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Detection of Fake Videos using Convolutional Generative Method

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Abstract: Fake videos are used in different industries for positive aspects, but mostly, people use fake videos to defame politicians and celebrities. Fake videos create great social and security concerns because people use fake videos and images to gain illegal access to biometric security systems. Detection of fake videos is a challenging task. Recently deep learning methods have been applied to solve this problem. A generative novel deep convolutional generative adversarial network (DCGAN) is proposed to detect fake videos in this research work. The proposed novel model is evaluated on celeb-DF and DFDC datasets with different batch and epoch sizes in this research work. The proposed novel DCGAN model gained the highest accuracy of 96% on a celeb-DF dataset, and the DFDC dataset gained an accuracy of 93.5%. The model is compared to available state-of-the-art methods.

Keywords: Fake Vidoes; GAN; Supervised Learning; Unsupervised Learning; DCGAN.

1. Introduction

The word fake has recently attained more importance and attention with advancements in fake images and video synthesis techniques. Fake video means creating fake multimedia content like video or image using techniques like face 2 face, face swap, neural texture, and deep fake [1]. Due to social and security challenges detection of fake videos is important. These algorithms change the subject Face into the target Face to generate fake videos. Advancements in the neural network made GAN more popular among researchers. GAN has a powerful generator and discriminator model used in fashion industries and constructing 3D objects from images [2]. The most famous example in this regard is a" Mona Lisa" sketch generated by Samsung Aditi [3] using only one image. The first deep-fake video is a celebrity pornographic video that REDDIT generated in 2017 [4]. After that, fake videos were generated by Face swap, Face APP continuously increased. These fake videos encourage researchers in this field, but on the other hand, it creates a security problem in society. Because these features can be used in fake news, generating videos for defaming celebrities and politicians [5].

Fake videos are used in different industries, like TV shows; the film industry uses these videos positively [6]. Fake videos generated through face swap, Face 2 faces, and neural texture is used to defame celebrity and politicians. Many fake videos are spreading online, mostly used to target politicians and celebrities [7]. Fake video-generating techniques like face 2 face, deep fake, and face swap create a huge panic in the world by damaging someone's privacy [8]. Most politicians use these fake videos in their political campaigns to defame other politicians [9]. So nowadays, with advancements in fake video-generating techniques, detecting fake videos has become a hot issue for companies worldwide [10].

In recent years fake video-generating technologies have gained significant progress in developing models to detect fake videos using GAN, supervised and un-supervised based models [11]. The number of video datasets for training a model is increased. The datasets (such as FF++ [12], DFD, celeb-DF [13], style [11], replay attack [12], MUCT [16], and deep fake TIMIT [40]) are used for training a model.

Fake videos are spreading through social media, causing great social and security threats in the real world [14]. People use fake videos and images to gain illegal access to a biometric security system. So these problems are necessary to detect fake videos to tackle these social and security problems.

The contribution of this work is considered in the following ways:

1. A deep learning-based generative model was introduced to identify fake videos.
2. A novel framework created based on viola jones and deep convolutional generative neural networks.
3. To detect fake videos using novel DCGAN, resnet-50, and VGG-16 models.
4. Image frames are extracted from DFDC and celeb-DF videos dataset using OpenCV. Facial parts are detected from images using the viola jones algorithm.
5. State-of-the-art fake video detection method's comparison.

The paper is organized into the following sections: section 1 describes the introduction, section 2 explores the literature related to fake video detection, section 3 discusses the study's methodology, and section 4 explains the experiment's results.

