Biometric Retina Identification Using Artificial Approach

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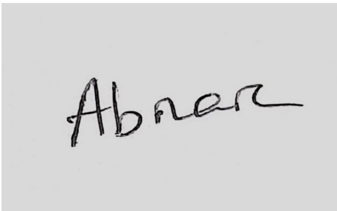

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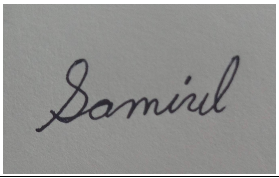

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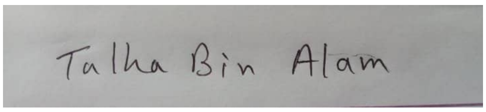

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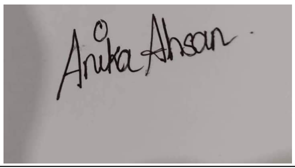

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Abstract

In this paper, we considered recognizing 2D retina pictures with a Convolutional Neural Network (CNN) for greater accuracy since retina-based identification is the most secure way of establishing identity and identifying people. An artificial neural network that is used to examine pixel input and recognize and process images is called a CNN. CNN algorithm has been selected to identify 2D retina images because through the CNN algorithm faster and better accuracy can be achieved. The retina identification process includes gray scaling of the RGB retina images, vessel extraction of the retina in the 2D images and then data augmentation is performed to increase datasets. Our method was evaluated on 3 databases- ARIA, DRIVE and STARE and we achieved test accuracy of 1 multiple times within 45 epochs. Test accuracy of 0.983 is received as the highest average accuracy among every 10 epochs. The implementation of the identification process was done using the PyTorch package.

Keywords: CNN, Retina, Biometric, Vessel, Grey Scale, Segmentation, Augmentation

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Above all, our outstanding teamwork has benefited us in crossing the finish line.
Last but not least, our heartfelt gratitude to ARIA(Automated Retina Image Analysis), STARE(Structured Analysis of the Retina) and DRIVE(Digital Retinal Images for Vessel Extraction) for providing us with the retina images datasets for our research work.

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Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

$ARIA$ Automated Retinal Image Analysis

CNN Convolutional Neural Network

$DRIVE$ Digital Retinal Images for Vessel Extraction

MLP Multilayer Perceptron

$STARE$ Structured Analysis of the Retina

Chapter 1

Introduction

1.1 Overview

CNNs, or Convolutional Neural Networks, have lately gained popularity in the domains of computer vision and medical image processing. During the last few years, CNNs have been employed in an expanding variety of applications when it comes to medical photography. In contrast to other image grouping methods, CNNs need very minimal pre-processing. This suggested that the network uses automatic learning to evaluate the filters, whereas traditional procedure needs hand-engineering. In feature extraction, the lack of prior information and human contact is a significant upper hand.
Convolutional Neural Networks (CNNs) are a powerful tool for identifying visual representations from images, as they typically consist of multiple layers of nonlinear processes and a large number of trainable parameters. The behavioral and physical traits of a person that may be used to digitally identify them and allow access to systems, equipment, or data is called Biometrics. Biometric identifiers include voice, facial patterns, fingerprints, and typing cadence [9]. Retina identification is a biometric method of identifying people based on their distinct retinal vassal patterns. In the case of a retinal scan, an infrared beam of minimal energy is projected into an individual's eye as the person's eye is placed before the scanner's eyepiece. On the retina, this beam of light follows a preset course. It is claimed to be the most secure means of identifying and differentiating individuals. The retina, which is located in the back of the eyeball, is thought to be extremely stable, seldom altering over a person's life. Therefore, retinal identification is regarded by far as the most reliable biometric system present today. Although identical twins share similar genetic information, they have distinct patterns of retinal vessels.[6] This research study proposes the use of a Convolutional Neural Network to identify an individual's retina. When it comes to categorizing characteristics, CNN is 2x more significant than MLP. Furthermore, CNN requires less time to compute than MLP. Near East University conducted one of the studies, which used a multilayer feed-forward neural network to analyze retinal pictures. The steps of retina identification, such as retina image capture, feature extraction, and feature classification, are discussed. The DRIVE[4] database is used to verify the correctness of the system they recommend. With a neural network comprising 35 neurons[5]. they were able to achieve a recognition rate of 97.5 percent. [5] We have used ARIA[24], DRIVE[4] and STARE[22]. The blood vessel pattern is used in this work to suggest a biometric authentication

