TOUCHLESS FINGERPRINT IDENTIFICATION USING DEEP LEARNING

A Project Report

Submitted by

Mr. DILAVAR P D

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Under the guidance of
Dr. ANZAR S M

Thangal Kunju Musaliar College of Engineering
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DECLARATION

I undersigned hereby declare that the project report “TOUCHLESS FINGERPRINT IDENTIFICATION USING DEEP LEARNING”, submitted for partial fulfillment of the requirements for the award of degree of Master of Technology of the APJ Abdul Kalam Technological University, Kerala is a bonafide work done by me under supervision of Dr.Anzar S M. This submission represents my ideas in my own words and suggestion given by my guide where also taken in account. I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my 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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Date: DILAVAR P D

Thangal Kunju Musaliar College of Engineering
Centre for Artificial Intelligence

C E R T I F I C A T E

This is to certify that,this report titled ***TOUCHLESS FINGERPRINT IDENTIFICATION USING DEEP LEARNING*** is a bonafide record of the **Project** presented by **DILAVAR P D (TKM20MEAI05)**, under our guidance and supervision, in partial fulfillment of the requirements for the award of the degree, **M.Tech in Mechanical Engineering (Artificial Intelligence)** in **APJ Abdul Kalam Technological University** .

Internal Supervisor	Project Coordinator	Head of the Department
Dr.Anzar S M	Prof. Sumod Sundar	Dr. Imthias Ahamed T P
Assistant Professor	Assistant Professor	Professor & Head
Dept. of ECE	Centre for Artificial Intelligence	Centre for Artificial Intelligence
TKMCE	TKMCE	TKMCE

Internal Examiner

External Examiner

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Abstract

Fingerprint identification technology is used as one of the most reliable technologies for authenticating people. The main reason for its popularity is the high reliability and uniqueness. Fingerprint identification technology currently on the market is based on contact-based fingerprint scanners or 2D enrollment fingerprint sensors. In the early stages of research, many basic feature extraction techniques were used, such as dividing samples into discrete marker skeletons or tediously calculating the shape of adjacent grooves. Obtaining fingerprint image is one of the major stumbling blocks. This is a problem faced by all the researchers, and further studies and techniques are being developed in this area. The contactless fingerprint recognition system is a new choice for the old conventional touch-based fingerprint recognition system. In this work, IIT-Bombay Touchless and Touch Based Fingerprint Database is used for classification which contains 200 subjects. Deep learning is currently popular in computer vision and pattern recognition. CNNs and deep learning models have proven to be extremely effective in solving image processing problems and provide breakthrough results. In this work, pre-trained deep learning models such as VGG-16, VGG-19, Inception-V3 and ResNet-50 architecture by using transfer learning. The results obtained where promising in which VGG-16 architecture performed better among other pretrained model architecture with an accuracy of 98% for training the preprocessed datasets and 93% for unprocessed datasets.

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Chapter 1

Introduction

Fingerprinting is one of the most popular methods of authenticating individuals that has been around for a long time and is still in use. The automatic method of comparing a stored fingerprint pattern with an input fingerprint to identify a person is called fingerprint recognition [1]. It remains unchangeable over time and can be easily recognized for a lifetime.
The imprint or model of the protrusions and indentations on the top of a person's fingers is called a fingerprint. The patterns and protrusions on the fingers are unique to each person, and no two people have identical fingerprints. Because their uniqueness is highly reliable, fingerprint authentication is used in a variety of applications. Fingerprint identification is used in the military, courts, healthcare, education, public service, logging into cell phones and laptops, and many other areas. The most important area where fingerprint identification is used is in forensics to track and identify criminals. Recently, modern techniques and approaches have been used to replace the old ink in fingerprint capture. These techniques differ in accuracy, effectiveness, speed, advantages, and problems. The conventional fingerprint identification techniques use touch-based fingerprint scanners to capture the fingerprints [2]. These images are then subjected to a series of image processing techniques or feature matching algorithms. The normal way of authentication is to extract features such as ridges, core points, and minutiae points, etc. The algorithm first tries to find the minutiae points, core points and groove alignments to classify the fingerprints [1]. The main problem with this method is the fingerprint acquisition. Since it is based on touch-based sensors, the image quality depends on the pressure applied by each person at each moment. This creates a serious problem of damage to the fingerprint capture process and can sometimes lead to fingerprint mismatch. When each person places their finger on the scanner, the fingerprints smear and become blurred depending on how much pressure the person applies. This raises the problem of latent fingerprint capture. To avoid or address this problem, a novel fingerprint recognition technology has been introduced. Unlike the conventional touch-based scanners, here we use non-contact fingerprint recognition [3].
Touchless fingerprint recognition is considered as a viable alternative to contact-based fingerprint recognition technology [2]. It is a contactless fingerprint recognition system that uses a digital camera. By using these digital cameras as fingerprint capture devices, we can avoid the latent fingerprint problems that occur with contact-based scanners. Instead of finding the fingerprint features like core dots, minutiae and grooves, here we use the deep learning algorithms to learn and authenticate the fingerprint features [2][6].
The images are preprocessed and forwarded to a Convolutional Neural Network. The train-

ing, testing and validation datasets are created from the main dataset. The non-contact fingerprint images are then trained and tested with different neural networks, focusing on deep neural networks. The performance of feature extraction and matching is completely dependent on the quality of the fingerprint images. Better images lead to better feature extraction and matching performance.

1.1 Major Contribution

The aim of this proposed work is to review the conventional fingerprint identification methods and find a fruitful solution to the current methods. The main focus of the research is on pre-processing of non-contact fingerprint images and deep learning techniques. The proposed approach is based on transfer learning using deep learning for contactless fingerprint identification [6][17]. The proposed system is expected to be able to identify the fingerprint and predict the identity of the subject. The performance of the work is measured in terms of accuracy The contributions of the work are:

1.1.1 Creation of an automatic preprocessing pipeline

The preprocessing stages of touchless fingerprint images are made to a pipeline process where all the necessary image processing and transformations are done[5]. Almost all the preprocessing stages are adaptive method, so the changes in the instance of image will not be much effected. The input and out put of this pipeline will be a touchless finger image and preprocessed fingerprint image respectively.

1.1.2 A feature matching free method

This work is free of the matching stages and matching algorithm that has been currently used. The conventional ways of identification use feature mapping, minutiae mapping, core point detections and ridge orientation detections etc. But instead of all these here we use a predictive or classifying method in which a deep learning model is developed.

1.1.3 An optimized and hyper parameter tuned CNN model

For the purpose of identifying and prediction of user, a deep learning model is hyper tuned to learn the features of fingerprints[6][8]. The model is tuned so that there will not be an over-fitting or under-fitting. As a part of hyper parameter tuning the optimizer are carefully chosen for this current work

1.2 Organization of Work

The rest of report is organized as follows. The following section gives a brief survey of the related works with touchless fingerprint identification. The proposed methodology for touchless fingerprint identification using deep learning is explained in chapter 3. Along with dataset preparation and experimental setups the results are also shown in the chapter 4. The final chapter ends with a brief conclusion of the proposed work.

Chapter 2

Related Works

2.1 Literature Review

Here are the some of the prominent work in the field of Touchless Fingerprint Identification

2.1.1 Mobile Touchless Fingerprint Acquisition And Enhancement System

The goal of this project is to identify individuals from photographs of their fingers taken with mobile devices. This study first identifies the difficulties in capturing fingerprints with mobile devices and develops a device to overcome these difficulties. The finger photos taken with the mobile device are compared with the fingerprints captured by the sensor to evaluate the feasibility, test the proposed device, and improve the approach. The proposed method is evaluated using 104 fingerprints from 52 different individuals that form the database. It was found that the fingerprints captured by the optical sensor and the device attached to the mobile device matched. The overall results of the proposed approach show a performance with a FAR of 0.05% and a FRR of 0.54% using the developed device.

2.1.2 A CNN-based Framework for Comparison of Contactless to Contact-based Fingerprints

The new 2D non-contact fingerprint technologies, which enable more hygienic and deformation-free fingerprint feature capture, are based on the accurate comparison of 2D non-contact fingerprint photos with contact-based fingerprints. Convolutional neural networks (CNNs) have demonstrated impressive capabilities in biometric feature recognition. However, the use of CNN-based methods for matching fingerprint images has hardly been tested. In order to accurately compare contact and contactless fingerprints, a CNN-based method is developed in this work. Using fingerprint minutiae, the corresponding ridge map, and a specific region of the ridge map, our system first trains a multi-siamese CNN. Using a distance-dependent loss function, this network generates deep fingerprint representations. For a more accurate cross-comparison, the deep fingerprint representations generated in such a multi-siamese network are linked together. Using two publicly available datasets of 2D contactless fingerprints and the corresponding contact-based fingerprints, the proposed approach for fingerprint comparison is investigated.

2.1.3 Contactless Fingerprint Recognition System Based On CNN

A common topic in pattern recognition is fingerprint recognition. It is mainly used in modern authentication technology, for example in cell phone access devices. In this study, we investigate whether convolutional neural networks can be used for fingerprint recognition. In order to perfectly match images of contactless and contact fingerprints, a CNN-based system is developed in this study. Using fingerprint information, the corresponding ridge map and a specific region of the ridge map, a multi-siamese CNN is first trained in this framework. The deep fingerprint representation is used to create a loss function tuned for distance. The deep fingerprint representations created in such a multi-siamese network are concatenated for more accurate cross-comparison. The proposed fingerprint comparison method is computed using two publicly available datasets. The available database contains contactless 2D fingerprints and corresponding contact-based fingerprints.

2.1.4 Touchless Multiview Fingerprint Acquisition and Mosaicking

Compared to traditional touch-based methods, non-contact fingerprint capture devices offer the advantage of being hygienic and preventing finger contact distortion. However, single capture technologies have disadvantages, such as scene discrimination and low effective range. Therefore, the contactless multi-viewpoint fingerprint capture system described in this study simultaneously captures three different perspectives of a fingerprint image. Factors such as the size of the device and the resolution of the captured fingerprint image were considered in the development of this device. A fingerprint mosaic technique is proposed to combine the captured photos of a finger into a new image with a larger usable print area. By describing our design process and comparing it with existing non-contact multi-page fingerprint capture devices, we can show how well the design of our device has been optimized, and by comparing the recognition rates of fingerprint images created using touch technology with mosaic images, the effectiveness of our device is further demonstrated. According to the experimental data, our proposed mosaic method is more resistant than other methods even for fingerprints with low groove contrast. A comparison of the similar error rates of our mosaic method with those of mosaic algorithms evaluated using our database of 541 fingers further demonstrates its effectiveness.