2. Literature Review

Recent advancements in face-manipulating technologies can spread disinformation in society. Deep learning CNN-based classification model [12] to detect fake faces from videos and then exception net and Mesonet model to evaluate this FF++ dataset. Recent advancements in face-manipulating technologies can spread disinformation in society, and also this technique is used to defame some politicians. In deep fake, the subject Face is modified into the target Face by using apps like face swap, Face 2 Face, etc. Face Forensics ++ dataset used that contains 70 videos consisting (of 29,764) frames, and this dataset is created by using Face 2 Face, Deep fake, and neural texture. In this work, he proposed a deep learning CNN-based classification model to detect fake faces from videos and then the exception net and Mesonet model to evaluate this dataset. Firstly, in preprocessing, he chooses victim detectors based on the CNN model for data classification. Secondly, the face tracking model is used to extract faces from frames. Thirdly the coped Face is resized. After evaluating the dataset, the accuracy of Xception net on DF is (97.49%) and on F2F is (97.69%). Meso net shows accuracy on DF (89.55%) and F2F (88.6%). This study shows that the current methods can be easily bypassed if anyone knows six detectors [12].

Face liveness identification is important for avoiding Face spoofing attacks. In the past, many researchers worked on different methods for identifying faces, but this work recommended an (SCNN) model for identifying faces. In this work, he tests his network on a replay attack dataset containing 1200 videos and a mobile replay dataset. After the evaluation of the network, the accuracy of the proposed model SCNN is about 98.56% which is higher than the other deep network methods. But in the future, the parameters of CNN-LSTM can be improved to increase the fake face identification accuracy from live streaming videos [15]. Fake videos and images are widely spread through social media, spreading false information in society. This study proposed the inception of ResNet v2 and a CNN-based model for detecting fake faces. He worked on the Kaggle deep fake detection challenge dataset and the fake face detection set; he proposed model accuracy on the deep fake is about 92% [16].

The 2D convolutional neural network cannot perform well on unobserved data, so this paper recommended a 3D-CNN model that abstracts features from spatial and temporal areas of videos [17]. In an experiment, he tested the model on replay attack and CASIA dataset in which face localization is done. Then by using the max, min strategy, detects the bounding box. The EER% of the proposed model on CASIA shows the proposed model performs well on real-world data [32]. DNN-based methods mostly used black-box testing methods for the detection of adversarial attacks. The accuracy of the proposed model on the PaSC dataset with light CNN is 80-90%. Still, in the future adversarial sample, attacks must be corrected to increase the robustness of deep neural networks [18]. Deep fake videos generated through different machine learning techniques can be used for political misuse or blackmailing. The accuracy of the CNN model is greater than 97%, but the future robustness of the network needs more research to detect unseen fake videos [19] .

The deep fake videos can be detected through an eye-blinking pattern, and he proposed the CNN and LRCN method for detecting deep fake videos. He performed an experiment on the CEW dataset in which faces are detected from videos, and then Face landmarks are detected. The accuracy of LRCN is about 99%, but in the future, some physiological signals will be developed in LRCN to detect deep fake videos [20]. The AOS-based method is proposed to detect deep fake faces in which non-linear diffusion is used to detect edges of images, and then CNN is used to detect faces from the replay attack dataset [43]. LSTM-CNN model proposed that take the single image as input from the CASIA video data set to experiment. The LSTM layer is put after the fully connected layer to classify fake faces [21].

Due to presentation attacks, a multi-feature scheme proposed to detect faces and a biometric-based security system have great concerns in face recognition. LBP extracts features from the face region; optical flow analysis calculates the movement of consecutive frames. Then SVM is used to classify real or fake images [22]. Tempered Multimedia content is increasing in cyber-crimes like fake news and digital kidnapping, so the proposed SVM-DFT method for classifying the real and fake faces. DFT extracts the features from the Celeb-DFv1 dataset. Output features are labeled, and the SVM classifier is used to detect real and fake faces [23]. SVM is used to classify dataset features extracted by WPT [24].

3. Materials and Methods

This section discusses a novel generative framework for fake video detection in detail. Firstly, videos were taken from two datasets named celeb-DF and DFDC. Secondly, frames were extracted from videos. Opencv library was adopted for frame extraction. Thirdly, image resizing was performed and finally converted into grayscale. In the detection phase, Deep Convolutional Generative Adversarial Network (DCGAN), VGG16, and Resnet50 adopted and finally detected fake or real video. The block diagram of the model is shown in (Figure 1).

