Chapter 5

Modular Neural Network Match Score Fusion based Iris Recognition

In chapter 4, a hybrid ensemble of feed-forward neural network and statistical city block distance is presented for iris image recognition. However, the perfomance of this method deteriorates when iris information is degraded by noise such as eyelids, eyelashe and reflection. To address this problem and to further enhanced the iris image recognition performance a Modular Neural Network (MNN) with score level fusion is proposed in this chapter. The modular neural network has the capability to learn different task simultaneously and to reduce the system complexity. It has robustness and incremental property. The system performance both in iris image identification and verification are analyzed and presented in this chapter.

5.1 Introduction

In today's technological world, biometric systems are considered as a highly secure and reliable for authorization of an individual over traditional systems based on PIN or password (Park *et al.*, 2007). Over various biometric recognition such as face, fingerprint, gait, palm print, iris recognition is found to be more appropriate when high-security is concerned due to non-invasiveness and unique property of an iris. After the Daugman's first commercial iris recognition systems (Daugman, 1994), a lot of contributions are made by different authors in iris biometric domain in order to improve the system performance (Daugman, 2007; Rahulkar *et al.*, 2012; de Mira *et al.*, 2015; Mozumder *et al.*, 2015). The iris recognition system based on fusion technique is one of the approaches towards the improvement of system's recognition performance. Park *et al.* (2007) proposed a new score level fusion based iris recognition system by using Gabor wavelet filters and Support Vector Machines (SVM). Hollingsworth *et al.*(2011) performed score level fusion of fragile bit distance and Humming Distance for the recognition of an iris image. The authors Eskandari *et al.*(2013), Islam (2014), Ganorkar *et al.* (2013), Thul *et al.*(2016) and Madane *et al.*(2016) also adopted score level fusion scheme to improve the performance of the recognition system.

The captured iris image may not be consistently equal in size all the time due to the presence of noise such as eyelashes, reflection, and eyelids etc. which significantly affects the recognition performance of the system. To improve the recognition performance of the iris recognition system, MNN match score level fusion has been proposed in this chapter. The modular neural network has the capability to learn different task simultaneously and to reduce the system complexity. It has robustness and incremental property i.e. size of the network can be increased gradually and can be made fault tolerant (Rojas, 2013). Here, each iris image is divided into six equal size blocks. During enrolment, each network module is trained independently with corresponding blocks and during recognition, the final result is obtained by voting among the output returned by each network module.

A brief introduction to MNN followed by Score level fusion and proposed recognition approach is presented in the following sections.

5.2 Modular Neural Network

A modular Neural Network consists of several modules of neural neworks that operate on individual inputs without communicating with each other. The arbitration of the outputs of modules is performed by an integrating unit that is not permitted to feed information back to the modules. Modeling of complex task reduction, robustness, scalability and computational efficieny are the motivations behind the design of modular neural network (Rojas, 1996). A MNN-classifier via a "divide and conquer" approach attempts to reduce the problems face by monolithic neural networks such as high internal interface due to strong coupling among the hidden layer weights and deviation from efficient learning due to wide range of overlap introduce by complex task. A modular neural network, generally, decomposes the large complex task into several sub-tasks, each one is handled by a particular module. Then, the outputs of each module are integrated via a multimodule decision-making strategy. Hence, MNN classifiers, generally, is more efficient than the non-modular neural networks (Auda, 1998)

The MNN performed well for classification problems compaered to non-modular models. Kocer, (2008) analyses the performance of MNN with neural network in iris recognition system. A system based on modular neural network architecture for iris image recognition has been proposed by (Gaxiola *et al.*, 2010; Melin *et al.*, 2012). In this system, the inputs to the modular neural network are the processed iris images and the output is the number of the person identified. The integration of the modules was done with the gating network method.

5.3 Score Level Fusion

Match score is a measure of the similarity between the input and template biometric feature vectors. Each module of the system provides matching scores indicating the proximity of the feature vector with the template vector. These scores can then be combined to improve the matching performance. When match score outputs by different biometric matchers are consolidated in order to arrive at a final recognition decision, fusion is said to be done at the match score level. This is also known as fusion at the measurement level or confidence level.

In match score level fusion, different biometric matchers provide match scores indicating the degree of matching between the input and query templates. The degree of matching between the input and query templates may be similarity score or distance score. These match scores are consolidated to reach the final recognition decision. After the sensor level and feature level information, match scores contain the richest information about the input biometric sample.

5.4 Proposed Iris Recognition with Modular Neural Network Match Score Fusion

In the present work, a modular neural network with score level fusion is proposed for recognition of genuine or imposter person based on their iris feature. The normalized iris images of MMU2 iris dataset (MMU2 Iris Database, 2010) are obtained by using the method described in section 4.2 of chapter 4. The sample of the normalized iris image from MMU2 dataset is shown in Figure 5.1. The features are extracted from each of the normalized iris by using Discrete Cosine Transform (DCT) (Dabbaghchian *et al.*, 2010) according to the Algorithm 5.1.

Algorithm 5.1 Extraction of Iris Features

Input: Normalized iris image of size $[64 \times 192]$.

Output: Extracted iris feature, I_f.

i. Read and enhanced iris image with Adaptive Histogram Equalization (AHE).
ii. Subtract 128 from enhanced iris image.
iii. Calculate DCT coefficient from the whole resultant image and select the coefficients, α, with a zonal mask of size $[m \times n]$.
iv. Next, the resultant image obtained in step ii is divided into six blocks of equal size $[32 \times 64]$ and perform DCT on each block.
v. Select the DCT coefficient, $\beta_i (i = 1,2, \dots ,6)$, with a zonal mask of size $[m \times n]$.
vi. From each normalized iris image, six feature vector is obtained as:

$$I_{f(i)} = [\alpha, \beta_i], i = 1,2, \dots ,6$$

The value of m and n varies from 4 to 8 respectively. The feature vector, f_{vect}(i), is constructed by combining the I_f obtained from all the normalized iris image where $i = 1,2, \dots ,6$.

