International Journal on Smart Material and Mechatronics
IJSMM Vol. 13 No.1 2026 DOI. 10.20342/IJSMM.13.1.404
p-ISSN: 2356-5314
e-ISSN: 2460-075X

Development of a Non-Invasive Glucometer Prototype Based on Infrared Transmittance Method

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Abstract*—Diabetes mellitus is a chronic disease requiring routine blood glucose monitoring, yet conventional invasive methods are painful and infection-prone. This study developed a non-invasive blood glucose measurement prototype based on the light transmittance method using a red LED (620–640 nm) and photodiode. The research employed the ADDIE model (Analysis, Design, Development, Implementation, Evaluation), with main system components consisting of the red LED, photodiode, ADS1115 ADC module, and Raspberry Pi 3B, with results displayed on a Waveshare LCD and printed via a thermal printer. The absorption value is converted into an estimated blood glucose level using a linear regression equation calibrated against 10 reference points from a GCU Easy Touch 3-in-1 invasive glucometer, yielding an R^2 of 0.9017 and a calibration accuracy of 93.76%. In-vivo testing on 25 subjects compared the prototype's results against the invasive glucometer as the gold standard. The results showed an average measurement difference of 42.04 mg/dL, an average error of 44.29%, and an average accuracy of 55.71%, with a systematic overestimation bias observed in 23 of 25 subjects (92%). Bland-Altman analysis yielded a mean bias of −40.7764 mg/dL and indicated the presence of proportional bias. Based on ISO 15197:2013, only 5 of 25 measurements (20%) fell within the required tolerance range. These findings indicate that the prototype was successfully developed and is capable of performing non-invasive measurements. However, its accuracy still requires improvement, particularly in wavelength selection and calibration data quantity, before it can be considered an alternative to conventional invasive glucometers.

Index Terms—Non-invasive glucometer, red LED, photodiode, light absorption, Bland-Altman, proportional bias.

I. INTRODUCTION

Blood glucose or glucose is a group of simple carbohydrate compounds or monosaccharides that function as an energy source for body cells. Normal blood glucose levels range from 70 mg/dL to 130 mg/dL. If blood glucose levels fall below 70 mg/dL, hypoglycemia occurs, while levels above 200 mg/dL indicate hyperglycemia, commonly known as diabetes [1]. Diabetes is a chronic disease characterized by elevated blood glucose levels. Based on data from the International Diabetes Federation (IDF) Atlas 2017, Indonesia ranks sixth globally in diabetes prevalence. Furthermore, the Indonesian Basic Health Research (Riskesdas) showed a significant increase in diabetes prevalence from 6.9% in 2013 to 8.5% in 2018 [2].

Currently, no definitive cure for diabetes has been found. Monitoring and controlling blood glucose levels remain the only solution to optimize the lifestyle of diabetes patients and prevent complications [3]. Various blood glucose monitoring techniques have been developed, including invasive (IN), minimally invasive (MI), and non-invasive (NI) methods. The majority of glucometers in Indonesia are invasive, requiring blood sample collection (50 µL) via finger-prick, which is painful and carries infection risks [4], [5].

Invasive methods have numerous disadvantages, including patient discomfort, fear of needles, infection risks, skin tissue damage, and the generation of medical waste [6]. Based on these limitations, a non-invasive glucometer is needed. Non-invasive methods can be categorized into optical, transdermal, and electrochemical approaches [7]. For routine glucose monitoring, both transdermal and electrochemical methods are not recommended as they require regular calibration [8]. Optical-based non-invasive methods offer high accuracy in predicting and determining blood glucose levels [3], [9].

Optically, blood glucose monitoring can be performed using near-infrared spectroscopy (NIRS), mid-infrared spectroscopy (MIRS), far-infrared spectroscopy (FIRS), thermal emission, photoacoustic, polarimetry, Raman, and occlusion spectroscopy. Among these methods, NIRS has the greatest potential because it requires simple sample preparation and has better optical penetration compared to other methods [10]. The disadvantage of NIRS is that results cannot be used directly, requiring calibration and validation processes.

