

# Emotions Don't Lie: An Audio-Visual Deepfake Detection Method using Affective Cues

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Project Page: <https://gamma.umd.edu/deepfakes/>

## ABSTRACT

We present a learning-based method for detecting real and fake deepfake multimedia content. To maximize information for learning, we extract and analyze the similarity between the two audio and visual modalities from within the same video. Additionally, we extract and compare affective cues corresponding to perceived emotion from the two modalities within a video to infer whether the input video is “real” or “fake”. We propose a deep learning network, inspired by the Siamese network architecture and the triplet loss. To validate our model, we report the AUC metric on two large-scale deepfake detection datasets, DeepFake-TIMIT Dataset and DFDC. We compare our approach with several SOTA deepfake detection methods and report per-video AUC of 84.4% on the DFDC and 96.6% on the DF-TIMIT datasets, respectively. To the best of our knowledge, ours is the first approach that simultaneously exploits audio and video modalities and also perceived emotions from the two modalities for deepfake detection.

## CCS CONCEPTS

• Computing methodologies → Visual content-based indexing and retrieval; Neural networks.

## KEYWORDS

DeepFakes, Multimodal Learning, Emotion Recognition

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## 1 INTRODUCTION

Recent advances in computer vision and deep learning techniques have enabled the creation of sophisticated and compelling forged versions of social media images and videos (also known as “deep-fakes”) [1–5]. Due to the surge in AI-synthesized deepfake content, multiple attempts have been made to release benchmark datasets [6,

23, 33, 49] and algorithms [9, 26, 36, 38, 42, 43, 49, 50, 57, 61, 64] for deepfake detection. DeepFake detection methods classify an input video or image as “real” or “fake”. Prior methods exploit only a single modality, i.e., only the facial cues from these videos either by employing temporal features or by exploring the visual artifacts within frames. Other than these modalities, multimodal approaches have also exploited the contextual information in video data to detect fakes [45]. There are many other applications of video processing that use and combine multiple modalities for audio-visual speech recognition [28], emotion recognition [40, 63], and language and vision tasks [17, 29]. These applications show that combining multiple modalities can provide complementary information and lead to stronger inferences. Even for detecting deepfake content, we can extract many such modalities like facial cues, speech cues, background context, hand gestures, and body posture and orientation from a video. When combined, multiple cues or modalities can be used to detect whether a given video is real or fake.

In this paper, the key idea used for deepfake detection is to exploit the relationship between the visual and audio modalities extracted from the same video. Prior studies in both the psychology [56] literature, as well as the multimodal machine learning literature [13] have shown evidence of a strong correlation between different modalities of the same subject [56]. More specifically, [48, 51, 55, 65] suggest some positive correlation between audio-visual modalities, which have been exploited for multimodal perceived emotion recognition. For instance, [12, 27] suggests that when different modalities are modeled and projected into a common space, they should point to similar affective cues. Affective cues are specific features that convey rich emotional and behavioral information to human observers and help them distinguish between different perceived emotions [59]. These affective cues comprise of various positional and movement features, such as dilation of the eye, raised eyebrows, volume, pace, and tone of the voice. We exploit this correlation between modalities and affective cues to classify “real” and “fake” videos.

**Main Contribution:** We present a novel approach that simultaneously exploits the audio (speech) and video (face) modalities and the perceived emotion features extracted from both the modalities to detect any falsification or alteration in the input video. To model this multimodal features and the perceived emotions, our learning method uses a Siamese network-based architecture. At training time, we pass a real video along with its deepfake through our network and obtain modality and perceived emotion embedding vectors for the face and speech of the subject. We use these embedding vectors to compute the triplet loss function to minimize the similarity between the modalities from the fake video and maximize the similarity between modalities for the real video.

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**Table 1: Benchmark Datasets for DeepFake Video Detection.** Our approach is applicable to datasets that include the audio and visual modalities. Only two datasets (highlighted in blue) satisfy that criteria and we evaluate the performance on those datasets. Further details in Section 4.1.

Dataset	Released	# Videos			Video Source		Modes	
		Real	Fake	Total	Real	Fake	Visual	Audio
UADFV [61]	Nov 2018	49	49	98	YouTube	FakeApp [2]	✓	×
DF-TIMIT [33]	Dec 2018	0	620	620*	VidTIMIT [52]	FS_GAN [5]	✓	✓
Face Forensics++ [49]	Jan 2019	1,000	4,000	5,000	YouTube	FS [1], DF	✓	×
DFD [6]	Sep 2019	361	3,070	3,431	YouTube	DF	✓	×
CelebDF [37]	Nov 2019	408	795	1,203	YouTube	DF	✓	×
DFDC [23]	Oct 2019	19,154	99,992	119,146	Actors	Unknown	✓	✓
Deeper Forensics 1.0 [31]	Jan 2020	50,000	10,000	60,000	Actors	DF	✓	–

The novel aspects of our work include:

- (1) We propose a deep learning approach to model the similarity (or dissimilarity) between the facial and speech modalities, extracted from the input video, to perform deepfake detection.
- (2) We also exploit the affect information, *i.e.*, perceived emotion cues from the two modalities to detect the similarity (or dissimilarity) between modality signals, and show that perceived emotion information helps in detecting deepfake content.

We validate our model on two benchmark deepfake detection datasets, DeepFakeTIMIT Dataset [33], and DFDC [23]. We report the Area Under Curve (AUC) metric on the two datasets for our approach and compare with several prior works. We report the per-video AUC score of 84.4%, which is an improvement of about 9% over SOTA on DFDC, and our network performs at-par with prior methods on the DF-TIMIT dataset.

## 2 RELATED WORK

In this section we summarise prior work done in the domain. We first look into available literature in multimedia forensics in Section 2.1. We elaborate on prior work in unimodal deepfake detection methods in Section 2.2. In Section 2.3, we discuss the multimodal approaches for deepfake detection. We summarize the deepfake video datasets in Section 2.4. We give references from affective computing literature motivating the use of affective cues from modalities in our method for deepfake detection in Section 2.5.

### 2.1 Multimedia Forensics

Media forensics deals with the problem of authenticating the source of digital media such as images, videos, speech, and text in order to identify forgeries and other malicious intents [15]. Classical computer vision techniques [15, 60] have sufficed to tackle media manually manipulated by humans. However recently, malicious actors have begun manipulating media using deep learning, *e.g.* deepfakes [22], that use artificial intelligence to present false media as realistic in highly sophisticated and convincing ways. Classical computer vision techniques are unsuccessful when identifying false media corrupted using deep learning [58]. Therefore, there has been a growing interest in developing deep learning-based methods for multimedia forensics [11, 20, 39]. There has also been prior interest in

exploring affect for detection deception [47]. Our proposed method falls in this category and is complementary to other deep learning-based approaches.

