

Leveraging Real Talking Faces via Self-Supervision for Robust Forgery Detection

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Abstract

One of the most pressing challenges for the detection of face-manipulated videos is generalising to forgery methods not seen during training while remaining effective under common corruptions such as compression. In this paper, we examine whether we can tackle this issue by harnessing videos of real talking faces, which contain rich information on natural facial appearance and behaviour and are readily available in large quantities online. Our method, termed *RealForensics*, consists of two stages. First, we exploit the natural correspondence between the visual and auditory modalities in real videos to learn, in a self-supervised cross-modal manner, temporally dense video representations that capture factors such as facial movements, expression, and identity. Second, we use these learned representations as targets to be predicted by our forgery detector along with the usual binary forgery classification task; this encourages it to base its real/fake decision on said factors. We show that our method achieves state-of-the-art performance on cross-manipulation generalisation and robustness experiments, and examine the factors that contribute to its performance. Our results suggest that leveraging natural and unlabelled videos is a promising direction for the development of more robust face forgery detectors.

1. Introduction

Automatic face manipulation methods can realistically change someone’s appearance or expression without requiring substantial human expertise or effort [34, 57, 62, 67, 89]. This technology’s potential social harm has spurred considerable research efforts to detect forgery content [3, 22, 33, 41, 46, 47, 49, 58, 63, 76, 87, 106, 110, 112].

It is known that although deep learning-based detectors can achieve high accuracy on in-distribution data, performance often plummets on videos generated using novel manipulation methods (*i.e.*, not seen during training) [17, 32, 49, 63, 67, 100, 112].

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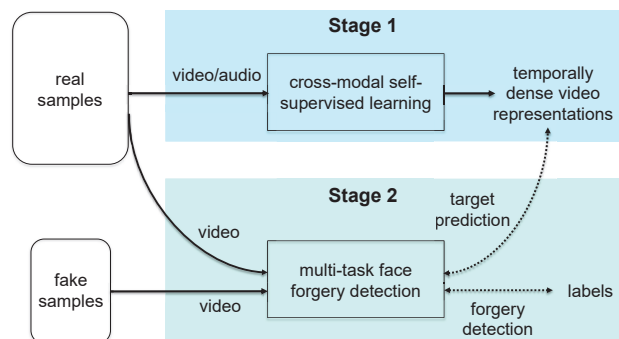


Figure 1. **Overview of our two-stage method.** First, we learn temporally dense video representations in a self-supervised way, by exploiting the correspondence between the visual and auditory modalities of real videos. Second, the network is presented with real and fake data and is tasked with performing face forgery detection while simultaneously predicting, for the real videos, the representations learned in stage 1. We use many more real than fake samples, as the former are more easily acquired.

Various frame-based methods (*i.e.*, that take a single frame as input) have been proposed to tackle cross-manipulation generalisation, including using data augmentation [100], truncating classifiers [17], using 3D decomposition [112], amplifying multi-band frequencies [74], and targeting the blending boundary between the background and the altered face [63]. Nevertheless, many still significantly underperform on novel forgery types or focus on low-level cues which can easily be corrupted by common perturbations like compression [49].

It is reasonable to believe that incorporating the temporal dimension can improve performance, especially since many synthesis methods do not take into account temporal consistency during the generation process [89]. However, as with frame-based methods, naively training deep networks on videos can lead to overfitting to the seen forgeries [49, 92, 108]. To counteract this, LipForensics [49] pre-trains on a large-scale lipreading dataset and then freezes part of the network to prevent it from focusing on low-level cues. It achieves strong performance in cross-

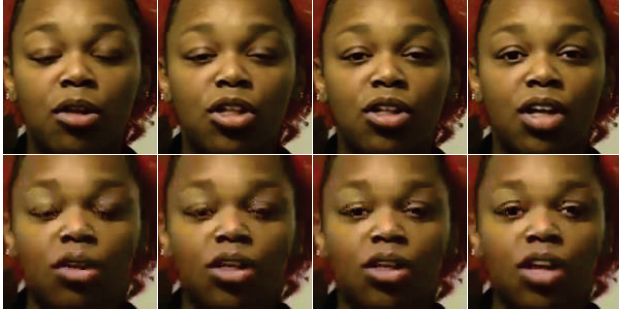


Figure 2. Top: consecutive frames of a fake video [34]. Bottom: same frames but heavily compressed. High-level semantics remain largely undisturbed under compression.

