Performance Evaluation of Selected Classification Algorithms for Iris Recognition System

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ABSTRACT: *Quite a lot of techniques proven to be resourceful have been espoused to develop iris recognition system. Nearly hybridized, supervised and unsupervised artificial neural network techniques have been used individually in iris recognition system and other pattern recognitions but have not been compared based on some performance metrics. Counter Propagation Neural Network (CPNN) is a hybridized technique, Self-Organizing Feature Map (SOFM) is an unsupervised learning technique and Back Propagation Neural Network (BPNN) is a supervised learning technique. This research conducted a performance comparison of CPNN, SOFM and BPNN techniques to recognize iris dataset and establish the more efficient among the three techniques. A database of Three hundred (300) iris images was acquired from LAUIRIS dataset from LAUTECH Biometric Research Group database. The original images of 640*360 dimensions were resized to 200*200 without any alteration in the image using 80% for training and 20% for testing. Hough transform was applied to segment locate the iris region of eye image. Daugman's Rubber Sheet Model was used to create a dimensionally consistent representation. Principle Component Analysis was applied for feature extraction and dimensionally reduction. Finally, classification and matching were done by using CPNN, SOFM and BPNN techniques. This was implemented using MATLAB (Matrix Laboratory) R2016b. The performance metrics used for classification were False Positive Rate (FPR), Sensitivity, Specificity, Re, cognition Accuracy and Recognition Time at 0.70 threshold value.The Recognition Accuracy (RA), Recognition Time (RT), False Acceptance Rate (FAR), Sensitivity and Specificity of the three selected techniques (CPNN, SOFM and BPNN) resulted in values of 95.17%, 177.48s, 6.33% and 93.67% for CPNN 92.50%, 179.69s, 9.00%, 94.00% and 90.99% for SOFM while BPNN had 91.17%, 187.88s, 10.33%, 92.67% and 89.67% respectively.This paper showed that CPNN classification technique performed best for iris recognition system in terms of RA and recognition time. This research output will serve as a basis to pre-inform and guide researchers in choosing an efficient kernel based feature extraction technique.*

KEYWORDS: Iris images, finger print, input vector, segmentation process, sensitivity, database.

INTRODUCTION

Iris Recognition is usually known as eye iris network pattern recognition technology. The technique uses human's iris network features map information. This is utilized as a unique and auto-conspicuous personality card contributing the PC utilizing Computer Science Technology and Imaging Technique. A run of the mill iris acknowledgment framework comprises of four procedures which incorporate iris assortment, pretreatment, include extraction and example arrangement{8}. Iris is a unique thing which does not change with age, iris remain stable and fixed from about one year of age throughout life span. Some of the key advantages of iris recognition system are simplicity, accuracy, and applicability. Iris recognition is very efficient method of biometrics and error rate is very low according to statistics{6}.

Biometrics does not require knowledge and tokens, and thus become more convenient and friendly for users. Biometric traits such as face, iris, voice, fingerprint, and palm print have also proved to be unique to each person and constant throughout its lifetime. Among all biometric characteristics, iris pattern has been revealed as one of the most reliable biometric traits to distinguish among different persons[5}. The need for accurate identification of people has evolved over time for the purpose of security and identity supervision. Various accurate and feasible methods have been designed for this purpose using inimitable features of a person such as fingerprints, facial features, sutures, ear and iris patterns. Such biometric techniques have gained acceptance and popularity for its accuracy and precision.

Self-Organizing Feature Maps (SOFM) is normally a sort of cutthroat discovering that only one neuron will fire after shared rivalry of neurons. The central objective of self-arranging highlight maps is to change an approaching sign example of self-assertive measurement into a couple of dimensional discrete guide and to play out this change adaptively in a topologically requested design. The main objective of the SOFM calculation is to change high-dimensional information designs into a couple of dimensional discrete guide and to play out this change adaptively in a topological arranged style. In pattern recognition, the SOFM also called as Kohonen network performs a high-quality classification. Assigning the similar input vectors to the same neuron or to neighbor neurons. Thus, this network transforms the relation of similarity between input vectors into a relation of neighborhood of the neurons. The map uses the competition principle, by evaluating the distances between the input vector and the weight vectors corresponding to each neuron, instead of using the classical Euclidean distance**{1}**.

