FINGER VEIN BIOMETRIC RECOGNITION USING CONVOLUTIONAL NEURAL NETWORK

A PROJECT REPORT

Submitted by

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DEPARTMENT OF COMPUTER APPLICATIONS

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DECLARATION

I undersigned hereby declare that the project report on **FINGER VEIN BASED BIOMETRIC RECOGNITION USING CONVOLUTIONAL NEURAL NETWORK** , submitted for partial fulfillment of the requirements for the award of degree of Master of Computer Applications of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under supervision of **Prof.Natheera Beevi M**. This submission represents my ideas in my own words and where ideas or words of others have been included,I have adequately and accurately cited and referenced the original sources. I also declare that we have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in our submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree, diploma or similar title of any other University..

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C E R T I F I C A T E

This is to certify that, this report titled ***Finger Vein Biometric Recognition Using Convolutional Neural Network*** is a bonafide record of the **Main Project** presented by, **GAYATHRI CHANDRALAL (TKM19MCA011)**, under our guidance and supervision, in partial fulfillment of the requirements for the award of the degree, **Master of Computer Application** in **APJ Abdul Kalam Technological University** .

Internal Supervisor | Head of the Department | External Examiner

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Gayathri Chandralal

Abstract

The use of human finger-vein traits for the purpose of automatic user recognition has gained a lot of attention in recent years. Current state-of-the-art techniques can provide relatively good performance, yet they are strongly dependent upon the quality of the analysed finger-vein images. In this paper, I propose a convolutional-neural-network-based finger-vein identification system and investigate the capabilities of the designed network over four publicly available databases. The main purpose of this paper is to propose a deep-learning method for finger-vein identification, which is able to achieve stable and highly accurate performance when dealing with finger-vein images of different quality. The reported extensive set of experiments show that the accuracy achievable with the proposed approach can go beyond 95 percent correct identification rate for all the four considered publicly available databases.

Index Terms :- Convolutional neural network, finger-vein, biometrics, identification.

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Chapter 1

Introduction

Finger vein recognition is a method that specifies an individual using the vein pattern inside one's fingers. Finger vein patterns are unique to each individual, even among identical twins. The false acceptance rate is very low (close to zero). Placing a hand or finger is less intrusive compared to other biometric technologies. Because veins are located inside the body, it is extremely difficult to read or steal and hence cannot be duplicated. Finger veins are less likely to be influenced by changes in the weather or physical condition of the individual. Finger vein authentication works by utilizing the differences of vein patterns for personal identification. The authentication process is carried out by comparing the vein pattern that is previously captured during enrollment to the vein pattern that is taken during authentication, and checking if they match.

- The present proposal has applied Sobel detector, enhancement filter and a binarization process to get the vein pattern.
- The system uses a dataset of human index finger, middle finger and ring finger images acquired on infrared range.
- We use VGG16 a type of CNN that detects the object i.e the vein pattern.
- Which works by utilizing the differences of vein patterns for personal identification.
- Compares the vein pattern with existing pattern.
- Thus proves the given pattern is authenticated.

Chapter 2

Literature Survey

When one uses literature review research questions are identified, then one seek to answer this research questions by searching for and analyzing relevant literature. Some importance of literature reviews is that new insights can be developed by the re-analyzing the results of the study. A literature review is both a summary and explanation of the complete and current state of knowledge on a topic as found in academic books and journal articles. There are two kinds of literature reviews you might write at university: one that students are asked to write as a stand-alone assignment in a course, and the other that is written as part of an introduction to, or preparation for, a longer work, usually a thesis or research report. The focus and perspective of your review and the kind of hypothesis or thesis argument you make will be determined by what kind of review you are writing. One way to understand the differences between these two types is to read published literature reviews or the first chapters of theses and dissertations in your own subject area. Analyses the structure of their arguments and note the way they address the issues.

2.1 Purpose of the Literature Review

1. It gives readers easy access to research on a particular topic by selecting high quality articles or studies that are relevant, meaningful, important and valid and summarizing them into one complete report.
2. It provides an excellent starting point for researchers beginning to do research in a new area by forcing them to summarize, evaluate, and compare original research in that specific area.
3. It ensures that researchers do not duplicate work that has already been done.
4. It can provide clues as to where future research is heading or recommend areas on which to focus.
5. It highlights the key findings.
6. It identifies inconsistencies, gaps and contradictions in the literature.
7. It provides a constructive analysis of the methodologies and approaches of other researchers.

2.2 Related Works

[1]**Finger Vein Recognition with Anatomy Structure Analysis**

Finger vein recognition has received a lot of attention recently and is viewed as a promising biometric trait. In related methods, vein pattern-based methods explore intrinsic finger vein recognition, but their performance remains unsatisfactory owing to defective vein networks and weak matching. One important reason may be the neglect of deep analysis of the vein anatomy structure. By comprehensively exploring the anatomy structure and imaging characteristic of vein patterns, Hsu CM et al. in 2020 proposed a novel finger vein recognition framework, including an anatomy structure analysis-based vein extraction (ASAVE) algorithm and an integration matching strategy. Specifically, the vein pattern is extracted by the orientation map-guided curvature based on the valley- or half valley-shaped cross-sectional profile. In addition, the extracted vein pattern is further thinned and refined to obtain a reliable vein network.

[2]**Tri-branch Vein Structure Assisted Finger Vein Recognition**

In template matching of finger vein recognition, the probe will be accepted if the number of its overlapped vein points with the enrolled user is larger than the predefined threshold. However, the acceptance may be false owing to ignoring the structure of the vein pattern. We find that local vein branches near the bifurcation point of vein pattern vary largely between the imposter images. So, Nguyen MT et al.in 2019 proposed in this paper tries to explore this kind of local vein structure to improve the recognition performance of the template matching. The bifurcation point and its local vein branches, named tri-branch vein structure, are extracted from the vein pattern, and fused with the whole vein pattern by a user-specific threshold-based filter framework. The experimental results on two public databases prove the effectiveness of the proposed framework for improving the performance of vein pattern-based finger vein recognition.

[3]**Cancelable Permutation-Based Indexing for Secure and Efficient Biometric Identification**

This paper schemes transform biometric features and perform pattern matching without restoring the original features. Although they strongly prevent the leakage of the original features, the response time can be very long in a large-scale biometric identification system. Most of the existing indexing schemes cannot be used to speed up the biometric identification system over networks since a biometric index leaks some information about the original feature. Secure and efficient indexing is a major challenge in large-scale biometric identification over networks. In this paper, Aslahi-Shahri BM et al. in 2019 developed a novel indexing scheme that is promising with regard to both security and efficiency. The proposed indexing scheme transforms a permutation-based index, which is the state-of-the-art index in the field of similarity search, and performs a query search without recovering the original index.

[4]**Design and Development of low-cost Sensor to capture ventral and dorsal Finger-vein**

for Biometric Authentication Biometrics-based authentication of subjects is widely deployed in several real-life applications. Among various biometric characteristics, finger-vein characteristic has demonstrated both reliable and highly accurate authentication for access control in secured applications. However, most of these systems are based on commercial sensors where the image level data is not available for academic research. In this paper, Gao J et al. 2018 developed a we present the design and development of a low-cost finger-vein sensor based on a single camera that can capture finger-vein images from dorsal and ventral part of the finger with high quality. The system consists of multiple Near-Infra-Red (NIR) light sources to illuminate the finger from both sides (left and right) and top. The camera in the sensor is also coupled with the custom designed physical structure to facilitate high reflectance of the emitted light and distribute the light uniformly on the finger to capture good quality dorsal and ventral finger-vein pattern.

