Journal of Information Systems Engineering and Management
2025, 10(38s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Non-Invasive Blood Cholesterol Monitoring Using Artificial Neural Networks on Smartphone

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ARTICLE INFO

Received: 20 Dec 2024

Revised: 18 Feb 2025

Accepted: 25 Feb 2025

ABSTRACT

Artificial Intelligence is increasingly utilized, particularly in creating medical devices. This research aims to establish a model for an application that can identify and monitor cholesterol levels in a non-invasive manner. The research presents the innovative cholesterol detection (Choldet) application, which operates on smartphones to keep track of cholesterol levels. Cholesterol levels are identified through image processing of images captured from the skin on the hands. The research involved collecting hand skin images alongside corresponding lab blood cholesterol measurements. Samples were gathered from male and female participants aged between 20 and 65 years, amounting to a total of 57 sample images. To identify cholesterol levels, artificial neural networks (ANN) were employed to analyze hand textures, thereby generating a database. The training outcomes from the ANN were incorporated into the Choldet application for smartphones, utilizing the Application Programming Interface (API). The development of the Choldet application, designed for Android, can be installed on smartphones, allowing for real-time non-invasive monitoring of blood cholesterol levels. The efficacy of this novel evaluation method was validated using confusion matrix analysis, leading to an F-1 score of 80%, and analysis with Clarke-Error Grid Analysis (C-EGA) resulted in 92.98% in zone A indicating good accuracy. This application significantly contributes to facilitating early monitoring of health indicators, enabling individuals to assess their health status at any time, and aids in progressing health equipment technology.

Keywords: Non-Invasive Blood Cholesterol, Artificial Neural Networks, Smartphone.

INTRODUCTION

In the human body there are cells containing cholesterol that have their respective roles and functions. Food consumed every day produces cholesterol that is in the form of wax or fat. Cholesterol is an oil-like compound that cannot be combined in blood plasma which is water-based [1]. Cholesterol has a compound with the chemical formula C27H46O which is a small molecule, which in biology is known as a wax-like lipid that is mixed in blood plasma which is very difficult to dissolve in water (0.095 mg/L at a temperature of 30°C) and moves in blood circulation at low concentrations [2]. In body tissues, cholesterol is transported by lipoproteins through the blood.

High levels of cholesterol in the blood are a symptom of Hypercholesterolemia, which is included in Low-Density Lipoprotein (LDL), which can cause the onset of cardiovascular disease which is a disorder in the function of the heart and blood vessels, which is often the main cause of death [3]. Increased blood cholesterol levels cause cardiovascular diseases, such as arteriosclerosis and hypertension [4]. In 2012, the World Health Organization (WHO) released data on the deaths of 17.5 million people caused by heart attacks and strokes, of which 34% of the total deaths from cardiovascular diseases affect individuals aged less than 70 years. It is predicted that in 2030 there will be an increase in casualties by 80% (World Health Organization (WHO). 2016). Lipoproteins transport cholesterol or triglycerides and Low-Density Lipoprotein (LDL) that flows in the blood and can cause myocardial infarction (heart attack), stroke, or peripheral vascular disease [5]. In order not to experience heart problems and stroke, it is necessary to check cholesterol levels periodically by each individual. In general, individuals do not consider checking the condition of cholesterol levels in their bodies, because the cost of checking blood cholesterol is quite high.[6].

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The method of checking blood cholesterol levels can be done by two methods, namely invasive and non-invasive. They are checking blood cholesterol levels that are commonly used in invasive procedures, by taking blood samples which in the process is done by injuring individual body parts. Meanwhile, non-invasive techniques were developed to make it easier to check blood cholesterol levels without injuring individual body parts and minimize the use of disposable tools or materials. So, this method can be done comfortably and at a more affordable cost.

Non-invasive methods to monitor blood cholesterol levels were developed in several studies, including research conducted by Umar et al. developed a non-invasive method of measuring blood glucose and blood cholesterol using Near Infrared [9], and measuring blood glucose by using digital images of the participant's skin surface [7]. A Non-Invasive Method for Forecasting Total Cholesterol Levels Utilizing Learning sought to estimate cholesterol levels through non-invasive and readily obtainable data. In particular, this research utilized clinical and anthropometric information gathered by a dietitian throughout a weight loss intervention timeframe. The experimental outcomes indicated a mean absolute percentage error (MAPE) of 4.39% in cholesterol estimation based on regression.[8]. Utilizing Smart Contact Lenses for Non-Invasive Cholesterol Monitoring with Wireless which focuses on real-time quantitative recording of cholesterol in tear fluid to monitor hyperlipidemia patients using smartphones. The first testing method used rabbit tears to confirm the correlation between cholesterol levels in tear fluid. and Vivo testing with human subjects demonstrated biocompatibility. [9].

In addition, non-invasive cholesterol level monitoring was also developed by Ref. [10] performed a noninvasive skin cholesterol test: a potential representative for the measurement of serum LDL-C and apoB. This study examines the differences between LDL-C and apo B to evaluate lipid management as well as monitor cholesterol status in the skin. This prospective study included 121 patients diagnosed with acute coronary syndrome (ACS). LDL-C decline was lower than the rate of apoB decline with rosuvastatin treatment. Non-invasive cholesterol measuring tool using photodiode sensor with BLYNK interface. Using infrared (NIR) light and lasers, noninvasive techniques for detecting cholesterol levels have been developed. These results demonstrate that noninvasive level monitoring is both a measure of accuracy and a measure of error. The error when measuring blood cholesterol using the module using a non-invasive method is 1.46% with an accuracy of 98.54%. In the future, the non-invasive deep cholesterol measurement device designed in the study could reduce medical waste and be more convenient to use.[11]. Creating a non-invasive method for monitoring blood cholesterol levels involves using optical sensors equipped with 940 nm infrared LEDs and photodiodes positioned on the fingertip, linked to a microcontroller. This approach offers approximately 80% accuracy in measuring blood cholesterol levels. [12].

Research aimed at blood cholesterol levels through eye images by employing fuzzy logic binary pattern (FLBP). This research utilized eye images taken with mobile phone cameras, alongside the measurement of invasive cholesterol levels. The images processed through FLBP were analyzed to establish correlations between image values, FLBP values, and invasive cholesterol levels using linear regression analysis, resulting in a linear regression model (RLM) designed to estimate cholesterol levels.[13]. In this study, a smartphone-based optical device called Smart is intended to use ratiometric fluorescence sensors to perform point-of-care glucose and cholesterol testing (POCT) on patients with metabolic syndrome. It uses the Ag NPs/UiO-66-NH2 ratio fluorescence probe. The fluorescence intensity ratio response (F555 nm/F425 nm) increases along with a noticeable color shift from blue to yellow-green as a result of filter action inside the Ag NP/UiO-66-NH2 and o-phenylenediamine detection system, which exhibits a dual emission reaction for H_2O_2 (the primary product of glucose and cholesterol catalyzed by glucose oxidase and cholesterol oxidase) [14].

