems for biomedical or sensing applications.

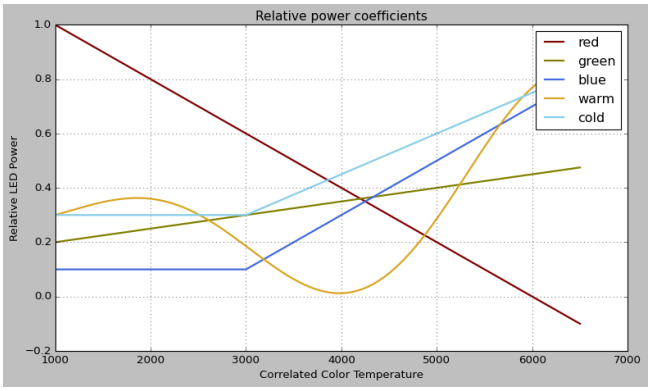

Fig. 7. Emission power as a function of LED luminous temperature

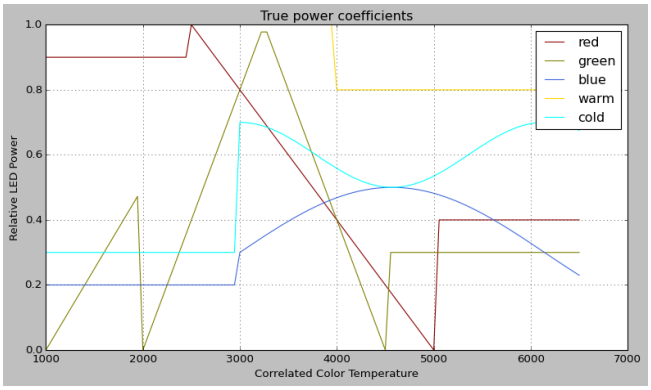

Fig. 8. Consumed electric power in relation to LED brightness

Fig. 8 illustrates the relationship between consumed electric power and LED brightness, represented through correlated color temperature across different LED types: red, green, blue, warm, and cold. The data reveal highly non-linear and discrete behavior in power consumption across temperature ranges, especially for the red and green LEDs, which show abrupt transitions in power levels. The red LED initially demonstrates high power output at lower temperatures but experiences a sharp drop beyond approximately 3000 K. The green LED similarly displays sudden increases and decreases, indicating unstable power response across the measured temperature spectrum. Blue and cold LEDs, in contrast, exhibit smoother, gradually rising curves, implying more stable and consistent brightness performance as temperature increases. The warm LED fluctuates but maintains moderate power usage across most of the range. These trends underscore the importance of color temperature in LED power management and highlight that certain LED types – particularly red and green – may require more precise thermal regulation for consistent performance in optical sensing applications.

Research indicates that red LEDs offer superior illumination efficiency and response time compared to other types of light-emitting diodes, making them particularly suitable for biomedical sensing applications. When integrated into an electrical circuit, red LEDs activate rapidly and deliver focused light across the skin surface due to their strong beam intensity and short response delay.

The inverse relationship between color temperature on the Kelvin scale and perceived brightness explains why lower-temperature light appears reddish, while higher intensities produce bluish or white tones. In measurement setups, both red and infrared LEDs are preferred due to their low power consumption and operational stability, which contribute to more consistent sensor outputs. A quantifiable relationship exists between the intensity of transmitted infrared radiation and the glucose concentration in a patient's blood, allowing for reliable optical monitoring.

When red and infrared light pass through human skin or tissue, their brightness diminishes due to scattering and internal distortion effects. This optical interference becomes more pronounced

at wavelengths above 1000 nm, where tissue absorption and dispersion increase. Nonetheless, red and infrared sensors are noted for their speed and accuracy in detecting light signals compared to other spectral sensors. Experimental results indicate that voltage readings from the sensor decrease as glucose concentration rises, confirming the system's ability to detect physiological changes based on optical signal attenuation.

Two independent studies [8, 17] confirm that the intensity of transmitted infrared light can serve as a reliable indicator of glucose concentration in biological tissues. Using spectrophotometric analysis, researchers are able to investigate not only the optical properties of tissue but also its structural composition, chemical constituents, and potential internal anomalies.

Spectrophotometry is particularly valuable in the context of medical diagnostics, where it enables precise assessment of tissue integrity and can help identify morphological changes associated with early-stage disease. This method is instrumental in detecting abnormalities in epithelial layers and in diagnosing early neoplastic developments, thereby improving the likelihood of successful intervention. Additionally, near-infrared (NIR) spectrophotometry supports the non-destructive visualization of tissue slices due to the penetrative and partially transparent nature of infrared light.

Despite its diagnostic potential, several limitations must be considered. Accurate measurements often require device recalibration to account for variables such as skin hydration, temperature, and individual tissue composition. These biological factors can affect light transmission, leading to signal variability. Furthermore, the relatively high cost of manufacturing and calibrating such non-invasive systems may hinder their widespread deployment and commercial scalability.

3. Conclusions

Experimental results support the use of an infrared photodiode as a core component in non-invasive blood glucose monitoring systems. This type of sensor offers significant advantages over traditional optical detectors, including high sensitivity and compact form factor, which enables reliable operation even in environments with minimal lighting. Unlike visible light sensors, infrared photodiodes are well-suited for low-illumination conditions, such as nighttime use or dim clinical settings.

Laboratory data showed a clear linear correlation between the sensor's output voltage and variations in glucose concentration, indicating a direct relationship between infrared signal strength and blood glucose levels. These findings further validate the potential of real-time optical glucose tracking using near-infrared light.

The main outcome of the present work is the optimisation of the optical sensing configuration for non-invasive glucose monitoring. By analysing several wavelength channels and the influence of LED operating conditions on the detected signal, a configuration providing a more stable and sensitive response to glucose-induced changes in tissue optical properties was identified. This optimisation at the hardware and optical levels forms a necessary basis for building more advanced non-invasive monitoring systems.

This optimisation resulted in an increased signal-to-noise ratio, reduced sensitivity to supply voltage fluctuations and thermal drift of the light sources, and improved repeatability of optical measurements under varying physiological and environmental conditions. These improvements directly translate into higher stability of glucose estimation and more reliable operation of compact wearable monitoring devices.

The study reinforces the role of near-infrared (NIR) spectroscopy as a promising non-invasive diagnostic method. In future research, this optical platform can be paired with Internet of Things (IoT) technologies and machine-learning-based data analysis to enable remote health monitoring, more accurate prediction of glucose trends and timely medical intervention. However, such AI- and IoT-oriented extensions are beyond the scope of this paper and will be addressed in subsequent work.

Enhancing the performance of data processing algorithms will be critical to improving the speed and accuracy of diagnosis. Integrating NIR-based sensor systems with other healthcare technologies – such as mobile health applications, artificial intelligence tools, and electronic health records – could pave the way for a comprehensive diabetes management ecosystem. This holistic approach would aid in early detection, promote better patient compliance, and ultimately improve the quality of life for individuals living with diabetes by helping to prevent complications.

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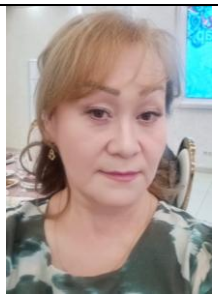

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