Chapter 3

Methodology

3.1 Datasets

Since there is limited number of publicly available database for finger vein recognition, we have developed an infrared finger image database. The database consists of the information of finger vein and also finger geometry. It can be used to verify either unimodal biometrics (finger vein and finger geometry) or bimodal biometrics (fusion of vein and geometry) systems. Complete with the extracted ROI (region of interest) for finger vein recognition, this database is made available on the web for the sake of assisting other researchers in the related fields to test and evaluate their algorithms based on standard benchmark database.

The images in the database were collected from 65 volunteers comprising of 35 males and 30 females. The age of the subject ranged from 20 to 52 years old. Every subject provided four fingers:index, middle, and ring fingers resulting in a total of 113 finger classes obtained. The captured finger images provided two important features: the geometry and the vein pattern. Each finger was captured six times in one session and each individual participated in two sessions, separated by more than two weeks' time. In the first session, a total of 2952 (123 x 4 x 6) images were collected. Therefore, from two sessions, we obtained a total of 5904 images from 492 finger classes. The spatial and depth resolution of the captured finger images were 640 x 480 and 256 grey levels, respectively.

3.2 Magnification of Vein Pulsations

The EVM reveals subtle motion in a video by magnifying the intensity variations over time. The vein structures are magnified by applying EVM on the vein videos. However, the noise in the video frames may also get magnified along with the vein region. To minimize this effect and reliably detect the vein patterns from the magnified videos, the video has to be pre-processed using a filter that can enhance the vein patterns. The filter response will give high value on the vein region and low value on the other regions as the filter is designed to detect the curvilinear structures. The pre-processed videos may include other texture details such as prominent prints, wrinkles etc. on the skin. Nevertheless, only veins which are showing rhythmic changes are filtered out and magnified by the EVM. This guarantees the accurate detection of veins from the magnified vein videos.

3.3 Vein Image Template Generation

In this section, a template generation approach is proposed for finger-vein verification. To reduce intra-class variations, similar to existing approaches, we merge multiply templates from same class to generate a "super-template" and then improve it by using the vein features in finger-vein images captured at different time. The template generation aims at reducing the intra-class variations, so a "super-template" is directly generated by minimizing the intra-class distance. First, we define the optimal template for finger-vein verification. Based on the definition, we convert the template generation into an optimization problem. Second, the weights are computed by matching the samples from same class or different class. Thirdly, a robust template is obtained by solving an optimization problem.

3.3.1 Template Quality Definition for Verification

Current template generation methods [16–21] aim at improving performance, mainly verification error rates. Therefore, the biometric template generation should target its minimization instead of being based on subjective human perception of enrollment template quality. In a practical verification system, a user's biometric data is once again acquired and processed, and the extracted features are matched against the template(s) stored in the database for verification. The verification accuracy relies on the stability (permanence) of the biometric data associated with an individual over time [17]. On other words, the verification error rates are mainly triggered by the intra-class variations, so we assume that a good quality finger-vein template has smaller intra-class distance with respect to all enrollment samples.

3.3.2 Similarity Computation

For finger-vein verification, the vein textures are segmented and stored in binary images, which are employed for matching for verification. As the weight is related to the similarity, a similarity between two enrollments is firstly defined in Equation (2) to obtain robust weight. Then, a weight is automatically assigned for each sample based on the intra-class similarity and inter-class similarity.

$$V(x, y) = \sum_{i=2}^{n} |\tilde{I}(x, y, t_i) - \tilde{I}(x, y, t_{i-1})|,$$

3.4 VGG-16 — CNN

The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is an annual computer vision competition. Each year, teams compete on two tasks. The first is to detect objects within an image coming from 200 classes, which is called object localization. The second is to classify images, each labeled with one of 1000 categories, which is called image classification. VGG 16 was proposed by Karen Simonyan and Andrew Zisserman of the Visual Geometry Group Lab of Oxford University in 2014 in the paper "VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION". This model won the 1st and 2nd place on the above categories in 2014 ILSVRC challenge. This model achieves 92.7%

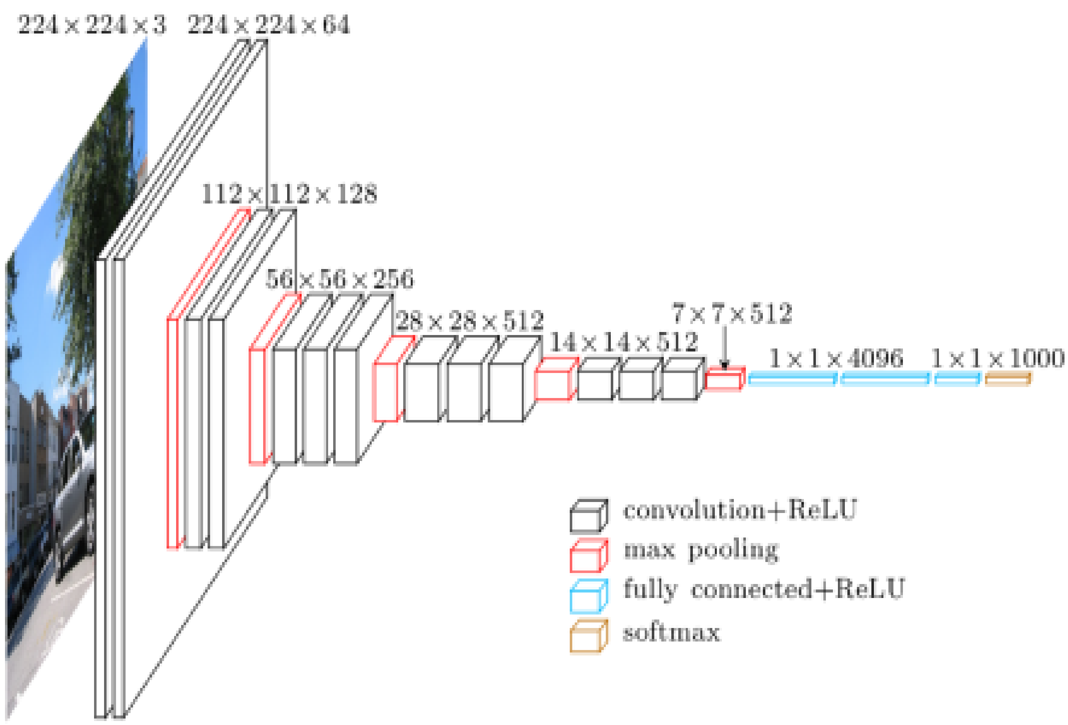

Figure 3.1: VGG-16 System

top-5 test accuracy on ImageNet dataset which contains 14 million images belonging to 1000 classes.

Objective: The ImageNet dataset contains images of fixed size of 224*224 and have RGB channels. So, we have a tensor of (224, 224, 3) as our input. This model process the input image and outputs the a vector of 1000 values. This vector represents the classification probability for the corresponding class. Suppose we have a model that predicts that image belongs to class 0 with probability .1, class 1 with probability 0.05, class 2 with probability 0.05, class 3 with probability 0.03, class 780 with probability 0.72, class 999 with probability 0.05 and all other class with 0.

Architecture: The input to the network is image of dimensions (224, 224, 3). The first two layers have 64 channels of 3*3 filter size and same padding. Then after a max pool layer of stride (2, 2), two layers which have convolution layers of 256 filter size and filter size (3, 3). This followed by a max pooling layer of stride (2, 2) which is same as previous layer. Then there are 2 convolution layers of filter size (3, 3) and 256 filter. After that there are 2 sets of 3 convolution layer and a max pool layer. Each have 512 filters of (3, 3) size with same padding.This image is then passed to the stack of two convolution layers. In these convolution and max pooling layers, the filters we use is of the size 3*3 instead of 11*11 in AlexNet and 7*7 in ZF-Net. In some of the layers, it also uses 1*1 pixel which is used to manipulate the number of input channels. There is a padding of 1-pixel (same padding) done after each convolution layer to prevent the spatial feature of the image.