Ref [15], conducted a study to create a framework for non-invasive glucose and cholesterol screening and estimation utilizing Fake Insights and Cloud computing, to compare the forecast efficiency of two models: Auto-Regressive Coordinates Moving Normal (ARIMA) and Long Short-Term Memory (LSTM) simulations. This study is the development of a tool model for non-invasive glucose and cholesterol estimation, using Near Infra-Red (NIR) sensors. Validation of the results by comparing the RMSE values of the two simulation models, showed ARIMA values (about 71.7% lower for Glucose and 50.3% lower for Cholesterol) compared to LSTM, which showed higher forecast precision. This hypothesis provides a coordinate setting for non-invasive estimation, leading to early monitoring and screening of diabetes and cardiovascular risks.

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As previously said, non-invasive blood cholesterol level monitoring that relies on the use of sensors and optical media like skin, sweat, and tears is typically developed. Not much research has been done on combining smartphones and artificial neural networks to track cholesterol levels in real time using digital photos of bodily parts. Using the Choldet app for Android cellphones, this study suggests a novel approach to blood cholesterol monitoring that makes use of artificial neural networks. This technique makes use of digital pictures of the hand's skin surface that are analyzed to forecast the body's blood cholesterol levels; the outcomes are available in real time.

LITERATURE REVIEW

Cholesterol Measurement Techiquee

Hoisted LDL cholesterol (LDL-C) could be a hazard figure for cardiovascular malady and is considered an critical treatment target. Can be measured and calculated based on the comes about of other lipid tests. The Friedewald equation is the foremost used formula to calculate LDL-C. We have adjusted the Friedewald equation to create LDL-C gauges more exact and reasonable. The foremost common way to test for LDL is with a blood test. This strategy regularly demonstrates low-density lipoprotein levels as a cause of cardiovascular infection. Clinically calculate the cholesterol rate utilizing the equation given by the Friedewald equation.[16].

$$L = C - H - kT \qquad (1)$$

Where H is the value of HDL cholesterol, L is the value of LDL cholesterol, C is total cholesterol, T is triglycerides and k = 0.20 when the quantities are measured in mg/dl and 0.45 when measured in mmol/ll

Measurement of blood cholesterol levels (LDL and HDL) can be done by taking a sample of the patient's blood by injuring one of the human body parts (invasive) or by using techniques that do not involve injury or contact with the patient (non-invasive). The amount of excess cholesterol transported by the blood can cause blockage of arteries due to the accumulation of lipoproteins. Lipoproteins are classified into two, namely Low-density lipoprotein (LDL) and High-density lipoprotein (HDL) [17]. National Cholesterol Education Program – Adult Treatment Panel (NCEP-ATP III) [18], which is referred to by the Indonesian Ministry of Health to determine the standard reference value for total blood cholesterol. According to the Indonesian Ministry of Health's reference, the standard reference value for total blood cholesterol is in Table 1 below.

Table 1. Standard referent values of total blood cholesterol.

Category	LDL (mg/dl)	Total (mg/dl)
Optimal	<100	
Desirable		<200
Near optimal/above optimal	100-129	
Borderline high	130-159	200-239
High	160-189	>240
Very high	>190	

In common, the method of picture extraction isn't known to be a difficult processor. Be that as it may, within the restorative world in a few cases, it is necessary to require pictures on the portion of the patient's body. This can be called an intrusive imaging method. Intrusive imaging strategies include the intrusion of needles, tubes, or imaging gadgets that are embedded into the body with major surgery or surgery for restorative conclusion. Cases of intrusive methods such as coronary angiography, Intravascular Ultra Sonography (IVUS), Virtual Histology Intravascular Ultra Sonography (VH-IVUS), Coordinates Backscattered Intravascular Ultra Sonography (IB-IVUS), (IMAP), and Coronary computed tomography angiography (CCTA). NIRS-IVUS, CORONARY MRA is an rising strategy, and NIRF is considered beneath examination [19]. In the interim, non-invasive imaging procedures may be a strategy utilized for taking pictures to discover out the interior of the human body without performing a surgical handle. Illustrations of non-invasive imaging are Radiography, attractive reverberation imaging (MRI), computed tomography (CT),

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Ultrasound or therapeutic ultrasonography, thermography, Positron Outflow Tomography (PET), and Photo Acoustic Imaging [20][21].

Digital Picture Processing

A computerized picture may be a two-dimensional picture that can be shown on computer media called pixels (picture components) or discrete sets of computerized values. The picture handling handle is a picture examination prepare that includes a part of visual discernment, where this handle has the characteristics of input information and yield data within the frame of pictures. A picture can be characterized as a work (x, y) that features a measure of M in columns and N in columns, where x and y are halfway facilitates, sufficiency f at facilitate focuses (x, y) called degrees or levels of grayness in a picture. In the event that x, y, and f are all finite and discretely esteemed at that point the picture could be a advanced picture. The picture is in framework frame as appeared underneath.

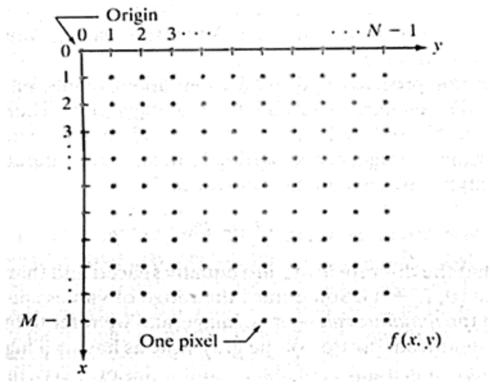

Figure 1. Digital picture coordinates

The picture is in matrix form as shown below

$$f(x,y)\begin{bmatrix} f(0,0) & f(0,1) & \cdots & f(0,N-1) \\ f(1,0) & f(1,1) & \cdots & f(1,N-1) \\ \vdots & \vdots & \ddots & \vdots \\ f(M-1,0) & f(M-1,1) & \cdots & f(M-1,N-1) \end{bmatrix} \quad (2)$$

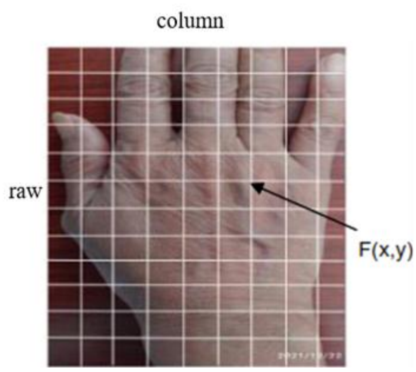

Figure 2. Pixel matrix illustration on digital picture

Pictures delivered by smartphone cameras are for the most part displayed in RGB picture organize. Where RGB picture could be a type of picture that presents colors within the frame of components R (red = red), G (green = green), and B (blue = blue). To optimize computerized picture handling, in this ponder the RGB organize picture delivered by the smartphone camera will be changed over into grayscale arrange where grayscale is a picture that as it were has colors at the gray level. This gray level can be depicted as spatially related between gray values in two-dimensional pictures utilizing the gray level co-occurrence matrix (GLCM) method.

