FakeAVCeleb: A Novel Audio-Video Multimodal Deepfake Dataset

Hasam Khalid
Computer Science & Engineering
Department, Sungkyunkwan
University
Suwon, South Korea
hasam.khalid@g.skku.edu

Shahroz Tariq
Computer Science & Engineering
Department, Sungkyunkwan
University
Suwon, South Korea
shahroz@g.skku.edu

Simon S. woo
Computer Science & Engineering
Department, Sungkyunkwan
University
Suwon, South Korea
swoo@g.skku.edu

ABSTRACT

With the significant advancements made in generation of forged video and audio, commonly known as deepfakes, using deep learning technologies, the problem of its misuse is a well-known issue now. Deepfakes can cause serious security and privacy issues as it can impersonate identity of a person in an image by replacing his/her face with a another person's face. Recently, a new problem of generating cloned or synthesized human voice of a person is emerging. AI-based deep learning models can synthesize any person's voice requiring just a few seconds of audio. With the emerging threat of impersonation attacks using deepfake videos and audios, new deepfake detectors are need that focuses on both, video and audio.

Detecting deepfakes is a challenging task and researchers have made numerous attempts and proposed several deepfake detection methods. To develop a good deepfake detector, a handsome amount of good quality dataset is needed that captures the real world scenarios. Many researchers have contributed in this cause and provided several deepfake dataset, self generated and in-the-wild. However, almost all of these datasets either contains deepfake videos or audio. Moreover, the recent deepfake datasets proposed by researchers have racial bias issues. Hence, there is a crucial need of a good deepfake video and audio deepfake dataset. To fill this gap, we propose a novel Audio-Video Deepfake dataset (FakeAVCeleb) that not only contains deepfake videos but respective synthesized cloned audios as well. We generated our dataset using recent most popular deepfake generation methods and the videos and audios are perfectly lip-synced with each other. To generate a more realistic dataset, we selected real YouTube videos of celebrities having four racial backgrounds (Caucasian, Black, East Asian and South Asian) to counter the racial bias issue. Lastly, we propose a novel multimodal detection method that detects deepfake videos and audios based on our multimodal Audio-Video deepfake dataset.

KEYWORDS

Datasets, Deepfakes, Fake Audio, Media Forensics, Fake Video, Multimodal

1 INTRODUCTION

With the advent of new AI technologies, particularly deep neural networks (DNNs), a rise in forged or manipulated images, videos, and audios has been fueled. Even though forging and manipulating images or videos has been done in the past [36], generating highly realistic fake human face images [12] or videos [40] and cloning human voices [14] has become much easier and faster than

before. Recently, generating deepfakes, a DNN based technique to replace a person's face with another person, has risen. The most common deep learning-based generation methods make use of Autoencoders (AEs) [33], Variational Autoencoders (VAEs) [33], and Generative Adversarial Networks (GANs) [12]. These methods are used to combine or superimpose a source human face image onto a target image. The recent advancements in deep learning-based deepfake generation methods have resulted in generating not only realistic forged images or videos but also voice-cloned human voices in real-time [5, 14]. Human voice cloning is a network-based speech synthesis method to generate high-quality speech of target speaker [14]. One famous example of deepfakes is of former U.S. Presidents Barack Obama, Donald Trump and George W. Bush, which were generated as part of research [39]. The individuals in the videos can be seen speaking with very accurate lip-sync.

Deepfakes has become a wide and well-known issue now. Numerous discussions are being held on state news channels and social media related to the potential harms of deepfakes [1]. A recent article was published on Forbes [31], which discussed a TV commercial ad by ESPN [37] which became a center of discussion over social media. In the ad, they showed footage from 1998 of an ESPN analyst making shockingly accurate predictions about the year 2020. It later turned out that the clip was fake, and it was generated using cutting-edge AI technology [8].

Therefore, many ethical, security and privacy concerns arise due to the ease of generating deepfakes. Keeping in mind the misuse of deepfakes and the potential harm they can cause, the need for deepfake detection methods is inevitable. Many researchers have dived into this domain and proposed a variety of different deepfake detection methods [2, 3, 13, 16, 21, 24, 44, 45] create an efficient and usable deepfake detection method, deepfake datasets are required. Keeping in mind the essence of datasets, researchers have also proposed different deepfake datasets, generated using the latest deepfake generation methods [9, 11, 15, 19, 22, 32] to help researchers train and evaluate their deepfake detection methods. Most of the recent deepfake detection methods [16, 27, 38] make use of these publicly available datasets. However, these deepfake datasets only focus on generating realistic deepfake videos and do not consider generating fake audio for them. Some neural networkbased synthesized audio datasets exist, but they do not contain the respective lip-synced or deepfake videos. This limitation of deepfake datasets also limits the deepfake detection methods. Since any state-of-the-art deepfake detection method aims to detect the deepfakes, either video or audio, to prevent the potential harm, the available datasets are limited to detect deepfake videos or audio individually.

As per our knowledge, there exist only one deepfake dataset, Deepfake Detection Challenge (DFDC) [10], that contains a mix of deepfake video and synthesized cloned audio, or both. However, the dataset is not labeled with respect to audio and video. It is not possible to tell if the audio was fake or the video. Table 1 contains quantitative comparison of FakeAVCelebwith other publicly available deepfake datasets. Therefore, we propose a novel Audio-Video Multimodal Deepfake Detection dataset (FakeAVCeleb) which contains not only deepfake videos, but respective synthesized cloned audios as well. FakeAVCelebconsists of videos of celebrities having different ethnic background, belonging to diverse age groups with equal proportions of each gender, see Table 2. We also performed some baseline experiments and proposed a ResNet50 based multimodal deepfake detector, out performing state of the art baseline ResNet50 in detecting Audio-Video deepfakes.

The main contributions of our work are summarized as follows:

- We present a novel Audio-Video Multimodal Deepfake Detection dataset, FakeAVCeleb, which contains both videos and audio deepfakes which are perfectly lip-synced. This multimodal deepfake dataset is not generated in the past.
- Our FakeAVCeleb dataset contains three types of Audio-Video deepfakes, which were generated from a carefully selected real YouTube video dataset using recently proposed popular deepfake generation methods.
- The individuals in the dataset are selected based four major ethnic backgrounds speaking English language to get rid of racial bias issue. Moreover, we performed baseline benchmark evaluation and prove the crucial need of a multimodal deepfake dataset.

