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Exploring the World of Deep Fake Detection - A Comprehensive Review of Existing Literature

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Abstract— Recent advancements in AI have surpassed our wildest expectations, particularly in the realm of Deep Neural Networks. These breakthroughs have enabled AI to manipulate various forms of multimedia, including video, audio, and photos. Deepfakes, a novel technique, allow for the complete transformation of multimedia, molding it into any desired perspective, whether positive or negative. The implications of realistic and high-quality deepfake videos are concerning, as they contribute to the dissemination of invasive information, incite political unrest, create social imbalances, and instill fear in vulnerable individuals. While creating deepfakes using AI-powered tools has become easier, detecting them and restoring the original layered multimedia from rasterized or altered versions remains a significant challenge. This situation fosters a sense of fear, instability, and profound desperation within national democracies. Consequently, the need arises for a system capable of assessing the authenticity of photos, ensuring the safeguarding of individuals' security and privacy.

Keywords—***Deep learning, Face-Swapping, DeepFake,super-imposition, MesoNet4, Generative Adversarial Networks (GANs), Autoencoders, etc.***

I. Introduction

In recent years, there has been a tremendous evolution in the field of artificial intelligence and has led to many astonishing innovations in the overall technological realm. Especially, many security systems face biometricsrecognition and others, suitably use artificial intelligence for increasing the efficiency of the security as well as the comprising technology. Rather than security, there are also many achievements in the field of artificial intelligence. The technology has made it possible to create jaw dropping and mind bogging applications like "Re-Face App", "Fake App" and so on. Despite the support provide these technologies, there has also been effective increase in the usage of these technologies for illegal/illicit purposes. One such technological hazard is"DeepFake".

A. The DeepFakes:

Deepfakes (a portmanteau of "deep learning" and "fake") are synthetic media[2], where a person in an existing image or video is replaced with another person's likeness. Creating fake contents is nothing new, but deepfakes use powerful machine learning and media manipulation techniques to manipulate or generate gullible visual and auditory content.[1][3] The main machine learning techniques used to create deepfakes are based on deep learning and involves training generative neural network architectures, such as autoencoders,[3] or generative adversarial networks (GANs).[4][5]

Deepfakes have garnered widespread attentionfor their uses in creating child sexual abuse material, celebrity pornographic videos, revenge porn, fake news, hoaxes, bullying, and financial fraud. This has elicited responses from both industry and governmentto detect and limit their use.

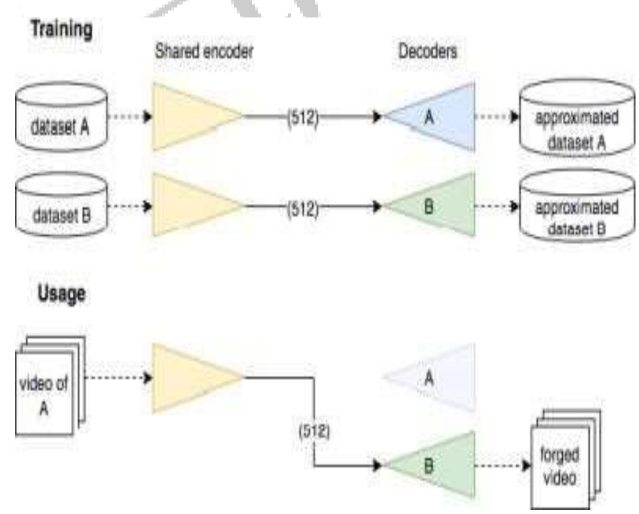

Fig 1. General DeepFake creation using AutoEncoders

B.History:

The origin of the primary technology was dated back in 1997, developed by Christoph Bregler, Michele Covell, and Malcolm Slaney, the famous “Video Rewriter”[6][7]. This modifies an existingvideo footage of a speaking person to show the personshaping the words contained in another audio track with their lips. This was the first system to fully automate this type of facial reanimation. To do this, they used machine learning techniques to associate the sounds produced by a video’s subject and the shape of their face. Primarily and originally, the program was intended for movie dubbing applications, where the program was able to modify film sequences so that actors' lip movements could besynchronized with new soundtracks.

Here are some example events that are based on deepfakes:

1) ***Barack Obama:*** Jordan Peele et al. and Monkey Productions published a deepfake of Obama in the second trimester of 2018, where Obama was depicted calling and imprecating Donald Trump [8]. It was said that the fake footage was uploaded to portray the dangerousness of the technology, and how worse it can be.

