REALIZATION OF THE 1D LOCAL BINARY PATTERN (LBP) ALGORITHM IN RASPBERRY PI FOR IRIS CLASSIFICATION USING K-NN CLASSIFIER

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by

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LIST OF ABBREVIATIONS

1D-LBP	One-dimensional local binary pattern
2D	Two dimensional
ANN	Artificial Neural Network
AUC	Area Under the Curve
CASIA	Chinese Academy of Sciences' Institute of Automation database
CPU	Central Processing Unit
DWT	Discrete Wavelet Transformation
EEG	Electroencephalography
EER	Error Equal Rate
FAR	False Acceptance Rate
FRR	False Rejection Rate
FT	Functional Tree
GLCM	Grey Level Co-occurrence Matrix
K-NN	K-Nearest Neighbour
LBP	Local Binary Pattern
LR	Logistic Regression
MATLAB	Matrix Laboratory
MMU	Multimedia University
NB	Navie Bayes
NoIR	No Infrared
NOOBS	New Out OF the Box Software
OpenCV	Open Source Computer Vision
PCA	Principal Component Analysis
PHM’09	Prognostic Health Monitoring

ROC	Receiver Operating Characteristics
RR	Recognition Rate
SIFT	Scale-Invariant Feature Transform
SVM	Support Vector Machine
T-DCT	Triangular Discrete Cosine Transform
UPOL	University of Palack´eho and Olomouc database

MEREALISASIKAN ALGORITMA CORAK BINARI TEMPATAN 1D PADA RASPBERRY PI UNTUK IRIS KLASIFIKASI

ABSTRAK

Identiti seseorang dapat dikenali dengan menganalisa pengenalan biometrik seseorang. Iris mata merupakan salah satu biometrik yang digunakan secara meluas dalam bidang keselamatan kerana keunikannya. Corak binari tempatan merupakan salah satu kaedah pengekstrakan ciri iris yang paling berguna. Selain itu, pengelasan K-jiran terdekat (K-NN) adalah salah satu kaedah klasifikasi digunakan secara meluas kerana mudah dipakai. Dalam projek ini, satu kaedah pengekstrakan ciri yang baru iaitu corak binari tempatan satu dimensi (1D-LBP) bergabung dengan pengelasan K-NN. Raspberry Pi 3 digunakan untuk melaksanakan sistem tersebut. Terdapat lapan subjek yang berbeza digunakan dalam sistem klasifikasi ini dan tujuh imej iris dalam setiap subjek. Terdapat dua peringkat dalam pembangunan sistem ini. Pertamanya, algoritma 1D-LBP digunakan untuk mengekstrak ciri-ciri iris dan maklumatnya dicatatkan dalam format teks. Kedua, pengelasan K-NN digunakan untuk mengelaskan maklumat-maklumat tersebut. Dua kaedah digunakan untuk menilai ciri-ciri tersebut, iaitu satu lawan satu dan satu lawan banyak. Dua puluh lapan pasang yang diklasifikasikan oleh kaedah satu lawan satu mencapai 100% ketepatan. Terdapat tujuh kombinasi diklasifikasikan dengan kaedah satu lawan banyak. Prestasi terbaik apabila tiga kelas terlibat dalam kaedah tersebut, iaitu 100% ketepatan. Kaedah satu lawan banyak mencapai ketepatan yang lebih rendah apabila bilangan subjek meningkat. Prestasi kaedah tersebut dipengaruhi oleh maklumat-maklumat iris dan nilai K yang digunakan dalam pengelasan K-NN. Kesimpulannya, kaedah 1D-LBP berjaya direalisasikan untuk iris klasifikasi.

REALIZATION OF THE 1D LOCAL BINARY PATTERN (LBP) ALGORITHM IN RASPBERRY PI FOR IRIS CLASSIFICATION USING K-NN CLASSIFIER

ABSTRACT

The identity of a person can be identified by analyzing biometric identification. Iris is one of the biometric that widely used in the field of security due to its uniqueness. There are a lot of feature extraction methods and classification methods for iris classification. Classic local binary pattern (LBP) is one of the most useful feature extraction methods. Moreover, K-Nearest Neighbour (K-NN) classifier is one of the widely use classifier due to its simplicity. Due to the current methods in feature extraction are still improving, this project proposed a new feature extraction method to increase the performance of iris classification. In this project, a classification system is proposed with the one-dimensional local binary pattern algorithm (1D-LBP) with the K-Nearest Neighbour (K-NN) classifier and the system is developed by using a Raspberry Pi 3. There are eight different subjects used to classify in this classification system and each subject consists of seven samples of normalized iris image as input to the system. There are two stages in the proposed classification system. Firstly, the 1D-LBP algorithm is used to extract the features of the normalized iris images and save the data in a text file according to the subject and the combinations to evaluate for the next stage. Secondly, the K-NN classifier is used to classify the 1D-LBP based features from the first stage. There are two methods to evaluate the features, which are one versus one and one versus many. Twenty-eight pairs of subjects are saved in different text files and classified under one versus one method. There are twenty pairs of the subjects are achieved 100% of classification accuracy. There are seven combinations of the subjects are classified by using the one versus many method. The best performance of the one versus many is when the data cluster involves three classes. The accuracy is 100%. The classification accuracy is decreased when the number of subjects in the test data is increased. The performance of the one versus many classification is affected by the 1D-LBP based information and the value of K in K-NN classifier. In conclusion, the 1D-LBP algorithm is performance well with K-NN classifier.

CHAPTER ONE

INTRODUCTION

1.1 Research Background

People are getting more concerned about the security of their personal property or information. The need for the highly accurate practical authentication technology is growing and almost everything has a security system, such as a car, a smartphone, a personal computer, etc. Therefore, there are various applications of biometric systems are applied to the security system, such as fingerprint identification, face detection and many more.

Biometric refers to the metrics related to a human physiological or behavioral characteristic. In the 1980s, two ophthalmologists Aran Safir and Dr. Leonard Flom proposed that iris can be used as a human identifier just like a fingerprint, but they did not develop an algorithm to prove the idea. In 1990, Dr. John Daugman successfully created an algorithm to perform iris recognition. Among the physiological biometrics, an iris is one of the suitable to apply because it has the characters of uniqueness and stability [1]. Its structure is stable over time if compared with the face. Besides that, it is well visible and easy to localize with eye localization technique. Moreover, the iris is well protected from the environment, so the problem such as degraded fingerprints of hard workers, can be avoided for iris recognition technique.

The iris does not have the inherent 3D structure like a human face, thus the problem of distortion that caused by self-occlusion can be eliminated [2]. Today, the biometrics system by using iris is complementary to face and fingerprint biometrics for subject authentication. Iris recognition systems are included and widely used in a lot of fields, such as airport security system, national ID cards, social networks, mobile devices, research organization, etc. The image of iris need to be captured at distances of less than a meter and therefore iris biometrics is an alternative approach to reliable visual recognition of persons. The trait of iris can provide a high accuracy in these conditions. The human iris is a ring-shaped that in between the cornea and lens. It resides at the bottom part of the pupil as depicted in Figure 1.1. So, the iris is well protected, and the trait is stable over time.

