IRIS RECOGNITION BY USING IMAGE PROCESSING TECHNIQUES

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By
MOHAMED AHMED ALI ALHAMROUNI
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Approval of the Graduate School of Natural and Applied Sciences, Atilim University.

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ABSTRACT

IRIS RECOGNITION BY USING IMAGE PROCESSING TECHNIQUES

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Iris recognition system has become very important, especially in the field of security, because it provides high reliability. Many researchers have suggested new methods to iris recognition system in order to increase the efficiency of the system. In this thesis, various methods have been proposed to achieve high performance in iris recognition. In the proposed system, three feature extraction approaches, Histogram of Oriented Gradient (HOG), Gray Level Co-Occurrence Matrix (GLCM) and Local Binary Pattern (LBP) are used to extract the features from iris image. On other hand, two classifiers; K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) are used in the classification stage. The iris image passes through several stages before extracting features stage; first, pre-processing stage which includes image resizing that unifies all images' size, second, segmentation stage which determines the iris region in eye image, finally, normalization stage which converts the iris region to suitable shape with specific dimensions. The proposed methods have been applied on two iris databases, UPOL and IITD. However, the proposed system achieved recognition rate of 100% when HOG+KNN method is used.

Keywords: Iris Recognition; Histogram of Oriented Gradient; Gray Level Co-Occurrence Matrix; Local Binary Pattern**.**

ÖZ

GÖRÜNTÜ İŞLEME TEKNİKLERİ KULLANILARAK İRİS TANIMA

ALHAMROUNI, MOHAMED

Bilgisayar Mühendisliği Bölümü Yüksek Lisans

Danışman: Yrd. Doç. Dr. Gökhan Şengül

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İris tanıma sistemi yüksek güvenilirlik özelliğinden dolayı özellikle güvenlik alanında çok önemli bir yer edinmiştir. Bir çok araştırmacı sistemin verimliliğini artırmak için iris tanıma sistemine dair öneriler sunmaktadır. Bu tezde ise, iris tanıma sisteminde yüksek performansa ulaşmak için yöntemler önerilmektedir. Bu önerilen sistemde, üç öznitelik çıkarımı yaklaşımı Histogram of Oriented Gradient (HOG) *(Yönlü Gradyan Histogramı),* Gray Level Co-Occurence Matrix (GLCM) *(Gri Düzey Eşdizimlilik Matrisi)* ve Local Binary Pattern (LBP) *(Yerel İkili Model)* iris görüntüsünden özellik çıkarmak için kullanılmıştır. Öte yandan, K-Nearest Neigbors (KNN) *(K-En Yakın Komşular)* ve Support Vector Machine (SVM) *(Destek Vektör Makinesi)* ise sınıflandırma aşamasında kullanılmıştır. Iris görüntüsü özellikleri çıkarma aşamasından önce bir kaç aşamadan geçer. Bunların birincisi, tüm görüntülerin yeniden boyutlandırmasını içeren ön-işleme aşaması; ikincisi ise göz görüntüsünde iris bölgesini belirleyen bölütleme aşamasıdır. Son aşama ise, iris bölgesini spesifik boyutlu uygun şekle çeviren normalizasyon evresidir. Önerilen yöntemler, iki iris veritabanında (UPOL ve IITD) test edilmiştir. Bununla birlikte, önerilen sistem HOG+KNN metodu kullandığı zaman % 100'e varan tanıma oranına ulaşmıştır.

Anahtar kelimeler: İris tanıma, Yönlü Gradyan Histogramı, Gri Düzey Eşdizimlilik Matrisi, Yerel İkili Model.

To My Mother

HOUN NAJAH

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LIST OF ABBREVIATIONS

HOG	Histograms of Oriented Gradients
GLCM	Gray-Level Co-Occurrence Matrix
LBP	Local Binary Pattern
ALBP	Average Local Binary Pattern
MLBP	Modify Local Binary Pattern
KNN	K- Nearest Neighbors
FKNN	Fuzzy K- Nearest Neighbor
SVM	Support Vector Machine
UPOL	University of Palack´eho and Olomouc database
IITD	Indian Institute of Technology Delhi database
MMU	Multimedia University Iris database
CASIA	Chinese Academy of Sciences' Institute of Automation database
NB	Navie Bayes
PCA	Principal Component Analysis
DWT	Discrete Wavelet Transform
HE	Histogram Equalization
RF	Random Forest
LMI	Legendre Moment Invariants
DRLS	Distance Regularized Level Set
LS	Level Set
HD	Hamming Distance
ED	Euclidean Distance
NFL	Nearest Feature Line
DCT	Discrete Cosine Transform
ANN	Artificial Neural Network
WED	Weighted Euclidean Distance
CT	Curvelet Transform

LDA	Linear Discriminant Analysis
IDO	Integro-Differential Operator
HT	Haar Transform
GW	Gabor Wavelet
LVQ	Learning Vector Quantization
NBP	Neighbourhood - based Binary Pattern
GLRLM	Gray-Level Run Length Matrix
HWT	Haar Wavelet Transform
CED	Canny Edge Detector
SIFT	Scale-Invariant Feature Transform
CE	Chunked Encoding
DLDA	Direct Linear Discriminant Analysis
EMD	Empirical Mode Decomposition
TEM	Texture Energy Measure
RT	Radon Transform
BPSO	Binary Particle Swarm Optimization
LMT	Logistic Model Trees
DTCWT	Dual Tree Complex Wavelet Transform

CHAPTER 1

1. INTRODUCTION

A term "Biometric" indicates to the identification and authentication of an individual identity based on unique features or characteristics in the individuals [1]. Biometric systems consist of physiological characteristics and behavioral characteristics. Physiological characteristics are a group of biometrics which include the physiological and biological features as dominated by a biometric system. It specifically contains DNA, Hand, Face, Earlobe, and iris. Behavioral characteristics are a group of biometrics which is concerned by the non-physiological or non-biological features as dominated by a biometric system. It consists of four categories: Signature, Voice, Gait and Keystroke recognition [2].

To meet security requirements [3] of the current networked society, personal identifiers are becoming more important. Conventional methods that are used for personal identifiers can be either token-based methods or knowledge –based methods. Token-based methods use keys or ID cards for authentication, and knowledge-based methods use preset code or password by the user. However, conventional methods become not reliable if, for example the token is lost or the password is forgotten, therefore; the needs of new & developed reliable methods for personal identification become more and more important research area [4]. The iris is one of the most reliable methods that used to identify individuals because it is fixed and does not change throughout life. Moreover, it is impossible to find two persons have the same iris features even for the twins [5]. The iris is a circular anatomical structure which is located between the cornea and the lens of the eye as shown in Figure 1-1. The iris's task is to control the light that is entering through the pupil; this is done by the sphincter and the dilator muscles, which regulated the size of the pupil. The average of iris diameter is between 11.6 mm and 12.0 mm, and the pupil size is between 10% and 80% of the iris diameter. Human iris consists of two layers; the epithelium layer which consists of intensive pigmentation cells and the

stroma layer which contains blood vessels. It is responsible for reducing the size of the pupil. This layer lies on top of the epithelium layer [3].

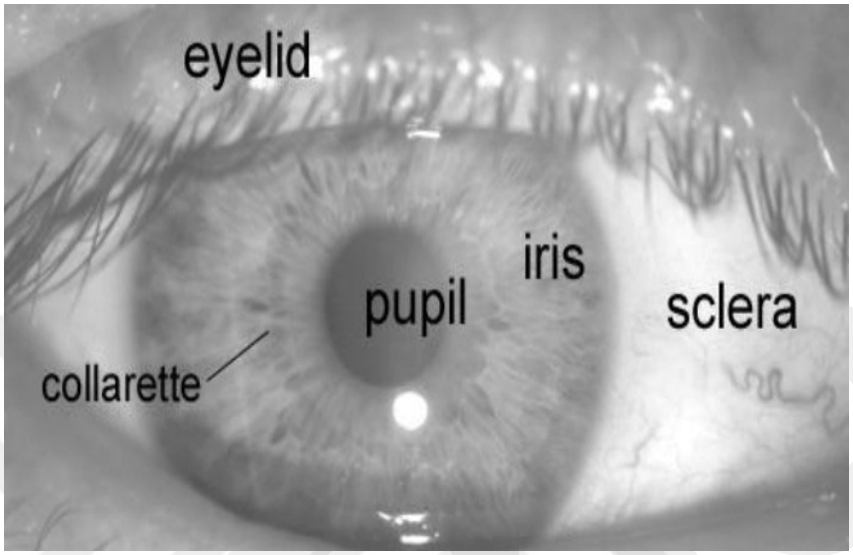

Figure 1-1: A front view of the Human Iris [3]

Iris recognition is a method that is used to identify people based on unique features within the iris. Moreover, the iris usually has a grey, blue, brown or green color. Iris recognition is considered a form of biometric verification [6]. The first concept in iris recognition was proposed in 1987 by Flom and Safir. They proposed highly controlled and non-functional conditions to change the illumination so that size of the pupil in all images remains same for suitable Iris segmentation. They outlined the basic subsystems of Iris recognition system, namely image acquisition phase, preprocessing, Iris segmentation phase, Iris analysis, feature extraction phase, classification phase along with appropriate image processing, and pattern recognition techniques. This theoretical work on Iris recognition system has considered as a basis for all practical approaches of Iris recognition system [7]. A typical iris recognition system includes six main stages [8]. The first stage, image acquisition that is done with capturing the series of images of the iris using cameras, in order to ensure acquiring the best images to increase flexibility and provide strong recognition. The second stage, image preprocessing that means the control of size, color and light of the image in order to be ready for segmentation stage. The third stage, segmentation which includes iris and pupil boundary detection, and

additionally detect eyelids and eyelashes. The fourth stage, normalization means converting the iris region into a form like a rectangle. The fifth stage, feature extraction, extracts features from the normalized iris image and encodes these features to a design that is suitable for recognition. The last stage in iris recognition system, classification, that means comparison the features created by imaging the iris with stored features in the database. Figure 1-2 shows the above-mentioned stages.

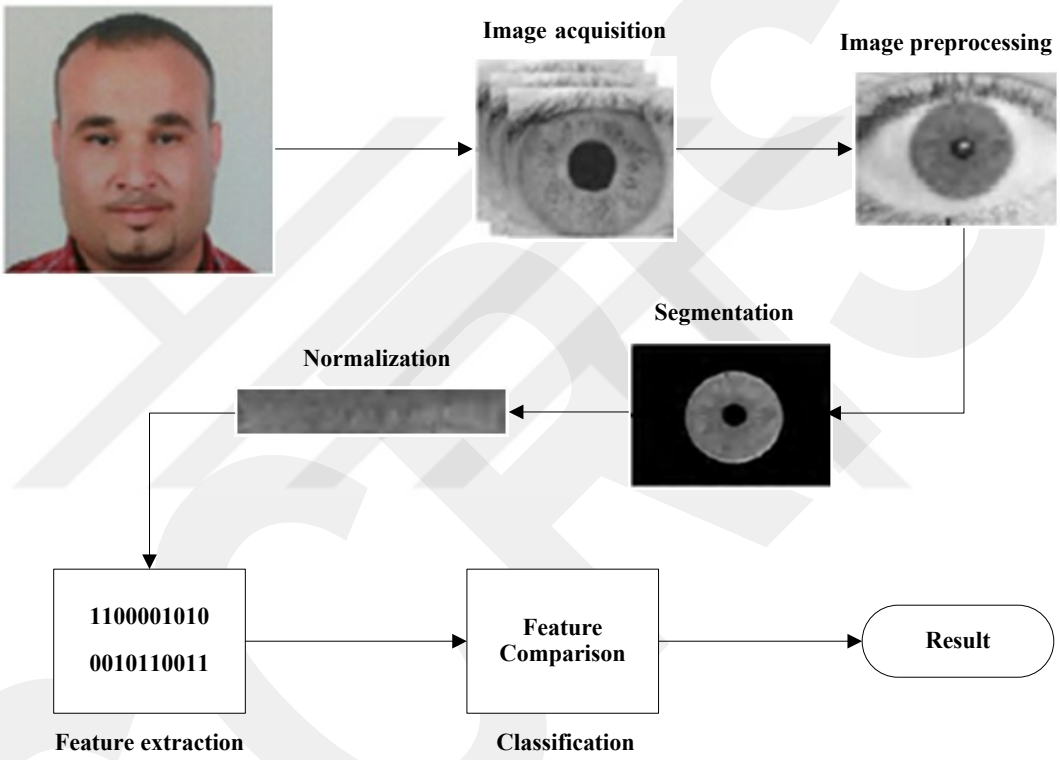

Figure 1-2: Typical stages of iris recognition system [9]

1.1. Motivation

Iris recognition system has become one of the best authentication systems at the present time due its beneficial uses for many computer vision applications such as security systems, and visual surveillance. There are many examples that proved the importance of iris recognition system. For example, fight against crime, increase of terrorist threats, and security measures in airports. The iris is considered suitable for an individual's identity because it has many advantages such as, it is an internal organ of the eye,

therefore; it is a highly protected, the iris is a visible organ, therefore; remote imaging. Is possible. Iris is formed in the human in the seventh month of gestation before natal, therefore; considered a fixed feature throughout human life, and last but not least researches have proved that even the twins have different iris patterns, therefore; it is considered to be better than other biometric applications to define the individual's identity [10]. The major aim of this thesis is to implement a system that is able to recognize human iris patterns in order to use it for biometric identification. Emphasis will be on implementing three methods that can perform iris recognition and compare the obtained results from these methods.

