PRZEGLĄD ELEKTROTECHNICZNY

Ukazuje się od 1919 roku **5'2023**

Organ Stowarzyszenia Elektryków Polskich • Wydawnictwo SIGMA-NOT Sp. z o.o.

1. Usman UMAR[1,2], 2. Syafruddin SYARIF[1], 3.Ingrid NURTANIO[1], 4.Indrabayu[1]

Department of Electrical Engineering, Faculty of Engineering University of Hasanuddin Makassar Indonesia (1),
Department of Electro-medical Technology, Health Polytechnic Muhammadiyah Makassar Indonesia (2)
ORCID: 1. 0000-0002-2027-6018; 2. 0000-0003-1285-1323,. 3. 0000-0002-3053-4201, 4. 0000-0003-2026-1809

doi:10.15199/48.2023.05.01

Applied a Non-invasive Method to Blood Glucose Monitoring by Hand Skin Image Based on Gray Level Co-occurrence Matrix (GLCM) and Artificial Neural Networks (ANN)

***Abstract**. This study develops a non-invasive method to predict blood glucose through image processing. For investigation, several invasive images and glucose levels were taken. Types of samples based on age classification, 20-60 years. For accuracy and simple analysis, 37 images of participants as volunteers, samples were evaluated and investigated under the gray level co-occurrence matrix (GLCM). In this study, an artificial neural network (ANN) was used for all training and hand texture testing to detect glucose levels. The performance of this model is evaluated using Root Mean Square Error (RMSE) and correlation coefficient (r). Clarke Error Grid Analysis (EGA) variance was used in this investigation to determine the accuracy of the method. The results showed that the RMSE was close to the standard value, the regression coefficient was 0.95, and the Clarke EGA analysis: 81.08% was in the A .% zone. So that the blood glucose prediction model using the GLCM-ANN method is feasible to apply.*

***Streszczenie.** Niniejsze badanie rozwija nieinwazyjną metodę przewidywania stężenia glukozy we krwi poprzez przetwarzanie obrazu. W celu zbadania wykonano kilka inwazyjnych obrazów i poziomów glukozy. Rodzaje próbek na podstawie klasyfikacji wiekowej, 20-60 lat. Dla dokładności i prostej analizy, 37 obrazów uczestników jako ochotników, próbki zostały ocenione i zbadane w ramach macierzy współwystępowania poziomu szarości (GLCM). W tym badaniu sztuczna sieć neuronowa (ANN) została wykorzystana do wszystkich testów treningu i tekstury dłoni w celu wykrycia poziomu glukozy. Wydajność tego modelu ocenia się za pomocą błędu średniokwadratowego (RMSE) i współczynnika korelacji (r). W tym badaniu zastosowano analizę wariancji siatki błędów Clarke'a (EGA) w celu określenia dokładności metody. Wyniki pokazały, że RMSE była zbliżona do wartości standardowej, współczynnik regresji wyniósł 0,95, a analiza Clarke EGA: 81,08% znajdowała się w strefie A.%. Aby model przewidywania stężenia glukozy we krwi przy użyciu metody GLCM-ANN był możliwy do zastosowania (**Zastosowane nieinwazyjnej metody monitorowania poziomu glukozy we krwi za pomocą obrazu skóry dłoni w oparciu o macierz współwystępowania poziomów szarości (GLCM) i sztuczne sieci neuronowe (ANN**))*

Keywords: Glucose, Non-Invasive, GLCM,ANN.
Słowa kluczowe: Stężenie glukozy we krwi, nieinwazyjna, macierz współwystępowania poziomu szarości.

Introduction

Blood glucose is a very important component in human body tissues.[1]. Glucose is a carbohydrate element that is a source of energy for all body cell tissues, glucose functions to speed up metabolism and is the main fuel for the brain, and controls body temperature.[2]. If blood sugar is not controlled properly, it can lead to vascular disease.[3]. Glucose in the blood if excessive and in the long term will cause diabetes, and can cause other diseases such as nerve damage, vision loss, kidney damage, increased risk of cardiovascular disease, and even death.[4]. According to investigations that have been carried out there are around 1.2 million Australians who suffer from diabetes mellitus (DM). In 2015, DM was the leading cause of death, around 5 million deaths were contributed by DM worldwide. The global population of individuals with DM will reach 642 million people.[5]. According to data from the International Diabetes Federation (IDF), in 2017 there were 451 million people with diabetes and it is predicted that this will increase by 693 million by 2045, and about 5 million people died from diabetes.[6] Increased blood glucose levels can affect the increase in the occurrence of various diseases, to prevent this from happening, it is necessary to monitor blood glucose regularly.[7]. The current condition is measuring blood glucose levels using invasive techniques, invasive technique procedures must use blood samples for measuring strips. Blood sampling must be performed by means of injuring the tip of the finger, causing pain to the patient and causing bruising and inflammation of the skin. Invasive measuring devices measure blood glucose levels currently available in health clinics such as Easy Touch GCU, Nesc Multi check, Auto check, and Accu-Check.

