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

Alexandros Haliassos\textsuperscript{1,†} Rodrigo Mira\textsuperscript{1} Stavros Petridis\textsuperscript{1,2} Maja Pantic\textsuperscript{1,2}

\textsuperscript{1}Imperial College London \textsuperscript{2}Meta AI

\{alexandros.haliassos14,rs2517,stavros.petridis04,m.pantic\}@imperial.ac.uk

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. Code is available.\textsuperscript{1}

1. Introduction

Automatic face manipulation methods can realistically change someone’s appearance or expression without requiring substantial human expertise or effort [37,62,67,72,94]. This technology’s potential social harm has spurred considerable research efforts to detect forgery content [3, 24, 35, 44, 49, 50, 53, 63, 68, 81, 92, 112, 116, 118].

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) [19, 34, 53, 68, 72, 105, 118].

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 [105], truncating classifiers [19], using 3D decomposition [118], amplifying multi-band frequencies [79], and targeting the blending boundary between the background and the altered face [68]. 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 [53].

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 [94]. However, as with frame-based methods, naively training deep networks on videos can lead to overfitting to the seen forgeries [53, 97, 114]. To counteract this, LipForensics [53] pre-trains on a large-scale lipreading dataset and then freezes part of the network to prevent it from focusing on

\textsuperscript{†}Corresponding author.

\textsuperscript{1}https://github.com/ahaliassos/RealForensics
low-level cues. It achieves strong performance in cross-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 \cite{FTCN}, 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 \cite{BYOL}, 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 \cite{lexical-content}, emotion \cite{emotion}, and identity \cite{identity}. 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 \cite{steganalysis_CNN}, constraining convolutional filters \cite{constraint_filters}, and using shallow networks \cite{shallow_networks} to suppress high-level content. However, an unconstrained Xception \cite{Xception} network outperforms these approaches on more recent forgery types \cite{recent_forgeries}. Other works aim at detecting inconsistent head poses \cite{head_pose} or irregular eye blinking \cite{eye_blinking}, although more recent fakes may not exhibit such anomalies. More recently, works have focused on attention mechanisms \cite{attention_mechanisms}, exploiting the frequency spectrum \cite{frequency_spectrum}, detecting anomalies in features from a face recognition network \cite{FR_network}, or using extra identity information \cite{extra_identity_info}. \cite{self_supervision} and \cite{LipForensics} 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 \cite{generalisation_poorly}. Approaches to improve generalisation include applying augmentations \cite{augmentations}, reconstructing the input as an auxiliary task \cite{auxiliary_task}, mining frequency cues \cite{frequency_cues}, truncating classifiers \cite{truncation}, focusing on self-consistency \cite{self_consistency}, or using spatio-temporal convolutional networks \cite{spatio-temporal_networks}.

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 \cite{corrupted_data}. A closely related work to ours is LipForensics \cite{LipForensics}, 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. Recently, \cite{RealForensics} report high generalisation by reducing the spatial kernel sizes of convolutional layers to 1, thus learning temporal inconsistencies while ignoring spatial ones. We target spatio-temporal irregularities that may be more

Figure 2. Top: consecutive frames of a fake video \cite{fake_video}. Bottom: same frames but heavily compressed. High-level semantics remain largely undisturbed under compression.
consistent with human perception of forgery cues. Finally, some works have focused on mismatches between the visual and auditory modalities in fake videos [5, 26, 65, 81, 117]. 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 [88] has become a popular approach in image representation learning [20, 21, 54, 57, 88, 100, 107]. 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 [91, 106]. However, recent works that remove negatives generally outperform contrastive approaches [11, 16–18, 22, 48, 109]. Our work is partly inspired by BYOL [48], 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 [86] and [42,93] 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 [7–10,29,64,76,82,90]. 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 [77] 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 [29–31]. Conversely, works that learn identity embeddings tend to match misaligned video-audio pairs from the same person for invariance to lexical content [83,84]. 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 [47] or solving jigsaw puzzles [87], can improve generalisation on the main task at hand [15,46,58]. 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 [48]; (2) it incentivises the network to retain all information shared by the two modalities [48]; and (3) it obviates the need for large batch sizes [20] or a queue [54] to store the negatives.

