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Iris Recognition Using Hybrid Self-Organizing Map Classifier and Daugman's Algorithm

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Abstract

One of the neural network algorithms that can be used in iris recognition is self-organizing map (SOM). This algorithm has a weakness in determining the initial weight of the network, which is generally carried out randomly, which can result in a decrease in accuracy when an incorrect determination is made. The solution that is often used is to apply a hybrid process in determining the initial weight of the SOM network. This study takes an approach using the cosine similarity equation to determine the initial weight of the network SOM in order to increase recognition accuracy. In addition, the localization process needs to be carried out to limit the area of the iris image being studied so that it is easy for the recognition process to be carried out. The method proposed in this study for iris recognition, namely hybrid SOM and Daugman's algorithm, has been tested on several people by capturing the iris of the eye using a digital camera. The captured eyes have been localized first using the Daugman's algorithm, and then the image features were extracted using the GLCM and LBP methods. In the final stage of the study, an iris recognition comparison test was performed, and the results obtained an accuracy of 85.50% using the proposed method and an accuracy of 73.50% without performing a hybrid process on the SOM network.

Keywords: iris recognition, SOM, hybrid SOM, cosine similarity, daugman's algorithm

1. Introduction

The security system by utilizing biometric principles, such as iris recognition, is a computational method using biological aspects by displaying the unique characteristics possessed by humans [1]. Scans that utilize these biometric principles will use biometric data to identify individuals based on measurements of their physiological characteristics [2]. Physiological characteristics are able to control and protect sensitive data contained in information systems.

Recognition using the iris is done because the retina of each individual has a different texture, just like human fingerprints [3]. The security system with iris recognition has several advantages over other security systems. This recognition has the highest level of accuracy so far because it utilizes eye patterns that are unique to each person [2]. Each person's unique irises would make them difficult to fake. The iris recognition system has a very important role in the security sector, such as providing access to government offices, airports, electronic device security and others [4].

The method that is quite often used for iris recognition is the artificial neural network technique [5]. Research on iris recognition using the backpropagation neural network method with several modifications and settings obtained the highest accuracy of 98%. The results were carried out with a total of 500 images from testing as many as 100 different individuals [6]. Another study that uses neural network techniques for iris biometric recognition is the radial basis function (RFB) and a feed-forward neural network (FNN). The results obtained show that the RBFNN method obtains recognition accuracy results of 97% and the FNN method obtains recognition accuracy results of 95% [4].

Iris recognition can be tested using a self-organizing map (SOM) neural network and feature extraction techniques that get an accuracy of 83%. In testing, there were some iris that were as heavily distorted as if half of the iris were closed. For this type of data, the network outputs an unrecognized pattern rather than matching it to the nearest pattern. However, the performance of the recognition system can be improved by acquiring the images captured by the camera or digital sensor at high resolution while paying attention to the correct alignment of the input data [7]. In addition to these methods, iris recognition can be improved by using a hybrid model on the SOM network or by improving the image processing before the recognition stage is carried out. The process is carried out by adding a method that

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can optimize the initial weighting value of the SOM network in the network training process.

From previous research, it can be concluded that the neural network is effective in handling cases of iris recognition. The problem that is often seen in iris recognition is the segmentation process, which has suboptimal performance due to inaccurate localization factors in the capture process for iris images [8]. This localization process is needed to delimit the region of the iris under study so that it is easy for the recognition process to be carried out. Iris recognition consists of several processes, namely: iris localization or segmentation, normalization, feature extraction, and training the iris image data set followed by the recognition process [9]. The image that has been collected will be localized first so that only the iris image is extracted to obtain features that are suitable for the recognition process and improve the accuracy of iris recognition.

There are several iris localization methods that have been carried out by previous researchers so that the iris recognition process gets good accuracy. Iris recognition research using Daugman's algorithm for iris image localization and an artificial neural network for the recognition process obtained the highest accuracy of 99.7% [10]. Another study conducted iris recognition using a neural network and the Hough transform. In this study, the accuracy obtained by the combination of the two methods was 96.5% [5]. From these two studies, it can be seen that the iris localization process needs to be carried out so that iris recognition obtains conformity and increases recognition accuracy.