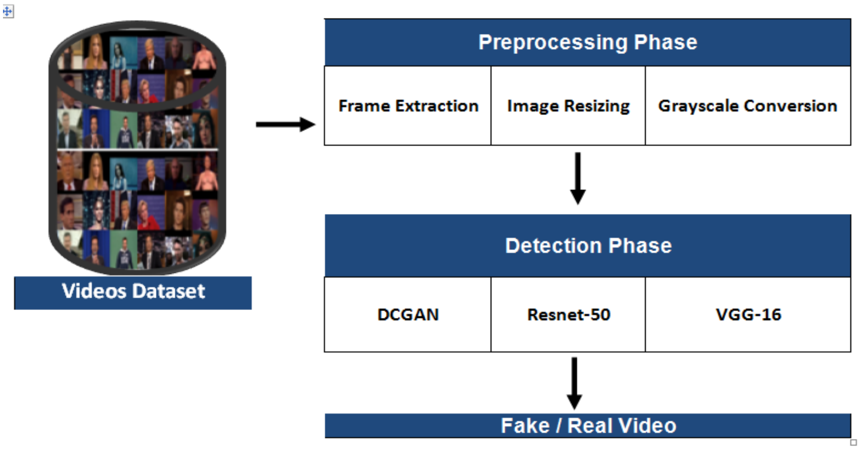

Figure 1. Deep Convolutional Generative Adversarial Network (DCGAN) based fake Video Detection Model

3.1. Dataset

The suggested method is trained and tested on Celeb-DF [13] and DFDC [25] datasets. Celeb-DF, a new deep fake video dataset, consists of 250 real YouTube videos, 158 real celeb videos, and 795 celeb synthesis videos containing 25,237 real and 62,877 fake images. The deep fake detection challenge (DFDC) [25] dataset contains 400 real and 400 fake videos, which contain 24000 real and 24000 fake images.

3.2. Data Preprocessing

Celeb-DF [13] and DFDC [25] are publically available datasets for experimental work to detect deep fake videos. In this research work, firstly, every 5th frame [3] is extracted from videos using OpenCV. OpenCV, which stands for Open Source Computer Vision Library, was developed in C and C++ and is supported by most operating systems [26]. OpenCV contains more than 500 functions that can be used in Image Processing, Computer Vision, Motion Tracking, and Object and Face recognition [27]. After frame extraction, the facial part is detected using the viola jones algorithm, the first-ever real-time face detection system [28]. Viola jones algorithm detects and recognizes social parts such as eyes, nose, mouth, and Face [29]. Images are also resized (256*256) and converted into grayscale images.

3.3. Deep Convolutional Generative Adversarial Network (DCGAN)

DCGAN is a generative model consisting of a discriminator and a generator [30]. The DCGAN generator model is used to learn images that look like real images, and the discriminator model is used to learn and tell real images apart from fake ones [31]. The generator model used convTranspose2d with kernel size (4x, 512) with stride (1x1). Afterward, the batch normalization function and ReLU function are used [32], [33]. The architecture of DCGAN is shown in (Figure 2).

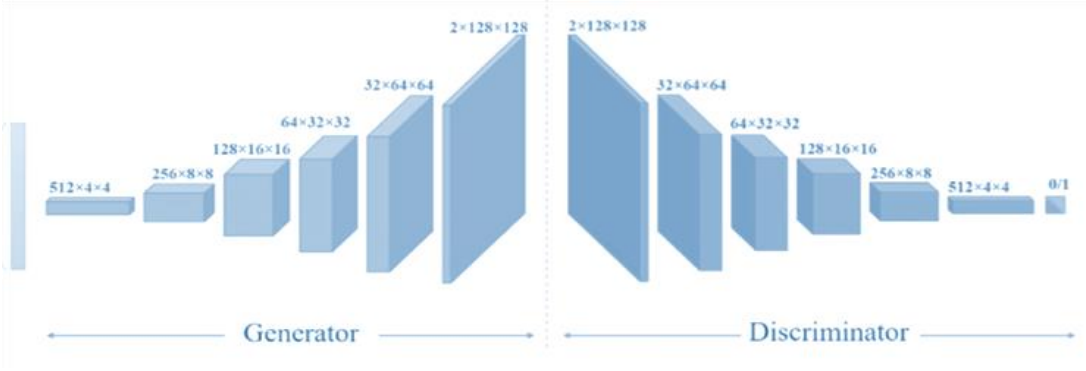

Figure 2. Deep Convolutional Generative Adversarial Network (DCGAN) architecture [34]