### 2.2 Unimodal DeepFake Detection Methods

Most prior work in deepfake detection decompose videos into frames and explore visual artifacts across frames. For instance, Li et al. [36] propose a Deep Neural Network (DNN) to detect fake videos based on artifacts observed during the face warping step of the generation algorithms. Similarly, Yang et al. [61] look at inconsistencies in the head poses in the synthesized videos and Matern et al. [38] capture artifacts in the eyes, teeth and facial contours of the generated faces. Prior works have also experimented with a variety of network architectures. For instance, Nguyen et al. [43] explore capsule structures, Rossler et al. [49] use the XceptionNet, and Zhou et al. [64] use a two-stream Convolutional Neural Network (CNN) to achieve SOTA in general-purpose image forgery detection. Previous researchers have also observed and exploited the fact that temporal coherence is not enforced effectively in the synthesis process of deepfakes. For instance, Sabir et al. [50] leveraged the use of spatio-temporal features of video streams to detect deepfakes. Likewise, Guera and Delp et al. [26] highlight that deepfake videos contain intra-frame consistencies and hence use a CNN with a Long Short Term Memory (LSTM) to detect deepfake videos.

### 2.3 Multimodal DeepFake Detection Methods

While unimodal DeepFake Detection methods (discussed in Section 2.2) have focused only on the facial features of the subject, there has not been much focus on using the multiple modalities that are part of the same video. Jeo and Bang et al. [30] propose FakeTalkerDetect, which is a Siamese-based network to detect the fake videos generated from the neural talking head models. They perform a classification based on distance. However, the two inputs to their Siamese network are a real and fake video. Korshunov et al. [34] analyze the lip-syncing inconsistencies using two channels, the audio and visual of moving lips. Krishnamurthy et al. [35] investigated the problem of detecting deception in real-life videos, which is very different from deepfake detection. They use an MLP-based classifier combining video, audio, and text with Micro-Expression features. Our approach to exploiting the mismatch between two modalities is quite different and complimentary to these methods.

## 2.4 DeepFake Video Datasets

The problem of deepfake detection has increased considerable attention, and this research has been stimulated with many datasets. We summarize and analyze 7 benchmark deepfake video detection datasets in Table 1. Furthermore, the newer datasets (DFDC [23] and Deeper Forensics-1.0 [31]) are larger and do not disclose details of the AI model used to synthesize the fake videos from the real videos. Also, DFDC is the only dataset that contains a mix of videos with manipulated faces, audio, or both. All the other datasets contain only manipulated faces. Furthermore, only DFDC and DF-TIMIT [33] contain both audio and video, allowing us to analyze both modalities.

## 2.5 Affective Computing

Understanding the perceived emotions of individuals using verbal and non-verbal cues is an important problem in both AI and psychology, especially when self-reported emotions are absent to be able to infer the actual emotions of the subjects [46]. There is vast literature in inference of perceived emotions from a single modality or a combination of multiple modalities like facial expressions [10, 53], speech/audio signals [54], body pose [41], walking styles [16] and physiological features [32]. There are also works exploring correlation in the affective features obtained from these various modalities. Shan et al. [56] state that even if two modalities representing the same emotion vary in terms of appearance, the features detected are similar and should be correlated. Hence, if projected to a common space, they are compatible and can be fused to make inferences. Zhu et al. [65] explore the relationship between visual and auditory human modalities. Based on the neuroscience literature, they suggest that the visual and auditory signals are coded together in small populations of neurons within a particular part of the brain. [48, 51, 55] explored the correlation of lip movements with speech. Studies concluded that our understanding of the speech modality is greatly aided by the sight of the lip and facial movements. Subsequently, such correlation among modalities has been explored extensively to perform multimodal emotion recognition [12, 27, 44]. These works have suggested and shown correlations between affect features obtained from the individual modalities (face, speech, eyes, gestures). For instance, Mittal et al. [40] propose a multimodal perceived emotion perception network, where they use the correlation among modalities to differentiate between effectual and ineffectual modality features. Our approach is motivated by these developments in psychology research.

## 3 OUR APPROACH

In this section, we present our multimodal approach to detecting deepfake videos. We briefly describe the problem statement and give an overview of our approach in Section 3.1. We also elaborate on how our approach is similar to a Siamese Network architecture. We elaborate on the modality embeddings and the perceived emotion embedding, the two main components in Section 3.2 and Section 3.3, respectively. We explain the similarity score and modified triplet losses used for training the network in Section 3.4, and finally, in Section 3.5, we explain how they are used to classify between real and fake videos. We list all notations used throughout the paper in Table 2.

**Table 2: Notation:** We highlight the notation and symbols used in the paper.

Symbol	Description
$x_y$	$x \in \{f, s\}$ denote face and speech features extracted from OpenFace and pyAudioAnalysis. $y \in \{\text{real}, \text{fake}\}$ indicate whether the feature $x$ is real or fake. E.g. $f_{\text{real}}$ denotes the <i>face features</i> extracted from a <i>real</i> video using OpenFace.
$a_c^b$	$a \in \{e, m\}$ denote emotion embedding and modality embedding. $b \in \{f, s\}$ denote face and speech cues. $c \in \{\text{real}, \text{fake}\}$ indicate whether the embedding $a$ is real or fake. E.g. $m_{\text{real}}^f$ denotes the <i>face modality</i> embedding generated from a <i>real</i> video.
$\rho_1$	Modality Embedding Similarity Loss (Used in Training)
$\rho_2$	Emotion Embedding Similarity Loss (Used in Training)
$d_m$	Face/Speech Modality Embedding Distance (Used in Testing)
$d_e$	Face/Speech Emotion Embedding Distance (Used in Testing)

## 3.1 Problem Statement and Overview

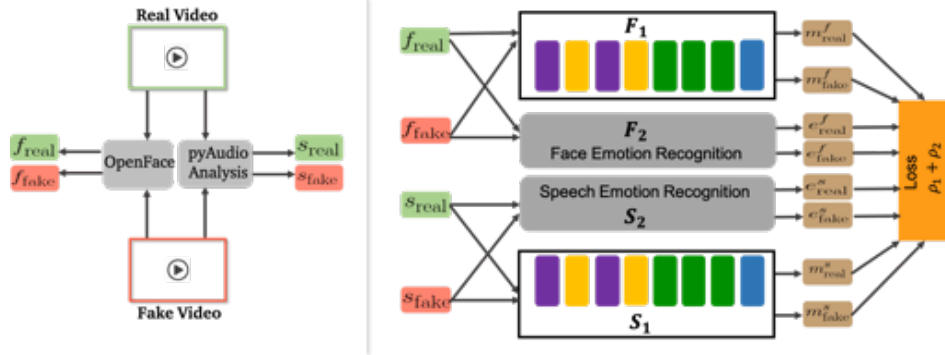
Given an input video with audio-visual modalities present, our goal is to detect if it is a deepfake video. Overviews of our training and testing routines are given in Figure 1a and Figure 1b, respectively. During training, we select one “real” and one “fake” video containing the same subject. We extract the visual face as well as the speech features,  $f_{\text{real}}$  and  $s_{\text{real}}$ , respectively, from the real input video. In similar fashion, we extract the face and speech features (using OpenFace [14] and pyAudioAnalysis [25]),  $f_{\text{fake}}$  and  $s_{\text{fake}}$ , respectively, from the fake video. More details about the feature extraction from the raw videos have been presented in Section 4.3. The extracted features,  $f_{\text{real}}, s_{\text{real}}, f_{\text{fake}}, s_{\text{fake}}$ , form the inputs to the networks ( $F_1, F_2, S_1$ , and  $S_2$ ), respectively. We train these networks using a combination of two triplet loss functions designed using the similarity scores, denoted by  $\rho_1$  and  $\rho_2$ .  $\rho_1$  represents similarity among the facial and speech modalities, and  $\rho_2$  is the similarity between the affect cues (specifically, perceived emotion) from the modalities of both real and fake videos.

