SDHF: Spotting DeepFakes with Hierarchical Features

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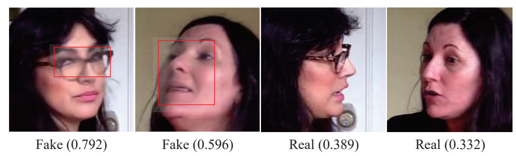
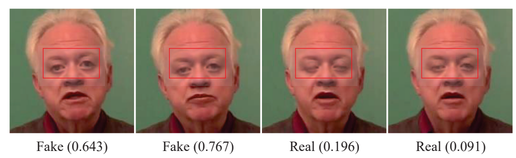
***Abstract*—DeepFake videos are widely distributed on social media platforms, which has seriously affected the authenticity of digital media content, calling for robust DeepFake detection methods. Although numerous detection methods are formulated as frame-based binary classification, less attention has been paid to aggregate the features over individual frames to get a video-based judgement. We observed that for the detection of DeepFake videos, three different level forgery features from frame, clip and video can complement each other. We also found that discrete, large interval sampling strategy is more suitable for DeepFake detection, which can sample more complex video scenes, including multiple subjects, diverse facial expressions and head poses. In this work, we propose a hierarchical framework, using 2D convolutional neural networks for frame-level features extraction followed by a 1D convolutional aggregator to extract clip-level and video-level features, which can comprehensively exploit three different levels of features to make decisions. Evaluation was performed on four datasets, including DFDC, Celeb-DF, FaceForensics++ and UADFV, which provides competitive results compared to other methods. Experimental results of cross-test demonstrate that our hierarchical framework has excellent generalization performance in the face of unknown datasets.**

***Index Terms*—DeepFake detection, Hierarchical features**



(a) Two speakers in a video



(b) Difficult samples due to blurry faces

Fig. 1. Some difficulties encountered in the process of integrating frame-based results to get video-based results: 1(a) a fake video containing multiple subjects' faces, in which only one or a few faces are manipulated for a fraction of the frames. 1(b) a real video with some highly blurred or compressed frames, lead the model to judge it as fake. The label under the picture indicates the probability of face being manipulated reported by EfficientNetB0 trained on DFDC. (Zoom in to see better)

I. Introduction

In recent years, facial manipulation videos, also widely known as DeepFakes, have been increasing on social media platforms. Especially, huge steps forward in variational auto-encoders (VAEs) [1], generative adversarial networks (GANs) [2], [3] and computer graphics (CGs) based methods [4], [5] have made facial image manipulations reach photo-realistic level. Through face swapping, an individual can be placed at some location he or she was never present at. By changing lip movements and related speech signals, real video can be generated that allows people to say words they have never actually said. When this technology is deliberately used by criminals, it seriously affect the security of public opinion. In addition, as one of the most important biological signals, face is widely used in various applications, such as face payment and face access control. The forged face becomes a key to open our privacy. All mentioned above are calling for robust facial manipulation detection methods.

To spot such DeepFake videos, significant progress has been made by handcrafted features [6], [7] and deep learning [8], [9]. The predominant efforts are focused on still images, less attention has been paid to aggregate the features over individual frames to get a video-based judgement. In practical applications, we need to make a judgment on the authenticity of a video. In order to aggregate the predictions over individual frames to get a video-based judgement, a natural approach is to average the predictions across all frames. However, this approach has several drawbacks and encounters many difficulties as shown in Figure 1. First, a fake video containing multiple subjects' faces, in which only one or a few faces are manipulated for a fraction of the frames. Second, some highly blurred or compressed frames in a real video will lead the model to judge it as fake. Also, some frames might contain blurry faces where the presence of manipulations might be difficult to detect. In such complicated scenarios, a model could provide a correct prediction for each frame but an incorrect video-based prediction after averaging.

Meanwhile, some previous clip-based works tried to leverage RNN [10] or optical flow [11] to capture manipulation traces in temporal, which demand a small interval between frames in the clip. These methods are robust compared to averaging all frames in obtaining video-based prediction. Nevertheless, such methods rely on carefully processed data and small frame interval to effectively capture traces in temporal. When encountering the complex situation mentioned above, the effectiveness of such methods drop sharply.

