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RESEARCH PAPER

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Identification of Blood Sugar Based on Non-invasive Measurements Using Photoplethysmography Method Signal Decoding in Diabetics in Tasikmalaya

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ABSTRACT

Non-invasive blood sugar testing tools are now in great demand among the public. This research aims to develop a non-invasive blood sugar examination tool with a Photopletysmograph signal decoding system based on data acquisition from a wearable sensor device on the wrist. The tool used for data acquisition uses Near Infra Red Light-emitting Diode NIR LED 880 nm, 660 nm and 537 nm. This acquisition transfers signals from the body via a photodiode to a PC Personal Computer for processing using Matlab. The method used in this research is to look for the height of the systolic and diastolic amplitude of the Photopletysmograph PPG signal and use the peak-to-peak voltage Vpp to implement Beer Lambert's law. This method was tested on 54 people, randomly aged 26-89 years, with normal blood sugar to high blood sugar. The results show an error of 18.37% from the gold standard. In conclusion, the use of the PPG signal decoding method has proven to be significant in producing blood sugar values. Furthermore, this method was developed for real-time remote measurements via wearable sensor devices.

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1. INTRODUCTION

Diabetes mellitus (DM) is a disease characterized by blood glucose levels that exceed normal. Indonesia is ranked 5th out of 10 countries with the most people with DM in Southeast Asia, which is 19.5 million people [1]. The prevalence of DM based on a doctor's diagnosis at the age of over 15 years in Indonesia was 1.3% in 2013 and has increased to 1.9% in 2018 [2]. Current tests to diagnose DM are the Fasting Plasma Glucose test (FPG), Oral Glucose Tolerance Test (OGTT), Random blood sugar test, and Hemoglobin A1c test (HbA1c). This procedure requires high costs, complicated equipment, invasive measurements, and a relatively long process until the results can be known. Currently, only invasive tools are used to check sugar levels, which still causes discomfort in DM sufferers [3][4][5]. Invasive blood glucose checks cause discomfort and pain[6][7]. Based on several previous studies, alternative methods were used to reduce the use of invasive blood sugar level testing tools. Non-invasive sampling methods are used to support this alternative by utilizing optoelectronic components and reflectors such as Raman spectroscopy methods and near infrared and mid infrared spectroscopy.[8]–[10]. Several studies related to methods for measuring blood sugar levels include using spectroscopic methods by taking samples from fingertips [11]. Apart from that, approaches using near infrared spectroscopy methods are also often carried out using various methods, especially the use of NIR-LED. An example is the use of NIR-LED with a wavelength of 940nm [12]–[14], 950nm [10], [15], [16], and 1550nm [17].

The approach taken in previous research was to carry out photopletysmogram extraction. However, previous research reported that the approach to extracting photopletysmograph results from NIR-LED detection and Raman spectroscopy methods was carried out using the regression method. [22] [24] and has weaknesses in the form of unable to interpret PPG accurately [8]. Through research that is currently being developed, PPG extraction can be done using signal decoding methods to reduce the error rate. Based on this, the formulation of the research problem is "how to model a non-invasive blood sugar level measuring device in the form of a smart watch using NIR LEDs and photodiodes that

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produce accurate PPG waves?". Based on previous research, the aim of this research is to identify PPG signals taken from acquisition results using a device designed using NIR LEDs worn on the wrist. This research can provide an overview of the PPG decomposition method to produce blood sugar levels with more accurate signal decoding.

2. MATERIALS AND METHOD

A. Subjects

The research subjects were patients with diabetes mellitus (DM) who often visited the Kersanagara, Sukarame and Cilembang Tasikmalaya Primary Health Care. The sample size or respondents in this research according to the sample formula for the instrument sensitivity test was 54 respondents. The expected sensitivity of the tool is 85% (P=0.85), with an acceptable deviation (d) of 10%, 95% confidence interval (α=0.05; Zα=1.96), with a representative sample size range ±10%. Statistically 54 respondents is a sample size in the ideal range. Samples were obtained in a simple random way, namely taken from a sequence of DM patients at the Primary Health Care and who met the research criteria.

Characteristics of respondents ranging in age from 29 years to 84 years consisting of 12 men and 42 women. Of the 54 participants, 6 people had a previous history of diabetes mellitus. Figure 1 shows a graph of the number of each participant with an age range of ten years.. This study has obtained a letter of ethical test from the ethics committee of the Tasikmalaya Poltekkes with no. DP.04.03/16/95/2023. Ethical implementation has been carried out during the study by giving respondents the freedom to be involved or not in this study by providing an informed consent sheet. The researcher also guarantees the confidentiality of the respondent's identity and the data collection results and that the actions taken in this study are not harmful to respondents.

