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A Non-invasive Approach to Detection Blood Glucose Levels with Hand Skin Image Processing Using Smartphone

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ABSTRACT Measuring blood sugar levels today still use invasive techniques that are painful so non-invasive monitoring is needed. This study aims to develop a non-invasive technique to identify and detect blood glucose through hand-skin image processing. This development method is by taking invasive blood glucose hand images and 30 participants aged 20-60 years, data analysis is done by image preprocessing, determining the Gray level co-occurrence matrix (GLCM) value, using the backpropagation algorithm to conduct training and data testing. to define a blood glucose monitoring model. The blood glucose detection model is implemented through the android operating system on smartphones by developing the GULAABLE application on smartphones which is simple and easy to use and without blood sampling. This GULAABLE application is to determine the condition of low or high blood glucose and can be used routinely at a low cost. Validating the results by identifying this non-invasive application compared with the results of invasive glucose measurements by applying to 10 participants, the identification results show an accuracy of 80%, so it can be concluded that the GULAABLE application method on smartphones can be used to monitor blood glucose conditions at any time by simply taking hand skin image.

INDEX TERMS Blood glucose, Invasive, Non-invasive, Smartphone, GULAABLE

I. INTRODUCTION

Blood glucose (C6H12O6) is a very important component in human body tissues.[1]. Glucose is a carbohydrate element that produces an energy source for all body cell tissues, accelerates metabolism and functions as the main fuel for the brain, and controls body temperature.[2]. Uncontrolled blood sugar conditions can cause blood vessel disease [3]. Excessive glucose levels over a long period of time can lead to diabetes, which can be complicated by other diseases such as nerve damage, vision loss, kidney damage, kidney disorders, and an increased risk of cardiovascular disease.[4]. Ref [5] Investigation of diabetes mellitus (DM) which currently affects 1.2 million Australians. In 2015, DM was the leading cause of death globally and accounted for 5 million deaths in the world [6]. The global population of individuals with DM will reach 642 million people [5][6]. 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, with around 5 million people dying from diabetes.[7] Consequently, the patient's glucose may influence disease progression.[8]. Measurement of glucose levels is currently still using invasive techniques that use blood samples for measuring strips. Blood samples are taken by pricking the fingertips, causing pain to the patient. Several invasive measuring devices that exist can measure blood glucose t such as Easy Touch GCU, Nesc Multi check, Auto check, and Accu-Check. Research that has been developed to minimize the shortcomings of invasive techniques include. The study conducted by.[9] Proposed an invasive method to monitor 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) were applied to identify glucose levels. As a result, the device showed good stability for 7 days and lost its functional activity after 7 days. Other research is developing microneedle (MN) technology in medical sensing devices. This technology was developed because of the advantages of minimally invasive, real-time, and convenience. The study was developed based on electrochemical biosensors, conducting polymers (CPs), enzymes, nanoparticles, and their composites. The results show the application of MN that can be used to selectively monitor glucose [13]. The impact of this invasive technique is to cause pain when taking blood samples at the fingertips. This causes many patients not to want to check their glucose levels continuously. Currently, monitoring glucose levels without blood samples was introduced by several researchers in the development of non-invasive techniques to measure blood glucose levels. Ref [10] applied silver nanoparticles (AgNPs) and graphene quantum dots (GQDs) nanocomposite as sensor glucose. Moreover, the fabricated sensors perform good sensitivity and selectivity with a low detection limit of 162 nM and 30 µM for H2O2 and glucose sensing, respectively. The authors in [11] applied multi-sensor fusion to detect blood glucose levels. by applying the K-mean clustering algorithm to improve accuracy in detecting glucose levels, by classifying various categories of parameters characteristic of diabetics. As a result, the grid error is 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. This research was conducted at the National Medical Products Administration of China. Research using near-infrared optical biosensors for the development of non-invasive blood glucose monitoring with lower cost and effectiveness. There were 12 patients tested to justify the accuracy of this tool. Based on these results, the standard of prediction of the estimated standard error of prediction (SPE) is 6.16 mg/dl.[12]. Author in [13]. Propose A low-cost mobile platform for detecting blood glucose levels using 3D printed smartphone-based optics enabling easy reading and analysis of glucose detection by avoiding the intensity influence of ambient light variations. This system successfully detects various 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 whole human blood samples was performed. Results with relative errors ranging from 4.37% to 14.41% compared to spectrophotometric methods, and 3.83%-14.53% compared to commercial glucose meters. Author in.[14]. Filed the gluCam application - a new, autonomous, non-invasive, optical-based model for intelligent diabetes sensing. Using polynomial regression was developed to predict blood glucose levels. Diabetes is diagnosed via an easy smartphone, gluCam incorporates image processing techniques to measure blood glucose levels. Testing the model on 81 patients with a sensitivity of 94.28%, specificity of 82.61%, mean absolute error of 10.7%, and overall accuracy of 91.89%. The model remains unaffected by lighting conditions and is independent of the device platform.