Formulation. We assume access to a large dataset $D_r$ of real talking faces. A sample $x \in D_r$ is a video $x^n \in \mathbb{R}^{T_v \times H \times W \times 3}$ (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, $f_v^T$ and $f_a^T$, produce embeddings $e_v^T_i = f_v^T(x^n_i)$ and $e_a^T_i = f_a^T(x^a_i)$ from the inputs, which are then passed through projectors, $g_v^T$ and $g_a^T$, to yield dense video and audio targets, $z_v^T_i = \operatorname{norm}(g_v^T(e_v^T_i)) \in \mathbb{R}^{T_v \times C}$ and $z_a^T_i = \operatorname{norm}(g_a^T(e_a^T_i)) \in \mathbb{R}^{T_a \times C}$, where $C$ is the dimensionality of the embeddings and $\operatorname{norm}()$ 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 $p_v = \operatorname{norm}(h_v'(z_v^a))$ and $p_a = \operatorname{norm}(h_a'(z_a^v))$, respectively, where $h_v'$ and $h_a'$ denote the predictors and $z_v^a$ and $z_a^v$ are the unnormalised student representations after the student projectors; then the loss is

$$L = \frac{1}{2}||\operatorname{sg}(z_v^a) - p_v||_F^2 + \frac{1}{2}||\operatorname{sg}(z_a^v) - p_a||_F^2,$$

where $|| \cdot ||_F$ denotes the Frobenius norm, and $\operatorname{sg}$, which stands for “stop-gradient,” emphasises that the targets are
treated as constants. The total loss is averaged over all samples. The students are optimised via gradient descent, and the teachers are exponential moving averages of the students. That is, if we denote the video teacher weights as $\psi^v$ and the corresponding student weights as $\theta^v$, then at each iteration

$$
\psi^v \leftarrow \mu \psi^v + (1 - \mu) \theta^v,
$$

where $\mu$ is a momentum parameter close to 1. The audio teacher weights are updated similarly.

**Transformer as predictor.** BYOL shows that the predictor is a necessary component to avoid *representation collapse*, a situation where the representations for all samples are the same [48]. We observe the same for our framework (see Section 5). Whereas BYOL outputs global representations and thus uses an MLP as a predictor, we find that a shallow transformer is suitable for our dense representation learning task (see the appendix for an ablation).

**Random masking.** We also find that random masking results in better representations (see Section 5). For videos, we zero random rectangular regions in frames [115], consistent across a whole video clip, as well as erase a random number of consecutive frames. For spectrograms, we erase a random number of consecutive audio frames and frequency bins. This is similar to the SpecAugment method [89], but without the time warping step. We apply this masking only to the inputs of the students. Intuitively, this forces the students to make use of context to infer the missing information and prevents them from overly relying on specific features of the input, e.g., the mouth region.

**Implementation details.** Unless specified otherwise, we use the following settings for this stage (see the appendix for more details).

- **Inputs.** We extract the faces using face detection and alignment. A clip consists of 25 frames. The log-mel spectrograms contain 80 mel filters and 100 audio frames. During training, we randomly crop the video clips to size $140 \times 140$ and resize them to $112 \times 112$. We randomly apply horizontal flipping and grayscale transformation, each with probability 0.5. As mentioned, we also randomly mask the students’ inputs.

- **Backbones.** The video backbone is a Channel-Separated Convolutional Network (CSN) [101]; we set the temporal strides to 1 to prevent temporal subsampling. The audio backbone is a ResNet18 [55], with the strides in the convolutional layers modified such that it subsamples the temporal dimension by 4, thus matching the temporal span of the video backbone’s output.