manipulation generalisation and robustness to common corruptions. On the other hand, (1) it requires pre-training on a *labelled* dataset, limiting its scalability; (2) it focuses exclusively on the mouth region; and (3) it freezes almost one third of the network when training on forgery data, which could sacrifice performance. A very recent method, FTCN [108], demonstrates high cross-manipulation generalisation by constraining all spatial convolutional kernel sizes to one. But, as we show, the impressive generalisation may come at a cost of reduced robustness to compression changes.

In this work, we are motivated by the observation that fake videos often exhibit anomalous facial movements (including mouth, eyes, and brows) and expressions, as well as subtle changes in facial form over time. Such cues are high-level in nature and thus more resilient to corruptions which destroy low-level content, *e.g.*, compression or blurring (see Figure 2). We ask ourselves whether it is possible to guide a detector to focus on such cues by utilising *unlabelled* real videos, which are relatively easy to obtain with tools like face and voice activity detectors.

To this end, we propose a two-stage approach, termed *RealForensics* (see Figure 1). We first use self-supervision to exploit the known correspondence between the visual and auditory modalities in *natural videos*. Inspired by the state-of-the-art method in image representation learning BYOL [45], we use a cross-modal student-teacher framework, where a student processing the video stream must predict representations formed by a slowly-improving teacher from the audio stream, and vice versa. We learn *temporally dense* representations (one embedding per frame), since cues related to facial movements are often fast-varying. Our goal is to capture *all* shared information between the two modalities, including factors associated with lexical content [27], emotion [91], and identity [78]. Hence, we *directly predict* the teachers’ outputs. In the second stage, the forgery detector is tasked with performing classification while simultaneously predicting video targets generated by the video student from the first stage. This prediction task incentivises

the detector to focus on the aforementioned cues when classifying the samples and, as a result, alleviates overfitting.

Our contributions are as follows: (1) We present a novel two-stage detection approach that uses large amounts of natural talking faces for strong generalisation and robustness performance; this opens up the avenue for future forgery detection works to exploit the ubiquitous real videos online. (2) We propose, for the first stage, a non-contrastive self-supervised framework that learns temporally dense representations, and we validate its design for our task through ablations. (3) We achieve state-of-the-art performance in experiments that test cross-manipulation generalisation and robustness to common corruptions, and highlight the factors responsible for our method’s performance.

2. Related Works

2.1. Face forgery detection

General approaches. Earlier works using convolutional neural networks (CNNs) include recasting steganalysis features as CNNs [30], constraining convolutional filters [12], and using shallow networks [3] to suppress high-level content. However, an unconstrained Xception [23] network outperforms these approaches on more recent forgery types [89]. Other works aim at detecting inconsistent head poses [103] or irregular eye blinking [64], although more recent fakes may not exhibit such anomalies. More recently, works have focused on attention mechanisms [33, 97, 106], exploiting the frequency spectrum [38, 40, 61, 68, 70, 74, 87], detecting anomalies in features from a face recognition network [99], or using extra identity information [5, 31, 35]. [41] and [105] use self-supervision for frame-based detection, but do not study the effect of using many real samples.

Cross-manipulation generalisation. Detectors often generalise poorly to unseen forgeries [17, 32, 49, 63, 100]. Approaches to improve generalisation include applying augmentations [100], reconstructing the input as an auxiliary task [32, 37, 80], mining frequency cues [70, 74], truncating classifiers [17], focusing on self-consistency [55, 63, 65, 107], or using spatio-temporal convolutional networks [42].

