Detecting Forged Facial Videos Using Convolutional Neural Networks

1st Neil Sambhu  
Computer Science and Engineering Department  
University of South Florida  
Tampa, United States  
sambhu@mail.usf.edu

2nd Shaun Canavan  
Computer Science and Engineering Department  
University of South Florida  
Tampa, United States  
scanavan@usf.edu

Abstract—In this paper, we propose to detect forged videos, of faces, in online videos. To facilitate this detection, we propose to use smaller (fewer parameters to learn) convolutional neural networks (CNN), for a data-driven approach to forged video detection. To validate our approach, we investigate the FaceForensics public dataset detailing both frame-based and video-based results. The proposed method is shown to outperform current state of the art. We also perform an ablation study, analyzing the impact of batch size, number of filters, and number of network layers on the accuracy of detecting forged videos. Index Terms—deepfake, convolutional neural network, videos, deep learning

I. INTRODUCTION

In recent years there has been tremendous progress in manipulating videos, which includes real-time generation, use of audio to synthesize videos, and animating static images. This can undermine applications of biometrics, affective computing, and forms of digital communication such as social media videos and teleconferences. Considering this, we propose a solution to detect forged (i.e. fake) facial videos, using convolutional neural networks (CNN) that are much smaller (fewer parameters to learn) than the current state-of-the-art solutions. The use of smaller networks has the advantage of having less parameters while still being able to learn complex functions similar to deeper networks [1].

Detecting fake facial videos can broadly be categorized into 3 categories (physical, signal, and data-driven). Physical approaches tend to focus on features of the face such as eye blinking and head pose. Li et al. [2] used a combination of CNNs and long-term recurrent CNNs to analyze eye blinks. They show that blinking is not well represented in the fake videos, which their proposed network takes advantage of for detection. Yang et al. [3] used a Support Vector Machine (SVM) along with 3D head pose to detect fake face videos. They found that the landmark locations between the original and fake videos differ, due to the synthesis methods used to create the fake videos. For synthesizing videos, Suwajanakorn et al. [4] investigated synthesizing video from audio around the mouth region. They note that there can be inconsistencies between the lips and speech as they may not be synchronized, resulting in an area of the face for analysis of fake videos (i.e. the mouth can be used, similar to eye blinking). Agarwal et al. [5] captured behavioral patterns, from 2D facial landmarks, of individuals to detect deepfake videos. From these landmarks, they investigate the occurrence and intensity of Facial Action Units [6], training an SVM, with this data, to detect fake video sequences.

Signal-based approaches tend to focus on artifacts that are introduced during the deepfake synthesis (creation) phase. Matern et al. [7] showed that visual artifacts such as changes in eye color can be reliably exploited to detect fake videos. They characterize the differences in eye color based on the HSV color space, which is used along with a bagged version of k-nearest neighbors, to detect fake face videos. Li et al. [8], developed an approach motivated by the idea that deepfake generation algorithms have a limited resolution and require warping. They showed that CNNs can capture this information to distinguish between fake and real videos.

Data-driven approaches are generally simpler in that they don’t look for specific artifacts but focus on large amounts of training data that contain both real and deepfake data. Guera et al. [9] used convolutional neural networks (CNNs) to extract frame-level features which are then used to train a recurrent neural network to detect whether a video has been manipulated or not. They show that their proposed approach can detect fake vs. real videos with less than 2 seconds of data. Nguyen et al. [10] used capsule networks [11] to detect forged videos that include replay attacks [12], as well as computer generated (e.g. Generative Adversarial Networks [13]). They showed that by adding random Gaussian noise to their network, then can improve the detection accuracy.

The proposed approach to detecting forged facial videos can be categorized as data-driven and is motivated by the works detailed here.

Since 2019, new works have showcased various means of improving deepfake detection. Wang et al. described how features extracted from the frequency domain are spatially irrelevant [14]. The Spatial-Frequency Dynamic Graph method uses dynamic graph learning to exploit features in the spatial and frequency domains. Dong et al. showed how binary classifiers overfit by learning the identity of images [15]. ID-unaware Deepfake Detection Model uses “in dataset” and “cross dataset” images to enforce generalizability. Cozzolino et al. explained how deepfake forgery detection mostly learns...
to detect a specific fake method [16]. ID-Reveal learns how a person moves while talking and trains only on real videos. Using high-level semantic features provides robustness to low-quality videos. Zhou et al. described how exploiting the synchronization of visual and auditory modalities could benefit deepfake detection [17]. Nirkin et al. exemplified how deepfake detection can include separating the face from the body surrounding the face [18]. Zhao et al. described how deepfake detection as a binary classification problem omits the subtle and local differences between real and fake images [19]. Spatial attention heads make the network extract features from different parts of the face; the detection method zooms in and combines features at high and low levels. These works from 2021 through 2023 showcase more detailed methods of deepfake detection than simply refining the structure of a convolutional neural network.