There are two basic measurement modes in the NIR method: transmittance and reflectance. Transmittance mode is generally used for thinner skin layers such as fingertips and earlobes, while reflectance mode is more suitable for forearms and cheeks as it requires greater wavelength and energy to penetrate deeper into tissue [11].

Previous research by Suryono and Hambali (2020) designed a non-invasive blood glucose meter using an Arduino Uno microcontroller, utilizing infrared sensors and photodiodes [12]. Zhang and Li (2023) developed a real-time non-invasive blood glucose monitoring device using near-infrared spectroscopy, achieving 89% accuracy [13]. Pionis et al. (2024) designed a non-invasive blood glucose meter based on ESP 8266 integrated with Thingspeak, with error rates ranging from 1.55% to 3.23% [14]. Dede Sutarya (2021) developed a non-invasive monitoring system using the GY-MAX 30100 sensor, achieving an accuracy of 97.13% [15].

Based on this background, this research designs a non-invasive blood glucose measurement device based on a Single-Board Computer (SBC), namely Raspberry Pi 3B, as the main processing unit. The device operates on the optical method with transmittance mode, using a red LED (620–640 nm) and photodiode placed on opposite sides of the finger. The choice of red LED was made for three considerations: first, the 620–640 nm range lies within the optical window of biological tissue (600–1300 nm); second, silicon-based photodiodes have

p-ISSN: 2356-5314
e-ISSN: 2460-075X

spectral response in the 400–1000 nm range; third, red LEDs and silicon photodiodes are economical and readily available components.

It should be emphasized that glucose does not have a strong absorption band in the visible light range, as significant glucose absorption occurs in the near-infrared region. Therefore, this research is positioned as an exploration to test the extent to which a visible red light approach can estimate blood glucose levels, along with its inherent limitations. The consequences of this wavelength choice on measurement accuracy are discussed further in the results section.

II. METHODOLOGY

A. Research Design

This research employs the ADDIE model (Analysis, Design, Development, Implementation, Evaluation). The system design uses a red LED (620–640 nm) as the light source and a photodiode as the detector, with an ADS1115 16-bit ADC module for analog-to-digital conversion, and a Raspberry Pi 3B as the main processor. Results are displayed on a Waveshare 5-inch LCD touchscreen and printed via a thermal printer.

B. System Block Diagram

The system block diagram is shown in Fig. 1. The measurement process begins with an automatic blank calibration for 5 seconds to obtain reference voltage (V_blank). The subject then places their index finger between the LED and photodiode for 30 seconds of sample reading (V_sample). The absorption value is calculated using the Lambert-Beer law: $A = \log_{10}(V\_blank/V\_sample)$. This absorption value is then converted to estimated blood glucose level using a linear regression equation obtained from sensor characterization against 10 reference data points from a GCU Easy Touch 3-in-1 invasive glucometer.