Fig 2. Obama deepfaked by Jordan Peele

2) ***Donald Trump and Barack Obama:*** On May 2019, a youtube handle named “Derpfakes” created a deepfaked content of Donald trump, which was based on the skit done in “NBC’s Tonight show”. The protagonist, “Jimmy Fallon” was dressed up like Donald Trump to enact a scene, where he would be act like speaking with Obama and boasting for his victory in Indiana. So the channel made this video into a deepfake as like trump isspeaking. [9]

Fig 3. Deepfake created by derpfakes

3) ***Kim Jong-un and Vladimir Putin*:** On September 2020, a nonpartisan advocacy group named “RepresentUs”, did a deepfake containing the Kim and Putin, thinking that the intervention of these leaders in US election could lead to the detrimentation of the contry’s democracy.But due to fear about how the americans will react, the group didn’t air the deepfake.[10]

Fig 4. DeepFake Of Kim Jong Un created by "Represent Us"

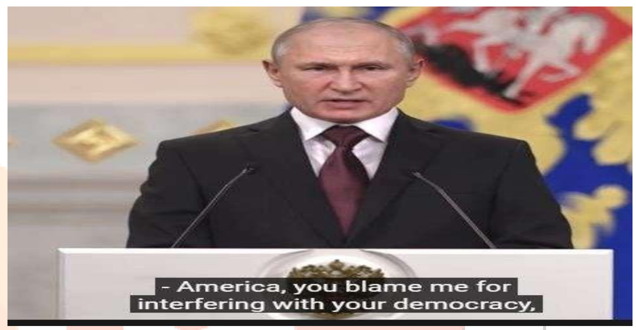

Fig 5. DeepFake Of Putin created by "Represent us"

4) ***Tom Cruise*:** In 2021, a Belgian VFX artisit named “Chris Ume”, created the deepfakes of the actor Tom Cruise, were the actor was made to perform various actions.[11]

Fig 6. Deepfake Of Tom Cruise by Ume

Fig 7. Deepfake Of Tom Cruise by Ume

5) ***<u>Volodymyr Zelenskyy:</u>*** On March 16, 2022, a one-minute long deepfaked video of the Ukranian President "Zelenskyy" went viral which was portrayed that the president said to callback the arms and troops, and surrenderto the Russian army. Despite the video being fake, the video was actually channelized in various parts of Ukraine, especially in the station's website. Various social media's like Instagram, Facebook banned such videos, while twitter didn't ban a few as that had the information that such videoshave been deepfaked. But soon after these videos were also removed by twitter as they spread misconceptions. The creator of the video is still unknown.[12]

Fig 8. Deepfakes of Zelenskyy

Fig 9. Deepfakes of Zelenskyy

II. TRENDS IN DEEPFAKE CREATION:

A) Deepfakes using GANs:

By utilising two algorithms that are in competitionwith one another, deepfake content is produced. One isreferred to as a generator, and the other as a discriminator. The discriminator is tasked with determining if the generated fraudulent digital stuff is real or manufactured. Every time the discriminator correctly distinguishes between authentic and fake content, it sends that knowledge to the generator to enhance the subsequent deepfake. These two algorithms combine to create a generative adversarial network known as GAN. It trains itself to recognise patterns usinga series of algorithms, which enables it to understand the genuine properties required to create fake images.**Solution: As a best effort, a CounterGAN can be created to find the deepfake created.**

B) Deepfake creation using Synthesia:

Step 1: Select an AI avatar: Choose from 70+ deepfake video avatars or create your own custom avatar. No actors or camerasneeded.

Step 2: Type in your text: Just type or upload in your text. We support 70+ languages. No voiceovers needed.

Step 3: Generate video: Your deepfake video file will be created in just a few minutes. Translate, download orstream it after.

C) Deepfake creation using Unreal Engine andSynthetic audiotools:

Unreal engine is a game engine, that is used to create dektop platform games and games for other platforms like HMD's and etc. The engine has now provided support to create characters for game assets, whichcan incredibly realistic create characters for games. These characters can be as realistic, for instance, consider **Matrix Awakens**, that has the Keanu Reaves character developed using Unreal Engine, which shows the extensive performance the enginecan perform. Using this and the altered audio created by **Altered Studio, Synthesia,** and **many other DeepLearning Techniques**.