The development of non-invasive measuring instruments to date by conducting research such as; The research proposes the development of invasive techniques to monitor blood glucose levels continuously without pain. the proposed method by developing a highly porous black platinum. This black platinum surface was modified using the biocompatible ionomer Nafion (Nf). In the study, it was proposed that scanning electron microscopy (SEM) and energy dispersive X-ray analysis (EDX) be applied to identify glucose levels. As a result, the device showed good stability for 7 days and lost its functional activity after 7 days.[8]

Author at.[9]. proposes the application of gluCam - a new, autonomous, non-invasive, optical-based model for the detection of diabetes. by developing polynomial regression as a formula for predicting blood glucose levels diagnosed via a smartphone, which is easy to use. The gluCam app uses an image processing method to measure blood glucose levels. tested the model on 81 patients with a sensitivity of 94.28%, specificity of 82.61%, the mean absolute error of 10.7%, and overall accuracy of 91.89%. The developed model is not affected by lighting conditions and does not depend on the device platform.

This invasive technique has the effect of being painful during blood sampling and can cause bruising and cuts to the fingertips. This causes many patients not to want to check their glucose levels continuously. Currently, to overcome this, monitoring glucose levels without blood samples was developed by several researchers to facilitate continuous monitoring of blood glucose levels. The research focuses on non-invasive techniques by implementing silver nanoparticles (AgNPs) and graphene quantum dots (GQDs) nanocomposites as glucose sensors. In addition, the developed sensor has good sensitivity and selectivity with low detection limits of 162nM and 30µM for H_2O_2 and glucose sensing, respectively.[10]. The authors in [11] applied multi-sensor fusion to non-invasively detect blood glucose levels and analyzed using the K-mean clustering algorithm to improve the accuracy of glucose level prediction, by classifying the characteristic parameters of diabetics. The results of developing this method, with grid errors, are as follows: 58.33% in Zone A, 39.43% in Zone B, and 2.24% in Zone C, with a correlation coefficient of 0.69. Research has been conducted at the National Medical Products Administration of China. developed a near-infrared optical biosensor for non-invasive blood glucose monitoring with lower cost and greater effectiveness. There were 12 patients tested to prove the accuracy of this tool. Based on these results, the standard for predicting the standard error of forecast (SPE) is 6.16 mg/dl.[12]. Research of . implemented a low-cost mobile platform for blood glucose level prediction using smartphone optical light to facilitate glucose detection reading and analysis by avoiding the influence of ambient light intensity variations.[13] This method was successful in predicting blood glucose levels (0.5-2.84 mg/ml) with a detection limit of 5 mg/dl (0.28 mM). Direct blood glucose detection from human blood samples was performed. results with relative errors ranging from 4.37% to 14.41% compared with the spectrophotometric method, and 3.83%-14.53% compared to commercial glucose meters.[14]

Based on the explanation above and the results of previous studies that monitoring blood glucose levels with minimally invasive and non-invasive techniques generally uses optical sensors. But there are also those who use smartphones to detect blood glucose levels through images of blood vessels. The proposed study is the development of a blood glucose detection system based on hand skin image processing using an Artificial Neural Network (ANN) with a backpropagation algorithm to predict blood glucose levels. The results of this study will be validated with data testing methods based on the results of training data and determine clinical accuracy using error analysis and Clarke-Error Grid Analysis

Digital Image

A digital image is a two-dimensional image that can be displayed on computer media called pixels (picture elements) or a set of discrete digital values. Image can be defined as a function (x, y) which has size M in rows and N in columns, where x and y are partial coordinates, amplitude f at coordinates (x, y) which is called the degree or level of gray in an image. If x, y, and f are all finite and have discrete values, then the image is a digital image.[15].[16]. Image processing is an image analysis process that involves a lot of visual perception, where this process has the characteristics of input data and output information in the form of images.[17].

Gray Level Co-occurrence Matrix (GLCM)

Gray level co-occurrence matrix (GLCM), is an image processing methodology used to describe the spatial relationship between gray values in two-dimensional images. Subsequent developments have advanced further to demonstrate its applicability to gray level photomicrographs of a series of sandstone samples. Since then, GLCM has been widely used in various applications.[18]. Of all the texture analysis techniques, currently perhaps the most widely used is the one based on the gray level co-occurrence matrix (GLCM) algorithm. The GLCM method as a way to classify images uses a second-order statistical measurement.[19]. The image with the matrix characteristics produced by GLCM has 4 extractions, namely contrast (Ct), correlation (Cn), energy (Ey), and homogeneity (Hy), the four extractions can describe the entire image and are generally used in image processing, sequentially as shown. described in the following equation.[20].

$$GLCM = P_r(i,j) | \, d, \ \theta, N \tag{1}$$

$$Ct = \sum_{i,j} | \, (i-j)^2 \, S\,(i,j) \tag{2}$$

$$Cn = \sum_{i,j} \frac{(i-\mu i)(j-\mu j)S(i,j)}{\sigma_i \sigma_j} \tag{3}$$

$$Ey = \sum_{i,j} S\ (i,j)^2 \tag{4}$$

$$Hy = \sum_{i,j} \frac{S(i,j)}{1+|\ i-j|} \tag{5}$$

where: GLCM determines the likelihood of a gray level i occurring in the vicinity of another gray level j at a given distance d and angle θ, assuming the total number of gray levels N is known. The kind of image represents contrast (Ct), correlation (Cn), energy (Ey) and homogeneity (Hy).