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Gray Level Co-Occurrence Matrix (GLCM)

The Gray Level Co-occurrence Matrix (GLCM) is a statistical method used in image processing to analyze image texture. GLCM Method can decide the likelihood of a gray level $\boldsymbol{i}$ happening around another gray level $\boldsymbol{j}$ at a certain remove $\boldsymbol{d}$ and point $\boldsymbol{\theta}$, expecting the number of gray levels $\boldsymbol{N}$ is known. GLCM has 4 angles of neighboring points between pixels, to be specific 0^0, 45^0, 90^0 and 135^0. Figure 4 is an outline of the heading of the GLCM pixel neighboring point. Pixels are within the frame of a co-occurrence matrix with their pixel pairs, because pixels are within the shape of a network, the pixel network will have rehashed values so hat there are pairs of gray directions. The state of the pixel value is marked as a matrix with a distance of 2 positions (*X1, Y1*) and (*X2, Y2*). Agreeing to these conditions, to recognize between picture matrix can be seen based on the characteristics of the network. The picture with the framework characteristics delivered by GLCM has 4 extractions, specifically *contrast (Ct), correlation (Cn), energy (Ey)* and *homogeneity (Hy),* these four extractions can depict the complete picture and are by and large utilized in picture preparing, consecutively as depicted within the taking after condition [22].

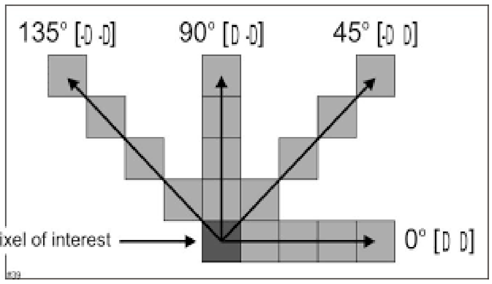

Figure 3. Illustration of the direction of neighboring pixel angles using the GLCM method

$$GLCM = P_r(i,j)|\, d, \theta, N \tag{3}$$

$$Contrast\ (Ct) = \sum_{i,j} |\, (i-j)^2\ S\ (i,j) \tag{4}$$

$$correlation\ (Cn) = \sum_{i,j} \frac{(i-\mu i)(j-\mu j)S(i,j)}{\sigma_i \sigma_j} \tag{5}$$

$$Energy\ (Ey) = \sum_{i,j} S\ (i,j)^2 \tag{6}$$

$$homogeneity\ (Hy) = \sum_{i,j} \frac{S(i,j)}{1+|\, i-j|} \tag{7}$$

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

Dataset

In this study, the results of invasive blood cholesterol measurements were used as a reference. The population participating in this study were young to elderly people, with ages ranging from 20 to 65 years old, from Makassar City, South Sulawesi, Indonesia. In addition, digital image samples of the backs of the hands of these people were taken from a distance of 20 cm using the camera of an Android smartphone. The smartphone used was a 16 mega pixel camera. The characteristics of the image samples were examined to find correlations with traditional cholesterol measurement results.

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Table 2. Representation of clinical data dan image data

Image		Category	GLCM Texture analysis				
			0°	45°	90°	135°	Average
	Age	35 years					
	Gender	Female					
	Cholesterol invasive	180 mg/dl					
	Level	Normal					
	Contrast		0.084	0.133	0.082	0.096	0.099
	Correlation		0.899	0.841	0.902	0.885	0.882
	Energy		0.357	0.324	0.357	0.348	0.347
	Homogeneity		0.958	0.934	0.959	0.952	0.951

METHODS

Research Desaign

The flow of this research as in the proposed design is shown in Figure 4, The process begins with invasive cholesterol level data collection and secondly taking pictures of the back of the hand using a 16 mega pixel smartphone camera at a distance of about 20 cm from the object. Cholesterol level data collection and hand images in patients aged 20 to 65 years

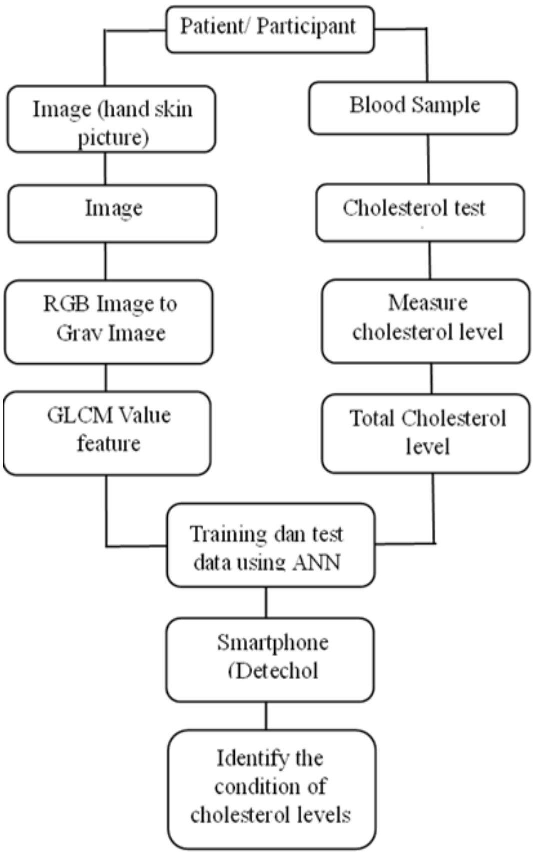

Figure 4. Research Design

The next step is to perform preprocessing to process the image by resizing and cropping it to remove noise or unnecessary parts of the image. The image is cropped to a size of 1000 x 1000 pixels, then texture analysis is performed on the image using the Gray Level Co-occurrence Matrix (GLCM) method to determine the values of

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e-ISSN: 2468-4376
https://www.jisem-journal.com/

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contrast, correlation, energy, and homogeneity values. The cholesterol value pairs and texture feature extraction in the dataset will be used to train and test the data through Artificial Neural Network (ANN) using back propagation algorithm. These results will serve as the basis for the creation of Choldet application on Android smartphone for non-invasive cholesterol monitoring.

In this study, blood cholesterol levels were grouped into two categories, normal and high. Participants with cholesterol values less than or equal to 200 mg/dl were placed in the "NORMAL" category and participants with cholesterol values greater than 200 mg/dl were placed in the "HIGH" category and were included in the program's data set. The data and digital image processing were performed using artificial neural networks which are explained in the next step.

Artificial Neural Network (ANN)

Artificial neural networks (ANN) are one of the machine learning methods used to model complex systems.[23][24]. ANN are often referred to as neural networks because they are inspired by the structure and function of biological neural networks.[25]. This model consists of artificial neurons or nodes connected to each other by weights, which represent the strength of the connections between neurons. In this study, five basic steps are used to explain the function and operation of ANN:

1. Read hand texture as input data.
2. Create a cholesterol prediction model (Linear function)
3. Calculate the prediction model error.
4. Inform and apply the necessary model corrections until the model with the least number of errors is found.
5. Use this model to estimate cholesterol levels based on the hand surface texture connected to an Android Smartphone.