Our training method is similar to a Siamese network because we also use the same weights of the network ( $F_1, F_2, S_1, S_2$ ) to operate on two different inputs, one real video and the other a fake video of the same subject. Unlike regular classification-based neural networks, which perform classification and propagate that loss back, we instead use similarity-based metrics for distinguishing the real and fake videos. We model this similarity between these modalities using Triplet loss (explained elaborately in Section 3.5).

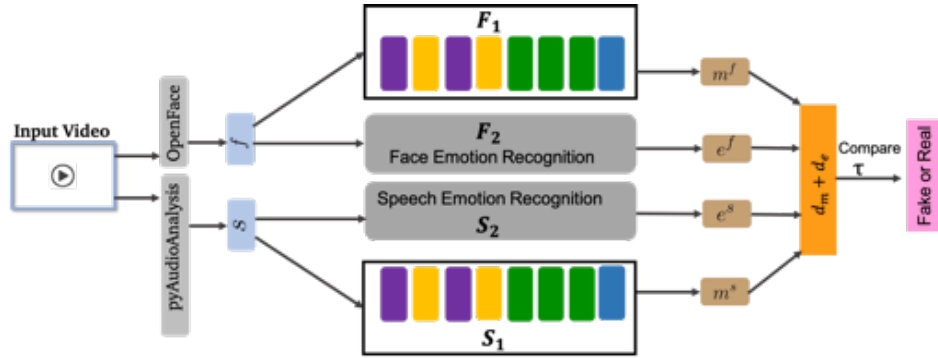
During testing, we are given a single input video, from which we extract the face and speech feature vectors,  $f$  and  $s$ , respectively. We pass  $f$  into  $F_1$  and  $F_2$ , and pass  $s$  into  $S_1$  and  $S_2$ , where  $F_1, F_2, S_1$ , and  $S_2$  are used to compute distance metrics,  $dist_1$  and  $dist_2$ . We use a threshold  $\tau$ , learned during training, to classify the video as real or fake.

## 3.2 $F_1$ and $S_1$ : Video/Audio Modality Embeddings

$F_1$  and  $S_1$  are neural networks that we use to learn the unit-normalized embeddings for the face and speech modalities, respectively. In Figure 1, we depict  $F_1$  and  $S_1$  in both training and testing routines. They are composed of 2D convolutional layers (purple), max-pooling layers (yellow), and fully connected layers (green). ReLU non-linearity is used between all layers. The last layer is a unit-normalization layer (blue). For both face and speech modalities,  $F_1$  and  $S_1$  return 250-dimensional unit-normalized embeddings.



(a) Training Routine: (left) We extract facial and speech features from the raw videos (each subject has a real and fake video pair) using OpenFace and pyAudioAnalysis, respectively. (right) The extracted features are passed to the training network that consists of two modality embedding networks and two perceived emotion embedding networks.



(b) Testing Routine: At runtime, given an input video, our network predicts the label (real or fake).

**Figure 1: Overview Diagram:** We present an overview diagram for both the training and testing routines of our model. The networks consist of 2D convolutional layers (purple), max-pooling layers (yellow), fully-connected layers (green), and normalization layers (blue).  $F_1$  and  $S_1$  are modality embedding networks and  $F_2$  and  $S_2$  are perceived emotion embedding networks for face and speech, respectively.

The training is performed using the following equations:

$$\begin{aligned} m_{\text{real}}^f &= F_1(f_{\text{real}}), m_{\text{fake}}^f = F_1(f_{\text{fake}}), \\ m_{\text{real}}^s &= S_1(s_{\text{real}}), m_{\text{fake}}^s = S_1(s_{\text{fake}}) \end{aligned} \quad (1)$$

And the testing is done using the equations:

$$m^f = F_1(f), m^s = S_1(s) \quad (2)$$

### 3.3 $F_2$ and $S_2$ : Video/Audio Perceived Emotion Embedding

$F_2$  and  $S_2$  are neural networks that we use to learn the unit-normalized affect embeddings for the face and speech modalities, respectively.  $F_2$  and  $S_2$  are based on the Memory Fusion Network (MFN) [62], which is reported to have SOTA performance on both emotion recognition from multiple views or modalities like face and speech. MFN is based on a recurrent neural network architecture with three main components: a system of LSTMs, a Memory Attention Network, and a Gated Memory component. The system of LSTMs takes in different views of the input data. In our case, we adopt the trained

single-view version of the MFN, where the face and speech are treated as separate views, i.e.  $F_2$  takes in the video (view only) and  $S_2$  takes in the audio (view only). We pre-trained the  $F_2$  MFN with video and the  $S_2$  MFN with audio from CMU-MOSEI dataset [63]. The CMU-MOSEI dataset describes the perceived emotion space with 6 discrete emotions following the Ekman model [24]: happy, sad, angry, fearful, surprise, and disgust, and a “neutral” emotion to denote the absence of any of these emotions. For face and speech modalities in our network, we use 250-dimensional unit-normalized features constructed from the cross-view patterns learned by  $F_2$  and  $S_2$  respectively.

The training is performed using the following equations:

$$\begin{aligned} e_{\text{real}}^f &= F_2(f_{\text{real}}), e_{\text{fake}}^f = F_2(f_{\text{fake}}), \\ e_{\text{real}}^s &= S_2(s_{\text{real}}), e_{\text{fake}}^s = S_2(s_{\text{fake}}). \end{aligned} \quad (3)$$

And the testing is done using the equations:

$$e^f = F_2(f), e^s = S_2(s). \quad (4)$$



### 3.4 Training Routine

At training time, we use a fake and a real video with the same subject as the input. After, passing extracted features from raw videos ( $f_{\text{real}}, f_{\text{fake}}, s_{\text{real}}, s_{\text{fake}}$ ) through  $F_1, F_2, S_1$  and  $S_2$ , we obtain the unit-normalised modality and perceived emotion embeddings as described in Eqs. 1-4.

