CONTACTLESS FINGERPRINT RECOGNITION USING DEEP LEARNING

M.Tech. Thesis

By

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DISCIPLINE OF ELECTRICAL ENGINEERING

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Submitted in partial fulfillment of the

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VIJAY NAGAR

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **CONTACT-LESS FINGERPRINT RECOGNITION USING DEEP LEARNING** in the partial fulfillment of the requirements for the award of the degree of **MASTER OF TECHNOLOGY** and submitted in the **DISCIPLINE OF ELECTRICAL ENGINEERING, Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from July 2019 to June 2020 under the supervision of Dr. Vivek Kanhangad, Associate Professor, IIT Indore.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

विजय नागर (18-06-2020)

Signature of the student with date

(VIJAY NAGAR)

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

18/06/2020

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Abstract

Contactless fingerprint recognition has become a popular field of research in biometrics in the last decade. Contactless fingerprint systems provide the advantages such as easy capturing and cost-effectiveness, along with the solutions to the problems in respect of hygiene, forgery, and latent fingerprint. Although many advancements have been taken place in this area, fingerprint recognition in contactless environment is still a challenging problem due to various constraints. For example, the presence of limited information in the image, background noise and low contrast between the ridges and the valleys. The contactless fingerprint system proposed in this work uses a Siamese model in deep learning framework to extract global features from a contactless fingerprint image. The method achieves an equal error rate (EER) of 10.07%, which is better than the EER obtained by the methods that employ handcrafted features namely, the minutia based NBIS Matcher and texture feature based Gabor filter bank. The score-level fusion of Siamese model, NBIS Matcher and CompCode yields the best matching performance with an EER of 3.53% on the contactless fingerprint dataset of HKPU Contactless 2D to Contact-based 2D Fingerprint Images Database Version 1.0.

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List of Abbreviations

A/D	Analog to Digital
CNN	Convolutional Neural Network
CompCode	Competitive Coding
EER	Equal Error Rate
FAR	False Acceptance Rate
FC	Fully Connected
FRR	False Rejection Rate
GA	Genetic Algorithm
GPU	Graphics Processing Unit
NIST	National Institute of Standards and Technology
NN	Neural Network
ReLU	Rectified Linear Unit
RGB	Red Green Blue
ROC	Receiver Operating Characteristics
UNIFIT	Unconstrained Fingerphoto

Chapter 1

Introduction

Biometrics refers to the automatic biometric recognition of an individual by using anatomical or behavioral traits associated with that person [17]. There are many biometrics traits associated with humans, but fingerprint has various advantages over the other biometrics traits due to its distinctiveness, permanence, and low-cost system availability [30].

Contactless biometrics systems demand increased when the pandemic situation surfaced in the world due to the spreading of COVID-19, where the spreading of the virus human to human is by just touching the surface that has been contaminated by the infected person. The biometrics methods such as contact-based fingerprint recognition require contact with the surface of the sensor and which leads to the hygienic threat of spreading the deadly diseases, e.g., severe acute respiratory syndrome (SARS) and COVID-19, which transmit by contact with contaminated objects or surfaces. In contact-based fingerprint recognition, when the surface of the sensor is touched to give finger imprints, the leftover or latent can be spoofed very easily by commonly available materials, such as silicone, gelatin, play-doh, etc. [7]. Therefore, it is a security threat. To avoid contact with the surface contactless fingerprint recognition system is a good alternative to contact-based fingerprint recognition. Several recent types of research are focusing on contactless fingerprint recognition [45],[22],[37], due to its advantages over contact base fingerprint recognition. Contactless fingerprint provides advantages of cost-effectiveness, easy capturing process, faster and hygienic alternative to physical and behavioral traits such as palmprint, iris, voice, signature, and gait recognition.

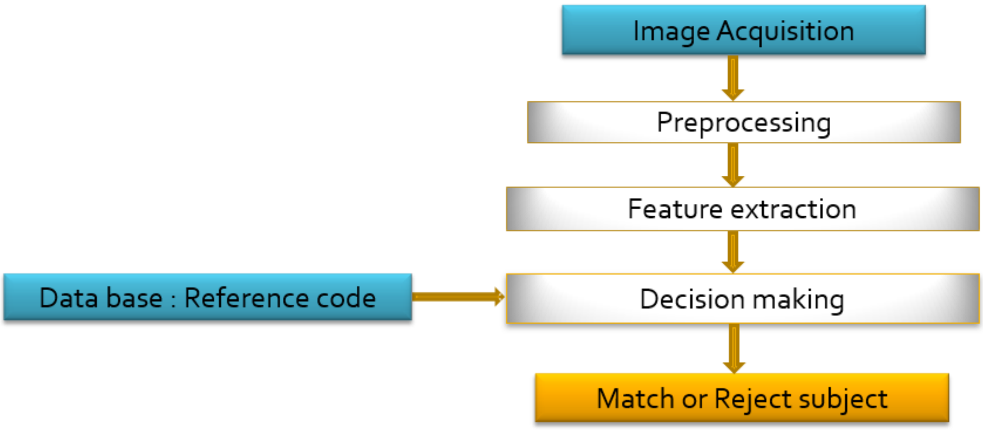

Figure 1.1: Basic structure of typical biometric system

Figure 1.1 shows the key steps that follow in biometric recognition systems. A detailed discussion of these steps is given in further introductory sections. At the time of image acquisition of the contactless fingerprint images due to various environmental conditions and quality of imaging sensor, the minutia features are challenging to extract from the contactless fingerprint images. Thus level zero features availability is more common in the contactless fingerprint systems. Deal with such type of features is more complicated than higher-level features because of less information is present with these features [2]. There are very fewer possibilities to get the results to make the contactless systems commercially realizable by using the traditional approaches and handcrafted tools.

Recent advancements in deep learning due to the availability of high computational devices, the deep learning algorithms demonstrated the state-of-the-art performance [21],[3] in a variety of image problems such as classification, pattern recognition, and feature extraction. Deep learning approaches have been utilized to address various contactless fingerprint problems such as comparison of contactless to contact-based fingerprint [28], fingerphoto segmentation [6] to discard background.

One of the most powerful deep learning structure is Convolutional neural network (CNN) which performs better results than old hand-crafted feature extractor or traditional approaches in image recognition task. CNN removes the requirement of extracting the features manually and provide distinct features from the image. It provides new features that would be very difficult to find by traditional methods. It is invariant to image deformations, like rotation and translation [1]. Therefore any success of the CNN based approach for the contactless finger image can have a range of applications such as law enforcement, digital forensics, indexing, mobile and remote biometrics identification.