1.2. Problem Description

The main problem studied in this thesis is iris recognition. Thus, our main challenge in this thesis is to propose a methodology, design, and implementation of iris recognition system in order to achieve high accuracy in recognizing human iris by using three separate approaches. There are many studies focusing on iris recognition using images that are taken from eyes of individuals. However, many of the negative results occur because of errors in the method of capturing images, image dimensions, quality, shadows, image background, eyes color, in addition to contact lenses in the eyes, etc. All of these characteristics may lead to incorrect classification, and thus negative results will be obtained.

1.3. Thesis Outline

In this thesis, background information about biometric technology and the biometric applications that are used in some of the life fields is firstly presented. Then general definition about the iris and its location in the eye is given. Moreover, some details about iris recognition system and a historical perspective about this system are provided. In the second Chapter, literature reviews about iris recognition and the results obtained in each study are reviewed and presented. In the third Chapter, the major methodology steps in this thesis are explained; firstly, a general overview of the databases that are used in this thesis is given, then a detailed explanation of the most important stages of the iris recognition is provided. These stages are; preprocessing, segmentation and

normalization, finally, a general description of the basic algorithms that are used to extract iris features is presented. These algorithms are HOG, GLCM and LBP. Furthermore, two classifiers SVM and KNN that are used to classify features obtained from iris are explained in details. In the fourth Chapter, the most important results obtained from the experiments and the steps that have accompanied the implementation of these experiments are discussed. In the last Chapter, an overall observation of the results obtained and the important major point noticed in this thesis are provided.

CHAPTER 2

2. LITERATURE REVIEW

In this chapter, section 2.1 provides an overview of the papers that studied the iris recognition system. Then in section 2.2 a briefly summarized table of previous studies of iris recognition is presented. Finally, the summary of these papers in part of differences and important approaches are discussed.

2.1. Previous studies of iris recognition system

Chengqiang and Mei [11] presented Direct Linear Discriminant Analysis (DLDA) algorithm to extract iris features. DLDA is combined with Wavelet Transform (WT) algorithm which decomposes the normalized iris. The Euclidean distance (ED) classifier is used to classify the features. This experiment is tested on 1200 iris images from CASIA iris database version 2. The performance of proposed method is evaluated by Equal Error Rate (EER) which equal 1.44%. This method achieved an accuracy of 98.56%.

Kaushik and Prabir [12, 13] tried to improve iris recognition system by using chain code and zigzag collarette area. The main idea of using zigzag collarette area is to capture only the important area of iris region. The features are extracted from iris images by Gabor wavelet (GW) technique then classified by SVM algorithm. The proposed method is applied on CASIA database version 2, which contains 756 images. The proposed method achieved success rate of 99.56%.

Ahmed M Sarhan [14] used Discrete Cosine Transform (DCT) algorithm to extract the features from iris image. On the other hand, Artificial Neural Network (ANN) classifier is used to classify these features. The proposed method is applied on CASIA iris database version 2, which contains 1200 images for 30 persons, each person having 40 images, 20 images for left eye and 20 images for the right eye, the image size is 480*640 pixels. In this experiment, only the iris images of the right eye were used, thus 600 images were used here. This experiment achieved 96.00% of recognition.

Tallapragada and Rajan [15] combined Gray-Level Co-occurrence Matrix (GLCM) with Haar Wavelet Transform (HWT) in order to increase the efficiency of iris recognition system. These techniques were used to extract features from iris image. Artificial Neural Network (ANN) classifier is used to classify the extracted features. Researchers applied their experiments on 100 images from CASIA database and they obtained efficiency rate about 94%.

Kumar, Raja, Chootaray and Pattnaik [16] have adopted (PCA) to extract features from iris using Discrete Wavelet Transform (DWT). The proposed method ignores the upper and lower portion of the iris which is covered by the eyelids and eyelashes using morphological processing. They have considered forty-five pixels to right and left of pupil's boundary as iris template to get the best recognition, and used Histogram Equalization (HE) to enhance the image and get high contrast. Then DWT is applied on histogram equalized image to get DWT coefficients, and then the features are extracted from the image using (PCA). Finally, Support Vector Machine (SVM), K- Nearest Neighbors (KNN) and Random Forest (RF) classifiers were used for matching. CASIA database version 1 which consists of 756 images for 108 individuals were used in the proposed method, the accuracy achieved with different classifiers are 99.07% using KNN, 98.15% using RF, and 97.22% using SVM.

Rashad, Shams and El-Awady [17] proposed Local Binary Pattern (LBP) algorithm to extract features and combined two classifiers; Artificial Neural Network (ANN) classifier and Learning Vector Quantization (LVQ) classifier for classification. The combination produced a hybrid pattern depending on both features. On the other hand, in localization stage and segmentation stage, Hough Circular Transform and Canny edge detection are applied to separate an iris from an entire eye as well as for noise detection. Features which are extracted from iris by LBP are classified by both LVQ & ANN classifiers with different classes in order to determine the minimum agreeable performance. Three iris databases are combined and used in this work; CASIA, MMU1, MMU2. The proposed method achieved a recognition rate of 99.87%.

Yuqing, Guangqin, Yushi and Evangelia [18] presented iris feature extraction stage based on Local Binary Pattern (LBP) approach with Chunked Encoding (CE) technique. Here LBP is used to the normalize iris image. On other hand, the features were extracted

from iris via CE technique. Hamming Distance (HD) classifier is used for features classification. CASIA iris database Version 3 is used in this method. Experiments achieved a recognition rate of 99.27%. This result has shown that the proposed technique is better than the other traditional methods of features extraction.

Savithiri and Murugan [19] made a comparison between different techniques on feature extraction for iris recognition, whole iris template and half template. They used Gabor Wavelet (GW), Histogram Oriented Gradient (HOG), and Local Binary Pattern (LBP) to extract the features from a specific portion of the iris in order to improve the performance of iris recognition. Their basic aim was to choose the half portion of the iris to recognize instead of entire extension of the iris. The proposed techniques are evaluated by using (FAR) and (FRR). Moreover, 130 images from MMU database were selected for these experiments. These images divided into 26 classes, and each class has 5 images. The first image from each class is chosen to be the template. The remaining 4 images of each class are selected to be the test set. Hamming Distance (HD) classifier is applied to classify the extracted features. GW+HD method achieved recognition rate of 99.94%, FAR 0.006%, LBP+HD method achieved 99.90%, and HOG+HD method achieved 99.95%.

Iris features are extracted by Empirical Mode Decomposition (EMD) approach. These features are classified by the K-Nearest Neighbors (KNN) algorithm. This method is performed by Zhang and Guan [20] in order to improve the performance of iris recognition system. This experiment is applied on 756 images from CASIA iris database Version 1. The proposed method achieved 99% of recognition rate.

Manisha and Sanjay [21] suggested different method for iris recognition by using Daugman's Integro-Differential Operator technique (IDO) to segment the iris and Daugman's Rubber Sheet technique (DRS) is used for iris normalization. On the other hand, Haar Transform (HT) algorithm is applied to extract features from iris region. Finally, Hamming Distance classifier (HD) is used to classify iris. The proposed method is applied on two databases, MMU and BATH together and the achieved recognition rate is 99.94%.

Sarode and Patil [22] used Canny Edge Detection technique for segmentation in order to determine boundaries of the iris, then used local Binary Pattern(LBP) to extract the

features from the iris image. Finally, they used two classifiers to classify the features extracted from the iris image; these classifiers are K_ Nearest Neighbors classifier (KNN) and Navie Bayes classifier (NB). These experiments were applied on MMU database. LBP+KNN method achieved 100% and LBP+NB method achieved 94.18% of recognition.

Sarmah and Kumar [23] have suggested a new system for iris verification. The system proposes a new mechanism to verify the personal in order to verify the uniqueness of the iris. This system consists of two stages, iris pre-processing and iris authentication. Legendre Moment Invariants algorithm (LMI) is used to extract the features of the iris. On other hand, KNN classifier is used for feature classification. In this method, they have used UPOL database which contains 384 images for 64 individuals. The obtained results reached up to 100% of recognition rate.

Ankit and Sunil [24] have reviewed different methods for iris recognition, in each method they used different techniques. In Daugman method; Integro-Differential Operator technique is used in the segmentation stage in order to locate the outer boundaries of the iris, also to determine the lower and upper eyelids, Rubber Sheet Model technique is used in normalization stage to map the iris pixels, Gabor's 2-D Filter technique is applied in feature extraction stage as it provides important information in the normalized image, and finally, Hamming Distance is used in classification stage. However, Daugman method is implemented in MATLAB and they used CASIA database V3 which contains 756 images from 108 individuals. The performance results are based on FAR and FRR. This method achieved a recognition rate of 99.90% with FAR 0.01% and FRR 0.09%. In Wildes method, Gradient-based edge detection and Hough Transform techniques are used in segmentation stage to determine the portion of iris, Image Registration is used in normalization stage to repair the warps in newly acquired image, Isotropic Band Pass Decomposition technique is applied in feature extraction stage, and then Normalized Correlation technique is used in classification stage. This technique captures the same type of features as standard correlation. Moreover, CASIA database is used in this method, and accuracy of 98.68% achieved with FAR 0.03% and FRR 12.09%. In Li Ma method, Nearest Feature Line (NFL) technique is applied in the segmentation stage. This technique helps to find region of iris

in the image by showing the iris image in vertical and horizontal directions, Rubber Sheet Model is used in normalization stage, Gabor's 2-D Filter is used in feature extraction stage, and Weighted Euclidean Distance (WED) is used in classification stage. In Li Ma method, CASIA database is used and the achieved accuracy is 98%, FAR 0.02% and FRR 1.98%. In Tisse method, Integro - Differential Operators and Hough Transform techniques are used in the segmentation stage, Rubber Sheet Model is used in normalization stage, Instantaneous - Phase and Emergent - Frequency techniques are used in feature extraction stage, and in the classification stage Hamming Distance is applied in order to compare the extracted features. CASIA database was used and the achieved accuracy is 89.37%, FAR 1.84% and FRR 8.79%.

Kulkarni, Shweta and Hegadi [25] applied three approaches to extract the features from normalized iris; the first approach is Gray-Level Co-Occurrence Matrix (GLCM). The second approach is Gray-Level Run Length Matrix (GLRLM). The third approach is combined (GLCM & GLRLM). In order to classify the features which are extracted by the previous approaches, they used Support Vector Machine (SVM) one-against-all. The experiments were applied on CASIA Database version 3. They used 180 images, 100 images are used for the training set and 80 images are used for the testing set. The features extracted by GLCM in offset '0' degree, while the features that extracted by GLRLM in offsets 45 degrees and 90 degrees. The performance of GLCM is better than GLRLM, but the best performance achieved with the combination of (GLCM& GLRLM). GLCM achieved 75%, GLRLM achieved 57.14%, while the combined (GLCM & GLRLM) approach achieved 88.89%.

Kovoor, Supriya and Jacob [26] suggested a technique based on Daugman's approach. The technique is applied to examine the iris segmentation mechanisms, eyelid detection, and additionally to remove the area undesired. Haar Wavelet Transform (HWT) is used to encode the iris region to obtain the iris code that contains the best feature in iris pattern. It is concluded that Canny Edge Detector (CED) is the best approach to extract the edges to produce the iris code for the comparison. On other hand, Hamming Distance classifier (HD) is applied to classify the features. In this work, they have used UBIRIS database which includes 1877 images from 241 persons, and the achieved accuracy is 89% of recognition rate.

Emrullah Acar and Mehmet Ozerdem [27] extracted the features from iris image using Laws Texture Energy Measure (TEM) technique. The obtained features are classified by K-Nearest Neighbor (KNN). UPOL database is used to evaluate the performance of the proposed method. The best performance observed is 80.74%.

Brian and Kaushik [28] investigated the challenge of iris segmentation using Distance Regularized Level Set (DRLS) technique. This technique is implemented with a new Level Set mode (LS) and averts re-initialization process that is costly; therefore, it takes a minimal computational time to determine the iris boundary. This technique outperforms on Hough Transform approach in segmentation stage. An additional benefit from this technique is that there is no need for eyelid detection as well as using the flexible contour for iris detection. Moreover, the Modify Local Binary Pattern (MLBP) is used to extract the features from the iris in order to improve the feature extraction performance. The proposed technique is validated by the CASIA database V3 which contains 2639 images from 249 individuals. The method achieved an accuracy of 81.45%.

Jie, Zhe-Ming and Zhou [29] proposed a method based on Curvelet Transform (CT), Principal Component Analysis (PCA), and Linear Discriminant Analysis (LDA) approaches. In this experiment, the images are processed by the iris localization, remove eyelashes, and iris normalization. Then, the Curvelet Transform is adopted to convert the normalized images into three layers, and choose the first layer of these layers. LDA and PCA are used to extract the features. The proposed method considers the iris texture curve features and removes the influence of environment noise, also decrease the feature dimension. K-Nearest Neighbor (KNN) classifier is used here to evaluate the performance of proposed techniques. In this work, CASIA database that contains 270 iris images for 27 persons used, and the achieved accuracy is about 96.30% of recognition.

