Finger Knuckle Pattern Recognition Through The Fusion of Major and Minor Knuckles

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ABSTRACT

Fingerprints, palm veins, face recognition, DNA, palm print, hand geometry, iris recognition, retina, voice, gait, signature, and other physical or behavioral features have long been employed in biometric systems. The finger knuckle print is a new biometric feature that has piqued the interest of academics in recent years. Recently it was discovered that the skin's knuckle image pattern comprises of wrinkles or lines, and that the texture pattern created by the finger knuckle is very unique in each user, making the surface unique for biometric identification. The minor finger knuckle patterns can be utilized as standalone biometric patterns or in conjunction with the major finger knuckle patterns to increase performance. A vast number of research suggest that multibiometric fusion and multi-modality employed can greatly increase the biometric identification system's recognition rate, anti-attack, and resilience which might be incredibly useful in forensics applications and other related domains. In this study, a multimodal biometric system which combines minor and major finger knuckles is developed and experimented on PolyU-FKP finger knuckles datasets. Feature extraction techniques used include hand-crafted feature extraction descriptors, PCA and BSIF, CNN models, AlexNet and modified AlexNet.

The results obtained showed that major finger knuckle system fared better in both PCA and BSIF, accounting for the clearer patterns on the major finger knuckle, based on early testing results comparing it to the minor finger knuckle system. Additionally, the outcomes demonstrate that when the two traits are mixed at different phases, the system is noticeably improved, particularly in the case of PCA, where up to 15.1% improvement was achieved. The best accuracy overall obtained is a 100% in AlexNet model.

Keywords: Major finger knuckle, Minor finger knuckle, Fusion methods, Biometric, Recognition.

ÖZ

Parmak izleri, avuç içi damarları, yüz tanıma, DNA, avuç izi, el geometrisi, iris tanıma, retina, ses, yürüyüş, imza ve diğer fiziksel veya davranışsal özellikler uzun süredir biyometrik sistemlerde kullanılmaktadır. Parmak eklemi izi, son yıllarda akademisyenlerin ilgisini çeken yeni bir biyometrik özelliktir. Son zamanlarda, derinin boğum görüntü deseninin kırışıklıklardan veya çizgilerden oluştuğu ve parmak boğumunun oluşturduğu doku deseninin her kullanıcıda çok benzersiz olduğu ve yüzeyi biyometrik tanımlama için benzersiz kıldığı keşfedildi. Küçük parmak eklemi modelleri, performansı artırmak için bağımsız biyometrik modeller olarak veya ana parmak eklemi modelleriyle birlikte kullanılabilir. Çok sayıda araştırma, kullanılan multibiyometrik füzyon ve çoklu modalitenin, adli tıp uygulamalarında ve diğer ilgili alanlarda inanılmaz derecede yararlı olabilecek biyometrik tanımlama sisteminin tanıma oranını, saldırı önleme ve esnekliğini büyük ölçüde artırabileceğini göstermektedir. Bu çalışmada, minör ve majör parmak boğumlarını birleştiren multimodal bir biyometrik sistem geliştirilmiş ve PolyU-FKP parmak boğumları veri kümeleri üzerinde denenmiştir. Kullanılan özellik çıkarma teknikleri, el yapımı özellik çıkarma tanımlayıcıları, PCA ve BSIF, CNN modelleri, AlexNet ve değiştirilmiş AlexNet'i içerir.

Elde edilen sonuçlar, majör parmak eklemi sisteminin hem PCA hem de BSIF'de daha iyi sonuç verdiğini gösterdi; bu, onu küçük parmak eklemi sistemiyle karşılaştıran ön test verilerine göre, ana parmak eklemindeki daha net desenleri açıklıyor. Sonuçlar ayrıca, iki seviye ayrı aşamalarda birleştirildiğinde, özellikle PCA durumunda, %15,1'e varan iyileşmenin sağlandığı sistemde gözle görülür bir iyileşme olduğunu göstermektedir. Genel olarak elde edilen en iyi doğruluk, AlexNet modelinde %100'dür.

Anahtar Kelimeler: Büyük parmak eklemi, Küçük parmak eklemi, Füzyon yöntemleri, Biyometri, Tanıma.

DEDICATION

This work is dedicated to Haruna, Muhammadu Muhseen and Muhammad.

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LIST OF ABBREVIATIONS

AGAM	Angular Geometric Analysis Method
ANN	Artificial Neural Networks
BSIF	Binarized Statistical Image Features
CLTP	Completed Local Ternary Patterns
CNN	Convolutional Neural Network
DIP	Distal Phalangeal
DNA	Deoxyribonucleic acid
DLF	Decision Level Fusion
DRB	Deep Rule-Based
ECG	Electrocardiogram
EiFi	Eigen and Fisher
EEG	Electroencephalography
FLF	Feature Level Fusion
FT	Finger Texture
FBKS	Finger Back Surface
F-SIFT	Fourier - Scale Invariant Feature Transform
FKP	Finger Knuckle Print
FRB	Fuzzy Rule Base
FN	Fingernail
ICA	Independent Component Analysis
LBP	Local Binary Patterns
LDA	Linear Discriminant Analysis
MMBOA	Modified Magnetostatic Bacterial Optimization Approach

PIN	Personal Identification Number
PIP	Proximal Interphalangeal
PCA	Principal Component Analysis
ROI	Region of Interest
SLF	Score Level Fusion
2DLGF	2D Log Gabor Filter

Chapter 1

INTRODUCTION

Biometric features are increasingly being used in personal authentication systems due to their reliability in comparison to more conventional approaches such as token passwords and PIN numbers. Fingerprints, palm print, face recognition, DNA, palm veins, signature, hand geometry, voice, iris recognition, retina, gait and other behavioral or physical features have long been employed in biometric systems. Recent studies have demonstrated that the image pattern of wrinkles or lines on the skin, together with the texture pattern generated by the knuckles of each individual's fingers, makes the surface a useful instrument for biometric identification. The knuckle image has a random roughness that makes each person stand out. The restored knuckle image is noted to have exceptionally steady local and global properties. The data can then be utilized to verify the identity of specific users [1]. Biometric features-based personal identification is gaining popularity these days since it is more trustworthy than previous approaches and has a wide range of applications. Academics' interest in the finger knuckle print has increased in recent years. Finger knuckle prints are the inherent skin patterns that form at the knuckles of the back of the hand. According to recent study, the finger knuckle print is extremely rich in textures and may be utilized to uniquely identify a person. Hand-based biometrics have a better user acceptability, and this new characteristic has the added benefit of being less susceptible to harm. In published works, the researchers' acquisition procedures and strategies for finger knuckle-based recognition systems are detailed [2]. The fingerprint at the knuckles is a relatively new biometric. It has a lot of texture and has curved line structures. The finger knuckle print has been subjected to several image processing techniques previously utilized in personal identity biometric systems, with promising results.

The patterns on the finger knuckles were examined utilizing feature, decision, and score-level fusion to combine the major and minor fingerknuckles to ascertain human identity. Dorsal Finger knuckle patterns are extracted using three distinct feature extraction methods. For feature extraction of the major and minor dorsal finger knuckles, PCA, BSIF and AlexNet models are used. The experiments were carried out and the results showed the performance of each model in biometrics recognition of a person. The studies are carried out using the PolyU-FKP finger knuckle database, which is open to the public. Images in this database are entirely in bitmap (*.bmp) format and are divided into two portions of segmented Major and Minor Finger Knuckles, each having 2515 dorsal finger knuckle images from 503 subjects.

1.1 Statement of the Problem

"Biometric systems" can be broadly categorized as 'unimodal' (i.e., establishing identity utilizing a single biometric data source) and 'multibiometric systems' (i.e., utilizing several biometric data sources) [3]. And yet, there are a number of flaws in unimodal biometric systems, including a high error rate, poor usability, the potential for these systems to be hacked, and other issues (e.g., aging)[4]. A different approach is multibiometrics, which combines data from various biometric sources. The data sources may include many implementations of identical modality, a number of biometric techniques, several different sensor prototypes for identical modality, or multiple feature extraction techniques for a single modality. Numerous studies, both theoretical and practical, have demonstrated that multimodal biometric systems outperform unimodal systems when assessing performance [5]. Enhancing recognition rates is the primary practical motivation for researching and combining various biometric modalities. The use of finger knuckles in multibiometric systems has drawn a lot of interest in the literature because it is a relatively new concept.

1.2 Significance of the Study

To improve biometric identification accuracy and uniqueness, this thesis identified human identity by analyzing finger knuckle patterns utilizing Feature, Decision, and Score level fusion of major and minor finger knuckles. We use three different feature extraction methods to get the knuckle patterns from the dorsal finger. The finger knuckles provide a secure and trustworthy means of identification due to their individual shape, ridge count, and curvature. At the fusion stage, the major and minor dorsal knuckles of the finger are analyzed, and features are extracted using Principal Component Analysis (PCA), Binarized Statistical Image Feature (BSIF), and the AlexNet models.