2.2 Background of the work

Fingerprints are the most often used biometric to verify a human being. The reasons behind its wide acceptance are already discussed.The only method of fingerprint identification relies on taking elements from the prints and comparing them to those that have been previously registered.There have been three levels of feature classification from the earliest research days to the present: level 1, level 2, and level 3.Level 1 fingerprint features mostly consisted of the general fingerprint characteristics, and level 2 fingerprint features are the minute details that can identify between fingerprints from different people.Pores, ridge frequencies, and any other features not already present in the prior two levels were included in Level 3 features, which provided even finer information.
Minutiae-based fingerprint identification systems have gained greater attention and advancement due to several restrictions and limitations.The location where fingerprint ridges either converge or diverge is known as a minutia point.There are two conceivable instances when

a point can be categorised as minutiae: ridge bifurcations and ridge ends. To extract these minute details, the image must be of a decent quality.There are many algorithms for extracting details, and the method of crossing numbers has proven to be the most effective[7][8]. The resolution of the sensor and the way the finger is placed on it both affect how many minute points there are.The amount might range from 25 to 100 on average. If the finger is perfectly positioned, there may be 80 to 100 minute details available for comparison. It is obvious that there are practical challenges in accurately extracting minute details like dry fingertips, those with scratches and scars etc..
These conventional methods depends on the orientations and other fingerprint features and these conventional methods are easy to breach. To find a better alternative method for fingerprint authentication, Touchless fingerprint identification using deep learning technique has been proposed. Apart from the conventional ways of fingerprint matching this proposed method will be based on deep neural network learning[6][17].

2.2.1 Transfer Learning

Transfer learning is the method used in machine learning or in deep learning to reuse a previously trained model on a different task[17]. A machine uses the knowledge learned from a prior assignment to increase prediction about a new task in transfer learning. The knowledge of an already trained machine learning model is transferred to a different but closely linked problem throughout transfer learning. With transfer learning, we basically try to use what we have learned in one task to better understand the concepts in another. weights are being automatically being shifted from a performed network to a performing network.
Typically, neural networks used in computer vision are designed to identify edges in the first

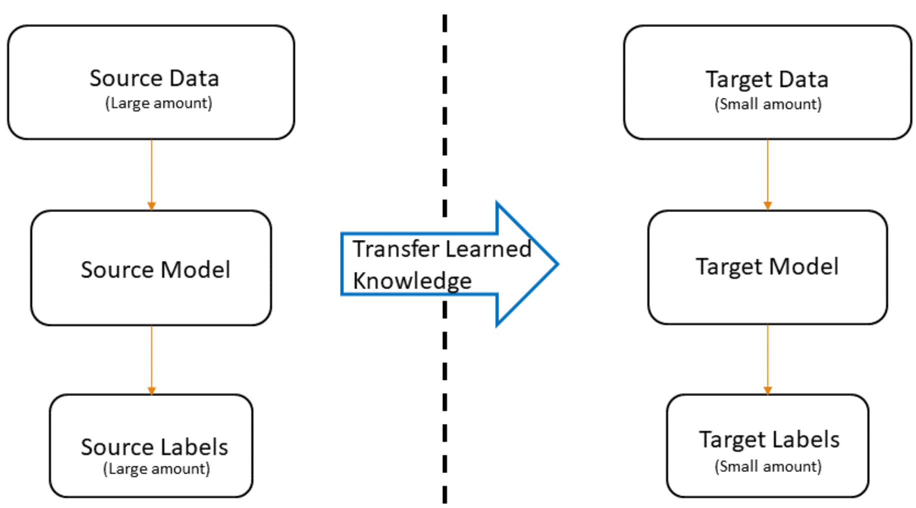

Figure 2.1: Transfer Learning Block Diagram

layer, shapes in the middle layer, and task-specific properties in the latter layers. In transfer learning, only the early and central layers are used; the latter layers are only retrained. Reduced training time, enhanced neural network performance (in most cases), and will maintain the problem of small amount of data are three of transfer learning's most significant benefits. A lot of data is normally required to train a neural model from start, but access to that data isn't always feasible. – this is when we use the advantages of transfer learning or in case if we don't have enough annotated data to train our model with[6][17]. The figure 2.1 shows the functional block diagram of transfer learning.If TensorFlow was used to train the initial model, you could just recover it and retrain a few layers to suit your needs. On the other hand, transfer learning only functions if the skills acquired in the initial task are universal, meaning they can be used in different contexts. Additionally, the input size of the model must be identical to that of its initial training. Two common approaches are as follows:

- Develop Model Approach
- Pre-trained Model Approach

Transfer learning is an optimization, a shortcut to saving time or getting better performance. Transfer learning facilitates these advantages.

- Higher start:-The initial skill (before refining the model) on the source model is higher than it otherwise would be.
- Higher slope:-The rate of improvement of skill during training of the source model is steeper than it otherwise would be.
- Higher asymptote:-The converged skill of the trained model is better than it otherwise would be.

Chapter 3

Proposed Methodology

The proposed work is carried out in two different ways, in which one method is trained by preprocessing the datasets and other method doesn't have preprocessing.The work includes the deep learning techniques such as transfer learning using VGG-16 architecture[6],VGG-19, Inception-V3 and ResNet-50.The datasets are preprocessed and given to convolutional neural network for the deep learning.The processed images are categorized into a training and testing directory.The number of classes depends on the number of identity we use, IIT Bombay datasets contains 200 subjects. The train and test folders contains 200 folders, each folder contains each augmented and original images of corresponding subjects.This train and test directory is used for deep learning. After the training the model, the model evaluation metrics are calculated and finally the model is used for authentication. The functional block diagram of the work is shown in the figure 3.1.

Figure 3.1: Block diagram of proposed work

3.1 VGG-16

VGG-16 is a 16 layer convolutional neural network architecture which is used for ImageNet dataset which is a large visual database used in visual object recognition. In the year 2014 Karen Simonyan and Andrew Zisserman from the University of Oxford has developed and introduced the architecture of vgg16 through their article"Very Deep Convolutional Networks for Large-Scale Image Recognition"[6]. The main peculiarity of the vgg16 is its unchanged filter size. Compare to other convolutional models vgg16 has a fixed filter size of 3x3. The optimizer of output dense layer is softmax.

3.1.1 VGG-16 Architecture

During training, the input to the convnets is a fixed-size 224 x 224 RGB image. Subtracting the mean RGB value computed on the training set from each pixel is the only pre-processing done here. The image is passed through a stack of convolutional layers, where filters with a very small receptive field: 3×3, is used. It is deeper, has more non-linearities, and has fewer parameters. In one of the configurations, 1×1 convolution filters, which can be seen as a linear transformation of the input channels, are also utilized. The convolution stride and the spatial padding of conv. layer input is fixed to 1 pixel for 3 x 3 convolutional layers, which ensures that the spatial resolution is preserved after convolution. Five max-pooling layers, which follow some of the convolutional layers, helps in spatial pooling. Max-pooling is performed over a 2×2 pixel window, with stride 2.
There are three Fully-Connected (FC) layers that follow a stack of convolutional layers (these have different depths in different architectures): the first two have 4096 channels each, the third layer is the soft-max layer consists of number of classes as its number of channels. The configuration of the fully connected layers is the same in all networks. The VGG16 architecture is depicted in figure 3.2.

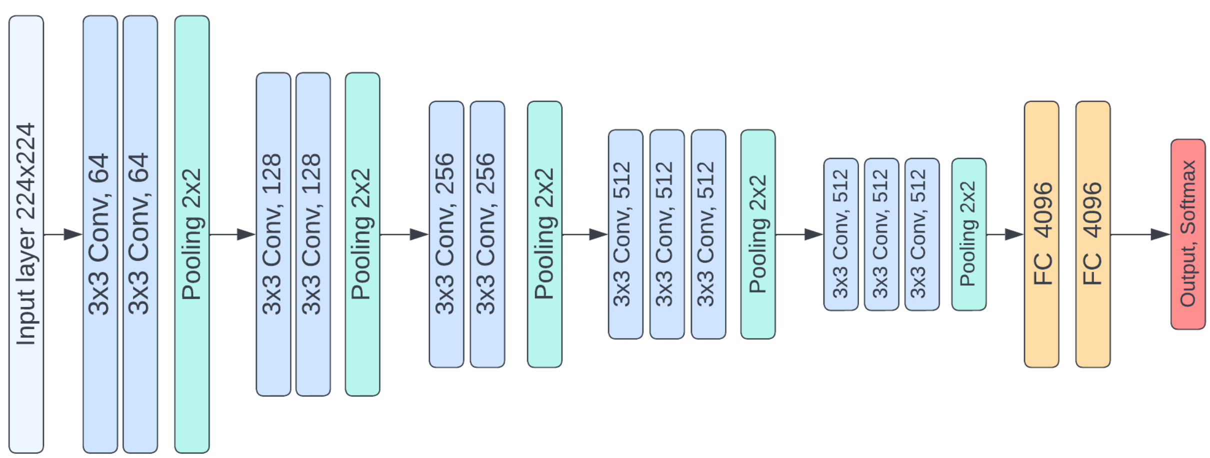

Figure 3.2: Architecture of VGG-16

3.2 VGG-19

VGG-19 is a 19 layer convolutional neural network architecture which is used for ImageNet dataset which is a large visual database used in visual object recognition. The main peculiarity of the vgg19 is its unchanged filter size. Compare to other convolutional models vgg16 has a fixed filter size of 3x3. The optimizer of output dense layer is softmax.

3.2.1 VGG-19 Architecture

The input to the convnets is a fixed-size 224 x 224 RGB image. Subtracting the mean RGB value computed on the training set from each pixel is the only pre-processing done here. The image is passed through a stack of convolutional layers, where filters with a very small receptive field: 3×3, is used. It is deeper, has more non-linearities, and has fewer parameters. In one of the configurations, 1×1 convolution filters, which can be seen as a linear transformation of the input channels, are also utilized. The convolution stride and the spatial padding of conv. layer input is fixed to 1 pixel for 3 x 3 convolutional layers, which ensures that the spatial resolution is preserved after convolution. Five max-pooling layers, which follow some of the convolutional layers, helps in spatial pooling. Max-pooling is performed over a 2×2 pixel window, with stride 2.
There are three Fully-Connected (FC) layers that follow a stack of convolutional layers (these have different depths in different architectures): the first two have 4096 channels each, the third layer is the soft-max layer consists of number of classes as its number of channels. The configuration of the fully connected layers is the same in all networks. The VGG19 architecture is depicted in figure 3.3.

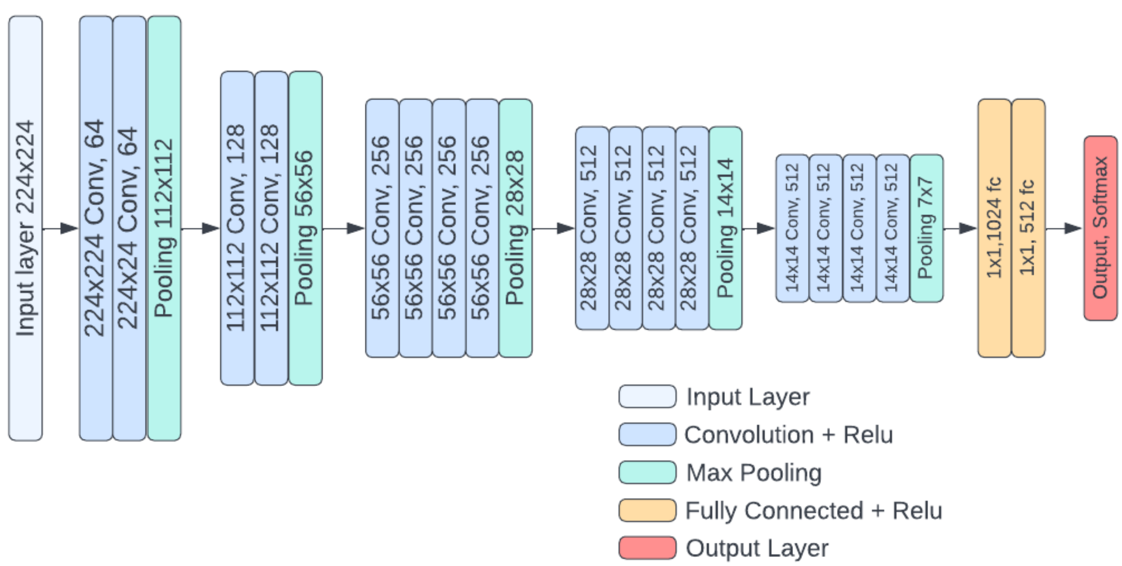

Figure 3.3: Architecture of VGG-19

3.3 Inception-V3

Inception v3 is an image recognition model that has been shown to attain greater than 78.1% accuracy on the ImageNet dataset. The model is the culmination of many ideas developed by multiple researchers over the years. It is based on the original paper: "Rethinking the Inception Architecture for Computer Vision" by Szegedy, et. al. The model itself is made up of symmetric and asymmetric building blocks, including convolutions, average pooling, max pooling, concatenations, dropouts, and fully connected layers. Batch normalization is used extensively throughout the model and applied to activation inputs. Loss is computed using Softmax.

