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Comparative assessment of back propagation neural network and self organising feature map for iris-based access control system

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Abstract

Iris recognition is considered as one of the best biometric methods used for human identification and verification because of its unique features that differ from one person to another. Self-Organizing Feature Map (SOFM) and Back Propagation Neural Network (BPNN) are two techniques that have been used previously for iris recognition but their performance comparison has not been adequately investigated. This research, therefore, carried out a comparative analysis between SOFM and BPNN in iris recognition. Three hundred (300) iris images from one hundred and fifty (150) subjects were acquired from Covenant University Iris dataset. The acquired iris images were pre-processed by segmenting the iris portion using Hough Transform and were normalized using Daugman's Rubber Sheet Model. Local Binary Pattern was used for feature extraction and dimension reduction of the iris images. Each of the two algorithms, SOFM and BPNN was used individually as iris image classifier, this technique was implemented using MATLAB (R2016a). The performance of the two iris classifiers was evaluated individually and compared at 0.75 threshold value based on Recognition Accuracy (RA), False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (EER), Training Time (TT) and Recognition Time (RT). The SOFM and BPNN techniques were validated by carrying out a t-test to compare the differences between the two techniques at 5% significance level. The SOFM technique gave RA, FAR, FRR, EER, TT and RT of 97.14%, 1.67%, 3.75%, 3.18%, 104.47s and 81.98s, respectively, while the corresponding values for BPNN were 94.29%, 5.00%, 6.25%, 5.91%, 116.23s and 101.77s respectively. The P value between the SOFM and BPNN techniques was 0.002. This research outcome revealed that SOFM outperformed BPNN in iris recognition system with respect to RA, FAR, FRR, EER, TT and RT. The SOFM technique could be used for more robust iris recognition system than BPNN in security surveillance systems or other related systems.

Keywords: Back Propagation: Authentication: Security: Feature Extraction: BPNN

1. Introduction

Data collection, storage, and sharing among government agencies and commercial sectors have been made easier because of IT advancements in the previous 30 years. New types of privacy invasions were also discovered. It's not just identity theft and data selling that's becoming more common; it's also things like selling counterfeit credit cards and breaking into your home. (Hassan, Abdelnasser and Ahmed, 2012; Sardar, Mitra and Shankar, 2018). When it comes to

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protecting sensitive data, the security of access control systems is becoming increasingly important. Even highly sensitive information can be compromised if it is widely disseminated without restriction. (Hassan et. al., 2012).

For most of the 20th century, individuals relied on technology (such as personal computers, laptops, mobile devices like smartphones and smart watches, etc.) to perform anything from browsing social networking sites to storing personal images and videos to texting or video-messaging with buddies. Personal data is being saved on mobile devices at an increasing rate. Without biometric authentication, unauthorized individuals cannot access a person's personal information. To identify and prevent unauthorized people from entering private facilities, access control systems can be authenticated by using biometric. (Yung-Hui, Po-Jen and Yun, 2019; Falohun, Fenwa and Oke, 2016).

The most accurate recognition technology currently available is the biometric iris; yet, it is not foolproof. Iris has a lot of confusing surface information easily available for authentication as a biometric identity proof technique (Sheeba and Veluchamy, 2013; Daugman, 2006; Sardar, Mitra and Shankar, 2018). A user's fingerprints, an iris image, speech pattern, or even DNA grouping are used by these BAC systems to allocate resources according to a user's deep discriminative actual features. Pattern recognition algorithms are used in biometric iris identification to identify a specific individual based on iris scans (Sheeba and Veluchamy, 2013; Hui, Tan, Zhang and Sun, 2005). In comparison to other biometric technologies like iris, fingerprints, face, and palm veins, iris-based identification offers the highest level of security and trustworthiness for human recognition (Sheeba and Veluchamy, 2013; Chang, Bowyer, Sarkar and Victor, 2003; Falohun, Fenwa, and Ajala, 2016) The iris recognition technology has undergone a lot of development over the previous decade to make it more useful (Abbasi, Khan, and Khan, 2013). The invention of iris recognition systems has shown to be incredibly beneficial for both scientific study and real-world application. Since that time (Savita, Sharda, Asha and Anjali, 2012). This system can be utilized to verify the identity of a user or to prevent unauthorized access to a system.

Researchers evaluated the neural back propagation network's performance to that of a self-organizing feature map by using an iris access control system. Collection of iris images, extraction of characteristics and properties, as well as segmentation of the iris image are all modules in the system for iris recognition. Self-organizing maps and back propagation neural networks were researched for iris image categorization to train and assess them.

Public access and free usage of several iris image archives. Databases like the Chinese Academy of Sciences Automation Institute, Multimedia University, the Bath Iris Database of Non-Africans, the University of Beira's Interior Iris Database, and the Covenant University of Beira's Iris Database are just a few examples (CUIRIS). In this research, CUIRIS data was utilized.

A variety of categorizers have been used in iris recognition categorization studies. Backpropagation neural networks (BPNNs), self-organizing feature mappings (SOFMs), and linear vector quantization (LVQs) have all been employed, but they all suffer the same problems: huge dimensionality, randomness, and recognition accuracy (Ujval et.al., 2012).