1.3 Literature Review

Biometric systems have been in use for quite some time, and they typically make use of fingerprints, palm veins, hand geometry, DNA, palm print, iris identification, facial recognition, retina, voice, gait, and signature, among other physical or behavioral aspects. It has only recently been found that the texture pattern formed by the finger knuckle is particularly distinct in each user, making the surface a unique for biometric identification since it consists of wrinkles or lines. The knuckle image has a random roughness that makes each person stand out. The restored knuckle image is noted to have exceptionally steady local and global properties. The identity of some users may then be verified using this data [1].

Finger knuckle print is a biometric characteristic that has only existed for a few years. It contains a substantial amount of roughness and curved line structures. The finger knuckle print has been subjected to several image processing techniques previously utilized in personal identity biometric systems with promising results. The finger knuckle print has recently been discovered to be extremely rich in textures and can be utilized to uniquely identify a person. Hand-based biometrics have a better user acceptability, and this new characteristic has the added benefit of being less susceptible to harm. In the literature, the researchers' acquisition methods and strategies for recognition systems based on finger knuckle print are explained in [2].

Automated biometrics identification using images of finger knuckles is gaining popularity among researchers due to its potential applications in human forensics and biometrics. Inspecting the juncture of the distal and middle phalanx bones reveals patterns of the finger knuckles. On the surface of the finger, these patterns are created. It is possible to employ the minor finger knuckle patterns separately or in conjunction with the major finger knuckle patterns to enhance performance. In the literature, finger knuckle patterns from images taken over time are shown to be stable, and the experimental results gave new information about how finger patterns can be used in forensics and biometrics [6]. Finger knuckle patterns can be used both openly and covertly for the purpose of identifying a suspect.

In [7], a method of personal authentication combines the Contourlet Transform-based Feature Extraction Method with the Angular Geometric Analysis-based Feature Extraction Method. Furthermore, current studies only focused on the proximal phalanx knuckle region, but "geometric and textural" analysis methodologies incorporate feature information from both the major and minor knuckle. In addition, results from all four tests reveal that the state-of-the-art has significantly improved.

People can be identified by their unique patterns of bone, tissue, and skin at the knuckles of their fingers. There has been some research into the possibility of using the unique patterns created by the metacarpal and proximal phalanx joints of the fingers for biometric authentication purposes. Contactless imaging allows for the automatic segmentation and normalization/enhancement of the region of interest in palm dorsal pictures, adjusting for factors such as lighting, scale, and position. Several methods in the spatial and spectral domains are used to assess the efficiency of the matching of normalized knuckle images [8].

Usha and Ezhilarasan [9] makes a substantial contribution to a new approach by the analysis of the 'geometric and texture' features of finger knuckles for use in a personal recognition system. In their first method, the authors combined extracted pattern elements to improve accuracy. The study of the knuckle texture characteristic is performed utilizing the Curvelet-transform, which is a multi-resolution transform. With the least number of Curvelet coefficients, this Curvelet transform can approximate curved singularities. Finger knuckle patterns are represented using the "Curvelet-transform" since they are made up of lines and curves. The image of the finger knuckles is segmented into Curvelet bands using the "Curvelet-transform," also known as the "Curvelet knuckle". Finally, each Curvelet knuckle is subjected to PCA using the covariance matrix produced from its Curvelet coefficient.

On the other hand, Fingerback surface images are used to probe and create a novel method of individual authentication. Finger knuckle bending creates a one-of-a-kind texture pattern that can be used as a biometric identifier. Finger geometry features can be acquired concurrently from the same image at the same time to improve the user-identification accuracy of such a system. By standardizing the fingerback surface shots from each user, we may reduce the scale, translation, and rotational variances in the knuckle images may be reduced [10].

In addition, the performance of a finger knuckle recognition system is heavily influenced by biometric factors. Every person has their own skin patterns that are unique to them. These designs can be seen on both the interior and exterior of the finger joints. According to a recent study, these patterns have a lot of roughness and can be utilized to identify the person. This paper is an attempt to look at the numerous ways that have been utilized in the past for obtaining data and constructing systems based on it. In the literature, the comparative performance of the various approaches is also discussed [11].

Furthermore, authentication is based on a variety of physical and behavioral traits. Behavioral traits include a person's voice, electrocardiogram (ECG), electroencephalogram (EEG), keystroke, handwriting and lip movements in addition to physical details like their face, fingerprint, iris, retina, palm print, finger vein, and finger knuckle print. Because of these tangible features, finger knuckle print is currently one of the most discussed subjects in the scientific community. Low-cost gadgets are employed to capture the image since it is easily accessible; it cannot be taken by others, and so on. According to Sathiya and Palanisamy, the finger knuckle print contains a plethora of merits and limits [12].

Additionally, another study looks into the full dorsal surface of the finger for human identity, which might be incredibly useful in forensics and related domains. Furthermore, this research proposes a novel method for improving performance by extracting and integrating finer knuckle geometric and textural features simultaneously via score level fusion. The "Angular Geometric Analysis Method" (AGAM) is used to produce the geometric features, which use extracted angular-based features for unique identification. To identify the specific features of the local texture of a newly acquired finger's back knuckle, the authors employed the Feature Extraction from Textures as "Completed Local Ternary Pattern" generation method (CLTP), "2D Log Gabor Filter" (2DLGF), and "Fourier - Scale Invariant Feature Transform" (F-SIFT) methods [13].

Moreover, security solutions based on hand biometrics are a fantastic option for both access management and individual authentication. In [14], the authors introduced a novel multimodal biometric system that uses finger geometry and inner knuckle prints to authenticate users. In addition, knuckle prints of varying sizes are employed. They also provided a statistical method for selecting finger geometry features. Different methods of biometric fusion are analyzed, and the results of experiments showed that the proposed system achieves high recognition rates.

A novel approach to individual authentication is proposed [15], which makes use of deep learning techniques. Fingernail plates and knuckle features are used together in the approach. Biometric information was extracted from three digits of the hand (index, middle, and ring) using low-resolution dorsal images of the hand. Both attributes are mined for deep learning features using a custom-built Convolutional Neural Network (CNN). These elements have been included at the score and ranking levels for a number of different combinations.

Rathod and Science [16] used a finger knuckle print image as an evidence of person identification. Finger knuckle lines, creases, folds, and other surface characteristics can be used alone or in concert with other biometrics to establish identity. The improvement of a finger knuckle based biometric ID framework is proposed in that research. After pre-processing and upgrading information from knuckle surface, the framework joins Local Binary Pattern (LBP) for feature extraction. For individual identification, the framework also employs the Bernoulli classifier as a coordinating classifier.

Moreover, literature work of Kumar [17] is the first of its kind to present similar imges of entirely contactless finger knuckles in various poses in prospect of detecting entirely contactless finger knuckle images captured in a variety of positions. To improve efficiency, the authors present a novel method for automatically normalizing and aligning images of contactless finger knuckles. The research results show that normalization and matching algorithms can differentiate between finger knuckles in various positions. Integrating information from the spatial and spectral domains yields useful additional clues and enhanced performance.

The study of Finger Texture (FT) [18] has received a lot of interest as a biometric trait in recent years. Because it possesses different human-specific traits of apparent lines, wrinkles, and ridges dispersed around the inside surface of all fingers, it can provide efficient human recognition performance. Furthermore, such pattern structures are dependable, unique, and consistent throughout a person's lifetime. Finger Textures alone can be used to create effective biometric systems (FTs). Al-Nima et al. [18] presented a detailed review of the relevant Finger Textures (FT) investigations. They also discussed the major limitations and challenges of using Finger Textures (FT) as a biometric feature, as well as practical suggestions for improving Finger Textures research (FT).

In terms of accuracy and processing speed in [19], deep learning-based algorithms and machine learning approaches have performed better for image recognition. The authors suggested modified designed of Convolutional Neural Network (CNN) by adding two normalization procedures to two of the layers. The network was accelerated via the batch normalizing normalization procedure. In the fully connected layer of CNN, Softmax classifier was used to categorize faces while CNN architecture was utilized to extract features that distinguished faces. In the experiment part, Georgia Tech Database revealed that the recommended technique improved face recognition performance with better recognition outcomes.

In [20], the authors introduced a novel approach to person identification based on the finger knuckle pattern by employing a deep rule-based (DRB) classifier with multiple layers of neural networks (FKP). The proposed approach is fully automated and data-driven. The classifier for DRB, on the other hand, is generic and may be used to solve a wide range of classification and prediction issues. The results of the experiment prove that the "DRB" classifier can be useful in "FKP-based" biometric identification systems.