2 BACKGROUND AND MOTIVATION

There are several deepfake detection datasets proposed by different researchers [10, 15, 17, 19, 22, 44] that are available publicly. Most of these datasets are manipulated images of a person's face, i.e., swapped with another person. These datasets contain real and respective manipulated fake videos. Nowadays, many different methods exist to generate deepfakes [12, 13], in which Autoencoders are used most of the time. To generate a pairwise swap between two videos requires retraining a single model that takes an excess of time and computational resources. Recently, researchers are proposing more realistic deepfake datasets with better quality and in larger quantity [19, 30, 32]. However, their only focus was to generate deepfake videos and not their respective fake audios. Moreover, these datasets either contain real audio or no audio at all. In this paper, we propose a novel deepfake video and audio dataset. We generate a cloned voice of the target speaker and apply lip sync with the video using facial reenactment. As per our knowledge, this is the first of its kind dataset containing deepfake video with fake audio . We believe it will help researchers develop deepfake detector which will consider both, deepfake videos and audios.

The UADF [44] and Deepfake TIMIT [35] are some early deepfake datasets. These datasets contain fewer real videos and respective deepfake videos. These datasets act as baseline datasets, and many researchers proposed deepfake detection methods using these

datasets. However, the quality and quantity of these datasets are low. UADF consists of only a few (98) videos; meanwhile, Deepfake TIMIT contains audio along with the video as well, except the audios are real and not synthesized or fake. In our FakeAVCeleb , we propose an Audio-Video Deepfake dataset that contains not only deepfake videos, but also synthesized lip-synced audios.

Due to the limitations of the quality and quantity of previous deepfake datasets, researchers proposed more deepfake datasets with a large number of videos and better quality. FaceForensics++ (FF++) [32] and Deepfake Detection Challenge (DFDC) [9] dataset were the first large-scale datasets containing a huge amount of deepfake videos. FF++ contains 5,000 and DFDC contains 128,154 videos. Both of these datasets were generated using multiple deepfake generation methods (FF++: 4, DFDC: 8). FF++ used a base set of 1,000 real YouTube videos and used 4 types of deepfake generations models, resulting in 5,000 deepfake videos. Later, FF++ added two more types of deepfake datasets, Deepfake Detection (DFD) [32] and FaceShifter [20] datasets. On the other hand, Amazon Web Services, Facebook, Microsoft, and researchers belonging to academics collaborated and released Deepfake Detection Challenge Dataset (DFDC) [9]. The videos in the DFDC dataset were captured in different environmental settings and used 8 types of synthesizing methods to generate deepfake videos.

Most deepfake detectors [3, 4, 16, 23, 34] use FF++ and DFDC datasets to train their models to detect deepfakes. However, despite being widely used, most these datasets lack diversity as the people in the videos belong to a specific ethnic backgrounds. Moreover, DFDC contains videos in which participants record videos while walking and not looking towards the camera, with extreme environmental settings (i.e., dark or very bright lighting conditions, camera angles), making it much harder to detect. As per our knowledge, DFDC is the only dataset that contains synthesized audios along with the videos, but they label the entire video as fake. They do not specify if the video is fake or the audio. Furthermore, the synthesized audios are not lip-synced with the respective videos, and they even label a video fake if the voice in the video was replaced with some other person's voice. Meanwhile, our FakeAVCeleb addresses these issues of environmental conditions, diversity and respective audiovideo labeling, and contains real and fake videos of people with different ethnic background, ages and gender. We carefully selected 490 videos belonging to different ages, gender, and ethnicity from the VoxCeleb dataset [6], which consists of a huge amount of real YouTube videos.

Recently, some new deepfake datasets have come into the light in which researchers have tried to overcome previous datasets' limitations and also used new deepfake generation methods to generate deepfake videos. Celeb-DF [22] was proposed in 2020, in which researchers used 490 YouTube real videos of 59 celebrities. They applied the modified version of the popular Faceswap method [18] to generate deepfake videos. Google also a proposed Deepfake Detection dataset (DFD) [32] containing 363 real videos and 3,000 deepfake videos, respectively. The real videos belong to 28 individuals having different ages and gender. Deepfake Videos in the Wild [30] and DeeperForensics-1.0 [15] are the most recent deepfake datasets. Deepfake Videos in the Wild dataset contains 1,869 samples of some real-world deepfake videos from YouTube and performed a comprehensive analysis of the popularity, creators,

DFDC

KoDF

FakeAVCeleb

Dataset	Real Videos	FakeVideos	Total Videos	Rights Cleared	Agreeing subjects	Total subjects	Methods	Real Audio	Deepfake Audio
UADFV	49	49	98	No	0	49	1	No	No
DeepfakeTIMIT	640	320	960	No	0	32	2	No	Yes
FF++	1000	4,000	5,000	No	0	N/A	4	No	No
Celeb-DF	590	5,639	6,229	No	0	59	1	No	No
Google DFD	0	3,000	3,000	Yes	28	28	5	No	No
DeeperForensics	50,000	10.000	60.000	No	100	100	1	No	No

Table 1: Quantitative comparison of FakeAVCeleb to existing publicly available Deepfake dataset.

Table 2: Comparison of ethnic diversity of FakeAVCeleb with existing publicly available Deepfake dataset.

Yes

Yes

Yes

960

403

0

960

403

600+

8

6

5

Yes

No

Yes

Yes

Yes

Yes

Dataset	American	European	African	South Asian	East Asian
UADFV	Yes	No	No	No	No
DeepfakeTIMIT	Yes	No	No	No	No
FF++	Yes	Yes	Yes	Yes	Yes
Celeb-DF	Yes	Yes	Yes	Yes	Yes
Google DFD	N/A	N/A	N/A	N/A	N/A
DeeperForensics	No	No	No	No	No
DFDC	N/A	N/A	N/A	N/A	N/A
KoDF	No	No	No	No	Yes
FakeAVCeleb	Yes	Yes	Yes	Yes	Yes

manipulation strategies, and deepfake generation methods. The latter one consists of real videos recorded by 100 paid consensual actors. They also used 1,000 real videos from the FF++ dataset and used them as target videos to apply face swap. They used a single face-swapping method and applied augmentation on real and fake videos, resulting in 50,000 real and 10,000 fake videos.

