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Article

Iris-based Image Processing for Cholesterol Level Detection using Gray Level Co-Occurrence Matrix and Support Vector Machine

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Abstract. Serious illnesses such as strokes and heart attacks can be triggered by high levels of cholesterol in human blood that exceeds ideal conditions, where the ideal cholesterol level is below 200 mg/dL. To find out cholesterol levels need a long process because the patient must go through a blood sugar test that requires the patient to undergo fasting for 10–12 hours first before the test. Iridology is a branch of science that studies human iris and its relation to the wellness of human internal organs. The method can be used as an alternative for medical analysis. Iridology thus can be used to assess the conditions of organs, body construction, and other psychological conditions. This paper proposes a cholesterol detection system based on the iris image processing using Gray Level Co-Occurrence Matrix (GLCM) and Support Vector Machine (SVM). GLCM is used as the feature extraction method of the image, while SVM acts as the classifier of the features. In addition to GLCM and SVM, this paper also construct a preprocessing method which consist of image resizing, segmentation, and color image to gray level conversion of the iris image. These steps are necessary before the GLCM feature extraction step can be applied. In principle, the GLCM method is a construction of a matrix containing the information about the proximity position of gray level images pixels. The output of GLCM is fed to the SVM that relies on the best hyperplane. Thus, SVM performs as a separator of two data classes of the input space. From the simulation results, the system built was able to detect excess cholesterol levels through iris image and classify into three classes, namely: non–cholesterol (< 200 mg/dL), risk of cholesterol (200–239 mg/dL) and high cholesterol (> 240 mg/dL). The accuracy rate obtained was 94.67% with an average computation time of 0.0696s. It was using each of the 75 training and test data, with the second-order parameters used are contrast–correlation–energy–homogeneity, pixel distance = 1, quantization level = 8, Polynomial kernel types and One Against One Multiclass.

Keywords: Cholesterol, iris eye, feature extraction, classification, accurate.

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1. Introduction

Cholesterol is a waxy fat compound produced by the human body, especially in the liver. If cholesterol levels in the human body are not properly considered, it can cause excess cholesterol levels in the blood. The ideal cholesterol level in the human body is ≤ 200 mg/dl, while a high cholesterol level is >200mg/dl. Excess cholesterol levels or hypercholesterolemia can increase the risk of stroke and heart attack. Considering that excessive cholesterol levels can cause serious illness, an initial examination is needed to determine cholesterol levels in the human body. In general, checking cholesterol levels through blood sugar requires a long process because it requires the patient to undergo fasting for 10-12 hours before the test. Iridology is a science that studies the pattern and arrangement of fibers in the iris is an alternative that can be used for medical analysis [1]. In a journal compiled by R.A. Ramlee, K.A. Azis, S. Ranjit, and Masran Esro at the Faculty of Electrical and Computer Engineering, University of Melaka, Malaysia, said that Arcus Senilis is a grayish or whitish circle that is visible around the edges of the eye corner. Senilis Arcus is caused by fat deposits in the inner lining of the peripheral cornea. This statement proves that excess cholesterol levels in the body can be detected through iris patterns [2].

In a previous study entitled "Detection of Excess Cholesterol through Eye Iris Images with the Discrete Wavelet Transform Method and K-Nearest Neighbor Classification", a detection of excess cholesterol levels in the human body was carried out with a system that was inputted as a digital image of the iris to be detected, then the process of image standardization, feature extraction and classification will be carried out which results in an average level of accuracy of 55.39% [1]. The research about Cancer classification using Gray Level Co-Occurrence Matrix (GLCM) features is obtained an accuracy of more than 90% [3] and in the study of Detection of Senile Cataract Stadium using the GLCM method as feature extraction and SVM method as its classification yielded an average accuracy rate of 93.33% [4]. Whereas the paper about detection cholesterol level through iris using moment invariant and K-Means Clustering provides a result of accuracy of 95% [5].

In this study, for feature extraction the author uses the GLCM method which is a matrix that contains information about the position of neighboring pixels that have a certain gray level [6–14]. While for classification using the Support Vector Machine (SVM) method that relies on the best hyperplane which functions as a separator of two data classes in the input space [15–24]. Thus the hope of using the GLCM and SVM methods on excess cholesterol levels in the human body can provide a higher level of accuracy than previous similar studies.

2. Research Method

Basically, this research is divided into two stages, namely feature extraction using the GLCM method and classification using the SVM method.