Using Finger-Knuckle-Print (FKP) databases, Arora et al. [21] attempted to solve the identifying issue that has arisen. It is through identification that the uniqueness of a query inside the FKP sample is determined. Each template in the database must be compared to the FKP query to determine which sample best fits the criteria. It's a computational approach for really large datasets that takes a long time and costs a lot of money. In order to improve the identification process, it is required to employ a technique that can reduce the search space and restrict the number of comparisons. The term "indexing" is used to describe this method. For a given FKP sample, it continuously generates a small candidate list of a defined size for searching. The study introduces FKPIndexNet, which learns similarity-preserving hash codes, for creating an index table. Using a unique autoencoder network, it learns feature embeddings with high intra-class and low inter-class similarity. The authors tested the proposed method on two publicly accessible FKP databases, PolyU-FKP and IITD-FKP.

Finger knuckle print (FKP) is a biometric that uses a person's hands to verify their identity. In pattern recognition, one of the biggest issues is the high dimensionality of the visual characteristics extracted. The proposed FKP system utilizes a multi-algorithm fusion technique founded on subspace algorithms at the feature level. In [22], the authors presented a novel feature-selection algorithm for finger knuckle detection called the Modified Magnetotatic Bacterial Optimization Approach (MMBOA). It picks out relevant and useful characteristics to improve classification precision. The unique feature of this bacteria has an impact on the development of a new optimization technique. Finger knuckle is used to extract hybrid features like Eigen and Fisher (EiFi). When compared to unimodal identifiers, the results show a substantial improvement.

Heidari and Chalechale [23] introduced a deep learning strategy for human authentication using dorsal aspects of the hand. Fingernail (FN) and finger knuckle print (FKP) impressions from the ring, middle, and index fingers are used in the proposed method. The proposed method was evaluated on a variety of hand skin identification, denoising, and knuckle and fingernail extraction tasks. Using a multimodal biometric method, the suggested system's authentication performance is enhanced and it becomes more resistant to spoofing attempts. AlexNet is used as a pre-trained model in a deep learning approach based on Convolutional Neural Networks. The authors proposed combining data from multiple levels of hand pictures through normalization and fusion techniques. The experimental results show that the suggested biometric system outperforms the state-of-the-art in terms of accuracy, reliability, and longevity.

Finger knuckle print, along with fingerprint and palm print, is a biological trait that gives human hands a distinct texture. There has been a lot of attention paid to the single-mode identification system's hand shape and finger knuckle print, both at home and abroad. Multiple studies have shown that increasing the number of biometrics used in a biometric identity system increases its recognition rate, security, and longevity. Images of finger knuckle prints can now be recognized using a technique that combines both global and local properties [24]. One technique that helped with recognition times was Principal Component Analysis. Extracting features from textures that accurately depict details required the use of a local feature, and the Local Binary Patterns (LBP) operator was used for this purpose. To combine universal and particular features, a two-layer serial fusion method is recommended.

The fusion of major and minor finger knuckles will be examined in this thesis using a number of fusion methodologies, including decision-level fusion and score-level fusion. Several feature extraction methods will be applied to images of minor and major finger knuckle patterns in order to identify the patterns. On finger knuckle biometrics for identity verification, feature extraction techniques like Principal Component Analysis, Binarized Statistical Image Features, and Convolutonal Neural

Networks will be investigated. The tests will be performed on databases for finger knuckles that are open to the public, like PolyU-FKP. The outcomes of fusing together finger knuckle patterns from the main and minor phalanges will be described in the final chapter of the thesis.

Chapter 2

DORSAL FINGER KNUCKLE PATTERNS FOR PERSON IDENTIFICATION

This chapter explain the texture patterns of individual dorsal finger knuckle for person identification. Figure *0.1* shows Pattern Regions of Major-Minor dorsal finger knuckle.

2.1 Major and Minor Dorsal Finger Knuckle Patterns

The accuracy of personal identification can be increased by merging many features, such as major and minor knuckle patterns, from a single dorsal image of a finger. Some research studies compared linear and nonlinear methods for combining match scores, with the goal of fusing minor and major knuckle patterns [6] [19]. To assess the stability of the finger knuckles, finger dorsal images from a number of subjects were collected over a period of more than 5 years. The feature extraction and matching technique described in [6] may be used to compare images taken at different times to see if finger knuckle patterns are consistent over time. Randomly textured patterns appear to be extremely distinguishable in images of the second minor knuckle from different fingers or subject. As shown in Figure *0.1*, such designs typically have folds, lines, and wrinkles of variable thickness that change as the finger progresses. The procedure for comparing images of the second minor knuckle is explored and described in detail in [8]. Forensic images may only reveal the minor knuckle parts of a finger if the hair covers the major knuckle pattern. Due to this difficulty, the use of both the major and minor components is now required [10].

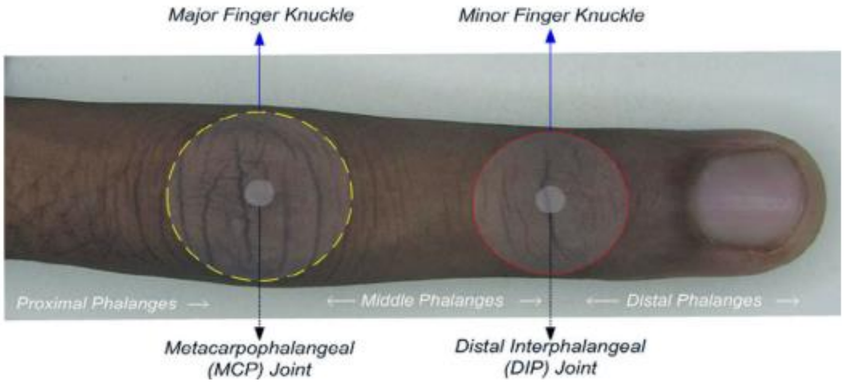

Figure 2.1: Pattern Regions of Major-Minor dorsal finger knuckle [5]

2.2 Region of Interest (ROI) Extraction

Every FKP image needs its own unique coordinate system. These coordinates can be used to trim an area of interest (ROI) from the source image in preparation for feature extraction [25]. To improve personal identification methods based on ‘major-minor’ finger knuckle shapes, particular Region of Interest image extraction is required [5]. The major and minor areas' ROI traits are present in the database that was used for this thesis.

The ROI templates were derived according to the following steps:

- All the dorsal views of fingers that were collected have been converted to binary. In this procedure, Otsu's thresholding approach was utilized.
- Images are denoised by selectively erasing the isolated pixels, leaving only the longest object (the finger) in focus.
- In order to determine where the fingertip is on each image's convex hull, the finger's binarized shape has been adopted.
- To get rid of the background image, the fingertip's location hiding has been utilized.

- The methods of moment have been applied to estimate the orientation of the fingers from the binarized image, comparable to the technique in [26].
- The minor finger knuckle region may be segmented using coarse segmentation, which excludes the major finger knuckle region and the majority of the fingernail.

The aforementioned segmentation method makes some uneasy assumptions regarding the greatest distance between nails and fingers since it relies on the prediction that the major finger knuckle area will be located in the middle of the produced finger dorsal image. Then, operations to inspect and remove nails are performed on the resulting coarsely segmented image, which divide the image into segments. By computing the resultant width image, the scale normalization factor is determined. By employing an edge detection method, the minor knuckle's anatomical center can be pinpointed. Segmenting the major/minor knuckle region of the finger dorsal image into a fixed-size chunk of 160 by 180 pixels, as shown in Figure *0.2*, and locating its center in the resulting edge detection image are the required steps.

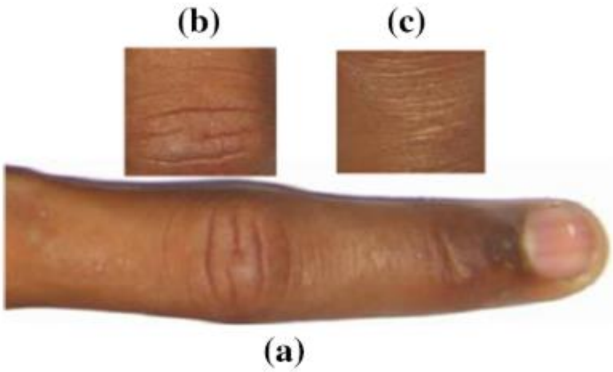

Figure 2.2:Image of a sample of finger knuckles showing various regions [5].

Chapter 3

FEATURE EXTRACTION METHODS AND MATCHING

This chapter explains the feature extraction methods used for finger knuckle recognition in this study. PCA, BSIF and AlexNet are used in this study for feature extraction and/or classification. Additionally, the matching process is described in detail.

3.1 Feature Extraction Methods

The approaches for feature extraction we used in this thesis include Principal Component Analysis, Binarized Statistical Image Features and Convolutional Neural Network architecture, namely AlexNet.