However, it has been shown that it is especially challenging to achieve cross-manipulation generalisation and at the same time perform well on corrupted data [49]. A closely related work to ours is LipForensics [49], which addresses this by finetuning a network that was pre-trained to perform lipreading. Unlike our method, it requires a large-scale *labelled* dataset and focuses exclusively on the mouth region. Very recently, [108] report high generalisation by reducing the spatial kernel sizes of convolutional layers to 1, thus learning temporal inconsistencies while ignoring spatial ones. By contrast, we target *spatio-temporal* irregularities that may be more consistent with human perception

of forgery cues. Finally, some recent works have focused on mismatches between the visual and auditory modalities in fake videos [4, 24, 60, 76, 111]. Our work, on the other hand, is *visual-only* at test-time: It uses the audio modality only for cross-modal supervision in an intermediate step, in which only real videos are used.

2.2. Self-supervised learning

Image SSL. Recently, contrastive learning using the InfoNCE loss [83] has become a popular approach in image representation learning [18, 19, 50, 52, 83, 95, 102]. In this paradigm, the similarity between two views of an image is maximised, while different images (“negatives”) are repelled. Contrastive learning has also been used to learn dense visual representations [86, 101]. However, recent works that remove negatives generally outperform contrastive approaches [10, 14–16, 20, 45, 104]. Our work is partly inspired by BYOL [45], which uses a slowly-evolving teacher network that produces targets for a student to predict. The first stage of our approach can be viewed as an extension of BYOL to the audiovisual setting, in which we have a student-teacher pair for each modality and the output representations are temporally dense. Recent works [81] and [39, 88] also use BYOL-style training but are for audio-only learning and action recognition, respectively.

Audiovisual SSL. Many works exploit audiovisual correspondence for video action recognition [6–9, 27, 59, 71, 77, 85]. However, these approaches learn a single representation for a video clip, which is less suitable for modelling the fine-grained movements of a speaking face. The very recent work [72] proposes to learn, in a contrastive manner, both global and local representations that are agnostic to the specific downstream task. In contrast, aside from methodological differences, our work focuses on cross-dataset generalisation and robustness for face forgery detection. Audiovisual methods have also been proposed for applications involving faces (e.g., audiovisual synchronisation and biometric matching). In general, methods that model lexical content tend to contrast samples from the same video for identity invariance [27–29]. Conversely, works that learn identity embeddings tend to match misaligned video-audio pairs from the same person for invariance to lexical content [78, 79]. We posit that it is beneficial to capture both types of information for forgery detection and hence directly predict aligned embeddings.

Generalisation via self-supervision. It has been shown that using self-supervision as an auxiliary task, e.g., predicting rotations [44] or solving jigsaw puzzles [82], can improve generalisation on the main task at hand [13, 43, 53]. We use a similar idea for improving generalisation for forgery detection, but we *learn* the targets in a separate stage before using them to define the auxiliary task.

3. Method

RealForensics comprises two stages (see Figure 3). The first stage involves learning temporally dense video representations using cross-modal self-supervision from many natural talking faces. These representations are subsequently used as prediction targets in the second stage to regularise the binary forgery classification task.

3.1. Stage 1: representation learning

Given real videos and the corresponding audio, we aim to learn video representations that capture information associated with facial appearance and behaviour. Cues like facial movements are temporally fine-grained by nature, and hence we wish to learn *temporally dense* representations, i.e., an embedding per frame. We use a student-teacher framework without contrasting negatives for the following reasons. (1) This style of training has resulted in state-of-the-art results in image representation learning [45]; (2) it incentivises the network to retain all information shared by the two modalities [45]; and (3) it obviates the need for large batch sizes [18] or a queue [50] to store the negatives.

Formulation. We assume access to a large dataset \mathcal{D}_r of real talking faces. A sample $x \in \mathcal{D}_r$ is a video $x^v \in \mathbb{R}^{T_v \times H \times W \times 3}$ (of T_v video frames, height H , and width W) with its corresponding audio, represented as a log-mel spectrogram, $x^a \in \mathbb{R}^{T_a \times L}$ (of T_a audio frames and L mel filters). We ensure that $T_a = 4T_v$.