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In fact, traces of video forgery may exist in frames, clips and videos at the same time. In this work, we propose to use discrete, large interval sampling strategy, which can sample diverse facial expressions and head poses, and sample the complex scenes mentioned above as much as possible, so as to make a comprehensive decision for a video. we propose a novel hierarchical framework named **SDHF**, using 2D convolutional neural networks for frame-level features extraction followed by a 1D convolutional aggregator to extract clip-level and video-level features, which can comprehensively exploit three different levels of features to make decision. Especially when real frames are mixed with a manipulated video, our approach can still confidently judge it as fake. The contributions of our work are summarized as follows:

(1) we propose a novel hierarchical framework **SDHF** for DeepFake video detection, which combines three different levels of features, including frame-level, clip-level and video-level, to comprehensively determine whether a video is manipulated.

(2) We observed that discrete, large interval sampling strategy is more suitable for DeepFake video detection, which can sample more comprehensive video scenes, including multiple subjects, diverse facial expressions and head poses. Correspondingly, we propose to apply the 1D convolutional module as an aggregator to automatically extract typical forged features present in the video.

(3) We evaluate the performance of the proposed SDHF on four datasets: DFDC [12], Celeb-DF [13], FaceForensics++ [8] and UADFV [7]. The results shows our approach achieves comparable performance compared to others.

II. Related Work

A. Facial Manipulation

Facial manipulation methods mainly fall into face replacement [14]–[16] and face reenactment [8], while the former transforms the identity information from one to another and the latter focuses on motion transfer.

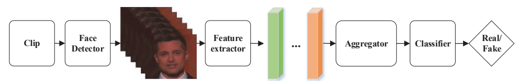
Fig. 2. Overview of a typical video facial manipulation pipeline.

The above two types of facial manipulation methods all share the same typical pipeline, as shown in Figure 2. The generation of DeepFake video is usually performed frame by frame, which strongly depends on the performance of the face detector. Therefore, in a fake video, it is inevitable that part of the original real face will be retained due to failure of detection.

B. DeepFake Video Detection

Despite the great development of facial manipulation technology, detection methods are still far behind. Previous works on DeepFake video detection fall into two categories: frame-based [17]–[20] and clip-based [6], [10], [21]–[23]. The former treat video as a frame set and convert the problem to detect fake faces in a single frame, whereas the latter treat video as a clip set attempt to model the temporal inconsistency between frames. Now we propose a video-based framework.

(a) Basic pipeline of current DeepFake image detection



(b) Basic pipeline of current DeepFake clip detection

Fig. 3. Basic pipeline of current DeepFake image/clip detection

Frame-based. As shown in Figure 3(a), current DeepFake image detection approaches share the same pipeline. The main innovations of different methods focus on the feature extractor. Several algorithms using handcrafted features, deep learning algorithms and lately GAN-based methods are being explored. [24] utilized 3D head pose inconsistencies to distinguish real and fake videos. In MesoNet [9], shallow architectures with an inclusion of inception module learns the discriminative feature from frames. [17] proposed a two-stream CNN for tampered face detection, combing RGB space features with steganalysis features. This is a combination of deep learning features and handcrafted features. In multi-task learning approach, classification, segmentation [25], and reconstruction [26] is performed altogether to boost classification performance. However, all of these methods only consider spatial information in a single frame.

Clip-based. As shown in Figure 3(b), the current DeepFake clip detection approaches share the same pipeline. The main differences between various methods are the feature extractor and aggregator. Some clip-based approaches sought for physiological signals as features, like eye blinking [6] and rPPG [22], but quickly lost its effect when facing more training data and advanced generative models. [21] introduced RNN as the aggregator to capture temporal inconsistencies between frames. The above methods are sensitive to clip length, but the length of test video in real world is unknown. The core idea of [21] are borrowed from action recognition approaches. However, due to the difference between action recognition and DeepFake detection, it's sub-optimal to directly use the method of action recognition. Although these methods are robust compared to averaging all frames in obtaining video-based prediction, such methods rely on carefully processed data to effectively capture features in temporal.