2.1. Gray Level Co-Occurrence Matrix

GLCM is a matrix that contains information about the proximity of pixels that have a certain gray level value. One technique for obtaining texture characteristics is to calculate certain angles and distances [12], [25]. One method to find out is to use the GLCM method. GLCM is defined as a matrix of image pixel data where it is described how often different combinations of gray values in the image appear. The algorithm for forming GLCM is a few steps [26]:

(i). Quantization

Quantization is a conversion of gray scale values (256 gray values) image into a range (level - level) of certain values. This quantization aims to reduce the number of calculations and reduce the computational process. Suppose the set of eight is a range of values (0-7) where each range represents 32 gray values such as Table 1 [26].

Table 1. Quantization Value.

No.	Quantization Value	Value Range
1	0	0-31
2	1	32-63
3	2	64-95
4	3	96-127
5	4	128-159
6	5	160-191
7	6	192-223
8	7	224-255

Suppose there is an image A with a 5x6 order with a gray scale value like in Eq. (1).

$$A = \begin{bmatrix} 33 & 130 & 46 & 27 & 97 & 85 \\ 100 & 66 & 112 & 71 & 45 & 129 \\ 34 & 44 & 141 & 160 & 245 & 3 \\ 54 & 137 & 99 & 78 & 168 & 253 \\ 144 & 190 & 143 & 182 & 136 & 169 \end{bmatrix} \quad (1)$$

Then the B matrix is obtained from the quantization of the gray scale image as in (2).

$$B = \begin{bmatrix} 1 & 4 & 1 & 0 & 3 & 2 \\ 3 & 2 & 3 & 2 & 1 & 4 \\ 1 & 1 & 4 & 5 & 7 & 0 \\ 1 & 4 & 3 & 2 & 5 & 7 \\ 4 & 5 & 4 & 5 & 4 & 5 \end{bmatrix} \quad (2)$$

(ii). Co-Occurence

Co-Occurrence means a shared event, that is the number of occurrences of one level of intensity values of neighboring pixels with one level intensity of another level in distance (d) and a certain angle orientation (θ). Orientation is formed in four angles, namely 0^0, 45^0, 90^0 and 135^0 while the distance between pixels is set at 1 pixel [26].

The representation of the orientation of 0^0 is if there is a reference pixel, based on Fig. 1 in the central pixel box, then the direction 0^0 is shown to the right of the center pixel. For distance, it is a neighboring pixel to the central pixel starting from one to whatever is needed based on the direction of its orientation. Suppose that it is determined from the 4 directions of the matrix co-occurrence (C matrix) is 0^0 and the distance of pixels is 1 as shown in Table 2. Then the C matrix in Eq. (3) is obtained.

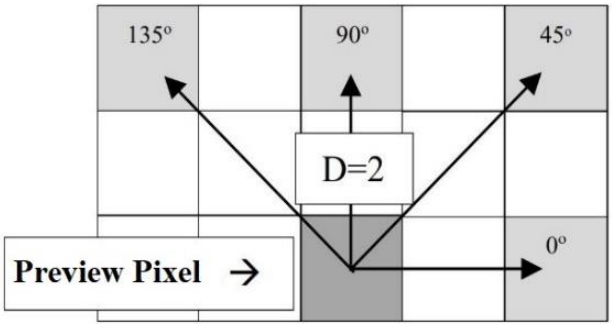

Fig. 1. Orientation (Offset) and Distance (d) [26].

$$C = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 4 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 4 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & 0 & 0 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (3)$$

Table 2. Value of Co-occurrence Matrix.

Main Pixel	Neighboring Pixels							
	0	1	2	3	4	5	6	7
0	0,0	0,1	0,2	0,3	0,4	0,5	0,6	0,7
1	1,0	1,1	1,2	1,3	1,4	1,5	1,6	1,7
2	2,0	2,1	2,2	2,3	2,4	2,5	2,6	2,7
3	3,0	3,1	3,2	3,3	3,4	3,5	3,6	3,7
4	4,0	4,1	4,2	4,3	4,4	4,5	4,6	4,7
5	5,0	5,1	5,2	5,3	5,4	5,5	5,6	5,7
6	6,0	6,1	6,2	6,3	6,4	6,5	6,6	6,7
7	7,0	7,1	7,2	7,3	7,4	7,5	7,6	7,7

(iii). Symmetric

Symmetric interpreted as the appearance of the same pixel position. Suppose there is a pixel (2,3), then horizontally equal to pixels (3,2). Therefore, symmetric is the sum of the matrix co-occurrence with its own transpose matrix like Eq. (4) [26].