23,654

62,166

570

104,500

175,776

25,000+

128,154

237,942

25,500+

Moreover, a variety of new research is being done to simulate a human voice using neural networks. Most of these models use Tacotron [42] developed by Google to generate increasingly realistic, human-like human voices. Google proposed the Automatic Speaker Verification Spoofing (ASV) [41] challenge dataset with the goal of speaker verification and spoofed voice detection. However, all of the aforementioned datasets either contain deepfake videos or synthesized audios but not both. In our FakeAVCeleb, we propose a novel deepfake dataset containing deepfake videos with respective lip-synced synthesized audios.

3 DATASET COLLECTION AND GENERATION

In this section, we describes the Audio-Visual Deepfake Detection dataset (FakeAVCeleb), and how it was generated from the real videos, including the data collection and preprocessing of real videos from YouTube.

3.1 Dataset Collection

3.1.1 Real Dataset. To generate our FakeAVCeleb, We gathered real videos from the VoxCeleb-V2 [6] dataset. VoxCeleb-V2 consists of real YouTube videos of 6,112 celebrities. It contains 1,092,009 videos in the development set and 36,237 in the test set, where each video contains interviews of celebrities and the speech audio spoken in the video. We gathered 570 videos from VoxCeleb-V2, one video for each celebrity to generate the Deepfake dataset. The VoxCeleb-V2 dataset is relatively gender-biased; therefore, we hand-picked videos based on gender, ethnicity, professions, and age. The individuals in the real video set belong to 5 different ethnic backgrounds, Caucasian (Americans), Caucasian (Europeans), Black (African), South Asian (Indian), and East Asian (e.g., Chinese, Korean, and Japanese). Each ethnic group contains 100 real videos of 100 celebrities, 50 for each gender, except for Asians, consisting of 40 men and 50 women, resulting in 90 videos.

After carefully watching and listening to each of the sampled videos, we incorporated 570 unique real videos to our FakeAVCeleb as real base videos set, each belonging to a single individual, with an average of 7 seconds duration. Since we are focusing on a specific and most likely usage of deepfakes, each video was selected based on some specific criteria, i.e., there is a single person in the video with a clear and centered face, and he or she is not wearing any hat, glasses, mask or anything that might cover the face. Furthermore, the quality of the video should be good, and the speaker is talking in

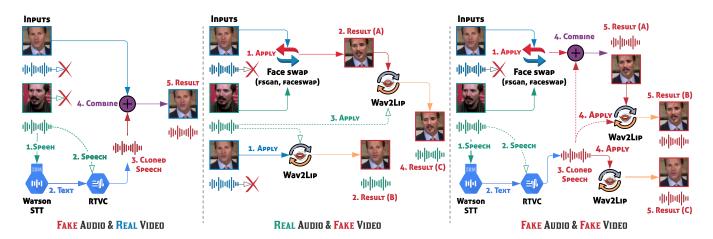


Figure 1: A step-by-step description of our FakeAVCeleb pipeline. Steps at the same level can be performed simultaneously. Fake Audio & and Real Video (Left): We begin with a source and target inputs. Then, we extract text from audio using IBM Watson and generate a cloned speech using IBM Watson and RTVC using the target's speech signal (Step 1–3). Lastly, we combine them to make the Fake Audio & and Real Video, shown in Step 5. Real Audio & and Fake Video (Middle): This is typically a deepfake video generation pipeline. The source and target videos are processed with a face swap method such as FSGAN or reenactment method such as Wav2Lip [29] to create deepfakes, as shown in Step 1–2. To further enhance the quality of face swap deepfakes, we also perform lip-sync using the target's speech signal, as shown in Steps 3–4. Fake Audio & and Fake Video (Right): In this type, we combine the previous two methods (i.e., left and middle) to create Audio-Video deepfakes. We use the videos from source and target for face swap, and at the same time, we use the target's speech signal to generate a cloned speech using IBM Watson and RTVC (Step 1–3). We combine this cloned speech with the face-swapped video or use Wav2Lip to enhance its quality further, as shown in Steps 4–5.

the English language, regardless of their ethnic background. Since we selected videos from the VoxCeleb-2 dataset, which consists of real YouTube videos, more videos of the same celebrity can be selected if required to increase the number of real videos set as we are providing the original celebrity ids as well used in the Vox-Celeb-2 dataset. Due to this edge, our FakeAVCeleb dataset is more scalable, and we can generate more deepfake videos to increase the number of real and deepfake videos if required.

3.2 Dataset Generation

We used the latest and effective deepfake and synthetic voice generation methods to generate our FakeAVCeleb dataset. Using the 470 real videos as a base set, we generated 18,000+ deepfake videos using several deepfake generation methods, including face-swapping and facial reenactment methods. We also used synthetic speech generation methods to generate cloned voice samples of the people in the videos. Throughout the following sections, we will use the term *source* to refer to the source video from which we will extract the frames, and the term *target* will refer to the video in which the face from the extracted frames will be swapped. To generate deepfake videos, we use Faceswap [18], Faceswap GAN (FSGAN) [25], and DeepFaceLab [18] to perform face swaps, and use Wav2Lip for facial reenactment based on source audio. On the other hand, the Real-Time Voice Cloning tool (RTVC) [14] was used for synthetic cloned voice generation.

Since our real video set contains people from 4 different ethnic backgrounds, we apply above mentioned chosen synthesis methods for each ethnicity separately (i.e., Caucasian with Caucasian or

Table 3: All possible combinations of real and fake video and audio datasets that we covered in our FakeAVCeleb.