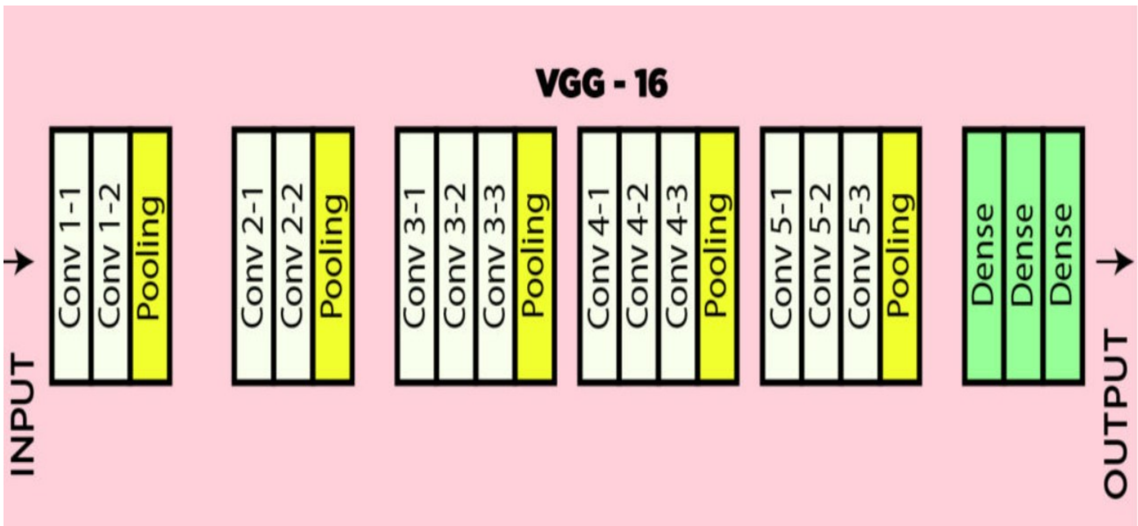

Figure 3.2: VGG-16 Architecture

3.5 Finger Vein Recognition

Finger vein recognition is a method that specifies an individual using the vein pattern inside one's fingers.

Since deoxy hemoglobin in the blood absorbs near-infrared lights, vein patterns appear as a series of dark lines. The near-infrared lights combined with a special camera capture an image of the finger vein patterns. The image is then converted into pattern data and stored as a template of a person's biometric authentication data. During authentication, the finger vein image is captured and compared against the stored template of the user.Finger-vein recognition can be considered as an image classification problem. It must be interesting to use CNNs to handle the finger-vein recognition problem! How should we design experiments to adapt to needs of biometric authentication systems. According to previously used finger-vein recognition methods, many of them conduct feature extractions then calculate the distance between two features. A threshold is fixed according to distributions of feature distances. If the distance value is higher than the threshold, these two features are not categorized as being from the same person. Otherwise, if the distance is lower than the threshold, these two features are treated as being from the same person.

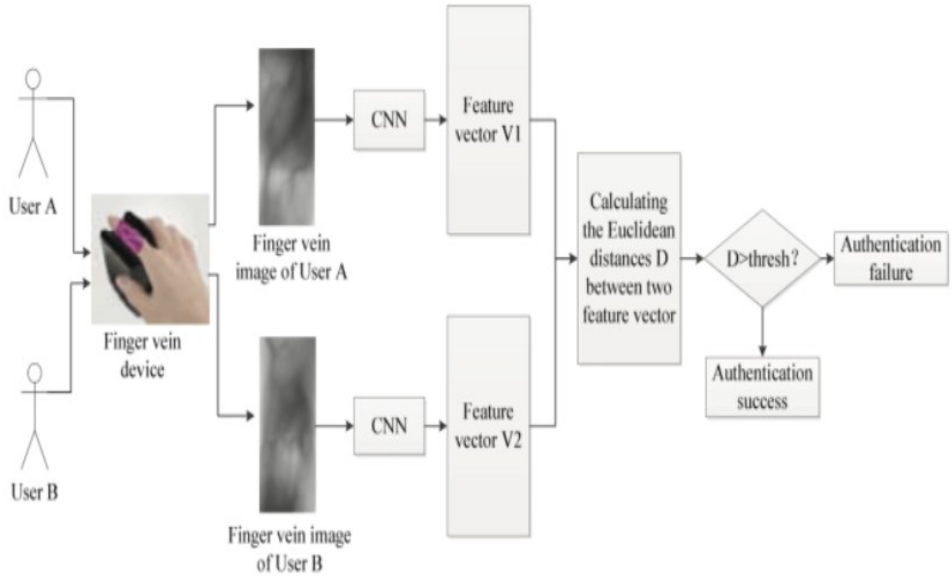

Figure 3.3: Finger Vein Recognition Module

The features of finger vein recognition are as follows: Finger vein patterns are unique to each individual, even among identical twins. The false acceptance rate is very low (close to zero). Placing a hand or finger is less intrusive compared to other biometric technologies. Because veins are located inside the body, it is extremely difficult to read or steal. There is little risk of forgery or theft. Finger veins do not leave any trace during the authentication process and so cannot be duplicated. Finger vein patterns remain relatively constant through the adult years so that re-enrollment of the vein pattern will not be required once enrolled. Finger veins are less likely to be influenced by changes in the weather or physical condition of the individual. Rushes, cracked and rough skin do not affect the result of authentication.

3.5.1 Image Data Preprocessing

Image preprocessing are the steps taken to format images before they are used by model training and inference. This includes, but is not limited to, resizing, orienting, and color corrections.

Image augmentation are manipulations applied to images to create different versions of similar content in order to expose the model to a wider array of training examples. For example, randomly altering rotation, brightness, or scale of an input image requires that a model consider what an image subject looks like in a variety of situations.

Image augmentation manipulations are forms of image preprocessing, but there is a critical difference: while image preprocessing steps are applied to training and test sets, image augmentation is only applied to the training data. Thus, a transformation that could be an augmentation in some situations may best be a preprocessing step in others..

3.5.2 Image Scaling

Once we've ensured that all images are square (or have some predetermined aspect ratio), it's time to scale each image appropriately. We've decided to have images with width and height of 100 pixels. We'll need to scale the width and height of each image by a factor of 0.4 (100/250). There are a wide variety of up-scaling and down-scaling techniques and we usually use a library function to do this for us.

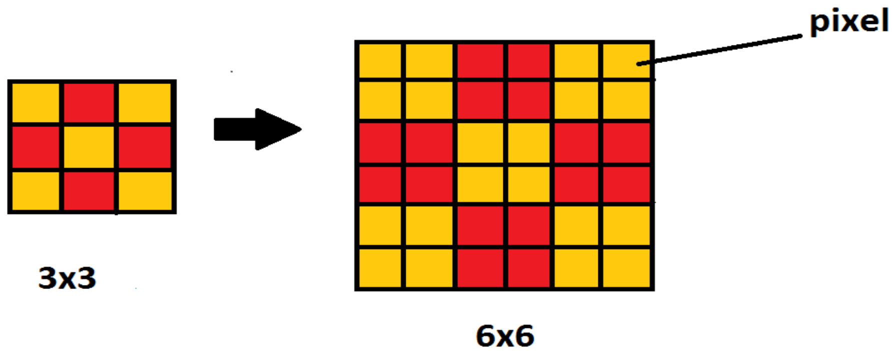

Figure 3.4: Image Scaling Method

3.5.3 Mean, Standard Deviation of input data

Sometimes it's useful to look at the 'mean image' obtained by taking the mean values for each pixel across all training examples. Observing this could give us insight into some underlying structure in the images. For example, the mean image from the first 100 images of our data-set is shown below to the left. Clearly, this has the loose impression of a human face and lets us conclude that the faces are somewhat aligned to the center and are of comparable size. We may choose to augment our data with perturbed images if we don't want our input data to have this innate structure. The standard deviation of all images is shown to the right. Higher variance values show up whiter, so we see that the pictures vary a lot at the boundaries compared to the center

$$S_i = (x, y)|b(T_i + 1) <= r < b(T_i + 2), \theta_i <= \theta <= \theta_(i + 1), 1 <= x <= N, 1 <= y <= M \tag{3.1}$$

where $\mathrm{T}_i = i \text{ div } k, \theta_i = (i \bmod k) * (2\pi/\mathrm{k})$, r=$\sqrt{(x - x_c)^2} + \sqrt{(y - y_c)^2}, and$
$\theta = ((y - y_c)/(x - x_c))$

3.5.4 Dimensionality reduction

Another common pre-processing technique involves augmenting the existing data-set with perturbed versions of the existing images. Scaling, rotations and other affine transformations are typical. This is done to expose the neural network to a wide variety of variations. This makes it less likely that the neural network recognizes unwanted characteristics in the data-set.