$$D = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 & 4 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 4 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 4 & 0 & 0 \\ 0 & 0 & 0 & 0 & 2 & 0 & 0 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 4 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 4 & 0 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 1 & 0 & 4 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 1 & 0 & 0 & 0 & 1 \\ 1 & 2 & 1 & 0 & 5 & 0 & 0 & 0 \\ 0 & 1 & 0 & 5 & 0 & 1 & 0 & 0 \\ 1 & 0 & 5 & 0 & 1 & 0 & 0 & 0 \\ 0 & 5 & 0 & 1 & 0 & 6 & 0 & 0 \\ 0 & 0 & 1 & 0 & 6 & 0 & 0 & 2 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 2 & 0 & 0 \end{bmatrix} \quad (4)$$

$$E = \begin{bmatrix} \frac{0}{50} & \frac{1}{50} & \frac{0}{50} & \frac{1}{50} & \frac{0}{50} & \frac{0}{50} & \frac{0}{50} & \frac{1}{50} \\ \frac{1}{50} & \frac{2}{50} & \frac{1}{50} & \frac{0}{50} & \frac{5}{50} & \frac{0}{50} & \frac{0}{50} & \frac{0}{50} \\ \frac{0}{50} & \frac{1}{50} & \frac{0}{50} & \frac{5}{50} & \frac{0}{50} & \frac{1}{50} & \frac{0}{50} & \frac{0}{50} \\ \frac{1}{50} & \frac{0}{50} & \frac{5}{50} & \frac{0}{50} & \frac{1}{50} & \frac{0}{50} & \frac{0}{50} & \frac{0}{50} \\ \frac{0}{50} & \frac{5}{50} & \frac{0}{50} & \frac{1}{50} & \frac{0}{50} & \frac{6}{50} & \frac{0}{50} & \frac{0}{50} \\ \frac{0}{50} & \frac{0}{50} & \frac{1}{50} & \frac{0}{50} & \frac{6}{50} & \frac{0}{50} & \frac{0}{50} & \frac{2}{50} \\ \frac{0}{50} & \frac{0}{50} & \frac{0}{50} & \frac{0}{50} & \frac{0}{50} & \frac{0}{50} & \frac{0}{50} & \frac{0}{50} \\ \frac{1}{50} & \frac{0}{50} & \frac{0}{50} & \frac{0}{50} & \frac{0}{50} & \frac{2}{50} & \frac{0}{50} & \frac{0}{50} \end{bmatrix} \quad (5)$$

(iv). Normalization

Divide each matrix number into a D (symmetric) matrix with the sum of all the numbers in the matrix. Equation (5) is the result of normalization [26].

(v). Feature Extraction

GLCM is one way to extract a second-order characteristic of textured features. The features extracted are contrast, correlation, energy, and homogeneity. The following are some of the similarities in the textural features [27]:

a. Contrast

Contrast is a color difference that can distinguish objects in images. Measure the contrast between review pixels and neighboring pixels in the entire image as shown in Eq.(6).

$$Contrast = \sum_{i,j} | i - j |^2 \; p(i,j) \quad (6)$$

b. Correlation

Correlation is a measurement of the dissimilarity of a texture. The value is small if the texture is uniform, and the value will high if the texture is random.

$$Correlation = \sum_{i,j} \frac{(i - \mu i)(j - \mu j)\, p(i,j)}{\sigma i \, \sigma j} \quad (7)$$

c. Energy

Energy is global uniformity in an image. It measure the number of squares in the GLCM.

$$Energy = \sum_{i,j} p(i,j)^2 \quad (8)$$

d. Homogeneity

Homogeneity is a local similarity in an image. It measure the proximity of the distribution of elements in the GLCM to the diagonal GLCM.

$$Homogeneity = \sum_{i,j} \frac{p(i,j)}{1 + | i - j |} \quad (9)$$

where i = row, j = column and p = number of pixels.

2.2. Support Vector Machine Classification

SVM as a classification method becomes very popular lately. It is used not only for classification but also as a regression technique. Boser, Guyon, Vapnik proposed SVM, and their work was presented at the fifth annual workshop on Computational learning theory in 1992. Basically, SVM combines the computational theories that existed a few decades before, such as margin hyperplane as proposed by Duda and Hart in 1973. The SVM kernels, on the other hand, were introduced by Aronszajn long before SVM itself in 1950.

The SVM method is included in the supervised learning class for classification and ensures performance in predicting a new classification. The use of SVM as a classifier produces high accuracy as shown in [28]. The purpose of the SVM method is to find the hyperplane function that can be from objects with different classifications. Finding the hyperplane function can use kernel functions. There are several types of kernels. The kernel functions used in this study are Gaussian, Linear, Radial Basis Function (RBF), and Polynomial.

