

INTEGRATING AUDIO-VISUAL FEATURES FOR MULTIMODAL DEEPFAKE DETECTION

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ABSTRACT

Deepfakes are AI-generated media in which an image or video has been digitally modified. The advancements made in deepfake technology have led to privacy and security issues. Most deepfake detection techniques rely on the detection of a single modality. Existing methods for audio-visual detection do not always surpass that of the analysis based on single modalities. Therefore, this paper proposes an audio-visual-based method for deepfake detection, which integrates fine-grained deepfake identification with binary classification. We categorize the samples into four types by combining labels specific to each single modality. This method enhances the detection under intra-domain and cross-domain testing.

Index Terms— Deepfake detection, Multi-modality deepfakes, Audio-visual feature learning

I. INTRODUCTION

Deepfakes are a type of synthetic media that alter and fabricate media in various ways, from images, videos, and audio recordings. They involve the use of generative adversarial networks (GANs) [1], Autoencoder [2], Diffusion models [3] and other machine learning algorithms to be formed. The rapid development of such algorithms has made the process to create these synthetic videos increasingly easier and faster. The most well-known form of deepfakes involves generating a video in which one person’s face is swapped onto another person’s body. This creates a convincing illusion that the person whose face was used is the one acting in the video. This technology has found practical applications in various industries, particularly in the entertainment sector with film production and video gaming.

However, at the same time, deepfakes can be easily used for malicious purpose, posing a significant threat to media security and the integrity of information authentication. For example, financial frauds have occurred through the use of fake and stolen identities to open bank accounts. Bank robbers used an artificial intelligence cloning voice to steal 35

million from the UAE bank ¹ in 2021. Yet, the main concerns regarding deepfakes revolve around the spread of misinformation and the development of inappropriate content. In 2022, a deepfake video featuring Ukraine’s President Volodymyr Zelensky announcing a surrender ² was spread out to the public, causing widespread panic and confusion.

The great threat posed by deepfakes has prompted researchers to create effective deepfake detection methods in recent years [4, 5, 6, 7]. Most methods use deep learning models to classify the input into “real” or “fake”, which is a binary classification. A majority of these methods target only a single modality [8], mostly exploring the visual artifacts in videos. In the past few years, multimodal deepfakes, involving manipulations in either audio or video, have begun to emerge with a more realistic and diverse generation [9, 10]. Audio-visual detection methods [11, 12, 13, 14] have been proposed to combine features from audio and video for deepfake detection. The analysis of two modalities, such as by fusing audio-visual features [9, 11] or learning audio-visual inconsistencies [14, 12, 15], can provide rich information to expose the deepfakes. However, existing studies reveal that employing multimodalities does not guarantee a higher accuracy compared to the application of a single modality [9, 11, 15]. Exploring how to leverage multiple modalities to enhance deepfake detection deserves further research.

Given that audio-visual deepfakes can be manipulated in various manners, such as pairing real video with synthesized audio, combining authentic audio with face-swapped video, or altering both modalities, it’s important to consider these categories in exploring multi-modality features. However, existing feature fusion methods treat different types of deepfakes as the same fake type. This may confuse the feature learning of a single modality, especially in ensemble-based fusion [9, 11, 15]. For example, in the case of deepfakes with real video and fake audio, as well as deepfakes with fake video and fake audio, the labels of the samples are the same, yet the video branch might learn unstable features for fusion. Incorporating a single modality detection loss [15] can alleviate the confusion. However, the fusion performance

¹<https://gizmodo.com/bank-robbers-in-the-middle-east-reportedly-cloned-someo-1847863805>

²<https://www.youtube.com/watch?v=X17yrEV5sl4>

is not necessarily enhanced. We believe that constrained by the audio and video generation models, the inconsistencies in audio-visual artifacts vary among different types of deepfakes. Therefore, in this paper, instead of treating the audio-visual sample as a simple binary classification task as previous detection methods did, we propose to integrate a fine-grained deepfake identification module to guide the detection model to discern the distinct artifacts present in videos that are fake in a single modality or in both modalities. We present a simple yet effective approach to identify the visual-audio artifacts among four types of videos, including real video real audio, real video fake audio, fake video real audio, and fake video fake audio. Combined with the artifact learning from each single modality, we improve the performance of the audio-visual feature fusion method. We apply our approach to two detection backbones, including the widely-used Capsule network [16] and the recent Swin Transformer [17] models. Experiments on two public multimodal deepfake datasets under intra-domain and cross-domain testing show superior performance of the proposed method to existing detectors.