Neighbourhood - based Binary Pattern (NBP) technique is used by Izem and Saliha [30] in order to extract the features from iris region. NBP technique is an extraction method of the relative connection between neighbours of features. In other words, each neighbour of each feature is captured by another neighbour then encoded, after that the NBP image is dismantled to several blocks. Then the average of each block is

calculated. Finally, all calculated blocks will be encoded, and then the obtained features are classified by Hamming Distance classifier (HD). The binary matrix is used to store the results. In this experiment, they used CASIA database V1 and achieved accuracy 76.25%.

S. Kulkarni, R. Kulkarni, U. Kulkarni and Hegadi [31] used Gray-Level Co-Occurrence Matrix (GLCM) for extracting the features from iris pattern. In this study two classifiers were used to classify the extracted features: K- Nearest Neighbor (KNN) classifier and Fuzzy K- Nearest Neighbor (FKNN) classifier. They applied this study on CASIA-IrisV3 database which contains 2639 images. Here KNN and FKNN classifiers achieved the same accuracy which is 88.50%.

Walid, Nade, Nouri and Lotfi [32] suggested using the monogenic filters and 1D Log-Gabor Filter techniques to extract the features. They combined these techniques to increase the performance of iris recognition system. Features were classified by Hamming Distance (HD) classifier. In this study, CASIA iris database is used, which contains 2655 images. The obtained result achieved an accuracy of 97.85%.

Chengcheng, Weidong and Shasha [33] proposed Average Local Binary Pattern (ALBP) approach to extract the features from the iris. This approach is a various approach of (LBP), and it is selected because it is characterized by several advantages such as low computation complexity, less sensitive to histogram equalization, it places a high value on the importance of centre pixel. KNN and SVM are used for classification. Experimental results are applied on CASIA V4 database which includes 2,639 images, many of the subjects contains two branches, right eye and left eye images. The proposed system achieved a recognition accuracy of 99.91%, therefore this method is considered efficient and satisfying.

In order to improve the efficiency of iris recognition system, a unique combination of three feature extraction techniques was proposed by Mrinalini, Pratusha, Manikantan and Ramachandran [34]. These techniques are Triangular DCT based Feature Extraction (T-DCT), Binary Particle Swarm Optimization (BPSO) based feature selection, and Radon Transform (RT) based Pre-processing. The proposed techniques were applied on three databases: MMU which consists of 225 images, IITD which includes 1120 images, and UPOL database which contains 384 images. Moreover, Euclidean Distance (ED)

Classifier is used to evaluate the techniques performance which achieved accuracy of 78.04% on MMU database, 88.89% on UPOL database, and 94.04% on IITD database.

Aalaa, Israa and Ja'far [35] reviewed four feature extraction approaches, HOG, Gabor, DCT, and GLCM. These approaches are used to extract features from iris image. UBIRIS database version1 is used to test the proposed approaches. They used Logistic Model Trees (LMT) classifier to classify the extracted features. Results show that GLCM approach is better than other approaches. The approaches achieved accuracy 20% by HOG, 76% by combined (Gabor+ DCT), 96% by GLCM, and 92% by combined (HOG+ Gabor+ DCT+ GLCM).

Dual Tree Complex Wavelet Transform technique (DTCWT) is combined with Over Lapping Local Binary Pattern technique (OLBP) to extract and analysis the complex features to obtain the useful features from an iris. This study performed by Arunalatha, Rangaswamy [36], and Shaila. Euclidean Distance (ED) is used to classify the iris features to recognize the person. The proposed system is tested by CASIA iris database version1 and the achieved accuracy is about 98.48% of recognition.

Scale-Invariant Feature Transform (SIFT) technique is performed by Sachdeva and Kaur [37] to extract features from iris pattern and they used Support Vector Machine (SVM) classifier to classify these features. Various parameters were used to evaluate the obtained results like FAR and FRR. The researchers have taken the database from UCI machine learning website; this database is IITD database which contains 1120 images. The researchers obtained accuracy is about 99.14%.

An improved novel technique to identify the person is proposed by Salve and Narote [38]. This technique is based on SVM and ANN classifiers. Moreover, the proposed technique is applied 1D Log-Gabor wavelet approach to extract the features from iris pattern, then classified by SVM and ANN classifiers. The experimental tests are applied on 1000 images from CASIA iris V4 database. The classification accuracy achieved is 92.5% by ANN classifier and 95.9% by SVM classifier.

2.2. Brief table of previous studies

Table 2-1 includes a summary of iris recognition studies, each row contains researchers name, method, used database, number of images and the obtained accuracy.

Researcher	Method	Database	Number of images	Test images	Train images	Accuracy
Chengqiang & Mei [11]	DLDA + ED	CASIA V2	1200	-	-	98.56%
Kaushik & Prabir [12, 13]	GW + SVM	CASIA V2	756	-	-	99.56%
Ahmed Sahran [14]	DCT+ANN	CASIA V2	600	200	400	96.00%
Tallapragada & Rajan [15]	(GLCM+HWT) + ANN	CASIA V3	100	-	-	94%
Kumar,Chootaray Raja & Pattnaik [16]	(PCA + DWT) + KNN	CASIA V1	756	108	648	99.07%
	(PCA + DWT) + RF	CASIA V1	756	108	648	98.15%
	(PCA + DWT) + SVM	CASIA V1	756	108	648	97.22%
Rashad, Shams & El-Awady [17]	LBP + (LVQ & ANN)	CASIA & MMU1 & MMU2	-	-	-	99.87%
Yuqing, Guangqin, Yushi & Vangelia [18]	(LBP+CE) + HD	CASIA V3	-	-	-	99.27%
Savithiri & Murugan [19]	GW + HD	MMU	130	104	26	99.94%
	LBP + HD	MMU	130	104	26	99.90%
	HOG + HD	MMU	130	104	26	99.95%
Zhang & Guan [20]	EMD + KNN	CASIA V1	756	90	666	99%
Manisha & Sanjay [21]	(IDO + HT +DRS) + HD	MMU & BATH	-	-	-	99.94%
Sarode & Patil [22]	LBP+KNN	MMU	460	138	322	100%
	LBP+NB	MMU	460	138	322	94.18%
Sarmah & Kumar [23]	LMI + KNN	UPOL	384	64	320	100%
Ankit & Sunil [24]	Daugman	CASIA V3	756	-	-	99.90%
	Wildes	CASIA V3	756	-	-	98.68%
	Li Ma	CASIA V3	756	-	-	98.00%
	Tisse	CASIA V3	756	-	-	89.37%
Kulkarni, Shweta & Hegadi [25]	GLCM + SVM	CASIA V3	180	80	100	75%
	GLRLM + SVM	CASIA V3	180	80	100	57.14%
	(GLCM&GLRLM) + SVM	CASIA V3	180	80	100	88.89%
Kovoor, Supriya & Jacob [26]	(HWT + CED) + HD	UBIRIS	18	6	12	89%
Emrullah & Mehmet [27]	TEM + KNN	UPOL	384	-	-	80.74%

Brian & Kaushik [28]	DRLS + MLBP	CASIA V3	2639	-	-	81.45%
Jie, Zhe-Ming & Zhou [29]	(CT+PCA+LDA) + KNN	CASIA V4	270	27	243	96.30%
Izem & Saliha [30]	NBP + HD	CASIA V1	140	80	60	76.25%
S. Kulkarni, R. Kulkarni, U. Kulkarni & Hegadi [31]	GLCM + KNN	CASIA V3	2639	-	-	88.50%
	GLCM + FKNN	CASIA V3	2639	-	-	88.50%
Walid, Nade, Nouri & Lotfi [32]	1D Log-Gabor filter + HD	CASIA V3	2655	-	-	97.85%
Chengcheng, Weidong & Shasha [33]	ALBP + KNN	CASIA V4	2639	-	-	99.91%
	ALBP + SVM	CASIA V4	2639	-	-	99.91%
Mrinalini, Pratusha, Manikantan &Ramachandran [34]	(T-DCT + BPSO) + ED	MMU	225	-	-	78.04%
		UPOL	384	-	-	88.89%
		IITD	1120	-	-	94.04%
Aalaa, Israa & Ja'far [35]	HOG + LMT	UBIRIS V1	1877	-	-	20%
	(Gabor+ DCT) + LMT	UBIRIS V1	1877	-	-	76%
	GLCM + LMT	UBIRIS V1	1877	-	-	96%
	(HOG+ Gabor+ DCT+ GLCM) + LMT	UBIRIS V1	1877	-	-	92%
Arunalatha, Shaila & Rangaswamy [36]	(DTCWT+OLBP) + ED	CASIA V1	756	-	-	98.48%
Sachdeva & Kaur [37]	SIFT + SVM	IITD	1120	-	-	99.14%
Salve & Narote [38]	1D Log GW+ ANN	CASIA V4	1000	-	-	92.50%
	1D Log GW+ SVM	CASIA V4	1000	-	-	95.90%

Table 2-1: Summary of iris recognition studies

2.3. Summary

Many different databases are used in these studies. The most popular is CASIA database but UPOL database is more efficient because the images in this database are free of impurities. On the other hand, using methods (like LBP + KNN) and using it in a correct way may help to increase the performance. GLCM approach performance is lower than the other approaches like LBP and HOG. Moreover, Hamming Distance classifier (HD) has been used so much here and proved its efficiency. In addition, some studies applied more than one method and compare these methods together.

CHAPTER 3

3. METHODOLOGY

In this chapter, the main methodology of this thesis is illustrated as a flow chart in Figure 3-1. Then detailed description of each stage is provided. Firstly, detailed information about the two databases used in this thesis are presented. Then the pre-processing stage of iris recognition is explained. Then details about iris segmentation stage and the technique that is used in this stage are presented. And then, the iris normalization stage is described including the technique that is used in this stage. After that, the feature extraction algorithms (HOG, LBP and GLCM) are explained in details. Finally, details about classification algorithms (SVM and KNN) are provided.

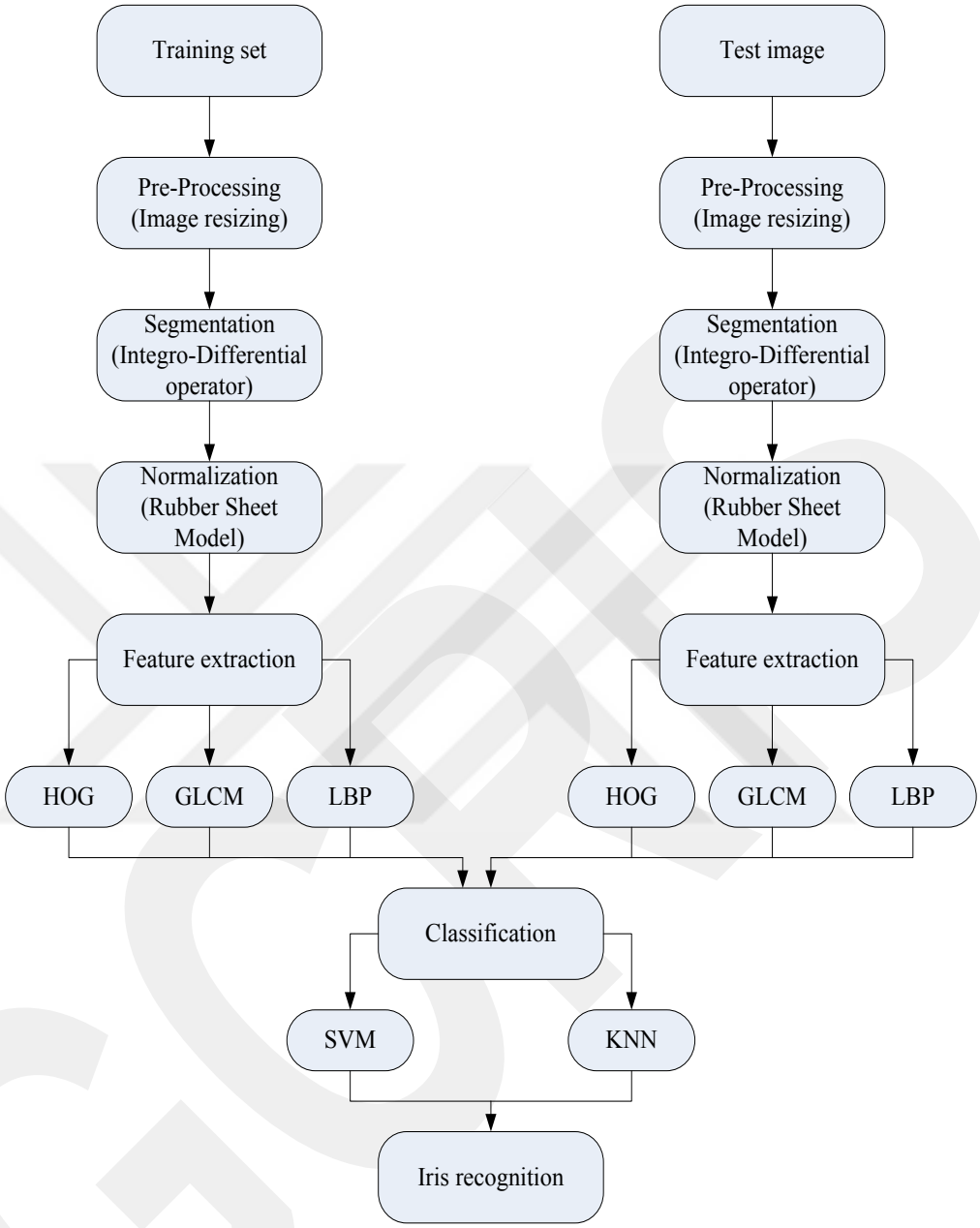

Figure 3-1: Methodology of iris recognition system

3.1. Databases

In this thesis, two databases are used to implement the proposed system, which are the University of Palack´eho and OLomouc (UPOL) database and Indian Institute of Technology Delhi (IITD) database. Each of them will be explained in the next two sections**.**

3.1.1. UPOL Database

University of Palack´eho and OLomouc (UPOL) database [39, 40] includes 384 images that were taken from 64 people, each person has 6 images, 3 images from left eye and 3 images from right eye (*See figure 3-2*). The images are 24-bit and RGB type, their size is 576×768 pixels and PNG format. This database was built within the University of Palack´eho and OLomouc. These images were captured by a TOPCON TRC50IA optical device that connected with a SONY DXC-950P3CCD camera, due to this, the images are high quality and convenient to evaluate the iris recognition system. Moreover, images are completely free of noise and characterized by homogeneity and inclusiveness making it easier in iris segmentation stage.