Our architecture consists of a student and teacher pair for each modality. The teachers produce targets that the students from the other modality must predict. Specifically, teacher video and audio backbone networks, f_t^v and f_t^a , produce embeddings $e_t^v = f_t^v(x^v)$ and $e_t^a = f_t^a(x^a)$ from the inputs, which are then passed through projectors, g_t^v and g_t^a , to yield dense video and audio targets, $z_t^v = \text{norm}(g_t^v(e_t^v)) \in \mathbb{R}^{T_v \times C}$ and $z_t^a = \text{norm}(g_t^a(e_t^a)) \in \mathbb{R}^{T_v \times C}$, where C is the dimensionality of the embeddings and $\text{norm}(\cdot)$ denotes l_2 normalisation across the channel dimension. Note that the audio backbone subsamples the temporal dimension such that the video and audio embeddings have the same shape. The students have the same architecture as their corresponding teachers, except that each student additionally contains a predictor, whose job is to predict the targets from the other modality. Let the video and audio predictions be $p^v = \text{norm}(h^v(z_s^v))$ and $p^a = \text{norm}(h^a(z_s^a))$, respectively, where h^v and h^a denote the predictors and z_s^v and z_s^a are the unnormalised student representations after the student projectors; then the loss is

$$\mathcal{L} = \frac{1}{2} \|\text{sg}(z_t^v) - p^a\|_F^2 + \frac{1}{2} \|\text{sg}(z_t^a) - p^v\|_F^2, \quad (1)$$

where $\|\cdot\|_F$ denotes the Frobenius norm, and sg , which stands for “stop-gradient,” emphasises that the targets are

- *Predictors.* The predictor for both modalities is a 1-block transformer encoder. It follows the design of a ViT block [36]. We use 8 attention heads, each with dimension 64, MLP dimension of 2048, and replace layer normalisation [11] with batch normalisation [56] before the MLP.
- *Optimisation.* We use the AdamP optimiser [54] with learning rate 7×10^{-4} and weight decay 10^{-2} . We train for 150 epochs, with an initial 20-epoch linear warmup followed by a cosine decay schedule for the learning rate [69]. The predictors' lr are kept fixed [20]. The EMA momentum parameters for the teachers are set to 0.999.

3.2. Stage 2: multi-task forgery detection

The aim of this work is to learn a *visual-only* forgery detector. Indeed, many forgery datasets do not officially release audio along with the videos [57, 67, 89]. As a result, at this stage we discard the audio student-teacher pair, after having served its purpose in stage 1.

We propose to use the video teacher from stage 1 to produce targets for our network to predict. At the same time, the network performs forgery detection, in a multi-task fashion. Note that the teacher is frozen in this stage. Using this auxiliary loss likely encourages the network to classify real and fake videos by focusing on high-level spatio-temporal characteristics of facial appearance and behaviour.

Formulation. We again use our dataset of real faces \mathcal{D}_r , but we now also assume access to a dataset of fake videos, \mathcal{D}_f .¹ Our full dataset is thus $\mathcal{D} = \mathcal{D}_r \cup \mathcal{D}_f$. Our architecture consists of a shared backbone f with weights θ_b and two heads: a supervised head with weights θ_s for the forgery classification loss and an auxiliary one q with weights θ_a for the target prediction loss. The auxiliary loss is given by

$$\mathcal{L}_a(\mathcal{D}_r; \theta_b, \theta_a) = \mathbb{E}_{x \sim \mathcal{D}_r} \|q(f(x^v; \theta_b); \theta_a) - t(x^v)\|_F^2, \quad (3)$$

where t is the teacher from stage 1, and the auxiliary head's and teacher's outputs are l_2 -normalised as in stage 1.

The supervised loss $\mathcal{L}_s(\mathcal{D}; \theta_b, \theta_s)$ is a logit-adjusted version of binary cross entropy, as proposed in [75], to address any class imbalance (see the appendix for details). Moreover, to obtain the logits, we l_2 -normalise the feature vectors and the weights of the last linear layer (and set its bias to 0), thus obtaining a cosine classifier [98]. This combines better with the auxiliary loss, which can also be cast in terms of cosine similarity. Finally, the objective is given by

$$\min_{\theta_b, \theta_s, \theta_a} \mathcal{L}_s(\mathcal{D}; \theta_b, \theta_s) + w \mathcal{L}_a(\mathcal{D}_r; \theta_b, \theta_a), \quad (4)$$

where w is a scaling factor, which we set to 1.