Artificial Neural Network (ANN)

ANN is a method for making prediction models that are accurate, efficient, and effective [21][22]. The technique and its implementation are called "neural networks" because they resemble traditional neural networks. According to [23] ANN consists of neurons or artificial nodes. In this study, backpropagation will be used as an algorithm to build a Linear Regression Neural Network. Backpropagation optimization algorithm can be used to train artificial neural network models. The backpropagation algorithm requires a gradient calculation for each variable in the model to generate a new value for the variable. According to [24][25] although simple, the backpropagation algorithm approach is a popular and successful numerical optimization in machine learning to model classification algorithms with greater accuracy. Backpropagation sticks to the identified batch to speed up training with more gradient updates, and also has the constraint of penalizing extreme parameter changes [26].

Evaluation Criteria

In this study, the root mean square error (RMSE), correlation coefficient (r), and Clarke Error Grid Analysis (C-EGA) were used to evaluate a non-invasive blood glucose level prediction model to justify the study findings. The following equations (6), (7) describe RMSE, and r, respectively.[27][28][29].

$$RMSE = \sqrt{\frac{\sum_{y=1}^{n}(y-y_p)^2}{n}} \tag{6}$$

$$r = \frac{\sum(y-y_{avg})(yp-yp_{avg})}{\sqrt{(y-y_{avg})^2}.\sqrt{(yp-yp_{avg})^2}} \tag{7}$$

Where yp and y represent the observed values and model fitting values, and $\overline{y}p_{avg}$ represents the mean values of the observed values

The Clarke error grid method was used to assess the clinical significance of differences between predictive (non-invasive) glucose measurements and reference venous blood glucose measurements (invasive). This method uses a Cartesian diagram, the predicted value of non-invasive measurement results is on the y-axis and the value of invasive measurement results as a reference on the x-axis. The diagonal line represents the perfect result between the two, the dots above and below the diagonal line indicate, the value is too high and too low for the actual value. Divided into 5 zones to determine the accuracy of non-invasive measurement results, where Zone A represents glucose values that deviate from the reference value by ±20% or are in the hypoglycemic range (<70 mg/dl), if the reference is also in the hypoglycemic range. Values in zone A are clinically precise and are thus characterized by the correct measurement. Zone B located above and below zone A is a benign fault; zone B represents values that deviate from the reference value, which is increased by 20%. However, values belonging to zones A and B are clinically acceptable, while values belonging to areas C, D, and E are potentially dangerous, and there is a possibility of making clinically significant measurement errors.[30].

Method

A. Model Design

This study uses image processing to detect glucose levels non-invasively using artificial neural networks (ANN). The research method is shown in Figure 1:

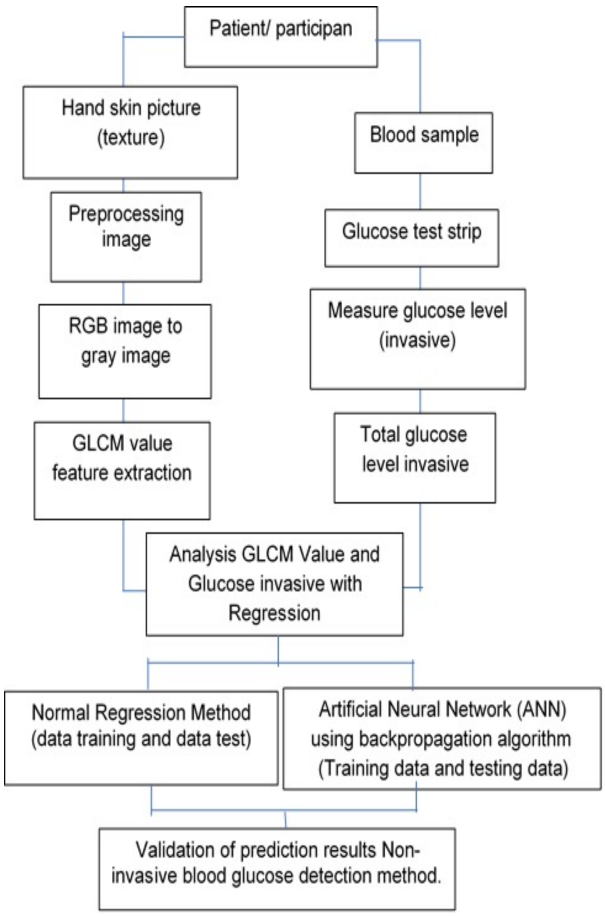


Fig.1. Architecture design model

Figure 1 illustrates the design of this study, blood samples, and hand texture images were taken at the same time from 37 participants or patients aged 20 -60 years. Blood samples are taken to determine invasive glucose levels. A collection of hand skin images and invasive blood glucose levels corresponding to each image is used to create a database system. To remove unnecessary parts of the image, a pre-processing step is required. Furthermore, the Gray Level Co-occurrence Matrix (GLCM) method was used to analyze various hand textures by adjusting the invasive glucose values using an Artificial Neural Network (ANN).

B. Pre-processing Image

Image pre-processing is the first step to improving image quality with the aim of reducing noise or unnecessary information from the image or reducing the possibility of variations that arise during image collection so that the required information can be obtained. Based on.[31]. the purpose of pre-processing is to improve the quality of the photo and make an analysis to facilitate further processing. Image pre-processing can also highlight its features, and improve experimental results. Image pre-processing is illustrated in Figure 2

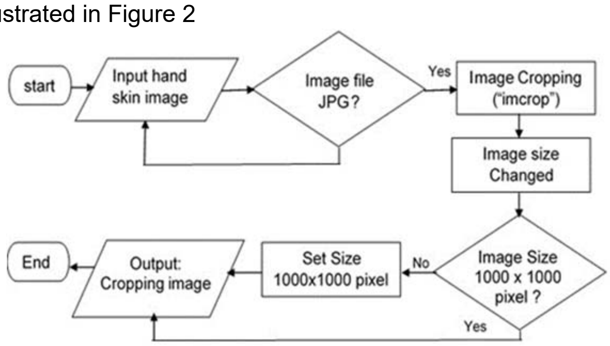


Fig.2. Image pre-processing flow.

