Fingerprint Recognition Using: ResNet50

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Abstract.

The use of biometric systems is to detect the authenticity based on users' distinct physiological characteristics for identification purposes. They are difficult to hack or get passed compared to the traditional password systems. Using the FVC2000 fingerprint dataset gotten from Kaggle, i design a deep neural network for fingerprint recognition using ResNet50 to ease the training of the network with a larger number of layers. Training the images without pre-processing ensures the model is time efficient. The algorithms output estimates how confident it is that the prints in the test image sample are a match to those in the train image sample. The neural network is trained with 800 images of class 0-9 and its performance is tested using 10 images that have ever been seen before by the model but is a subset of the original dataset. The experimental results show a good accuracy achieved by the ResNet50 model, revealing a performance accuracy on average of 74.33 percent and an average loss of 48 percent. This model can be executed with a larger database and different parameters to achieve a better performance.

1 Introduction

To make an application more secure and less accessible to undesired people, we need to be able to distinguish between people. So far, the most secure options are biometric methods of identification, which cannot be imitated by others. These biometric features are divided into behavioural features that a person can uniquely create or express like signatures and physiological features that a person possesses such as fingerprints, facial features, iris pattern. Amongst the various biometric attributes, fingerprints are one of the top standouts, due to its permanence, uniqueness, and individuality. As such it is usually utilised for identification. it has been used in various applications such as forensics, transaction authentication, cellphone unlocking. The accuracy and efficiency of fingerprint matching and indexing are crucial in companies today for identification and security purposes. [6] describes fingerprints as imprints formed by friction rides of the skin in fingers and thumbs, stating that due to their individuality, the probability of two fingerprints being alike is about 1 in 10 to the power of 15. Recently, automated fingerprint recognition is desirable in many applications such as police work. From [9] we see that classification is usually performed by locating distinctive features known as Minutiae, the major minutiae features of fingerprint ridges are ridge endings, bifurcation and short ridge. Minutiae are typically extracted from test and input images, and the number of corresponding minutiae pairings between the two images is used to verify the test image.The goal of fingerprint recognition systems is to strive for robust and fast detection, despite this, fingerprint recognition systems are also sensitive to errors due to the positioning of prints during authorisation. Or in the case of low-quality fingerprint images, new segmentation approaches can be used to extract minutiae from fingerprints with an enhanced quality. There have also been various works on fingerprint recognition using hand crafted features followed by some classification [8]. [2] also proposed a new representation based on 3D data structure, built from minutiae distances and minutiae cylindrical code. Fingerprint recognition using Scale Invariant Feature Transform features (SIFT) where SIFT feature points are extracted in scale space and matching is performed based on texture information around the feature points using the SIFT operator [8]. Although many of these works achieve highly accurate performances, they involve a lot of pre-processing. In this paper, i will be looking at a deep convolutional neural network approach to fingerprint recognition using a residual network.

2 Background

Deep learning has been used in various problems such as classification, segmentation, super-resolution, face recognition and fingerprint recognition, and has significantly improved the performance over traditional approaches. It has also been used for several Natural Language Processing (NLP) tasks, such as sentiment analysis, machine translation, name-entity recognition and question answering [3]. However, despite the numerous uses and the crucial importance of network depth, [11][12] shows that deeper neural networks are more difficult to train.

From the figure above, we see that the deeper network has a higher training error and test error. For larger datasets such as ImageNet, increasing the number of layers and as such increasing the depth of the network is being used more frequently in today's climate. Driven by the significance of depth, a question posed by [5] – "is learn-

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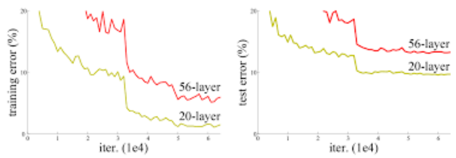

Figure 1. Training error(left) and test error(right) on CIFAR-10 with 20-layer and 56-layer "plain" networks.

ing a better network equivalent to stacking more layers?" was introduced. Along with this question, came the problem of vanishing/exploding gradient and degradation [1] [4],which hamper convergence. The ResNet model introduced by Microsoft research, introduced an architecture called "residual network", to tackle the problem of vanishing gradient and degradation by employing a technique known as skip connections, which skips training from a few layers and connects directly to the output.It is a popular convolutional neural network which provide easier gradient flow for more efficient training.