1.1 Related Work

The contact-based fingerprint comparison has been widely researched with great success[33]; this gives the basis for the contactless fingerprint biometrics. The contact fingerprint systems required contact with the surface of the solid flat sensors and left a latent fingerprint, which can lead to forgery and hygienic issues, to overcome these disadvantages, the contactless fingerprint comparison getting the attention in biometrics. [11] developed the sensor for the touchless fingerprint using a camera. Lee et al. [26] proposed a contactless fingerprint recognition system using the contact-based matching [8]. Labati et al. [23] proposed the neural network (NN) approach for the contactless fingerprint recognition system in which estimate the rotation between two fingerprints by using the NN, for recognition purpose used the traditional algorithm MINDTCT and BOZORTH3 [41]. Yin et al. [45] introduced the new genetic algorithm (GA), which is called the loose GA to optimize the energy function of the similarity matrix and perform the contactless fingerprint recognition based on global minutia topology. Tiwari and Gupta [39] present the fingerphoto authentication by using a non-conventional scale-invariant feature. The built-in camera of the mobile is used for capturing the fingerphoto for biometrics; it removes the dependency of an extra sensor from the device. In [38] minutia-based fingerphoto system proposed that achieved the EER of 19.7% on the database that contains photos of the two test devices from 41 test subjects. In all these methods, the traditional approaches are used for recognition.

Lin and kumar [29] used the convolutional neural network for contactless 3D fingerprint features representation and obtained promising recognition accuracy. Reference [6] developed the unconstrained fingerphoto (UNFIT) dataset and used the deep learning based segmentation to discard the background information, select only foreground finger information, thereafter apply the CompCode and Resnet50 representation based matching. Dian and Dongmei[10] used CNN in contactless palmprint recognition, they used AlexNet for the feature extraction and hausdorff distance in machining and achieved remarkable accuracy. In [27] proposed multi Siamese networks to match the contactless to contact-based fingerprint accurately.

Literature review indicates, there are possibilities for the improvement in low-resolution contactless fingerprint feature representation as well as matching. The use of CNN in the contactless fingerprint biometrics can lead to significant improvements that are difficult to achieve by solely traditional approaches.

1.2 Challenges

For the Contactless fingerprint Biometrics, traditional as well as deep learning based approaches applied and achieved state-of-the-art performance, but Contactless fingerprint matching is still a challenging problem. It is a difficult problem due to high intra-class variations and small inter-class variations between the contactless fingerprints. Intra-class variations refers to difference of biometric knowledge between the two different images of the same subject and do not become identical throughout verification process. It increases the false rejection rate (FRR) in the biometric recognition system, which means the system is likely to reject the genuine user wrongly. Inter-class similarity refers to the overlapping of feature area which are belongs to different persons, It increases in false acceptance rate (FAR). The factors which are responsible for intra-class variations such as translation, rotation, and scaling on account of finger orientation and motion. The addition factors such as occlusions occurrence during the image acquisition and lightning conditions.

While doing the Contactless fingerprint matching using CNN, the same difficulties arise due to intra-class variation, as mentioned above. Convolution block in CNN is a grid structure by design, and it creates trouble when the image rotates and translates, the content of each cell into grid changes. In this way, the system accuracy degrades as described in [12].

1.3 Organization of the Thesis

This chapter has introduced contactless fingerprint recognition, related work, and open challenges in the implementation of contactless fingerprint biometrics systems. The remaining contents are organized as follows:

- **Chapter 2** : This chapter includes details about the fundamentals used further in the thesis. It provide basic knowledge of fingerprint recognition system, Section 2.3 covers the basics of CNN.

- **Chapter 3** : This chapter provides a detailed description of the proposed approach that has been used during the experimentation, describe the loss function, Siamese network architecture. Then, we cover NBIS Matcher, CompCode, and the possibility of fusion for improving the performance.

- **Chapter 4** : Consist of the description of the database, evaluation protocol, and results along with a detailed description of performance.

- **Chapter 5** : In this chapter, conclusions are made, and a discussion on the possibility of future work is presented.

Chapter 2

Background

In this Chapter we will discuss about some important topics that will help to understand further sections.

2.1 Biometric Recognition

A wide variety of applications required recognition systems to identify the person, either confirm or determine the identity of individuals to give access to the legitimate user of their service. Biometric recognition refers to the utilization of distinctive anatomical (e.g., face, iris, fingerprints) and behavioral (e.g., Signature, speech, Keystroke) characteristic, called biometrics identifier or traits for automatically recognizing individuals [30].

2.2 Fingerprints as Reliable Biometrics

There are many traits available in the human body to use in biometrics. Still, the fingerprint is very popular in the verification and identification of a person because of its many advantages over the other biometric trait.

Fingerprints are physiological traits that are captured when a person leaves a finger impression (which is ridges pattern of person's finger) on the surface of various material. The fingerprint of every individual remains the same during his lifetime even if the finger gets any cut or contusion; then also it gets back the same pattern after healing. It has been demonstrated that every person has a unique pattern of fingerprints, and it is easy to collect to the fingerprints of the individual. Because of all these advantages, fingerprints are being used in biometric recognition systems for over a century. The foundation of modern fingerprint recognition was established when Henry Faulds suggested the individuality of fingerprints scientifically [30]. In the late nineteenth century minutiae, features for comparing the fingerprints were introduced by Sir Francis Galton. The formation of fingerprints was well understood, and the usage of fingerprints was started with the development of bureaus for storage, identification, and verification of criminal records by the early twentieth century. Now it is being used in every possible area such as education, business sector, protection of data and information, medical, health, law enforcement applications, etc. Nowadays, boarding control police departments and private companies have databases that contain millions of samples of the imprint.

2.2.1 Fingerprint Sensing and Enhancement

Fingerprint sensing is the task where it takes finger imprints as input and converts into digitized form. Fingerprint can be obtained by smearing ink on the fingertip and place it on paper or on the sheet where it can be scanned by good quality scanners, or either we can use sensors to get fingerprints directly by placing the fingers tip on to sensor directly. The Figure 2.1 represent the general steps of a typical fingerprint scanner follows. The sensor is used to read the ridge pattern and transformed it into analog signals. Thereafter A/D converter converts the analog signals to digital form, some of the scanners do not require A/D converter because sensor of these scanners read the pattern of the fingerprint direct into digital form. The interface is used to establish communication with external devices.