The best hyperplane is one that is able to center and maximize margins until it passes through the middle of a different classification. Centering and separating margins can increase the probability of grouping data correctly. For example, hyperplane 1 has a smaller margin than hyperplane 2. Then there is data entered with an output worth +1 that must be grouped on one of the hyperplane. If in a hyperplane 1 the grouping is wrong, then use hyperplane 2 for the correct grouping [29].

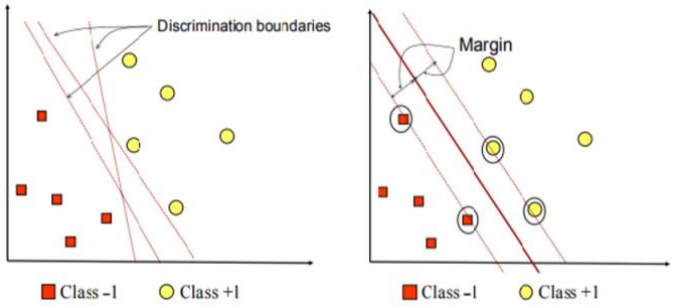

Fig. 2. Support Vector Machine Hyperplane [4].

Figure 2 shows several patterns that are members of two classes: +1 and -1. The red square symbolizes a pattern that is joined in class -1, while the yellow circle represents the pattern in class +1. To get the best hyper lane is by finding the middle position between two class boundary fields or find the maximum margin or the distance between two sets of objects from different classes [16]. SVM has advantages such as: (i). Generalization, namely the ability of a classifying method that is not included in the pattern, (ii). Curse of Dimensionality, namely the ability to estimate parameters, (iii). Implementation is relatively easy, the process of determining support vectors can be formulated in the Quadratic Programming Problem, (iv). Having an optimal global solution, It means that when testing is done with certain parameters, it will produce the same results in the next test. In contrast, the lack of SVM is difficult to use in large-scale cases. A large scale in this case, is meant by the number of samples processed.

Multiclass on Support Vector Machine

There are two options for implementing SVM multiclass, the first one is by combining some binary SVM data, and the second one is by combining all data consisting of several classes into an optimal problem form. The second approach where the optimization problem must be solved is far more complicated than the first approach. The following are two common methods for implementing SVM multiclass:

(i) One Against All (OAA)

In this method, a k (k is the number of classes) binary SVM model is built. Each of the i classification models is

trained by using the whole data, to find solutions to problems.

(ii) One Against One (OAO)

In this method, $k(\frac{k-1}{2})$ is built into a binary classification model (k is the number of classes). This method uses a voting system. So in this method there are $k(\frac{k-1}{2})$ quadratic programming problems, each of which has $\frac{2n}{k}$ variables (n is the number of training data).

3. System Design

The system that will be designed in this study uses a matrix simulator. In system design, a block diagram is needed to present the system in general, as shown in Fig. 3. Each block has its own function. The block diagram gives a more directed boundary than the design of a detection system for excess cholesterol levels through the iris image using the GLCM and SVM methods. Figure 3 shows the system design block diagram

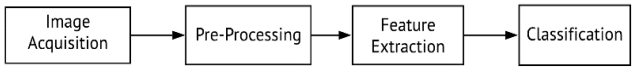

Fig. 3. System Block Diagram.

In this research, the system designed consists of two stages, namely the training stage and the testing phase. The training stage is the process of setting up a database that stores the value of the characteristic vector of each image that is used as a reference for the test image later. The testing phase is the process used to test image data so that it can be classified by the system. In this study, 75 image data were used as training data and testing data.

At the training stage, each process starts from pre-processing the training data of the inserted image, then feature extraction is done using the GLCM method. The training matrix process is carried out which contains vectors - the characteristic vectors of training data and the target results of the training extraction feature to get network weight to be used in the classification process. At the test stage, after pre-processing and extraction of features, the image is detected using the SVM classification method to determine the compatibility of the characteristic vectors of the test data against the training data so that the classification results are obtained.

The general description of the simulation and analysis system from this study is divided into two scenarios, as shown in Fig. 4.

Image Acquisition

The acquisition is the stage for taking pictures in order to get digital images as training data and test data so that the image can be processed in the system. The first step to getting digital images is image acquisition. The iris images are taken from eye hospital that has a patient's medical history and checked through a cholesterol detector. The iris image was taken using the cellphone camera with the .bmp format. The image obtained is divided into training images and test images that will be processed in the pre-processing stage. At the stage of image acquisition, the image that has been taken is done by cropping manually. This is done so that the image that appears is only the area that will be detected.

