THE UNIVERSITY OF TURKISH AERONAUTICAL ASSOCIATION
INSTITUTE OF SCIENCE AND TECHNOLOGY

LOW-QUALITY FINGERPRINT IDENTIFICATION MODEL USING GLOBAL MAP FEATURE INDICATION (GMFI) METHODOLOGY

MASTER THESIS

Noaman Ahmed Yaseen AL-FALAHI

THE DEPARTMENT OF INFORMATION TECHNOLOGY

JANUARY 2018

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THE UNIVERSITY OF TURKISH AERONAUTICAL ASSOCIATION
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I hereby declare that all the information in this study I presented as my Master's Thesis, called: "Low-Quality Fingerprint Identification Model Using Global Map Feature Indication (GMFI) Methodology", has been presented in accordance with the academic rules and ethical conduct. I also declare and certify with my honor that I have fully cited and referenced all the sources I made use of in this present study.

05.01.2018

Noaman Ahmed Yaseen AL-FALAHI

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With all my love

January 2018 Noaman Ahmed Yaseen AL-FALAHI

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ABSTRACT

LOW-QUALITY FINGERPRINT IDENTIFICATION MODEL USING GLOBAL MAP FEATURE INDICATION (GMFI) METHODOLOGY

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Biometric Fingerprint Identification (BFI) is one of the most challenge tasks in the image processing, computer vision task, and machine learning. It is the most well-known biometric since of their uniqueness and the consistency over time. Over a century, biometric fingerprints have been widely used for human identification. More recently, due to the advantages of the computational capability, biometric fingerprint identification becomes an automated system. Biometric fingerprint image identification presents a key issue in the intelligent technology and information security.

In this thesis, we propose an enhancement approach for the localization based minutia feature extraction approach for fingerprint identification. We propose such a robust and efficient model for low quality fingerprint identification approach based on a Global Map Features Indication (GMFI) methodology to improve the Localized based approach. Our main contribution of this thesis is to jump over this difficulty to make the localization approach stronger than the original one to make more suitable to deal with all fingerprint image identification cases such a low-quality fingering image identification. The proposed system has been tested using FCV 2006 database that has shown the most challenges low-quality fingerprint image cases.

The experimental results show our approach has achieved about 98.74%) while the localization approach based minutia feature extraction has achieved (58.13%)

which means that our proposal by (40%) more than the standard approach. Although, our approach has consumed (10.0854 sec.) as the mean average time while the local approach has consumed (6270 sec.) as the means average consuming time for the preprocessing.

Keywords: Minutiae, ridges, low quality fingerprint, global mapping, feature indication, matching score, Gabor filter, localization approach, image frequency.

ÖZET

GLOBAL HARİTA ÖZELLİK GÖSTERGELERİ (GMFI) METODOLOJİSİ KULLANARAK DÜŞÜK KALİTELİ PARMAK İZİ TANIMLAMA MODELİ

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Ocak 2018, 105 sayfa

Biyometrik Parmak İzi Tanımlama (BFI), görüntü işleme, bilgisayar görme görevi ve makine öğrenmede en zor görevlerden biridir. Eşsizliği ve zaman içindeki tutarlılığı nedeniyle en iyi bilinen Biyometrik yöntemdir. Yüzyılı aşkın bir süredir, biyometrik parmak izleri insanların kimliğini saptamak için yaygın olarak kullanılmaktadır. Son zamanlardaysa, bilgisayar kapasitelerinin avantajlarından dolayı biyometrik parmak izi tanımlama otomatik bir sistem haline gelmiştir. Biyometrik parmak izi görüntü tanımlama akıllı teknoloji ve bilgi güvenliğinde önemli bir husus oluşturmaktadır.

Bu tezde, parmak izi tanımlama için lokalizasyona dayalı ufak ayrıntılar çıkarımı yöntemi için bir geliştirme yaklaşımı önermekteyiz. Lokalizasyona dayalı yaklaşımı geliştirmek için bir Global Harita Özellik Göstergeleri (GMFI) metodolojisine dayanan düşük kaliteli parmak izi tanımlama yaklaşımı için güçlü ve etkin bir model önermekteyiz. Bu tezin ana katkısı, düşük kaliteli parmak izi görüntü tanımlaması ile bütün parmak izi tanımlama durumlarını ele almak, lokalizasyon yaklaşımını orijinal halinden daha güçlü ve daha uygun bir duruma getirerek bu sorunun üstesinden gelmektir. Önerilen sistem, düşük kaliteli parmak izi görüntüsü durumlarında en çok zorluk yaşanan FCV 2006 veri tabanı kullanılarak test edilmiştir.

Deneysel sonuçlar lokalizasyon yaklaşımına dayanan ufak detay çıkarımının (%58.13) oranda başarı göstermesine rağmen, bizim yaklaşımımızın yaklaşık (%98.74) oranında başarı gösterdiğini ortaya koymuştur, bu da önerdiğimiz yöntemin standart yaklaşımdan (%40) daha fazla başarılı olduğu anlamına gelmektedir. Bununla beraber bizim yaklaşımımız ön işleme için ortalama süre olarak (10.0854 saniye) alırken, lokal yaklaşım (6.270 saniye) almıştır.

Anahtar kelimeler: Ufak detaylar, uzun şeritler, düşük kaliteli parmak izi, global haritalama, özellik göstergesi, eşleme skoru, Gabor filtresi, lokalizasyon yaklaşımı, görüntü frekansı.

CHAPTER ONE

INTRODUCTION

1.1 Motivation

Person identification schemes to either identity or verify the identity of the individual using a variety of system requires reliable person information. This information in such as these cases are very important to the individual who are participating and requesting such service from the system that are required these identification information [1].

The purpose of the scheme is to make sure that is the rendered service such as person identification and verification task are accessed by a legitimate user which is not anyone else can use the user information for access [1]. Such good examples of the systems which include secure access to the building, computer system, cellular phones, personal laptop, bank account, and Asynchronous Teller Machine (ATMs). However, in the absence of robust and reliable authentication system which required and include (identification and verification) procedure that is vulnerable to the wiles of an impostor [1].

Basically, different identification information based security requirements such as identification card (Token-Based Security) and password (knowledge-based security) have been suggested and used to restrict access to systems. Therefore, the security task can be easily latched in the system when the provided information such as a password is divulged to unauthorized used or the identification card that has been stolen [2]. In this case, may be simple passwords that will be simply to guess by the person who is the imposter and also difficult password may be hard to recall by the person who is a legitimate user. For this critical situation and difficult condition, the biometric information has address this kind of problem for the plague traditional verification and identification task [2].

Among all the biometric information that are shown in Figure 1.1 which are proposed and used in such different systems, fingerprint information's have shown that they have one of the highest levels of the reliability that is basically used by forensic experts to detect and discover the criminal investigation. Basically, fingerprints refer to the flow and organize such of ridge pattern in the tip of the finger. Those patterns are being organized in a practical and unique pattern for each person [2].

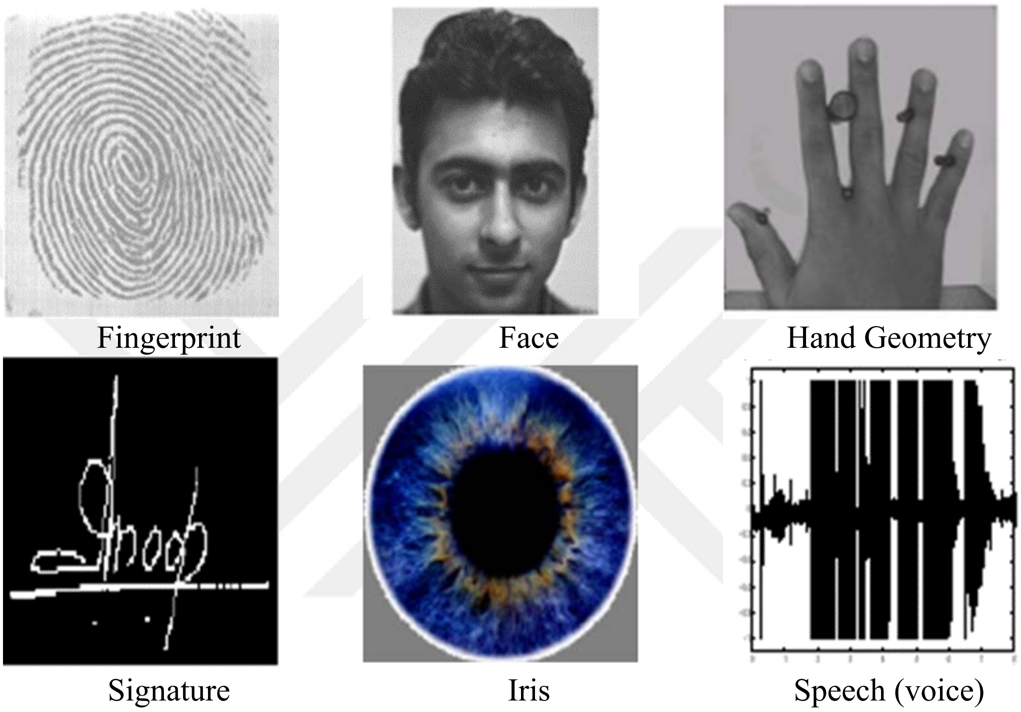


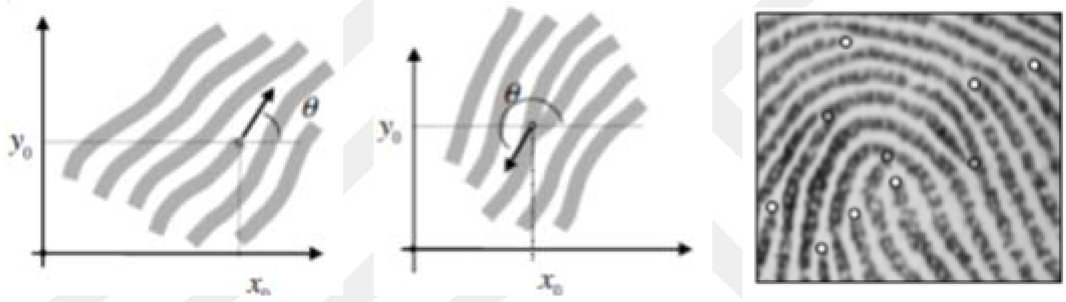
Figure 1.1: Some example of biometric traits information that used for authenticating (identification/verification) for an individual [2].

The ridge flow exhibits anomaly in local regions of the fingerprint is represented as the position and orientation. In this case, those positions and orientations are used to represent and identify (match) the fingerprints. Although, scientifically established of the fingerprints are believed to be unique across the individuals and across fingers of the same individual [2]. Even the identical twins that having similar Deoxyribo Nucleic Acid (DNA), are believed that having different fingerprints. Traditionally, fingerprint patterns that have been extracted by creating an inked impression of the fingertip on paper [1].

The electronic era device that has ushered in the range of the compact sensor which is basically used to provide digital images of the fingerprint pattern. This type of acquisition sensor can be easily incorporating into such existing computer peripherals such as a mouse or a keyboard. There are making this mode of identification very useable and attractive. This kind is led to push up and increased the participant to use the automatic fingerprint identification and verification system based on authentication approach [2].

1.2 Fingerprint Identification Concept

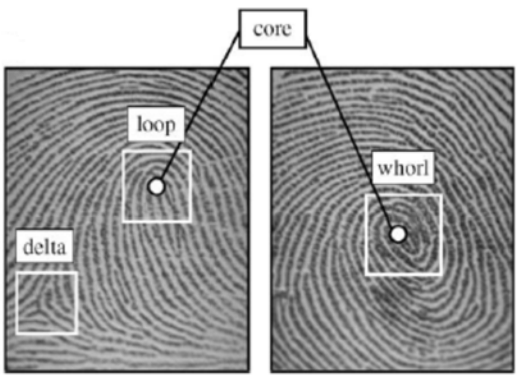
Fingerprints are the most important part in biometric for human identification. They are unique and stable from birth to death. So, fingerprints have been used for the forensic application and personal identification. Fingerprint has some unique points on the ridge which is known as minutiae point. A minutia can be in one of two main types which are termination point and bifurcation point [3]. As shown in Figure 1.2.



(a) (b) (c)

Figure 1.2: Fingerprint minutia features (a) a termination minutia feature (b) bifurcation minutia feature (c) termination feature [3].

Fingerprint pattern contains such one or more regions. These regions are constructed forms such lines that create special shapes which may be classified into three main classes as it shown in Figure 1.3 [4].



(a) (b)

Figure 1.3: Fingerprint landmark core point and region detection (a) Delta and Loop features, (b) Whorl feature [4].

Loop, Delta, and whorl are the main shapes that are regions are classified to. Many fingerprint identification and verification algorithms depend on matching approach as a final stage of the fingerprint processing as well as to some pre-processing techniques that based on the landmark point detection or to the center point of the fingerprint which is called the core point. The region and core point detection in the fingerprint is called the Region of Interest (ROI) inside the fingerprint image as it shown above in Figure 1.3 [4].

Ridges and furrows in the fingerprint area present good similarity indication such as parallel are mind average [5]. Technically, fingerprints are not distinguished by the ridges and furrows that are detected and extracted in particular case inside the fingerprint, but it by the minutia feature. Minutia features are some abnormal and traditional cases of the feature points in the fingerprint which is originally used the ridges as it shown in Figure 1.3 [6]. Those features are traditionally the standard features which most of the fingerprint identification and verification systems depend on in the matching stage. Typically, the individual young man has an average on 20.7 ridges per centimeter while the individual female has on 23.4 ridges per centimeter [6].

1.3 Automatic Fingerprint Identification System

Personal identification and verification systems most widely used biometric characteristic such as fingerprint information for personal verification. This is due to the well-known fingerprint permanence, distinctiveness, ease of acquisition, universality, stability over time and high matching accuracy rates [7]. The fingerprint attributes can be divided into three levels, as shown in Figure 1.4 [6]:

The first level of features is the Level-1 feature attributes such as the overall fingerprint ridge patterns. The second level of the features is Level-2 attributes such as the local ridges attributes which represented by the minutiae, have been extensively studied and they are employed in most existing Automatic Fingerprint Recognition Systems (AFRS). Level-3 feature attributes which are the third level of the feature represented by the ridges dimensional attributes. This type of feature is ignored in many AFRS, even though they are also very distinctive and have been used for a long time in the forensic community [8]. Level-3 features refer to Ridge dimensional attributes such as ridge contours and pores, which are fine details on ridges [9].

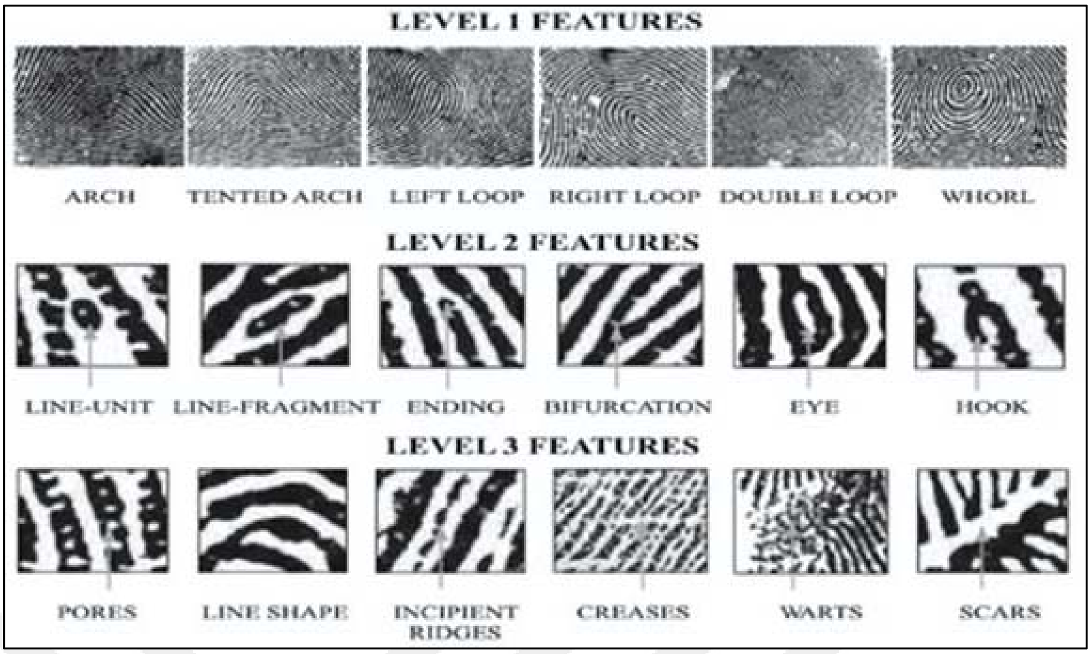


Figure 1.4: Fingerprint attribute at level1 (i.e., overall fingerprint ridge patterns), level2 (i.e., local ridges attributes), and level3 (i.e., ridges dimensional attributes) [6].

1.4 Problem Statements

Accurate and reliable fingerprint identification and recognition task is a big challenge task of data recognition sine it depends on the quality of the fingerprint information which is in regularly on the scanned fingerprint image quality. In other words, fingerprint recognition systems are very sensitive to the image noise and the degradation level since it depends on the recognition performance in term of the feature extraction and the matching stage [10].

Generally, Fingerprint Identification Systems (FIS) such as fingerprint identification approach that rely on the quality of the fingerprint images in many cases such as the preferable to an elimination of the low -quality fingerprint image as well as to replace them with the acceptable high-quality fingerprint images. There are several factors that determine the quality of a fingerprint image: acquisition device conditions (e.g., dirtiness, sensor, and time), individual artifacts (e.g., skin environment, age, skin disease, and pressure) etc. Many of these factors may lead to partially loss of fingerprint images as they shown in Fig.1. shows some cases of the low and bad quality fingerprint image are shown in the Figure 1.5, those images has been take form different dataset such as FCV 2004, and FCV2006. The fingerprint images quality is usually depending on the clarity of ridges and valleys and, consequently, on the "extractability" of the features used for recognition [2].

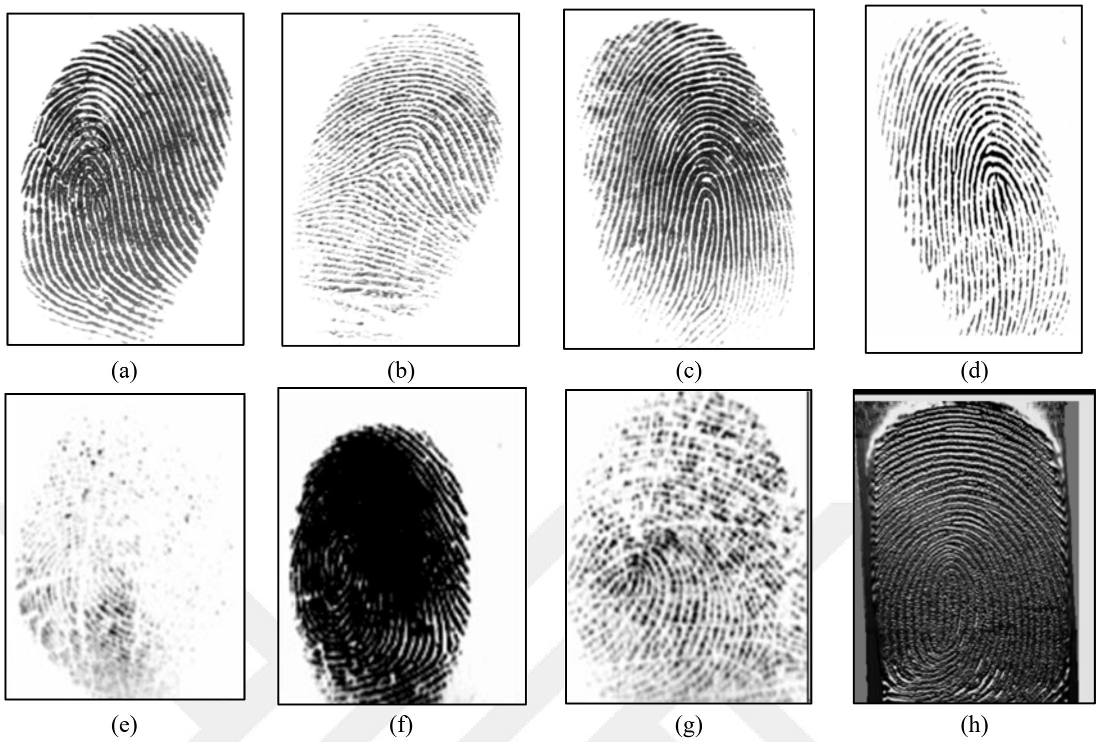


Figure 1.5: Some cases of the fingerprint image (a) rotated at angles -50, (b) rotated at angles -30, (c) rotated at angles -10, (d) rotated at angles 10, (e) rotated at angles 30, (f) rotated at angles 50 (e) Dry (f) Wet (g) Scarred (h) Bad quality.

1.5 Main Problem Scope

The bad and low-quality fingerprint processing required to achieve better performance accuracy rather than attempting steps to enhance the input image in the pre-processing stage during the identification and verification task [11]. There are several factors which can determine the quality of the fingerprint image such as [12]:

1. **First factor:** Fingerprint acquisition device condition such as dirtiness, sensor, and time-consuming for fingerprint images.
2. **Second Factor:** Individual artifacts such as the skin environment, age, skin disease, and pressure condition.

Many of these factors lead to partial loss some of the fingerprint images attribute. Fingerprint image quality is usually depending on the clarity of feature points such as ridges and valleys which consequently depend on the extraction stage of the fingerprint feature points which will use later for the matching stage [12].

Most of the existing Automatic Fingerprint Recognition System (AFRS) use the local feature extraction approach for fingerprint authentication system. This approach depends on the local feature points which are determined by minutia features such as the terminations and bifurcations of fingerprint ridges. However, this approach for the fingerprint identification and verification task has many issues that related with the minutia features such as [13].

1. **The Noisy Fingerprint Images**: The amount of noise and distortion during the acquisition stage of the fingerprint image which causes error in minutia extraction by missing minutia feature points where the performance of the recognition (identification and verification approach) relies on [14].
2. **The Rotation Fingerprint Images:** Rotational, different orientation, and the displacement of the fingerprint image that placed on the sensor during the scanning or image acquisition step. this issue can lead to different images for the basically the same fingerprint image by having just a part that only overlaps area which is resulting in only a small number of the corresponding minutia feature points [15].
3. **The Poor and Bad-Quality Fingerprint Images:** Poor or low-quality fingerprint images be very difficult to rely on those to obtain the minutia features. Therefore, it is very necessary to exploit such a novel model for attributed extraction like local ridge features as well as developed a new methodology which is more suitable for partial fingerprint recognition (identification and verification task) [16].

1.5.1 Standard Fingerprint Verification and Identification System

This thesis focuses on the incomplete image problem in fingerprint verification and identification task of the fingerprint image.

1.5.2 Fingerprint Verification Task

Identification of the fingerprint image task is the comparison of the tested (claimant) fingerprint against an enrollee one. In this task, the main intention of the verification task is to match the claimant fingerprint image. This should be done by finding the better matches for the claimant or the tested fingerprint image to the enrolled fingerprint images that have been stored in the database [17].

To prepare for verification task, the tested person is initially enrolling his or her fingerprint image into the verification system. Then, a representation of that fingerprint feature is stored in some compressed format along with the person's name or another identity [17].

1.5.3 Fingerprint Identification Task

Identification task is the also one of the most important tasks for the fingerprint identification and verification (fingerprint recognition). In this task, both verification and identification are used to identify the users [17].

In the identification stage, an individual person is recognized by comparing his/her fingerprint image with the entire fingering images that have been extracted and stored in the database. This step as the fingerprint identification is required for finding the best template matching [18]. In this case, the system conducts the identification stage as the one-to-many comparison to establish the identity of the individual user that is trying to enroll in the system. The individual user that is trying to be identified does not have to claim that any identification such as (Who am I?). In contrast, in the verification system, the individual user that to be identified must claim his/her identity such as (Am I whom I claim to be?). Then, this template compared to the individual's biometric features (characteristic) [18]. More precisely, the identification task conducts one-to-one comparisons to establish the identity of the individual used in contrast with the verification task [19].

In general, before the fingerprint identification and verification system is able to verify/identify the specific biometrics of the individual user, the system requires some initial data to compare with the database. In this case, a profile or template containing the biometric features or properties such as specific features to store in the system. This step is called the used enrolling, identification, and the verification which is described and illustrated in Figure 1.6 [20].

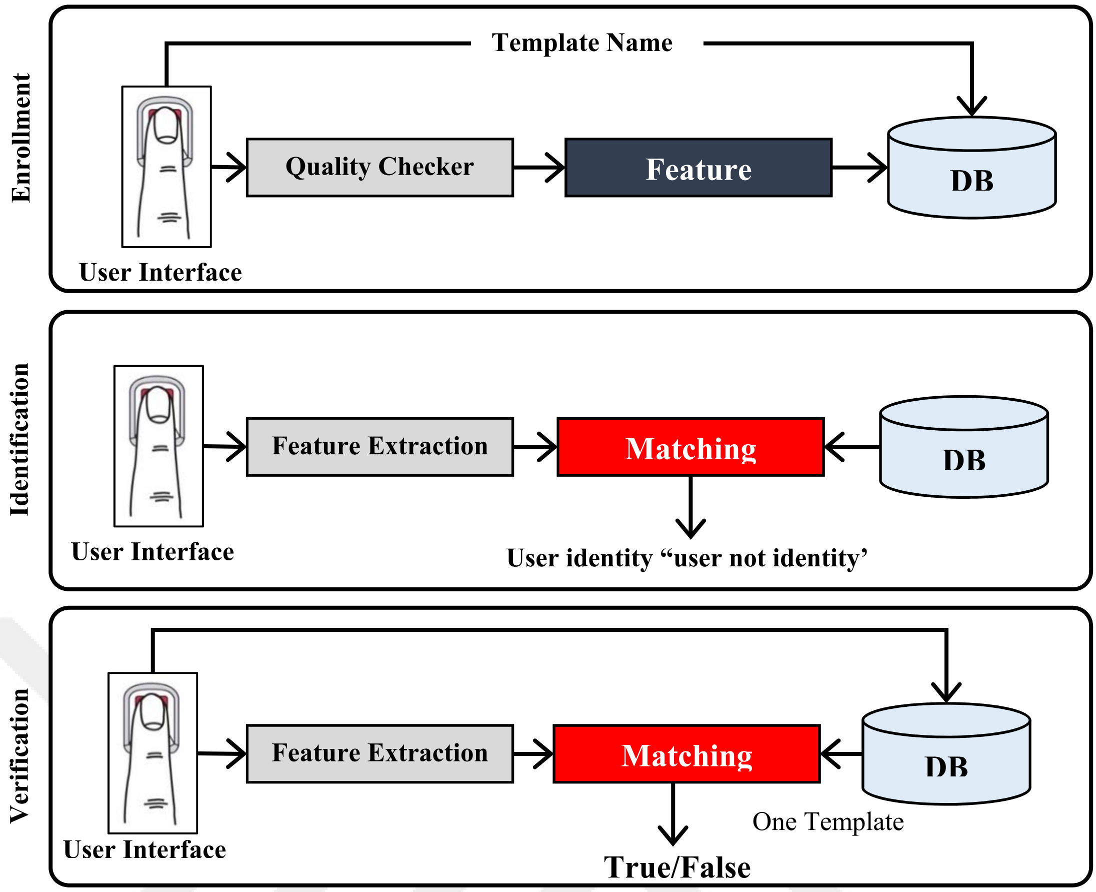


Figure 1.6: Enrollment, identification and verification system.

1.6 Research Objectives

The main objective of this research work is to develop a fingerprint identification approach for low-quality fingerprint images. The success rate accuracy of the proposed algorithm for the low-quality fingerprint images should be significantly better than that suing of the standard approach of the local minutia approach. The system performance will be investigated to determine the system performance behavior that has been tested on the low-quality fingerprint images, and its dependency on the partial fingerprint features loss will be investigated.

1.7 Aim of Thesis

Because of the uniqueness and invariability of the low-quality fingerprints images, fingerprints identification and verification system (fingerprint recognition) have been used in several applications such as access control to such particular systems like the bank account, or banking system. In additional to the security verification of purchasers and firearm as well as to the driver's license application verification system which is usually associated with the police work.

Fingerprint identification and verification approach in some cases is very challenge task such as in noisy finger, rotation, and bad quality fingerprint image. Since the most popular standard approach that relies on the minutia feature extraction for fingerprint identification and verification approach which is a (Local Minutia Approach) which is not robust enough to deal with such those problems, in this thesis we propose such a different approach to solving the low-quality fingerprint identification approach that the local approach has felt on that.

