

Inference of FTIR Characterization Results of Human Blood Glucose Levels using Artificial Neural Network (ANN)

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ABSTRACT

1. Introduction

An invasive measuring method is one that involves the patient having their limbs pinched to collect blood samples. This method of monitoring blood sugar levels has several disadvantages including the risk of disease, the high risk of failure and the high costs associated with it [1-3]. Although conventional or invasive techniques for checking blood glucose levels are already highly accurate [4]. To reduce the issues caused by current methods of blood glucose monitoring, however, efforts to create alternate techniques must still be made [5]. Non-invasive procedures are an alternative to invasive methods because they do not require puncturing a body part to get a blood sample, have a relatively quick analysis time, have sensitive equipment, are ecologically friendly, have

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lower measuring costs and do not need reagents [6-8]. This technique, known as the spectrophotometric approach, does not require cutting off the limbs because it relies on blood sugar concentration. In this research, skin penetration with light was used as an alternative to cutting limbs [1,9].

Artificial Neural Network (ANN) approaches are applied in many different domains, including computing, chemistry, physics and biology. In the modern day, strategies for integrating the computer and medical fields are being used to solve algorithmic and mathematical problems to address complicated issues like diseases and medical equipment. Artificial neural network (ANN) technology is one such method. This method is employed by researchers because it is extremely helpful in the diagnosis of a disease and can enhance the performance of a method in the prediction of a disease by employing various input and output changes to provide substantial clinical output [10].

The goal of this study is to create a non-invasive technique for measuring blood glucose levels using Artificial Neural Network (ANN) methods to predict blood glucose levels from a sample of blood fluid without the use of reagents and to evaluate the effectiveness of the technique using specific and precise calculations such as RMSE and perform diagnostic test calculations such as Error Grid Analysis (EGA), sensitivity and specificity (NND). This will result in the potential wavelength of the LED being used as part of a non-invasive blood glucose meter.

2. Methodology

2.1 General Methods

From June 2021 to September 2021, this experimental study was conducted at the Laboratory of Electronic Material Physics and Biophysics, Physics Department, Faculty of Mathematics and Natural Sciences, Bogor Agricultural University. The results of the near-infrared test spectrum for blood glucose samples using the Buchi NIRFLEX 500 spectroscopy instrument with a variation of wavelength 1000-2500 nm were the main data used in this study in the form of secondary data from earlier research by Alatas *et al.*, [11].

2.2 Secondary Data Collection

This experimental study involves reference to secondary information from earlier studies. There are ten study participants who have already read the research papers. Additionally, they gave their written permission before taking part in this study. Randomization and blinding were not used in the previous research either. The total of blood samples was taken from the arm veins is 10 respondents. The volunteers, who were either male or female and aged 18 to 60, did not take any medication for a glucose issue. Those who are pregnant or nursing are not allowed to have their blood drawn during this observation. Before the process to take their blood, the subjects had to fast for eight hours.

Secondary data from previous research is used in this experimental study. Near-infrared test spectrum results for glucose samples from three conditions—fasting, 15 minutes after drinking sugar water and 30 minutes after drinking sugar water—were used as secondary data. For each sample, repeated measurements were taken three times. Each respondent had 6 ml of blood drawn from them in each circumstance. A single-use, sterile syringe was used for each subject to draw venous blood from the fold of their hand during the blood sample procedure. The Buchi NIRFLEX 500 spectroscopic device was used to measure glucose absorption utilizing a total of 3 ml of blood sample, with a range of wavelengths from 1000 to 2500 nm [11].



Fig. 1. Flow chart of the research

2.3 Data Preparation

The process of preparing obtained data so that it is ready to be processed and analysed using ANNs is known as data preparation. The wavelength that will be used for testing in this study, between 1000 nm and 2500 nm, was chosen by the researcher to produce the data. The wavelength

is calculated using 50 intervals of each wavelength in the 1000–2500 nm range. When training data using an artificial intelligence inference engine or artificial neural network, the chosen wavelength will be employed as a formation parameter (ANN). The overall number of wavelengths chosen is 30, with a total of 29 wavelength ranges in the 1000–1500 range.

The data is then projected with the generated parameters to equalize the range of each formation parameter in the range of 0 to 1. Then, 67% of the training data and 30% of the test data are combined to create training data and test data from the predicted data [12]. The LibreOffice Calc program was used for the steps of data preparation and parameter development.

2.4 Artificial Neural Network (ANN) Inference Engine Training

The ANN inference engine is then trained on the data that has been in the form of training data and test data to produce an estimated blood glucose level value from several generated parameters that have been employed [12]. The 29 repetitions of data training were done, each time using two inputs and one output. Data will now be produced in the form of plot findings. ANN inference engine training was carried out with the aid of FANNTools.