Dataset	Real Audio	Fake Audio		
Real Video	(a) VoxCeleb-2 YouTube videos	(b) RTVC		
Fake Video	(c) FSGAN Faceswap DeepFaceLab Wav2Lip	(d) FSGAN Faceswap DeepFaceLab Wav2Lip RTVC		

Asian with Asian). In addition to this, we apply synthesis for each gender separately (i.e., Men with Men and Women with Women). We applied this setting to make a more realistic fake dataset since cross-ethnic, and cross-gender face swaps results in non-natural faces hence are easily detecTable. Moreover, we use a facial recognition service called Face++, which measures the similarity between two faces. The similarity score helps us find the most similar source and targets, resulting in more realistic deepfakes. We used their API to measure the similarity of a face in a source video with faces in many other target videos. We selected the top 5 videos with the highest similarity score. After calculating the similarities, each video was then synthesized with the chosen 5 videos by applying synthesis methods. We use a total of 5 synthesis methods, including video and audio synthesis methods, so that the resulting fake



Figure 2: Samples from the Dataset. We divide the dataset into 5 ethnic groups African, East Asian, Asian (Indians), Caucasian (American) and Caucasian (European). We also equally divide our dataset between male and female gender. Top-Left are the samples from our base dataset which contains real videos with real audio. Top-Right are the samples from real video with fake audio which are developed using the cloned speech of the target speaker. Bottom-Left are the samples with fake videos with real audio, representing the current state of most of the deepfakes benchmark datasets. Bottom-Right are the samples with fake video and fake audio, representing the main contribution of this work.

videos will be $5 \times 5 = 25$ for each input video. The total number of fake videos comes out to be $470 \times 25 = 11,750$, however, because of multiple audio-video combinations, the total fake video count increases to 25,000 or more.

After applying synthesis methods to generate deepfake videos, these videos are then passed through a manual inspection. While inspecting the generated videos, we filter the videos based on these criteria: 1) The resulting fake video must be of good quality and realistic, i.e., hard to detect through the human eye. 2) The synthesized cloned audio should also be good. 3) The video and corresponding audio should be lip-synced. Since we apply the manual screening process on all synthesized videos, the final video count is 25,000+. Some of the synthesis methods, FSGAN and Wav2Lip, for Faceswap and reenactment resulted in a large number of fake videos with excellent and realistic quality. Meanwhile, Faceswap and DeepFace-Lab resulted in several defective videos since they are sensitive to different lightning conditions and require excessive time and resources to train. Some of the frames from the final real and fake

videos are shown in Figure 2. We will now briefly explain each of our synthesis methods below.

3.2.1 Faceswap. Face swap refers to swapping faces between images or videos, maintaining the body and environment context. Faceswap [18] is an open-source face-swapping tool used to generate high-quality deepfake videos. Due to its popularity, it was used in FaceForensics++ datasets to generate the face-swapped dataset. The core architecture of this method consists of the encoder-decoder paradigm. A single encoder and two decoders (one for each source and target video) are trained simultaneously to build the face-swap model. The encoder extracts features from both videos while decoders reconstruct the source and target videos, respectively. The model is fed with frame-by-frame images of source and target video and trained for at least 80,000 iterations. We use this method because of its popularity as being a widely used deepfake generation method.

3.2.2 FSGAN. FSGAN, proposed by [25], is the latest face-swapping method that has become popular recently. The key feature of this

method is that it performs reenactment along with the face-swap. First, it applies reenactment on the target video based on the source video's pose, angle, and expression by selecting multiple frames from the source having the most correspondence to the target video. Then, it transfers the missing parts and blends them with the target video. This process makes it much easier to train and does not take much time to generate face-swapped video. We use the code from the official FSGAN GitHub Repository [26]. We used the best quality swapping model recommended by the authors of FSGAN for the preparation of our dataset. It fine-tunes the input video pairs and generate better quality results. We adopt this methods because of its efficiency and better quality of the results.

- 3.2.3 DeepFaceLab. DeepFaceLab [28] is a leading deepfake generation method. According to them, more than 95% of deepfake videos are generated from DeepFaceLab. They provide a complete, easy-to-use pipeline and provide end-to-end code with a windows software tool as well. They have also shared some synthesis models that can be used to generate deepfakes based on our requirements. Their method is a modification of the original Faceswap model in which they added an intervening network between encoder and decoders. It helps the network to extract common features between source and target videos. Moreover, their loss function includes a mean squared error along with a structural dissimilarity index. We used this deepfake generation method in our paper to include the most recent and widely used method in our FakeAVCeleb.
- 3.2.4 Wav2Lip. Recently, audio-based facial reenactment techniques along with lip-syncing have been proposed by researchers [7, 29]. In lip-sync, the source person controls the mouth movement, and in face reenactment, facial features are manipulated in the target video. One of the most recent audio-driven facial reenactment methods is Wav2Lip [29], which aims to lip-sync the video with respect to any desired speech signal by reenacting the face. Unlike LipGAN [7], which further fine-tuned the model on the generated frames, using a pretrained lip-sync discriminator to learns the lip-sync with respect to the desired audio accurately. The model used 5 video frames and the respective audio spectrogram to capture the video's temporal context. We used this facial reenactment method because of the efficiency of its synthesis process, and it does not take much time to generate lip-synced video.
- 3.2.5 Real Time Voice Cloning. Transfer Learning from Speaker Verification to Multispeaker Text-To-Speech Synthesis (SV2TTS) [14] is a real-time voice cloning tool that allows us to clone a voice from a few seconds of input audio. SV2TTS consists of three submodels which are trained independently. First, an encoder network is trained on a speaker verification task. It generates a fixed-dimensional embedding vector of input audio, a synthesis network based on Tacotron 2 that generates Mel spectrogram, and a WaveNet-based vocoder network that converts the Mel spectrogram into time-domain waveform samples. SV2TTS works in real-time. It takes the text and reference audio as input and generates a cloned audio based on the input audio. We used this synthesizing tool to generate cloned audios of our real video dataset.

