IJRAR.ORG E-ISSN: 2348-1269, P-ISSN: 2349-5138

INTERNATIONAL JOURNAL OF RESEARCH AND ANALYTICAL REVIEWS (IJRAR) | IJRAR.ORG

An International Open Access, Peer-reviewed, Refereed Journal

Face Anti-spoofing based on Deep Residual Network

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Abstract : Security based applications seek Face biometrics as an integral part of the Biometrics system which are vulnerable to Spoof attacks. A registered user can be impersonated by a malicious individual by presenting a photograph or a video of the registered user's face. Latest advances in the Deep learning in the field of anti-spoofing is enabling to delineate between real and spoofed faces with a better accuracy. In this paper, we perform an explorative study on face spoof detection by employing a new Anti-spoof method consisting of state-of-the-art Convolution neural network, Resnet-34, modified and retrained efficiently over NUAA Photo Imposter dataset. The model exhibit highest accuracy of 99.76% for presentation attacks. The effectiveness of the proposed method is demonstrated using performance evaluation experiments and the architectures show impressive results.

IndexTerms **– Hybrid Residual Network, Residual34, Transfer Learning, Face Anti-spoofing.**

I. INTRODUCTION

The advancement in computer vision technologies has gained a lot of attention with respect to usage of face biometrics systems for personal authentication. Though Face Biometric systems are achieving greater accuracies, they remain vulnerable to presentation attacks. Face Biometric system is fooled by presenting few artifacts like a printed photograph or a video against the input sensor like camera. Presentation attack detection systems try to protect face biometrics system against such malicious acts. There are variety of presentation attacks in which 2D photo print and replay attacks are the most common ones. Hence to prevent such spoofing attacks we have to many anti-spoofing algorithms in place to distinguish whether the input image/video has a real face or fake one.

Face presentation attack detection/spoof detection is an arduous task of all face biometric systems. Presentation attack detection methods initially relied on few of the conventional techniques like Eigen faces, LBP, HOG, DCT and DWT. But in recent years Convolutional Neural Networks and Deep Neural Networks [1] earning more points for face spoof detection. Though deep convolutional neural networks (CNNs) have achieved promising success in detecting spoofed faces, they are data-hungry. They require a huge voluminous dataset to train before making any reasonable prediction, thus avoiding over-fitting.

Our Face Anti-spoofing dataset NUAA Photo Imposter dataset [2] is a publicly available one having 12,614 images, which is relatively a smaller dataset to be trained with deep learning technique thus can incur over-fitting problem. Also training all the layers of convolutional neural network from the scratch i.e. from the initial layer is expensive with respect to both resources and time. A machine learning technique known as Transfer learning [3] solves above problems by reusing a previously learnt model over a large dataset over a new problem or a new dataset. Recent days, transfer learning has become an effective method to reuse an eminent pre-trained CNN model to take care of different machine learning problems. For example, CNN models based on transferred knowledge was applied for the detection of fatigue crack initiation sites [4], tumors detection [5], diagnosis of pneumonia [6], wildfire detection [7], classification of seizures [8], remote sensing applications [9], and fault detection in machineries [10], face recognition [11] and etc. But, the utilization of transfer learning of a pre-trained deep network is a newer concept with respect to liveness detection [12] and not many have explored. Hence in this work we propose a Hybrid Residual network which is a pre-trained deep model, Resnet34 to investigate the problem of face spoof detection.

II. RELATED WORKS

Previous works on anti-spoofing in the literature, have followed many approaches. Major ones are texture based, temporal based, frequency based. All the above approaches incorporated handcrafted texture features like HoG, and LBP followed by conventional classifiers like K-means, SVM to carry out the antispoofing task [13], [14]. The temporal based methods use the facial motion patterns like eyes blinking or facial movements which utilize optical flow for face movement tracking to distinguish between real faces and the fake ones [15]. Some methods require specific 3D devices that extract depth information from 2D images, or the 3D shape information being recorded using 3D sensors is analyzed and compared with a genuine face [16]. In few techniques pulse signals are extracted from face images without making any contact with skin, such method is based on rPPG (Remote Photoplethysmography) [17]. Masks, fake face attacks and assistance of auxiliary data make these systems vulnerable and also for above systems require depth information. Spoof detection can also be classified into other categories too based on spatial and temporal properties: feature-level static and dynamic [18] methods. Static methods exploit the spatial relationship in the image but dynamic techniques analyze the images based on their temporal properties. Static techniques that utilize Local Binary Patterns and its variants [13, 19, 20], Fourier analysis [14, 21], Lambertian models [22], Difference-of-Gaussian (DoG) [21]. Dynamic techniques exploit the time correlation between consecutive frames of a video [23]. In multiple works, facial movements act like an indicator to recognize the attack (e. g.: eye blink [24], face natural movements [25] or movement of lips). Above mentioned methods mostly rely on hand-crafted features. Few approaches utilize CNN [26] to extract features from images, thus recognize the attacks. For example technique that uses an AlexNet [27] to extract the features, and classify them using SupportVector Machines (SVM).