Based on the background and previous research that monitoring blood glucose levels with minimally invasive and non-invasive invasive techniques generally uses optical sensors. However, there are also those who use smartphones to detect blood glucose levels through blood vessel images. The proposed study describes a blood glucose detection system based on hand skin image processing under Artificial Neural Networks. Which is implemented on a smartphone with QS android through the gulaable application. This paper is organized into four sections: section 2 presents the methodology; section 3 discusses the results and discussion, and section 4 presents conclusions.

II. METHODS

A. ARCHITECTURAL DESIGN.

FIGURE 1 illustrates the stages of image processing through a smartphone to detect glucose levels non-invasively with a GULAABLE application. In this study, blood samples and hand texture images were taken from patients aged 20 -60 years. Blood samples are taken to determine invasive glucose levels. A collection of hand texture images and invasive blood glucose levels corresponding to each image was used to create a database system. In order to remove unnecessary parts from the incoming 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 for glucose values under the Artificial Neural Network. The analysis is implemented on a smartphone to design a GULAABLE application using Android on a smartphone.

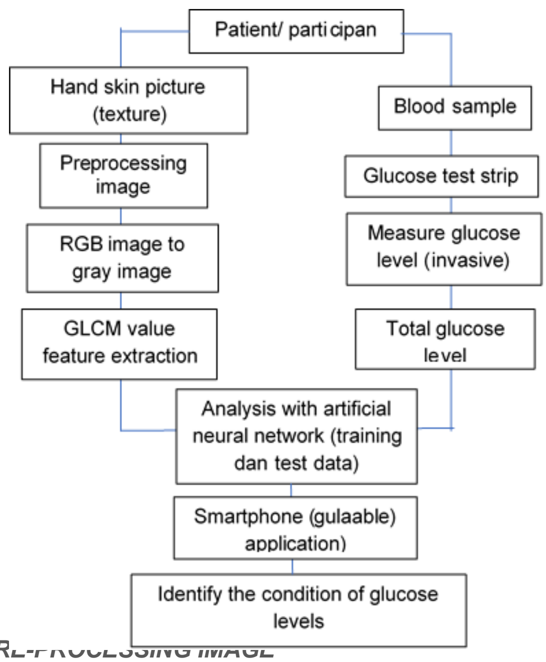

FIGURE 1. Architectural design

B. PRE-PROCESSING IMAGE

The first step is to take an image of the skin of the hand, then the next step is to improve the image quality by preprocessing the image. This step aims to reduce noise or unnecessary information from the image or reduce possible variations that arise during image collection without losing important information. According to. [15]. The purpose of pre-processing is to improve the quality of the photo and make analysis to facilitate further processing. Image pre-processing can also highlight its features, and improve experimental results.