3.3 Different Multimodal Dataset Generation Details

In this section, we will discuss dataset generation using the aforementioned synthesis methods and explain the resulting possible types of deepfake datasets. Since we are generating cloned voice along with the fake video, we come up with four possible combinations of audio-video pair, see Table 3. We will explain these combinations and their respective use-cases below:

- a) Real-Video & Real-Audio. This dataset is the base set of real videos with real audios that we selected from the VoxCeleb-2 dataset, see top left block in Figure 2. Currently, we sampled 490 videos with diverse ethnicity, gender, and age. Since VoxCeleb-2 contains more than a million videos, more real video from the VoxCeleb-2 dataset can be collected to train a deepfake detector. Moreover, this can be used to train a deepfake detection model for real audios as well along with real videos, see block (a) in Table 3.
- b) Real-Video & Fake-Audio. This deepfake contains cloned fake audio of a person along with the real video. We generate cloned fake audio using a transfer learning-based real-time voice cloning tool (SV2TTS), which takes real audio and text as input and gives synthesized audio (with voice matching) of the same person, as shown in Table 3 block (b). Please refer to the top right block in Figure 2 for some sample results. Since we do not have the text spoken in the video, we used IBM Watson speech-to-text service that converts audio into written text. This text, along with the corresponding audio, is then passed to the SV2TTS. Later, we merge the synthesized audio with the original video, resulting in Real-Video-Fake-Audio pair, see Figure 1. Since it is impossible to generate fake audio with the same timestamp as the original audio, this type of deepfake is not lip-synced. The possible use-case of this type of deepfake is a person doing identity fraud and fooling a person or speaker recognition system. This type of dataset can also be used as anti-voice spoofing attacks since we have real-fake pairs of audio with similar text.
- c) Fake-Video & Real-Audio. This type of deepfake consists of a face-swap or face reenacted video of a person along with the real audio. To generate deepfake videos of this type, we employ four types of deepfake generation methods, Faceswap, DeepFaceLab, FSGAN for face-swapping, and Wav2Lip for audio-driven facial reenactment, see block (c) in Table 3. The face-swapping methods were chosen based on the most popular and most recent deepfake generation methods. Wave2Lip was chosen because of its efficiency, lesser time consumption, and better quality output, see Figure 1. The sample results can be seen in bottom left block in Figure 2. Attackers can employ this type of deepfake for identity fraud, making a person say anything by reenacting the face given any input audio, forging a person's image by swapping his or her face with someone else. Since we kept the audio intact for this type, i.e., used real audio, and manipulation is done with the video only, the audio is perfectly lip-synced with video. Researchers can use this Fake-Video & Real-Audio dataset to train their detection models for a possible forged or face-swapped video detection.
- **d)** Fake-Video & Fake-Audio. This type of dataset contains both fake video and respective fake audio. We maneuver all five types of deepfake generation methods, Faceswap, DeepFaceLab,

FSGAN for face-swapping, Wav2Lip for audio-driven facial reenactment, and RTVC for cloning a person's voice, see block (d) in Table 3. It is basically a combination of our two types mentioned above (b and c) of the dataset, see bottom right block in Figure 2. We first generate cloned fake audio using the SV2TTS tool by giving a text-audio pair as input. Then we employ Wav2Lip to reenact the video based on cloned audio, see Figure 2.

Moreover, we used face-swapping methods, Faceswap, DeepFace-Lab, and FSGAN, to generate swapped deepfake videos. Later, we apply Wav2Lip on generated deepfake videos using cloned voices for audio-driven facial reenactment. As a result, we have a fake video with a fake audio dataset that is perfectly lip-synced. The type of dataset is minacious as an attacker can generate fake video and fake audio and impersonate any potential target person. This type of our FakeAVCeleb dataset is unique of its kind as all of the previous datasets either contain deepfake videos or synthesized audios, except for the DFDC. However, DFDC does not contain respective audio or video labels and is not perfectly lip-synced. This type of deepfake dataset can be used for training a detector for both, deepfake video and deepfake audio datasets.

4 EXPERIMENTS AND RESULTS

In this section, we present our experimental setup along with the detailed training procedures. We report the performance of some baseline deepfake detection methods and their limitation of detection one modality at a time. Also, we will talk about our baseline multimodal deepfake detector to detect deepfake video and audio. Later,

4.1 Preprocessing

To perform experimentation, we preprocessed the dataset to train the models. Preprocessing was done separately for videos and audios. Since we collected videos from VoxCeleb-2 dataset, these are already face centered and cropped. We extract respective frames from each videos and store them separately, and then extract audios from the videos and store them in wav format with sampling rate of 16 kHz. Before giving audio directly to the model, we first compute Mel-Frequency Cepstral Coefficients (MFCC) features by applying a 25ms Hann window [43] with 10ms window shifts, followed by a fast Fourier transform (FFT) with 512 points. As a result, we obtain a 2D array of 80 MFCC features (D=80) per audio frame and stored the resulting MFCC features as a 3 channel image, which is then passed to the model as an input to extract speech features so that it learns the difference between real and fake human speeches.

4.2 Deepfake detection

For the detection methods, performed some experiments separatly for deepfake video detection, deepfake audio detection, and then multimodal deepfake detection using our Audio-Video multimodal deepfake detection. We will briefly explain the detection models below.

4.2.1 ResNet. To show the importance and need of our FakeAVCeleb, we performed experiments using ResNet-50 as a baseline model. ResNet50 is a variant of ResNet model having 48 convolution layers along with a single MaxPool and Average Pool layer, and a single fully connected layer at the end of the network. It is a widely

used model was proposed to solve the problem of vanishing gradient that arises when we make a model deeper by adding more layers. The problem was solved by introducing deep residual learning framework having shortcut connections that simply perform identity mappings. The benefit of these shortcut identity mappings was that no additional parameters were added to the model and the computational time was kept in check. We trained ResNet50 for audio and video separately and report the respective results. First, we trained ResNet50 on real and fake video frames that we extracted earlier. We ran the training for 100 epochs and saved the best performing model checkpoint. Similarly, we trained a separate ResNet50 deepfake audio detector using MFCC features extracted from real and fake audios. We trained it for 100 epochs as well and saved the best performing checkpoint. After training the models, we evaluated the model on test set for each real and fake dataset types separately. The precision, recall and F_1 -scores for each model on each fake dataset are report in Table 4.