3.1.1 Principal Component Analysis

Performing a PCA analysis entails three steps: calculating eigenvalues, eigenvectors, and feature vector covariance matrices. These templates can be made smaller while still retaining the most critical features by using an approach that combines feature extraction with dimension reduction [27]. To calculate mean feature vectors, equation (1) is used:

$$\text{Mean } (\bar{A}) = \frac{1}{n} \sum_{i=1}^{n} a_i \tag{1}$$

where a_i is image vector.

In order to obtain $(a_i - \overline{A_\iota})$ and $(b_i - \overline{B_\iota})$, we divide the image mean by the image vector respectively, let each vector be represented as a mean-centered image. In order to generate the covariance vectors of the covariance matrix, equation (2) is used:

$$\mathrm{cov}(a,b) = \frac{\sum_{i=1}^{n}(a_i - \overline{A_\iota})\,(b_i - \overline{B_\iota})}{n} \qquad (2)$$

where $\overline{A_\iota}$ and $\overline{B_\iota}$ represent the average vector value and the two parameters a_i and $b_i$represent the current values of $\bar{a}$ and $\bar{b}$. As a whole, there are n rows. To obtain eigenvalues of the covariance matrix, the following equation (3) is applied:

$$\det\left(cov_{(a,b)} - I\right) = 0 \qquad (3)$$

The eigenvector V in equation (4) is then calculated for each eigenvalue λ as follows:

$$\det\left(cov_{(a,b)} - \lambda I\right)V = 0 \qquad (4)$$

3.1.2 Binarized Statistical Image Features

The BSIF, a local image descriptor, is used to implement binarized statistical image features. Implementing BSIF requires binarizing the outputs of linear convolution filters. We utilized BSIF to learn a collection of convolution filters using an unsupervised model and Independent Component Analysis (ICA). Both the major and minor dorsal finger knuckle images can be represented by these trained filters, which calculate the responses of each pixel to the learnt convolution filter. Every pixel's binary string is considered as Local descriptor in terms of image intensity patterns surrounding that pixel [5].

In this thesis, we employed open-source filters that had been trained on $503 \times 5 \times 2$ images. In order to generate the BSIF filters, we first subtract a "mean" value from each patch, apply Principal Component Analysis to minimize the number of dimensions, and finally apply Independent Component Analysis. Finally, the filter response x_i in equation (5) is obtained when we feed in a finger knuckle pattern image (input image I) of size $m \times n$ and a filter (of the same size, output image, F_i).

$$x_i = \sum_{m,n} I(m,n) F_i(m,n) \tag{5}$$

Binary representation of the convolution filter with parameters $i = \{1,2,3, \dots \dots m\}$, where F_i is an integer representing a "statistically independent filter" whose outputs may be computed using (6) in parallel, yields the string [5].

$$b_i = \begin{cases} 1 \; if \; x_i > 0 \\ 0 \; otherwise \end{cases} \tag{6}$$

where x_i is filter response.

The BSIF descriptor emphasizes the importance of both the filter's size and its length (i). It is possible that a single, fixed-length filter would not be able to appropriately generalize finger knuckle patterns of varying intensities, sizes, and orientations [5].

In Figure *0.1*, an example of a dorsal finger knuckle image that has been modified with BSIF filters is shown. The primary input region of interest (ROI) for the finger knuckle image is seen in Figure *0.1*(a). Figure *0.1*(b) displays the results of a BSIF filter with output dimensions of 9x9 and 15x15 and bit lengths of 12, while Figure *0.1* (c) displays the input ROI of a minor finger knuckle image. Figure *0.1*(d) shows the outcomes of the minor dorsal finger knuckle image's separate convolution ROI using BSIF filters, size of 9x9 and 15x15, and bit lengths of 12 bits.

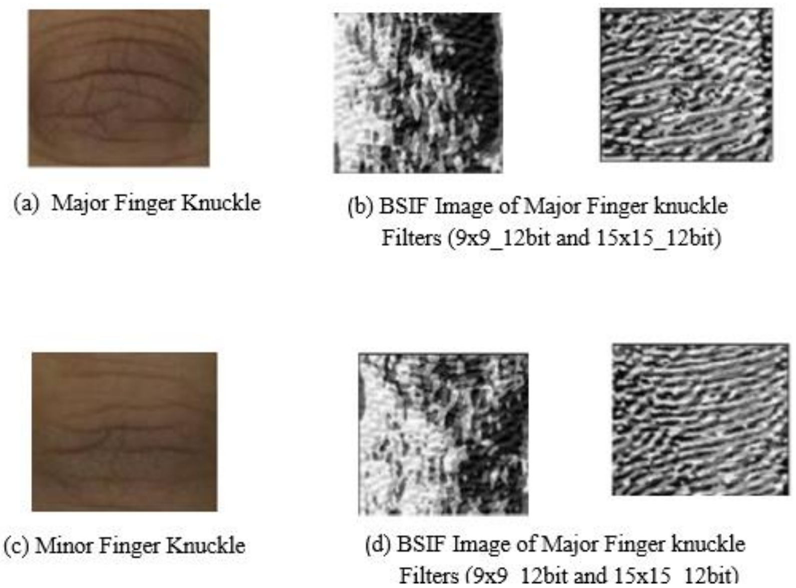

Figure 3.1:: ROI Image For the Major and Minor Dorsal Finger Knuckles and Their Respective BSIF Filters Output with Dimensions Of 9x9, 15x15, And Length 12 bits

3.1.3 AlexNet

AlexNet is a Convolutional Neural Network model that consists of five convolution layers followed by the activation functions ReLU, Batch Normalization and Maxpool. The framework is a series of convolution layers whose filter sizes range from 3 x 3 to 11 x 11 kernel. Filters range in number from 96 to 384 throughout the layers. The structure is finished off with a Dropout layer, fully connected layer, and Softmax function [28]. The layers of the model are described in the following subsections.

3.1.3.1 Batch Normalization

When normalizing a network's activation sets, it is possible to do it in batches. In this case a nonlinearity in the elements and an affine transformation is considered:

$$z = g(Wu + b) \tag{7}$$

The model's optimization targets are denoted by W and b, respectively. Function $g(.)$ stands for the non-linearity function known as ReLU. Batch normalization is performed on all convolutional layers and all connected layers. As an additional step before reaching non-linearity, the batch normalization transform is introduced through normalizing equation (8).

$$x = Wu + b. \tag{8}$$

The input layer u should be normalized since it reflects the output of another non-linear layer whose distribution may shift during training. Also, the covariance shift is reduced and the first and second phases of the input layer are constrained. Because equation (8) is symmetric and has a non-sparse distribution, normalization increases the likelihood that the excitation function's distribution will remain stable.

Because the mean subtraction may cancel out the effects of bias b, we may discard b and rewrite the formula in equation (7) as in (9):

$$z = g(BN(Wu\,)) \tag{9}$$

At each layer where the BN transform is used, we optimize a set of two parameters, $\gamma(k)$ and $\beta(k)$ is optimized.

Normalization is also required for convolutional layers to respect the convolutional property, which allows us to normalize the same feature maps with different components in different locations. In order to achieve this goal, mini-batch activations from each site are normalized. All activations in a given feature map undergo the same linear modification.

3.1.3.2 Convolutional Layer

The central building component of a Convolutional Network, namely the Convolutional Layer, is responsible for the bulk of the computation. Feature extraction is the primary goal of the Convolution layer, whose input data is an image. Convolution preserves the spatial relationship between pixels by discovering their properties from small squares of the input image. Through the use of a network of plastic neurons, the original image gets deformed during training. The output image includes an activation map (sometimes called a feature map) that is fed into the next convolutional layer [19].

3.1.3.3 Pooling Layer

The pooling layer reduces the size of all activation maps, but retains the most important information. In order to separate the input images, non-overlapping rectangles are employed. Each region is down-sampled using a non-linear procedure, such as average or maximum. Positioned in the middle of a series of convolutional layers, this one allows for greater generalization, faster convergence, and resistance to translation and distortion [19].

3.1.3.4 ReLU Layer

ReLU is a non-linear process that makes use of rectifier devices. Negative values in the feature map are converted to zero in a pixel-by-pixel, element-by-element procedure.

Equation (7) is an expression for the ReLU activation function:

$$f(x) = \max(0, x) \tag{10}$$

In cases when the input is less than or equal to 0, the response is also 0, in all other cases it is equal to the input. The output of the ReLU function is rather sparse as a result of its characteristics, which can speed up network convergence and enhance the classification skills of the CNN as follows:

$$f`(x)\begin{cases}0, & x \leq 0\\ 1, & x > 0\end{cases} \tag{11}$$

Since equation (11) gradient is only saturated when $x > 0, f^{`}(x) = 1$; the issue of gradient dispersion may be mitigated during backward propagation, and the parameters of CNN can be updated rapidly.