C. Texture Extraction Gray Level Co-Occurrence Matrix (GLCM).

The texture extraction process to determine the GLCM value is described in Figure 3 below:

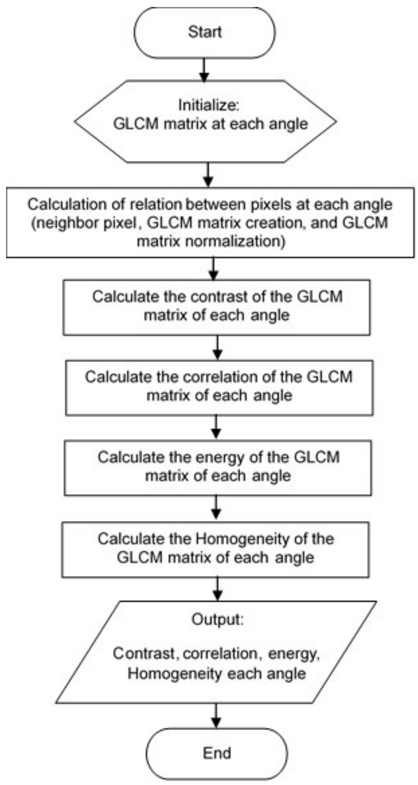
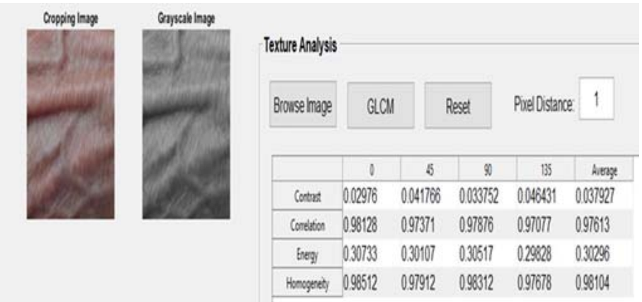


Fig.3. Stages of the GLCM texture extraction process

Figure 3 describes the texture extraction process to determine the GLCM value. The GLCM method is a matrix that shows various combinations of gray levels that can be obtained in an image and helps identify different locations in the image.[24] According to.[32]. GLCM is an image that displays complete information about directions, neighbor intervals, and variable ranges at the gray level of the image using a gray level co-occurrence matrix so that feature extraction can have a positive effect. According to [33]. for GLCM determine the probability that gray level i occurs around another gray level j at a distance d and at a certain angle, assuming the number of gray levels N is known. Image types represent contrast (Ct), correlation (Cn), energy (Ey), and homogeneity (Hy) respectively as described in the following equations (2) to (5).

Based on Ref [32]. determining the right area to investigate the type of tissue, the area to be observed, and the anatomical structure assisted by image segmentation. In this study, image segmentation is applied using the GLCM method. The first step is to determine the region of interest (ROI) in the organ to eliminate unimportant processing areas. The next step separates the disease from the ROI after the ROI has been created. Precise prediction of disease boundaries helps in the classification and categorization of diseases. To maintain the accuracy and sensitivity of the lesion detection and classification system, strong image segmentation is required. so, once a disease has been segmented, its features can be calculated to reduce false detection rates and increase diagnostic accuracy.



	0	45	90	135	Average
Contrast	0.02976	0.041766	0.033752	0.046431	0.037927
Correlation	0.98128	0.97371	0.97876	0.97077	0.97613
Energy	0.30733	0.30107	0.30517	0.29828	0.30296
Homogeneity	0.98512	0.97912	0.98312	0.97678	0.98104

Fig.4. GLCM texture extraction

Figure 4 shows the grayscale calculation of each image for each texture extraction arranged based on the GLCM matrix by taking into account the neighboring pixels of each angle, namely 0^{O}, 45^{O}, 90^{O}, and 135^{O}. each corner has a different GLCM matrix

D. Training Data

After extracting the GLCM texture on the image, the next step is to classify it using regression to determine the relationship between glucose invasion levels and GLCM texture values. The image pattern of 37 participants in each age group was trained (training data) to calculate the weights and biases. The skin images of each participant's hands were coded according to their glucose levels. training data using normal regression and using an artificial condition network (ANN).

ANN with Backpropagation uses parameters of momentum (0.9), epoch (1000), error (0.01), learning rate (0.01), and the input signal in the input layer is 4. Neurons in the hidden layer are 5 and the output is 1. Sigmoid bipolar is an activation function that is used. The stages of training are as follows:

1. The output of each layer (Zj and Yk) is calculated, then the error value (ε) is calculated and the weights and biases (Wjk and Vik) are updated until the error value is less than specified or until the iteration is complete.
2. Save in the database. mat the training results of the parameters after all iterations are complete. The data training process is explained with the flow chart in Figure 5