4.2.2 Multimodal Deepfake Detector. To create a baseline deepfake detector for our FakeAVCeleb, We present a novel multimodal deepfake detection methods based on ResNet50 architecture. The model consists of two ResNet50 models, one for each deepfake video and deepfake audio detection. We train models on video and audio datasets separately for 100 epochs and save the best model checkpoints. After training the models, we extract video and audio features on entire dataset, including train and test dataset. Since last layer of the ResNet50 is a fully connected layer with output size 2 to predict real and fake class, we remove the last layer from the network resulting in average max pooling layer as the last layer, which gives us an output of $2048 \times 1 \times 1$ dimensions, i.e., the feature vector. Hence, we extract features from both, audio and video deepfake datasets and store the feature vectors. Then, we first concatenate video feature vectors with their corresponding audio feature vectors, and then pass the extracted feature vectors through another network which is simple feed forward network having 4 fully connected layers with ReLU activation after each layer, see figure . We train it for a good number of epochs and evaluate on test dataset. The results shows our multimodal deepfake detector outperforms other baselines giving us 100% of average accuracy on each dataset type.

4.3 Results

After splitting the FakeAVCelebdataset into train and test sets, considering the racial and gender bias, we trained all three models motioned above. The standard ResNet50 baselines were trained on audio and video datasets separately and then tested on the test dataset. Later, we train our ResNet50-based multimodal deepfake detector and test it on test data, consisting of real and deepfake video and audio data for each fake type separately. We report the precision, recall and F_1 -scores of all three model in Table 4. Looking at the F_1 -scores, it can be seen that the multimodal ResNet50 easily outperforms the detectors trained only on single type of data, i.e, audio or video. The average F_1 -scores comes out to be 40.98, 88.50 and 94.29 for ResNet50 (Audio), ResNet50 (Video), and our multimodal deepfake detector.

Table 4: Performance of ResNet50 (Audio), ResNet50 (Video), and Multimodal ResNet50 (Audio+Video) on each deepfake dataset type generated using five various popular deepfake generation methods. The highest performing values are shown in bold.

Dataset	Class	ResNet50 (Audio)			ResNet50 (Video)			Multimodal ResNet50 (ours)		
		Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
W2L (c)	Real	0.447	0.644	0.528	0.968	0.938	0.953	1.000	0.947	0.973
	Fake	0.417	0.242	0.306	0.931	0.964	0.947	0.950	1.000	0.974
W2L (d)	Real	0.382	0.576	0.459	0.985	0.917	0.950	0.990	0.949	0.969
	Fake	0.219	0.113	0.149	0.889	0.980	0.932	0.951	0.990	0.970
Faceswap-W2L (d)	Real	0.387	0.621	0.477	1.000	0.963	0.981	1.000	0.947	0.973
	Fake	0.214	0.095	0.132	0.944	1.000	0.971	0.950	1.000	0.974
FSGAN-W2L (d)	Real	0.436	0.661	0.526	1.000	0.882	0.938	1.000	0.949	0.974
	Fake	0.222	0.102	0.140	0.840	1.000	0.913	0.951	1.000	0.975
Faceswap (c)	Real	0.450	0.632	0.526	0.940	0.940	0.940	0.898	0.951	0.924
	Fake	0.488	0.312	0.381	0.926	0.926	0.926	0.948	0.892	0.920
FSGAN (c)	Real	0.539	0.621	0.577	0.947	1.000	0.973	0.965	0.951	0.958
	Fake	0.444	0.364	0.400	1.000	0.933	0.966	0.952	0.966	0.959
RTVC (b)	Real	0.354	0.648	0.458	0.545	1.000	0.706	0.765	0.951	0.848
	Fake	0.136	0.045	0.067	0.000	0.000	0.000	0.936	0.708	0.806

5 DISCUSSION AND FUTURE WORK

In this section, we discuss the quality assurance of our dataset, issues that we encountered, availability, limitations and the lessons learned during collection and generation of our FakeAVCeleb dataset.

5.1 Data Quality

In the process of collection and generation of our FakeAVCeleb dataset, we tried to ensure the best quality that we could achieve. All of the selected real youtube videos went through a manual screening process in which we carefully selected those video having high quality and faces center aligned and not covered. The generated deepfake videos also went through the same process in which we removed the corrupted videos. Before we apply face swapping methods, we employed a facial recognition service, Fave++, that measures the similarity between two face and then applied face swapping methods between faces having highest similarity score.

5.2 Data Availability

Since we used the deepfake video and audio generation methods that are open sourced and anyone can access and use them, we are not releasing a separate code repository. A preview version of our FakeAVCeleb is available here¹. in which we have included samples of real and all types of deepfake videos that we generated as a zip file. The repository also contains detailed documentation with all relevant metadata specified to the research community and users. To make the dataset reusable for almost any purpose, it is freely accessible under the Creative Commons Attribution 4.0 International license.

5.3 Limitations

Despite covering all possible combinations of real and deepfake video and audio, FakeAVCelebstill have some limitations and suffers from bias in dataset since the pretrained models used for deepfake video and audio generation was were trained on s specific ethnicity. Since we have included videos of people with four different ethnicities, the resulting face swapped deepfakes for people other than Caucasian had many corrupted samples. Similarly, the synthesized voices does not clone properly when we perform real time voice cloning for the races other than Caucasian having a unique English speaking accent. Also, training deepfake detectors on FakeAVCeleb may lead to bias in dataset if not carfully used since it contains datasets of individuals with diverse ethnicity. Moreover, as deepfakes were generated from multiple deepfake generation methods, the resulting deepfakes are more in quantity than the real videos, which can also cause bias dataset. Since we selected real videos from VoxCeleb-2 dataset, researchers and used can refer to and use more real videos from there if required.

5.4 Future Directions

We plan to provide future updates to FakeAVCeleband keep it updated with the latest deepfake video and audio generation methods. Also, with the rise in adversarial attacks to fool deepfake detectors, we will take into account the potential adversarial attack and construct dataset accordingly. Another are of improvement is that we will make use of recent deepfake polishing methods that will help removing the fake artifacts caused by deepfake generation methods. Since this is the first version of the datasets of this type and it covers variety of video and audio combinations with multiple deepfake generation methods, the number of deepfake videos lacks in numbers as compared to other large-scale deepfake datasets. We plan to increase the dataset size in future releases.