There are superior classification methods for iris recognition when the self-organizing Feature Map (SOFM) and the back propagation neural network (BPNN) are used independently on different datasets (Fengzhi, Li, Chunyu, Bo and Ruixiang, 2015; Shivaniand Rajeev, 2012; Savita, et. al., 2012).

Individually, these approaches were used to identify patterns, but they were not compared to see how well they worked together in iris recognition systems. This is essential since several research have revealed that there is no method to obtain the optimum answer for all iris-recognition-specific issues. Certain methods outperform others and provide a better answer than others to some problems (Engelbrecht, 2005). Thus, this study tested SOFM and BPNN's performance on an authentication system using a comparable iris dataset to detect coherent and superior grading methods. Evaluating the performances of SOFM and BPNN categorization methods for authentication systems using iris biometric is the main purpose of this research.

1.1. Literature review

1.1.1. Back Propagation Neural Network (BPNN)

ANN types are widely available and widely used. An ANN, which learns from the back propagation technique to acquire appropriate weight, is a common model for NNs. The back propagation technique is used in layered feedforward ANNs. A layering of artificial neurons transmits impulses in the "forward" direction. After then, the errors start to trickle backwards. Supervised learning is used in the backpropagation algorithm. When algorithm inputs and network outputs are provided, the error (difference between actual and expected results) may be calculated (Indo and Naveeta, 2014; Omidiora et. al. 2016).

Until the ANN learns the training material, the goal is to keep this error to a minimum. A weighted sum represents the activation function of artificial neurons in ANNs utilizing the back propagation technique (the sum of the inputs multiplied by their respective weights). For smooth transitions between low and high neuron output, the sigmoidal function is the most often used activation function. To obtain a certain outcome, the training must include precise inputs. Due to differences in the planned output and actual output, the error depends on weights, thus weight changes are needed to minimize the mistake. Error propagation depends on input, output, and weight, and this is determined by the background propagation technique Gradient descent may be used to adjust the weights after that (Indo and Naveeta, 2014).Gradient descent is used in back propagation to reduce the network's squared error function by changing the parameters of a function periodically. There may be more than one minimal gradient descent method in a function, making it more difficult to identify the best approach. The sigmoid function is used to calculate the output of each network layer and is defined as follows:

$$f(x) = \frac{1}{1 - e^{-x}} \dots\dots\dots\dots 2.1$$

The squared error function is defined as follows:

$$E = \frac{1}{2}(y - f(x))^2 \quad \dots\dots\dots\dots 2.2$$

Where $f\ (x)$ is the network's prediction obtained from the output unit and y is the instance's class label. To find the weights of a neural network, the derivative of the squared error function must be determined. The derivative of the error function concerning a particular weight is defined as:

$$\frac{dE}{dw_i} = \big(y - f(x)\big)f'(x)a_i \quad \dots\dots\dots\dots 2.3$$

Where $w_i$the weights for the ith input variable, x are is the weighted sum of the inputs, and a_i are the inputs to the neural network. This computation is repeated for each training instance and the changes associated with a particular weight w_i are added up, multiplied by the learning rate (small constant), and subtracted from the w_i's the current value. This is repeated until the changes in the weights become very small.

1.1.2. Self-Organizing Feature Map (SOFM)

A popular feature map for artificial neural networks that organise as the network mature is the Kohonen Map. An unsupervised learning strategy that teaches the distribution of patterns without supplying any class information is known as unsupervised reinforcement learning (UNSL). Because of this property, topology is retained. The neurons that can fire compete with one another for activation. It was determined that the winning neuron was the sole one in the study conducted by Kumar, Rai, and Kumar. Using the competitive layer's winning neuron selection method, a SOFM network selects a winner. The Kohonen rule updates all neurons in a particular region rather than just the winning neuron. With the Kohonen rule, the weights of a neuron can learn an input vector and become useful for reconnaissance. SoFM is used by Nagi (2007) to classify DCT-based vectors to determine whether or not the subject is in the input image. There have been several different network architectures developed, including the following:

Kumar et al. (2005) state that SOFMs can be one-dimensional or multidimensional maps, depending on the situation and the data available. When building a SOM network, the number of characteristics it will employ determines how many input connections it will have.

A vector containing S items as input can be produced by feeding it the weight matrix IW1,1 and the ||ndist||box. They measure how far apart input vector and weight matrix rows are from each other (IW). The net input n in the || ndist|| box is computed using the distance from the Euclidean vector to its weight vectors for a competing layer. Transferring businesses in a competitive environment When the net input vector of a layer is passed to the C function, all neurons save the winner — the neuron with the most favorable input — return 0. The outputs of all the other neurons in the layer are all set to 0. The final product of the winning entry is

The neuron with the closest weight to the input vector has the least negative net input. According to their findings, the competitive transfer function C generates the element a1i's winning output, which is a1 (Lu and Wei, 2004). Everything else in a1 is a 0 (zero).

$$n' = -\|IW_{1,1} - p\| \dots\dots\dots\dots 2.4$$

$$a^1 = C(n^1) \dots\dots\dots\dots 2.5$$

When p is provided, the weights of the winning neuron and its close neighbours are shifted towards p. Neurons next to one another learn vectors that are similar through repeated exposure. In this way, the SOFM network accumulates competence in classifying input vectors that it comes across. This is what occurs if you use the SOFM algorithm:

