A FACE PREPROCESSING APPROACH FOR IMPROVED DEEPFAKE DETECTION

A PREPRINT

Polychronis Charitidis  Giorgos Kordopatis-Zilos  Symeon Papadopoulos  Ioannis Kompatsiaris
Information Technologies Institute, CERTH, Thessaloniki, Greece
{charitidis,georgekordopatis,papadop,ikom}@iti.gr

June 15, 2020

ABSTRACT

Recent advancements in content generation technologies (also widely known as DeepFakes) along with the online proliferation of manipulated media and disinformation campaigns render the detection of such manipulations a task of increasing importance. There are numerous works related to DeepFake detection but there is little focus on the impact of dataset preprocessing on the detection accuracy of the models. In this paper, we focus on this aspect of the DeepFake detection task and propose a preprocessing step to improve the quality of training datasets for the problem. We also examine its effects on the DeepFake detection performance. Experimental results demonstrate that the proposed preprocessing approach leads to measurable improvements in the performance of detection models.

Keywords  DeepFake Detection · Preprocessing · Convolutional Neural Networks

1 Introduction

The latest advances in synthetic media manipulation have reached a point where significant concerns are raised with respect to new risks and threats posed for society and democracy. Although the ability to generate or manipulate facial cues using artificial intelligence could have positive applications for humanity [1, 2] (e.g. cinematography, art, video games, face anonymization), there are several cases where its applications pose serious risks to individuals, communities and the society as a whole.

More specifically, the term “DeepFake” is referring to a deep learning based method able to tamper media by swapping the face between two people, and initially appeared in 2017 when a machine learning algorithm was used to transpose celebrity faces into porn videos. Apart from pornography, some of the most harmful usages of such technology include its use in the context of online disinformation campaigns and attempts of financial fraud. Recently, the term “DeepFake” has become synonymous with most types of facial and/or audio manipulation. Such manipulations usually include face swap, face generation from scratch, facial attribute manipulation, and facial expression manipulation or facial reenactment [3]. Figure 1 illustrates real faces and their corresponding DeepFake manipulations. The number of malicious uses of such manipulations largely dominates the positive ones [4].

The harmful effects of DeepFakes are widely acknowledged in the research community and lately a lot of efforts has been made towards improving forgery detection in media. There have been numerous methods proposed to detect DeepFakes [6, 7, 8, 9, 10, 11, 12, 13, 14, 15]. Such methods leverage recent advances in deep learning, like the ability to automatically learn rich features with Convolutional Neural Networks (CNNs). Usually the detection problem is treated by training a neural network in a supervised fashion. To distinguish DeepFake from authentic media, these methods are often trained by extracting and using only the face region instead of using the whole image or keyframe as input.

Deep learning approaches for DeepFake detection require the availability of large scale datasets. There are numerous DeepFake datasets and the field is progressing rapidly. Besides academic contributions, even large companies like

arXiv:2006.07084v1 [cs.CV] 12 Jun 2020
Google, contribute to DeepFake detection research by providing face manipulation datasets \cite{16}. Recently, Facebook in collaboration with other companies and academic institutions such as Microsoft and others launched a Kaggle challenge named the DeepFake Detection Challenge\cite{5} (DFDC). The DFDC offers $1,000,000 total prize, which is an indication of the importance that major stakeholders attribute to this task.

Despite the rapid progress in DeepFake detection and dataset availability, there has been very little focus on the preprocessing step of these datasets and how this affects the performance of the resulting DeepFake detection models. Preprocessing includes all transformations that are performed on the raw data before they are inserted to a detection model for training or inference. In terms of videos, such transformations usually include frame extraction, image normalization and resizing, image augmentation, and face extraction.

The frame extraction process is required in order to transform video to image format that can be used by detection models. The image normalization is a typical process that is employed in most deep learning methods and depends on the task and classification architecture. In a deep learning setup, image normalization often occurs inside the model architecture. Augmentation is another standard process that is found to improve the robustness and accuracy in various classification tasks. The face extraction process is optional, but it empirically demonstrates a significant increase in terms of detection performance \cite{7}. The common practice in this step is to use a pretrained face detector that detects every depicted face in an image or video frame and is used to extract the face region information.