C. GRAY LEVEL CO-OCCURRENCE (GLCM)

Based on Ref [16] the determination of the right area to investigate the type of tissue, diseased area, and anatomical structure is assisted by image segmentation. In this study, image segmentation is applied using the GLCM method. The first step is to determine the desired area (ROI) on the organ to eliminate unimportant processing areas. The next step separates the disease on 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, when the disease has been segmented, its features can be calculated to reduce the false detection rate and increase the accuracy of the diagnosis. 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.[17]. According to [18]. GLCM is an image that displays complete information about the direction, neighbor intervals, and variable ranges at the gray level of the image using a gray level co-occurrence matrix for feature extraction can have a positive effect. According to [19] GLCM determines the probability of gray level i occurring around another gray level j at a certain distance θ and angle, as illustrated in the following Eq (1).

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

D. ARTIFICIAL NEURALNETWORK (ANN)

ANN is one of the methods to make prediction models that are accurate, efficient, and effective. [20][21]. It is called a "neural network" because it resembles a traditional neural network. According to [22] ANN consists of neurons or artificial nodes. The ANN functionality in this study has five simple stages, the following can be explained:

1. Reads hand texture as input data.
2. Create a Glucose prediction model (Linear Function)
3. Calculate the prediction model error.
4. Inform and apply the necessary model corrections until the model has the least number of errors found.
5. Use this model to classify glucose levels based on hand texture applied to an android smartphone.

In this study, the Backpropagation method is used as an algorithm to build a Linear Regression Neural Network. A backpropagation optimization algorithm can be used to train 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.[23] Although simple, Backpropagation Approach is a popular and successful numerical optimization in machine learning to model classification algorithms more accurately.

This model performs the same training for each group or batch but ignores the fact that the gradient variance, as a result of Sampling Bias and Intrinsic Image Differences, results in different training dynamics in the batch. A new training technique based on hand texture and glucose values has been established in this study. The main strategy of this training is against inconsistency, which is dynamically adjusted through training efforts to reduce losses.[24]. Image processing on an artificial neural network (ANN) for data training and data testing is shown in the following FIGURE 2.

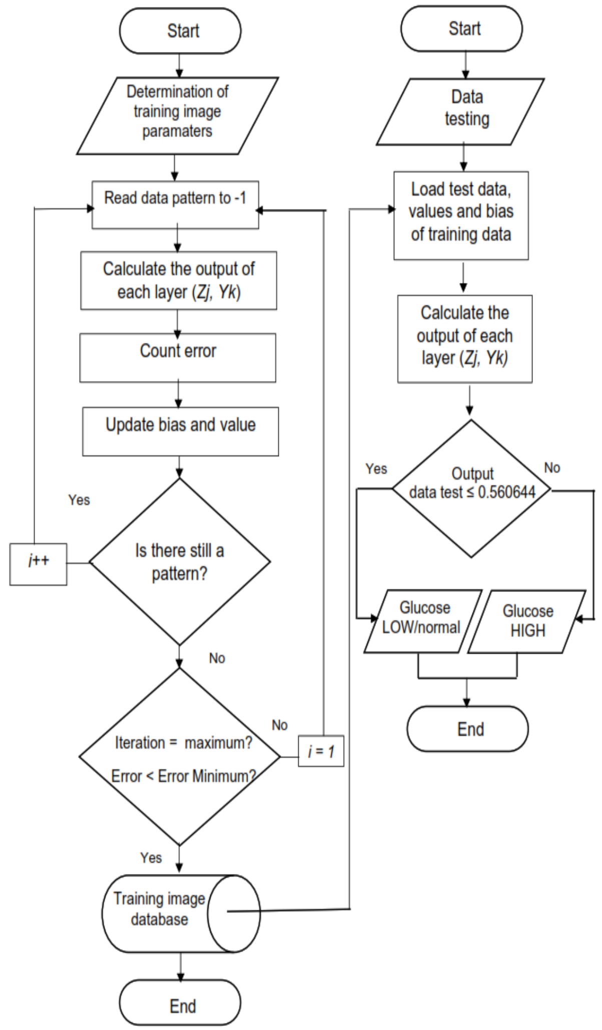

FIGURE 2. Flowchart for data training, and data testing image

FIGURE 3 is an image process flow on an artificial neural network (ANN) with the stages of training and testing data. These stages 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 stages of testing are as follows;

1. Load input data (load data input), weights, and biases.
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 texture of the cropping image. The data training stages on the artificial neural network (ANN) are then tested to determine the success of the previous training process [25].