Based on the previous description, the researcher is interested in conducting research on iris recognition to identify a person. The method proposed in this research is a combination of Daugman's algorithm and a hybrid self-organizing map. Daugman's algorithm will localize part of the iris in an image and remove other parts. The localized iris image will be extracted texture features using the GLCM (Gray Level Co-occurrence Matrix) method and the LBP (Local Binary Pattern) method to obtain the unique characteristics of the iris image. In the last stage, the iris image will be trained and tested using the hybrid self-organizing map method, and the recognition accuracy level will be calculated.

Hybrid methods or optimization on the SOM network are needed for the process of determining the initial weight of the network [11]. Incorrect initial weight determination can give poor cluster results and have an effect on decreasing the accuracy of the resulting classification [12]. Solutions to problems on the SOM network are mostly done by optimization methods or using hybrid methods. Testing of the hybrid method on the SOM network has been proposed in the image recognition process to obtain higher accuracy.

Several research results with the hybrid SOM process show that the hybrid algorithm has better results in clustering accuracy and computational speed, so it can accurately group data sets compared to the usual SOM neural network model [13]. Hybrid SOM research using Gray Wolf Optimization for iris recognition obtains the highest accuracy of 99.3% and has better performance than without hybrid [14].

The hybrid process on the SOM network needs to be carried out in determining the initial weight to increase the accuracy of classification or recognition. In addition, this process helps the SOM algorithm in reducing the amount of computation in calculating the optimal network weight search.

In this study, a method of measuring distance similarity, namely cosine similarity, will be used, which will determine the initial weight of the SOM network. The contribution offered by measuring each data similarity based on features in the same class and the highest feature similarity from the data will be used as the initial weight. The concept of the proposed method is the basis of classification, where data that has a high similarity of features to one another will be grouped in the same cluster and vice versa.

The purpose of this study was to improve the accuracy of iris recognition using a hybrid SOM network with the cosine similarity method. The stages in this research are done by collecting data, developing network architecture, performing computations, and calculating the performance of iris image recognition. In this study, we used a dataset obtained from direct capture using a digital camera on a person's eye.

This study was conducted to identify 10 students by taking 20 shots of each student's eyes, so that there were 200 images used as objects of research. This research was carried out in the Computer Vision laboratory of Prima Indonesia University, where the device used to perform iris recognition was sufficient for conducting research that had been designed previously. The results of the data collection are then used as training and testing data for the proposed iris recognition method.

In the early stages of the research, it is necessary to do image processing to determine the location of the iris in the image that has been collected to obtain the value of image feature extraction as the network input used. The results of the extraction are used as a network training process, where the cosine method will look for data with the highest feature similarity from each data class to serve as the initial weight.

The next step is that the SOM network will improve the initial weight value with a training process to obtain the optimal network final weight value. The final stage of this process is the recognition, which is done by calculating the final weight of the network and the input features of the new image, also known as the testing

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process. The results of all recognition will be collected and then calculated to determine the accuracy obtained between the tests carried out using the hybrid SOM network and the usual SOM network to determine the performance improvement of the proposed method.

2. Research Methods

The initial stage of this research will be to localize or segment the iris part of the image using Daugman's algorithm, so that the feature extraction value is only the iris part. The next stage will be the iris recognition process using SOM and hybrid SOM networks. The last step is to calculate the accuracy, which aims to determine the performance of the proposed method. The steps of the proposed research can be seen in Figure 1.