In this work, we focus on the face extraction process, which is important for building accurate DeepFake detectors. A face detector with large number of false positives will potentially generate a noisy dataset and this might hurt the overall DeepFake detection accuracy. Consequently, a DeepFake detector’s performance depends heavily on the accuracy of the face detection model. After experimenting with various face detectors, we noticed that they produce false positives in many cases. Many of these detectors provide options for detection confidence and further manual tuning of their parameters to slightly improve their performance, but manual tuning is time consuming and each dataset requires different tuning settings. To this end, we propose a simple and universal preprocessing approach that can be applied after the face extraction step and efficiently remove a large amount of false positive images.

The rest of the paper is organised as follows. Section\textcolor{red}{2} presents a review of the DeepFake detection task, lists the most popular DeepFake detection approaches, datasets and preprocessing schemes. In Section\textcolor{red}{3} we present a baseline DeepFake detection pipeline, which includes a preprocessing procedure. We propose an approach to reduce false detections in the preprocessing step in Section\textcolor{red}{4}. Section\textcolor{red}{5} presents the experiments and results of our study. Finally, in Section\textcolor{red}{6} we conclude the paper and outline some future steps.
Figure 2: Baseline DeepFake detection pipeline.

Table 1: DeepFake datasets

| Dataset                  | Year | # Real / Fake |
|--------------------------|------|---------------|
| UADFV [19]               | 2019 | 49 / 49       |
| DeepFakeTIMIT [21]       | 2018 | - / 620       |
| FaceForensics++ [17]     | 2019 | 1,000 / 4,000 |
| DFD [16]                 | 2019 | 363 / 3,068   |
| Celeb-DF [22]            | 2019 | 408 / 795     |
| DFDC Preview Dataset [23]| 2019 | 1,131 / 4,113 |
| DFDC [5]                 | 2019 | 19,154 / 100,000 |
| DeeperForensics-1.0 [24] | 2020 | 50,000 / 10,000 |

2 Related Work

2.1 DeepFake detection

With the advent of deep learning most classification tasks employ deep learning architectures that usually outperform traditional machine learning solutions. Following this trend recent approaches in DeepFake detection use deep learning to distinguish manipulated media.

Work in [6] presents two simple architectures with a small number of layers that exploit mesoscopic features. Meso-4 has four layers of convolutions and pooling and is then followed by a dense network with one hidden layer. MesoInception4 instead is based on a simple variant of the inception module [17]. XceptionNet [18] is proposed as an efficient DeepFake detection architecture in [7]. The same work shows that very deep general-purpose networks outperform shallow CNNs in the detection task, especially in cases where the video compression is high. Work in [8] includes an attention mechanism to increase the detection performance. A capsule-network is presented in [9] which requires fewer parameters to train compared to very deep networks. In [10], the presented approach exploits the fact that current DeepFakes generation methods are able only to generate limited resolution images and detects these artifacts. Works in [19, 20] detect manipulations utilizing head pose and eye blinking information respectively. A more generalizable approach is presented in [11], where an autoencoder-based architecture is proposed in order to adapt to new manipulations with just a few examples. The same approach is used in [12] where it combines the detection and segmentation task to further assist the learning process. Some other works also exploit the temporal information. In [13] a convolutional Long Short Term Memory (LSTM) network is used to exploit temporal dependencies. A recurrent convolutional model has been proposed in [14]. Features are extracted at multiple levels and processed in separate recurrent networks, in order to exploit multilevel features for manipulation detection. In [15] the optical flow is estimated to exploit temporal discrepancies among frames.

2.2 DeepFake datasets

As we mentioned in Section 1 there are 4 different categories of DeepFake manipulations. In this paragraph we mainly present the datasets that are related with face swapping and facial expression manipulation, as they are the ones we focus in this work. UADFV [19] is an initial small-scale dataset employing face swapping. The authors in [21] present DeepFakeTIMIT dataset. This dataset consists of 620 fake videos created using a GAN-based faceswapping algorithm.
Figure 3: Extracted face detection regions from random DFDC videos. Among the detected faces there are cases of false positives. Each row corresponds to different video and the extraction rate is one frame per second.