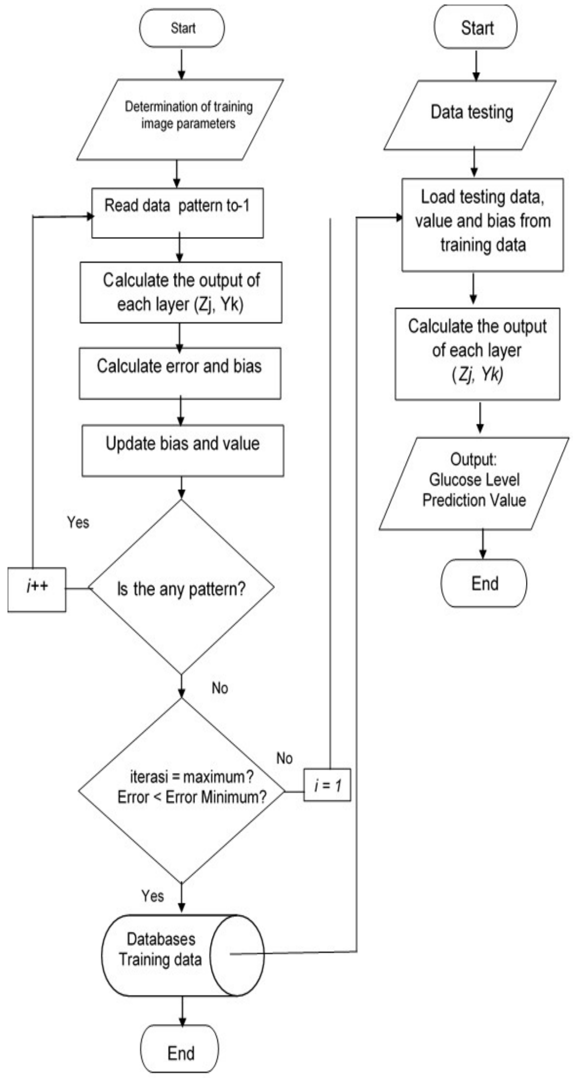


Fig.5. The process of data training and image testing on ANN.

E. Test data

The stages of testing are as follows;

1. Load input data, values and bias.
2. Calculation of test values by calculating the output of each layer (Zj and Yk), from the calculation results will produce test values that will be categorized as predictions of glucose levels. This value can be obtained from the test value generated by each image that has been processed from the cropping image texture.

After the training stages in the artificial neural network (ANN) are carried out, then the ANN testing is carried out to determine the success of the previous training process as shown in Figure 5

Results and discussion

The main goal of the proposed project is to use image processing to develop a non-invasive method for determining blood glucose levels. The main idea is to create a glucose model and convert it to glucose levels depending on the skin texture of the hands in the age range of 20 - 60 years

A. Training data

The training phase begins with initializing all data files, which includes reading RGB images, converting them to grayscale images, then pre-processing with intensity adjustments. Compile the co-occurrence matrix and extract GCLM features by determining the values of 'contrast, correlation, energy, and homogeneity' and save the results as training data. Then, as a training target, read the glucose data. By building a network architecture, it is possible to perform transposition operations on the training data to achieve the training objectives

In this study, the blood glucose prediction method (BGPM) used the GLCM value from the extraction of the skin texture of each participant/patient. Analysis using the GLCM-normal regression method and the GLCM-ANN method. The analysis of the two methods uses MATLAB 2018R, for data training and data testing

The results of the training data using the GLCM-Normal Regression method (without ANN) are shown in Figure 6:

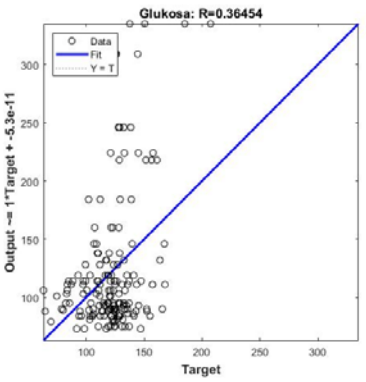


Fig.6. The results of training data using the GLCM-Normal Regression method (without ANN)

The results of the training data using the GLCM-ANN method are shown in Figure 7:

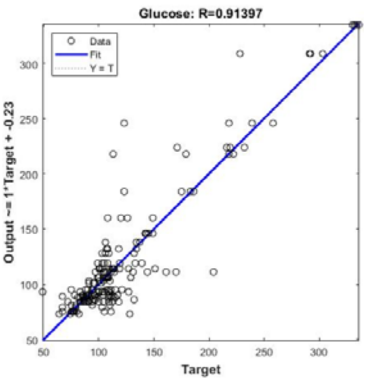


Fig.7. Results of training data using the GLCM-ANN method

Figures 6 and 7 show a graph of the linear regression plot of the training data using the GLCM - Normal Regression (without ANN) method with an R value of 0.36454 and a regression plot using the GLCM-ANN method with an R value of 0.91397. The R value determines the regression correlation between GLCM feature values and invasive glucose levels. R with a value of 1 means that there is a very strong relationship between GLCM features and glucose levels, otherwise if the R value is close to 0 it means that the relationship between invasive glucose levels and GLCM features is very weak. The GLCM-ANN method can be applied to non-invasively predict blood glucose levels through hand skin images.

B. Model Evaluation

A data testing program that uses a Graphical User Interface (GUI) program with the first step taking pictures from the patient directly or taking pictures from data files, after the original image is visible, the cropping process is carried out, then performs the analysis process and the output will display the total blood glucose and GCLM value for each characteristic (characteristic). Total glucose prediction reading data is processed as cholesterol image data. GUI program to evaluate data as in figure 8:

Fig.8. The results of data testing using the GLCM-Artificial Neural Network (ANN) method in the GUI program.