Counter Propagation Neural Network (CPNN) is the combination of an unsupervised and supervised learning algorithm. CPNN architecture consists of an input layer, a hidden Kohonen layer and a Gross berg output layer. The competitive units in hidden layer do unsupervised learning whereas the output unit does supervised learning.

The aim of this paper is to carry out performance evaluation of selected classification algorithms (Counter Propagation Neural Network (CPNN), Self-Organizing Feature Map

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(SOFM) and Back Propagation Neural Network (BPNN)) in iris recognition and the objectives are to :Design an iris recognition system using the selected Neural based techniques (Counter Propagation Neural Network (CPNN), Self-Organizing Feature Map (SOFM) and Back Propagation Neural Network (BPNN)) for comparison in iris recognition; Implement the selected techniques for iris recognition system using Matrix Laboratory (MATLAB) R2016b; and Evaluate the performance of the techniques using sensitivity, specificity, recognition accuracy and recognition time performance metrics.

.Biometrics refers to the identification of humans by their characteristics or traits. It is used in Computer Science as a research area that deals with identification, access control and surveillance {11}. Some researchers have coined the term "behavrometrics" to describe the latter class of biometrics{13}. With the recent technological advances in audio and visual microelectronic systems and the increasing emphasis on security requirements of the current commercial society, a significant development of intelligent personal identification systems based on biometrics has been achieved. Iris recognition has been regarded as one of the most reliable biometrics technologies in recent years {12}Iris recognition is one of the most promising biometric technologies in terms of identification and verification performance. The distinguishing trades should have the properties such as uniqueness, stability, collectability, performance and acceptability. The iris is delicate circular diaphragm which lies between cornea and the lens of the human eye. The pattern for the human iris varies from person to person. The iris is considered as one of the most stable biometric, as it is believed to not alter significantly during a person's lifetime {3}

{4} defined PCA as a valuable factual strategy that has discovered application in fields, for example, face acknowledgment and picture pressure, and is a typical method for discovering designs in information of high measurement. It is a method of recognizing designs in information, and communicating the information so as to feature their likenesses and contrasts. It was discovered that having found these patterns in the data, and being compressed, then PCA reduced the number of dimensions, without much loss of information.

This method was introduced by Rumelhart, Hinton, and Williams in 1986 and through their work artificial neural network research gained recognition in machine learning {14}. Back propagation utilizes a mathematical algorithm called gradient descent, which iteratively adjusts a function's parameters to minimize the squared error function of the network's output. If the function has several minima the gradient descent method might not find the best one. 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 current value. This is repeated until the changes in the weights become very small. {10} stated maps are an important part of both natural and artificial neural information processing systems. {15} presented self-arranging guide, or SOM as an unaided learning measure which learns the dissemination of a bunch of examples with no

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class data. An example is projected from an info space to a situation in the guide - data is coded as the area of an initiated hub.

{7} introduced a calculation to perform design characterization. Iris picture is restricted with the assistance of Hough change method and Canny edge identifier by applying it both even and vertical way. Annular iris picture is planned to a rectangular fixed square followed by extending it onto a 1-d Log Gabor wavelet to extricate the surface attributes. From the surface, the examples are then distinguished and their similitudes and contrasts are featured with the assistance of a direct change plot called Principal Component Analysis (PCA). In characterization stage, a bunch of preparing information is utilized for preparing classifier and one more set for testing the classifier utilizing Bayes, Euclidean and K-NN probabilistic and non-probabilistic distance measures. Execution assessment of the trial was performed on picture datasets present in CASIA V3.0 and MMU information bases. In light of the outcomes the creator has demonstrated this calculation to be vigorous and adaptable.