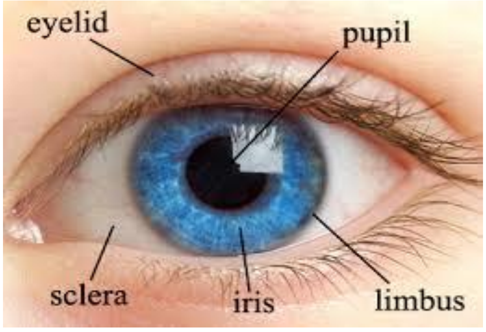


Figure 1. 1 The human eye [3]

The features of the iris can be extracted by using local binary pattern (LBP) algorithms [4]. It is one of the most widely studied local texture descriptors. A texture feature extraction is playing important role in the fields of computer vision and pattern recognition. A good feature extraction improves the performance of classification and thus increases the accuracy of the pattern recognition. The various LBP methods have been proposed for different problems, such as texture classification, dynamic texture recognition, image matching, visual inspection, image retrieval, biomedical image analysis, face image analysis, motion and activity analysis, object detection, and background subtraction [5]. A gray-scale and normalized iris image as shown in Figure 1.2 is suitable for LBP operator.

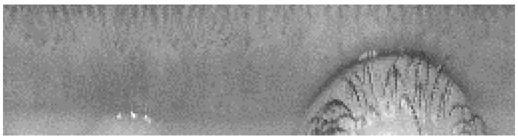


Figure 1. 2 Normalized iris image

The basic LBP method produces 256 texture patterns based on a 3x3 neighboring pixels. The pixels are set to 0 or 1 after compared with the center pixel value. After that, the patterns of the sequence of 0s and 1s are knowns as local binary pattern and a histogram of the pattern is generated [6].

LBP methods have been extensively used for texture analysis of two dimensional (2D) images. In this project, one-dimensional local binary pattern (1D-LBP) algorithm is used for feature extraction. The 1D-LBP method has been proposed by Chatlani et al. [7] and the speech signals are detected by using the method. Therefore, the method can be used as an approach of extracting features of iris. The performance of the proposed method has to be verified for iris classification with the K-NN classifier.

Data classification is the procedures to sort out data and determine the distinct types and category. Classification is the supervised learning in the machine learning field. Supervised learning is an algorithm is used to learn the mapping function from the input variable to the output variable. All training data is labeled and the algorithms learn to predict the output from the input data. There are three major factors involve in data classification, such as the data, the classifier and the classes. A classifier is used to determine the input data with the training dataset and matches the data into the correct class [8].

The K-Nearest Neighbors (K-NN) classifier is one of the most popular supervised learning method due to its simplicity and usefulness. The classifier does not rely on building a model during the training phase and the classification is based on the similarity between the training instances and the test instance [9]. In short, there are two stages in this project. The first stage is feature extraction of iris by using the 1D-LBP method. The normalized iris images are used at this stage. The second stage is to classify the 1D-LBP based features by using the K-NN classifier to verify the performance of the 1D-LBP algorithm. The classification results are based on one versus one and one versus many. The 1D-LBP method and the K-NN classifier are implemented in Raspberry Pi 3, which serves as a single computer board. The programming language that will use in this project is Python.

1.2 Problem Statement

In this new era, biometric authentication technique is one of the fast-growing technique in term of demands. There are several techniques developed based on fingerprint, voice, face and etc for subject authentication. However, there are not secure and hard to maintain the condition for authentication [2]. Therefore, iris authentication is an alternative way for the biometric authentication technique due to its unique and stability.

In order to achieve high performance in iris classification, different methods are proposed from previous work. Ruchi et al. [10] proposed the Gray Level Co-occurrence (GLCM) technique for feature extraction and the classification is done using multiclass

SVM. The system extracts fourteen features and achieved 94.23% accuracy of iris classification. The features are trained and a classification model is built. Besides that, Shubhangi et al. [11] used texture feature extraction LBP and K-NN classifier to read the gesture. The accuracy of the hand reader dataset is 92%. This shows that the feature that extracted by using LBP performs well with the K-NN classifier. However, the method is classical based LBP method which is normally fully in two dimensional. The properties and the characteristics of iris are less discriminative by using classic local binary pattern.

Due to the current local binary pattern methods in feature extraction are still improving, this project proposed a new feature extraction which is 1D-LBP algorithms with the K-NN classifier for iris classification by using Raspberry Pi to evaluate the performance of the feature extraction.

1.3 Objectives of Research

The main objectives to be achieved through this project are:

i. To determine the iris feature by using one-dimensional local binary pattern (1D-LBP) algorithm
ii. To evaluate the 1D-LBP based iris by using the K-Nearest Neighbour (K-NN) classifier
iii. To measure the classification accuracy according one versus one and one versus many

1.4 Scope of Research

In this project, Raspberry Pi 3 is the main hardware that performs the iris classification system. Python is the main programming language that will be used throughout the whole project. A set of localized and normalized iris image is stored in the Raspberry Pi 3 for classification. Then, the features of the normalized iris images are extracted by using 1D-LBP algorithms. The data is stored in a text file with classes labelling. After that, the data is split into train data and test data. The K-NN classifier is applied for matching with the train data and test data to get the accuracy of the 1D-LBP based features. The performance of the 1D-LBP based features will determine with one versus one and one versus many in K-NN classifier.

1.5 Thesis Outline

This thesis includes five chapters, which are Introduction, Literature Review, Methodology, Results and Discussion, and Conclusion.

Chapter Two is Literature Review, which is described the related work that proposed or presented by other researchers. The concept of 1D-LBP and the K-NN classifier is further explained in this chapter.

Chapter Three is explained the methodology for the project. Methods and procedures that involve in software and hardware are explained systematically. The overall flowchart of this project will present in this chapter. The development of the 1D-LBP algorithm and K-NN classifier by using Python coding will explain respectively with flowchart.

Chapter Four shows the results obtain from the 1D-LBP and K-NN classifier. Histograms are generated from the features extracted by 1D-LBP algorithm and the accuracies of the 1D-LBP based features are calculated based on of the K-NN classifier.

Chapter Five discuss the conclusion of this project and future improvement that can be done for iris classification.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

Iris classification system is one of the development technology that is applied in the various field nowadays and there are a lot of research papers related to the system. In section 2.2, an overview of the papers that related to this project, such as iris recognition system, several feature extraction methods and different classifiers are provided. In section 2.3, background studies about local binary pattern, one-dimensional local binary pattern, k-NN classifier and Raspberry Pi 3 are provided. Lastly, a summary of this chapter is given in Section 2.4.

2.2 Related Work

There are a lot of techniques for biometric classification that has been done by other researchers. This section mainly reviews on the previous works with different techniques of feature extraction and classification based on iris characteristics.