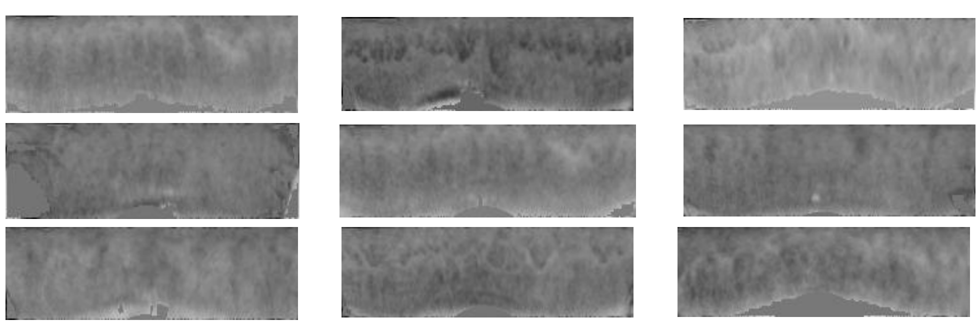


Figure 5.1 A sample of normalized iris images of MMU2 iris dataset

The proposed iris image recognition approach with Modular Neural Network Match Score Fusion is shown in Figure 5.2. Figure 5.3 represents the architecture of each module. The system consists of six modules where each module has five feed-forward neural networks. Each module is trained with its corresponding feature vector i.e. module (1) is trained with feature vector, $f_{vect}(1)$, module (2) is trained with feature vector, $f_{vect}(2)$ and so on.

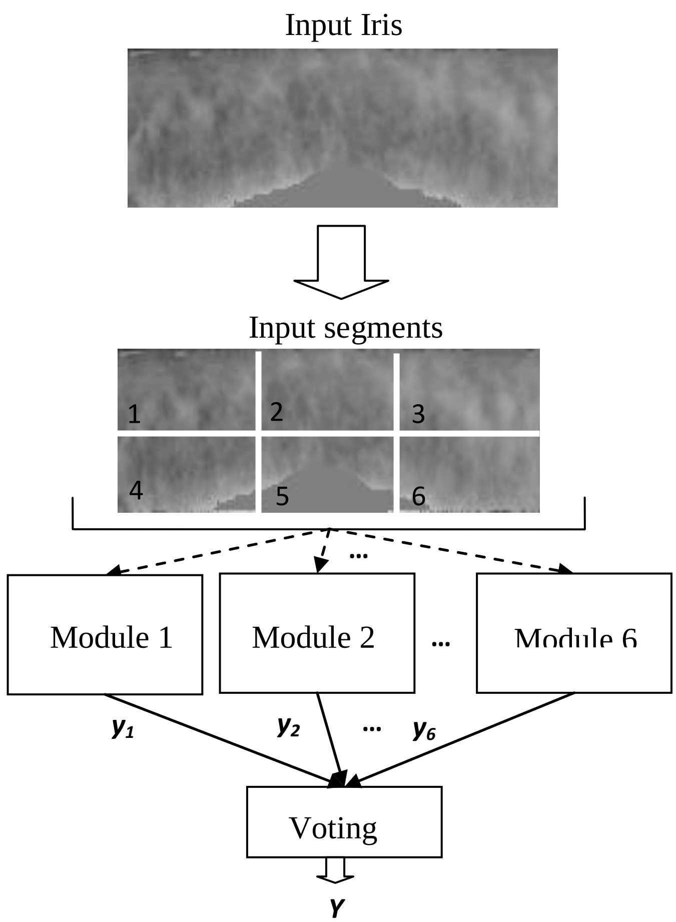


Figure 5.2 Proposed recognition approach

After training, feature vectors are presented onto its corresponding trained network to generate the reference vectors. During recognition, Algorithm 5.1 is applied to the query image to obtain the query features, Q_f. The query features $Q_f(i)$ is presented onto the trained $module(i), i = 1,2,\ldots,6$. The Similarity Distance (SD) is computed between the network output vectors, O_i, generated by the networks within the module and the reference vectors. Each module returns the class of the query image, y_i, as the output based on SD. The minimum SD represents the maximum belongingness, a mean absolute error between O_i and reference vector, f_{ref}, computed by equation (5.1):

$$SD = \frac{1}{n}\sum_{j=1}^{n}\left|O(j) - f_{ref}(j)\right| \tag{5.1}$$

where, n represents the number of network output ($n = 14$). The final query image class, y, is determined by voting among the classes returned by each module i.e. the class returned by most of the modules will be considered as a final class of the query image.

