ASHESI UNIVERSITY

FINGERPRINT RECOGNITION SYSTEM

UNDERGRADUATE THESIS

B.Sc. Management Information System

Abraham Junior Abbey

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FINGERPRINT RECOGNITION SYSTEM

UNDERGRADUATE THESIS

Undergraduate Thesis submitted to the Department of Computer Science, Ashesi University in partial fulfilment of the requirements for the award of Bachelor of Science degree in Management Information Systems.

Abraham Junior Abbey

2022

DECLARATION

I hereby declare that this Undergraduate Thesis is the result of my own original work and that no part of it has been presented for another degree in this university or elsewhere.

Candidate's Signature:

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Candidate's Name:

Abraham Junior……………………………………………………………………

Date:

12/04/2022……………………………………………………………………

I hereby declare that preparation and presentation of this Undergraduate Thesis were supervised in accordance with the guidelines on supervision of Undergraduate Thesis laid down by Ashesi University.

Supervisor's Signature:

……………………………………………………………………………………

Supervisor's Name:

JUSTICE KWAME APPATI……………………………………………………………

Date:

13/MAY/2022……………………………………………………………………

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Abstract

Fingerprint recognition is one of the most popular biometric techniques in personal identification. The widespread use of fingerprint recognition as a biometric is because each fingerprints pattern of ridges and valleys is unique and does not vary with time and age. While there are several algorithms or methods for fingerprint recognition systems, the quest to develop a robust fingerprint recognition system remains a significant research area. One major challenge in designing a system for fingerprint recognition is its ability to perform well on both full and partial fingerprint images. Most fingerprint recognition systems developed so far use minutiae-based algorithms which tend to perform well under full fingerprint but poorly under partial occlusion. In partial occlusion, the minutiae, which are the core points of the fingerprints, get completely distorted. The distortion of minutiae makes minutiae-based algorithms perform poorly. Therefore, this study proposed a novel non-minutiae-based algorithm that adapts the Fisherface and Eigenface method from facial recognition. The proposed algorithm is insensitive to partial occlusion. The Eigenface and Fisherface methods were tested on FVC 2002 Datasets and yielded an accuracy of 86.67% and 90% respectively. These accuracy results indicates that there is a possibility of recognizing fingerprint images using non-minutiae-based algorithms from different domain.

Keywords *– Minutiae, Biometrics, fingerprint recognition, image pre-processing, LDA, PCA.*

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Chapter 1: Introduction

1.1 Background of Study

In recent years, there has been widespread use of Automatic fingerprint identification and recognition systems (AFIS/AFRS)[1] in personal identification applications, for instance, access control [8-10]. Fingerprint recognition systems offer the benefits of being both simple to use and inexpensive. Minutiae-based fingerprint recognition techniques are often generally utilized in these AFIS systems [10]. The minutiae-based algorithms for matching seem to perform well under good quality and complete fingerprint images [9]. However, these algorithms generally perform poorly under partial fingerprints, which degrades the credibility and ability of the Automatic Identification/Recognition System (AFIS/AFRS) with a minutiae-based algorithm. Therefore, this study seeks to leverage this limitation by proposing an efficient approach to combat the challenges faced by the minutiae based AFIS/AFRS.

Fingerprint recognition is one of the widely used biometric technologies for human identification. It has proven to be very efficient in ensuring security in our daily lives. Fingerprint recognition is by far the most globally used biometric for verification on computerised systems [8]. The automated process of validating an individual's identity based on the comparison of two fingerprints is known as fingerprint recognition. It has drawn more significant attention in recent decades than other biometric technologies [9]. Since its inception, there have been several moves planned out by individuals to befall the efficiency of fingerprint recognition systems. Therefore, this study explored some algorithms used and tested by other researchers for fingerprint recognition systems and

[1] AFIS/AFRS refers to automated systems that search and compare fingerprints records to identify or recognize known and unknown fingerprints.

proposed an efficient and effective method which identifies and recognizes all fingerprints images, including occluded ones.

1.2 Problem Statement

In the past decades, several systems have been proposed for fingerprint identification and recognition. Irrespective of the many works done in this jurisdiction, these systems cannot perform well when it comes to fingerprints that are occluded. The poor performance is mainly because all these fingerprint systems depend on the basic definition of fingerprints [9]. However, the identification of fingerprints is subjected to minutiae[2] which are known to be unique for all persons.

Therefore, when the fingerprints are occluded, these minutiae that happen to be the fundamental orientation for fingerprints are distorted. As a result, systems are not able to organise these fingerprints and identify them accordingly. In effect, several false positives and negatives are recorded at the various security checkpoints. The false outcomes have weakened both current and existing systems, and there is an urgent need to circumvent the highlighted limitation hence the objective and aim of this project.

1.3 Research Question

There are a lot of limitations to the use of minutiae as the prime definition for fingerprint, especially in the case of partial fingerprints or occlusions. Therefore, the research seeks to answer the question highlighted below.

- Can the existing biometric techniques in different domains that work well under partial occlusion be used for this study?

[2] Minutiae are the core points located on fingerprints. These points are mostly tiny but significant feature for fingerprint recognition. In short terms, minutiae are the key characteristics of fingerprint.

1.4 Aims and Objectives of Study

The main objective of this study is to develop a robust fingerprint recognition system that is insensitive to partial occlusion. To achieve this objective, the study seeks to:

- Implement non-minutiae-based algorithms that can identify fingerprints and organise them for easy identification.
- Compare the performance of the proposed non-minutiae-based algorithms.

1.5 Justification

Fingerprint recognition is essential as far as personal identification is concerned. According to Gaikwad et al. [7], effective fingerprint recognition helps enable easy identification among people in our society. Fingerprint recognition has been incorporated in several devices such as laptops, mobile phones, smartwatches etc. According to the Ghana Public Safety and Crime Report, the number of house robbery and crimes have gone up from 183 in January 2020 to 220 in June 2021, indicating a 20 percent increment. During robbery operations, robbers always leave behind fingerprints after the crime scene. These fingerprints are mostly partial. That is, the minutiae points in the fingerprint are distorted. Now, recognizing these types of fingerprints is not always feasible with the normal minutiae-based fingerprint recognition systems. Therefore, there is a need to devise a robust fingerprint recognition system that is insensitive to partial occlusion.

1.6 Organization of Study

The remaining parts of the thesis report are structured into various chapters. The ensuing chapter, which is Chapter 2, discusses the literature review with much focus on identifying loopholes of other works. Chapter 3 outlines the methodologies explored and utilised by other authors, as well as the suggestion of feasible methods to be applied in this study. In chapter 4, the processes and procedures of the implementation and testing of the fingerprint recognition are extensively discussed. Finally, chapter 5 summarises the research by highlighting the key successes, limitations of the study and recommendation for future works.

Chapter 2: Literature Review

2.1 Introduction

In recent years, fingerprint recognition has become a standard routine in forensics; and various techniques have been devised in that space [4]. Fingerprint recognition has been a field of interest and research over the past decades due to the influence of biometrics[3] and its application in banking services, mobile and stationary devices etc. Fingerprint recognition plays a significant role in personal identification, apart from the face, iris, and other biometrics. This chapter investigates the algorithms proposed and tested by other researchers to depict the current advancements in the space of fingerprint recognition.

2.2 Review of Algorithms for Fingerprint Recognition

Zeng et al. [12] proposed a partial fingerprint recognition algorithm based on deep learning to recognize partial fingerprints. This deep learning model was proposed to salvage the issue of partial fingerprint images resulting from small-area scanners. It was observed that the algorithm proposed by the authors improved the recognition performance of partial fingerprints images by 20 percent. In 2019, Chen et al. [13] addressed the issue of occlusion by proposing convolutional neural networks to perceive the occluded region of the fingerprint. The proposed CNNs were evaluated on natural and synthetic occlusions, including self-collection facial expressions and other datasets such as RAF-DB and AffectNet. It was observed that the CNNs improved the recognition accuracy on both the non-occluded fingerprints and occluded fingerprints by 10 percent.

Apart from Zeng and Chen attempting to solve the problem of partial fingerprints, Darlow et al. [14] also proposed a neural network for the minutiae extraction for the partial

[3] Biometrics refers to the measurements of human's unique features like face, fingerprint, iris etc.

fingerprint. They made use of FVC (both FVC2002 and FVC2004) datasets to evaluate and test their models. It was observed that their model reduced the Equal Error Rate (EER) for the two datasets. It was observed that their model reduced the Equal Error Rate (EER) for the two datasets by 6%.

LaythKamil et al. [10] proposed a fingerprint recognition system that uses associative memory with a modified multi-connect architecture (MMCA) algorithm. The proposed approach was set to enhance the authentication of persons. The proposed method focuses more on minutiae points. The algorithm was evaluated using FVC 2004 datasets, internal datasets and NIST dataset 4. It was observed that the MMCA algorithm has an average accuracy of 99.56% and a pattern recognition processing time of approximately 30s on full fingerprint images. The authors failed to test the proposed algorithm on the partial fingerprint. Therefore, if this algorithm is tested on partial fingerprints, it may perform poorly because it uses minutiae which, in most uncontrolled scenes, can get completely distorted, and recognition probably might become a problem.