3.4. Resnet-50

ResNet-50 is a convolutional neural network that consists of 50 layers, 48 convolutional layers, one max pool layer, and one average pool layer. The resnet-50 model is a pre-trained model trained on the image-net dataset [35], [36] (Figure 3) shows Resnet-50 architecture.

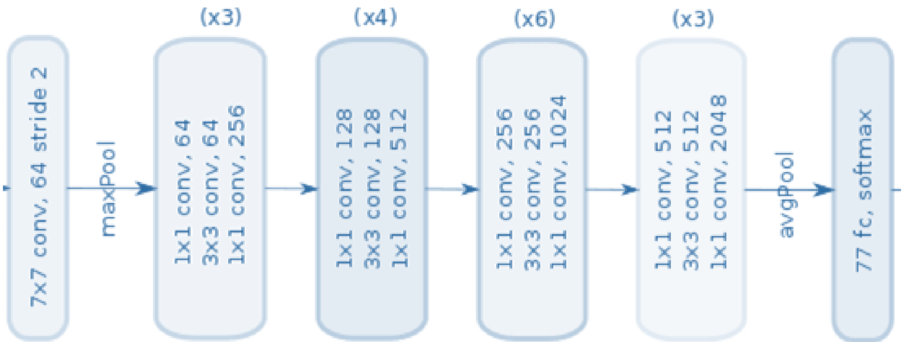

Figure 3. Resnet-50 Architecture [37]

3.5. VGG-16

VGG-16 is a pre-trained model trained on the ImageNet dataset and uses convolutional neural network (CNN) architecture for Image classification [38]. VGG-16 consists of 16 weight layers in a convolutional layer of 3x3 filter and max pooling of 2x2 filter. The image does not take input images of (224, 224, 3), and the VGG-16 model's first two layers have 64 channels of (3x3) filter size and the same padding [39]. The architecture of VGG16 showed in (Figure 4).

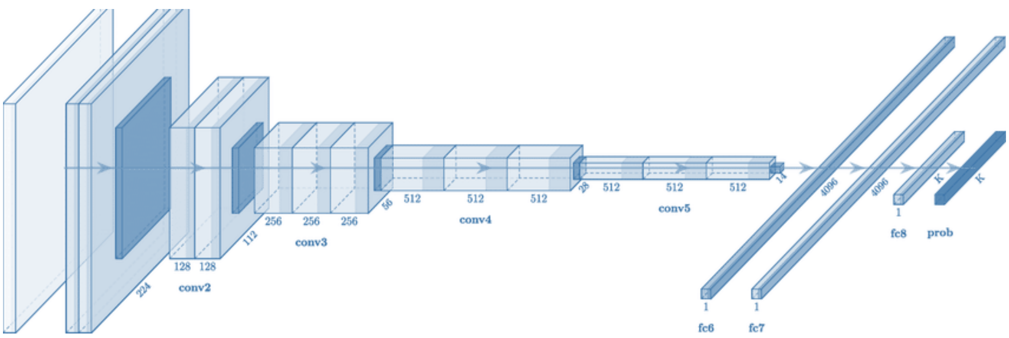

Figure 4. VGG-16 Architecture [40]

4. Results

In this research work, a novel deep convolutional generative adversarial network (DCGAN), VGG-16, and resnet-50 model is proposed and evaluated on celeb-DF and DFDC datasets. There are different evaluation measures used to check the performance of any model. Accuracy, Precision, Recall, F1-score, True Positive, False Positive, True Negative, and False Negative are the most common performance evaluation factors [41], [42]. Accuracy is one of the most prominent and widely adopted measures used to show the performance of any algorithm or model [43]. The experimental results of the proposed model were evaluated using accuracy.