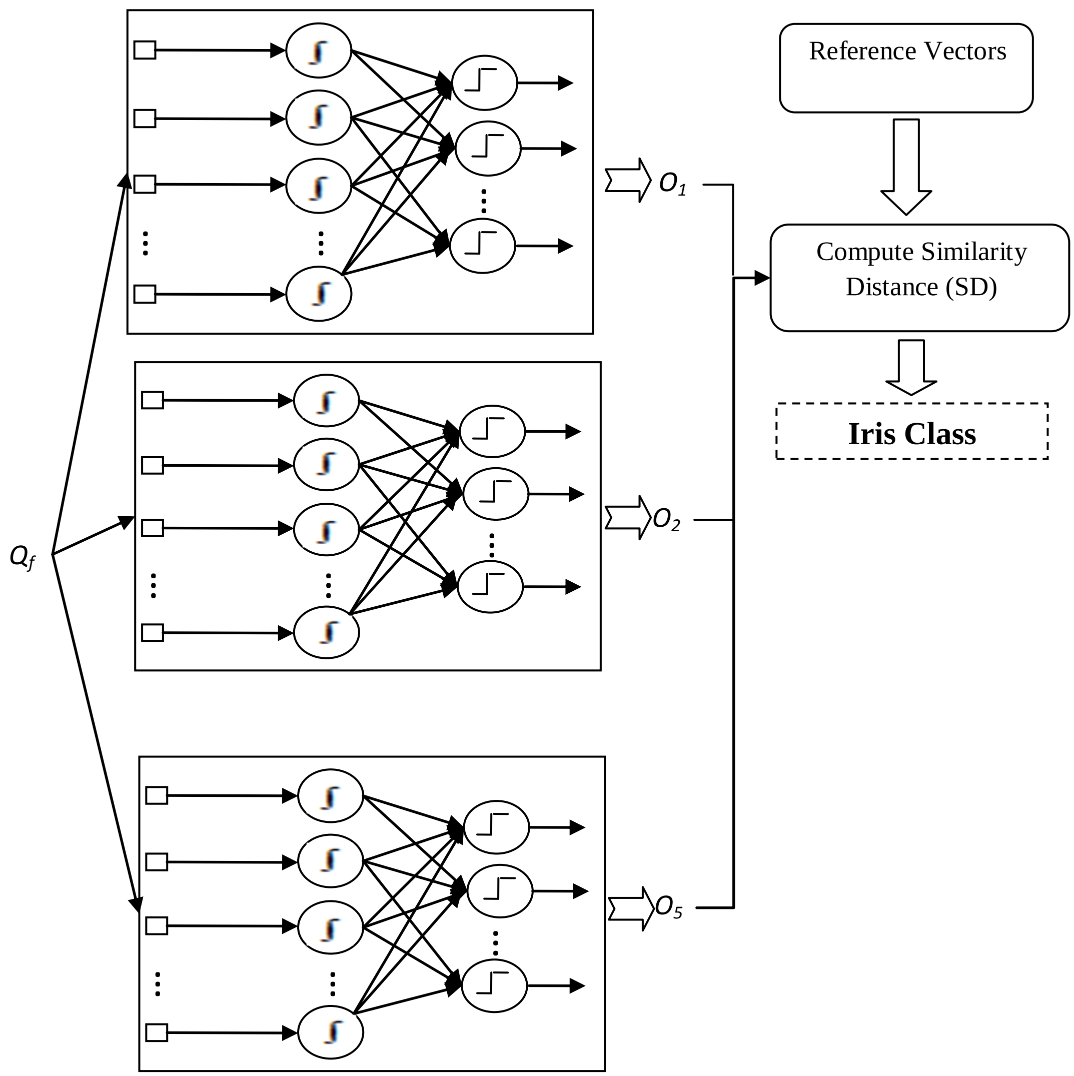


Figure 5.3 Architecture of each module of the neural network

The experimental results of the proposed modular neural network with score level fusion based iris image recognition approach are presented in the next section.

5.5 Experimental Results

The experiments were performed on Windows 7 environment with Intel i3 processor (2.4 GHz) and 3 GB RAM by using MATLAB 7.0 software. The proposed recognition approach was evaluated on MMU2 iris dataset. The left eye of each person is selected for experimentation and the images considered for experiments from MMU2 dataset is tabulated in Table 5.1.

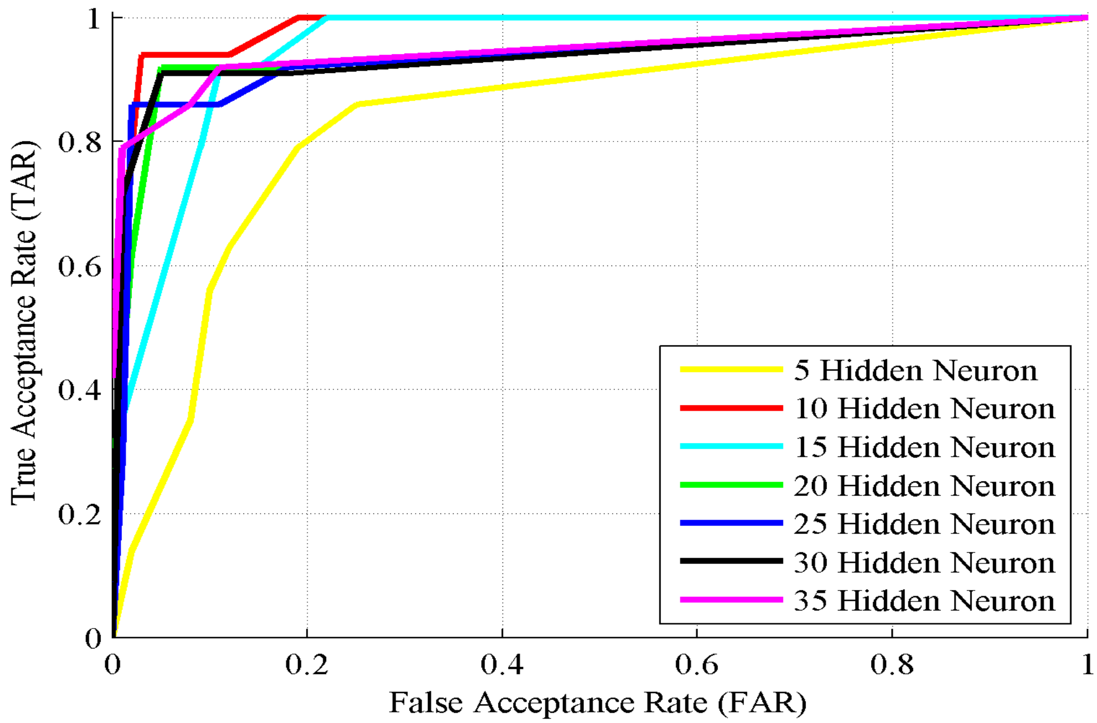
Table 5.1 Images considered for experiments from MMU2 dataset

<table>
<tr><th colspan="4">Number of person used as reference</th><th colspan="2">Number of person used as imposter</th></tr>
<tr><td colspan="4">70</td><td colspan="2">30</td></tr>
<tr><th colspan="2">Image per person</th><th colspan="2">Total</th><th>Image per person</th><th>Total</th></tr>
<tr><td colspan="2">5</td><td colspan="2">350</td><td rowspan="3">5</td><td rowspan="3">150</td></tr>
<tr><th>Training</th><th>Testing</th><th>Training</th><th>Testing</th></tr>
<tr><td>4</td><td>1</td><td>280</td><td>70</td></tr>
</table>