Furthermore, Kouamo and Tangha [11] proposed a fingerprint recognition system that uses a neural networks algorithm. This proposed algorithm aims at authenticating access to an E-learning platform. They used NIST special database four and the local database to evaluate and test their models. It was reported that the proposed algorithm produced good results when tested on full fingerprints. Similarly, Alexander and Pravol [4] proposed a novel fingerprint recognition system that uses artificial neural networks as a feature extractor to boost the recognition accuracy of the automatic fingerprint recognition system. The proposed algorithm was evaluated on FVC 2004 and NIST special datasets. They used FMR/FNMR and ROC indicators to assess the system's performance. It was reported that the artificial neural network impacted the overall recognition rate, especially in low-quality fingerprint images. The method yielded 70 percent accuracy in terms of recognition.

In the works of Kai Cao and Anil Jain [8], an automated latent fingerprint recognition that uses Convolutional Neural Networks algorithm (ConvNets) was proposed to compare latent found at crime scenes. They used WVU and NIST SD27 datasets to evaluate their proposed algorithm. The system was compared with the existing latent recognition system. It was observed that the proposed algorithm improved upon the recognition performance from 64.7% and 75.3% to 73.3% 15 and 76.6% on NIST SD27 and WVU latent databases, respectively. Also, Feng Luis et al. [6] presents a fingerprints recognition system based on Optical Coherence Tomography (OCT). Their proposition was tailored towards the resolution of the poor performance of traditional fingerprint recognition systems due to low-quality fingerprints. The proposed method was evaluated on FVC 2004 and the special NIST datasets. The performance of the proposed method was evaluated with FMR100 and EER metrics and resulted in 0.42% and 0.36% for both metrics. The proposed method was reported to have improved upon the FMR100 and EER results from the traditional fingerprints recognition system, which was 8.05% and 18.18%, respectively.

Also, Cho et al. [5] proposed a new partial fingerprint-matching method incorporating new ridge shape features (RSFs) in addition to the conventional minutiae features. In testing their model, they used FVC2002, FVC2004 and BERC datasets. It was discovered that the proposed method improves the accuracy of fingerprint recognition, especially for implementation in mobile devices where small fingerprint scanners are adopted. By introducing machine learning in biometrics, Kashif Noor et al. [6] proposed a classifiers method to enhance the performance of the fingerprint recognition systems. The classifier methods included Decision Tree, Medium Gaussian Support Vector machine (MG-SVM), K-nearest neighbour etc. The proposed algorithms were evaluated on FVC2002 databases. Amongst the instances mentioned above of the classifiers, Medium

Gaussian Vector Machine (MG-SVM) resulted in a higher verification rate of 98.90 per cent.

Moreover, Candana et al. [10] attempted to solve partial fingerprint issues by proposing minutiae-based matching techniques as a method of extracting useful information about minutiae for fingerprint recognition systems. The authors extensively talked about Fingerprint Classification, Fingerprint Matching Techniques and Partial and Full Fingerprints. Also, Sang et al. [17] proposed an efficient fingerprint identification algorithm based on minutiae and invariant moments. The algorithm uses a Short-time Fourier transform (STFT). In evaluating their models, a cosine similarity metric was used to judge the similarities between fingerprint objects. It was observed after an experiment that the proposed algorithm provides better performance in terms of matching accuracy. The accuracy of the proposed algorithm is up to 96.67%.

Lianhua Liu et al. [18] presented a support vector machine-based fingerprint quality assessment method that used five features extracted from an image. This method classifies the fingerprint images into three classes: high, average, and low quality and achieved an accuracy of 96.03%. Angel et al. [19] proposed new algorithms based on the use of clustering independent of the minutiae descriptors. Some latent fingerprint databases were used to validate their models. It was observed that the new algorithm improves the robustness of identification in the presence of sizable non-linear deformation. The proposed algorithm achieved higher accuracy than those presented in the state-of-the-art literature. However, the proposed algorithm was not compared with other algorithms, which is flagged as a weakness of the entire system.

2.3 Summary And Conclusion of Literature Review

It was evident that many different authors have extensively researched the fingerprint recognition domain by proposing different methods and approaches. It was observed that a vast number of methods and algorithms the authors proposed used fingerprint minutiae in one way or the other. Following the methods proposed so far, the issue of partial occlusion remains unsolvable because most of the techniques were minutiae-based. However, these minutiae, which are the fundamental definition of fingerprint, might get distorted, making it difficult for mere minutiae-based algorithms to perform well under partial occlusion. Therefore, the contribution of this research is to devise a robust fingerprint recognition system that is insensitive to the nature of the fingerprint (whether occluded or not) by using non-minutiae-based algorithms from facial recognition domain. These proposed methods seek to outperform the state-of-the-art methods that rely on the minutiae points.

Chapter 3: Methodology

3.1 Introduction

This research seeks to address the issue of partial occlusion by proposing an efficient and robust fingerprint recognition system. A thorough review of existing fingerprint systems revealed that most of the proposing systems solely depend on minutiae. These minutiae-based systems, upon several tests, do not perform well under partial occlusion. In this study, a non-minutiae-based algorithm are used to build the proposed fingerprint recognition system. Susara et al. [20] argued that facial recognition methods such as Fisherface and Eigenface work well under partial occlusion. Therefore, this study seeks to adapt these methods mentioned above (Fisherface and Eigenface) to build a robust fingerprint recognition system. The steps involved in fingerprint recognition include image acquisition, pre-processing, feature extraction and fingerprint recognition[4]. The fisher face method uses a Linear Discriminant Analysis (LDA) for image dimensionality reduction and linear separability retention. Similarly, the Eigenface method utilises a Principal Components Analysis (PCA) to reduce dimensionality and decompose features into eigenfaces. Figure 3.1 presents an outline of the steps required in fingerprint recognition coupled with instances of methods used in accomplishing them.

[4] Fingerprint recognition is a process of identifying a person by juxtaposing two fingerprints. It checks if a fingerprint belongs a particular person.

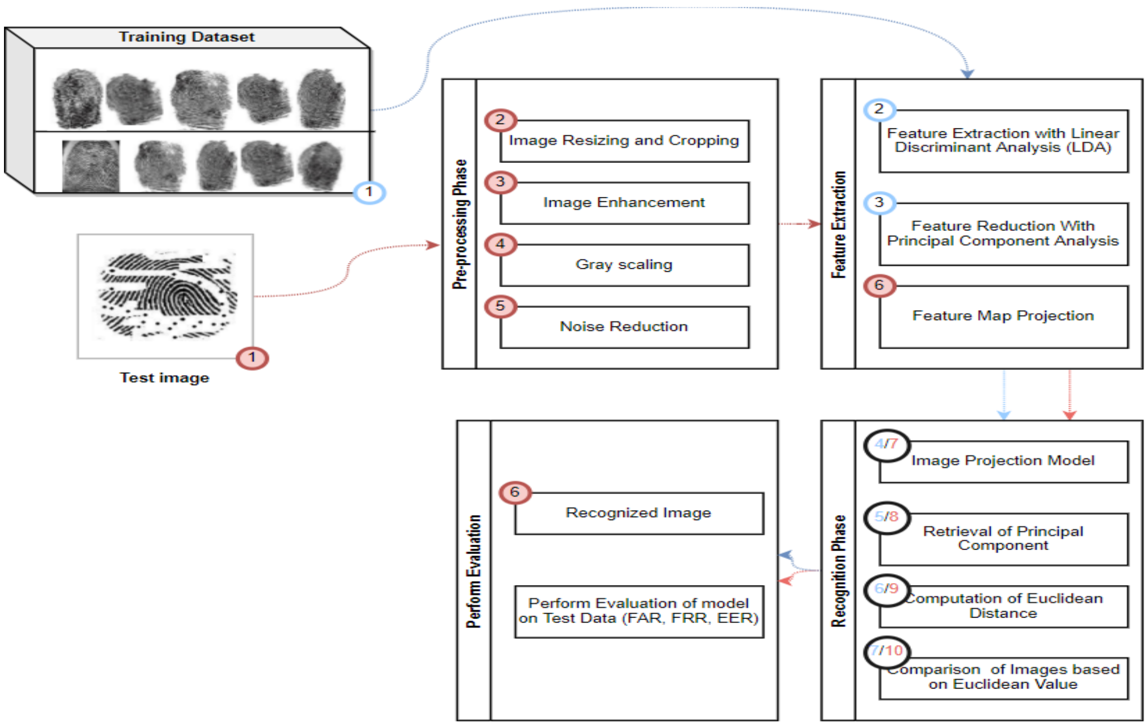

Figure 3.1: A high-level outline of fingerprint Recognition Methodology

3.2 Image Datasets

The fingerprint recognition starts with image acquisition, as shown in Figure 3.1 above. For fingerprint recognition to commence, there must be some images to train the proposed model [20]. In this study, the images are acquired from some selected databases, such as the Fingerprint Verification Competition 2000 (FVC 2002) and the National Institute of Standards and Technology (NIST). These two databases were chosen because they are the predominant datasets for fingerprint related studies. The description of the chosen datasets is provided in the subsections below.