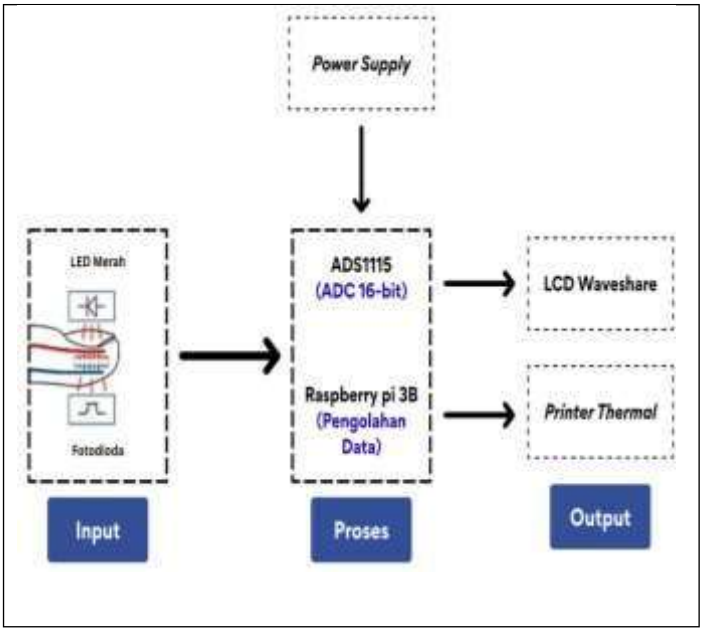

Fig. 1 System Block Diagram of the Non-Invasive Glucometer Prototype

C. Data Collection

Data collection was conducted through in-vivo testing on 25 volunteers aged 20–24 years who had signed informed consent forms. Each subject underwent one measurement using the non-invasive prototype, followed by one measurement using the invasive glucometer (GCU Easy Touch 3-in-1) as the gold standard.

D. Data Analysis

Data were analyzed using Microsoft Excel 365 and Origin 2026b. Statistical analyses included:

- Mean measurement calculation
- Measurement difference
- Relative error percentage
- Accuracy percentage
- Linear regression analysis
- Bland-Altman analysis
- Assessment against ISO 15197:2013 standards

III. RESULTS AND DISCUSSION

A. Sensor Characterization

The sensor characterization was performed in-vivo on finger tissue, comparing the voltage signals read by the photodiode. The sensor was configured vertically, with the red LED placed on the upper surface of the index finger and the photodiode positioned directly opposite on the lower surface.

Characterization results from 10 measurement points are presented in Table I. The average measurement difference was 5.95 mg/dL, with an average relative error of 6.24% and an accuracy of 93.76%. Linear regression analysis (Fig. 2) yielded the equation:

$$Y = -186.63485 + 294.91268X$$

with an R^2 value of 0.9017, indicating that 90.17% of blood glucose variation can be explained by changes in absorption values.

TABLE I
SENSOR CHARACTERIZATION RESULTS

No	Absorption	Comm. (mg/dL)	Prot. (mg/dL)	Diff. (mg/dL)	Error (%)	Accur. (%)
1	1.10763	146	140.02	5.98	4.1	95.9
2	1.04473	129	121.47	7.53	5.84	94.16
3	1.02737	117	116.35	0.65	0.56	99.44
4	0.99241	94	106.04	12.04	12.81	87.19
5	0.97725	91	101.57	10.57	11.61	88.39
6	0.95208	87	94.15	7.15	8.21	91.79
7	0.94530	97	92.15	4.85	5	95
8	0.91621	84	83.57	0.43	0.52	99.48
9	0.88734	78	75.05	2.95	3.78	96.22
10	0.85882	74	66.64	7.36	9.94	90.06
	Average			**5.95**	**6.24**	**93.76**

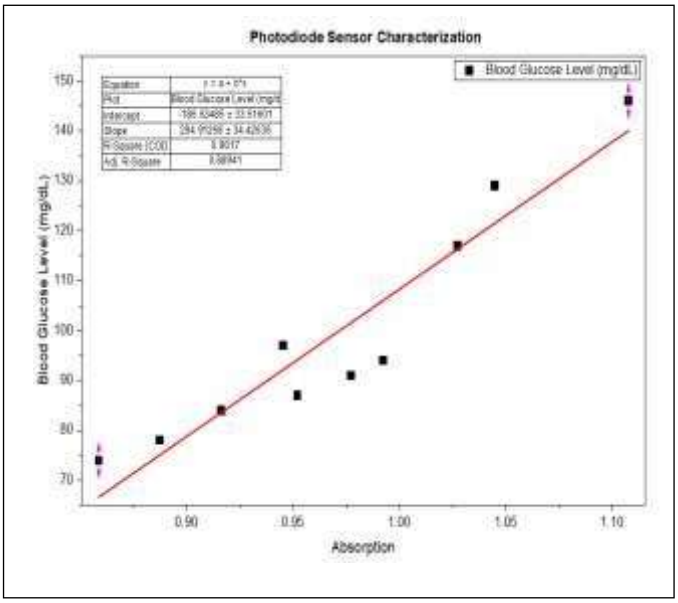

Fig. 2 Linear Regression Graph of Sensor Characterization

B. System Integration and User Interface

The complete system integration includes power supply distribution via a step-down converter to the Raspberry Pi 3B, Waveshare 5-inch LCD, and thermal printer. The user interface was developed using Python programming language with multiple libraries to create an interactive display showing:

1. Home screen with device name and play button
2. User profile input (name, age, gender, measurement condition)
3. Measurement results display with blood glucose level and classification
4. Printing status and completion confirmation

C. In-Vivo Testing on 25 Subjects

The prototype was tested on 25 subjects aged 20–24 years. Table II presents the complete results including measurement differences, error percentages, and accuracy for each subject.

TABLE II
PROTOTYPE TESTING RESULTS AGAINST COMMERCIAL GLUCOMETER

No	Age	Sex	Absorp.	Comm.	Prot.	Diff.	Error (%)	Accur. (%)
1	20	F	0.97386	69	100.57	31.57	45.75	54.25
2	20	F	1.04126	98	120.45	22.45	22.91	77.09
3	21	F	0.91315	97	82.66	14.34	14.78	85.22
4	21	F	1.00100	85	108.57	23.57	27.73	72.27
5	21	F	1.22858	99	175.69	76.69	77.46	22.54
6	21	F	1.28365	129	191.93	62.93	48.78	51.22
7	21	M	0.98498	69	103.85	34.85	50.51	49.49
8	21	M	1.11896	107	143.36	36.36	33.98	66.02
9	21	M	1.08770	116	134.14	18.14	15.64	84.36
10	22	F	1.20399	94	168.44	74.44	79.19	20.81
11	22	F	1.08593	77	133.62	56.62	73.53	26.47
12	22	F	1.25059	87	182.18	95.18	109.4	-9.4
13	22	F	1.21807	124	172.59	48.59	39.19	60.81
14	22	F	0.93100	74	87.93	13.93	18.82	81.18

No	Age	Sex	Absorp.	Comm.	Prot.	Diff.	Error (%)	Accur. (%)
15	22	F	1.11786	103	143.04	40.04	38.87	61.13
16	22	F	1.11382	104	141.84	37.84	36.38	63.62
17	22	F	0.99509	78	106.83	28.83	36.96	63.04
18	22	M	1.11206	89	141.33	52.33	58.8	41.2
19	22	M	1.26568	86	186.63	100.63	117.01	-17.01
20	22	M	1.04264	111	120.85	9.85	8.87	91.13
21	22	M	1.02684	116	116.19	0.19	0.16	99.84
22	23	F	1.08719	110	133.99	23.99	21.81	78.19
23	23	M	1.41305	125	230.09	105.09	84.07	15.93
24	23	M	0.97710	103	101.53	1.47	1.43	98.57
25	24	F	1.08082	91	132.11	41.11	45.18	54.82
			Average			**42.04**	**44.29**	**55.71**

(M: Male, F: Female)

The average measurement difference was 42.04 mg/dL, with an average relative error of 44.29% and an accuracy of 55.71%. A systematic overestimation bias was observed in 23 out of 25 subjects (92%), where the prototype read higher values than the commercial glucometer. Only 2 subjects showed underestimation (subjects 3 and 24).

D. Regression Analysis

Figure 3 shows the linear regression between absorption values and commercial glucometer readings. The regression yielded:

Intercept = 20.64012 ± 28.06925; Slope = 69.8605 ± 25.3148; $R^2 = 0.24875$

This indicates that only 24.88% of blood glucose variation can be explained by absorption changes at 620–640 nm, with 75.12% influenced by other factors. The large scatter in data demonstrates that absorption at this wavelength is insufficient to uniquely determine blood glucose levels.