Raju et al. [12] shows his review on biometric person authentication on different physiological characteristics and compare the performance of unimodal and multimodal of biometric during authentication to determine the best method on biometric authentication. A simple biometric recognition system which consists of four basic components are described in the paper. Sensor module is used to capture biometric data, feature extraction module is used to extract feature vectors, matching module is used to compare the feature vectors between input biometric and template biometric, and the last one is decision module where the identity of the user is established. The paper did research on the multimodal biometric system. The multimodal biometric system is the system that integrates two or more biometric to achieve higher performance and reliability. Some problems of single trait biometric systems can be solved by designing multimodal biometric systems which provides multiple evidences of the same feature. The unimodal biometric systems face a variety of problems such as noisy sensor data, non-universality, intra-class variations, and unacceptable error rates. The paper concluded that the problems can overcome by the multimodal biometric system.

Sheela et al. [13] stated that a typical iris recognition system involves four main modules: (i) images captured by using cameras and sensors, (ii) image pre-processing which included iris liveness detection, pupil and iris boundary detection, eyelid detection and removal and normalization, (iii) feature extraction for classification purpose, (iv) comparison the feature with stored features in the database. The main modules are as shown in Figure 2.1.

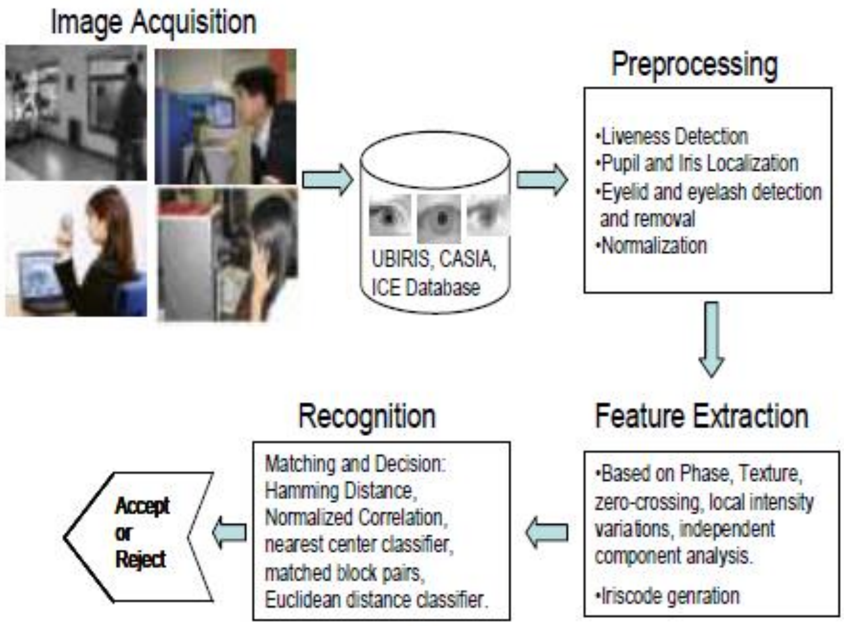


Figure 2. 1 Iris recognition system [4]

The paper did the survey on different methods of iris recognition and analysed each of them. The methods included phase-based method, texture-analysis based method, zero-crossing representation method, approach based on intensity variations, an approach using independent component analysis and authentication based on continuous dynamic programming. The accuracy of iris recognition had improved by Karen Hollingsworth by using Daugman's method. The studied is focus on the different dilation of the pupil. The equal error rate (EER) is 3.88×10^{-3} which showed the high accuracy for the small pupil, whereas the subset data with large pupils showed the worst performance of EER. Besides that, the system that developed by Ya-Ping Huang is performed at various illumination and noise levels. The recognition rate is 93.8% for variant illumination and 62.5% for noise interference images.

Suralkar et al. [14] proposed the steps of iris detection for biometric technology by using Gabor filter to extract the feature. Figure 2.2 shows the block diagram of the system.

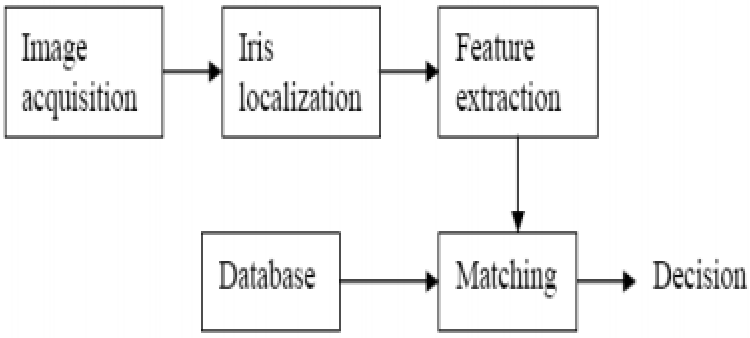


Figure 2. 2 Block diagram of the iris recognition system [5]

The iris localization is used to determine the boundary of the pupil and iris. After localizing and aligning the image containing the iris, the step of feature extraction is carried out for matching. The Hamming distance is chosen for matching part. The algorithm is developed by using MATLAB and it is tested on CPU. 30 images are tested and the result shows that the system is able to authenticate the identity of the person. However, the system is costly because it developed on 2.4GHz CPU.

Mrinalini, Pratusha, Manikantan and Ramachandran [15] presented the Triangular Discrete Cosine Transform (T-DCT) based feature extraction and Radon Transform based pre-processing technique to improve the performance of iris recognition. T-DCT is chosen due to its efficiency to extract feature. It helps to reduce the training and testing time. Radon Transform performs as curve detection and it has varied orientation of texture information to analysis on the iris image. It also can perform well under varying illumination conditions. The average recognition rate is 88.89% for the database which consists of 64 subjects, each subject consisting of 3 variations for each eye. The average testing time is 236.3ms for the database that consisting 45 subjects, each provided 5 left eye iris images. The system is run by 2.4GHz CPU using MATLAB.

Gourav Sachdeva and Dr. Bikrampal Kaur [16] proposed a technique by utilizing fuzzy support vector machine (SVM), scale-invariant feature transform (SIFT) and genetic algorithm for iris recognition system. The SIFT is used for feature extraction. After that, the genetic algorithm is applied to reduce the features to increase the probability when matching with the database. The classification of the images is using fuzzy SVM. The simulation is carried out by using MATLAB. The accuracy of the method is 99.14064%, false acceptance rate (FAR) is 0.62496% and false rejection rate (FRR) is 0.2344%.

Rana et al. [17] presented a technique that uses Principal Component Analysis (PCA) based on Discrete Wavelet Transformation (DWT) to increase the efficiency of iris recognition. The iris image can be converted into four frequency band by applying DWT but only one band will be used in this system. The PCA is applied to extract the feature. 40 iris images are used to get the experimental result and the average recognition rate is 92.6%, which is performed better than other methods, which are DCT feature extraction technique based, DWT feature extraction technique based and PCA based recognition.

Tallapragada et al. [18] combined the Grey Level Co-occurrence Matrix (GLCM) and Haar wavelet transforms to extract iris feature based on texture. Besides that, neural network classifier is used to classify the feature. Figure 2.3 shows the iris recognition system with the localized image input.