- Initialize weights W_{jk}^{o}, learning rate η^{o} and neighbourhood h_{jk}^{i}
- Pick a sample x^i
- Find out the best matching neuron using the Euclidean distance criterion

$$||\, x^i - w_{jk}^i || = \min_{jk}\{||x^i - w_{jk}^i||\} \dots\dots\dots\dots 2.6$$

- Update synaptic vectors of winning cluster

$$w_{l,jk}^{i\neq 1} = w_{l,jk}^{i} + \eta^{i}\left(x_l^i - w_{l,jk}^i\right) jk \in h_{jk}^{i} \dots\dots\dots\dots 2.7$$

- If a noticeable change in mapping GOTO STEP 2 ELSE STEP 4
- SOFM weight matrix

Brain information processing systems, whether natural or fabricated, rely heavily on maps, according to Hans-Ulrich and Klaus (1992). Visually-cortex retinotopic maps, auditory cortex tonotopic maps, and skin-to-somatosensory cortex mappings are all examples of nervous system mappings described by Hajime and Yoshikazu (1993); Obermayer, Ritter and Schulten (1990). According to Kohonen (1995), an uncontrolled learning process that learns how to disperse patterns without any class data is known as a self-organizing map (SOM). The information is encoded as a location for an active node and projected to a point on the map from the input space. The SOM, in contrast to most other techniques of classification or clustering, provides a topological order of categorization. The output of the procedure maintains the similarity of the input patterns.

Researchers compared two well-known artificial neural network classifiers, back propagation and self-organizing maps, using experimental results from a classifier classification investigation in various pattern recognition applications. There are many more processing components in the hidden levels of a BPN than there are in the self-organization map, just to start with (Ivica and Slobodan, 2000). It is important to note that for supervised self-organizing map neural networks, accuracy in classifying them is dependent on the application's classification accuracy. The speed difference between BPNN and SOFM algorithms is the most important factor to consider when comparing them. Using a Back Propagation Network has the major drawback of requiring a considerable learning time due to the enormous sample sizes. Studies suggest that employing a self-organizing map network rather than a back propagation network can effectively overcome this disadvantage (Ivica and Slobodan, 2000).

1.1.3. Related Works

Chandra & Reddy (2009) presented an algorithm to perform pattern classification. Iris image is localized with the help of Hough transform technique and Canny edge detector by applying it in both horizontal and vertical direction. Annular iris image is mapped to a rectangular fixed block followed by projecting it onto a 1-d Log Gabor wavelet to extract the texture characteristics. From the texture, the patterns are then identified and their similarities and differences are highlighted with the help of a linear transformation scheme called Principal Component Analysis (PCA). In classification phase, a set of training data is used for training classifier and another set for testing the classifier using Bayes, Euclidean and K-NN probabilistic and non-probabilistic distance measures. Performance evaluation of the experiment was performed on image datasets present in CASIA V3.0 and MMU databases. Based on the results the author has proved this algorithm to be robust and versatile.

Manikandan and Sundararajan (2010) proposes feature extraction method based on the Discrete Wavelet compared with (2D-DWT) two dimensional-discrete wavelet transform in order to improve the classification accuracy. Two types of iris databases was used and the Correct Recognition Rate (CRR) of 99.83% and 98.15% was achieved on DB1 and DB2 respectively.

Karthikeyan (2010) proposes an algorithm based on Fuzzy Neural, the located iris after preprocessing, feature vector was used with the neural network to recognize iris patterns. The accuracy of the proposed method for the trained pattern is 99.25%.

Mitsuyoshi and Seitaro (2001) compared the classification result for satellite image of Modified Counter Propagation network (MCP) with the result by the Self-Organizing Map (SOM). MCP was observed to be superior to the SOM and has the qualitative method for the classification. Queiroz and Braun (2006) have proposed an invertible conversion to grayscale. The idea is to transform colors into high frequency textures that are applied onto the gray image and can be later decoded back to color. The method is based on wavelet transformations and on the replacement of sub-bands by chrominance planes.

Dinesh, Rai, and Shakti (2000) compared three unsupervised techniques along two techniques SOM and PCA which were combined together for dimensionality reduction and feature selection. The simulation results indicated that the performance of face recognition system decreases as the number of classes (subjects) is increased. This is true for all the three methods which are; SOM, PCA, ICA (I & II), SOM & PCA combined and local and global processing as well. The decrease is more in case of SOM & PCA combined as compared to other methods. The reason for the decrease in performance of recognition system was that, as the number of classes (subjects) increase, the chances of mismatch are more because of more similar faces.

Jawad *et. al*.(2008) presented a novel iris recognition technique that used features derived from DCT coefficients, along with an SOFM-based classifier. The system was evaluated in MATLAB using an image database of 25 face images, containing five subjects and each subject having 5 images with different facial expressions. After training for approximately 850 epochs the system achieved a recognition rate of 81.36% for 10 consecutive trials.

Ujval and Chakoli (2012) provided a walkthrough for image acquisition, image segmentation, feature extraction and pattern forming based on iris imaging by using BPNN on classifying the pattern formed and verifying one's identity. The recognition rate was found to be accurate and identification result obtained showed efficient use of BPNN in the recognition of an iris.

