



Original Research

Effectiveness of Non-Invasive Sensor-Based Tools for Blood Glucose Detection

Yudha Anggit Jiwantoro^{1*}, Ni Putu Dian Ayu Anggraeni², Ninik Nurhidayah³
I Gusti Ayu Sri Puja Warnis Wijayanti⁴, Cembun Cembun⁵

^{1,2,4,5} Department of Nursing Poltekkes Kemenkes Mataram, Indonesia

³ Department of Occupational Therapy, Poltekkes Kemenkes Surakarta, Indonesia

ABSTRACT

Background: Monitoring blood glucose levels is one of the main pillars of diabetes management to prevent complications and reduce the risk of morbidity and mortality. Today's blood glucose monitoring is a non-invasive method that offers speed, accuracy, and painless convenience. Referring to this need, this study aims to demonstrate the effectiveness of non-invasive sensor-based detection devices in checking blood glucose levels in order to provide a more comfortable and efficient alternative for diabetes patients.

Methods: This study developed a non-invasive glucometer using the latest and smaller version of Arduino Uno and tested it on 20 samples, consisting of 10 diabetes mellitus patients and 10 with normal blood glucose. The test was carried out by comparing the measurement results from the non-invasive device and the standard GCU Easy Touch 3-in-1 device to determine the accuracy of the device. The tool-testing method uses sensitivity, specificity, and accuracy.

Results: This non-invasive measuring tool is more effective when used to measure patients with diabetes mellitus. This device shows an error rate of 9.21%, a sensitivity of 80%, and a specificity of 50%. Meanwhile, the overall measurement accuracy, calculated at 83.3%, reinforces the tool's effectiveness in providing reliable results.

Conclusion: This device has the potential to be a convenient and painless method of blood glucose monitoring for diabetic patients. However, further development is needed to improve the development of machine learning-based algorithms to process sensor data so that tools can identify unique patterns from each individual and provide more accurate results.

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CONTACT

Yudha Anggit Jiwantoro



yudhaanggit148@gmail.com

Department of Nursing, Poltekkes Kemenkes Mataram. Dasan Cermen, Sandubaya, Mataram City, West Nusa Tenggara 83232 Indonesia.

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INTRODUCTION

The Indonesian Endocrinology Association defines hyperglycemia as a medical condition in which blood glucose levels increase beyond the normal standard value, which is a characteristic of several diseases, especially diabetes mellitus, in addition to

various other conditions (PERKENI, 2021). Diabetes mellitus is a metabolic disorder that increases the percentage of glucose in the blood, caused by dysfunction of production (type 1) or effectiveness (type 2) of insulin in the body. According to the International Diabetes Federation (IDF) in 2021, worldwide there were 530 million people with diabetes, causing more than 6.7 million deaths (IDF, 2021). The number of diagnosed diabetics is growing rapidly and continuously, which draws attention to the demand for developing better functional blood glucose monitoring techniques (Punthakee et al., 2018).

Blood glucose monitoring is a critical component of diabetes management, yet current invasive methods pose challenges such as discomfort and reduced patient compliance, highlighting the need for non-invasive alternatives (Wu et al., 2023). Regular glucose monitoring is an essential part of effective diabetes mellitus management (Sanai et al., 2023). In addition, glucose monitoring and glycaemic control are associated with the incidence of complications, as well as preventing morbidity and mortality related to hypoglycemia and hyperglycemia. However, the monitoring methods currently available are all invasive, providing an uncomfortable experience so that people with diabetes are reluctant to undergo examination (Hadar et al., 2019).

Invasive technology is considered painful and uncomfortable because blood is drawn repeatedly every day. The ideal method for monitoring diabetes is one that can obtain glucose concentration levels with fast, accurate, and painless measurements. The most accurate way to diagnose diabetes is to monitor fluctuations in blood glucose concentrations for a certain period of time after eating (Stefanovski et al., 2020). Currently, the most practical approaches to blood glucose monitoring are invasive monitoring methods, which require a finger prick and blood test. So patients inevitably have to endure the pain of skin piercing and even risk infection (Houlden, 2018).