1.8 Contribution of Research

The main contribution of this thesis is to develop and enhancement the low-quality fingerprint identification and verification approach by proposing a Global Map Feature Indication and extraction (GMFI). The Aim of this proposal is to improve the Localization approach for minutia feature based feature extraction by propose a globalization methodology for generating a Global Map Features Indication (GMFI) to enhance and improve the localized feature extraction and detection approach (Minutia).

In this thesis, we have done some technical contributions that depend on the combination between two different scenarios that used to representation the fingerprint image forms which are:

1. Minutia-based Feature Extraction Approach: The first approach, which is minutia-based, represents the fingerprint by its local minutia features (Localization based Feature Extraction Approach), like terminations and bifurcations (valley and furrow). This approach has been intensively studied, also is the backbone of the current available fingerprint recognition products. We also concentrate on this approach in our project.
2. Image-based Approach: The second approach, which uses image-based methods, tries to do matching based on the global features (Globalized Map Feature Indentation Approach) of a whole fingerprint image. It is an advanced and newly emerging method for fingerprint recognition. And it is useful to solve some intractable problems of the first approach. But our

project does not aim at this method, so further study in this direction is not expanded in our thesis.

Our contribution of this proposal is proposed a Global Map Features Indication (GMFI) Approach that is extracted after we design an enhancement approach for the low-quality fingerprint image using localization approach. The proposed localization approach has been designed by using local image normalization and localized image filtering (by multidimensional Gabor filter). It has been used to extract the local point of minutia features of that are not appear in the standard (Localization approach). (Localization Approach). To design that, we have to used many steps to implement the full approach which has three main stages, fingerprint image enhancement, Global Map Feature Indication and Extraction, Localized feature extraction 9Minuteia features). The main steps of the localization enhancement based feature extraction approach is summarized by using the localized feature orientation and feature vector detection, the localized features ridge frequency detection, and the localized feature filter bank (generation).

Finally, our contributions for the proposed approaches that we have used for this thesis are:

1. Implement the Local approach for fingerprint authentication which is based on the Minutia feature extraction as a main approach for fingerprint identification and verification task.
2. Implement our proposed approach the Global Map Feature Indication approach for the low-quality fingerprint identification which is based on another methodology for feature extraction to avoid the main limitations of the local approach. In this approach, we proposed another technique of adaptive way for solving the rotation, noisy, and the fingerprint orientation.
3. Compare between the main standard approach for Minutiae feature extraction and our proposed approach for the low-quality fingerprint identification.
4. Draw a conclusion after we calculate the final conclusion and the behavior of each approach separately and discuss them in detail.

1.9 Thesis Organization

This thesis shows the design of fingerprint authentication system by obtaining the global fingerprint features and apply the matching alignment algorithm (invariance moment function) on incomplete fingerprint images. The system consists of three main stages: image pre-processing stage, feature extraction stage, and finally the matching stage. The thesis consists of five chapters:

Chapter 1: This chapter gives a brief introduction to the biometric fingerprint systems, and describes the Biometrics types and the definition. It also gives their application areas.

Chapter 2: Lists the related works and the recently literature survey of the biometric fingerprint authentication system.

Chapter 3: System design and implementation of the proposed system: it illustrates the proposed system which is the robust and efficient model for low-quality fingerprint identification approach based on a Global Map Features Indication (GMFI).

Chapter 4: Describes the implementation results and discussion of the proposed approaches for fingerprint identification system.

Chapter 5: Contains the conclusion and gives some suggestion for future works.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

Biometrics is an emerging technology that provides accurate and highly secure personal identification systems for civilian and forensic applications [21]. The positive impact of biometric modalities on forensic science began with the rapid developments in computer science, computational intelligence, and computing approaches [22]. These advancements have been reflected in the biometric modality especially in capturing process, feature extraction, feature robustness, and features matching [23]. In contrast, low and poor-quality fingerprint image for fingerprint identification task using a popular approach such as a minutia-based feature extraction can cause many problems and low performance [24]. Therefore, it is being very necessary to investigation for different approaches that depend on another scenario that have been already proposed to solve the low-quality fingerprint identification issue [25].

2.2 Literature Survey and Related works

Several researches have done to develop and enhancement several techniques to be the best algorithms for low and poor-quality fingerprint identification since the emergence of this concept at the first time. In this chapter, we show and review the newly and recently literature in which associated to this goal of enhancement the minutia-based feature extraction for low and poor-quality fingerprint images.

Zaixing He et al. [26] presented a novel method for low quality fingerprint recognition that based on a limited ellipse-band-based matching approach to enhance the low-quality fingerprint image recognition.

Mainly, this work depends on proposes a Fourier-Mellin transformation method to improve and enhance the original algorithm that has been proposed for fingerprint identification which relies that an ellipse band on the frequency amplitude which is been used to suppress fingerprint image noise that is originally introduce as a high frequency in the fingerprint image.

The experimental results in this approach show that the low-quality fingerprint image recognition is being enhanced using Fourier-Mellin transformation were the final accuracy for this approach has been enhanced and increased.

Duy Hoang et al. [27] worked depends on study the error that can be accrue during the fingerprint image recognition for the low-quality image. They found that negative impact on the fingerprint recognition can be accrue during the image segmentation step where the true foreground can be labeled as a background and in this case the minutia feature could be lost. In contrast, the true background can be misclassified by predicted as a foreground where introduce the spurious features. In this works, they produce a novel approach for directional bandpass (FDB) based approach for fingerprint image segmentation.

The main contribution of this work is based on the texture information for directional Hebert transformation of a Butterworth bandpass (DHBB) approach which is a filter interwoven with soft-thresholding. Then, they depend on a manually mark ground for truth segmentation as a ground truth for the fingerprint images.

Finally, the experimental results of this work show that the idea of conduct a systematic approach for performance result of the FDB-based segmentation approach which shows that the FDB segmentation clearly outperform for fingerprint image segmentation which will used for enhancing the low-quality fingerprint image in a feature extraction stage.

Hasan Fleyeh et al. [28] presented a new approach for low quality fingerprint image segmentation which focus on the automatically segment and enhance the low-quality fingerprint images by reducing the false minutia detection.

The main contribution of this approach first proposes fingerprint segmentation by using morphological filters which are used mainly to find the largest object in the image. This step allows the segmentation approach to detect the foreground of the fingerprint and isolated on the background. Then, there is an adaptive design that has been produce in this work by using adaptive thresholding for image segmentation which is used to deal with the fingerprint images. This algorithm has designed to fit the curve between the gray-scale level pixels in each row or column of the fingerprint image and present the binarization thresholding of each pixel in the fingerprint image which is corresponding to the row or the column. Later, the noise has been reduced in this approach as a third step to enhance the ridge in the low-quality fingerprint images by invoking and design a rotational invariance filter. Finally, another adaptive design for the image thinning is also produces and proposed in this work to prevent system against the spurs which is invoked to generate the low-quality fingerprint images.

Finally, he experimental results of this work which is based on the low-quality fingerprint images segmentation improving that performed on 100 fingerprint images from the FCV2002, FVC2004 show that this approach has achieved about 96% of images under the test scheme which have been correctly segmented.

M. Hamed et al. [29] presented an approach for low quality fingerprint image recognition enactment by propose a minutia cylinder-code pairs based approach for improved the low-quality fingerprint images comparison and matching.

In this work, a local minutia descriptor has been proposed as main contribution for this work. The local minutia descriptor which depends on the fingerprint image quality has been improved by evaluate several different discarding methods to do image filtering in case of smooth out the low-quality fingerprint images. Pairs on MCC descriptor have been used using minutia qualities in such other to improve the fingerprint minutia features comparison. This work proposes another method for matching technique to improve the comparison between the fingerprint images by using efficient MCC based fingerprint image comparison that originally based on the discarding the low-quality elements from the local similarity matrix.

The experimental results of this work which aimed on improving the comparing accuracy which has been applied and used different dataset such as (FVC2002 DB2 FVC2002 DB3, and FVC2002 DB3) show that the discarding of the low-quality fingerprint images using MCC pairs from the local similarity matrix either in an independency way or pairwise measure can improve the low-quality fingerprint matching performance. Although, the quality of the central minutia is more efficient than the cylinder quality for low quality fingerprint enhancement during measuring the average minutia qualities in each feature descriptor.

Yanming Zhu et al. [30] presented a robust multi-constrained based model for fingerprint image orientation field construction as an approach for low-quality fingerprint image construction which is a way to solve the low-quality fingerprint image issue.

In this work, the main contribution is produce a multi-constructed model for orientation filed construction has been proposed to overcome the equalization system for low-quality fingerprint image recognition. In this approach, there are three main constraints that this work has presented to incorporated to ensure the recognition accuracy which are:

1. A least square data term aiming to maintain consistency between the constructed and original orientation field.
2. A total variation regularization aiming to smooth the orientation field and eliminate the global noise.
3. A nuclear norm regularization aiming to eliminate sparse noise while preserve the structure of the orientation field.

The experimental results of this approach show that for both high-quality and low-quality fingerprint images higher performance results by achieving accurate orientation features as well as to the short running time that this approach as achieved. Although, the proposed model of this approach is applicable such as for the fingerprint image indexing.

Raoni F. et al. [31] presented a new framework for quality assessment of high-resolution fingerprint images. This model based on the quality assessment of sets of features that extracted from the fingerprint patterns.

The main contribution of this work is mainly proposed a new analyzing methodology for the high-resolution fingerprint images is proposed. This approach containing a set of fingerprint pores which leads into account the special interrelationship between the considered features and some basic transformation that has involved the point of the process and anisotropic analysis. The proposed system of this work presents a new methodology by using new quality indexing algorithm which is following by special and structural analysis classes. During the work of this approach, these algorithms have achieved an effective as a performance predictor and filter excluding for the low-quality feature extraction in a recognition process.

The experimental results of this approach show that higher performance for error reject curve which give an indication about the proposed approach outperform for the state-of-the-art low-quality assessment. Future more, the algorithms present a good performance results as well for the high-quality image resolution for the fingerprint images recognition.

Ogechukwu N. et al. [32] presented an effective statistical-based and dynamic methodology for fingerprint preprocessing technique. Challenges to contextual filtering techniques that include difficulties in estimation of the orientation filed in a low and poor-quality fingerprint images are the main topic of this work. Reliably ridges extraction in a large region of the low-quality fingerprint images is the main approach that has been proposed in this work.

The main contribution of this work is to present a statistical-based methodology for dynamic fingerprint preprocessing. This technique which is design in this work for adaptive the contrast enhancement and binarization of fair and poor qualities plain and rolled fingerprint users. Those images present large regions of low-quality which is prior knowledge to do the orientation filed estimation. The proposed algorithm effectively enhances smudged and faded ridge which is the main issue that has been solved in this work. The proposed preprocessing algorithm implies a locally adaptive thresholding approach for each fingerprint images region to improve the binarization images in a preprocessing stage as a feature extraction improving idea.

The experimental results of this approach show a higher performance of the proposed algorithm that was determined by depending on carrying out the biometric verification and evaluation. This model has been done by using a popular commercial biometric matching software, on databases of fingerprints that have been used in this approach. Also, the experiment results show that fingerprints are uniformly improved and enhanced and by binarized stage as well as with the smudged or faded ridges in recoverable regions made visible. Fingerprint verification and verification evaluation on preprocessed fingerprints shows a lower error rates which in 12 databases that have been used in this work.

P. Pravallika et al. [33] presented an approach using SVM classification model for fake biometric detection using Image quality assessment which is an application to iris, face and palm print. In this work, a novel software based fake biometric detection is proposed to be used in multiple biometric system verification and identification approach using different types of fraudulent access.

The main contribution of this work is using fingerprint image assessment for liveness detection. This model expected that the fake image for the fingerprint which capture in an attack attempt will present different fingerprint images quality than the real fingerprint images. The proposed model uses a very low quality and degree of complexity. This makes the approach more suitable for the real-time application that is using for general image quality that uses for feature extraction.

The experimental results show that the proposed approach enhances the security of the biometric fingerprint image recognition by relies on the liveness detection through study the fingerprint image quality assessment and fusion using SVM classifier. SVM classifier is mainly used for detecting the differentia between the fake and the real fingerprint images by using many classifiers like LDA, QDA to train and test the fingerprint samples. Finally, it shows that the SVM classifier is efficient and accurate.

Yani Wang et al. [34] In this work, a deep learning approach for damaged fingerprint which present an approach for low-quality fingerprint images using fuzzy feature points has been proposed. In this approach, a recognition improving for damaged fingerprint which is low and poor quality of fingerprint images has been proposed depends on the feature extraction points based on the Convolutional Neural Network (CNN).

The main contribution of this approach is proposed a Deep Learning scheme using more advance neural network that represent by the Convolutional Neural Network (CNN). For the low-quality fingerprint image authentication and identification purpose were the traditional fingerprint feature extraction that required a complex model still gives a low recognition rate. Therefore, an automatic fingerprint identification and verification method mainly using CNN for low-quality fingerprint images in this proposal not just for recognition improving only, but for save time consuming. Kernel Principal Component Analysis (KPCA) and k-Nearest Neighbor (KNN) are the main framework of this approach.

The experimental results of this work show that fingerprint recognition based on using Deep Learning approach has achieved a higher recognition rate. Future more, for the future this approach needs to conduct some comprehensive researches I term of the preprocessing the fingerprint images as well as a strengthening the improvement of the algorithm.

Jan Svoboda et al. [35] presented a generative Convolutional Neural Networks (CNN) for latent and low-quality fingerprint reconstruction. This approach enhancement of the minutia feature extraction by detects the fingerprint ridge pattern. The preprocessing step that is noticeably reducing the false positive and negative detection rate is the main step of this approach.

The main contribution of this work is using a Convolutional Neural Network (CNN) by proposed auto encoders models which are amongst popular methods extensively that used in image processing tasks for image denoising and inpainting. Although, feature extraction and matching approaches that have been also used in this approach are designed as an objective function that should both well selected to reflect on important fingerprint properties and used for efficient optimization.

In this approach, the state-of-the-art results have obtained on several datasets challenging tasks such as latent-to-latent fingerprint matching and latent-to-sensor database fingerprint matching on IIIT-D standard datasets. The outperforming and experimental results of the existing results by using on the same data are evaluated on very challenging IIIT-D MOLF dataset compensates for the fact that cannot evaluate on NIST-SD27 as it is discontinued and no longer provided by NIST. On the other hand, this approach observed that the reconstruction is not only always successfully achieved. For the future work this approach needs to examine in other direction such as minutia feature extraction performance. Although, reconstruct the correct ridge pattern for the low-quality fingerprint images that affected by disease which is another issue of this approach.

CHAPTER THREE

THE PROPOSED APPROACH FOR LOW-QUALOTY FINGERPRINT IDENTIFICATION SYSTEM

3.1 Introduction

This chapter is dedicated to present the design considerations, implementation requirements and the steps taken throughout the establishment of the fingerprint proposed models. Two models have been studied in this thesis. These models for fingerprint authentication and verification are local approach which is the first one, and global approach as the second one. The implementation steps are illustrated in detail using diagrams and/or pseudo code.

In general, the proposed model has the essential stages to perform all relevant recognition and verification tasks. The general structure of the typical fingerprint authentication and verification system has two main models as it is shown in Figure 3.1. The first one is the enrolment model and the second one is the authentication and verification model. Each main model has many sub models or stages. Each model from the main model has main sub-stages or (sub-models), the four important modules for each main model are:

1. **Sensor Module**: In this model, the biometric fingerprint image is scanned or captured for the individual user who is a participant in the fingerprint identification and verification system.
2. **Feature Extraction Module:** The main purpose of this model is to acquires the data which is processed to extract the features from the fingerprint image that has been scanned and captured from the Sensor Model. For example, the feature points, as well as feature orientation, be detected and extracted from the fingerprint image using this model.
3. **Matching Module**: The third model of the fingerprint indentation and verification system is the Matching Model where the feature values are

compared against all the template feature that are extracted from the users and store in the system database. The matching model using matching score by generating a matching score based on the template matching, for example, the number of the minutia feature that matched between the query fingerprint image and the template one.

4. **Decision-making Module**: The last model of the fingerprint identification and verification model is the Decision-making Model which in this model the user is claimed that is in either way accepted or rejected depending on the matching score.

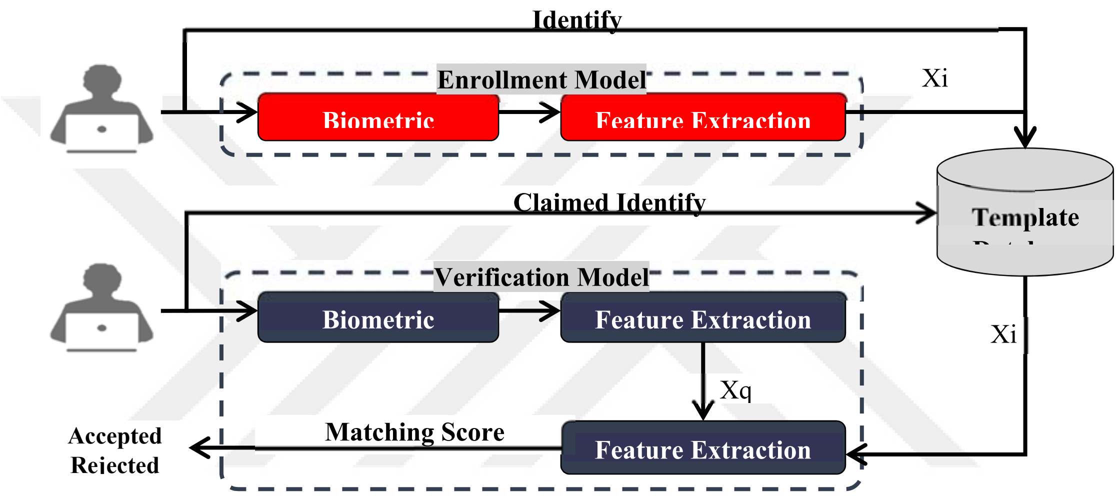


Figure 3.1: The enrollment model and the verification model a biometric system.

3.2 Proposed System Layout

In our proposed system, we develop and test a fingerprint identification and verification algorithm which is functional designed on the bad-quality fingerprint image scans by utilizing the global features in fingerprint by proposing a global feature vector extraction approach. In our approach.

In order to prove our approach is more efficient than the standard one (Local Approach) based minutia feature extraction approach for fingerprint identification and verification the proposed approach used identification and verification algorithm is functional on bad-quality fingerprint images we have run the Local feature methods as well to be able to compare the results which show that our Global feature approach has score better than the Local feature approach as it will show in details in chapter 4.

Rotation, noisy, and bad-quality fingerprint image are the most important cases that have been failed on the first approach, and we assume that our approach has been successes on them. The general approach structure of the proposed system is shown in Figure 3.2.

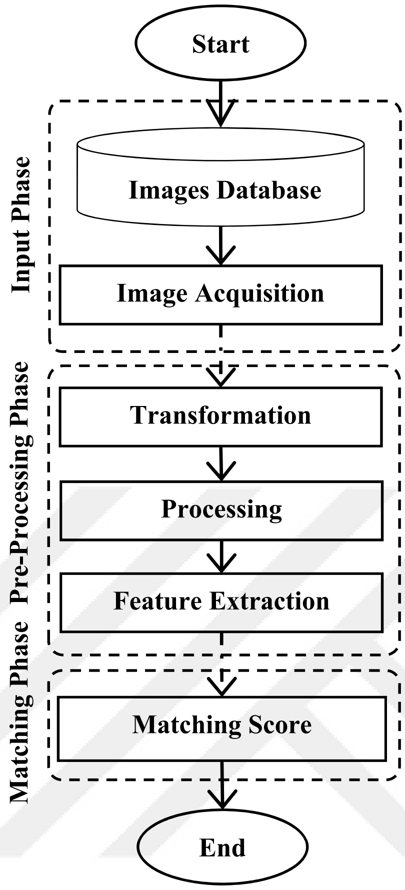


Figure 3.2: The Framework of fingerprint authentication and verification general approach.

1. **Input phase:** This phase consists of uploading images from datasets into the authentication and verification system in this phase we have to do two general steps:
   - ***Database image selection*:** In this step, the dataset has been selected based on different datasets version that we want to use in our system such as FCV2002, FCV2004, and FVC2006.
   - ***Image acquisition***: In this step, the fingerprint image that it has to be tested is loaded from hard disk (where the dataset is located and saved) to the memory of the authentication system.
2. **Pre-processing phase:** In this phase, there are many steps should be implemented in term of enhanced the fingerprint images such as:
   - ***Transformation*:** In this step, depending on the approach that we are going to used which is mainly depends on the fingerprint image type

(color, gray), there is some transformation steps should be implemented to prepare the fingerprint image to the next stage which is the feature vector extraction.

- ***Processing*****:** in this step, some pre-processing step has been done, like convert the fingerprint image from domain to another domain, specifically depends on the type of feature extraction approach. For example, minutia features for fingerprint required some specific step and preprocessing tools to extract those feature as will have explained briefly in the local approach.
- ***Feature Extraction:*** in this step, depends on the type of the authentication and verification approach the appropriate features will be extracted.

3. **Matching Phase:** in this phase, the feature vector for the tested fingerprint will be in two cases. The first one if the fingerprint image in the test part which is already in the authentication and verification system, the feature vector will be matched and tested with the whole feature vectors in the authentication system and the matching score will be computed.

Depending on the matching score the final decision will be made in the fingerprint will be authorized or not. The second case if the fingerprint feature vector is not in the authentication system it will automatically store the database on the system.

3.3 Localization Based Feature Extraction Approach

Localization based feature extraction depends on the minutia feature extraction which is a local feature extraction approach. This model has the essential stages to perform all relevant recognition and verification tasks. The general structure of the local approach for fingerprint authentication and verification system is shown in Figure (3.3).

The implementation of the fingerprint biometric template system (fingerprint identification and verification system) is based on developed some stages to be consisting of four major stages such as pre-processing, feature extraction, post-processing, and matching (or enrollment). These five stages are executed sequentially. The performance stage of feature extraction and matching stage which mainly depends on the quality of the input fingerprint image. There are several reasons may degrade the quality of the fingerprint image. Therefore, the main stage of the local feature extraction approach for fingerprint authentication can be summarized in:

1. **Pre-processing Stage:** The preprocessing stage in the fingerprint identification and verification system is considered as a necessary step in the established model. For fingerprint cognition (identification and verification) tasks, the preprocessing stage should cover two main tasks such as:
   - ***Image Binarization:*** The first task is image transformation; the applied fingerprint in the binarization algorithms is applied mainly on the gray-scale level image which is based on automatic determination of optimum threshold value such as the local thresholds. However, it should cause efficient separation of objects ROI from their background.
   - ***Thinning:*** The second task is thinning the edges appeared in the produced binary image. The thinning process should preserve the connectivity of the ridge structures while forming a skeleton version of the binary image. The thinning process should preserve the connectivity of the ridge structures while forming a skeleton version of the binary image. The skeleton image is normally used to extract the existing minutia in the image.
2. **Feature Extraction Stage:** In this stage of the fingerprint identification and verification system which is the feature extraction stage, a simple image scan aims to detect the minutia pixels. according to different types of distortions which may appear locally in the fingerprint image such as under-inking, over-linking, scars, or excessively worn prints, as well as due to thinning process, many false minutia may be nominated among the candidate minutia detected in the thinned image.
3. **Post-processing Stage:** A post-processing phase of minutia purification represents an important part of the local feature extraction model for fingerprint authentication and verification approach. Also, this phase includes:
   - ***Remove False Minutia:*** This step is important because holes will reduce the accuracy of the thinning algorithm thus creating false minutia point(s).

- ***Detect the Region of Interest:*** The ROI contains the desired fingerprint impression which is extracted to avoid detection of false features outside the fingerprint pattern.

4. **Matching Stage:** The fourth stage, the matching scores are determined for each set of extracted features from the feature vectors. At the matching stage, the calculated distance either matched with the previously extracted vectors listed in fingerprints database for recognition or verification purpose, using match module or stored in fingerprint database, during the enrollment phase.

The main diagram of the local feature extraction approach for fingerprint authentication and verification system is illustrated in Figure 3.3. This figure shows the main stages of the local approach which has many stages.

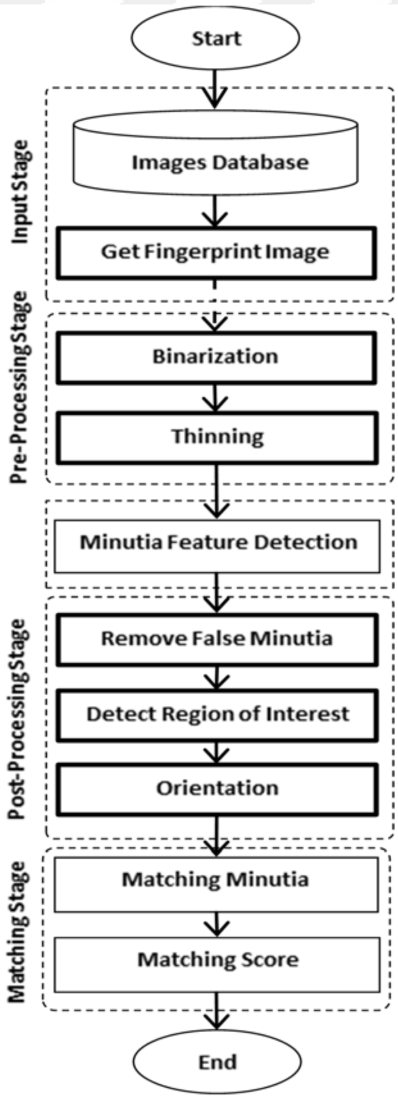


Figure 3.3: The local feature extraction model architecture.

3.3.1 Read Fingerprint Image

In this stage, the fingerprints images are fed to the system as a PNG image files; the color resolution of the image is taken 24 bit/pixels. The image data (i.e. RGB components) is loaded and then used to compute the Gray array from the loaded Red, Green, and Blue data.

3.3.2 Pre-processing Stage

The first stage in any authentication and verification system is the pre-processing phase. This phase includes many steps as explained in Figure 3.3. The main focusing of this stage is to transform the image and skeletonized the image. Fingerprint image preprocessing stage is crucial for both enrollment and cognition tasks.

3.3.3 Convert to Gray-scale image

The first one is to convert the image colour representation to gray image representation. The Gray value is computed from Red, Green, and Blue arrays by converting them to YIQ which is (Luminance (Y), color chrominance (I and Q)) models, then the gray value is set equal to the intensity, Y, component [36].

3.3.4 Image Binarization

The selected threshold used to convert gray image to black and white is chosen manually, and it is choosing Gray image represents the red, green and the blue color components of the pixels in an image take the same value between 0-255. Hence the model fixed value by trailed and error threshold values 128 will be chosen using the gray value component, threshold. A simple output is a jpeg image which consists of only two gray levels (black and white), then the output is a binary image in which black generally represents the foreground pixels or the pixels of interest and white represents the background pixels [37]. Blow a process of thresholding has represented in algorithm as shown in algorithm (3.1).

3.3.5 Global (Automatic) threshold

The fingerprints in the database are all gray-scale images. A global threshold is determined. The value of the threshold value depends on brightness of the image.

Then each pixel is smaller than the threshold will be set to zero, otherwise, it is kept unchanged. Algorithm (3.1) presents the implemented steps for global thresholding task [38, 39, 40].

Algorithm 3.1: Fingerprint global thresholding.

Inputs:
Gray: image array of gray pixels values
Hgt : Image Hight
Wid : Image width
Output:
Glo : the array of enhanced gray image

Initialize minimum (Min) and Max values
Min ←Gray (0, 0); Max← Gray (0, 0);
Compare each pixel with Min and Max
For all pixels in the image // x as row number, y as column number
If Gray_value (x, y) < Min Then
Min← Gray (x, y)
End If
If Gray_value (x, y) > Max Then
Max← Gray (x, y)
End If
End For // x & y
Thr ← (Min + Max) / 2 // Calculate threshold
For all pixel in the image // I as row number, J as column number
If Gray_value (x, y) ≥ Thr Then
Glo (x, y) ← Gray (x, y)
Else
Glo(x, y) ← 0
End If
End For
END

The result of the binarization algorithm that applied on the fingerprint image is shown in Figure 3.4

Original Fingerprint Image Global Binarization Result

Figure 3.4: Global (automatic) image threshold.