2.0.1 *Proposed Framework*

For fingerprint recognition, there are several public datasets with a reasonable size, but most come with a limited number of images per class, which makes it more challenging to train a convolutional neural network from scratch on these datasets [7].In this work we propose a deep learning framework for fingerprint recognition for the case where only a few samples are available. We train a convolutional neural network on one of the fingerprint datasets from Kaggle, as well as using data augmentation techniques such as (flipping, random cropping, stretching), to increase the visibility of the images. By doing so, we can achieve a high recognition accuracy rate on the test samples of the dataset.

2.0.2 *Residual network*

Comparing the structure and functionality of a plain network layer with a residual block to understand the working of a residual block properly. A plain network consists of linear(z) and non-linear (ReLU, here) activations whose output serves as an input for the subsequent layer. Only a single activation function gets used in this case, for every layer. However, a residual block in its [l+2] layer, along with

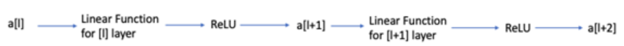

Figure 2. One layer of A Plain Network.

the activations from a[l], also uses the parameters from the previous activation function. This happens through a skip connection shown below. The connection shown, adds a[l] to the ReLU non-linearity

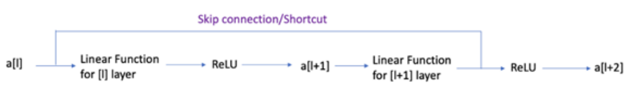

Figure 3. One layer (Residual Block) of a ResNet.

function of [l+1] layer. So, the information in a[l] gets fast forwarded deeper into the network, through the shortcut. a deeper comparison was shown in [5], where a 34-layer plain network showed higher validation error than the shallower 18-layer plain network, revealing the issue to be that of degradation as the depth of the network increases.Using a residual network with the same baseline architecture as the plain network, except that a shortcut connection is added to each pair of 3×3 filters. The 34-layer ResNet shows lower training error, indicating that degradation problem is addressed using in a deep network using a ResNet model.

2.0.3 *Fingerprint Classification Using Residual Convolutional Network*

In this work, we addressed the fingerprint recognition task and chose a dataset with many subjects but with a limited number of subjects per class. Using a residual learning approach, i was able to perform fingerprint identity recognition using deep residual convolutional network. I used a ResNet50 model and trained it with our dataset.

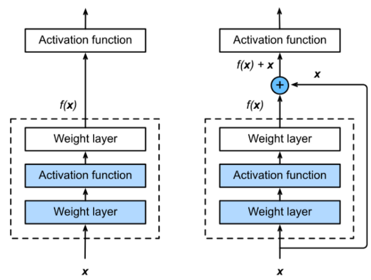

Figure 4. Residual Block and Skip connections For Identity mapping.

To perform recognition on our fingerprint dataset, i trained a ResNet model with 50 layers. Different from the architecture of the 34 layered model, the ResNet 50 model skips 3 blocks instead of 2 [5]. As seen in the diagram above, the stacked layers in the resid-

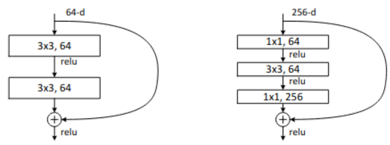

Figure 5. Left: Skip 2 layers, ResNet-34. Right: Skip 3 layers including 1× 1 convolution in ResNet-50

ual block will have a 1x1,3x3 and 1x1 convolution layer, where the first 1x1 convolution reduces the dimensions of the feature maps, the features are then calculated in the 3x3 layer and then increased in the next 1x1 layer.The absence of a pooling layer within the residual block, is because of the 1x1 convolution layer increasing and decreasing the dimensions of the feature maps. I first define the simplest residual block where the dimension of the input does not change but the depth does. The second residual block sees a change in the dimensions of the input by using the 1x1 convolution with a stride 2, thereby changing the dimension of the skip connections as well. The combination of these two residual blocks, builds the ResNet 50 layer. Below is a a diagram representing the architecture of ResNet 34.