mechanism. This is a one-of-a-kind pattern for each person, and it's very hard to duplicate it in a dummy. Unless there is an illness in the eye, the pattern does not alter over the course of the individual's life. This biometric characteristic has previously been proven to be a solid option.

1.2 Research Problem

Identification of a person is critical in the case of security. Accurate identification of a person may help prevent forgeries and illegal activity, as well as save time and money. When it comes to precise verification of an individual, biometric systems are quite crucial. As the cost of biometric sensors continues to fall, the underlying technology advances and the public becomes more aware of biometrics' capabilities and inabilities, biometrics has become a popular and important component of identification technology. Retinal-based biometric systems are emerging as a security and authentication technique due to the high degree of uniqueness of the pattern of retinal blood vessels [1].

Biometric Retina Identification is a biometric system that distinguishes persons based on their retinal blood vessel patterns [8]. A person's security and privacy may be jeopardized if they are not properly recognized. This problem might develop as a result of technological faults or the technology's poor accuracy rate. Because the theft of personal information and data is becoming more common, the accuracy of the technology must be sufficient.

In comparison to other biometric technologies, biometric retinal identification is a time-consuming operation. The user feels a lot of discomfort when an infrared laser beam is shone directly into the retina for approximately a minute. The calculation time of biometric retina identification technology can be decreased to lessen user discomfort and other difficulties. The CNN model, or convolutional neural network, may be used to save processing time and improve accuracy when detecting a person. As previously stated, reducing computing time will minimize the total identification procedure. The max-pooling strategy in CNN minimizes the number of dimensions and computations. The computing time of the entire process is reduced when the computation time is reduced. A multilayer feed-forward network is a collection of connected input-output networks in which each connection [2] has a weight. In the case of MLP, or Multilayer Perceptron, picture categorization takes longer to compute. CNN, on the other hand, uses less computing time since it does not spend much time categorizing pictures[3].

Along with that, we choose CNNs over RNNs because CNNs are faster than RNNs in the case of image processing because RNNs are made to deal with textual data whereas CNNs are made to deal with pictures. Since CNNs function best with spatial data, they are the best choice for image and video processing. RNN, on the other hand, works with sequential data, making it a good choice for text and speech analysis.

Appropriate neural network techniques or models must be incorporated to improve the accuracy of the identification system. The accuracy of image categorization is a major concern. An incorrect picture categorization might result in erroneous output acquisition. In hyperspectral image categorization,[3] CNN has shown to be quite effective. Because it has just a few parameters, this neural network reduces overfitting.

This study and the trials that go along with it will answer questions like how successful our Convolutional Neural Network in Biometric Retina Identification technology is and if it outperforms and outperforms most other previously presented approaches.

1.3 Research Objectives

The goal of this study is to create a better retinal identification mechanism that employs a Convolutional Neural Network to reduce computing time. To improve accuracy, sufficient volumes of data will be employed. When picture input is required, CNN tends to be more powerful and accurate than any other neural network model. The purpose of our research is:-
1. To gain a thorough understanding of CNN and how it operates
2. To increase the accuracy of identifying retinal image
3. To increase time efficiency and strategy
4. To automatically detect the significant features of the retinal image without any human supervision

Chapter 2

Background and Related Works

2.1 Convolutional Neural Network (CNN)

Convolution neural networks will be used to recognize images for biometric retina identification. Because of its great accuracy, For image recognition and categorization, CNN is utilized. Compactness, Efficiency, and a highly reduced network architecture for the division of fine structures in volumetric images are developed. As a result, basic and flexible components of current convolutional networks, such as increased convolution and surviving association, have to be considered. A totally convolutional downsample-upsample approach was used in the bulk of contemporary network architectures.