- **Projectors.** The projection network used for both the video and audio modalities is a single $1 \times 1$ convolutional layer with output dimension of 256, followed by batch normalisation (BN) [61]. We find that this BN layer helps with training, similarly to [22].
• **Predictors.** The predictor for both modalities is a 1-block transformer encoder. It follows the design of a ViT block [39]. We use 8 attention heads, each with dimension 64, MLP dimension of 2048, and replace layer normalisation [12] with batch normalisation [61] before the MLP.

• **Optimisation.** We use the AdamP optimiser [59] with learning rate $7 \times 10^{-4}$ 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 [74]. The predictors’ lr are kept fixed [22]. 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 [62,72,94]. 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 $D_r$, but we now also assume access to a dataset of fake videos, $D_f$. Our full dataset is thus $D = D_r \cup D_f$. Our architecture consists of a shared backbone $f$ with weights $\theta_b$ and two heads: a supervised head with weights $\theta_s$ for the forgery classification loss and an auxiliary one $q$ with weights $\theta_a$ for the target prediction loss. The auxiliary loss is given by

$$L_a(D_r; \theta_b, \theta_a) = \mathbb{E}_{x \sim D_r} ||q(f(x^v; \theta_b); \theta_a) - t(x^v)||_2^2,$$

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 $L_s(D; \theta_b, \theta_s)$ is a logit-adjusted version of binary cross entropy, as proposed in [80], 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 [103]. This combines better with the auxiliary loss, which can also be cast in terms of cosine similarity. Finally, the objective is given by

$$\min_{\theta_b, \theta_s, \theta_a} L_s(D; \theta_b, \theta_s) + wL_a(D_r; \theta_b, \theta_a),$$

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

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### 4. Experiments

**Auxiliary dataset.** We use the LRW dataset [28] 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 [53], 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 [27], in Section 5.

**Forgery datasets.** We use the following forgery datasets:

1. **FaceForensics++ (FF++)** [94] 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 [99] and NeuralTextures [98]. Unless stated otherwise, we use the mildly compressed version of the dataset (c23). As in [53,94], we take the first 270 frames for each training video, and the first 110 frames for each validation/testing video.

2. **FaceShifter** [67] and (3) **DeeperForensics** [62] 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.

3. **CelebDF-v2** [72] is a challenging face swapping dataset with 518 test videos.

4. **DFDC** is a subset of the Deepfake Detection Challenge Dataset (DFDC) [37] used in [53]. It features 3,215 videos, many of which have been subjected to strong perturbations.

**Evaluation metrics.** Following e.g., [2,53,94,114,117], 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 [53,68,85,114]. In this section, we follow the protocol used in [53,70,85] to evaluate our detector’s ability to generalise to unseen manipulations.
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.

| Method                  | DF   | FS   | F2F  | NT  |
|-------------------------|------|------|------|-----|
| Xception [94]           | 93.9 | 51.2 | 86.8 | 79.7 |
| CNN-aug [105]           | 87.5 | 56.3 | 80.1 | 67.8 |
| Patch-based [19]        | 94.0 | 60.5 | 94.5 | 92.5 |
| Face X-ray [68]         | 99.5 | 93.2 | 94.5 | 92.5 |
| CNN-GRU [95]           | 97.6 | 47.6 | 85.8 | 86.6 |
| LipForensics [53]       | 99.7 | 90.1 | 99.7 | 99.1 |
| AV DFD [117]            | 100  | 90.5 | 99.8 | 98.3 |
| FTCN [114]              | 99.9 | 99.9 | 99.7 | 99.2 |