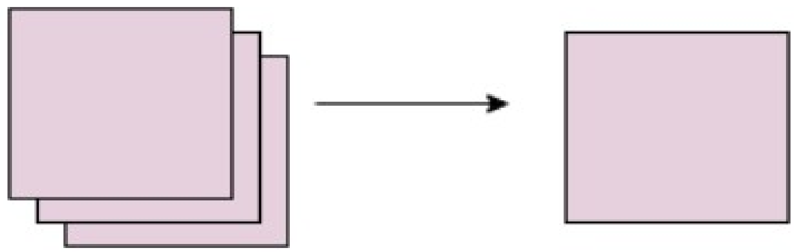

Figure 3.5: Dimensionality reduction Method

Handling the high-dimensional data is very difficult in practice, commonly known as the curse of dimensionality. If the dimensionality of the input dataset increases, any machine learning algorithm and model becomes more complex. As the number of features increases, the number of samples also gets increased proportionally, and the chance of overfitting also increases. If the machine learning model is trained on high-dimensional data, it becomes overfitted and results in poor performance.

Hence, it is often required to reduce the number of features, which can be done with dimensionality reduction.

3.5.5 Data augmentation

Another common pre-processing technique involves augmenting the existing data-set with perturbed versions of the existing images. Scaling, rotations and other affine transformations are typical. This is done to expose the neural network to a wide variety of variations. This makes it less likely that the neural network recognizes unwanted characteristics in the data-set. Image augmentation creates new training examples out of existing training data. It's impossible to truly capture an image that accounts for every real world scenario a model may encompass. Adjusting existing training data to generalize to other situations allows the model to learn from a wider array of situations.

This is particularly important when collected datasets may be small. A deep learning model will (over)fit to the examples shown in training, so creating variation in the input images enables generation of new, useful training examples.

3.6 Finger Vein Biometric

Finger vein biometrics, also called vein matching or vascular technology, is a technique for biometric authentication that analyzes the patterns of blood vessels visible from the surface of the skin of fingers. This technique relies on capturing images of the veins inside one's hand by shining near-infrared light on their fingers. This makes it almost impossible to counterfeit. In addition, blood flow in the veins during identification ensures that the individual is alive and real, rather than a fraudster.

3.6.1 Preprocessing

Finger vein recognition biometrics is based on the images of the unique veins beneath the skin of an individual's hands. To capture the pattern, an attester terminal containing a near-infrared LED (light-emitting diode) light and a monochrome CCD (charge-coupled device) camera is utilized. The hemoglobin in the blood absorbs the light, which makes the veins appear as a pattern of lines. The camera records the image and the raw data is digitized and sent to a database of similar images.

For authentication, the finger is scanned by a special camera in the same way as before, and the data is verified against the database of registered images. The whole process takes less than two seconds. These near-infrared camera systems can also be built into mobile devices, to enable ubiquitous and secure identification.

Since it is based on the vein patterns under the skin surface, it is said to be more accurate than a fingerprint, which have been faked in the past. Also, since it's the veins, this authentication process provides proof that the individual whose identity is being verified is a live person.

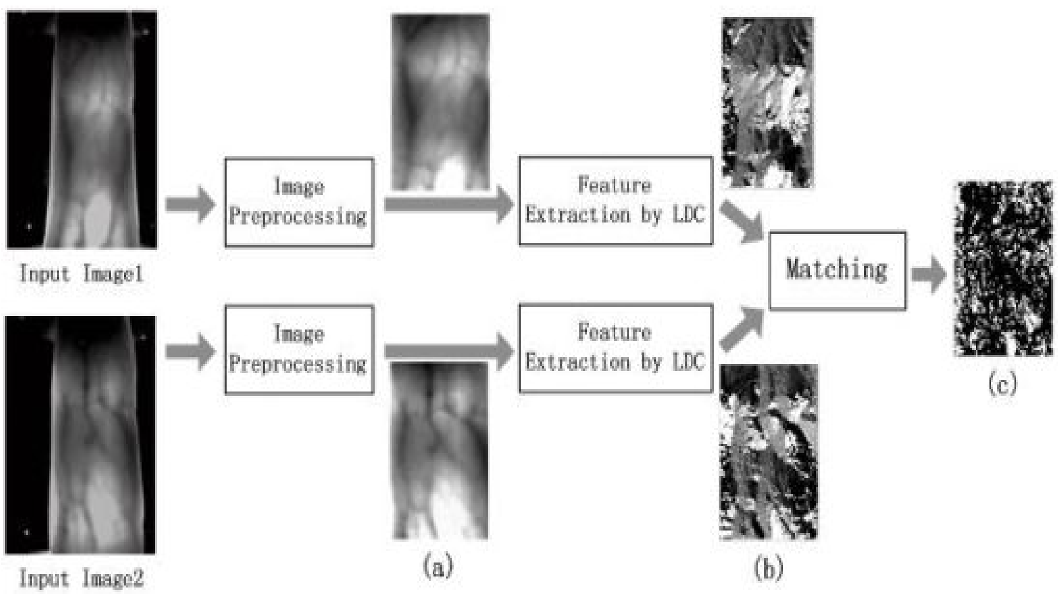

Figure 3.6: Finger Vein Entrollment

3.6.2 Feature Extraction

For the needs of the study, the analyzed feature extraction algorithms were divided into five categories:

(1) algorithms based on vein patterns,

(2) algorithms based on dimensionality reduction,

(3) algorithms based on local binary patterns,

(4) algorithms based on image transformations, and

(5) other feature extraction methods.

For each category, a cumulative and comparative table is presented for the methodologies belonging to the specific category. It should be noted that, in most cases, the feature extraction method's performance is evaluated according to the Recognition Rate (RR), Accuracy, and Equal Error Rate (EER) metrics. In our case, we regarded the performance of a methodology as having a high RR or accuracy when its performance was equal to or higher than 99and its performance in terms of the EER was regarded as low when it was lower than 1The selection of these thresholds was based on the high demands imposed by the critical application of the biometric systems. A finger vein image is acquired by placing a finger on a camera, with a near-infrared (NIR) light pointed towards it from the opposite side of the camera. With the NIR light pointing towards the finger, the veins become visible and thus a feature extraction process can be applied.