The discomfort and risks associated with invasive blood glucose monitoring highlight the urgent need for alternative methods that prioritize patient comfort and efficiency. This development of a photodiode sensor-based non-invasive blood glucose device has become a highly relevant solution, offering significant benefits for both patients and healthcare providers. This photodiode sensor-based non-invasive blood glucose device is very relevant in supporting the nursing process, especially in monitoring the health of patients with diabetes or who require regular glucose level monitoring (Chandrasekaran & Swamy, 2019). For nurses, a non-invasive blood glucose device is a more convenient, faster, and less painful method, allowing them to monitor blood sugar levels without injuring or taking blood samples from patients.

This reduces patient discomfort and saves nurses time in monitoring procedures because results can be obtained in seconds and immediately displayed on the LCD screen (Sangeetha & Mahesh, 2015). This research will develop a tool to find out the blood glucose results in the blood without having to hurt the patient (non-invasive) utilizing Arduino Uno, a microcontroller-based development board that is very popular in various electronic applications, including developing blood glucose detection devices. The Arduino Uno acts as a central controller that manages the entire system and reads sensor signals to process and display detection results. Photodiodes can be controlled through microcontroller components such as Arduino Uno R3 (Pratomo & Sugiyama, 2019).

Therefore, the research question is: How do the results of non-invasive blood glucose measurements compare with conventional invasive methods? This research aims to test the sensitivity, specificity, and accuracy of the tool.

MATERIALS AND METHODS

This research began in February-October 2024 by developing tools for a non-invasive glucometer and continued with testing. This research has conducted an ethical test with the number DP.04.03/F.XLVIII.14/568/2024. The development began by replacing the Arduino Uno series with a newer version and smaller size. Improvements to the reset connector and power pins on the Arduino Uno R3 will improve the stability and reliability of the development board when used in long-term applications. This research includes development research, commonly known as research and development (R&D) (Sugiyono, 2017).

Materials

Photodiode – A light sensor that detects infrared light that penetrates the patient's finger.
Arduino Uno R3 – Microcontroller used to control the photodiode and process measurement data.

Infrared Lamp—A light source projects a beam through the patient's fingers.

Digital LCD—Screen that displays the patient's blood glucose level results based on processed data.

Arduino Uno Nano Every—This is the latest version of the Arduino Uno Nano, which is used as the main chip in the system.

ATMega 4809—Chip embedded in the Arduino Uno Nano Every.

Drone Battery (four cells) – A battery with four cells is the primary power source.

DC Cable – Cable used to connect batteries in parallel.

AA Battery Connector

Principle of the Device

This tool projects infrared light through the patient's finger between the lamp and the photodiode. Infrared technology detects blood glucose levels by emitting infrared light onto the skin, which body tissue then absorbs and reflects. Optical sensors, such as photodiodes, measure the intensity of reflected light and convert it into an electrical signal. This signal is then converted into digital data via an analogue-to-digital converter (ADC) and analyzed using a calibration algorithm that correlates changes in light intensity with blood glucose levels (Asada et al., 2003).

Some light will be absorbed by tissue and blood, while the rest is transmitted to the photodiode. The photodiode then converts the received light intensity into an electrical signal. Arduino Uno R3 processes this signal to calculate blood glucose levels based on the intensity of light penetrating the finger (Huang et al., 2018). The final results are displayed on a digital LCD so patients can read blood sugar levels noninvasively without taking a blood sample (Sawaryn et al., 2021).

To use this tool, the patient inserts a finger into the examination hole so that the finger is between the infrared lamp and the photodiode. The researcher then presses the "Start" button to begin the measurement process. Within 15-30 seconds, the tool will project infrared light through the finger while the photodiode detects the remaining light. Blood glucose level results will appear automatically on the LCD screen, ready to be read and recorded.