In previous works that were carried out, machine learning based approaches were predominantly used for spoof detection. But later Deep learning based techniques pitched into this domain [28, 29] which are basically representation-learning methods with different representations utilized at different levels of the neurons in deep neural networks (DNN) [30]. Here the representations at one level is transformed into a higher level using a non-linear module. Also DNNs are fed with unprocessed input data unlike the conventional algorithms, later the DNNs perceives the representations required for classification, detection or recognition. Hence Deep learning based methods have demonstrated commendable task while determining the spoofed faces. Xiaoguang et al. [31] proposed a multi-modal fusion method for Face Anti-spoofing by upholding multiple visual modalities on their presented face images. Yang et al. [32] considered both local spatial and global temporal information in the form of an anti-spoofing network. Liu et al. [33] generated a large dataset with spoofing attacks of 13 different types and utilized a deep tree network for recognition of these spoofing attacking types. These deep learning-based methods generally performs good on trained face spoofing data but observes performance degradation when newer attacking types start appearing. But as the layers in the DNN gets deeper, it seeks for more data for training at each level and the standard datasets in our problem domain fails to cater those numbers. Thus a technique known as Transfer learning evolved out of the regular CNNs where a Machine Learning model yields trained knowledge to drive another model for a particular task [34, 35]. There are two ways to perform transfer learning. In first approach, the source model acts as a feature extractor, and selected layer's output in the CNN serves as input for the aimed model. Second approach tweaks the source model partially or completely and its weights are retrained using back propagation. Transfer learning prevents the over fitting problem in a large network when the data is too small in size to train from scratch. Computational resources are also spared using transfer learning, since conventional machine learning approaches may take from days to weeks to train from the scratch. Our approach for spoof detection is formed on transfer learning used on a CNN [12, 36, and 41].

Our work investigates the transfer learning based procedures of Residual network for face spoof detection. The remaining part of this paper consists of the proposed transfer learning model in Section III, a series of experiments has been conducted to evaluate the proposed approach in Section IV and a brief summary of the research findings and conclusions of this study is presented in Section V.

III. PROPOSED DEEP RESIDUAL NETWORK

Face spoof detection attempts to differentiate between real and spoofed images. Usually, number of fake faces presides over the real ones due to the various forms of attacks as spoofed images. Hence an imbalanced training data will be exposed to the system. Various datasets are available for face spoof detection problem. One of them is NUAA Photo imposter dataset, which has been publicly available, that we have considered to evaluate. The proposed method evaluates Resnet34 architecture which has been pretrained on the ImageNet [37], a larger classification dataset. From this pretrained base model we fine tune our ResNet34 to improve generalization. This process is called as Transfer learning. This Transfer learnt Resnet34 model forms a Hybrid Residual Network to performing the Face-antispoofing task.

3.1 Resnet34 Architecture

Residual Network (ResNet) [38] is a state of the art convolutional neural network and one of the famous deep learning models that is used majorly for image classification task.