3.3.1 Architecture of Inception-V3

The architecture of an Inception v3 (figure 3.4) network is progressively built and can be explained by this steps, Factorized Convolutions: this helps to reduce the computational efficiency as it reduces the number of parameters involved in a network. It also keeps a check on the network efficiency. Smaller convolutions: replacing bigger convolutions with smaller convolutions definitely leads to faster training. Say a 5 × 5 filter has 25 parameters; two 3 × 3 filters replacing a 5 × 5 convolution has only 18 (3*3 + 3*3) parameters instead.
Asymmetric convolutions: A 3 × 3 convolution could be replaced by a 1 × 3 convolution followed by a 3 × 1 convolution. If a 3 × 3 convolution is replaced by a 2 × 2 convolution, the number of parameters would be slightly higher than the asymmetric convolution proposed. Auxiliary classifier: an auxiliary classifier is a small CNN inserted between layers during training, and the loss incurred is added to the main network loss. Grid size reduction: Grid size reduction is usually done by pooling operations.

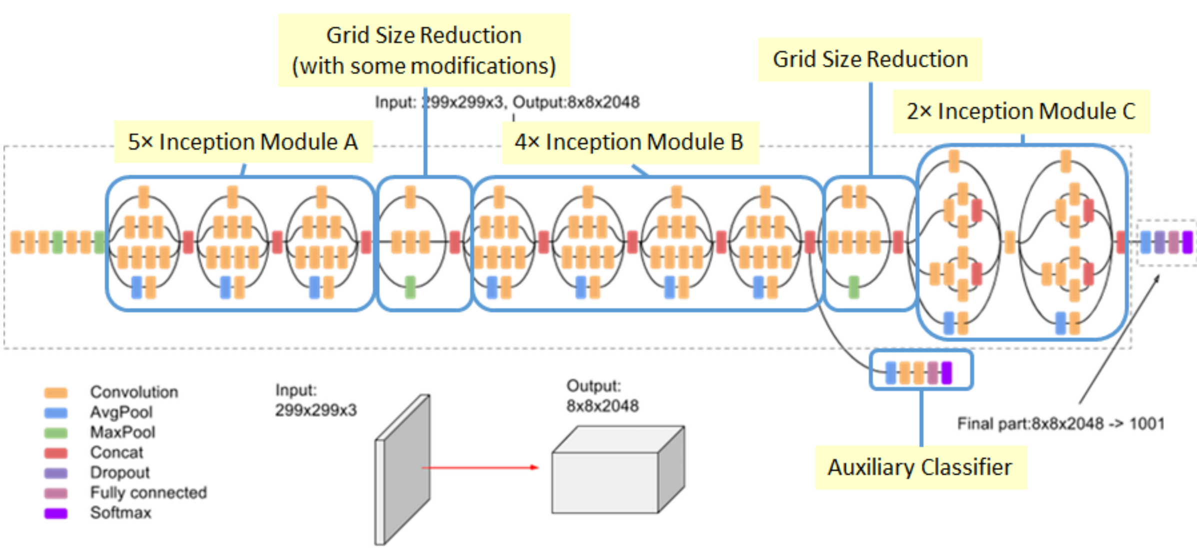

Figure 3.4: Architecture of Inception-V3

3.4 ResNet-50

ResNet50 is a variant of ResNet model which has 48 Convolution layers along with 1 maxPool and 1 Average Pool layer. It has 3.8 x 10$\hat{9}$ Floating points operations.The framework that ResNet-50 presented was made possible to train ultra deep neural networks. The network can contain hundreds or thousands of layers and still achieve great performance.The ResNets were initially applied to the image recognition task but as it is mentioned in the paper that the framework can also be used for non computer vision tasks also to achieve better accuracy.There was a small change that was made for the ResNet 50 and above that before this the shortcut connections skipped two layers but now they skip three layers and also there was 1 * 1 convolution layers added that we are going to see in detail with the ResNet-50 Architecture.

3.4.1 Architecture of ResNet-50

A convoultion with a kernel size of 7 * 7 and 64 different kernels all with a stride of size 2 giving us 1 layer. Next we see max pooling with also a stride size of 2. In the next convolution there is a 1 * 1,64 kernel following this a 3 * 3,64 kernel and at last a 1 * 1,256 kernel, These three layers are repeated in total 3 time so giving us 9 layers in this step. Next we see kernel of 1 * 1,128 after that a kernel of 3 * 3,128 and at last a kernel of 1 * 1,512 this step was repeated 4 time so giving us 12 layers in this step. After that there is a kernal of 1 * 1,256 and two more kernels with 3 * 3,256 and 1 * 1,1024 and this is repeated 6 time giving us a total of 18 layers. And then again a 1 * 1,512 kernel with two more of 3 * 3,512 and 1 * 1,2048 and this was repeated 3 times giving us a total of 9 layers. After that we do a average pool and end it with a fully connected layer containing 1000 nodes and at the end a softmax function so this gives us 1 layer. We don't actually count the activation functions and the max/ average pooling layers. so totaling this it gives us a (1 + 9 + 12 + 18 + 9 + 1) = 50 layers Deep Convolutional network. The figure 3.5 shows the architecture of ResNet-50.

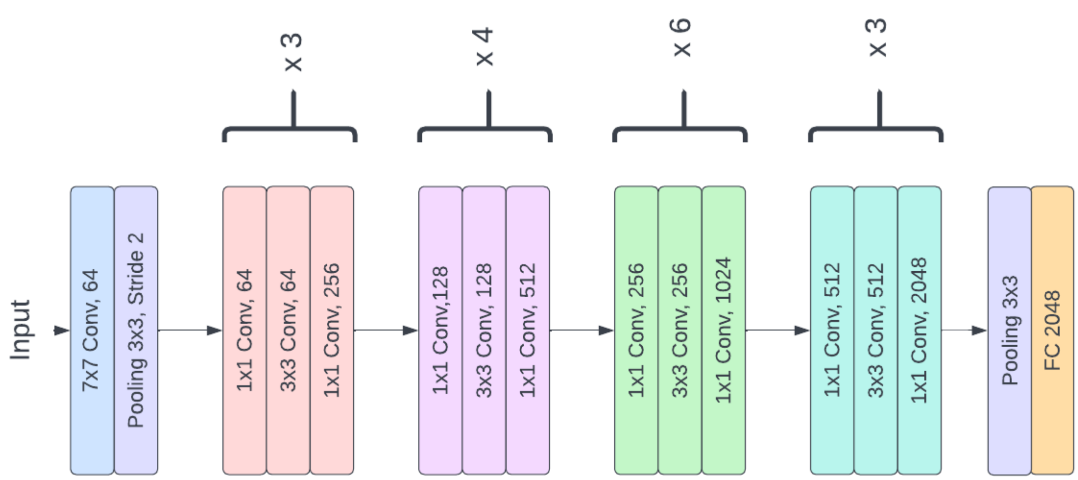

Figure 3.5: Architecture of ResNet-50

3.5 Touchless fingerprint Identification with Preprocessing

In this method the image dataset is passed through a series of preprocessing stages so as extract the ridges and patterns of the touchless fingerprint images.The preprocessed image is then given to deep neural network for training and testing.

3.5.1 Block Diagram

The block diagram Figure 3.6 shows the functional methodology of the touchless fingerprint identification using deep learning with a series of preprocessing stages.

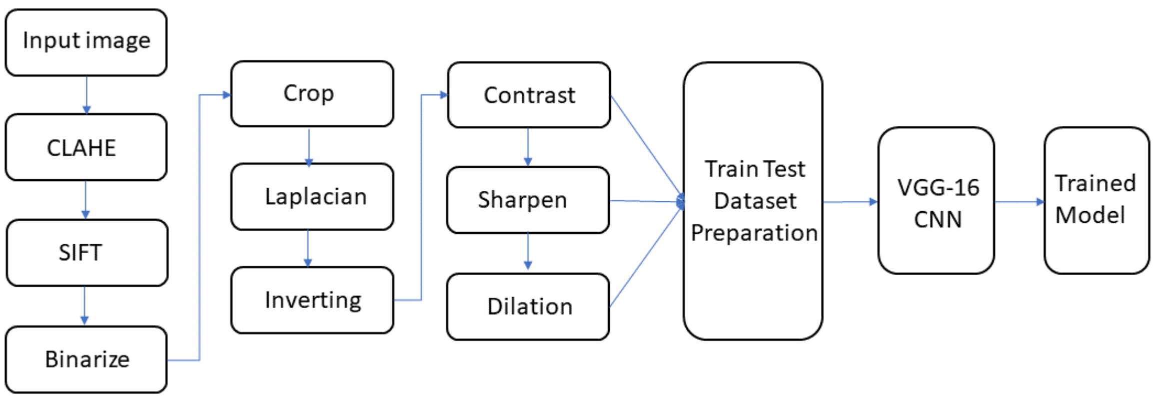

Figure 3.6: Block diagram of Touchless fingerprint Identification with Preprocessing

3.5.2 Preprocessing Steps

The input image is passed through a series of image processing techniques. The steps involves (i) Normalization, (ii) CLAHE Enhancement Method, (iii) SIFT Algorithm, (iv) Threshold, (v) Cropping, (vi) Laplacian filter, (vii) Image inverting, (viii) Contrast, (ix) Sharpening, (x) Dilation

Normalization

Normalization is the process of reducing the range of pixel values of an image[12]. By doing this we can achieve a uniformity in the pixel values of images. Normalizing also helps to reduce the computation complexity. When normalizing an image what we are doing is intensifying the color channels. For an RGB values, we will divide each pixel values by the sum of three channels.The figure 3.7(i) shows the corresponding result.