3.3.6 Fingerprint Manual (Selective) Threshold

The conversion step from the gray-scale fingerprint image to black and white fingerprint image is performed by applying thresholding upon the fingerprint gray image. The selection of threshold value is either done manually by the user, or it is assessed manually. In our developed system, the proper value of threshold is selected manually. Also, the local thresholding method is adopted which is based on some category such as the local characteristics of fingerprint image. The threshold assessment process is started with calculating the average intensity value. Then, all the pixels belong to a small block lay within the central area of the large block are binarized by comparing its value with the determined threshold value to decide whether each pixel belong to ridge or background [41]. Algorithm 3.2 presents the taken steps for making local thresholding [41].

Algorithm 3.2: local thresholding (selective).

Inputs:
Gray: Gray Image
Output:
Binarized Image

1. **Initialize** minimum (Min) and Max values
2. **Set** thr= 128 or any number // threshold value
3. **For** all pixel in the image // I as row number, J as column number
4. **If** (pixel < thr)
5. **Set** pixel=1 // white pixel
6. **Else**
7. **Set** pixel=0 // black pixel
8. **End If**
9. **End For**
10. **END**

The result of the local fingerprint image thresholding (Manual) by selecting different threshold values is shown in Figure 3.5.

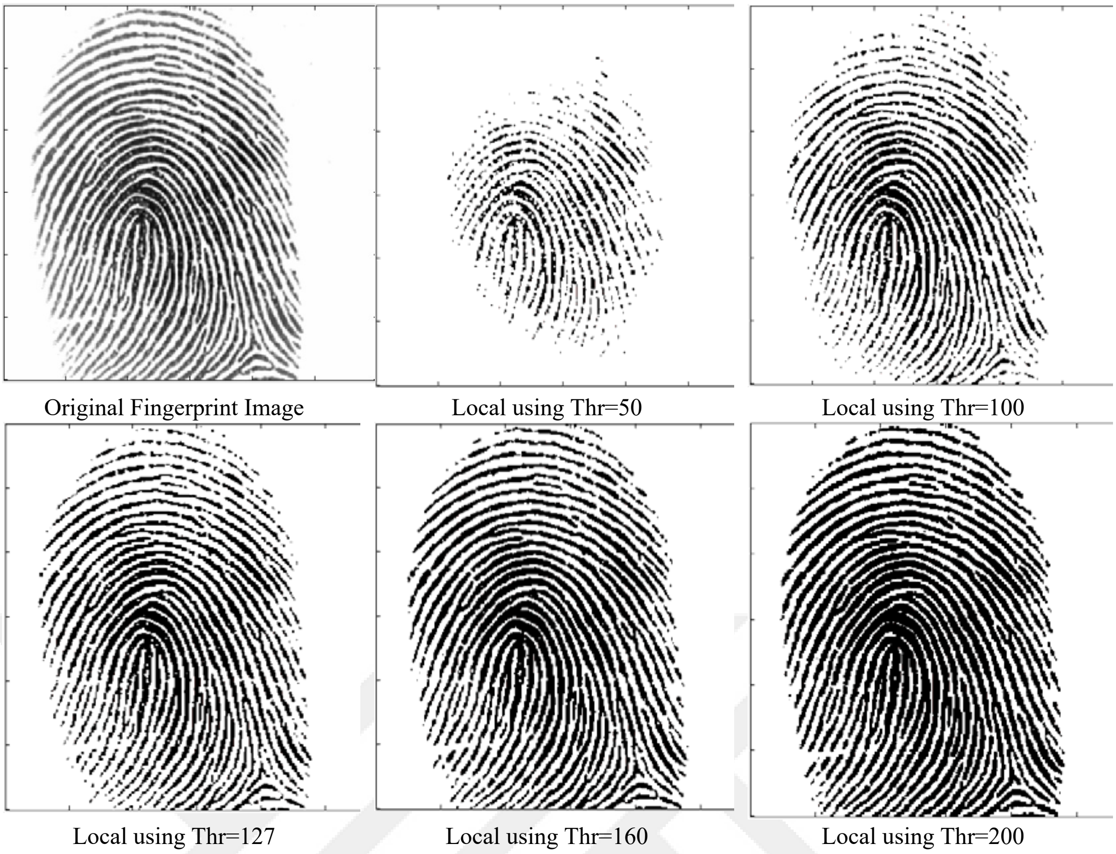


Figure 3.5: Local (manual) Image threshold.

3.3.7 Fingerprint Image Thinning (Skeletonizing)

The Zhang-Suen algorithm (ZS algorithm) is the Fast-Parallel based Algorithm for Thinning Digital Patterns. In this algorithm, a 3x3 window (mask) is moved down throughout the image and calculations are carried out on each ridge pixel, which has the value "1" and black colour, in this case to decide whether it needs to stay in the image or not. Figure 3.6 which presents a description of the window and the classification that given to the pixels that surround the center pixel. Usually, the method consists of successive passes of two basic sub-iterations, until the image reaches a stable state. The iteration from one pixel to another used in this algorithm is clockwise [42].

P_9 (x-1,y-1)	P_2 (x-1,y)	P_3 (x-1,y+1)
P_8 (x,y-1)	P_1(x,y)	P_4 (x,y-+1)
P_7 (x+1,y-1)	P_6(x+1,y-1)	P_5 (x+1,y+1)

Figure 3.6: 3x3 Structuring element.

Regarding the 8-neighbourhood notation in Figure 3.6. The Odd sub-iteration flags a point P_1 for deletion or pixel ignoring if all the following conditions have been satisfied:

a. Count with connectivity 1.

   A(P1) = 1

b. Have several nonzero black neighbours, B(P1), between 2 and 6 (included).

   $2 \leq B(P1) \leq 6$

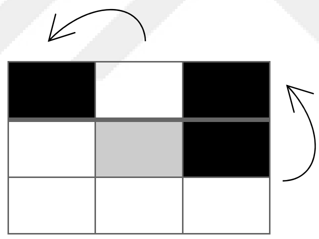
c. Have at least one of the following pixels in zero white:

   $[x-1, y], [x, y+1], [x+1, y]$ $P2 \times P4 \times P6 = 0$

d. Have at least one of the following pixels in zero white $[x-1, y], [x+1, y], [x, y-1]$

   $P4 \times P6 \times P8 = 0$

Where $A(P_1)$ is total occurrences of 0-1 patterns (current pixel value 0 and next pixel value 1) in the ordered sequence P_2, P_3, P4, P_5, P_6, P_7, P_8, and P_9, the "×" expresses logic "AND" operation, and the B(P1) function returns the number of nonzero black pixels in the structuring element as it shown in Figure 3.7 [43].



$A(P1) = 2, B(P1) = 3$

Figure 3.7: A(P1) and B(P1) example.

The proposed model used a compact representation called skeleton. In order to achieve faster processing and smaller memory fingerprint. A skeleton must preserve the structure of the shape, but all redundant pixels should be removed. In this module, the outer edge point of the fingerprint image is deleted iteratively until the skeleton points remain as a binary fingerprint image [44]. Algorithm 3.3 shows a thinning process [45].

Algorithm 3.3: Fingerprint Image Thinning.

```
Inputs:
    The binarized image
Output:
    Thinning image
---------------------------------------------
a [8]= kernel 3x3
For image height and width do
ar= image data (0 and 1)
p1 = a [0] * a[2] * a[6]
p2 = a [0] * a[4] * a[6]
b = number of 1's in current window (mask)
If ar=1 and b>=2 and b<=6 and p1=0 and p2=0
y =1
Else
y =0
End If
End For
Set y to new image
End
```

The output of thinning module results for the local fingerprint feature extraction is illustrated by the example shown in Figure 3.8.

Original Fingerprint Image   Global Binarization Result   Thinning Result

Figure 3.8: Skeletonizing (Thinning) process result.

We can notice that different binary fingerprint image gives different thinning (skeleton) image output. For example, if we used the local binarization (manual) process that effects on the output of the thinning results, as it is shown in Figure 3.9.

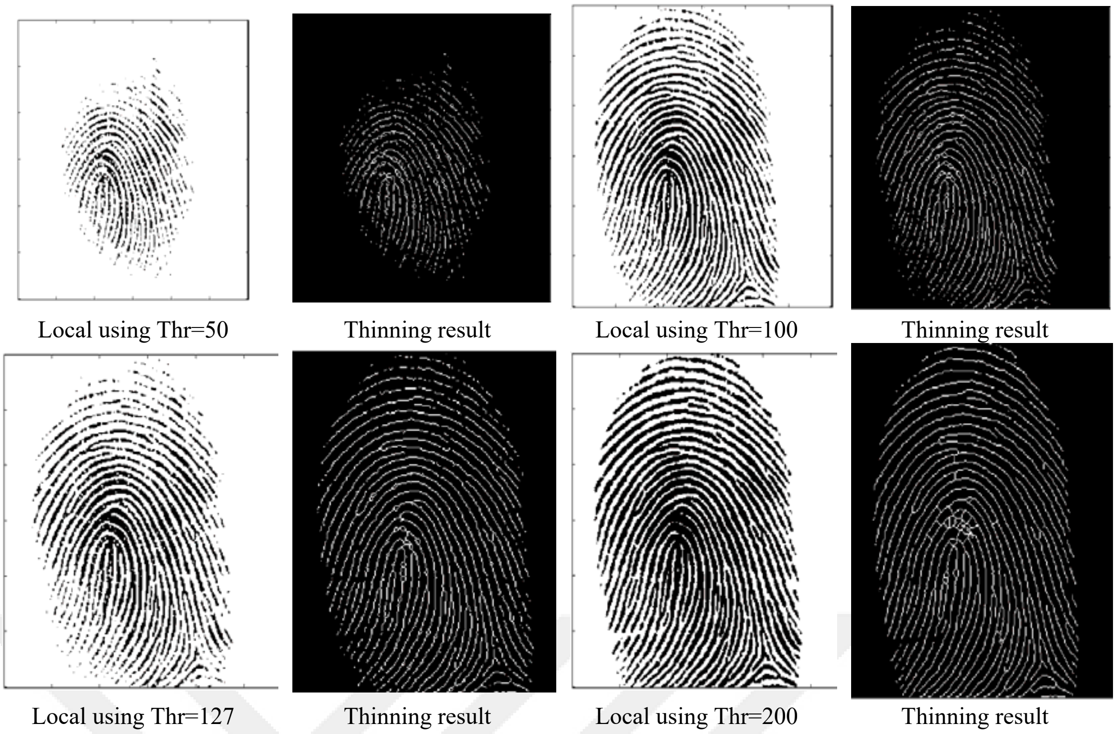


Figure 3.9: Different thinning results.

3.3.8 Minutia Extraction

The extraction of minutiae points is a critical step in fingerprint authentication and verification systems. Ridge ending points and ridge bifurcation points are extracted from the thinned image after going through the minutiae extraction module in the local feature extraction approach. The extraction process starts by defining 3×3 structure element which is used to scan each pixel in the image.

The concept of Crossing Number (CN) is widely used for extracting the minutiae. This method extracts the minutia points from the skeleton image by examining the local neighborhood of each ridge pixel using a 3×3 window. CN is defined by Rutovitz as half the sum of the differences between the pairs of adjacent pixel. Rutovitz's definition [46] of CN for a pixel P_1 is shown below.

P_9	P_2	P_3
P_8	P_1	P_4
P_7	P_6	P_5

$$CN = \frac{1}{2}\sum_{i=2}^{9}|P_i - P_{i+1}| \qquad (3.1)$$

Where P_i is the binary pixel value in the neighborhood of P1 with Pi = (0 or 1) and P10 = P2. Minutiae detection in a fingerprint skeleton is implemented by scanning thinned fingerprint and counting the CN [47]. Thus, the minutiae points can be extracted, as depicted in Table 3.1 and Figure 3.10.

For a pixel P1, the eight pixels are scanned in a clockwise direction. The pixel can be classified after obtaining its pixel value. A CN value of zero refers to an isolated point, value of one to a ridge ending, two to a continuing ridge point, three to a bifurcation point and a CN of four means a crossing point. The coordinates and type of minutiae of each minutiae point is recorded for each minutia [48].

Table 3.1: Crossing Number (CN).

CN	Property
0	Isolated point
1	Ending point
2	Connective point
3	Bifurcation point
4	Crossing point

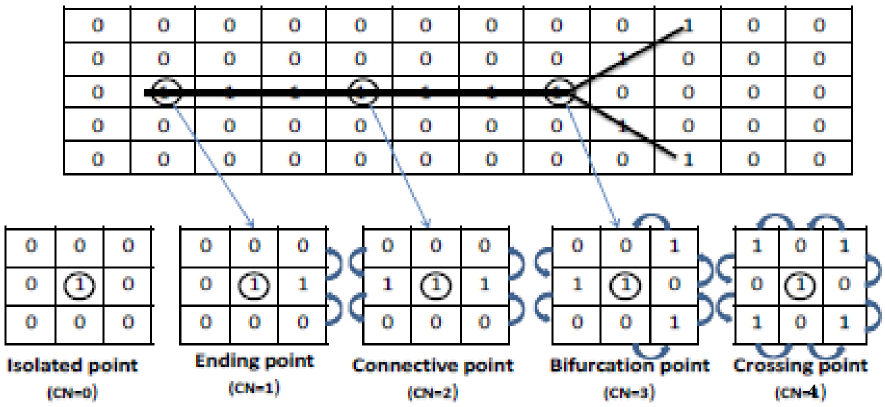


Figure 3.10: Illustration of CN properties ("1": black pixels in the skeleton image).

The CN for each pixel, which is the center of this structure, is calculated using equation (3.1). If the cross number for the pixel is 1, the pixel is considered as an end point and the position of the pixel and its neighbor are stored in "end points" list, and if the cross number for the pixel is 3, the pixel is nominated as "bifurcation point" the position of the pixel and its three neighbors are stored in bifurcation points list. The way to calculate CN is shown in Figure 3.10. This process is shown in the Algorithm 3.4 [48].

Algorithm 3.4: Minutia extraction.

Inputs:

Lin() : continuous ridge thinning Image
Hgt : the height of thinning Image
Wid : the width of thinning Image

Output:

End(),Bi() // arrays of the position of end and bifurcation point

---

Define 3×3 structuring element p[9], 3×3 structure element for ridge position p1[9]
Initialize the counters
end_counter ← 0;
bi_counter ← 0;
Scan image with 3×3 structure element
Calculating CN for each pixel
$CN = \frac{1}{2}\sum_{i=2}^{9}|P_i - P_{i+1}|$
Check the value of the CN
If CN=1 Then
End(end_counter).x_position ←x;
End(end_counter).y_position ←y;
End(end_counter).x0_position ←x0;
End(end_counter).y0_position ←y0;
end_counter ← end_counter+1;
Else if CN=3 Then
Bi(bi_counter).x_position ←x;
Bi(bi_counter).y_position ←y;
Bi(bi_counter).x0_position ←x0;
Bi(bi_counter).y0_position ←y0;
Bi(bi_counter).x1_position ←x1;
Bi(bi_counter).y1_position ←y1;
Bi(bi_counter).x2_position ←x2;
Bi(bi_counter).y2_position ←y2;
bi_counter ← bi_counter+1;
End If
Return Bi(),End(), bi_counter, end_counter;

The results of the minutia feature extraction for different fingerprint images in the local fingerprint authentication approach are shown in Figure 3.11.

Figure 3.11: Minutia feature extraction results for the local approach.

3.3.9 Remove False Minutia

The minutia extraction step incurs many errors as there will be many ridge-ends in border regions and spurious bifurcations and ridge-endings inside the fingerprint. Most of them are clearly recognizable to the trained eye, but in the case of an automatic system, a series of rules have to be used to delete the so-called "false-minutiae" [49].

The set of rules employed in false minutiae detection are able to efficiently find false minutiae that form one of the following structures: broken ridges, bridge, short ridges, hole, spur, and ladders [50]. Explanations of some false minutia structures are given in the following [51]:

- **Broken ridges:** Because of scars and insufficient finger pressure on the input device, a ridge may break into two ridges creating two endpoints. Obviously, these two endpoints are false minutiae and should be eliminated. These two endpoints are identified as a broken ridge structure.
- **Bridge structure:** Due to excessive finger pressure or noise in the image, two separate ridges are sometimes connected by a short ridge to make a bridge structure.

- **Short Ridge Structure**: All short ridges should be considered as false minutiae because they are usually artifacts introduced by image preprocessing procedure such as ridge segmentation and thinning.
- **Hole Structure:** Hole structures occur due to pores and dirt's on fingerprints. Vary wide ridges may generate hole structures.
- **Spur Structure:** Vary wide valley may generate spurs.
- **Spike Structure:** The spike structure generates two false minutiae and may occur when thinning a non-smooth ridge.
- **Ladder Structure:** Ladder structures usually occur between close ridges.

The most common types of false minutia structures which may be encountered into a thinned fingerprint image are shown in Figure 3.12. Each such structure generates two or more false minutiae [52].

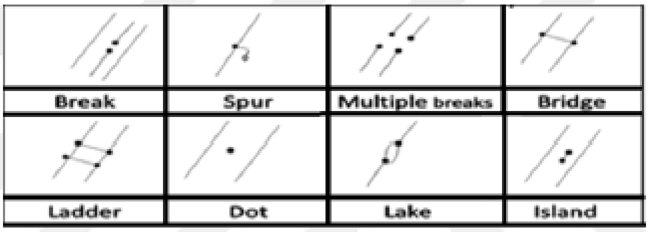


Figure 3.12: The most common false-minutia structure [52].

The minutiae points extracted in minutiae extraction module may contain false minutiae points due to noisy image or artifacts created by the thinning process. Some of the structures shown in Figure 3.13 with blue central point which have three neighbors may have three bifurcation points in the same structure, (i.e., the central is bifurcation point and two of its neighbors are also bifurcation points). If this case occurred, then we should consider the central point in the structures as the bifurcation point and its neighbors must be deleted from the bifurcation points list [52].

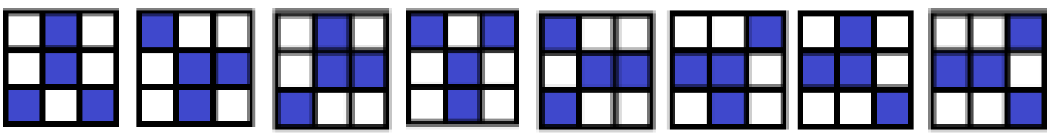


Figure 3.13: Structure elements for bifurcation points [51]

After the minutiae are extracted, it is necessary to employ post processing stage in order to validate that they are real minutia points. The two steps of post-processing stage for minutia manipulation are:

1. Minutia invalidation with false minutia structures
2. Minutia validation. It can be seen.

The implemented steps for noise elimination module are illustrated in Algorithm 3.5. The process starts by defining a list of 3×3 structures which will be used to test each black pixel in the image. Then these 3×3 structures are passed over the image pixels to scan each black pixel in the image.

Figure 3.14 presents the adopted 3×3 structures in this work. If the central element of the structure has blue color then it will not be considered as noise point and must not be deleted; while those central pixels with the other colors (i.e., red, green, brown) are considered as noise points and must be deleted.

The central pixel of each structure, shown in Figure 3.14, represents the black pixel in the examined image that needs to be tested. All surrounding pixels within the area of the structure are tested and checked if they are black. If the surrounding black pixels in the (3×3) neighborhood met one of structures, then the central pixel should be deleted if its color in the found structure is not blue. After the entire pixels in the image are tested, the process is repeated. The repeated process includes handling black pixels which have two black neighbors and those have three black neighbors. The repetition is used to remove the remaining noise point which may not delete (or they created) in first iteration.

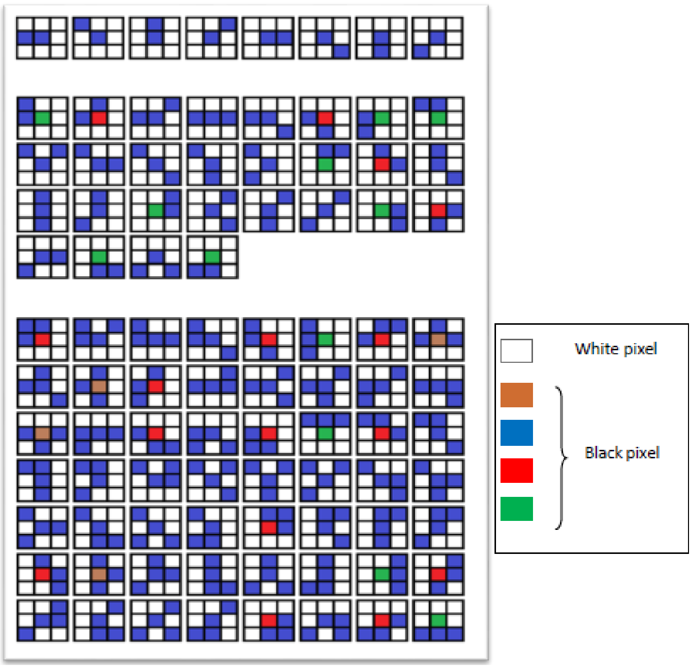


Figure 3.14: Structuring elements used in noise elimination process [52].

In third group, the cases with red and green center pixels lead to ridge points that have three neighbors belong to the ridge. This will confuse the minutia extraction algorithm by deciding that these ridgeline points are ridge bifurcations. The cases with brown centered pixels produce double ridge bifurcation points lying next to each other while, in fact, there is only one bifurcation point there. Algorithm 3.5 presents the implemented steps for noise removal task [52].

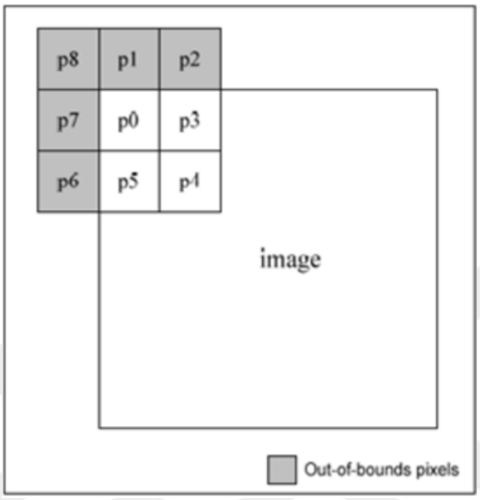


Figure 3.15: Example of out-of-bounds structuring elements [52].

Figure 3.15, that the spur structure generates false ridge ending, where both the hole and triangle structures generate false bifurcations. The spike structure creates a false bifurcation and a false ridge ending point. The set of rules employed for detection of false-minutiae that form one of the following structures: broken ridges, bridge, short ridges, spur, and ladders.

For minutia validation, this approach incorporates the validation of different types of minutiae into a single algorithm. It tests the validity of each minutiae point by scanning the skeleton image and examining the local neighborhood around the minutiae. The algorithm is then able to cancel out [52].

Algorithm 3.5: Remove false minutia features (Noise elimination).

Inputs:

Thin : array of binarized Thinning Image
Hgt : the height of Binary Image
Wid : the width of Binary Image

Output:

bb: noise free array

1. **Define** 3×3 structuring element p[9],and expand the boundaries of the image with zero.
2. **Enter** Number of iteration for handling the Points with Two Neighbors
3. j←0;
4. **Repeat**
5. **Scan** each pixel, which has the value 1, with the 3×3 structuring element, p [9].
6. **Count** the number of surrounding neighbors which have values = 1
7. n ← 0;
8. **For** all i = 0 → 7
9. n ← n + p(i);
10. **End For** // i
11. **Meet** the conditions, when the pixel has two neighbors
12. **Check If** n = 2 Then
13. flg ← 0; //initialize flag with 0
14. **For** all i = 0 → 6 step 2 // check L shape
15. **Check If** p(i) = 1 And p(i + 2) = 1
16. Then flg ← 1;
17. **End If**
18. **End For** // i
19. **Check If** flg = 0 Then
20. **For** all i = 0 → 7
21. **Check If** p(i) = 1 And p(i + 1) = 1 Then flg ← 1; End If
22. **End For** // i
23. **End If**
24. **Delete** the pixel exactly like the condition met
25. **Check If** flg = 1
26. Then pixel ← 0;
27. **End If**
28. **End If**
29. **Until** j=itr;
30. **Enter** Number of iteration for handling the points with three neighbors
31. **Set** j←0;
32. **Repeat**
33. **Scan** each pixel, which has the value 1, with the 3×3 structuring element, p [9].
34. **Repeat** Step (6)
35. **Meet** the conditions, when the pixel has three neighbors
36. **Check If** n = 3 Then
37. flg ← 0; //initialize flag with 0
38. **For all** i = 0 → 6 step 2
39. **Check If** p(i) = 1 And p(i + 2) = 1 And p(i + 4) = 1
40. Then flg ← 1;
41. **End If**
42. **End For** // i
43. **Check If** flg = 0 Then
44. **For** all i = 0 → 7
45. **Check If** p(i) = 1 And p(i + 1) = 1 And p(i + 2) = 1
46. Then flg ← 1;
47. **End If**
48. **End For** // i
49. **End If**
50. **Check If** flg = 0 Then
51. **For** all i = 0 → 3
52. **Case I** of
53. 0: **Check If** p(0) = 1 And p(2) = 1 And (p(7) = 1 Or p(3) = 1)
54. Then flg ← 1;
55. **End If**
56. 1: **Check If** p(2) = 1 And p(4) = 1 And (p(1) = 1 Or p(5) = 1)
57. Then flg ← 1;
58. **End If**
59. 2: **Check If** p(4) = 1 And p(6) = 1 And (p(3) = 1 Or p(7) = 1)
60. Then flg ← 1;
61. **End If**
62. 3: Check If p(6) = 1 And p(0) = 1 And (p(5) = 1 Or p(1) = 1)
63. Then flg ← 1;
64. **End If**
65. **End case**
66. **End For** // i
67. **End If**
68. **Delete** the pixel exactly like the condition met
69. **Check If** flg = 1 Then
70. pixel ← 0;
71. **End If**
72. **Until** j= itr;
73. **Repeat** Step 2 and all Step 3
74. **Return** bb();

The results of false minutia removing algorithm for local feature extraction are shown in Figure 3.16.

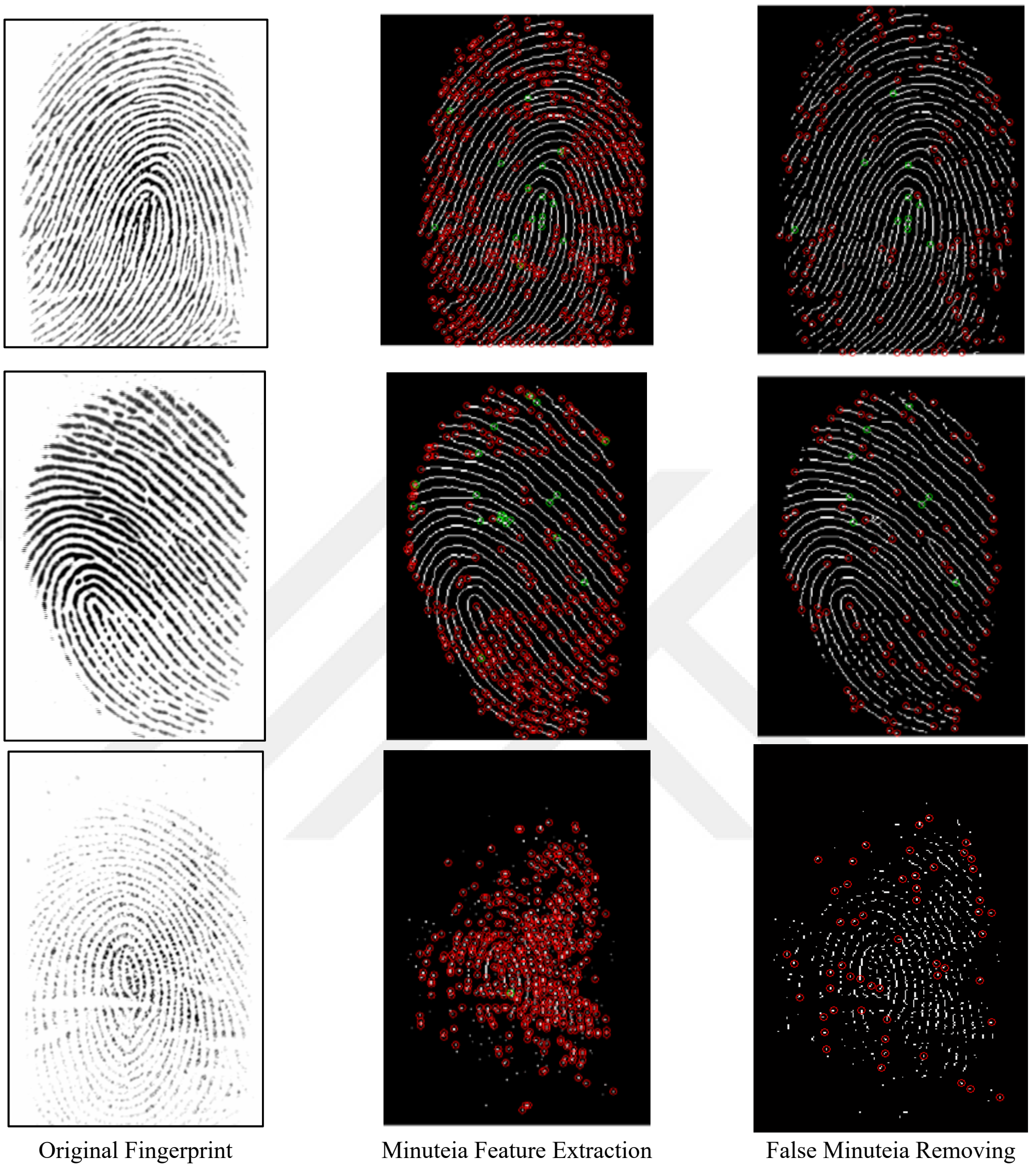


Figure 3.16: False minutiae feature removing.