Murugan and Savithiri (2011) presented an iris recognition system based on the partial portion of iris patterns using Back propagation neural network (BPNN) by proposing new system. The experimental result showed the effectiveness of the proposed system in terms of recognition accuracy as compared with other techniques.

Savita *et al.*(2012) described the iris recognition system such that images for the experiment were captured using digital camera and preprocessed to remove unwanted factors which include; non-uniform illumination and camera-to-face distance. The images obtained were trained using SOM. The results showed that iris recognition system performed remarkably well at the preliminary stage of testing.

Adebayo and Sandra (2012) proposed a robust face recognition system for efficient facial recognition. In the proposed system, two-level haar wavelet transform was used to decompose frontal face image into seven sub-image bands. Thereafter, eigenface feature was extracted from these bands. The feature was used as input to the classification algorithm based on Back Propagation Neural Network (BPNN). The proposed system was tested using 150 frontal face samples with illumination and pose variation.

Oladele, Omidiora and Adepoju (2015) proposed an age group estimation method using facial features to classify input face images into eight groups; babies, young teenagers, mid teenagers, teenagers, young adults, mid adults, young and old. SOFM was used for classification and an accuracy of 99.2% was recorded.

Oladele, Omidiora and Afolabi (2016) used principal component analysis to extract facial features and back propagation neural network to classify age groups; babies, young teenagers, mid teenagers, teenagers, young adults, mid adults, young and old. The experiment produced an accuracy of 88.2% and Mean Absolute Error of 3.88 when experimented with 180 testing samples.

However, authors have worked on iris recognition system using SOFM and BPNN independently on face and iris images. These studies have achieved promising results in terms of recognition accuracy. In this work, a simulation and evaluation of SOFM and BPNN shall be done using iris images for access control.

2. Material and method

2.1. Research Approach

This research employed the Self-Organizing Feature Map (SOFM) and the Neural Networks Back Propagation (NNBP) to examine the efficiency of two distinct Artificial Neural Network (ANN) approaches (BPNN).

The following steps are involved in putting this study into action: Data acquisition, Segmentation, Normalization, Feature Extraction and Dimension Reduction and Classification and matching. The CUIRIS iris database was used. This image's iris eye region was located using the Hough transformation technique (see below). To create a dimensionally uniform picture, we utilised the Daugman Rubber Sheet Model and histogram equalisation. For feature extraction and dimensional reduction, researchers have turned to local binary patterns. As a final step, the data were classified using the SOFM and BPNN systems, which were completed independently. Specifically, we examined the accuracy of recognition, False Acceptance Rate, False Rejection Rate, and Equal Error Rate (EER) for the SOFM and the propagation of the back neural network (BPNN) (EER).