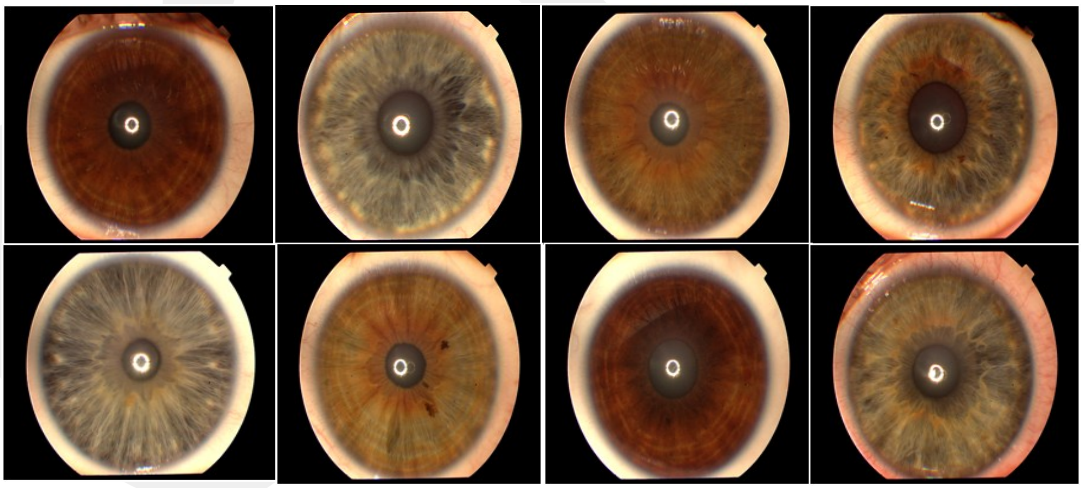

Figure 3-2: Examples from UPOL Database

3.1.2. IITD Database

Indian Institute of Technology Delhi (IITD) database was collected from the students and staff at IIT Delhi, India [73] and captured in the Biometrics Research Laboratory in the period from January to July 2007 by IRIS, JPC1000, and digital CMOS camera. The obtained images were in bitmap format. This database contains 1120 images captured from 224 persons, their ages are 14 and 55 years. These people are 176 males and 48 females (*See figure 3-3*). Sizes of the images are 320×240 pixels and RGB type. Moreover, the images were collected in the indoor environment from the volunteers who didn't pay them and didn't provide them honorarium, thus, they made it available freely to the researchers.

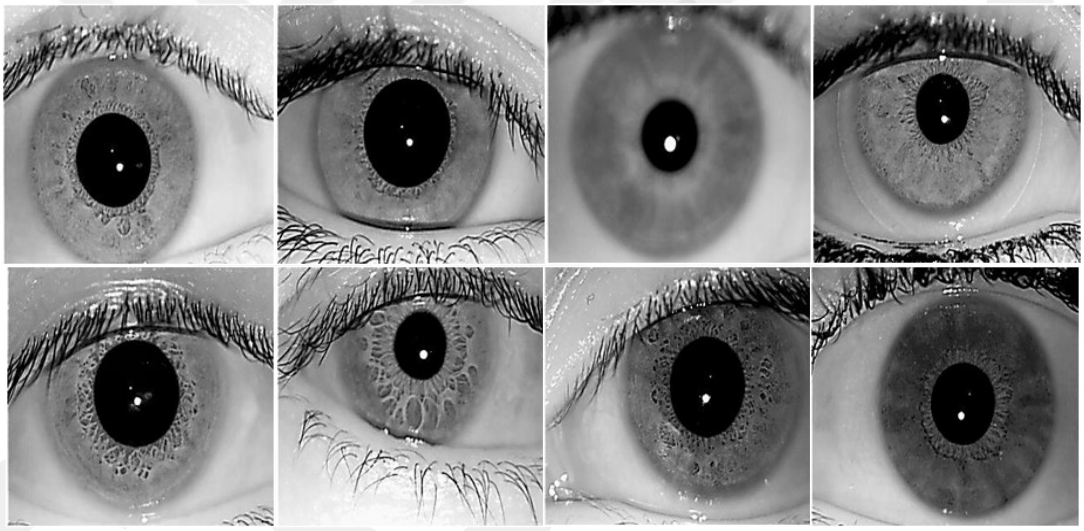

Figure 3-3: Examples from IITD Database

Table 3-1 makes a comparison between the most important information of these two databases such as; number of persons whose images were taken, number of images in each database, type of images, and format of images as well as size of images in each database, and type of device that used to capture these images. Because of that the eye image in IITD database has eyelids and eyelashes, but the eye image in UPOL database doesn't have eyelids and eyelashes, therefore, the segmentation process in UPOL database will be easy. On the contrary, the segmentation process in IITD database will be complicated to remove these eyelids and eyelashes.

Databases	Number of persons	Number of images of each person	Number of images	Images type	Images format	Images size	Used camera
UPOL	64	6	384	RGB	PNG	576×768 pixels	SONY DXC-950P3CCD camera
IITD	224	5	1120	RGB	BMP	320×240 pixels	JIRIS JPC1000 digital CMOS camera

Table 3-1: Comparison between UPOL database & IITD database

3.2. Image Pre-processing

Achieving high performance of iris recognition system requires overcoming some of the major difficulties, such as choosing the appropriate database and unifies dimensions of the image, and recruits a sufficient number of images in each experiment. In this section, the technique used in image resizing, and unify dimensions for images in each database will be explained.

3.2.1. Image Resizing

Image resizing means changing the image size from smallest to largest and from largest to smallest in order to solve the problem of a difference image sizes in a single database. This leads to get the same number of features from all images. In this thesis, decreasing the size of the images is carried out, because the databases used contain large and varying sizes images.

Moreover, decreasing of the size of the images helps to decrease the processing time, and hence increases the system performance.

(Figures 3-4 & 3-5) show the original image of the IITD database which its original size is (320×240 pixels), and the resized image with the new size that is equal to (160×120 pixels).

Figure 3-4: Example of Original image of IITD database

Figure 3-5: Example of resizing image of IITD database

Moreover, the image resizing technique is also applied on the original image of UPOL database (*See Figures 3-6 & 3-7*) which its original size is (576×768 pixels), and the obtained image with size is equal to (288×384 pixels). In other words, image resizing applied on original images of both databases in order to be ready for segmentation stage.

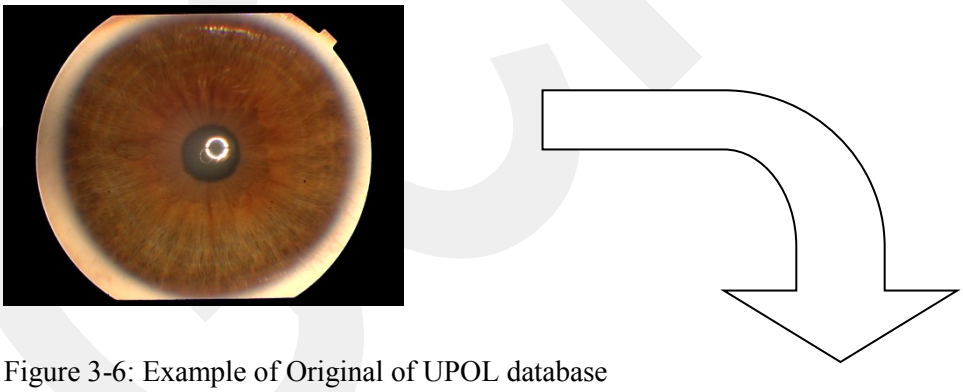

Figure 3-6: Example of Original of UPOL database

Figure 3-7: Example of resizing image of UPOL database

3.3. Segmentation

Iris segmentation [41] refers to an Automatic detection of the boundaries of iris and the boundaries of pupil of an iris in eye image in order to exclude the surrounding regions. This process helps in extracting the features from the iris for personal identification in a correct and clear manner.

In other words, the major aim of segmentation is removing non useful regions such as the parts outside the iris (eyelids, eyelashes and skin) [42]. The success of the segmentation process depends on the quality of eye image. The segmentation process determines the iris boundaries and pupil boundaries and then converts this part to a suitable template in normalization stage.

Many studies have reviewed the iris segmentation, these studies have focused on developing the techniques which are used in iris segmentation in order to increase the performance.

The studies classified the iris segmentation techniques into two categories:

- Classification according to the region of starting of segmentation process.
- Classification according to the techniques used.

On other hand, there are three groups of studies according to where the segmentation processes start:

- The first group of studies suggested that segmentation process starts from pupil, because it is the darkest part in the image [43]. According to this, pupil is localized and the boundary of the iris is fixed, then determine the iris using different techniques. Finally detect and isolate the noises from the iris part.
- The second group of studies [44] suggested that segmentation process starts from the sclera part *(see Figure 3-8, an eye region)*, because the sclera is less saturated (white) than other parts of the image, especially; the dark parts in the image are more affected by the noises than other parts. After determining the sclera part, detect the iris using different techniques. Finally detect and isolate the pupil and noises from the iris.
- The third group [45, 46] suggested to determine the iris directly using edge operators. Further, there are two techniques to determine the iris:

- The first approach uses edge detection [47] and Hough Transform for segmentation.
- The second approach uses different types of techniques to detect the iris boundary like Camus and Wildes operator and Daugman‘s [48] Integro-Differential operator.

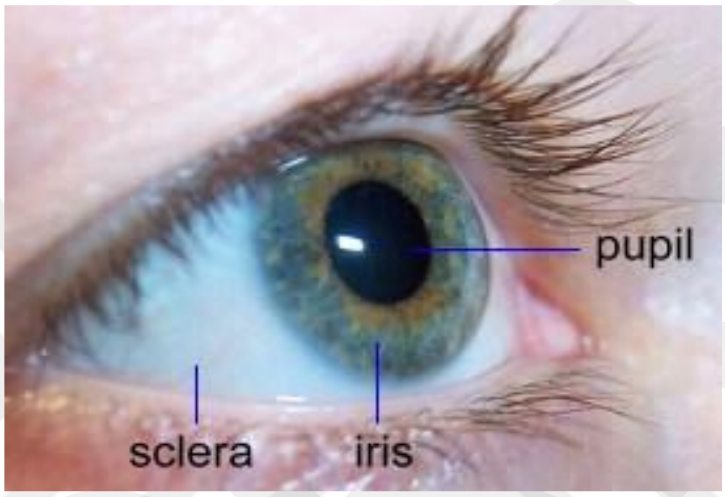

Figure 3-8: Image of an eye appears the iris, pupil and sclera [49]

3.3.1. Daugman‘s Integro-Differential Operator

In this thesis, Daugman‘s Integro-Differential operator is used for iris segmentation. In this technique, both iris and pupil are assumed two circular forms [50] *(See figures 3-10&3.12)*. The main task in this technique is to define the center coordinates, and the radius of the pupil and the iris. Daugman’s equation that is used for this task is given by:

$$\max_{(r,x_0,y_0)} \left| G\sigma(r) * \frac{\partial}{\partial r} \oint_{r,x_0,y_0} \frac{I(x,y)}{2\pi r} ds \right| \qquad (3\text{–}1)$$

Where,

I(x,y), is the density of the pixel at the coordinates (x,y) in the iris image.

r, refers to the radius of different circular regions with the coordinates center at (x_0, y_0).

σ , is the standard perversion of the Gaussian distribution.

Gσ(r), refers to a Gaussian filter of scale sigma (σ).

(x_0, y_0), considered the center of coordinates of the iris.

s, is the contour of the circle assumed by the parameters (r, x_0, y_0).