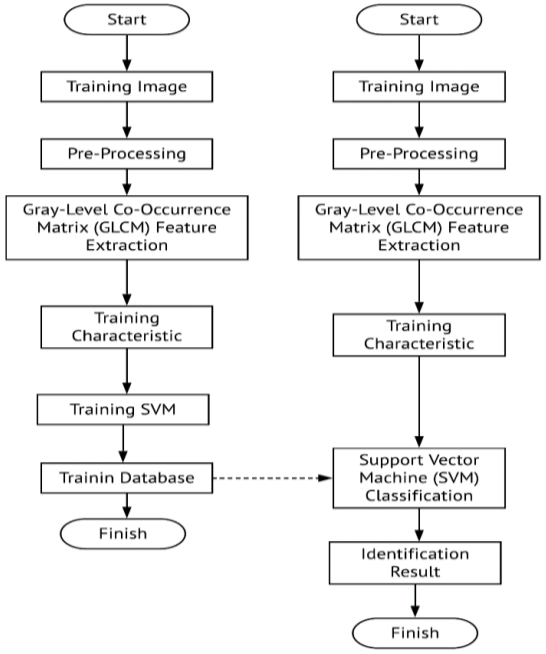

Fig. 4. Diagram Block of the Training and Testing Process.

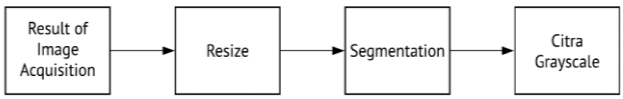

Fig. 5. Pre-Processing Phase Block Diagram.

Pre-Processing

Pre-processing is the step taken to prepare a still rough image so that it can be processed further. The purpose of preprocessing is to improve the quality of the input images obtained. In pre-processing, the first step is resize, which is the uniformity of the pixel size of all images both training and testing to a certain size. The next stage is segmentation, which functions to copy some parts of the image that will be detected such as the texture characteristic. Then the results of the segmentation will be changed to grayscale with the aim of reducing three-dimensional images into just two dimensions with the

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same intensity value, so as to speed up the computational process. Block diagram of the pre-processing and image result of pre-processing process are shown in Fig. 5 and Fig. 6 respectively.

Fig. 6. Pre-Processing Result Image.

Feature Extraction

The GLCM method in this study used to get features on the image of the object to be studied. GLCM is calculated as a second-order histogram of the gray image. GLCM is a matrix where the dimensions depend on the amount (intensity) of gray levels (N) in an image. GLCM contains frequency information found in two combinations of neighboring pixels in a gray image.

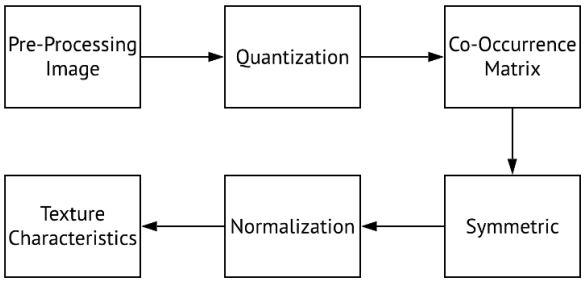

Fig. 7. GLCM Feature Extraction Block Diagram.

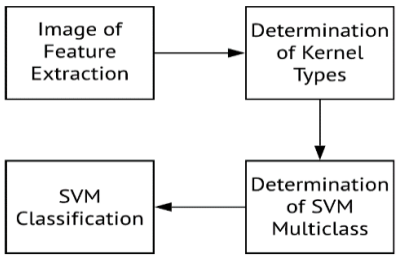

Fig. 8. SVM Classification Block Diagram

Classification

The next stage is the classification process which aims to group images according to classification. The characteristic vectors that have been obtained through the feature extraction process will be classified according to the class of normal cholesterol, risk of cholesterol, and high cholesterol. The method used in the classification process is SVM, while the parameters used in the SVM method are kernel type and multiclass. The data used in this research can be divided into two groups [30], which are the training data arranged in a training database and the test data taken from the test data folder. The next step is the SVM classification process by testing test data to be compared with image data taken from the training database.

System Performance Parameters

After all the processes are done, it is necessary to have a system performance test. This test is useful to determine the success or failure of the application system for the detection of excess cholesterol levels through the iris image using the GLCM and SVM methods so that they can be used accurately. Accuracy can be written as follows:

$$Accuracy = \frac{Amount\ of\ correct\ data}{Amount\ of\ all\ data}\ X\ 100\% \quad (10)$$

Computer Specifications

The computation time is measured relative to the computer that is used in this simulation. The computer specifications are 3 GHz later Pentium Core with 8 GB memory of RAM.