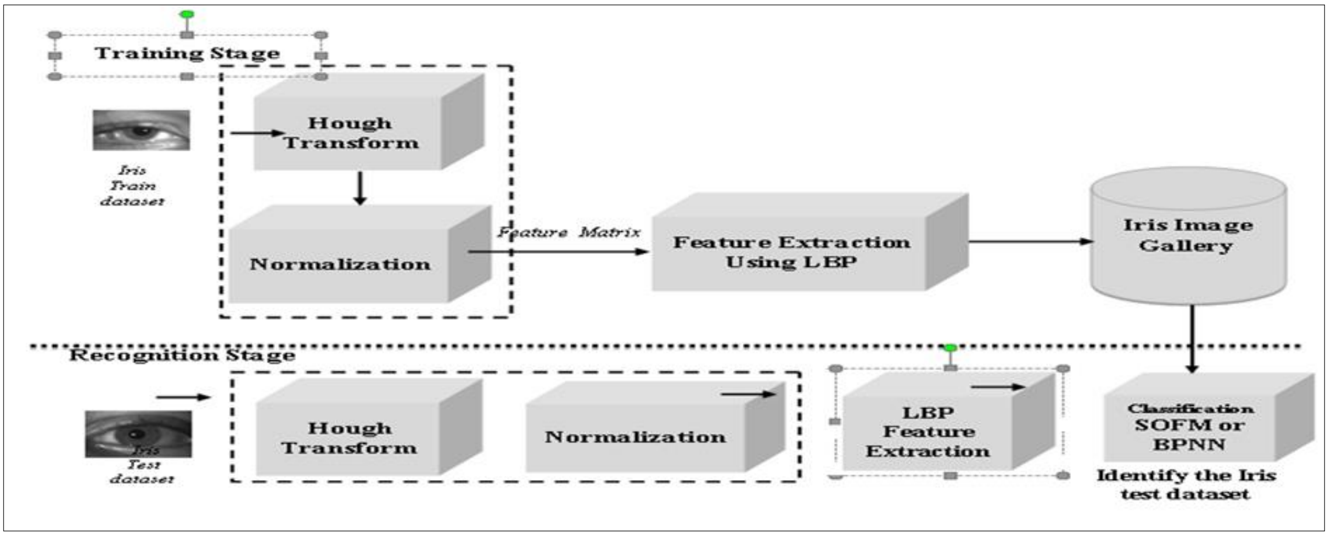

Figure 1 The Block diagram representing the process flow of the techniques

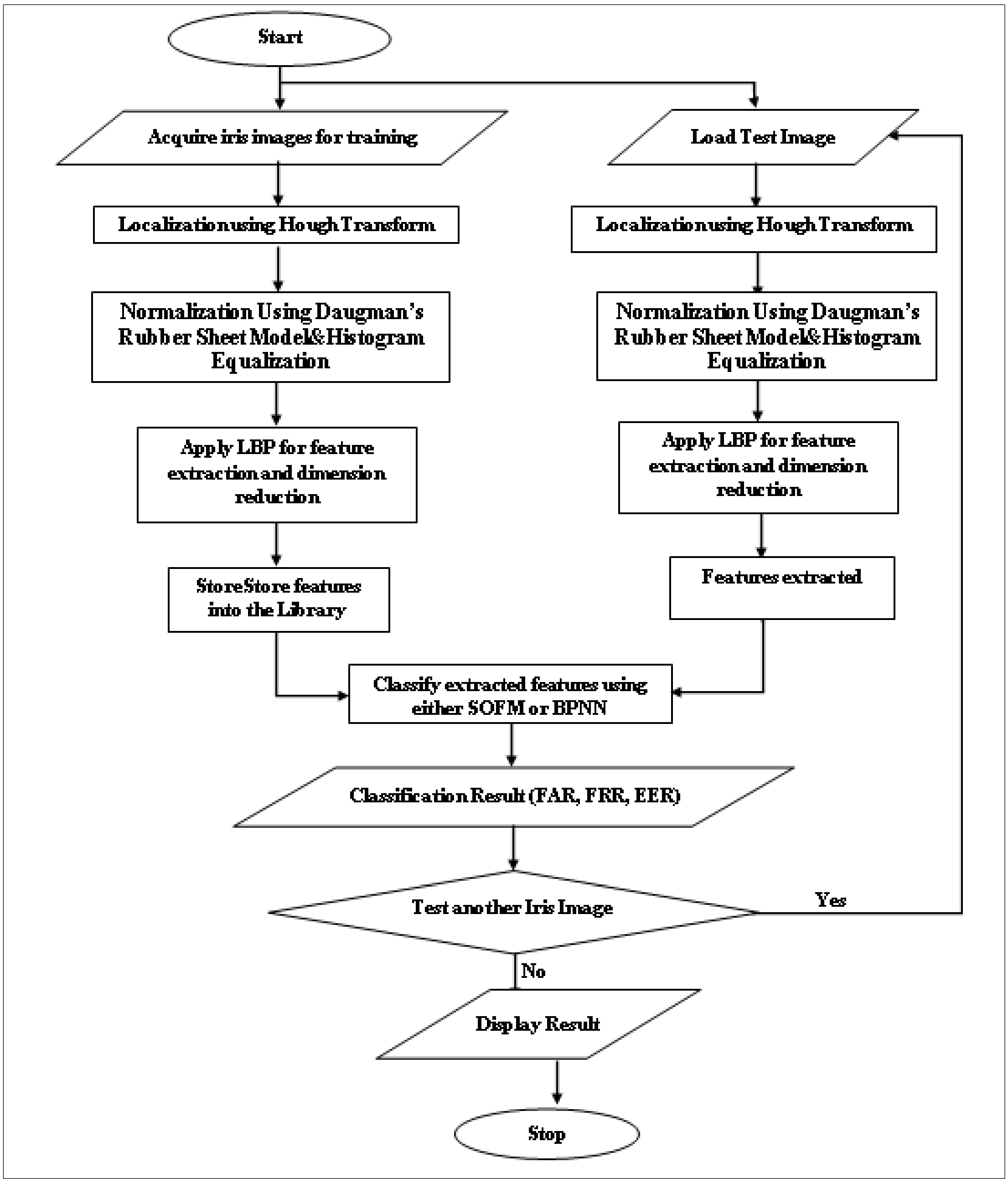

Figure 2 Flowchart showing trained and tested Iris images with either SOFM or BPNN

3. Results

It is shown in this ch that the BPNN and SOFM techniques for iris identification yielded similar results when using backpropagation neural networks. Table 4.1 shows the amount of time taken by each method for training the iris dataset. It was shown that BPNN was capable of learning the datasets for trials 1, 2, 3, and 4 in as little as 112.08 seconds (the average training time). The datasets for the first, second, third, and fourth trials of SOFM were each 109.00s in length, 105.77s in length, 102.76s in length and 100.36s in length accordingly. After four trials with the iris dataset, the average training time produced by BPNN is 116.23s, whereas the average training time created by SOFM is 104.47s. The results demonstrated that the SOFM approach is less computationally intensive in terms of training time than the BPNN technique.

Threshold values of 0, 1, 0, 15, 0, 35, 0, 45, and 75 were also used to test the system. Figure 4.1 depicted the selection of threshold values, such as 0.15, 0.35, 0.45, and 0.75, respectively, in this research. To have the same precision while setting the threshold value during execution, it was necessary to set a number bigger than 0.15. The recognition accuracy was the same for threshold values set during implementation ranging from 0.16-0.35, 0.36-0.45, and 0.46-1. For the first three range groups, 0.15, 0.35, and 0.45 were chosen as the threshold values; however, the final range group's threshold was set at 0.75.