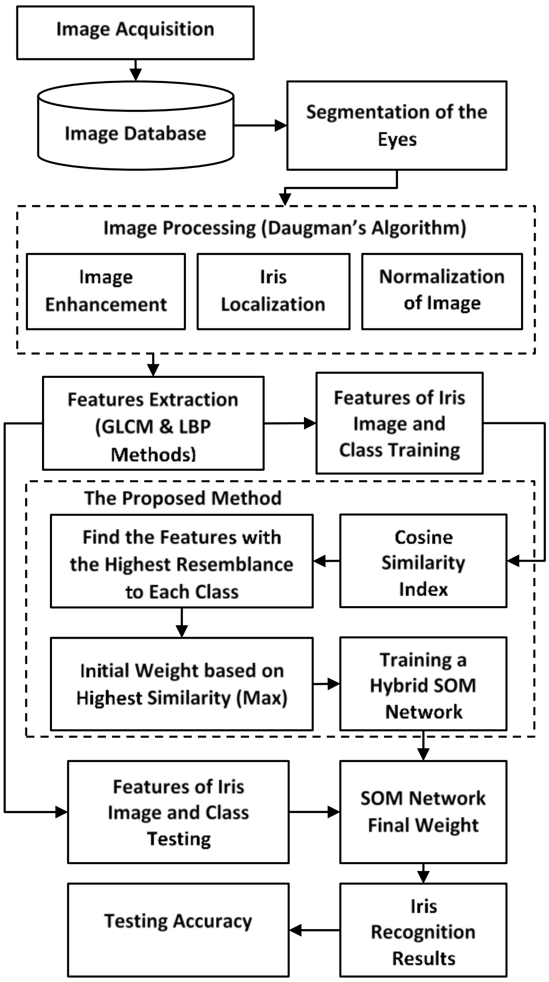

Figure 1. The Proposed Method for Iris Recognition

The explanation of each research step on iris recognition using the proposed method, among others:

Image acquisition is the process of capturing eye images using a digital camera as input for the iris recognition process. The image will be divided into 2, namely the train image for the training process and the test image for the recognition process.

Iris image localization using Daugman's algorithm is a process to localize the presence of iris in an image. The previously entered image is an image that still has noise in the form of the appetizing part of the eye. This process will remove the part and save the image of the cropped part of the iris for the recognition process.

Feature extraction is the process of obtaining the characteristics of an image based on the texture of the iris image using the GLCM (Gray Level Co-occurrence Matrix) and LBP (Local Binary Pattern) methods. The results of feature extraction in the form of numerical values will be divided into two groups, namely data training and data testing, for the training process and testing of the proposed method.

Cosine similarity is a similarity method for determining the initial weight value in the SOM network. The determination is done by calculating the closeness of features between one set of data and other data that are in the same class. The data with the highest feature similarity measurement results is the data that will be set as the initial weight on the SOM network to perform network training. In the usual SOM method, this process is carried out in a random way and is updated in the network training process.

SOM/hybrid SOM network training is a network training stage using the SOM algorithm. This process begins with determining the initial weight of the network and other parameters to train the network.

In the proposed method, namely hybrid SOM, this process is carried out by calculating the initial weight value using the cosine similarity equation. The results of this approach will be entered as the initial initialization of the network to obtain the final parameter, namely the final weight of the network.

Recognition using the SOM/hybrid SOM network is a pattern matching process that is used to generate data classes on the test image. This process is done by calculating the feature value of the test image with the final parameters of the previous SOM network. The final result is a class on the test image based on the closeness between the features of the test image and the final weight of the network.

The calculation of accuracy in iris recognition is a process to calculate the accuracy of grouping the data obtained from the proposed method with the actual results. This process has the aim of knowing how high the performance of the proposed method is, so that a conclusion can be drawn.

The data in this study were images taken directly with a digital camera on the eyes of ten different people in order to perform iris recognition using the proposed method. Each person will be given as many as 20

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images of his eyes, with the exception of the right and left eye, each being taken as many as 10 images. The next process is to determine the eye position for each image and perform the cropping process with an image size of 500 pixels x 250 pixels. Then, the image will be localized using Daugman's algorithm to find parts of the iris image and perform texture feature extraction using GLCM and LBP methods. An example of an eye object that has been taken can be seen in Figure 2.

Figure 2. An Example of an Image of the Eyes

2.1 Daugman's Algorithm

Daugman's algorithm is an integro-differential operator that looks for the pupil circle and iris circle from the eye image, which is very effective. The integro-differential operator is an operator that contains both integral and derivative functions [10]. The integro-differential operator is used by Daugman to find the iris region using equation 1 below [10].

$$Z = max(r, x_0, y_0)\left|G_\sigma(r)\frac{\partial}{\partial r}\oint_{r,x_0,y_0}^{r,x_f,y_f}\frac{I(x,y)}{2\pi r}ds\right| \quad (1)$$

Where: $I(x, y)$ is the eye image input, r is the radius, s is the circle contour, and G_σ is the smoothing function of the Gaussian filter.