Table 1. Prediction results of non-invasive blood glucose levels using the GLCM-ANN method.

No	Participant	Glucose Level Reference (Invasive) mg/dl	Glucose Level GLCM-ANN. (Non-invasive) mg/dl
1	Arianti	84	98
2	Ahmad	184	178
3	Alfina	73	100
4	Arifah	103	98
5	Deti Y	119	117
6	Eda	81	97
7	Hadayati	75	86
8	Hania	146	151
9	Ida	90	103
10	Jumiati	93	103
11	Kamsia	224	219
12	Kurnia	138	143
13	Lina	75	79
14	Mardiah	79	86
15	Mardiana	218	215
16	Mashud	90	100
17	Masnawati	95	128

Table 2. Prediction results of non-invasive blood glucose levels using the GLCM-ANN method.

No	Participant	Glucose Level Reference (Invasive) mg/dl	Glucose Level GLCM-ANN. (Non-invasive) mg/dl
18	Nahdia	106	105
19	Nasrum	84	98
20	Ningsih	111	148
21	Norma	86	105
22	Rahayu	160	136
23	Rahmawati	106	127
24	Ramalia	84	88
25	Ratna	114	109
26	Reni	84	118
27	Rini	88	125
28	Rohana	309	277
29	Rosmini	89	92
30	Salawati	111	118
31	Samsul	88	101
32	Santi	119	124
33	Sumiati	95	112
34	Tenriana	246	221
35	Vera	114	105
36	Wanda	114	112
37	Yaya	93	109

The results of data testing with GUI applied to 37 participants are summarized in table 1;

Table I shows the results of glucose measurements in 37 participants with invasive and non-invasive techniques from the age of 20-60 years. There are differences in measurement findings between invasive and non-invasive methods using the GLCM-ANN method. Imaging processing methods and invasive methods for all data used were taken simultaneously. The output value varies for
each participant due to differences in hand skin texture, as result, the total glucose level of each participant is different.

C. Statistic analysis

Statistical analysis was used to evaluate the non-invasive blood glucose prediction method with GLCM-ANN, determine accuracy and correlation using Root Mean Square Error (RMSE), regression coefficient (r) and Clarke-Error Grid Analysis (C-EGA) which is a method that used to determine clinical accuracy.

Equations (6) to (7) are applied to determine the statistical error analysis. Based on these results, the RMSE value was 18.85 mg/dl. This shows that the predictive value of the standard error of the RMSE method is smaller than the reference value.

Equations (6) to (7) are applied to determine the statistical error analysis. Based on these results, the RMSE value was 17.16 mg/dl. This indicates that the predictive value of the standard error of the RMSE method is close to the reference value. According to.[33], the National committee for Clinical Laboratory Standards (NCCLS) that the difference in the predicted measurement results with the reference value is not more than 0.8 mmol/L (14.94 mg/dl) at a glucose level of 5.5 mmol/L (99 mg/dl. In addition, to determine the effect of GLCM on glucose values, it can be calculated using the r approach. Equation (7) illustrates that the value of r is 0.95. This r value close to 1 means that the effect of GLCM on blood glucose values is very strong by using the GLCM-ANN method to predict blood glucose.

Furthermore, when compared to reference values, the Clarke EGA is used to measure the clinical accuracy of a patient's glucose levels. Figures 9 show the Clarke EGA analysis for glucose.

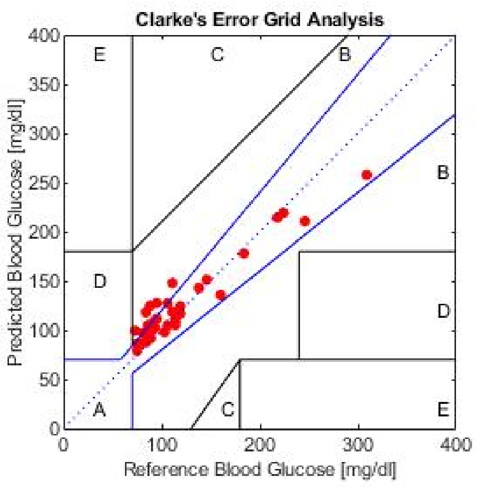


Fig.9. Clarke EGA analysis

The EGA analysis is based on blood glucose levels defining accuracy-dependent percentage value. Classified clinical accuracy for 20-60 years old, as follows: A zone has a value of 81.08% (30 participants), B zone has a value of 19.92% (7 Participants), C zone has a value of 0%, D zone has a value of 0%, and E zone has a value of 0%. This indicates that all of the results values are in the medically acceptable A zone. This discovery revealed that the non-invasive method's consistent performance is feasible to implement.

Conclusions

The proposed research has developed an innovative, smart controller to measure glucose levels. In this research, the glucose level can be identified under image processing. To analyze the image and identify distinct locations in the images that gray-level co-occurrence matrix (GLCM) has been applied in order to eliminate non-essential processing areas. An artificial neural network (ANN) is utilized in this study to train and test hand texture to identify the glucose level. Based on the findings of this study, the glucose level of the non-invasive technique is equivalent to the result of laboratory testing. The statistical analysis indicated that the RMSE and r were measured in accordance with the standard. Moreover, the analysis result under the Clarke EGA method illustrated the accuracy is acceptable to apply.