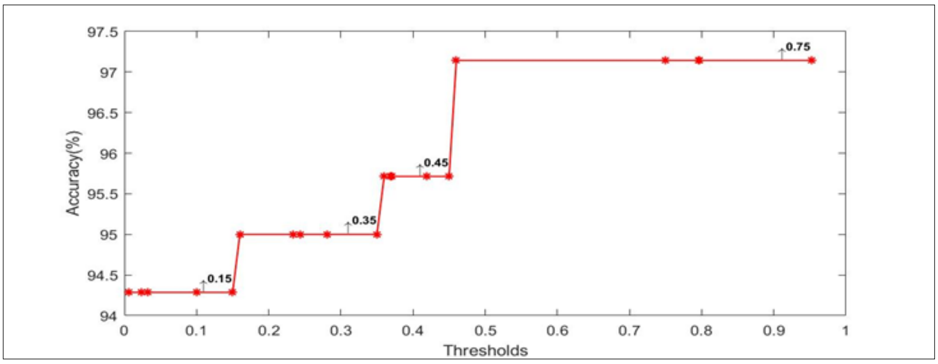

Figure 3 Graph of Thresholds against Accuracy

3.1. Evaluation of the Results

False Rejection Rate (FRR), False Acceptance Rate (FAR), Equal Error Rate (EER)recognition accuracy and calculation time were used to evaluate the system. A variety of thresholds were used to evaluate all metrics.

3.1.1. Evaluation Results for BPNN

For the performance metrics, Table 4.2(a) displayed the BPNN results for threshold values of 0.15, 0.35, 0.45, and 0.75. With a different threshold, the performance of the BPNN algorithm changes. FRR and accuracy rise with increasing threshold values; a drop in accuracy is seen with an increase in threshold values.

At a threshold of 0.75, however, BPNN obtained an FRR of 6.25 per cent, and the accuracy was 94.49% at 101.77 seconds, with an FRR of 6.25 per cent, FAR of 5.00, and an FRR of 6.25 per cent. There is a range of 101.77 to 107.00 seconds in the calculation time with increasing threshold values, according to the data in the table.

3.1.2. Evaluation Results for SOFM

SOFM approaches were tested at thresholds of 0.15, 0.35, 0.45, and 0.75 concerning performance indicators in Table 4.2(b). SOFM's performance changes depending on the threshold value, according to a table in the report. Aside from these findings, it was shown that the FRR rose with increasing threshold values, but the accuracy declined. For example, SOFM produced an FRR of 3.75 per cent at a threshold value of 0.75, a FAR of 1.67 per cent, and 97.14% accuracy at 81.98 seconds at this threshold value. Additionally, the table indicated that the calculation time ranges from 81.98 to 87.58 seconds as the threshold values rise.

Table 1 Evaluation Results for BPNN and SOFM

a) The BPNN Technique

Threshold	FRR (%)	FAR (%)	Accuracy (%)	Recognition Time (sec)
0.15	3.75	16.67	90.71	105.93
0.35	3.75	11.67	92.86	105.57
0.45	5.00	8.33	93.57	107.80
0.75	6.25	5.00	94.29	101.77

b)SOFM Technique

Threshold	FRR (%)	FAR (%)	Accuracy (%)	Recognition Time (sec)
0.15	1.25	11.67	94.29	83.08
0.35	2.50	8.33	95.00	84.74
0.45	2.50	5.00	96.43	87.58
0.75	3.75	1.67	97.14	81.98

3.2. Comparison Results of BPNN and SOFM.

Results for all measures for iris recognition were shown in Table 4.3, which included results from both the BPNN and SOFM. It is assumed that the SOFM approach is computationally less costly than the matching BPNN technique regardless of threshold setting in Table 4.2a and 4.2b results. Table 4.3 shows that the SOFM model outperforms the BPNN model in terms of accuracy, FRR, and FAR when the threshold is set at 0.75. There were 97.14 per cent accuracy, 3.75 per cent FRR, and 1.67 per cent False Alarm Rate (FAR) for the SOFM method whereas there were 94.29 per cent accuracy, 6.25 per cent FRR, and 5.05 per cent FAR for the BPNN approach. Thus, the SOFM strategy outperformed the BPNN method in this regard.

An equal error rate (EER) was shown in Figures 4.2 (BPNN) and 4.3 (SOFM) in the context of iris recognition. When using SOFM, the EER was 3.18 per cent, but the EER using BPNN was 5.91 per cent. Results from the EER indicated that SOFM maintained its lower EER.

Table 2 The BPNN and SOFM technique at 0.75 threshold value

Technique	FRR (%)	FAR (%)	Accuracy (%)	Recognition Time (sec)
BPNN	6.25	5.00	94.29	101.77
SOFM	3.75	1.67	97.14	81.98