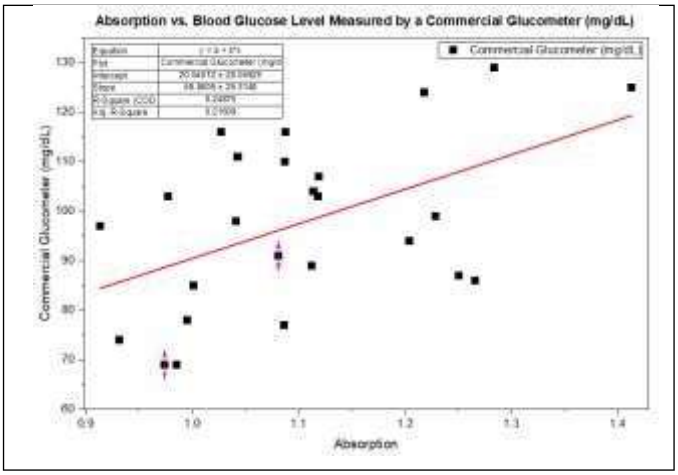

Fig. 3 Linear Regression of Absorption vs Commercial Glucometer

Figure 4 presents the regression between prototype and commercial glucometer readings, yielding:

Intercept = 35.88814 ± 37.70901; Slope = 1.05006 ± 0.38052; $R^2 = 0.24874$

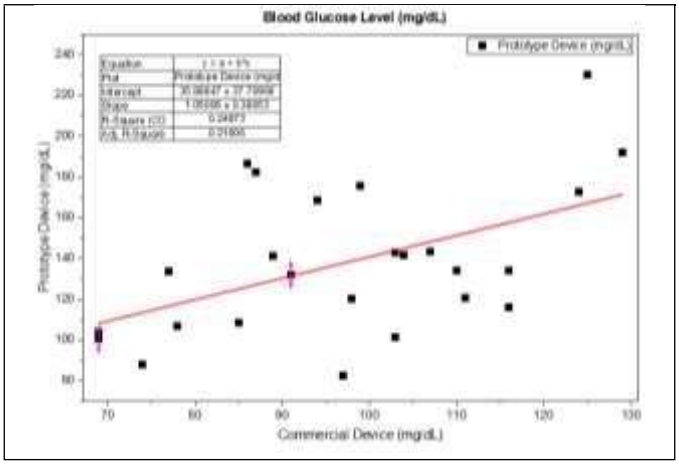

Fig. 4 Linear Regression Comparison of Prototype and Commercial Glucometer

E. Bland-Altman Analysis

Bland-Altman analysis (Fig. 5) was conducted to assess agreement between the two measurement methods. Results showed a mean bias of −40.7764 mg/dL, limits of agreement from −102.63075 mg/dL to +21.07795 mg/dL, and a 95% CI for mean bias of −53.80 mg/dL to −27.75 mg/dL.

The negative mean bias indicates the prototype consistently overestimates compared to the commercial glucometer. The width of limits of agreement (>123 mg/dL) exceeds the range of measured blood glucose levels (69–129 mg/dL), indicating high variability between subjects.

p-ISSN: 2356-5314
e-ISSN: 2460-075X

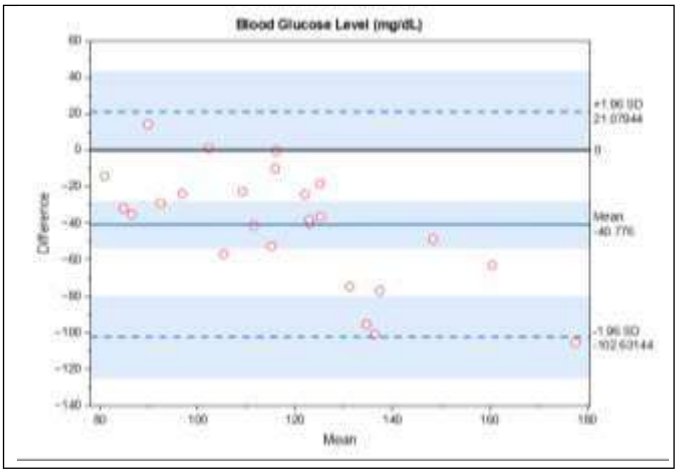

Fig. 5 Bland-Altman Plot Comparing Prototype and Commercial Glucometer

Proportional bias testing showed a slope of −0.91144 ± 0.20205 ($t = -4.51$, $p < 0.001$) with $R^2 = 0.4694$, indicating that the overestimation increases with higher blood glucose levels.