Applying Daugman's Integro-Differential Operator on the original images of UPOL database (*See figure 3-9*) and IITD database (*See figure 3-11*) gives the images illustrated in (*figure 3-10*) for UPOL database, and (*figure 3-12*) for IITD. Moreover, this technique makes two circles, the red circle on the pupil shows how to separate between the pupil and the iris and the green circle on the iris shows how to separate between the iris and the other eye parts.

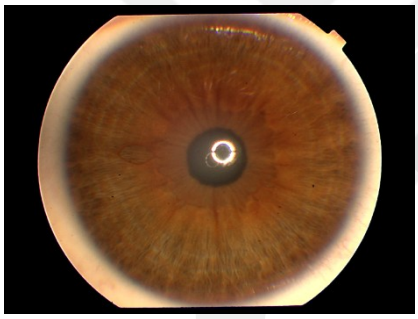

Figure 3-9: Original image of UPOL database

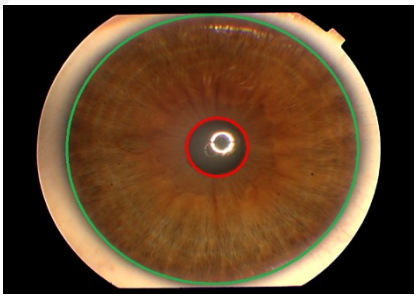

Figure 3-10: Iris segmentation using Daugman's Integro-Differential operator (UPOL DB)

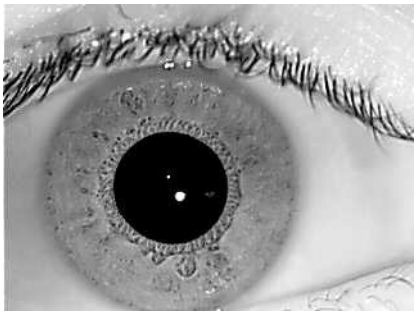

Figure 3-11: Original image of IITD database

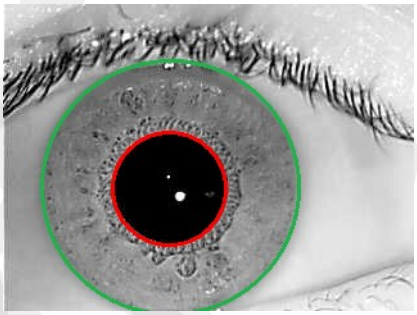

Figure 3-12: Iris segmentation using Daugman‘s Integro-Differential operator (IITD DB)

In brief, Iris segmentation process is the most important stage in iris recognition system, because if the iris segmentation process succeeded this will lead to extract features correctly, and therefore; a high performance in iris recognition system will be achieved.

3.4. Normalization

After the iris is segmented successfully from an eye image, the next step is to transform the iris part to a specified dimensional pattern in order to allow extracting the features. The normalization process [51] creates iris regions, which have the same fixed dimensions, so that two images of the same iris in different conditions will have distinctive features at the same spatial location. Dimensional [3] inconsistencies in the normalized iris may occur due the expansion in pupil size which causes the stretching of iris size. Moreover, some factors such as, the varying levels of illumination falling on the eye, imaging distance, head tilt, and camera rotation may cause incorrect normalization process for iris.

3.4.1. Daugman's Rubber Sheet Model

Daugman's Rubber Sheet Model [52] is used for iris normalization in this study. Daugman has designed a rubber sheet model *(See figure 3-13)* which aims to reset each point inside the iris region on a pair of polar coordinates (r, θ), where r ranges from [0, 1], and θ ranges from [0, 2π].

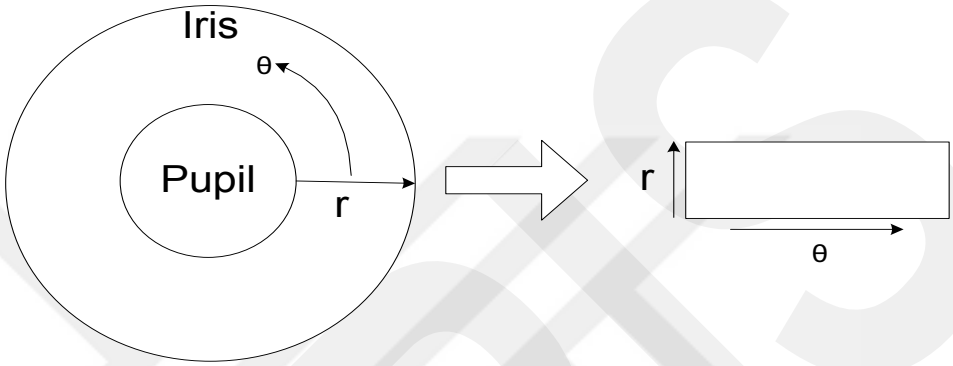

Figure 3-13: Daugman's Rubber Sheet Model

The Cartesian to polar transform can be represented as:

$$I(x(r, \theta), y(r, \theta)) \rightarrow I(r, \theta) \quad (3–2)$$

Where

$$x(r, \theta) = (1-p) \times x_p(\theta) + p \times x_i(\theta) \quad (3–3)$$

$$y(r, \theta) = (1-p) \times y_p(\theta) + p \times y_i(\theta) \quad (3–4)$$

Where;

I(x, y), refers to iris image.

(x & y), are the actual coordinates.

(r & θ), are the corresponding polar coordinates.

(x_p & y_p) and (x_i & y_i), are the coordinates of pupil and iris boundaries respectively along the θ direction.

On other hand, rubber sheet model [53] is characterized with taking into account the sizes inconsistencies and pupil dilation, therefore; it produces a normalized patterns with fixed and persistent dimensions.

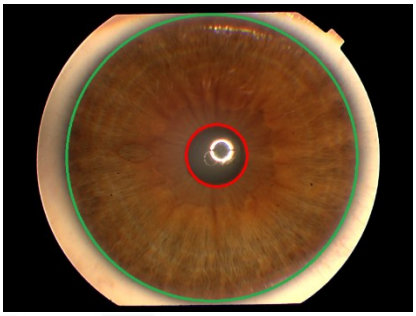

Figure 3-14: Iris segmented of UPOL database

Figure 3-15: Iris normalization using Daugman's Rubber Sheet Model (UPOL DB)

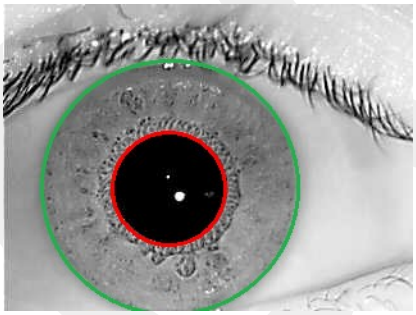

Figure 3-16: Iris segmented of IITD database

Figure 3-17: Iris normalization using Daugman's Rubber Sheet Model (IITDDB)

Applying the rubber sheet model on iris segmented of UPOL database *(Figure 3-14)* and iris segmented of IITD database *(Figure 3-16),* yields the iris as shown in *(Figure 3-15)* for UPOL database & (*Figure 3-17)* for IITD database that are converted from circular shape to rectangular shape, thus the iris has become ready to feature extraction stage. Moreover, type of images in both databases has been converted from RGB to gray scale. The image resizing technique is applied on original images to prepare for segmentation stage. However, this technique is applied again on normalized iris patterns to prepare for feature extraction stage. The size of normalized iris pattern of UPOL database is equal to (125×15 pixels) as shown in *(Figure 3-19)*.

Figure 3-18: Example of normalized Iris of UPOL database

Figure 3-19: Example of resizing Iris of UPOL database

Also, image resizing technique applied on normalized iris pattern of IITD database and the size of normalized iris made equal to (216×24 pixels) as shown in (*Figure 3-21*).

Figure 3-20: Example of normalized Iris of IITD database

Figure 3-21: Example of resizing Iris of IITD database

3.5. Feature Extraction

After the completion of the normalization process for iris part, iris pattern is ready for feature extraction stage. Extracting features from the iris image is the most important stage in iris recognition system; especially this system depends on the features that are extracted from iris pattern.

Here, three approaches are used to extract the features from the iris; these approaches differ from each other in terms of method of extracting features. These approaches are HOG approach, GLCM approach and LBP approach, however; a detailed explanation of these approaches will be presented in the next following sections.

3.5.1. Histograms of Oriented Gradients (HOG)

In 2005 Dalal and Triggs [54] invented Histogram of Oriented Gradients (HOG) which is feature descriptors that are used in image processing and computer vision in order to detect the objects [55]. It has achieved high performance in computer vision through finding radical solutions for a variety of problems related to the objects detections, extracting the features from these objects, and achieving the recognition [56]. The input image is divided by HOG into square cells. The main idea behind the Histogram of Oriented Gradient descriptors is that object appearance within an image can be described by the distribution of intensity gradients, and these descriptors can be implemented by dividing the image into small regions, these regions are called cells. Then the histogram of gradient directions in each cell are compiled, these histograms represent the descriptor (*See Figure 3-22*). Moreover, the histograms can be normalized by computing the intensity through a larger region of the image, this region is called block, and then normalize all cells within the block. However, computing the intensity across a large region of the image can improve the accuracy. The HOG descriptor operates on local cells; therefore it maintains a few key advantages if compared with other methods [56].

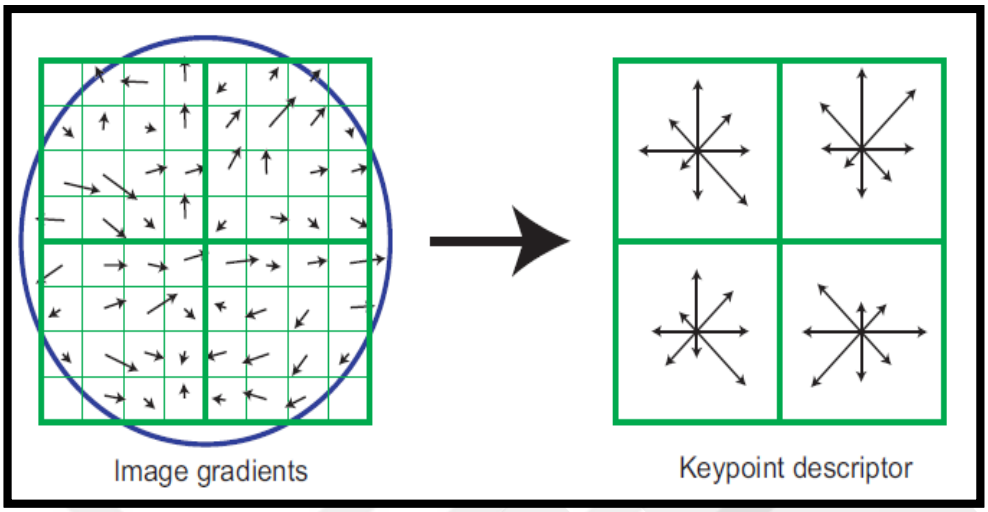

Figure 3-22: Image Gradients and Orientation Histogram [57]

When Dalal & Triggs presented HOG algorithm, Dalal has recommended some values for the HOG parameters to get good performance. The recommendations are for setting window size equal to 64×128, block size equal to 16×16, and cell size equal to 8×8. However, now this algorithm is a ready function, which is simple and very easy to use, in many image processing tools (e.g., Matlab), so no need to change any parameters [54].

However, Histograms of Oriented Gradients is applied on iris normalized of UPOL database *(Figures 3-23),* and iris normalized of IITD database *(Figure 3-25)*. The results illustrated in *(Figures 3-24)* for UPOL database, and *(Figures 3-26)* for IITD database reveal how the HOG algorithm captures the iris patterns and distribute the intensity gradients on these patterns, then computes all pixels in each pattern through extracting all the features of this pattern and make a one-dimensional array of these features.