III. LITERATURE SURVEY:

There are various aspects for deepfake detection.The classification for methods used in deepfake detection are as follows:

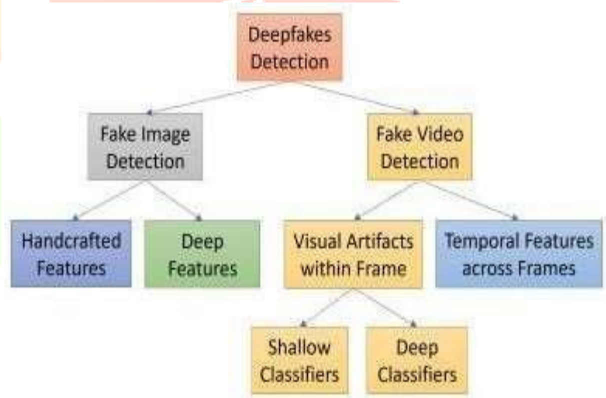

Fig 10: DeepFakes detection classification

1. Ali Bou Nassif et al. proposed an improved optical flow estimation-based method to detect and expose the augmentations between video frames.

Augmentation and modification are experimented upon to try to improve the system's overall accuracy. Furthermore, the system is trained on graphics processing units (GPUs) and tensor processing units (TPUs) to explore the effects and benefits of each typeof hardware in deepfake detection. TPUs were found to have shorter training times compared to GPUs. VGG-16 is the best performing model when used as a backbone for the system, as it achieved around 82.0% detection accuracy when trained on GPUs and 71.34% accuracy onTPUs.[13]

2. Matern et al. [14] proposed a method that focused on exploiting visual artifacts in generated and manipulated faces. The authors focused on the three most notable artifacts in the deployed detection method. The first artifact is the discoloration of the eyes. When a face generation algorithm creates a new face, the data points are interpolated between faces to find a plausible result. The algorithm tries to find two eyes from different faces that are matching in color. Utilizing the knowledge obtained by observing the fake data, the authors created their dataset from ProGan [15] andGlow [16] face generation datasets and generated deepfake and face2face [17] images using data from the Celeb-A dataset. Although the dataset used was limited to a small number, the results are very promising in this method.

3. Qi et al. [18] proposed an effective detection method utilizing remote visual photoplethysmography (PPG). Capturing and comparing the heartbeat rhythms of both the real and fake faces is the key idea of this method. The PPG monitors small changes of skin color caused by the blood moving through the face [19]. Using this information, PPG calculates an accurate estimation of the person's heartbeat. The general concept assumes that fake faces should have a disrupted or non-existent heartbeat rhythm compared to the normal rhythms produced by real videos. The authors have done extensive testing on FaceForensics++ [20] and DFDC[21] datasets to demonstrate not only the effectiveness but also the generality of this method on different deepfake techniques.

4. Guera et al. [22] proposed a temporal method to detect deepfake videos. The system uses CNN to extract features from a video for each frame. The extracted features are then used to train a recurrent neural network (RNN). Thenetwork learns to classify if the input video has been altered or not. The key advantage of this method is that it considersa sequence of frames when detecting deepfake videos. The authors chose to train the system on the HOHA dataset [23] because this dataset contains a realistic set of sequence samples from famous movies from which most deepfake videos are generated.

5. Amerini et al. [24] proposed a detection method exploiting the discrepancies in optical flow in fake faces as compared to real ones. The system transfers extracted cropped faces from video to PWC- Net [25], an optical flow CNN predictor. The authors conducted their tests on two well-known networks: VGG-16 [26] and ResNet50 [27]. Transfer learning was utilized to reduce training time and improve system accuracy. FaceForensics++ [20] uses multiplemanipulation methods that the authors used intheir tests. The three methods used are deepfakes, face2face, and face swap. Only the binary detection accuracy of face2face was shared in the research paper, with VGG-16 and ResNet50 detecting AI-generated faces with an accuracy of 81.61% and 75.46%, respectively.