Our main contributions are 3-fold and can be summarized as follows:

1. A CNN that has fewer parameters to learn is proposed to detect fake face videos. We report frame- and video-level results.
2. Proposed network outperforms current state of the art on the FaceForensics [20] dataset.
3. Details on the impact of batch size, number of filters, and number of network layers (i.e. ablation study) on the accuracy of detecting fake face videos are given.

II. EXPERIMENTAL DESIGN

To detect fake face videos, we propose to use a convolutional neural network (CNN) that is smaller (i.e. less parameters to learn) compared to other state-of-the-art works for detecting fake face videos [20]. To evaluate our proposed CNN, we conduct experiments on the publicly available FaceForensics datasets [20]. Details on our proposed network architecture and this dataset are given in the following subsections.

A. Convolutional Neural Network Architecture

Our proposed CNN, has 5 layers with 58, 221 parameters. This is compared to other works [20] that use XceptionNet [21], which has 71 layers and approximately 23 million parameters. In our network, the first 4 blocks represent 2D convolutions, with 4 filters of size $3 \times 3$ for each convolutional layer. Batch normalization follows each convolutional layer, with a final dense layer of size 1. The Adam optimizer [22] with a learning rate of 0.001 was used along with binary cross-entropy as the loss function, and accuracy as the evaluation metric. A batch size of 128 was used and the network was trained for 10 epochs. We implemented early stopping when the difference in validation accuracy was less than 0.01. As the network outputs a probability between $[0, 1]$, we implement a threshold where any value $< 0.5$ is classified as original and any value $\geq 0.5$ is classified as fake. In Section III, we detail the impact of batch size, number of filters and layers, on the proposed architecture’s ability to detect fake face videos. See Figure 1 for an overview of the proposed architecture.

B. FaceForensics Dataset

The FaceForensics dataset [20] consists of 1004 videos that have a resolution greater than 480p from the youtube8m [23] dataset. Videos that were tagged with labels such as “face” were selected for the dataset. Face2Face [24] was used to create the face forgery videos (called “altered” videos) from the parent videos (called “original” videos). As such, there is perfect class balance in the dataset between altered and original videos. The FaceForensics dataset is split into training, validation, and testing sets that includes 736,270 samples of training data sourced from 704 videos, 151,052 samples of validation data sourced from 150 videos, and 155,490 samples of testing data sourced from 150 videos. The aforementioned frame count values are split evenly between altered and original videos resulting in a balanced dataset of original and forged videos. For our experiments, we used all of the data in the training, validation, and testing sets. See Figure 2 for examples of an original and fake image from this dataset.

III. RESULTS

To evaluate the utility of the proposed CNN to detect fake videos, we conducted frame- and video-based experiments. We also evaluated the impact of batch size, the number of filters, and the number of convolutional layers.

A. Frame-based Results

As noted in Section II-B, the FaceForensics dataset contains pre-sorted training, validation and testing sets. To conduct
TABLE I
CONFUSION MATRIX FOR FRAME-BASED RESULTS ON ENTIRE TESTING SET FROM THE FACEFORENSICS DATASET [20].

| Ground Truth | Detected Original | Detected Fake |
|--------------|-------------------|---------------|
| Original     | .999              | .001          |
| Fake         | .007              | .993          |

Fig. 3. Consecutive frames from the 1 misclassified video. Ground truth of video is fake. Left: misclassified as original, right: correctly classified as fake.

our experiments, we trained our proposed network (Section II-A) on the entire training set, and here we report our frame-based results (i.e. individual detection result for each video frame) on the entire testing set (155, 490 images). Using the proposed CNN, we achieve an accuracy of 99.6%, where 627 images were misclassified. As can be seen in Table I, a small percentage of frames were misclassified as fake, when they were original (70 frames). While more frames were misclassified as original, when they were fake (557 frames), the overall accuracy is high for both, showing the proposed smaller CNN is robust to detect fake face videos.