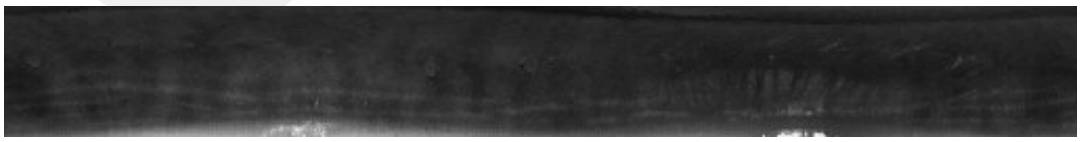

Figure 3-23: Normalized iris of UPOL database

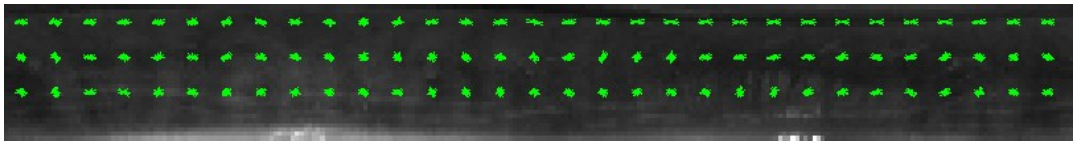

Figure 3-24: Example of Histogram of Oriented Gradients (UPOL DB)

Figure 3-25: Normalized iris of IITD database

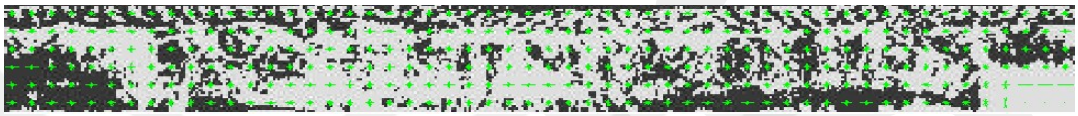

Figure 3-26: Example of Histogram of Oriented Gradients (IITD DB)

3.5.2. Gray Level Co-Occurrence Matrix (GLCM)

GLCM approach is a method of extracting features from patterns. It has been used in a various applications such as extracting textural feature from images [58]. In addition, GLCM is a matrix that contains a number of rows and columns that are equal to the number of gray levels. It considers a popular statistical method for feature extraction from images. Moreover, GLCM is also called Gray level Dependency Matrix and defines as two-dimensional histogram of gray levels for pixels pair [59].GLCM is calculated by a displacement vector d using radius δ and direction θ. Here we consider an image with 4×4 pixels as shown in *(Table 3-2)*, the image is represented with four gray-tone values 0 to 3. GLCM for this image is represented in *(Table 3-3)*. # (i, j), is a number of times gray tones, i and j represent neighbors. In addition, GLCM calculates through specifying the number of times to repeat the two neighbor's elements in the same order in the matrix. For instance: for two elements (1, 0), the number of times repeated the two elements neighbors (1, 0) in the same order is calculated, and put the value of repetition in the location (1, 0) in GLCM matrix. More explanation of working mechanism of GLCM will be given at a later example. On other hand, dimensions of GLCM is determined by using 'NumLevels' parameter, which takes one of the following values (2,4,8,16,32,64,128,256...etc.).

1	0	0	1
0	2	1	0
2	3	0	1

Table 3-2: Example of original image

Gray tone	0	1	2	3
0	#(0,0)	#(0,1)	#(0,2)	#(0,3)
1	#(1,0)	#(1,1)	#(1,2)	#(1,3)
2	#(2,0)	#(2,1)	#(2,2)	#(2,3)
3	#(3,0)	#(3,1)	#(3,2)	#(3,3)

Table 3-3: General form of GLCM

GLCM contains Four angels (*Figure 3-27*), Horizontal (0°) takes the coordinates (0, D), Vertical (90°) takes the coordinates (-D, 0), Bottom left to top right (45°) takes the coordinates (-D, D) and Top left to bottom right (135°) takes the coordinates (-D, -D). Where , D represents the distance parameter and takes value 1 by default, and every offset parameter a different GLCM will be calculated, which may affect the performance of the proposed method [60].

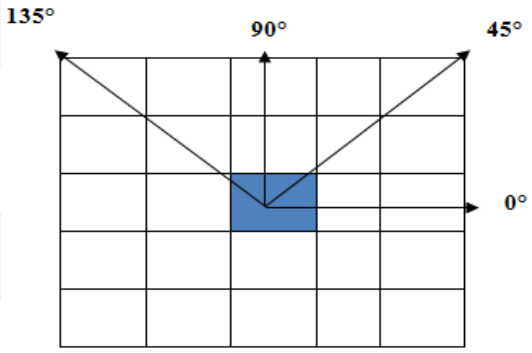

Figure 3-27: GLCM angles

Here, we investigate GLCM angels on image 4×4 pixels *(See Table 3-4)*. In the first case, when θ = 0° we check the first location of GLCM (0,0) and calculate how many times neighbor's elements 0 and 0 is repeated in horizontal direction and in two directions (left to right and right to left), we find two times repeated, once from left to right and second from right to left, then put value 2 in location (0,0) in GLCM matrix. Then in the same case we check the second location of GLCM (0,1) and calculate how many times neighbor's elements 0 and 1 is repeated in horizontal direction and in two directions (left to right and right to left), we find four times repeated, then put value 4 in

location (0,1) in GLCM. The same steps have applied on the other cases (45°, 90° and 135°) with the difference of direction

1	0	0	1
0	2	1	0
2	3	0	1
1	3	2	1

Original Image

	0	1	2	3
0	2	4	1	1
1	4	0	2	1
2	1	2	0	2
3	1	1	2	0

GLCM for θ = 0°

1	0	0	1
0	2	1	0
2	3	0	1
1	3	2	1

Original Image

	0	1	2	3
0	4	0	1	1
1	0	2	1	2
2	1	1	2	0
3	1	2	0	0

GLCM for θ = 45°

1	0	0	1
0	2	1	0
2	3	0	1
1	3	2	1

Original Image

	0	1	2	3
0	0	5	3	0
1	5	2	1	0
2	3	1	0	1
3	0	0	1	2

GLCM for θ = 90°

1	0	0	1
0	2	1	0
2	3	0	1
1	3	2	1

Original Image

	0	1	2	3
0	2	2	1	1
1	2	2	1	0
2	1	1	0	2
3	1	0	2	0

GLCM for θ = 135°

Table 3-4: GLCM for Four angels

We applied GLCM approach on normalized iris of UPOL database *(Figure 3-28),* and normalized iris of IITD database *(Figure 3-30)*, and the results for the two databases are illustrated in *(Figure 3-29) & (Figure 3-31)* respectively. We have allocated value 64 for 'NumLevels' parameter and combined four angles together (0°, 45°, 90° and 135°) in order to achieve high performance in feature extraction. Combining four angles together makes GLCM approach able to gather features from iris in different directions.

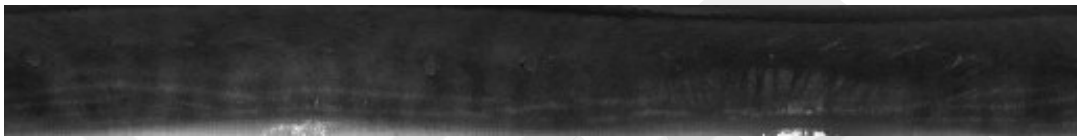

Figure 3-28: Normalized iris of UPOL database

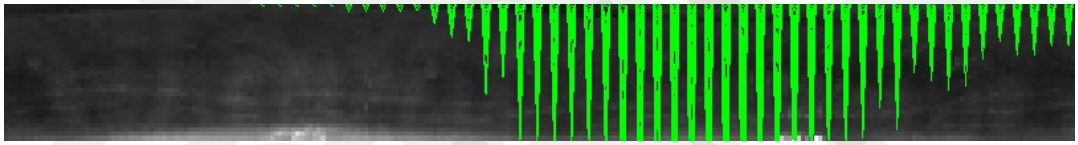

Figure 3-29: Example of Gray Level Co-Occurrence Matrix (UPOL DB)

Figure 3-30: Normalized iris of IITD database

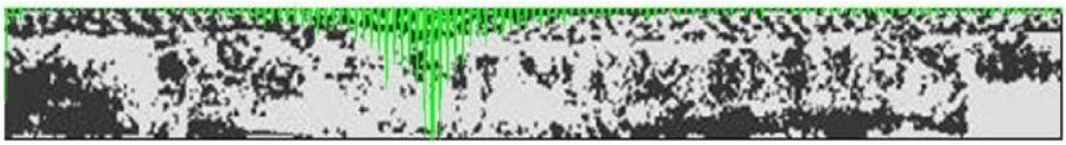

Figure 3-31: Example of Gray Level Co-Occurrence Matrix (IITD DB)

3.5.3. Local Binary Pattern (LBP)

LBP approach is a simple technique that is very efficient in extracting features from patterns, it is able to label the pixels of an image by thresholding the neighbors of each

pixel and the results are considered as a binary value [61]. Moreover, LBP approach has become a popular technique in feature extraction field from the patterns, because of its computational simplicity and it has a discriminative power, therefore; it performs analysis on the patterns in real time settings. On other hand, the most important attribute of the LBP approach in its applications is its ability to control in gray-scale changes, such as illumination variations [62].

In LBP approach *(see Figure 3-32)*, the input image is divided into 'N×N' of local regions, and each region is composed of a '3×3' neighborhood of each pixel of the central pixel's value. Then, type of binary pattern will be assigned a label to each pixel according to its intensity value, and these binary patterns in each block are distributed, and then; the results are represented with an 8-bits integer. Finally, the patterns are calculated and used to represent the feature [62].

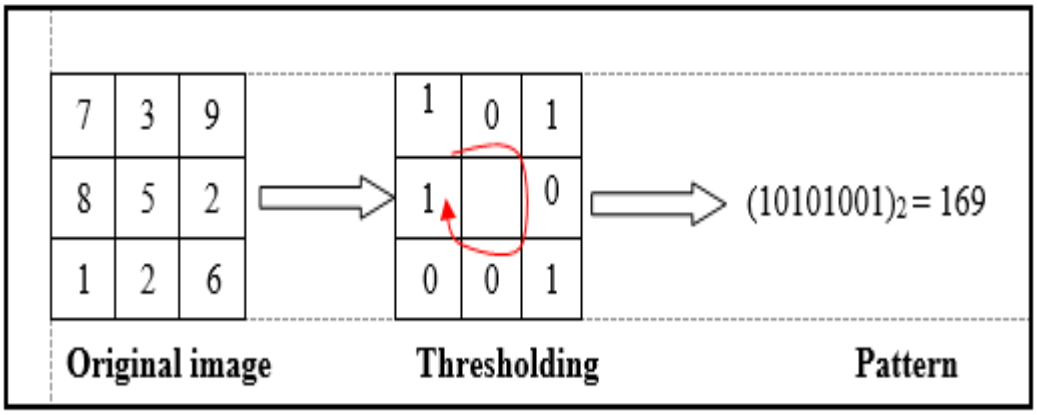

Figure 3-32: Mechanism of LBP approach

(Figure 3-32) explains the main mechanism of LBP approach, an input image has divided by LBP approach into several blocks, each block is divided into '3×3' neighbourhood pixels (9 cells), then each pixel is encoded by its intensity value, then threshold the value of the central pixel which is 5 in *(Figure 3-32)*, LBP ordering all surrounding pixels within the block from the upper-left corner down to the right one depending on whether it has bigger or smaller intensity value than the central pixel (bigger value = 1; smaller = 0). Finally, we get binary number which is (10101001), this

number is converted to decimal number to become (169) and stored in one dimensional array.

Here, LBP approach is applied on iris normalized of UPOL database *(Figure 3-33)* and Iris normalized of IITD database *(Figure 3-35)*, and the results shown in *(Figure 3-34) & (Figure 3-36)* show the ability of LBP approach to capture entire the iris by looking to each pixel's neighbors, these pixels will be computed, where the LBP will extract all the features of this iris and create a one-dimensional array of patterns that can be classified later by using any classification algorithm.

Figure 3-33: Normalized iris of UPOL database

Figure 3-34: Example of LBP approach (UPOL database)

Figure 3-35: Normalized iris of IITD database

Figure 3-36: Example of LBP approach (IITD database)

3.6. Classification

In this thesis, two different classifiers are used. They are Support Vector Machine (SVM) and K-Nearest Neighbor (KNN). These classifiers are trained and tested by features extracted from iris pattern, each classifier is trained several times by the set of iris images then tested by other set of iris images.

3.6.1. Support Vector Machine (SVM)

Support Vector Machine (SVM) was introduced in 1992 by Vapnik, Boser and Guyon. SVM is a learning based method that is used for classification. It belongs to a linear classifiers family. In another term, SVM is a classification and prediction tool that employs machine learning theory in order to achieve greater predictability while avoiding ignoring valid data. SVM was a part of Neural Information Processing Systems (NIPS) community, but now it becomes one of the most famous learning machines in the world, as it uses pixel maps as input, moreover; this technique is used in a various applications such as face analysis and patterns classification [63]. SVM approach is used to solve the patterns classification problems. Using SVM to solve specific practical problem, resolve many of the questions that depend on the definition of the problem. The main challenge in using SVM is choosing a suitable kernel for the applications which are needed to use SVM [64].

SVM has many advantages such as it is comparatively easy to the training and it is suitable to high dimensional data and its ability to control clearly on the trade-off between classifier complexity and error. On the other hand, the weakness of SVM is it needs a suitable kernel function [65, 66].

Kernel functions help to handle data as though it were projected into a higher dimensional space, by operating on it in its original space and this leads to efficient algorithms [67].

The SVM mechanism is based on choosing the closest point to the border between two classes, that is called "Optimal Separating Hyper-plane"(OSH). In (*figure 3-37*), the line Z1 is Located in the center of the distance between the class-1 that represented by the circles, and the class-2 that represented by the stars. The distance between line Z1 and the closest point of two classes was measured, it is normal to find two or more points in

the same level such as in class-1, two circles in the same level. Then the same distance is placed between Line Z1 and the second class. By increasing the distance between Line Z1 and classes, SVM can compute more points of two classes, therefore; increase the performance [68].