6. Jeon et al. [28] proposed a light-weight robust fine-tuning neural network-based classifier capableof detecting fake faces. This system excels in its use of existing classification networks and its ease infine- tuning these networks. The authors aim to reuse popular pre-trained models and fine-tune them with new images to increase detection accuracy. The system takes the cropped face images from the videos and transfers them to the backbone model, which is trained on a large number of images (78,000 images training/validation). The preliminary results show a substantial improvement in the accuracy of the models, with around 2 to 3% on the Xception [29] models and 33 to 40% for SqueezeNet models. The datasets used in this research paper includedPGGAN [30], deepfakes, and face2face from the FaceForensics++ [20] dataset. The proposed augmentations and fine-tuning were applied only to the raw pixels of the image. However, discrepancies in the raw images, as mentioned before, are decreasing and may disappear entirely in the near future. Instead, implementing these techniques on the networks that analyze optical flow may increase the efficiency of thesenetworks.

7. Habeeba et al. [34] used GAN based MLP [Multi- layer Perceptron or feedforward neural network for their version of deepfake detection. Also Zhang et al. [35] used GAN based artifacts (the lip movements, the eye movements, etc.) to identify deepfaked contents.This implementation of GAN's are therefore significant as they have a properly trained discriminator , which could identify the deepfaked images by properly discrimating them. These are actually Machine learning based methods.

FINDINGS:

The findings from the Literature survey conducted is given in the following table:

S.No	Algorithm	Dataset	Accuracy
1)	**Canny – Edge detection and Hough tramsformation with KNN**	**Face2Face and Celeb-A**	**80-81%**
2)	**PWCNet + VGG-16 PWCNet + ResNet50**	**FaceForen -sics++**	**81.86% 75.46%**
3)	**FDFtNet**	**DeepFake and Face2Face**	**90.29%**
4)	**MMSTR + DualST AttenNet**	**FaceForen -sics++ and DFDC Preview**	**97.5%**

5)	**CNN + LSTM**	**HOHA**	**95-97%**
6)	**MesoNet4**	**DeepFake** **Face2Face**	**95-98%** **90-95%** **(73.1% - Actual)**
7)	**MesoInception-4**	**DeepFake** **Face2Face**	**96-98%** **93-96%**
8)	**ResNet + LSTM**	**DeepFake ,** **Face2Face**	**75-78%**
9)	**MLP and HOG based Visual artifacts classifier**	-	-
10)	**ResNet34 + AutoGAN**	**CycleGAN and GauGAN generated outputs**	**93 – 96%**
11)	**XceptionNet**	**DFDC, FaceForen -sics+++, Face2Face, Faceswap**	**96% and more**

CHALLENGES

As the technological development is too increasing, the probability to create a perfectly realistic deepfake is also increasing. This is a serious issue as there is always only cure presentin such problems as we cannot predict the upcoming efficient models that can be used to create realistic deepfakes.The solution proposedfor certain type of dataset might not beefficient to detect the deepfakes present in the other. Also, present systems don’t have higher computationalpower to detect deepfake for a large crowd and increased noise inflammations. So, there is a requirement to effectively implement deepfake detection for crowds, as this might be done too ascreating deepfaked content using technologieslike Blender, Maya, etc,. is absolutely very easy.A prominent way is we can create a 3d character,who can be whomsoever, can be adjusted toanother person too, or the entire animation canbedone from scratch too, and this when recursivelydone cancreate many deepfaked rigged fragments, which can be placed in anenvironment to create the crowd set-up.

DISCUSSIONS

As there is a famous saying, thorn can be only removed by a thorn, it is possible to detect high quality deepfakes only by its parent technology.For example, if a deepfake is made by using a certain GAN, then there is always a Counter GAN for the same to be detected. Famous MNC“Meta” also quoted that “DeepFakes” can be found effectively using reverse engineering techniques”. So if the deepfake is created using Blender, Maya, Cinema4D, etc,. an appropriate reverse engineering method is to be found for the same so that such contents can be rooted outof existence.

CONCLUSION:

DeepFake creation is actually a never-ending boon for Cine industry as well as threat to the human privacy and insecurity. For detection, from the survey, we have XcpetionNet and DeepRythm algorithms to be the state of arts method, which has high hardware requirements, whereas VGG-16 and ResNet 50 and mid rangehardware requirements and MesoNet4 can be handled by low ranged hardwares. Thus, appropriate models can be developed for the detection. Whatever has happened sofar is only the beginning or rise of the technology. There is still way more to go for the technology to reach it’s saturation of development. So appropriate privacy concerns and rules should be kept wherever and whenever possible. Strong amendments from the appropriate legal bodies for the respective judicial sections must be done.Rather than all, it’s primarily important to face the problem than fearing as DeepFake will grow with us in the upcoming era, like an endemic.

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