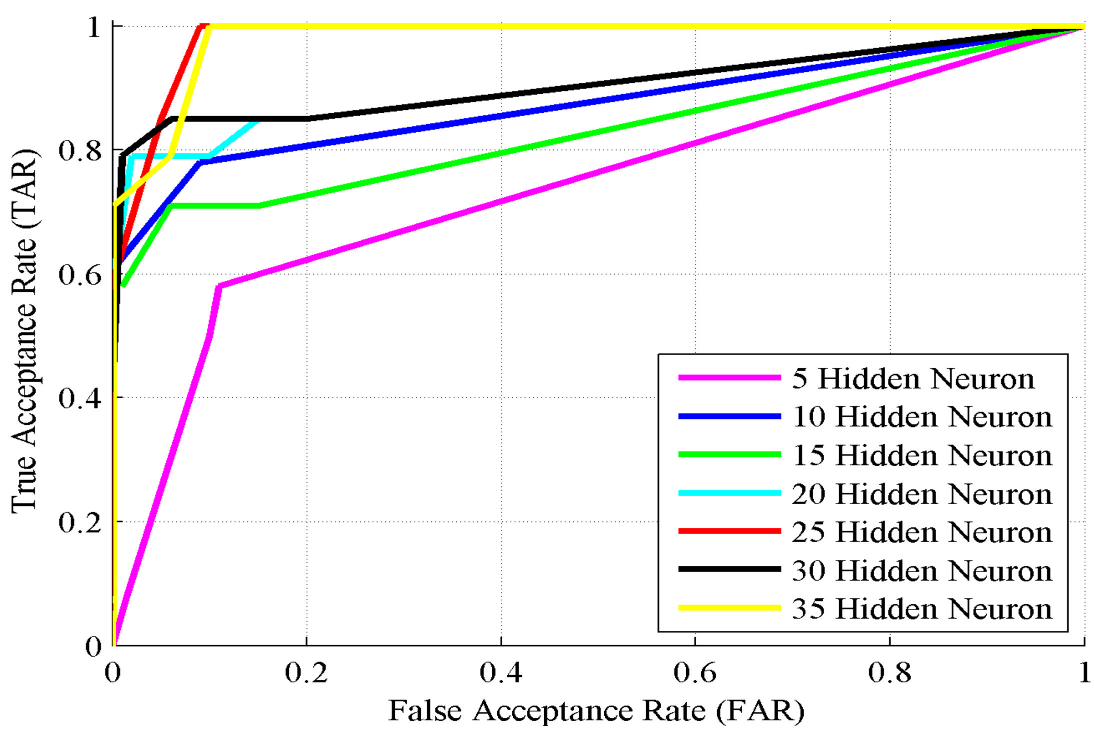
In the present work, the False Acceptance Rate (FAR) and False Rejection Rate (FRR) of the proposed recognition approach were computed to determine the threshold value (minimum similarity distance) for class separation. Also, Receiver Operating Characteristics (ROC) curve, Cumulative Math Curve (CMC) and accuracy of the system were presented as an assessment of the proposed recognition approach. In order to verify the efficiency of the proposed approach, the performance of the proposed approach is compared with the performance of some of the existing iris recognition algorithms *viz.* Al-allaf *et al.* (2012) and Mozumder *et al.* (2015).

5.5.1 Optimal Network Architecture

The module of the feed-forward neural network with only one hidden layer is used for experimentation. The classification result of the network on the MMU2 testing dataset by varying the number of hidden neuron with 32, 50, 72, 98 and 128 DCT coefficients is presented in Figure 5.4 (a-e), respectively, as ROC curve.