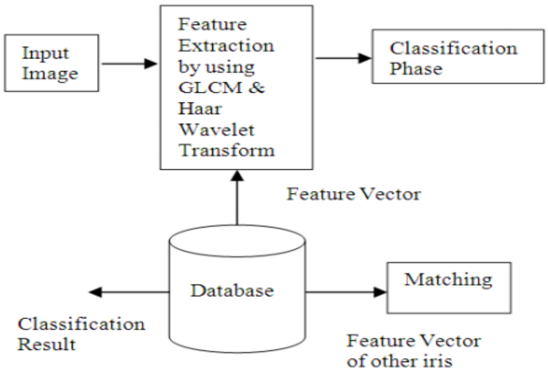


Figure 2. 3 Iris recognition system [18]

There are 100 iris images taken from CASIA database for testing and the overall system efficiency is 94%. However, the error rate of this system is 6.57%. The false rejection rate is higher than the false acceptance rate.

Sarode et al. [19] compared the method of the combination of the local binary pattern (LBP) with the k-nearest neighbour (K-NN) and the combination of LBP with Navie Bayes (NB). Canny Edge Detection technique for segmentation is used to determine boundaries of the iris and the image colour is transformed into a grayscale level because LBP operator is working on the grayscale level. The image pixels are labeled by thresholding the neighbourhood of each pixel. After that, LBP is used to extract the features from the iris image. Finally, K-NN classifier and NB classifier are applied to classify the features extracted from the iris image. The database from MMU is taken for this experiment. The result shows that the LBP+K-NN method achieved 100% and LBP+NB method achieved 94.18% of accuracy. This shows that LBP+K-NN is more reliable for obtaining accurate results for iris recognition.

Arup Sarmah and Chandan Jyoti Kumar [20] proposed a mechanism to verify the iris based on Legendre moment. Firstly, iris localization is carried out to reduce the image noise for feature extraction. Then, Legendre moment is applied to extract iris moment-based rotation invariant features without iris rotation adjustment. A near zero value of redundancy in a set of moment functions is achieved so that it corresponds to independent characteristics of the iris. For matching, the K-NN classifier is used for feature classification. The performance is taken based on 100 samples and the recognition rate is 100%.

Luhadiya et al. [21] presented the iris authentication system with SVM classifier. Total 384 images are tested by using the system. Image pre-processing is taken on the input image. The input image is being localized to remove the image noise. Circular Hough transform is applied to locate the boundary between pupil and iris. Gray Level Co-occurrence (GLCM) technique is used to extract the iris features. Finally, the SVM classifier has been used to classify the iris. The recognition rate is 94.23% when tested on University of Palack´eho and Olomouc (UPOL) database.

There are some papers discusse the 1D-LBP based feature extraction method. Even though the method is not applied to the biometric system, it is discussed and reviewed the performance of the 1D-LBP method. Y. Kaya et al. [22] proposed a new technique to extract the feature of the epileptic EEG signals for classification. The new approach based on the implementation of one-dimensional local binary patterns (1D-LBP) was presented and the experimental results showed that the method could acquire a high accuracy in classification of epileptic EEG signals. The data consists of five sets which are called set A to E and there are 100 samples for each class. The results were taken from various combinations of the sets, such as A-E, A-D, D-E, E-CD, AB-CDE, and A-D-E clusters, by using four types of classification, which are SVM, ANN, LR and FT. The accuracy for each combinations of the sets is 99.5%, 99.5%, 95.5%, 97.0%, 95.4% and 95.67% respectively. The results show that generally high accuracy was achieved with features based on 1D-LBP method. The paper also concluded that 1D-LBP is one of the best choices for real-time signal processing applications with its high performance and low computational complexity features.

L. Houam et al. [23] proposed a new method that adapts the 2D classical LBP to 1D signals to classify textures from osteoporotic and healthy control cases which is the one-dimensional local binary pattern (1D-LBP). The 1D projection shows useful characteristics of shapes and the 1D patterns increases the discriminative properties compared to the 2D representation. A normalized histogram is used to encode the texture descriptor consists in the distribution of the local patterns. A dataset composed of 80 women with 39 images of patients with osteoporotic fractures and 41 images of control cases was tested to compare the performance between classical LBP and 1D-LBP. The Receiver Operating Characteristics (ROC) curves and cross-validation process have been used to evaluate the classification performance. Results show that the classical LBP achieved 72% area under the curve (AUC) score whereas the score is 91% with the 1D-LBP. The results show that the 1D-LBP method has better separation between the osteoporotic cases and the healthy controls.

A. Benzaoui et al. [24] proposed one-dimensional local binary pattern (1D-LBP) combined with Principal Component Analysis (PCA) for face recognition. ORL database and AR database are used to test the performance of the proposed method. The databases are separated into the training set and testing set. The performances of different LBP texture analysis, such as classical LBP, extended LBP, Elliptical LBP, and 1D-LBP are compared based on their recognition rate (RR) and false alarm rate (FAR). The results show that the method with 1D-LBP+PCA achieved the average 96.9% RR and the average 1.44% FAR. It concluded that the 1D-LBP with less dimensional with PCA enhances the recognition performance in all configurations and presents significant results in recognition rate, false alarm rate against other variants of LBP.

R.Y.F Ng et al. [25] proposed an effective iris segmentation method which evaluates on iris images taken from the CASIA iris image database version 1.0. The method included iris inner and outer boundaries localization, upper and lower eyelids detection, and eyelashes, reflection and pupil noise removal algorithm. The feature extraction that been used is 1D Log Gabor filter. It is used to extract the normalized iris features. The filter is a Gaussian transfer function on a logarithmic scale with strictly bandpass filter to remove the DC components that caused by the background brightness. The pixel of the normalized image is demodulated into two bits code in the template and the phase information is extracted. For matching, Hamming distance is used to determine that the two templates are from the same person or different person based on a threshold value. The Hamming distance is the fractional measure of dissimilarity between two binary templates which would give zero if the two templates are the perfect match and a value that near to 0.5 if the two templates are completely independent. The proposed method with the method of feature extraction and matching has achieved a high recognition rate which is 98.62% with Equal Error Rate (EER) of 1.38%.

Z.K.Abdul et al. [26] proposed 1D local binary pattern (1D-LBP) to extract the features from the vibration signal. The features are then classified by using the K-NN and SVM classifier for three classes, which are normal, break and crack. The effectiveness of the proposed method is evaluated on the vibration data obtained from the Prognostic Health Monitoring (PHM'09) Data Challenge. The 1D-LBP labels every single value of the vibration signal and using the center value as a threshold value. If the neighbor value is less than the center value, a zero value is assigned to the neighbor, otherwise a value of one is assigned to it. A local binary pattern code is then produced. A histogram is used to display the various patterns of the signal. The features are then utilized as input to the K-NN and SVM classifier. The experimental results are partitioned into four different models to detect the fault in the gear. For the data of the model that collected from all speeds and both loads together, the performance of the K-NN classifier outperforms the SVM classifier with the accuracy up to 90.83%. However, the performance of the 2D-LBP and the K-NN classifier is better than the 1D-LBP and the K-NN classifier with accuracy up to 96.67%.

