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Application of Artificial Neural Network and Gray Level Co-Occurrence Matrix to Detect Blood Glucose Levels Through The Skin of The Hands.

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Abstract

Increased glucose in the blood can cause a buildup so that it cannot be absorbed by all of the body's cells, this problem can cause various disorders in the body's organs. To avoid problems, it is necessary to check the blood glucose level regularly. Monitoring blood sugar levels is currently still using invasive techniques that are painful, non-invasive monitoring is needed. 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.

Keywords: *Blood Glucose, Non-Invasive, GLCM, ANN*

I. 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-Checkext.

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

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days and lost its functional activity after 7 days. [8].

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.[9].

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 162 nM and 30 μM for H2O2 and glucose sensing, respectively.[10]. The authors.[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. 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 %-14.5 3% compared to commercial glucose meters. [13].

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.

II. LITERATURE REVIEW

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.[14]. 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. [15].

2.1. Gray Level Co-Occurrence Matrix (GLCM)

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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. [16]. 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. [17]. 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.[18].

$$GLCM = P_r(i,j)|\, d,\ \theta, N \qquad (1)$$

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

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

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

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

where: i - GLCM determines the likelihood of a gray level, j - occurring in the vicinity of another gray level, d - at a given distance, θ - angle and N - assuming the total number of gray levels

The kind of image represents contrast (Ct), correlation (Cn), energy (Ey) and homogeneity (Hy).

2.2. Artificial Neural Network (ANN)

ANN is a method for making prediction models that are accurate, efficient, and effective [19]. The technique and its implementation are called "neural networks" because they resemble traditional neural networks. According to.[20]. 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.[21]. The backpropagation algorithm requires a gradient calculation for each variable in the model to generate a new value for the variable. According to [22] 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.[23].

III. METODE PENELITIAN

3.1. Model Design

The design of this study, starting with blood sampling, and hand texture delineation was carried out simultaneously from 36 participants from male and female patients aged 20 -60 years. Blood samples were taken to determine blood glucose levels using invasive techniques as primary data. A collection of hand skin images and blood glucose levels adjusted to the image of each participant, was used for training data. Removing parts of the image that are not needed, with a pre-processing step and then determining the required image segment by cropping the image. 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). The research method design is shown in Figure 1.

Figure. 1. Architecture design model

3.2. Pre-processing Image

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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. [27]. 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.

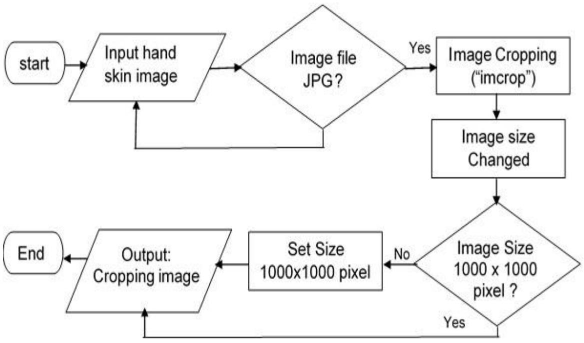

Figure. 2. Image preprocessing flow.

3.3. Gray Level Cooccurrence Matrix (GLCM) extraction feature

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. 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.[28].

According to [18]. 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 Reference by [29] to determine the right area to investigate the type of tissue, the area to be observed, and its anatomical structure assisted by image segmentation. In this study, image segmentation was 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. The grayscale calculation of each image for each texture extraction arranged based on the GLCM by taking into account the neighboring pixels of each angle, namely 0O, 45O, 90O, and 135O. each corner has a different GLCM value.

3.4. Data Training Process

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.[30]. 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 3.

The stages of training are as follows:

- 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.
- Save in the database. mat the training results of the parameters after all iterations are

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complete. The data testing process is explained with the flow chart in Figure 3

The stages of testing are as follows;

- Load input data, values and bias.
- 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.