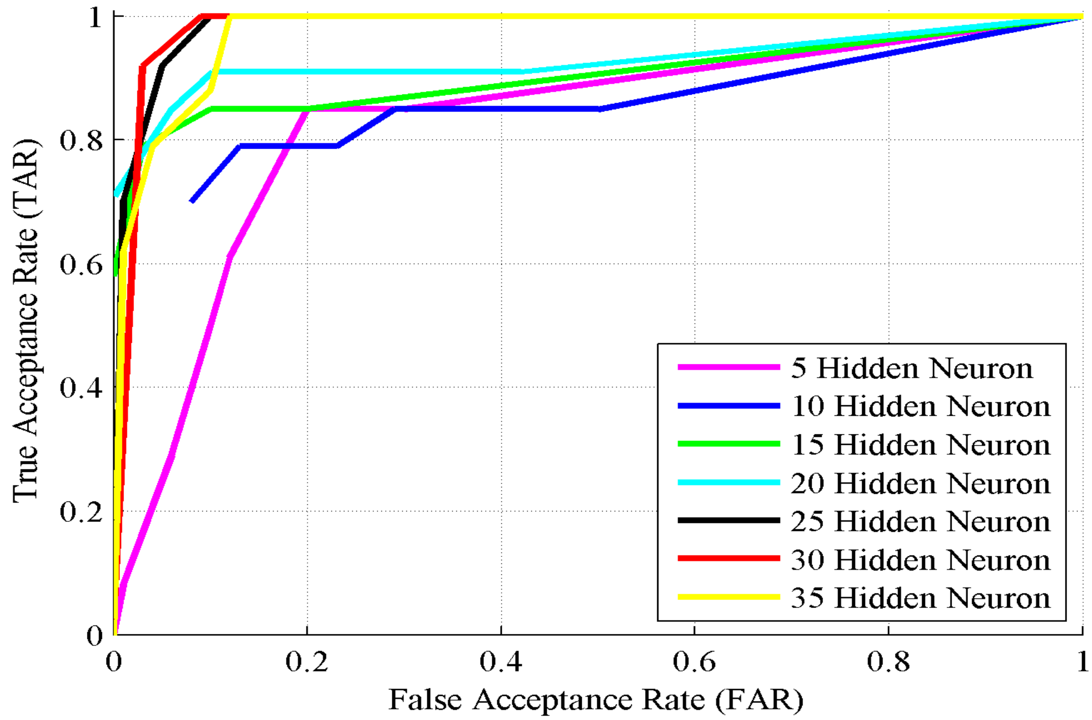


(a) 32 DCT coefficients

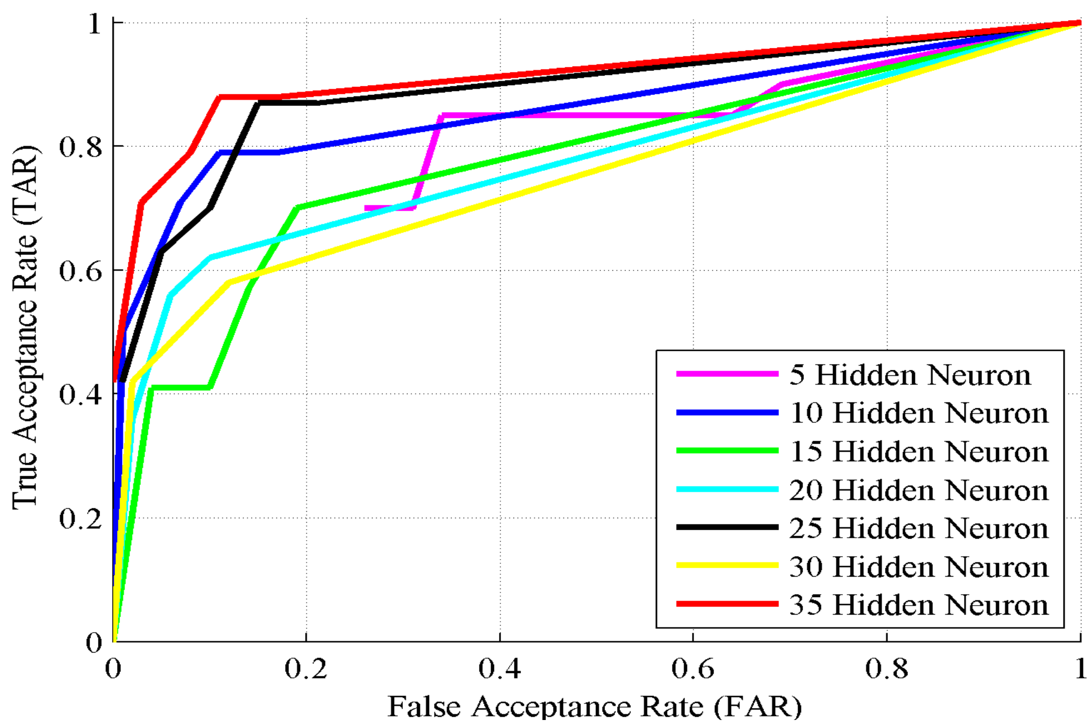


(b) 50 DCT coefficients

Figure 5.4 Network ROC curve on testing dataset with different DCT coefficients by varying the number of hidden neuron over MMU2 iris dataset

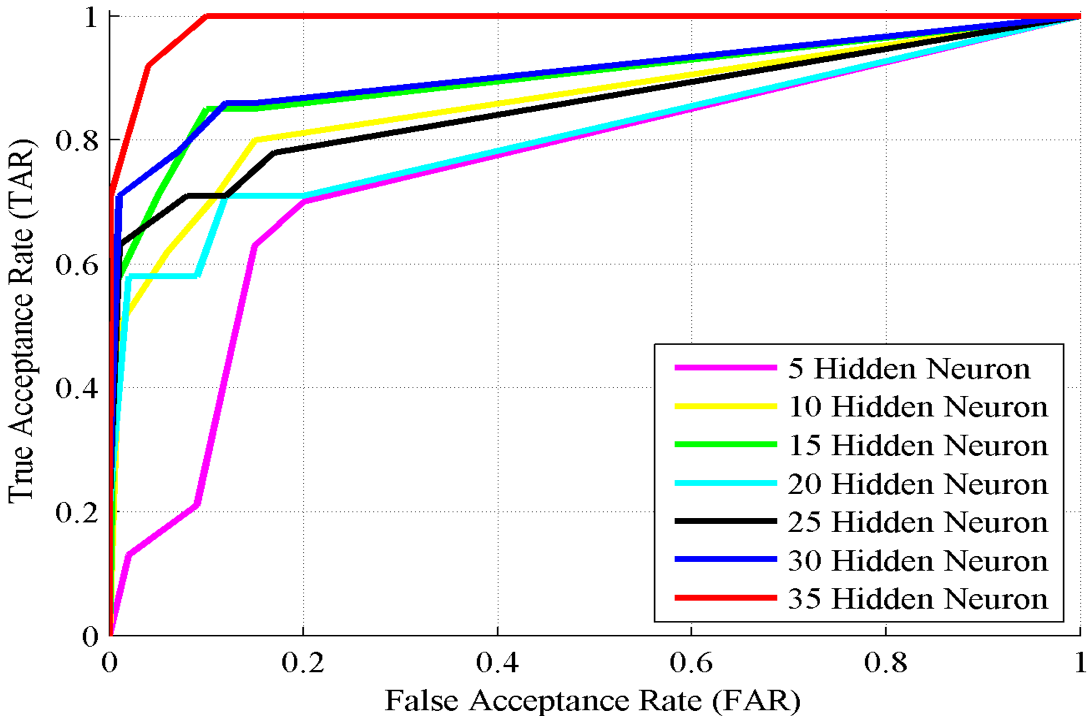


(c) 72 DCT coefficients



(d) 98 DCT coefficients

Figure 5.4 Network ROC curve on testing dataset with different DCT coefficients by varying the number of hidden neuron over MMU2 iris dataset (Continued…)



(e) 128 DCT coefficients

Figure 5.4 Network ROC curve on testing dataset with different DCT coefficients by varying the number of hidden neuron over MMU2 iris dataset (Continued…)

Thes ROC curves (Figure 5.4) indicate that the optimal number of hidden neuron for 32, 50, 72, 98 and 128 DCT coefficients are 10, 25, 30, 35 and 35, respectively as tabulated in Table 5.2.

Table 5.2 Optimal number of hidden neuron

No. of DCT Coefficient	**No. of hidden neuron**
32	10
50	25
72	30
98	35
128	35

The network architecture and its design parameters are shown in Figure 5.5 and Table 5.3, respectively.