FaceForensics++ [7] is a popular DeepFake dataset that contains 1000 real videos from YouTube. This dataset provides fake videos using face swapping and face reenactment manipulation techniques. This dataset also supports different video qualities. The Google/Jigsaw also contribute to FaceForensics++ dataset by providing the DeepFake detection dataset (DFD) [16]. Celeb-DF [22] dataset aims to provide face swapping videos of better visual qualities, as previous databases exhibit low visual quality with many visible artifacts. Celeb-DF consists of 408 real videos extracted from Youtube, and 795 fake videos, which were created through a refined version of a public DeepFake generation algorithm. More recently, the DeepFake Detection Challenge (DFDC) [5, 23] first released a preview dataset consisting of 1131 real videos from 66 paid actors, and 4113 fake videos. The complete DFDC dataset was released on 11th of December and contains approximately 20,000 real videos and 100,000 fakes. Although the manipulation algorithms were not revealed, the dataset mainly contains face swapping and facial attributes manipulation videos, and possibly facial expression manipulation videos. The authors in [24] present another DeepFake dataset, comprising of 10,000 fake videos, built using 100 actors and applying various perturbations to better represent a real world scenario. Table 1 lists all available DeepFake datasets.

2.3 Dataset preprocessing

Although many DeepFake detection related works describe the data preprocessing step that is performed, there is very little focus on the impact of this preprocessing step to the final detection model.

To detect manipulations in videos, many works extract the video frames and apply a single face detector on these frames in order to extract the face regions. There are many face detection works available [25, 26, 27, 28] and multiple implementations of them. These implementations mainly differ in accuracy, detection speed and setting availability (e.g. batched detection, detection threshold, etc.). In addition to face detection some other works adopt face tracking or face alignment approaches. For example, the authors in [14] examine the impact of explicit alignment using facial landmarks and implicit alignment that uses a Spatial Transformer Network (STN) [29] in the DeepFake detection task.

In related tasks, works in [30, 31] examine the impact of preprocessing in face recognition. The impact of preprocessing is examined in a more general supervised setup in [32] and the importance of preprocessing for image classification tasks is highlighted in [33]. The importance of augmentation techniques for image related tasks is studied in [34]. Studies among others the impact of input resolution and argues that higher resolution input images lead to better performance in image related tasks.

3 Baseline DeepFake Detection Pipeline

In this Section we describe a baseline approach to build a video DeepFake detection model. Figure 2 shows a schematic representation of such an approach.
Figure 4: Proposed preprocessing step. Images that are similar with each other are connected (solid lines) and form connected components. Dashed lines show images that are not similar with each other. For simplicity we demonstrate the similarity of the images in component 1 with only one image in component 2. Images from components with size less or equal than $N/2$ are removed. Such components are depicted with dashed border

Subsection 2.2 provides an overview of the most popular DeepFake video datasets available. For training and evaluation of a DeepFake detection model one or more of these datasets should be selected. In order to transform the raw videos into a format that can be used by deep learning architectures we apply the steps depicted in the preprocessing block in Figure 2. The first preprocessing step after selecting one or more of these datasets is to extract their frames. The number of frame extraction varies among training and inference processes. Training process requires more frames in order to provide detailed information that will contribute to the learning task. In terms of inference, detection speed is a factor that should be taken under consideration. This means that inference usually uses a subset of the total video frames to make the final prediction.

After extracting the frames the next step is to extract the face regions detected in each frame. In this step face detectors presented in 2.3 can used to detect faces and return the face coordinates in each corresponding frames. Using this information faces images are retrieved. Note that in this step, it is common practice to extract background information along the face region. In 7 multiply the face bounding boxes by a factor of 1.3. The main reason for this is to enable deep learning models detect resolution inconsistencies or other discrepancies between the face and its surroundings.

The final preprocessing step includes various transformations that make the data compatible to the deep learning model and improve the its learning ability and performance. Resizing of face images depending on the deep learning model requirements is one of these transformations. Another important preprocessing transformation is augmentation. Augmentation can prevent over-fitting in training and generally lead to more robust classifiers. Finally, data normalization is another crucial preprocessing task. data normalization in usually debentant on the classification model and different deep learning frameworks use different data normalization approaches.