In deep learning, a convolutional neural network is an artificial neural network that examines data in graphic form. For any image-related challenge, CNN has become the go-to model. In terms of precision, they outperform the competition. It's also utilized in things like recommender systems and natural language processing. CNN's key advantage over its previous neural networks is that without human interaction, it can detect crucial characteristics. It may learn distinguishing traits for each class on its own if a huge amount of photos of goods and animals are supplied.

For medical image processing activities, one of the most difficult aspects of employing CNNs was that, unlike traditional image applications, medical applications often had low data preparation abilities. Despite the fact that the clinical image datasets used in the two solicitations in the technique were not very large at the subject level, they achieved cutthroat execution of the best-in-class tactics.

Furthermore, CNN models may now run on any device, allowing them to reach a broader audience. CNN employs pooling methods and advanced convolution, as well as parameter sharing.

CNN employs a tensor as an input, which allows it to better understand spatial connections (the relationship between neighboring pixels in an image) between pixels and perform better on more complicated images.

2.2 CNN Architecture

A CNN typically has three layers:
1. A convolutional layer,
2. A pooling layer,
3. A fully connected layer.

When the input image is supplied, CNN executes a sequence of convolution and then pooling operations followed by a number of fully connected layers.

2.3 Convolution

Convolutional Layer basically implements a mathematical operation on input data using its filter. It is considered the most crucial part of the whole procedure. Firstly, the image is taken as input in the convolutional layer. Then it performs a mathematical operation using its 3x3 kernel.
Generally, the convolutional operation takes place in the receptive field. As we have used a 3x3 kernel, our receptive field was a 3x3 matrix as well. The kernel is slid over the input to achieve a convolution and at each position, the sum of the result of component-wise matrix multiplication is plotted on the feature map.

2.4 ReLU Activation

Non-linearity must be present in any neural network in order for it to be effective.
The ReLU activation function receives the result of the convolution operation. So instead of the sums, the final feature maps are the ReLU functions applied. For clarity, we've left it out of the data above.
To achieve non-linearity, ReLU activation is applied to the feature map. ReLU activation takes the feature map and replaces all negative values with 0; if the value is greater than 0, it remains unchanged.

2.5 Stride and Padding

In convolution, stride indicates the number of pixels we can move in each convolution. When we apply convolution, there is a filter window which we can move by 1 pixel (by default) in either the x or y-direction. This is called a stride of 1 by 1. We can apply a stride of 2 by 2 which means the filter window will move in either x or y direction by 2 pixels. The striding is 1 by 1 by default.
We apply a filter matrix to the input image and we get an output feature map having a reduced size. This process of reducing the size of the input image is called padding. Thus through the padding, we reduce the size of the input image and get a featured map having a reduced size.

2.6 Pooling

In the pooling layer, the dimension of the feature map is reduced. Pooling is done on the feature map. In pooling at first, a spatial neighborhood which is a 2 pixel by 2-pixel window is taken. We can take any size of the window for pooling.
Here we have taken 2 by 2 windows for pooling. We take the largest value from the pooling window of the feature map and ignore the rest of the 3 elements. Through this process, we are preserving the important features. In pooling, the redundant pixels are canceled out and the important pixels are preserved. So through pooling, we get to reduce the size of the feature map which makes our program more efficient.

2.7 Hyperparameters

There are four crucial hyperparameters to choose from:
Filter size: We commonly utilize 3x3 filters, however depending on the purpose, 5x5 or 7x7 filters are also used. There are other 1x1 filters, which will be discussed in a separate post. They may appear unusual at first glance, but they have interesting applications.
Filter count: The filter count can be changed. It consists of two powers that can range from 32 to 1024. More filters show a much more powerful model, however, the risk rises of overfitting due to the count of higher parameters. Generally, at first, we start our proceedings with a definite number of filters in the first layer and eventually increase the number of filters as we approach deeper into the network.
Stride: We keep it at 1 because it's the default.
Padding: Padding is something that we frequently utilize.