CLAHE Enhancement Method

CLAHE stands for Contrast Limited Adaptive Histogram Equalization. CLAHE[5] is used to increase the contrast of the image. It is an advanced version of adaptive histogram equalization which is introduced to rectify the over amplification of the contrast. The normal

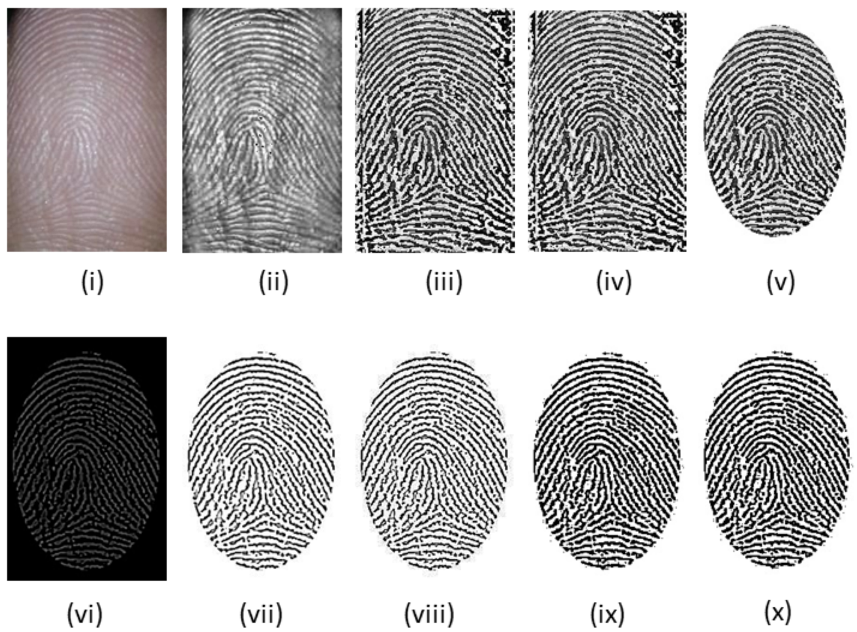

Figure 3.7: (i) Normalization, (ii) CLAHE Enhancement Method, (iii) SIFT Algorithm, (iv) Threshold, (v) Cropping, (vi) Laplacian filter, (vii) Image inverting, (viii) Sharpening, (ix) Contrast, (x) Dilation

histogram equalization works on entire image as whole, but in CLAHE method the entire images are treated a as small tiles. The algorithm is done on each tiles separately and are combined using bi-linear interpolation method.The figure 3.7(ii) shows the corresponding result.

SIFT Algorithm

SIFT stands for Scale-Invariant Feature Transform. It was introduced in 2004. The SIFT[12] algorithm has very useful steps that helps to extract the features. The main four steps in SIFT algorithms are Scale-pace peak selection, Keypoint Localization, Orientation Assignment and Keypoint descriptor. The scale-space peak selection helps in finding the potential location for finding the features. The keypoint localization helps in accurately locating the feature keypoints. The orientation assignment will assign the orientation to keypoints and finally keypoint descriptors will describe the keypoints as high dimensional vector.The figure 3.7(iii) shows the corresponding result.

Threshold

Image thresholding is the process of converting the pixels of an image into binary image[5]. The binary image consists of only o and 1 value pixels.It is the main steps of a segmentation process. In order to convert an image in a binary image its is first converted to a grayscale image. The grayscale image consist of pixel values ranging from 0 to 255, where 0 being the black pixel and 255 being the white pixel and all value in between 0 and 255 will be the gray pixel values. The best method to binarize an image is by applying thresholding. The adaptive binary thresholding like otsu threshold technique is best suited for automated thresholding where there is a sequence of image.The figure 3.7(iv) shows the corresponding result.

Cropping

The binarized image is then cropped to oval shape using a binary mask image. This step is done in order to prevent the learning of unwanted fingerprint area in the image. The mask image and the binarized image is passed to a bit-wise OR operation.The figure 3.7(v) shows the corresponding result.

Laplacian filter

Laplacian filters are the derivative filters which are normally used to find the edges or sudden changes in the image[5]. Where the image is basically uniform, the LoG will give zero. The LoG will respond positively on darker side and negatively on brighter side. At a sharp edge between two regions, the response will be zero away from edge, positive just to one side, negative just to other side and zero at some point in between on the edge itself. In LoG operation the second derivative of the image is taken. The figure 3.7(vi) shows the corresponding result.

Image inverting

The output of the laplacian filter will be inverted one. So, the binary image has to be inverted. By inverting means we will invert the pixel values. The 0 will be replaced with 1 and 1 will be replaced with 0.The figure 3.7(vii) shows the corresponding result.

Contrast

The contrasting of image is done here so as to improve the clarity of each pixels. by applying contrast technique we are increasing the difference between bight and dark pixels.The figure 3.7(viii) shows the corresponding result.

Sharpening

Sharpening is the technique of passing an high passed version of same image and adding that image to original image. By doing this we will be able to achieve fine tuned edges or refined edges and also helps to remove some amount of noises also. The figure 3.7(ix) shows the corresponding result.

Dilation

Dilation is the process of adding pixels to the edges or boundaries of an image. In dilation morphology a pixel is made 1 if the any of its neighbouring pixels have 1. by doing this process the entire image will be thickened. Dilation also helps in connecting small crack and joints in the image. For the dilation purpose we use a structure elements such as sobel mask etc.The figure 3.7(x) shows the corresponding result.

3.6 Touchless fingerprint Identification without Preprocessing

In this method we use some of the image enhancement techniques to improve the quality and diversity of the dataset. By dong these image enhancement we increase the total number of samples as well as the diversity of image. The geometrical augmentation has not been done since the fingerprints are sensitive to ridges and patterns.

3.6.1 Block Diagram

The block diagram Figure 3.8 shows the functional methodology of the touchless fingerprint identification using deep learning without any of the preprocessing stage other than augmentations.

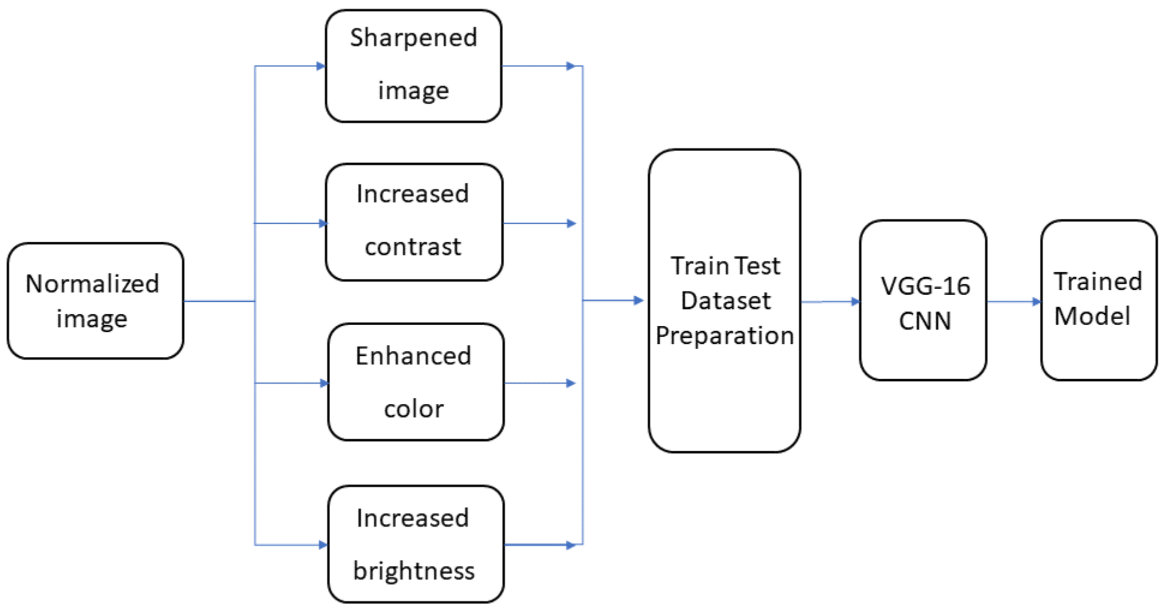

Figure 3.8: Block diagram of Touchless fingerprint Identification without Preprocessing

3.6.2 Augmentation Steps

The augmentation is done here so as to increase the diversity of the datasets as well as to increase the total number of samples. here we have done four image augmentation techniques such as to increase the contrast of image, to increase the brightness of the image, to sharpen the image and to increase the color spectrum of the image.The figure 3.9 shows the entire augmentation result.

Normalization

The Normalization is the process of reducing the range of pixel values of an image. By doing this we can achieve a uniformity in the pixel values of images. Normalizing also helps to reduce the computation complexity. When normalizing an image what we are doing is intensifying the color channels. For an RGB values, we will divide each pixel values by the sum of three channels. So, if we have an image with intensities R, G and B, then their normalized values will be R/N, G/N and B/N where N = (R+G+B). The figure 3.9(ii) shows the corresponding result.

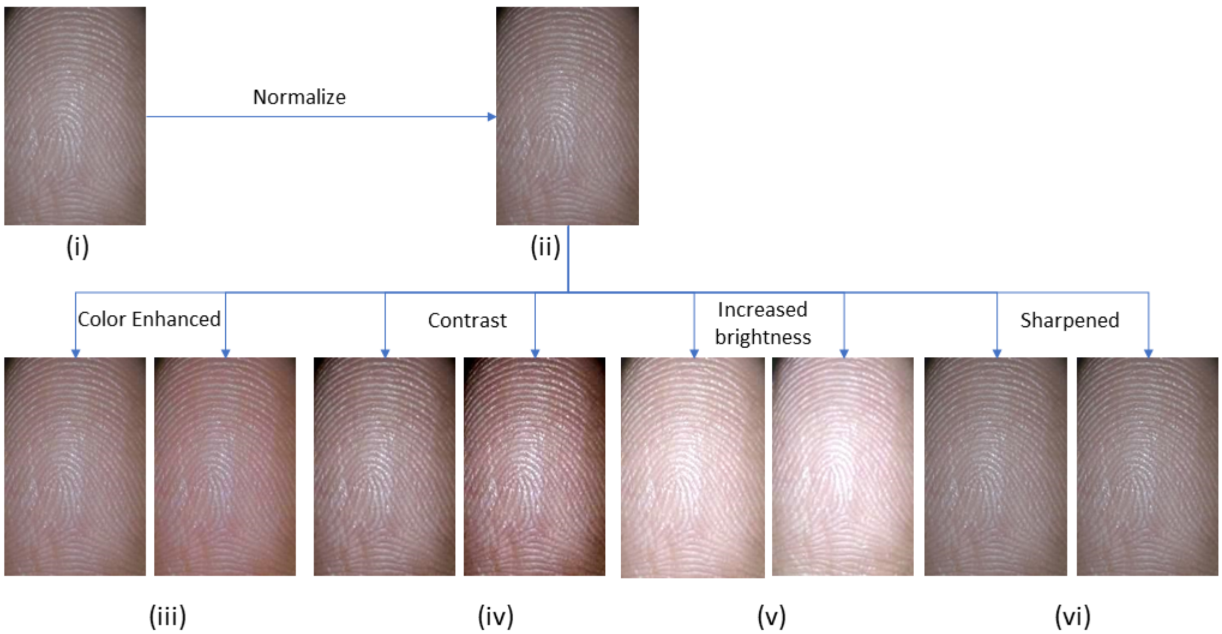

Figure 3.9: (i) Input image, (ii) Normalized image, (iii) Color Enhanced image, (iv) Contrast increased image, (v) Increased brightness (vi) Sharpened image

Contrast

The contrasting of image is done here so as to improve the clarity of each pixels. by applying contrast technique we are increasing the difference between bight and dark pixels.The figure 3.9(iii) shows the corresponding result.