3.2.1 The Fingerprint Verification Competition 2002 (FVC 2002)

The FVC 2002 is a database project presented at the second International Competition for Fingerprint Verification Algorithms conference. This database is selected because it is one of the predominant datasets that have been used for this type of academic work. It contains images of various fingerprints. In the 20 FVC 2002, the datasets are grouped into four different databases (DB1, DB2, DB3, DB4). The DB1 dataset was extracted and used in this study. The DB1 datasets contain fingerprints images acquired using an *Indentix TouchView* II scanner with an image size of 388x374 and a resolution of 500 dpi. The DB1 dataset contains 80 images from 10 subjects[5], thus 8 images per subject. All sample images are from different fingers and are ordered by quality (top-left: high quality, bottom-right: low quality). Images are labelled as 101_1, 101_2, …, 102_1, …, 1,110_1 where the third digit, before the underscore, represent the person who donated the fingerprint. That is, for 101_1 refers to the first person's fingerprint, 102_1 represent the second person's fingerprint and so on. The snippet of the images in DB1 dataset is shown in Figure 3.2 below.

Figure 3.2: Fingerprint Images from DB1 Datasets

[5] Research subjects are the volunteers who donated their fingerprints into the database.

3.2.2 The National Institute of Standards and Technology (NIST)

The National Institute of Standards and Technology (NIST) comprises partial and complete fingerprint images. The NIST is the most used database for partial fingerprint recognition studies. The NIST database contains approximately 600 images from 30 research subjects. The partial fingerprint images come in a variety of forms. The pixel resolution of all the images in the dataset is 512x512. Likewise other paid databases, the NIST database is not freely available for use as compared to the FVC 2002 database.

3.3 Image Pre-processing Phase

During the pre-processing phase, several adjustments need to be performed on the images before proceeding to feature extraction and recognition phases. Sometimes the acquired images are blurry and noisy. Therefore, in these processes, the acquired images undergo some refinements such as image enhancement, Gray-scaling and noise reduction. The purpose of this phase is to get the images in an appropriate form for the next phases. Most often than not, the selected datasets contain limited data to carry out the research. That is, the data in the dataset are not enough to embark on successful research. In such situation, the data need to be augmented to get new samples.

For this research study, the FVC 2002 DB1 dataset had limited images to perform the recognition. Therefore, images were artificially generated from the original ones to get reasonable datasets for the study. A thorough description of the image augmentation is provided in the subsequent section (See details in Section 3.3.1 below).

3.3.1 Image Augmentation

Juxtaposing the nature of the available dataset and the proposed methods, there is a need to increase the size of the dataset in order to obtain better accuracies. The available datasets used for this study contains fingerprints images of ten subjects (persons) donating

8 fingerprints from different fingers (see details in Section 3.1). Therefore, training and testing with such datasets always yield low accuracy. One of the best techniques for increasing the number of training datasets is data augmentation. According to Khoshgoftaar et al [26], data augmentation involves an artificial generation of new samples from an existing data. The augmentation process utilises either data warping or oversampling. For this study, data warping augmentation was used because the labels of the images needed to be kept for the recognition process. Image augmentation helped to increase the total number of images from 80 to 400 images. During the augmentation process, four different samples were generated for each of the images in datasets (i.e., 101_1 through to 110_1) using the data augmentation techniques discussed in the subsections below.

Some of the augmentation techniques applied were Translation, Rotation, Reflection and Scaling. The description of how the techniques were used are provided in the subsections below.

3.3.1.1 Rotation Technique

With rotation data augmentation technique, the new samples for each image were generated through 45° rotation. The results of rotation technique are shown in figure 3.3 below.

Figure 3.3: Augmented fingerprint images using Rotation technique

3.3.1.2 Translation Technique

The augmented images were generated by moving the original image along x-axis and y-axis. In this process, *Xtranslation* and *Ytranslation* were performed using [-50 50] for both axes. The results of translation technique are shown in figure 3.3 below.

Figure 3.4 Augmented Fingerprint images using Translation technique

3.3.1.3 Reflection Technique

During reflection data augmentation, new images were generated by reflecting the original image around the y-axis (also known as upside-down flip) or x-axis (also known as left-right flip). Both *XReflection* and *YReflection* were performed. The results of reflection technique are shown in figure 3.5 below.

Figure 3.5 Augmented Fingerprint images using Reflection technique

3.3.1.4 Scaling Technique

With the Scaling technique, the new samples were generated by resizing the original images to a specified size. The snippets of the results obtained from the scaling technique are shown below.

Figure 3.6 Augmented Fingerprint images using Scaling technique

After the image augmentation, some adjustments such as Gray-scaling, noise reduction and image enhancement are then made to all images in the dataset. These processes are discussed briefly in the subsections below.

3.3.2 Gray Scaling

Gray scaling involves the conversion of RGB images to a grayscale representation for image dimensionality reduction. Image gray scaling is possible with MATLAB *rgb2gray( )* function. The *rgb2gray( )* converts RGB image or colormap to grayscale. The implementation of the rgb2gray function is shown in eqn (3.1) below.

$$RGBA[A] \rightarrow Gray: Y \rightarrow 0.289 * R + 0.5870 * G + 0.1140 * B \qquad 3.1$$

3.3.3 Histogram Equalisation

The Histogram equalisation is an image enhancement method used for the increment of contrast of images through a transformation of image intensity [9]. MATLAB *histeq( )* function makes it possible to increase the contrast of the fingerprint image, as shown in Figure 3.7.

Figure 3.7: A histogram equalization effect on fingerprint image

3.3.4 Noise Reduction

Image noise reduction refers to the removal of unwanted content on a picture such as dust masks, scarves to obtain the true image. Image noise reduction can be made possible through some image processing techniques [21]. These techniques include Median filter, Min filter, Linear filter and Max filter. The description and equation of the highlighted techniques are provided in the subsections below.

3.3.4.1 Median filter

The median filter is an unsequential filter, employed in removing noise in an image [22]. It is used for the smoothing of images through a replacement of a pixel value with its average intensity value. It is computed using eqn (3.2) below.

$$f^{(x,y)} = median\ \{g(s,t)\} \qquad 3.2$$

where $S(x,y) \in Sxy$

3.3.4.2 Min filter

The min filter is used to discover the darkest points in an image and augment those points by utilising the least intensity level of the closest input pixels. The min filter is also referred to as the *0th* percentile filter. It is mainly used in salt noise removal. The eqn (3.3) below shows the computation of the min filter.

$$f^{(x,y)} = \min\{g(s,t)\} \qquad 3.3$$

where $S(x,y) \in Sxy$

3.3.4.3 Linear Filter

The linear filter is a technique that is mainly employed in random noise reduction process. It is computed as a sum of the closest pixels. The linear filter is calculated in eqn (3.4) below.

$$r(j,k) = \sum_{s}^{k} = -k \sum_{t}^{k} = -kf(-s,-t)l(j+s,k+t) \qquad 3.4$$

3.3.4.4 Max filter

The max filter is a technique used to find the brightest points in an image and augment those points using the maximum intensity level of the closest pixels. Max filter is primarily utilised in pepper noise removal. It is also referred to as the *100th* percentile filter. The mathematical computation of the technique is given in the eqn (3.5) below.

$$f^{(x,y)} = \{g(s,t)\} \qquad 3.5$$

where $(s,t) \in Sxy$

3.4 Feature Extraction

In this phase, several elements or characteristics of the processed images are selected or extracted as well as the feature vector generation. This is done with Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA); the predominant algorithms from Eigenface and Fisherface, respectively.

3.4.1 Principal Component Analysis (PCA)

The Principal Component Analysis method is used to transform the high dimensional (mostly 2D images) into low dimensional (mostly 1D) [20]. This is termed image dimensionality reduction. The sizes of M x M training images are converted into low dimensional fingerprint images by the application of PCA [23]. The transformation of 2D fingerprint image into 1D fingerprint image vector[6] can be either row or column vector. The result of the transformation is called eigenfaces but for clarity and brevity in this study, coined as eigen-fingers. The steps involved in PCA include the arrangement of Fingerprint

[6] Vector is a matrix that has either one row or column. A matrix with one row is called a row vector and a matrix with one column is referred to as a column vector.

Images, computation of mean or average fingerprint images, the computation of centred fingerprint images, the computation of the covariance matrix, the computation of eigenvectors of the covariance matrix, and finally, the selection of the eigenvalues.

3.4.1.1 Fingerprint Image Arrangement

The fingerprint images are arranged to form a data matrix[7] X such that the size of the matrix [X] is n x MN. In this case, n is the number of fingerprint images representing the column, and MN is the row.

3.4.1.2 Mean or Average Image Computation

The average or the mean of the fingerprint image is calculated by summing all the images (n) and dividing the number of rows M. It is computed in the eqn (3.6) below.

$$Mean\ Image\ (m) = \frac{1}{M}\sum_{n=0}^{M} Xn \qquad 3.6$$

where X is the image matrix.

3.4.1.3 Centred Image Computation

The centred image is obtained by subtracting the mean image from the data matrix [X] in section 3.4.1.1. It is calculated in eqn (3.7) below.

$$Centred\ Image\ (Xm) = X - m \qquad 3.7$$

[7] Matrix refers to a two-dimensional array of numbers.

3.4.1.4 Covariance Matrix Computation

The covariance[8] matrix is computed by summing the centred image. This is calculated in eqn (3.8) below.

$$Covariance\ (Q) = \sum_{N=0}^{M} X\, m(n).Xm^{T}(n) \qquad 3.8$$

3.4.1.5 Eigenvectors Computation

In this step, we diagonalize the matrix to decorrelate the matrix using the transformative matrix. The MATLAB *eig( )* function makes it possible to calculate the eigenvector matrix. This is computed in eqn (3.9) below.

$$Eigenvector = P^{-1}.Q.P \qquad 3.9$$

3.4.2 Linear Discriminant Analysis (LDA)

The Linear Discriminant Analysis (LDA) is a fisher face method that is purposely used in dimensionality reduction and linear separability retention. Moreover, LDA can be used for discrimination and classification [23]. This method increases the recognition rate and can be used to curtail the challenges of Principal Component Analysis. Linear Discriminant Analysis (LDA) works like Principal Component Analysis (PCA), but it focuses on maximizing the separability among known classes. The steps involved in LDA include the arrangement of Fingerprint Images, computation of the separability between the mean of different classes, the computation of the distance between means and sample of classes, construction of lower-dimensional space between classes, conservation of data matrix, projection of images onto Fisher Linear space and finally the Euclidean distance computation.