2.8 CNN model -VGG 16:

The abbreviation of VGG is Visual Geometry Group which is a multi-layer CNN that is Convolutional Neural Network Architecture. Here the term deep indicates the number of layers. VGG16 and VGG19 have 16 and 19 convolutional layers, respectively.
VGG16 is a 16-layer deep convolutional neural network. The image input size of the network is 224 x 224 pixels. VGG16 is unusual in that instead of focusing on a huge number of hyperparameters, mainly this method emphasizes on 3x3 filter convolution layer with the step size of 1 and every time uses the padding which is the same and the filter with 2x2 has step size 2 has the maximum pool layer. In VGG 16 here number 16 indicates the reality that it has a number of 16 layers which are of different weights. About 138 million(approximately) parameters and this is a huge network. The VGG model, often known as VGGNet, is a type of convolutional neural network. The researchers described the model in their script which is a Large- Scale Image Recognition by Very Deep Convolutional Networks.
Initially, we applied the VGG16 model of CNN for retina identification.VGG16 is a pre-trained CNN model which is used for image classification. However, we did not achieve efficient results from the VGG16 model in retina identification. As a result, we applied traditional CNN with 3 layers in retina identification where we achieved test accuracy of 100 percent multiple times within 45 epochs.

2.9 Fully Connected

To complete the CNN design, we add a pair of fully linked layers after the convolution + pooling layers.

2.10 Previous Findings

We will be comparing the already utilized multilayer feed-forward neural network with CNN for Biometric Retina Identification and see which way is more efficient.

After the neural network has been started, the parameters of the neural network are trained. The network is trained with the PyTorch library. The 10-fold cross-validation method is used to test classification accuracy during the learning phase. To get the needed accuracy in the neural network output, a number of tests should be carried out. In the hidden layer, the simulation uses different numbers of neurons. The number of output neurons was the same as the number of classes, which was eight.

RGB retina pictures from DRIVE, ARIA and STARE datasets are converted to grayscale images. Grayscale tones are the only colours used in grayscale images.

A feature map is created by performing a convolutional operation on the picture. The feature map is then subjected to ReLU activation. After that, pooling is used to minimize the image's size.

Our main goal is to achieve a better recognition rate than other models used for retinal identification since CNN can automatically detect the important features without any human supervision. As RNN, DNN or other models can reach up to 0.9 to 0.975 recognition rate, we've set our target to more than 0.975 recognition rate with CNN.

Chapter 3

Approach

As previously stated, the goal of the suggested retina identification model implementing CNN is to make the identification process more robust and rapid. Moreover, it is easier to make it learn or train it, as it requires fewer parameters and performs well in image classification. To do this, retina images are used as input, and a convolution neural network is applied to the image, which employs convolution and pooling operations, as well as parameter sharing, to identify and recognize it with prior retinal images data.

The goal of our suggested model "Biometric retina identification using the artificial technique" is to use a Convolution Neural Network to identify retina pictures in order to reduce computation time and increase accuracy. To do so, retina pictures are used as input, and a convolution neural network is applied to the image, which conducts parameter sharing and employs convolution and pooling operations to identify and detect it with prior retinal image data.

3.1 Acquiring Retina Images

In order to reach our goal, the neural network model must be trained on a retina dataset. Therefore, STARE [22], DRIVE[4] and ARIA [24] are used as input datasets.

Figure 3.1: ARIA

Figure 3.2: DRIVE

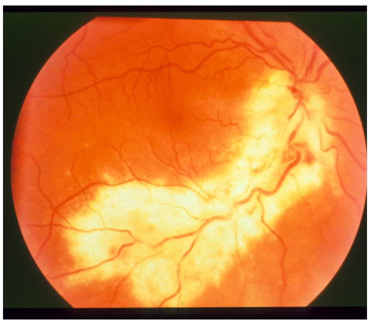

Figure 3.3: STARE

STARE is a retina image database for retina image research purposes with 397 images. ARIA is a multiscale line operator-based augmentation of blood vessels in digital fundus pictures. This dataset consists of 122 retina images. Lastly, DRIVE dataset is a dataset for segmenting retinal vessels made up of JPEG 40 color fundus images. After augmenting these datasets, we have acquired in a total of 686 images of the retina. Different datasets are used to increase the accuracy of our Neural Network system.