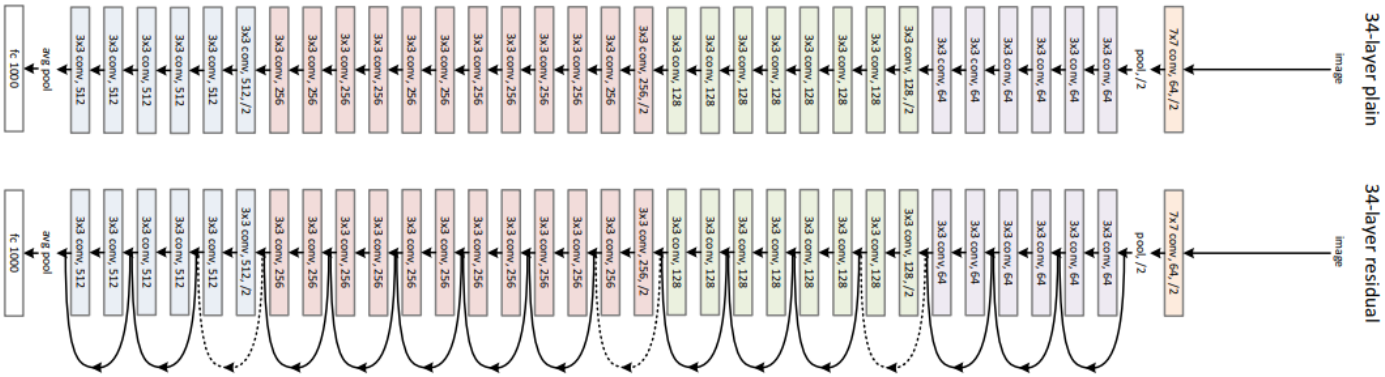

Figure 1: Resnet 34 architecture

Here, we can observe that the ResNet34 (Fig 1) is made up of four layers of similar behavior after a convolution and pooling stage. The same pattern is followed by each layer. Every two convolutions, they skip the input and conduct a 3x3 convolution with a fixed feature map dimension (F) of [64, 128, 256, 512] correspondingly. Throughout the entire layer, the measurements of width (W) and height (H) stay unchanged. The dotted line shows how the input volume's dimension has changed. Note that this layer reduction is accomplished by increasing the stride from 1 to 2 at each layer's initial convolution, rather than using a pooling operation, which is what we are accustomed to seeing as down samplers. The output size at each layer and the dimension of the convolutional kernels at each location in the structure are both summarized in the Table 1.

Table 1. Sizes of outputs and Convolutional kernels for Resnet34

layer name	output size	34-layer
conv1	112×112	
conv2_x	56×56	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$
	1×1	average pool,
FLOPs		3.6×10^9

3.2 Transfer learnt Deep Residual Network

Our paper primarily uses the ImageNet dataset to train ResNet34. In general context transfer is carryover of skill or knowledge from one scenario to other. In transition learning, a machine can exploit the expertise gained from the previous work to enhance the generalization on another. In normal CNNs, edges are detected in the initial layer, it gets shaped in layers in the center and the later layers carry some functional features (Fig 1).

In Transfer learning, we make use of initial and middle layers and later layers are replaced. Pre-Trained models reduce the time required for feature engineering and training drastically. So we use the model which has the large dataset to make the best of the training. The custom Resnet34 architecture employed here has been trained in advance on ImageNet dataset. Tiny ImageNet has 200 classes within which it has over 100,000 images. The large Imagenet is a voluminous one with diverse image classes amongst which data similar to ours will be used in pre-training. Having a well trained model in hand, the model is started from the pre-trained checkpoint and Resnet34 is fine-tuned from this base state. This is known as "transfer learning".
Initially NUAA dataset is loaded into fastai data loader and is normalized to the standard deviation and mean of the ImageNet dataset. In next step pre-trained Resnet model from torch vision model library is employed. We initialize our model and fine tune the final layer of the model and freeze the rest of the model. By doing this we learn the relevant pre-trained features. Early stopping is a training callback that will halt the training process if the validation loss has not decreased for 20 epochs. Then model parameters are unfreezed and optimal learning rate is calculated. If the learning rate is too less the model won't learn much and if it's too high we have to back propagate the way off the map in function space. Next we unfreeze the model and train it for 50 more epochs to fine-tune our model to yield maximum performance. As the performance increases the validation error rate decreases. In our case its error rate is 0.002377 and validation loss is 0.010181 which is quite small.

IV. EXPERIMENTS AND DISCUSSIONS

We evaluate the accuracy of TLA framework for face biometric system by conducting experiments on NUAA face anti-spoofing dataset. In the Resnet model, the weights from bottom layers up to third block were frozen and from fourth block up to the layers are fine-tuned via back propagation. Then, our method was evaluated on NUAA test folders. The implementation carried out using fastai and pytorch and MobilenetV2 was implemented using tensorflow.

4.1 NUAA Photo Imposter Dataset

NUAA Photograph Imposter data set [2] was the first public dataset that was made available for face anti-spoofing. Images here were captured by regular webcams in different environments under varied illumination conditions, in three sessions, between each of which with an interval of two weeks were taken. Printed flat and warped attacks are evaluated. Training and Test sessions were constructed in different sessions. This dataset consists of 15 subjects. 500 images are collected for each subject and contains 7509 spoofed and 5105 real face images All the images have frontal view of the face with neutral expression. Figure 2 shows some of the examples of it.