Color enhancement

The color of an image is represented by the pixel values, each pixel contains three RGB values ranging from 0-255 for each. According to the values of red,green and blue ranging from 0-255 the color of that pixel is defined. Each pixel represents the each dots in the image so collectively all together makes an image.So here we have enhanced the dominant color channel.The figure 3.9(iv) shows the corresponding result.

Brightness

The pixel values of all the pixel in image is added by a constant brightness factor, adding positive factors will make the image more brighter and adding negative factor will make the image darker. The increase in the brightness is done on small percentage of its original pixel value since too much brightness can remove the important features. The figure 3.9(v) shows the corresponding result.

Sharpening

Sharpening is the technique of passing an high passed version of same image and adding that image to original image. By doing this we will be able to achieve fine tuned edges or refined edges and also helps to remove some amount of noises also. The figure 3.9(vi) shows the corresponding result.

Chapter 4

Results and Discussions

4.1 Datasets

IIT-Bombay, Touchless and Touch Based Fingerprint Database is a set of fingerprint data prepared by Indian Institute of Technology – Bombay, Mumbai, India[7]. The dataset consist of 800 touchless fingerprint images of 200 subjects, 4 samples per subject having image size 170 x 260. It also consist of 800 touch based fingerprint images of the same 200 subjects having image size 260 x 330. The touchless fingerprints are captured using Lenovo Vibe k5 plus smartphone with the developed Android App. The images are captured using embedded flash for illumination.

- 800 touchless fingerprint images(170 x 260).
- 800 touchbased fingerprint images(260 x 330).
- 200 subjects, 4 samples per subject.

The preprocessed images and augmented images are then made into training, testing and validation. Training, testing folders consists of 200 folders which indicates each identity or class. The Figure 4.1 shows how the directory is prepared.

4.1.1 Preparation of Dataset for method 1 (with preprocessing)

- Dataset consists of 200 IDs.
- Total of 800 images , 4 images for each ID.
- After the augmentation and preprocessing, for training we have 1800 images and for testing we have 600 images.
- Total number of class is equal to number of IDs(here class = 200).

4.1.2 Preparation of Dataset for method 2 (without preprocessing)

- Dataset consists of 200 IDs.
- Total of 800 images , 4 images for each ID.

- After the augmentation, for training we have 3200 images and for testing we have 1600 images.
- Total number of class is equal to number of IDs(here class = 200).

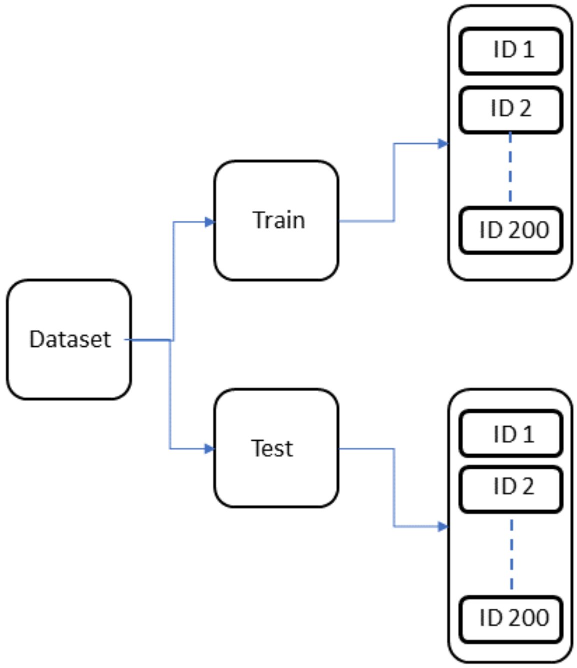

Figure 4.1: Dataset directory arrangement

4.2 Experimental Setups

The entire program is written in python programming language. The Hardware configuration of the system is Intel i5 10th gen processor with 8GB of ram. The GPU used is NVIDIA GE-FORCE GTX 1650. The IDE used for running program is jupyter notebook.These are the initial values and setups done before the training.

Notebook presets and hyper-parameter setups

- Architecture = VGG-16, VGG-19, Inception-V3 and ResNet-50
- Loss = categorical crossentropy
- Optimizer = Nadam
- Target size = 224 x 224 pixel
- Batch size = 32
- Class mode = categorical
- Epochs = 100

4.3 Results of Touchless fingerprint Identification with Preprocessing

The results obtained in each model is plotted and confusion matrix for best model is also plotted.

4.3.1 Results of VGG-16

After training and testing the model for 100 epochs in which the model accuracy converges to an accuracy of 98% before reaching 50 epochs. The figure 4.2(i) shows the overall training and validation accuracy over the epoch of 50 and figure 4.2(ii) is the graph of training loss and validation loss. The training and validation recall and precision graph is shown in figure 4.3(i),(ii) respectively. The figure 4.4 shows the confusion matrix.

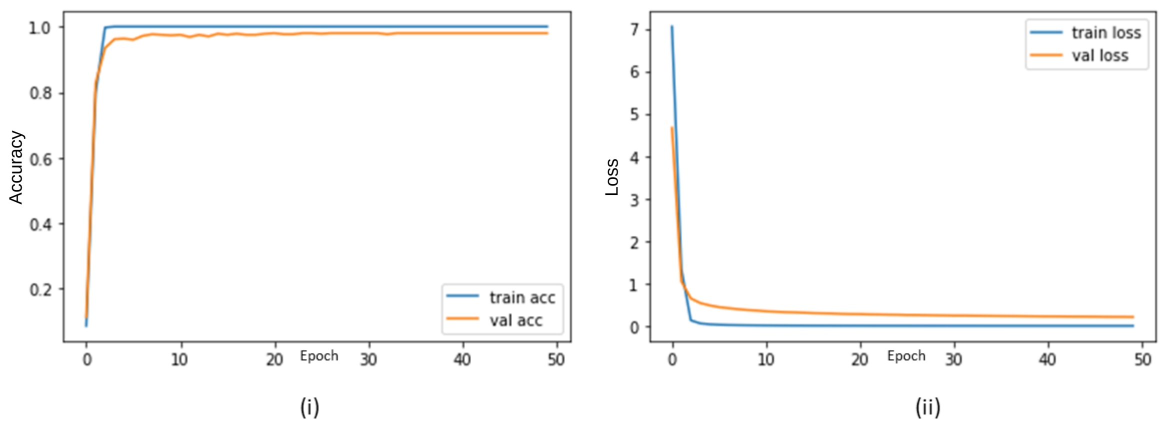

Figure 4.2: (i)Training and Validation Accuracy of VGG16(ii)Training and Validation Loss of VGG16

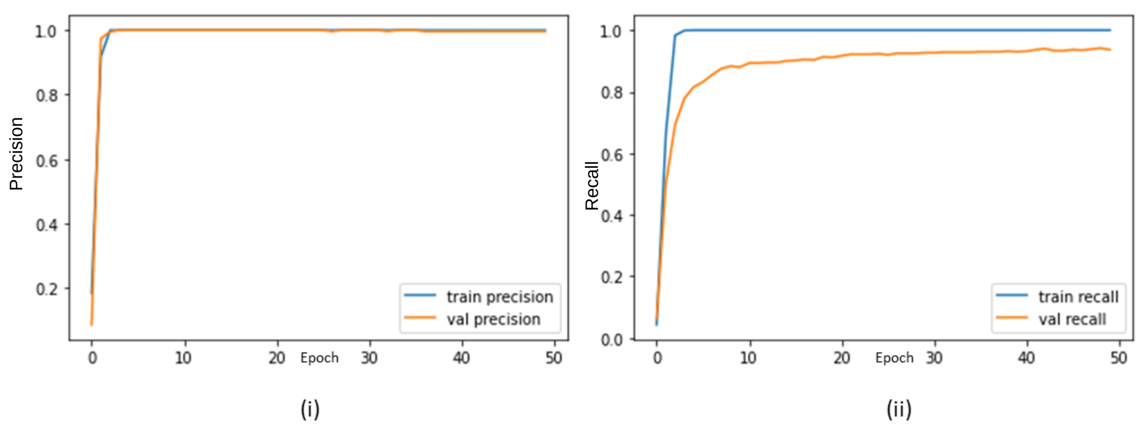

Figure 4.3: (i)Training and Validation Precision of VGG16 (ii)Training and Validation Recall VGG16

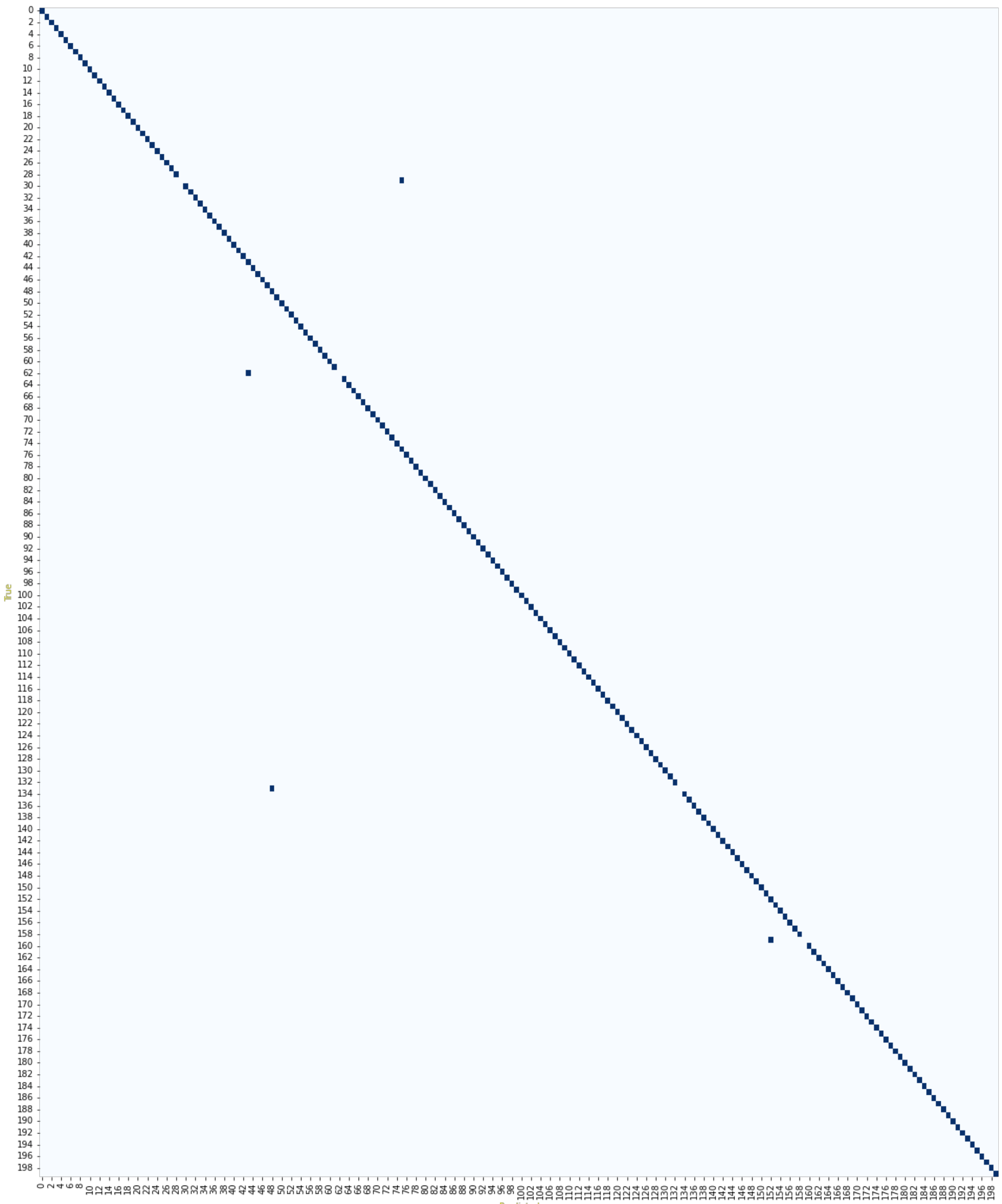

Figure 4.4: Confusion matrix(with preprocessing in VGG-16)

4.3.2 Results of VGG-19

After training and testing the model for 100 epochs in which the model accuracy converges to an accuracy of 97% before reaching 50 epochs. The figure 4.5(i) shows the overall training and validation accuracy over the epoch of 50 and figure 4.5(ii) is the graph of training loss and validation loss. The training and validation recall and precision graph is shown in figure 4.5(iii),(iv) respectively.From the graph we can clearly see that the number of learning parameters of the features to learn is lesser since the training accuracy rapidly converges to 100%.