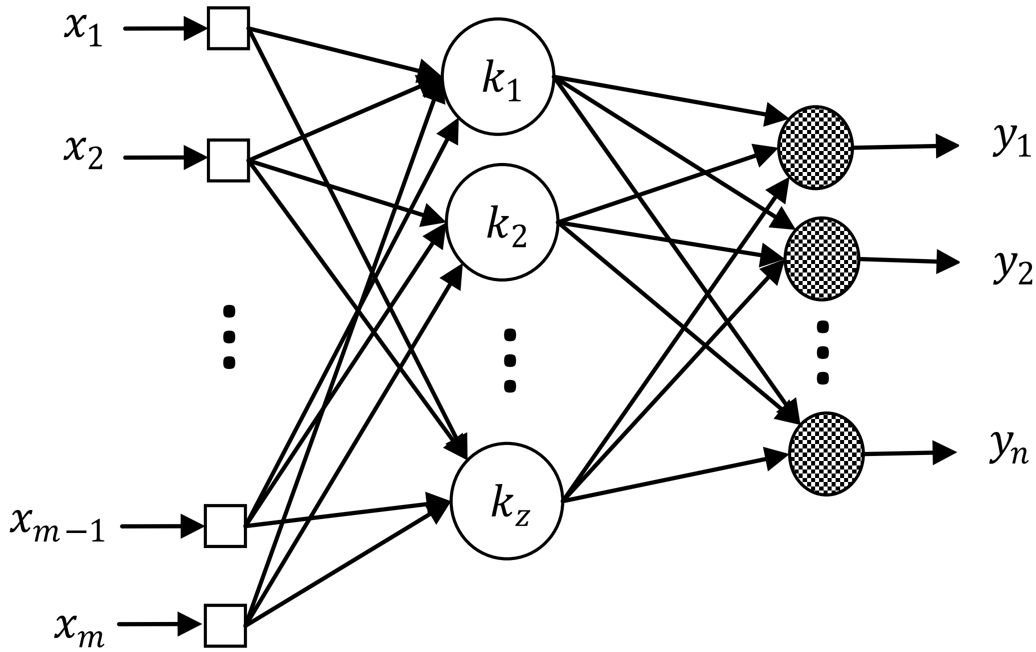


Figure 5.5 Network architecture, m varies from 32 to 128, z varies from 10 to 35 and $n = 14$

Table 5.3 Optimal network parameters

Training function	:	*'trainrp'*
Transfer function	:	'*tansig'* for first layer
		'*purelin'* for second layer
Initial learning rate	:	0.3
Epochs	:	2000
Error goal	:	0.00001
Minimum gradient	:	0.0001

5.5.2 Selection of DCT Coefficients

Among the different sets of the feature vector, the feature vector with 128 DCT coefficients provides more discriminating feature as it is evident from the ROC curve as seen in Figure 5.6. This ROC curve represents the classification result of the neural network on a testing dataset with optimal network architecture. Therefore, it can be concluded from the Figure 5.6 that feature vector with 128 DCT coefficients of each iris image is suitable to be chosen for the proposed recognition approach.

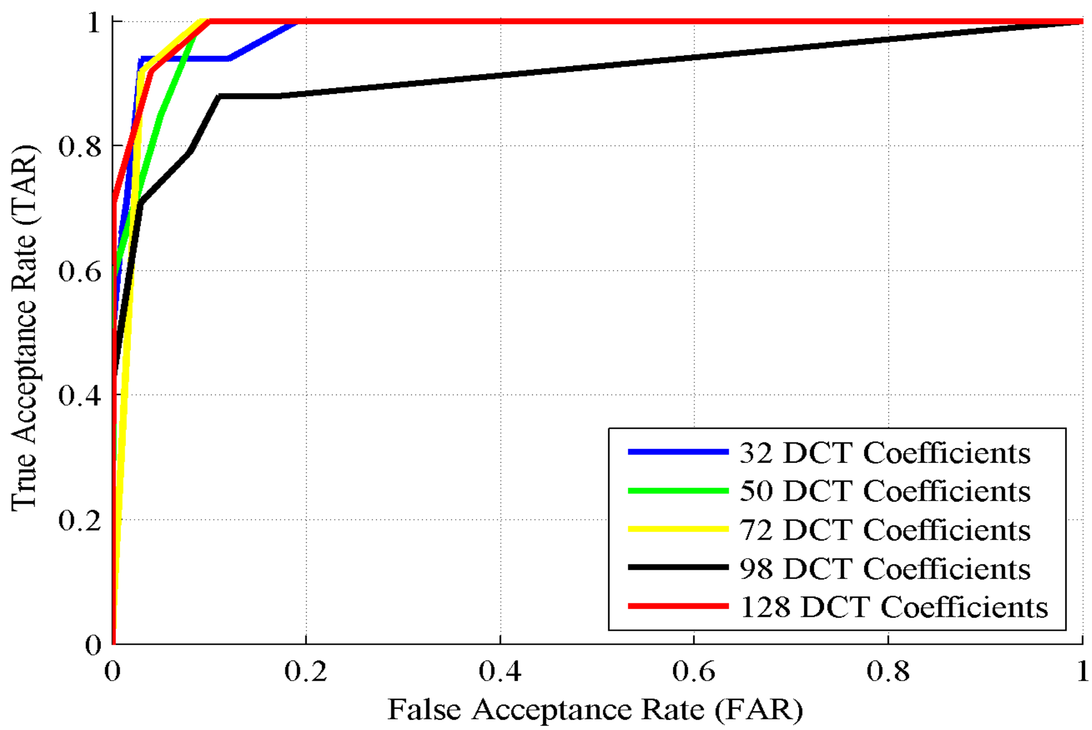


Figure 5.6 ROC curve of the optimal neural network with 32, 50, 72, 98 and 128 DCT coefficients

5.5.3 Recognition

Modular neural network with score level fusion scheme has been used for iris image recognition. The performance of the proposed recognition approach is evaluated on both verification (one-to-one comparison) mode and identification (one-to-many comparison).