CSN  98.8  87.9  98.7  88.6
RealForensics (ours)  100  97.1  99.7  99.2

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 [53], (2) heavily constraining the network by freezing large parts [53] or removing spatial convolutions [114], nor (3) using audio at test-time [117]. We also outperform the baseline of training a CSN [101] 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 [72], DFDC [37], FaceShifter [67], and DeeperForensics [62]. 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 [53] to assess robustness to unseen perturbations. As in [53], 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 in [62], 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 [19, 68], and also outperforms LipForensics and FTCN. (We use FTCN’s publicly available model3, 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 performance.
Table 4. Robustness to common corruptions. Average AUC scores (%) across five intensity levels for each corruption type proposed in [62]. 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.

| Method                | Clean | Saturation | Contrast | Block | Noise | Blur | Pixel | Compress | Avg  |
|-----------------------|-------|------------|----------|-------|-------|------|-------|----------|------|
| Xception [94]         | 99.8  | 99.3       | 98.6     | 99.7  | 53.8  | 60.2 | 74.2  | 62.1     | 78.3 |
| CNN-aug [105]         | 99.8  | 99.3       | 99.1     | 95.2  | 54.7  | 76.5 | 91.2  | 72.5     | 84.1 |
| Patch-based [19]      | 99.9  | 84.3       | 74.2     | 99.2  | 50.0  | 54.4 | 56.7  | 53.4     | 67.5 |
| Face X-ray [68]       | 99.8  | 97.6       | 88.5     | 99.1  | 49.8  | 63.8 | 88.6  | 55.2     | 77.5 |
| CNN-GRU [95]          | 99.9  | 99.0       | 98.8     | 97.9  | 47.9  | 71.5 | 86.5  | 74.5     | 82.3 |
| LipForensics [53]     | 99.9  | 99.9       | 99.6     | 87.4  | 73.8  | 96.1 | 95.6  | 95.6     | 92.5 |
| FTCN [114]            | 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 |

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).

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 [88] with a temperature of 0.07. Note that global learning with negatives is similar to cross-modal contrastive learning used in e.g., [76,82]. 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 [23], 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 [48]. 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 [27] for our extra real samples. It con-
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**.

| 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 |

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 [51], including forgery detectors; thus, an important future direction would be to apply methods in calibration literature [51] 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. We hope our study encourages future research on leveraging real faces for robust forgery detection.

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| Method          | Accuracy (%) | AUC (%) |
|-----------------|--------------|---------|
|                | Raw  | c23 | c40 | Raw  | c23 | c40 |
| Xception [94]   | 99.0 | 97.0 | 89.0 | 99.8 | 99.3 | 92.0 |
| CNN-aug [105]   | 98.7 | 96.9 | 81.9 | 99.8 | 99.1 | 86.9 |
| Patch-based [19] | 99.3 | 92.6 | 79.1 | 99.9 | 97.2 | 78.3 |
| Two-branch [79]  | —   | —   | —   | 99.1 | 91.1 | —   |
| Face X-ray [68]  | 99.1 | 78.4 | 34.2 | 99.8 | 97.8 | 77.3 |
| CNN-GRU [95]    | 98.6 | 97.0 | 90.1 | 99.9 | 99.3 | 92.2 |
| LipForensics [53]| 98.9 | 98.8 | 94.2 | 99.9 | 99.7 | 98.1 |
| FTCN [114]      | 99.1 | —   | —   | 99.8 | 98.3 | —   |

RealForensics (ours) | 99.3 | 99.1 | 96.1 | 99.9 | 99.8 | 99.5 |

Table 7. In-distribution performance. Accuracy and AUC scores on the test set of FaceForensics++ (FF++) after training on FF++. We repeat experiments for the dataset’s three compression types: raw (no compression), c23 (mild compression), and c40 (strong compression). Best results are in bold.

| Method          | Accuracy (%) | AUC (%) |
|-----------------|--------------|---------|
|                | ForgeryNet | Ours | LipForensics [53] | FTCN [114] |
|                |            | 71.8  | 66.7  | 57.3   |

Table 8. Generalisation to ForgeryNet. AUC scores (%) on the test set of ForgeryNet after training on FF++. Best results are in bold.