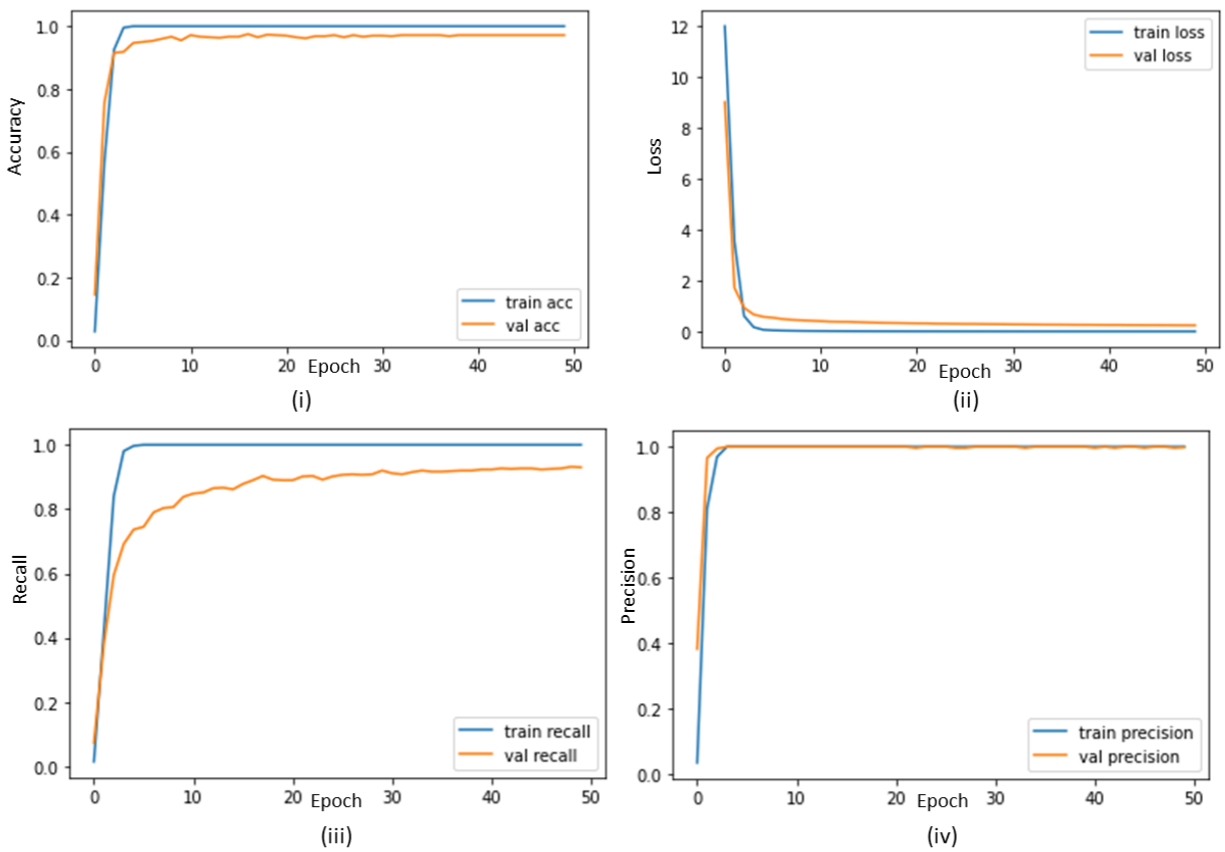

Figure 4.5: (i)Training and Validation Accuracy of VGG19 (ii)Training and Validation Loss of VGG19 (iii)Training and Validation Precision of VGG19 (iv)Training and Validation Recall of VGG19

4.3.3 Results of Inception-V3

The dataset is trained and tested in inception-V3 architecture obtained an accuracy of 64%.The figure 4.6(i) shows the overall training and validation accuracy over the epoch of 50 and figure 4.6(ii) is the graph of training loss and validation loss. The training and validation recall and precision graph is shown in figure 4.6(iii),4.6(iv) respectively. From the accuracy graph we take conclude that the learning is constant through each batch and each epoch and no further improvement is occurring.

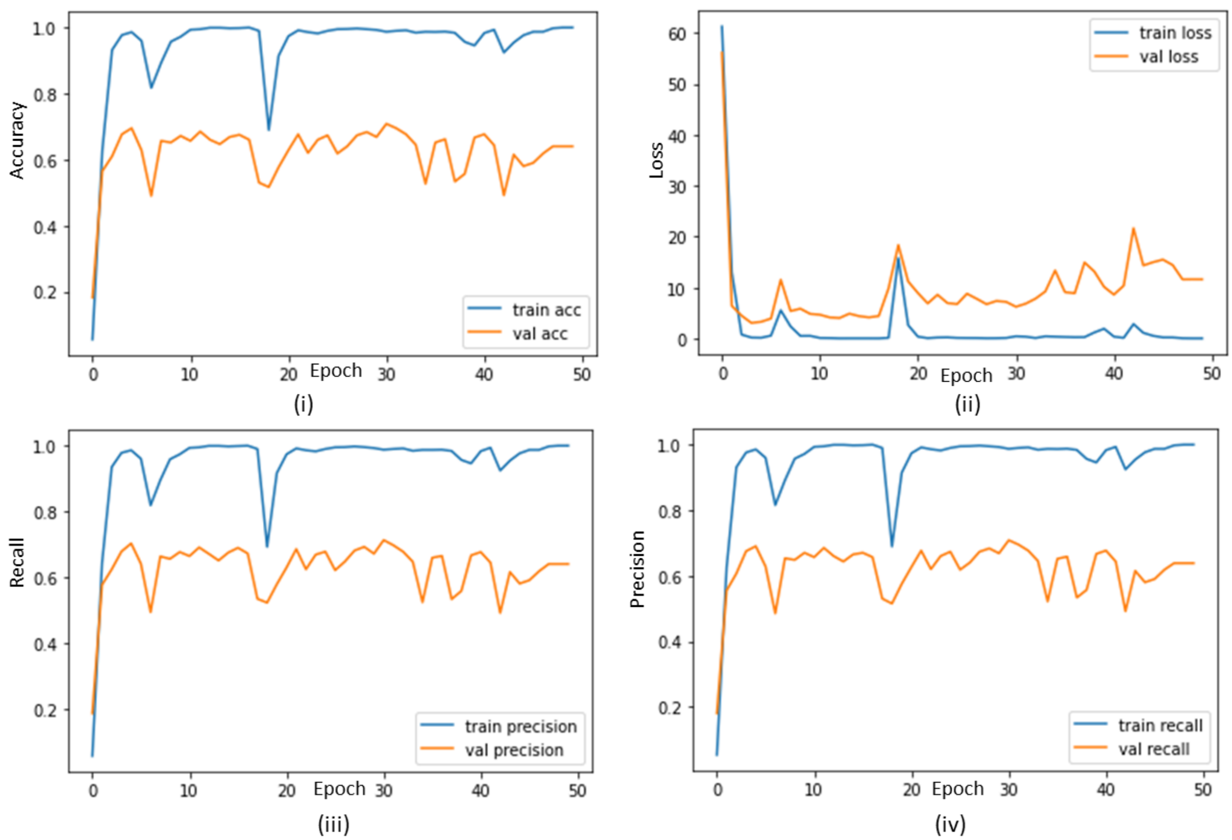

Figure 4.6: (i)Training and Validation Accuracy of Inception-V3 (ii)Training and Validation Loss of Inception-V3 (iii)Training and Validation Precision of Inception-V3 (iv)Training and Validation Recall of Inception-V3

4.3.4 Results of ResNet-50

After training and testing the model for 100 epochs in which the model accuracy converges to an accuracy of 76.33% before reaching 50 epochs. The figure 4.7(i) shows the overall training and validation accuracy over the epoch of 50 and figure 4.7(ii) is the graph of training loss and validation loss. The training and validation recall and precision graph is shown in figure 4.7(iii),(iv) respectively. In the figure 4.7(i) from the accuracy graph we can clearly see that learning has been occurred for some epochs and after that the accuracy rarely changes.