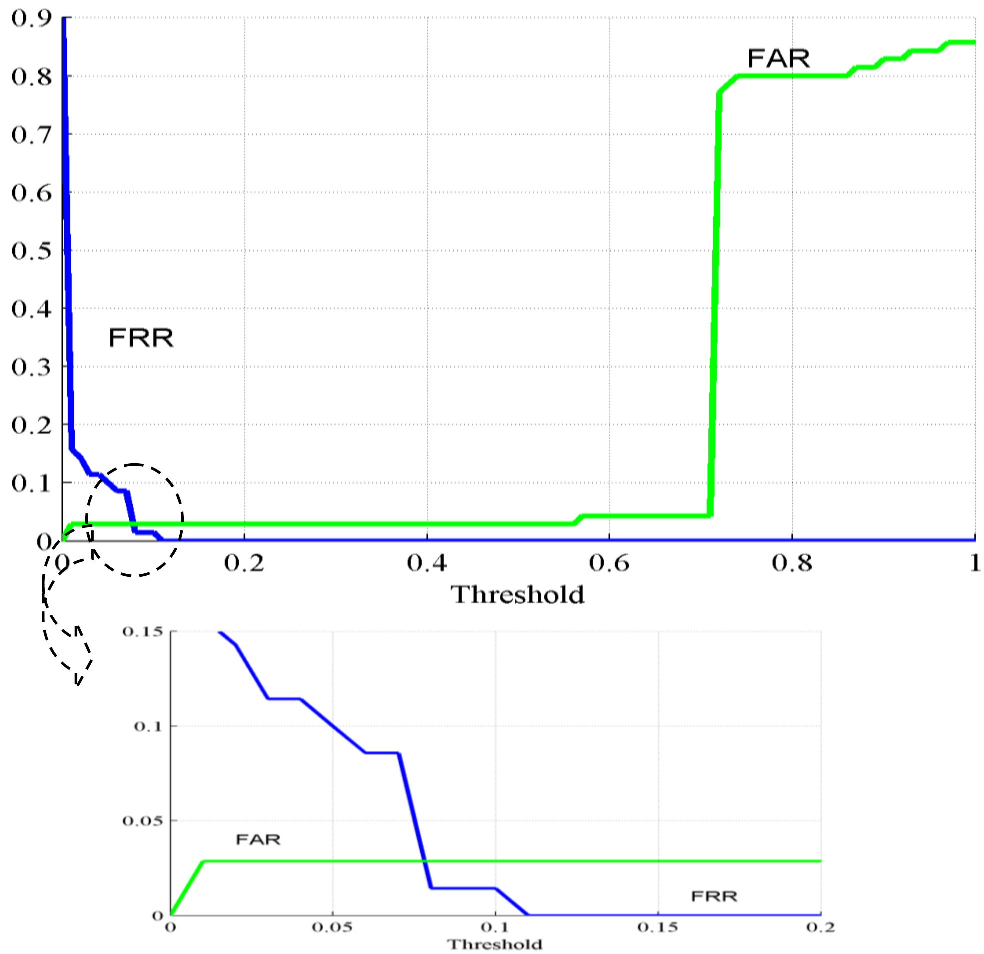
Verification mode: In verification mode, the system tries to match the biometric template presented by the person against a specific template already on the database. The threshold value for class separation is determined from the False Acceptance Rate (FAR) and False Rejection Rate (FRR) of the system. The FAR and FRR is calculated by equation (5.2) and (5.3) (Bodade *et al.*, 2014):

$$FAR = \frac{No. of\ time\ unathorized\ person\ accepted}{Total\ No. of\ comparison} \tag{5.2}$$

$$FRR = \frac{No. of\ time\ athorized\ person\ rejected}{Total\ No. of\ comparison} \tag{5.3}$$

The *FAR* and *FRR* of the proposed iris recognition approach on verification mode at different threshold over MMU2 iris dataset is presented in the Figure 5.7 and it is concluded that the minimum similarity distance equal to 0.11 is suitable to choose as a threshold value for class separation. The corresponding FAR and FRR values with 0.11 threshold value are 0.0285 and 0.00, respectively. The proposed recognition has achieved verification accuracy of 98.57% over the MMU2 iris dataset. The accuracy is calculated by equation (5.4) (Bodade *et al.*, 2014):

$$Accuracy = \left(1 - \frac{FAR + FRR}{2}\right) \times 100 \tag{5.4}$$



Threshold	0.00	0.05	**0.11**	0.30	0.57
FAR	0.0	0.0285	**0.0285**	0.0286	0.0429
FRR	0.9000	0.1000	**0.000**	0.000	0.000

Figure 5.7 Comparison of FRR and FAR at different threshold over the MMU2 iris dataset

To evaluate the proposed recognition approach on verification mode, its performances are compared with two existing iris recognition approaches *viz.* Al-allaf *et al.* (2012) and Mozumder *et al.* (2015). These algorithms are implemented and tested on the same set of iris images. The ROC curve of the proposed recognition approach, Al-allaf *et al.* (2012) approach and Mozumder *et al.* (2015) approach on verification mode over MMU2 iris dataset is shown in Figure 5.8.

It is observed from the ROC curve (Figure 5.8) of the proposed recognition approach on verification mode with different approaches that the proposed approach outperforms the existing approaches in terms of verification performance of the system.

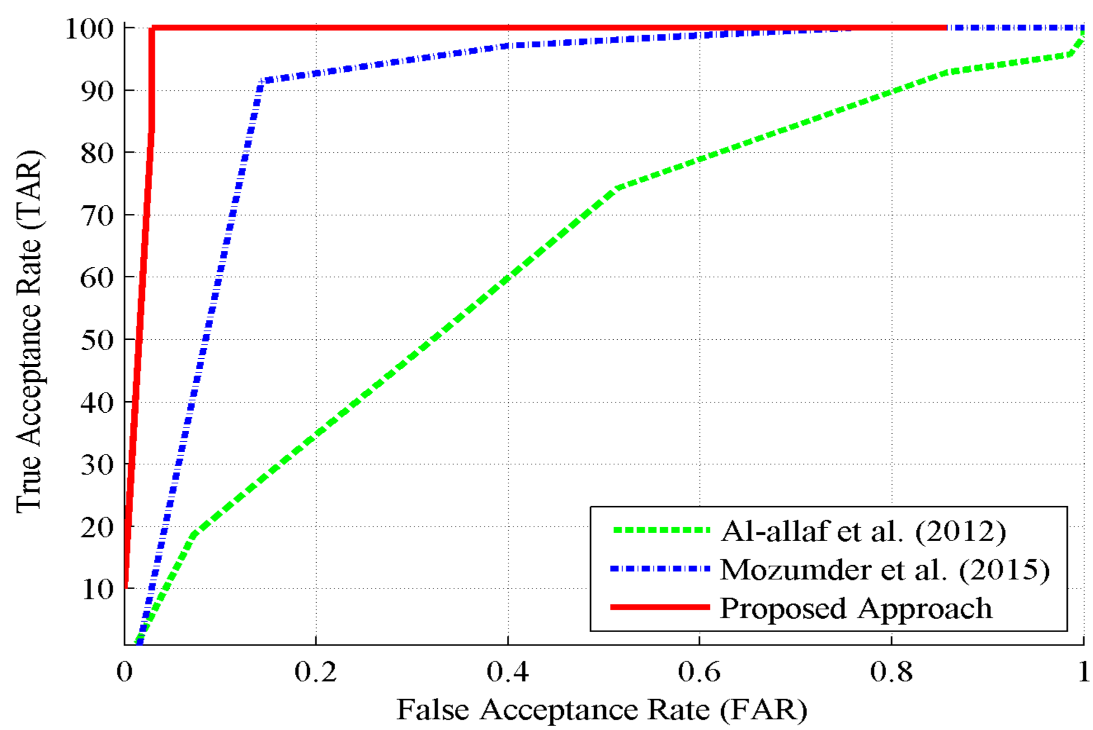


Figure 5.8 ROC curve of the proposed recognition approach, Al-allaf *et al.* (2012) approach and Mozumder *et al.* (2015) approach on verification mode over the MMU2 iris dataset