A. More Experiments

A.1. In-distribution performance

Although our approach has been developed for cross-manipulation generalisation and robustness, for completeness we present results for in-distribution performance in Table 7. For each compression level (raw, c23, c40), we train on the training set and show results on the corresponding test set. We are on par with the state-of-the-art in the no/low compression regime, while outperforming the other methods on the more compressed data.

A.2. Generalisation to ForgeryNet

In Table 8, we provide results on generalisation performance to the newly-released ForgeryNet dataset [56]. We compare our model with the publicly-available LipForensics and FTCN models (all trained on FF++). RealForensics significantly outperforms both.

A.3. Detailed analysis of robustness

Following [53], we present more detailed results on robustness by plotting AUC as a function of corruption severity (see Figure 7). On average, RealForensics deteriorates less abruptly as severity increases than other methods, with especially noteworthy results on video compression, which is ubiquitous on social media. We also highlight our significantly higher results over LipForensics on block-wise...
A clean frame from a real FaceForensics++ video along with the same frame but corrupted with various perturbations. For more information on this set of corruptions, see [62].

![Examples of corruptions](image)

Table 9. **Full face versus mouth.** Accuracy and AUC scores when training on full faces and mouth crops. We test on FaceShifter (FSh) and DeeperForensics (DFo) after training on FaceForensics++ (FF++). We also test on FaceSwap (FS) after training on the remaining three FF++ types. Best results are in **bold**. Default setting is **highlighted**.

| Crop       | Acc (%) | AUC (%) |
|------------|---------|---------|
|            | FSh     | DFo     | FS      |
| Full face  | 97.1    | 97.1    | 97.1    |
| Mouth      | 95.5    | 95.0    | 88.9    |

Table 10. **Effect of clip size.** Accuracy (%) as a function of the clip size. We test on FaceShifter and DeeperForensics after training on FaceForensics++. Best results are in **bold**.

| Clip size (# frames) | 5   | 10  | 15  | 20  | 25  | 30  |
|----------------------|-----|-----|-----|-----|-----|-----|
| DeeperForensics      | 88.2| 95.0| 96.1| 96.4| 97.1| 97.4|
| FaceShifter          | 87.9| 93.4| 95.4| 95.7| 97.1| 96.7|

Table 11. **Backbones.** Accuracy scores (%) on FaceShifter (FSh) and DeeperForensics (DFo) after training on FaceForensics++. We show results for two different backbones. Best results are in **bold**. Default setting is **highlighted**.

| Backbone               | FSh | DFo |
|------------------------|-----|-----|
| CSN                    | 97.1| 97.1|
| ResNet+MS-TCN          | 94.0| 95.7|

Distortions (i.e., occlusions), which are likely influenced by our method’s use of the whole face rather than solely the mouth. For example, in some cases the mouth may be occluded while other parts of the face are not.

**A.4. More ablations**

**Full face versus mouth.** In the main text, we argue that focusing only on the mouth region, like LipForensics [53], may be suboptimal for performance. We validate this by training (for both stages 1 and 2) on mouth crops and comparing the performance with the default setting. As shown in Table 9, our method consistently benefits from using the full face rather than the mouth, which was not observed for LipForensics [52]. This may be due to the cross-modal prediction task being more general than lipreading. For example, the video network is encouraged to retain information about the eyes to better model expression (which correlates with audio); on the other hand, a model trained to perform lipreading may focus predominantly on the mouth region.

**Effect of clip size.** Table 10 shows the effect on generalisation when changing the video clip size (default is 25 frames per clip). We observe that generalisation improves with clip size, up to a point.

**Different backbone.** Our default video backbone is a CSN network [101]. In Table 11 we also show generalisation results for ResNet+MS-TCN [78], used in [53]. We significantly outperform LipForensics with the same backbone and auxiliary dataset (compare with Table 3 in the main text), without requiring any auxiliary labels.