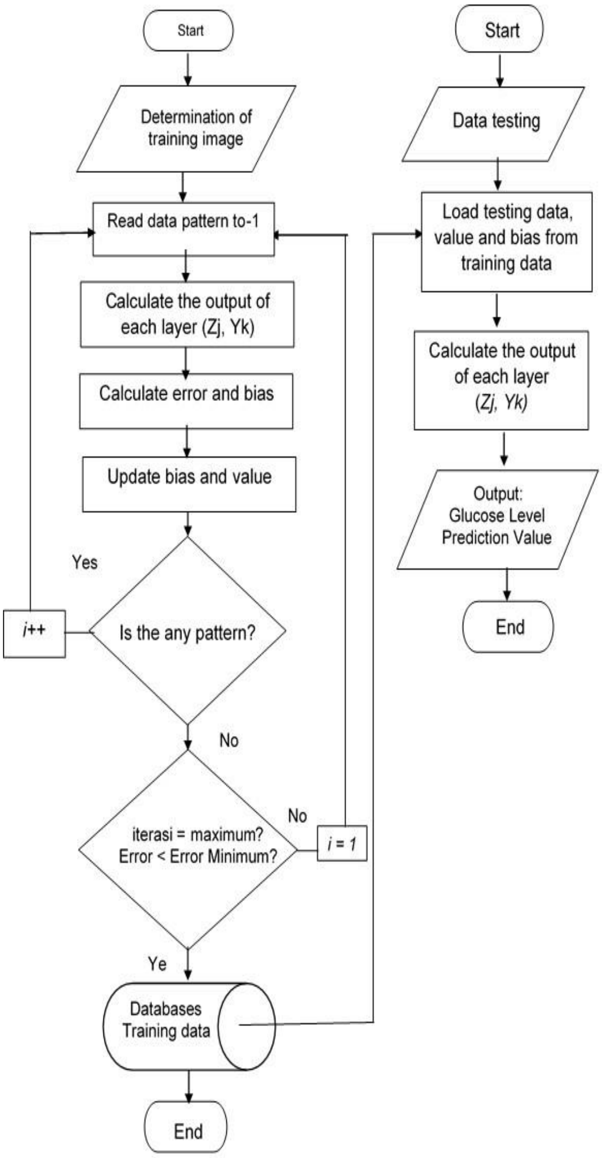

Figure. 3. The process of data training and image testing on ANN

3.5. Statistical Analysis

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.[24].

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

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

Where; r – correlation coefficient regression, yp - represent the observed values, y- model fitting values, and $\bar{y}$pavg - 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.[25] 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.[26].

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VI. RESULT 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.

4.1. Training Data

The training phase begins with initializing all data files, including reading RGB images, converting them to grayscale images, then pre-processing with intensity adjustments. Compile the co-occurrence matrix and extract the 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

Figure. 4. Sample image cropping for data training process

The following Figure 4 shows an example of a cropped image as the result of the preprocessing image stage; 36 photographs from participants were utilized for training data. The "im-crop algorithm" is used for image cropping, which results in a rectangular image with a dimension of 1000 by 1000 pixels. Using the backpropagation process on an artificial neural network (ANN)., this cropping is regressed with the reference total cholesterol data for each sample. The data training process uses ANN with a backpropagation algorithm operated on MATLAB R2018b, with invasive blood glucose and GLCM data. In the process of training this data using the GLCM-ANN method. Figure 5 shows the data training process."