4. Simulation and Analysis

(i). Comparison Test of Number of Training Data with Test Data

At this stage, testing is done by testing the comparison of training data, namely 50%: 50% (75 images of training data: 75 images of test data), 80%: 20% (120 images of training data: 30 images of test data), 20%: 80 % (30 images of training data: 120 images of test data). The second-order parameters on GLCM used are contrast, correlation, energy, homogeneity, pixel distance (d) = 1, quantization level (n) = 8, and the SVM parameters used are Polynomial as kernel type and OAO as multiclass.

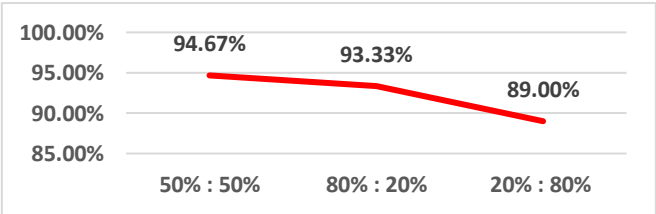

Fig. 9. Accuracy of Comparison of Number of Training Data with Testing Data

From the results of testing the comparison of training data with test data in Fig. 9, the highest accuracy is in data comparison of 50%: 50% (75 images of training data: 75 images of test data) with a value of 94.67% and average computational time is 0.0677s. The lowest accuracy is in data comparison 20 %: 80% (30 training data images: 120

images of test data) with a value of 89.00% and average computational time is 0.0701s.

(ii). Testing of Pixel Distance Parameters (d) and Quantization Levels (n)

The following are test results data to determine the effect of pixel distance parameters (d) and quantization level (n) on accuracy and computation time. Where the pixel distance parameter (d) and quantization level (n) consist of d = 1, 2, and 3 and n = 8, 16 and 32. The second order GLCM parameters used for testing at this stage are contrast, correlation, energy and homogeneity. The SVM parameters used are polynomial as kernel type and OAO as multiclass.

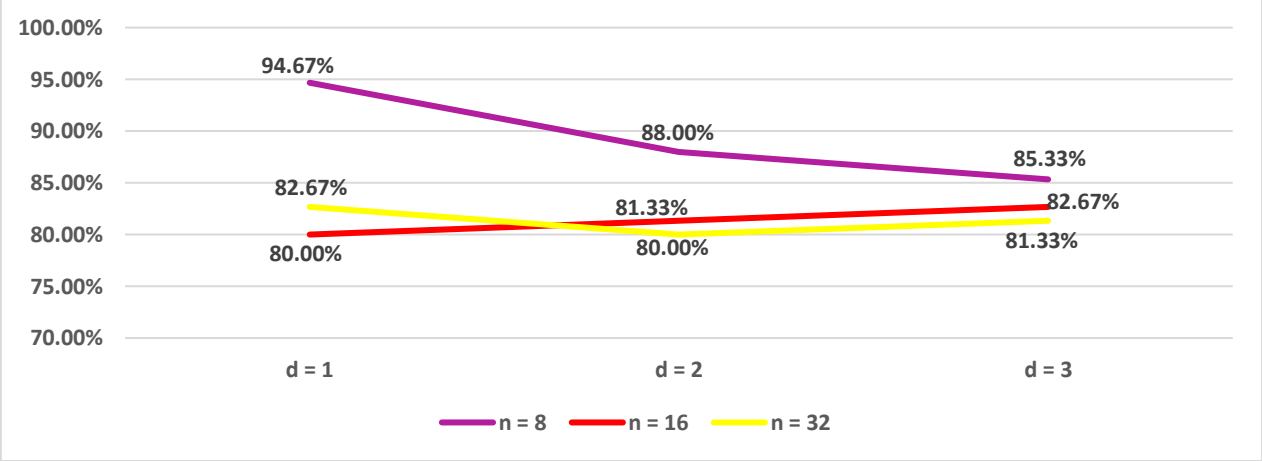

Fig. 10. Accuracy of Pixel Distance Parameters (d) and Quantization Levels (n).

Based on Fig. 10, the highest accuracy (94.67%) is obtained when the pixel distance parameter (d) and the quantization level (n) used are d = 1 and n = 8 with an average computational time is 0.0691 s. The lowest accuracy (80.00%) occurs at d = 1 and n = 8 with average computational time is 0.0677s or at d = 2 and n = 32 with average computational time is 0.0686 s. From the simulation results, it appears that the best quantization level is 8, and with the graph (n = 8), the higher the d, the lower the accuracy.

(iii). Testing of Second-Order Parameter

The following is the test data to determine the effect of one second-order parameter on accuracy and computational time. The combination of second-order parameter consists of contrast, correlation, correlation–energy, contrast–correlation–energy, correlation–energy–homogeneity, and contrast–correlation–energy–homogeneity. The GLCM parameters used for testing at this stage are distance (d) = 1, and the quantization level (n) = 8. The SVM parameters used are Polynomial as type of kernel and OAO as multiclass.