METHODOLOGY

In this paper,a relative study among three classifiers namely CPNN, SOFM and BPNN in iris recognition system was carried out. LAUIRIS (LAUTECH Iris dataset) was acquired. Noise and other unwanted elements were removed from the iris image. Hough transform was applied to locate the iris region of the eye image. Daugman's Rubber Sheet Model was used to create a dimensionally consistent representation. Principal Component Analysis was applied for feature extraction and dimensionality reduction. Finally, classification and matching were done using CPNN, SOFM and BPNN classifier.

Acquisition of Iris Images

In order to develop a well-structured iris recognition system, the challenge of acquiring an appropriate database must be resolved. In this research, iris database used was obtained from LAUTECH Biometric Research Group (LAUIRIS dataset, an iris image dataset from LAUTECH Ogbomoso Nigeria). The obtained images were captured with a CMITECH Iris digital camera at different times, under different illumination and converted into values suitable for processing by the computer. The camera resolution was 640by360 pixels. The original iris images of 640by360 dimensions were downsized into 200 by 200 without any alteration in the images. The acquired images were divided into two sets: training and testing sets. The iris database had a total of 300 iris images, 80% were taken for training and placed into a folder called "TrainImage" while the remaining 20% were taken for testing and placed into a folder called "TestImage". These acquired images were used for the training and the recognition stage to evaluate the techniques such as CPNN, SOFM and BPNN.

Iris Pre-processing Phase

In this phase, segmentation and normalization of the acquired iris image dataset were performed. In the segmentation process which could be otherwise called iris localization process, the iris region was segmented or isolated from the eye by performing a pupil separation

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process followed by approximately identifying two circular boundaries. Hough Transform was used to perform segmentation. Localization involved locating the iris in an eye image while segmentation involved detection and exclusion of occluding eyelids, eyelashes or reflections. It is also the process of decomposing the images into regions and objects by associating or labeling each pixel with the object that it corresponds to Hough Transform approach was used for the iris segmentation. As it is a standard computer vision algorithm that is used to determine the parameters of simple geometric objects, such as lines and circles, present in an image. In the normalization process, the segmented iris region was transformed to have fixed dimensions, which enhanced feature extraction and matching. Daugman's Rubber Sheet Model was used to achieve normalization.

Iris localization (segmentation) phase

The center of the iris image acquired was located through iris localization and the radius of the pupil was determined in order to separate the iris image. Circular hough transform algorithm was used to localize the iris by applying edge detector to gray scale iris image to generate the edge map and the edge map was obtained by calculating the first derivative of intensity values and threshold the results. Gaussian filter was applied to smooth the image to select the proper scale of edge analysis.

Hough Transform applied the edge detector to the iris image to generate an edge map for the iris region. At first, the entire iris image $I(x, y)$ is smoothed with a Gaussian filter $G(x, y)$ with centers (x_0, y_0) and a standard deviation of ¾ using equation above. Then, the intensity gradient image map $M(x, y)$ was generated from the smoothed Image $F(x, y)$ with equation (3.2) using the gradient operation. Subsequently, the binary edge map was generated by setting a threshold on the intensity gradient image $M(x, y)$. The threshold was selected based on experimental data and depending on the application. Finally, using the binary image map, the Hough transform was performed to locate a circle with the largest number of edge points and with circular parameters (x_0, y_0, r) which is denoted by equation (3.3). (x_0, y_0, r) represents a circle to be located within the iris image such that the circle is characterized by a radius, and center coordinates with possible edge point (x, y).