In this regard, the backpropagation method is used as an algorithm to build a Straight Relapse Neural model.The backpropagation optimization algorithm can be used to prepare a neural recurrent model.The backpropagation algorithm requires an angle calculation for each variable in the demonstration to generate the latest value of the variable. Although the backpropagation method is simple, it is a common and effective numerical optimization in machine learning to demonstrate classification algorithms more accurately.[26].

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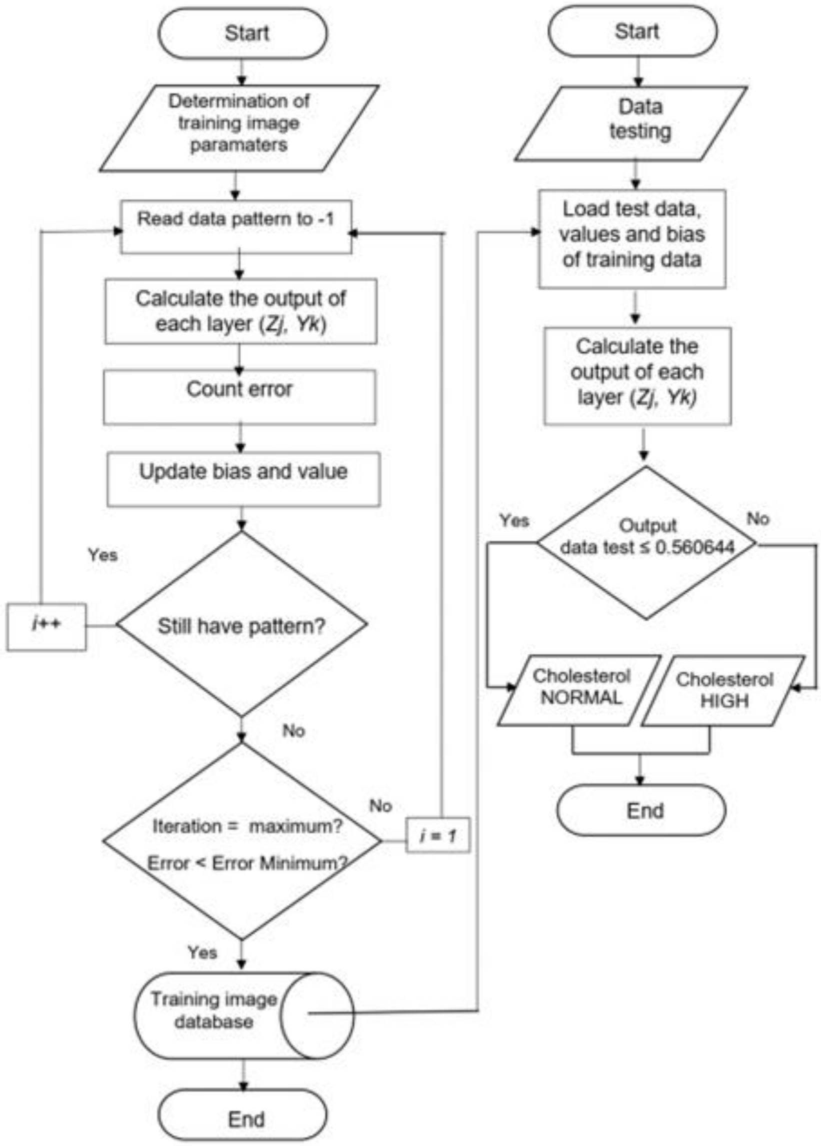

Figure 5. Flowchart for data training, and data testing

Figure 5 shows the image processing steps of the training and test data in ANN. These models perform the same training for each group, but ignore the fact that the gradient variance causes different training dynamics within groups due to sampling bias and inherent image differences. In this study, a new training method based on hand texture and blood cholesterol levels is developed. The main strategy of this training is to address the discrepancy, which is dynamically adjusted through the training effort to reduce the loss [27].

The training phase is as follows:

- The performance of each layer (Zj and Yk) is calculated, then the error value (ε) is calculated and the weights and predispositions (Wjk and Vik) are updated until the error value is smaller than the specified time or until the cycle is completed.
- Save it in the database. Parameter preparation is done after all cycles are completed. The data testing process is explained in the flowchart in Figure 6.

The test phase is as follows:

- Stacking input information, values and predisposing factors.

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- Calculating the results of each layer (Zj and Yk) to calculate a test value. The calculation result is used to derive a test value that is classified as the expected value of blood glucose level. This evaluation can be obtained from the test score generated from each image edited from the image editing interface

Cholesterol Detection (Chodet) Applications

Choldet is a blood cholesterol monitoring app built into the Android operating system. Apps on the Android operating system use the Java language. App development on Android smartphones is very flexible with the platform providing a dynamic Java IDE and Android Java libraries for third-party development and technologies [28].

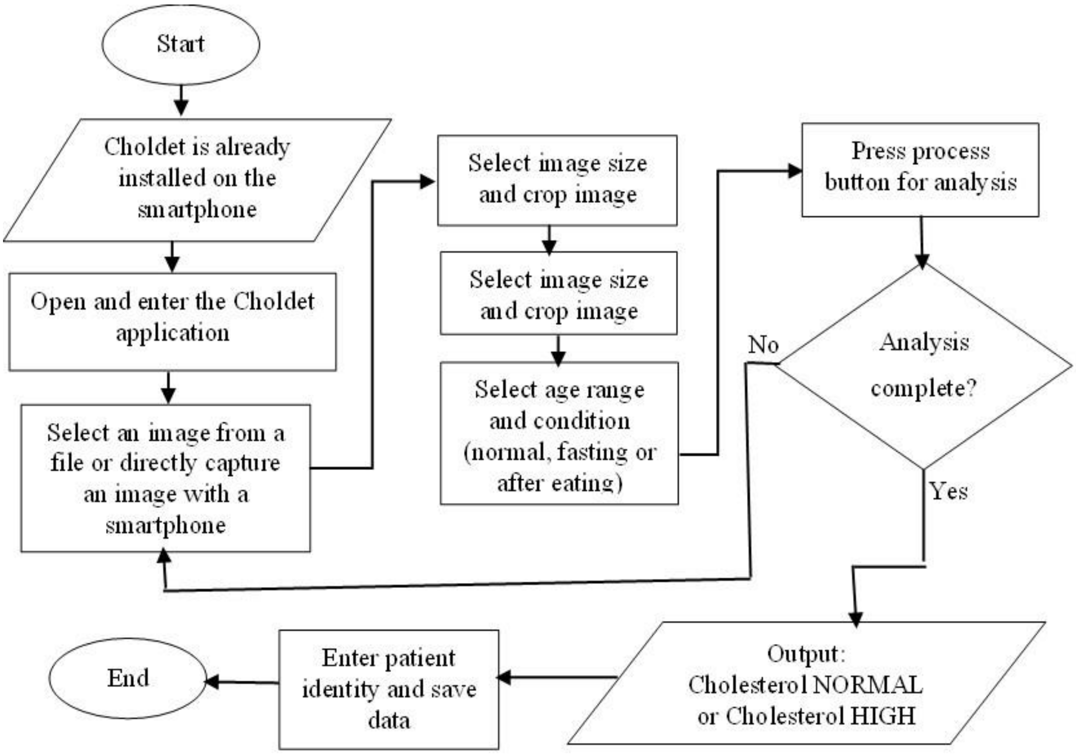

Figure 6. Choldet application operation process

This study resulted in the Choldet application to analyze hand skin images to predict and classify cholesterol levels into normal or high based on cholesterol reference values in Table 1. The "normal" category for cholesterol levels is below 200 mg/dL, and above 200 mg/dL is included in the "high" category.