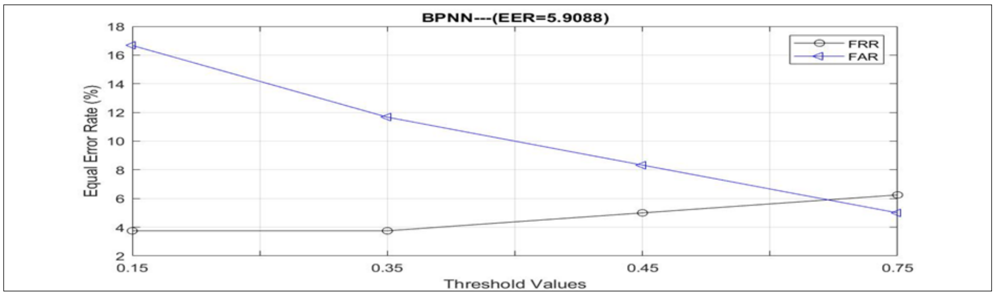

Figure 4 Graph Showing Equal Error Rate (EER) with BPNN

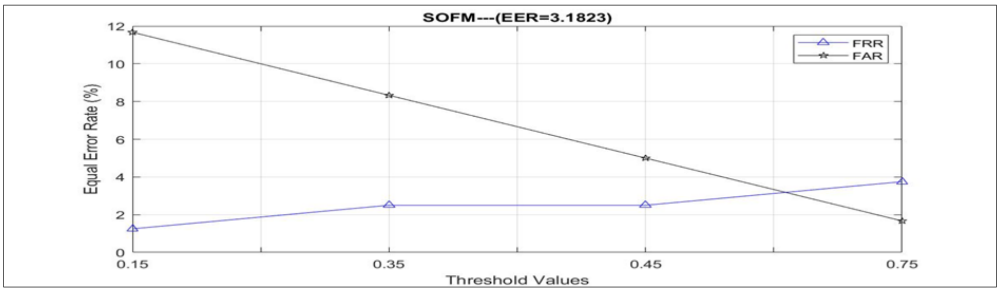

Figure 5 Graph Showing Equal Error Rate (EER) with SOFM

4. Discussion

This part discusses the assessment outcomes in terms of training and recognition's computation time analysis, evaluation of other performance indicators and statistical analysis.

4.1. Computation Time Analysis

Table 4.1 shows that the SOFM method trains the iris dataset substantially more quickly than the BPNN method does. As a result, the SOFM requires less processing power than the BPNN. Figure 4.4 depicted the relationship between training time and the number of tries. A similar connection between average recognition time and threshold values for the BPNN and SOFM techniques can be shown in Figures 4.5 and 4.6. From the graph; the relationship between the recognition time (T_R) and the threshold values (th) was found to be quadratic with a high correlation coefficient for both SOFM and BPNN as shown in equation 4.1 and 4.2 respectively.

$$T_R = -43.8th^2 + 38.325th + 78.021 \quad R^2 = 0.8162 \ldots \ldots (4.1)$$

$$T_R = -31.467th^2 + 22.132th + 103.02 \quad R^2 = 0.8262 \ldots \ldots \ldots (4.2)$$

SOFM was shown to be less computationally intensive than BPNN in terms of training and temporal recognition time, as a result of the computation time study. To train and recognize the dataset, the BPNN required additional time. Training time predictions based on the threshold value may be made using the aforementioned relationships.

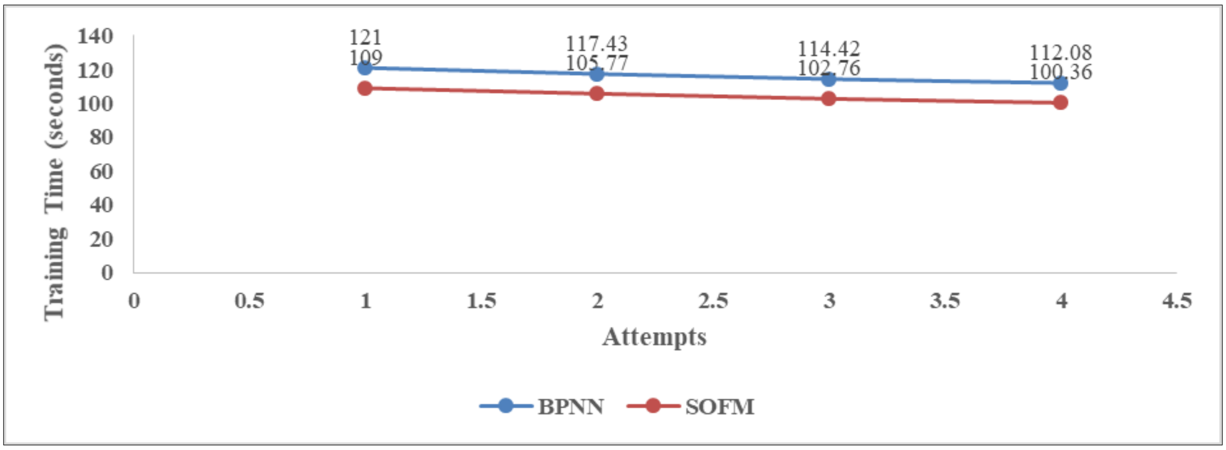

Figure 4 A graph showing the relationship between training time (seconds) and Attempts