Khalid et al. [27] proposed two mathematical operations to extract the features from the normalized iris image. The first method is called mean thresholding. A center is marked at the sixth column of the first row. Then, a mean value of the five preceding pixels and five succeeding pixels is determined and compared with the pixel value at the center. A value of one is set if the value of the center pixel is greater than the mean value, else a value of zero is set. The procedure is repeated until the size of the resulting binary feature vector is 5x120. The second method is called mean-by-median thresholding. It is almost the same as the first method. The mean and median value is determined from the twelve preceding and succeeding pixels. A threshold value, which is the square root of the multiplication of the mean and median value, is compared with the center pixel. If the center pixel is greater than the threshold value, a value of one is set, else zero is set. The procedure is repeated until the resulting binary feature vector size is 5x130. The Hamming distance is used as matching due to its good performance with binary templates. The results show that the recognition rate for both methods is 98.3264%. This shows that the methods are able to implement in iris recognition system to achieve high recognition rate.

Febus et al. [28] developed an iris recognition device by using Daugman's algorithm on Raspberry Pi. The components used are a camera, Raspberry Pi and LED light. The algorithm will locate and determine the size of the iris. Then, Gabor filter is applying to the pixels of iris and the Hamming distance is used to match with the database. The device is used as less as components as possible. The overall accuracy of the device is 93.34%.

Zuzanna et al. [29] presented a Raspberry Pi based iris recognition. A dedicated Raspberry Pi Camera Module NoIR with an additional infrared-passband filter is used to capture eye image. Algorithms for segmentation, normalization and encoding are implemented in C++ and Python. OpenCV library is used for image processing. 233 images are taking to test the system. The FAR and FRR are equal to 0.0259%. This shows the system is quite accurate. The comparison time between the input image and the database is 13.77 seconds.

2.3 Background Studies

This section is about the basic principles and knowledge of LBP algorithm, 1D-LBP algorithm and K-NN classifier that will apply to this project. The introduction of the main board which is Raspberry Pi 3 is also included in this section.

2.3.1 Local Binary Pattern (LBP) Algorithm

This algorithm is designed for texture description and it is efficient for feature extraction which was first introduced by Ojala et al in 1996 [30]. Due to its good performance and computational simplicity, the operator is one of the popular approaches in various applications, such as visual inspection, image retrieval, remote sensing, biomedical image analysis, motion analysis, environmental modelling, and outdoor scene analysis. The pixels of the image are labelled as binary value by thresholding the 3x3 neighbours of each pixel with the centre pixel value [31]. Figure 2.4 shows the mechanism of the basic LBP approach and how the contrast measure is derived.

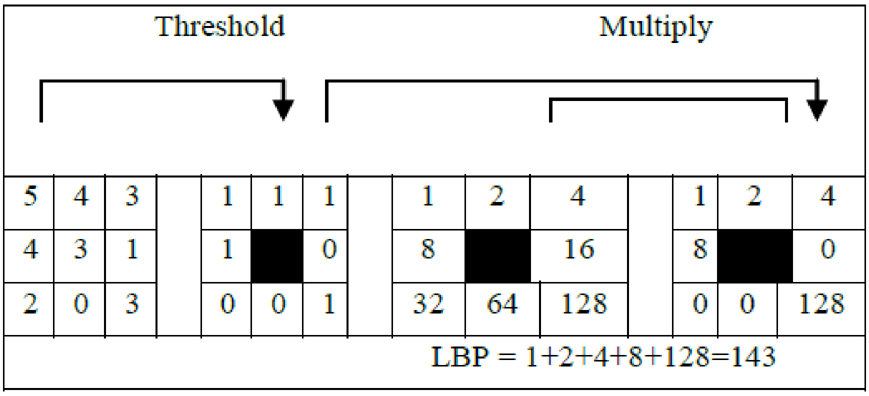


Figure 2. 4 The mechanism of the basic LBP [32]

The input normalized image is divided into cells with different pixel's value in each cell. The value of the central pixel which is "3" becoming a threshold value for the other pixels that surrounding it. The value of "1" is given if the surrounding pixel is bigger, whereas "0" is given if smaller. After that, a LBP code is produced by multiplying the threshold values with the weights given to the corresponding pixels and the result is summed up as shown in Figure 2.4. The equation is as shown as below [33]:

$$LBP_{P,R} = \sum_{p=0}^{p-1} r(g_p - g_c)2^p \, , r(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{1}$$

where

g_c refers to the gray level value of the center pixel,

g_p refers to the value of the neighbouring pixels of the center,

P refers to the total number of neighbouring pixels,

R refers to the radius of the neighbourhood.

After the LBP pattern is computed, a 256-bin histogram of the labels is computed to represent the iris texture. The histogram contains information about the patterns on a pixel-level, then the histograms are summed to produce information on a regional level and the regional histograms are concatenated to build a global description. For each iris images, a composition of micro-patterns is considered so the LBP operator can detect the patterns effectively. Figure 2.5 shows the LBP histogram that extracted from each iris sub-regions.

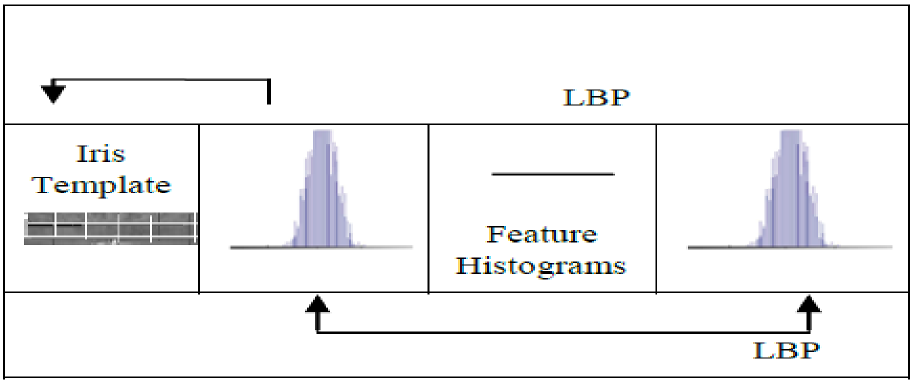


Figure 2. 5 LBP based feature histogram [32]

The LBP histograms are concatenated into a single feature histogram that defined as below:

$$H_{i,j} = \sum_{x,y} I(f_1(x,y) = i)I((x,y) \in R_j) \tag{2}$$

where

i = 0, 1, 2…, L-1

j = 0, 1, 2…, M-1

R = iris region that divided into small non-overlapping region

The extracted feature histogram describes the local binary pattern for the global iris images. The main disadvantage of the LBP operator is it describes the features by comparing with the neighbourhood pixels in circle. It is unable to perform for fine characteristics.

