FakeBuster: A DeepFakes Detection Tool for Video Conferencing Scenarios

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ABSTRACT

This paper proposes ***FakeBuster***, a novel DeepFake detector for (a) detecting impostors during video conferencing, and (b) manipulated faces on social media. *FakeBuster* is a standalone deep learning-based solution, which enables a user to detect if another person's video is manipulated or spoofed during a video conference-based meeting. This tool is independent of video conferencing solutions and has been tested with *Zoom* and *Skype* applications. It employs a 3D convolutional neural network for predicting video fakeness. The network is trained on a combination of datasets such as Deeperforensics, DFDC, VoxCeleb, and deepfake videos created using locally captured images (specific to video conferencing scenarios). Diversity in the training data makes *FakeBuster* robust to multiple environments and facial manipulations, thereby making it generalizable and ecologically valid.

CCS CONCEPTS

• **Computing methodologies** → **Computer vision problems**;
• **Applied computing**;

KEYWORDS

Deepfakes detection, spoofing, neural networks

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1 INTRODUCTION AND BACKGROUND

Sophisticated artificial intelligence techniques have spurred a dramatic increase in manipulated media content, which keep evolving and becoming more realistic, making detection increasingly difficult. While their usage in spreading fake news, pornography and other such online content has been widely observed with major repercussions [7], they have recently found their way into video-calling platforms through spoofing tools based on facial performance transfer [17]. Facial transfer enables individuals to mimic others through real-time transfer of facial expressions, and the resulting videos (known as *deepfakes*) are often convincing to the human eye. This may have serious implications, especially in a pandemic situation, where virtual meetings are primarily employed for personal and professional communication.

There are a few deepfake detection software such as the recently introduced *Video Authenticator* by *Microsoft* [4]. However, these can only verify genuineness of pre-recorded videos. Also, Microsoft's tool is not publicly available to prevent its misuse. As an alternative, we present *FakeBuster* - a deepfake detection tool, which works in both offline (for existing videos) and online (during video conferencing) modes. A snapshot of the tool being used during a Zoom meeting is shown in Figure 1.

Additional Use Cases: Tools for deepfake detection can help in identification of impostors during events such as online examinations, video-based authentication and job interviews. Organisations can use deepfakes detection tools to ensure the legitimacy of a candidate. The same tool can also be used to validate any media content seen online by the user on social media platforms such as *YouTube* and *Twitter*.

2 FAKEBUSTER

As seen in Fig. 1, *FakeBuster* has a compact interface designed for ease of use alongside video-calling applications and internet browsers. It has been developed using PyQt toolkit [2] which offers the following advantages:- a) It is a Python binding of QT [1], which is a cross-platform application development framework, and b) use of Python language enables flexible integration of deep learning models. We have used the python MSS [3] library for screen recording, OpenCV [6] for image processing, and Pytorch [16] to train and test the deep learning models. The standalone aspect of the tool enables its usage with different video conferencing tools such as *Zoom*, *Skype*, *Webex* etc.

2.1 Workflow

The tool works in three steps (Figure 2): a) The user clicks on "Detect Faces", and the tool detects and shows all the faces present on the screen. In case of change in the video conference software's view