After the iris is detected, the next process is normalization using the Daugman Rubber Sheet method by changing the ring-shaped iris region into a rectangular shape can be seen in Figure 3. This method remaps each point in the iris region from Cartesian coordinates (x,y) to polar coordinates (r,θ), where r is the interval [0,1] and θ is the angle [0,2π] [4].

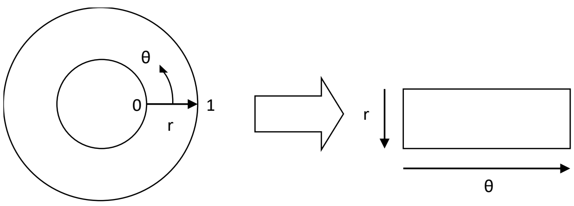


Figure 3. Daugman Rubber Sheet Model

The procedure for remapping the iris region from Cartesian (x,y) to polar (r,θ) coordinates using equations 2, 3, and 4 below [4].

$$I(x(r,\theta), y(r,\theta)) \rightarrow I(r,\theta) \quad (2)$$

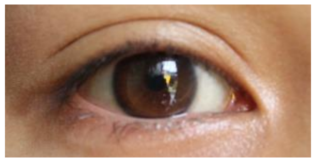
$$x(r,\theta) = (1-r)x_p(\theta) + rx_1(\theta) \quad (3)$$

$$y(r,\theta) = (1-r)y_p(\theta) + ry_1(\theta) \quad (4)$$

Where,

I(x,y) : Iris region discovered
(x,y) : Cartesian coordinates
(r,θ) : Polar coordinates normalized
x_p, y_p : The coordinates of the pupillary circumference are in the direction as θ
x_1, y_1 : The coordinates of the circumference of the iris are in the same direction as θ

The results of Daugman's algorithm can be seen in Figure 4.



(a) Image of the eye

(b) Image of the iris

Figure 4. Iris Image Localization Result with Daugman's Algorithm

2.2 Gray Level Co-occurrence Matrix (GLCM)

Gray Level Co-occurrence Matrix (GLCM) is a technique for evaluating the value of texture features from regions of interest (ROI) of an image. Texture features commonly used in GLCM, namely: energy, contrast, correlation, and homogeneity, with the final extraction result being the average value of the four directions (0, 45, 90, and 135) [15].

The GLCM feature exploits a certain grayscale relationship between two pixels that are given a certain distance in an image, namely the grayscale spatial correlation characteristic [16]. The GLCM feature has values that change rapidly in the fine-texture area and slowly-changing values in the coarse-textured area [17]. The equation used to find the feature value of an image using the GLCM method can be seen using equations 5, 6, 7, and 8 below: [18].

$$Contrast = \sum_i \sum_j (i-j)^2 P(i,j) \quad (5)$$

$$Correlation = \frac{\sum_i \sum_j i,j \ P[i,j] - \mu_i \mu_j}{\sigma_i \sigma_j} \quad (6)$$

$$Energy = \sum_i \sum_j P[i,j]^2 \quad (7)$$

$$Homogeneity = \sum_i \sum_j \frac{P[i,j]}{1+[i-j]} \quad (8)$$

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Where: P is the pixel value of an image, i is the row position of a pixel, j is the column position of a pixel, μ is the mean value, and σ is the variance value.

2.3 Local Binary Pattern (LBP)

Local Binary Pattern (LBP) is a local spatial structure that describes an image that has gray invariance and has good resistance to background noise and visible light [19].

The basic idea of LBP is the number of results that compare the pixels of an image with the surrounding pixels. At the center pixel, the pattern number is calculated by comparing its threshold value with the threshold value of its neighboring pixels. If the threshold of the center pixel is greater than or equal to the adjacent pixels, then it is marked as 1, otherwise it is marked as 0 [20]. The equations used in finding the LBP feature value can be seen using equations 9 and 10 below: [21].

$$LBP_p = \sum_{i=0}^{P} s(g_i - g_c)2^i \quad (9)$$

$$s(x) = \begin{cases} 1 & x \geq t \\ 0 & x < t \end{cases} \quad (10)$$

Where: p is the pixel center value, g_c is the brightness, g_i is the brightness of adjacent pixels, and t is the threshold value.