2.3.2 One-Dimensional Local Binary Pattern (1D-LBP)

One-dimensional local binary pattern (1D-LBP) algorithm is derived from the classic local binary pattern (LBP). Its concept consists of a binary label describing the local agitation of the 1D signal [23]. A threshold value is taken from the centre pixel and the neighbour values are assigned “1” if they are greater than the threshold value, whereas “0” is given if they are smaller than the threshold value. Figure 2.6 shows the mechanism of 1D-LBP with eight neighbours. The 1D-LBP operator can work with two, four, six or eight neighbours. After assigned the value “1” or “0” to the neighbours pixel, each binary element is multiplied by a weight depending on the position. For the case as shown in Figure 2.6, a natural number belonging to [0, 255] is generated.

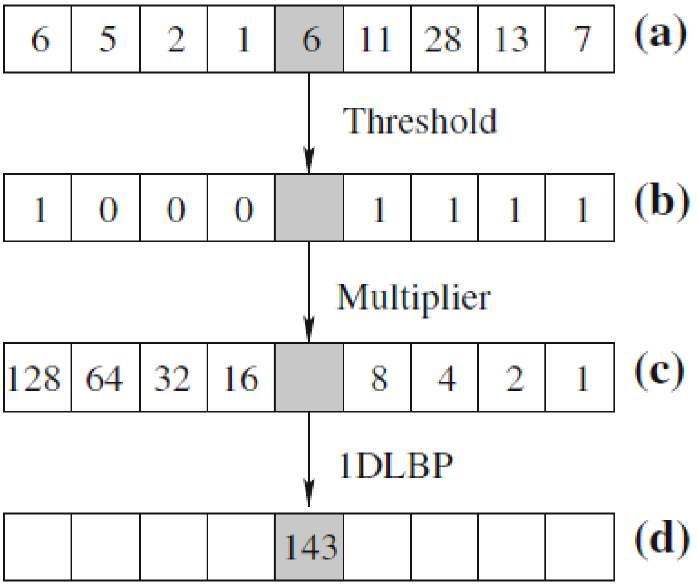


Figure 2. 6 The mechanism of 1D-LBP (a) threshold, (b) coding, (c) result of 1D-LBP, (d) summation of the result

The mechanism of 1D-LBP can be defined as the equation below:

$$1DLBP_{m,W} = \sum_{p=0}^{m-1} u\left(t_p - t_c\right)2^p, u(x) = \begin{cases} 1, if\ x \geq 0 \\ 0, otherwise \end{cases} \qquad (3)$$

where

m refers to the total number of neighbouring pixels,

W refers to the linear mask of size and is normally an odd number,

t_p refers to the gray level value of the centre pixel,

t_c refers to the value of the neighbouring pixels of the centre,

A histogram is used to display the 1D-LBP patterns. The size of the histogram is depending on the size of the neighbourhood. For example, the size of the histogram for the eight neighbours as shown in Figure 2.6 is 256 bins.

2.3.3 K-Nearest Neighbour (K-NN)

K-NN classifier is used in machine learning applications, regression and pattern recognition [34]. The classification algorithm is widely applied for its simplicity and low error rate. The basic principle of the classifier is taking the nearest value of the check data in feature space. The concept of the K-NN classifier is as shown in Figure 2.7.

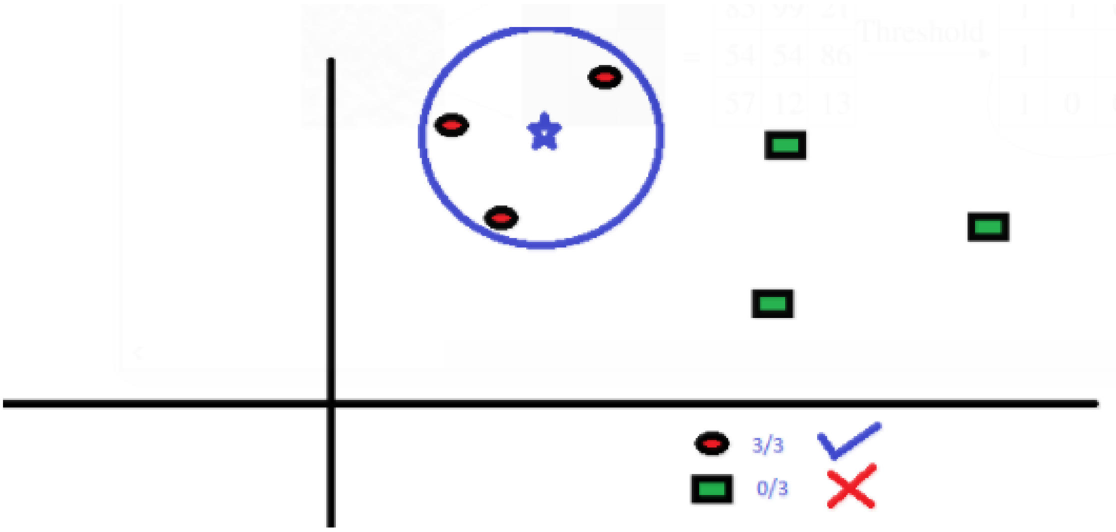


Figure 2. 7 Simple case for K-NN mechanism [35]

Figure 2.7 shows an example for K-NN classifier. There are three red circles, three green rectangles and one blue star. The red circles and green rectangles represent two different classes which are Class 1 and Class 2 respectively. K-NN classifier is used to classify the class of the blue star either it belongs to Class 1 or Class 2. Let's say the K=3, the three closest point for the blue star is the red circles. Thus, the blue star belongs to Class 1. The classifier is suitably used for iris classification due to its simplicity and yet highly competitive results.

The equation (4) as shown below is used in this system. Euclidean distance is used for the purposes of distance comparing [20].

$$d(p,q) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \tag{4}$$

where

d = dimensional train data set

q_i = query data

p_i = test point data

The query data q_i is unknown and is presented by a vector in the feature space. Its distance with every point in the train data will be calculated. The result is computed according to the label of the k-nearest points in the training dataset. The test data that will be classified is compared according to the distance metric with the data that determined from the training set. The test data is classified into the class based on the value of K.