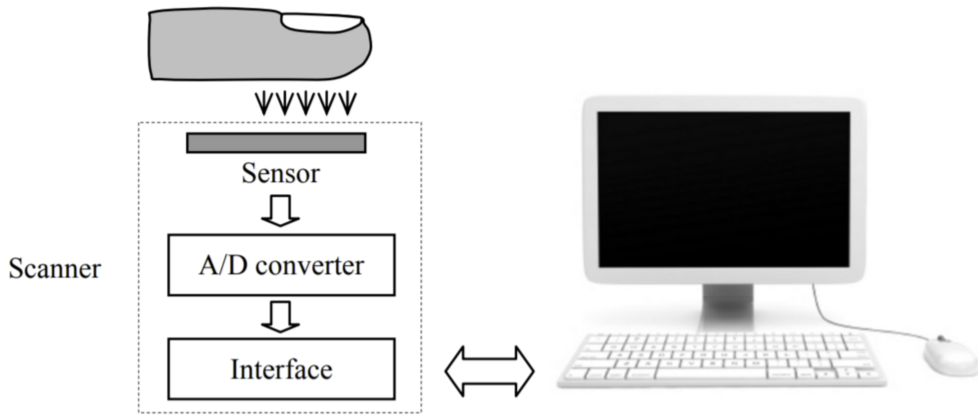

Figure 2.1: Block diagram of a typical fingerprint scanner [30]

After sensing enhancement of fingerprints is required to improve the quality of fingerprint image because, during the acquisition process, the fingerprints get distorted, and fingerprint recognition accuracy gets reduced, and it led to wrong decisions for the organization. Fingerprint recognition is hugely used in forensic where a big record of fingerprints of criminals is stored so criminals can be caught if the latent fingerprint is left at crime scenes.

2.2.2 Fingerprint Representation and Feature Extraction

Fingerprint representation is an essential part of the fingerprint recognition system; without this part, fingerprint matching is not possible. A good fingerprint recognition system should consist the following representation properties: suitability and saliency. suitability means that the fingerprint representation can be extracted easily, stored in compact, and finally can be used in comparison of fingerprints and saliency means that the extracted features or the representation of the fingerprints should contain the unique information [30].

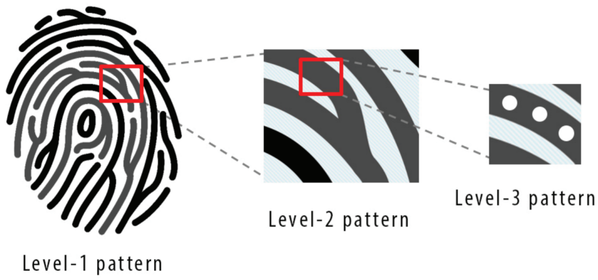

Figure 2.2: Representation of fingerprint feature levels (Level-1,Level-2 and Level-3) [15]

In Figure 2.2, Level-1 features represent global fingerprint patterns; the pattern of fingerprint contains regions where the ridge lines assume unique shapes. These regions known as singularities or singular regions. These regions are classified into three typologies: delta, whorl, and loop [18]. Level-2 features represent the local ridge details and called as minutia details. Minutia indicate to points at which the ridges can be discontinuous such as a ridge can divide into two ridges (bifurcation) or can abruptly come to an end (ridge ending or termination) [18]. In Figure 2.3 white and gray dots in the fingerprint image are representing the minutiae. Level-3 features are fine details such as sweat pores, ridges contours, incipient ridges. The process of feature extraction is to determine essential features from the fingerprint image and use them in the matching process to compute the two fingerprints. Various techniques for extracting salient features such as computing local ridge frequency, local ridge orientation, singular points, and minutiae are summarized in [30].

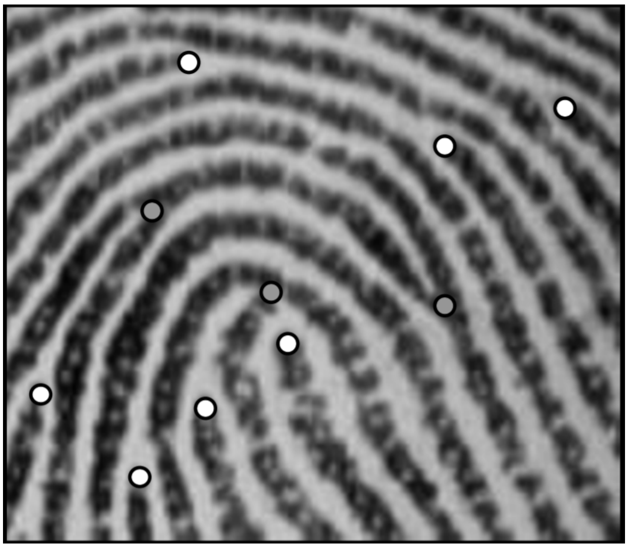

Figure 2.3: Representation of minutiae (termination and bifurcation), white dots are termination point, and gray dots are bifurcation points [18]

2.2.3 Matching

After detection of the valuable features information from the fingerprints through a feature extraction stage, the next step is to compare the fingerprint by using matching algorithms to find the degree of similarity and generate the scores (between 0 and 1) or give binary decision (matched or non-matched) [30]. Matching of fingerprints with less intra-subject variation don't require the much efforts or the difficult process. The problem arises when intra-subject variation high and inter-subject variations low. In matching process many challenges arise depending on the fingerprints information.

To deal with the matching problems there number of approaches exist, they are mainly classified into into three categories [18] 1)**Correlation-**

based Matching: the cross-correlation is well known for measure the similarity between images. In this type of matching, two fingers images superimposed on each other and compute the correlation between the corresponding pixels [30]. 2)**Minutiae-based Matching:** It is the most commonly used technique in fingerprint matching. In this matching scheme, extract the minutiae from the fingerprints and stored them as sets of points in the two-dimensional plane [18]. In minutiae-based techniques do not require fingerprint representation coincide with finger images as it happens in correlation-based techniques, here the representation is a feature vector that contains the minutiae elements [30]. The popular minutiae matching algorithms examine each minutia as a triplet m = {x, y, θ }, where (x, y) locate minutia coordinates and the θ is minutia orientation [18]. 3)**Ridge (non-minutiae) Feature-based Matching:** The approaches belonging to this family use the feature extracted from the ridge pattern to compare the fingerprints. The main reason to choose Ridge Feature-based matching is that extraction of minutiae points from low-quality images is very difficult, it is a time-taking process, and extra features may be used in conjunction with minutiae to increase system robustness and accuracy [18]. The correlations-based and minutiae-based algorithms can be related as a subfamily of Ridge Feature-based matching since both depend on Ridge pattern [30].

2.3 CNN

CNN is a class of deep neural networks that refers to a convolution neural network. CNN is also called a deep convolution neural network where deep represents a "few" to many combinations of convolution layers. As we earlier discussed for fingerprint recognition, we need to extract features. It is used to overcome the traditional machine learning limitations [25]. In machine learning, there is a need to select appropriate features for a given problem. A deep neural network does not require manual work in the selection of features; it automatically extracts the features from given input [32]. CNN is generally used for learning local features autonomously.