The Choldet app works in several steps. The first step is to load the app for general system initialization, the second step is to find an edited image or capture an unused image to edit in the next step, and the third step is to edit or create an image according to the estimate required for editing. The next step is to analyze the processed image to determine the cholesterol level based on the database processing data. The analysis takes about 1-3 minutes to determine what is happening. The last step is to manage user data and save the analysis data. The Choldet app must be installed on a smartphone with an Android 12 or higher operating system, which already has excellent and fast image editing capabilities built in. To operate the Choldet app on your smartphone, follow the process flow shown in Figure 6.

RESULTS

Based on the methodology proposed in this study as in Figures 4, 5 and 6 which illustrate the flow of data collection and processing processes. The data that has been collected based on the method of collecting data samples such as laboratory blood cholesterol levels and taking digital images of participants, after all data is collected, further processing is carried out using an Artificial Neural Network (ANN) with steps as in Figures 5 and 6.

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e-ISSN: 2468-4376
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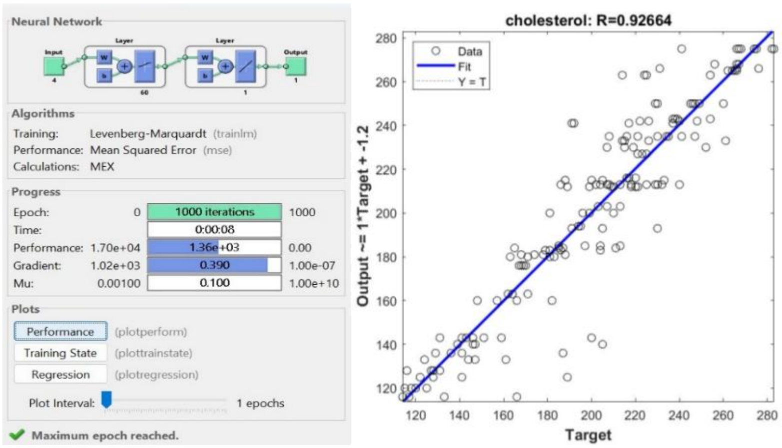
Figure 7. Sample digital picture of the back of the hand

The recordings are taken indoors using a mobile camera under indoor lighting conditions. To improve image quality, the recordings are determined by a distance of 20 cm between the skin of the hand and the camera, focusing on the skin on the back of the hand. All captured images are tagged with a code or ID to avoid confusion with personal information. After the images were taken, the blood cholesterol levels of each participant were measured using an invasive technique adapted to the identity of the image. The database with collected images and cholesterol values is from 60 people of all gender groups, all ages and all cholesterol values. Examples of participants' imaging and cholesterol level measurements are shown in Figure 7. All data are processed using SVM (Support Vector Machine) before training. The entire process is carried out using Matlab software.

Training Data

Data training is performed using 60 cropped images, processed and output in the form of feature values or extraction results using GCLM (Gray Level Co-occurrence Matrix) and reference data. In data training, the first process performed on the images is to change the format of the camera image results from RGB to grayscale by extracting the RGB color components and substituting each component value into equation (3). After that, the texture feature extraction process is performed by using GCLM to determine the contrast, correlation, energy and uniformity values of all the datasets stored in the feature and label matrices. These features and labels are used as inputs to train the SVM model and are saved in Matlab code format.



(a) (b)

Figure 8. Training data on cholesterol levels and GLCM with artificial neural networks, and regression plot of training data results

The data training process is shown in Figure 8a. This is the training process of an artificial neural network (ANN) on cholesterol data and GLCM features using the Levenberg-Marquardt algorithm. The ANN architecture in the input layer consists of four neurons corresponding to the number of GLCM functions, the hidden layer consists of 60 neurons with the activation function used (usually Sigmoid or ReLU), and the output layer has only one neuron to predict cholesterol levels. . Training progress. The iterative process lasts up to 1000 epochs. The training performance is determined using the mean squared error (MSE). The results show a fairly large error of 1.70e + 04 in the first

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e-ISSN: 2468-4376
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training, and at the end of training, the error has decreased significantly to 1.36e + 03. The final gradient value is 0.390 which is close to the small tolerance value (usually <1e-6) and the damping factor value (Mu = 0.1), a small Mu value indicates stability in iteration. The training process only required 8 seconds, which reflects the efficiency of the Levenberg-Marquardt algorithm. The training process shows that the optimization method is approaching the Gauss-Newton solution and the model is close to reaching the optimal convergence point.

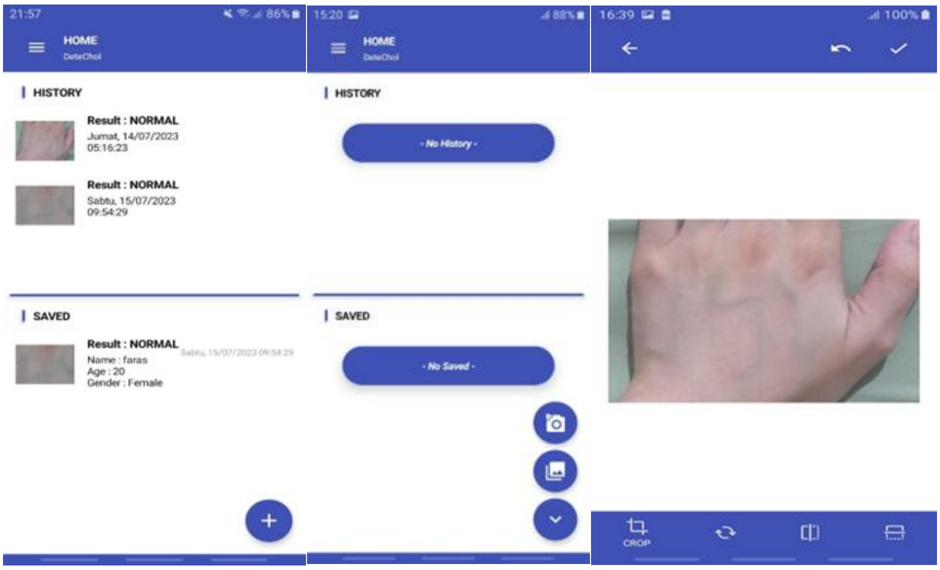
The training results shown in Figure 8b yielded a correlation value of R = 0.92664, where R (correlation coefficient) measures the strength and direction of the linear relationship between the target (total cholesterol value) and the prediction (the output of the ANN). R values range from -1 to +1, meaning that R = 0 indicates no linear relationship, R = 1 indicates a perfect linear relationship (positive), and R = -1 indicates a perfect linear relationship (negative). In this case, R = 0.92664 indicates a very strong linear relationship between the target and the output, indicating that the model is able to predict the total cholesterol value with a very strong relationship to the target.