3.1.3.5 Fully Connected Layer

A completely linked layer connects every filter in the layer before and after it. The convolutional, pooling, and ReLU layers produce high-level input image attributes. The fully connected layer uses these properties to sort incoming images by training dataset. The last pooling layer, or fully connected layer, feeds characteristics to the classifier using Softmax activation.

In this study, the major/minor finger knuckles biometric characteristic was fused at the decision and scoring levels using a deep learning-based convolutional neural network architecture. Several hidden layers and parameters make up a CNN, making it a type of deep neural network. Applications include "natural language processing" and "image processing", and it seeks to detect patterns in images directly. CNNs typically have two sections to their structure. The first stage, which is typically referred to as feature extraction, combines convolutional and pooling layers. Classification, the second phase, employs completely connected layers. The CNN architecture is made up of multiple layers that fall into three categories: The first three stages are convolutional, pooling, and fully-connected [29].

3.1.3.6 Convolutional part

The CNN stage is essential at the moment. In order to isolate specific aspects of the input, it typically consists of multiple layers. These layers are designed to extract features from the input images using trainable kernels or filters. In contrast to the first layer's collection of broad characteristics like edges, corners, textures, and lines, the subsequent layers are responsible for extracting finer details [29].

3.1.3.7 Pooling section

This section reduces the quantity of data used and the computational complexity by subsampling the convolutional layer results. Consequently, it renders our system resistant to little changes. Max or Mean Pooling are options [29].

Full-Connected component Convolutional and pooling layer output data are prominent characteristics (fine details) of the source image as in Figure *0.2*. This section's goal is to classify the output features into different categories. Traditional artificial neural networks (ANNs) have a fully connected layer that produces a probability for each classification label using a softmax activation function (by means of a loss function referred to as cross-entropy loss) [29].

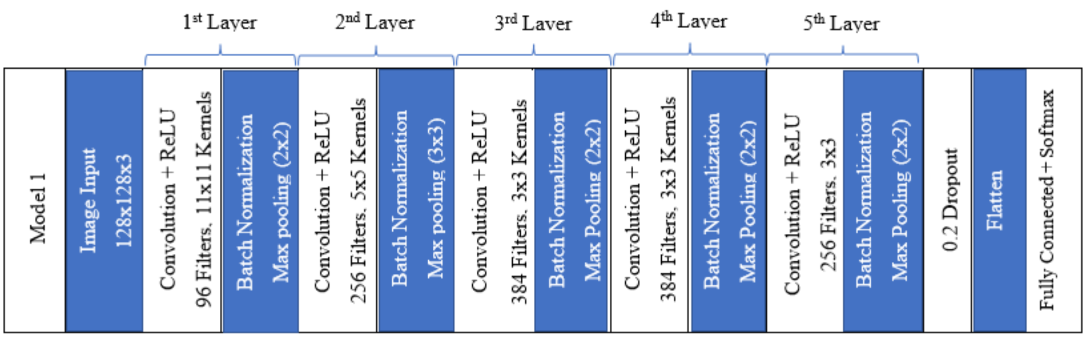

Figure 3.2:CNN Model I (Original AlexNet)

3.1.4 Modified AlexNet

In this thesis, we use feature, score and decision-level fusion in both two models (Model1 and Model2) of Convolutional Neural Networks that are based on deep learning. Numerous studies have demonstrated how effective CNN is at solving image classification issues [28]. However, in this research, the computing time required to train the model was considerably lowered by drastically reducing the number of kernels in each convolution layer. In this experiment, we also employed a consistent filter size of 3 x 3 throughout all convolution layers, as opposed to the original AlexNet model's usage of variable kernel sizes.

Figure *0.3* illustrates Model II with lower filters compared to "AlexNet model" ModelI CNN Model II (Modified AlexNet) characteristics are as follows:

- 32 distinct filters of size 3x3 are included in the first layer, and 2x2 filters are used for Max pooling.
- Max pooling is done with 64 distinct filters of size 3 x 3 in the second layer.
- The third and fourth layers each include 96 distinct 3x3 filters, and 2 x 2 filters are used for Max pooling.
- Max pooling is implemented with 128 distinct filters of size 3 x 3 in the fifth layer.

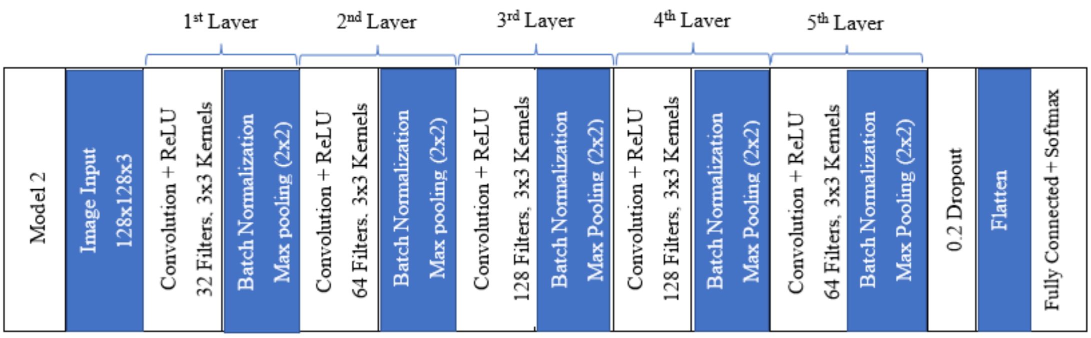

Figure 3.3: CNN Model II (Modified AlexNet) [29]

Table *3.1* compares the updated AlexNet model's level alteration to the original AlexNet model. A different number of filters are used in Model II as shown in Figure *0.3*, a second model that is comparable to Model I (Original AlexNet). The last layers of Model II (modified AlexNet) are Dropout, Fully-connected plus Softmax, and Classification. To achieve low training error, deep learning often needs thousands of training samples. The datasets created by the Keras data generator modifies images by changing their brightness, width, and height as well as small rotation, shear, and zoom. These improved the training and testing results [28]. CNN Model I (Original AlexNet) and Model II (Modified AlexNet) are both implemented using Python.

Table 3.1: Original and Modified AlexNet Model.

Layer	Original (Model I)	Modified (Model II)
First Layer	11 x 11 x 96	3 x 3 x 32
Second Layer	5 x 5 x 256	3 x 3 x 64
Third Layer	3 x 3 x 384	3 x 3 x 128
Fourth Layer	3 x 3 x 384	3 x 3 x 128
Fifth Layer	3 x 3 x 64	3 x 3 x 64

3.2 Matching System

In this chapter we explain the Nearest-Neighbor classifier. The similarity or dissimilarity between the query trait and the saved template is measured by comparing two sets to the minimum possible distance (score).

3.2.1 Finger Knuckle Matching

Images of finger knuckles, especially after being enhanced or augmented, can reveal a seemingly random texture pattern that is strikingly unique across fingers. Images of minor/major finger knuckles can be matched using a number of feature extraction strategies, both in the spatial and spectral domains [30]. In order to evaluate effectiveness, this thesis makes use of deep learning (AlexNet), Principal Component Analysis and Binarized Statistical Image Features.

3.2.2 Matching Module and Normalization of Scores

For the purpose of matching in this thesis, we have employed the nearest-neighbor classifier, which employs the cosine Mahalanobis distance. The similarity or dissimilarity between the query trait and the saved template is measured using (12) by comparing the two sets to the minimum possible distance (score).

Let's assume X_i and V_j are the query and template "feature" vectors for the images in the database, then

$$d_{Ma}\left(X_i, X_j\right) = \left(X_i - X_j\right)^T C^{-1}(X_i - X_j) \tag{12}$$

where C is the covariance matrix, in this case. Matching score was converted to [0, 1] using the ‘min-max normalization’ model approach before decision was made. A set of matching scores, V_K, are calculated from the given normalization scores, where $K = 1,2,3 \dots \dots, n$.

$$\mathrm{V}'_{\mathrm{K}} = \frac{\mathrm{V_K - min}}{\mathrm{max - min}} \tag{13}$$

where V'_K stands for the scores after normalization. The ultimate choice regarding the individual (accept/reject) is made using this normalized score.

The degree of similarity between the feature test and feature train vectors is calculated in the matching score step of the CNN architecture. The high match score usually represents the true score, or the identity of the targeted person [29]. In this respect, the fusion at the level of the matching score stands out for its transparency and efficient performances and is thus the most important. To increase accuracy of biometric identification system we, combined the extracted features of major and minor finger knuckles are combine in this thesis.