**Projector and predictor.** We propose in the main text to use a single linear layer as our projector and a shallow transformer as the predictor. In Table 12, we show generalisation results when using different types of projectors/predictors. Since we output dense representations, the linear layers in the MLPs can be thought of as convolutional layers with kernel size 1. We use a learning rate of $3 \times 10^{-4}$ when employing MLP predictors, as we found it to perform best in that setting.

Notably, we observe that using a transformer improves results over the MLP variant. This suggests that allowing the predictor to model temporal dynamics can benefit representation learning for our task. Further, in Table 13 we show results for a 1-block and a 2-block transformer predictor. We find that the 1-block variant performs slightly better.

**Different contrastive baselines.** As mentioned in the main text, self-supervised methods that aim to learn representations for lipreading tend to contrast samples from the same video to achieve invariance to identity [4, 29, 30]. Here, instead of our proposed non-contrastive approach, we apply the strategy of the audiovisual method Perfect Match [30] for stage 1 of our method. For fair comparison, we use the same backbones as for RealForensics. We follow the instructions from the paper for implementation. In particular, the inputs to the video and audio backbones
Figure 7. **Robustness to unseen perturbations.** AUC scores (%) on FaceForensics++ samples which have been corrupted by various unseen perturbations of varying severity. We also present the average scores across all perturbations. All methods were trained on FF++ without these corruptions. To avoid visual clutter in the plots, we show results for five representative methods. For more results, see [53] and [114].

Table 12. **Projector and predictor.** We test different types of projectors and predictors for the representation learning stage of our method (stage 1), and see how generalisation to FaceShifter (FSh) and DeeperForensics (DFo) is affected after training on FaceForensics++. Refer to subsection “Projector and predictor” for a discussion. Best results are in **bold**. Default setting is highlighted.

| Settings       | Accuracy (%) | FSh | DFo |
|----------------|--------------|-----|-----|
| Projector      | Predictor    | FSh | DFo |
| Linear         | MLP          | 91.8| 92.9|
| Linear Transformer | 97.1         | 97.1|
| MLP            | MLP          | 96.1| 97.5|
| MLP            | Transformer  |     |     |

Table 13. **Number of transformer blocks.** Accuracy scores (%) on FaceShifter (FSh) and DeeperForensics (DFo) after training on FaceForensics++. We show results for a 1-block and a 2-block transformer predictor. Best results are in **bold**. Default setting is highlighted.

| # blocks | FSh | DFo |
|----------|-----|-----|
| 1        | 97.1| 97.1|
| 2        | 96.8| 96.4|

Table 14. **Different contrastive baselines.** Accuracy scores (%) on FaceShifter (FSh) and DeeperForensics (DFo) after training on FaceForensics++. We show results by employing the learning strategy of Perfect Match [30] (PMatch) for stage 1 of our method. We also use a symmetrised version of Perfect Match, which we call PMatch++. Best results are in **bold**.

| Method      | FSh | DFo |
|-------------|-----|-----|
| PMatch      | 91.4| 87.9|
| PMatch++    | 91.8| 90.2|
| RealForensics (ours) | **97.1** | **97.1** |

are 5-frame video clips and 20-frame log mel spectrograms. Each network yields a single feature (via a temporal pooling layer). Then, for a single video feature, a contrastive loss is employed to match it to its aligned audio feature while repelling misaligned ones from the same video. We found that symmetrising this loss by additionally adding the loss corresponding to the reversal of the roles of the video and audio features yielded improvements; we refer to this variant as Perfect Match++. The results in Table 14 suggest that our proposed method, which does not target identity invariance, is better suited for forgery detection.