2.4 Cosine Similarity

Cosine similarity is a method to measure the level of similarity between two vectors, which in this case is every feature in the data. The Cosine Similarity will decide whether the size of the similarity between the two vectors has a cosine angle in the same direction or not [22].

Based on the principle of the value of the cosine of the angle, the value of the angle cosine 0 is 1 (one) and is greater than the value of the other angles. The similarity value of two vectors is said to be equal when it is 1 (one), and when the two vectors have no similarity at all, it will be worth 0 (zero). The equation used to find the similarity value with cosine similarity can be seen using equation 11 [23].

$$Cos\ \theta = \frac{A.B}{\|A\|.\|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n}(A_i)^2} * \sqrt{\sum_{i=1}^{n}(B_i)^2}} \quad (11)$$

Where: Cos θ is a measure of feature similarity (values ranging from 0 - 1), A is a comparison vector feature, and B is a compared vector feature.

In the proposed research, this method will find features in the data that are in the same data class. The highest value of the highest feature of the data will be used as the beginning of the network, so that the total initial weight is as much as the specified data group. As an illustration, the initial weights for data in class 1 can be seen in Figure 5.

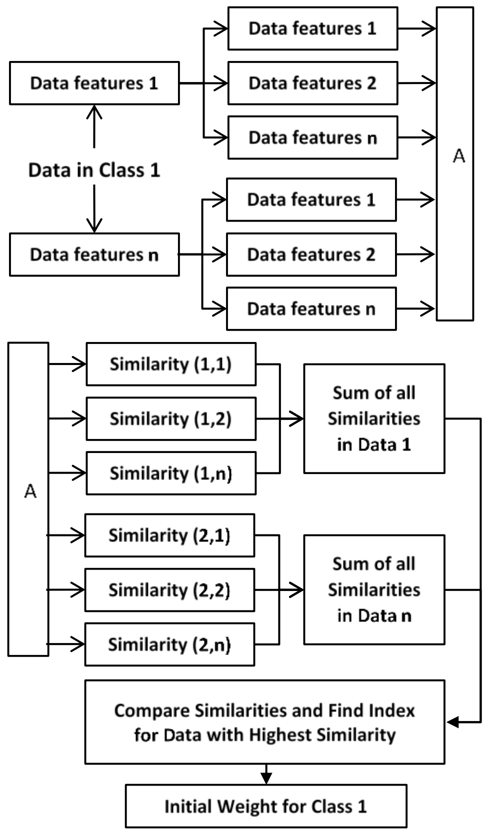

Figure 5. The Process of Finding Initial Weight Values with Cosine Similarity

2.5 Self-Organizing Map (SOM)

The self-organizing map (SOM), or self-organizing feature map, was first introduced by Teuvo Kohonen in 1982 [24]. SOM is a technique for analyzing high-dimensional input data using unsupervised neural networks and is a network training with a competitive model. The architecture of the SOM network consists of two layers, namely input (x) and output (y) [25]. Each neuron in the input layer will be connected to every neuron in the output layer. The architecture of the SOM network can be seen in Figure 6.

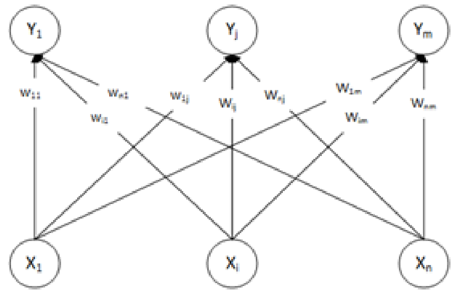

Figure 6. The SOM Network Architecture

The initial stage of the SOM network training is to initialize the initial weighting (w_{ij}) with a random value, set the value of the learning rate (α) parameter and the number of epochs (t) used. In the proposed method, the initial weight determination process is carried out using

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the cosine similarity equation. The next step, for each input vector x, calculate the Euclidean distance with the initial weight of the network using equation 12.

$$Dist\ (x, w) = \sqrt{\sum_{i=1,j=1}^{n} (x_i - w_{ij})^2} \quad (12)$$

Where: x_i is the input vector ($x = x_1, x_2, x_3..., x_n$) and w_{ij} is the initial weight of the network.