Considering a input real and fake video, we first compare  $f_{\text{real}}$  with  $f_{\text{fake}}$ , and  $s_{\text{real}}$  with  $s_{\text{fake}}$  to understand what modality was manipulated *more* in the fake video. Considering, we identify the face modality to be manipulated more in the fake video, based on these embeddings we compute the first similarity between the real and fake speech and face embeddings as follows:

$$\textbf{Similarity Score 1: } L_1 = d(m_{\text{real}}^s, m_{\text{real}}^f) - d(m_{\text{real}}^s, m_{\text{fake}}^f), \quad (5)$$

where  $d$  denotes the Euclidean distance.

In simpler terms,  $L_1$  is computing the distance between two pairs,  $d(m_{\text{real}}^s, m_{\text{real}}^f)$  and  $d(m_{\text{real}}^s, m_{\text{fake}}^f)$ . We expect  $m_{\text{real}}^s, m_{\text{real}}^f$  to be closer to each other than  $m_{\text{real}}^s, m_{\text{fake}}^f$  as it contains a fake face modality. Hence, we expect to maximize this difference. To use this correlation metric as a loss function to train our model, we formulate it using the notation of Triplet Loss

$$\textbf{Similarity Loss 1: } \rho_1 = \max(L_1 + m_1, 0), \quad (6)$$

where  $m_1$  is the margin used for convergence of training.

If we had observed that speech is the more manipulated modality in the fake video, we would formulate  $L_1$  as follows:

$$L_1 = d(m_{\text{real}}^f, m_{\text{real}}^s) - d(m_{\text{real}}^f, m_{\text{fake}}^s).$$

Similarly, we compute the second similarity as the difference in affective cues extracted from the modalities from both real and fake videos. We denote this as follows:

$$\textbf{Similarity Score 2: } L_2 = d(e_{\text{real}}^s, e_{\text{fake}}^s) - d(e_{\text{real}}^s, e_{\text{fake}}^f). \quad (7)$$

As per prior psychology studies, we expect that similar un-manipulated modalities point towards similar affective cues. Hence, because the input here has a manipulated face modality, we expect  $e_{\text{real}}^s, e_{\text{fake}}^s$  to be closer to each other than to  $e_{\text{real}}^f, e_{\text{fake}}^f$ . To use this as a loss function, we again formulate this using a Triplet loss.

$$\textbf{Similarity Loss 2: } \rho_2 = \max(L_2 + m_2, 0), \quad (8)$$

where  $m_2$  is the margin.

Again, if speech was the highly manipulated modality in the fake video, we would formulate  $L_2$  as follows:

$$L_2 = d(e_{\text{real}}^f, e_{\text{fake}}^f) - d(e_{\text{real}}^f, e_{\text{fake}}^s).$$

We use both the similarity scores as the cumulative loss and propagate this back into the network.

$$\textbf{Loss} = \rho_1 + \rho_2 \quad (9)$$

### 3.5 Testing Routine

At test time, we only have a single input video that is to be labeled real or fake. After extracting the features,  $f$  and  $s$  from the raw videos, we perform a forward pass through  $F_1, F_2, S_1$  and  $S_2$ , as depicted in Figure 1b to obtain modality and perceived emotion embeddings.

To make an inference about real and fake, we compute the following two distance values:

$$\textbf{Distance 1: } d_m = d(m^f, m^s), \quad (10)$$

$$\textbf{Distance 2: } d_e = d(e^f, e^s).$$

To distinguish between real and fake, we compare  $d_m$  and  $d_e$  with a threshold, that is,  $\tau$  empirically learned during training as follows:

$$\text{If } d_m + d_e > \tau,$$

we label the video as a fake video.

Computation of  $\tau$ : To compute  $\tau$ , we use the best-trained model and run it on the training set. We compute  $d_m$  and  $d_e$  for both real and fake videos of the train set. We average these values and find an equidistant number, which serves as a good threshold value. Based on our experiments, the computed value of  $\tau$  was almost consistent and didn't vary much between datasets.

## 4 IMPLEMENTATION AND EVALUATION

### 4.1 Datasets

We perform experiments on the DF-TIMIT [33] and DFDC [23] datasets, as only these datasets contain modalities for face and speech features (1). We used the entire DF-TIMIT dataset and were able to use randomly sampled 18,000 videos from DFDC dataset due to computational overhead. Both the datasets are split into training (85%), and testing (15%) sets.

### 4.2 Training Parameters

On the DFDC Dataset, we trained our models with a batch size of 128 for 500 epochs. Due to the significantly smaller size of the DF-TIMIT dataset, we used a batch size of 32 and trained it for 100 epochs. We used Adam optimizer with a learning rate of 0.01. All our results were generated on an NVIDIA GeForce GTX1080 Ti GPU.

### 4.3 Feature Extraction

In our approach (See Figure 1), we first extract the face and speech features from the real and fake input videos. We use existing SOTA methods for this purpose. In particular, we use OpenFace [14] to extract 430-dimensional facial features, including the 2D landmarks positions, head pose orientation, and gaze features. To extract speech features, we use pyAudioAnalysis [25] to extract 13 Mel Frequency Cepstral Coefficients (MFCC) speech features. Prior works [18, 19, 21] using audio or speech signals for various tasks like perceived emotion recognition, and speaker recognition use MFCC features to analyse audio signals.

## 5 RESULTS AND ANALYSIS

In this section, we elaborate on some quantitative and qualitative results of our methods.

### 5.1 Comparison with SOTA Methods

We report and compare per-video AUC Scores of our method against 9 prior deepfake video detection methods on DF-TIMIT and DFDC. To ensure a fair evaluation, while the subset of DFDC the 9 methods were trained and tested are unknown, we select 18,000 samples

randomly and report our numbers. Moreover, as per the nature of the approaches the prior 9 methods report per-frame AUC scores. We have summarized these results in Table 3. The following are the prior methods used to compare the performance of our approach on the same datasets.

- (1) Two-stream [64]: uses a two-stream CNN to achieve SOTA performance in image-forgery detection. They use standard CNN network architectures to train the model.
- (2) MesoNet [9] is a CNN-based detection method that targets the microscopic properties of images. AUC scores are reported on two variants.
- (3) HeadPose [61] captures inconsistencies in headpose orientation across frames to detect deepfakes.
- (4) FWA [36] uses a CNN to expose the face warping artifacts introduced by the resizing and interpolation operations.
- (5) VA [38] focuses on capturing visual artifacts in the eyes, teeth and facial contours of synthesized faces. Results have been reported on two standard variants of this method.
- (6) Xception [49] is a baseline model trained on the FaceForensics++ dataset based on the XceptionNet model. AUC scores have been reported on three variants of the network.
- (7) Multi-task [42] uses a CNN to simultaneously detect manipulated images and segment manipulated areas as a multi-task learning problem.
- (8) Capsule [43] uses capsule structures based on a standard DNN.
- (9) DSP-FWA is an improved version of FWA [36] with a spatial pyramid pooling module to better handle the variations in resolutions of the original target faces.