A final matching score can be produced using a variety of fusion rules [31] as follows:

- Simple Sum Rule: The final matching scores are added together under this rule. The formula (14) is as follows:

$$S = {}^{1}/_{N} \sum_{i=1}^{N} S_i \tag{14}$$

- Product Rule: Is calculated using equation (15) by multiplying all of the matching scores together.

$$S = {}^{1}/_{N} \prod_{i=1}^{N} S_i \tag{15}$$

- Minimum Rule: It is determined using the minimal matching score in the manner shown in equation (16).

$$S = \min(S_i) \tag{16}$$

- Maximum Rule: It is determined using the highest matching score as in equation (17).

$$S = \max(S_i) \tag{17}$$

- Weighted Sum Rule: Similar to the sum rule equation (18), it governs the process through which fusion is generated as follows:

$$S = \sum_{i=1}^{N} w_i S_i \tag{18}$$

  where w_i is a weighted average of the matching scores for the i_{th}biometric characteristic of the k_{th} individual as in equation (19)

$$w_i = \frac{{}^{1}/_{\sum_{i=1}^{N} {}^{1}/_{EER_i}}}{EER_i} \tag{19}$$

- Weighted Product Rule: This rule is calculated using equation (20) in a manner identical to the preceding Product Rule using the same formula as follows:

$$S = \prod_{i=1}^{N} w_i S_1 \tag{20}$$

where w_i is weight of matching score and S_1 is matching score.

The biometric identification system's classification determination will be based on the fusion's final score [29].

Chapter 4

PROPOSED SYSTEMS

This study suggests a novel approach to biometric identification based on the extraction of characteristics from the major and minor finger knuckle. Binarized Statistical Image Feature, Principal Component Analysis and the Convolutional Neural Network model are used in the initial step to locate significant feature points and extract feature information from them. A vector representation of the retrieved features from each registered finger knuckle image is stored. Each of these recorded vectors' pieces of data are combined to make one larger vector. To reach a conclusion, a weighted Euclidean distance is calculated between the input vector and the reference vector.

There are 4 steps in the proposed method as follows:

- Step 1: ROI extraction
- Step 2: Implementation of BSIF, PCA and AlexNet to extract features.
- Step 3: Methods of Fusion (i.e Feature, Score and Decision Level Fusion)
- Step 4: A decision-making classifier that can identify a person

Figure 4.1 depicts the four steps involved in using the proposed dorsal finger knuckle patterns for personal identification system.

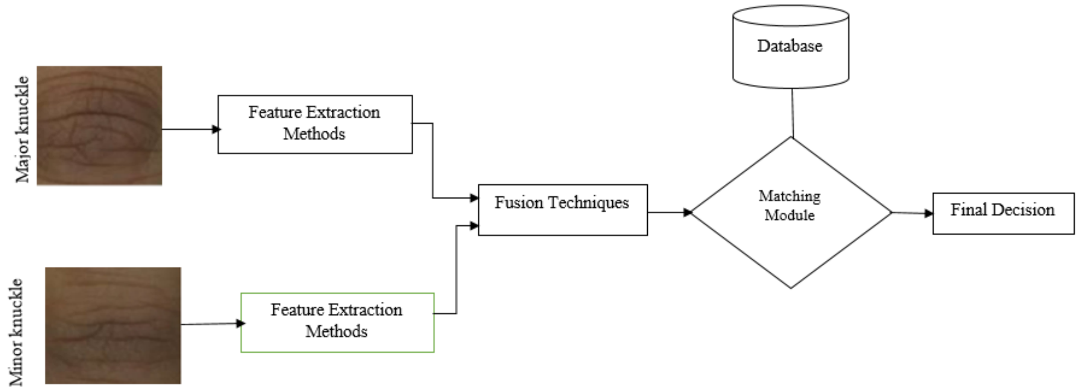

Figure 4.1:Proposed system showing the major and minor personal identifying areas on the dorsal finger knuckle.

4.1 Preprocessing Stage

Preprocessing and ROI extraction of features are performed for the major and minor knuckle regions from the finger back surface (FBKS). During the acquisition phase, it aligns the images of the finger knuckles, and then uses those images to construct the proximal and distal knuckle areas, as well as the surface of the finger's back knuckles with their own coordinate systems [7].

The back of the finger is made up of the metacarpal joint, the proximal interphalangeal (PIP) joint, and the distal phalangeal (DIP) joint. However, most of the published works concentrate on combining proximal and distal knuckle patterns for identification purposes [13].

Furthermore, acquired finger knuckle print is preprocessed in order to locate a specific knuckle region with significant attributes for reliable individual identification. Because the FKP images are acquired in diverse settings with scaling, translational, and rotational variations, the region of interest (ROI) segmentation method is necessary. A sample section of 90 x 180 pixels is cut from the collected finger knuckle print (FKP) to obtain its sub-image. Empirical analysis was used to determine the pixel size detailed in [12][9].

Additionally, Normalization, scaling, rotation, and picture segmentation are examples of pre-processing techniques. There are numerous feature descriptors that the DRB classifier can employ, as well as the Parallel Fuzzy Rule Base (FRB) layer, which includes system startup, preparation, and updating, as well as the production of fuzzy rules [20].

4.2 Feature Extraction Stage

When examining images of knuckles, you may notice an irregular texture pattern that appears to be somewhat different in each finger. Minor finger knuckle images were utilized to evaluate the matching accuracy using a number of feature extraction techniques, including Local Binary Patterns (LBP), 1-D Log-Gabor Filter, and Band Limited Phase Only. An abundance of information on correlation can be found in the literature [6]. Individual authentication for finger knuckle surface detection was provided by [7] using a mixture of geometric and textural data. Three different methods—the Random Transform, the Gabor Wavelet Transform and a combination of features from matched fingers were used to get the characteristics of the surface of the finger knuckles. In addition, the Completed Local Ternary Patterns (CLTP), 2D Log Gabor Filters (2DLGF) and Fourier Scale-invariant Feature Transform techniques are used to extract local texture feature information from the knuckle regions of the proximal and distal fingers. The aforementioned methods of texture creation represent different aspects of data, as described in [13] [18] [20].

Once the desired texture was located, a rapid discrete Curvelet transform was applied to the region of interest (ROI) of a "finger knuckle print". Since finger knuckle texture patterns are curved, the Curvelet transformation method will work well for characterizing finger knuckle print details [12] [9]. Moreover, curved lines and folds dominate the magnified knuckle image. It is important to look for curved lines and creases on the knuckles. The features of the knuckles are then extracted. In addition, two appearance-based methods, Principal Component Analysis and Linear Discriminant Analysis, are employed [24]. The PCA and LDA are linear transformations that speed up computation and save money [22].

Principal Component Analysis, Binarized Statistical Image Feature and deep learning based AlexNet are used to extract characteristics of the major and minor knuckles in this thesis. Extracted features from the finger knuckles were used for matching on the Feature, Score, and Decision levels of the biometric system's fusion framework.

4.3 Feature-Level Fusion (FLF)

By including the major and minor dorsal finger knuckle into a unimodal system, recognition performance is improved. To evaluate the whole biometric system, we use the PolyUFK dataset (version 1.0). After the features for each attribute have been extracted separately, the fusion approach is used using the serial rule to generate a novel pattern for classification and decision making by combining facial and iris characteristics. Based on these two feature extraction methods, two multimodal biometric systems are developed, as illustrated in Figure *0.2*. The following equation (21) explains how the serial rule works [27]:

$$Fusion_{MaMi} = \{U_{Ma2} \dots \dots U_{Maq}, V_{Mi1}, V_{Mi1} \dots \dots \dots \dots . V_{Mim}\} \tag{21}$$

where U_{Ma2} denote Major finger knuckle features with vector size q and V_{Mim} is assigned as the Minor finger knuckle feature with vector size m, when both m and q are unequal.

In this dissertation, features are extracted independently from each finger knuckle image before being fused together to form a single vector of features for each individual. Both the major and minor dorsal finger knuckle features are included in this final feature vector (feature level fusion).

When fusing images from the same format and source, the features from the numerous biometric attributes are in the same range, making fusion faster and more accurate without the need for normalization. The Nearest Neighbor classifier is applied with a Manhattan distance strategy, same as in the unimodal setting [28].