¹https://github.com/hasam6400/fakevaceleb

6 CONCLUSION

We present a novel Audio-Video multimodal deepfake dataset, FakeAVCeleb, to help researchers to develop multimodal deepfake detectors which can detect not only deepfake videos but audios as well. FakeAVCeleb contains deepfake videos along with the respective synthesized cloned audios. It is gender and racially unbiased as it contains videos of men and women of four major races, Caucasian, Black, East Asian and South Asian belonging to different age groups. A range of recent most popular deepfake video and audio generation methods have been employed to generate videos that are perfectly lip-synced with respective audios. Apart from deepfake detection, FakeAVCeleb can be employed in various task such as identity verification, automatic speaker verification and recognition, anti-voice spoofing attacks detection and identity theft detection. Furthermore, we ensured the quality of the dataset by manually selecting good quality real YouTube videos. We also performed experiments using baseline model and present a multimodal deepfake detection methods that deepfake audio and video simultaneously. We hope FakeAVCeleb will help researchers in strengthening their deepfake detectors.

REFERENCES

- [1] Adam Smith. 2020. DEEPFAKES ARE THE MOST DANGEROUS CRIME OF THE FUTURE, RESEARCHERS. https://www.independent.co.uk/lifestyle/gadgets-and-tech/news/deepfakes-dangerous-crime-artificialintelligence-a9655821.html [Online; accessed 31-May-2021].
- [2] Darius Afchar, Vincent Nozick, Junichi Yamagishi, and Isao Echizen. 2018. Mesonet: a compact facial video forgery detection network. In 2018 IEEE International Workshop on Information Forensics and Security (WIFS). IEEE, 1–7.
- [3] Shruti Agarwal, Hany Farid, Yuming Gu, Mingming He, Koki Nagano, and Hao Li. 2019. Protecting World Leaders Against Deep Fakes.. In CVPR Workshops. 38-45
- [4] Irene Amerini, Leonardo Galteri, Roberto Caldelli, and Alberto Del Bimbo. 2019. Deepfake video detection through optical flow based cnn. In Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops. 0–0.
- [5] Sercan O. Arik, Jitong Chen, Kainan Peng, Wei Ping, and Yanqi Zhou. 2018. Neural Voice Cloning with a Few Samples. arXiv:1802.06006 [cs.CL]
- [6] Joon Son Chung, Arsha Nagrani, and Andrew Zisserman. 2018. Voxceleb2: Deep speaker recognition. arXiv preprint arXiv:1806.05622 (2018).
- [7] Béatrice Daille, Éric Gaussier, and Jean-Marc Langé. 1994. Towards automatic extraction of monolingual and bilingual terminology. In COLING 1994 Volume 1: The 15th International Conference on Computational Linguistics.
- [8] David Griner. 2020. State Farm and Kenny Mayne Brilliantly Faked Us All Out During The Last Dance. https://www.adweek.com/brand-marketing/state-farmand-kenny-mayne-brilliantly-faked-us-all-out-during-the-last-dance/ [Online; accessed 31-May-2021].
- [9] Brian Dolhansky, Joanna Bitton, Ben Pflaum, Jikuo Lu, Russ Howes, Menglin Wang, and Cristian Canton Ferrer. 2020. The deepfake detection challenge dataset. arXiv preprint arXiv:2006.07397 (2020).
- [10] Brian Dolhansky, Russ Howes, Ben Pflaum, Nicole Baram, and Cristian Canton Ferrer. 2019. The Deepfake Detection Challenge (DFDC) Preview Dataset. arXiv:1910.08854 [cs.CV]
- [11] Nick Dufour and Andrew Gully. 2019. Contributing data to deepfake detection research. Google AI Blog (2019).
- [12] Ian J Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative adversarial networks. arXiv preprint arXiv:1406.2661 (2014).
- [13] David Güera and Edward J Delp. 2018. Deepfake video detection using recurrent neural networks. In 2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS). IEEE, 1–6.
- [14] Ye Jia, Yu Zhang, Ron J. Weiss, Quan Wang, Jonathan Shen, Fei Ren, Zhifeng Chen, Patrick Nguyen, Ruoming Pang, Ignacio Lopez Moreno, and Yonghui Wu. 2019. Transfer Learning from Speaker Verification to Multispeaker Text-To-Speech Synthesis. arXiv:1806.04558 [cs.CL]
- [15] Liming Jiang, Ren Li, Wayne Wu, Chen Qian, and Chen Change Loy. 2020. Deeperforensics-1.0: A large-scale dataset for real-world face forgery detection. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2889–2898.