**Table 3: AUC Scores. Blue denotes best and green denotes second-best. Our model improves the SOTA by approximately 9% on the DFDC dataset and achieves accuracy similar to the SOTA on the DF-TIMIT dataset.**

S.No.	Methods	Datasets		
		DF-TIMIT [33]	DFDC [23]	
		LQ	HQ	
1	Capsule [43]	78.4	74.4	53.3
2	Multi-task [42]	62.2	55.3	53.6
3	HeadPose [61]	55.1	53.2	55.9
4	Two-stream [64]	83.5	73.5	61.4
5	VA-MLP [38]	61.4	62.1	61.9
	VA-LogReg	77.0	77.3	66.2
6	MesoInception4	80.4	62.7	73.2
	Meso4 [9]	87.8	68.4	75.3
7	Xception-raw [49]	56.7	54.0	49.9
	Xception-c40	75.8	70.5	69.7
	Xception-c23	95.9	94.4	72.2
8	FWA [36]	99.9	93.2	72.7
	DSP-FWA	99.9	99.7	75.5
<b>Our Method</b>		96.3	94.9	84.4

While we outperform on the DFDC dataset, we have comparable values for the DF-TIMIT dataset. We believe this is because all 640

**Table 4: Ablation Experiments. To motivate our model, we perform ablation studies where we remove one correlation at a time for training and report the AUC scores.**

Methods	Datasets		
	DF-TIMIT [33]	DFDC [23]	
	LQ	HQ	
Our Method w/o Modality Similarity ( $\rho_1$ )	92.5	91.7	78.3
Our Method w/o Emotion Similarity ( $\rho_2$ )	94.8	93.6	82.8
<b>Our Method</b>	<b>96.3</b>	<b>94.9</b>	<b>84.4</b>

videos in the DF-TIMIT dataset are face-centered with no body pose. In DFDC, the videos are collected with full-body poses, with the face taking less than 50% of the pixels in each frame. The FWA and DSP-FWA methods identify deepfakes by detecting artifacts caused by affine warping of manipulated faces to match the configuration of the source’s face. This is especially useful for the face-centered DF-TIMIT dataset than the DFDC dataset.

## 5.2 Qualitative Results

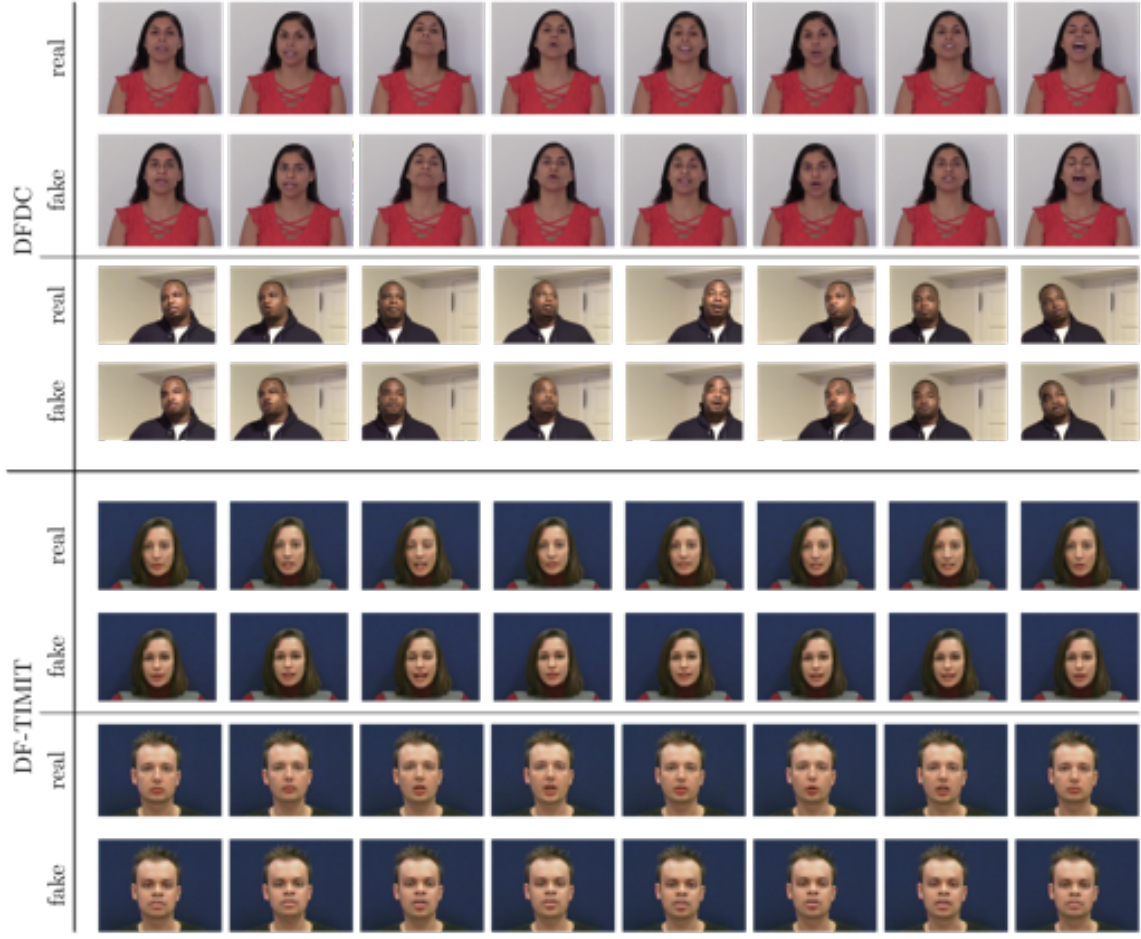
We show some selected frames of videos from both the datasets in Figure 2 along with the labels (real/fake). For the qualitative results shown for DFDC, the real video predicted a “neutral” perceived emotion label for both speech and face modality, whereas in the fake video the face predicted “surprise” and speech predicted “neutral”. This result is indeed interpretable because the fake video was generated by manipulating only the face modality and not the speech modality. We see a similar perceived emotion label mismatch for the DF-TIMIT sample as well.

## 5.3 Interpreting the Correlations

To better understand the learned embeddings, we plot the distance between the unit-normalized face and speech embeddings learned from  $F_1$  and  $S_1$  on 1,000 randomly chosen points from the DFDC train set in Figure 3(a). We plot  $d(m_{\text{real}}^s, m_{\text{real}}^f)$  in blue and  $d(m_{\text{fake}}^s, m_{\text{fake}}^f)$  in orange. It is interesting to see that the peak or the majority of the subjects from real videos have a smaller separation, 0.2 between their embeddings as opposed to the fake videos (0.5). We also plot the number of videos, both fake and real, with a mismatch of perceived emotion labels extracted using  $F_2$  and  $S_2$  in Figure 3(b). Of a total of 15,438 fake videos, 11,301 showed a mismatch in the labels extracted from face and speech modalities. Similarly, out of 3,180 real videos, 815 also showed a label mismatch.