Video-based. To our knowledge, we are the first to propose a video-based framework for DeepFake detection other than averaging across all frames/clips. DeepFake videos have their inherent characteristics. On one hand, Each frame and each sparse clip can be used as a criterion, and action recognition must take temporal continuous clip as a criterion. On the other hand, discrete, large interval sampling strategy is more suitable for DeepFake video detection, which can sample more comprehensive video scenes, including multiple subjects, diverse facial expressions and head poses. Based on these two observations, we propose to utilize hierarchical features for DeepFake video detection. Combining multi-level features, we can make an accurate judgment on a video. Last but not least, our approach is robust to variable video length.

III. METHODOLOGY

The goal of our framework, **SDHF**, is to extract hierarchical features in DeepFake videos, including frame-level, clip-level and video-level, and synthesize three different levels of features to comprehensively determine whether the video is manipulated. Our SDHF also follows the structure shown in Figure 3(b). Figure 4 presents the whole framework.

A. Data Processing Strategy

For a given video, our purpose is to determine whether there are manipulations at a minimum cost. Initially, we extract 16 frames uniformly from a given video and the frame interval is relatively large and discrete. Because all visual manipulations are located within face regions, and faces are typically present in a small region of the frame, we focus on extracting traces only in regions where a face is present. Although some datasets provide face masks, which can be used for accurate face positioning and cropping, we cannot obtain masks in online DeepFake detection scenarios. Therefore, we try to simulate real business scenarios and use a pretrained Retinaface [27] for face detection. Then, we get the minimal square box by warping the bounding box. Finally, the box is enlarged by 1.3 times as cropped region, where not only the core areas of face but also sufficient surrounding areas are covered.

B. 1D MBConv block

Variations and replacements for 2D convolutional blocks have sprung up. With the successful experience of 2D convolutional block in MobileNets [28], we generalize it to 1D convolutional to get the basic block. Its main structure is mobile inverted bottleneck MBConv [28], [29] with squeeze-and-excitation (SE) [30] optimization added. Note that we use pointwise convolutional in the SE attention structure instead of full connection. In addition, both drop connection [31] and residual connection [32] is adopted to prevent overfitting.

C. Framework

Frame-level Feature Extractor. After cropping face regions, a binary classifier is trained to extract features that can be used to classify the real/fake faces. Among the family of EfficientNets [33], we choose EfficientNetB0 as the baseline in our work for fair comparisons. This module takes videos as inputs $\mathbf{X} \in \mathbb{R}^{B\times T\times C\times H\times W}$ and generates the frame-level features $\mathbf{F}_{frame} \in \mathbb{R}^{B\times T\times C\times H\times W}$ and the probability of each frame being fake $logits_{frame}$,

$$\mathbf{F}_{frame}, logits_{frame} = EfficientNet(X) \tag{1}$$

where B, T, C, H and W, are batch size, number of frames, number of channels, height and width, respectively. Then we adopt spatial global average pooling to get the 1D frame-level features $\mathbf{F'}_{frame} \in \mathbb{R}^{B\times T\times C}$ for the analysis of next stage.

Feature Aggregator. In the previous step we have obtained the frame-based predictions $logits_{frame}$, the simplest choice is to average the predictions across all frames to obtain a video-based prediction. However, this approach has several drawbacks and encounters many difficulties as shown in Figure 1. In such complicated scenarios, a model could provide a correct prediction for each frame but an incorrect video-based prediction after averaging. In order to address this problem, we propose to adopt 1D convolution as aggregator, which can automatically extract typical features from $\mathbf{F'}_{frame}$ as criteria. The feature aggregator is composed of multiple 1D MBConv [28], [29] blocks. The aggregator details are shown in Table I.

TABLE I
1D MBConv Aggregator

Stage i	Operator $\hat{\mathcal{F}}_i$	Resolution $\hat{T}_i$	#Channels $\hat{\mathcal{C}}_i$	#Layers $\hat{\mathcal{L}}_i$
1	1D-MBConv,k=3,s=2	16	1280	1
2	1D-MBConv,k=3,s=2	8	1280	4
3	Pooling	8	1280	1

In the first stage, we exploit a 1D MBConv block with a step size of 2 to halve the video multi-frame feature map. In the second stage, we stack 4 1D MBConv blocks with the same step size of 1 to refine the feature map. All the above 1D MBConv blocks maintain the same feature dimension. This module takes the transposed frame-level features as input $\mathbf{F'}^{T}_{frame}$ and generates clip-level features $\mathbf{F}_{clip} \in \mathbb{R}^{B\times C\times T'}$. Then, the clip-level features are squeezed into video-level features $\mathbf{F}_{video} \in \mathbb{R}^{B\times C}$ by an average pooling along T dimension. Finally, three different level features are independently sent to the fully connected layers for classification, and we weight the results of the three levels to make a comprehensive decision. From another perspective, the 1D convolutional aggregator has no restrictions on frame interval or sequence length, so our framework is robust to video length.