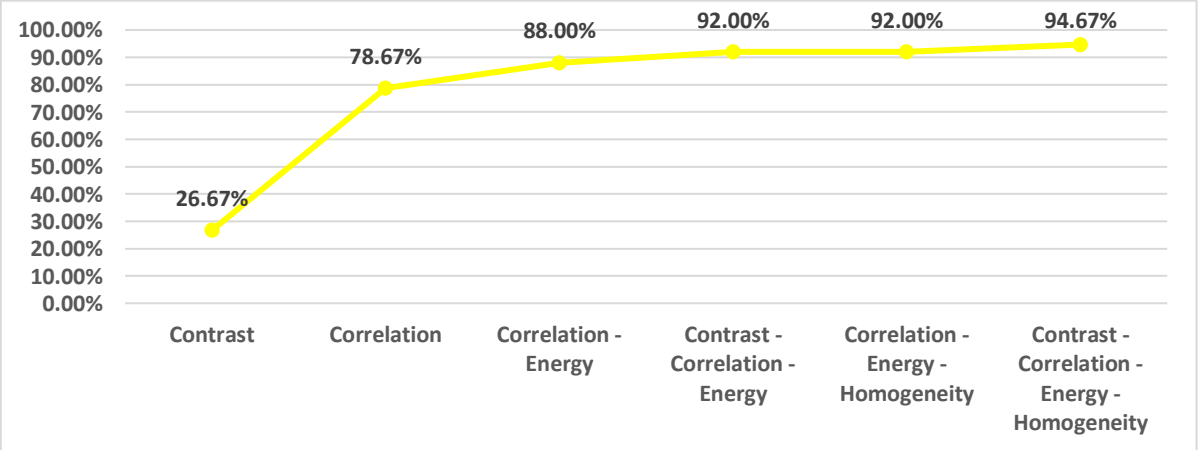

Fig. 11. Accuracy of Second-Order Parameter.

Based on Fig. 11, the highest accuracy rate was obtained when the second-order parameters used were contrast–correlation–energy–homogeneity with a value of 94.67% and the average computational time is 0.0702s.

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The lowest accuracy was obtained when the second-order parameters used is contrast with a value of 26.67% and the average computational time is 0.0691s. From the results above, the more second-order parameters are used, the higher the accuracy of the system.

From the results of second-order parameters that have been done, the authors get the results of the texture feature values with orientation angles 0^0, 45^0, 90^0, and 135^0 from each class that is non-cholesterol, risk of cholesterol, and high cholesterol.

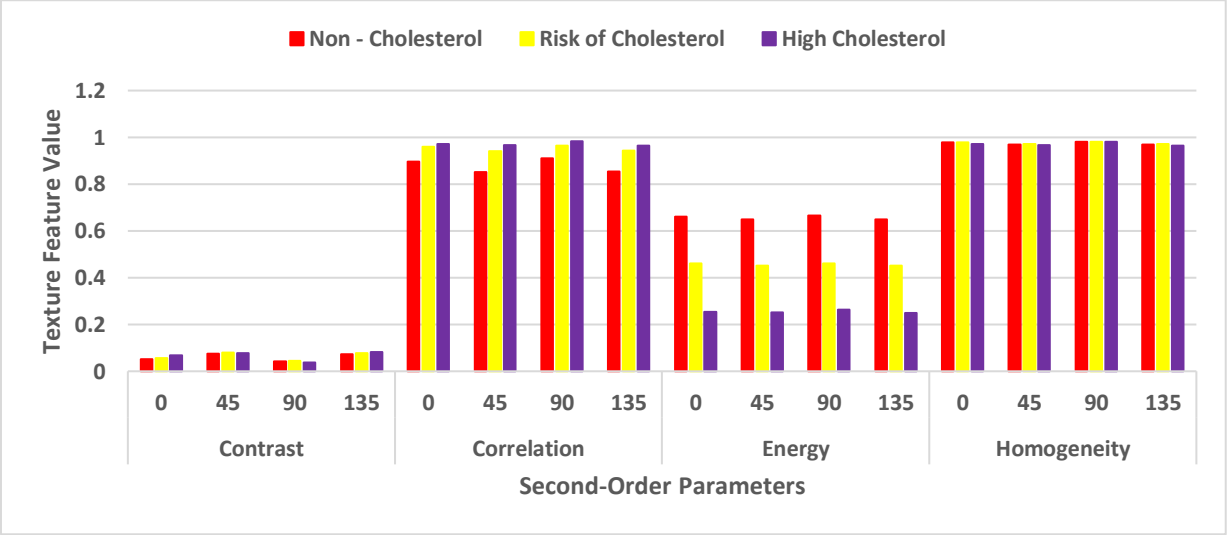

Fig. 12. Value of Second Order Parameters in Each Class.