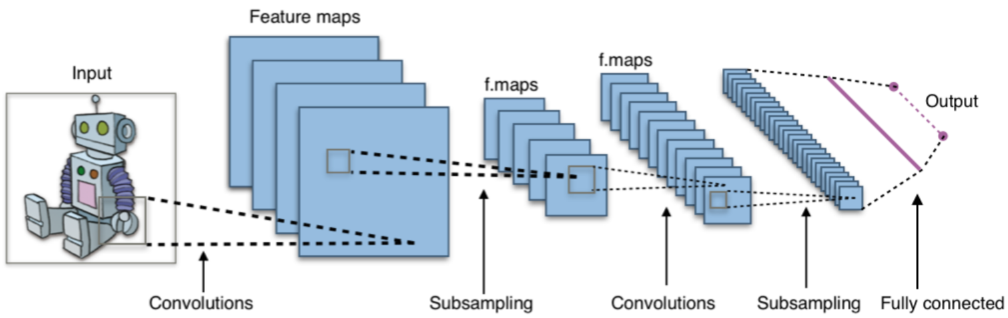

Figure 2.4: Basic CNN Architecture [43]

CNN mainly consists of the combination of convolutional layers, activation function (nonlinear layers), pooling layers, and fully connected layer, Where the convolution layer do use the kernel and it slides over the image to extract features. Choose proper Activation functions to get none-linearity in features of convolution layer. There is various type of activation function available that are applied in element-wise fashion. Pooling layers downsample the feature map to make more robust to changes in the position of the input feature map, it is done using max, average, etc. After many convolution layers and pooling layers in the last fully connected layer is used to complete the neural network, all the neurons are attached with activations in the previous layer.

2.3.1 Convolution

Convolution block is the core part of CNN, which has local connections and weights of shared characteristics. Convolution filter is used to detect visual features such as edge, lines, color drops, etc. The convolution operation is a mathematical operation where the input image matrix convolved with a weighted kernel. In deep neural networks, the convolution layer has two advantages over just using fully connected layers. The first advantage is the sparsity of connections, which means, in each layer, each output value depends on the small number of inputs. The second advantage is parameter sharing, which means a feature detector (such as a horizontal edge detector) that is useful in one part of the image probably useful in another part of the image. Due to the above concepts, the parameters reduce largely, and translation invariance is achieved for convolution operations.

In Figure 2.5, 2-D convolution is shown, Where kernel of size 2×2 slid over the input to perform convolution operation. In the Figure 2.5 boxes with arrows illustrating the formation of the upper-left component of output tensor by performing the convolution operation using the kernel to the corresponding upper-left part of the input tensor. This operation continues on the remaining part to complete the convolution over the entire input tensor.

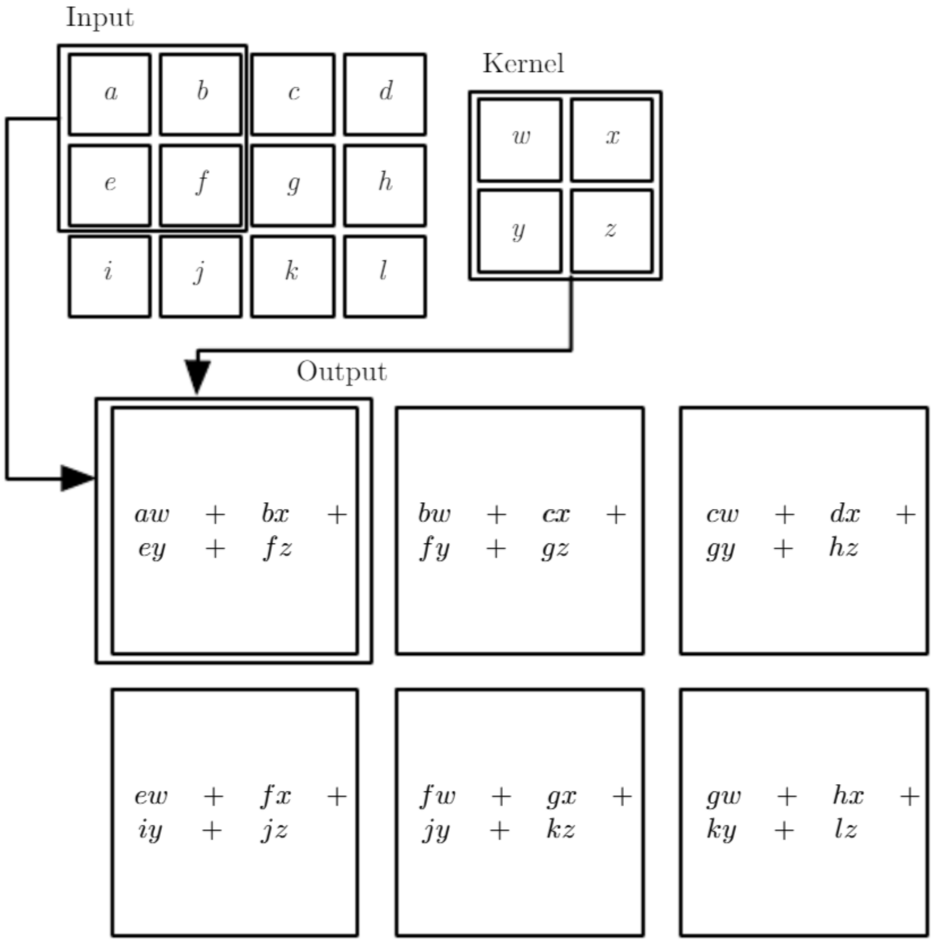

Figure 2.5: Example of 2-D convolution using 2×2 kernel over the 3×4 size input without kernel flipping [13].