E. GULAABLE

GULAABLE is an application designed to monitor the condition of blood glucose levels built on the Android operating system. Applications on the Android operating system use the Java language. Application development on android mobile is very flexible with a platform that provides a dynamic java IDE and java android library for third-party development and innovation.[26]. This study developed the GULAABLE application to process hand skin images to classify glucose levels at LOW or HIGH levels based on glucose reference values. Based on the National Committee for Clinical Laboratory Standards (NCCLS) 70 mg/dl < 180 mg/dl categorized as LOW and HIGH if >180 mg /dl.
The operation of this GULAABLE application is carried out in several stages, the first stage is loading for system initialization in general, the second stage is looking for previously distorted images or capturing new images to be processed in the next step, and the third stage is editing or cropping images according to the size required for processing. Analyzed the next stage is the analysis of the cropped image to determine glucose levels based on the database training data, the analysis takes about 10 minutes to realize the results. The last stage is to save the data from the analysis by setting user data.

The GULAABLE application must be installed on a smartphone with a minimum operating system of Android 12 and above which already has a good and fast image cropping feature. How to operate the GULAABLE application on a smartphone according to the process flow in the following FIGURE 3.

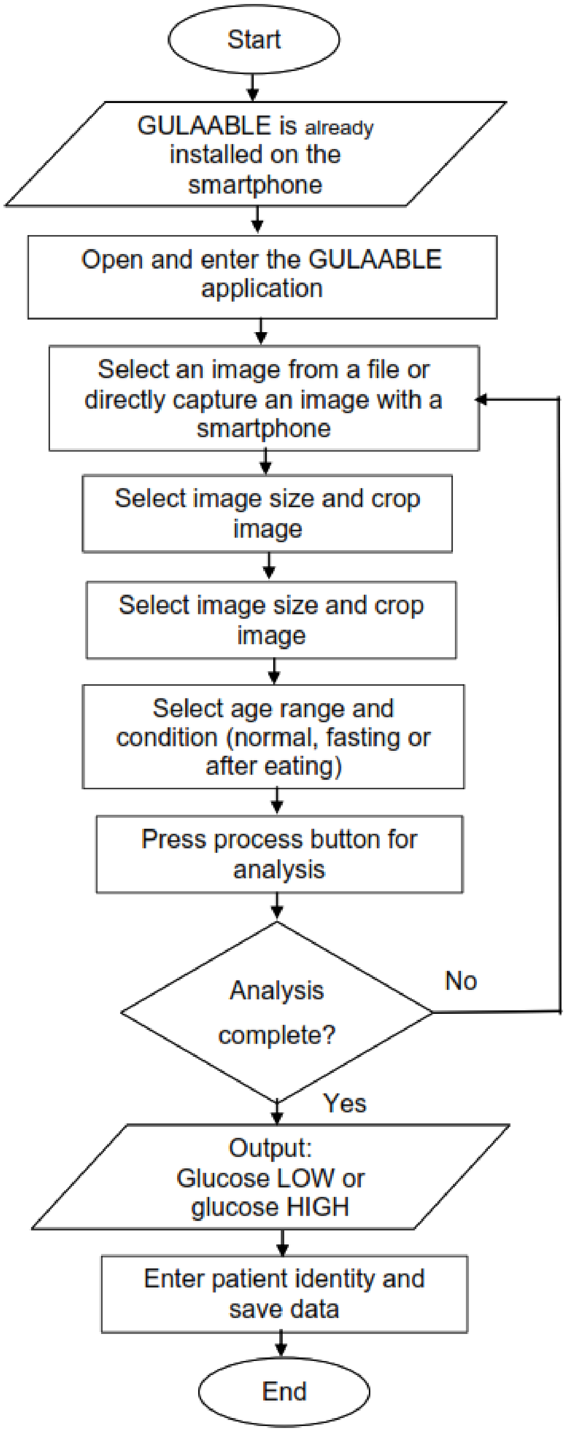

FIGURE 3. **GULAABLE application operation process**

III. RESULT

This research focuses on developing non-invasive monitoring of blood glucose levels using image processing methods through artificial neural networks (ANN) and android OS. The main idea is to create a GULAABLE application model and which is implemented on the android operating system on smartphones that classifies blood glucose levels. This study