Subjects will be measured for blood glucose using two devices for gold standard blood glucose measurement using an Accu check tool with venous blood collection. In addition, data measurement of subject characteristics was also carried out using a questionnaire. Based on Figure 2, it shows a graph of the percentage who have a history of DM as much as 11% of all respondents based on the questionnaires collected.

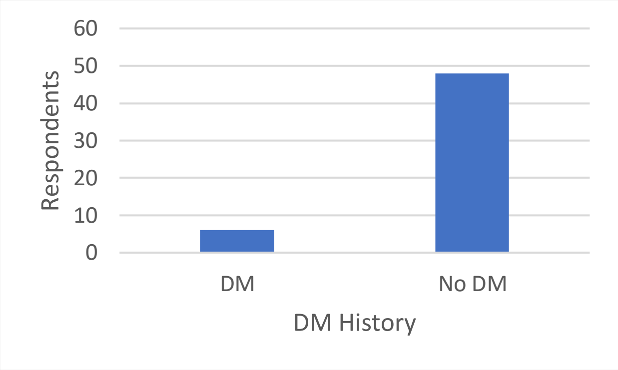

Figure 1. comparative data on the number of correspondents who have a history of diabetes mellitus and those who do not have a history of diabetes mellitus

B. Data Collection

Data collection on blood sugar levels was carried out on research subjects or respondents who met the criteria. Blood sugar levels were measured twice. The first measurement used a blood glucose meter with biosensor technology. This tool is obtained from a medical equipment shop, a standardized and licensed factory for free sale. 0.5 cc of blood was taken from the respondent's fingertip with a sterile needle and the wound was covered with alcohol cotton, then the sugar level was measured. The test results can be waited for 11 seconds after the blood sample is dropped onto the device sensor. The results of the first measurement are used as the gold standard for blood sugar levels.

The second measurement uses the instrument model under study, namely measuring blood sugar levels non-invasively using a photopletysmograph signal made in the shape of a watch and worn on the wrist. The signal journey in this instrument (hardware) model is described through a mathematical Eq. (1) to (6). The photopletysmograph signal obtained is processed in this model instrument to show the blood sugar level value in mg/dl units.

C. Hardware

In data collection, a smart wristband installed with a MAX30102 sensor was used as a PPG signal detector. The smart wristband designed has an ESP32-S1 microcontroller as an acquirer for the data to be retrieved. The MAX30102 containing NIR LEDs and photodiodes to take light rays reflected by the wearer's skin surface. By using I2C serial communication, These rays are then processed and

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produce PPG waves, which are transferred to the Personal Computer.

In addition, the smart wristband. used has a TFT LCD monitor with a resolution of 1.8" and is powered by an ST7735 processor which is used to display data signal stability acquisition conditions. Figure 2 shows the smart wristband used for data collection along with the PPG signal measurement results displayed on the monitor wristband.

Figure 2. Hardware for Data Acquistion

D. Data Acquisition

The data acquisition process uses a smart wristband containing NIR LEDs and photodiodes to take light rays reflected by the wearer's skin surface. These rays are then processed and produce PPG waves, which are transferred to the Personal Computer. With the help of Matlab, this PPG wave is detrended for signal smoothing, entering into a high pass filter so that a clean PPG signal is produced. This PPG signal is then processed to produce systolic, diastolic and minimum wave point values. After obtaining the systolic and minimum point values, the peak-to-peak voltage Vpp is found by subtracting the systolic from the minimum point. Using Lambert Beer's law, the data acquisition results obtained Blood Glucose Levels.

The captured light is then enumerated using an 18-bit ADC with a sampling rate of 10.24 MHz [23], which is in the internal processor with previously performed light cleaning using Ambient Light Cancellation ALC, to reduce ambient light coming from the light around the sensor. After being enumerated, the cleaning process is carried out with Digital Noise Cancellation DNC as a digital filter sent to the MCU microcontroller unit, ESP32, via I2C. ESP32 will display the PPG signal resulting from data acquisition to see the signal's stability. After we see the display of PPG wave stability, we can set the start of file storage as a CSV file. The process of taking data from respondents can be seen in Figure 3.