3.3.10 Region of Interest Detection and Extraction (RPI)

The aim of this stage is to allocate the actual region in the fingerprint image by keeping the area within the bounding rectangle of ROI from the original image. The binary image is the input to this stage where the fingerprint ridges have the value "one" while the background has the value "zero". In order to determine the ROI in the image each side of the image boundary is scanned until we reach the row or column that contains ridge pixel(s) [52], as shown in Algorithm 3.6.

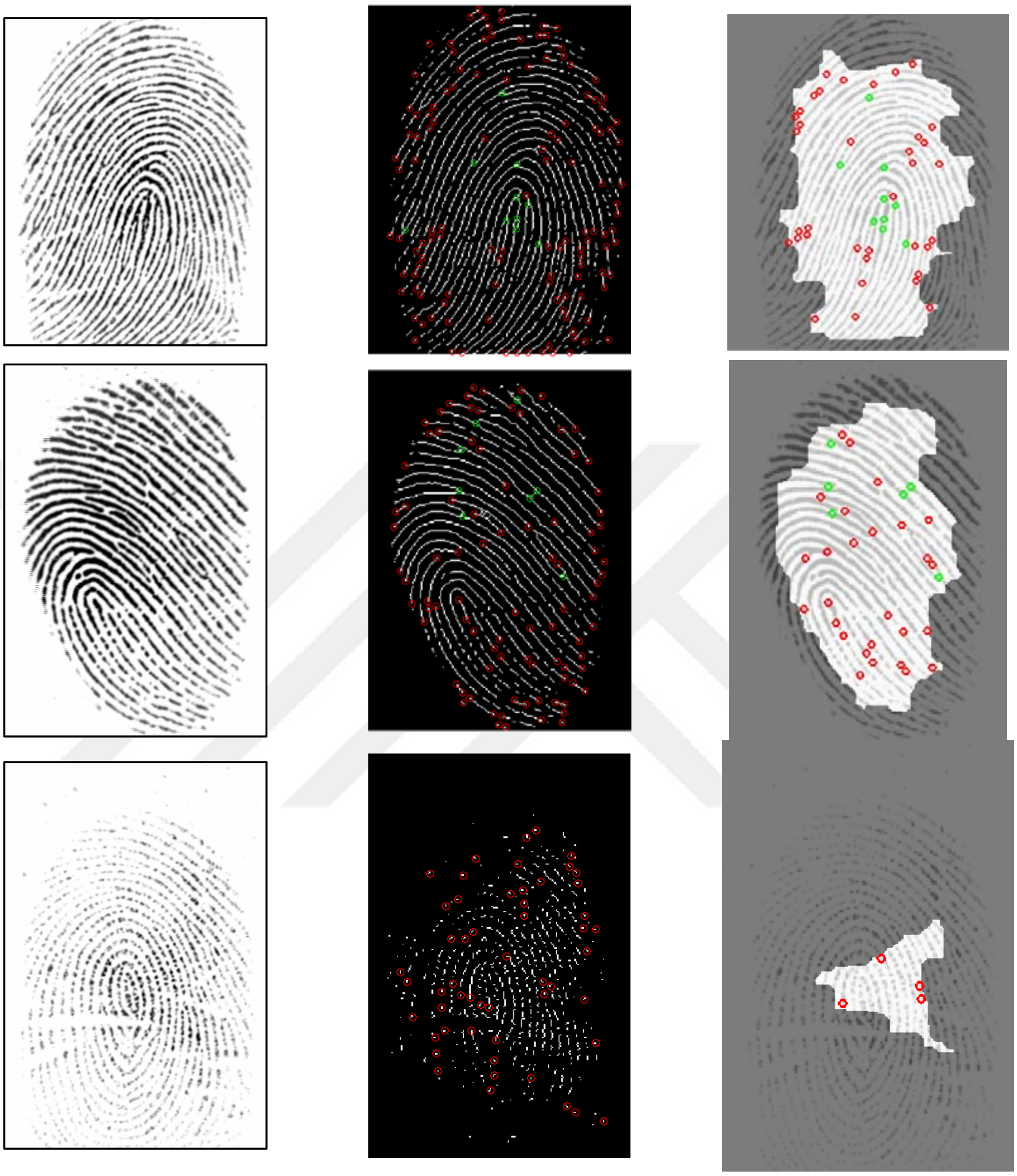
Algorithm 3.6: ROI extraction.

Inputs:
Bin() : array of binary image
Hgt : the height of binary image
Wid : the width of binary image

Output:
Clip() : ROI image

```
Find first row in the ROI
For all x = 0 → Wid-1
Set S←0; // initialize summation parameter
For all y = 0 → Hgt-1
S ← S + Bin(x, y);
End For // y
Check If S <> 0 Then
X1 ← x;
Exit For;
End If
End For // x
Find last row in the ROI
For all x = Wid-1 → 0
S←0; // initialize summation parameter
For all y = 0 → Hgt-1
S ← S + Bin(x, y);
End For // y
Check If S <> 0 Then
X2 ← x;
Exit For;
End If
x←x-1;
End For // x
Find the first column
For all y = 0 → Hgt-1
S←0; // initialize summation parameter
For all x = 0 → Wid-1
S ← S + Bin(x, y);
End For // x
Check If S <> 0 Then
Y1 ← y;
Exit For;
End If
End For // y
Find last column in the ROI
For all y = Hgt-1→ 0
S←0; // initialize summation parameter
For all x = 0 → Wid-1
S ← S + Bin(x, y);
End For // x
Check If S <> 0 Then
Y2 ← y;
Exit For;
End If
y←y-1;
End For // y
Cut the region w ← X2 - X1 : Wid ← w; h ← Y2 - Y1 : Hgt ← h;
For all y {where Y1 ≤ y ≤ Y2}
For all x {where X1 ≤ x ≤ X2}
Clip(x, y) ← Bin(x, y);
End For // x
End For // y
Return Clip();
```

The results of region of interest detection (ROI) algorithm for local feature extraction are shown in Figure (3.17).

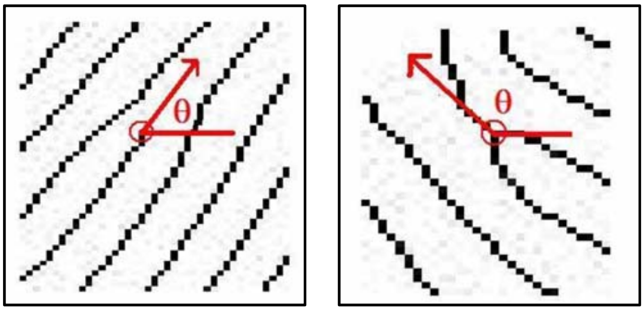


Origibnal Fingerprint | Minuteia Feature Extraction | False Minuteia Removing

Figure 3.17: ROI detection.

3.3.11 Features Orientation

A termination angle is the angle between the horizontal and the direction of the ridge, while a bifurcation angle is the angle between the horizontal and the direction of the valley ending between the bifurcation. Figure 3.18 provides a visual description of these definitions [51].



Termination Angle Bifurcation Angle

Figure 3.18: Definition of minutiae angles.

To compute the termination angles, the row and column indices for each termination are first recorded. Beginning at each termination, the corresponding ridge is traced backwards by five pixels, and the resulting row and column indices are stored. Care must be taken to ensure the angle is calculated correctly. Algorithm (3.7) explain the orientation detection of each feature in the local feature extraction approach for fingerprint authentication [50, 51].

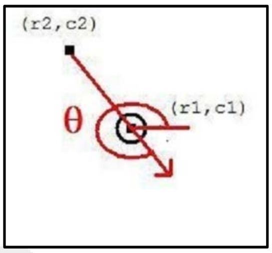
Algorithm 3.7: Features orientation.

Inputs:
ROI image
Output:
Orientation of each feature

1. **Find** the location of termination
2. **Find** location of the final pixel
3. **Set** r_1: row index of termination
4. **Set** c_1: Colum index of termination
5. **Set** r_2: row index of five-pixel ridge trace
6. Set c_2: column index of five-pixel ridge trace
7. **Check If** (r_1>r_2) and (c_1>c_2) then
8. $\theta = 360^{\circ} - tan^{-1}\left(\frac{r1-r2}{c1-c2}\right)$
9. **End IF**
10. **Check If** (r_2>r_1) and (c_1>c_2) then
11. $\theta = 90^{\circ} - tan^{-1}\left(\frac{r1-r2}{c1-c2}\right)$
12. **End IF**
13. **Check If** (r_1>r_2) and (c_2>c_1) then
14. $\theta = 180^{\circ} + tan^{-1}\left(\frac{r1-r2}{c1-c2}\right)$
15. **End IF**
16. **Check If** (r_2>r_1) and (c_2>c_1) then
17. $\theta = 90^{\circ} + tan^{-1}\left(\frac{r1-r2}{c1-c2}\right)$
18. **End IF**
19. **Check If** (r_1=r_2) and (c_1>c_2) then
20. $\theta = 0^{\circ}$
21. **End IF**
22. **Check If** (r_1=r_2) and (c_2>c_1) then
23. $\theta = 180^{\circ}$
24. **End IF**
25. **Check If** (c_1=c_2) and (r_2>r_1) then
26. $\theta = 90^{\circ}$
27. **End IF**
28. **Check If** (c_1=c_2) and (r_1>r_2) then
29. $\theta = 270^{\circ}$
30. **End IF**

The summarization of the rules that developed by the author in calculating of each angle is illustrated in Figure 3.19.

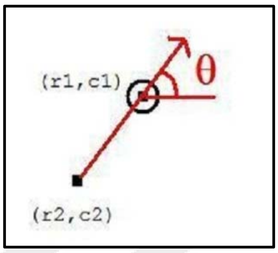
⊙	Location of termination
▪	Location of final pixel of five-pixel trace



Check If ($r_1 > r_2$) and ($c_1 > c_2$) then

$$\theta = 360^{\circ} - tan^{-1}\left(\frac{r1 - r2}{c1 - c2}\right)$$

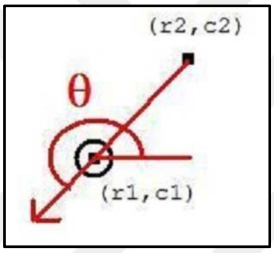
End IF



Check If ($r_2 > r_1$) and ($c_1 > c_2$) then

$$\theta = 90^{\circ} - tan^{-1}\left(\frac{r1 - r2}{c1 - c2}\right)$$

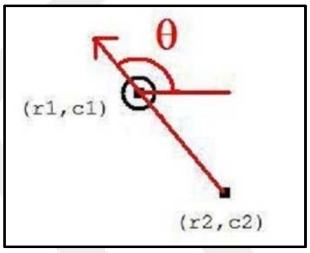
End IF



Check If ($r_1 > r_2$) and ($c_2 > c_1$) then

$$\theta = 180^{\circ} + tan^{-1}\left(\frac{r1 - r2}{c1 - c2}\right)$$

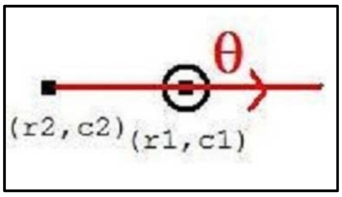
End IF



Check If ($r_2 > r_1$) and ($c_2 > c_1$) then

$$\theta = 90^{\circ} + tan^{-1}\left(\frac{r1 - r2}{c1 - c2}\right)$$

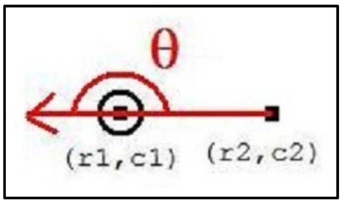
End IF



Check If ($r_1 = r_2$) and ($c_1 > c_2$) then

$$\theta = 0^{\circ}$$

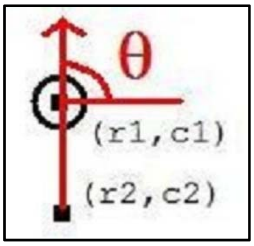
End IF



Check If ($r_1 = r_2$) and ($c_2 > c_1$) then

$$\theta = 180^{\circ}$$

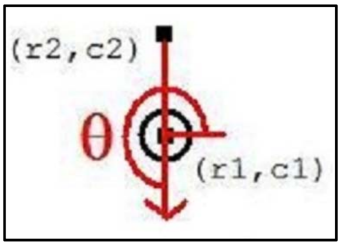
End IF



Check If ($c_1 = c_2$) and ($r_2 > r_1$) then

$$\theta = 90^{\circ}$$

End IF



Check If ($c_1 = c_2$) and ($r_1 > r_2$) then

$$\theta = 270^{\circ}$$

End IF

Figure 3.19: Rules for calculating termination angles.

The results of minutia feature orientation detection algorithm for local feature extractions are shown in Figure 3.20.

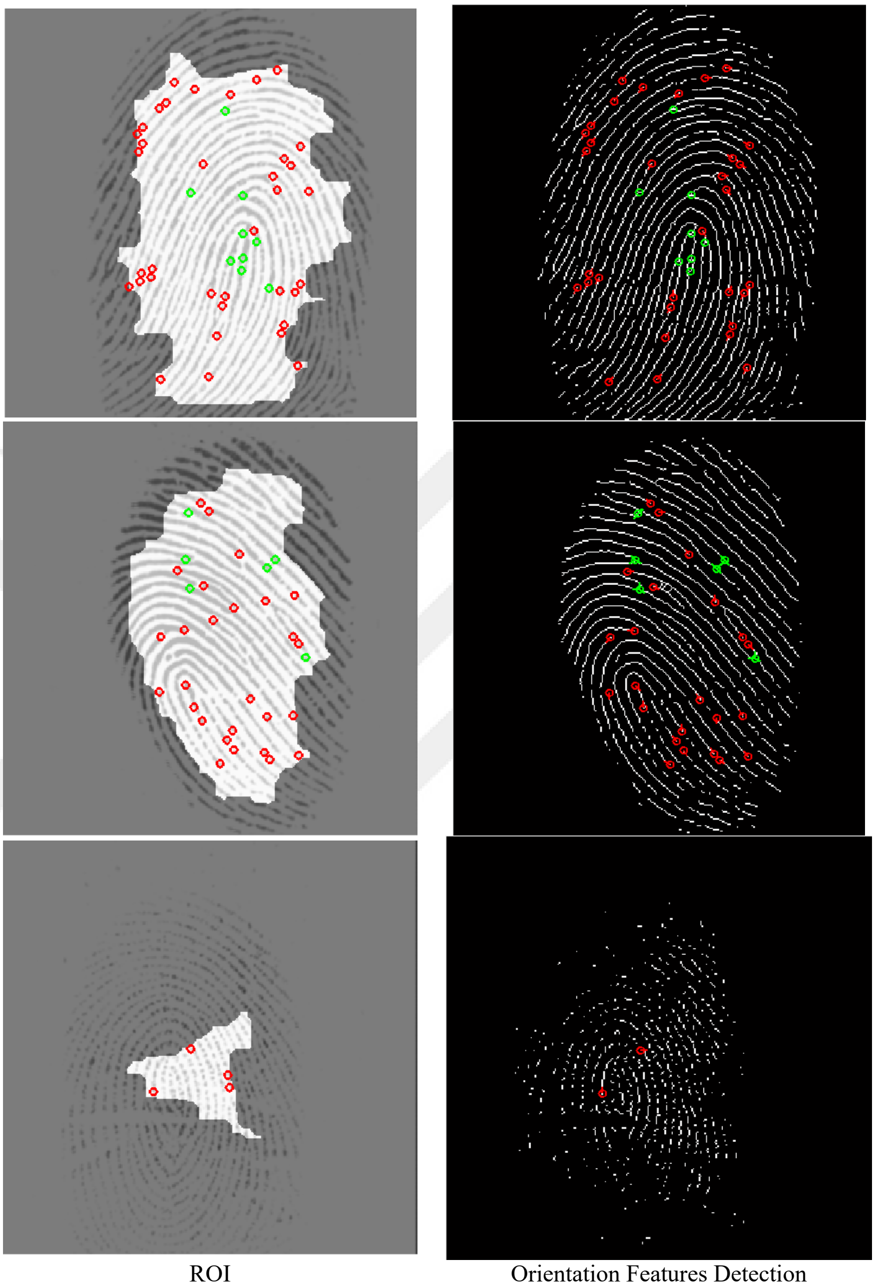


Figure 3.20: Feature orientation detection.

3.3.12 Matching Stage

In this stage, the matching process step involves the comparing between one set of the minutia features to another set. The compares process in this staged depend on the input features set that is previously stored data set with a known identity, referred to as a template. The matching template is also creating during the enrollment process by the user when presents a fingerprint image to the system as a purpose to collect the data. This feature information (data) is then stored as the defining characteristics (features) for that particular user [52].

Matching stage is the most important part for the local feature extraction approach for fingerprint authentication and verification. In this stage, the two features of the registered and requested features temples (I and$R$) that are extracted from the query and the references (registered) are compared between each other. In this stage, it returns a binary decision (matching/non-matching) or similarity score ($S(I, R)$) to indicate how the similar two participating fingerprints are in local feature extraction approach [51].

Minutia based fingerprint matching approach involves each for the correspondence between the two lists of the points in Hight-dimensional feature space which is usually in three dimensional or higher space. Then, a triple $m = \{x, y, \theta\}$ is the most common representation of a minutia, where (x, y) is the location and $\theta$is the orientation of the minutia [51]. Therefore, the templates are represented as [52]:

$$I = \{m_1, m_2, \dots, m_a\}, m_i = \{x_i, y_i, \theta_i\}, \qquad i = 1, \dots, a \tag{3.2}$$

$$R = \{m'_1, m'_2, \dots, m'_a\}, m_i = \{x'_j, y'_j, \theta'_j\}, \qquad i = 1, \dots, b \tag{3.3}$$

Where a and b are the number of the minutia in I and R respectively. A minutia m'_j in R matches of the minutia m_i in I, if they are sufficiently close in terms of the spatial distance and orientation difference. Given two tolerance distance r_0 and θ_0, minutia m_i matches minutia m'_j if and only if according to the following equation [52].

$$\sqrt{\left(x_i - x'_j\right)^2 + \left(y_i - y'_j\right)^2} \leq r_0 \tag{3.4}$$

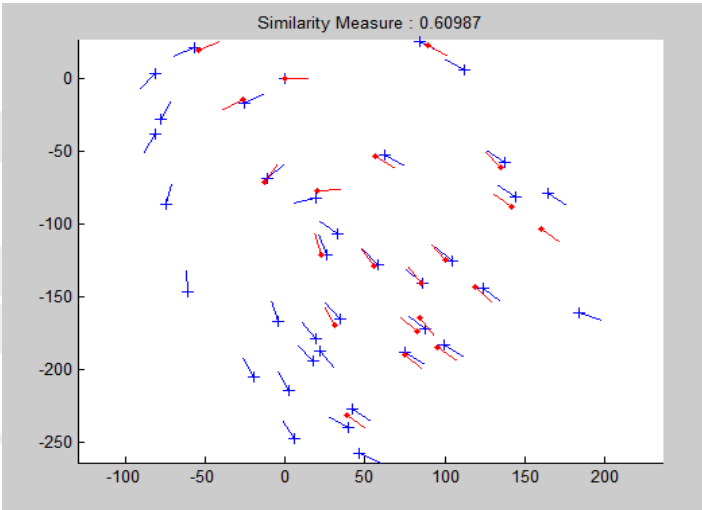
and

$$min\left(\left|\theta_i - \theta'_j\right|, 360 - \left|\theta_i - \theta'_j\right|\right) < \theta_0 \tag{3.5}$$

The results of minutia feature matching for local feature extraction are shown in Figure 3.21

Original Fingerprint image (I)

Requested fingerprint image (R)



Matching Score result

Figure 3.21: Minutia matching score.

3.4 Proposed Approach for Low-Quality Fingerprint Identification Based on Global Map Based Feature Extraction Approach.

Our proposed system for the low-quality fingerprint enhancement system has is based mainly on using the Global Map based Feature Indication and extraction approach (GMFI). In this approach for the low-quality fingerprint enhancement we rely on the GMFI which is based on the ability of low-quality (poor) fingerprint images. Basically, the GMFI approach is designed in our proposal by relying on the contextual concept of image filtering. This concept mainly depends on the localization approach for the local ridge frequency of the fingerprint that allows to detect and extract the ridges orientation which is the main step of the Global Map based Feature indication approach. In this proposal approach, the fingerprint ridges and the valleys feature of the fingerprint which is the main key that is used here to detect the missing features in the fingerprint that is in a low and poor quality.

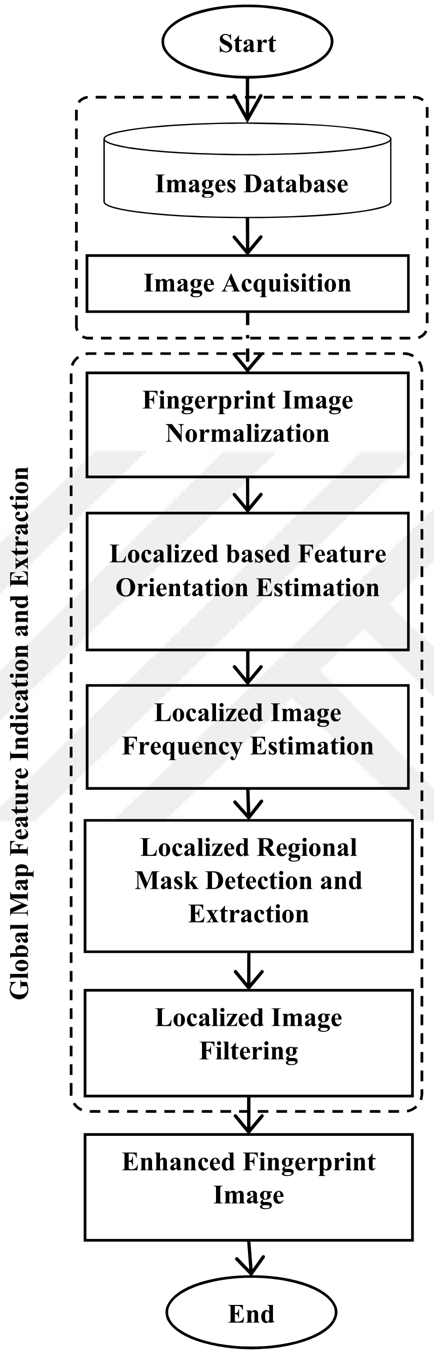


Figure 3.22: Proposed system flowchart for the low-quality fingerprint enhancement using GMFI.

In contrast with the Localization based feature extraction that depends on the minutia feature extraction which is a local feature extraction approach. This model has the essential stages to perform all relevant recognition and verification tasks to extract the missing features that the Localization approach has failed on. The general structure of the GMFI using localization ridges features extraction approach for fingerprint authentication and verification system is shown in Figure (3.22).

The flow-quality fingerprint enhancement algorithm based on the proposed Global Map Feature Indication and Extraction approach is described in Algorithm (3.8) below.

Algorithm 3.8: Global map feature indication (GMFI) algorithm.

Inputs:
Low-quality fingerprint image
Output:
Accurate Minutiae Features

1. **Fingerprint Image Normalization:** in this step the input fingerprint is normalized according the pre-specified mean and variance values.
2. **GMFI:** Localized Global Map Feature Indentation Extraction
3. **Localized based Feature Orientation Estimation**: In this step the fingerprint image features orientation is estimated based on the image normalization that has been done in the previous step.
4. **Localized Image Frequency Estimation:** in this step, the image frequency of the fingerprint image is calculated based on the normalized image rely on the localized based feature orientation estimation.
5. **Localized Regional Mask Detection and Extraction:** In this step, the local regional mask is obtained based on each local block in the normalized fingerprint image where the image is converted to recoverable set of blocks.
6. **Localized Image Filtering:** In this step, an oriental Gabor filter has been proposed and used for the local ridge features orientation detection, in this case the frequency approach of the ridge features is applied to the original ridge and the furrow pixels based on the normalized fingerprint image which is obtained to an enhancement fingerprint image.
7. **Localized Feature Extraction:** Finally, the traditional Minutia feature extraction approach is applied on the enhanced fingerprint image to extract robustness and reliable features for the low-quality fingerprint images.

Then, the final approach of our proposed system that is mainly designed to identify the low-quality fingerprint image is shown in Figure 3.23, where we have added to the original approach that is shown in Figure 3.22 above. The modification on the original approach is done by add the Global Map Feature Indication and Extraction (GMFI) approach to enhance and extract optimal minutia features that the standard approach of the Localization based minutia features extraction approach has failed on.

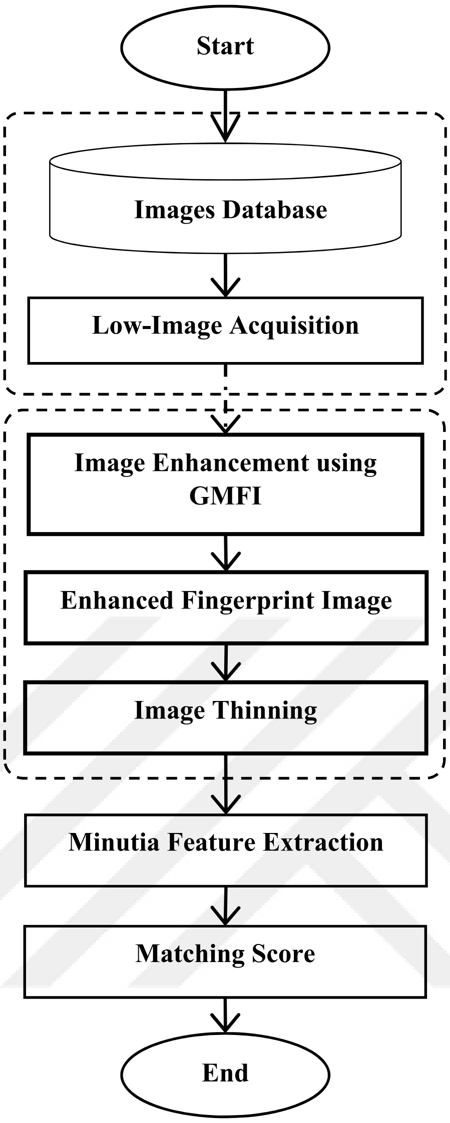


Figure 3.23: Low-quality fingerprint identification proposed approach using GMFI.

3.4.1 Guided Image Normalization

In term to enhance the fingerprint image, guided image normalization is the first step to do that. In this case, let assume that $\mathcal{I}(i,j)$ is donated as the fingerprint image input which is in this form it should be a gray-scale image with intensity level value from 0 to 255. Although, M and Var are donated as the mean and variance estimated values for the fingerprint image $\mathcal{I}$.In additional to that, $\mathcal{N}(i,j)$ is denoted as the gray-scale fingerprint image normalization at the pixel value (i,j). Then the normalized image formula that is mainly used to normalize the fingerprint image below in (3.6) [53].

$$\mathcal{N}(i,j) = \begin{cases} M_0 + \sqrt{\dfrac{Var_0(\mathcal{I}(i,j) - M)^2}{Var}} & if\ \mathcal{I}(i,j) > M \\ M_0 - \sqrt{\dfrac{Var_0(\mathcal{I}(i,j) - M)^2}{Var}} & Otherwise \end{cases} \tag{3.6}$$

Where M_0 is denoted as the mean value, and Var_0 is denoted as the variance.