$$f\ (x,y) = G(x,y) * I(x,y)$$

$$G_0(r) = \frac{1}{2\pi\sigma^2}\, e^{\frac{-(x-x_0)^2+(y-y_0)}{2\sigma^2}} \tag{3.2}$$

$$M(x,y) = \ |\triangle f(x,y)|$$

$$\triangle = \left(\frac{\partial}{\partial x}, \frac{\partial}{\partial y}\right)$$

$$r^2 = (x_i - x_0)^2 + (y_i - y_0)$$

From this, the Hough transform was then performed through the entire collection of the edge points. Whenever equation above is satisfied, it means that the circular contour goes through (r, x_0, y_0) and one extra vote is added to the histogram count for possible circular contours. Once the entire image is scanned for all possible contours, the contour that obtained the highest number of votes represents the most likely circle in the edge map.

Conversion of Segmented Images into dimensionless coordinate

The segmented doughnut shaped iris portion was converted into a rectangular shape, which could be achieved by converting the segmented portion of the iris to dimensionless pseudo-polar coordinates through a method called Homogenous Rubber Sheet Model. Each pixel in the iris area was mapped into a pair of polar coordinates (r, θ), where r and θ are on the intervals of [0 1] and [0 2π]. This unwrapping formulated as

$$I\big(x(r,\theta), y(r,\theta)\big)(\text{ Khormuji } et\ al. 2014) \qquad such\ that$$

$$x(r,\theta)(1-r)X_p(\theta) + r\, x(\theta)\ y(r,\theta)(1-r)Y_p(\theta) + r\, y(\theta)$$

Where I(x, y), (x, y), (r, θ), (X_p, Y_p), (xi, yi) represent the iris region, Cartesian coordinates, polar coordinates, coordinates of the pupil and iris boundaries along θ direction respectively.

RESULTS AND DISCUSSION

The BPNN, SOFM and CPNN techniques were experimented by implementing the iris recognition using 200 x 200-pixel resolution. The iris recognition system was tested and evaluated using the following performance metrics: Sensitivity, Specificity, False Positive Rate, Recognition Accuracy and Computation Time.

Performance of evaluation of iris recognition system using CPNN classifier

Table 3.1 shows the result obtained by the CPNN at 200 x 200-pixel resolution at threshold value of 0.20, 0.30, 0.40 and 0.70 with respect to the performance metrics. The table reveals that the performance of CPNN varies with change in the threshold value. Also, it was discovered that Accuracy, Specificity increases with increase in threshold value while the false positive rate and sensitivity decreases with increase in the threshold value. However, the optimum performance was achieved at threshold value of 0.70. The CPNN achieved a false positive rate of 1.33%, sensitivity of 94.67%, specificity of 98.67% and accuracy of 98.67% at 180.07 seconds. The Table 3.1 also shows that the computation time is within the range of 176.15 to 180.07 seconds with increase in the threshold values.

Performance of evaluation of iris recognition system using SOFM classifier

Table 3.2 shows the result obtained by the SOFM at 200 x 200-pixel resolution at threshold value of 0.20, 0.30, 0.40 and 0.70 with respect to the performance metrics. The Table reveals that the performance of SOFM varies with change in the threshold value. Also, it was discovered that accuracy, specificity increases with increase in threshold value while the false positive rate and sensitivity decreases with increase in the threshold value. However, the optimum performance was achieved at threshold value of 0.70. The SOFM achieved a false positive rate of 4.00%, sensitivity of 92.00%, specificity of 96.00% and accuracy of 94.00% at 180.76 seconds. The Table 3.2 also shows that the computation time is within the range of 179.06 to 180.76 seconds with increase in the threshold values.

Performance of evaluation of iris recognition system using BPNN classifier

Table 3.3 shows the result obtained by the BPNN at 200 x 200-pixel resolution at threshold value of 0.20, 0.30, 0.40 and 0.70 with respect to the performance metrics. The Table reveals that the performance of BPNN varies with change in the threshold value. Also, it was discovered that accuracy, specificity increases with increase in threshold value while the false positive rate and sensitivity decreases with increase in the threshold value. However, the optimum performance was achieved at threshold value of 0.70. The BPNN achieved a false positive rate of 5.33%, sensitivity of 90.67%, specificity of 94.67% and accuracy of 92.67% at 189.73 seconds. Table 3.3 also shows that the computation time is within the range of 185.76 to 189.73 seconds with increase in the threshold values.