¹In practice, the real samples for this stage include our auxiliary dataset as well as the real samples from the forgery dataset.

Implementation details. The video teacher is transferred from stage 1 and remains frozen henceforth. The backbone's architecture is the same as the video backbone in stage 1, and we initialise it with the learned weights. The auxiliary head is comprised of a randomly initialised projector and predictor as in stage 1. The supervised head is a cosine classifier, as previously described. A batch consists of 32 fake and 256 real samples, to effectively make use of the many more real samples available. We use the AdamP optimiser with learning rate 3×10^{-4} and the same preprocessing and augmentations described in stage 1. We train for 150 epochs and use the validation set for early stopping.

4. Experiments

Auxiliary dataset. We use the LRW dataset [26] without the labels for our extra real samples. It contains 500,000 videos of talking faces with hundreds of different identities. This dataset was also used by LipForensics [49], which allows for fairer comparisons. In addition, its size strikes a balance between meaningful results and non-prohibitive computational costs. We present results for another dataset, VoxCeleb2 [25], in Section 5.

Forgery datasets. We use the following forgery datasets: (1) **FaceForensics++** (FF++) [89] consists of 1,000 real videos and 4,000 fake videos, generated using two face swapping methods, Deepfakes [1] and FaceSwap [2], and two face reenactment methods, Face2Face [94] and NeuralTextures [93]. Unless stated otherwise, we use the mildly compressed version of the dataset (c23). As in [49, 89], we take the first 270 frames for each training video, and the first 110 frames for each validation/testing video. (2) **FaceShifter** [62] and (3) **DeeperForensics** [57] are state-of-the-art face swapping methods that have been applied to the real videos of FF++; we use the test videos, according to the FF++ split. (4) **CelebDF-v2** [67] is a challenging face swapping dataset with 518 test videos. (5) **DFDC** is a subset of the Deepfake Detection Challenge Dataset (DFDC) [34] used in [49]. It features 3,215 videos, many of which have been subjected to strong perturbations.

Evaluation metrics. Following *e.g.*, [2, 49, 89, 108, 111], we use accuracy and area under the receiver operating characteristic curve (AUC) for evaluation. We use video-level metrics: For a single video we first uniformly sample non-overlapping clips and then average all clip predictions across the video.

4.1. Cross-manipulation generalisation

A deployed detector is expected to recognise fake videos that were created using methods *not seen during training*, a non-trivial task in practice [49, 63, 80, 108]. In this section, we follow the protocol used in [49, 65, 80] to evaluate our detector's ability to generalise to unseen manipulations.

Method	Train on remaining three			
	DF	FS	F2F	NT
Xception [89]	93.9	51.2	86.8	79.7
CNN-aug [100]	87.5	56.3	80.1	67.8
Patch-based [17]	94.0	60.5	87.3	84.8
Face X-ray [63]	99.5	93.2	94.5	92.5
CNN-GRU [90]	97.6	47.6	85.8	86.6
LipForensics [49]	99.7	90.1	<u>99.7</u>	99.1
AV DFD [111]	<u>100.</u>	90.5	<u>99.8</u>	98.3
FTCN [108]	99.9	<u>99.9</u>	<u>99.7</u>	<u>99.2</u>
CSN	98.8	87.9	98.7	88.6
RealForensics (ours)	<u>100.</u>	<u>97.1</u>	<u>99.7</u>	<u>99.2</u>

Table 1. **FF++ cross-manipulation generalisation.** AUC scores (%) for each FF++ manipulation type after training on the remaining types. We use the test sets of Deepfakes (DF), FaceSwap (FS), Face2Face (F2F), and NeuralTextures (NT), as well as the real test videos. Top-2 best methods are underlined.