The result of the normalization step for the fingerprint image enhancement is shown in Figure 3.24. where in this case, the normalization does not change the feature structure since it is a pixel wise operation. Basically, in the normalization step, the ridges and the furrow structure still the same as the input form.

Original Fingerprint image (I) Requested fingerprint image (R)

Figure 3.24: Fingerprint image normalization.

3.4.2 Global Map Feature Indication Extraction

To extract the GMFI that is used mainly for local feature addressing map, we will have used some steps to get that such as:

1. Localized based Feature Orientation Estimation (LBFE):

In this step, the fingerprint image features orientation is estimated based on the image normalization that has been done in the previous step. The orientation image represents the property of the fingerprint image. Localized based feature orientation defines the invariant coordinates of the local neighborhoods of the ridges and furrows. The main steps of the local based feature orientation estimation (LBFE) algorithm are shown in Algorithm (3.9) [54].

Algorithm 3.9: Localized feature based orientation estimation (LBFE).

Inputs:

$\mathcal{G}$: The normalized fingerprint images

Output:

$\mathcal{O}$: Local ridge orientation

1. **Divided** the normalized image $\mathcal{G}$ into a set of blocks with size $w \times w$
2. **Compute** the image gradient using Sopel Operator in two different directions, the x-axis $Gx(i,j)$ and y-axis $Gy(i,j)$ for each pixel in the normalized image. The magnitude of the gradient is then calculated using the formula:

$$|G(i,j)| = \sqrt{G_x(i,j)^2 + G_y(i,j)^2} \tag{3.7}$$

An approximate magnitude can be calculated using:

$$|G| = |G_x(i,j)| + |G_y(i,j)| \tag{3.8}$$

3. **Estimate** the localized orientation of each singe block that centered at the $pixel$ (i,j) by using

$$\mathcal{V}_x(i,j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{i-\frac{w}{2}}^{j+\frac{w}{2}} 2G_x(u,v)2G_y(u,v) \tag{3.9}$$

$$\mathcal{V}_y(i,j) = \sum_{u=i-\frac{w}{2}}^{i+\frac{w}{2}} \sum_{i-\frac{w}{2}}^{j+\frac{w}{2}} \left(G_x^2(u,v) - G_y^2(u,v)\right) \tag{3.10}$$

$$\theta(j,j) = \frac{1}{2} tan^{-1}\left(\frac{\mathcal{V}_y(i,j)}{\mathcal{V}_x(i,j)}\right) \tag{3.11}$$

where $\theta(j,j)$ is denoted as the Least Square Estimation (LSE) of the orientation for each local ridge in each block.

4. **Convert** the 2D image into a continuous vector filed, by using:

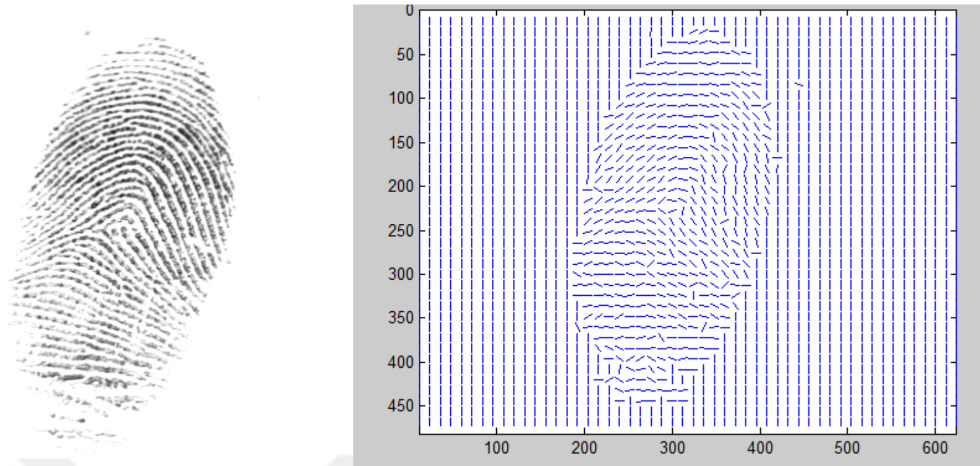
$$\Phi_x(i,j) = \cos\left(2\theta(i,j)\right) \tag{3.12}$$

$$\Phi_y(i,j) = \sin\left(2\theta(i,j)\right) \tag{3.13}$$

5. **Compute** the localized ridge orientation for each (i,j) using

$$\mathcal{O}(i,j) = \frac{1}{2} tan\left(\frac{\Phi'_x(i,j)}{\Phi'_y(i,j)}\right) \tag{3.14}$$

The result of the localized based feature orientation estimation step for the low-quality fingerprint image enhancement is shown in Figure 3.25.



(a) (b)

Figure 3.25: Localized based feature orientation estimation result (a) Original fingerprint image, (b) GMFI.

2. **Localized Frequency Based Image Estimation (LFIE):**

The image frequency of the fingerprint image is calculated based on the normalized image rely on the localized based feature orientation estimation. In this case, where there is no minutia feature has appeared, the intensity level along the ridge lines can be detected as an indication shape (wave) along the normal direction to the local ridge orientation.

Let assume that $\mathcal{G}$ is the normalized fingerprint images, and $\mathcal{O}$ is the local ridge image orientation that have been obtained through the previous step. Then, to estimate the localized image frequency, we should follow the following Algorithm (3.10) [55].

Algorithm 3.10: Localized frequency image estimation.

Inputs:

$\mathcal{O}$: Local ridge orientation

Output:

Ω: The frequency ridge estimation

---

1. **Divided** the normalized image $\mathcal{G}$ into a set of blocks with size $w \times w$ (16×16)
2. **For** each block that centered at the pixel(i,j), compute the local oriented window with size $l \times w$, using window dimension (32×16).
3. **For** each block that centered at the pixel (i,j), compute the x-signature values by 1D vector using:

$$X[k] = \frac{1}{w}\sum_{d=0}^{w-1} \mathcal{G}(u,v), k = 0,1,\dots,l-1 \tag{3.15}$$

$$u = i + \left(d - \frac{w}{2}\right) cos\mathcal{O}(i,j) + \left(k - \frac{l}{2}\right) sin\mathcal{O}(i,j) \tag{3.16}$$

$$v = j + \left(d - \frac{w}{2}\right) cos\mathcal{O}(i,j) + \left(k - \frac{l}{2}\right) sin\mathcal{O}(i,j) \tag{3.17}$$

4. **Estimate** the frequency ridge from the 1D vector of the x-signature by letting $\mathcal{T}(i,j)$ be the average number of the pixel between two peaks in the x-signature. Then, the frequency $\Omega(i,j)$ is computed based on:

$$\Omega(i,j) = \frac{1}{\mathcal{T}(i,j)} \tag{3.17}$$

The result of the localized frequency image estimation step for the low-quality fingerprint image enhancement is shown in Figure 3.26.

(a) (b)

Figure 3.26: Localized frequency image estimation result (a) Original Image (b) GMFI with fingerprint projection.

3. Localized Regional Mask Detection and Extraction

In this step, the local regional mask is obtained based on each local block in the normalized fingerprint image where the image is converted to recoverable set of blocks. The main task of classification the pixels into recoverable or not depends on the assessment wave shape, in this case it the wave shape is formed by the local ridges and the furrow fingerprint image features.

4. Localized Image Filtering (using Multi-Dimensional Filter)

In this step, an oriental Gabor filter has been proposed and used for the local ridge features orientation detection, in this case the frequency approach of the ridge features is applied to the original ridge and the furrow pixels based on the normalized fingerprint image which is obtained to an enhancement fingerprint image. In this case, For each pixel (i,j) in the low-quality fingerprint of fingerprint image $\mathcal{J}(x, y)$, the localized 1-D convolution by using a Gabor filter $G_{\phi}(x, y)$ is performed based on using four direction ϕ, which referring to different angles such as 0° , 45° , 90° and 135°. Then, the localized image filtering using (Gabor multidimensional filters) output vector is donated by $V(x, y)$ in different ϕ directions is given by [56]:

$$V(x, y) = \{F_{0^\circ}(x, y), F_{45^\circ}(x, y), F_{90^\circ}(x, y), F_{135^\circ}(x, y)\} \tag{3.18}$$

where

$$F_{\phi}(x, y) = I(x, y) \times G_{\phi}(x, y) \tag{3.19}$$

where $F_{\phi}(x, y)$ represents the localized image filtering using Gabor filter, and $G_{\phi}(x, y)$ is donated as the Gabor filter donation using multi-dimensional filter angles. The results of the localized image filtering using Gabor filter are illustrated in the Figure 3.27.

(a) (b) (c)

Figure 3.27: Localized image filtering results (a) The original low-quality fingerprint, (b) Gabor Filter, (c) Image enhancement.

CHAPTER FOUR

EXPERMENTAL RESULTS

4.1 Introduction

In this chapter, the results of conducted tests are presented. A set of tests have been conducted in order to evaluate the accuracy of the established fingerprint identification system, as well as to explore the effects of the different involved system parameters on the overall system performance. Also, the results of the analysis stage which was conducted to assess the discrimination capabilities of the extracted fingerprint features are illustrated. There are some experiential results expiration and discussion that this chapter will provide according to the main problem of the low-quality fingerprint identification based on using the standard approach as well as using the same dataset that has been used in the standard approach to be used in our proposed approach. To present this chapter we have produce some research methodology cheques that this chapter will start with such as our research methodology plan, and how we have done the experimental results.

4.2 Research Methodology

In this part, we will introduce the research methodology that we rely on to use the dataset for the experimental results for the fingerprint identification and for the low-quality fingerprint image system. In this task, we use both the standard approach that based on the localization based minutia feature extraction approach and our approach for enhanced the localization approach by using global Map Feature Indication and extraction approach (GMFI) for fingerprint low-quality identification system.

The main framework of our research methodology for the low-quality fingerprint identification system is illustrate in Figure (4.1) which describes the mainly steps that we have taken during our research methodology time period such as choose the main topic, define the problem, choose the main approach, proposed our model and methodology to address the main issue of the previous (related works) approaches, and do the experimental results.

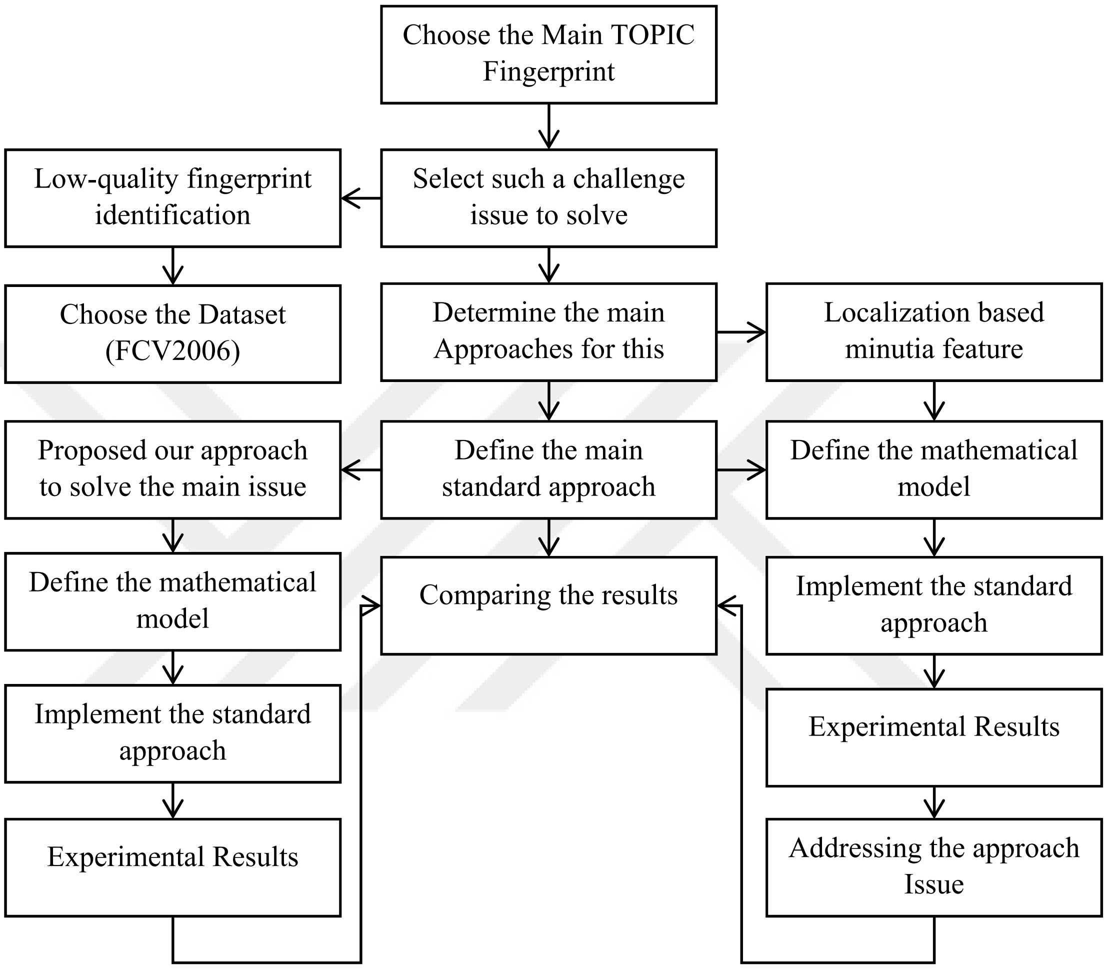


Figure 4.1: Our research methodology.

Our research methodology can be summarized in the following steps:

1. The first step of our research plan methodology is a problem definition, in this step, we have defined and fig-rout which problem we are going to work on in a main topic which is the BIOMETRIC FINGERPRINT IDENTIFICATION. Then we define such a specific problem that we have select to solve in this thesis, in our goal we have select the low-quality fingerprint identification challenge as a main issue of the fingerprint identification approach.

2. The next step of our research methodology is a literate survey and related works which in this this step, we have listed such a recently approaches that have mainly proposed and used for the main topic that we have select. The, we describe the mathematical model for the main standard approach that uses for the fingerprint identification approach.
3. We have implement the standard approach for the fingerprint identification (localization based feature extraction approach) which is the standard approach for the fingerprint identification and verification task in the market as we have discussed before in chapter three in details.
4. We have address the main issue of the main approach (standard approach) that is main frequently used for fingerprint identification approach based on the localization approach for feature extraction such as the difficulty in minutia feature extraction in such a bad and low-quality fingerprint images.
5. We proposed such a model based on extract such stronger indication map that is used mainly as a guidance and enhancement step for the low-quality fingerprint image to extract the robustness minutia feature that have been lost when it used the standard localization based feature extraction approach. Also, we have defined the mathematical approach for our proposed system that is going to solve the main issues that the main stranded approach has when it has been applied for the low-quality fingerprint identification approach.
6. Then, we have select the data set the present an appropriate description for the low-quality fingerprint issue. In our proposed system, the fingerprint images are adopted from database names (FCV2006) loaded from (http://atvs.ii.uam.es/atvs/fvc2006.html) web a BMP 8 bit/pixel (bit depth), the size of each used image is 400×560 pixels with resolution 96 dpi.
7. Implement the Global Map Feature Indication and extraction approach (GMFI) as a proposed approach to solve such a issue in the fingerprint identification system task which is the low-quality fingerprint images identification task. In case to state that that the localization based feature, extraction approach is the more efficient and standard one that has been used in the fingerprint identification and verification market, we have

implemented this approach and compare it with the other more recently related works as it will show later in the experimental results.

8. In this part, we have select the bad or low-quality fingerprint image identification problem as the main challenge issue that we would like to present in this approach which present such a challenge problem that still an open problem till now. This kind of problem is most recently fingerprint problem that has been studied since it presents such a difficult situation in this task.
9. Study the behavior (performance results) of both approaches that have been used in this thesis such as the localization based feature extraction (standard approach) and our approach the Global Map Feature Indication Approach (GMFI).
10. Our testing methodology is based on doing the experimental results by two main parts as they will have illustrated and discuss later in the experimental results.
    A. Experimental Results 1: we first test the localization based feature extraction approach on such a standard dataset that presents the low-quality fingerprint images such as FCV2006 just in term to see how this approach will act and achieve accuracy in this task.
    B. Experimental Results 2: In this experimental result, we test our enhancement approach Global Map Feature Indication and extraction Approach (GMFI) on the low-quality fingerprint images dataset that we have used before in the main standard approach. In case to study the behavior of the localization approach on such a challenged dataset. Moreover, we have tested our feature extraction approach on same low-quality fingerprint images dataset just in case to measure the ability of our proposed approach to solve this issue.
    C. Experimental Results 3: Finally, we compare the results of the localization based feature extraction approach and our approach (Global Map Feature Indication Approach) that has achieved better accuracy on the low-quality fingerprint image identification system.

4.3 Implementation Environment

The developed system has been established and implemented using Visual C++ programming language, MATLAB 2014, Microsoft Excel 2010, and the tests have been implemented under the environment of Windows-10 operating system, laptop computer processor: Intel Core i5-3337U, CPU 1.80 GHz, and (4GB) RAM.

The overview of the hardware environment of our system that has been used for testing our approach local and global approaches for fingerprint authentication and verification system is shown in Figure 4.2.

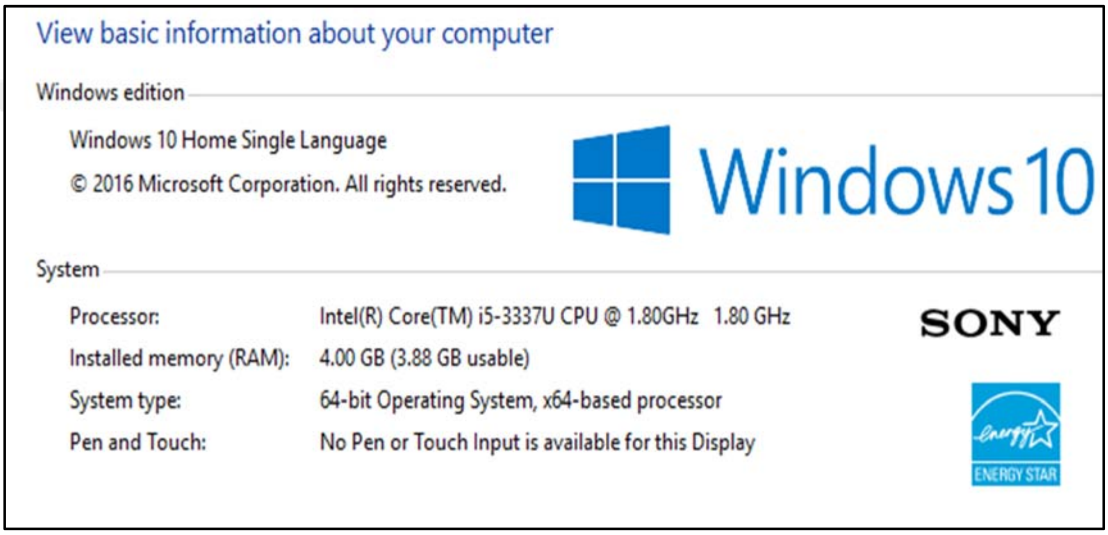


Figure 4.2: Computer specification that used for our program execution.

4.4 Datasets

In this proposed system, we have used a most challenge low-quality fingerprint images FCV2006. The dataset is the last version of the fingerprint dataset which is gray scale fingerprint images (FVC2006 fingerprint database) that has been proposed and used by "R. Cappelli, M. Ferrara, A. Franco and D. Maltoni, "Fingerprint verification competition 2006", Biometric Technology Today, vol.15, no.7-8, pp.7-9, August 2007". The second dataset is the colored fingerprint images that we have collected by ours from some participants in our study.

In our proposed system, the fingerprint images are adopted from database names (FCV2006) loaded from (http://atvs.ii.uam.es/atvs/fvc2006.html) web a BMP 8 bit/pixel (bit depth), the size of each used image is 400×560 pixels with resolution 96 dpi. The dataset has 8 data bases (DB1_A, DB1_B, DB2_A, DB2_B, DB3_A, DB3_B, DB4_A and DB4_B). The number of fingerprint samples in A Groups (1680) and (120) in B Groups, 12 images for each person (i.e. 30 sample were taken) are of different contrast (dark and light) and moves belong to a specific person [71].

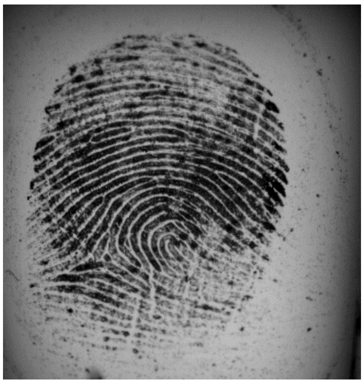
Two options were adopted in the proposed system; the first one is to find bifurcation points and their distance while the second stage is to find the matched features for their types. The elapse time has been calculated during matching process to evaluate the proposed system.

Table (4.1) shows the dataset information of the first dataset that has been used in our proposed system depending on the local feature extraction approach by extract minutia features.

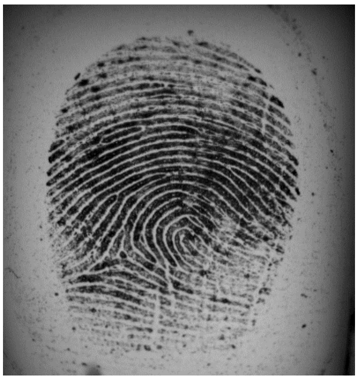
Table 4.1: FCV2006 datasets information.

Dataset Size	Description							
	DB1_A	DB1_B	DB2_A	DB2_B	DB3_A	DB3_B	DB4_A	DB4_B
7200 images	1680 images	120 Images	1680 Images	120 images	1680 Images	120 images	1680 Images	120 Images

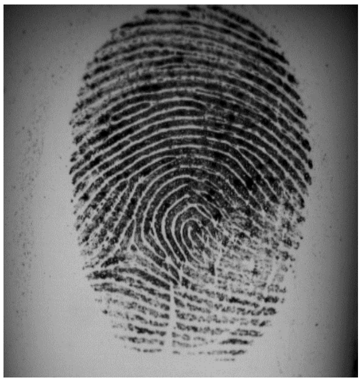
Figure 4.3 shows some fingerprint image examples (one case) from the FCV2006 DB1. In this figure, we can notice that there is sub sequence on fingerprint images numbers that is started from 7_1 which is the original case to 7_12 image. Each case presents a different situation that has been generated from the original case (7_1 fingerprint image). Also, Figure 4.4, Figure 4.5, and Figure 4.6 represents DB2, DB3, and DB4 fingerprint images cases respectively.



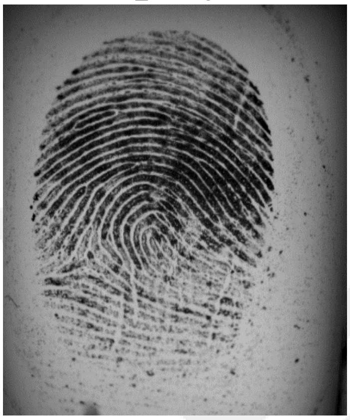
7_1 Image



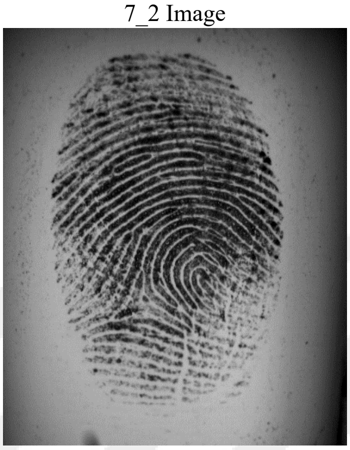
7_2 Image



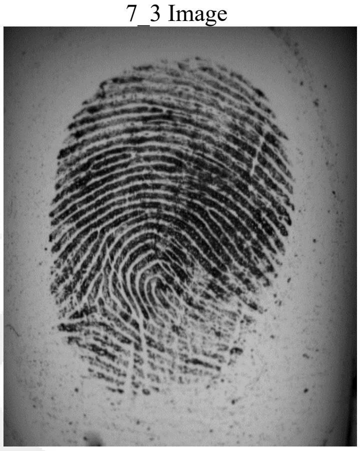
7_3 Image



7_4 Image



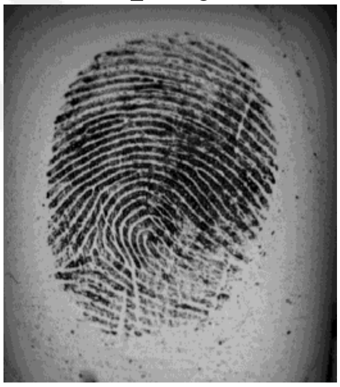
7_5 Image



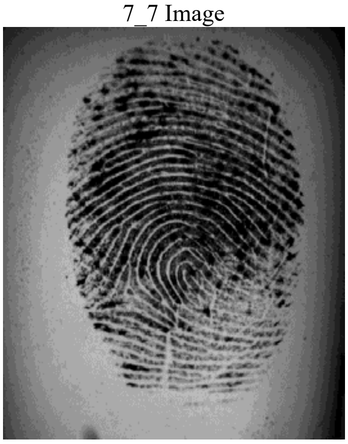
7_6 Image

7_7 Image

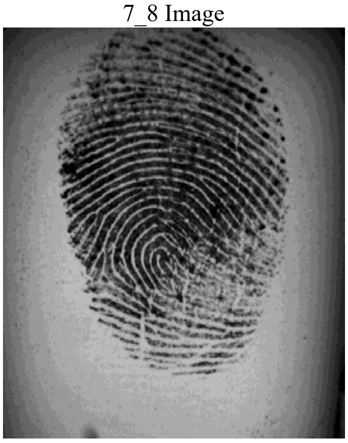
7_8 Image



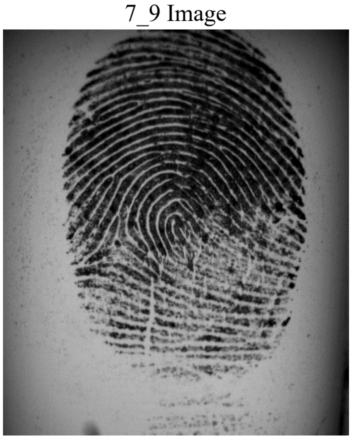
7_9 Image



7_10 Image



7_11 Image



7_12 Image

Figure 4.3: Sample of fingerprint images from FCV2006 DB1 dataset.

In DB2 from the FCV2006 dataset, we can notice that each fingerprint case has just 8 different cases that have been generated based on the first case (101_1 image) till (101_8 image) each case presents different situation for the sane fingerprint image such as rotation, noisy, and position for the low-quality fingerprint image.

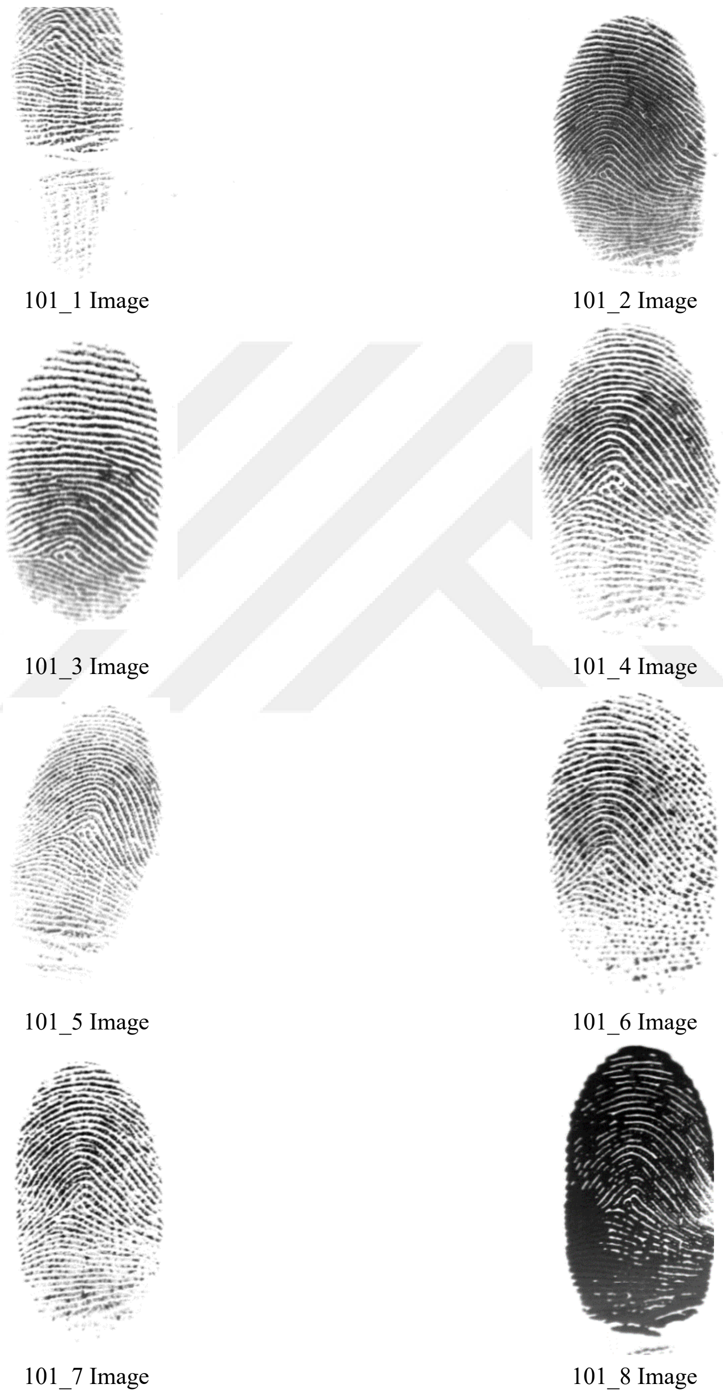


Figure 4.4: Sample of fingerprint images from FCV2006 DB2 dataset.