Following the preprocessing step, the data are ready for training, evaluation or inference. In this baseline detection setup we train state-of-the-art DeepFake detection architectures. Implementation details about training and inference can be found in Section 5. The architectures we employ in this step operate at frame level, meaning that in order to make video predictions on inference, an additional postprocessing step is required to aggregate the individual frame predictions. We experiment with different postprocessing aggregation methods which we will describe in subsection 5.3.

The issue with this preprocessing pipeline is that it depends on the face detection model for the face image generation. Having experimented with multiple face detectors we noticed that the amount of false positive is higher than expected. Of course one can fine-tune the detection settings (e.g increase the detection confidence threshold) to remove false detections, but this process is time-consuming, depends on the examined dataset and runs the risk of removing correctly detected faces. Using the default settings of an implementation 26 of the face detector presented in 26, we extracted the face regions from some random DeepFake Detection Challenge videos. The results are presented in Figure 3. One can observe that among correctly detected faces, there are cases where the face detector failed to detect a human face. False detections usually include random shapes, various human body parts (e.g hands, neck) and regions with small proportion of the face available. Another observation is that usually false detections are not constant across the duration of a video, meaning that they do not appear in every extracted frame.
Figure 5: Example of generated components (right) using the proposed approach. In this example we uniformly extract 10 frames from a DFDC video and apply the face detector from [36] retrieve the faces (left). We use low detection confidence in order to extract noisy images alongside detected faces and illustrate the limitations of our approach. In this case, components that have size greater than 6 are considered to be valid, so the component 2 is incorrectly assumed to be a face and not removed from the dataset.

A large number of false detections can potentially lead to a noisy training dataset. In this work, we operate under the assumption that noisy data will hurt the DeepFake detection model performance. To address this issue, in next Section we propose an additional preprocessing step to clean the dataset by removing incorrectly detected images.

4 Proposed Preprocessing Approach

In this Section we describe the proposed preprosessing step for removing false positive detections. Note that we apply this step after the face extraction step, which is depicted in the preprocessing block in Figure 2.

4.1 Method description

The main intuition behind the proposed approach is the generation of clusters with correct and incorrect detections in order to remove the latter. This intuition is based on the observation that false detections occur randomly throughout the video and they are not repeated in every frame. This means that clusters of incorrect detections will have smaller size than clusters of correctly detected faces. This also implies that the face will be present throughout the video, which is the usual case for DeepFake datasets. We discuss the advantages and limitations of our approach more extensively in the next subsection.

Following this intuition, we employ a face recognition model [36], based on the work presented in [37], in order to compute facial embeddings from extracted images. Embeddings encode the facial information in 512-dimensional vectors. Using the embedding information for each detected face we calculate the similarity between them. Essentially we calculate the dot product between the corresponding embedding vectors. More formally, let \( i, j \in \{1, 2, \cdots, D\} \) where \( D \) is the number of detected faces in \( N \) extracted frames and \( N \leq F \) where \( F \) is the number of the total frames of a video, then the similarity between the \( i \)-th and \( j \)-th detected face is defined as:

\[
S(i, j) = f_w(i)^T \cdot f_w(j)
\]

where \( f_w(\cdot) \) is the embedding function that is applied on any arbitrary face image to extract its facial embedding, and \( S(\cdot, \cdot) \) is the function that assesses the similarity between two provided face images.

We utilize the similarity information between the detected faces to generate clusters. This is accomplished by forming a graph structure. Nodes in the graph correspond to extracted faces or false detections, and nodes \( i, j \) are connected with an edge if \( S(i, j) > \theta \), where \( \theta \) is a defined similarity threshold. After experimenting we set the similarity threshold to 0.8. Figure 4 demonstrates this process. Nodes that have similarity greater than 0.8 are connected with each other (solid line), otherwise there is no edge between nodes (dashed line). After this process is completed the graph will contain different connected components. If there are no false detections we expect the number of this components to be equal to the number of different faces appearing on a video. In cases where there are false detections, these will form an independent connect component. Component 2, which is depicted in Figure 4, is an example of such component. As mentioned above, these connected components will usually contain less nodes than the ones that are formed by correct
detections. This is true in most cases because the face detectors make false detection only in a subset of the extracted frames. After conducting qualitative experiments we found that removing components with size less or equal than \( N/2 \), where \( N \) is the number of the extracted frames, leads to better dataset quality. In the example if \( N = 4 \), then the component 2 which has 2 nodes is removed and only images from component 1 are forwarded to the next step of the preprocessing pipeline.