3.2 Gray Scale Transformation

A grayscale picture is one where the only colors are different shades of gray. In other words, grayscale indicates that the value of each pixel simply represents the intensity of the light. The reason that such images vary from other types of color images is that less information is required for every pixel. Grayscale pictures provide two crucial pieces of information: the grayscale variation and the image's specific geometric properties.

Figure 3.4: Gray Scale Image of Retina

The grayscale intensity is represented as an 8-bit integer, resulting in 256 discrete shades of gray ranging from black to white. It is utilized to keep things simple. Smaller data allows us to do more complicated processes in less time. Moreover, Color information does not assist us in identifying crucial edges or other characteristics in our scenario.

3.3 Segmentation

Segmentation is a typical procedure in pre-processing methodologies and is required for the majority of image processing viewing, manipulation, and analysis activities. As a result, segmentation is the most important of all image operations. The goal of segmentation is to recognize and differentiate items [25].The process of segmenting vessels in retina images is known as retina vascular segmentation. Segmentation of retinal blood vessels is essential for retinal image analysis. The Gray Scaled image has to be segmented to get visual information.

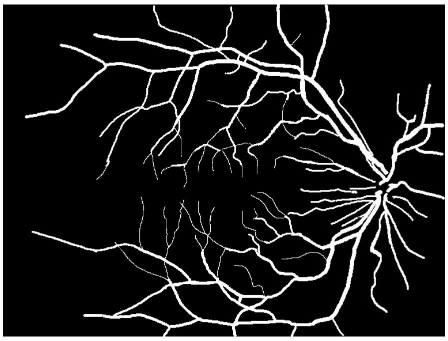

Figure 3.5: Gray Scale Image of Retina

3.4 Data Augmentation

Data Augmentation is the process in which expansion of the amount of the given data by making small modifications to the present data or by giving rise to the synthetic data which is a very common training for compensating for low reference observations. Using the present data which is as a reference may be more efficient also side by side with the data from prior research initiatives or authority, rather than obtaining new reference data. As a result, user-friendly databases containing categorized remote sensing data are becoming increasingly important, although they are still insufficient. These databases will not only improve the effectiveness of model training by allowing researchers to develop and examine the calculation and transferability to the other domains of these models.
As a result, databases can be used to assess and improve the transferability of the model to the new domains like a variety of remote sensing acquisitions, improvement stages and vegetation types. Additionally, sufficiently big datasets may play a key role in the creation of backbones tailored to vegetative remote sensing. We improved the performance of our model by augmenting our dataset photos with variations of the same image.

3.5 Feature vector acquisition

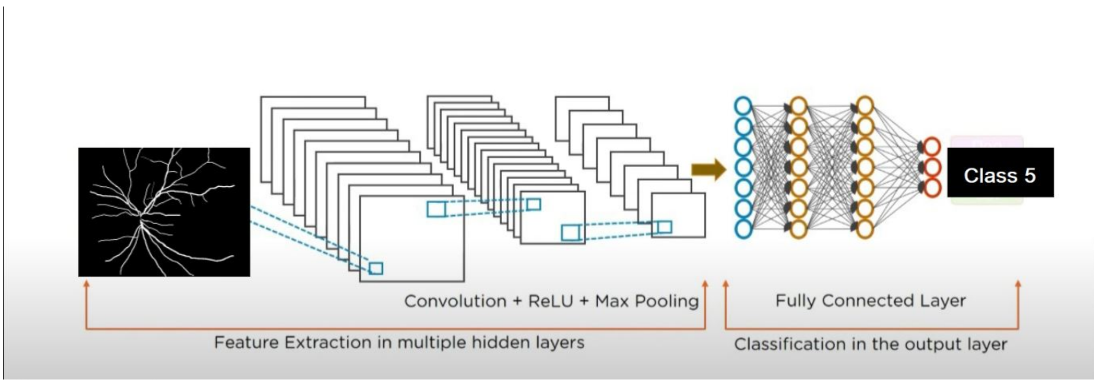

Figure 3.6: Feature Vector Extraction

A feature vector is the type of vector that contains information about an item in the form of many elements. In layman's terms, the output of a CNN is a feature vector, which implies that the input is an image and the output is a feature vector of that picture. Feature vectors are very effective when it comes to image classification. The feature vector is created by transforming the segmented picture to numerical values.