Figure 3. Data Acquisition Process

E. PPG Signal Processing

Signal decoding is done after the CSV file formed on the smart wristband is moved to the PC. On the PC, with the help of Matlab, the signal is processed to flatten and remove noise through detrending and filtering. Comparison of detrend and filtering results before and after can be seen in Figure 4.

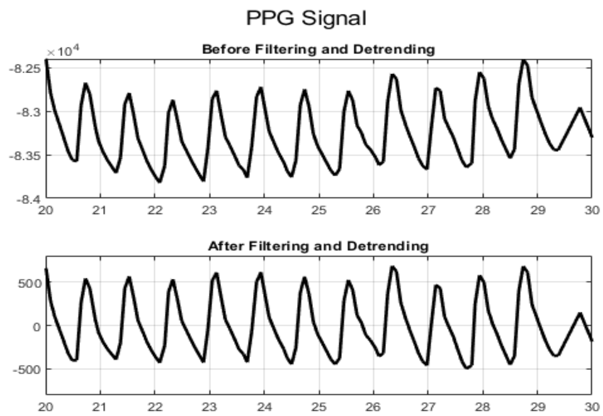

Figure 4. Detren process for PPG signal

Figure 5 shows the PPG signal before and after detrending and filtering using a high-pass filter with a cut-off frequency of 55mHz. The PPG waveform's necessary points must be searched first at this stage. These points include the PPG wave's systolic, diastolic, and minimum points, as shown in Figure 6.

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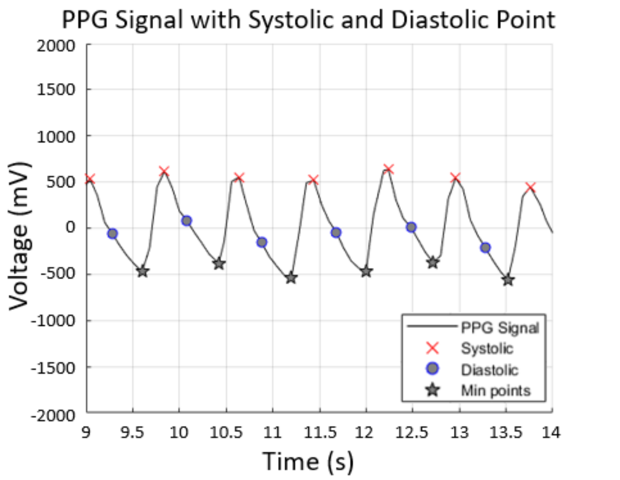

Figure 6. Systolic, diastolic and minimum points of the subject

Systolic is the condition in which the heart pumps or contracts. In this condition, the blood pressure reaches its peak. The peak of the PPG signal waveform corresponds to high blood pressure. Figure 6 shows the systolic points marked with crosses obtained using the findpeaks function. The same procedure is also performed to find the diastolic value by finding the PPG signal's first change, the systolic point's lower peak, and the minimum value by inverting the PPG signal. If the systolic, diastolic, and minimum point results are known, the plotting results are as follows:

The data searched using the findpeaks function will be used to find the Vpp value, especially the minimum and systolic points. Vpp value search by the equation below:

$$V_{pp} = \frac{\sum_{i=0}^{n} Systolics(i) - Minimum\ Points(i)}{n} \quad (1)$$

where n is the number of samples, in 1 sample, there are systolic and minimum point values, each sample starting from i = 0 to n, the systolic and minimum point subtractions are then summed up. The sum of the difference between systolic and minimum points is then divided by many samples n to obtain the Vpp value.

F. Theoritical Bacground

After the systolic, diastolic, and minimum points are known, and the Vpp value has been searched and collected, the data is analyzed spectroscopically with the Beer-Lambert law approach as follows:

$$A = -log\left(\frac{I}{I_0}\right) \quad (2)$$

$$A = \varepsilon C l \quad (3)$$

where A is the absorptive capacity, ε is the molar absorption coefficient, and C is the solution concentration (mmol/L). The length of light traveled by before reaching the reflector is called l. for I_0 is the intensity of light emitted, and I is the intensity of light passing and receiving

However, since the voltage value is known, the light intensity variable is replaced by the variable of voltage change as a representation of light intensity. This makes equation 2 change to equation 4 as follows:

$$A = -log\left(\frac{V_{pp}}{V_0}\right) \quad (4)$$

where A is the absorption voltage then V_0 is the input voltage with a value of 3300 mV and V_{pp} is Peak-to-peak Voltage (mV).

