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Reconstructing Fingerprint Images using Deep Learning

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Abstract – In today's technology world, a majority of users across the world have access to Internet for communication via fingerprint ,images, audio and video. It is a need to understand and recognize the behavior of such larger text information on people by analysing their finger. This Paper focuses on collect a database of fingerprint images, we design a neural network algorithm for fingerprint recognition.In one experiment, the neural network is trained using a few hundred pairs of images and its performance is subsequently tested using several thousand pairs of images originated from a subset of the data base corressponding to 20 individuals. At the end, a comparative study of the performance of different classifiers is discussed.

Keywords : Sentiment analysis , deep learning , fingerprint detection.

I. INTRODUCTION

Social media has become an integral part of the people In 21st century. Due to rapid progress in information & Technology sector, people have access to any kind of Information at the click of a button . Moreover, with the invent of smart- phone and 4G networks, even people from the remote areas are getting connected to Tier 1 & Tier 2 cities. With the growing population in countries like India, it has led to tremendous growth in the number of people using social networks. Social networks like Facebook , WhatsApp, Twitter, etc. has eliminated the gap between lives of people. One of the reasons to use these social networks to know the current happening around them and to express their views and suggestions in the form of likes, share ,tweets ,polls ,email, etc. This has created a new category of people called netizens. Communication via social media is done in the form of text, image,audio and video which contains information and consumes and video which contains information and consumes spaces, memory and Internets bandwidth . All these of activites done on socials media has resulted into vast amount of information being generated on a daily basis. Social media analysis has become a interesting field of research to understand the behaviour and thoughts of people in response to social, economic cultural, educational and all activities happening around the world [1]. In this reconstructing fingerprint images using FVC2002 fingerprint dataset to train your network. To observe the effectiveness of your model, We have be testing your model on two different fingerprint sensor dataset namely secugen and Lumidigm sensor. The FVC2002fingerprint dataset is a fingerprint verification competition dataset which was organized back in the Year 2000 and then again in the year 2002. This dataset consists of four different sensor fingerprint namely Low -cost optical sensor, Low-cost Capacitive sensor,Optical sensor and Synthetic Generator, each sensor having varying image sizes.The dataset has 3200 images in set A,800 images per sensor. After collecting a database of fingerprint images, We design a neural network algorithm for fingerprint recognition. When presented with a pair spaces, memory and Internets bandwidth . All these of the probability that the two images originate from . the same finger. In one experiment, the neural network is trained using a few hundred pairs of images and its performance is subsequently tested using several thousand pairs of images originated from a subset of the database corresponding to 20 individuals. This paper is organized in following sections related works discussed in section II. The proposed system details are provided in section III followed by experiments and result in section IV.[2]

II. RELATED WORK

In reconstructing fingerprint images using deep learning, first of all we are read jpeg format fingerprint images, reconstructing them using convolutional autoencoder .We are using FVC-2002 fingerprint dataset to train your network .To observe the effectiveness of your model, you will be testing our model on two different fingerprint sensor datasets namely :- Secugen and Lumidigm sensor. The Biometric System Lab (University of Bologna), the Pattern Recognition and Image Processing Laboratory of Michigan State University and the U.S. National Biometric Test Center(San Jose State University) are pleased to announceFVC2002(the Second International fingerprint verification competition).FVC2002 results will be presented at the 16th Internationa lConference on Pattern Recognition

(ICPR 2002 - http://www.icpr2002.gel.ulaval.ca) which will be held in Quebec City (Canada), August 11-15, 2002.[3] The FVC2002 competition focuses only on the fingerprint verification software. Databases collected with various sensors will be provided by the competition organizers to the participants. Raw data representation is a essential procedure to obtain extracted feature of fingerprint images. Through deep learning , the simple features are extracted from the raw data, and then more complex features are learned through multiple fingerprint. In particular, CNN is a Transformation based on neural network, which is used to represent features via supervised learning. CNN is often implemented of image analysis , speech recognition and text analysis , etc. Four different databases (DB1, DB2, DB3 and DB4) were collected by using the following sensors/technologies.