## 5.4 Ablation Experiments

As explained in Section 3.5, we use two distances, based on the modality embedding similarities and perceived emotion embedding similarities, to detect fake videos. To understand and motivate the contribution of each similarity, we perform an ablation study where we run the model using only one correlation for training. We have summarized the results of the ablation experiments in Table 4. The modality embedding similarity helps to achieve better AUC scores than the perceived emotion embedding similarity.



**Figure 2: Qualitative Results:** We show results of our model on the DFDC and DF-TIMIT datasets. Our model uses the subjects’ audio-visual modalities as well as their perceived emotions to distinguish between real and deepfake videos. The perceived emotions from the speech and facial cues in fake videos are different; however in the case of real videos, the perceived emotions from both modalities are the same.

### 5.5 Failure Cases

Our approach models the correlation between two modalities and the associated affective cues to distinguish between real and fake modalities. However, there are multiple instances where the deepfake videos do not contain such a mismatch in terms of perceived emotional classification based on different modalities. This is also because humans express perceived emotions differently. As a result, our model fails to classify such videos as fake. Similarly, both face and speech are modalities that are easy to fake. As a result, it is possible that our method also classifies a real video as a fake video due to this mismatch. In Figure 4, we show one such video from both the datasets, where our model failed.

### 5.6 Results on Videos in the Wild

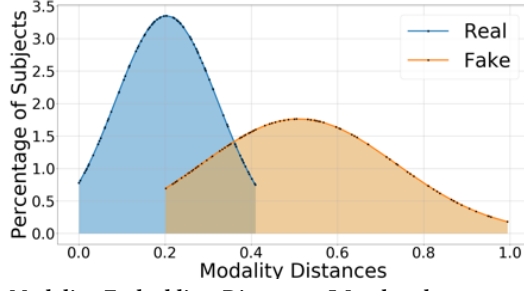
We tested the performance of our model on two such deepfake videos obtained from an online social platform [7, 8]. Some frames from this video have been shown in Figure 5. While the model successfully classified the first video as a deepfake, it could not for the second deepfake video.

## 6 CONCLUSION, LIMITATIONS AND FUTURE WORK

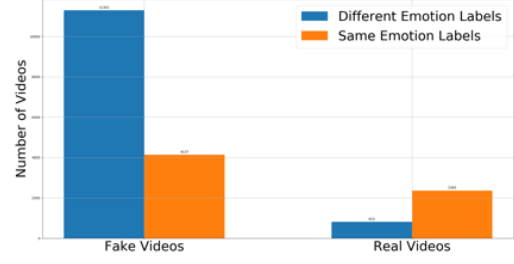
We present a learning-based method for detecting fake videos. We use the similarity between audio-visual modalities and the similarity between the affective cues of the two modalities to infer whether a video is “real” or “fake”. We evaluated our method on two benchmark audio-visual deepfake datasets, DFDC, and DF-TIMIT.

Our approach has some limitations. First, our approach could result in misclassifications on both the datasets, as compared to the one in the real video. Given different representations of expressing perceived emotions, our approach can also find a mismatch in the modalities of real videos, and (incorrectly) classify them as fake. Furthermore, many of the deepfake datasets primarily contain more than one person per video. We may need to extend our approach to take into account the perceived emotional state of multiple persons in the video and come with a possible scheme for deepfake detection.

In the future, we would like to look into incorporating more modalities and even context to infer whether a video is a deepfake or not. We would also like to combine our approach with the existing

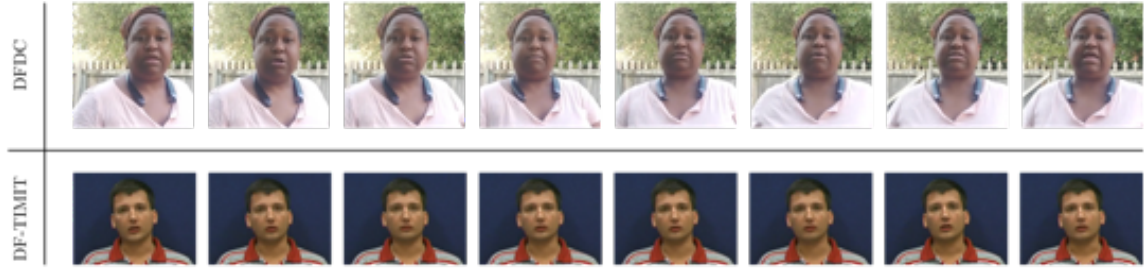


(a) Modality Embedding Distances: We plot the percentage of subject videos versus the distance between the face and speech modality embeddings. The figure shows that the distribution of real videos (blue curve) is centered around a lower modality embedding distance (0.2). In contrast, the fake videos (orange curve) are distributed around a higher distance center (0.5). Conclusion: We show that audio-visual modalities are more similar in real videos as compared to fake videos.



(b) Perceived Emotion Embedding in Real and Fake Videos: The blue and orange bars represent the total number of videos where the perceived emotion labels, obtained from the face and speech modalities, do *not* match, and match, respectively. Of the total 15,438 fake videos, 73.2% videos were found to contain a mismatch between perceived emotion labels and for real videos this was only 24%. Conclusion: We show that perceived emotions of subjects, from multiple modalities, are strongly similar in real videos, and often mismatched in fake videos.

**Figure 3: Embedding Interpretation:** We provide an intuitive interpretation of the learned embeddings from  $F_1$ ,  $S_1$ ,  $F_2$ ,  $S_2$  with visualizations. These results back our hypothesis of perceived emotions being highly correlated in real videos as compared to fake videos.



**Figure 4: Misclassification Results:** We show one sample each from DFDC and DF-TIMIT where our model predicted the two fake videos as real due to incorrect perceived emotion embeddings.



**Figure 5: Results on In-The-Wild Videos:** Our model succeeds in the wild. We collect several popular deepfake videos from online social media and our model achieves reasonably good results.

ideas of detecting visual artifacts like lip-speech synchronisation, head-pose orientation, and specific artifacts in teeth, nose and eyes across frames for better performance. Additionally, we would like to approach better methods for using audio cues.