The model is then exported to JavaScript Object Notation (JSON) format so that it can be integrated into Kodular Creator. The JSON file of the SVM model is also uploaded to Firebase storage for integration with Kodular Creator to the android operating system on smartphones.

Testing Results of Chodet Applications

The Choldet app was created with Kodular Creator. Figure 9a shows how this Android application looks. The main page shows the history of previous exams and the saved menu. The new exam has a cross in the bottom right corner, which displays the choice of the digital image source of the back of the hand you want to use. Capturing a digital image can be done from an existing file or directly from the smartphone camera.

The another organize is to carry out the picture altering prepare appeared in Figure 9b. After selecting the picture, the client will be coordinated to the picture altering menu to choose the back of the picture that they need to utilize. The alter page has a few alternatives: trim, pivot, vertical flip, and flat flip. The picture estimate is edited to 1 MP to decrease the surface zone to be checked.



(a) *(c)

Figure 9. (a) Choldet app main page view, (b) Display page for editing images

After modifying the picture, another step is to enter the picture checking arrangement, a appear will appear up as inside the picture on the cleared out, at that point press the channel button underneath the picture at the point the examination handle for choosing blood cholesterol levels will run, the time required is around 3-5 minutes for add up to the checking and the cholesterol comes almost can appear up on the layer. The checking handle shows up as in Figure 10a.

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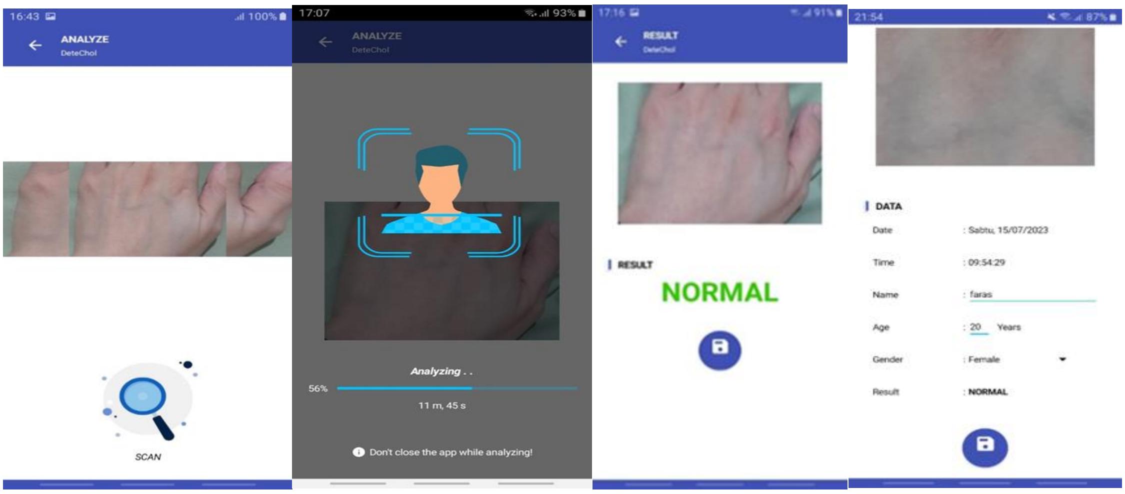

(a) (b) (c)

Figure 10. (a) Analyze and Scanning process, (b) Display of checking results, (c) user data input and save data

As shown in Figure 10b, after reviewing and analyzing the 1MP cropped image, the Choldet app will display the test result and convert the blood cholesterol classification into two categories: NORMAL or HIGH. The final solution is to input customer data and process the user's blood cholesterol test result, as shown in Figure 11c.

Choldet app tests were conducted on 57 participants of different age groups and genders. The app test result data is shown in Table 2 below

Table 3. Choldet App test results data

Number	Age (y.o.)	Gender	Cholesterol levels reference (mg/dl)	Cholesterol condition (reference)	Choldet app result
1	61	Male	116	NORMAL	NORMAL
2	38	Female	125	NORMAL	NORMAL
3	58	Female	235	NORMAL	HIGH
4	60	Female	193	NORMAL	NORMAL
5	68	Female	133	NORMAL	NORMAL
6	50	Female	176	NORMAL	NORMAL
7	42	Female	142	NORMAL	NORMAL
8	59	Female	241	HIGH	HIGH
9	65	Male	250	HIGH	HIGH
10	43	Female	250	HIGH	HIGH
11	60	Female	266	HIGH	HIGH
12	48	Female	275	HIGH	HIGH
13	55	Female	263	HIGH	HIGH
14	54	Female	268	HIGH	HIGH
15	35	Female	180	NORMAL	NORMAL
16	23	Female	143	NORMAL	HIGH
17	58	Female	235	NORMAL	HIGH
18	52	Female	215	NORMAL	HIGH
19	44	Female	233	NORMAL	NORMAL
20	61	Male	116	NORMAL	NORMAL
21	64	Female	203	NORMAL	HIGH
22	53	Female	200	NORMAL	NORMAL
23	60	Female	266	HIGH	HIGH
24	62	Male	128	NORMAL	NORMAL
25	50	Female	216	HIGH	NORMAL

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26	59	Female	241	HIGH	HIGH
27	42	Female	142	NORMAL	NORMAL
28	35	Female	180	NORMAL	NORMAL
29	55	Female	263	HIGH	HIGH
30	50	Male	213	NORMAL	HIGH
31	43	Female	250	HIGH	HIGH
32	54	Female	268	HIGH	HIGH
33	55	Female	185	NORMAL	NORMAL
34	46	Female	243	HIGH	NORMAL
35	40	Female	227	NORMAL	NORMAL
36	33	Female	235	NORMAL	HIGH
37	50	Female	230	NORMAL	NORMAL
38	51	Female	275	HIGH	HIGH
39	47	Male	184	NORMAL	NORMAL
40	65	Male	242	HIGH	HIGH
41	51	Male	120	NORMAL	NORMAL
42	50	Male	140	NORMAL	NORMAL
43	41	Female	213	NORMAL	NORMAL
44	50	Female	265	HIGH	HIGH
45	60	Female	260	HIGH	HIGH
46	60	Female	252	HIGH	HIGH
47	52	Male	212	NORMAL	NORMAL
48	64	Female	203	NORMAL	HIGH
49	48	Female	275	HIGH	HIGH
50	52	Female	215	NORMAL	NORMAL
51	43	Female	163	NORMAL	NORMAL
52	65	Male	250	HIGH	HIGH
53	27	Female	212	NORMAL	NORMAL
54	53	Female	200	NORMAL	NORMAL
55	58	Female	194	NORMAL	NORMAL
56	44	Female	244	HIGH	HIGH
57	23	Female	143	NORMAL	NORMAL

Confusion Matrix Analysis

The first method to analyze the detection results of the Choldet application uses confusion matrix analysis (CMA), a commonly used tool to evaluate the performance of classification models. This matrix represents a comparison between the actual values (reference data) and the predicted values generated by the model. Figure 11 shows the results of the CMA analysis of the Choldet app in predicting blood cholesterol values.