Identification mode: In identification mode, the system tries to find the biometric template from the entire reference templates present in the database. It corresponds to one-to-many comparisons. The proposed recognition approach achieves identification accuracy of 96.86% with the considered images of MMU2 iris dataset. The Cumulative Match Characteristics (CMC) is used to present the identification performance of the proposed approach with the MMU2 iris dataset. The CMC curve of the proposed approach, Al-allaf *et al.* (2012) approach and Mozumder *et al.* (2015) approach is shown in Figure 5.9.

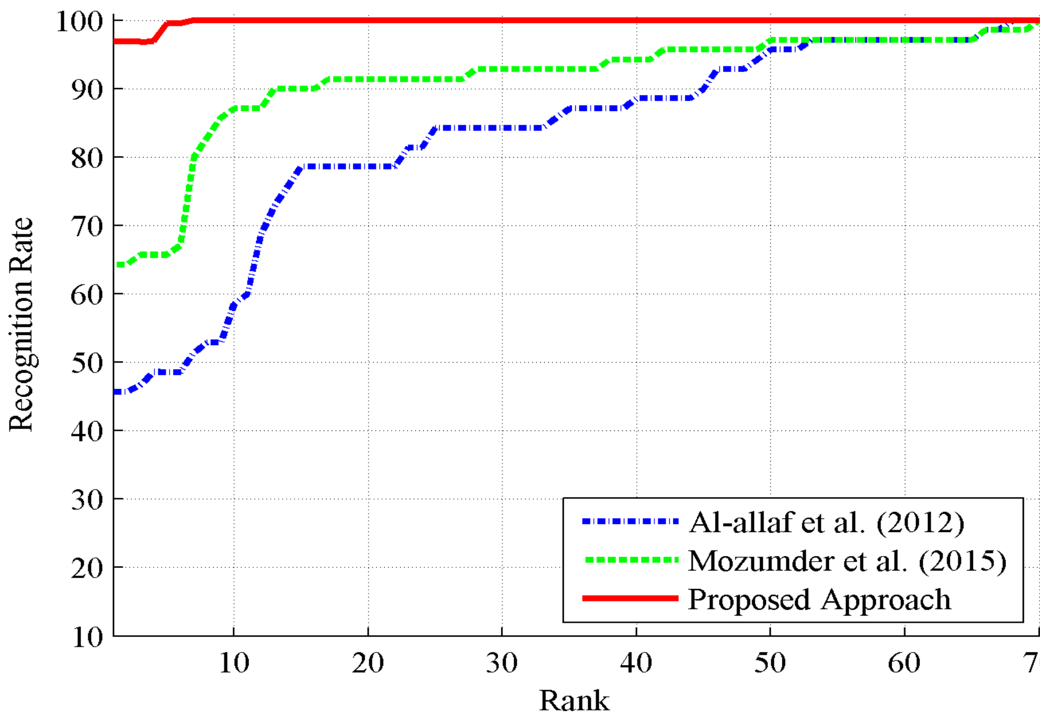


Figure 5.9 CMC curve of the proposed approach, Al-allaf *et al.* (2012) approach and Mozumder *et al.* (2015) approach over the MMU2 iris dataset

The CMC curve (Figure 5.9) indicates that, in case of identification mode, proposed iris image recognition approach outperforms the existing approaches over the MMU2 iris dataset.

The average CPU running time and recognition accuracy of proposed modular neural network with score level fusion based iris recognition approach, Al-allaf *et al.* (2012) recognition approach and Mozumder *et al.* (2015) recognition approach over the MMU2 iris dataset during identification and verification is tabulated in Table 5.4. The average CPU running time of the proposed iris recognition on both verification and identification mode is 1.27 sec. and 9.38 sec. with the recognition accuracy 98.57% and 96.86%, respectively (highlighted in bold) over MMU2 dataset.

It is observed from the Table 5.4 that the proposed approach outperforms the approaches of Al-allaf *et al.*(2012) and Mozumder *et al.* (2015) in terms of CPU running time and recognition accuracy on both verification and identification mode with considered MMU2 iris dataset.

Table 5.4 CPU running time and recognition accuracy of the proposed approach, Al-allaf *et al.* (2012) approach and Mozumder *et al.* (2015) approach over the MMU2 iris dataset

Method	**Mode**			
	Verification		**Identification**	
	Time (s)	Accuracy (%)	Time (s)	Accuracy (%)
Al-allaf *et al.* (2012)	1.86	61.43%	9.95	45.71%
Mozumder *et al.* (2015)	1.95	78.57%	12.27	64.28 %
Proposed iris recognition	**1.27**	**98.57 %**	**9.38**	**96.86%**

The time complexity of modular neural network during testing is $O(k.m.w)$, where k represents number of modules, m represents size of input pattern and w represents size of weight vector. The complexity of SD is $O(m)$. Therefore, total time complexity is equal to $O(k.m.w)$.

5.6 Chapter Summary

In this chapter, iris image recognition based on a modular neural network with score level fusion scheme has been proposed. The performance of the system is evaluated on both verification (one-to-one comparison) and identification (one-to-many comparison) mode. The proposed approach achieved the verification and identification accuracy of 98.57% and 96.86% respectively on the considered dataset. The ROC and CMC curve demonstrate the efficiency of the proposed approach.

The task of iris recognition system is to recognize an iris image precisely and accurately with less FAR and FRR. In the next chapter, in order to reduce the FAR and FRR of the recognition system, hybrid approach based on modular neural network and fuzzy inference system is presented.