- [16] Hasam Khalid and Simon S Woo. 2020. OC-FakeDect: Classifying deepfakes using one-class variational autoencoder. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops. 656–657.
- [17] Pavel Korshunov and Sébastien Marcel. 2018. Deepfakes: a new threat to face recognition? assessment and detection. arXiv preprint arXiv:1812.08685 (2018).
- [18] Iryna Korshunova, Wenzhe Shi, Joni Dambre, and Lucas Theis. 2017. Fast Face-Swap Using Convolutional Neural Networks. In Proceedings of the IEEE International Conference on Computer Vision (ICCV).
- [19] Patrick Kwon, Jaeseong You, Gyuhyeon Nam, Sungwoo Park, and Gyeongsu Chae. 2021. KoDF: A Large-scale Korean DeepFake Detection Dataset. arXiv preprint arXiv:2103.10094 (2021).
- [20] Lingzhi Li, Jianmin Bao, Hao Yang, Dong Chen, and Fang Wen. 2019. Faceshifter: Towards high fidelity and occlusion aware face swapping. arXiv preprint arXiv:1912.13457 (2019).
- [21] Yuezun Li, Ming-Ching Chang, and Siwei Lyu. 2018. In ictu oculi: Exposing ai generated fake face videos by detecting eye blinking. arXiv preprint arXiv:1806.02877 (2019)
- [22] Yuezun Li, Xin Yang, Pu Sun, Honggang Qi, and Siwei Lyu. 2020. Celeb-df: A large-scale challenging dataset for deepfake forensics. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 3207–3216.
- [23] Trisha Mittal, Uttaran Bhattacharya, Rohan Chandra, Aniket Bera, and Dinesh Manocha. 2020. Emotions Don't Lie: An Audio-Visual Deepfake Detection Method Using Affective Cues. arXiv:2003.06711 [cs.CV]
- [24] Huy H Nguyen, Junichi Yamagishi, and Isao Echizen. 2019. Use of a capsule network to detect fake images and videos. arXiv preprint arXiv:1910.12467 (2019).
- [25] Yuval Nirkin, Yosi Keller, and Tal Hassner. 2019. Fsgan: Subject agnostic face swapping and reenactment. In Proceedings of the IEEE/CVF International Conference on Computer Vision. 7184–7193.
- [26] Yuval Nirkin, Yosi Keller, and Tal Hassner. 2020. FSGAN Official PyTorch Implementation. https://github.com/YuvalNirkin/fsgan [Online; accessed 31-May-2021].
- [27] Mohil Patel, Aaryan Gupta, Sudeep Tanwar, and MS Obaidat. 2020. Trans-DF: A Transfer Learning-based end-to-end Deepfake Detector. In 2020 IEEE 5th International Conference on Computing Communication and Automation (ICCCA). IEEE, 796–801.
- [28] Ivan Petrov, Daiheng Gao, Nikolay Chervoniy, Kunlin Liu, Sugasa Marangonda, Chris Umé, Jian Jiang, Luis RP, Sheng Zhang, Pingyu Wu, et al. 2020. Deepfacelab: A simple, flexible and extensible face swapping framework. arXiv preprint arXiv:2005.05535 (2020).
- [29] KR Prajwal, Rudrabha Mukhopadhyay, Vinay P Namboodiri, and CV Jawahar. 2020. A lip sync expert is all you need for speech to lip generation in the wild. In Proceedings of the 28th ACM International Conference on Multimedia. 484–492.
- [30] Jiameng Pu, Neal Mangaokar, Lauren Kelly, Parantapa Bhattacharya, Kavya Sundaram, Mobin Javed, Bolun Wang, and Bimal Viswanath. 2021. Deepfake Videos in the Wild: Analysis and Detection. arXiv preprint arXiv:2103.04263 (2021).
- [31] Rob Toews. 2020. Deepfakes Are Going To Wreak Havoc On Society. We Are Not Prepared. https://www.forbes.com/sites/robtoews/2020/05/25/deepfakes-aregoing-to-wreak-havoc-on-society-we-are-not-prepared/?sh=7885d8737494 [Online; accessed 31-May-2021].
- [32] Andreas Rossler, Davide Cozzolino, Luisa Verdoliva, Christian Riess, Justus Thies, and Matthias Nießner. 2019. Faceforensics++: Learning to detect manipulated facial images. In Proceedings of the IEEE/CVF International Conference on Computer Vision. 1–11.
- [33] David E Rumelhart, Geoffrey E Hinton, and Ronald J Williams. 1985. Learning internal representations by error propagation. Technical Report. California Univ San Diego La Jolla Inst for Cognitive Science.
- [34] Ekraam Sabir, Jiaxin Cheng, Ayush Jaiswal, Wael AbdAlmageed, Iacopo Masi, and Prem Natarajan. 2019. Recurrent convolutional strategies for face manipulation detection in videos. *Interfaces (GUI)* 3, 1 (2019).
- [35] Conrad Sanderson and Brian C Lovell. 2009. Multi-region probabilistic histograms for robust and scalable identity inference. In *International conference on biometrics*. Springer, 199–208.
- [36] M Sridevi, C Mala, and Siddhant Sanyam. 2012. Comparative study of image forgery and copy-move techniques. Advances in Computer Science, Engineering & Applications (2012), 715–723.
- [37] State Farm Insurance. 2020. Deepfakes Are Going To Wreak Havoc On Society. We Are Not Prepared. https://www.youtube.com/watch?v=FzOVqClci_s [Online; accessed 31-May-2021].
- [38] Shahroz Tariq, Sangyup Lee, and Simon S Woo. 2021. One detector to rule them all: Towards a general deepfake attack detection framework. arXiv preprint arXiv:2105.00187 (2021).
- [39] Justus Thies, Mohamed Elgharib, Ayush Tewari, Christian Theobalt, and Matthias Nießner. 2020. Neural voice puppetry: Audio-driven facial reenactment. In European Conference on Computer Vision. Springer, 716–731.
- [40] Ruben Tolosana, Ruben Vera-Rodriguez, Julian Fierrez, Aythami Morales, and Javier Ortega-Garcia. 2020. Deepfakes and beyond: A survey of face manipulation and fake detection. *Information Fusion* 64 (2020), 131–148.

- [41] Xin Wang, Junichi Yamagishi, Massimiliano Todisco, Héctor Delgado, Andreas Nautsch, Nicholas Evans, Md Sahidullah, Ville Vestman, Tomi Kinnunen, Kong Aik Lee, et al. 2020. ASVspoof 2019: A large-scale public database of synthesized, converted and replayed speech. Computer Speech & Language 64 (2020), 101114.
- [42] Yuxuan Wang, RJ Skerry-Ryan, Daisy Stanton, Yonghui Wu, Ron J Weiss, Navdeep Jaitly, Zongheng Yang, Ying Xiao, Zhifeng Chen, Samy Bengio, et al. 2017. Tacotron: Towards end-to-end speech synthesis. arXiv preprint arXiv:1703.10135 (2017).
- [43] Wikipedia contributors. 2021. Hann function Wikipedia, The Free Ency-clopedia. https://en.wikipedia.org/w/index.php?title=Hann_function&oldid=1001711522. [Online; accessed 9-March-2021].
- [44] Xin Yang, Yuezun Li, and Siwei Lyu. 2019. Exposing deep fakes using inconsistent head poses. In ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 8261–8265.
- [45] Peng Zhou, Xintong Han, Vlad I Morariu, and Larry S Davis. 2017. Two-stream neural networks for tampered face detection. In 2017 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW). IEEE, 1831–1839.