After obtaining the distance value, then find the minimum distance, correct the weight, and improve the learning rate (α) value. The closest node, or in this case, the smallest distance, is the winner or Best Match Units (BMU) [25]. The equations used to improve the weight value can be seen using equations 13 and 14.

$$w_{ij}(new) = w_{ij}(old) + \alpha[x_i - w_{ij}(old)] \quad (13)$$

$$\alpha\ (t+1) = 0.5\ \alpha t \quad (14)$$

The process is carried out repeatedly according to the amount of data and the number of epochs determined at the beginning of the network training. The algorithm will stop when the epoch value has been met or the weight value no longer changes, or in other words, has a stable value. The weight from the network training results is called the final network weight and is stored to determine the data class in the test data entered according to the smallest minimum value generated.

3. Results and Discussions

This section will describe the results obtained by applying the proposed method of performing iris recognition. The results of the recognition using the SOM network, which has been combined with the cosine similarity method in determining the initial weight, will be compared with the results of the recognition using the usual SOM network. The testing process is carried out on the test iris image that has been localized with the Daugman's algorithm, and then the texture feature extraction value is calculated using the GLCM (Gray Level Co-occurrence Matrix) method and the LBP (Local Binary Pattern) method. The extraction value is used as an input to the SOM network, which will be tested to get the data class in the test data. In this study, the data tested on the SOM network or hybrid SOM is training data, totaling 200 images with a total of 10 classes. Table 1 will show the results obtained based on the comparison of results using the method used in this study.

Table 1. Iris Recognition Test Using SOM Network and Hybrid SOM Network

Methods	Epoch Value	No. of Correct	Accuracy
SOM	10	125	62.50%
	50	141	70.50%
	100	147	73.50%
Hybrid SOM	10	167	83.50%
	50	171	85.50%
	100	171	85.50%

In Table 1, it can be seen the accuracy of the test using the SOM network method and the hybrid SOM network for iris recognition. The epoch values determined in the network training process are 10, 50, and 100 with an alpha (α) of 10^{-4} with a Dec alpha (α) of 0.05. The result with the best initial parameters will be taken as the final recognition result. The results of the recognition of each data class using the proposed method and the usual SOM network can be seen in Figure 7.

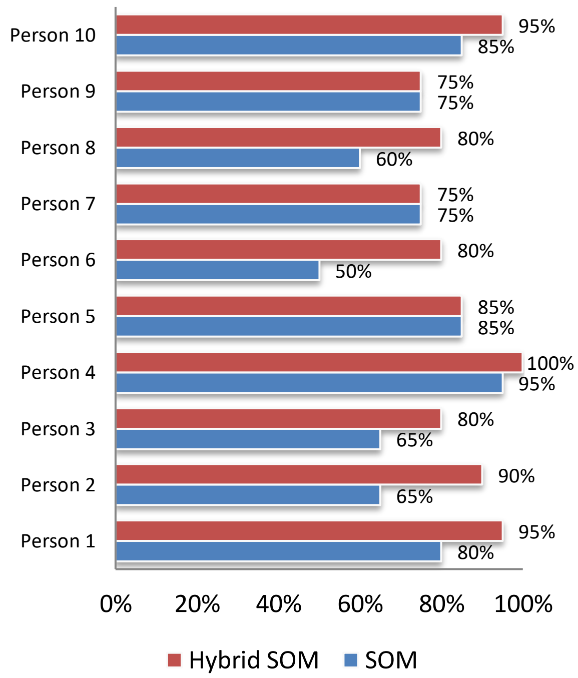

Figure 7. Iris Recognition Accuracy in Each Data Class

Based on the results obtained from Figure 7, the iris recognition process using the proposed method has better test accuracy results in each data class. Overall, the accuracy obtained using the proposed method has a good improvement, namely by training the SOM network using the cosine similarity method in determining the initial weight of the network. The results obtained in Table 1 can be seen that in the usual SOM network, the highest accuracy results when the epoch process is carried out 100 times to obtain better accuracy. Meanwhile, with the proposed method, the highest value has been achieved in the 50th epoch, and when it is continued to the next epoch, the results obtained are the same value.