2.3.2 Activation Functions

In the convolution neural network, the convolution layer performs the linear operation. The primary importance of the activation function in an artificial neural network is to provide non-linearity. The activation function of neurons constructs the output of the neuron given a set of inputs. It is biologically inspired by activity in the human brain, Where different neurons are fired or activated by different stimuli. The activation function is a nonlinear transformation of the input signal. Many different types of activation functions are available. One of the most widely used activation function is ReLU, which stands for the Rectified linear unit, and it blocks the values, which is zero or less than zero, and pass positive values only. Some of the Activation functions are illustrated in Figure 2.6

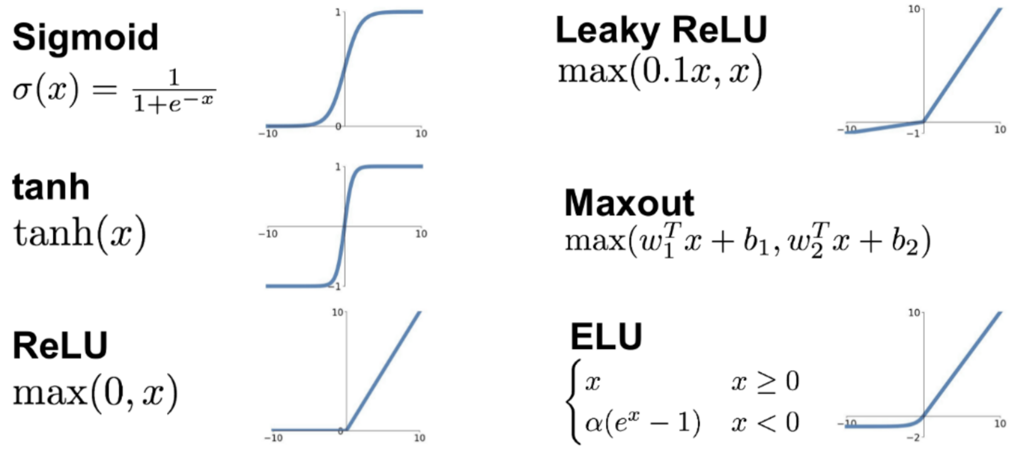

Figure 2.6: Different Activation functions [19]

The hyperbolic tangent function and Sigmoid function are standard activation functions that are counteractive almost everywhere, and the gradients of these functions at large values become almost zero. The stochastic gradient descent becomes very small, and it is known as the vanishing gradient problem. ReLU activation function can be used to avoided the problem of vanishing gradient. The speed of learning parameters in the deep neural networks can be improved by using the ReLU activation function [16].

2.3.3 Pooling Layers

Apart from convolutional layers, CNN often use polling layers, pooling layers generally functioning as for reducing the size of representation and speed up computation as well as make to detect the more robust features and also to control overfitting. Pooling operation can be done with various methods, which is depends on the type of pooling layer. Its working is similar to convolution filters.

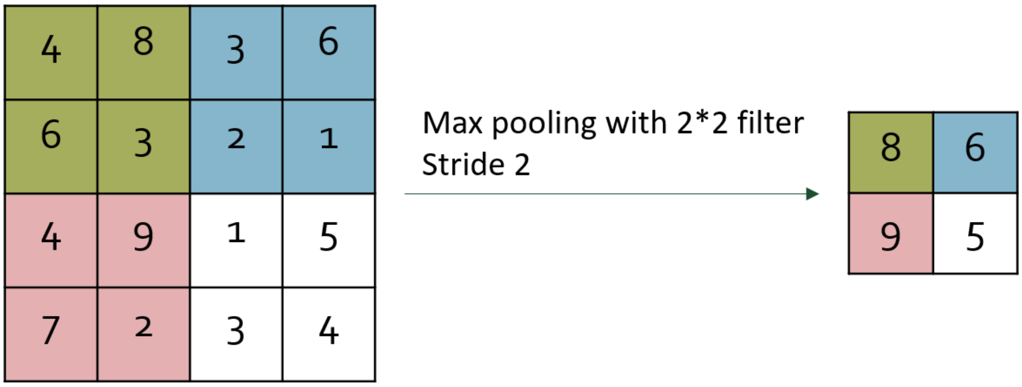

Figure 2.7: Illustration of Max Pooling operation

if translation of the input is small then Pooling layers are useful for making the representation nearly invariant [13]. It means, the input translate by a slight amount, most of the values of pooled outputs remain unchanged. The widely popular examples of pooling layers is the max-pooling layer, which down-sample the features by selecting a maximum value from the given rectangular neighborhood (filter block) and place it at the output. This operation performed by sliding the filter window over the input and output replace with the filter max value. Figure 2.7 is an example of max-pooling operation, the kernel size of max-pooling filter is 2×2 with the stride of 2 that is sliding over a 4×4 input image.

Max-pooling layer in a neural network have its drawback also. when applying a max-pooling operation it reduces spatial resolution. If a network have numerous max-pooling layers with large stride may drop the much spatial information of the input features. This issue can be solved by avoiding the large stride and/or reducing the number of max-pooling layers [24].

2.3.4 Fully Connected Layer

Fully Connected (FC) layers are usually used in last part of CNN, where the output of last layer Conv or ReLU or pool layer first using flattening to convert the matrix into a vector and then fed into the FC layer and gives output N-dimensional vector, where N represent the number of elements in the feature vector, it can be number of classes in the classification problem. It's one layer neuron connected with another layer. The FC layer is also known as Dense layer. In the above figure x (x1, x2, x3, and x4) is feature vector that is input to the FC layers, and (y1,y2, and y3) are the element of the output feature vector.

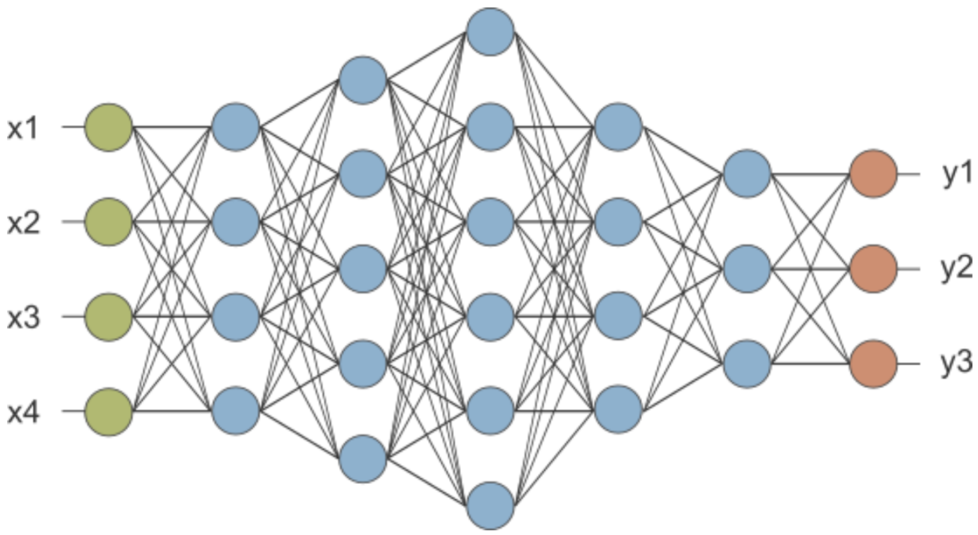

Figure 2.8: Example of FC Layers [36]

Chapter 3

Proposed Approach

In this Chapter, we provide the detail of the proposed method that we performed during the contactless fingerprint recognition experiments. In the proposed method, the deep neural network we used is the Siamese model, which is a comparison-based model, where two inputs are feed into two neural networks with shared weights. The loss function for the model is contrastive. The minutia base feature extractor we used NBIS Matcher, and for texture-based, we used CompCode that are handcrafted based feature extractors. In the end, we discuss the fusion of scores.