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[8] Covariance matrix refers to a square matrix that produce covariance among each pair of components of given vector.

3.5 Fingerprint Recognition

In the recognition process, the fingerprint images are classified into training and testing images. Testing images are then projected into the model. The principal components of the projected image are retrieved, and the Euclidean distance is calculated between the projected images and the training sample images. The comparison decision is made based on the value obtained from the Euclidean distance computation.

3.5.1 Euclidean Distance Measurement

The Euclidean distance measurement is most frequently used in Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA). It is a similarity distance algorithm that is used to calculate similarity between test and training images [29]. The comparison of the images can be identified by calculating the distance between the vectors of two images [20]. The MATLAB *norm( )* function can be used to compute the Euclidean distance. The Euclidean distance is calculated in eqn (3.10).

$$Euclidean\ Dist\ (X,Y) = \sqrt{\sum_{n=1}^{N}(Xn - Yn)^2} \qquad 3.10$$

where Yn represent test image at *nth* position

Xn represent test image at *nth* position

3.5.2 Comparison Decision

As mentioned in section 3.5, the comparison decision is made based on the Euclidean distance value. A threshold is set and matched against the Euclidean value in this decision process. If the Euclidean value is higher than a specific set threshold, then the image is unknown or not recognized, else the fingerprint image is recognized.

3.6 Performance Evaluation Metrics

Several metrics were used to evaluate the performance of the proposed methods. These metrics include False Acceptance Rate (FAR), False Rejection Rate (FRR), Equal Error Rate (ERR). FAR refers to the probability that a fingerprint recognition system incorrectly recognizes a false input fingerprint image. FRR also refers to the probability that a fingerprint recognition system incorrectly rejects an actual fingerprint image. Lastly, the ERR is established when FRR and FAR are in equilibrium. The lower the ERR value, the higher the accuracy of the biometric system and vice versa. The computation of the highlighted metrics is given below.

3.6.1 False Acceptance Rate (FAR)

False Acceptance Rate (FAR) is computed as a division of false acceptances and number of recognition attempts. Thus,

$$\text{FAR} = \frac{FA}{TA}$$

where FA = Number of False Acceptance

TA = Number of Attempts

3.6.2 False Rejection Rate (FAR)

False Acceptance Rate (FAR) is computed as a division of false rejections and number of recognition attempts. Thus,

$$\text{FAR} = \frac{FR}{TA}$$

where FR = Number of False Rejection

TA = Number of Attempts

Chapter 4: Experiments, Results and Discussion

4.1 Introduction

This chapter focuses on the implementation of a fingerprint recognition system that includes the feature extractions, image map projections and fingerprint recognition model which were discussed and surveyed in the preceding chapter. With regards to the implementation specifics, the experiments conducted in training and evaluating the proposed methods are assessed in this chapter. For the sake of this study, the two proposed methods which are the eigenface and fisherface methods for fingerprint recognition processes were studied and tested. In addition, the proposed algorithms were implemented, and their respective accuracies were recorded. This chapter, therefore, provides vivid reports and discussion on the results that were recorded from the implementation of the proposed methods.

4.1 Implementation Tools and Resources

The fingerprint recognition system was built in Ubuntu Linux 20.04 LTS. The following software and tools were installed for the development:

Tools and Resources	Specifications
Operating System	Ubuntu 20.04 LTS
Programming Language	MATLAB R2022a
Toolboxes (MATLAB Libraries)	Statistics Toolbox, Image Processing Toolbox
Others	Internet Connection

Table 4.1: Tools and resources used in development process

These highlighted tools and resources above are suitable for this study because they are predominantly used by many researchers for this kind of project. Therefore, using them increases the validity and acceptance of the project results.

4.2.1 Statistics Toolbox

Statistics Toolbox[9] is one of the predominantly used toolboxes in MATLAB. Statistics toolbox provides data description, analysis, and modelling functions and apps. Statistics toolbox contains some supervised and unsupervised machine learning algorithms such as boosted decision tree, k-means and support vector machines (SVM) [31]. This toolbox is primarily used for principal component analysis (PCA) regularization, dimensionality reduction, and feature extraction.

4.2.2 Image Processing Toolbox

Image Processing Toolbox is a MATLAB toolbox that provides algorithms and workflow applications for image processing, visualization, analysis and algorithm development [32]. Image Processing Toolbox makes it possible to perform image enhancement, image segmentation, noise reduction, image registration and geometric transformations. It was primarily used for data (image) augmentation in this study.

4.3 Implementation Design

The implementation processes are categorized into four steps. The first step is the data acquisition, the second step is the feature extraction, the third step is the image projection, and the final step is fingerprint recognition. The two proposed methods follow similar development patterns with slight differences. For the data acquisition, fingerprint images are taken from the selected databases (see details in section 3.1). Images are then

[9] Toolbox refers to collection of in-built functions in MATLAB.

classified into training datasets and test datasets. For the feature extraction, the Principal Component Analysis (PCA) method and Linear Discriminant Analysis (LDA) were used. Finally, the fingerprint recognition was performed using the Euclidean distance measure. All these methods are adapted and modified from the facial recognition domain but modified to work under fingerprint recognition in this thesis project.

The Principal Company Analysis (PCA) method which is mostly referred to as the eigenface method is employed as a feature extraction method in this project. The PCA finds the eigenvectors of a covariance matrix with highest eigenvalues and then uses those to project the data into a new subspace of equal or less dimension. The PCA works by converting a matrix of N features into a new dataset of N features. This is called dimensionality reduction. That is, it reduces the number of features by constructing a new, smaller number of variables which capture a significant portion of the information found in the original features. In PCA implementation, four computations were made; feature covariance, eigen decomposition, principal component transformation, and finally selection of components for projection based on variances. The PCA method that was modified and used for the feature extraction task was retrieved from the MATLAB facial recognition code implemented by Kalyan Sourav Dash [27].

The Linear Discriminant Analysis (LDA) method which is also known as fisherface method is one of the feature extraction methods used in facial recognition. For the sake of this project, it is adapted to work under fingerprint recognition. LDA follows the procedures of PCA, but it focuses on maximizing the separability among known categories or classes. In LDA, fingerprints are grouped into separate classes and the variation between the image of different classes are discriminated using the eigenvectors (fisher faces) at the same time maximizing the covariance within the same classes. Similarly, the LDA method that was modified and used for the feature extraction task was retrieved from the MATLAB facial recognition code implemented by Merve Buyukbas [28].

For fingerprint recognition, the Euclidean distance measure was used to compute the average distance between test feature vectors and all the training feature vectors. The features extracted using the PCA and LDA method were used to compute the Euclidean distance. Here, the recognition decision is made based on the recognized index of the image. It is then checked whether the image is in the dataset and as well belongs to an appropriate person or not. The algorithm is simpler to implement and requires shorter time to execute. The procedure of the recognition shown below.

```
[Euclidean_dist_min, Recognized_index] = min(Euclidean_dist)

if datalabel(Recognized_index) == datalabel_test(i)

      %%Then it belongs to the person, therefore increment count

      recognized_count = recognized_count + 1;

end

%%Here, i refers to the index of the test_image
Both datalabel and datalabel_test are matrices containing
image labels of training images and test images respectively.
```

4.4 Experiment Results

The dataset used for the project consists of 80 images acquired from the FVC 2002 database. There are 10 subjects donating 8 fingerprint images from both hands. To obtain a better accuracy, the images were augmented to increase the samples of the images (See details in Section 3.3.1). The datasets, after augmentation, became 400 images from 10 research subjects. To test the accuracies of the proposed methods, the fingerprint images were divided into training samples and test images. For the test images, two or three fingerprints were taken from each of the 10 subjects making 30 or 20 test images and 370 or 380 training images. However, the size of the test images for the proposed algorithms differs due to the fact that they work differently. The ensuing sections show and discuss the performance of the proposed methods coupled with their respective accuracies.

4.4.1 Results of Testing

Here, the images are tested to check whether it can be found in the dataset and belongs to an appropriate person. As discussed in Chapter 3 (See details in Section 3.2.1), images are labelled as 101_1, 101_2, …, 102_1, 102_2...,110_1, 110_2. The goal of the test is to check if the test image is in the training dataset and also belongs to the appropriate person. For instance, if the testing image 101_5 is projected to the training dataset, the expected outcome should be that it is in the training dataset and as well belongs to the first person. The entire test images are compared with the images of the training dataset. The result of the experiment is shown in table 4.2 below:

Methods	No. of Test Images	No. of Successful Recognition	No. of Unsuccessful Recognition	Accuracy (%)
Fisherface (LDA)	20	18	2	90.00
Eigenface (PCA)	30	26	4	86.67

Table 4.2: Performance of Eigenface and Fisherface method

For the Eigenface method, 26 out of 30 images were recognized correctly and 4 did not recognize successfully. Since the total number of test images is 30, the accuracy of the Eigenface method is (26/30) 0.86667. Similarly, for the fisherface method, 18 out of 20 images recognized correctly and 2 were unsuccessful. And the total number of test images is 20. Therefore, the accuracy of the Fisherface method is (18/20) 0.90. Some snippet results of the recognition on test images for both methods are shown in Figures 4.1 to 4.10 below.