Methods

Stage testing tool to determine the level of accuracy of the tool is done by comparing the measurement results of non-invasive measuring tools and standard

measuring tools as a comparison, namely GCU Easy Touch 3 in 1 (mg/dl). In testing this tool, 20 samples were used, consisting of 10 people with diabetes mellitus and 10 with normal blood glucose. For this research, a limited sample size was appropriate to explore the feasibility of a non-invasive glucose monitoring device. Despite the high prevalence of diabetes mellitus, the aim is not generalisation but to validate the technology's initial performance in a controlled environment. A larger sample size would be recommended for subsequent stages involving population-level validation.

This is done to determine the difference in tool accuracy when used on people with diabetes mellitus and people with blood glucose. Inclusion criteria: adults aged 30–70 years to ensure measurements could be performed in a more physiologically homogeneous population. Patients with diabetes who have had stable blood glucose levels in the last 2 weeks. Exclusion criteria were pregnant or breastfeeding women, because metabolic changes during pregnancy can affect blood glucose levels. Data analysis using univariate, specification, sensitivity, and accuracy.

The results of diagnosing samples with diabetes mellitus were obtained from the Banyuanyar Health Centre, Surakarta. The instrument's accuracy is obtained by using the percentage error of the non-measuring instrument *Invasive* from the following equation:

$$\%Error = \frac{GCU \text{ blood sugar data} - \text{Non} - \text{Invasive sugar data}}{GCU \text{ blood sugar data}} \times 100\%$$

RESULTS

The following is a sample distribution based on research respondent characteristics.

Table 1. Sample Distribution Based on Research Respondent Characteristics

| Characteristics | Total | |
|---------------------------|-------------|----------------|
| | DM patients | Normal Patient |
| Gender | | |
| Male | 5 | 4 |
| Female | 5 | 6 |
| Age (years old) | | |
| 30-40 | 0 | 2 |
| 41-50 | 3 | 3 |
| 51-60 | 6 | 4 |
| > 60 | 2 | 0 |
| Level of education | | |
| Elementary School | 1 | 0 |
| Middle School | 2 | 0 |
| High School | 8 | 6 |
| Bachelor's Degree | 1 | 2 |

The results of the univariate analysis show that there are more female respondents than male respondents, with 11 (55%) individuals identifying as female. Most respondents are aged 51-60, totalling 10 (50%) individuals. The highest level of education among respondents is at the Senior High School (SMA) level, with 14 (70%) individuals.

Table 2. Distribution of Respondents' Glucose Levels with GCU Easy Touch and Non-Invasive tools in the Banyuwangi Health Center Area, Surakarta City, Central Java

| DM patients | | | Normal Patient | | |
|----------------|--------------|-------------|----------------|--------------|--------------|
| GCU | Non invasive | %error | GCU | Non invasive | %error |
| 300 | 293 | 2.33 | 122 | 150 | 22.90 |
| 360 | 351 | 2.50 | 102 | 97 | 4.90 |
| 300 | 260 | 13.33 | 95 | 127 | 22.60 |
| 296 | 280 | 5.41 | 105 | 135 | 28.50 |
| 125 | 146 | 16.80 | 92 | 100 | 8.70 |
| 295 | 300 | 1.69 | 118 | 130 | 10.70 |
| 245 | 224 | 8.57 | 96 | 130 | 35.40 |
| 135 | 160 | 18.00 | 88 | 130 | 47.70 |
| 267 | 280 | 4.87 | 107 | 140 | 30.80 |
| 129 | 153 | 18.60 | 94 | 115 | 22.34 |
| Average | | 9.21 | Average | | 23.45 |

Table 2 shows that the samples were divided into two types: ten people with diabetes mellitus and ten with normal high blood sugar levels. The percentage error of non-invasive measuring instruments in samples with diabetes mellitus was 9.21%, while in samples with normal blood sugar levels, it was 23.45%. This shows that this non-invasive measuring instrument is more effective when used to measure patients with diabetes mellitus.