The proportion of correctly labeled data to the total data measures accuracy. The mathematical representation of accuracy is shown in Equation 1.

$$ACC = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + True\ Negative + False\ Negative} \tag{1}$$

Precision is the proportion of true positives to the sum of false positives and true negatives. It is also referred to as positive predictive value [44], [45]. Equation 2 showed the Precision.

$$Percision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{2}$$

The ratio of correctly predicted outcomes to all predictions is known as Recall. It is also referred to as sensitivity or specificity [46]. Equation 3 showed the Recall.

$$Percision = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{3}$$

F1 Score considers both Precision and recall [47]. Equation 4 showed F1-score

$$F1\ Measure = 2\ x\ \frac{Percision * Recall}{Percision + Recall} \tag{4}$$

For experiments, DFDC and Celeb-DF datasets were taken. After preprocessing, DCGAN, VGG16 and Resnet50 were used to detect Fake or Real videos. Firstly, the dataset was divided into an 80-20 ratio i.e, 80% training and 20% testing, and secondly, the whole experiments were again performed using a 70-30 ratio, i.e, 70% training, and 30% testing. In both experiments, results were evaluated using the Accuracy measure.

For the first experiment, the DFDC dataset was taken for both 80-20 and 70-30 training-testing ratios. The DFDC dataset contains eight hundred videos, four hundred fake and four hundred real. These eight hundred videos were converted into twenty-four thousand image frames. In the detection phase using an 80-20 training-testing ratio, nineteen thousand two hundred real and the same number of fake images were taken for training purposes. In contrast, forty-eight hundred real and the same number of fake images were taken for testing purposes. After the deployment of DCGAN, VGG16, and Resnet50, the results showed that DCGAN produced 93.5% accuracy, VGG16 showed 71%, and Resnet50 produced 59% accuracy. The same dataset was used for a 70-30 training-testing ratio. Sixteen thousand eight hundred fake and the same number of real images were used for training purposes. In contrast, collectively, seventy-two hundred images were used for testing purposes for fake and real videos. Using a 70-30 training-testing ratio, DCGAN, VGG16, and Resnet50 produced 93.5%, 81%, and 68% accuracy, respectively. (Table 1) shows the experimental results.

Table 1. Experimental Results using DFDC dataset.

Method	**Training-Testing Ratio (80%-20%) Accuracy**	**Training-Testing Ratio (70%-30%) Accuracy**

DCGAN	93.5%	93.5%
VGG16	71.0%	81.0%
Resnet50	59.0%	68.0%

The graphical representation of experimental results using the DFDC dataset showed in (Figure 5)