## 7 ACKNOWLEDGEMENTS

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## REFERENCES

- [1] [n.d.]. Faceswap: Deepfakes Software For All. <https://github.com/deepfakes/faceswap>. (Accessed on 02/16/2020).
- [2] [n.d.]. FakeApp 2.2.0. <https://www.malavida.com/en/soft/fakeapp/gref>. (Accessed on 02/16/2020).
- [3] [n.d.]. GitHub - dfaker/df: Larger resolution face masked, weirdly warped, deepfake. <https://github.com/dfaker/df>. (Accessed on 02/16/2020).
- [4] [n.d.]. GitHub - iperov/DeepFaceLab: DeepFaceLab is the leading software for creating deepfakes. <https://github.com/iperov/DeepFaceLab>. (Accessed on 02/16/2020).
- [5] [n.d.]. GitHub - shaoanlu/faceswap-GAN: A denoising autoencoder + adversarial losses and attention mechanisms for face swapping. <https://github.com/shaoanlu/faceswap-GAN>. (Accessed on 02/16/2020).
- [6] [n.d.]. Google AI Blog: Contributing Data to Deepfake Detection Research. <https://ai.googleblog.com/2019/09/contributing-data-to-deepfake-detection.html>. (Accessed on 02/16/2020).
- [7] [n.d.]. YouTube Video 1. [https://www.youtube.com/watch?time\\_continue=1&v=cQ54GDM1eL0&feature=emb\\_logo](https://www.youtube.com/watch?time_continue=1&v=cQ54GDM1eL0&feature=emb_logo). (Accessed on 02/16/2020).
- [8] [n.d.]. YouTube Video 2. [https://www.youtube.com/watch?time\\_continue=14&v=aPp5lccqgISk&feature=emb\\_logo](https://www.youtube.com/watch?time_continue=14&v=aPp5lccqgISk&feature=emb_logo). (Accessed on 02/16/2020).
- [9] 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.
- [10] Kingsley Oryina Akputu, Kah Phooi Seng, and Yun Li Lee. 2013. Facial emotion recognition for intelligent tutoring environment. In *IMLCS*. 9–13.
- [11] Kanchan Bahirat, Nidhi Vaishnav, Sandeep Sukumaran, and Balakrishnan Prabhakaran. 2019. ADD-FAR: attacked driving dataset for forensics analysis and research. In *Proceedings of the 10th ACM Multimedia Systems Conference*. 243–248.
- [12] Themis Balomenos, Amarilys Raouzaoui, Spiros Ioannou, Athanasios Drosopoulos, Kostas Karpouzis, and Stefanos Kollias. 2004. Emotion analysis in man-machine interaction systems. In *International Workshop on Machine Learning for Multimodal Interaction*. Springer, 318–328.
- [13] Tadas Baltrušaitis, Chaitanya Ahuja, and Louis-Philippe Morency. 2018. Multimodal machine learning: A survey and taxonomy. *IEEE transactions on pattern analysis and machine intelligence* 41, 2 (2018), 423–443.
- [14] Tadas Baltrušaitis, Peter Robinson, and Louis-Philippe Morency. 2016. Openface: an open source facial behavior analysis toolkit. In *2016 IEEE Winter Conference on Applications of Computer Vision (WACV)*. IEEE, 1–10.
- [15] Sebastiano Battiato, Oliver Giudice, and Antonino Paratore. 2016. Multimedia forensics: discovering the history of multimedia contents. In *Proceedings of the 17th International Conference on Computer Systems and Technologies 2016*. 5–16.
- [16] Uttaran Bhattacharya, Trisha Mittal, Rohan Chandra, Tanmay Randhavane, Aniket Bera, and Dinesh Manocha. 2019. Step: Spatial temporal graph convolutional networks for emotion perception from gaits. *arXiv preprint arXiv:1910.12906* (2019).
- [17] Jeffrey P Bigham, Chandrika Jayant, Hanjie Ji, Greg Little, Andrew Miller, Robert C Miller, Robin Miller, Aubrey Tatarowicz, Brandyn White, Samuel White, et al. 2010. VizWiz: nearly real-time answers to visual questions. In *Proceedings of the 23rd annual ACM symposium on User interface software and technology*. 333–342.
- [18] Konstantinos Bougiatiotis and Theodoros Giannakopoulos. 2018. Enhanced movie content similarity based on textual, auditory and visual information. *Expert Systems with Applications* 96 (2018), 86–102.
- [19] Linqin Cai, Yaxin Hu, Jiangong Dong, and Sitong Zhou. 2019. Audio-Textual Emotion Recognition Based on Improved Neural Networks. *Mathematical Problems in Engineering* 2019 (2019).
- [20] Yifang Chen, Xiangui Kang, Z Jane Wang, and Qiong Zhang. 2018. Densely connected convolutional neural network for multi-purpose image forensics under anti-forensic attacks. In *Proceedings of the 6th ACM Workshop on Information Hiding and Multimedia Security*. 91–96.
- [21] Vladimir Chernykh and Pavel Prihodko. 2017. Emotion recognition from speech with recurrent neural networks. *arXiv preprint arXiv:1701.08071* (2017).
- [22] Robert Chesney and Danielle Keats Citron. 2018. Deep fakes: A looming challenge for privacy, democracy, and national security. (2018).
- [23] Brian Dolhansky, Russ Howes, Ben Pfaff, Nicole Baram, and Cristian Canton Ferrer. 2019. The Deepfake Detection Challenge (DFDC) Preview Dataset. *arXiv preprint arXiv:1910.08854* (2019).
- [24] Paul Ekman, Wallace V Freisen, and Sonia Ancoli. 1980. Facial signs of emotional experience. *Journal of personality and social psychology* 39, 6 (1980), 1125.
- [25] Theodoros Giannakopoulos. 2015. pyaudioanalysis: An open-source python library for audio signal analysis. *PLoS one* 10, 12 (2015).
- [26] 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.
- [27] Hatice Gunes and Massimo Piccardi. 2007. Bi-modal emotion recognition from expressive face and body gestures. *Journal of Network and Computer Applications* 30, 4 (2007), 1334–1345.
- [28] Mihai Garban, Jean-Philippe Thiran, Thomas Drugman, and Thierry Dutoit. 2008. Dynamic modality weighting for multi-stream hmms in audio-visual speech recognition. In *Proceedings of the 10th international conference on Multimodal interfaces*. 237–240.
- [29] Micah Hodosh, Peter Young, and Julia Hockenmaier. 2013. Framing image description as a ranking task: Data, models and evaluation metrics. *Journal of Artificial Intelligence Research* 47 (2013), 853–899.
- [30] Hyeonseong Jeon, Youngoh Bang, and Simon S Woo. 2019. FakeTalkerDetect: Effective and Practical Realistic Neural Talking Head Detection with a Highly Unbalanced Dataset. In *Proceedings of the IEEE International Conference on Computer Vision Workshops*. 0–0.
- [31] Liming Jiang, Wayne Wu, Ren Li, Chen Qian, and Chen Change Loy. 2020. DeepForensics-1.0: A Large-Scale Dataset for Real-World Face Forgery Detection. *arXiv preprint arXiv:2001.03024* (2020).
- [32] R Benjamin Knapp, Jonghwa Kim, and Elisabeth André. 2011. Physiological signals and their use in augmenting emotion recognition for human-machine interaction. In *Emotion-oriented systems*. Springer, 133–159.
- [33] Pavel Korshunov and Sébastien Marcel. 2018. Deepfakes: a new threat to face recognition? assessment and detection. *arXiv preprint arXiv:1812.08685* (2018).
- [34] Pavel Korshunov and Sébastien Marcel. 2018. Speaker inconsistency detection in tampered video. In *2018 26th European Signal Processing Conference (EUSIPCO)*. IEEE, 2375–2379.
- [35] Gangeshwar Krishnamurthy, Navonil Majumder, Soujanya Poria, and Erik Cambria. 2018. A deep learning approach for multimodal deception detection. *arXiv preprint arXiv:1803.00344* (2018).
- [36] Yuezun Li and Siwei Lyu. 2018. Exposing deepfake videos by detecting face warping artifacts. *arXiv preprint arXiv:1811.00656* (2018).
- [37] Yuezun Li, Xin Yang, Pu Sun, Honggang Qi, and Siwei Lyu. 2019. Celeb-df: A new dataset for deepfake forensics. *arXiv preprint arXiv:1909.12962* (2019).
- [38] Falko Matern, Christian Riess, and Marc Stamminger. 2019. Exploiting visual artifacts to expose deepfakes and face manipulations. In *2019 IEEE Winter Applications of Computer Vision Workshops (WACVW)*. IEEE, 83–92.
- [39] Owen Mayer, Belhassen Bayar, and Matthew C Stamm. 2018. Learning unified deep-features for multiple forensic tasks. In *Proceedings of the 6th ACM workshop on information hiding and multimedia security*. 79–84.
- [40] Trisha Mittal, Uttaran Bhattacharya, Rohan Chandra, Aniket Bera, and Dinesh Manocha. 2019. M3ER: Multiplicative Multimodal Emotion Recognition Using Facial, Textual, and Speech Cues. *arXiv preprint arXiv:1911.05659* (2019).
- [41] Costanza Navarretta. 2012. Individuality in communicative bodily behaviours. In *Cognitive Behavioural Systems*. Springer, 417–423.
- [42] Huy H Nguyen, Fuming Fang, Junichi Yamagishi, and Isao Echizen. 2019. Multi-task learning for detecting and segmenting manipulated facial images and videos. *arXiv preprint arXiv:1906.06876* (2019).
- [43] Huy H Nguyen, Junichi Yamagishi, and Isao Echizen. 2019. Capsule-forensics: Using capsule networks to detect forged images and videos. In *ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2307–2311.
- [44] Maja Pantic, Nicu Sebe, Jeffrey F Cohn, and Thomas Huang. 2005. Affective multimodal human-computer interaction. In *Proceedings of the 13th annual ACM international conference on Multimedia*. 669–676.
- [45] Olga Papadopoulou, Markos Zampoglou, Symeon Papadopoulos, and Yiannis Kompatsiaris. 2017. Web Video Verification Using Contextual Cues. In *Proceedings of the 2nd International Workshop on Multimedia Forensics and Security (Bucharest, Romania) (MFSec '17)*. Association for Computing Machinery, New York, NY, USA, 64–70. <https://doi.org/10.1145/3078897.3080535>
- [46] Karen S Quigley, Kristen A Lindquist, and Lisa Feldman Barrett. 2014. Inducing and measuring emotion and affect: Tips, tricks, and secrets. (2014).
- [47] Tanmay Randhavane, Uttaran Bhattacharya, Kyra Kapsaskis, Kurt Gray, Aniket Bera, and Dinesh Manocha. 2019. The Liar's Walk: Detecting Deception with Gait and Gesture. *arXiv preprint arXiv:1912.06874* (2019).
- [48] Lars A Ross, Dave Saint-Amour, Victoria M Leavitt, Daniel C Javitt, and John J Foxe. 2007. Do you see what I am saying? Exploring visual enhancement of speech comprehension in noisy environments. *Cerebral cortex* 17, 5 (2007), 1147–1153.
- [49] 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 International Conference on Computer Vision*. 1–11.
- [50] 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 (2019), 1.
- [51] Derek A Sanders and Sharon J Goodrich. 1971. The relative contribution of visual and auditory components of speech to speech intelligibility as a function of three conditions of frequency distortion. *Journal of Speech and Hearing Research* 14, 1 (1971), 154–159.
- [52] Conrad Sanderson. 2002. *The vidtimit database*. Technical Report. IDIAP.
- [53] Jason M Saragih, Simon Lucey, and Jeffrey F Cohn. 2009. Face alignment through subspace constrained mean-shifts. In *ICCV*. IEEE, 1034–1041.