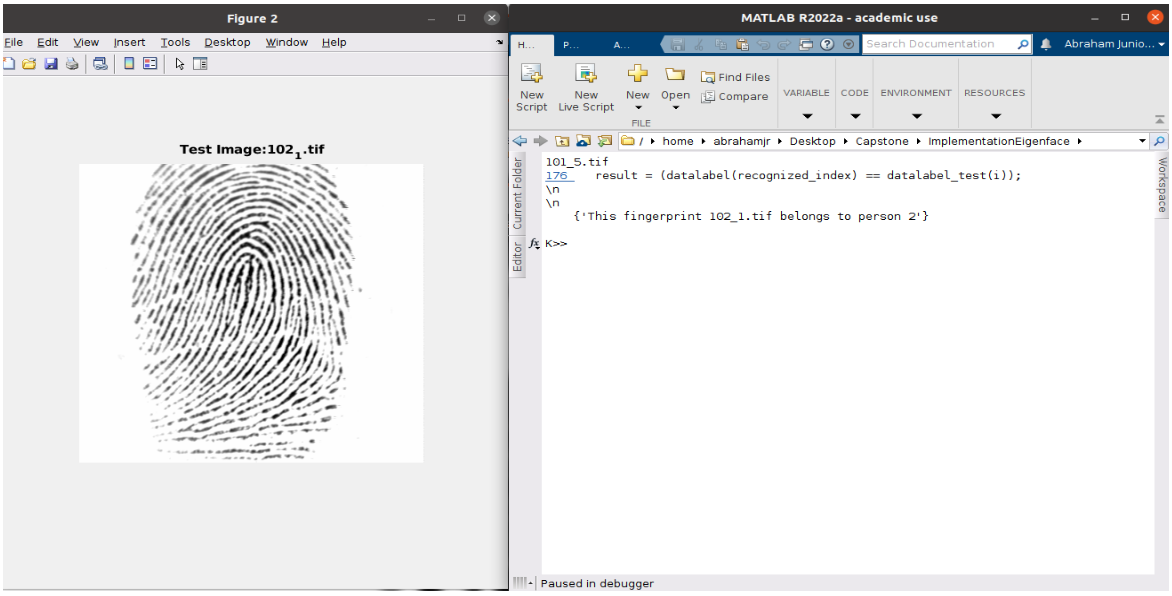

Figure 4.1: A true recognition of 2nd person

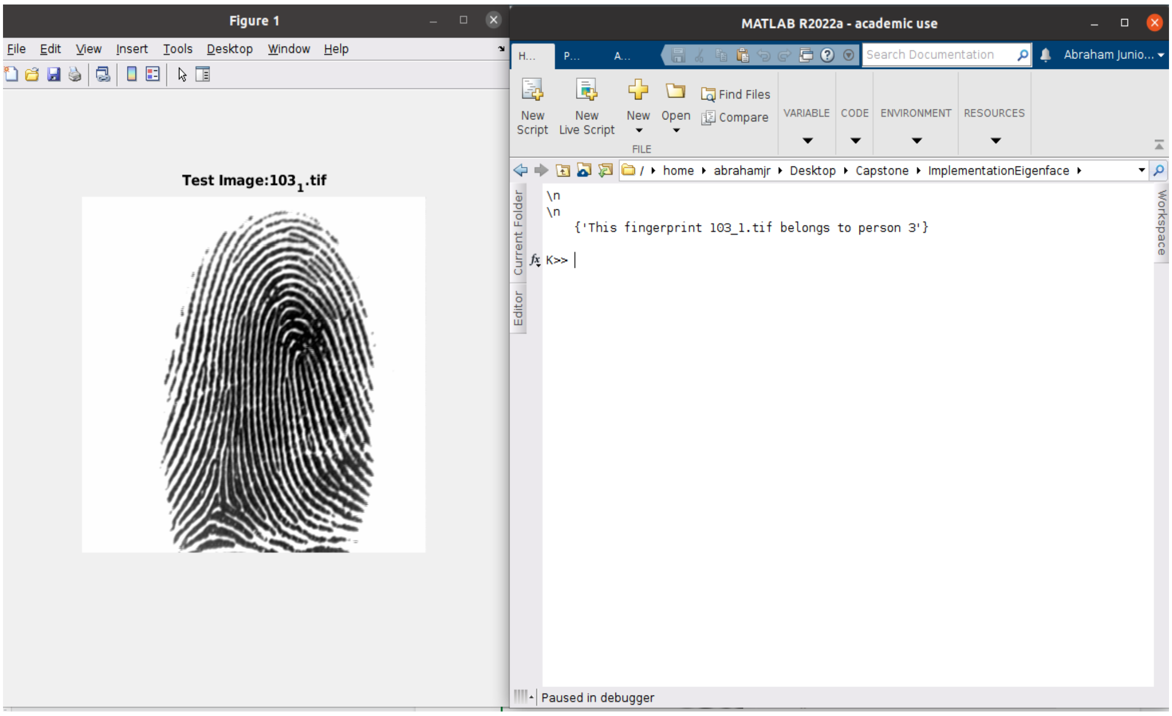

Figure 4.2: A true recognition of 3rd person

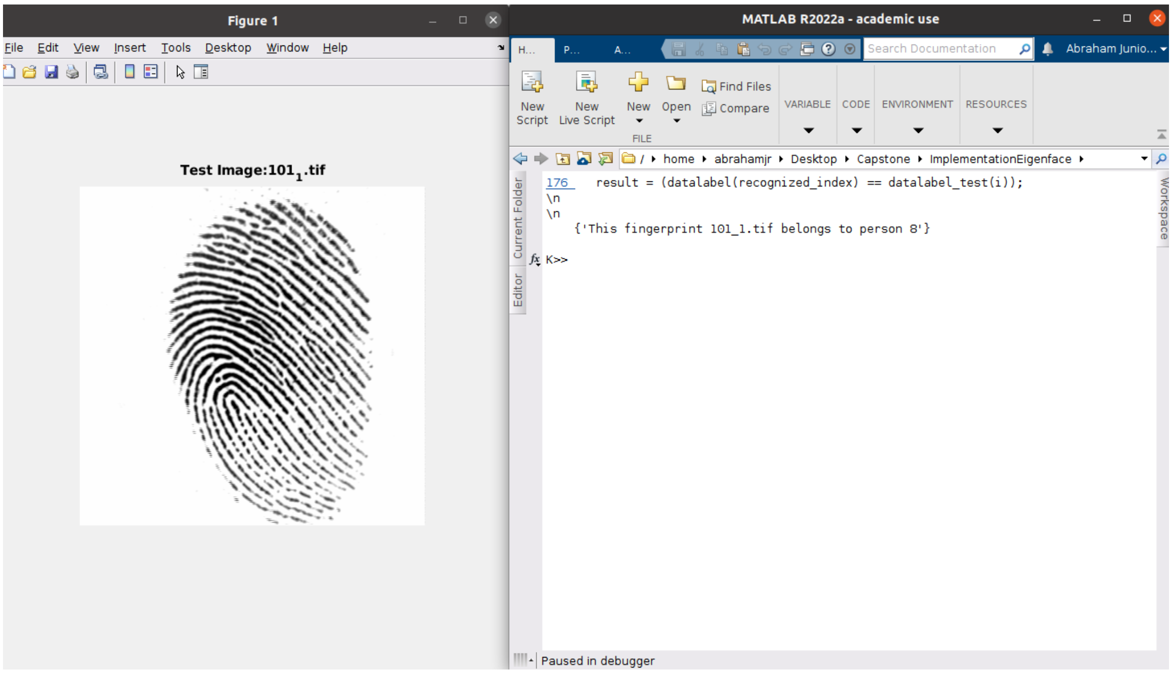

Figure 4.3: A false recognition of 8th person

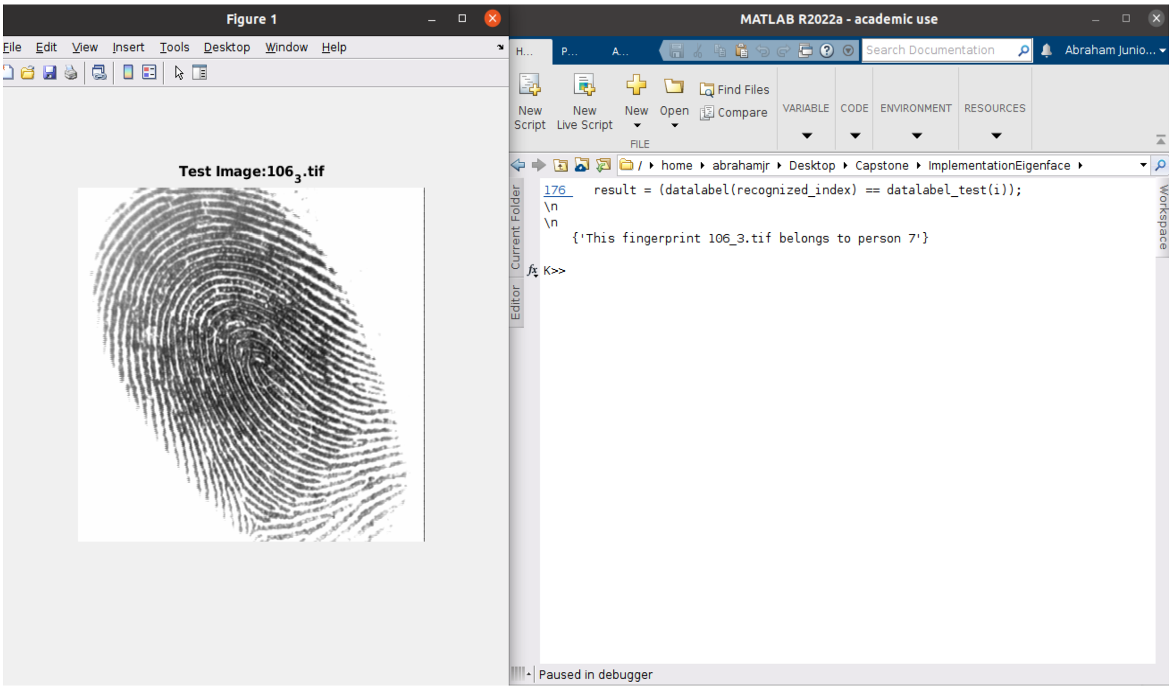

Figure 4.4: A false recognition of 7th person

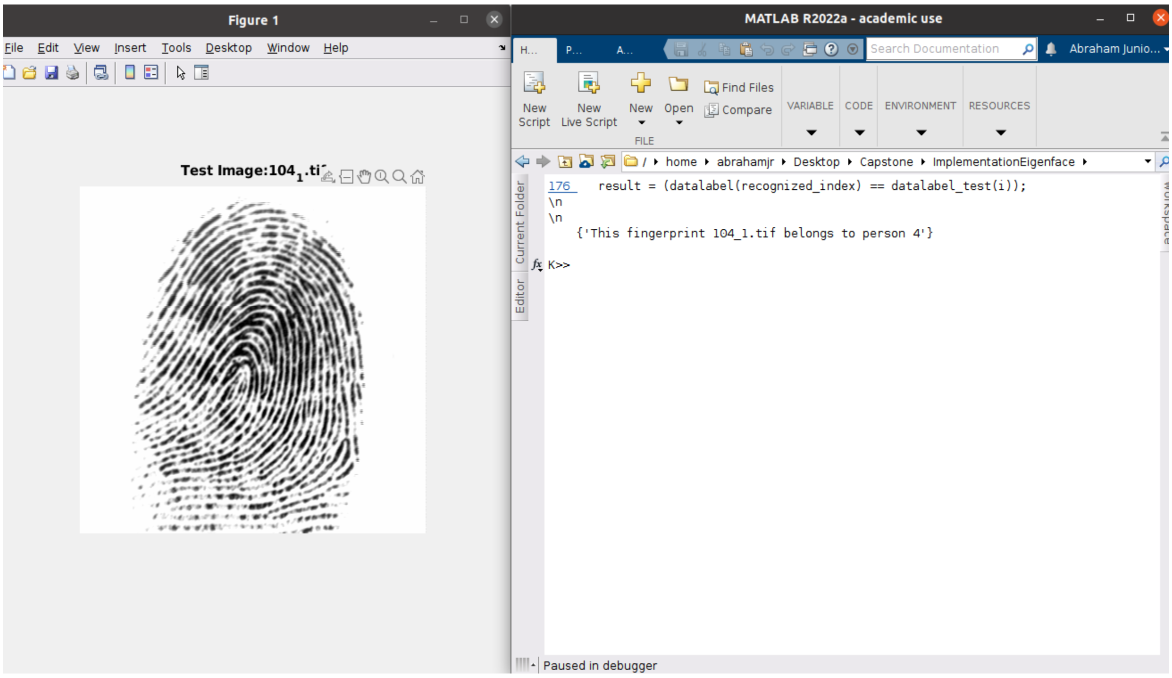

Figure 4.5: A true recognition of 4th person

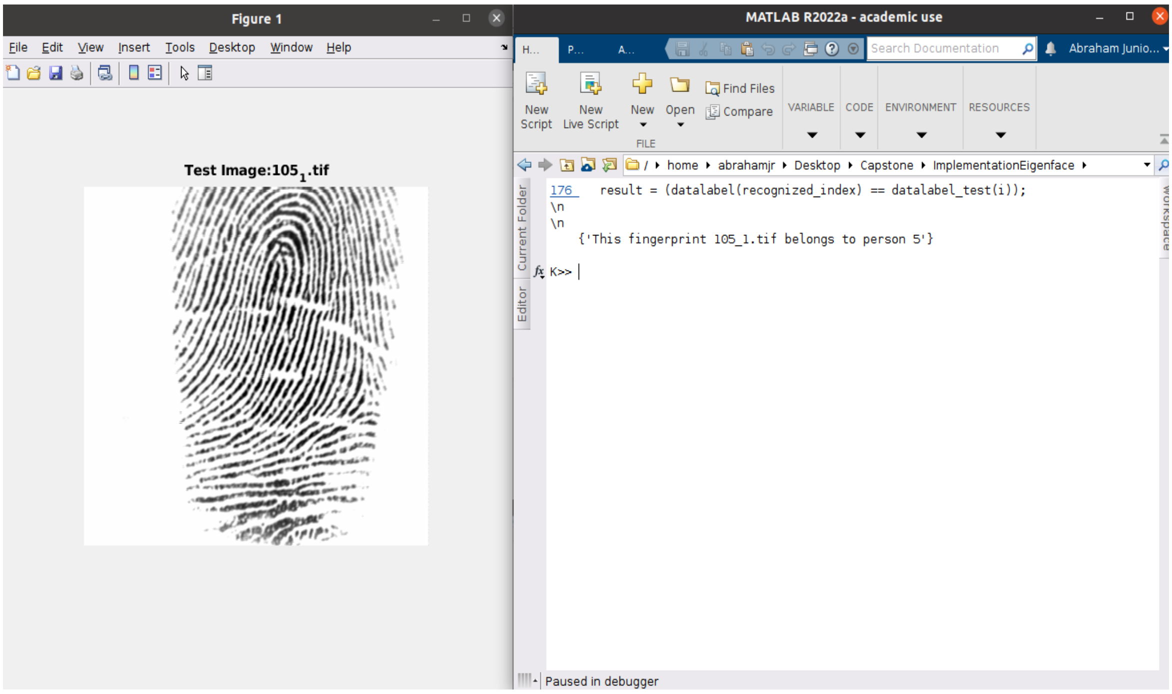

Figure 4.6: A true recognition of 5th person

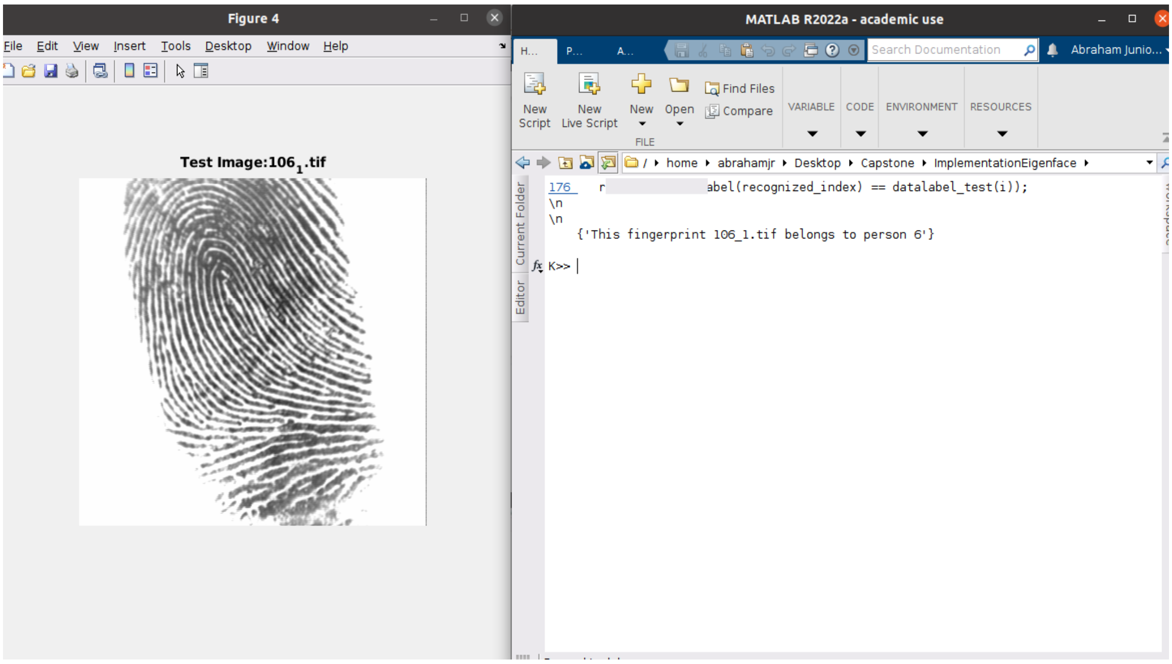

Figure 4.7: A true recognition of 6th person

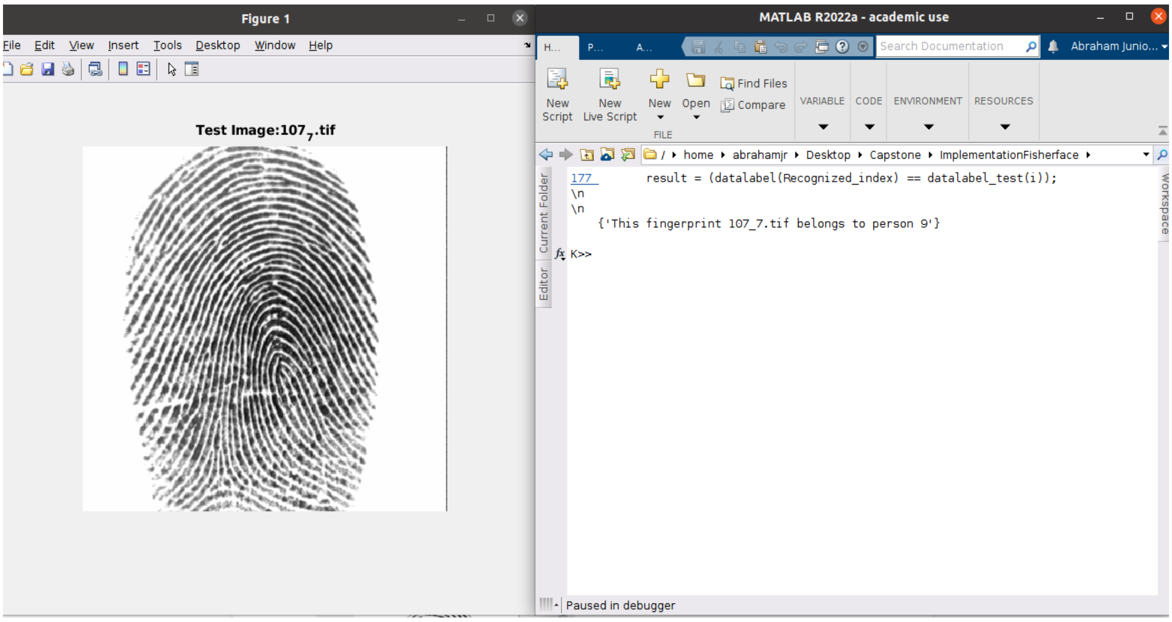

Figure 4.8: A false recognition of 9th person

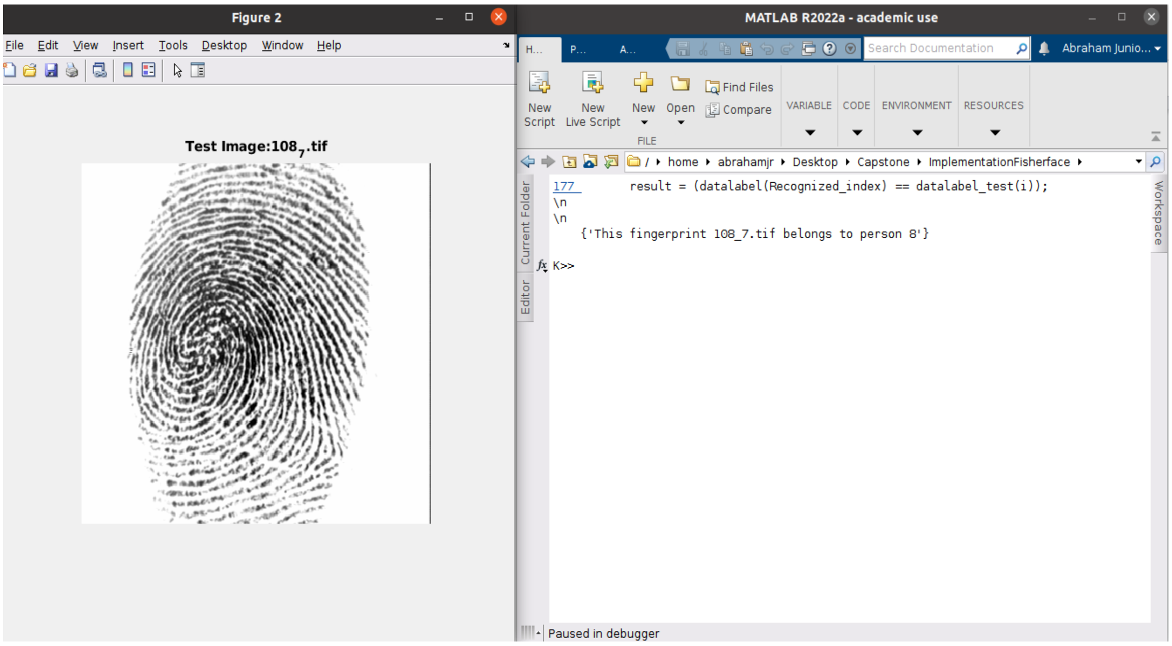

Figure 4.9: A true recognition of 8th person

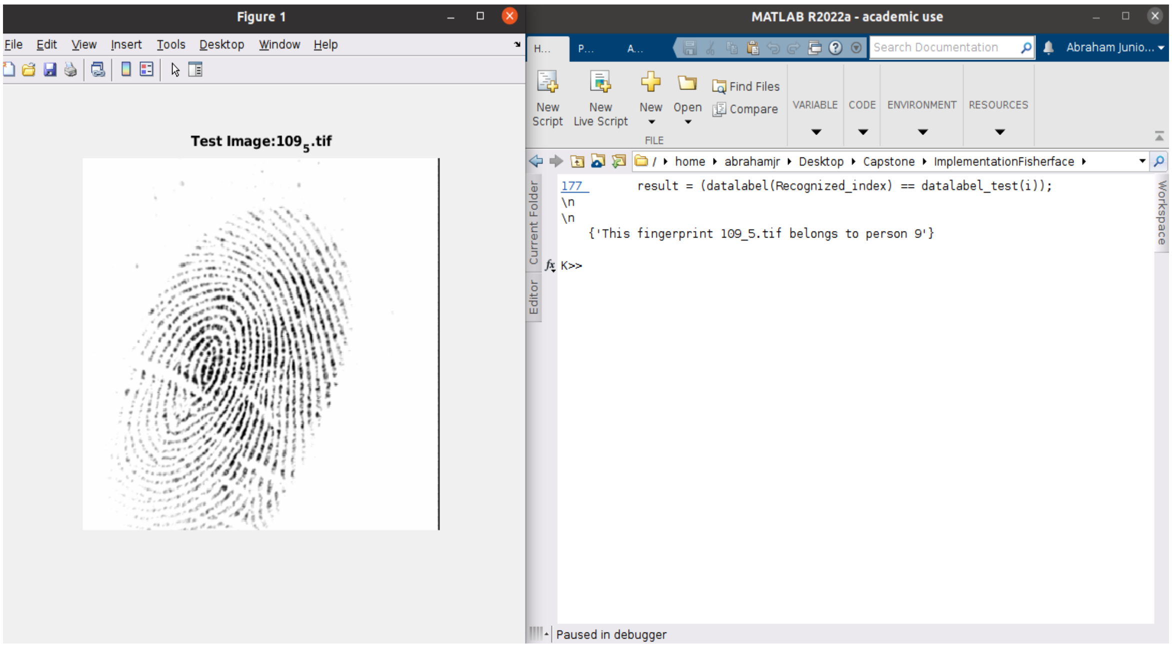

Figure 4.10: A true recognition of 9th person

4.4.2 Results of Errors

In every recognition system, there is a possibility for unexpected errors. These errors are computed to establish the accuracy and efficiency of the proposed system. In this study, the errors