Table 1 shows results obtained by RealForensics on each manipulation type in the FF++ dataset after training on the remaining types. Our detector works on par with the state-of-the-art without (1) using auxiliary labelled supervision [49], (2) heavily constraining the network by freezing large parts [49] or removing spatial convolutions [108], nor (3) using audio at test-time [111]. We also outperform the baseline of training a CSN [96] network on the forgery data (with the same augmentations as RealForensics), indicating the effectiveness of leveraging real data using our approach.

We also evaluate *cross-dataset* generalisation by training on FF++ and then testing *a single model* on unseen, challenging datasets: CelebDF-v2 [67], DFDC [34], FaceShifter [62], and DeeperForensics [57]. The AUC results are given in Table 2. Our method achieves state-of-the-art results on all datasets, suggesting that our detector performs well when exposed to more advanced forgeries than originally trained on. RealForensics also beats the CSN baseline by a large margin. Finally, as seen in Table 3, we achieve higher generalisation accuracy on FaceShifter and DeeperForensics than related methods, with fewer network parameters at test-time.

4.2. Robustness to common corruptions

In addition to good cross-manipulation generalisation, detectors should also be able to withstand common corruptions that videos may be subjected to on social media. We follow [49] to assess robustness to *unseen* perturbations. As in [49], we train on FF++ with grayscale clips and no augmentation other than horizontal flipping and random cropping, to avoid any intersection between train- and test-time perturbations. The set of perturbations, proposed

Method	CDF	DFDC	FSh	DFo	Avg
Xception [89]	73.7	70.9	72.0	84.5	75.3
CNN-aug [100]	75.6	72.1	65.7	74.4	72.0
Patch-based [17]	69.6	65.6	57.8	81.8	68.7
Face X-ray [63]	79.5	65.5	92.8	86.8	81.2
CNN-GRU [90]	69.8	68.9	80.8	74.1	73.4
Multi-task [80]	75.7	68.1	66.0	77.7	71.9
DSP-FWA [66]	69.5	67.3	65.5	50.2	63.1
Two-branch [74]	76.7	—	—	—	—
LipForensics [49]	82.4	73.5	97.1	97.6	87.7
FTCN [108]	86.9	74.0	98.8	98.8	89.6
CSN	69.4	68.1	87.9	89.3	78.7
RealForensics (ours)	86.9	75.9	99.7	99.3	90.5

Table 2. **Cross-dataset generalisation.** AUC scores (%) on CelebDF-v2 (CDF), DeepFake Detection Challenge (DFDC), FaceShifter (FSh), and DeeperForensics (DFo), after training on FaceForensics++. Best results are in **bold**.

Method	Settings		Accuracy	
	Arch	# params	FSh	DFo
LipForensics [49]	RN+TCN [73]	36.0	87.5	90.4
FTCN [108]	FTCN [108]	26.6	93.9	91.1
RealForensics (ours)	CSN [96]	21.4	97.1	97.1

Table 3. **Parameters and generalisation accuracy.** Number of parameters (in millions), at test-time, for related state-of-the-art methods, and accuracy on FaceShifter (FSh) and DeeperForensics (DFo) after training on FaceForensics++. Best results are in **bold**.

in [57], are changes in saturation and contrast, block-wise occlusions, Gaussian noise and blur, pixelation and video compression. Each perturbation type is applied at five different intensity levels. Table 4 presents the average AUC across all intensity levels for each corruption type. RealForensics suffers significantly less from common corruptions than frame-based methods that target low-level cues, such as [17, 63], and also outperforms LipForensics and FTCN. (We use FTCN’s publicly available model², which was trained on FF++ c23.) We notice that, relative to RealForensics and LipForensics, FTCN struggles on Gaussian noise and video compression (see also Figure 4), which disturb temporal coherence. This may be explained by FTCN’s lack of spatial convolutions.

5. Ablations

In this section, we present ablations to understand the factors responsible for our method’s performance. See the appendix for more ablations.