Table 3. Results of sensitivity, specificity, and measurement accuracy of Non-Invasive tools

| | Sensitivity | Specificity | Accuracy |
|--------------|-------------|-------------|----------|
| Non-invasive | 80% | 50% | 83,3% |
| GCU | 90% | 80% | 85% |

Table 3 shows that the tool is good at detecting favorable conditions (sensitivity) but has shortcomings in detecting adverse conditions (specificity). In comparison, the standard tool demonstrated higher performance with 90% sensitivity, 80% specificity, and 85% accuracy. The non-invasive tool has quite good sensitivity performance because its sensitivity reaches 80%, meaning it can correctly detect 80 out of 100 individuals with favorable conditions. Although non-invasive tools are still below the standard of 90% sensitivity, these results are promising, especially in the early stages of development.

DISCUSSION

The device's testing results demonstrate an accuracy rate of 83.3%, reflecting its reasonably good capability in measuring blood glucose levels. However, the tool tends to produce false positives, where individuals without the condition are misclassified as positive (Melheim et al., 2018; Srichan et al., 2022). This limitation is attributed to its low specificity in distinguishing actual negative cases. Compared to standard devices, non-invasive tools require further refinement, particularly in enhancing specificity, to minimize false favourable rates and improve diagnostic reliability (Suyono & Hambali, 2020).

The sensitivity, specificity, and accuracy of GCU and non-invasive were compared to assess their diagnostic reliability. Sensitivity, representing the ability to

correctly identify true positives, was higher in GCU due to its invasive nature, which allows direct blood analysis (Pratomo & Sugiyama, 2019). In contrast, GUINO exhibited lower sensitivity, attributed to its reliance on indirect measurement techniques like photometry. Specificity, or the ability to correctly identify true negatives, was slightly higher in GUINO, as the non-invasive approach avoids potential contamination in invasive samples (Kurniawan & Utomo, 2018).

Non-invasive tools have shortcomings in detecting adverse conditions, so the possibility of producing false positives is higher. The standard tool's specificity is 80%, meaning it correctly detects 80 out of 100 normal individuals. However, non-invasive tools require further improvement in this aspect.

The non-invasive method demonstrated an accuracy of 83.3%, meaning it provided correct results on 83 out of 100 measurements. Meanwhile, the standard tool (GCU) has an accuracy of 85%, which means it gives correct results in 85 out of 100 measurements. The difference in accuracy between these two tools is only 1.7%. This shows that although non-invasive tools are still in the development stage, their performance is already approaching standard tools that are widely used.

The development of a non-invasive tool for measuring blood sugar levels aims to provide a more comfortable alternative to invasive methods that require sample-taking blood. Based on the accuracy of non-invasive devices, they are often compared with invasive standards to evaluate their effectiveness (Kurniawan & Utomo, 2018). This woundless blood sugar measurement utilizes photodiode technology and microcontrollers, such as Arduino, which can detect changes in glucose concentration through photometry or spectroscopy techniques.

These advancements align with the findings of Chung et al., (2012) who emphasized that spectroscopy-based glucose monitoring has the potential to offer real-time, pain-free solutions for diabetes management. This technology can improve the quality of life of diabetes patients because it reduces the risk of infection and discomfort due to repeated punctures on the skin (Pratomo & Sugiyama, 2019). In this study, testing was carried out on two sample groups: the group with diabetes mellitus and the group with normal blood sugar levels.

The test results showed that the non-invasive device error rate was lower in the diabetes mellitus group (9.21%) than in the group with regular blood sugar (23.45%). These findings indicate that non-invasive devices have higher accuracy rates in individuals with high glucose levels. This is likely caused by a more striking difference in light concentration in the infrared spectrum at higher glucose levels, according to infrared spectroscopy theory, which states that glucose molecules show specific light absorption characteristics at infrared wavelengths (Melheim et al., 2018).

In contrast, the higher error rate in the group with normal blood sugar levels suggests that the device requires further refinement to improve accuracy at lower sugar levels. This may be related to the sensor's sensitivity to small changes in light absorption, as explained in optoelectronic theory, which states that small fluctuations in glucose concentration can significantly affect the detection signal (Brown & Lee, 2021). Thus, developing these devices should focus on increasing sensitivity to minimize errors in groups with normal blood sugar levels.