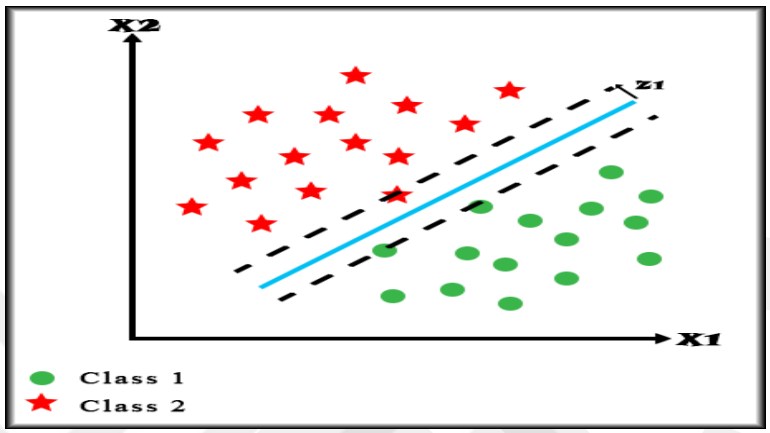

Figure 3-37: Support Vector Machine Mechanism

3.6.1.1. Multi-Class SVM problem

By default, SVM is used to classify only two classes. Here we have many classes, therefore; default SVM couldn't be used. Researchers have developed several techniques that simulates SVM mechanism for more than two classes; such as One-vs.-One approach [69], One-vs.-All [70] approach and Error-Correcting Output Coding (E-COC) approach [71]. One-vs.-All approach has been used in this thesis. This approach helped us to solve multi- class's problem and implement iris recognition system. In this thesis, each person is considered representing a class, therefore; we have 64 classes in UPOL database and 224 classes in IITD database.

The main idea of One-vs.-All approach is using each class against all other classes, the SVM trains up a binary classification as: Class_1 vs. not Class_1, Class_2 vs. not Class_2;.....until last Class, in this case, Class_1 represents the positive samples and the all other classes together represent the negative samples. Moreover, in the second case, Class_2 has trained up with not Class_2, in each case, Class_2 represents the positive samples and the all other classes together represent the negative samples including Class_1 and the classifier continues up to the last class. Finally, the classifier selects the suitable class related to each tested sample.

3.6.2. K-Nearest Neighbor (k-NN)

KNN classifier is one of the simplest algorithms for classifying objects, it operates under supervision. KNN is used in machine learning applications, regression and pattern recognition [60]. Furthermore, it is very easy to implement and highly efficient in various applications that use classification techniques. The basic idea of its function is taking the neighboring value of the check data in a feature space *(Figure 3-38)*. In addition, it is a nonparametric statistic, because it doesn't make assumption about probability distributions of the variables being used. Moreover, KNN algorithm classifies the objects by three steps [68];

- Computes the distance between all training vectors and test vector.
- Chooses K closest vectors.
- Computes the average of closest vectors distances.

In other words, in KNN; the output considered is membership of a class. Any new object is classified depending on vote's number of its neighbors. In k nearest neighbors; if $K = 1$, this means the object belongs to the class of that single nearest neighbors. However, in KNN, there is no particular way to select K, only we try to select the best one. KNN doesn't need to the training examples, it uses the training, therefore; it is a lazy learning algorithm. Moreover, it uses training set directly to train and then classify an input when inputs and k value are given.

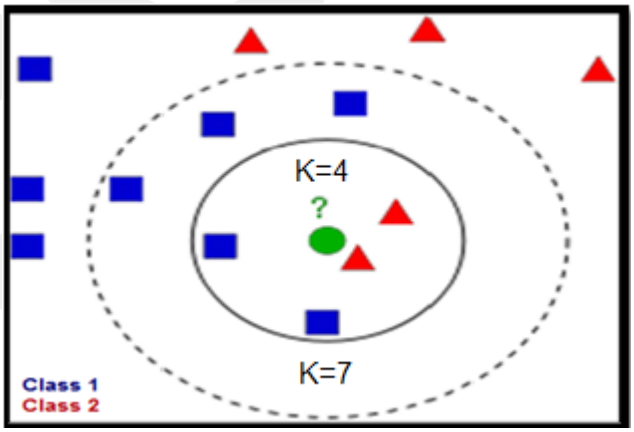

Figure 3-38: K-Nearest Neighbor mechanism [72]

In above figure, there are two sets, blue squares represent the first Class and the red triangles represent the second Class, and these Classes are represented on a feature space. Features can be imagined as a space like a space that includes all the data, for example, two-dimensional space. So, these data have two features which are two coordinates x and y and these data can be represented in our space. For example, the data that represented by a green circle is a new data and we want to add it to the combined red & blue set, this step is called the classification. In order to do classification there is method to check the closest neighbor; in the figure, the red triangle is the closest neighbor for the new data (green circle), therefore; the new data is added to Class 2. In this example, the classification process relies on the nearest neighbor, therefore; this technique is called the Nearest Neighbor. Moreover, if we let $K = 4$, this means 4 closest objects. Thus, there are two red objects and two blue objects, in this case the new data will added to red objects. On other hand, if we let $k = 7$, that means there are 2 red objects and 5 blue objects, thus, we must add the new data to the blue objects (Class 1). In KNN algorithm, it is good to give importance for k neighbors, at the same time; we should give equal importance for the all. For example, if $K = 4$, this means there are two blue objects (Class 1) and two red objects (Class 2), but the new data (green circle) is nearer to red objects than others, therefore; it is added to red objects (Class 2).

CHAPTER 4

4. EXPERIMENTAL RESULTS

In this chapter, the proposed experiments will be examined in order to iris recognition from eye image collected from different individuals. Here, the experiments will be implemented using two databases, each database separately. Firstly, results obtained using UPOL database will be presented, then the results that obtained from IITD database.

4.1. UPOL DATABASE RESULTS

As mentioned earlier, this database consists of 384 images that are collected from 64 individuals, each individual has 6 images. The database is divided into testing set and training set. When the testing set contains 1 image and the training set contains 5 images for each person, it means that database divided to 64 images for testing and 320 images for training, and if the testing set contains 2 images, and the training set contains 4 images for each person, it means that database is divided to 128 images for testing and 256 images for training. Moreover; when the testing set consists of 3 images and the training set consists of 3 images for each person that means database divided to 192 images for testing and 192 images for training, and if the testing set contains 4 images and the training set contains 2 images for each person, that means database divided to 256 images for testing and 128 images for training. Finally; when the testing set contains 5 images and the training set contains only 1 image for each person that means database divided to 320 images for testing and 64 images for training.

Various methods are applied on this database in order to evaluate the performance of proposed system. Each method is applied separately, and then the obtained results are compared with each other to determine which method is the best between the methods used.

4.1.1. Histogram Oriented Gradient (HOG) Method

In this method, features are extracted by using HOG approach, and then KNN & SVM classifiers are applied each one separately to classify these features. In here, the images are distributed in different ways as shown in (Table 4-1). The best performance was when the testing set contains 1 image and the training set contains 5 images for each person. In this arrangement, HOG+KNN method achieved 100% of recognition rate, while HOG+SVM method achieved 96.87% of recognition rate.

Method	**Images for each person**				
	1 image for test & 5 images for train	2 images for test & 4 images for train	3 images for test & 3 images for train	4 images for test & 2 images for train	5 images for test & 1 image for train
HOG + KNN	100%	99.12%	98.43%	95.24%	93.50%
HOG + SVM	96.87%	87.14%	79.69%	75.28%	73.84%

Table 4-1: Results of HOG approach on UPOL database

4.1.2. Local Binary Pattern (LBP) Method

In this method, LBP approach is used to extract the features from iris image, then these features are classified using two classifiers KNN and SVM. The method is applied in the same way as the previous method. And also, the best performance was When the testing set contains 1 image and the training set contains 5 images for each person as shown in *(table 4.2)*, the achieved accuracy was 98.43% by LBP+KNN method, and 96.87% by LBP+SVM method.

Method	**Images for each person**				
	1 image for test & 5 images for train	2 images for test & 4 images for train	3 images for test & 3 images for train	4 images for test & 2 images for train	5 images for test & 1 image for train
LBP + KNN	98.43%	97.14%	94.27%	93.08%	92.00%
LBP + SVM	96.87%	90.69%	85.41%	82.66%	81.29%

Table 4-2: results of LBP approach on UPOL database

4.1.3. Combined (HOG &LBP) Method

In this method, the combination of two approaches together (HOG & LBP) are implemented to extract the features from iris image, and then the extracted features were classified by using KNN and SVM classifiers. The main idea of this method, HOG & LBP are extracting the features each one separately then these features are collected together, and stored in one dimensional matrix. Equally, the database is divided to testing set and training set as illustrated in *(table 4.3)*. The best performance was when the testing set includes 1 image and the training set includes 5 images for each person, the achieved accuracy was 93.75% by (HOG&LBP) +KNN method, and 88.90% by (HOG&LBP) +SVM method.

Method	**Images For each person**				
	1 image for test & 5 images for train	2 images for test & 4 images for train	3 images for test & 3 images for train	4 images for test & 2 images for train	5 images for test & 1 image for train
Combined (HOG&LBP) + KNN	93.75%	89.17%	85.93%	83.96%	80.25%
Combined (HOG&LBP) + SVM	88.90%	86.81%	85.32%	82.41%	81.73%

Table 4-3: Results of Combined HOG&LBP approaches on UPOL database

4.1.4. Gray Level Co-Occurrence Matrix (GLCM) Method

GLCM approach differs from HOG & LBP approaches in the method of extracting features and storing these features. However, different parameters such as 'Num Level' and 'Offset' are used in this approach. 'NumLevel' parameter means the matrix dimensions and takes the values ‘2, 4, 8, 16, 32, 64, 128, 256, etc.’ 'Offset' parameter means directions which through it the features can be calculated, and includes 0° which takes the coordinates(0, D), 45° that takes the coordinates(-D, D), 90° which takes the coordinates (-D, 0), and 135° which takes the coordinates (-D, -D) as D takes any value. In our experiments, these offsets combined together, because after many examples, the

combination of these offsets together achieved better performance. In this method, similarly; the database is divided to testing set, and training set. On other hand, all parameters applied on each case of database *(Table 4-4),* and the best accuracies observed to be achieved by using 'NumLevel=64' in each case. When the testing set arranged to contain 1 image, and the training set to contain 5 images for each person; GLCM+KNN method achieved recognition rate of 90.63%, while GLCM+SVM method achieved recognition rate of 81.45%.

	Images	**Parameters**					
Method	**Images for each person**	**N_level 8**	**N_level 16**	**N_level 32**	**N_level 64**	**N_level 128**	**N_level 256**
GLCM+KNN	1 image for test & 5 images for train	67.81%	76.56%	82.81%	90.63%	89.06%	85.94%
GLCM+SVM		64.22%	69.84%	73.94%	81.45%	78.71%	76.33%
GLCM+KNN	2 images for test & 4 images for train	66.02%	72.90%	77.61%	82.23%	79.45%	74.98%
GLCM+SVM		62.19%	68.90%	73.14%	74.89%	72.51%	68.76%
GLCM+KNN	3 images for test & 3 images for train	58.02%	66.45%	73.22%	76.56%	74.87%	71.37%
GLCM+SVM		56.89%	59.77%	62.93%	68.60%	66.10%	64.77%
GLCM+KNN	4 images for test & 2 images for train	56.03%	63.97%	71.11%	74.10%	72.95%	68.02%
GLCM+SVM		53.91%	57.07%	61.00%	65.27%	64.08%	61.45%
GLCM+KNN	5 images for test & 1 image for train	52.97%	61.00%	68.81%	72.50%	69.63%	66.22%
GLCM+SVM		51.08%	56.98%	57.41%	61.91%	61.37%	59.01%

Table 4-4: Results of GLCM approach on UPOL database

A summary results of all methods that we applied on UPOL database are illustrated in (*Table 4-5*) below.

Method	**Overall accuracy**
HOG + KNN	100%
HOG + SVM	96.87%
LBP + KNN	98.43%
LBP + SVM	96.87%
Combined (HOG&LBP) + KNN	93.75%
Combined (HOG&LBP) + SVM	88.90%
GLCM + KNN	90.63%
GLCM + SVM	81.45%

Table 4-5: Overall accuracies of UPOL database when 1 image is used as testing and 5 images is used as training

From above experimental results, we notice that the performance of HOG and LBP approaches separately is better than the performance of GLCM approach. Moreover, the performance of KNN classifier is better than SVM classifier. However; *(Figure 4-1)* reviews a general comparison between all results of UPOL database.