2.5 Data Processing

The data resulting from the ANN inference engine training will be reprocessed so that it becomes a requirement before continuing with other stages of analysis. Data processing includes projecting back values to form an estimated value. The data processing stage includes analysis of accuracy test and analysis of diagnostic test. Accuracy analysis in the form of Root Mean Square Error (RMSE). Analysis of diagnostic tests includes analysis of Error Grid Analysis (EGA), analysis of sensitivity, specificity, accuracy of diagnosis and Number Needed to Diagnose (NND).

2.6 Accuracy Analysis in the form of Root Mean Square Error (RMSE)

LibreOffice Calc will be used to process and calculate the accuracy of the data training plot results produced by the Artificial Neural Network (ANN) or Artificial Intelligence Inference Engine (AIE) methods. The accuracy of the ANN method is tested at this stage and depending on measurement accuracy, the ANN inference engine determines the candidate wavelength training outcomes. Calculating the Root Mean Square Error (RMSE) value gives the accuracy value [13]. Later, the accuracy number expressed as a Root Mean Square Error (RMSE) will be contrasted with the standard accuracy for determining blood glucose levels in humans, which is 10 mg/dl ISO 15197: 2016 [14].

2.7 Error Grid Analysis (EGA)

EGA analysis is a diagnostic test parameter that compares measurements of reference blood glucose levels made using the spectrophotometric venipuncture method from earlier studies to the results of ANN inference engine training in the form of plot results of presumed blood glucose levels [14]. The EGA analysers used in this study were Parkes EGA [15] and Clarke EGA [16]. EGA measures use the EGA, R, Rstudio and LibreOffice Calc libraries, according to research [14].

2.8 Analysis of Sensitivity, Specificity, Diagnostic Accuracy and NND

The parameters used to evaluate the effectiveness of the artificial intelligence inference engine method in diagnosing glycaemic status as well as being a parameter determining candidate wavelengths in making a diagnosis are analysis of sensitivity, specificity, accuracy of diagnosis and Number needed to Diagnose (NND). This stage is completed by comparing the reference blood glucose level values produced by the spectrophotometric venipuncture method against the estimated glucose level values produced from the outcomes of the data training plot of the artificial intelligence inference machine. The data will be divided into two groups of data with a cut-off point for the median value. the blood glucose reference [12]. Calculations of sensitivity, specificity, diagnostic accuracy and NND were made using the epiR, R, RStudio and LibreOffice Calc libraries, according to [12,17].

3. Result

3.1 Root Mean Square Analysis (RMSE)

Accuracy analysis was performed by calculating the Root Mean Square Error (RMSE) of the training plot results of the Artificial Neural Network (ANN) inference machine. There were 2 pairs of wavelength ranges that were closest to the reference accuracy of measuring human blood glucose levels, 10 mg/dl ISO 15197: 2016 [14], namely at the wavelength range pairs of 1041 nm to 1063 nm (Range 3) and 1063 nm to 1086 nm (Range 4) with Root Mean Square Error (RMSE) of 9.58 mg/dl and 11.50 mg/dl, respectively. This shows that the 2 best lamp wavelength candidates are in those wavelength pairs and are eligible to be wavelength candidates in further research. The analysis results are presented in Figure 2, Range 3 and Range 4 respectively.



Fig. 2. Correlation between pairs of wavelengths to Root Mean Square Error (RMSE)

3.2 Error Grid Analysis (EGA)

The results of the Error Grid Analysis (EGA) Clarke and Parkes have been conducted on 29 selected data pairs and show that almost all wavelength pairs are in zone A and B. This indicates that there are no adverse clinical consequences in the selected wavelength range [16], so that the ANN

inference machine method is feasible to be realized. In the 2 pre-determined lamp candidates based on accuracy in the form of RMSE, Range 3: 1041 nm to 1063 nm and Range 4: 1063 nm to 1086 nm, show that in the wavelength range, both Clarke EGA and Parkes EGA, there are no clinical consequences that will occur if the 2 candidates are used.