Also, in DB3 from the FCV2006 dataset, we can notice that each fingerprint case has just 8 different cases that have been generated based on the first case (101_1 image) till (101_8 image) each case presents different situation for the sane fingerprint image such as rotation, noisy, and position for the low-quality fingerprint image.

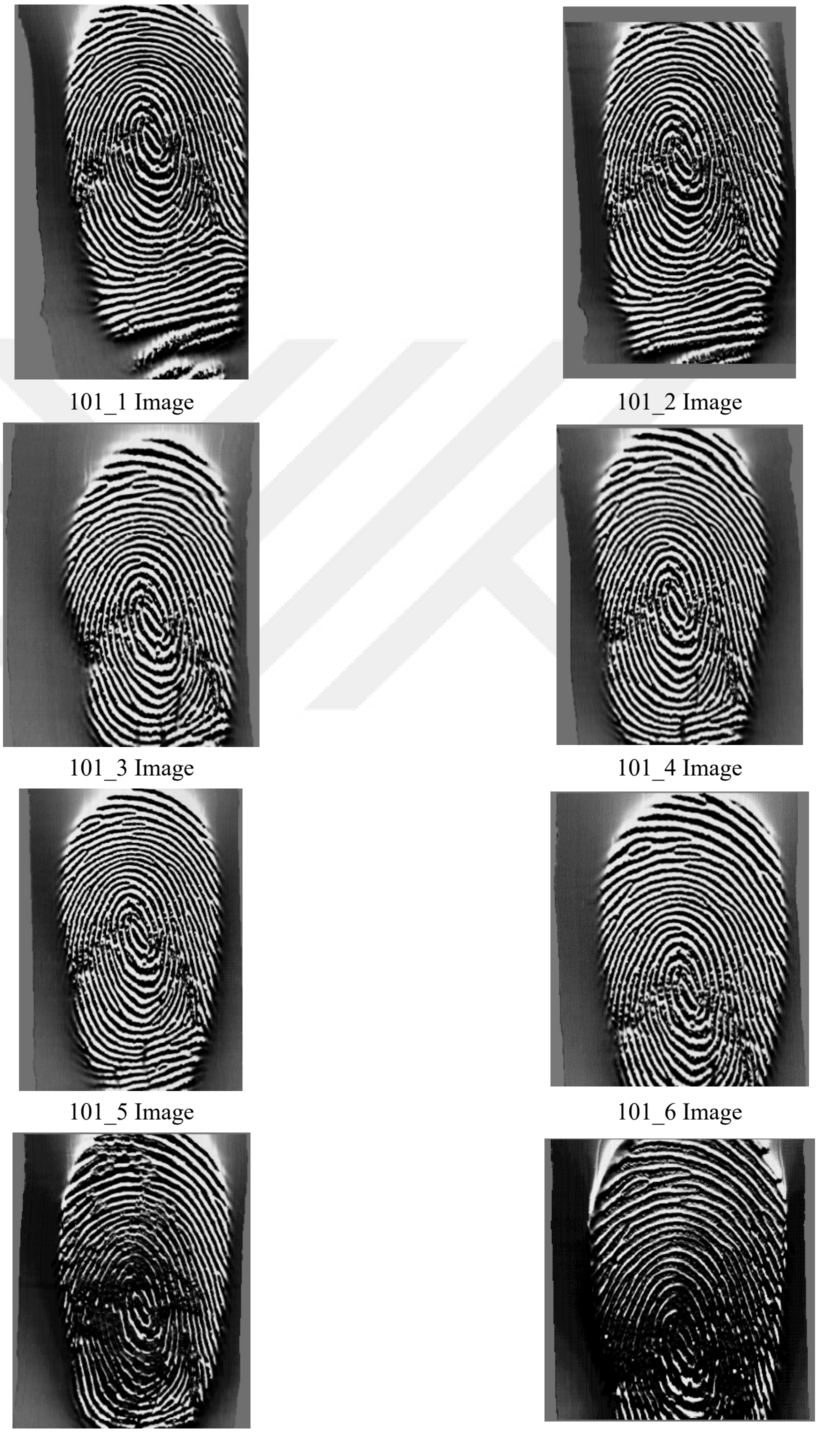


Figure 4.5: Sample of fingerprint images from FCV2006 DB3 dataset.

Finally, in DB4 from the FCV2006 dataset, we can notice that each fingerprint case has just 8 different cases that have been generated based on the first case (101_1 image) till (101_8 image) each case presents different situation for the sane fingerprint image such as rotation, noisy, and position for the low-quality fingerprint image.

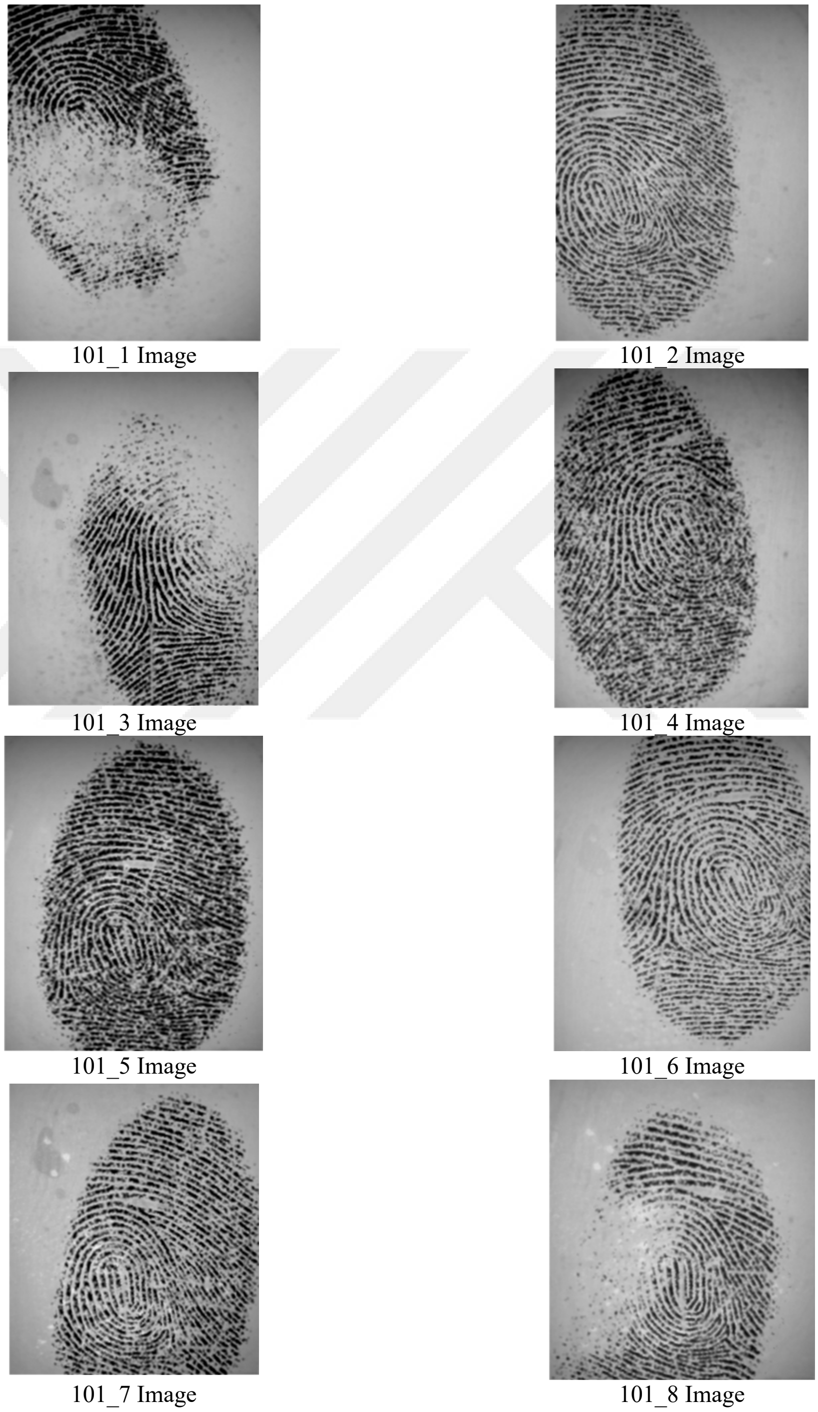


Figure 4.6: Sample of fingerprint images from FCV2006 DB4 dataset.

4.5 Evaluation Criteria

The evaluating performance of fingerprint authentication and verification system based on minutia features feature extraction system using the distances between the detected bifurcation points are calculated by Calculate the minimum distance, the Euclidian distance is used between the extracted bifurcation point to the others.

We can define the squared distance between two vectors $x = [\ x1\ x2\ ]$ and $y = [\ y1\ y2\ ]$ is the sum of squared differences in their coordinates, which denotes that the squared distance between points $(P\ and\ Q)$. To denote the distance between vectors x and y we can use the notation $d_{x,y}$ so that this last result can be written as shown in Equation (4.1) [72]:

$$d^2 = (x_1 + y_1)^2 + (x_2 + y_2)^2 \tag{4.1}$$

which is, the distance itself is the square root as it shown in Equation (4.2) [72]:

$$d_{x,y} = \sqrt{(x_1 + y_1)^2 + (x_2 + y_2)^2} \tag{4.2}$$

What we called the squared length of x, the distance between points P and O, is the distance between the vector $x = [x1\ x2]$ and the zero vector $0 = [0\ 0]$ with coordinates all zero as it given in equation (4.3) [72]:

$$d_{x,y} = \sqrt{x_1^2 + x_2^2} \tag{4.3}$$

4.6 Experimental Results

In this section, we will explain the different experiential results for the fingerprint authentication and verification system depending on the using different datasets and different approaches. The first experimental results rely on the first approach that we have proposed in this thesis which is the Local feature extraction based methodology for fingerprint authorization and verification. This approach is based on using minutia feature extraction and calculates the minimum distance using the first dataset FCV2006 dataset. The second experimental results rely on the second approach which is the Global based feature extraction approach. This Approach relies on the moment function based methodology for feature extraction and matching approach. In this approach, we used the second dataset that we have collected by our self which present the low-quality fingerprint images.

4.6.1 Localization Based Feature Extraction Approach Experimental Results

During our research methodology, we have defined two three experimental results methodology. The first one is the experimental results of the main standard approach (localization based minutiae minutia feature extraction) which is general approach to extract the features for low-quality fingerprint identification. Then we compute the minimum distance to find the accurate matching results using FCV2006 dataset. We have select 30 random fingerprint image that have been randomly selected form the FCV2006 dataset as a main criterion of doing our experimental results in this approach. Practically, we have randomly select subset of fingerprint images from each Data Base (DB) from our testing dataset which is the (FCV2006) that presents the low-quality fingerprint images challenges. In appendix table A.1 shows the experimental results of the localization approach based feature extraction for low-quality fingerprint identification that has been tested using FCV2006 dataset.

We can notice In appendix table A.1 that each column represents the fingerprint image. for each fingerprint image, we have found there is 12 different sample for each fingerprint image and each row represent different results the final matching accuracy the time consuming for each finger that has been tested that has been calculate using a MATLAB function “tic-toc” starting from the final stage of the preprocessing image, feature extraction, false features removing till the final stage of the matching calculation.

The average mean of the performance result for the fingerprint identification system for low-quality fingerprint image using localization based feature extraction approach is shown in Figure 4.7 and table A.1 in appendix A.

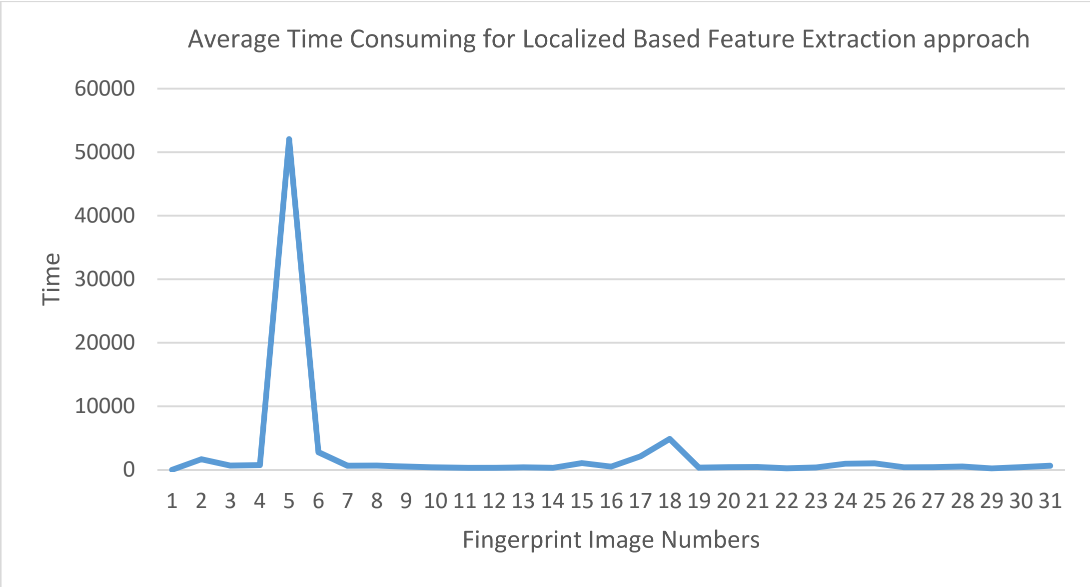


Figure 4.7: Average time consuming for Localized based feature extraction approach.

We can notice that the localization based feature extraction approach works very accurate in the matching results for the low-quality fingerprint when it has been applied on the same fingerprint image which the accuracy results is (100%) when it is applied in the same view and image position. In contrast, the accuracy is different from the lower range which is (19 %) to the higher range which is (89%) when it has been applied on the difficult situation (low-quality fingerprint images) such as rotational and noisy fingerprint images and as it has been shown in Figure 4.8.

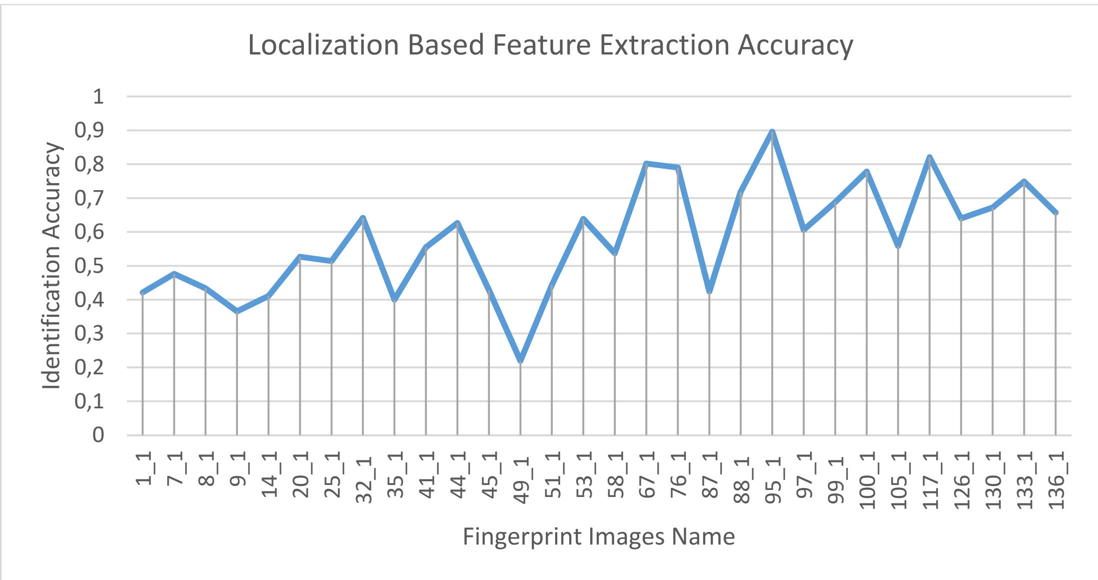


Figure 4.8: AVERAGE Accuracy result of the local approach for fingerprint authentication and verification system using FCV2006 dataset.

Table A.3 in appendix and Figure 4.5 show the time consumption for the fingerprint identification that has been consumed using the localization based feature extraction approach for the low-quality fingerprint identification system. We can notice that the localization based feature extraction approach is highly time consuming since it needs a lot of preprocessing steps. In this approach which is the local fingerprint approach based on minutia feature extraction model, we can notice that in monastically increasing in time consuming since the samples of the fingerprint images have been different in the difficulties like rotational degree, noise, and other factors. Table A.3 in appendix shows the time consuming for the low-quality fingerprint identification based minutia points detection and extraction in the low-quality fingerprint images.

Figure 4.9 shows the average time consuming for the low-quality fingerprint identification based minutia points detection and extraction in the low-quality fingerprint images.

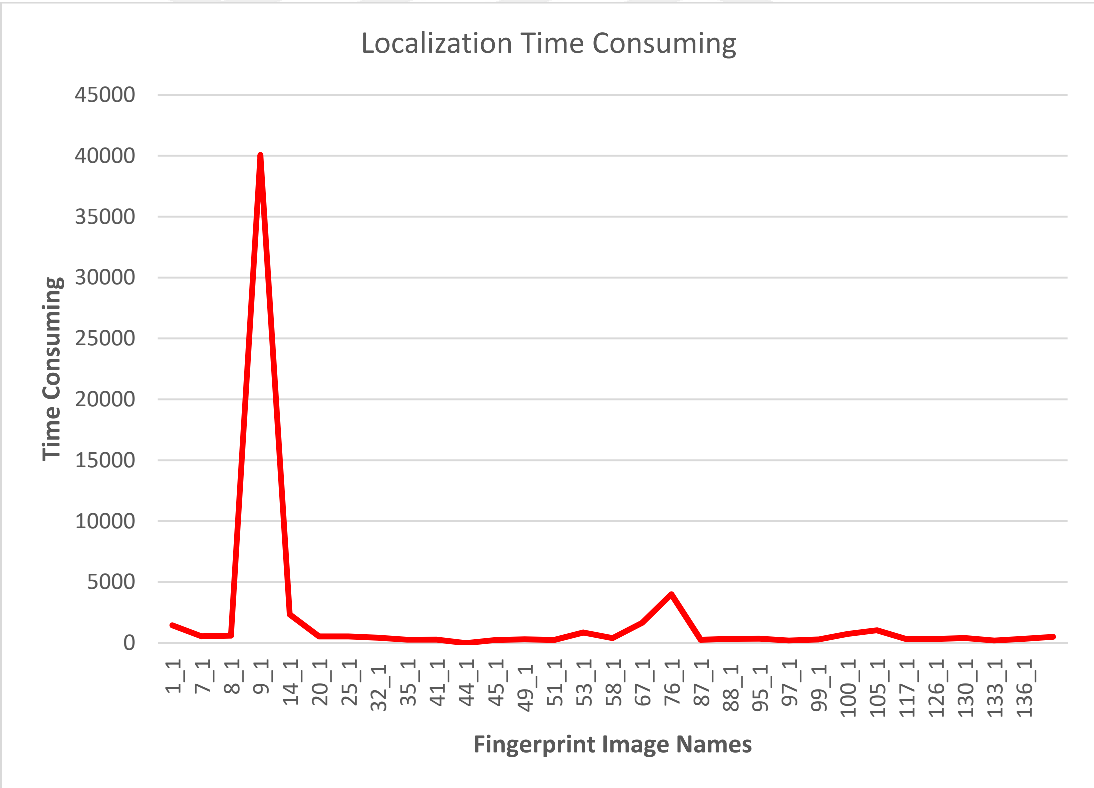


Figure 4.9: Time consuming result of the localization based feature extraction approach for fingerprint identification System using FCV2006 dataset.

We can easily notice that there is a big jump between 5th and 6th images which is clearly seen that all the time consuming in monotonality increasing in the time consuming according to the fingerprint image samples complexity such as amount of noise, rotation and other distribution that have done in this dataset. Figure 4.10 shown the increased in time consuming for the localization based feature extraction approach when it has been applied for the low-quality fingerprint identification using FCV 2005 dataset.

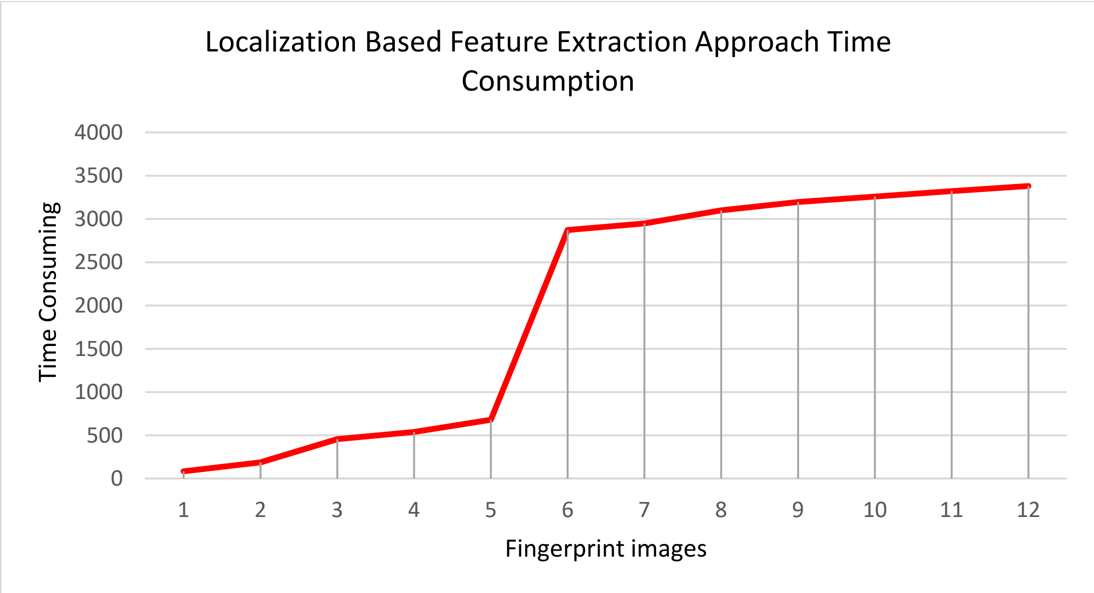


Figure 4.10: Time consumption of the local approach for fingerprint authentication and verification system using FCV2006 dataset.

4.6.1 Our Proposed Localization Approach based (GMFI) Experimental Results

Our proposed approach based on define a Global Feature Map Indication and extraction (GFIM) that is mainly we proposed to enhance the localization based feature extraction approach for low-quality fingerprint identification. In this case, we are doing the second experimental results that we have defined in our research methodology. After we have defined the GMFI and enhance the low-quality fingerprint image we compute the minimum distance to find the accurate matching results using FCV2006 dataset. We have select 30 random fingerprint image that have been randomly selected form the FCV2006 dataset as a main criterion of doing our experimental results in this approach. Practically, we have randomly select subset of fingerprint images from each Data Base (DB) from our testing dataset which is the (FCV2006) that presents the low-quality fingerprint images challenges. Table A.4 in appendix shows the experimental results of our Localization based GMFI feature extraction approach for low-quality fingerprint identification that has been tested using FCV2006 dataset.

In this appendix Table A.4, we can notice that each column represents the fingerprint image. for each fingerprint image, we have found there is 12 different sample for each fingerprint image and each row represent different results the final matching accuracy the time consuming for each finger that has been tested that has been calculate using a MATLAB function "tic-toc" starting from the final stage of the preprocessing image, feature extraction, false features removing till the final stage of the matching calculation.

The average mean of our proposed system performance result for the fingerprint identification system of low-quality fingerprint image using localization based Global Map Feature Indication and extraction (GMFI) is shown in appendix table A.5.

The average mean of the performance result for the fingerprint identification and verification system using local feature extraction approach is shown in Figure 4.11. We can notice that the local approach works accurate in the matching results when it has been applied on the same fingerprint image which the accuracy results is (100%) when it is applied in the same view and image position. In contrast, the accuracy is different from the lower range which is (75%) to the higher range which is (100%) when it has been applied on the difficult situation like rotational and noisy fingerprint images.

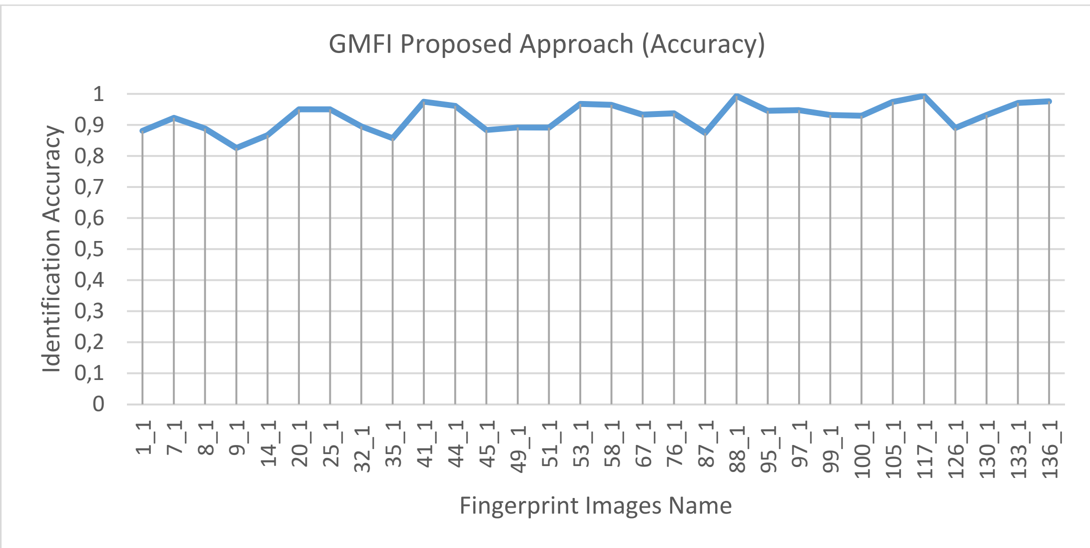


Figure 4.11: AVERAGE accuracy result of the localization based GMFI approach for fingerprint Identification and verification system using FCV2006 dataset.

Table A.6 in appendix and Figure 4.8 show the time consumption for the fingerprint identification that has been consumed using the proposed approach (localization based GMFI feature extraction) approach for the low-quality fingerprint identification system. In our proposed approach which is the localization based Global Map Feature Indication and extraction (GMFI) for fingerprint approach based on minutia feature extraction model. Table A.6 shows the time consuming for the low-quality fingerprint identification based minutia points detection and extraction in the low-quality fingerprint images.

Figure 4.12 shows the average time consuming for the low-quality fingerprint identification based minutia points detection and extraction in the low-quality fingerprint images.