II. RELATED WORK

A. Multimodal deepfake dataset

Several deepfake datasets have been established to advance the development of detection techniques. Early datasets focused on visual modality generation, either utilizing authentic audio or excluding audio entirely, such as FaceForensics++ (FF++) [18], CelebDF [19], DFDC (Deepfake Detection Challenge) [13], and KoDF (Korean Deepfake Detection Dataset) [20]. With the development of audio generation, audio-visual deepfake datasets combining the generation of cloned fake audio and generated faces have been created recently, including FakeAVCeleb dataset [9] and TMC [10]. These two datasets both cover fake video with real audio, real video with fake audio, fake video with fake audio, and real video with real audio categories.

B. Multimodal deepfake detection

There has been a surge of interest in deepfake detection. A majority of unimodal detection methods [8] focused on the visual and facial features. For multimodal deepfake detection, deep learning-based audio-visual models have been proposed by researchers. One branch of detection methods uses the fusion of features or scores from two modalities [11, 12, 15]. However, the ensemble of audio and visual networks does not yield as impressive results as the detection methods that focus on a single modality. Another branch of methods leverages multimodal detectors that extract the audio-visual inconsistencies in deepfakes [14, 21, 12, 22]. These methods have limitations in either delivering superior performance [9, 11], or offering computationally efficient detection.

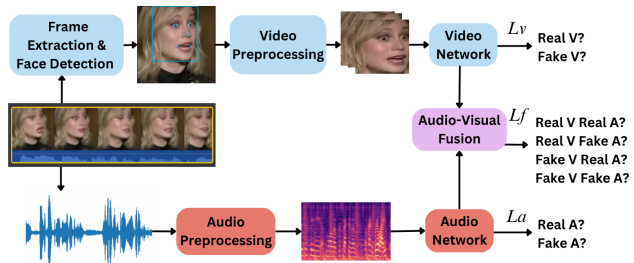


Fig. 1. Pipeline of the proposed detection method.

III. METHODOLOGY

A. Overview

We propose a simple yet effective detection method to improve the detection performance of multimodal deepfakes. The proposed method involves the fusion of audio and visual branches with a fine-grained deepfake classification loss. We further incorporate the binary classification losses from each modality to guide the detection model to capture both the inconsistency of multi-modality and the artifacts from each individual modality. In this section, we will first describe the preprocessing modules for each single modality, and then introduce the feature extraction networks, followed by a multi-task learning strategy.

B. Preprocessing

B.1. Video Branch

First, frame extraction is applied to each input video to output images. Considering the varying lengths of video samples, we extract one frame per second for videos that are longer than a minute, such as the videos in TMC dataset [10], and extract all frames for shorter videos, such as those in FakeAVCeleb [9] dataset. For each frame, a face detection method based on MTCNN [23] is used to detect and crop the face regions based on facial landmarks.

B.2. Audio branch

For the audio modality, we first extract the audio in a WAV format from the input video. The WAV file has the audio in a raw format, which cannot be passed into the detection model directly. Therefore, we further convert the audio into a mel-spectrogram image. A mel spectrogram [24, 25] is a spectrogram where the frequencies are converted into the mel scale. To do this, the raw audio files are first used to take samples of air pressure over time in order to digitally represent an audio signal, thereby capturing a waveform for the signal. This converts the audio file into a digital representation of an audio signal. Then, the audio signals are mapped from the time domain to the frequency domain using the Fast Fourier Transform (FFT), an algorithm that can efficiently compute the Fourier transform, a mathematical formula that breaks down a signal into its individual frequencies and the frequency's amplitude. This results in a spectrum. We then convert the frequency scale (y-axis) to a log scale and the color dimension (amplitude scale) to decibels to form the spectrogram. The y-axis