2.3.4 Raspberry Pi 3

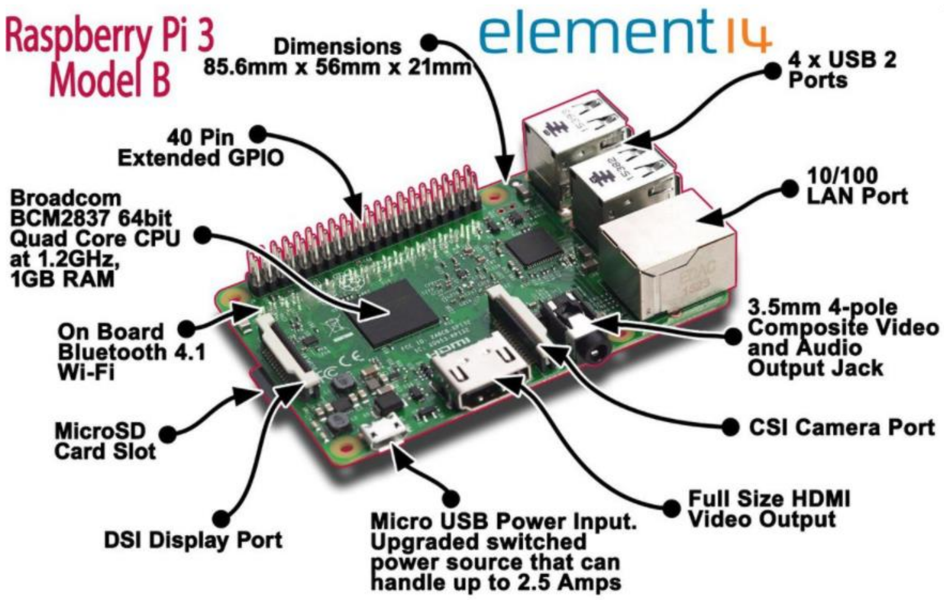


Figure 2. 8 Raspberry Pi 3 Model B 1GB Project Board [36]

Figure 2.8 shows the overview of Raspberry Pi 3 Model B. It is a single board computer developed in the United Kingdom by Raspberry Pi foundation with the intention of simulating the teaching of basic computer science in schools. The Raspberry Pi 3 Model B is the latest version and its quad-core is faster and more capable than Raspberry Pi 2. Raspberry Pi 3 uses Broadcom BCM2837 SOC 64-bit quad-core ARM Cortex A53 (ARMv8 CPU) with 512KB shared L2 cache. The Raspberry Pi 3's CPU has approximately 60% better performance in 32-bit mode if compare with the Raspberry Pi 2. The board provides 1GB of RAM and four USB ports which allow connection of four different USB devices, such as keyboard, mouse, etc. There is Ethernet port for users to access internet quickly. Normally, it is useful for users to setup Raspberry Pi for the first time without a monitor. Besides that, the board supports wireless internet with built-in Wi-Fi and Bluetooth. A monitor can be attached to the board through HDMI port with HDMI cable. There are 40 GPIO (General Purpose Input Output) Pins can be used to drive LED, switches, sensors, etc. Camera interface (CSI) and Display interface (DSI) enable users to interface camera module and display module respectively. A MicroSD card slot is used to hold the operating system for Raspberry Pi 3. An operating system called New Out Of the Box Software (NOOBS) is used for the Raspberry Pi 3. It is designed to make it easy to select and install operating systems for the Raspberry Pi with a SD card.

The programming language that will be used in Raspberry Pi 3 is Python. It is a powerful programming language and easy to use. There are two version of IDLE, a Python development environment, in Raspberry Pi 3, Python 2 and Python 3 as shown in Figure 2.9.

Figure 2. 9 Python IDLE in Raspberry Pi 3 [37]

Even though Python 3 is recommended for users to use, however Python 2 is available for legacy applications which do not support Python 3 yet.

2.4 Summary

A lot of methods are used in the previous work. Among the different techniques, the method which is LBP+K-NN classifier most likely help to increase the performance of the iris classification. Section 2.3 explained briefly the concept of LBP, 1D-LBP and K-NN classifier which will apply to this project. Besides that, Raspberry Pi 3 and the programming language are also introduced in this chapter.

CHAPTER THREE

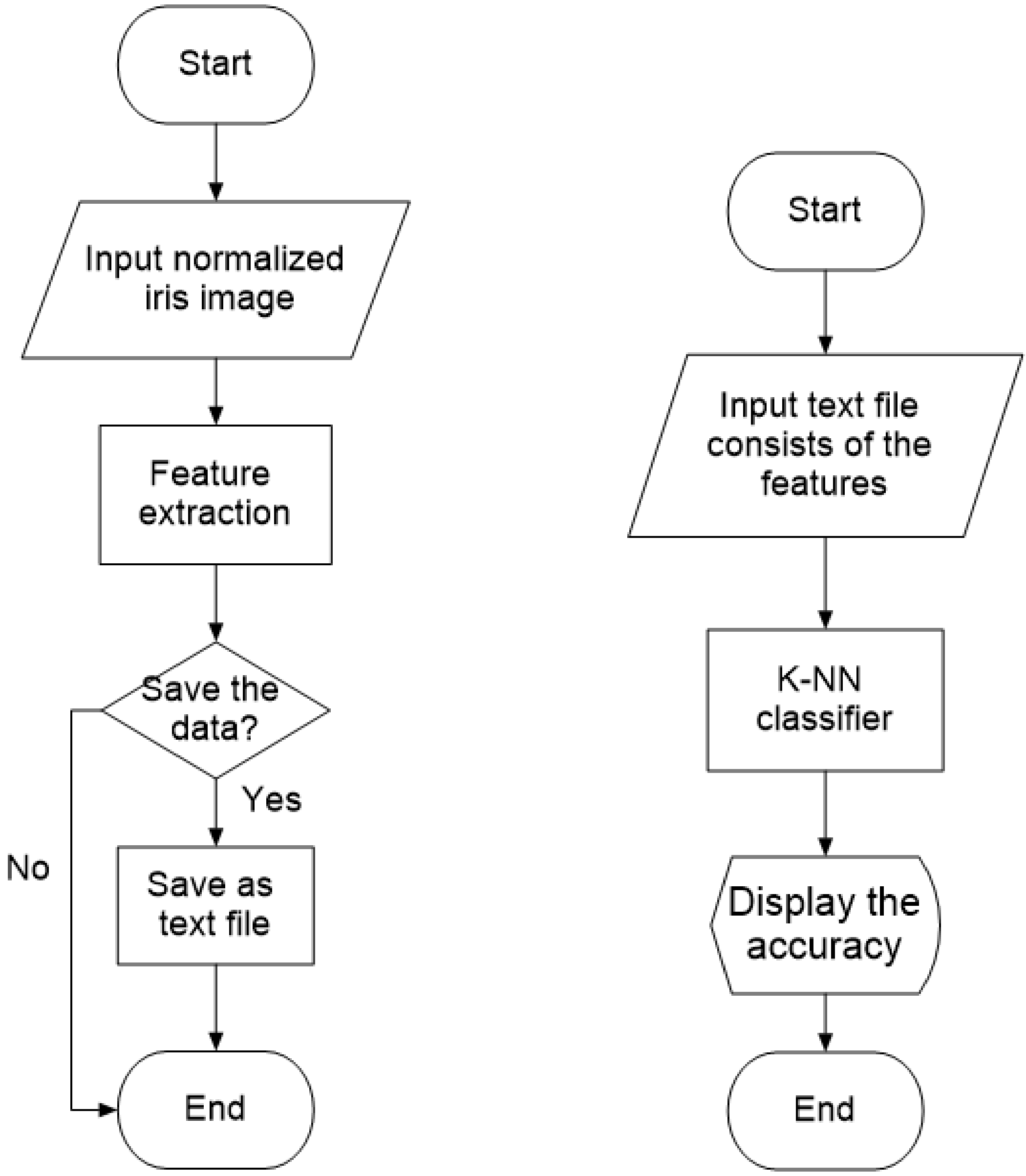
METHODOLOGY

3.1 Introduction

This chapter discusses the methods used in the realization of the 1D-LBP algorithm in Raspberry Pi 3 for iris classification using K-NN classifier. Python is used to develop the 1D-LBP operator and K-NN classifier. Section 3.2 shows the flow of this project and the block diagram of the entire project. Section 3.3 describes the hardware implementation of this project. Section 3.4 explains the development of the Python coding for the 1D-LBP algorithm. Section 3.5 shows the development of the Python coding for the K-NN classifier. Lastly, a summary of this chapter is presented in Section 3.6.