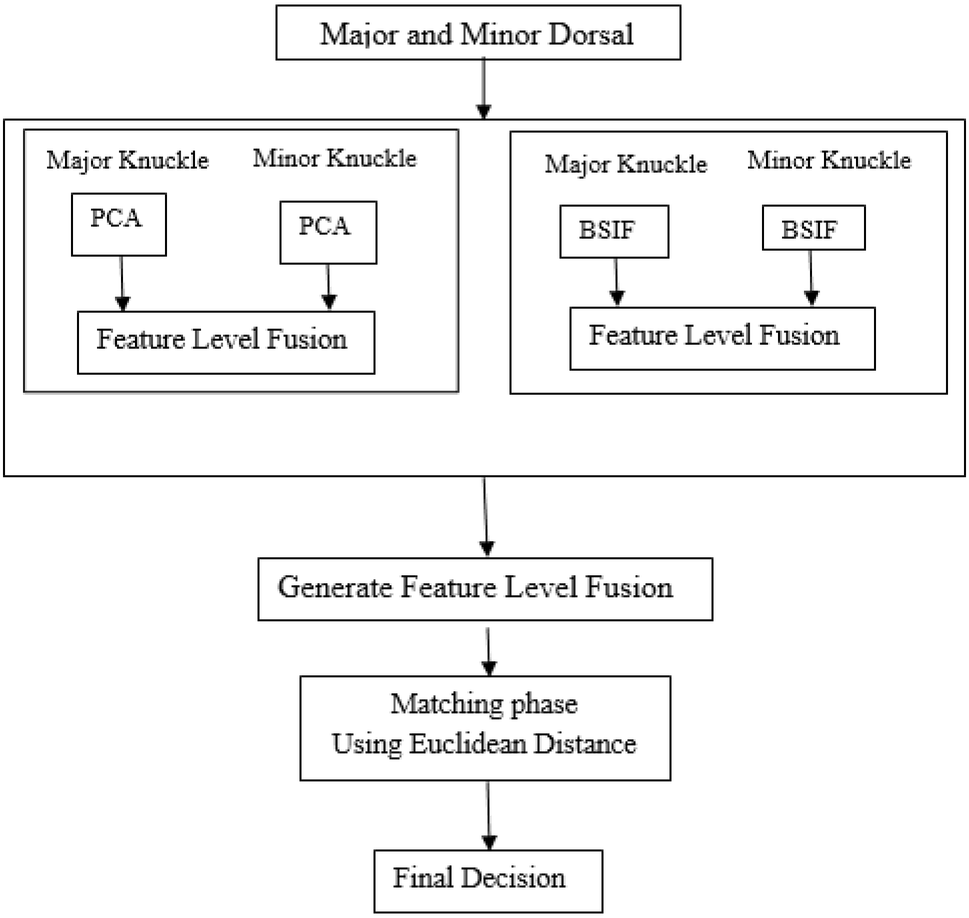

Figure 4.2: Biometric Finger Knuckle System with Feature Level Fusion of Major and Minor Finger Knuckles

4.4 Score-Level Fusion (SLF)

Multibiometric systems frequently use the fusion at the score level[27]. In this method, each unimodal system's recognition results are calculated individually, and once the scores have been compiled, a multimodal system is created to enhance the system's overall performance, as shown in Figure *0.3* below. Before beginning the classification process, the score vectors for each feature (Major and Minor finger knuckles) are generated independently and normalized as at the minimal EER value. The second step involves combining the Major and Minor scores using the Sum Rule. The selection is made using the minimum threshold necessary to ensure the maximum performance of the fused system [32].

$$SC_i = \frac{SC_i - min_{sci}}{max_{sci} - min_{sci}} \quad (22)$$

$$F_{score} = \sum_i^M (SC_{Mai} + SC_{Mii} \quad (23)$$

where SC_{Mai} and SC_{Mii} are the scores for the facial and iris biometric samples, and SC_i is the normalized score for the facial and iris biometric samples. The score vector sample has a minimum value of i and a maximum value of M, where i is the minimum number of biometric systems and M is the maximum number of biometric systems. Figure *0.3* shows the process followed to create four multimodal systems using the score-level fusion method.

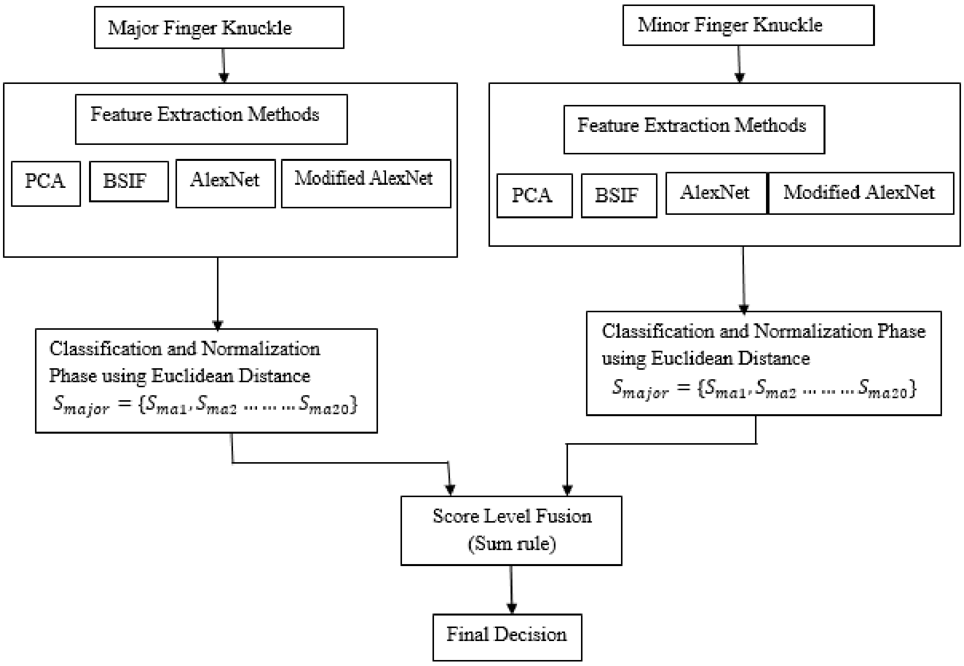

Figure 4.3: Score Level Fusion of Major and Minor Finger Knuckle Biometric System

4.4 Decision-Level Fusion (DLF)

Combining features taken from CNN decisions for each biometric attribute is done via decision level fusion [28]. After combining the two (major and minor knuckle) decisions, the CNN comes at its final decision utilizing a Weighted Rule. Every classifier is modified to restore its marginal distance from the decision hyperplane (opinion). A feature vector of size k, which reflects the number of approaches, groups opinions into categories [33]. Each decision yields either the proper recognition (True) or the wrong recognition (False) as shown in Figure *0.4*. The weight presented to a true decision is 1, while the weight given to a false decision is 0. To arrive at the final decision, the weights of the two features are combined and tested against a 0.9 threshold. However, when there are two minimum scores, a random selection is done at >0.9 threshold.

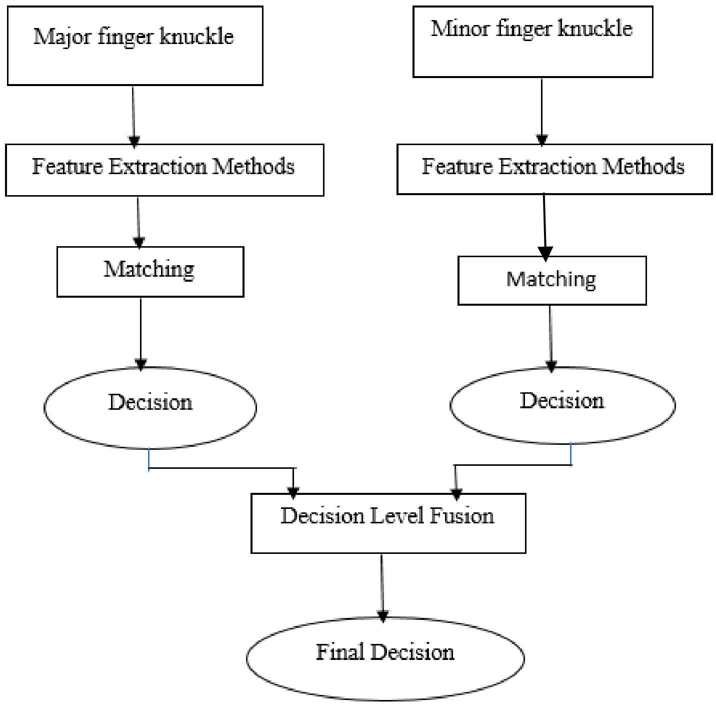

Figure 4.4: Major and Minor Finger Knuckle Biometric System Based on The Decision Level Fusion Technique.

Chapter 5

EXPERIMENTS AND RESULTS

In this section, we thoroughly test the Hong Kong Polytechnic University's (v1.0) publicly available finger knuckle images database and assess its performance using five different experiments. The first set of experiment is conducted on Major Finger Knuckle Recognition System, while the second set is based on Minor Finger Knuckle Recognition System. Fusion based experiments are performed based on Feature-level Fusion of Major and Minor Finger Knuckle Recognition System, Score-level Fusion of Major and Minor Finger Knuckle Recognition System and Decision-level Fusion of Major and Minor Finger Knuckle Recognition System. Afterwards comparison of experimental results using PCA, BSIF and AlexNet are presented.