3.1 Loss Function

We used the contrastive loss function to minimize the loss and optimize the proposed Siamese model. It was introduced by Hadsell et al. [14]. It is similar to other distance-based loss functions, e.g., triplet loss; it is calculated on pairs of input and gives the final output as distance. It tries to make semantically similar examples embedded close together and vice-versa.
The Equation 3.1 refers to the contrastive loss function

$$ContrastiveLoss = Y_{true} \times D^2 + (1 - Y_{true}) \times (max\{margin - D, 0\})^2 \quad (3.1)$$

Where D is Euclidean distance between two feature vectors, D will be small if features are from the same objects and large if features are from dissimilar objects. Y_{true} is a label between two inputs pairs, which is $\{0, 1\}$ and $margin$ should be always greater than zero ($margin > 0$).

3.2 Deep Learning Network for Contactless Fingerprint

Siamese networks are getting popular for image recognition purposes in deep learning. Siamese network is first proposed for the signature verification [4], then it modified and use Siamese CNNs in face verification [5], where the Siamese architecture comprises two identical sub-networks and one cost module. In this Siamese architecture, two input face images pass and find whether images belong to the same person or not. Here in our research, we use the Siamese model for the contactless fingerprint recognition. Two identical CNN used as sub-network in the Siamese model, these two CNN have identical weights and hyperparameters.

The proposed Siamese model is illustrated in the Figure 3.1. The input to the Siamese model is a pair of contactless fingerprint images with label. These images pass through the sub-networks and representing them with Convolutional neural network (CNN) based feature vectors. The distance between these feature vectors is measured by Euclidean distance. The contrastive loss function combine label with the distance. The loss of the network reduces and learn optimal feature representations of the input pairs where similar pairs close together, and dissimilar pairs push far, the similarity of

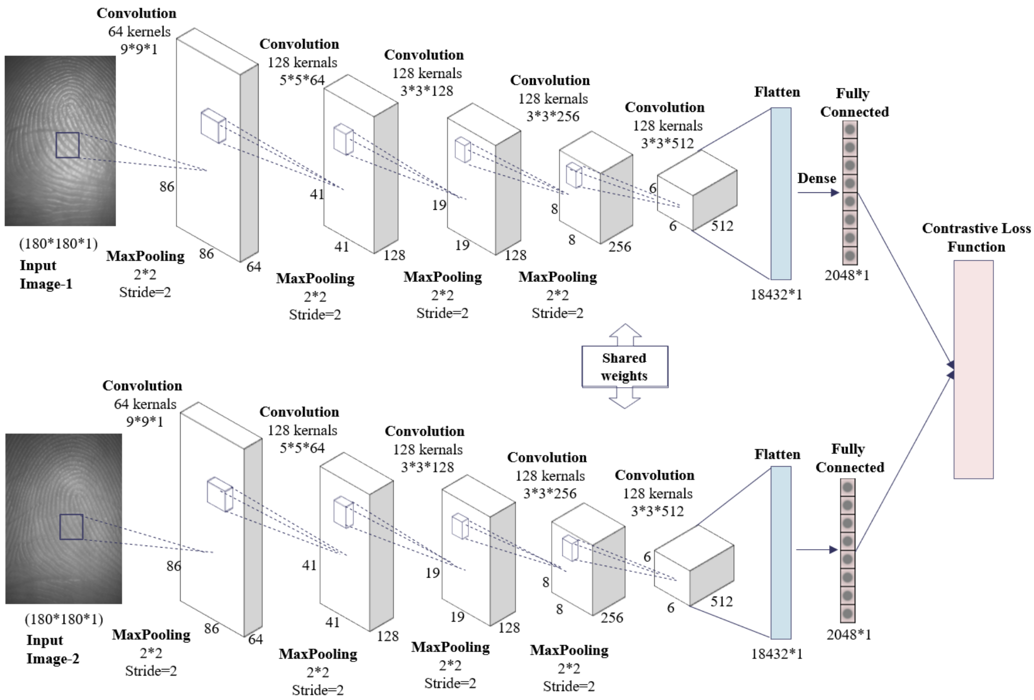

Figure 3.1: Schematic Diagram of Siamese Network Architecture

these pairs is measured by Euclidean distance [31].

In CNN, the convolutional layer with the rectified linear unit (ReLU) helps to provide non-linearity in output, Max-Pooling layer for selecting maximum values from each block, thereafter flatten layer, in last dense layer with activation function ReLU helps to take the output feature vector of the CNN. Siamese model gives distance-based scores so that we can use them in matching directly. Details of CNN layers are given in the Table 3.1.

Table 3.1: Siamese network architecture

Layer	Output Shape	Kernel	Stride	Parameters
Conv1, ReLu	(172,172,64)	9x9	-	5248
MaxPooling	(86,86,64)	2x2	2	-
Conv2, ReLu	(82,82,128)	5x5	-	204928
MaxPooling	(41,41,128)	2x2	2	-
Conv3, ReLu	(39,39,128)	3x3	-	147584
MaxPooling	(19,19,128)	2x2	2	-
Conv4, ReLu	(17,17,256)	3x3	-	295168
MaxPooling	(8,8,256)	2x2	2	-
Conv5, ReLu	(6,6,512)	3x3	-	1180160
flat	18432	-	-	-
fc1, ReLu	2048	-	-	37750784
Total				39,583,872

3.3 NBIS Matcher for Minutiae Matching

NBIS Software was Developed by the FBI and the National Institute of Standards and Technology (NIST). In an Automated Fingerprint Identification System, two major biometric algorithms play an indispensable role that are features extractor and matcher. NBIS Software for feature extraction uses a program called MINDTCT, for matcher BOZORTH3. NBIS software come up with MINDTCT, which is a minutiae detector, it automatically locates and records ridge ending and bifurcations in a fingerprint image [42, 44]. MINDTCT program provides the detail of minutiae features in the form of ".xyt" file format. The minutiae values write in "x y theta quality" format, each minutia per line. Where x and y give the detail about location of minutiae point and theta gives the orientation information of minutiae point.

MINDTCT minutiae files are input to the matcher algorithm. The program BOZORTH3 computes matching scores of fingerprint minutiae files. It uses minutiae data tracked by MINDTCT program to find whether two fingerprints are similar or dissimilar. Here in our method, we calculated the matching scores on the 100 classes of dataset. We extract features with the help of bash script using MINDTCT program and generate scores using BOZORTH3 in octave enviroment [35].