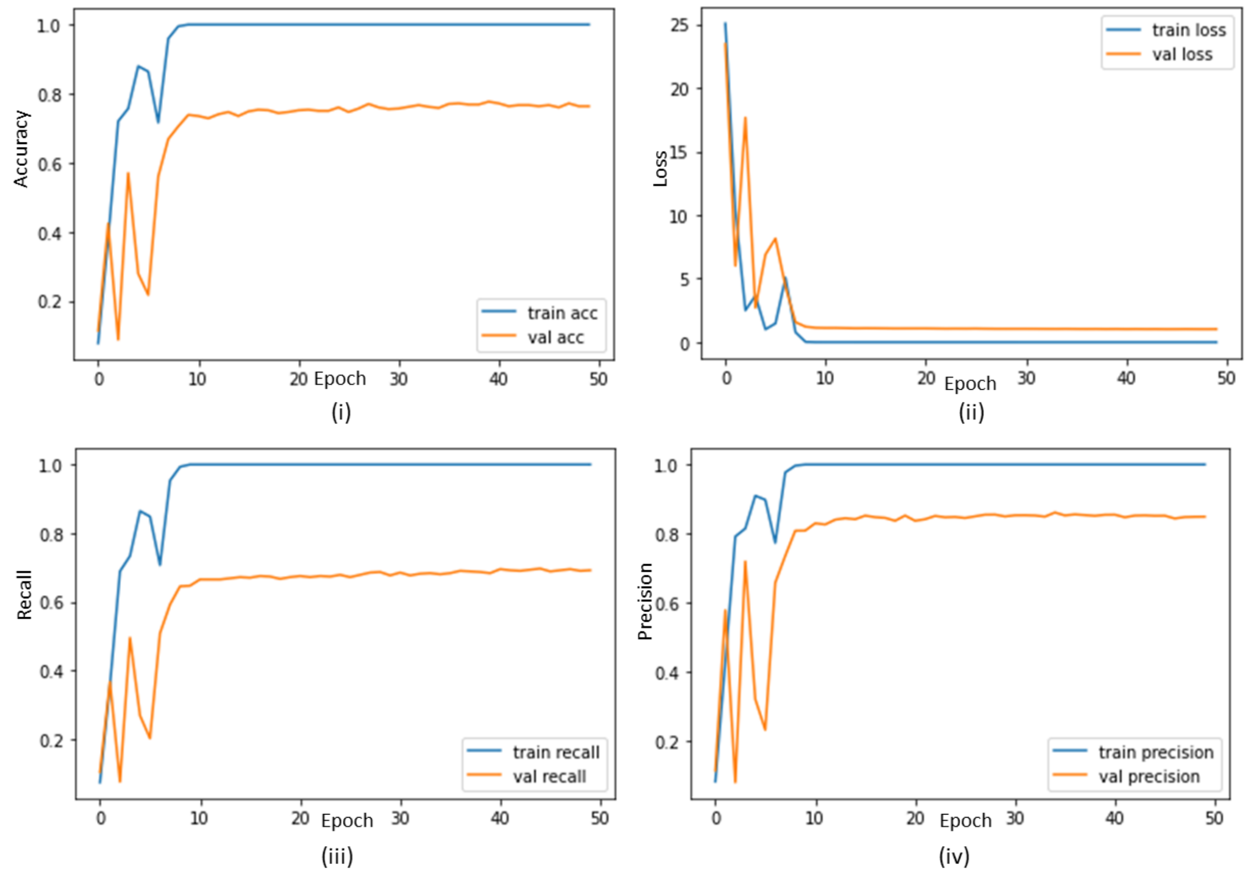

Figure 4.7: (i)Training and Validation Accuracy of ResNet-50 (ii)Training and Validation Loss of ResNet-50 (iii)Training and Validation Precision of ResNet-50 (iv)Training and Validation Recall of ResNet-50

Table 4.1: Comparison of Touchless fingerprint Identification with Preprocessing

Model	Accuracy	Loss	Precision	Recall	F1-Score
VGG-16	**.98**	**.20**	**.99**	**.93**	**.98**
VGG-19	.97	.24	.99	.93	.97
Inception V3	.64	1.16	.64	.63	.63
ResNet-50	.76	1.03	.84	.69	.76

4.4 Results of Touchless fingerprint Identification without Pre-processing

The results obtained in each model is plotted and confusion matrix for best model is also plotted.

4.4.1 Results of VGG-16

After training and testing the model for 100 epochs in which the model accuracy converges to an accuracy of 93% before reaching 50 epochs. The figure 4.8(i) shows the overall training and validation accuracy over the epoch of 50 and figure 4.8(ii) is the graph of training loss and validation loss. The training and validation precision and recall graph is shown in figure 4.9(i),4.9(ii) respectively. The figure 4.10 shows the confusion matrix.

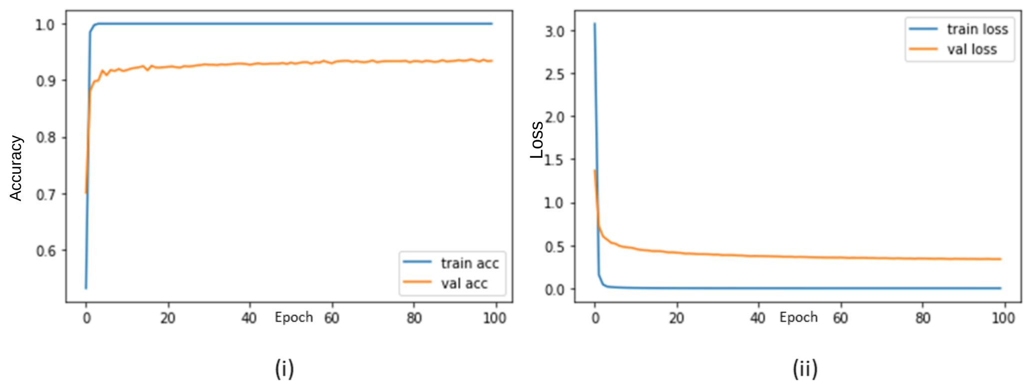

Figure 4.8: (i)Training and Validation Accuracy of VGG-16 (ii)Training and Validation Loss of VGG-16

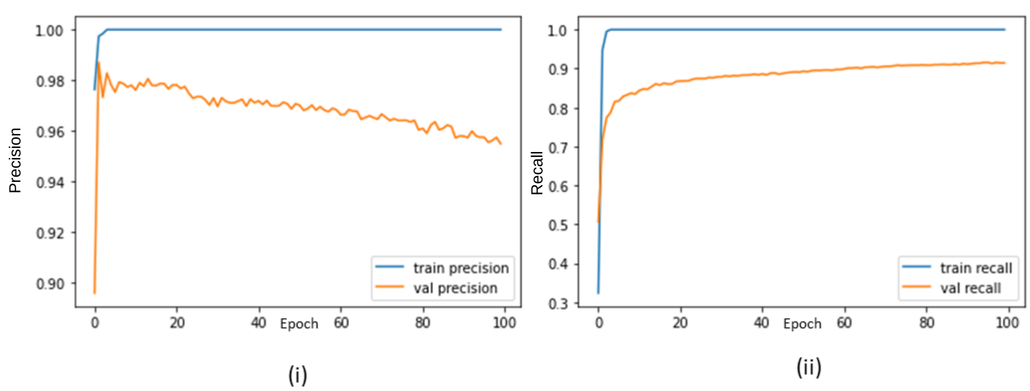

Figure 4.9: (i)Training and Validation Precision (ii)Training and Validation Recall

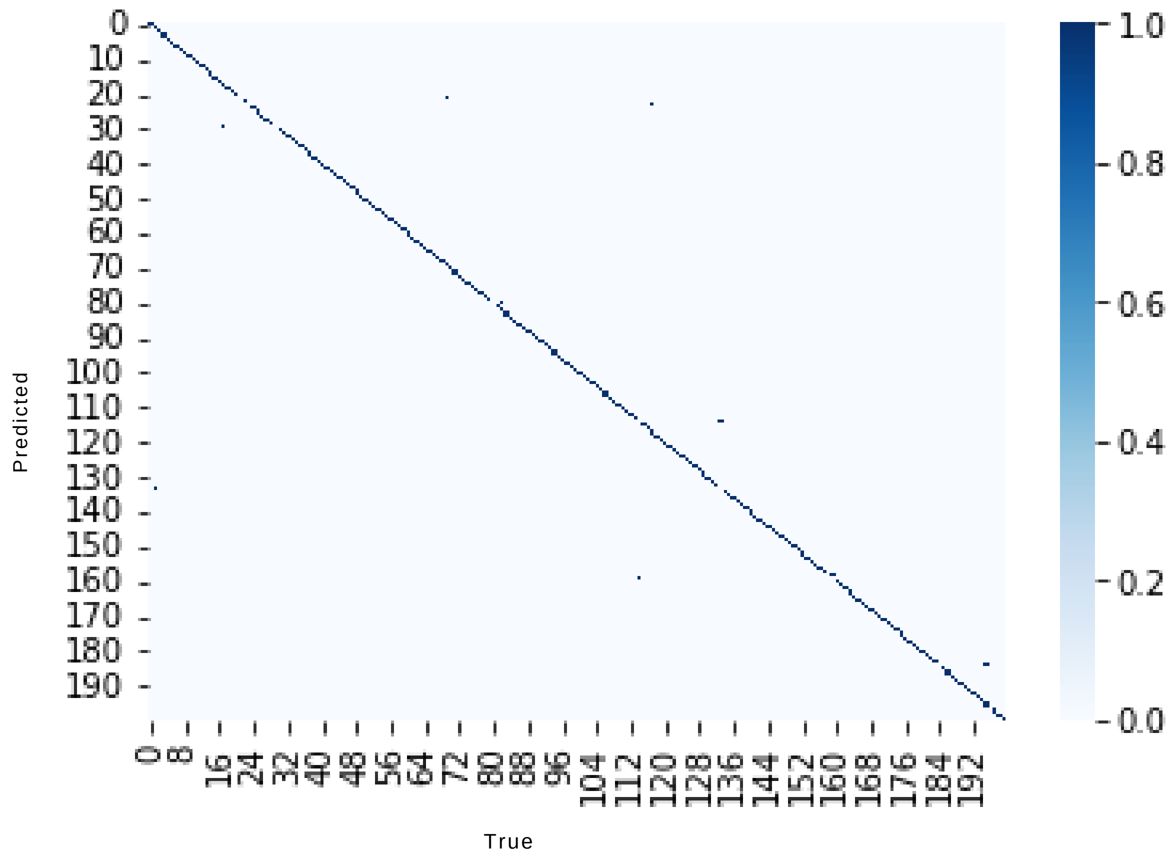

Figure 4.10: Confusion matrix(without preprocessing in VGG-16)

4.4.2 Results of VGG-19

After training and testing the model for 100 epochs in which the model accuracy converges to an accuracy of 92% before reaching 50 epochs. The figure 4.11(i) shows the overall training and validation accuracy over the epoch of 50 and figure 4.11(ii) is the graph of training loss and validation loss. The training and validation precision and recall graph is shown in figure 4.11(i),(ii) respectively.

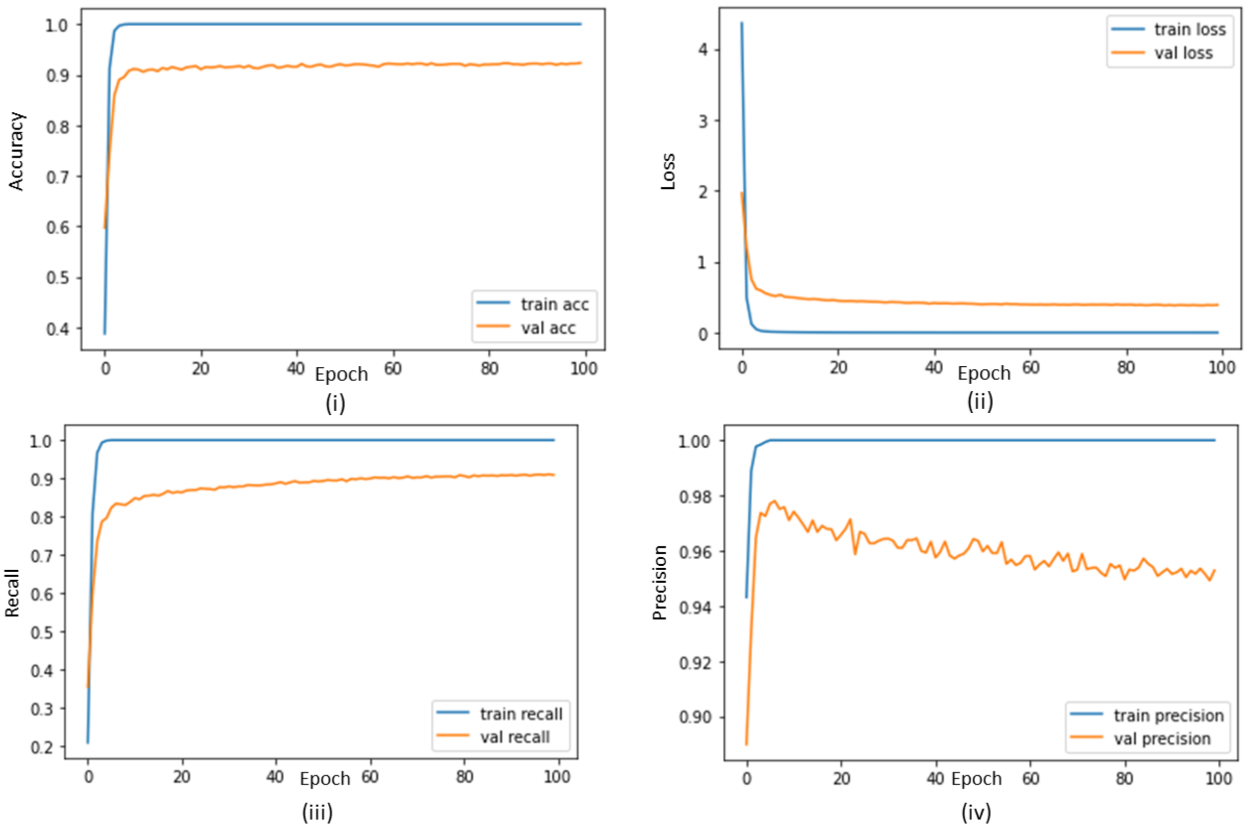

Figure 4.11: (i)Training and Validation Accuracy of VGG19 (ii)Training and Validation Loss of VGG19 (iii)Training and Validation Precision of VGG19 (iv)Training and Validation Recall of VGG19