Table 1 Types of Databases

	Sensor Type	Image Size	Set A (wxd)	Set B (wxd)	Resolution
DB1	Optical Sensor	388x374 (142 Kpixels)	100x8	10x8	500 dpi
DB2	Optical Sensor	296x560 (162 Kpixels)	100x8	10x8	569 dpi
DB3	Capacitive Sensor	300x300 (88 Kpixels)	100x8	10x8	500 dpi
DB4	SFinGe v2.51	288x384 (108 Kpixels)	100x8	10x8	about 500 dpi

The following figure shows a sample image from each database:

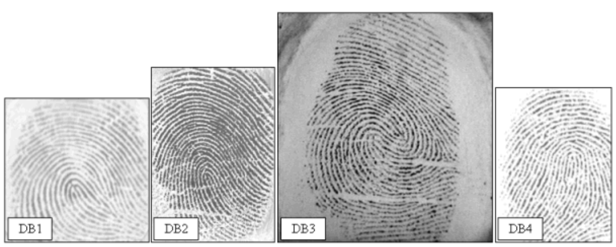

Figure 1. Images of Databases

III. PROPOSED SYSTEM

Fingerprint recognition is one of the most well known biometrics and it is by far the most used biometric solution for authentication on computerized system . Fingerprint images are classified into five categories : whorl, right loop, left loop, arch, and tented arch .Finger ridge pattern don't changes throughout the life of an individual . This property makes fingerprint an excellent biometric identifier. A fingerprint usually appear as a series of dark lines that represent the high peaking portion of the friction ridge skin , while valleys between these ridge appears as white space and are low, shallow portion of the friction ridge skin. The feature of certain values typically correspond to the position and orientation of certain critical points known as minutiae. In this section ,we introduced unsupervised machine learning algorithm that takes an image as input and tries to reconstruct it using fewer number of bits from the bottleneck also known as latent space. We demonstrate our fingerprintare more effective than other by the theory and experiment. The image is majorly compressed at the bottleneck. The compression in autoencoders is achieved by training the network for a period of time and as it learns it tries to best represent the input image at the bottleneck. The general image compression algorithms like JPEG and JPEG lossless compression techniques compress the images without the need for any s kind of training and do Fairly well in compressing the images.[4]

A: Autoencoderare similar to dimensionality reduction technique like principal component analysis(PCA). The major difference between autoencoder and PCA lies in the transformation part as PCA use linear transformation where autoencoder use non-linear transformation.

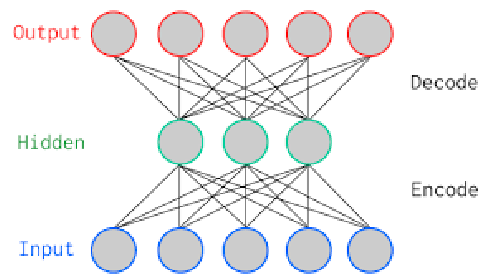

Figure 2 Combination of Decoder and Encoder

In this figure is a two layer vanilla autoencoder with one hidden layer. In deep learning terminology, the input layer is never taken into account while counting the total number of layer in an architecture. The total layer in an architecture only comprises of the number of hidden layer and the output. We feed an images with just five pixel values into the autoencoder which is compressed by the encoder into three pixel values at the bottleneck or latent space. Using these three values, the decoder tries to reconstruct the five pixel values or rather the input images which I fed as an input to the network. In is figure we are clearly see it that encoder is the input part of autoencoder and decoder is the output part of autoencoder . In this Input X use a code for your processing without know decoder user , also output X' use a code for your processing without know encoder user. Both user use a common code without knowning to eachother ,which code is common in between that is Z code.

In this figure, Autoencoder is a combination of encoder and decoder.[5]

Autoencoder can be broken in two parts :-

- Encoder : In this network compresses or downsamples the input into fewer number of bits. The space represented by these fewer number of bits is often called the latent-space or bottleneck. The bottleneck is also called the “maximum point of compression” since at this point the input is compressed the maximum. These compressed bits that represent the original input are together called an “encoding” of the input.[6]
- Decoder : In this network tries to reconstruct the input using only the encoding of the input. When the decoder is able to reconstruct the input exactly as it fed to the encoder, we can say that the encoder is able to produce the best encodings for the input with which the encoder is able to reconstruct well.[7]

B : Convolutional Autoencoder in Python with Keras : Input data consists of images, it is a good idea to use a convolutional autoencoder. It is not a autoencoder variant, but rather a traditional autoencoder stacked with convolution layer. We basically replace fully connected layer by convolutional layer. Convolutional layers along with maxpooling layers, convert the input from wide (28*28 images) and thin (a single channel or gray scale) to small (7*7 image at the latent space) and thick (128 channels). This network help to extract visual features from the images and therefore obtain a more accurate latent space representation. This reconstruction process uses upsampling and convolutions which are known as a decoder. The downsampling is the process in which the images compress into a low dimension also known as an encoder.[8]