3.4 Competitive Coding (CompCode)

CompCode features are non-minutiae based features. The CompCode scheme uses a 2-D Gabor filter bank to extract orientation information from a contactless finger image. After then, this information store in a feature vector, and it is known as the competitive code. CompCode utilizes Gabor filters with $\frac{\pi}{J}$ intervals with J different orientations of total available Gabor filter orientations [9] and choose different scales. The following equation defines a Gabor filter:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} e^{j(\pi)ifx} \tag{3.2}$$

where f denotes the frequency of sinusoid factor and σ is the standard deviation of Gaussian envelop. The CompCode features are extracted by convolving the image $I(x, y)$ with the real part of Gabor filter G_r, and this can be defined as:

$$CompCode(x, y) = argmin_j[I(x, y) * G_r(x, y)] \tag{3.3}$$

Gabor filter is used for texture analysis by extracting features. A set of Gabor filter banks with different orientations and scales is used for extracting useful features from an image. For the matching score computation, we use the cosine similarity-based function to compare the feature vectors of the output of the Gabor filter bank. Cosine similarity-based function gives high value if the features vectors have high similarity.

3.5 Fusion

In biometric recognition as new developments are coming, it becomes increasingly difficult to increase the system performance, and there is very little chance left to achieve good accuracy by a given biometric identifier. To improve performance, we need to explore other methods and areas. Fusion is one of them to enhance biometric system performance. The fusion approach can be used in many forms to improve the system accuracy, e.g., multiple biometric traits, numerous instances of the same biometric characteristic, even complimentary feature extraction and matching algorithms for the same example of a biometric trait [30]. Various identifiers can be used for fusion at the matcher decision level, matcher score, feature, and sensor.

In our proposed method, we used the score fusion of the Siamese network, CompCode, and NBIS Matcher. Where the Siamese network gave distance-based score, CompCode and NBIS Matcher gave a similarity-based score. In the fusion process, all scores are transformed into the similarity-based score and perform normalization after that, fusion of the scores is performed.

Chapter 4

Experiments and Results

4.1 Dataset Preprocessing and Augmentation

In experimentation, we used The HKPU Contactless 2D to Contact-based 2D Fingerprint Images Database Version 1.0 [40], which is freely available. This database contains 2976 contactless 2D fingerprint images from 336 different clients/fingers. Each client provided 6 different fingerprint samples from a finger (6 images of each finger). The PolyU database [40] contains contactless finger image in RGB colour image with size 1400×900 pixels. It also contains the processed contactless fingerprint sub-database; each image of the processed database is a grayscale image of size 350×225 pixels. To improve the quality of images the image enhancement techniques that have been used in our experimentation is Adaptive Histogram equalization [34].

As we know, CNN requires higher data to get the results based on the problem it introduced. Our data is in the form of images. To augment the database, we applied image data augment techniques. The techniques we used for our experimentation are the Rotation, Translation of image, Introduce pepper salt noise, and Gamma transformation. We augmented to

(a)

(b)

Figure 4.1: Sample images of the polyU database[40], (a) processed contactless fingerprint image, (b) Enhanced image using Adaptive Histogram equalization

30 images for each finger image. Thus after augmentation, the total images increase to 35,640 in the training dataset. Before feeding the data to the network, resize images to (180, 180, 1).

Table 4.1: Database detail

Dataset	**Image size**	**Fingers**	**Images per finger**	**Total images**
Training set	300 × 225	198	6	1188
Validating set	350 × 225	38	6	228
Test set	350 × 225	100	6	600

Detail of the processed contactless fingerprint images of PolyU database [40] that is divide into the training set, validating set and testing set for the Siamese network is described into Table 4.1.

4.2 Evaluation Protocol

The dataset is divided into the training, validation, and testing categories. The testing dataset is different from the training and validating dataset. Training and validating dataset used to train and validate the Siamese model. At the testing time, the dataset is used of different client fingerprint images. For training and validation, respectively 198, 38 client's images have been used. Remaining 100 client's finger images have been used for testing from PolyU database [40].

Every experiment performed during the research we used all-to-all matching protocol. It means every fingerprint is matched with other fingerprint images and find genuine and imposter scores. A set of genuine scores is generated by comparing each fingerprint image to all other remaining fingerprint images belong to the same finger and to generate imposter score compare each finger image to all others that do not belong to the same finger. Thus, from our test dataset, 1500 genuine matching scores and 178200 imposter matching scores are generated. To ascertain the performance of the proposed work, we use ROC (receiver operating characteristics) and equal error rate (EER). The decision threshold curve of False Rejection Rate (FRR) and False Acceptance Rate (FAR) shows that the operating point at which FAR and FRR are equal to each other gives the Equal Error Rate.

4.3 Experimental Evaluation and Results

The Deep learning methods required much time and extensive data in the training process to perform well during testing. For training purpose and reducing training time, we used an online platform Google Colab that provides exceptionally high computational GPU systems. To perform deep learning tasks, we used the Keras API with TensorFlow backend in the python environment. We trained our Siamese network to 30 epochs using batch size 128 and learning rate of 0.00005. The network parameters loss function is optimized using adaptive moment estimation (Adam) optimizer [20]. The margin of contrastive loss function was selected 2. Siamese CNN architecture in Table 3.1 is used to perform the deep learning task. It took more than 30 minutes to train the network on Google Colab and after that model is saved and used it to extract distance-based scores of the test data. The matching performance of the Siamese CNN architecture is illustrated in the Figure 3.1 . Decision threshold curve of Siamese model-based is shown in Figure 4.2(a). The equal error rate of the system is calculated using the scores, EER of 10.07% is observed for the Siamese model-based approach.

We used NBIS Matcher software in the bash and octave environment to generate the scores on the Linux operating system [35]. Where first used the MINDTCT program for minutiae extraction then these minutiae computed using BOZORTH3 program for scores generation. In the process of matching the score, EER of 11.24% is observed. Decision threshold curve of NBIS Matcher is shown in Figure 4.2(c).

