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Use of Convolutional Neural Network for Fingerprint Liveness Detection

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Abstract— In recent years the biometric authentication systems are gaining popularity and became the integral part of security systems in every organization. Now a day's spoof fingerprint detection is very important. There are several techniques proposed to tackle this problem. Liveness Detection is the method to detect real fingerprints. Since the emergence of deep learning the efficiency to solve this problem has been increased. In this paper we proposed a Convolution Neural Network (CNN) model which achieves average classification accuracy of around 93.12% on LivDet 2009, 85.16% on LivDet 2011, 86.76% on LivDet 2013, 82.20% on LivDet 2015 dataset.

Keywords— Convolutional Neural Network(CNN), Fingerprint Livness Detetction, Deep Learning, Livdet Dataset

I. INTRODUCTION

Security is the vital part of any organization. Biometrics is an important part of the security systems. It discriminate the two subjects based on the physical characteristics such as fingerprint, eyes, voice or face. Out of these fingerprint authentication has been widely used for identification, enrollment or for access control. The main advantage of this system is that you don't need to remember hard and long passwords or PIN.

However providing fake biometric to the sensor is an obvious way to overtake this system. Fingerprint system can be easily fooled by using artificial material like silicon, gelatin, latex and wood glue. Hence there is need of a system which can efficiently and reliably differentiate between real and fake fingerprints. Liveness detection is the method which is used to detect real fingerprints. There are two techniques used to implement this method i.e. hardware technique and software technique. In hardware technique the liveness of fingerprint is detected by adding more sensors to the device. But due to this method the cost of the product gets increased. Other technique is software technique which is discussed in this paper. In this approach detection of real fingerprint from spoofed is done by applying different algorithms and models on set of fingerprint images.

Deep learning is one of the most popular, powerful and growing technology which deals with spoof detection problem very efficiently. It has two types as supervised learning and unsupervised learning. Convolution Neural Network (CNN) and its different variants are well known supervised learning techniques for solving this problem. So far the problem statement has been discussed. Now in second section previously used techniques are reviewed. In third section proposed model along with its detailed architecture is presented. In fourth section experimental setup and its details has been given. In fifth section the analysis of experimental results is discussed. In sixth section conclusion is made based on the analysis.

II. 2 LITERATURE REVIEW

Previously there are many techniques already used to tackle this problem. Both hardware and software approaches are used. Out of these techniques four software approach techniques are discussed here. i.e. CNN-random, CNN-VGG, CNN-Alexnet, Local Binary Pattern (LBP).

In [1] the author has used Convolution Neural Network for feature extraction. Then feature vector is reduced using Principal Component Analysis. This vector then given as an input to Support Vector Machine (SVM) classifier. In [1] the author has used CNN-VGG. In this model 16 convolutional layers, 3 fully connected layers and two softmax layers are used. This model is pretrained on dataset from [2] and then fine-tuned with fingerprint liveness detection dataset. The pretraining has a good effect on accuracy of the model.

In [1] the author has used CNN-Alexnet. In this model 8 convolutional layers and 3 fully connected layers are used. This model is pretrained on [3] and then fine-tuned with fingerprint liveness detection dataset. Here also pretraining has a good effect on accuracy of the model.

In [2] the author also used Local Binary Pattern (LBP). In this model first features are extracted using LBP. Then the feature vector is reduced using Principal Component Analysis. This vector then given as an input to SVM classifier. Also in the above four techniques author has used dataset augmentation technique. Due to dataset augmentation the size of the dataset increased by nearly five times. This results in better accuracy of the model as demonstrated by author.

III. Proposed Architecture

The architecture of proposed Convolution Neural Network is shown in fig. 1. It consists of five steps: Convolution Operation, Rectified Linear Unit (ReLU), Max Pooling, Flattening and Fully Connected Network. Proposed model consists of two convolution layers and two poling layers and a fully connected layer of 128 nodes.

Before giving input image to our model we have performed data augmentation on Livdet dataset is performed. It increases dataset size by modifying the original images by shearing, zooming and horizontal flipping of an image. This step makes this model more robust.

In the first step convolution operation is performed. There are three elements in the convolution operation: Input image, feature detector also known as kernel or filter and a feature map. We use input image of size 64*64 *3. When the input image is given to the CNN it performs convolution operation with feature detector of size 3*3 as a result feature map is produced. Feature detector is the window which you put it over an image in the top-left corner and roll over image and compute the number of cells where feature detector matches the input image. This count of matching cell is then stored in feature map in its top-left cell. This step reduces the size of the image.

The Rectified Linear Unit, or ReLU, is the second step but it is supplementary step to the convolution operation. Since the images are non-linear in nature it is necessary to maintain their non-linearity throughout the process. Rectified Linear Unit helps to increase the non-linearity in our images which might have lost during convolution operation.