F. ISO 15197:2013 Compliance

Based on ISO 15197:2013 standards, which require at least 95% of measurements to fall within ±15 mg/dL of reference values for glucose below 100 mg/dL or within ±15% for glucose ≥100 mg/dL, only 5 of 25 subjects (20%) met this criteria (subjects 3, 14, 20, 21, and 24). This falls far below the 95% threshold, indicating the prototype does not meet international clinical accuracy standards.

G. Discussion

The significant performance gap between calibration (93.76% accuracy, $R^2 = 0.9017$) and testing (55.71% accuracy, $R^2 = 0.24874$) indicates overfitting of the linear regression model to the small calibration dataset (only 10 points). The model failed to generalize to the broader population with different tissue characteristics.

Several factors contributed to the high error rates:

1. Wavelength Selection: The 620–640 nm red LED operates outside glucose absorption bands. Glucose primarily absorbs in the near-infrared region (900–1700 nm). At 620–640 nm, hemoglobin is the dominant chromophore, making the signal more sensitive to blood perfusion, hemoglobin levels, and tissue scattering than glucose concentration.
2. Limited Calibration Data: Only 10 calibration points were used, insufficient to build a representative model for population variations, leading to overfitting.
3. Non-linear Relationship: The relationship between absorption and glucose concentration deviates from simple linearity as predicted by the Lambert-Beer law, especially in turbid biological media where scattering dominates.
4. Individual Physiological Variations: Differences in tissue thickness, skin pigmentation, hemoglobin levels, and tissue water content significantly affect light attenuation.
5. Extrapolation: 11 of 25 subjects (44%) had absorption values above the calibration range (0.85882–1.10763), requiring extrapolation beyond trained data.

Comparison with previous research confirms the importance of wavelength selection. Studies using NIR wavelengths achieved accuracies above 96% [16], [17], while this study using visible red light achieved only 55.71%. This underscores that optical glucose measurement requires wavelengths matching glucose absorption characteristics.

IV. CONCLUSION

A non-invasive glucometer prototype based on the red LED transmittance method with a Raspberry Pi 3B as the main processing unit has been successfully developed, performing measurements and blood glucose level classification through automatic blank calibration, optical signal acquisition, analog-to-digital conversion, absorption calculation, and glucose estimation via linear regression; however, its measurement performance still requires substantial improvement before clinical use. When compared with the GCU Easy Touch 3-in-1 invasive glucometer on 25 subjects, the prototype exhibited a systematic overestimation bias in 92% of measurements, with regression analysis showing a sharp drop in R^2 from 0.9017 (calibration) to 0.24874 (testing)—indicating model overfitting—and Bland-Altman analysis revealing a mean bias of −40.7764 mg/dL along with proportional bias ($t = -4.51$, $p < 0.001$), meaning that measurement error increases with glucose level. Overall, the prototype produced an average relative error of 44.29%, an accuracy of 55.71%, and an average deviation of 42.04 mg/dL, with only 20% of measurements (5 out of 25 subjects) meeting the ISO 15197:2013 accuracy standards—far below the required 95%—thus confirming that this prototype is not yet suitable as a replacement for conventional invasive glucometers.

V. RECOMMENDATIONS

Technical factors such as skin conditions, tissue thickness, body temperature, finger positioning, and ambient light interference must be investigated, alongside the exploration of non-linear conversion models, advanced signal processing algorithms, or machine learning methods to improve accuracy, followed by rigorous testing on more diverse populations under ISO 15197:2013 standards. Finally, personalized calibration models based on individual tissue characteristics should be considered, as a single generic model cannot adequately accommodate inter-individual physiological variations.