is mapped onto the mel scale, through another mathematical operation, and this forms the mel spectrogram [24]. The mel scale conversion equation is

$$Mel = \frac{(\log(1 + (Hz/1000))) \times 1000}{\log(2)} \quad (1)$$

where Hz is the frequency. We convert the file into a mel spectrogram instead of a spectrogram because the mel scale converts the frequencies such that equal distances in pitch sound equally distant to a listener. In order to make sure that the range in frequency and length shown for each mel spectrogram are the same, we set the frequency scale from 0 to 8000 Hz and the length to 4 seconds.

C. Feature Extraction

Feature extraction involves converting input images into high-level features, aiming to capture distinctive patterns within the data that are essential for detection tasks. The pre-processed visual face images and audio mel spectrograms are fed into deep neural networks to automatically extract features for deepfake detection. It is worth noting that our method does not impose any restrictions on the feature extraction models, and exhibits flexibility when applied across various network architectures. In our experiment, we will utilize the Capsule network [16], widely used in deepfake detection methods, and the Swin Transformer [17], which has recently demonstrated powerful feature learning capabilities in various image classification tasks, as two examples for the video and audio networks to show the flexibility of our method.

D. Multi-task Learning

As our method proposes the integration of a fine-grained deepfake identification module with the binary classification of each modality for distinct feature learning, we formulate a multi-task learning strategy by fusing three loss functions. The loss function is defined as,

$$L_{total} = L_a + L_v + L_f \quad (2)$$

where L_a and L_v are the binary cross-entropy losses applied to the each single audio and video modality, respectively, while L_f is a four-class cross-entropy loss that considers the different types of videos. Each of the cross-entropy loss is defined as:

$$L = -(y \log(\hat{y}) + (1 - y) \log(1 - \hat{y})) \quad (3)$$

where y is the ground truth label and \hat{y} is the predicted label.

For the audio-visual module which is a multi-class classification task, we average the video network output of multiple frames to represent the overall features of the input video. Two versions of audio-visual fusion can be implemented. The first involves feature fusion, where the average visual features from the video network are concatenated with the audio features from the audio network (after removing the classification head). The second approach is score fusion, which

averages the scores from the video and audio networks that include classification heads. Subsequently, either the fused feature or the fused score will be fed into the four-class classification head for video identification.

IV. EXPERIMENTS

A. Implementation Details

The frames extracted from videos were resized to 300×300 , and the image of the audio mel-spectrogram was also resized to 300×300 . The detection models were trained for 50 epochs, with a batch size of 10. We employed the Adam optimizer [26] with $\beta_1 = 0.9$, $\beta_2 = 0.999$, and a learning rate of 5×10^{-4} .

For comparison with other methods, we report two widely-used metrics in deepfake detection, namely Accuracy and Area Under Curve (AUC) which is a metric that quantifies the total area beneath the curve generated when plotting the True Positive Rate against the False Positive Rate.

B. Dataset

We evaluated the performance of our method on two multi-modal deepfake datasets, namely FakeAVCeleb [9] and TMC dataset [10] using the 80-20 training/testing split.

FakeAVCeleb [9] dataset was generated using videos from VoxCeleb2 [27] which consists of real Youtube videos of celebrities with five ethnic backgrounds: Caucasian (Americans), Caucasian (Europeans), African American, South Asian, and East Asian. There is also equal distribution between males and females for each of the ethnic backgrounds. Each ethnic group consists of 100 real videos of 100 celebrities, 50 for each gender. This outputs 600 different videos with an average duration of about 7 seconds. The dataset consists of three different types of audio-video deepfakes (fake audio only, fake video only, or both) using popular deepfake generation methods. These methods include face-swapping and facial reenactment methods. For fake audio generation, they used synthetic speech synthesis methods to generate cloned or fake voice samples. Wav2Lip was used for facial reenactment based on the audio source.