***Authors**: Usman Umar, Hasanuddin University Makassar, Indonesia, Politeknik Kesehatan Muhammadiyah Makassar, E-mail: umaru17d@student.unhas.ac.id. Prof.Dr.Ir.H. Syafruddin Syarif M.T, Hasanuddin University Makassar, Indonesia, E-mail: syafruddin.s@eng.unhas.ac.id; .Dr. Ir. Ingrid Nurtanio M.T, Hasanuddin University Makassar, Indonesia, E-mail: ingrid@unhas.ac.id. Dr. Indrabayu, ST. M.T, M.Bus.Sys. Hasanuddin University Makassar, Indonesia, E-mail: indrabayu@unhas.ac.id.*

REFERENCES

[1] W. Zheng *et al.*, "Highly-sensitive and reflective glucose sensor based on optical fiber surface plasmon resonance," *Microchem. J.*, vol. 157, no. February, p. 105010, 2020, doi: 10.1016/j.microc.2020.105010.

[2] X. Dong *et al.*, "Influence of blood glucose level on the prognosis of patients with diabetes mellitus complicated with ischemic stroke," no. 65, pp. 1–7, 2018, doi: 10.4103/1735-1995.223951.

[3] K. S. P and S. Am, "A study on the glycemic , lipid and blood pressure control among the type 2 diabetes patients of north Kerala , India," *Indian Heart J.*, vol. 70, no. 4, pp. 482–485, 2018, doi: 10.1016/j.ihj.2017.10.007.

[4] A. Kerimi, H. Nyambe, S. Alison, P. Ebun, O. Julia, and S. G. Yala, "Nutritional implications of olives and sugar : attenuation of post- prandial glucose spikes in healthy volunteers by inhibition of sucrose hydrolysis and glucose transport by oleuropein," *Eur. J. Nutr.*, vol. 58, no. 3, pp. 1315–1330, 2019, doi: 10.1007/s00394-018-1662-9.

[5] C. Beehan-quirk *et al.*, "Investigating the effects of fatigue on blood glucose levels – implications for diabetes," *Transl. Metab. Syndr. Res.*, 2020, doi: 10.1016/j.tmsr.2020.03.001.

[6] K. Ogurtsova *et al.*, "IDF Diabetes Atlas: Global estimates for the prevalence of diabetes for 2015 and 2040," *Diabetes Res. Clin. Pract.*, vol. 128, pp. 40–50, 2017, doi: 10.1016/j.diabres.2017.03.024.

[7] Y. Sun, Y. Song, C. Liu, and J. Geng, "Saudi Journal of Biological Sciences Correlation between the glucose level and the development of acute pancreatitis," *Saudi J. Biol. Sci.*, vol. 26, no. 2, pp. 427–430, 2019, doi: 10.1016/j.sjbs.2018.11.012.

[8] S. R. Chinnadayyala, J. Park, A. T. Satti, D. Kim, and S. Cho, "Minimally invasive and continuous glucose monitoring sensor based on non-enzymatic porous platinum black-coated gold microneedles," *Electrochim. Acta*, vol. 369, p. 137691, Feb. 2021, doi: 10.1016/j.electacta.2020.137691.

[9] S. Ghosal, A. Kumar, V. Udutalapally, and D. Das, "glucam: Smartphone based blood glucose monitoring and diabetic sensing," *IEEE Sens. J.*, vol. 21, no. 21, pp. 24869–24878, 2021.

[10] N. Duc, T. Van Nguyen, A. Duc, and H. Vinh, "ORIGINAL ARTICLE A label-free colorimetric sensor based on silver nanoparticles directed to hydrogen peroxide and glucose," *Arab. J. Chem.*, vol. 11, no. 7, pp. 1134–1143, 2018, doi: 10.1016/j.arabjc.2017.12.035.

[11] F. Rui, G. Zhanxiao, L. Ang, C. Yao, W. Chenyang, and Z. Ning, "Sensors and Actuators : B . Chemical Noninvasive blood glucose monitor via multi-sensor fusion and its clinical evaluation," *Sensors Actuators B. Chem.*, vol. 332, no. September 2020, p. 129445, 2021, doi: 10.1016/j.snb.2021.129445.