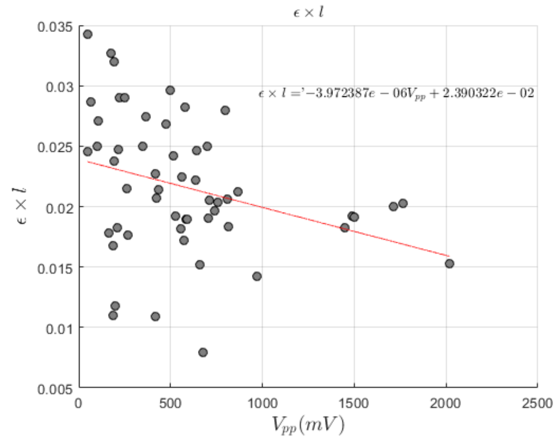

Figure 1. Vpp and el respons

If the above equation is combined with equation 2 and what we want to know is the value of the blood sugar level, it will result in equation 5 as follows:

$$A = \varepsilon C l$$

$$-log\left(\frac{V_{pp}}{V_0}\right) = \varepsilon C l$$

$$C = \frac{-log\left(\frac{V_{pp}}{V_0}\right)}{\varepsilon l} \quad (5)$$

where C is the solution concentration and then expressed as blood sugar level in this research, the ratio between input voltage and peak-to-peak is expressed as V_0 and V_{pp}, ε is the molar absorption coefficient, and the l variable is expressed as the length of light traveled by before reaching the reflector. When viewed from Equation 5 above, the known variables are the invasive blood sugar concentration and the voltage ratio. Then, we must first find the remaining variables, namely the variable length of the light path and the molar absorption coefficient, and the variable C is expressed as the invasive blood sugar level. The equation is in eq.6

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$$\varepsilon l = \frac{-log\left(\frac{V_{pp}}{V_0}\right)}{C_{Invasive}} \quad (6)$$

where εl shows the equation for calibrating the concentration value based on the variable length of the light path and the molar absorption coefficient with Vpp, which is the result of the peak-to-peak voltage taken from the sensor reading as the input value, expressed in a graph, the results are shown in Figure 7. After the variables of light trajectory length and molar absorption coefficient are known, they are expressed based on equation 5, but the variable C in equation 5 as the variable of invasive blood sugar level is replaced with the variable C as the output value of non-invasive blood sugar level:

$$C_{non-invasive} = \frac{-log\left(\frac{V_{pp}}{V_0}\right)}{\varepsilon l} \quad (7)$$

G. Data Processing

Data processing follows a stage mechanism; editing, coding. entry, and cleaning. Data processing is carried out in two separate parts. First, the photopletysmograph signal data processing on the model instrument under study follows the mathematical equation formula until the blood sugar level value is formed in mg/dl units. Second, statistical data processing, namely comparing the average blood sugar levels between the results of the research model instrument examination with the results of the gold standard instrument examination. the data analysis to determine the average difference between the two groups of data was carried out by the Mann-Whitney test.

3. RESULT

The PPG signal collection process is carried out in the working area of the Kersanegara Health Center and Cilembang Health Center of Tasikmalaya City and the working area of the Sukarame Health Center of Tasikmalaya Regency with the number of respondents within 3 minutes to get enough signals so that the average measurement process becomes accurate. Based on the flow carried out for data analysis, it produces data as in Table 1

Table 1. Stastistical Measurement

Blood Glucose Level test	Mean GD (mg/dl)	SD	Mean	Z	ρ - value
Model	128.9	8.9	10	-0.295	0.768
Gold Standart	138.9	47.9			

The assumption test shows that the blood sugar results of the model and standard device examination are not normally distributed, so the test used is the mann-whitney test. The results of the dependent t-test showed that the average blood sugar of the model tool (128.9 mg/dl; SD = 8.9) was no different compared to the average blood sugar of the standard tool (138.9 mg/dl; SD = 47.9), (p =0.768; Z = -0.295). Although statistically, the results are similar, there is still a significant difference/error of 10 points. In addition to being presented in a table that produces non-invasive blood sugar level data and error values, the data is displayed in Clarke's Error Grid Analysis in Figure 8.