3.2 Project Implementation Flow

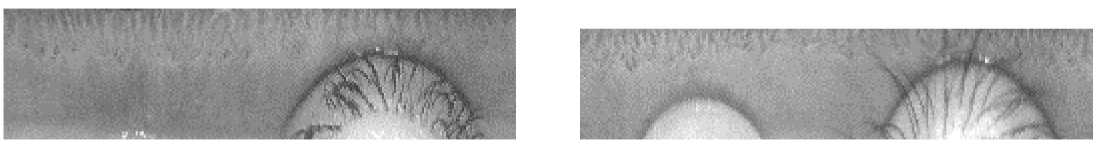
This section explains the overall project flow with the help of flowchart and a block diagram of the classification system. Figure 3.1 shows the overall flowchart of the iris classification. There are two parts for the overall flowchart, the first part is the overall flowchart for the 1D-LBP operator, whereas the second part is the K-NN classifier.



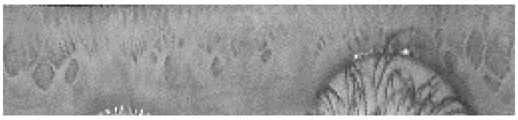
(a) (b)

Figure 3. 1 The overall flowchart (a) 1D-LBP operator, (b) K-NN classifier

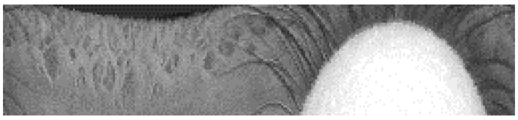
Figure 3.1 shows the overall flowchart for the 1D-LBP operator and K-NN classifier. This project is to show the performance of the 1D-LBP operator with K-NN classifier. Thus, normalized iris images in rectangle size as shown in Figure 3.2 were as an input for the 1D-LBP operator.



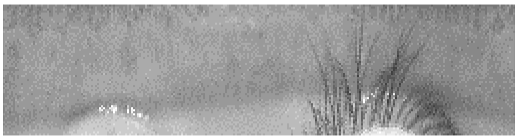
(a) (b)



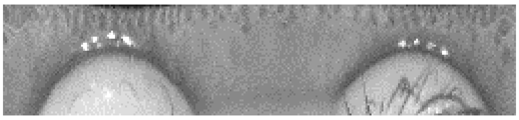
(c)



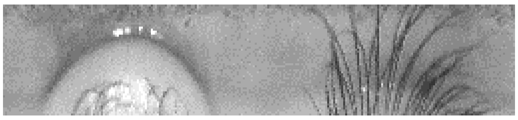
(d)



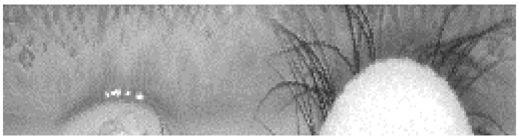
(e)



(f)



(g)



(h)

Figure 3. 2 Normalized iris image of Class A till Class G

Figure 3.2 shows the different normalized iris images from the different person. The iris images that used in this project are already been localized and normalized. So, there is no need to carry out the process of image processing in this project. Normalized iris images are used due to the fixed dimensions. The size of the iris may be varied with imaging distance. The variation affects the feature extraction and the performance of the classification system. Therefore, iris images need to normalize to suppress the effect of variation. In this project, the normalized images were directly been used instead of carry out the process of normalization.

The normalized iris images were named as Class A to H. Each class consists of seven samples, thus there are total fifty-six normalized iris images to extract the features and display in histograms. The data from histogram was stored as a text file. After that, the dataset was separate into train data and test data for K-NN classifier to classify the iris images. The flow of the 1D-LBP operator and K-NN classifier will be explained further in Section 3.4 and 3.5 respectively.

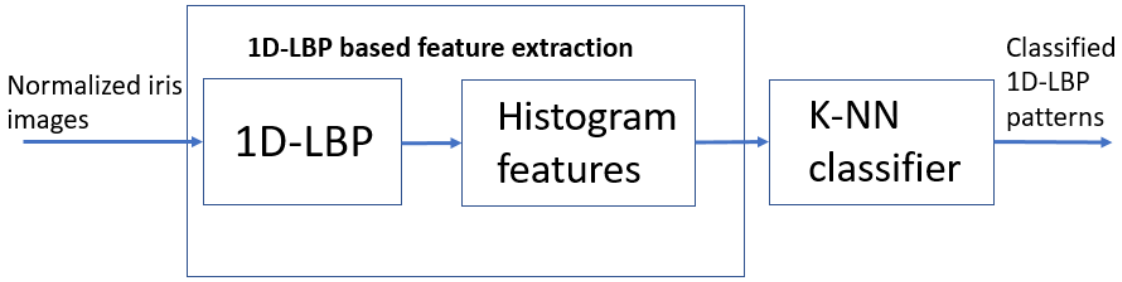


Figure 3. 3 Block diagram of the proposed classification system

Figure 3.3 shows the block diagram of the proposed classification system. Overall, the process of the system included feature extraction stage, which was explained briefly in Figure 3.1(a). The feature histograms obtained from the normalized iris image at this stage. In the classification stage, 1D-LBP based features were applied as the input to the K-NN classifier.

In this project, two types of method were evaluated using K-NN classifier, which were one versus one and one versus many. The two methods were constituted by the dataset to test the proposed method. There were train dataset and test dataset from each class by separated the features with the ratio 5:2. The details will explain further in Section 3.5.

3.3 Implementation of Hardware

In this project, a Raspberry Pi 3 is used as a single computer board that implemented the algorithm for iris classification and a monitor is used as display purpose. The overall implementation is shown in Figure 3.4.

Figure 3. 4 Hardware implementation

The Raspberry Pi 3 was used as a single computer board for the proposed classification system due to its easy implementation and low cost. A 16GB MicroSD card was used to hold an operating system for the Raspberry Pi 3. New Out Of the Box

Software (NOOBS) is the operating system that used for the Raspberry Pi 3. After install the operating system to the Raspberry Pi 3, the system is working by connecting the monitor with the Raspberry Pi 3. The 1D-LBP operator and K-NN classifier were developed by using the Python 3 IDLE. The normalized iris images were stored in the Raspberry Pi 3.

3.4 One-Dimensional Local Binary Pattern (1D-LBP)

The implementation step of 1D-LBP is almost the same as the classic local binary pattern. Figure 3.5 shows the flowchart of the 1D-LBP operator.