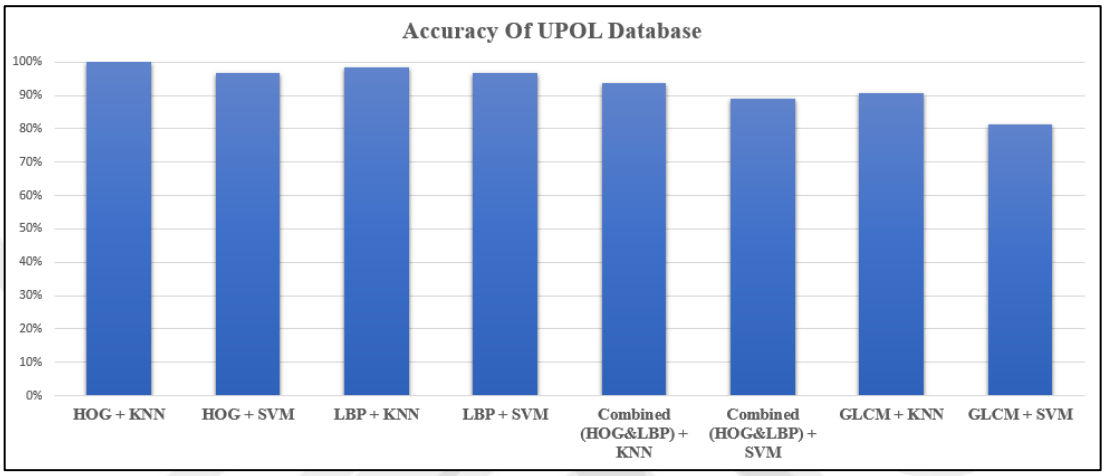

Figure 4-1: Comparison between the proposed methods on UPOL database

4.2. IITD DATABASE RESULTS

IITD database contains on 1120 images that are collected from 224 persons, each person has 5 images. Moreover, the same previous methods have applied on IITD database. And the database is divided to testing set and training set, when the testing set contains 1 image and the training set contains 4 images for each person; that means the database is divided to 224 images for the testing set and 896 images for the training set. Moreover, when the testing set contains 2 images and the training set contains 3 images for each person; that means the database is divided to 448 images for the testing set and 672 images for the training set. When the testing set consists of 3 images and the training set consists of 2 images for each person; that means the database is divided to 672 images for the testing set and 448 images for the training set. In last case, when the testing set contains 4 images and the training set contains 1 image for each person; that means the database is divided to 896 images for the testing set and 224 images for the training set. Now, all experiments will be examined based on this type of database and the obtained results that related to this database will be illustrated below.

4.2.1. Histogram Oriented Gradient (HOG) Method

When allocated 1 image for the testing set and 4 images for the training set for each person as shown in *(Table 4-6)*, HOG approach achieved recognition rate of 100% with KNN and 97.76% with SVM.

Method	**Images for each person**			
	1 image for test & 4 images for train	2 images for test & 3 images for train	3 images for test & 2 images for train	4 images for test & 1 image for train
HOG + KNN	100%	99.33%	98.21%	96.31%
HOG + SVM	97.76%	96.42%	95.83%	78.12%

Table 4-6: Results of HOG approach on IITD database

4.2.2. Local Binary Pattern (LBP) Method

LBP approach also is used to extract features from iris images, and then the classifiers KNN & SVM are used to classify the extracted features. In the division of database, same steps that are carried out in HOG method will be applied. The best performance was when the testing set contains 1 image and the training set contains 4 images for each person as in *(Table 4-7)*, the achieved accuracy was 99.55% by LBP+KNN method and 99.10% by LBP+SVM method.

Method	**Images for each person**			
	1 image for test & 4 images for train	2 images for test & 3 images for train	3 images for test & 2 images for train	4 images for test & 1 image for train
LBP + KNN	99.55%	99.33%	97.91%	96.43%
LBP + SVM	99.10%	98.66%	97.17%	91.85%

Table 4-7: Results of LBP approach on IITD database

4.2.3. Combined (HOG&LBP) Method

In this method, the same applied as the previous steps in the division of database. When the testing set contains 1 image and the training set contains 4 images for each person *(Table 4-8)*; the achieved recognition rate was 99.55% by Combined (HOG&LBP) +KNN method, and 99.10% by Combined (HOG&LBP) +SVM method.

Method	**Images for each person**			
	1 image for test & 4 images for train	2 images for test & 3 images for train	3 images for test & 2 images for train	4 images for test & 1 image for train
Combined (HOG&LBP) + KNN	99.55%	99.33%	98.21%	96.31%
Combined (HOG&LBP) + SVM	99.10%	98.66%	95.83%	78.12%

Table 4-8: Results of Combined HOG&LBP approaches on IITD database

4.2.4. Gray Level Co-Occurrence Matrix (GLCM) Method

In this method, again the offsets (0, 45, 90 and 135) are combined, and the parameters used in the previous database are applied. In here, the best performance achieved when 'NumLevel= 16" as shown in *(Table 4-9)*. When the testing set contains just 1 image and the training set contains 4 images for each person; the best recognition rate achieved at 90.05% by GLCM+KNN method and 85.52% by GLCM+SVM method.

	Images	Parameters					
Method	**Images for each person**	**N_level 8**	**N_level 16**	**N_level 32**	**N_level 64**	**N_level 128**	**N_level 256**
GLCM+KNN	1 image for test & 4 images for train	83.26%	90.05%	88.24%	85.97%	81.90%	75.11%
GLCM+SVM		80.11%	85.52%	84.71%	83.81%	81.57%	74.89%
GLCM+KNN	2 images for test & 3 images for train	85.29%	87.10%	86.33%	83.71%	80.14%	78.91%
GLCM+SVM		82.17%	84.91%	83.22%	82.07%	81.11%	76.00%
GLCM+KNN	3 images for test & 2 images for train	82.01%	83.86%	81.76%	80.09%	79.28%	77.84%
GLCM+SVM		79.12%	82.26%	80.42%	79.01%	78.52%	76.12%
GLCM+KNN	4 images for test & 1 image for train	74.57%	75.45%	73.19%	71.81%	68.01%	67.99%
GLCM+SVM		69.91%	72.37%	70.00%	67.97%	66.08%	63.45%

Table 4-9: Results of GLCM approach on IITD database

Additionally, a summarized result of all methods that used IITD database are illustrated in *(Table 4-10)* below.

Method	**Overall accuracy**
HOG + KNN	100%
HOG + SVM	97.76%
LBP + KNN	99.55%
LBP + SVM	99.33%
Combined (HOG&LBP) + KNN	99.77%
Combined (HOG&LBP) + SVM	99.33%
GLCM + KNN	90.05%
GLCM + SVM	85.52%

Table 4-10: Overall accuracies of IITD database when 1 image is used as testing and 4 images is used as training

(Figure 4-2) illustrates the disparity between the performances of the proposed methods in our system for IITD database.

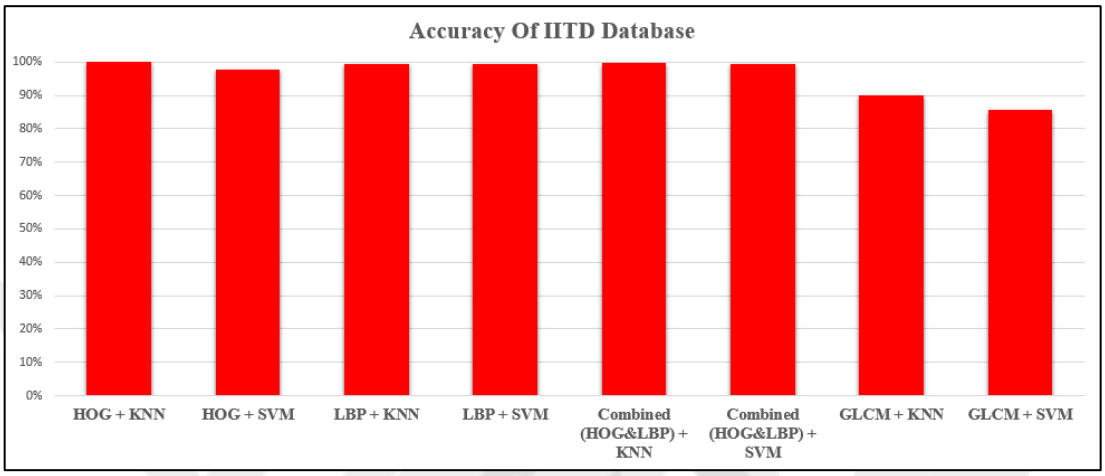

Figure 4-2: Comparison between the proposed methods on IITD database

Finally, *(Table 4-11 & Figure 4-3)* illustrate the final results of the proposed system, where they explain the proposed methods performance in each database.

Method	Accuracy Of UPOL DB	Accuracy Of IITD DB
HOG + KNN	100%	100%
HOG + SVM	96.87%	97.76%
LBP + KNN	98.43%	99.55%
LBP + SVM	96.87%	99.33%
Combined (HOG&LBP) + KNN	93.75%	99.77%
Combined (HOG&LBP) + SVM	88.90%	99.33%
GLCM + KNN	90.63%	90.05%
GLCM + SVM	81.45%	85.52%

Table 4-11: All results of the proposed system

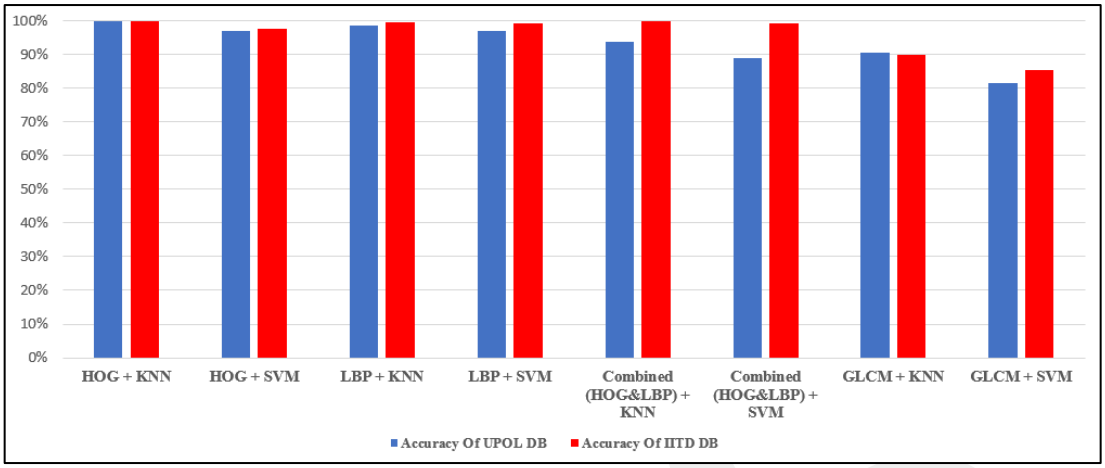

Figure 4-3: All results of the proposed system

4.3. Summary

In this chapter, all experiments are reviewed, and all the obtained results for each database are demonstrated. However, through these experiments we noticed and concluded several important points such as:

- Increasing the number of images in the training set leads to get high performance.
- The performance of HOG approach and LBP approach are close to each other.
- In UPOL database, the best value is allocated for Num-Level is 64, while in IITD database the best value is allocated for Num-Level is 16 for GLCM approach.
- The performance of GLCM approach is lower than performance of other approaches (HOG and LBP).
- The performance of combining (HOG& LBP) is lower than the performance of each approach of them separately.
- The best method used to implement this system is HOG+KNN method, and it achieved 100%.

CHAPTER 5

5. CONCLUSION & DISCUSSION

5.1. Conclusion

In this thesis, iris recognition system has been investigated using various techniques. Three approaches are applied in order to extract features from iris image, these approaches are HOG, GLCM and LBP. However, these approaches differ from each other in extraction features method and its performance. In addition, KNN & SVM classifiers are used to classify the iris features. Furthermore, these techniques are applied on two databases (UPOL & IITD), which have a main role in the evaluation of the proposed system performance. All proposed methods achieved different performances, the best accuracy was 100%, which is achieved by HOG+KNN method. However, based on the performance of the proposed methods, the performance of HOG and LBP are close to each other. In addition, the performance of combining (HOG & LBP) is lower than the performance of each one of them separately. On the other hand, the performance of GLCM approach is lower than HOG & LBP approaches.

5.2. Discussion

The comparison between the previous studies and the proposed study are provided in (*Table 5-3)*. The previous methods and the proposed methods are applied on two databases (IITD & UPOL). The performance of the proposed methods is better than the previous methods. However, the difference between the performance of the proposed methods and the previous methods depends on the techniques that are used in pre-processing, segmentation, normalization, feature extraction, and classification stages. For instance, in segmentation stage, Integro Differential Operator technique is used in the proposed methods, on other hand, Active Contour Models, Eyelash and Noise Detection techniques are used in the same stage in the previous methods.

Researcher name	Database	Method in the previous studies	Accuracy in previous studies	Method in the proposed system	Accuracy in the proposed system
Sachdeva & Kaur [37]	IITD	SIFT + SVM	99.14%	HOG + KNN	100%
Mrinalini & et al [34]		(T-DCT +BPSO) + ED	94.04%	LBP + KNN	99.55
Mrinalini & et al [34]	UPOL	(T-DCT +BPSO) + ED	88.89%	GLCM +KNN	90.63%
Sarmah & Kumar [23]		LMI + KNN	100%	HOG + KNN	100%
Emrullah & Mehmet [27]		TEM + KNN	80.74	LBP + KNN	98.43%

Table 5-1: Comparison between the performance of previous studies and proposed study

5.3. Future Work

The proposed methods are able to achieve high performance, but there are some issues that still hinder the achievement of better performance such as type of databases and quality of images in these databases. Also, the techniques that are used in pre-processing, segmentation and normalization stages. However, several suggestions are introduced below in order to improve the performance of the proposed system such as:

- Applying the proposed system on different databases such as CASIA database and compare the obtained results with the results in this thesis.
- Using another feature extraction algorithms such as Principal Component Analysis (PCA), and using other classifiers such as Artificial Neural Network (ANN) and compare the results with the results obtained in this thesis.
- Implementing the proposed system on a small organization; where the iris images are taken from the employees in this organization, and stored in the database, then apply the proposed system to identify the employees by their iris.

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