4.2 Advantages and limitations

The main advantages of the proposed approach are that it is simple to implement and very fast. It can be used on top of the face extraction process and can be applied in combination with any available face detection library. Also from the qualitative results in Figure 6, we can see that our approach can efficiently remove a large amount of false detections. Another advantage of our approach is that it is robust to face movements throughout the video, meaning that it can accurately detect moving faces without the need of face tracking technique. Additionally, the approach can efficiently work for cases where the extracted faces are very few compared to the total video frames, like the inference process.

Furthermore, the embedding information can also be utilized in order to separate the detected faces to clusters of different people’s faces. This functionality is not available by most face detection implementations and usually the returned order takes into account only the detection confidence. This functionality is particularly useful for making separate predictions per face, especially for cases where there is only one manipulated face among many in a video.

There are two main limitations in our approach. The first is that it assumes that faces are present throughout the duration of a video. So, in cases where a person appears only for a small fraction of the video duration then this face will be possibly considered false detection and consequently be removed. This is generally not the case for DeepFake datasets but can certainly be encountered in online manipulated videos. The second limitation is that we consider clusters of small sizes to be false detections. Although this is usually the case, there are cases where the face detector can make the same incorrect detections in every extracted frame. In that case, our approach will incorrectly assume that these components correspond to a correctly detected face. Figure 5 illustrates this case. Although most noisy images form small components like components 3 and 4, component 2 is large enough to be mistakenly considered as a face.

5 Experimental Study

In this Section, we describe the different preprocessing experiments we conducted and explain the training and evaluation strategies we follow. We also provide details about the implemented pipelines and demonstrate the outcomes of this study.

5.1 Preprocessing setup

To examine the impact of preprocessing on the final detection models, we experiment with two different preprocessing approaches.

First, we use the approach described in Section 3. For face detection, we use the MTCNN implementation developed in [36]. We empirically found from qualitative assessments that the proposed preprocessing step provides consistent results with face detection threshold greater than 0.7. For evaluation, we set the detection threshold to 0.9. We choose this value because, it reduces the number of false detections and at the same time mitigates the face information loss. Note that this step is optional and we could have experimented with the default detection threshold which is 0.7. We also
expand the size of a detected bounding box by a factor of 1.3 as reported in [7]. Additionally, we apply augmentation on the extracted images. This includes transformations like: horizontal and vertical flipping, random cropping, rotation, compression, Gaussian and motion blurring, and brightness, saturation and contrast transformation. We use the default data normalization functions as provided in the original implementations for every corresponding detection model.

For the second preprocessing approach, we add the proposed preprocessing step, as described in Section 4, after the face extraction step. We remove images that form connected components with sizes less or equal than $N/2$ where $N$ is the number of extracted frames per video.

### 5.2 Training setup

In this work, we use the DFDC dataset to train DeepFake detection networks. The dataset contains approximately 20,000 real videos and 100,000 fakes. The dataset is provided in 50 folders. Each folder contains videos with various transformations. We use the videos in the first and last folder for validation and the rest for training. To deal with the heavy imbalance among classes, we extract 16 frames from real videos and only 4 from fake ones during preprocessing. We select different frames from a certain video for every epoch.

We experiment with three different deep learning architectures: MesoInception4 [6], which was designed specifically for DeepFake detection, XceptionNet [18], which outperforms other models in [7], and EfficientNet [55] (the EfficientNet-B4 variant), which achieves state-of-the-art performance in most image classification tasks. To transfer the last two architectures to the DeepFake setting, we take the corresponding backbone networks and add two fully connected layers with 512 and 1 neurons respectively. We use the sigmoid activation for the final layer. Except for MesoInception4, the other models are initialized using the Imagenet pretrained weights [38]. For training, we use the Adam optimizer [39] and minimize the Log loss error. Note that the optimization process occurs on image level and not on video level. The batch size is set to 84 for MesoInception4 and 16 for XceptionNet and EfficientNet and we train them for 10 epochs.