Figure 2: Sample real (first four columns) and spoofed images (last four columns) from NUAA Photo Imposter Dataset

4.2 Evaluation Metrics

We have utilized the standardized ISO/IEC 30107-3 metrics [39] as the evaluation metrics for the Face anti-spoofing model. Mainly these metrics are akin to the types of errors and how they are measured and evaluated [40]. At the basic level Spoof detection will incur the False Positive (FP) and False Negative (FN) errors. Also we evaluate two more errors: False Positive Rate (FPR), which is the ratio between false positive samples and the total number of negative samples and False Negative Rate (FNR), which is the ratio between false negative samples and the total positive samples. Also, many authors have reported different error rates, but they are all equivalent. For example: The ratio of correctly classified positives is defined as True Positive Rate (TPR), which is computed as 1−FNR. The ratio of correctly detected negatives is defined as True Negative Rate (TNR), which is computed as 1−FPR. Similarly False Positive Rate (FPR) can be termed as False Acceptence Rate (FAR) or Attack Presentation Classification Error Rate (APCER). All the three metrics have different names given by different researchers but the calculations remain the same. False Negative Rate (FNR) is also called as False Rejection Rate (FRR) or Normal Presentation Classification Error Rate (NPCER). Hence for measuring the error rate of spoofed or real faces, FPR and FNR are utilized. Table 2 lists the different Performance metrics that we have evaluated for our Deep models.

Table 2. Performance metrics for Face Anti-spoofing

Performance Metrics	Formula
False Positive Rate (FPR) OR False acceptence Rate (FAR) OR Attack Presentation Classification Error Rate (APCER)	FPR or FAR or APCER = FP / (FP + TN)
False Negative Rate (FNR) OR False Rejection Rate (FRR)OR Normal Presentation Classification Error Rate (NPCER)	FNR or FRR or NPCER = FN / (FN+ TP)
True Positive Rate (TPR)	TPR = TP / (TP + FN)
Half Total Error Rate (HTER) OR Average Classification Error Rate (ACER)	HTER or ACER = (FPR+FNR) / 2

4.3 Resnet34 Performance

We can evaluate our custom Resnet34 Image classification model's performance by using it for test inference and it is visualized in form of Confusion matrix as shown in figure 3(a). We run inference on our test set, images that our model has never seen. An efficient model found with Accuracy of 99.7623 % and validation loss value, as low as 0.0102. Also, our model's top losses are as shown in the figure 3(b), which plots the predicted label over the actual label what is the loss incurred in each case and its probability. Model evaluation was performed using FAR, FRR and HTER: Lower FRR indicate that lesser number of real faces are classified as spoofed faces. Also lower FAR indicates less number of spoofed faces are incorrectly identified as real faces. So our transfer learnt Resnet34 model exhibited FAR of 0.00097%, FRR of 0.00333% and HTER of 0.00213%, whose values are very optimistic there by increasing the efficacy of the face biometric system.

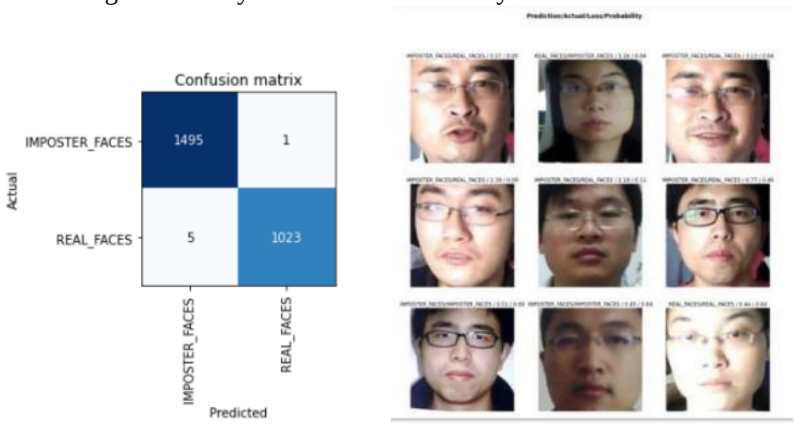

Figure 3: (a) Classifier performance (b) Top losses of our custom Resnet34 model

Table 2 list the test accuracies of the different Transfer learnt Deep networks for Face anti-spoofing, including the proposed models.

Table 2. Test Accuracies of different Transfer learnt Deep models

Technique	Attack type	Accuracy%	0.0024
Transfer learnt VGG-16	Presentation (CASIA)	93.75	-
FasNet (Transfer learnt CNN- VGG16) [3]	Presentation (REPLAY-ATTACK)	99.04	1.20
Transfer learnt Renet34 (ours)	Presentation (**NUAA**)	**99.76**	**0.00213**

V. Conclusion

In this paper, we introduced Deep Residual Network Resnet34 based on Transfer learning to detect spoofing attacks in face biometric systems. We discussed how pretrained architecture is modelled internally. We demonstrated how the base models helped in extracting features, and the dense layers classify the test set. At the end, we inspected how the feature transfer influenced the aimed problem from the pretrained CNN. The experimental results showed classification accuracy of 99.76% with HTER of 0.00213% for transfer learnt Resnet34 model. Lower HTER value denote that our models based on Transfer learning increases the performance of the Face anti-spoofing system.

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