In third step pooling operation is carried out. This step helps CNN to acquire spatial variance property. Due to this we can able to detect an object irrespective of their difference in image texture, distances from where they shot, their angles. Most commonly used pooling technique is max-pooling in which small window of size 2*2 is rolled over an image to get pooled feature map. Here maximum matching numerical value is inserted into pooled feature map.

In fourth step flattening of pooled feature map into column i.e. vector is performed. The neural network take this vector as input to process further.

In fifth step the vector which are formed after flattening step is given as an input to neural networks. There are 128 nodes in input layer.

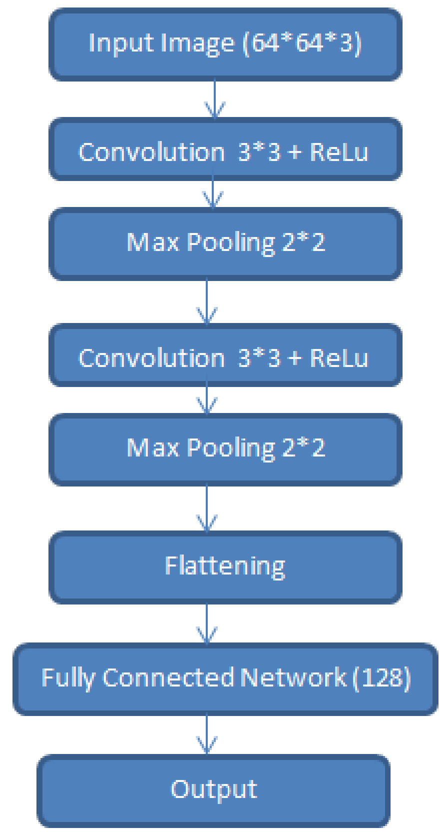

Fig. 1. Architecture of Proposed CNN

Then there is a fully connected layer in which every node is connected to every other node. These neural networks take the input data and combine the features into wide variety of attributes which make CNN capable of classifying an image. We have used sigmoid activation function in final layer. And after multiple iterations we get our final classifying result.

IV. Experiment

A. Dataset

We have used dataset which is given by Liveness Detection Competition in the year 2009[4], 2011[5], 2013[6], 2015[7]. LivDet 2009 contains total 17993 fingerprint images consisting of live and spoof fingerprints. These images are taken from Biometrika, Crossmatch, Identix. Spoof fingerprints obtained from gelatin, PlayDoh, silicon.

We have used nearly 80% of dataset for training and 20% for testing.

LivDet 2011 consists of total 16056 images of live and spoof fingerprints. These fingerprints are taken from Digital, Sagem, Biometrika, and Italdata. Spoof fingerprints were obtained from Silgum, Latex, Eco Flex, Wood Glue and Gelatin. There were around 1000 live images and 200 images of Gelatin, 200 images of Wood glue, 200 images of Eco Flex, 200 images of Latex and 200 images of Silgum in each of the dataset. We used equal amount of data for training as well as testing.

LivDet 2013 consists of total 16853 images of live and spoof fingerprints. The images are taken from Crossmatch, Italdata, Swipe Train and Biometrika. Spoof fingerprints are obtained from gelatin, Play Doh, latex, Modasil, Wood glue etc.We used equal amount of data for training as well as testing.

LivDet 2015 consists of total 28368 images of live and spoof fingerprints. The images are taken from Digital Persona, Crossmatch, Green Bit,Hi scan and Time Series. The spoof images are obtained from Ecoex, gelatin, Latex and Wood glue. It also contain Body double images. We have used 17919 images for training and 10449 for testing. In this dataset real and fake fingerprint are in equal ratio. In both training and testing set also real/fake ratio is equal. Since sizes of the images obtained from different sensors is different, we resize it to 64*64 as an input size to CNN.

B. Performance Metrics

The performance metric used in this study is classification accuracy. Average classification accuracy is the number of images which are correctly classified as real and fake fingerprints.

C. Implementation Details

Convolution Neural Network is trained using Keras and Tensorow packages. The model is trained on Intel core i3 machines with 2.40 GHz processor speed. We have used python Anaconda distribution and Spyder as IDE.

V. RESULT

The results of the experiment carried out on LivDet 2009 is shown in Fig. 2. The graph is plotted as number of epoch verses accuracy of testing of our model. We have got the average classification accuracy of around 93.12% in 25 epochs for LivDet 2009. It took around 18-19 hours for training on core i3 machine.

The results of the experiment carried out on LivDet 2011 is shown in Fig. 3. The graph is plotted as number of epoch verses accuracy of testing of our model. We have got the classification accuracy around 85.16% for LivDet 2011. It took around 16-17 hours for training on core i3 machine.
The results of the experiment carried out on LivDet 2013 is shown in Fig. 4.

The graph is plotted as number of epoch verses accuracy of testing of our model. We have got the average classification accuracy of around 86.76% in 25 epochs for LivDet 2013. It took around 13-14 hours for training on core i3 machine.