Comparison of CPNN, SOFM and BPNN classifiers

Table 4.2 illustrated a combined result of CPNN, SOFM and BPNN at the threshold value of 0.70 with respect to all metrics at 200 by 200-pixel resolution. Results obtained in Table 3.2 ascertain that CPNN model has the lowest recognition time compared with the corresponding SOFM and BPNN model irrespective of threshold value.

Similarly, Recognition Accuracy, Sensitivity, False Positive Rate and Specificity of CPNN, SOFM and BPNN model are compared at 200 by 200-dimensional size. The study discovered that CPNN model has better performance in Accuracy, Specificity and False Positive Rate than SOFM and BPNN model as enumerated in Table 3.2.

Evaluation Results for CPNN, SOFM and BPNN

Table 3.1 :CPNN at 200 x 200-pixel resolution

Threshold	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Recognition Time (sec)
0.30	12.00	98.67	88.00	93.33	176.15
0.40	8.00	97.33	92.00	94.67	176.25
0.50	4.00	96.00	96.00	96.00	177.45
0.70	1.33	94.67	98.67	96.67	180.07

Table 3.2:SOFM at 200 x 200-pixel resolution

Threshold	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Recognition Time (sec)
0.30	14.67	96.00	85.33	90.67	179.20
0.40	10.67	94.67	89.33	92.00	179.72
0.50	6.67	93.33	93.33	93.33	179.06
0.70	4.00	92.00	96.00	94.00	180.76

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Table 3.3: BPNN at 200 x 200-pixel resolution

Threshold	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Recognition Time (sec)
0.30	16.00	94.67	84.00	89.33	187.07
0.40	12.00	93.33	88.00	90.67	188.79
0.50	8.00	92.00	92.00	92.00	185.76
0.70	5.33	90.67	94.67	92.67	189.73

The recognition accuracy of 96.67% with CPNN, 94.0% with SOFM and 92.67 % with BPNN model. The CPNN model have a specificity of 98.67%, false positive rate of 1.33% and sensitivity of 94.67% at 180.07s; the SOFM model have a specificity of 96.00%, false positive rate of 4.00% and sensitivity of 92.00% at 180.76s while the BPNN model have a specificity of 94.67%, false positive rate of 5.33% and sensitivity of 90.67% at 189.07s. Hence, CPNN outperformed SOFM and BPNN.

Discussion based on Performance Metrics

The results obtainable in Table 3.1 show the performance of CPNN, SOFM and BPNN models. The results show that there is variation in the performance metrics with increase in threshold value and the best result is obtained at the threshold value of 0.70 across all metrics (false positive rate, specificity, sensitivity and accuracy) for CPNN, SOFM and BPNN. Therefore, the performance of these techniques is dependent on the threshold value.

It can be inferred from the results based on the performance metrics that the CPNN model gave an increased 2.67% recognition accuracy, 2.67% specificity, 2.67% sensitivity and a decreased FPR of 2.67% over the SOFM model at 0.70 threshold values. Similarly, CPNN model gave an increased 4.00% recognition accuracy, 4.00% specificity, 4.00% sensitivity and a decreased FPR of 4.00% over the BPNN model at 0.70 threshold value. Hence, CPNN outperformed SOFM and BPNN in terms of FPR, recognition accuracy, specificity and sensitivity.