Framework ablation. In Table 5, we ablate different components of our method and inspect its generalisation per-

²<https://github.com/yinglinzheng/FTCN>

Method	Clean	Saturation	Contrast	Block	Noise	Blur	Pixel	Compress	Avg
Xception [89]	99.8	99.3	98.6	99.7	53.8	60.2	74.2	62.1	78.3
CNN-aug [100]	99.8	99.3	99.1	95.2	54.7	76.5	91.2	72.5	84.1
Patch-based [17]	99.9	84.3	74.2	99.2	50.0	54.4	56.7	53.4	67.5
Face X-ray [63]	99.8	97.6	88.5	99.1	49.8	63.8	88.6	55.2	77.5
CNN-GRU [90]	99.9	99.0	98.8	97.9	47.9	71.5	86.5	74.5	82.3
LipForensics [49]	99.9	99.9	99.6	87.4	73.8	96.1	95.6	95.6	92.5
FTCN [108]	99.4	99.4	96.7	97.1	53.1	95.8	98.2	86.4	89.5
RealForensics (ours)	99.8	99.8	99.6	98.9	79.7	95.3	98.4	97.6	95.6

Table 4. **Robustness to common corruptions.** Average AUC scores (%) across five intensity levels for each corruption type proposed in [57]. We also present, for each method, the average score across all corruptions. Best results are in **bold**. For a more detailed analysis, see the appendix.

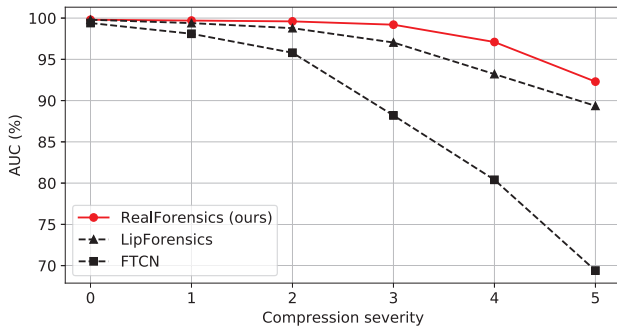


Figure 4. **Robustness to compression.** AUC scores (%) on FaceForensics++ (FF++) at various H.264 video compression rates (23, 30, 32, 35, 38, 40), after training on FF++ with light compression (rate of 23).

formance on FaceShifter and DeeperForensics after training on FaceForensics++. We make the following observations. First, simply training a CSN [96] model without our two-stage framework leads to a drop in accuracy of about 14%. Second, transferring the weights from stage 1 to the video backbone and finetuning the network on forgery data, without the auxiliary loss in stage 2, results in a drop of about 2%. This suggests that forcing the network to predict the video representations along with its main task has a positive regularisation effect. Finally, we observe modest improvements by employing logit adjustment [75] for imbalanced classification and using time masking and random erasing [109].

Representation learning ablation. For stage 1 of our method, we propose to learn temporally dense representations without contrasting negatives. Here, we test our choices against alternatives. We train the network with all combinations of the following settings: dense/global representations, with/without negatives, and with/without a predictor network. For global representation learning, we

average-pool the output of the backbone networks, and use MLPs for the projector and predictor. To employ negatives, we use a queue of 65,536 samples and use the InfoNCE loss [83] with a temperature of 0.07. Note that global learning with negatives is similar to cross-modal contrastive learning used in *e.g.*, [71, 77]. The predictor network used for global learning is an MLP and for dense learning a one-block transformer. Global learning with negatives and a predictor is analogous to the recent image representation learning method MoCo v3 [21], but for cross-modal learning. More information can be found in the appendix.

In Table 6, we show accuracy scores on FaceShifter and DeeperForensics after training on FaceForensics++. We see that dense representations lead to significantly better performance than global. Also, consistent with the original BYOL method, we find that without negatives and without a predictor the outcome is *representation collapse* [45]. Without negatives and with global representations, no collapse was observed (with a predictor), but we had trouble achieving competitive performance. This may have to do with optimisation difficulties encountered without contrastive learning, since the subsequent inclusion of negatives yielded better results. However, adding negatives *does not* seem to help when we use *dense* learning (and a predictor).

Effect of number of real samples. Next, we vary the number of LRW samples in both stages of our method to see the effect on generalisation. As a baseline, we also consider simply treating the problem as an imbalanced classification task, *i.e.*, training the model with logit adjustment (but without our proposed method). We can see in Figure 5 that RealForensics benefits from a large number of real samples. Moreover, although generalisation for the baseline does increase with more real samples, the increase is significantly less than for RealForensics.