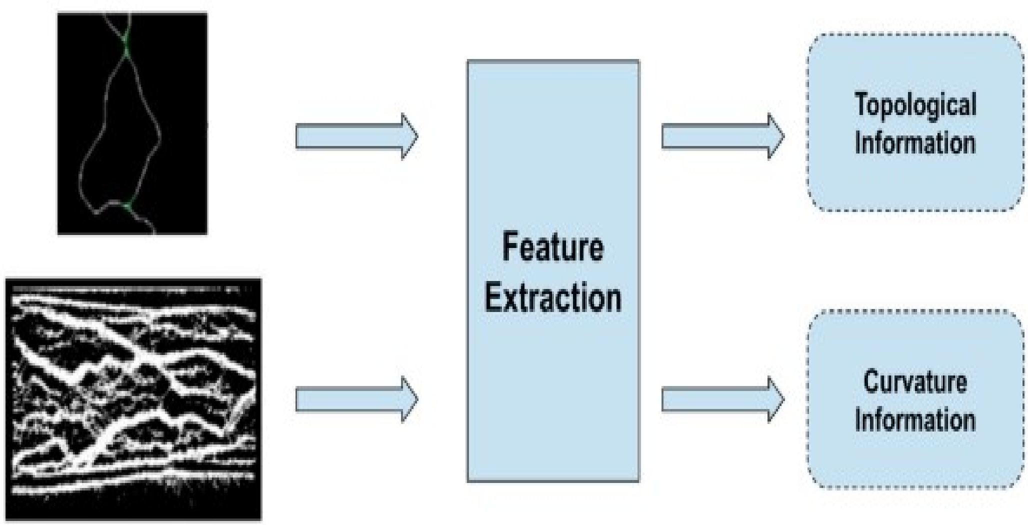

Figure 3.7: Typical extraction of information relative to the vein patterns

In general, the methodologies that extract features regarding the patterns of the finger veins depend on the preprocessing steps to a high degree, as the more visible the veins are in the binary image, the better the performance of each methodology. The algorithms, in general, are efficient enough to be ported into an ARM or low-power device and have low EER values (lower than 1calibration by setting parameters that can influence their performance, and the classification is done via a matching score or distance/similarity calculation, which can be efficient for small databases, but time consuming in large ones. Moreover, Gabor filters seem to be a useful feature extractor of vein patterns due to their ability to describe the frequency and orientation of texture patterns. This sums up the studies mentioned in this category, showing the key features, advantages, and disadvantages of each method.

3.6.3 Feature Extraction Based on Local Binary Patterns

the extraction process of Local Binary Pattern (LBP)-based features is depicted. These methodologies, after extracting the ROI of the finger vein, apply a type of LBP-based algorithm and extract the LBP images as shown in the figure. In some cases, the histogram of the image is used for the matching process instead.

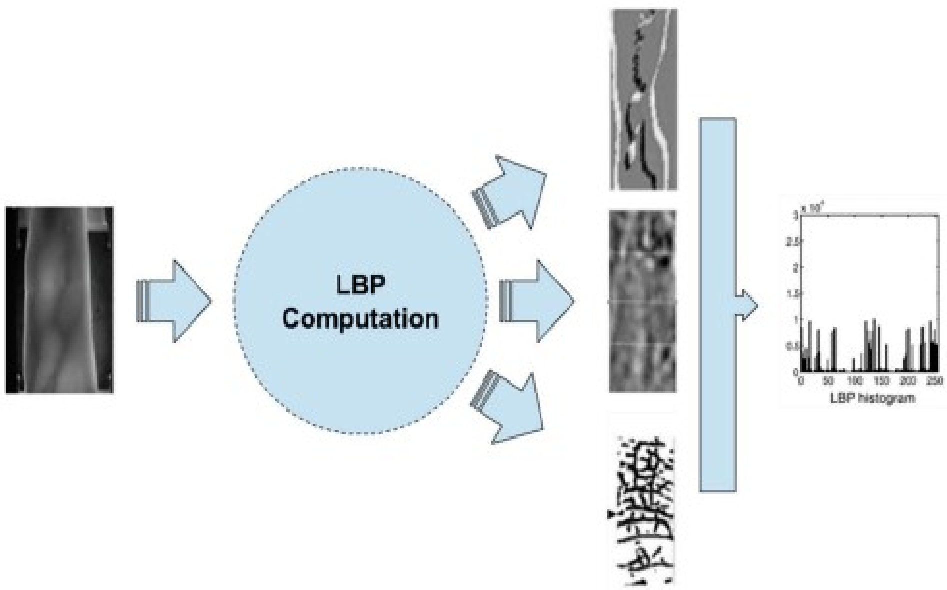

Figure 3.8: Feature extraction using LBP-based features

3.7 Image Data Preprocessing

Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subfield of digital signal processing, digital image processing has many advantages over analogue image processing. It allows a much wider range of algorithms to be applied to the input data — the aim of digital image processing is to improve the image data (features) by suppressing unwanted distortions and/or enhancement of some important image features so that our AI-Computer Vision models can benefit from this improved data to work on. Digital image processing is the use of computer algorithms to perform image processing on digital images. As a subfield of digital signal processing, digital image processing has many advantages over analogue image processing. It allows a much wider range of algorithms to be applied to the input data — the aim of digital image processing is to improve the image data (features) by suppressing unwanted distortions and/or enhancement of some important image features so that our AI-Computer Vision models can benefit from this improved data to work on.

3.7.1 Image sharpening

Image sharpening is an effect applied to digital images to give them a sharper appearance. Sharpening enhances the definition of edges in an image. The dull images are those which are poor at the edges. There is not much difference in background and edges. On the contrary, the sharpened image is that in which the edges are clearly distinguishable by the viewer. We know that intensity and contrast change at the edge. If this change is significant then the image is said to be sharp. The viewer can clearly see the background and foreground parts.

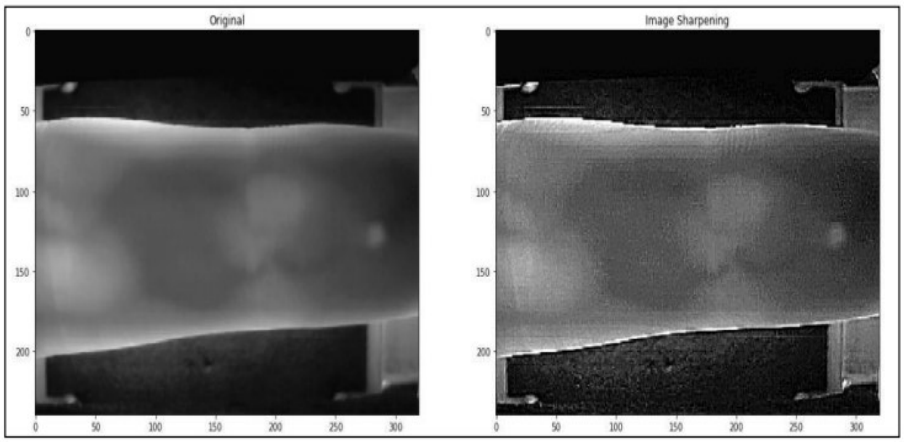

Figure 3.9: Sharpening of the identified veins

3.7.2 Threshold Binary

Thresholding is a type of image segmentation, where we change the pixels of an image to make the image easier to analyze. In thresholding, we convert an image from colour or grayscale into a binary image, i.e., one that is simply black and white. Most frequently, we use thresholding as a way to select areas of interest of an image, while ignoring the parts we are not concerned with. We have already done some simple thresholding, in the "Manipulating pixels" section of the Image Representation in skimage episode. In that case, we used a simple NumPy array manipulation to separate the pixels belonging to the root system of a plant from the black background. In this episode, we will learn how to use skimage functions to perform thresholding.