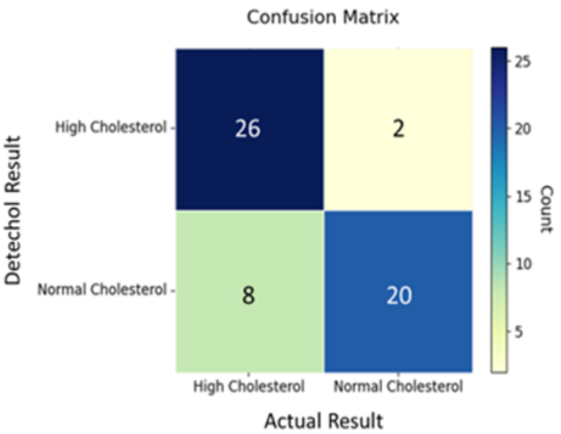

Figure 11. The confusion matrix of the Choldet app

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The accuracy is 82.14%, indicating a high accuracy. Overall prediction accuracy. The accuracy of 71.43% indicates that although this method is effective, it produces a significant percentage of false positives. The sensitivity or recall of 90.91% highlights the high ability of the method to accurately identify positive cases. Sensitivity or recall is a measure that shows how well a method can recognize or capture all positive cases that actually exist. Finally, the F1 score of 80 indicates a balanced performance between precision and recall. These results indicate that the method used has a fairly good and balanced performance in identifying positive cases correctly (precision) and comprehensively (recall). F1-score is one of the assessment measurements utilized to degree the execution of a classification demonstrat that combines Accuracy and Review into one concordant esteem that gives a comprehensive picture of the adjust between the two.

The results of testing and validation of the Choldet application were compared with previous studies. The Choldet app method showed a real sensitivity improvement over the previous study conducted by Umar et al. in 2023, where a sensitivity of 85% was reported.[17] However, the accuracy of the Choldet app method is slightly lower than that of Umar et al. in 2022, which achieved a precision value of 75%. [10] These differences highlight the different strengths of different models and the trade-off between precision and recall. Both cholesterol level monitoring applications or models use personal computers for digital image processing.

Clarke Error Grid Analysis (Clarke-EGA)

Clarke -Error Grid Analysis (Clarke-EGA) is a statistical method used to analyze clinical accuracy in blood glucose monitoring systems by comparing the developed equipment with laboratory results. However, Clarke-EGA was also developed to analyze the accuracy of blood cholesterol levels clinically.

The second way to analyze the findings of Choldet applications is with Clarke - Error Grid Analysis (EGA), a special accuracy assessment method often used to evaluate the performance of tools and models predicting quantitative data, especially in the medical field. EGA compares the prediction results (tool or model data) with a reference value (usually considered the gold standard) to determine the level of error and its impact on clinical decision-making. The analysis results are displayed in a chart divided into several zones with the following interpretations: Zone A: The prediction is very accurate. The value is within ±20% of the reference value or close to the absolute limit (usually a very low value). This error does not affect the clinical decision. Zone B: Minor error. The prediction is not accurate, but will not lead to an incorrect or harmful clinical decision. Zone C: Moderate error. This prediction may lead to an incorrect clinical decision, but the consequences are not very serious. Zone D: Severe error. This prediction is so abnormal that it may lead to an inaccurate and potentially harmful clinical decision.

The Clarke EGA method determines the total cholesterol reference value for each zone within ±20% (±10 < TC < ±30 mg/d1). Clarke-EGA analysis of the Choldet application results shown in Figure 12 revealed 92.98% (53 participants) in zone A, 7.02% (4 participants) in zone B, and 0% in zones C, D, and E. The consequences of the Clarke-GA can count on that the accuracy of measuring levels of cholesterol the use of the Choldet utility is withinside the true class and clean to use, however there need to be non-stop development to boom the accuracy value.

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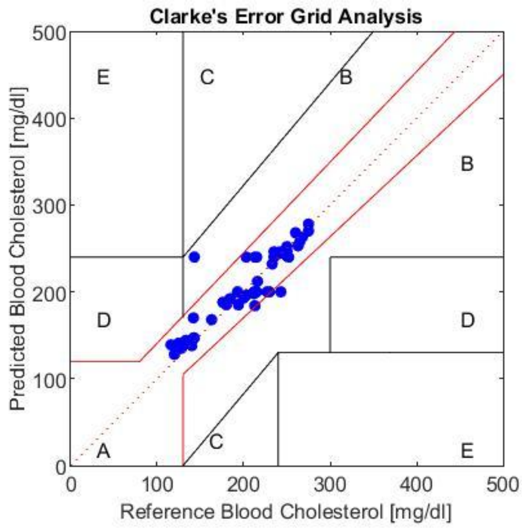

Figure 12. Clarke-Error Grid Analysis of the Choldet app

Other previous studies include a cholesterol level measurement system that extracts features from eye images using the FLBP method and a linear regression analysis proposed by Andana et al. in 2019 [13]. In experiments, the standard error of estimation was 20.40 for 30 images, the best FLBP was achieved with 8 sample points, radius 4, and blur 7, and the 58th feature accuracy was 91.40%. The more sampling points used, the more features are created, and therefore the higher the accuracy. The results of this analysis show that the accuracy of the study by Andana et al. is higher when Detechol is used on certain features. In a study by Krishnamoorthy et al., 2024 [29], the RMSE of the Autoregressive Coordinate Moving Normal Algorithm (ARIMA) method was found to be 50.3% for cholesterol, proving the accuracy of the Detechol application implemented on a smartphone to be better. However, continuous improvement is still required to achieve ideal accuracy and minimum error values.

The tall affectability demonstrates that the Choldet App strategy is especially viable at recognizing genuine positives, and is subsequently well suited for applications where lost positives is critical. Be that as it may, the moo exactness recommends that advance refinements are required to decrease the number of untrue positives. The adjusted F1-score shows that the Choldet App strategy offers a sensible compromise between exactness and hit rate, and thus demonstrates to be a strong choice for commonsense applications.