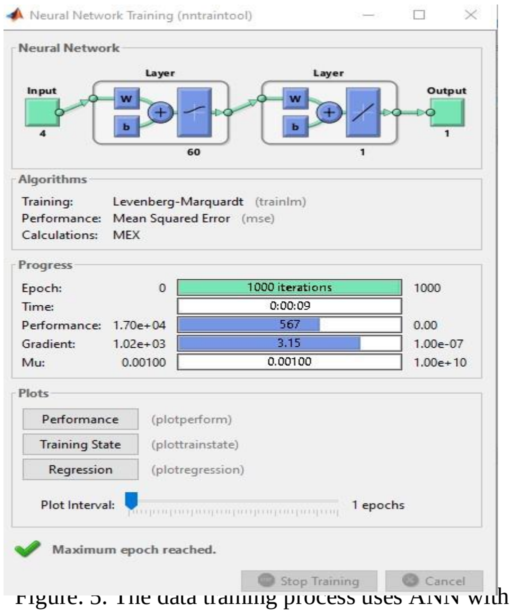

Figure. 5. The data training process uses ANN with backpropagation algorithm

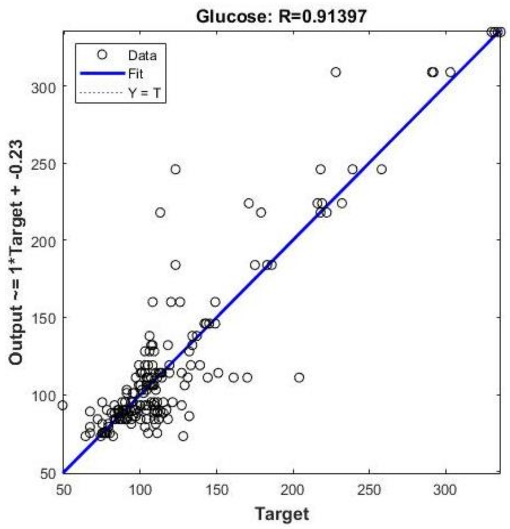

Figure. 6. Training data using the GLCM-ANN method

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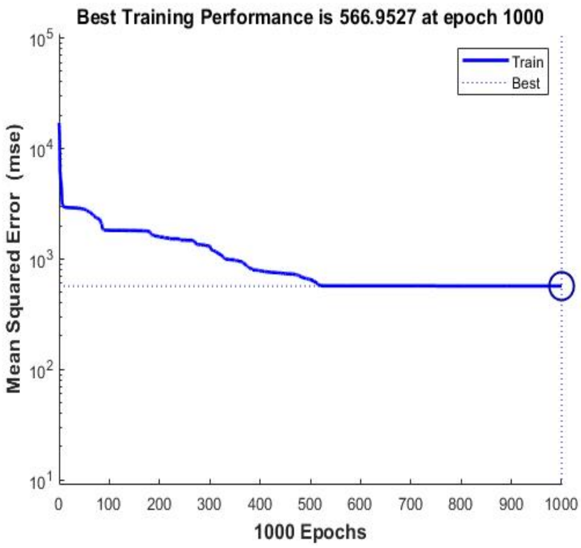

Figure. 7. Performance of training with nntool on a neural network using the GLCM-ANN method

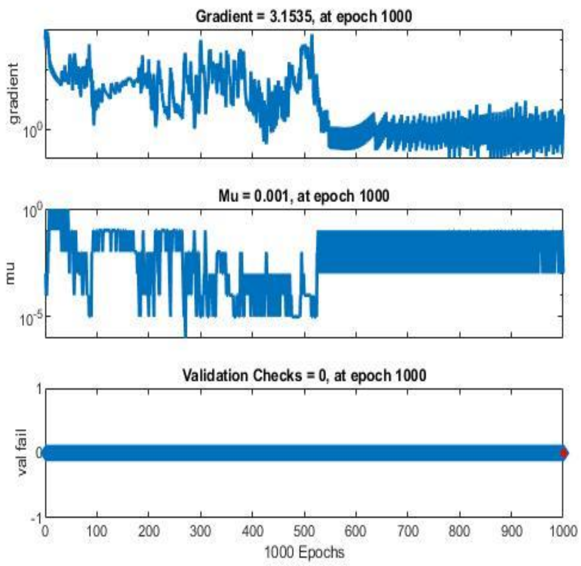

Figure. 8. Training state on a neural network using the GLCM-ANN method.