In theory, this non-invasive photodiode-based technology is capable of detecting changes in light absorbance. Which is reflected through the skin tissue. Light from the photodiode will pass through the tissue and be absorbed by glucose in the blood, resulting in different detected light intensities according to glucose levels (Kurniawan &

Utomo, 2018). However, variations in skin thickness, temperature, and humidity can affect the accuracy of the results, especially in patients with more stable normal blood sugar levels. Therefore, it is important for researchers to consider these physiological factors and adjustment algorithms to minimize variability in results.

According to the accuracy test findings, the tool's average accuracy percentage was 76.55% in the group with regular blood sugar and 90.79% in the group with diabetes mellitus. This device may be a valuable substitute for daily blood sugar monitoring for patients with elevated glucose levels, as it has a greater accuracy rate in diabetic patients. This device still needs development to improve its reliability across a wide range of glucose levels. However, these results already show great potential in reducing dependence on invasive methods in the future, especially for patients who require long-term blood sugar monitoring (Bergloff et al., 2019).

For healthcare providers, such as nurses, this tool significantly improves daily practice. Traditionally, nurses have had to perform multiple invasive procedures for blood glucose monitoring, which can be uncomfortable and time-consuming for patients. With a non-invasive device, nurses can quickly and efficiently assess glucose levels without causing pain or requiring blood samples.

This efficiency enhances patient comfort and allows nurses to monitor patients more frequently, leading to better management of blood glucose levels and reducing the risk of complications from diabetes (Srichan et al., 2022). Moreover, the ability to obtain results rapidly—often in less than a minute—also saves valuable time for nurses, enabling them to allocate their efforts to other critical tasks in patient care. As the field of non-invasive glucose measurement continues to evolve, several improvements can be made to enhance the accuracy and functionality of these devices. One of the main challenges lies in improving the device's accuracy for patients with normal blood sugar levels.

The higher error rate (23.45%) in this group, while not life-threatening, can lead to unnecessary discomfort for patients due to repeated testing. This underscores the need for further refinement to ensure reliable readings across a broader spectrum of glucose concentrations (Lin et al., 2018). Future developments could focus on adjusting the algorithms used to process the sensor data, considering various physiological factors, such as skin thickness, temperature, and hydration levels, which can significantly affect light absorption and scattering. Researchers could also explore the integration of multiple sensors or advanced spectroscopy techniques to improve detection precision at lower glucose levels. Additionally, incorporating machine learning models that can continuously learn from patient data may help optimize the device's performance over time, improving its accuracy and reliability (MDPI, 2023).

Furthermore, the potential of non-invasive glucose monitoring devices to align with patient-centered care is significant. By increasing the device's accessibility, especially in remote or under-resourced healthcare settings, we can provide significant benefits. If made more affordable and portable, this technology could offer a viable solution for routine glucose monitoring in diverse clinical environments, from primary care to home health settings. By reducing reliance on invasive techniques, this non-invasive glucose measurement tool aligns with the growing trend toward patient-centered care, prioritizing comfort, convenience, and long-term health management.

The research involved a small number of respondents, so the results still need to be generalized to a wider population. Future testing needs to involve more participants with various characteristics to increase the validity and reliability of the findings. The

error rate was higher in the group with normal glucose levels (23.45%), indicating the need to increase sensor sensitivity to small changes in glucose levels. Skin thickness, temperature, and humidity variations affect the tool's accuracy, especially in individuals with stable sugar levels. The tool's performance depends on the data processing algorithm and the accuracy of photodiode technology, which still requires further development.

CONCLUSION

Based on the obtained accuracy rates—90.79% for diabetic samples and an overall accuracy of 83.3%—this non-invasive blood sugar measuring device demonstrates a commendable level of reliability. While a minor error rate exists, it remains within an acceptable range for clinical and practical use, particularly in routine blood glucose monitoring. Furthermore, the device's ability to consistently provide accurate results suggests it is suitable for application in various healthcare settings.

However, development is needed to increase sensor sensitivity at normal sugar levels, improve data processing algorithms, and address the influence of physiological variations such as skin thickness, temperature, and humidity. Further testing with diverse respondents and machine learning-based algorithms may improve this tool's reliability and accuracy in various clinical conditions.

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