The results of the experiment carried out on LivDet 2015 is shown in Fig. 5. The graph is plotted as number of epoch verses accuracy of testing of our model. We have got the classification accuracy around 82.20% for LivDet 2015. It took around 40 hours for training on core i3 machine.

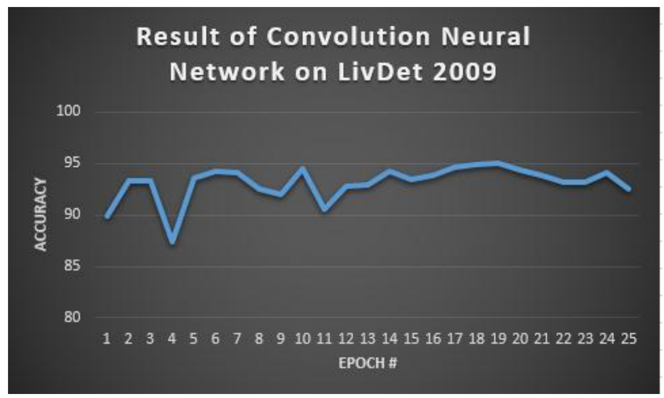

Fig. 2. Result of Convolution Neural Network on LivDet 2009

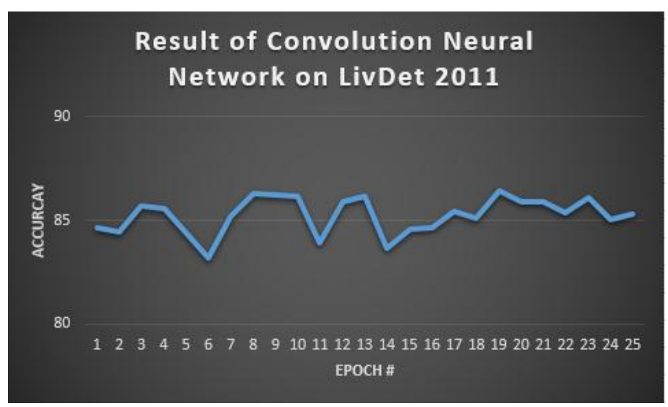

Fig. 3. Result of Convolution Neural Network on LivDet 2011

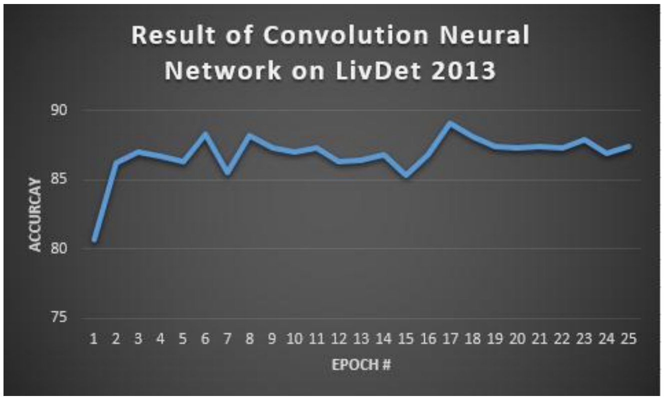

Fig. 4. Result of Convolution Neural Network on LivDet 2013

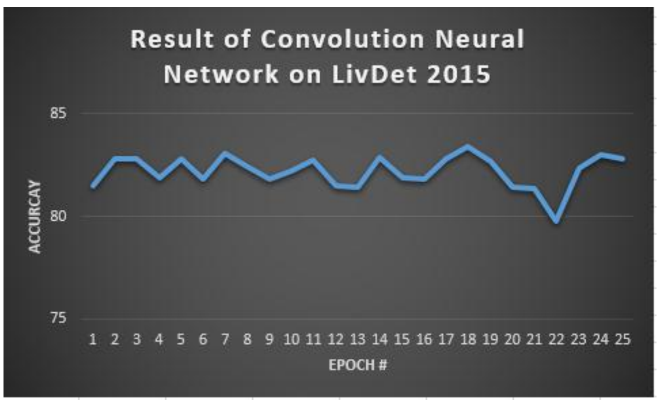

Fig. 5. Result of Convolution Neural Network on LivDet 2015

All the graphs shows impressive performance. The proposed model has learned well over course of 25 epochs. Hence the accuracy is improved with increasing number of epochs. Proposed model has got very good accuracies over all the four LivDet dataset.

VI. CONCLUSION

In our experiment Convolution Neural Network has successfully classified fake and real fingerprints. Our model has achieved good accuracy on all LivDet Dataset with very small input size of 64*64.

It has got average classification accuracy of around 93.12% on LivDet 2009, 85.16% on LivDet 2011, 86.76% on LivDet 2013, 82.20% on LivDet 2015 dataset which is very good as compared to some of the models and image processing techniques which are currently present. The performance of the model can be optimised by tuning the Hyperparameter.

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