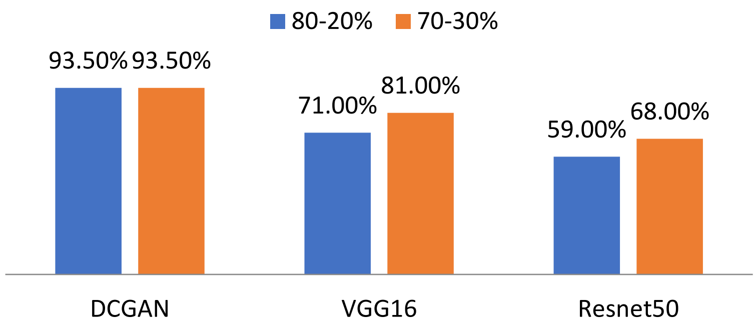

Figure 5. Graphical Representation of Experimental Results using DFDC dataset

The second experiment was performed using an 80-20% and 70-30% training-testing ratio of the Celeb-DF dataset. After preprocessing, DCGAN, VGG16, and Resnet50 were used to detect fake or real videos. The celeb-DF dataset contains Seven hundred ninety-five real and same fake videos. These videos were converted into sixty-two thousand five hundred images. For the 80-20 training–testing ratio, fifty thousand fake, and same real images were taken for training, and twelve thousand five hundred fake and same real images were used for testing. On the other hand, for the 70-30 training-testing ratio, Fourty three thousand seven hundred fifty real and the same fake images were taken for training purposes. In contrast, eighteen thousand seven hundred fifty real and the same fake images were used for testing purposes. The results showed that DCGAN, VGG16, and Resnet50 produced 95.6%, 84.0%, and 84.0% accuracy using an 80-20% training-testing ratio, respectively. On the other hand, DCGAN, VGG16, and Resnet50 showed 94.0%, 84.0%, and 78.0% accuracy using a 70-30% training-testing ratio, respectively.

Table 2. Experimental Results using Celeb-DF dataset.

Method	**Training-Testing Ratio (80%-20%) Accuracy**	**Training-Testing Ratio (70%-30%) Accuracy**
DCGAN	95.6%	94.0%
VGG16	84.0%	84.0%
Resnet50	84.0%	78.0%

The graphical representation of experimental results using the Celeb-DF dataset showed in (Figure 6)

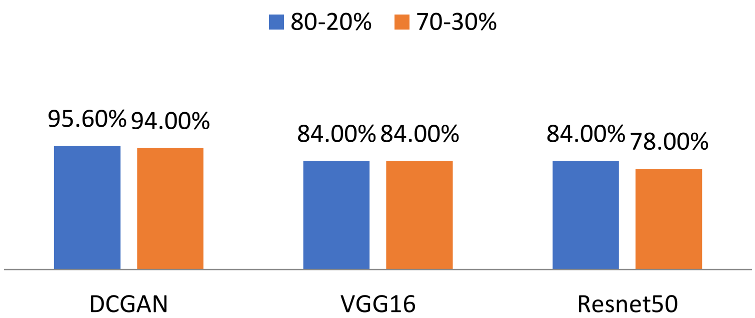

Figure 6. Graphical Representation of Experimental Results using Celeb-DF dataset

Hence, experiments showed that DCGAN produced better results using DFDC and Celeb-DF datasets. The proposed model outperformed in comparison with existing models for detecting fake videos. The following (Table 3) shows the proposed model's comparison with existing approaches for detecting fake videos.

Table 3. Comparison of proposed model with existing approaches.

Author	Method	Dataset	Performance
Sara.et.al [40]	SVM	Celeb-DF	89.1%
Daniel.et.al [25]	RNN	DFDC	92.6%
Safarzadeh.et.al [42]	VGG-16, Resnet-50	PASCAL VOC	94.0%
Zhao.et.al [10]	Xception,Efficient-B4	Celeb-DF	99.8%
Our proposed	**DCGAN**	**Celeb-DF**	**96.0%**
Our proposed	**DCGAN**	**DFDC**	**93.5%**

5. Conclusions

Fake video means creating fake multimedia content like video or image using techniques like face 2 face, face swap, neural texture, and deep fake. Some fake video detection techniques are also introduced in past years that accurately detect fake videos. Advancement in fake face representation techniques creates a great concern in social media, so detecting fake faces from videos is very important in recent times.

In this research work, GAN based (DCGAN) model is proposed to detect fake videos. The celeb-DF dataset contains 250 YouTube real videos, 158 celeb-real videos, and 795 celeb-fake videos. In this research, work frames are extracted from videos using Opencv then the facial part is extracted using the viola jones algorithm. DCGAN model achieved the highest accuracy of 96% at epoch size 10. DFDC dataset contains 400 training videos and 400 testing videos. The frames are extracted from videos using Opencv, and then the face part is extracted from frames using the viola jones algorithm. DCGAN model achieved accuracy at epoch size 15 is 93.5%.

Fake video detection is challenging due to advancements in fake video-generating techniques. In the future, more work is still needed to detect fake videos through eye-blinking patterns. And also, there is a need to generate different generative models and feature selection techniques to detect fake videos in the future

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