In CompCode, the Gabor filter scale and orientations choose 5 and 16 respectively. The number of rows and columns in a 2-D Gabor filter takes an odd integer number and set to 39. Extracted features create a column vector of the input image. Use the cosine similarity to generate the scores from the

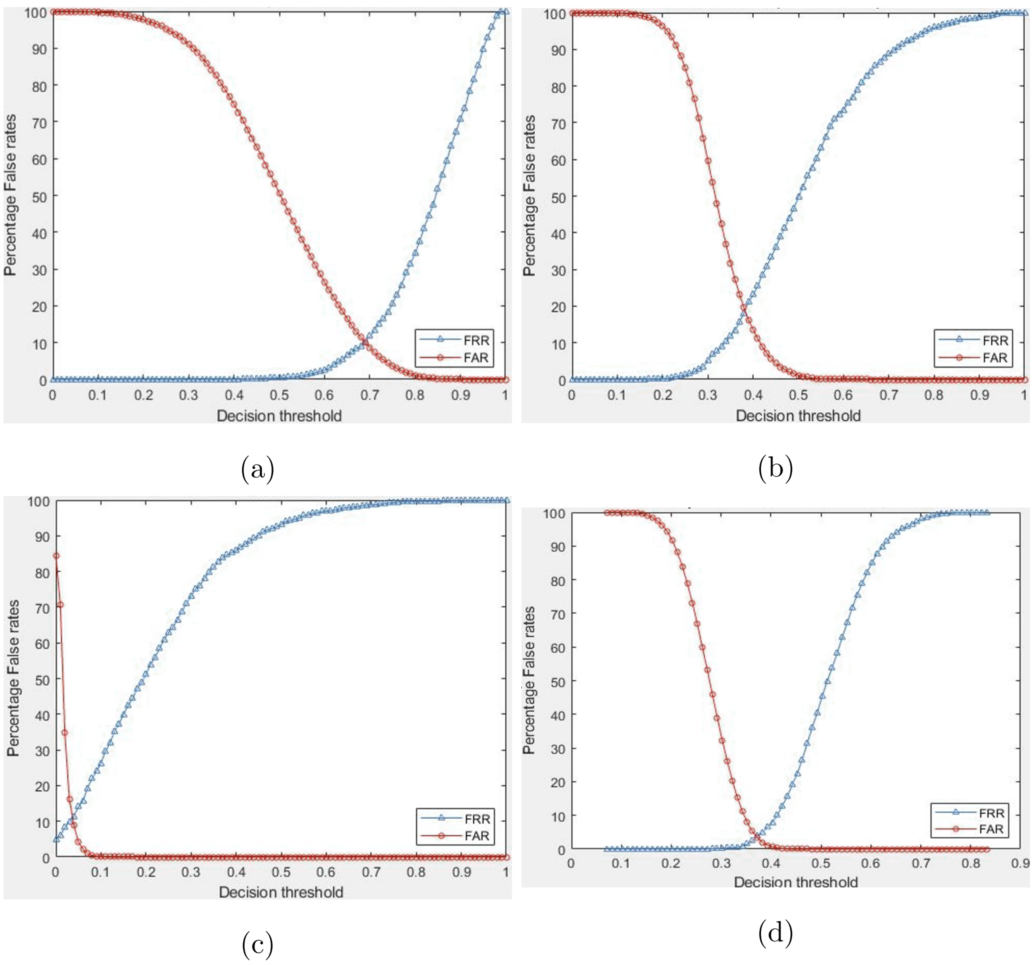

Figure 4.2: FAR and FRR derived from the score distribution of: (a) Siamese model; (b) Gabor filters; (c) NBIS Matcher; (d) fusion of scores of Siamese model, Gabor filters, and NBIS Matcher

feature vectors. After matching these scores, the EER of 18.71% is found.

Thereafter we performed scores fusion of the Siamese model and Gabor filters the EER reduced to 6.70%. After that fuse the scores of the Siamese model, Gabor filters and NBIS Matcher, the EER reduced to 3.53%. The matching performance illustrates in Figure 4.3, which shows the comparison of the ROC curves of all the methods that have performed in this research.

Table 4.2: Experimental performance on PolyU database[40]

Experiments	EER(%)
Siamese Model	10.07%
NBIS Matcher	11.24%
Gabor Filters	18.71%
Fusion (Siames+Gabor)	6.7%
Fusion (Siames+Gabor+NBIS)	3.53%

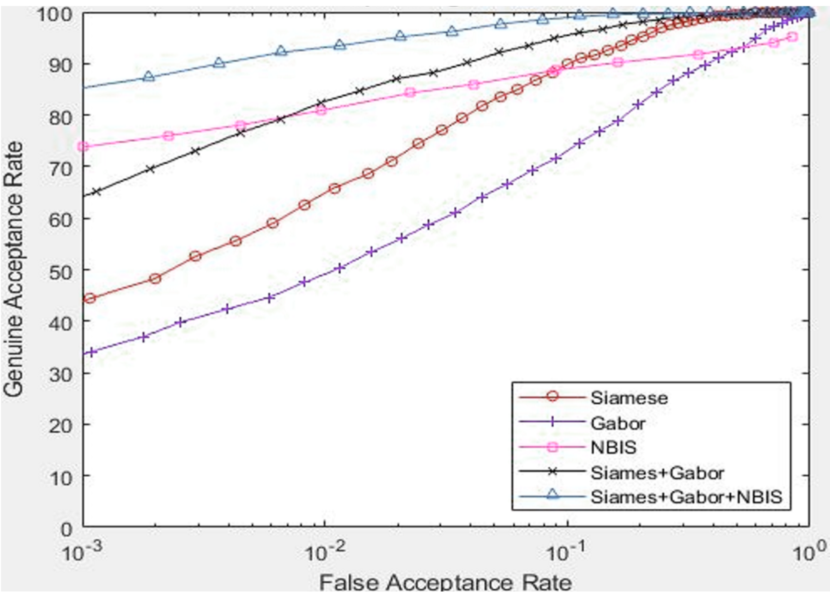

Figure 4.3: ROC curve for contactless fingerprint [40] performance using the Siamese model, Gabor filter, NBIS Matcher, Score-fusion (of Siamese model and Gabor filter), and Score-fusion (of Siamese model, Gabor filter, and NBIS Matcher)

Chapter 5

Conclusion and Future Work

In this research, the detailed analysis of the contactless fingerprint has been done and identify the possibilities of fusion of scores to improve the performance of the contactless fingerprint recognition. We work on the deep learning-based model to find the possible new features from the contactless fingerprint image, which are very difficult by handcrafted methods and minimize the difficulty in the deployment of contactless fingerprint systems. The results of our experimentation on PolyU database [40] show that the Siamese model performance is better than the minutiae-based system when the performance requirement does not demand a very low FAR. The matching performance is enhanced by combining the decisions of the matcher based on complementary (deep learning, Gabor filter, and minutiae-based) fingerprint information.

In future, we plan to improve the performance of the system with the help of better image enhancement techniques and advancement in the present CNN model. We work on the dataset that has more degrees of freedom, such as finger images in the various background with rotation, use deep learning segmentation techniques to find the accurate region of interest from these finger images.

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