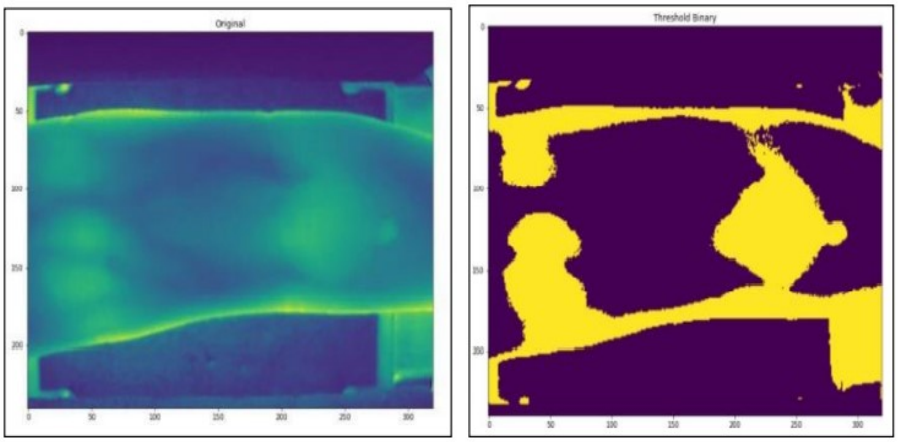

Figure 3.10: Threshold Binary done to create binary image

3.7.3 Sobel Filter

The Sobel method, or Sobel filter, is a gradient-based method that looks for strong changes in the first derivative of an image.

The Sobel edge detector uses a pair of 3×3 convolution masks, one estimating the gradient in the x-direction and the other in the y-direction. This edge detector maps well to CUDA, as each thread can apply the 3×3 convolution masks to its pixel and adjoining pixels in the image.

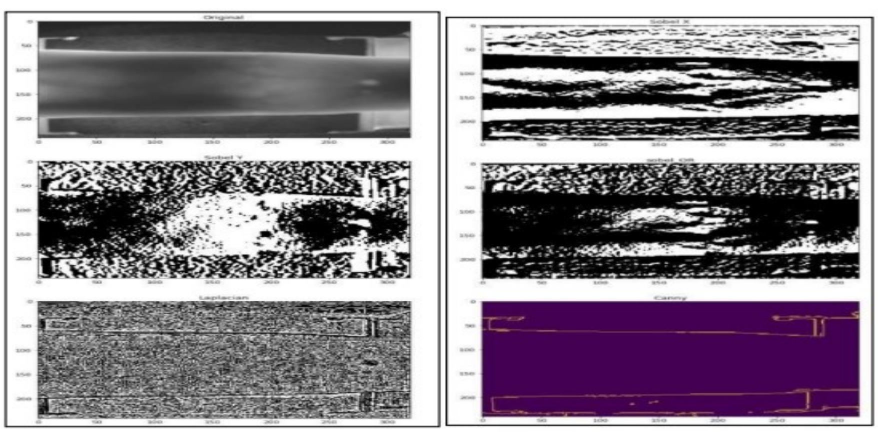

Figure 3.11: Sobel filter

Chapter 4

Results and Discussions

4.1 Recognition Accuracy Based Comparison

In order to evaluate the proposed network, I have first compared its performance with several state-of-the-art identification techniques by using the training and testing strategies adopted in referenced papers for our proposed network as well. We have then designed an optimal training strategy for our proposed network. Most of the state-of the-art techniques have used either a single image or images from a single session for their network's training, which may not be ideal for our CNN-based approach. It is in fact well known that the availability of a single sample of every class, here individual fingers, does not allow a CNN to get trained properly. Eventually, I have also evaluated the utility of exploiting image enhancement preprocessing techniques together with the proposed to understand if further performance improvement could be achieved. The identification accuracies achieved by the state-of-the art finger-vein-based biometric systems that are discussed together with the obtained performance with our proposed CNN-based approach, when using the same training and testing strategies. The results obtainable while exploiting two of the most-commonly employed methods for finger-vein recognition, i.e., MC and RLT, under all the considered settings, are additionally reported for further comparisons.

As it can be seen from the reported accuracies, our CNN based identification system cannot be properly trained under the experimental setup employed, where only session-1 images from HKPU dataset are used for training, and session-2 images for testing. A similar situation is encountered when comparing the proposed system, where tests over the FV-USM dataset have been performed by considering only the first image of every finger from session-1 for training and the 6 images per finger of session-2 for testing. Again, the reason behind such a low performance depends upon the number of training samples, along with the different quality of finger-vein images that exists in two distinct sessions . A different behavior of our network has been observed when considering the training/testing settings employed and the SDUMLA database, which contains images taken from a single session. In this scenario, the method here proposed is able to achieve identification performance better than those obtained. It is therefore reasonable to observe that the proposed CNN-based identification system can work properly when images of similar quality are used for both training and testing purposes, regardless the absolute quality level of the considered images. This assumption is confirmed by the results referred to the comparison of the proposed approach against MC and RLT, while taking one finger-vein image from each session of the

UTFVP dataset, and using the remaining ones for testing purposes. The proposed CNN-based identification system easily outperforms both MC and RLT. It is worth remarking that the aforementioned results have been obtained with the proposed CNN-based identification system without performing any kind of enhancement on finger vein images. Conversely, all the methods we are comparing with use some image enhancement technique and feature selection processes. Therefore, the use of original images without any preprocessing and automatic feature extraction are among the advantages of our proposed network

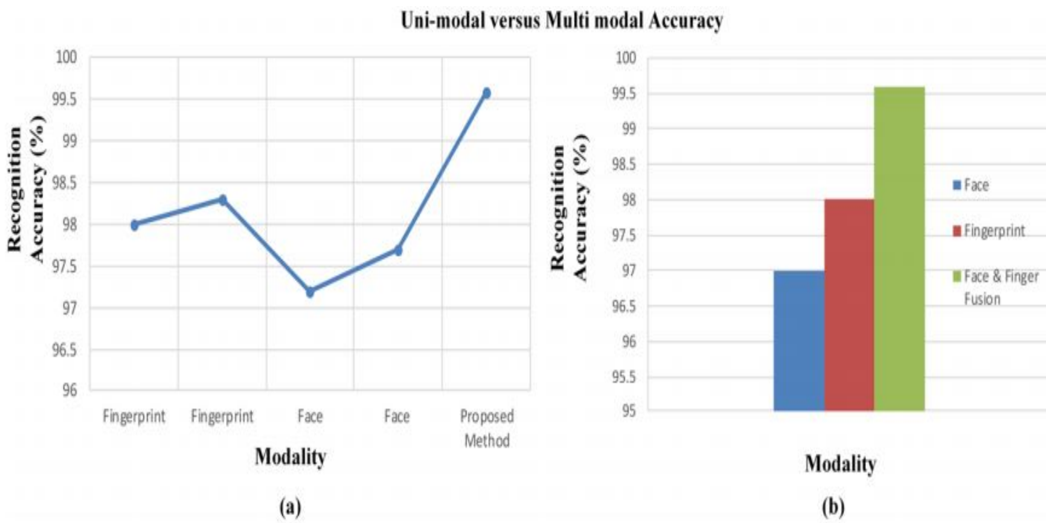

Figure 4.1: Accuracy Comparison Of Uni-modal Versus Multi Modal Biometrics

According to the performed experiment, the given method outperforms the un-imodal systems. The uni-modal system based on, finger print based identification system resulted in 85.9% accuracy, whereas the given method achieved 90%