Table 3.4: CPNN, SOFM and BPNN at 200 x 200-pixel resolution and 0.70 threshold values

Algorithm	FPR (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)	Recognition Time (sec)
CPNN	1.33	94.67	98.67	96.67	180.07
SOFM	4.00	92.00	96.00	94.00	180.76
BPNN	5.33	90.67	94.67	92.67	189.73

The result achieved in this study is as a result of good and stable convergence that was observed in CPNN and SOFM with interpolated output. BPNN got stuck early in local minima, making it difficult to find optimal training parameters. The results reveal that both SOFM and CPNN outperformed the basic BPNN with CPNN having the best performance. Figure 3.1 and Figure 3.2 show the graphical user interface (GUI) of training phase and testing phase respectively. In

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view of the aforementioned results, the CPNN is more accurate, specific and sensitive with minimal false positive than SOFM and BPNN. Therefore, in all the performance metrics considered, CPNN outperformed SOFM and BPNN.

Statistical Analysis of performance of CPNN, SOFM and BPNN

Hypothesis 1

H_0: There is no significant difference between the accuracy of CPNN and BPNN technique.
H_1: There is significant difference between the accuracy of CPNN and BPNN technique.

The paired t-test analysis conducted between the accuracy of CPNN and BPNN technique reveals that there is no much distinction in the test result; having a mean difference ($\mu = 4.25$). Nevertheless, the result confirmed that the CPNN technique is statistically significant at $P < 0.01; P = 0.000$ with $t\ value = 17$. Test of significance of the accuracy evaluated at 95% confidence level shows that there was significant difference between the CPNN and BPNN techniques. The t-test result validates the fact that CPNN outperformed the BPNN technique in terms of accuracy. Hence the alternative hypothesis is accepted.

Figure 3.1**:** Graphical User Interface (GUI) showing Training Phase.

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Figure 3.2**:** Graphical User Interface (GUI) showing Testing Phase

Hypothesis 2
H_0: There is no significant difference between the accuracy of CPNN and SOFM technique.
H_1: There is significant difference between the accuracy of CPNN and SOFM technique.

The paired t-test analysis conducted between the accuracy of CPNN and SOFM technique reveals that there is no much distinction in the test result; having a mean difference ($\mu = 2.92$). Nevertheless, the result confirmed that the CPNN technique is statistically significant at $P < 0.01; P = 0.001$ with $t\ value = 11.69$. Test of significance of the accuracy evaluated at 95% confidence level shows that there was significant difference between the CPNN and SOFM techniques. The t-test result validates the fact that CPNN outperformed the SOFM technique in terms of accuracy. Hence the alternative hypothesis is accepted.

Hypothesis 3
H_0: There is no significant difference between the recognition time of CPNN and BPNN technique.
H_1: There is significant difference between the recognition time of CPNN and BPNN technique.

The paired t-test analysis conducted between the recognition time of CPNN and BPNN technique reveals that there is distinction in the test result; having a mean difference ($\mu = -10.36$). Nevertheless, the result confirmed that the CPNN technique is statistically significant at $P < 0.01; P = 0.001$ with $t\ value = -11.486$. Test of significance of the recognition time evaluated at 95% confidence level shows that there was significant difference between the

CPNN and BPNN techniques. The t-test result validates the fact that CPNN outperformed the BPNN technique in terms of recognition time. Hence the alternative hypothesis is accepted.

Hypothesis 4

H_0: There is no significant difference between the recognition time of CPNN and SOFM technique.

H_1: There is significant difference between the recognition time of CPNN and SOFM technique.

The paired t-test analysis conducted between the recognition time of CPNN and SOFM technique reveals that there is no much distinction in the test result; having a mean difference ($\mu = -2.205$). Nevertheless, the result confirmed that the CPNN technique is statistically significant at $P < 0.05; P = 0.042$ with $t\ value = -3.429$. Test of significance of the recognition time evaluated at 95% confidence level shows that there was significant difference between the CPNN and SOFM techniques. The t-test result validates the fact that CPNN outperformed the SOFM technique in terms of recognition time. Hence the alternative hypothesis is accepted

CONCLUSION

This paper evaluated the essential features of BPNN, SOFM and CPNN iris recognition system. Two hundred and forty (240) iris images were trained and Sixty (60) images were used to test each of the three techniques at different threshold value. The experimental results obtained revealed that CPNN outperformed the SOFM and BPNN in terms of Recognition Accuracies, Specificity, FPR and Recognition Computation Time. In view of this, an iris recognition system based on CPNN would produce a more reliable security surveillance system than SOFM and BPNN. It should be considered in building a truly robust iris recognition system where high recognition accuracy and computational efficiency must not be compromised.