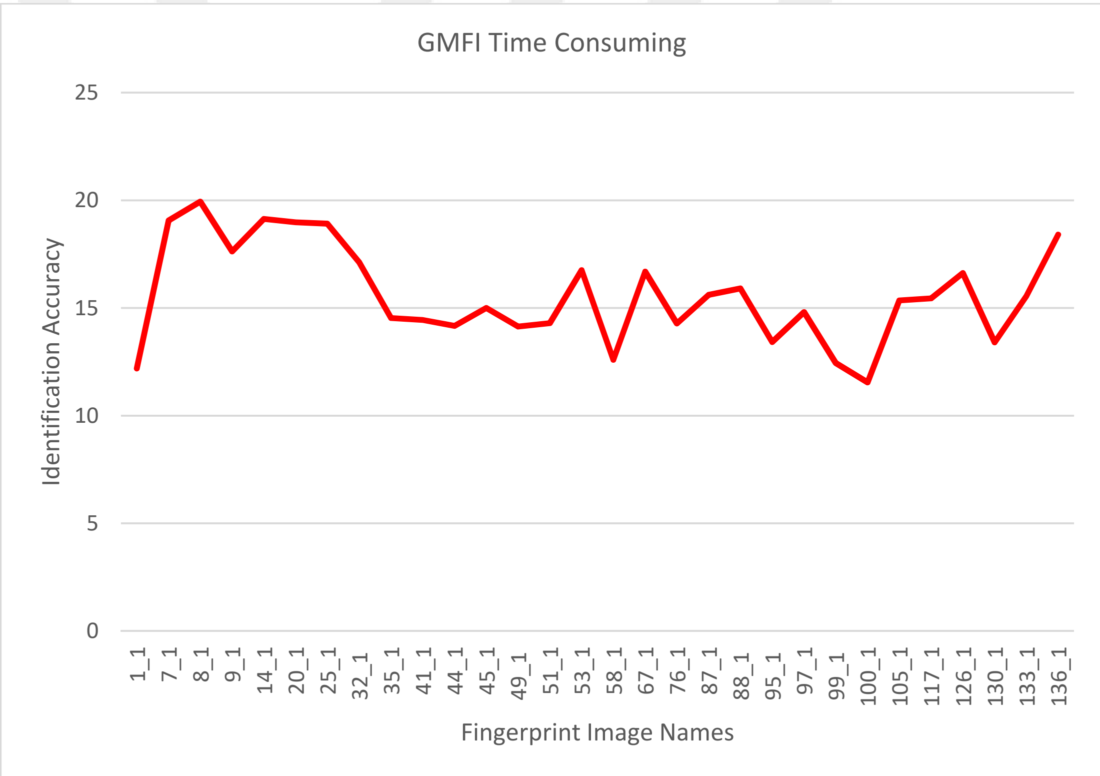


Figure 4.12: Time Consuming Result of the Localization based GMFI and feature extraction approach for fingerprint identification system using FCV2006 dataset.

Figure 4.11 shows that our proposed system Fingerprint identification based Global Map Feature Indication (GMFI) and extraction approach is such a stable approach in a time consuming that because our approach has provided such a robustness guide to detect the minutiae features that were unable to be extracted using the localization based feature extraction approach. For this reason, we notice that the Standard approach was not stable enough since it needs to do the same preprocessing for each different low-quality fingerprint image. That may be works for sub image but not for the whole dataset, then we notice that it is not stable. For example, we can easily notice that there is a big jump between 5^{th} and 6^{th} images which is clearly seen that all the time consuming in monotonality increasing in the time consuming according to the fingerprint image samples complexity such as amount of noise, rotation and other distribution that have done in this dataset.

4.6.2 Comparing between Localization based Feature Extraction Approach and Our Localization based GMFI

From the results above, we can easily notice that the Our Approach (Localization based Global Map Feature Indication and Extraction) for low-quality fingerprint approach has achieved about (98.74%) while the standard localization approach has achieved (58.13%) which our localization based Localization based Global Map Feature Indication and Extraction (GMFI) approach enhances the fingerprint identification and verification system for the low-quality fingerprint images by (40%). The reason for that is that our approach provides a robustness map which uses in our approach as a guide to detect the minutia features that were not able to be detected using the standard approach for fingerprint identification that based on the minutia feature extraction. In other words, any low-quality fingerprint image that is used to be tested any cut, noisy, distortion in the fingerprint image the GMFI function can gives a clear indication after enhancing the original fingerprint image and transform the low-quality fingerprint image to another domain that will be clearer to detect the minutia feature based on a reference point which originally extracted from the GMFI. So, instead of relying on the local features which are missed and effected by the image cutting, noisy, distortion. For this reason, our approach (Localization based Global Map Feature Indication and Extraction) is more robust that the local approach for incomplete fingerprint identification and verification task.

Figure 4.13 shows a comparing in the identification result between the localization based minutia feature approach and our proposed approach which is localization based Global Map Feature Indication and extraction (GMFI) approach for low-quality fingerprint identification and verification task.

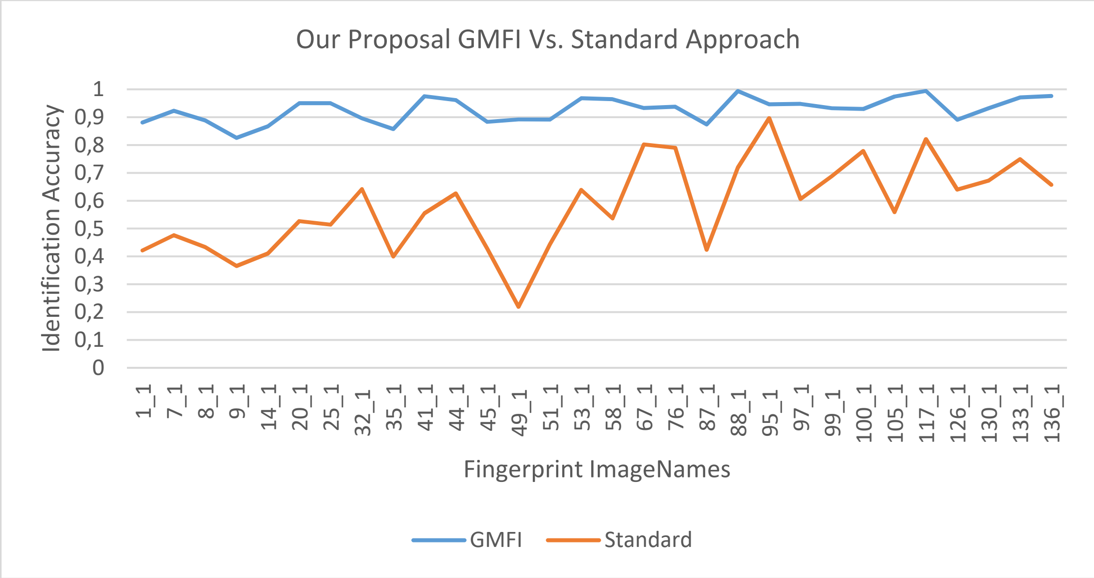


Figure 4.13: Comparing between localization based minutia feature approach and Our GMFI approach for fingerprint Identification

It is easily to see that the matching accuracy (identification) for the our GMFI approach is more efficient that the standard localization approach in the mean average. In the most cases of the localization approach we have notice from the matching accuracy that it is below 80% while the most cases of the incomplete image that have been tested in the our proposed approach (localization approach based Global Mao Feature Indication and Extraction) approach is above 90% which gives us an indentation about the different of the robustness behavior between the localization based minutia feature extraction and the our localization approach for the low-quality fingerprint image identification and verification task.

Also, we can notice that our proposed approach has consumed (15.61448 sec.) total mean average time to identify the low-quality fingerprint that includes the matching, while the standard approach has consumed about (33.10135 sec.) as a total mean average time for doing the fingerprint identification. That means our approach has consumed 32% from the total consuming time while the standard approach has consumed 68% from the total consumed time for the fingerprint identification which includes matching stage.

Figure 4.14 shows the different in time consuming between our approach (Localization based Global Map Feature Indication and Extraction) and the standard approach (Localization based minutia feature extraction) for low-quality fingerprint identification.

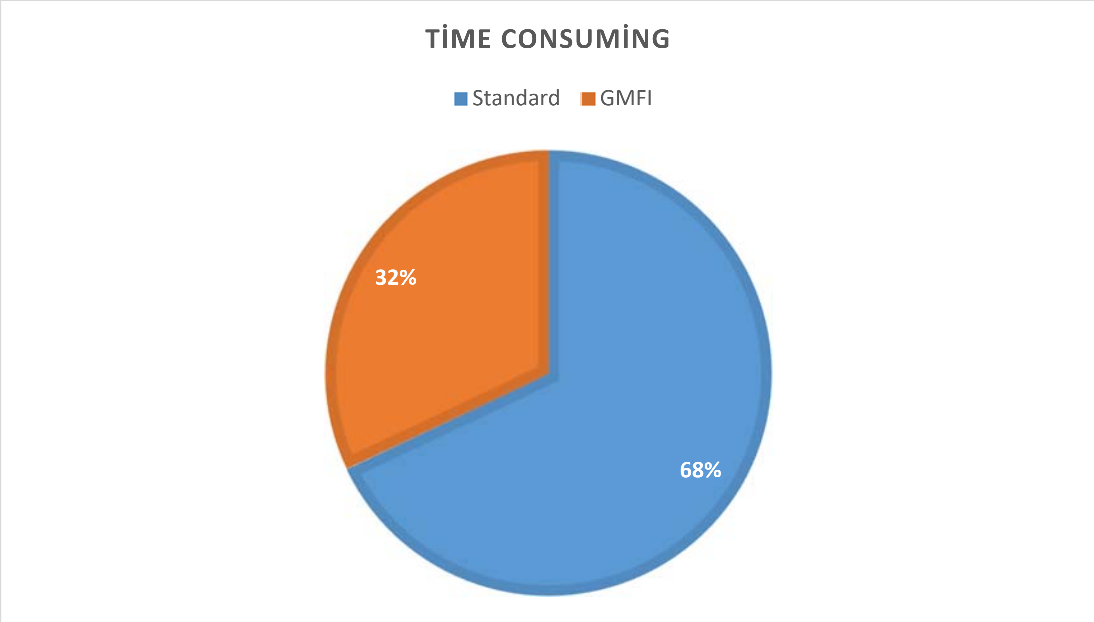


Figure 4.14: Comparing between localization based minutia feature approach and Our GMFI approach for fingerprint Identification in time consuming (preprocessing, feature extraction and matching) stages

4.6.3 Comparison with Previous Studies

In term of comparing our proposed system for low-quality fingerprint identification system using localization approach based Global Map Feature Indication (GMFI) and extraction approach which depends on using the Global Map Feature Indication to detect and extract the minutia feature, and compare our proposed system with different approach that has been tested using the same dataset. Table 4.8 compares the identification and recognition results that have been obtained by our proposed method with previous studies that have been applied on the same task which is fingerprint authentication and verification using FCV2006 dataset, where in these studies the same database and same local approach but different preprocessing methods have been used.

Table 4.2: FCV2006 datasets information.

No	Approach	Recognition Rate (%)
1	Competitive Learning Algorithm	95.82%
2	Singularity Detection	92.24%
3	Wavelet and Fourier–Mellin Invariant Transform	93.21%
4	Orientation Features	96.36%
Ours	Global Map Feature Indication	98.74%

CHAPTER FIVE

CONCLUSIONS AND SUGGESTION FOR FUTURE WORKS

In this chapter, we will summarize and conclude some achievements that we get according to the experimental results that we have done in Chapter Four according to the two models that we have proposed in this thesis. For a quick conclusion, we have select such a challenge biomedical problem which is a biometric fingerprint identification and verification task. In this thesis, we have focused on a low-quality fingerprint identification problem since it is such a biometric fingerprint challenged problem. Practically, we have deeply study the main problem by implementing the main standard approach of the fingerprint identification system by using the localization based minutia feature extraction approach for fingerprint identification, then by relying on the results of this approach we have addressed the main issues of this approach which helps us to proposed another approach to solve the issue of localization approach to identify the low-quality fingerprint images by proposing an enhancement approach. This enhancement approach relies on extract such a robustness global map for minutia feature point in a low-quality fingerprint image, then we used the same localization approach based on minutia feature extraction to identify the low-quality fingerprint images. So, this thesis and several conclusions that have been deduced from the obtained test results.

5.1 Conclusions

In this thesis, we considered our proposed approach localization based Global Map Feature Indication and Extraction (GMFI) for low-quality fingerprint identification and verification based on extract such a reliable and stable indication gaudiness feature map. This approach helps us to detect the reliable minutiae features that were unable to be extracted using the original approach (localization based minutiae feature extraction approach) which is the classical approach for extract the local minutiae feature extraction. Localization based munities feature extraction and our approach Localization based Global Map Feature Indication (GMFI) have been tested on random selected low-quality fingerprint images that we randomly selected from such a big challenge dataset which is FCV2006 for the low-quality fingerprint images. The testing results show that our approach Localization based Global Map Feature Indication and Extraction approach enhance the low-quality fingerprint identification and verification system by 40% more than the original approach which is the localization based minutia feature extraction approach. Our approach (GMFI) achieves about 98.74% identification (recognition) accuracy. Different feature extraction approach that we have proposed by considering the ineffectiveness of the localization approach which depends on the sensitivity of the minutia features allows us to deal with the low-quality fingerprint image authentication and varication problem. Our approach localization based Global Map Feature Indication and Extraction (GMFI) relies on the whole structure features that have been detected and extracted using the global map feature.

This technique which is a global feature vector using global map feature indication and extraction which gives such strong points to emphasize on the global approach to find a substitutional feature ration to fairly detect the local minutia feature points to identify the low-quality fingerprint image by computing the matching score while depending on the global features map instead of the local ones.

Finally, our final conclusion detects the low-quality fingerprint image identification and verification task suing our proposed system (Global Map Feature Indication and Extraction Approach) gives a higher matching score that the standard one (localization based minutia feature approach) since our proposed approach depends on the global feature map vector using Global Map Feature Indication and Extraction (GMFI) approach instead of the local feature points using minutia features which gives us an intensive way to jump put the missing feature that the local approach has felt to detected and extracted.

As a conclusion, our approach localization based Global Map Feature Indication (GMFI) has achieved better performance results when it has been compared with the localization approach (minutia based feature extraction approach) in two points:

1- Our approach (Global Map Feature Indication) has improved the performance result of the low-quality fingerprint identification and verification task by (40%) more than the localization approach (localization based minutia based feature vector).
2- Our localization based global map feature indication and extraction (GMFI) approach is faster that the localization based minutia feature approach in the low-quality fingerprint identification and verification approach has consumed (15.61448 sec.) as the mean average time for the matching stage.
3- In both cases (average accuracy and average time consuming) our proposed approach (GMFI) has acted better than the local approach (minutia based feature extraction approach) when both cases have been applied on the same problem which is the partial or incomplete fingerprint image identification and verification task.

5.2 Suggestions for Future Work

In our future work, we have suggested some point the will be our future plan for the future work for the fingerprint. In term to enhance our work that is based on enhanced the low-quality fingerprint identification based on proposed a Global Map Feature Indication and Extraction (GMFI) we will suggest some points that will be our future works plan.

1. Test our approach to solve another critical issue of the low-quality fingerprint images such as the incomplete or partial fingerprint image as well as to the rotation sensitivity of the low-quality fingerprint images.
2. Using another matching approach instead of based on the distance measurement such as learning approach like intelligent techniques which may apply during matching phase like Neural Networks (NN) or another algorithm.
3. An electronic device could be plugged to monitor system for real-time fingerprint acquisition and authentication or identification which will cause another issue for the fingerprint scanning image such as fingerprint image corruption that must be solved.
4. Using different types of database that have other challenges and compare between the localization based minutia feature extraction approach

fingerprint and our Global Map Feature Indication and Extraction (GMFI) approach to conclude another advantages and disadvantages though them.

5. Collect a special dataset which is a color fingerprint images and try to solve some problems that the color fingerprint images have by applying our Global Map Feature Indication based localization fingerprint identification and summarize our approach acting on that special edition of the fingerprint images (color fingerprint image identification approach).

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APPENDIX

Appendix-A:

In table A.1, we can notice that each column represents the fingerprint image. for each fingerprint image, we have found there is 12 different sample for each fingerprint image and each row represent different results the final matching accuracy the time consuming for each finger that has been tested that has been calculate using a MATLAB function "tic-toc" starting from the final stage of the preprocessing image, feature extraction, false features removing till the final stage of the matching calculation.

Table A.1: Localization Based Feature Extraction Approach Performance Result (Identification Accuracy and Time Consuming) using FCV2006 Dataset.

Fingerprint No.	Tested images from FCV 2006											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1_1- Accuracy	1	0.5063	0.4462	0.4261	0.3512	0.4544	0.4825	0.3791	0.3718	0.378	0.4357	0.4048
Time	625.3977	1.27E+03	380.3559	704.8512	1.15E+03	1.30E+03	1.56E+03	1.72E+03	1.89E+03	2.10E+03	2.29E+03	2.43E+03
7_1- Accuracy	1	0.5659	0.2948	0.5516	0.5977	0.5337	0.4763	0.5305	0.4577	0.4483	0.3449	0.4387
Time	198.4294	65.8937	308.7257	372.8286	462.6065	523.4125	588.2893	664.1344	731.0155	794.9503	872.4416	944.1432
8_1- Accuracy	1	0.3485	0.5497	0.4818	0.3532	0.3767	0.4719	0.3304	0.4856	0.4012	0.5149	0.4561
Time	73.2855	153.909	254.95	305.2913	361.1734	737.5365	785.0334	824.2709	859.1795	898.5833	933.9373	968.8024
9_1- Accuracy	1	0.3213	0.3613	0.3243	0.4958	0.3094	0.3461	0.411	0.3926	0.3271	0.4171	0.3157
Time	86.1686	142.4503	236.1467	289.756	436.0767	6.82E+04	6.83E+04	6.84E+04	6.85E+04	6.86E+04	6.87E+04	6.88E+04
14_1- Accuracy	1	0.3903	0.4706	0.4438	0.4904	0.3568	0.4351	0.3546	0.3551	0.3631	0.5063	0.3521
Time	317.1371	1.13E+03	1.51E+03	1.97E+03	2.33E+03	2.45E+03	2.70E+03	2.82E+03	3.03E+03	3.17E+03	3.31E+03	3.44E+03
20_1- Accuracy	1	0.4076	0.7435	0.5583	0.6155	0.489	0.5294	0.5847	0.4701	0.4654	0.5483	0.3814
Time	149.4655	228.3492	286.7853	368.7981	447.1531	512.5977	564.4125	647.1917	703.7585	783.1898	833.4576	939.4057
25_1- Accuracy	1	0.4549	0.6102	0.4315	0.6753	0.5215	0.4613	0.5042	0.5305	0.4529	0.5775	0.4348
Time	49.037	134.4133	213.3314	162.3982	523.8742	585.9663	650.3534	698.1655	757.8059	824.3904	881.9028	938.3959
32_1- Accuracy	1	0.6929	0.5909	0.6944	0.6312	0.6232	0.6903	0.5667	0.7314	0.6432	0.6614	0.5333
Time	44.2883	148.3338	228.4001	285.4622	341.2632	406.4891	477.5215	519.7182	574.2988	630.3202	712.9447	759.2279
35_1- Accuracy	1	0.4057	0.3741	0.366	0.5033	0.3878	0.4773	0.3421	0.4045	0.2916	0.4518	0.3939
Time	33.424	70.1547	114.9081	161.9323	201.1466	237.0536	284.3576	339.2889	389.5926	439.7275	478.1364	516.5673
41_1- Accuracy	1	0.551	0.6209	0.543	0.6339	0.491	0.593	0.4842	0.5264	0.4458	0.6668	0.5476
Time	30.513	68.6859	134.1299	176.078	211.5767	259.3974	292.5886	327.1324	363.4725	404.6947	446.4227	487.4477
44_1- Accuracy	1	0.5747	0.589	0.611	0.6181	0.7131	0.7064	0.5965	0.6649	0.5301	0.6079	0.6787
Time	38.8931	110.0455	190.0159	268.5857	172.4824	100.1777	42.6243	326.5567	370.3333	413.8914	465.3982	505.5111
45_1- Accuracy	1	0.3652	0.49	0.4741	0.3931	0.4364	0.3752	0.423	0.4413	0.4687	0.4531	0.3931
Time	54.5741	93.0292	147.267	190.1546	229.4932	271.6342	317.6559	354.3585	425.9221	468.5377	505.6243	544.4005
49_1- Accuracy	1	0.2548	0.1768	0.2462	0.252	0.1936	0.2021	0.2309	0.1725	0.2182	0.1944	0.2709
Time	32.9496	81.1093	151.7813	120.4757	192.6613	223.9693	267.8566	305.9618	345.1336	385.2906	420.3119	454.1459
51_1- Accuracy	1	0.3889	0.3475	0.4813	0.3716	0.6217	0.4514	0.4945	0.4456	0.438	0.438	0.3954
Time	60.5405	161.8237	344.5887	832.7331	910.8548	973.7084	1.03E+03	1.08E+03	1.13E+03	1.19E+03	1.27E+03	1.31E+03
53_1- Accuracy	1	0.5966	0.6611	0.6753	0.7082	0.7047	0.6254	0.6207	0.6132	0.632	0.5666	0.6207
Time	45.4473	95.1704	180.1677	227.2931	298.5989	350.9768	405.2602	551.5371	605.5165	644.8008	712.9236	748.9152
58_1- Accuracy	1	0.5098	0.4222	0.6212	0.6264	0.5026	0.576	0.449	0.6002	0.5207	0.5026	0.5704
Time	79.9803	185.3944	276.2838	347.2331	2.11E+03	2.18E+03	2.25E+03	2.33E+03	2.42E+03	2.49E+03	2.57E+03	2.63E+03
67_1- Accuracy	1	0.6405	0.8721	0.8406	0.8396	0.8285	0.8235	0.6132	0.9223	0.7849	0.8696	0.7866
Time	49.5492	116.9875	3.32E+03	3.37E+03	3.60E+03	3.69E+03	3.88E+03	5.92E+03	5.96E+03	6.00E+03	6.04E+03	6.07E+03

Table A.1 (Continued): Localization Based Feature Extraction Approach Performance Result (Identification Accuracy and Time Consuming) using FCV2006 Dataset.

Fingerprint No.	Tested images from FCV 2006											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
76_1- Accuracy	1	0.7675	0.8966	0.7548	0.8581	0.8741	0.798	0.651	0.7926	0.8664	0.7905	0.64
Time	36.4592	84.6616	124.4307	159.6236	195.8121	236.1291	279.9369	313.4003	353.7563	392.6621	431.6071	474.5107
87_1- Accuracy	1	0.3888	0.3081	0.2495	0.453	0.4603	0.4552	0.4874	0.3602	0.4134	0.6186	0.4696
Time	60.4992	108.0808	162.9314	208.8336	260.5744	297.7514	350.7218	424.7788	470.9243	511.6053	568.1978	615.9272
88_1- Accuracy	1	0.647	0.8193	0.7028	0.8847	0.7438	0.7226	0.6439	0.729	0.6536	0.7581	0.6016
Time	50.7313	140.5204	182.7461	233.8758	269.6998	352.101	391.0042	430.4929	468.3557	524.9921	564.8924	644.0975
95_1- Accuracy	1	0.9058	0.9098	0.9163	0.9027	0.9027	0.85	0.8948	0.7902	0.9358	0.9383	0.9136
Time	51.6567	172.4501	244.0228	293.4256	35.0762	83.7191	126.7945	160.2898	225.8639	322.5152	356.3602	391.8813
97_1- Accuracy	1	0.5008	0.5801	0.5384	0.6667	0.6833	0.51	0.6868	0.6736	0.5963	0.6339	0.598
Time	35.4673	79.5597	131.9417	167.3598	207.9659	254.3456	320.1944	359.5696	407.9308	448.2158	500.5573	549.0912
99_1- Accuracy	1	0.6971	0.7817	0.5766	0.6536	0.7765	0.7407	0.6118	0.5561	0.6603	0.7341	0.7817
Time	28.6486	74.1524	110.3392	146.4531	219.8858	255.2044	318.1901	726.9125	1.72E+03	1.75E+03	1.79E+03	1.82E+03
100_1- Accuracy	1	0.8102	0.8549	0.7506	0.8393	0.6938	0.768	0.7452	0.8369	0.7256	0.84	0.6993
Time	46.8617	86.125	3.52E+03	3.57E+03	3.61E+03	3.67E+01	9.04E+01	144.3564	287.4589	327.5148	425.9718	488.3501
105_1- Accuracy	1	0.4895	0.6183	0.4587	0.5421	0.4683	0.6533	0.6294	0.5336	0.665	0.5367	0.5505
Time	36.2076	83.7004	119.425	185.0357	238.0145	292.1956	338.4829	382.6819	478.1571	524.6032	565.2332	611.1438
117- Accuracy	1	0.9214	0.9072	0.8343	0.807	0.739	0.7337	0.777	0.9418	0.8154	0.7239	0.8315
Time	53.2664	107.2927	144.7912	193.1801	265.9001	301.4709	373.7139	410.5057	451.3263	504.4192	538.4533	578.3649
126- Accuracy	1	0.5963	0.7478	0.5729	0.6782	0.4865	0.6728	0.7176	0.6149	0.796	0.5948	0.5601
Time	38.1257	84.1997	136.3943	174.4576	213.1031	250.6377	479.5425	596.3753	632.2526	670.3046	724.764	770.9432
130- Accuracy	1	0.5982	0.754	0.6368	0.6774	0.5039	0.7376	0.6753	0.6857	0.7113	0.7069	0.7069
Time	48.33	105.7244	189.9386	150.7996	240.1527	56.2718	125.827	179.4299	228.8394	323.9397	368.6199	432.0019
133- Accuracy	1	0.7934	0.8433	0.6669	0.7851	0.7967	0.793	0.6481	0.7438	0.6615	0.8033	0.705
Time	41.1185	92.635	142.7233	216.1707	253.3437	295.9338	353.8318	400.7903	448.67	504.3243	544.6217	703.9172
136- Accuracy	1	0.5544	0.6436	0.6963	0.7425	0.6845	0.7585	0.6072	0.6338	0.6747	0.5509	0.6826
Time	57.9315	140.2121	216.9536	331.4389	415.2766	497.1483	578.6797	645.3651	699.7053	756.6488	816.8392	895.1569

The average mean of the performance result for the fingerprint identification system for low-quality fingerprint image using localization based feature extraction approach is shown in table A.2

Table A.2: Localization Based Feature Extraction Approach Performance Result (Identification Accuracy) using FCV2006 Dataset.

Fingerprint No.	Tested images from FCV 2006											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1_1-Accuracy	1	0.5063	0.4462	0.4261	0.3512	0.4544	0.4825	0.3791	0.3718	0.378	0.4357	0.4048
7_1-Accuracy	1	0.5659	0.2948	0.5516	0.5977	0.5337	0.4763	0.5305	0.4577	0.4483	0.3449	0.4387
8_1-Accuracy	1	0.3485	0.5497	0.4818	0.3532	0.3767	0.4719	0.3304	0.4856	0.4012	0.5149	0.4561
9_1-Accuracy	1	0.3213	0.3613	0.3243	0.4958	0.3094	0.3461	0.411	0.3926	0.3271	0.4171	0.3157
14_1-Accuracy	1	0.3903	0.4706	0.4438	0.4904	0.3568	0.4351	0.3546	0.3551	0.3631	0.5063	0.3521
20_1-Accuracy	1	0.4076	0.7435	0.5583	0.6155	0.489	0.5294	0.5847	0.4701	0.4654	0.5483	0.3814
25_1-Accuracy	1	0.4549	0.6102	0.4315	0.6753	0.5215	0.4613	0.5042	0.5305	0.4529	0.5775	0.4348
32_1-Accuracy	1	0.6929	0.5909	0.6944	0.6312	0.6232	0.6903	0.5667	0.7314	0.6432	0.6614	0.5333
35_1-Accuracy	1	0.4057	0.3741	0.366	0.5033	0.3878	0.4773	0.3421	0.4045	0.2916	0.4518	0.3939
41_1-Accuracy	1	0.551	0.6209	0.543	0.6339	0.491	0.593	0.4842	0.5264	0.4458	0.6668	0.5476

Table A.2 (Continued): Localization Based Feature Extraction Approach Performance Result (Identification Accuracy) using FCV2006 Dataset.