were computed for the two proposed algorithm using the equation given in chapter 3 (see details in Subsection 3.6.1 and 3.6.2). Table 4.3 below shows the proposed algorithms and their error rates results.

Methods	No. of Test Images	Correct Recognition	Error	FAR/FRR
Fisherface	20	18	2	0.10
Eigenface	30	26	4	0.154

Table 4.3: Error Rate (FAR/FRR)

From the table above, 2 out of 20 fingerprints were wrongly or falsely recognized during the execution of the Fisherface algorithm. Therefore, the error rate (FAR/FRR) is (2/20) 0.10 or 10%. The Eigenface, on the other hand, recorded 4 errors out of the 30 fingerprints recognition attempts. The total error rate (FAR/FRR) is (4/30) 0.154 or 15.4%. In a nutshell, the Eigenface method recorded a slightly higher errors as compared to the Fisherface.

Chapter 5: Conclusion, Limitation and Future Work

5.1 Project Summary

The research aimed at exploring the issue of identifying and recognizing occluded fingerprint images. This project seeks to adapt methods from other biometric domains to build a robust fingerprint recognition system that is insensitive to the nature of the fingerprint. This research project was categorized into three modules: image acquisition, feature extraction, image projection and fingerprint recognition. The research attempted to improve the accuracy of fingerprint recognition by proposing a non-minutiae-based algorithm that uses the facial recognition methods such as Fisherface and Eigenface method. In building the robust fingerprint recognition system, the Eigenface and Fisherface methods were implemented, trained and tested and obtained an accuracy of 86.67% and 90% respectively on the FVC 2002 datasets. The Fisherface method proved to be very efficient in recognizing the fingerprint images as compared to the Eigenface.

Even though Eigenface methods yielded slightly lower accuracy, its performance during evaluation on the test images proves that the method is capable of recognizing fingerprints images despite it being a predominant facial recognition method. In conclusion, these results indicate that the proposed methods have the potentials of working well in the fingerprint recognition domain.