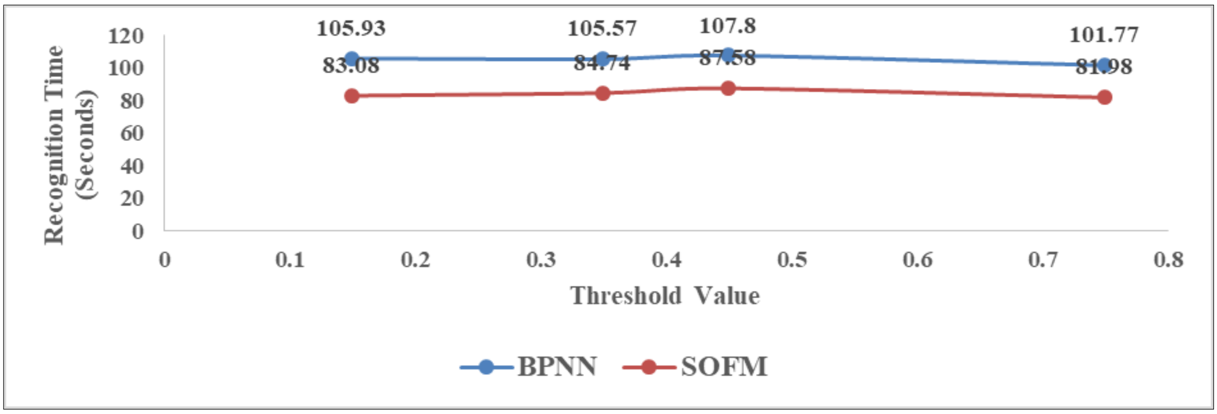

Figure 5 A graph showing the relationship between recognition time and threshold values

4.2. Discussion based on Performance Metrics

Table 4.2 shows the results of iris recognition using SOFM and BPNN techniques. The best results were achieved at a threshold value of 0.75 across all measures (FRR, FAR, and recognition accuracy) for SOFM and BPNN, respectively, when the threshold value was increased. The threshold value determines the effectiveness of various strategies. Appendix A summarizes the findings based on a measure for measuring threshold-induced confusion.

In this study, the SOFM approach had an improved 2.85 per cent recognition accuracy, a lower FRR of 2.50 per cent, and a lower FAR of 3.33% compared to the BPNN technique at 0.75 thresholds. SOFM's EER was 3.18 per cent, compared to BPNN's EER of 5.91 per cent. The results of this research show that SOFM outperforms BPNN in terms of FRR and EER, as well as recognition accuracy (FAR).

Goppert and Rosenstiel (1993) did an experimental investigation on self-organizing maps vs the backpropagation approach, and the results of this study are consistent with their findings. For some applications, Goppert and Rosenstiel (1993) stated that self-organizing map topology preservation combined with interpolated output values may be an alternative to backpropagation, that sometimes, the convergence of backpropagation turn out to be difficult because it gets stuck in local minimal and the over-learning effect made it difficult to find optimal training parameter; these don't lead to better results. Training 20 neurons of SOFM is quicker than training four neurons of BPNN. Unsupervised SOFM outperformed supervised BPNN, according to the study of (Sathya and Annamma, 2013) via empirical data. With empirical data, (Ivica and Slobodan, 2000) also confirmed that SOFM is an acceptable alternative to BPNN. SOFM outperformed the BPNN in this investigation, with SOFM showing the best outcomes.

A comparison of the findings shows that SOFM an unsupervised approach was more accurate than the better-monitored but less accurate BPNN technique. Because of this, SOFM outperformed BPNN in terms of iris recognition accuracy, FRR, EER, and FAR.

5. Conclusion

An iris recognition system was developed utilizing SOFM and BPNN during the classification stage, using 300 iris photos from the CUIRIS dataset. Iris datasets were used to train and evaluate a variety of algorithms at various thresholds, totaling one hundred sixty (160) total. In addition, MATLAB R2015b was used to replicate the design in an actual access control system. After that, a comparison of the two techniques, one using BPNN and the other using SOFM, was conducted.

The SOFM and BPNN are two of the most widely used ANN approach in the pattern recognition field. This research was able to reveal the best artificial neural network approach (SOFM or BPNN) for iris recognition under the same experimental conditions and criteria concerning both computing needs and other metrics such as FRR, FAR, EER, and recognition accuracy.

In terms of recognition accuracy, FRR, FAR, EER, training and recognition computation time, the SOFM outperformed the BPNN in the experiments conducted. System computation time and recognition accuracy were investigated further using statistical methods, which indicated that SOFM and BPNN performed significantly differently.

This means that an iris recognition system based on SOFM would be more reliable than BPNN for monitoring security. It has a better classification accuracy rate than BPNN, and it gives more implicit categorization data. Iris recognition systems must be built with high recognition accuracy and computing efficiency in mind, and this factor should be taken into account.

Recommendation

Iris recognition systems that employ artificial neural networks (ANNs) perform better than those that use BPNNs when it comes to dealing with security threats in banks, schools, military, and healthcare facilities.

It is recommended that SOFM may be compared to other artificial neural network-based techniques, such as Convolution Neural Networks (CNN), Multilayer Perceptrons, Counter Propagation Neural Networks and others, in iris identification systems. The performance of Hybrid of SOFM and a suitable evolutionary search algorithm like Ant Colony Optimization (ACO), Evolutionary. Also, to see whether an iris recognition system's performance may be enhanced, it should take into account artificial immune systems (AIS), genetic programming (GP), differential evolution (DE), and evolutionary programming (EP).

Compliance with ethical standards

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Disclosure of conflict of interest

The author hereby declares that the published data in the manuscript have no conflict of interest against any parties. If at a later date, this is found, the full responsibility for this matter lies with the author.

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