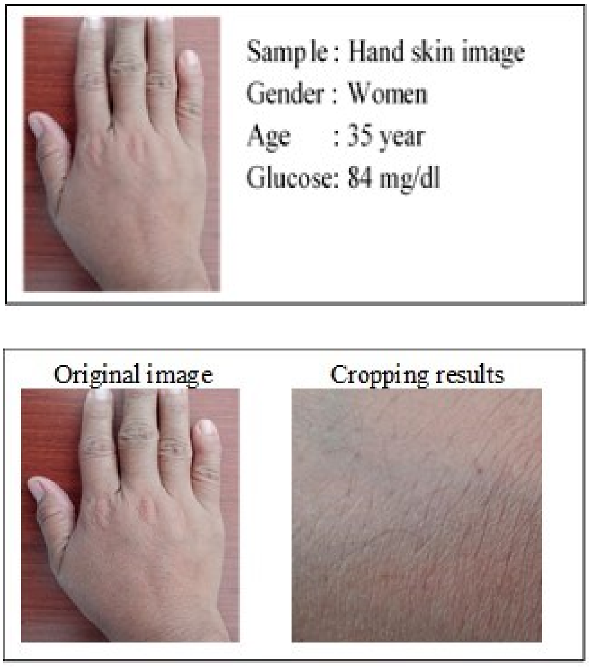

FIGURE 4. **Hand skin image and cropping results. Preprocessing image**

only considers two types of glucose classification LOW or HIGH in Normal or Fasting conditions at 20 to 60 years.

A. TRAINING DATA

FIGURE 4 below shows an example of a hand drawing of a patient with invasive glucose levels and a cropped image generated from the image pre-processing stage; 20 skin images of each participant were used for training data from 26 -60 years of age. The "im-crop algorithm" is used for image cropping, which produces a rectangular image with dimensions of 1000 by 1000 pixels. A backpropagation algorithm on an artificial neural network (ANN) is used to regress cropping images with total invasive glucose data for each sample. FIGURE 5 is the result of a training data regression plot with ANN, consisting of 176 cropping image files that have been adjusted to the output value of feature or texture extraction from GCLM with invasive blood glucose levels. The training stage begins with initializing all data files, which consists of 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 value contrast, correlation, energy, and homogeneity and save the training data results as a database.[27]. Then, as a training target, read the glucose data. By building a network architecture, it is possible to perform transposition operations on training data and training objectives. The results of the plot, show a regression coefficient (R) of 0.91397 Learning rate is obtained in the training process within 9 seconds, the epoch process ends in 1000 iterations with a gradient achievement of 3.15, and the R-value shows the relationship between GCLM values and glucose levels. very good for predicting total glucose because it is close to 1.