4.4.3 Results of Inception-V3

The model is trained and tested for 100 epochs in which the model accuracy converges to an accuracy of 64.31% before reaching 50 epochs. The figure 4.12(i) shows the overall training and validation accuracy over the epoch of 50 and figure 4.12(ii) is the graph of training loss and validation loss. The training and validation precision and recall graph is shown in figure 4.12(i),(ii) respectively.

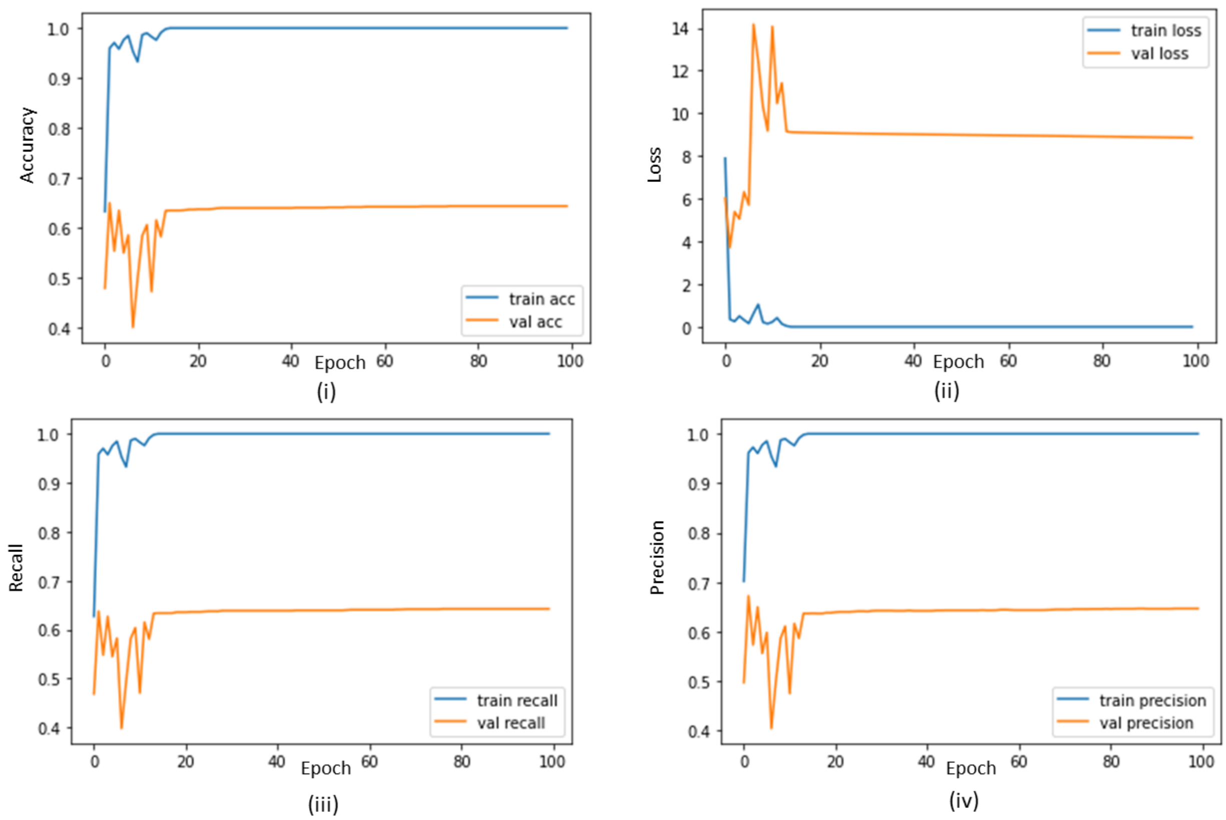

Figure 4.12: (i)Training and Validation Accuracy of Inception-V3 (ii)Training and Validation Loss of Inception-V3 (iii)Training and Validation Precision of Inception-V3 (iv)Training and Validation Recall of Inception-V3

4.4.4 Results of ResNet-50

After training and testing the model for 100 epochs in which the model accuracy converges to an accuracy of 17.19% before reaching 50 epochs. The figure 4.13(i) shows the overall training and validation accuracy over the epoch of 50 and figure 4.13(ii) is the graph of training loss and validation loss. The training and validation precision and recall graph is shown in figure 4.13(i),(ii) respectively.

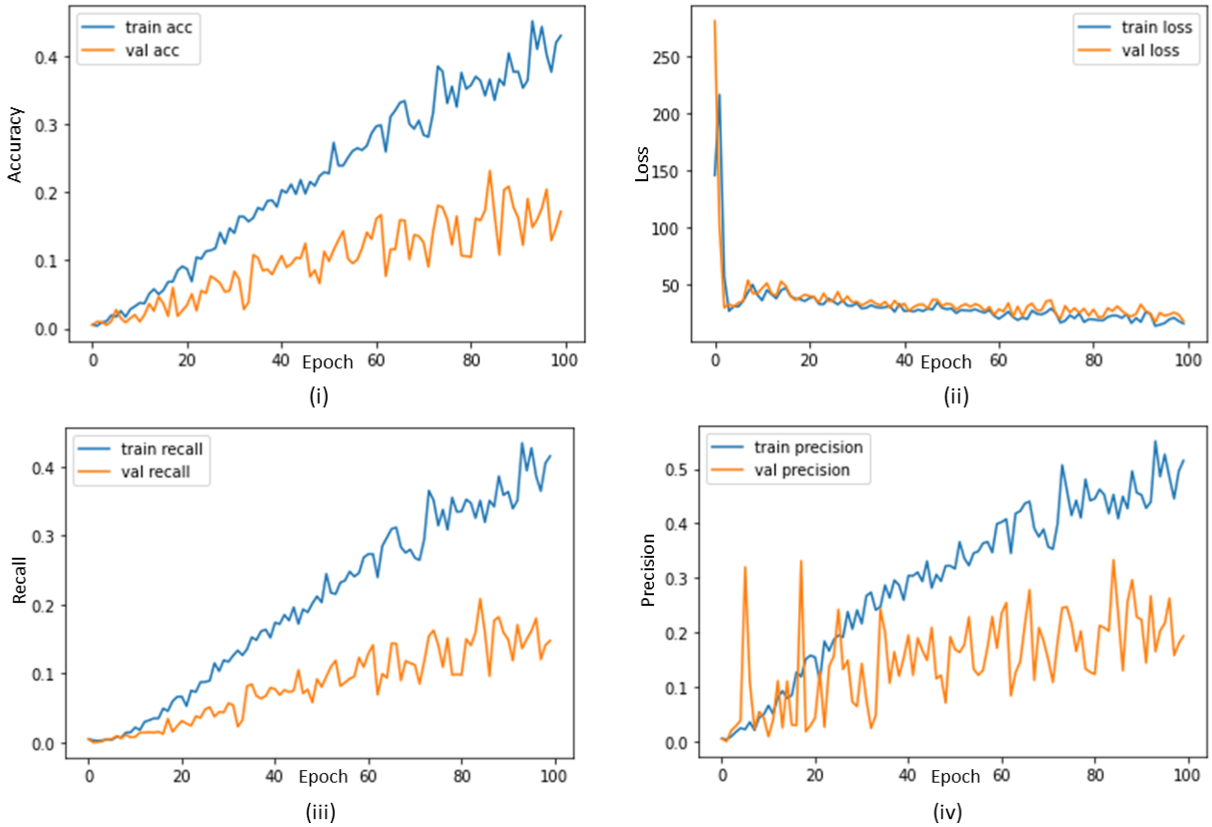

Figure 4.13: (i)Training and Validation Accuracy of ResNet-50 (ii)Training and Validation Loss of ResNet-50 (iii)Training and Validation Precision of ResNet-50 (iv)Training and Validation Recall of ResNet-50

Table 4.2: Comparison of Touchless fingerprint Identification without Preprocessing

Model	Accuracy	Loss	Precision	Recall	F1-Score
VGG-16	**.93**	**33.86**	**.95**	**.93**	**.94**
VGG-19	.92	.38	.95	.90	.93
Inception V3	.64	.88	.64	.64	.64
ResNet-50	.17	1.85	.19	.14	.16

4.5 Significance and future directions

In this world of cyber era the main threat is our security of data. For every secure system there is someone to exploit its security. The fingerprint biometric authentication is one of the top biometric authentication methods, but this conventional way of fingerprint identification can be breached and there are many ways to exploit its security. So there arise a need for a secure and reliable method which can overthrow the past methods problems. Thus in terms of security and reliability the touchless fingerprint recognition is a viable alternative.
Touchless fingerprint identification is new way of if identifying the fingerprints and more and more research is needed to optimise its performance. The proposed work in this work can be further extended to add more depth features like 3D capturing and mosaicking or learning sweat pore patterns or by detecting blood flow. By concatenating these methods to this work, the efficiency and reliability of the fingerprint recognition can be increased very high magnitude.

Chapter 5

Conclusions

In this work, we have trained and tested the touchless fingerprint using deep learning techniques by implementing on pretrained models such as VGG-16, Vgg-19, Inception-V3 and ResNet-50. The work is done in two ways, one method contains preprocessed images and the other contains no preprocessing stage. The total number of subjects used for this work is 200 identity. After training and testing in those pretrained models architecture, VGG-16 shows an accuracy of 98% was obtained for the preprocessed images and an accuracy of 93% was obtained for the images without preprocessing. The same data sets with the same notebook configuration were used for some of the pre-trained models such as VGG-19, Inception-V3 and ResNet-50. The conclusion that can be drawn from these results is that VGG-16 shows the best results among all the deep learning models. The results are prepared and presented in Table 4.1 and 4.2. From the obtained results, it can be seen that the model with preprocessed images has higher accuracy than the model without preprocessing images. These results shows that touchless fingerprint identification using deep learning is possible.

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