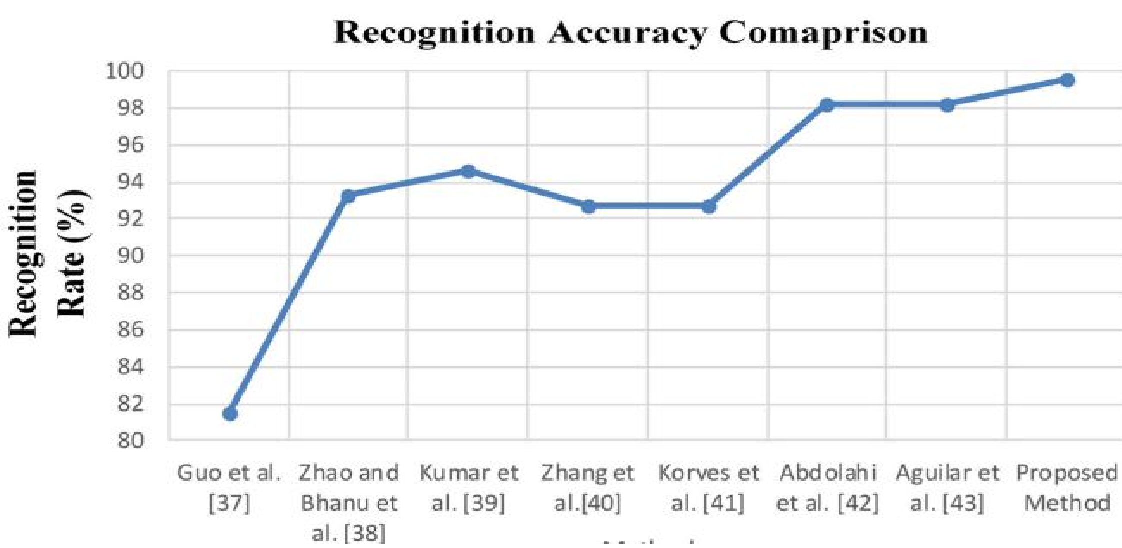

Figure 4.2: Recognition Accuracy Comparison

The given method achieved highest recognition accuracy as compared to all other techniques with highest recognition accuracy of 90%.

4.2 Results In Terms Of Error Rate

Error rate is the evaluation metric that decides the performance of the biometric system. Equal error rate (EER) corresponds to that value of error where both False acceptance rate(FAR) and False rejection rate(FRR) are equal. The lower the value of EER better is the performance of the biometric system. To evaluate the performance of the fused modalities with other existing multi-modal systems their corresponding EER have been compared.

Modality	Database	Equal error rate
Finger vein	FVC 2000 DB10	0.40%
Finger vein	FVC 2000 DB2	0.45%
Proposed	FVC 2000 DB1 , DB2, ORL, YALE	0.035%

Table 4.1: Equal Error Rate Comparison Of Different Modalities

The given multi-modal system has the least EER as compared to all the other paralleled multi-modal systems. Figure 4.3 shows the EER with respect to FAR and FRR for the given method and other existing techniques. With the given method EER is 0.035, with face EER is 0.0528 and for finger EER is 0.042. Hence the given method achieved lower EER in contrast to paralleled modalities.

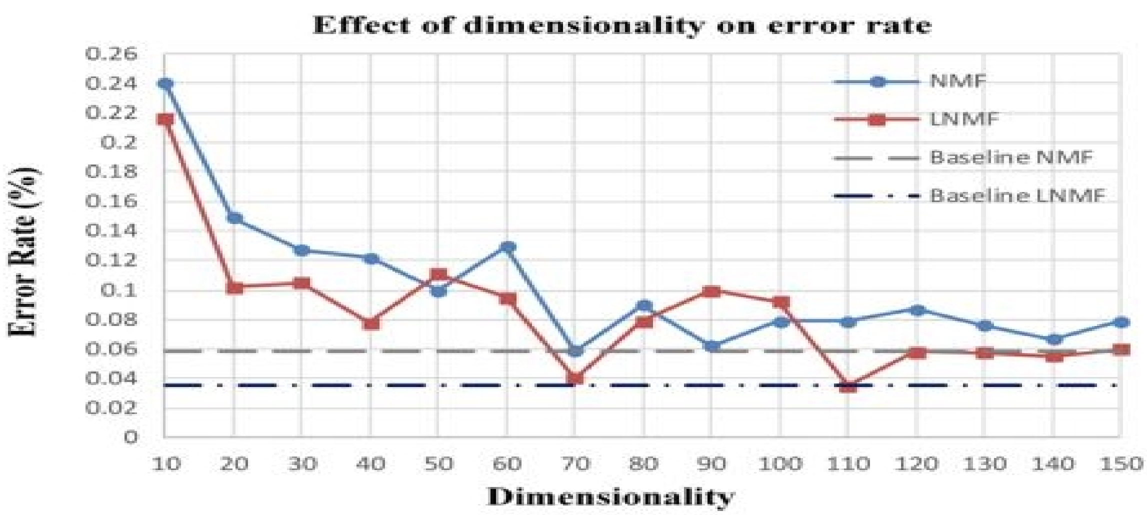

Figure 4.3: Error Rate Comparison

Furthermore, evaluated the EER with respect to dimensionality change. The effect of dimensionality change has been observed using NMF and LNMF and comparing the corresponding errors rates of the two techniques. The corresponding error rate of both methods clearly shows that LNMF have less error rate as compared to NMF. Error rate for LNMF ranges from 0.22 to 0.061 and for NMF it ranges from 0.24 to 0.09. The LNMF baseline shows that EER of 0.035 and NMF baseline shows that EER of 0.059 is achieved with LNMF and NMF respectively. These metrics clearly depict that the given method achieved the lowest EER as compared to the other existing techniques. In addition it uses LNMF with which lowest EER is achieved.

Chapter 5

Conclusion

This work presents a comprehensive review of the feature extraction methods proposed for finger vein biometrics. This review can be used as a guide for those who are interested and want a clear view of this research field. As this field is currently in the spolight and there is not as much information as on other biometrics, for example, fingerprints, that can guarantee a low error rate, it could be used as a starting point for newcomers who want to make a breakthrough in the field. Moreover, despite the fact that finger veins have a lower accuracy than other biometric traits, they are worth investigating because they have a number of advantages, such as being very difficult to forge, and a human has more than one finger, which can be used for authentication purposes. In the past several years, authentication based on finger vein images has seen an improvement as far as the performance goes. The best performance can be seen in the methodologies of feature learning, where deep learning is employed. Those have the best performance on average, with many methodologies achieving over 99the small (for deep learning) datasets available. Regarding the experiments in the literature, we conclude that most of the studies, especially in the early years, did not evaluate the proposed methodology on publicly available datasets. This is mainly attributed to the fact that some the currently available datasets only became available later on. Moreover, the chosen metric for the performance evaluation varies across studies, with most of the studies presenting the EER, RR, or ROC scores. As future work, for comparative reasons, it is highly recommended that researchers present their proposed methodology's performance using the same and more interpretable metrics. Additionally, the splitting of the training and testing set sizes, for those methodologies that apply any type of learning procedure, has to be the same too. In this context, the design of large-scale datasets (big data) that will permit the training and validation of customized CNN models from scratch is of paramount importance towards the development of more reliable finger vein biometric systems. .