3.3 Sensitivity, Specificity, Diagnostic Accuracy and Number Needed to Diagnose (NND)

The analysis of sensitivity, specificity, diagnostic accuracy and NND was conducted on the wavelength range of Range 14: 1351 nm to 1388 nm, with values of 87%, 80%, 83%- and 1.5-times repetition, respectively. The sensitivity of 87% is in accordance with the good sensitivity reference of 56% to 98% [18,19]. The specificity is said to be good if it is in the range of 88% to 96% [20,21]. However, at that wavelength, the specificity is 7% below, with the diagnostic accuracy reaching 83%. This indicates that the candidate is still not sufficient in diagnosing the specificity. NND at that wavelength, 1351 nm to 1388 nm, is 1.5 times. This indicates that the NND produced is good and is in accordance with Larner [22]. The smaller the Number Needed to Diagnose (NND) value, the better in diagnosing. It can be concluded that the wavelength range of 1351 nm to 1388 nm is a suitable candidate for non-invasive blood glucose measurement wavelength in diagnosing glycaemic status. However, RMSE in that wavelength range is far from the standard [14], 22.09 mg/dl, so it is not included in the 2 best lamp candidates based on the measurement accuracy perspective.

The values of Sensitivity, Specificity, Diagnostic Accuracy and NND for the 2 lamp candidates that have been selected based on accuracy in the form of RMSE, 1041 nm and 1063 nm and 1063 nm and 1086 nm, show values that are not yet good enough in diagnosing. In the first candidate, the wavelength pair of 1041 nm and 1063 nm, the sensitivity value is 47%, the specificity value is 73%, the diagnostic accuracy value is 60%, with 5 times repetition. The four measurement parameters produced are very far from what is expected and do not meet the sensitivity reference [18,19], specificity [19,20], diagnostic accuracy and NND [21]. Likewise, with the second candidate, 1063 nm and 1086 nm, the sensitivity value is 40%, the specificity value is 80%, the diagnostic accuracy value is 60%, with 5 times repetition.



Fig. 3. Correlation between pairs of wavelengths to diagnostic parameters

A comparison of the top lamp choices based on test parameters is shown in Table 1 as a summary of the research findings. This demonstrates that the Artificial Neural Network (ANN) method of

artificial intelligence results in candidates. For determining human blood glucose levels, as well as the precision of the RMSE and the capability to determine glycaemic status, the viable wavelength is realized.

Table 1 The Results of the study Test parameters Wavelength candidate Accuracy test **Diagnostic test** Candidate I Candidate II Candidate I 1041.67 nm-1063.83 1063.83 nm - 1086.96 1351.35 nm - 1388.89 nm nm nm 22 mg/dL Root Mean Square Error (RMSE 9.58 mg/dL 11.50 mg/dL Sensitivity 47% 40% 87% 80% 80% Specificity 73% 60% **Diagnostic accuracy** 60% 83% Number Needed to Diagnose 5 repetitions 5 repetitions 1.5 repetitions (NND)

4. Conclusions

The analysis results showed that the accuracy test in the form of RMSE and diagnostic test of 29 wavelength ranges produced 2 good candidates in the accuracy test in the form of RMSE and 1 good candidate in the diagnostic test. For all wavelength ranges, only 2 wavelength ranges approach the reference accuracy in the form of RMSE, 10 mg/dl, namely in the wavelength range of 1041 nm to 1063 nm and 1063 nm to 1086 nm, with RMSE of 9.6 mg/dl and 11.5 mg/dl respectively. However, these candidates produced poor values in making diagnoses with the sensitivity of 47%, specificity of 73%, diagnostic accuracy of 60% and NND of 1.5 repetitions.

The lamp candidate based on the diagnostic test analysis in the form of EGA, sensitivity, specificity, diagnostic accuracy and Number Needed to Diagnose (NND), produced 1 best lamp candidate. The lamp candidate that has a worthy diagnostic test is in the wavelength range of 1351 nm to 1428 nm with a sensitivity value of 87%, specificity of 80%, diagnostic accuracy of 83% and NND value of 1.5 repetitions. Clarke EGA and Parkes EGA in the first lamp candidate can still be tolerated because the glucose concentration distribution is at 70% zone A, 27% zone B and 3% zone C. This shows that the artificial intelligence method in the form of Artificial Neural Network (ANN) produces a wavelength candidate that is worthy of being realized for measuring human blood glucose levels, both accuracy in the form of RMSE and the ability to diagnose glycaemic status.

The artificial intelligence method in the form of Artificial Neural Network (ANN) was successfully carried out and produced a suitable wavelength candidate for measuring human blood glucose levels, both in terms of accuracy in the form of RMSE and the ability to diagnose glycaemic status. This study resulted in several suggestions for further research.

The findings from research on non-invasive methods for measuring human blood glucose levels can help address the limitations of traditional or invasive approaches. These drawbacks include patient discomfort, a higher risk of disease transmission, greater chances of errors and increased costs. Non-invasive methods involve using various light wavelengths to measure blood sugar levels, eliminating the need for piercing the body. Identifying accurate wavelength candidates can significantly reduce both the time and expenses involved.

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