- [54] Klaus R Scherer, Tom Johnstone, and Gundrun Klasmeyer. 2003. Vocal expression of emotion. *Handbook of affective sciences* (2003), 433–456.
- [55] Jean-Luc Schwartz, Frédéric Berthommier, and Christophe Savariaux. 2004. Seeing to hear better: evidence for early audio-visual interactions in speech identification. *Cognition* 93, 2 (2004), B69–B78.
- [56] Caifeng Shan, Shaogang Gong, and Peter W McOwan. 2007. Beyond Facial Expressions: Learning Human Emotion from Body Gestures.. In *BMVC*. 1–10.
- [57] Luisa Verdoliva and Paolo Bestagini. 2019. Multimedia Forensics. In *Proceedings of the 27th ACM International Conference on Multimedia* (Nice, France) (MM '19). Association for Computing Machinery, New York, NY, USA, 2701–2702. <https://doi.org/10.1145/3343031.3350542>
- [58] Luisa Verdoliva and Paolo Bestagini. 2019. Multimedia Forensics. In *Proceedings of the 27th ACM International Conference on Multimedia* (Nice, France) (MM '19). Association for Computing Machinery, New York, NY, USA, 2701–2702. <https://doi.org/10.1145/3343031.3350542>
- [59] Chuang Wang, Zhongyun Zhou, Xiao-Ling Jin, Yulin Fang, and Matthew KO Lee. 2017. The influence of affective cues on positive emotion in predicting instant information sharing on microblogs: Gender as a moderator. *Information Processing & Management* 53, 3 (2017), 721–734.
- [60] Longyin Wen, Honggang Qi, and Siwei Lyu. 2018. Contrast enhancement estimation for digital image forensics. *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM)* 14, 2 (2018), 1–21.
- [61] 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.
- [62] Amir Zadeh, Paul Pu Liang, Navonil Mazumder, Soujanya Poria, Erik Cambria, and Louis-Philippe Morency. 2018. Memory fusion network for multi-view sequential learning. In *Thirty-Second AAAI Conference on Artificial Intelligence*.
- [63] AmirAli Bagher Zadeh, Paul Pu Liang, Soujanya Poria, Erik Cambria, and Louis-Philippe Morency. 2018. Multimodal language analysis in the wild: Cmu-mosei dataset and interpretable dynamic fusion graph. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. 2236–2246.
- [64] 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.
- [65] Lin L Zhu and Michael S Beauchamp. 2017. Mouth and voice: a relationship between visual and auditory preference in the human superior temporal sulcus. *Journal of Neuroscience* 37, 10 (2017), 2697–2708.