B. Video-based Results

To conduct our video-based experiments (i.e. detect whether a video is fake or not), we followed the same experimental design as our frame-based detection, however, we also implemented majority voting for each video. For each video, the final classification (real or fake) is calculated by summing up the total classifications for each frame. The classification with the majority of frames labeled as such, is determined to be the final classification. Using majority voting results in a video-based accuracy of 99.67%, on the 150 testing videos, with only 1 video being misclassified. As can be seen in Table II, 1 video was detected as original, when it has a ground truth label of fake. As we used majority voting for our video-based detection, this video was incorrectly classified as 53% of the frames were classified as original.

To gain further insight into why this video was misclassified, we computed a histogram of the probabilities for each frame in this video. As can be seen in Figure 4, the network was largely confident in its predictions with 189 having a probability of 0 (original), and 217 frames having a probability of 1 (fake). The misclassification occurred, in part, due to the probabilities that were not 0 or 1, where a total of 90 frames were also classified as original, however, with a lower probability. It is also interesting to note that this video contributed to 45% of the misclassified frames from Section III-A (270 out of 627 total misclassified frames). Figure 3 shows two consecutive frames from this misclassified video. The frame on the left was misclassified as original, while the frame on the right was correctly classified as fake. As can be seen in this figure, visually the frames look similar, however, the network had different classification labels for each.

C. Impact of Fine-tuning CNN Architecture

To evaluate the robustness of the proposed network, we conducted experiments to investigate the impact of batch size, number of filters and number of convolutional layers.

Convolutional Layers. We evaluated the proposed network using 1, 2, 3, and 4 convolutional layers using 4 filters of size 3 × 3, with a batch size of 64. The number of layers had little impact on the overall accuracy. As can be seen in Figure 5, increasing the number of layers from 1 to 4 shows an increase for each layer added, however, this increase is < 3% when comparing the lowest accuracy of 96.9% with 1-layer to the max accuracy of 99.3% with 4-layers. These results are encouraging, showing the robustness of smaller CNNs to detect fake face videos.

Batch Size. Batch size in a CNN can impact the time to converge, as well as overfitting of the network [25]. Considering this, we evaluated the impact of batch size on accuracy by training our proposed network for one epoch with varying batch sizes. We chose one epoch as the main goal of this investigation is to find trends in the accuracy compared to
to the conducted experiments on the FaceForensics dataset using a subset of the available data. They selected 20 frames (10 original and 10 fake) from each of the 704 available videos in the training set. They also selected 20 frames from each of the 150 validation and testing videos.

**Filter Size.** Similar to the conducted experiments on the impact of batch size, we also trained our proposed network for one epoch. This was done, as again we are looking for trends in the accuracy compared to filter sizes. As can be seen in Table IV, when the number of filters is 4, we achieve the highest accuracy. This is also reflected in our final results, as 4 filters were used for the results shown in Sections III-A and III-B. Increasing the number of filters to 8 results in significant decrease in accuracy (∼20%). However, once the number of filters is ≥ 256, we see the accuracies converge to approximately 50% on both training and validation. Because the larger batch sizes we tested (≥ 256) needed 1-3 days to train, we inferred the accuracy of the testing sets for these number of filters based on the accuracy of using 8 filters.

**D. Comparisons to State of the Art**

Rössler et al. [20] conducted experiments on the FaceForensics dataset using a subset of the available data. They selected 20 frames (10 original and 10 fake) from each of the 704 available videos in the training set. They also selected 20 frames from each of the 150 validation and testing videos.

To conduct their experiments, they used XceptionNet [21] by freezing the first 36 layers and replacing the last layer with a dense layer of 2 nodes (original and fake). They trained the network for 10 epochs using the Adam optimizer with a learning rate of 0.001 and a batch size of 64. They achieved an accuracy of 99.3% compared to ours of 99.6%.

As a subset of the data was used for this experiment, we are interested in how using XceptionNet, with these changes, would impact the accuracy on the entire training, validation, and testing sets as we did in our experimental design. Considering this, we replicated this experimental design using XceptionNet (freezing first 36 layers, new dense layer, training for 10 epochs) and trained on the entire training set. This resulted in an accuracy of 50% for both the validation and testing sets. As can be seen in Table V, the training accuracy for this architecture was high (>99%) for all epochs, however, the validation and testing accuracies converged to 50% for all epochs. These results further validate the robustness of using a smaller network, compared to a larger one, to detect fake face videos.

**IV. Conclusion**

We proposed the use of a smaller (less parameters to learn) CNN for detecting fake face videos. We investigate both frame- and video-based approaches to this problem achieving accuracies of 99.6% and 99.67%, respectively, on the FaceForensics dataset [20]. We show state-of-the-art results and validation of the chosen hyperparameters (e.g. batch size, number of filters) for the proposed network. Due to the increase, in recent years, of manipulated videos, this work has broader impacts in security and digital communication.
ACKNOWLEDGMENT

This material is based on work that was supported in part by an Amazon Machine Learning Research Award.