3.6 Convolutional Operation

Convolution, in its most generic form, is an operation on two functions with a real value input. A perceptron is a single neuron that serves as the foundation for bigger neural networks. The multi-layer perceptron is made up of three layers: the input layer, the hidden layer, and the output layer. The hidden layer is invisible to the rest of the world. Only the input and output layers are visible. Data for all neurons must be numeric in character.

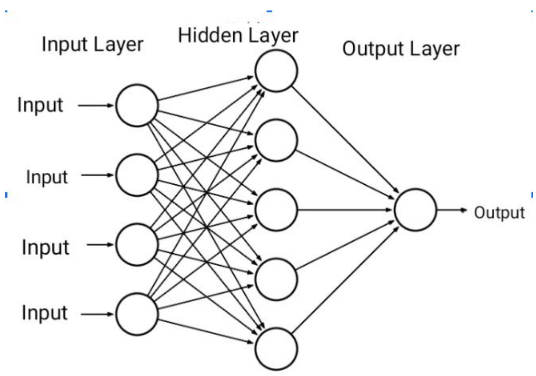

Figure 3.7: Convolutional Operation

One of the merits of a Convolutional Neural Network is that the acquired image does not need to be resized. The neurons of all the layers have to be calculated. The dataset will work better if converted into float type. We will apply Fourier Transformation to the images.

$$
\begin{aligned}
F(u) &= \frac{1}{K}\sum_{i=0}^{K-1} f(i)\; e^{-j2\pi ui/K} \\
F_{\tau}(u) &= \frac{1}{K}\sum_{i=0}^{K-1} f_{\tau}(i)\; e^{-j2\pi ui/K} \\
&= \frac{1}{K}\sum_{i=0}^{K-1} f(i-l)\; e^{-j2\pi ui/K} \\
&= \frac{1}{K}\sum_{i=-l}^{K-1-l} f(i)\; e^{-j2\pi u(i+l)/K} \\
&= e^{-j2\pi ul/K} F(u)
\end{aligned}
$$

Afterward, reshaping and normalizing the data should be done. The sigmoid function will be used in our model for the activation function. The equation of the sigmoid function is shown below:

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

The hidden layer will be using the activation function. After running the model, it will be clear that an increment of the number of epochs improves accuracy. The smaller the error rate, the more accurate our model will be.