### 5.3 Evaluation setup

To examine the impact of the different preprocessing approaches on the trained detection models we evaluate them on the Celeb-DF [22] and FaceForensics++ [7] datasets. Celeb-DF consists of 408 real and 795 fake videos. FaceForensics++ consists of 1000 real videos and 4000 fake videos. To balance the two classes, we randomly subsample the majority class in case of Celeb-DF. For FaceForensics++ we use 1000 real videos and only 1000 fake videos with DeepFakes manipulation, ignoring the other manipulations. For evaluation, we extract one frame per $T/40$ seconds, where $T$ is the video duration. This means that we extract 40 frames per video and run experiments using the detection models that have been trained with the two different preprocessing approaches. For inference we preprocess the data only with the proposed approach and make separate predictions for every detected image in a video. To aggregate these predictions we consider three approaches. a) averaging the individual predictions, b) taking the median prediction, and c) taking the maximum prediction as the final prediction on the video. Finally, we report the aggregated video level Log loss error for each setting.

### 5.4 Experimental results

Figure 6 shows qualitative results extracted from from DFDC videos. Images are extracted from 10 frames per video. We can observe from the extracted images in the left side of the image that non-face images appear among faces. These are removed when using the proposed preprocessing step in the right side. Note that in the last example, using the proposed approach creates three connected components. One corresponds to the face with 10 nodes, the other contains the image of the hand with 1 node, and the last contains a dark object with 5 nodes. In case there was one more incorrect detection of this object then our approach would incorrectly assume that this was a face and these images would have not been removed.

Table 2 presents the quantitative results on the Celeb-DF dataset. Note that the error for a baseline classifier that always predicts 0.5 for each video is 0.693. We notice that EfficientNet-B4 achieves the best performance among all models. MesoInception4 error is close to the 0.5 baseline. This verifies that shallow architectures are not best suited for the DeepFake detection task. In terms of aggregation methods, averaging individual predictions achieved the best performance, followed by the median approach. Taking the maximum proved to be a bad strategy. One possible explanation to this is that real frames that contain severe face movements are considered to be fakes by the models. Models that are trained with the proposed preprocessing approach outperform their baseline preprocessed counterparts by a large margin. The performance gain for the average aggregation method is in the range between [0.033-0.052] in terms of Log loss. In terms of relative performance comparison, models with proposed preprocessing score 5-10% better.
Table 2: Detection results for the Celeb-DF dataset

| Model       | Preprocessing | Aggregation Method | Avg  | Median | Max  |
|-------------|---------------|--------------------|------|--------|------|
| MesoInception4 | baseline      | 0.678              | 0.689| 0.782  |
|             | proposed      | **0.645**          | 0.657| 0.791  |
| XceptionNet | baseline      | 0.562              | 0.571| 0.599  |
|             | proposed      | **0.521**          | 0.528| 0.541  |
| EfficientNet-B4 | baseline  | 0.510              | 0.518| 0.561  |
|             | proposed      | **0.458**          | 0.484| 0.553  |

Table 3: Detection results for the FaceForensics++ dataset

| Model       | Preprocessing | Aggregation Method | Avg  | Median | Max  |
|-------------|---------------|--------------------|------|--------|------|
| MesoInception4 | baseline      | 0.668              | 0.678| 0.765  |
|             | proposed      | **0.633**          | 0.637| 0.701  |
| XceptionNet | baseline      | 0.582              | 0.597| 0.605  |
|             | proposed      | **0.541**          | 0.547| 0.570  |
| EfficientNet-B4 | baseline  | 0.563              | 0.573| 0.592  |
|             | proposed      | **0.497**          | 0.515| 0.712  |

Similar observations can be made about the FaceForensics++ dataset, which are presented in Table 3. The best performing model is still EfficientNet-B4 and averaging the best aggregation strategy. Once again, it is clear that preprocessing has a large impact on the detection models performance, even bigger compared to the Celeb-DF dataset. EfficientNet-B4 with average aggregation strategy, achieves lower error score when it is trained with the proposed approach compared to the baseline trained model. The performance gain is in range [0.035-0.066]. In terms of relative performance comparison, models with proposed preprocessing score 5-12% better.

Taking into account Tables 2 and 3, it is clear that preprocessing is beneficial for the DeepFake detection task and using the proposed preprocessing approach for training DeepFake detection models can result in significant gains in detection performance.