5.2 Limitation of Study

This section highlights some key factors of the research which in one way or the other affected the accuracies of the proposed algorithms. The performance or accuracies of the proposed algorithms were jeopardized by the following factors.

- One major restriction includes the datasets that were used. That is, the geometry of the dataset images. In the FVC2002 dataset, the fingerprint images come from both hands and the description of the datasets did not specify which hands came first or second. It became very difficult to select images to form the test datasets. The arrangement of the images could have led to the low accuracy value obtained from the test.
- Another limitation is that these methods were not purposely meant for fingerprint recognition but are adapted to make it work. There might be some missing features that could help in the recognition process.
- The database that contains occluded fingerprints are paid ones. Thus, accessing such database requires payment of money. Several attempts were made to obtain the database, but none worked. And self-creating such occluded images require much time and resources. Considering the life span of the project, it was not feasible for such task to be performed.

5.3 Future Work

Since these methods have the potential of performing well under fingerprint recognition, in the future works, the datasets to be used for testing could be self-acquired data instead using secondary data. Therefore, as a suggestion for future work, more effort could be channeled into creating own datasets for this kind of study in order to eliminate the limitation of the database. Also, the other datasets such as NIST and Kaggle Fingerprints highlighted in Chapter 3 on Methodology could be bought and used since they are not free to use. The different datasets can be used to test and record performance accuracy.

From the literature review and related work (see details in Chapter 2), a very little research has been conducted in the area of fingerprint occlusion. All the research works are geared towards the full fingerprint image. Therefore, researchers can concentrate their study on this jurisdiction for better recognition systems.

Finally, since this project tackled fingerprint recognition with a novel approach of domain adaptation, future research can be concentrated on domain adaptation of different methods into fingerprint recognition. Transfer of learning has become an integral part of discovering novel approaches to solving problems around us.

References

[1] Maltoni, D., Maio, D., Jain, A.K., Prabhakar, S. 2009. Handbook of Fingerprint Recognition, 2nd edn. Springer, London.

[2] Malathi S. and Meena, C. 2011. Improved Partial Fingerprint Matching Based on Score Level Fusion Using Pore and SIFT Features, *2011 International Conference on Process Automation, Control and Computing, Coimbatore*. 1-4.

[3] Ratha, N., Bolle, Ratha. 2004. Automatic Fingerprint Recognition Systems, Springer, New York, 2004.

[4] Alexander Hambalik and Pavol Marak. 2016. Fingerprint Recognition System Using Artificial Neural Network as Feature Extractor: Design and Performance Evaluation, *Tatra Mountains Mathematical Publications*, 67. 117-134. doi: 10.1515/tmmp-2016-0035.

[5] Cho, S., Choi, H., Lee, W., Kim, J. 2017. Partial fingerprint matching using minutiae and ridge shape features for small fingerprint scanners, *Expert Systems with Applications.* 87. 183-198. https://doi.org/10.1016/j.eswa.2017.06.019.

[6] Feng Liu, Guojie Liu, Qijun Zhao and Linlin Shen. 2020. Robust and high-security fingerprint recognition system using optical coherence tomography, *Neurocomputing,* 402. 14-28. https://doi.org/10.1016/j.neucom.2020.03.102.

[7] Gaikwad A.T, Moud Ali, Pravin Yannawar and Vivek Mahale. 2016. Overview of fingerprint recognition system, *2016 International Conference on Electrical, Electronics, and Optimisation Techniques (ICEEOT)*. 1334-1338. doi: 10.1109/ICEEOT.2016.7754900.

[8] Kai Cao and Anil Jain. 2019. Automated Latent Fingerprint Recognition, *IEEE Transaction on Pattern Analysis and Machine Intelligence,* 41(4). 788-800. doi: 10.1109/TPAMI.2018.2818162.

[9] Kashif Noor et al. 2019. Performances Enhancement of Fingerprint Recognition System Using Classifiers, *In IEEE Access,*7. 5760-5768. doi:10.1109/ACCESS.2018.2879272.

[10] LaythKamil Almajmaie, Osman N. Ucan and Oguz Bayat. 2019. Fingerprint Recognition System based on Modified multi-connect architecture (MMCA), *Cognitive Systems Research,* 58. 107-113. https://doi.org/10.1016/j.cogsys.2019.05.004.

[11] Stephen Kouamo and Claude Tangha. 2016. Fingerprint Recognition with Artificial Neural Networks: Application to E-Learning, *Journal of Intelligent Learning Systems and Applications*. 58(2). 1-11. doi: 10.4236/jilsa.2016.82004.

[12] Zeng, F., Hu, S. & Xiao, K. 2019. Research on partial recognition algorithm based on deep learning. *Neural Computing & Applications* **31**, 4789-4798. https://doi.org/10.1007/s00521-018-3609-8

[13] Chen, X., Li, Y., Zeng, S., Shan, S. 2019. Occlusion Aware Facial Expression Recognition Using CNN With Attention Mechanism, *In IEEE Transactions on Image Processing.* 28(5). 2439-2450. doi: 10.1109/TIP.2018.2886767.

[14] Darlow, L. N. and Rosman, B. 2017. Fingerprint minutiae extraction using deep learning. *2017 IEEE International Joint Conference on Biometrics (IJCB).* 22-30. doi:10.1109/BTAS.2017.8272678.

[15] Candana M., Mathuria, M. and Yadav, S. 2015. Fingerprint Recognition based on Minutiae Information, *Internal Journal of Computer Applications.* 120(10). 975-8887.

[16] Abhyankar, A., Garware, B. and Khurjekar, I. 2015. Towards minimising effect of partial fingerprint images on the performance of fingerprint recognition systems, *International Conference on Information Processing (ICP),* 839-842. doi: 10.1109/INFOP.2015.7489498.

[17] Sang, J., Chen, J., Qian, Q., Wang, H. and Wu, H. 2016. An efficient fingerprint Identification algorithm based on minutiae and invariant moment, *Personal and Ubiquitous Computing.22*(1).71-80.https://doi.org/10.1007/s00779-017-1094-1

[18] Liu, L., Tan, T., Zhan, Y. 2008. Based on SVM automatic measures of fingerprint image Quality*, In: Pacific-Asia Workshop on Computational Intelligence and Industrial Application, PACIIA 2008 Zhao*.10-17.

[20] Susara Thenuwara, Chinthaka Premachandra, Sagara Sumathipala. 2019. Hybrid Approach to Face Recognition System Using PCA & LDA in Border Control, *National Information Technology Conference (NTC)*. 1-7.

[21] Sudha Rani and Nageshwar Rao. 2018. A comparative Study of Various Noise Removal Using Filters, *Research & Reviews: Journal of Engineering and Technology, 7(2).* 47-52. Retrieved from https://pdfs.semanticscholar.org/710c/61387615e5bd720864e22833b71c7210af62.pdf

[22] Bruno Luong. 2021. Min/Max/Median, *MATLAB Central File Exchange.* Retrieved from https://www.mathworks.com/matlabcentral/fileexchange/24705-min-max-filter

[23] Frank Peprah, Michael Asante. 2017. Comparative Analysis of The Performance of Principal Component Analysis (PCA) And Linear Discriminant Analysis (LDA) As Face Recognition Techniques, *International Journal Of Scientific & Technology Research.* 6(10).

[24] Ming Li, Chengyang Yu, Fuzhong Nian, and Xiaoxu Li. 2015. A Face Detection Algorithm Based on Deep Learning, *International Journal of Hybrid Information Technology*. 8(11). 285-296.

[25] General News. 2021. Violent crimes in Ghana up by 20% from January to June 2021. *Ghana Business News*. https://www.ghanabusinessnews.com/2021/07/30/violent-crimes-in-ghana-up-by-20- from-january-to-june-2021-report/

[26] Khoshgoftaar, T., Shorten, C. 2019. A survey on Image Data Augmentation for Deep Learning, *AI international Conference, 6*(1). 3-10. DOI:10.1186/s40537-019-0197-0

[27] Kalyan Sourav Dash. 2014. Face recognition using PCA. *MATLAB Central File Exchange.* Retrieved from https://www.mathworks.com/matlabcentral/fileexchange/45750-face-recognition-using-pca

[28] Merve Buyukbas. 2022. Face Recognition Using FLD. *MATLAB Central File Exchange.* Retrieved from https://www.mathworks.com/matlabcentral/fileexchange/89228-face-recognition-using-fld

[29] Jagtap A., M., Kangale, V., Unune, K., Gosavi, P. 2019. A study of LBPH, Eigenface, Haar-like feature for Face Recognition. *International Conference on Intelligent Sustainable Systems.* 220 – 223.

[30] E., Himanshi and R., Kaur. 2015. Face Recognition Using Principal Component Analysis. *IEEE International Advance Computing Conference.* 585-589. Retrieved from https://ieeexplore.ieee.org/document/7154774

[31] Mathworks. 2022. *Statistics Toobox: User's Guide (R2022a).* Retrieved from https://www.mathworks.com/products/statistics.html?s_tid=srchtitle_statistics%20and%20machine%20learning%20toolbox_1

[32] Mathworks. 2022. *Image Processing Toobox: User's Guide (R2022a).* Retrieved from https://www.mathworks.com/products/image.html?s_tid=srchtitle_Image%20processing%20toolbox_1