TMC Dataset [10], created in 2022, was designed to tackle the issue of fake media in Singapore. This dataset consists of 4,380 fake videos and 2,563 real-life footage from several different sources, including presenters and journalists in news programs, interviews answering questions on live TV, and people talking about general topics. TMC contains 72.65% of subjects Asians, and 45.82% of female subjects. The duration of these videos varies from 10 seconds to a minute. There are 4 different types of fakes: fake audio only, fake video only, both aspects are fake, or both are real but the audio and video do not match. Similar to FakeAVCeleb, TMC was generated using popular deepfake generation methods, including face-swapping and deep learning techniques. StarGAN-VC was used for fake audio generation.

Dataset	Model	Method	Overall		Video		Audio	
			AUC	ACC	AUC	ACC	AUC	ACC
FakeAV-Celeb to FakeAV-Celeb	Capsule Forensics	Ours-S	99.30	99.20	97.27	96.43	99.75	99.80
		Video	-	-	96.53	96.51	-	-
		Audio	-	-	-	-	99.11	99.06
		Feature Score	99.44	99.16	26.74	26.78	55.61	55.57
			99.25	99.75	75.48	75.41	77.81	77.83
	Swin Transformer	Ours-S	91.65	90.51	88.13	96.21	93.47	94.79
		Ours-F	85.67	86.73	79.23	86.77	94.57	91.26
		Video	-	-	86.54	86.56	-	-
		Audio	-	-	-	-	88.06	88.06
		Feature Score	82.91	89.68	81.33	80.26	90.28	92.16
TMC to TMC	Capsule Forensics	Ours-S	93.67	93.15	92.03	91.98	99.73	99.68
		Video	-	-	90.97	90.91	-	-
		Audio	-	-	-	-	99.07	98.72
		Feature Score	88.89	89.24	50.57	51.79	29.91	28.85
			83.00	84.36	75.16	75.61	78.30	76.54
	Swin Transformer	Ours-S	80.11	85.57	72.39	73.02	83.10	87.29
		Ours-F	65.79	78.23	70.55	65.35	72.73	79.33
		Video	-	-	50.72	54.07	-	-
		Audio	-	-	-	-	72.63	76.81
		Feature Score	67.28	72.87	57.47	62.22	72.93	73.21
	75.41	78.77	68.84	72.04	81.30	80.59		

Table I. Comparison results under intra-domain testing.

Model	Overall	
	AUC	ACC
MesoInception-4 [28]	72.22	75.82
FTCN [30]	84.00	64.90
EfficientNet [29]	81.03	-
AVoID-DF [14]	89.20	83.70
AV-Lip-Sync [31]	-	94.00
Ours-S-Capsule Forensics	99.30	99.20
Ours-S-Swin Transformer	91.65	90.51

Table II. Comparison results with existing deepfake detection methods using reported results on FakeAVCeleb dataset.

C. Baselines

We first compare the proposed audio-visual method with different detection strategies under two feature learning backbones, namely the Capsule network [16] and the Swin Transformer [17] model. Then we conduct a comparison with existing deepfake detection methods [11, 21] that were evaluated on the FakeAVCeleb dataset, including ensemble frame-based methods of MesoInception-4 [28], EfficientNet [29], and FTCN [30], and audio-visual multimodal methods including AVoID-DF [14] and AV-Lip-Sync [31].

D. Intra-domain testing

Under intra-domain testing scenarios, the detection model is trained and tested in the same dataset. Table I compares our score fusion method ‘‘Ours-S’’ and feature fusion method ‘‘Ours-F’’ with two single modality models (‘‘Video’’ and ‘‘Audio’’) and traditional feature and score fusion methods based on a binary classification loss. With the advantage of the fine-grained video identification module, our method, especially with score fusion, clearly surpasses other approaches, achieving the highest AUC and ACC scores in the majority of cases. This shows the effectiveness of the proposed method in identifying the artifacts from multi-modalities. It is worth noting