**Visual-only representation learning.** Although it is natu-
Table 15. **Visual versus audiovisual representation learning.** Accuracy scores (%) on FaceShifter (FSh) and DeeperForensics (DFo) after training on FaceForensics++. We compare visual-only with audiovisual representation learning (using BYOL-style training) for stage 1 of our method. Best results are in **bold**. Default setting is **highlighted**.

| Type          | FSh | DFo |
|---------------|-----|-----|
| Visual        | 92.9 | 89.7 |
| Audiovisual   | **97.1** | **97.1** |

B. Further Implementation Details

B.1. Preprocessing

We use RetinaFace [36]⁴ for face detection and a 2-D FAN network [14]⁵ to extract 68 facial landmarks. For each frame, we take the mean landmarks around a 12-frame window to reduce motion jitter and then affine warp to LRW’s mean face based on eight stable points.

B.2. Dataset details

We provide further details on the used datasets. The licenses of all datasets permit their use for research purposes.

**FaceForensics++ [94]** (FF++). We use the dataset from the official webpage⁶. We use the provided train/validation/test splits, which include 720 training, 140 validation, and 140 test videos, respectively.

**FaceShifter [67]**. We use the dataset (at compression c23) from the FF++ webpage. Its real videos come from FF++. Note that we do not treat FaceShifter as part of FF++, consistent with the original paper [94].

**DeeperForensics [62]**. We use the dataset from the official webpage⁷. Its real videos also come from FF++ c23.

**CelebFD-v2 [72]**. We use the dataset from the official webpage⁸.

**DFDC [37]**. We use a subset of the dataset from the official webpage⁹. This subset was used in [53] and features single-subject videos for which the face and landmark detectors did not fail (since many videos have been subjected to extreme perturbations).

B.3. Architecture and training details

**Supervised loss details.** As described in Section 3.2 of the main text, we use a cosine classifier for our supervised head and also employ logit adjustment [80] to address data imbalance. Given the (average-pooled) output \( e \) of the backbone network and the weight vector \( w \) of the supervised head’s linear layer, the normalised score of a sample’s “fakeness” during training is given as

\[
p = \frac{1}{1 + e^{-\left(\frac{w^T e + \log \frac{\pi}{1 - \pi}}{\sqrt{\|w\|^2 + \|e\|^2}}\right)}}.
\]

where \( s = 64 \) scales the cosine similarity, as in e.g., [103], and \( \pi \) is the prior probability of a sample being fake, as described in [80]. We set \( \pi \) to be the ratio of fake samples to the batch size. We found using cosine similarity (i.e., normalising the feature and weight vectors) yielded slight improvements; the ablation on logit adjustment is given in Table 5 of the main text. The supervised loss \( L_s(D; \theta_b, \theta_s) \), introduced in Section 3.2 of the main text, is simply the standard binary cross entropy acting on these scores.

**Random masking.** We apply random erasing to video frames with probability 0.5, scale of (0.02, 0.33), and ratio of (0.3, 3.3). Moreover, we randomly erase a random number of video frames, ranging from 0 to 12, a random number of audio frames, ranging from 0 to 48, and a random number of mel filters, ranging from 0 to 27. This is applied with probability 0.5.

**Backbones.** Our video backbone is a modified Channel-Separated Convolutional Network (CSN) [101], chosen for its high accuracy in video action recognition [101] in conjunction with its relatively low parameter count. Unlike the original architecture, we set the temporal strides to 1 for all layers, thus preserving the temporal dimension. See Table 16 for more information.

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⁴https://github.com/blubug6/Pytorch_Retinaface  
⁵https://github.com/ladriahb/face-alignment  
⁶https://github.com/ondyari/FaceForensics  
⁷https://github.com/EndlessSora/DeepForensics-1.0/tree/master/perturbation  
⁸https://github.com/yuezunli/celeb-deepfakeforensics  
⁹https://ai.facebook.com/datasets/dfdc
Our audio backbone is a ResNet18 [55]. We modify the temporal strides to match the output size of the video backbone. In particular, the stem subsamples the temporal dimension by 4, after which no further temporal subsampling is performed. See Table 17 for more information.