D. Training

Now we get frame-level, clip-level and video-level features. After fully connected layers, we get frame-based, clip-based and video-based predictions. During training, we optimize the following, a hierarchical loss function:

$$\mathcal{L} = \lambda_v * \mathcal{L}_{\text{video}} + \lambda_c * \mathcal{L}_{\text{clip}} + \lambda_f * \mathcal{L}_{\text{frame}} \tag{2}$$

Here $\mathcal{L}_{\text{video}}, \mathcal{L}_{\text{clip}}, \mathcal{L}_{\text{frame}}$ represent the binary classification loss of frame, clip and video respectively. λ_v, λ_c and λ_f are the respective weights. The loss for the binary classification is as follows:

$$\mathcal{L}_{\text{bce}} = -\frac{1}{N}\sum_{i=1}^{N} y_i \cdot \log\left(p\left(y_i\right)\right) + \left(1-y_i\right) \cdot \log\left(1-p\left(y_i\right)\right) \tag{3}$$

where N is the number of features ($N = 1$ for video-based, $N = 8$ for clip-based and $N = 16$ for frame-based), $p\left(y_i\right)$ is

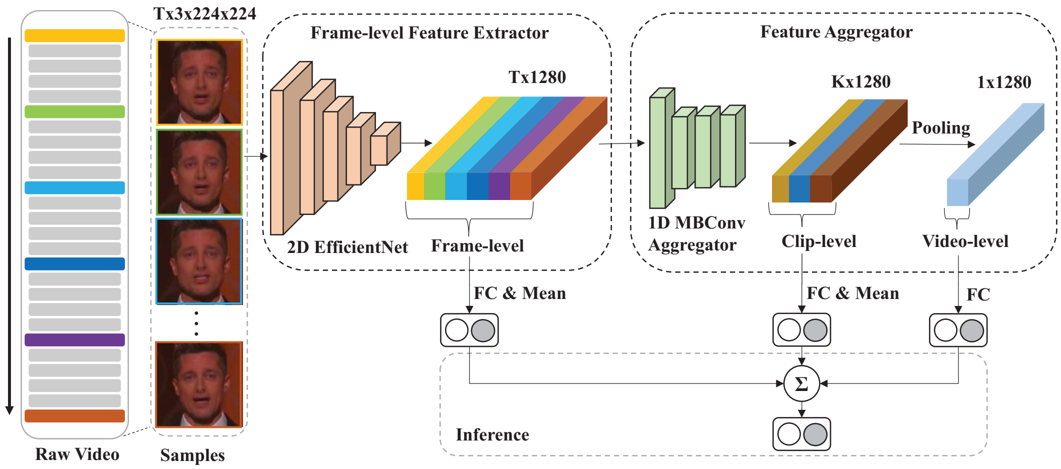


Fig. 4. The overall framework of SDHF. There are two stages in this framework. First, the EfficientNet is trained on the training frames minimizing cross-entropy loss for binary classification to extract features to discern real faces from synthetics. Second, use the previously trained classifier to separately extract multi-frame features, then stack these features and send it into a 1D convolutional aggregator to extract clip-level and video-level features respectively.

the probability of prediction as fake and y_i is the ground truth ($y_i = 0$ for real and $y_i = 1$ for fake).

IV. EXPERIMENTS

In this section, we first describe the four datasets. Then, we provide details of the experimental settings to ensure reproducibility and end up by analyzing the reported results.

A. Datasets

We evaluated the proposed SDHF on four different datasets. Table II shows the detailed descriptions of the datasets.