The testing in this study was carried out by comparing the parameters of the same SOM network training. This is done to see how far the proposed method has a good influence on the iris recognition process. Setting the initial parameter values, such as the epoch value and learning rate, is done by testing a value at random to obtain the appropriate parameter. This parameter value is the reference in the SOM network, so it can be seen how far the process of determining the initial weight

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using the proposed method affects the accuracy of iris recognition. A comparison of the final percentage accuracy of iris recognition using the SOM network and the proposed method can be seen in Table 2.

Table 2. Comparison of Accuracy Using Hybrid SOM Networks and SOM Networks

Methods	Accuracy
SOM	73.50%
Hybrid SOM	85.50%

Based on Table 2, the test results for iris recognition using the hybrid SOM neural network obtained better results than the usual SOM neural network. The results of the iris recognition test using the proposed method obtained an accuracy of 85.50%. While the results of the iris recognition performed using the usual SOM network obtained an accuracy of 73.50%. The determination of the initial weight used in this study can affect the results of better iris recognition. In addition, the training process of the proposed method has an impact on achieving a smaller epoch value, so that it can provide a faster program execution time. In a usual SOM network, the weight value is continuously updated up to the 100th epoch to get maximum accuracy. Meanwhile, the proposed method gives maximum results at the 50th epoch, and when it is continued to the next epoch, it gives the same value. The process of finding the best final weight in the training process using the proposed method can provide a short time.

Basically, the method used in determining the initial weight is a similarity measurement used for classification cases in determining data classes, such as the Euclidean distance equation. This study uses this equation at the beginning of the network training, which is intended to select data that is the center point of all data that is in the same class. This data is used as an initial guide in classifying the SOM network. The data cannot be said to be the optimal cluster point, so more training is needed to use the SOM network. The SOM network will carry out the training process by updating the weight values entered at the beginning of the training through a repetition process to get a stable final weight value. The proposed method helps the training process, which begins with finding the value of the data center that will be used as the initial weight of the SOM network.

Matching an image with another image can be done by measuring the level of similarity that exists between the two images or by measuring how close they are to each other [26]. The measure of similarity or distance is the core component used by distance-based grouping to group similar data points into the same cluster, while in different or distant algorithms, data points are placed into different clusters [27]. In this study, this method is used to get the image that has the highest similarity and is used as a data center, after which it will be used as the initial weight on the SOM network. The use of the cosine similarity method was chosen as a method of measuring the level of similarity of the data because of the acquisition of good accuracy in each test, where the similarity of the data using the cosine similarity method has better performance than the Euclidean distance method, with a precision for cosine of 90% and an Euclidean distance of 80% [28].

Previous research has carried out the iris recognition process and found other problems, namely the inaccurate segmentation of the iris image due to the image resolution being too low. This will also have an impact on the feature extraction process carried out and cause the accuracy to be suboptimal. Difficulty in obtaining the iris image is an obstacle found in this study because it requires a fairly expensive device to obtain a good iris image. In this research, the solution to increasing accuracy is done by using a hybrid method process to obtain good performance. The method used has succeeded in increasing the recognition accuracy compared to the general method using the same image. In addition, other obstacles were found during the segmentation process using the Daugman's algorithm. The segmentation results obtained are very good, but the segmentation results obtained from the computations are quite long. The solution that can be implemented is to improve the segmentation performance of the Daugman's algorithm so that the results obtained can be better and more efficient in terms of time.

4. Conclusion

From the previous description, the resulting test for iris recognition using the hybrid SOM network method or the proposed method obtained an accuracy of 85.50%, while the test for iris recognition using the usual SOM network obtained an accuracy of 73.50%. Thus, it can be concluded that the accuracy of iris recognition using the hybrid SOM network is better than that using the usual SOM network, with an increase in accuracy of 12%. Therefore, the iris recognition process using the proposed method has better performance and effect for iris recognition.

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