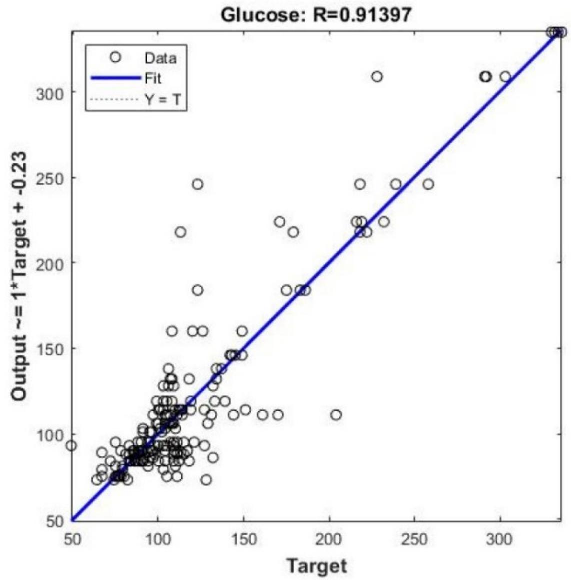

FIGURE 5. **Result of training data**

B. TOOL EVALUATION

Data testing program using the GULAABLE application on a smartphone with steps to open or take pictures from data files or directly capture the skin of the hand, after the original image is visible, the cropping process is carried out, then analyzed according to the training data database and the output displays LOW glucose levels or HIGH. The data is distorted according to the user's identity as glucose image data. As can be seen in FIGURE 4. The first step is to install and open the GULAABLE application on a smartphone, as shown in FIGURE 5:

FIGURE 6. **GULAABLE Apps and displays on smartphones**

The second step of the menu display gives the option to add the image of the skin of the hand with the choice of taking pictures from files that have been previously saved or taking pictures directly, the display on the smartphone is like in FIGURE 7.

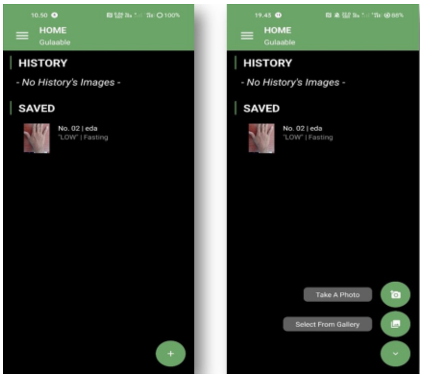

FIGURE 7. Menu display to select hand skin image and save image in history.

Then the third step after the skin image has been obtained, cropping is carried out according to the required size, and the cropping results will be displayed for analysis, shown in FIGURE 8 below:

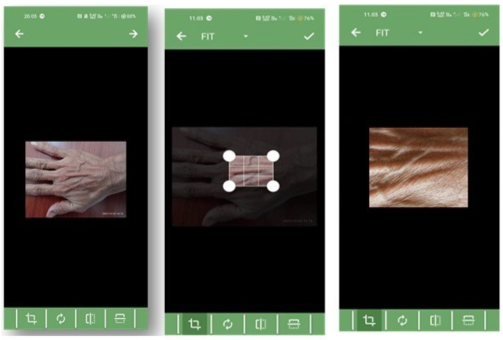

FIGURE 8. Menu display for image cropping processing

The next stage is the analysis process, this process takes about 10 minutes, depending on the size of the cropping image. The results of the analysis are based on the displayed LOW or HIGH blood glucose conditions, then the next step is finalization by editing or inputting the patient's identity and saving it. This stage is shown in FIGURE 9 and FIGURE 10.

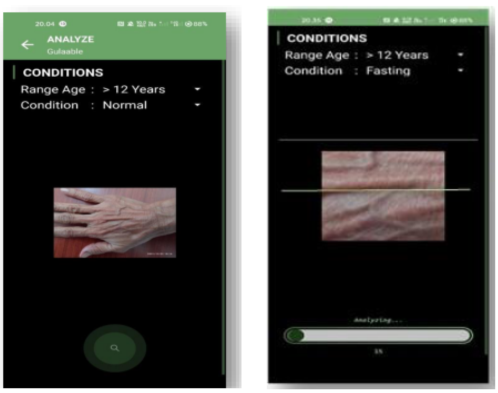

FIGURE 9. Process Image analysis process.