[12] V. P. Rachim and W. Y. Chung, "Wearable-band type visible-near infrared optical biosensor for non-invasive blood glucose monitoring," *Sensors Actuators, B Chem.*, vol. 286, pp. 173–180, 2019, doi: 10.1016/j.snb.2019.01.121.
[13] M. S. I. M. Zin1, 2. M. A. K. Mustafah1, 3. F. Arith1, 4. A. A. M. Isa1, 5. L. Barukang2, and 6. G. Markarian, "Development of Low-Cost IoT-Based Wireless Healthcare Monitoring System," *Przegląd Elektrotechniczny*, no. 1, pp. 222–227, 2022, doi: 10.15199/48.2022.01.48.
[14] H. Zhang, Z. Chen, J. Dai, W. Zhang, Y. Jiang, and A. Zhou, "A low-cost mobile platform for whole blood glucose monitoring using colorimetric method," *Microchem. J.*, vol. 162, no. October 2020, p. 105814, 2021, doi: 10.1016/j.microc.2020.105814.
[15] S. Muharom and B. Prasetyo, "Automatics Detect and Shooter Robot Based on Object Detection Using Camera," *Przegląd Elektrotechniczny*, no. 1, pp. 50–54, 2022, doi: 10.15199/48.2022.01.07.
[16] E. R. Dougherty, *Digital image processing methods*. CRC Press, 2020.
[17] E. Seeram, "Digital image processing concepts," in *Digital Radiography*, Springer, 2019, pp. 21–39.
[18] M. A. Jardine, J. A. Miller, and M. Becker, "Coupled X-ray computed tomography and grey level co-occurrence matrices as a method for quantification of mineralogy and texture in 3D," *Comput. Geosci.*, vol. 111, pp. 105–117, 2018, doi: 10.1016/j.cageo.2017.11.005.
[19] I. Pantic, D. Dimitrijevic, D. Nesic, and D. Petrovic, "Gray level co-occurrence matrix algorithm as pattern recognition biosensor for oxidopamine-induced changes in lymphocyte chromatin architecture," *J. Theor. Biol.*, vol. 406, pp. 124–128, 2016, doi: 10.1016/j.jtbi.2016.07.018.
[20] P. K. Bhagat, P. Choudhary, and K. M. Singh, *A comparative study for brain tumor detection in MRI images using texture features*. Elsevier Inc., 2019.
[21] N. J. Road, S. E. Inspection, Q. Bureau, F. Road, and F. District, "SYSTEM BASED ON NEURAL NETWORK COMPENSATING," vol. 15, no. 7, pp. 725–735, 2021, doi: 10.24507/icicel.15.07.725.
[22] D. A. Anggoro and D. Novitaningrum, "MACHINE (SVM) AND ARTIFICIAL NEURAL NETWORK (ANN)," vol. 15, no. 1, pp. 9–18, 2021, doi: 10.24507/icicel.15.01.9.
[23] P. Agarwal and R. K. Srivastava, "INTRUSION DETECTION WITH NEIGHBOURHOOD COMPONENT ANALYSIS," no. December, 2021, doi: 10.24507/icicel.15.12.XXX.
[24] M. N. S. ZAINUDIN1 *et al.*, "A Framework for Chili Fruits Maturity Estimation using Deep Convolutional Neural Network," *Przegląd Elektrotechniczny*, vol. 2021030955, no. 12, pp. 77–81, 2021, doi: 10.15199/48.2021.12.13.
[25] P. R. Vlachas, J. Pathak, B. R. Hunt, T. P. Sapsis, M. Girvan, and E. Ott, "Backpropagation algorithms and Reservoir Computing in Recurrent Neural Networks for the forecasting of complex spatiotemporal dynamics," *Neural Networks*, vol. 126, pp. 191–217, 2020, doi: 10.1016/j.neunet.2020.02.016.
[26] L. G. Wright *et al.*, "physical systems."
[27] T. Lu, X. Lü, H. Salonen, and Q. Zhang, "Novel hybrid modeling approach for utilizing simple linear regression models to solve multi-input nonlinear problems of indoor humidity modeling," *Build. Environ.*, vol. 213, no. November 2021, p. 108856, 2022, doi: 10.1016/j.buildenv.2022.108856.
[28] B. V. Ayodele, S. I. Mustapa, N. Mohammad, and M. Shakeri, "Long-term energy demand in Malaysia as a function of energy supply: A comparative analysis of Non-Linear Autoregressive Exogenous Neural Networks and Multiple Non-Linear Regression Models," *Energy Strateg. Rev.*, vol. 38, p. 100750, 2021, doi: https://doi.org/10.1016/j.esr.2021.100750.
[29] O. M. Olatunji, I. T. Horsfall, E. Ukoha-Onuoha, and K. Osa-aria, "Application of hybrid ANFIS-based non-linear regression modeling to predict the% oil yield from grape peels: Effect of process parameters and FIS generation techniques," *Clean. Eng. Technol.*, vol. 6, p. 100371, 2022.
[30] K. Chowdhury, A. Srivastava, N. Sharma, and S. Sharma, "Error Grid Analysis of Reference and Predicted Blood Glucose Level Values as Obtained from the Normal and Prediabetic Human Volunteers," vol. 5, no. 1, pp. 6–14, 2015, doi: 10.5923/j.ajbe.20150501.02.
[31] C. Hernandez-Matas, A. A. Argyros, and X. Zabulis, *Retinal image preprocessing, enhancement, and registration*. Elsevier Ltd., 2019.
[32] S. Gao, "International Journal of Cognitive Computing in Engineering Gray level co-occurrence matrix and extreme learning machine for Alzheimer ' s disease diagnosis," *Int. J. Cogn. Comput. Eng.*, vol. 2, no. July, pp. 116–129, 2021, doi: 10.1016/j.ijcce.2021.08.002.
[33] P. K. Bhagat, P. Choudhary, and K. M. Singh, "A comparative study for brain tumor detection in MRI images using texture features," in *Sensors for Health Monitoring*, Elsevier, 2019, pp. 259–287.
[34] D. Koundal and B. Sharma, "3 - Advanced neutrosophic set-based ultrasound image analysis," Y. Guo and A. S. B. T.-N. S. in M. I. A. Ashour, Eds. Academic Press, 2019, pp. 51–73.
[35] H. T. Ho, W. K. Y. Yeung, and B. W. Y. Young, "Evaluation of 'point of care' devices in the measurement of low blood glucose in neonatal practice," *Arch. Dis. Child. Fetal Neonatal Ed.*, vol. 89, no. 4, pp. 356–360, 2004, doi: 10.1136/adc.2003.033548.