Based on Fig. 12, it can be concluded that the highest Correlation texture feature values were obtained in the Cholesterol class, and the lowest was in the Non-Cholesterol class. These results indicate that the degree of dissimilarity between neighboring pixels is high in the Cholesterol class and vice versa in the Non-Cholesterol class. The highest Energy texture feature values obtained in the Non-Cholesterol class, and the lowest was in the Cholesterol class. These results indicate that the level of global uniformity is high in the Non-Cholesterol class and vice versa in the Cholesterol class. Meanwhile, the value of contrast texture features and homogeneity tend to be random and fixed in each class.

(iv). Testing of Kernel Types and Multiclass

The following is the test data to determine the effect of kernel type parameters and Multiclass on SVM on accuracy and computation time. Where kernel type parameters consist of Gaussian, Linear, RBF, and Polynomial. The multiclass consisting of OAO and One Agains All (OAA). Testing at this stage uses second-order GLCM parameters, namely contrast, correlation, energy homogeneity, quantization level (n) = 8, and pixel distance (d) = 1

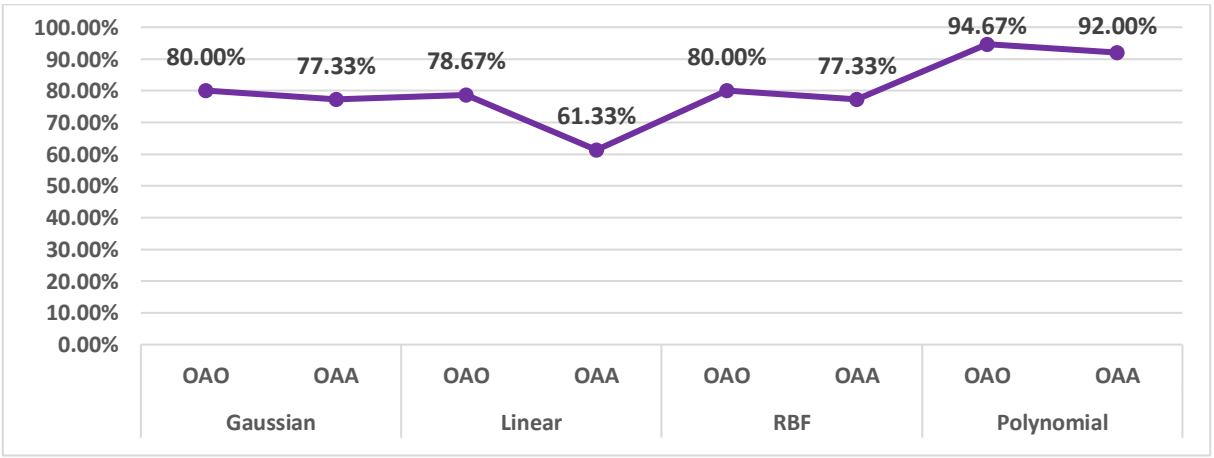

Fig. 13. Accuracy and Computation Time of Kernel Types and Multiclass.

Based on Fig. 13 the highest accuracy was obtained when the kernel and multiclass type parameters used were Polynomial and OAO which were 94.67% with average computational time is 0.0696s. The lowest accuracy was obtained when the kernel and multiclass type parameters used were Linear and OAA which were 61.33% with

average computational time is 0.0699s. From the results above, multiclass OAO is more suitable for each Kernel type.

5. Conclusion

In this study, a system has been designed to detect excess cholesterol levels through the iris image using the GLCM feature extraction method and SVM classification with an accuracy of 94.67% and computation time of 0.0696s. Based on the results of system testing and analysis, conclusions are obtained as follows:

(i). The GLCM method can detect excess cholesterol levels through the iris image optimally using second-order parameters namely contrast, correlation, energy and homogeneity, pixel distance (d) = 1, and quantization level (n) = 8.

- The more second-order parameters are used, the more detailed texture features are encoded, so the accuracy rate is higher and computation time is longer.
- The smaller the quantization level (n) is used, the smaller the gray scale value that is converted into a certain range of values, so the accuracy rate is higher and computation time is faster.
- The smaller the pixel distance (d), the closer the neighboring pixel distance becomes the orientation function, so that the accuracy level is higher and the computation time is faster.

(ii). The SVM method can detect excess levels of cholesterol through the iris image optimally with the Polynomial kernels and OAO multiclass.

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