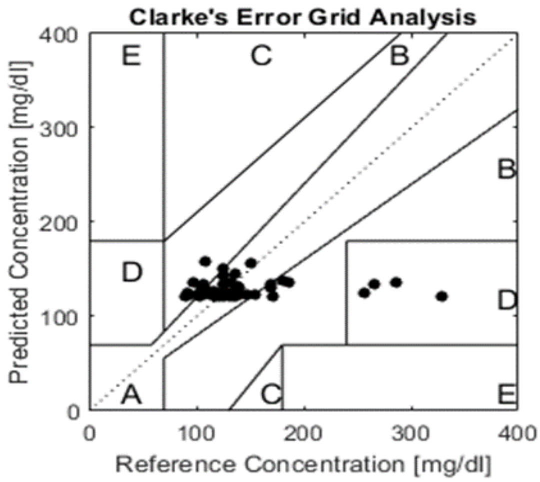

Figure 2. Clarke Error Grid Analysis

Figure 8 shows the measurement results and compares invasive and non-invasive blood sugar levels, primarily in area A. However, in the case of blood sugar levels >200mg/dl, the error is more significant when compared to 4 samples in area D with an error of >45%. That means this method still has weaknesses for measuring blood sugar levels >200mg/dl. More details about the percentage and amount of data in an area of Clarke's error grid analysis can be seen in Table 2.

Table 2. Tabulasi Clarke's Error Grid Analysis

Class	Sample	Percentage (%)
A	31	57.41
B	19	35.19
C	0	0
D	4	7.41
E	0	0

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4. DISCUSSION

The data collection process using 3 LEDs with different wavelengths successfully obtained PPG signals, although the filtering process had to be done with a low pass filter. The use of the peak-to-peak Voltage method and the use of high diastolic systolic signals produces a value of C. with a linear regression approach. The performance of non-invasive blood sugar level detection devices can be analyzed using Clarke Error Grid Analysis CEGA. CEGA analysis has also been used in blood sugar measuring instruments with the urine method [14] and the photoacoustic method [15].

From the test results, it can be seen that the PPG signal decoding process can produce a reasonably good BGL. This value can be seen from the CEGA results. 57.41% are in zone A. This matches the measurement results and the comparison tool or gold standard. Furthermore, 35.19% are in zone B, a safe zone, although 35.19% do not have a significant clinical impact. There are 7.41% in zone D, which significantly differs from the gold standard. This occurs with various measurement factors. Starting from obtaining data with unstable objects, not recalibrating both the gold standard and measuring instruments, and the need to add other supporting variables that will affect the peak-to-peak voltage value that will affect blood sugar levels. Non-invasive detection of blood sugar levels using PPG has been carried out by [16] but is used on the fingertip and is not a wearable sensor device. CEGA analysis produces tool accuracy in zone A of 73.7% and zone B 26.3%. Detection of blood sugar levels at the fingertips was also carried out by Hina [17] using the help of an additional extraction module, Support Vector Regression with Fine Gaussian kernel Machine Learning Regression (FGSVR) MLR so that the accuracy was 95% in zone A. Dhaheri [18] conducted testing on the fingertips and with the help of simple linear regression produced an R2 value for Zone A of 0.923. Saravanan [19] used a device, not only a wrist but also a neckband and a pair of socks, to monitor diabetes, but the test was not analyzed using CEGA. Vega [20] [25] conducted tests almost the same as Saravanan but only used wrist tools and fingertips and combined data with the help of the PLS partial least squares algorithm to produce accurate data. The peak-to-peak voltage system is straightforward even though the final results are not as good as other methods, but it is worth considering because of its simplicity and convenience. The limitation of this tool is that the process is carried out separately and cannot be done in real-time, so it takes time for the PPG data acquisition process to produce BGL. Testing with 54 respondents also has a short range of blood sugar, so the tool has not been tested for blood sugar with various levels. In addition, the sensitivity of this tool is still very high; changes in the position of PPG data collection will affect the accuracy of the value. With this study's results, non-invasive blood sugar measurements based on NIR-LED are increasingly proven to replace invasive blood sugar measurements.

The non-invasive blood sugar detection tool created provides a solid foundation for development with various modules and additional algorithms. With the development of machine learning ML and Artificial intelligence AI algorithms, it is possible to improve accuracy. This tool can be used as a general reference regarding blood sugar levels based on non-real-time conditions.

5. CONCLUSION

The process of decoding PPG signals to produce blood glucose levels was successfully developed and tested on respondents whose age-based characteristics were in the age range 24 -84 years and the majority were female, 42 of the total 54 respondents. Based on a comparison of measuring blood sugar levels between an invasive blood glucose test meter and a non-invasive blood sugar level check which is being developed using a photoplethysmograph signal worn on the wrist, shows statistically the same results, however there is still a difference of 10 points. In the future, this tool will be developed in real-time so that smart bracelets can display BGL with a signal decoding process in the cloud.

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