- **DFDC** [12]: The provided training videos are divided into 50 numbered parts. We use the first 30 parts for training, parts from 30-39 for validation and the last 10 parts for testing.
- **Celeb-DF** [13]: We use the test videos divided by the authors for testing, and the remaining videos for training except the YouTube-real collection.
- **FaceForensics++** [8]: It consists of 1000 original videos, which are manipulated by five different methods, with 720 in training and 140 for each validate and test. Besides, it covers three different versions based on compression including Raw, c23 and c40. In this experiment, we only use the Deepfakes subset of FaceForensics++ at c23 (FF++/DF).
- **UDAFV** [7]: UADFV was collected from FakeApp to validate the algorithms in [7].

TABLE II
STATISTICS OF THE DATASETS

Datasets	Real		Fake		Balanced
	train	test	train	test	
DFDC	10437	4300	58619	20219	×
Celeb-DF	711	178	5299	340	×
FF++/DF	720	140	720	140	√
UADFV	-	49	-	49	√

B. Evaluation Metrics

The testing set of DFDC and Celeb-DF, including training set, is unbalanced, which means that if the model predicts most samples are fake, it can still get a higher accuracy. So we choose balanced accuracy [34] (bACC) as our evaluation metric, which is robust to unbalanced testing sets. In addition, we introduce log loss (log$\mathcal{L}$) to evaluate the confidence of the model, which drastically penalizes being both confident and wrong.

$$bACC = \frac{TPR + TNR}{2} \tag{4}$$

TABLE III
QUANTITATIVE RESULTS FOR EACH METHOD WITH INTRA-TEST

Methods	DFDC		Celeb-DF		FF++/DF	
	bACC↑	log$\mathcal{L}$ ↓	bACC↑	log$\mathcal{L}$ ↓	bACC↑	log$\mathcal{L}$ ↓
Conv-mean	0.871	0.411	0.984	0.337	0.979	0.341
Conv-LSTM	0.873	0.371	0.986	0.056	0.979	0.155
I3D	0.822	0.418	0.974	0.088	0.971	0.154
C3D	0.695	0.499	0.886	0.532	0.896	0.498
SDHF	**0.910**	**0.199**	**0.994**	**0.040**	**0.982**	**0.117**

C. Baselines

- **Conv-mean**: The predictions in all frames are averaged to obtain video-based predictions.
- **Conv-LSTM** [10]: Using CNN To extract frame-level features, LSTM as an aggregator. There are three differences from [10] in our implementation: (1) we choose EfficientNet as our backbone. (2) instead of conduct face alignment, we maintain the original facial pose. (3) instead of small interval sampling, we choose discrete, large interval sampling. The video-level feature was averaged recurrent features across all time-steps.

- **C3D** [35]: A classic action recognition model that uses 3D convolution to simultaneously extract spatio-temporal information.
- **I3D** [36]: An efficient action recognition model extends 2D convolution to 3D convolution based on the InceptionV1 [37].

D. Implementation Details

We choose EfficientNetB0 as the backbone to verify the feasibility of our framework. For training frame-based EfficientNetB0, we initialize the model by pre-trained weights on ImageNet. The batch size is set to 64 and each sample is augmented with a probability of 0.1, including JPEG compress, gaussian noise, blur and gamma correction. In addition, all samples are flipped horizontally with a probability of 0.5. For Conv-LSTM and SDHF, we use the previously trained EfficientNetB0 as the feature extractor. Then it is extended with different aggregators. The batch size is set to 8 and each video takes 16 frames at equal intervals as a sample. All models are trained using Adam optimizer with learning rate $\eta = 1e-4$, with anneals every 10000 steps by $\eta * 0.7$ until 30000 steps were reached. Note that the input size of C3D is 112x112, and the input size of other methods are 224x224. For simplicity, the different losses in SDHF are set to equal weights.