4.2. Evaluation Model

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. Total glucose prediction reading data was processed from hand skin images with ANN using the GUI program as shown in Figure 9.

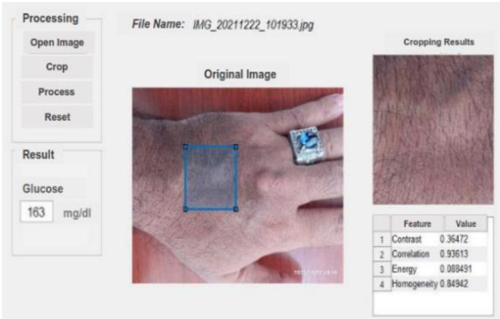

Figure. 9. Testing data with hand skin images

Figure 9 is the testing process as a proof of the training process to predict blood glucose levels based on the training database. Hand skin image data from participants to evaluate a non-invasive blood glucose level prediction model using GLCM and artificial neural networks (ANN). The results of non-invasive glucose level prediction and invasive glucose level measurement are shown in Table 2.

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

No	Participant Name	Glucose Level Reference (Invasive) (mg/dl)	Glucose Level GLCM-ANN. (Non-invasive) (mg/dl)
1	Agnes	84	98
2	Ahwan	184	178
3	Alena	73	100
4	Aryani	103	98
5	Desty	119	117
6	Erica	81	97
7	Hanifa	75	86
8	Hana	146	151
9	Indah	90	103
10	Jumala	93	103
11	Kinsia	224	219
12	Kinang	138	143
13	Leoni	75	79
14	Mariah	79	86
15	Maryama	218	215
16	Michael	90	100
17	Mardalena	95	128
25	Rachma	114	109
26	Resya	84	118
27	Rita	88	125
28	Rosna	309	277
29	Romiani	89	92
30	Scarlet	111	118
31	Sammiguel	88	101
32	Sarah	119	124

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33	Sumirah	95	112
34	Triana	246	221
35	Veronica	114	105
36	Winda	114	112

4.3. Statistical Analysis

Statistical analysis was used to evaluate the non-invasive blood glucose prediction method with GLCM-ANN, and determine accuracy and correlation using Root Mean Square Error (RMSE), regression coefficient (r), and Clarke-Error Grid Analysis (C-EGA) which is a method used to determine clinical accuracy. The comparison of the results of measuring blood glucose levels with the invasive method using blood samples as reference data with the results of predicting blood glucose levels using

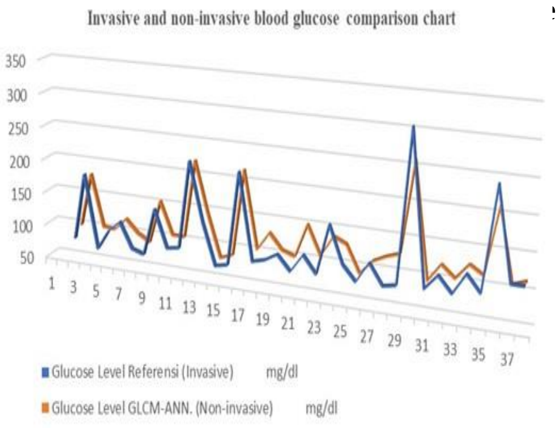

Figure. 10. Performance of the comparison characteristics of GLCM -ANN (non-invasive) blood glucose detection results and reference blood glucose from participants