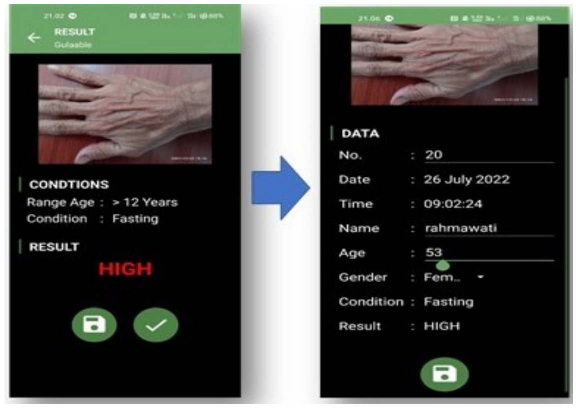

FIGURE10. Process Output , result, edit and save user data

C. RESULTS GULAABLE ANALYSIS

TABLE I shows the results of the identification of glucose levels in 10 participants with invasive and non-invasive methods applied at the age of 20 years to 60 years using the GULAABE application on a smartphone.

TABLE I
GULAABLE APP RESULT AND INVASIVE GLUCOSE LEVEL MEASUREMENT.

No	Name, Gender and Age (year)	Condition	Glucose Levels Invasive	Result GULAABLE
1	Rohana, (P.50)	Normal	304	HIGH
2	Mardiana .(P. 23)	Normal	218	HIGH
3	Eda, (P.44)	Fasting	81	LOW
4	Hadayati, (P. 59)	Fasting	75	LOW
5	Kamisa (P.43)	Fasting	224	HIGH
6	Ahmad (L.50)	Normal	184	HIGH
7	Sri Rahayu. P.50	Fasting	160	HIGH
8	Ramli D.S , L.60	After eat	211	HIGH
9	Kurnia, P.41	Normal	138	HIGH
10	Hakim Rewa L.39	Normal	266	HIHG

IV. DISCUSSION

Research for monitoring glucose levels with non-invasive techniques, generally using sensors utilizing infrared light and photodiodes. However, due to various parameters such as skin tissue pigmentation, backlight intensity, pulsating blood flow, machine-related aberrations, time-dependent aberrations, motion-related aberrations, and other physiological or pathological reasons, some unwanted error signals arise. All factors affect sensor accuracy, causing inaccurate glucose level monitoring results. So other alternatives are needed to monitor glucose in a non-invasive way that is easier and more efficient and at low cost.

In this study, GLCM is developed which is a method used to extract image features in order to obtain the characteristics of each image as the value used for training data and test data. The application of an artificial neural network (ANN) is needed to process data from the GLCM value of each image and the invasive glucose level value of each participant. ANN was used to plot linear regression with the backpropagation algorithm to determine the relationship between hand skin images and glucose levels. The results of the regression plot of the correlation value (R) obtained 0.9138 the value is close to 1 shown in figure 3, indicating that the relationship between hand skin texture and glucose levels is very strong TABLE I shows the results of monitoring blood glucose levels using the GULAABLE application, there are differences in the results of the analysis between invasive and non-invasive methods (image processing with a smartphone). Invasive methods and image processing were used to collect all data simultaneously. The output conditions of each participant are different due to the different textures of the skin of each participant's hands. As a result, the condition of each person's total glucose level is different.

Previous studies using image processing to identify blood glucose levels have been carried out in ref.[14]. Developed the gulCam application, by analyzing blood vessels in eye images. Mean absolute error 10.7% and 91.8% accuracy. This research develops the GULAABLE application to identify blood glucose levels through image processing of hand skin images. The results of measuring glucose levels in participants number 7 and 9 in table 1 show blood glucose results of 160 mg/dl and 138 mg/dl, these values are included in the LOW level, but the GULAABLE application shows the HIGH result is the inaccuracy of the analysis, the data tested shows 2 that not suitable. Which means the accuracy of the GULAABLE application is around 80% of the 10 participants for data testing. The results of this study show results with good accuracy, proving that non-invasive monitoring of blood glucose levels allows detection through the skin of the hands.