Details on MLPs used in ablations. In the ablations where we use MLPs for the projector and/or predictor, we follow the design proposed in [22], as we found it to perform well. Thus, the projector MLP has 3 layers with hidden dimension 2048, and each layer is followed by batch normalisation (BN); the output layer has no ReLU activation. The predictor MLP has 2 layers with hidden dimension 512 and output dimension 2048, and the output layer has no BN nor ReLU.

Further details on contrastive experiments. We provide more details on the experiments with contrastive learning given in Table 6 of the main text. For dense representation learning, the output of the network consists of 25 embeddings (one for each video frame); we select a random embedding to add to the queue of negative samples. We also use shuffling batch normalisation to prevent the network from cheating on the pretext task [54].

C. Visualisation

We use occlusion sensitivity analysis [110] for visualisation, as in [53]. We systematically occlude, in a sliding-window fashion, parts of the video via random erasing of size $40 \times 40 \times T$ (where $T$ is the number of frames). We record for each occluded pixel the effect that the occlusion has on the model predictions. A heatmap is produced by averaging the output probabilities for each pixel. After normalisation, we overlay the heatmap on the first video frame. We show examples for FaceForensics++ in Figure 8. We see that for NeuralTextures and Face2Face (first two examples), which modify expressions, our network usually focuses on the mouth region. On the face-swapping types, we observe that sometimes the network focuses on the mouth and sometimes on other facial regions.

Table 16. Video backbone architecture. The architecture of the modified CSN [101] network that we employ for the video backbone. The layers in the bottleneck blocks, shown in brackets, use depthwise convolutions. Next to the brackets we give the number of times the blocks are repeated in each stage. The output size is of the form $T \times H \times W$, where $T$ denotes time, $H$ height, and $W$ width. Note that differently from the original architecture [101], we do not subsample the temporal dimension at any stage and also only use spatial pooling at the end, rather than spatio-temporal, since we employ dense learning.

| stage | filters | output size |
|-------|---------|-------------|
| conv  | $7 \times 7$, stride $2 \times 2$ | $50 \times 40$ |
| pool  | max, $3 \times 3$, stride $2 \times 2$ | $25 \times 20$ |
| res1  | $[3 \times 3, 64]$, stride $2$ | $25 \times 20$ |
| res2  | $[3 \times 3, 128]$, stride $2$ | $25 \times 10$ |
| res3  | $[3 \times 3, 256]$, stride $2$ | $25 \times 5$ |
| res4  | $[3 \times 3, 512]$, stride $2$ | $25 \times 2$ |

Table 17. Audio backbone architecture. The architecture of our modified ResNet18 [55] network that we employ for the audio backbone. The layers in a residual blocks are in brackets, next to which we give the number of times the blocks are repeated in each stage. The output size is of the form $T \times F$, where $T$ denotes time and $F$ mel filters. Note that differently from the original architecture [55], we do not subsample the temporal dimension at any stage and also only use mel frequency pooling at the end, since we employ dense learning.

| stage | filters | output size |
|-------|---------|-------------|
| conv1 | $3 \times 7 \times 7$, stride $1 \times 2 \times 2$ | $25 \times 56 \times 56$ |
| pool1 | max, $1 \times 3 \times 3$, stride $1 \times 2 \times 2$ | $25 \times 28 \times 28$ |
| res1  | $[1 \times 1, 1, 256]$, stride $3 \times 3 \times 3, 64$ | $25 \times 28 \times 28$ |
| res2  | $[1 \times 1, 1, 512]$, stride $3 \times 3 \times 3, 128$ | $25 \times 14 \times 14$ |
| res3  | $[1 \times 1, 1, 1024]$, stride $3 \times 3 \times 3, 256$ | $25 \times 7 \times 7$ |
| res4  | $[1 \times 1, 1, 2048]$, stride $3 \times 3 \times 3, 512$ | $25 \times 4 \times 4$ |
| pool2 | global frequency average pool | $25 \times 1 \times 1$ |