44_1-Accuracy	1	0.5747	0.589	0.611	0.6181	0.7131	0.7064	0.5965	0.6649	0.5301	0.6079	0.6787
45_1-Accuracy	1	0.3652	0.49	0.4741	0.3931	0.4364	0.3752	0.423	0.4413	0.4687	0.4531	0.3931
49_1-Accuracy	1	0.2548	0.1768	0.2462	0.252	0.1936	0.2021	0.2309	0.1725	0.2182	0.1944	0.2709
51_1-Accuracy	1	0.3889	0.3475	0.4813	0.3716	0.6217	0.4514	0.4945	0.4456	0.438	0.438	0.3954
53_1-Accuracy	1	0.5966	0.6611	0.6753	0.7082	0.7047	0.6254	0.6207	0.6132	0.632	0.5666	0.6207
58_1-Accuracy	1	0.5098	0.4222	0.6212	0.6264	0.5026	0.576	0.449	0.6002	0.5207	0.5026	0.5704
67_1-Accuracy	1	0.6405	0.8721	0.8406	0.8396	0.8285	0.8235	0.6132	0.9223	0.7849	0.8696	0.7866
76_1-Accuracy	1	0.7675	0.8966	0.7548	0.8581	0.8741	0.798	0.651	0.7926	0.8664	0.7905	0.64
87_1-Accuracy	1	0.3888	0.3081	0.2495	0.453	0.4603	0.4552	0.4874	0.3602	0.4134	0.6186	0.4696
88_1-Accuracy	1	0.647	0.8193	0.7028	0.8847	0.7438	0.7226	0.6439	0.729	0.6536	0.7581	0.6016
95_1-Accuracy	1	0.9058	0.9098	0.9163	0.9027	0.9027	0.85	0.8948	0.7902	0.9358	0.9383	0.9136
97_1-Accuracy	1	0.5008	0.5801	0.5384	0.6667	0.6833	0.51	0.6868	0.6736	0.5963	0.6339	0.598
99_1-Accuracy	1	0.6971	0.7817	0.5766	0.6536	0.7765	0.7407	0.6118	0.5561	0.6603	0.7341	0.7817

Table A.2 (Continued): Localization Based Feature Extraction Approach Performance Result (Identification Accuracy) using FCV2006 Dataset.

100_1-Accuracy	1	0.8102	0.8549	0.7506	0.8393	0.6938	0.768	0.7452	0.8369	0.7256	0.84	0.6993
105_1-Accuracy	1	0.4895	0.6183	0.4587	0.5421	0.4683	0.6533	0.6294	0.5336	0.665	0.5367	0.5505
117-Accuracy	1	0.9214	0.9072	0.8343	0.807	0.739	0.7337	0.777	0.9418	0.8154	0.7239	0.8315
126-Accuracy	1	0.5963	0.7478	0.5729	0.6782	0.4865	0.6728	0.7176	0.6149	0.796	0.5948	0.5601
130-Accuracy	1	0.5982	0.754	0.6368	0.6774	0.5039	0.7376	0.6753	0.6857	0.7113	0.7069	0.7069
133-Accuracy	1	0.7934	0.8433	0.6669	0.7851	0.7967	0.793	0.6481	0.7438	0.6615	0.8033	0.705
136-Accuracy	1	0.5544	0.6436	0.6963	0.7425	0.6845	0.7585	0.6072	0.6338	0.6747	0.5509	0.6826

Table A.3: Localization Based Feature Extraction Approach Performance Result (Time Consuming) using FCV2006 Dataset.

Fingerprint No.	Tested images from FCV 2006											
	1	2	3	4	5	6	7	8	9	10	11	12
Time	625.3977	1.27E+03	380.3559	704.8512	1.15E+03	1.30E+03	1.56E+03	1.72E+03	1.89E+03	2.10E+03	2.29E+03	2.43E+03
Time	198.4294	65.8937	308.7257	372.8286	462.6065	523.4125	588.2893	664.1344	731.0155	794.9503	872.4416	944.1432
Time	73.2855	153.909	254.95	305.2913	361.1734	737.5365	785.0334	824.2709	859.1795	898.5833	933.9373	968.8024
Time	86.1686	142.4503	236.1467	289.756	436.0767	6.82E+04	6.83E+04	6.84E+04	6.85E+04	6.86E+04	6.87E+04	6.88E+04
Time	317.1371	1.13E+03	1.51E+03	1.97E+03	2.33E+03	2.45E+03	2.70E+03	2.82E+03	3.03E+03	3.17E+03	3.31E+03	3.44E+03
Time	149.4655	228.3492	286.7853	368.7981	447.1531	512.5977	564.4125	647.1917	703.7585	783.1898	833.4576	939.4057
Time	49.037	134.4133	213.3314	162.3982	523.8742	585.9663	650.3534	698.1655	757.8059	824.3904	881.9028	938.3959
Time	44.2883	148.3338	228.4001	285.4622	341.2632	406.4891	477.5215	519.7182	574.2988	630.3202	712.9447	759.2279
Time	33.424	70.1547	114.9081	161.9323	201.1466	237.0536	284.3576	339.2889	389.5926	439.7275	478.1364	516.5673
Time	30.513	68.6859	134.1299	176.078	211.5767	259.3974	292.5886	327.1324	363.4725	404.6947	446.4227	487.4477
Time	38.8931	110.0455	190.0159	268.5857	172.4824	100.1777	42.6243	326.5567	370.3333	413.8914	465.3982	505.5111
Time	54.5741	93.0292	147.267	190.1546	229.4932	271.6342	317.6559	354.3585	425.9221	468.5377	505.6243	544.4005
Time	32.9496	81.1093	151.7813	120.4757	192.6613	223.9693	267.8566	305.9618	345.1336	385.2906	420.3119	454.1459
Time	60.5405	161.8237	344.5887	832.7331	910.8548	973.7084	1.03E+03	1.08E+03	1.13E+03	1.19E+03	1.27E+03	1.31E+03
Time	45.4473	95.1704	180.1677	227.2931	298.5989	350.9768	405.2602	551.5371	605.5165	644.8008	712.9236	748.9152
Time	79.9803	185.3944	276.2838	347.2331	2.11E+03	2.18E+03	2.25E+03	2.33E+03	2.42E+03	2.49E+03	2.57E+03	2.63E+03
Time	49.5492	116.9875	3.32E+03	3.37E+03	3.60E+03	3.69E+03	3.88E+03	5.92E+03	5.96E+03	6.00E+03	6.04E+03	6.07E+03

Table A.3 (Continued): Localization Based Feature Extraction Approach Performance Result (Time Consuming) using FCV2006 Dataset.

Fingerprint No.	Tested images from FCV 2006											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Time	36.4592	84.6616	124.4307	159.6236	195.8121	236.1291	279.9369	313.4003	353.7563	392.6621	431.6071	474.5107
Time	60.4992	108.0808	162.9314	208.8336	260.5744	297.7514	350.7218	424.7788	470.9243	511.6053	568.1978	615.9272
Time	50.7313	140.5204	182.7461	233.8758	269.6998	352.101	391.0042	430.4929	468.3557	524.9921	564.8924	644.0975
Time	51.6567	172.4501	244.0228	293.4256	35.0762	83.7191	126.7945	160.2898	225.8639	322.5152	356.3602	391.8813
Time	35.4673	79.5597	131.9417	167.3598	207.9659	254.3456	320.1944	359.5696	407.9308	448.2158	500.5573	549.0912
Time	28.6486	74.1524	110.3392	146.4531	219.8858	255.2044	318.1901	726.9125	1.72E+03	1.75E+03	1.79E+03	1.82E+03
Time	46.8617	86.125	3.52E+03	3.57E+03	3.61E+03	3.67E+01	9.04E+01	144.3564	287.4589	327.5148	425.9718	488.3501
Time	36.2076	83.7004	119.425	185.0357	238.0145	292.1956	338.4829	382.6819	478.1571	524.6032	565.2332	611.1438
Time	53.2664	107.2927	144.7912	193.1801	265.9001	301.4709	373.7139	410.5057	451.3263	504.4192	538.4533	578.3649
Time	38.1257	84.1997	136.3943	174.4576	213.1031	250.6377	479.5425	596.3753	632.2526	670.3046	724.764	770.9432
Time	48.33	105.7244	189.9386	150.7996	240.1527	56.2718	125.827	179.4299	228.8394	323.9397	368.6199	432.0019
Time	41.1185	92.635	142.7233	216.1707	253.3437	295.9338	353.8318	400.7903	448.67	504.3243	544.6217	703.9172
Time	57.9315	140.2121	216.9536	331.4389	415.2766	497.1483	578.6797	645.3651	699.7053	756.6488	816.8392	895.1569

In this table A.4, we can notice that each column represents the fingerprint image. for each fingerprint image, we have found there is 12 different sample for each fingerprint image and each row represent different results the final matching accuracy the time consuming for each finger that has been tested that has been calculate using a MATLAB function “tic-toc” starting from the final stage of the preprocessing image, feature extraction, false features removing till the final stage of the matching calculation.

Table A.4: Localization Based GMFI Feature Extraction Approach Performance Result (Identification Accuracy and Time Consuming) using FCV2006 Dataset.

Fingerprint No.	**Tested images from FCV 2006**											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1_1-Accuracy	1	0.8906	0.8705	0.7956	0.8988	0.9269	0.8235	0.8162	0.8224	0.8801	0.8492	1
Time	10.4233	21.16667	6.339265	11.74752	19.16667	21.66667	26	28.66667	31.5	35	38.16667	40.5
7_1-Accuracy	1	0.7392	0.996	1	0.9781	0.9207	0.9749	0.9021	0.8927	0.7893	0.8831	1
Time	3.307157	1.098228	5.145428	6.21381	7.710108	8.723542	9.804822	11.06891	12.18359	13.24917	14.54069	15.73572
8_1-Accuracy	0.7929	0.9941	0.9262	0.7976	0.8211	0.9163	0.7748	0.93	0.8456	0.9593	0.9005	0.7929
Time	1.221425	2.56515	4.249167	5.088188	6.019557	12.29228	13.08389	13.73785	14.31966	14.97639	15.56562	16.14671
9_1-Accuracy	0.7657	0.8057	0.7687	0.9402	0.7538	0.7905	0.8554	0.837	0.7715	0.8615	0.7601	0.7657
Time	1.436143	2.374172	3.935778	4.829267	7.267945	1136.667	1138.333	1140	1141.667	1143.333	1145	1146.667

Table A.4 (Continued): Localization Based GMFI Feature Extraction Approach Performance Result (Identification Accuracy and Time Consuming) using FCV2006 Dataset.

Fingerprint No.	Tested images from FCV 2006											
	1	2	3	4	5	6	7	8	9	10	11	12
14_1-Accuracy	0.8347	0.915	0.8882	0.9348	0.8012	0.8795	0.799	0.7995	0.8075	0.9507	0.7965	0.8347
Time	5.285618	18.83333	25.16667	32.83333	38.83333	40.83333	45	47	50.5	52.83333	55.16667	57.33333
20_1-Accuracy	0.852	1	1	1	0.9334	0.9738	1	0.9145	0.9098	0.9927	0.8258	0.852
Time	2.491092	3.80582	4.779755	6.146635	7.452552	8.543295	9.406875	10.78653	11.72931	13.05316	13.89096	15.65676
25_1-Accuracy	0.8993	1.0546	0.8759	1	0.9659	0.9057	0.9486	0.9749	0.8973	1	0.8792	0.8993
Time	0.817283	2.240222	3.555523	2.706637	8.731237	9.766105	10.83922	11.63609	12.6301	13.73984	14.69838	15.63993
32_1-Accuracy	0.9373	0.8353	0.9388	0.8756	0.8676	0.9347	0.8111	0.9758	0.8876	0.9058	0.7777	0.9373
Time	0.738138	2.47223	3.806668	4.757703	5.68772	6.774818	7.958692	8.66197	9.571647	10.50534	11.88241	12.6538
35_1-Accuracy	0.8501	0.8185	0.8104	0.9477	0.8322	0.9217	0.7865	0.8489	0.736	0.8962	0.8383	0.8501
Time	0.557067	1.169245	1.915135	2.698872	3.352443	3.950893	4.739293	5.654815	6.49321	7.328792	7.96894	8.609455
41_1-Accuracy	0.9954	1	0.9874	1	0.9354	1	0.9286	0.9708	0.8902	1	0.992	0.9954
Time	0.50855	1.144765	2.235498	2.934633	3.526278	4.32329	4.876477	5.452207	6.057875	6.744912	7.440378	8.124128

Table A.4 (Continued): Localization Based GMFI Feature Extraction Approach Performance Result (Identification Accuracy and Time Consuming) using FCV2006 Dataset.

Fingerprint No.	Tested images from FCV 2006											
	1	2	3	4	5	6	7	8	9	10	11	12
44_1-Accuracy	0.9191	0.9334	0.9554	0.9625	1	1	0.9409	1	0.8745	0.9523	1	0.9191
Time	0.648218	1.834092	3.166932	4.476428	2.874707	1.669628	0.710405	5.442612	6.172222	6.89819	7.756637	8.425185
45_1-Accuracy	0.8096	0.9344	0.9185	0.8375	0.8808	0.8196	0.8674	0.8857	0.9131	0.8975	0.8375	0.8096
Time	0.909568	1.550487	2.45445	3.169243	3.824887	4.527237	5.294265	5.905975	7.098702	7.808962	8.427072	9.073342
49_1-Accuracy	0.6992	0.6212	0.6906	0.6964	0.638	0.6465	0.6753	0.6169	0.6626	0.6388	0.7153	0.6992
Time	0.54916	1.351822	2.529688	2.007928	3.211022	3.732822	4.464277	5.099363	5.752227	6.42151	7.005198	7.569098
51_1-Accuracy	0.8333	0.7919	0.9257	0.816	1	0.8958	0.9389	0.89	0.8824	0.8824	0.8398	0.8333
Time	1.009008	2.697062	5.743145	13.87889	15.18091	16.22847	17.16667	18	18.83333	19.83333	21.16667	21.83333
53_1-Accuracy	1.041	1.1055	1.1197	1.1526	1.1491	1.0698	1.0651	1.0576	1.0764	1.011	1.0651	1.041
Time	0.757455	1.586173	3.002795	3.788218	4.976648	5.849613	6.754337	9.192285	10.09194	10.74668	11.88206	12.48192
58_1-Accuracy	0.9542	0.8666	1	1	0.947	1	0.8934	1	0.9651	0.947	1	0.9542
Time	1.333005	3.089907	4.60473	5.787218	35.16667	36.33333	37.5	38.83333	40.33333	41.5	42.83333	43.83333
67_1-Accuracy	0.8849	0.8923	0.9932	0.9001	0.91276	0.9201	0.9542	0.9194	0.9433	0.91115	0.9629	0.8849
Time	0.82582	1.949792	55.33333	56.16667	60	61.5	64.66667	98.66667	99.33333	100	100.6667	101.1667

Table A.4 (Continued): Localization Based GMFI Feature Extraction Approach Performance Result (Identification Accuracy and Time Consuming) using FCV2006 Dataset.

Fingerprint No.	Tested images from FCV 2006											
	1	2	3	4	5	6	7	8	9	10	11	12
76_1-Accuracy	0.9119	1.041	0.8992	1	1	0.9424	0.7954	0.937	1	0.9349	0.7844	0.9119
Time	0.607653	1.411027	2.073845	2.660393	3.263535	3.935485	4.665615	5.223338	5.895938	6.544368	7.193452	7.908512
87_1-Accuracy	0.8332	0.7525	0.6939	0.8974	0.9047	0.8996	0.9318	0.8046	0.8578	1	0.914	0.8332
Time	1.00832	1.801347	2.715523	3.48056	4.342907	4.962523	5.845363	7.079647	7.848738	8.526755	9.469963	10.26545
88_1-Accuracy	0.9914	1	1	1	1	1	0.9883	1	0.998	1	0.946	0.9914
Time	0.845522	2.342007	3.045768	3.89793	4.494997	5.86835	6.516737	7.174882	7.805928	8.749868	9.414873	10.73496
95_1-Accuracy	0.9502	0.9542	0.9607	0.9471	0.9471	0.8944	0.9392	0.8346	0.9802	0.9827	0.958	0.9502
Time	0.860945	2.874168	4.067047	4.890427	0.584603	1.395318	2.113242	2.671497	3.764398	5.375253	5.939337	6.531355
97_1-Accuracy	0.8452	0.9245	0.8828	1	1	0.8544	1	1	0.9407	0.9783	0.9424	0.8452
Time	0.591122	1.325995	2.199028	2.78933	3.466098	4.239093	5.336573	5.992827	6.798847	7.470263	8.342622	9.15152
99_1-Accuracy	0.9415	1	0.821	0.898	1	0.9851	0.8562	0.8005	0.9047	0.9785	1	0.9415
Time	0.477477	1.235873	1.838987	2.440885	3.664763	4.253407	5.303168	12.11521	28.66667	29.16667	29.83333	30.33333

Table A.4 (Continued): Localization Based GMFI Feature Extraction Approach Performance Result (Identification Accuracy and Time Consuming) using FCV2006 Dataset.

Fingerprint No.	Tested images from FCV 2006											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
100_1-Accuracy	0.9546	0.9993	0.895	0.9837	0.8382	0.9124	0.8896	0.9813	0.87	0.9844	0.8437	0.9546
Time	0.781028	1.435417	58.66667	59.5	60.16667	0.611667	1.506667	2.40594	4.790982	5.45858	7.09953	8.139168
105_1-Accuracy	0.9339	1	0.9031	0.9865	0.9127	1	1	0.978	1	0.9811	0.9949	0.9339
Time	0.60346	1.395007	1.990417	3.083928	3.966908	4.869927	5.641382	6.378032	7.969285	8.743387	9.420553	10.18573
117-Accuracy	1	1	1	1	0.9834	0.9781	1	1	1	0.9683	1	1
Time	0.887773	1.788212	2.413187	3.219668	4.431668	5.024515	6.228565	6.841762	7.522105	8.406987	8.974222	9.639415
126-Accuracy	0.8407	0.9922	0.8173	0.9226	0.7309	0.9172	0.962	0.8593	1	0.8392	0.8045	0.8407
Time	0.635428	1.403328	2.273238	2.907627	3.551718	4.177295	7.992375	9.939588	10.53754	11.17174	12.0794	12.84905
130-Accuracy	0.9426	0.9984	0.8812	0.9218	0.7483	0.982	0.9197	0.9301	0.9557	0.9513	0.9513	0.9426
Time	0.8055	1.762073	3.165643	2.513327	4.002545	0.937863	2.097117	2.990498	3.81399	5.398995	6.143665	7.200032
133-Accuracy	1	1	0.9113	1	1	1	0.8925	0.9882	0.9059	1	0.9494	1
Time	0.685308	1.543917	2.378722	3.602845	4.222395	4.93223	5.897197	6.679838	7.477833	8.405405	9.077028	11.73195
136-Accuracy	0.8988	0.988	1	1	1	1	0.9516	0.9782	1	0.8953	1	0.8988
Time	0.965525	2.336868	3.615893	5.523982	6.921277	8.285805	9.644662	10.75609	11.66176	12.61081	13.61399	14.91928

The average mean of our proposed system performance result for the fingerprint identification system of low-quality fingerprint image using localization based Global Map Feature Indication and extraction (GMFI) is shown below in Table A.5.

Table A.5: Localization Based Feature Extraction Approach Performance Result (Identification Accuracy) using FCV2006 Dataset.

Fingerprint No.	**Tested images from FCV 2006**											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1_1-Accuracy	1	0.8906	0.8705	0.7956	0.8988	0.9269	0.8235	0.8162	0.8224	0.8801	0.8492	1
7_1-Accuracy	1	0.7392	0.996	1	0.9781	0.9207	0.9749	0.9021	0.8927	0.7893	0.8831	1
8_1-Accuracy	1	0.9941	0.9262	0.7976	0.8211	0.9163	0.7748	0.93	0.8456	0.9593	0.9005	0.7929
9_1-Accuracy	1	0.8057	0.7687	0.9402	0.7538	0.7905	0.8554	0.837	0.7715	0.8615	0.7601	0.7657
14_1-Accuracy	1	0.915	0.8882	0.9348	0.8012	0.8795	0.799	0.7995	0.8075	0.9507	0.7965	0.8347
20_1-Accuracy	1	1	1	1	0.9334	0.9738	1	0.9145	0.9098	0.9927	0.8258	0.852
25_1-Accuracy	1	1.0546	0.8759	1	0.9659	0.9057	0.9486	0.9749	0.8973	1	0.8792	0.8993
32_1-Accuracy	1	0.8353	0.9388	0.8756	0.8676	0.9347	0.8111	0.9758	0.8876	0.9058	0.7777	0.9373
35_1-Accuracy	1	0.8185	0.8104	0.9477	0.8322	0.9217	0.7865	0.8489	0.736	0.8962	0.8383	0.8501

Table A.5 (Continued): Localization Based Feature Extraction Approach Performance Result (Identification Accuracy) using FCV2006 Dataset.

Fingerprint No.	Tested images from FCV 2006										
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
41_1-Accuracy	1	1	0.9874	1	0.9354	1	0.9286	0.9708	0.8902	1	0.992	0.9954
44_1-Accuracy	1	0.9334	0.9554	0.9625	1	1	0.9409	1	0.8745	0.9523	1	0.9191
45_1-Accuracy	1	0.9344	0.9185	0.8375	0.8808	0.8196	0.8674	0.8857	0.9131	0.8975	0.8375	0.8096
49_1-Accuracy	1	0.6212	0.6906	0.6964	0.638	0.6465	0.6753	0.6169	0.6626	0.6388	0.7153	0.6992
51_1-Accuracy	1	0.7919	0.9257	0.816	1	0.8958	0.9389	0.89	0.8824	0.8824	0.8398	0.8333
53_1-Accuracy	1	1.1055	1.1197	1.1526	1.1491	1.0698	1.0651	1.0576	1.0764	1.011	1.0651	1.041
58_1-Accuracy	1	0.8666	1	1	0.947	1	0.8934	1	0.9651	0.947	1	0.9542
67_1-Accuracy	1	0.8923	0.9932	0.9001	0.91276	0.9201	0.9542	0.9194	0.9433	0.91115	0.9629	0.8849
76_1-Accuracy	1	1.041	0.8992	1	1	0.9424	0.7954	0.937	1	0.9349	0.7844	0.9119
87_1-Accuracy	1	0.7525	0.6939	0.8974	0.9047	0.8996	0.9318	0.8046	0.8578	1	0.914	0.8332
88_1-Accuracy	1	1	1	1	1	1	0.9883	1	0.998	1	0.946	0.9914

Table A.5 (Continued): Localization Based Feature Extraction Approach Performance Result (Identification Accuracy) using FCV2006 Dataset.

Fingerprint No.	Tested images from FCV 2006											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
95_1-Accuracy	1	0.9542	0.9607	0.9471	0.9471	0.8944	0.9392	0.8346	0.9802	0.9827	0.958	0.9502
97_1-Accuracy	1	0.9245	0.8828	1	1	0.8544	1	1	0.9407	0.9783	0.9424	0.8452
99_1-Accuracy	1	1	0.821	0.898	1	0.9851	0.8562	0.8005	0.9047	0.9785	1	0.9415
100_1-Accuracy	1	0.9993	0.895	0.9837	0.8382	0.9124	0.8896	0.9813	0.87	0.9844	0.8437	0.9546
105_1-Accuracy	1	1	0.9031	0.9865	0.9127	1	1	0.978	1	0.9811	0.9949	0.9339
117-Accuracy	1	1	1	1	0.9834	0.9781	1	1	1	0.9683	1	1
126-Accuracy	1	0.9922	0.8173	0.9226	0.7309	0.9172	0.962	0.8593	1	0.8392	0.8045	0.8407
130-Accuracy	1	0.9984	0.8812	0.9218	0.7483	0.982	0.9197	0.9301	0.9557	0.9513	0.9513	0.9426
133-Accuracy	1	1	0.9113	1	1	1	0.8925	0.9882	0.9059	1	0.9494	1
136-Accuracy	1	0.988	1	1	1	1	0.9516	0.9782	1	0.8953	1	0.8988

Table A.6: Localization Based GMFI and Feature Extraction Approach Performance Result (Time Consuming) using FCV2006 Dataset.

Fingerprint No.	Tested images from FCV 2006											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Time	10.4233	21.16667	6.339265	11.74752	19.16667	21.66667	26	28.66667	31.5	35	38.16667	40.5
Time	3.307157	1.098228	5.145428	6.21381	7.710108	8.723542	9.804822	11.06891	12.18359	13.24917	14.54069	15.73572
Time	1.221425	2.56515	4.249167	5.088188	6.019557	12.29228	13.08389	13.73785	14.31966	14.97639	15.56562	16.14671
Time	1.436143	2.374172	3.935778	4.829267	7.267945	1136.667	1138.333	1140	1141.667	1143.333	1145	1146.667
Time	5.285618	18.83333	25.16667	32.83333	38.83333	40.83333	45	47	50.5	52.83333	55.16667	57.33333
Time	2.491092	3.80582	4.779755	6.146635	7.452552	8.543295	9.406875	10.78653	11.72931	13.05316	13.89096	15.65676
Time	0.817283	2.240222	3.555523	2.706637	8.731237	9.766105	10.83922	11.63609	12.6301	13.73984	14.69838	15.63993
Time	0.738138	2.47223	3.806668	4.757703	5.68772	6.774818	7.958692	8.66197	9.571647	10.50534	11.88241	12.6538
Time	0.557067	1.169245	1.915135	2.698872	3.352443	3.950893	4.739293	5.654815	6.49321	7.328792	7.96894	8.609455
Time	0.50855	1.144765	2.235498	2.934633	3.526278	4.32329	4.876477	5.452207	6.057875	6.744912	7.440378	8.124128
Time	0.648218	1.834092	3.166932	4.476428	2.874707	1.669628	0.710405	5.442612	6.172222	6.89819	7.756637	8.425185
Time	0.909568	1.550487	2.45445	3.169243	3.824887	4.527237	5.294265	5.905975	7.098702	7.808962	8.427072	9.073342
Time	0.54916	1.351822	2.529688	2.007928	3.211022	3.732822	4.464277	5.099363	5.752227	6.42151	7.005198	7.569098
Time	1.009008	2.697062	5.743145	13.87889	15.18091	16.22847	17.16667	18	18.83333	19.83333	21.16667	21.83333
Time	0.757455	1.586173	3.002795	3.788218	4.976648	5.849613	6.754337	9.192285	10.09194	10.74668	11.88206	12.48192

Table A.6 (Continued): Localization Based GMFI and Feature Extraction Approach Performance Result (Time Consuming) using FCV2006 Dataset.

Fingerprint No.	Tested images from FCV 2006											
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Time	1.333005	3.089907	4.60473	5.787218	35.16667	36.33333	37.5	38.83333	40.33333	41.5	42.83333	43.83333
Time	0.82582	1.949792	55.33333	56.16667	60	61.5	64.66667	98.66667	99.33333	100	100.6667	101.1667
Time	0.607653	1.411027	2.073845	2.660393	3.263535	3.935485	4.665615	5.223338	5.895938	6.544368	7.193452	7.908512
Time	1.00832	1.801347	2.715523	3.48056	4.342907	4.962523	5.845363	7.079647	7.848738	8.526755	9.469963	10.26545
Time	0.845522	2.342007	3.045768	3.89793	4.494997	5.86835	6.516737	7.174882	7.805928	8.749868	9.414873	10.73496
Time	0.860945	2.874168	4.067047	4.890427	0.584603	1.395318	2.113242	2.671497	3.764398	5.375253	5.939337	6.531355
Time	0.591122	1.325995	2.199028	2.78933	3.466098	4.239093	5.336573	5.992827	6.798847	7.470263	8.342622	9.15152
Time	0.477477	1.235873	1.838987	2.440885	3.664763	4.253407	5.303168	12.11521	28.66667	29.16667	29.83333	30.33333
Time	0.781028	1.435417	58.66667	59.5	60.16667	0.611667	1.506667	2.40594	4.790982	5.45858	7.09953	8.139168
Time	0.60346	1.395007	1.990417	3.083928	3.966908	4.869927	5.641382	6.378032	7.969285	8.743387	9.420553	10.18573
Time	0.887773	1.788212	2.413187	3.219668	4.431668	5.024515	6.228565	6.841762	7.522105	8.406987	8.974222	9.639415
Time	0.635428	1.403328	2.273238	2.907627	3.551718	4.177295	7.992375	9.939588	10.53754	11.17174	12.0794	12.84905
Time	0.8055	1.762073	3.165643	2.513327	4.002545	0.937863	2.097117	2.990498	3.81399	5.398995	6.143665	7.200032
Time	0.685308	1.543917	2.378722	3.602845	4.222395	4.93223	5.897197	6.679838	7.477833	8.405405	9.077028	11.73195
Time	0.965525	2.336868	3.615893	5.523982	6.921277	8.285805	9.644662	10.75609	11.66176	12.61081	13.61399	14.91928

CURRIULUM VITAE

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