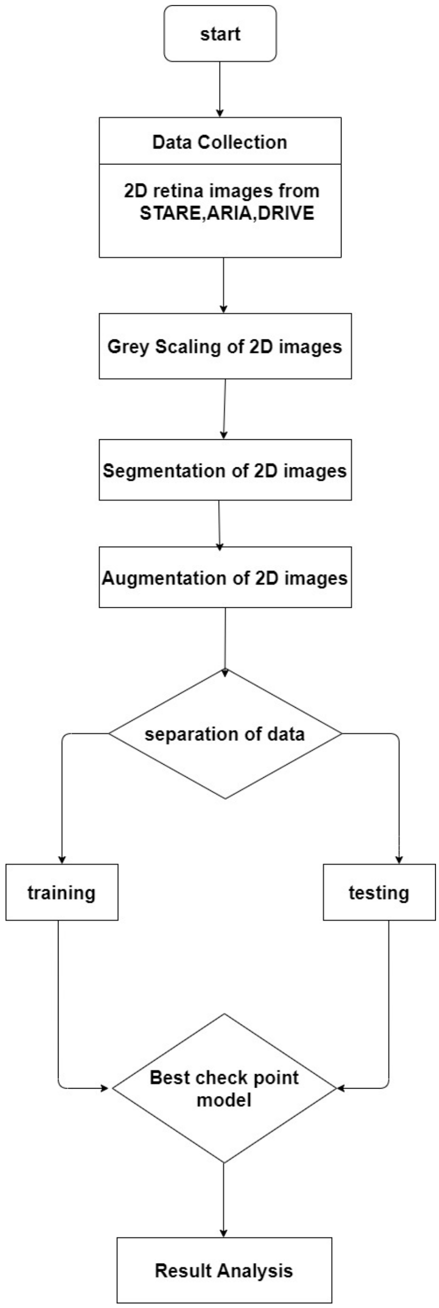

Figure 3.8: Workflow of our Model

Chapter 4

Result Analysis

The training of the network is implemented through PyTorch. The Train dataset is first taken to be tested with the Test dataset. Then the network initiates training for 45 epochs.

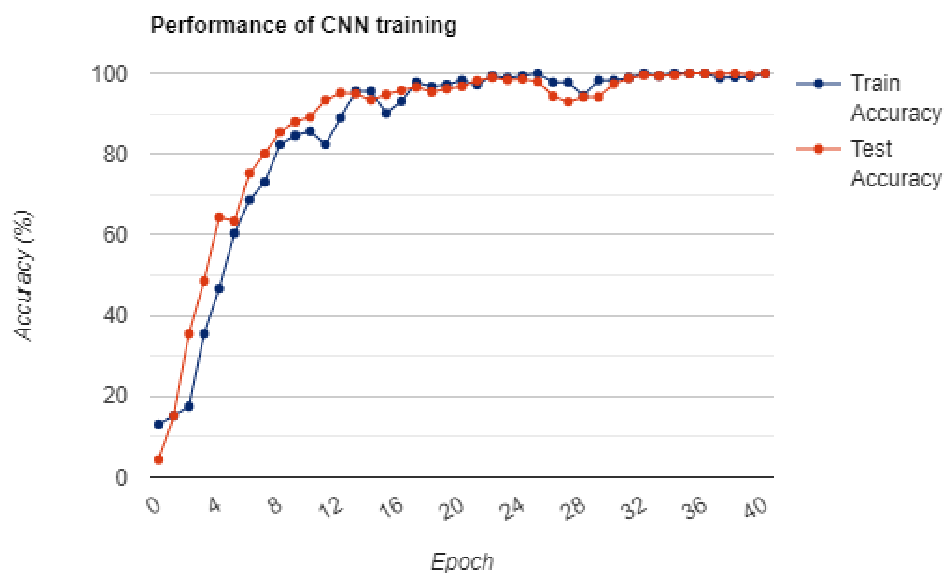

Figure 4.1: Performance of CNN Training

As shown in fig. 4.1, within the epochs, the best Test Accuracy is initialized as the checkpoint model. The test training starts with the test accuracy of only 0.13187

Techniques	**Accuracy (Per Cent)**	**Number of Images**
Perez [17]	93.20	40
Zana and Klein [8]	89.84	40
Fraz [11]	94.30	40
Sadikoglu and Uzelatinbulat[5]	97.50	40
Our Paper	**98.30**	**80**

and ends with an accuracy of 1. Throughout the training of 45 epochs, the best accuracy has hit the objective mark, 1, nine times with an average of 0.915 during the whole training.
We received 0.983 accuracy as the highest average for every 10 epochs. The learning rate of the network is set to 0.001 to minimize the loss function and the weight decay is set to 0.0001 to prevent overfitting.

Chapter 5

Conclusion

To conclude, we studied the identification of 2D retina pictures using a Convolutional Neural Network (CNN) for improved accuracy since retina-based identification is the most secure method of establishing identity and identifying humans. We picked the CNN method to recognize 2D retina pictures since it is quicker and has higher accuracy. Greyscale of RGB retina pictures, vascular extraction of the retina in 2D images, and data augmentation to enhance datasets are all part of the retina identification process. From our research, we found that CNN can acquire up to 100 per cent accuracy in a short dataset for Retina identification. We learned that, in this case, CNN, VGG-16 of CNN to be specific is robust and less time-consuming. We suggest that to identify an individual through a retinal scan, CNN should be implemented.

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