Using a different auxiliary dataset. Here, we use the VoxCeleb2 dataset [25] for our extra real samples. It con-

Method	FSH	DFo
RealForensics (ours)	97.1	97.1
only CSN	82.1	83.1
stage 1 + finetune	95.0	95.2
w/o logit adjustment	95.7	96.4
w/o time masking	96.1	95.9
w/o random erasing	96.3	96.3

Table 5. **Framework ablation.** Accuracy scores (%) on FaceShifter (FSH) and DeeperForensics (DFo) after training on FaceForensics++. Refer to subsection “Framework ablation” for a discussion. Best results are in **bold**.

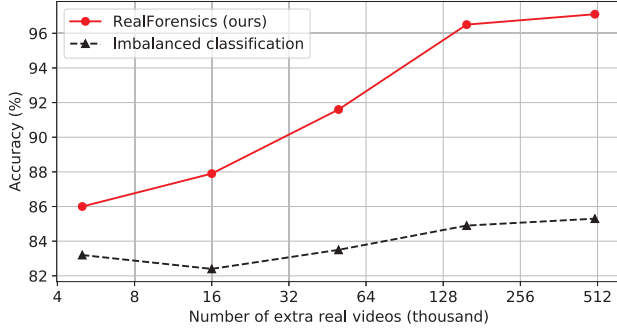


Figure 5. **Effect of number of real samples.** Accuracy scores (%) as a function of the number of real samples from LRW, in log-scale. We show results for our method as well as a baseline where we treat the task as an imbalanced classification one. We average the accuracy of FaceShifter and DeeperForensics after training on FaceForensics++.

Settings			Accuracy (%)	
Global/Dense	Negatives	Predictor	FSH	DFo
Global	✗	✗	n/a	n/a
Global	✗	✓	70.7	74.1
Global	✓	✗	87.9	88.6
Global	✓	✓	87.9	89.1
Dense	✗	✗	n/a	n/a
Dense	✗	✓	97.1	97.1
Dense	✓	✗	94.0	95.7
Dense	✓	✓	96.4	96.8

Table 6. **Representation learning ablation.** We ablate different components of our representation learning stage (stage 1). Note that “n/a” means that representation collapse was observed in stage 1. Refer to subsection “Representation learning ablation” for a discussion. Best results are in **bold**. Default setting is highlighted.

tains about 1 million videos of talking faces with various identities. We train with the same hyperparameters as for LRW. The AUC results (in %) on CelebDF-v2, DFDC,

FaceShifter, and DeeperForensics after training on FaceForensics++ are 82.9, 78.9, 99.3, and 98.8, respectively. This suggests that competitive results can be obtained with minimal tuning using a different dataset.

6. Limitations / Societal Impact

The strong generalisation of RealForensics comes at a cost of higher computational demands during training than methods that do not use auxiliary datasets; however, this is not the case at test-time. Moreover, our detector takes videos as input, and thus does not work for single images. Despite state-of-the-art accuracy, we also observe that when our network produces wrong predictions, they are often confidently wrong, so the probabilities outputted by the model should be interpreted with care. This issue of *model calibration* is common in deep learning models [48], including forgery detectors; thus, an important future direction would be to apply methods in calibration literature [48] to detectors.

Although the purpose of research on forgery detection is to protect society, there are a few concerns that should be kept in mind. For example, pointing out the flaws in current face forgeries could facilitate the development of even better fake videos in the future. This, however, is less of an issue for methods that do not target a *specific* cue, such as RealForensics. Further, it is not prudent for a deployed system to rely exclusively on a single detection method. For greater effectiveness, it should employ an ensemble of independent approaches.

7. Conclusion

In this paper, we propose RealForensics, an approach that uses large amounts of unlabelled real data to detect fake videos. We have shown that our method simultaneously achieves strong cross-manipulation generalisation and robustness to common corruptions. In the future, we would like to apply our method to even larger and more uncured real samples scraped from the web. We hope our study encourages future research on leveraging real faces for robust forgery detection.

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