6 Conclusions and Future Work

In this work we studied the impact of preprocessing on DeepFake detection models and we proposed a preprocessing step that improves the dataset quality. We found that preprocessing is important for the detection task and that it boosts model performance, through improving the quality of the generated training set.

For future steps, we plan to experiment with more architectures and datasets. We also plan to study the impact of different preprocessing approaches on the inference and investigate different performance metrics and how they are affected by preprocessing. Additionally, we will focus on improving the proposed preprocessing pipeline, by experimenting with different clustering methods and selecting more optimal thresholds. Finally we will investigate ways to tackle the reported limitations of the proposed approach using additional face detector models and provide ensemble detections as an extra verification step.

Acknowledgments

This work has been supported by the WeVerify project, partially funded by the European Commission under contract number 825297.

References

[1] Forbes, “Why deepfakes are a net positive for humanity.” [Online]. Available: https://www.forbes.com/sites/simonchandler/2020/03/09/why-deepfakes-are-a-net-positive-for-humanity/
[2] MIT Technology Review, “Deepfakes could anonymize people in videos while keeping their personality.” [Online]. Available: https://www.technologyreview.com/2019/09/17/132994/ai-deepfakes-anonymizes-faces-in-videos-photos/

[3] R. Tolosana, R. Vera-Rodriguez, J. Fierrez, A. Morales, and J. Ortega-Garcia, “Deepfakes and beyond: A survey of face manipulation and fake detection,” arXiv preprint arXiv:2001.00179, 2020.

[4] Deeptrace, “The State Of Deepfakes: Landscape, Threats and Impact.” [Online]. Available: https://deeptracelabs.com/resources/

[5] Kaggle, “Deepfake detection challenge.” [Online]. Available: https://www.kaggle.com/c/deepfake-detection-challenge

[6] D. Afchar, V. Nozick, J. Yamagishi, and I. Echizen, “Mesonet: a compact facial video forgery detection network,” in 2018 IEEE International Workshop on Information Forensics and Security (WIFS). IEEE, 2018, pp. 1–7.

[7] A. Rossler, D. Cozzolino, L. Verdoliva, C. Riess, J. Thies, and M. Nießner, “Faceforensics++: Learning to detect manipulated facial images,” in Proceedings of the IEEE International Conference on Computer Vision, 2019, pp. 1–11.

[8] J. Stehouwer, H. Dang, F. Liu, X. Liu, and A. Jain, “On the detection of digital face manipulation,” arXiv preprint arXiv:1910.01717, 2019.

[9] H. H. Nguyen, J. Yamagishi, and I. Echizen, “Capsule-forensics: Using capsule networks to detect forged images and videos,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 2307–2311.

[10] Y. Li and S. Lyu, “Exposing deepfake videos by detecting face warping artifacts,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, 2019, pp. 46–52.

[11] D. Cozzolino, J. Thies, A. Rössler, C. Riess, M. Nießner, and L. Verdoliva, “Forensictransfer: Weakly-supervised domain adaptation for forgery detection,” arXiv preprint arXiv:1812.02510, 2018.

[12] H. H. Nguyen, F. Fang, J. Yamagishi, and I. Echizen, “Multi-task learning for detecting and segmenting manipulated facial images and videos,” arXiv preprint arXiv:1906.06876, 2019.

[13] D. Güera and E. J. Delp, “Deepfake video detection using recurrent neural networks,” in 2018 15th IEEE International Conference on Advanced Video and Signal Based Surveillance (AVSS). IEEE, 2018, pp. 1–6.

[14] E. Sabir, J. Cheng, A. Jaiswal, W. AbdAlmageed, I. Masi, and P. Natarajan, “Recurrent convolutional strategies for face manipulation detection in videos,” Interfaces (GUI), vol. 3, p. 1, 2019.

[15] I. Amerini, L. Galteri, R. Caldelli, and A. Del Bimbo, “Deepfake video detection through optical flow based cnn,” in Proceedings of the IEEE Conference on Computer Vision Workshops, 2019, pp. 0–0.

[16] Google AI Blog, “Contributing Data to Deepfake Detection Research.” [Online]. Available: https://ai.googleblog.com/2019/09/contributing-data-to-deepfake-detection.html

[17] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke, and A. Rabinovich, “Going deeper with convolutions,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 1–9.