V. CONLUSION

The proposed research has developed an innovative intelligent control application for detecting glucose levels. In this study blood glucose levels can be detected by image processing applied to smartphones. To analyze images and identify different locations in images, a gray level co-occurrence matrix (GLCM) has been applied to reduce unimportant processing areas. To train hand skin texture data, an artificial neural network (ANN) is used which is then applied to the Android operating system to detect glucose levels. Based on the findings of this study, which has developed the GULAABLE application to detect glucose with a non-invasive technique, the detection results were compared with laboratory test results. The results of testing and data analysis show an accuracy value of 80%, this analysis illustrates that this application model is acceptable for application to society.

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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,” *J. Res. Med. Sci.* |, 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] N. H. Cho *et al.*, “IDF Diabetes Atlas : Global estimates of diabetes prevalence for 2017 and projections for 2045,” *Diabetes Res. Clin. Pract.*, vol. 138, pp. 271–281, 2018, doi: 10.1016/j.diabres.2018.02.023.
[8] 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.
[9] 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.
[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, no. October 2018, pp. 173–180, 2019, doi: 10.1016/j.snb.2019.01.121.
[13] 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.
[14] 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.
[15] C. Hernandez-Matas, A. A. Argyros, and X. Zabulis, *Retinal image preprocessing, enhancement, and registration*. Elsevier Ltd., 2019.
[16] D. Koundal and B. Sharma, *Advanced neutrosophic set-based ultrasound image analysis*. Elsevier Inc., 2019.
[17] J. Virmani, G. P. Singh, Y. Singh, and Kriti, *PNN-based classification of retinal diseases using fundus images*, no. 1. Elsevier Inc., 2019.
[18] 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.
[19] 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.
[20] N. J. Road, S. E. Inspection, Q. Bureau, F. Road, and F. District, “SYSTEM BASED ON NEURAL NETWORK COMPENSATING,” *ICIC Express Lett.*, vol. 15, no. 7, pp. 725–735, 2021, doi: 10.24507/icicel.15.07.725.
[21] W. The and W. Academy, “Comparison of Accuracy Level of Support

Vector Machine (SVM) and K-Nearest Neighbors (KNN) Algorithms in Predict ...”
[22] P. Agarwal and R. K. Srivastava, “INTRUSION DETECTION WITH NEIGHBOURHOOD COMPONENT ANALYSIS,” *ICIC Express Lett.*, vol. 15, no. 12, pp. 1–8, 2021, doi: 10.24507/icicel.15.12.XXX.
[23] X. Sun, X. Ren, S. Ma, and H. Wang, “meProp : Sparsified Back Propagation for Accelerated Deep Learning with Reduced Overfitting,” 2017.
[24] A. H. Jiang *et al.*, “ACCELERATING DEEP LEARNING BY FOCUSING ON THE BIGGEST LOSERS,” *Mach. Learn. (cs.LG); Mach. Learn. (stat.ML*, 2019.
[25] A. Bhimireddy, P. Sinha, B. Oluwalade, and J. W. Gichoya, “Blood Glucose Level Prediction as Time-Series Modeling using Sequence-to-Sequence Neural Networks,” vol. 2018, 2018.
[26] A. Sarkar, A. Goyal, D. Hicks, D. Sarkar, and S. Hazra, “ANDROID APPLICATION DEVELOPMENT : A BRIEF OVERVIEW OF ANDROID PLATFORMS AND EVOLUTION OF,” *2019 Third Int. Conf. I-SMAC (IoT Soc. Mobile, Anal. Cloud)*, pp. 73–79, 2019.
[27] 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.