REFERENCES

1. Anicham, S. and Murukesh, C. (2014). An Effective Iris Recognition System Using Contourlet Transform and neutral Networks. International Journal of Innovative Research in science ,Engineering and Technology, 3(4). India: Chennai-66. pp. 11 76-1181.
2. Al-waisy, Rami Qahwaji, Stanly Ipson, Shumoos Al-fahdawi, Tarekl A.M. Nagem (2017), A multi-biometric iris recognition system based on a deep learning approach. Pattern AnalApplic DOI 1007/510044-017-0656-1.
3. Borole S. and Sapkal S. D. (2013). Extraction of Dual Tree Complex Wavelet Feature for IRIS Recognition. *International Journal of Advanced Research in computer and Communication Engineering.* 2(7): pp. 2540-2542.
4. Boualleg, A.H., Bencheriet, Ch. And Tebbikh, H., (2006). Automatic Face Recognititon usingNeural Network- PCA. *In: Proc. 2nd Information and Communication Technologies ICTTA* ’06, Syria: Damascus, pp. 1920-1925.
5. Bowyer K. W, Hollingsworth K. and Flynn P. J. (2008). Image Understanding for iris Biometrics:A Survey. *Comput. Vis. Image underst., 110 (2); pp. 2*81-307.

6. Chandel, G. S. and Bhargava, A. (2014). Identification of people by Iris Recognition. IJCSNS International Journal of Computer Science and Network Security, vol.14 No. 3, 77-80.
7. Chandra M. and Reddy S. (2009). Iris Recognition System using Principal Components of Texture Characteristics. *TECHNIA International Journal of Computing Science andCommunication Technologies (2009). Pp. 6-9.*
8. *Godar, S. and Gupta R .(2012). Comparison of Different Neural Networks for Iris Recognition, Network and Complex Systems. India:Kota 324010, Vol 2, N0.4,pp.9-14.*
9. Gonzaga, A. and Dacosta, R. M. (2009). Extraction and Selection of dynamic features of the human Iris. Proceeding of the XXII Brazilian Symposium on Computer Graphics andImage Processing. Sarajevo, Brazil, pp. 202-208.
10. Hans-Ulrich Bauer and Klaus R. Pawelzik. (1992). Quantifying the Neighborhood Preservation of Self-Organizing Feature Maps. *IEEE Transactions on Neural Networks,*3(4), pp.570-579.
11. Jain A, Rose. *A. and* Flynn.*r, (200*8). Introduction to Biometrics: *a handbook of biometrics springerISBN. 97*8-0-387-71040-2. pp. 434-435.
12. Jain A. K., Bolle R, and Pankanti S. (1999). Biometrics: Personal Identification in Networked Society. *Biometrics recognition.* 1: pp. 434-435.
13. Jain.A, Rose. A. and Flynn. R.(2012). Biometrics for secure authentication. Retrieved 2012-07-29
14. Khormuji K. M., Bazrafkan M., Sharifian M., Mirabedini S. J., Harounabadi A. (2014) “Credit Card Fraud Detection with a Cascade Artificial Neural Network and Imperialist Competitive Algorithm” *International Journal Of Computer Applications* , 96(25): pp. 1-9.
15. Kohonen T., (1995). Self-Organizing Map. 2nd edition, Berlin: Springer-Verlag. pp.1-12.