[18] F. Chollet, “Xception: Deep learning with depthwise separable convolutions,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 1251–1258.

[19] X. Yang, Y. Li, and S. Lyu, “Exposing deep fakes using inconsistent head poses,” in ICASSP 2019-2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2019, pp. 8261–8265.

[20] Y. Li, M.-C. Chang, and S. Lyu, “In ictu oculi: Exposing ai created fake videos by detecting eye blinking,” in 2018 IEEE International Workshop on Information Forensics and Security (WIFS). IEEE, 2018, pp. 1–7.

[21] P. Korshunov and S. Marcel, “Deepfakes: a new threat to face recognition? assessment and detection,” arXiv preprint arXiv:1812.08685, 2018.

[22] Y. Li, X. Yang, P. Sun, H. Qi, and S. Lyu, “Celeb-df: A new dataset for deepfake forensics,” arXiv preprint arXiv:1909.12962, 2019.

[23] B. Dolhansky, R. Howes, B. Pflaum, N. Baram, and C. C. Ferrer, “The deepfake detection challenge (dfdc) preview dataset,” arXiv preprint arXiv:1910.08854, 2019.

[24] L. Jiang, W. Wu, R. Li, C. Qian, and C. C. Loy, “Deepforensics-1.0: A large-scale dataset for real-world face forgery detection,” arXiv preprint arXiv:2001.03024, 2020.
[25] D. E. King, “Dlib-ml: A machine learning toolkit,” *Journal of Machine Learning Research*, vol. 10, pp. 1755–1758, 2009.

[26] K. Zhang, Z. Zhang, Z. Li, and Y. Qiao, “Joint face detection and alignment using multitask cascaded convolutional networks,” *IEEE Signal Processing Letters*, vol. 23, no. 10, pp. 1499–1503, 2016.

[27] V. Bazarevsky, Y. Kartymnik, A. Vakunov, K. Raveendran, and M. Grundmann, “Blazeface: Sub-millisecond neural face detection on mobile gpus,” *arXiv preprint arXiv:1907.05047*, 2019.

[28] J. Deng, J. Guo, Y. Zhou, J. Yu, I. Kotsia, and S. Zafeiriou, “Retinaface: Single-stage dense face localisation in the wild,” *arXiv preprint arXiv:1905.00641*, 2019.

[29] M. Jaderberg, K. Simonyan, A. Zisserman *et al.*, “Spatial transformer networks,” in *Advances in neural information processing systems*, 2015, pp. 2017–2025.

[30] I. Masi, S. Rawls, G. Medioni, and P. Natarajan, “Pose-aware face recognition in the wild,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 4838–4846.

[31] I. Masi, A. T. Tran, T. Hassner, G. Sahin, and G. Medioni, “Face-specific data augmentation for unconstrained face recognition,” *International Journal of Computer Vision*, vol. 127, no. 6-7, pp. 642–667, 2019.

[32] S. Kotsiantis, D. Kanellopoulos, and P. Pintelas, “Data preprocessing for supervised leaning,” *International Journal of Computer Science*, 2006.

[33] K. K. Pal and K. Sudeep, “Preprocessing for image classification by convolutional neural networks,” in *2016 IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)*. IEEE, 2016, pp. 1778–1781.

[34] C. Shorten and T. M. Khoshgoftaar, “A survey on image data augmentation for deep learning,” *Journal of Big Data*, vol. 6, no. 1, pp. 1–48, 2019.

[35] M. Tan and Q. Le, “Efficientnet: Rethinking model scaling for convolutional neural networks,” in *International Conference on Machine Learning*, 2019, pp. 6105–6114.

[36] timesler, “facenet-pytorch.” [Online]. Available: https://github.com/timesler/facenet-pytorch

[37] F. Schroff, D. Kalenichenko, and J. Philbin, “Facenet: A unified embedding for face recognition and clustering,” in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2015, pp. 815–823.

[38] O. Russakovsky, J. Deng, H. Su, J. Krause, S. Satheesh, S. Ma, Z. Huang, A. Karpathy, A. Khosla, M. Bernstein *et al.*, “Imagenet large scale visual recognition challenge,” *International journal of computer vision*, vol. 115, no. 3, pp. 211–252, 2015.

[39] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” *arXiv preprint arXiv:1412.6980*, 2014.