ACKNOWLEDGMENT

The authors would like to thank the Laboratory of Instrumentation, Physics Study Program, Faculty of Mathematics and Natural Sciences, Universitas Negeri Jakarta, for providing facilities and support throughout this research. We also extend our gratitude to all volunteers who participated in this study.

REFERENCES

[1] M. A. Darwich et al., "Non-invasive IR-based measurement of human blood glucose," Engineering Proceedings, vol. 35, no. 1, p. 27, 2023.

[2] H. Mansoor and A. Patel, "Non-invasive monitoring of glucose levels in diabetic patients using wearable sensors: Advances and trends," IEEE Access, vol. 11, 2023.

[3] B. Alsunaidi et al., "A review of non-invasive optical systems for continuous blood glucose monitoring," Sensors, vol. 21, no. 20, 2021.

[4] U. Nasiba et al., "Determination of wavelength candidates for non-invasive hemoglobin measurement devices," AIP Conference Proceedings, vol. 2194, pp. 1-6, 2019.

[5] J. Yadav et al., "Prospects and limitations of non-invasive blood glucose monitoring using near-infrared spectroscopy," Biomedical Signal Processing and Control, vol. 18, pp. 214-227, 2015.

[6] W. V. Gonzales et al., "The progress of glucose monitoring—A review of invasive to minimally and non-invasive techniques," Sensors, vol. 19, no. 4, 2019.

[7] N. Nanayakkara et al., "Non-Invasive Blood Glucose Monitoring using a Hybrid Technique," 2018 Moratuwa Engineering Research Conference, pp. 7-12, 2018.

[8] J. Yadav et al., "Prospects and limitations of non-invasive blood glucose monitoring using near-infrared spectroscopy," Biomedical Signal Processing and Control, vol. 18, pp. 214-227, 2015.

[9] K. Shapovalov et al., "Non-invasive blood glucose monitoring using near-infrared spectroscopy," Sensors, 2019.

[10] M. Alauhdin et al., "Aplikasi Spektroskopi Inframerah untuk Analisis Tanaman dan Obat Herbal," in Inovasi Sains dan Kesehatan, pp. 92-93, 2021.

[11] S. Haxha and J. Jhoja, "Optical Based Noninvasive Glucose Monitoring Sensor Prototype," IEEE Photonics Journal, vol. 8, no. 6, 2016.

[12] H. Suryono and Hambali, "Perancangan Alat Pengukur Kadar Gula dalam Darah Menggunakan Teknik Non-Invasive Berbasis Mikrokontroler Arduino Uno," JTEV, vol. 6, no. 1, pp. 69-76, 2020.

[13] L. Li and W. Zhang, "Real-time non-invasive blood glucose monitoring through near-infrared spectroscopy," IEEE Transactions on Biomedical Engineering, vol. 70, 2023.

[14] A. Pionis et al., "Rancang Bangun Alat Pengukur Kadar Glukosa Darah Non-Invasif Berbasis ESP 8266 Terintegrasi Thingspeak dan Absensi Biometrik," 2024.

[15] D. Sutarya, "Sistem Monitoring Kadar Gula Darah, Kolesterol dan Asam Urat secara Non-Invasive menggunakan Sensor GY-MAX 30100," Jurnal Ilmiah Teknologi Energi, vol. 1, no. 1, pp. 25-34, 2021.

[16] Y. N. Stella, "Pengembangan Prototipe Glukometer Non-Invasif Berbasis Metode Transmitansi NIR 940 nm," Undergraduate Thesis, Universitas Negeri Jakarta, 2022.

[17] M. I. Yanti, "Pengembangan Prototipe Glukometer Non-Invasif Berbasis Metode Transmitansi NIR 940 nm dan 1550 nm," Undergraduate Thesis, Universitas Negeri Jakarta, 2024.