REFERENCES

[1] J. Ba and R. Caruana, “Do deep nets really need to be deep?,” in Advances in neural information processing systems, pp. 2654–2662, 2014.

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

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

[4] S. Suwajanakorn, S. M. Seitz, and I. Kemelmacher-Shlizerman, “Synthesizing obama: learning lip sync from audio,” ACM Transactions on Graphics (TOG), vol. 36, no. 4, pp. 1–13, 2017.

[5] S. Agarwal, H. Farid, Y. Gu, M. He, K. Nagano, and H. Li, “Protecting world leaders against deep fakes,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops, pp. 38–45, 2019.

[6] P. Ekman and E. Rosenberg, “What the face reveals: Basic and applied studies of spontaneous expression using the facial action coding system (facs),” Oxford University Press, 1997.

[7] F. Matern, C. Riess, and M. Stamminger, “Exploiting visual artifacts to expose deepfakes and face manipulations,” in 2019 IEEE Winter Applications of Computer Vision Workshops (WACVW), pp. 83–92, IEEE, 2019.

[8] Y. Li and S. Lyu, “Exposing deepfake videos by detecting face warping artifacts,” arXiv preprint arXiv:1811.00656, 2018.

[9] D. Giera 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), pp. 1–6, IEEE, 2018.

[10] 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), pp. 2307–2311, IEEE, 2019.

[11] S. Sabour, N. Frosst, and G. E. Hinton, “Dynamic routing between capsules,” in Advances in neural information processing systems, pp. 3856–3866, 2017.

[12] K. Patel, H. Han, A. K. Jain, and G. Ott, “Live face video vs. spoof face video: Use of moiré patterns to detect replay video attacks,” in 2015 International Conference on Biometrics (ICB), pp. 98–105, IEEE, 2015.

[13] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, “Generative adversarial nets,” in Advances in neural information processing systems, pp. 2672–2680, 2014.

[14] Y. Wang, K. Yu, C. Chen, X. Hu, and S. Peng, “Dynamic graph learning with content-guided spatial-frequency relation reasoning for deepfake detection,” in Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pp. 7278–7287, 2023.

[15] S. Dong, J. Wang, R. Ji, J. Liang, H. Fan, and Z. Ge, “Implicit identity leakage: The stumbling block to improving deepfake detection generalization,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 3994–4004, 2023.

[16] D. Cozzolino, A. Roissler, J. Thies, M. Niefeller, and L. Verdoliva, “Id-reveal: Identity-aware deepfake video detection,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 15108–15117, 2021.

[17] Y. Zhou and S.-N. Lim, “Joint audio-visual deepfake detection,” in Proceedings of the IEEE/CVF International Conference on Computer Vision, pp. 14800–14809, 2021.

[18] Y. Nirkin, L. Wolf, Y. Keller, and T. Hassner, “Deepfake detection based on discrepancies between faces and their context,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 44, no. 10, pp. 6111–6121, 2021.

[19] H. Zhao, W. Zhou, D. Chen, T. Wei, W. Zhang, and N. Yu, “Multi-attentional deepfake detection,” in Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pp. 2185–2194, 2021.

[20] A. Rössler, D. Cozzolino, L. Verdoliva, C. Riess, J. Thies, and M. Niefeller, “Faceforensics: A large-scale video dataset for forgery detection in human faces,” arXiv preprint arXiv:1803.09179, 2018.

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

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

[23] S. Abu-El-Haija, N. Kothari, J. Lee, P. Natesh, G. Toderici, B. Varadarajan, and S. Vijayanarasimhan, “Youtube-8m: A large-scale video classification benchmark,” arXiv preprint arXiv:1609.08675, 2016.

[24] J. Thies, M. Zollhofer, M. Stamminger, C. Theobalt, and M. Niefeller, “Face2face: Real-time face capture and remapping of rgb videos,” in Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 2387–2395, 2016.

[25] P. M. Radinik, “Impact of training set batch size on the performance of convolutional neural networks for diverse datasets,” Information Technology and Management Science, vol. 20, no. 1, pp. 20–24, 2017.

[26] Y. You, Z. Zhang, J. Demmel, K. Keutzer, and C.-J. Hsieh, “Imagenet training in 24 minutes,” arXiv preprint arXiv:1709.05011, 2017.