The strong affectability of the Choldet App strategy infers its potential utility in areas such as therapeutic diagnostics, where the recognizable proof of genuine positive cases is fundamental. The method's precision and adjusted F1 score moreover propose its pertinence in computerized decision-making frameworks, where reliable execution over distinctive measurements is vital.

One of the most qualities of Choldet App investigate is the tall affectability, which guarantees that most positive cases are accurately recognized. In any case, a eminent shortcoming is the accuracy, showing the next rate of wrong positives that may lead to pointless follow-up activities. Future work ought to center on upgrading exactness without compromising affectability.

Choldet App discoveries bolster the speculation that the proposed strategy can accomplish tall affectability and adjusted execution measurements. The comes about illustrate that whereas there's room for enhancement in exactness, the strategy is compelling in general, adjusting with Detechol App's introductory desires.

Whereas Choldet App comes about are promising, it is critical to consider the restrictions. The lower exactness recommends potential overfitting or an lopsidedness within the dataset. Recognizing these impediments, we legitimize Choldet App conclusions by the critical advancement in affectability and in general exactness, which are basic for the method's expecting applications. Comparable findings have been detailed within the writing, where tall

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affectability regularly comes at the taken a toll of lower exactness. Choldet App comes about prove these discoveries, strengthening the require for continuous refinement and optimization.

DISCUSSION

According to the results of application testing and statistical analysis with CMA and Clarke-EGA based on the Choldet application development method on smartphones via artificial neural networks (ANN), it is explained in detail in this discussion section. The artificial neural network training process was successful. The ANN was able to reduce the error from 17,000 to 1,360 in 1,000 iterations. The gradient reaches a small value, indicating that the ANN is close to optimal. The R value = 0.92664 (from the previous graph) indicates that the model is able to predict total cholesterol with a very strong relationship with the target.

The research method using the Choldet application model with CMA analysis to measure cholesterol levels showed an accuracy of 82.14%, precision of 71.43%, sensitivity of 90.91%, and F1 score of 80%. These results prove that a high F1 score indicates a good balance between the precision and recall of the model, which is important when both false positives and false negatives have a significant impact. Analysis with Clarke-EGA showed a 92.98% (53 participants) in zone A, 7.02% (4 participants) in zone B, and 0% in zones C, D, and E. This proves that the presence of zones A and B is an important performance goal for medical devices to ensure sufficient accuracy to ensure patient safety. Although this is not the case for zones C, D, and E, the Choldet application model still requires continuous improvement.

Compared to existing strategies, our approach appears a critical advancement in affectability. For occurrence, the demonstrate by Umar in 2022 detailed a affectability of 85%, though our strategy accomplished 90.91%. Be that as it may, the accuracy of 71.43% is somewhat lower than the 75% detailed by U. Umar, et.al, 2022. These comparisons highlight the trade-offs between distinctive models and emphasize the qualities and shortcomings of our strategy.

The high sensitivity of our method suggests its potential usefulness in applications where identifying true-positive cases is important, such as medical diagnostics for cholesterol screening. The balanced F1-score indicates that our method is robust and can be effectively used in automated decision-making systems, improving the reliability of cholesterol level predictions in real-world settings. Furthermore, implementing our method as an Android smartphone application expands its accessibility, allowing it to be used on any Android smartphone with a camera, enabling widespread and convenient cholesterol monitoring. The collection of primary data that is still minimal and less varied from various elements makes this research need to be developed further to prove that this application can be used with various participants, in order to improve better accuracy. The diversity of participants is very much needed such as skin color, hand skin texture, age, gender and origin and various other parameters as primary data are very much needed, due to limited costs and time so that the data obtained is not too varied.

This study presents new results in the field of high cholesterol detection, with a focus on high sensitivity. This absolute novelty is characterized by the higher sensitivity of our method compared to similar studies, allowing a more accurate identification of positive cases. In contrast to existing models, our method offers a unique balance between sensitivity and accuracy, making it an innovative approach in cholesterol diagnostics. This novelty is limited to the context of the dataset and model parameters. Theoretical applicability lies in the improvement of diagnostic algorithms, while practical applicability involves implementation in clinical decision support systems to improve patient outcomes. Additionally, by delivering it as a mobile application, it enables novel process innovations that greatly improve accessibility and ease of use.

Although our method shows promising results, the low accuracy suggests a high rate of false-positive results, which may lead to unnecessary follow-up tests. Moreover, the dataset used may not fully represent the diversity of cholesterol levels in different populations, which may limit the generalizability of the results. Furthermore, the method is limited to detecting high and normal cholesterol levels and cannot distinguish between different degrees of cholesterol abnormalities, such as borderline high or low cholesterol levels.

Future studies should focus on refining the model to improve accuracy without compromising sensitivity. Extending the dataset to a more diverse population would improve the generalizability of the results. Furthermore, considering the integration of additional features and advanced machine learning techniques may further improve the model's performance. To ensure its practicality and validity, it is also recommended to validate the model in clinical settings in collaboration with medical experts. Future studies should also aim to improve the method's ability to detect a wider range of cholesterol values, including borderline and low cholesterol values, to provide more comprehensive diagnostic support. Additionally, further development and testing needs to be carried out to ensure the app's usability and accuracy across a range of Android smartphone models and camera qualities.

CONCLUSIONS

In the proposed study, the Choldet app as an innovative smart controller application for detecting blood cholesterol levels is developed on a Smartphone. In this study, blood cholesterol levels can be measured using image processing applied to an Android-based smartphone with the Choldet app. To analyze the images and identify different locations in the images, Gray Level Coexistence Matrix (GLCM) is applied to reduce non-critical processing areas. Artificial Neural Network (ANN) is used to train the hand skin structure data and the data is applied to the Choldet app on the Android operating system to detect cholesterol levels.

Based on the results of this study, by developing the Choldet app to detect cholesterol in the blood using a non-invasive technique, the detection results are compared with previous studies. The results of this analysis show acceptable accuracy for public use. The development of the Choldet app is new to clinical laboratories and can enable the public and people with high cholesterol to monitor their health conditions early at any time. The Choldet application is a user-friendly and easy-to-use application for smartphone users, but it still needs further development to improve its performance, sensitivity and analysis speed.

The development of the Choldet application to monitor cholesterol levels non-invasively is a very potential step and is relevant to the digital health trend. Several important suggestions that can be considered from the technological, medical, user, and regulatory perspectives. Proper clinical validation is needed so that the application can be relied on, adding features such as graphic displays, personalized insights that learn from user habits and cholesterol level estimation (LDL, HDL, total) and other relevant parameters.

ACKNOWLEDGEMENTS

We would like to thank the Makassar Muhammadiyah Polytechnic for funding this research through independent funding. In addition, we also express our gratitude to the Electromedical Engineering Study Program of the Muhammadiyah Polytechnic of Makassar and the Faculty of Electrical Engineering, Sawerigading University, Makassar for providing facilities and infrastructure so that this research can be completed properly.

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