TABLE IV
BALANCED ACCURACY OF EACH METHOD WITH CROSS-TEST

Methods	Intra	Cross		
	DFDC	Celeb-DF	FF++/DF	UADFV
	bACC↑	bACC↑	bACC↑	bACC↑
Conv-mean	0.871	0.784	0.793	0.776
Conv-LSTM	0.873	0.800	0.807	0.816
I3D	0.822	0.666	0.725	0.684
C3D	0.695	0.671	0.654	0.694
SDHF	**0.910**	**0.811**	**0.846**	**0.857**

E. Results and Analysis

Our experiments have two goals: compare our approach to previous works and investigate our approach's performance vs the baselines. The first is necessary to validate that SDHF can outperform other approaches. The latter allow us to understand the reason why SDHF performs well and provide guidance for future research directions. **Intra-test.** In order to demonstrate the effectiveness of our approach, we first conducted intra-test, which means we independently train and test on DFDC, Celeb-DF and FF++/DF. Table III shows the balanced accuracy (bACC) and log loss (log$\mathcal{L}$) of all compared methods on three datasets. We observe that our SDHF achieves the best performance on all the datasets against other methods. It demonstrate that hierarchical framework is effective for DeepFake detection. For Celeb-DF and FF++/DF, Conv-mean can already achieve an accuracy of more than 97%, but it can only achieve an accuracy of 87.06% on DFDC, which shows that forgery scenarios of DFDC are more challenging. There are multiple subjects, partial manipulations and person walking back and forth in DFDC, which is more complex and closer to the forged scenes of spreading videos on the social media. Note that although some works [38], [39] reported that Conv-LSTM does not even achieve an accuracy of 75% on DFDC, our results indicate that Conv-LSTM achieve better results than Conv-mean. The main difference between our experiments and others was that we select frames with a larger interval as a sample from a video, while other experiments select continuous frames with a smaller interval. The reason for processing the data in this way is that we argue multiple faces with small differences are almost the same after extracting features through CNNs. It is hard to capture temporal information on small interval faces and we only regard LSTM as an aggregator. This also prove that our sampling strategy is effective, which can sample more video information, such as multiple subjects, diverse facial expressions and head poses. From another perspective, Table III shows the performance of I3D and C3D is relatively inferior to Conv-mean. However, we argue that the reason for the poor experimental results is that the frame-by-frame face crop operation loses the continuity of data. If proper data processing is performed, better results can be obtained by the 3D convolution model.

Cross-test. Obviously, a simple EfficientNetB0 can achieve more than 85% balanced accuracy in discerning fake/real videos if training and testing videos are from the same source. In order to further prove the generalization ability of our SDHF, we conducted cross-test experiments, and all models were trained on DFDC, and tested on the other three datasets. As shown in Table IV, our approach achieves the highest balanced accuracy on all the datasets against other methods, which prove that our hierarchical detection framework can extract multi-level complementary features, and has excellent generalization performance in the face of unknown datasets.

F. Ablation Studies

In order to verify the effectiveness of our proposed hierarchical framework and loss function, we conducted a set of ablation experiments in cross-test. As shown in Table V, F, C and V represent frame-level, clip-level and video-level features, respectively. For example, V+C+F means that three levels of features are adopted simultaneously to make decisions. For fair comparison, we set equal weights for the three losses $\lambda_v = \lambda_c = \lambda_f$. From Table V and Table IV, when only video-level features is leveraged to make decisions, our approach superiors to Conv-mean by 1.51% balanced accuracy on DFDC with intra-test, 2.45% for Celeb-DF and 1.52% for FF++/DF with cross-test. When clip-level and frame-level features are added to jointly guide learning, our approach has a stable improvement in all datasets. The results indicate that there is a good complement of features at different levels in DeepFake detection.

V. CONCLUSION

In this work, we present a novel framework, named SDHF, for DeepFake detection. Our contribution lies in proposing a hierarchical framework, using 2D convolutional neural networks for frame-level features extraction and 1D MBConv

TABLE V
BALANCED ACCURACY OF SDHF WITH ABLATION STUDIES

Methods	Intra	Cross		
	DFDC	Celeb-DF	FF++/DF	UADFV
	bACC↑	bACC↑	bACC↑	bACC↑
V	0.885	0.809	0.808	0.776
V+F	0.893	0.806	0.818	0.816
V+C	0.895	**0.811**	0.825	0.827
V+F+C	**0.910**	**0.811**	**0.846**	**0.857**

aggregator to extract clip-level and video-level features, which can synthesize three different levels of features to make a comprehensive decision. Due to the clever use of an interval sampling, our approach is robust to variable video length. The results of intra-test demonstrate that our approach achieves better performance compared to other methods. The results of cross-test prove that our hierarchical framework has excellent generalization performance in the face of unknown datasets.

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