3 Experiments and results

In this section, the experimental results for the proposed algorithm is shown. We train the model for 25,50 and 100 epochs. The batch

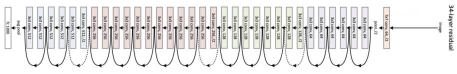

Figure 6. ResNet 34 Architecture

size for the ResNet model is set to 64 and an Adam optimiser is used to optimise the loss function. The images are split with a test size of 0.1, giving the train image a dimension of (720,160,160,1), the test/real image a dimension of (10,160,160,1) and a new validation shape after splitting of (80,160,160,1).

3.0.1 Dataset

We evaluated our work using the FCV2000 database provided by kaggle. It contains 810 fingerprint images, 10 of which have never been seen by the model and is classed as "real/test images", 800 train images with classes from 0-9. For each class, we have 80 example prints with 8 different fingerprints in the same class. The fingerprints in this dataset have different colour distributions, quality and size and as such for each print, 10 images are used as test samples and the rest are used for training and validation.

Figure 7. Sample fingerprint images from Kaggle

Model Accuracy	
No of Epochs	ResNet50(in percentage)
25	65
50	74
100	84

Table 1:Results from experiment

The table above shows the results of the accuracy of the model, run against 25,50 and 100 epochs with a batch size of 64. Using the test images and running it against the train images for the above listed number of epochs, it shows that the higher the number of epochs passed, the higher the accuracy of the model. Indicating the model is getting more and more confident that one or more of the prints in the test sample is a match to the print in the train sample of the dataset.

Results				
Epochs	Accuracy	Loss	Validation accuracy	Validation loss
25	0.6562	0.6044	0.6719	0.6368
50	0.7443	0.4986	0.7344	0.4919
100	0.8409	0.3443	0.7969	0.3864

Table 2:loss and accuracy values

Table 2 shows the results of training and testing accuracy of the RestNet50 across the various epochs. Table 2 also shows the results of the deep neural networks training and testing loss across the various epochs. The proposed neural network classifier achieved an overall testing 74.33 percent accuracy.

Accuracy across different networks			
Epochs	AlexNet	ResNet	Logistic Regression
25	60	65	-
50	90	74	40
100	80	84	40

Table 3:Accuracy across different networks, using the same dataset

Table 3 above shows the accuracy across different neural network frameworks, using the same FVC2000 dataset. We notice that the AlexNet has a better accuracy on average than the ResNet50 model.

4 Discussion

Table 2 compares my model against other deep neural network frameworks, running against same number of epochs but different batch sizes. The best performance can be seen in the methodologies where deep learning is used. These have the best accuracy with the average being above 60 percent, despite FVC2000 being a small dataset.

Regarding the experiment in the literature, I can conclude that most of the studies, especially in earlier years did not evaluate their proposed methodologies on publicly available datasets. Due to the lack of available datasets and the use of the small FVC dataset, despite this, my model achieved a good accuracy of 74 percent on average. Overfitting of the model was the biggest issue that had to be overcome, using data augmentation processes, I was able to curb this problem to a point. Testing this model against a larger dataset would show greater results but the problem of overfitting would be the biggest issue to be tackled as well as the value of the learning rate that should be used.

5 Conclusion and future work

In this paper i have presented a fingerprint recognition system that uses local features to identify fingerprints, using a deep learning framework by training a convolutional model on ResNet. Applying the proposed framework on the FVC2000 fingerprint dataset gotten from Kaggle, i achieved good results, having trained the model with 25,50 and 100 epochs and a batch size of 64. This framework can also be used for other biometric recognition problems such as facial recognition and is useful for cases where there are few labelled images available per class. The use of neural networks supports fast classification and identification and saves the user from spending a lot of time to identify a match.

In the future, we test on various FVC datasets to increase the precision of the framework and furthermore improve the execution of deep neural network with a smaller number of parameters. We can also extend our model to be able to match and identify prints based on finger veins not just prints. Despite the low accuracy of finger veins compared to other biometrics [10], it has several advantages such as being very difficult to forge/copy. From [10], we also notice that where deep learning is employed, authentication based on finger vein images have a 99 percent accuracy based on performance. Using ResNet to implement this model would reduce the degradation problem and possible increase the accuracy on average.

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