Dataset	Model	Method	Overall		Video		Audio	
			AUC	ACC	AUC	ACC	AUC	ACC
FakeAV-Celeb to TMC	Capsule Forensics	Ours-S	65.28	67.39	73.49	72.82	61.04	65.66
		Video	-	-	70.62	69.75	-	-
		Audio	-	-	-	-	53.74	55.65
		Feature Score	61.59	59.83	59.98	58.97	50.00	52.22
			60.67	65.11	63.89	63.48	50.03	47.84
	Swin Transformer	Ours-S	70.41	79.68	67.34	68.89	70.19	71.54
		Video	-	-	55.41	56.72	-	-
		Audio	-	-	-	-	65.04	64.68
		Feature Score	63.79	77.83	63.28	62.67	66.80	68.23
			64.82	76.23	66.83	68.19	69.25	69.23
TMC to FakeAV-Celeb	Capsule Forensics	Ours-S	77.89	81.12	70.29	77.96	69.33	71.65
		Video	-	-	65.59	62.24	-	-
		Audio	-	-	-	-	51.00	71.59
		Feature Score	64.60	66.87	49.00	28.55	60.34	63.87
			66.41	66.77	64.84	72.04	65.30	63.59
	Swin Transformer	Ours-S	82.17	89.73	78.77	78.89	87.55	88.32
		Video	-	-	72.77	72.11	-	-
		Audio	-	-	-	-	78.09	82.45
		Feature Score	76.10	84.17	71.97	74.23	80.48	85.91
			80.56	87.88	73.76	77.69	85.47	85.34

Table III. Comparison results under cross-domain testing.

Dataset	Method	Overall	
		AUC	ACC
TMC to TMC	Ours-S	82.18	75.29
FakeAVCeleb to TMC	Ours-S	63.83	69.63
FakeAVCeleb to TMC	Naive	-	44.00

Table IV. Comparison results using Swin Transformer under cross-type testing.

that all methods achieve higher results on the FakeAVCeleb dataset than on the TMC dataset. This can be attributed to the high diversity and additional perturbations added to both video and audio tracks in TMC dataset. We further compare our score-fusion-based method with existing deepfake detection techniques on the FakeAVCeleb dataset. The results in Table II show the outstanding performance of the proposed method in detecting multimodal deepfakes, especially using the Capsule network.

E. Cross-domain testing

To evaluate the generalization ability of the proposed method in detecting unseen deepfakes, the proposed method is trained and tested using different datasets. The comparison results in Table III show that our proposed method achieved the best performance under both cross-domain testing scenarios. We can also observe that training on TMC and testing on the FakeAVCeleb dataset leads to higher AUC and ACC for most cases. This is reasonable as the model trained on a more diverse dataset (i.e., TMC) would exhibit greater generalizability to unseen data. Moreover, it can be seen that the Swin Transformer obviously outperforms the Capsule network, demonstrating better generalization ability.

F. Cross-type testing

There is one type of cheap fake videos in the TMC dataset, namely real videos with mismatched real audio. To further

demonstrate the effectiveness of our method in capturing audio-visual consistency features, we use the pre-trained models to test these mismatched videos as cross-type testing. Table IV compares our score-fusion based Swin Transformer model with the naive fusion method which uses the maximum predictions of two modalities. It is evident that our method is capable of handling these previously unseen fake types, while the naive fusion method fails. We also find that the majority of mismatched real video and audio samples are categorized under the “Real Video Fake Audio” class within our multi-class identification module. This can be attributed to the similar audio-visual patterns, such as lack of synchronization, found in these two types of fake videos.

V. CONCLUSION

We introduce a method for audio-visual deepfake detection that identifies the multimodal inconsistency features across various deepfake types, as well as artifacts within each modality. The proposed method demonstrates good adaptability, allowing it to be applied across various feature extraction networks. Experimental results on two audio-visual deepfake datasets, both within-domain and cross-domain, highlight the effectiveness of the method. In our future work, we plan to focus on developing more robust multimodal networks to enhance the feature learning and fusion strategies for audio and video modalities. Additionally, exploring methods to improve the generalizability of multimodal deepfake detection methods to unseen deepfakes will be a key area of investigation.

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