5.1 Database Descriptions

The evaluation of the database used in this study was performed using the freely available knuckle image database (version 1.0) from Hong Kong Polytechnic University [5]. 2515 dorsal images of fingers from 503 individuals are stored in the database. Each dorsal finger image has its major and minor knuckles annotated as regions of interest by the owner of the database. Nearly 88% of the people in this dataset are under the age of 30. Bitmap (*.bmp) is the format used by these images. There are 5 images for each variety of finger. However, we used 5030 images for major and minor knuckles each with 503 x 5 = 2515 images. Table *0.1* shows dataset description used in descriptors PCA and BSIF.

Meanwhile, for the purpose of reducing training error, deep learning often needs training samples in thousands. However, the Hong Kong Polytechnic University dataset do not have as many as required quantity, consequently we created more images from the datasets using Keras data generator, which makes tiny but noticeable changes to the images such as shear-0.15, rotation-10^0, shift_width-0.05, zoom-0.2 and shift_height-0.02, brightness, etc. As a result, the total number of images increases to 12,575 (503x5x5= 12,575) images. Table *0.2* demonstrate dataset augmentation details used in AlexNet and Modified AlexNet models.

Table 5.1: Major and Minor Finger Knuckle Dataset Description Used with PCA and BSIF Methods

Dataset	**Trait**	**Model**	**Subject**	**Total Images**	**Train image**	**Test image**
PolyU Knuckle V1	**major and minor dorsal finger knuckle**	**PCA**	**503**	**503x5=2515**	**1509**	**1006**
		BSIF	**503**	**503x5=2515**	**1509**	**1006**

Table 5.2: Major and Minor Finger Knuckle Dataset Augmentation Description Used with AlexNet and Modified AlexNet Methods

Dataset	**Trait**	**Model**	**Subject**	**Total Images**	**Train image**	**Test image**
PolyU Knuckle V1	**major and minor dorsal Finger knuckle**	**AlexNet Model I (Original AlexNet)**	**503**	**503x5x5= 12575**	**10060**	**2515**
		AlexNet Model II (Modified AlexNet)	**503**	**503x5x5= 12575**	**10060**	**2515**

5.2 Experimental Results

The experiments carried out can be categorized into two phases; first phase is the recognition system using unimodal finger knuckles, namely major and minor, respectively. The second phase is the combination of the two systems at either the feature, score or decision level explained in Chapter 4. The feature extraction is performed using handcrafted feature extraction descriptors, PCA and BSIF described in Chapter 3, as well as CNN model AlexNet and its modified version. The system for recognition using minor finger knuckles is exactly the same with the major finger knuckles system.

Cross validation was performed for Binarized Statistical Image Feature (BSIF), 40% of the dataset was used for testing while 60% was used for training, the dataset used for training and testing were swapped for a second session of training and testing. Hence, we end up with two results in each case. The average of the two results is taken as the true accuracy of the system. However, the same process was performed for Principal Component Analysis (PCA).

Similarly, for AlexNet, 80% of the dataset were used for training while 20% were used for testing. For cross validation, a second set of training and testing datasets were used for second training and testing. The average of the two results was also taken as the true accuracy of the system as in BSIF and PCA.

Experimental results for the first phase shown in Table 5.3 indicates that the major finger knuckle system produces better result in both PCA and BSIF with 65.86 and 91.90 percent, respectively. These accounts for 3% better performance in both cases.

Table 5.3: Major and Minor Finger Knuckles experiments compared to fusion methods with PCA and BSIF in terms of Accuracy (%)

Experiment	**Accuracy using BSIF**	**Accuracy using PCA**

Major Knuckles	**91.90%**	**65.86%**
Minor Knuckles	**88.37%**	**62.535**
Feature Level Fusion (FLF)	**93.14%**	**59.15%**
Score Level Fusion (SLF)	**93.14%**	**76.64%**
Decision Level fusion (DLF)	**95.33%**	**80.97%**

Experimental results for the second phase are also presented in

Table *0.3* for handcrafted methods. The results reveal that combining the two images (that is major and minor finger knuckles) offer better results across all three fusion methods tested except in the case of feature-level fusion of PCA features. Out of the three fusion approaches, decision level fusion yielded the best results with accuracy of 95.33% in BSIF and 80.97% in PCA. These account for approximately 3.6% improvement compared in respect to the standalone systems in BSIF and as much as 15.1% improvement when PCA is used.

Table 5.4: Major and Minor Finger Knuckle Experiments Compared to Fusion Methods with AlexNet in terms of Accuracy (%)

Experiment	**Accuracy using AlexNet (Model I)**	**Accuracy using AlexNet (Model II)**
Major Knuckles	**97.97%**	**98.05%**
Minor Knuckles	**98.25%**	**98.01%**
Score Level Fusion (SLF)	**100%**	**99.72%**
Decision Level Fusion (DLF)	**99.89%**	**99.36%**

The deep learning aspect of the experiment is shown in Table *0.4* where results of AlexNet (Model I) and modified AlexNet (Model II) are presented. The results show that both models performed relatively close to one another with an accuracy of approximately 98% in major finger knuckle and minor finger knuckle systems. Two fusion methods, score and decision level fusion were employed in this case. Original

AlexNet (Model I) performed slightly better in these cases, reaching a 100% accuracy under score level fusion.

5.3 Comparison with Existing Studies

The proposed system is also compared with the state-of-the-art, including those from [5, 15, 29, 34] and the findings are shown in Table *0.5*. Both a unimodal system and a multimodal system are compared in terms of their recognition results. According to Table *0.5*, the proposed method outperforms the system developed in [5], using either the minor or major finger knuckle for unimodal system under identification, but [29] shows even higher performance, with a recognition rate of 99.93%. It can also be seen that the suggested approach performs better than the researches in [5, 15, 34] with the exception of [29], which performs equally well in terms of the fusion of modalities with a 100% recognition rate.

While both the proposed system and the study in [5] used the same dataset, these systems employed different approaches. In [5], BSIF, PCA and Feature level fusion are applied to the major knuckles, minor knuckle, and full finger, however in the proposed technique, BSIF, PCA AlexNet and Feature, Score, and Decision level fusion are applied to the major and minor finger knuckles.

Table 5.5: Comparison With The State-Of-The-Art

Ref. No	Publ. year	Trait	Method	Database	Total images	Unimodal Recognition rate	Multimodal Recognition rate
[34]	2017	Nail plate of index, middle, and ring fingers	deep CNN	ImageNet	5 images/178 users = 890 images per modality	N/A	98%
[15]	2019	Knuckle and nail plate of index, middle	AlexNet	ImageNet	5 images/178 users = 890 images per modality	N/A	97.19%

		and ring fingers					
[29]	2020	Left Index, Left Middle, Right Index and Right Middle fingers	Convolutional Neural Network (CNN)	PolyU-FKP	4 by 12 by 165 = 7920 images	99.93%	100%
[5]	2021	Major, Minor and dorsal finger knuckle	BSIF, PCA+LDA	PolyU Knuckle V1	5 images/503 users= 2515 per modality	95.43%	99.60%
Proposed system	**2023**	**Major and Minor dorsal finger knuckle**	**AlexNet, BSIF and PCA**	**PolyU Knuckle V1**	**5 images/503 users= 2515 per modality**	**98.25%**	**100%**

The proposed system in unimodal is better than most of the systems in the literature and it can be stated that it achieves superior result whenever multimodal recognition using both major and minor finger knuckles is employed.

Chapter 6

CONCLUSION

In recent years, scholars have become intrigued by a novel biometric trait called the finger knuckle print. Recent research has shown that the image pattern of the skin's knuckles is made up of wrinkles or lines, and that each user's finger's knuckle texture pattern is quite distinctive, making the surface unique for biometric identification. It is common knowledge that using a combination of traits can improve a biometric system's accuracy. Hence, this study explored the advantage of using multiple human traits in biometrics to create strong human recognition system. The experiments include using minor and major finger knuckles in a multimodal biometric system. Feature extraction methods include handcrafted feature extraction descriptors, namely Principal Component Analysis (PCA) and Binarized Statistical Image Feature (BSIF) Deep learning based Convolutional Neural Network (CNN) models, namely AlexNet and modified AlexNet have been used successfully in this study.

Preliminary experimental results comparing the individual accuracy of the major finger knuckle system and the minor finger knuckle system reveal that the former performed better in both PCA and BSIF due to the presence of clearer patterns on the major finger knuckles. However, this is not so in CNN models. Fusing the two traits at different stages show significant improvement in the system, especially in the case of PCA where as much as 15.1% improvement was made. The overall best accuracy achieved is a 100% accuracy reached by AlexNet model when score level fusion is used.

As a future work, other finger knuckle datasets may be employed to increase the validity of the experimental results. Additionally, various deep learning architectures such as ResNet, VGG-19, MobileNet, etc. should be used for finger knuckle recognition.

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