C: The convolutional Autoencoder :
The images are of size 28*28*1 or a 784- dimensional vector. You convert the images matrix to an array, rescale it between 0 & 1, reshape it so that it’s of size 28*28*1, and feed this as an input to the network.[9]
Encoder :

a. The first layer have 32 filters of size 3*3, followed by a downsampling (max-pooling) layer.
b. The second layer have 64 filter of size 3*3, followed by another downsampling layer ,
c. The final layer of encoder have 128 filter of size 3*3.]10]

Decoder :

a. The First layer have 128 filters of size 3*3 followed by aupsampling layer.
b. The second layer have 64 filters of size 3*3 followed by another upsampling layer.
c. The final layer of encoder have 1 filter of size 3*3.[11]

The max-pooling layer have downsample the input by two times each times, we use it, while upsampling layer have upsample the input by two times each times it is used.

IV. EXPERIMENT AND RESULT

We demonstrate the proposed method on several setting of Reconstructing fingerprint recognition . The experiment was carried out using publicly available datasets. With the help of Training and validation loss plots we are find out the images of the fingerprint of human being. Now we are told about you training convolutional autoencoder, we had fed the training images twice since the input and ground truth will both same. However in denoising autoencoder. we fed the noisy images as an input while our ground truth remains denoisy images on which we will applied noise. [12]

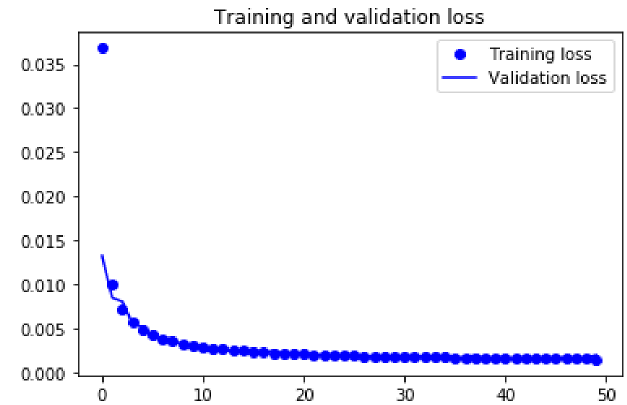

Figure 3 Plot the Training and Validation loss

Finally, I can see that the validation loss and the training loss both are in sync. It shows that your model is not overfitting : the validation loss is decreasing and not increasing, and there rarely any gap between training and validation loss.[13]

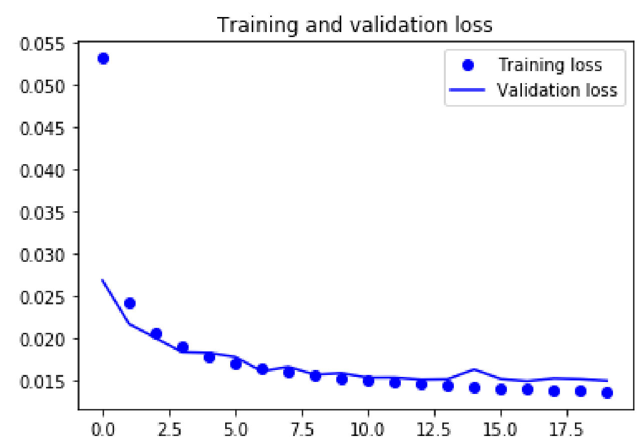

Figure .4 Graph change

From this plot, we can derive some intuition that the model is overfitting at some epochs while being in sync for most of the time. We can definitely try to improve the performance of the model by introducing some complexity into it so that the loss can reduce more, try training it for more epochs and then decide.[14]

Table 2. Average Result over all databases (original participants)

Algorithm	Avg EER	Avg FMR100	Avg FMR1000	AvgZeroFMR	Avg REJ_{ENROLL}	Avg REJ_{MATCH}	Avg Enroll Time	Avg Match Time
PA15	0.19%	0.15%	0.28%	0.38%	0.00%	0.00%	0.11 sec	1.97 sec
PA27	0.33%	0.28%	0.56%	1.44%	0.00%	0.00%	2.12 sec	1.98 sec
PB27	0.41%	0.34%	0.59%	1.29%	0.00%	0.00%	1.23 sec	1.13 sec
PB15	0.77%	0.77%	1.04%	1.29%	0.00%	0.00%	0.07 sec	0.22 sec

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