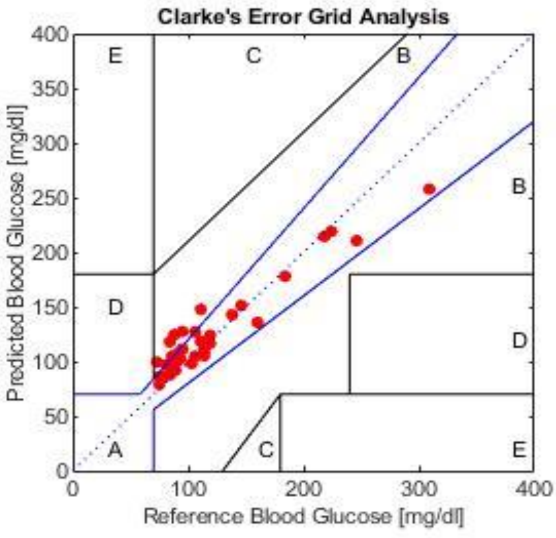

Figure. 11. Clarke- EGA analysis

4.4. Discussion.

This study has the main objective of detecting blood glucose levels with a non-invasive method through artificial neural network (ANN)-based image processing. The results of the study will be discussed in this section

Figure 5 shows the data training process in MATLAB R2018b using the neural network tool (nntool) to train data on the GLCM-ANN method with the backpropagation algorithm. based on the data training process flow in Figure 4. The data training was carried out with reference data on invasive blood glucose levels in table 1 and cropping image data in figure 5, using parameters of momentum (0.9), epoch (1000), error (0.01), and learning rate (0.01). The training process takes 9 seconds with a total of 176 files. The results of the training data performance, training state, and regression, are shown in Figures 6 to 8.

Figure 6 results of training data 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, Figure 7 shows the results of the performance training data using the GLCM-ANN method with the best performance being 566.95 at 1000 iterations, Figure 8 describes the training data status with a gradient of 3.15 and Mu 0.01 at 1000 iterations. The results of the training data prove that the GLCM-ANN method can be applied to predict blood glucose levels non-invasively through hand skin images.

Figure 9. is a data testing program that uses a graphical user interface (GUI) to predict blood glucose levels non-invasively, the test process by entering an image of the skin of the hand from a file that has been captured and saved previously. The next step after the image has appeared, cropping the image to determine the region of interest (ROI) with dimensions of 1000 x 1000 pixels. In the next stage after the cropping results are displayed, carry out the process to determine the prediction of blood glucose levels within < 3 seconds, the results of the prediction of blood glucose levels and the GLCM value of the cropping image are also displayed. The test results of 36 participants are shown in table 2.

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Table 1 is the result of testing hand skin images from 36 participants with reference to blood glucose data (invasive) and blood glucose prediction data (no-invasive). Blood glucose prediction is obtained from the results of data testing, to determine the accuracy and error of blood glucose prediction, then tested by statistical analysis methods. Root mean square error (RMSE), correlation coefficient, and Clarke-Error Grid Analysis (C-EGA) were chosen to statistically analyze the predicted results of the GLCM-ANN method. based on equation (6), mathematically calculated the RMSE value is 17.16 mg/dl. According to [31], 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. The RMSE value obtained is 17.16 > 14.96 mg/dl, this indicates that the predictive value of the standard error of the RMSE method is close to the reference value. The effect of GLCM on glucose values can be determined using the correlation method (r). equation (7) mathematically calculated the value of r is 0.95, with this r value close to 1, meaning that the influence of GLCM on blood glucose values is very strong. Figure 10 shows the correlation between blood glucose values with invasive techniques and blood glucose predictions by non-invasive techniques using the GLCM-ANN method, the blue line (representing the reference data) coincides with the orange line (representing the predictive data) this proves that the method gives excellent results.

Figure 11 shows the Clarke EGA analysis for glucose, the Clarke EGA was used to measure the clinical accuracy of the patient's glucose levels. The EGA analysis is based on blood glucose levels determining a percentage value that depends on accuracy. Clinical accuracy is classified for ages 20-60 years, as follows: Zone A is worth 81.08 % (30 participants), Zone B is worth 19.92 % (6 Participants), Zone C is worth 0 %, Zone D has a value of 0 %, and zone E has a value of 0%. This indicates that all the result values are in the medically acceptable zone A, and those in zone B need attention for the development of the GLCM-ANN method to be more accurate. These findings reveal that the consistent performance of non-invasive methods is feasible

V. 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.

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