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APPENDICES

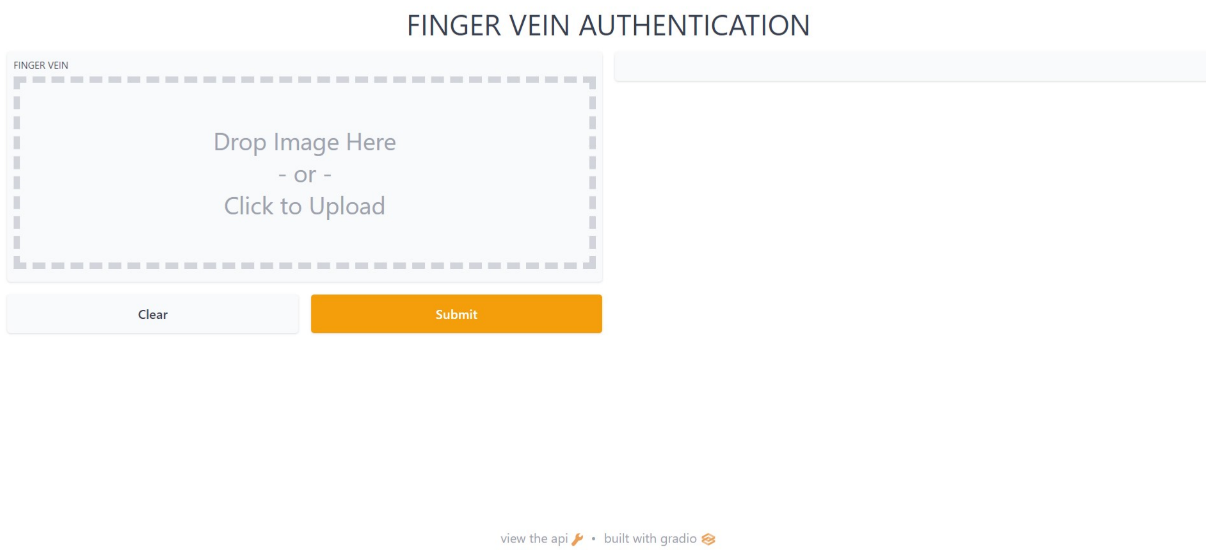

Figure 5.1: login page

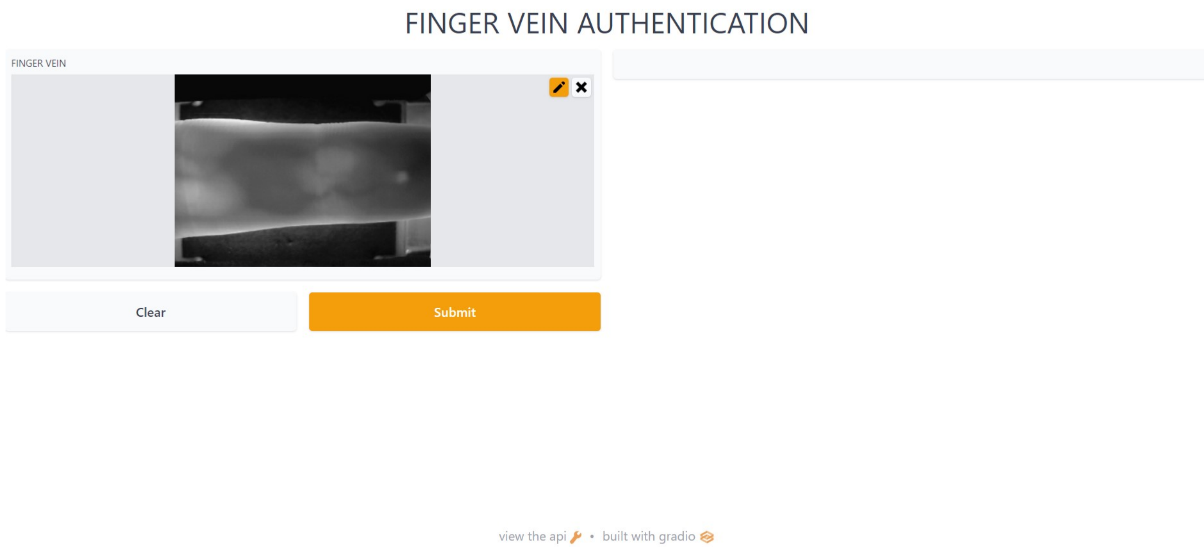

Figure 5.2: Uploading Fingervein

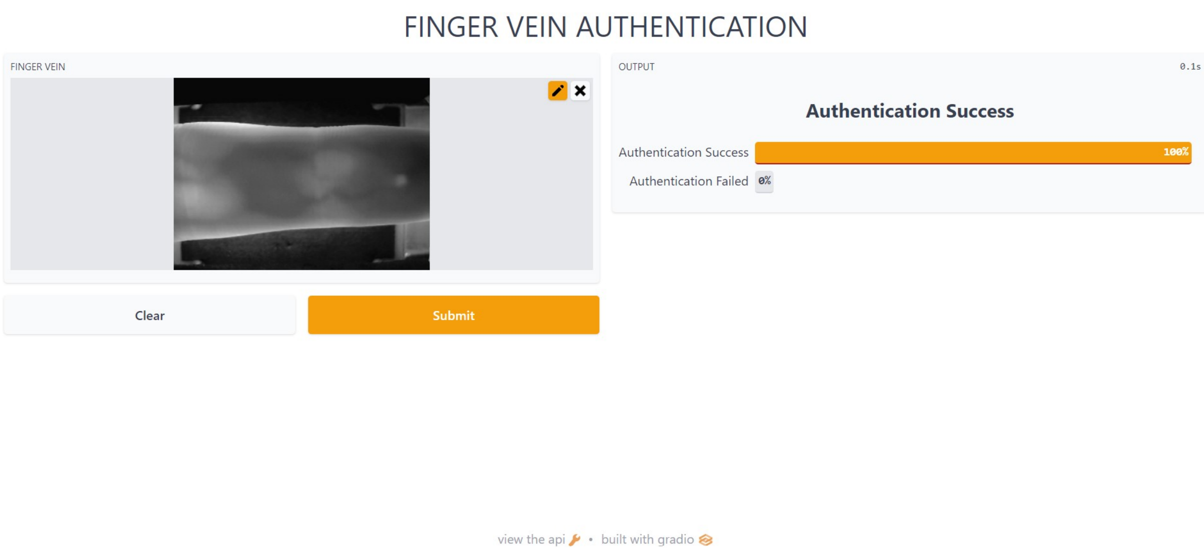

Figure 5.3: Prediction result (Success)

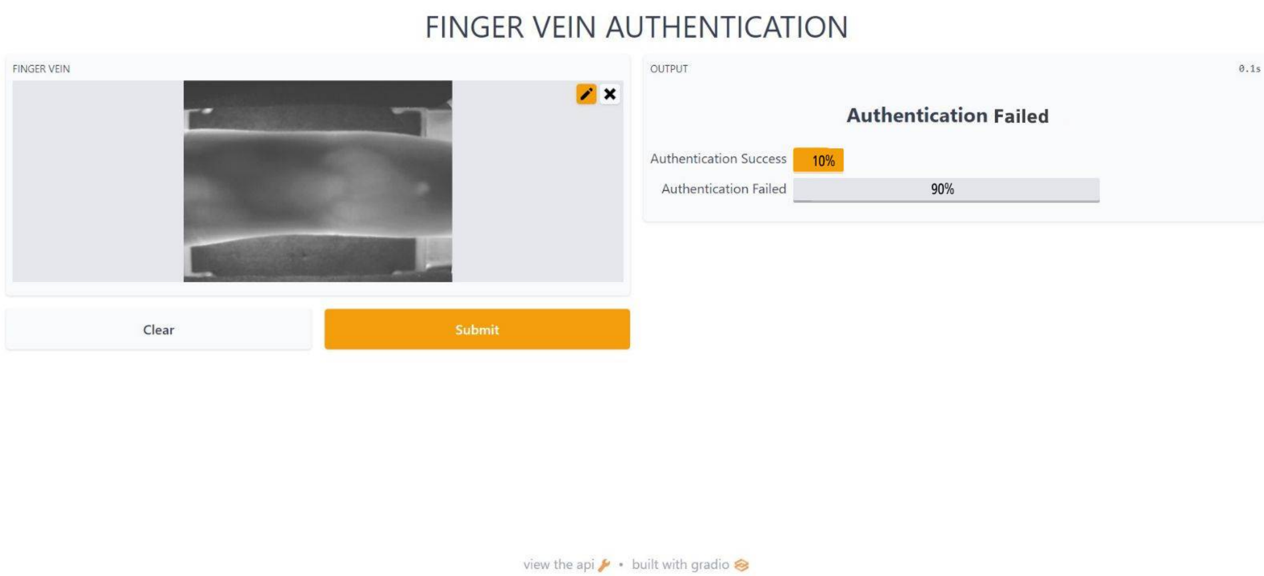

Figure 5.4: Prediction result (Failed)