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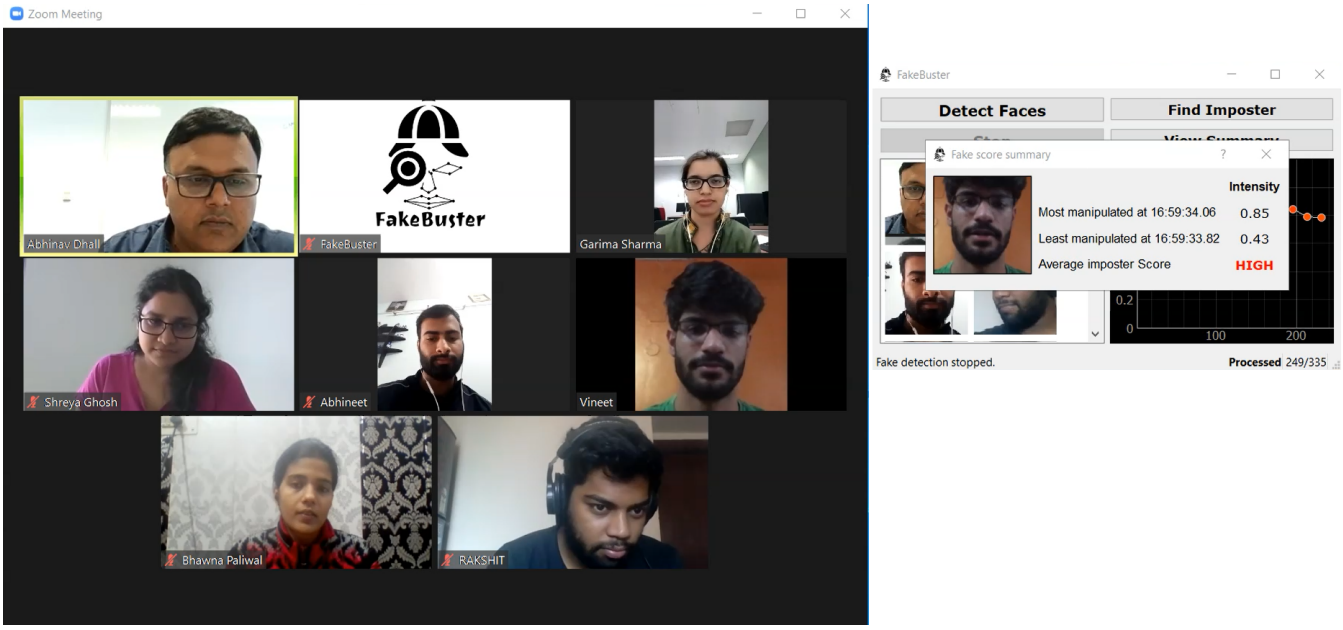
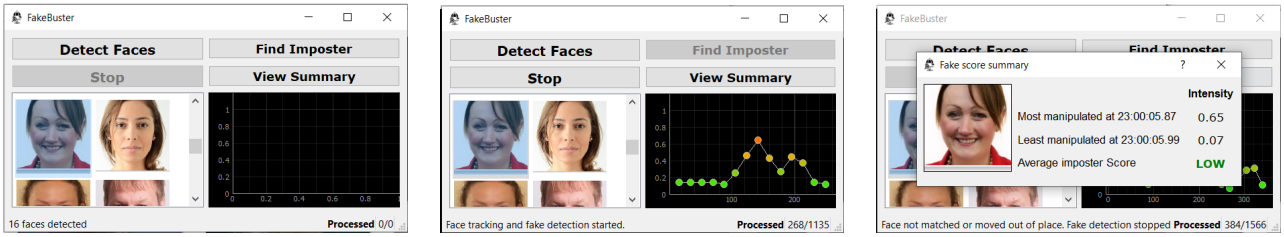


Figure 1: *FakeBuster* tool enables impostor detection in online meetings. Here, a user's *Zoom* video feed is detected as manipulated by *FakeBuster*. Please see *FakeBuster* demo video in the supplementary material.



(a) Step 1 - Face Select **(b) Step 2 - Find Imposter** **(c) Step 3 - Analysis**

Figure 2: Workflow of *FakeBuster*- a) User selects the faces detected by the tool from videoconferencing tool; b) User clicks on find impostor and the tool does prediction at snippet level; and c) User views the meta-analysis of fakeness of the video feed.

or positioning, the examined faces can be re-initialized by clicking "Detect Faces". The user then selects a face icon, whose video needs to validated; b) The user next clicks on the "Find Imposter" button to initiate deep inference. The tool runs face capturing, frame segmentation, and deepfake prediction for each segment in the background. The time-series graph on the right side of the tool (see Fig. 2 (b)) shows the prediction score at regular intervals. The prediction score varies between the range 0 to 1, which is color-coded, depicting the extent of face manipulation at a particular instant:- *green* (no manipulation), *yellow, orange* (some chance of tamper), and *red* (high probability of manipulation); c) The user can see the overall summary by clicking the "View Summary" button. It opens a new dialog screen (see Fig. 2 (c)), which shows the *average imposter score*, *highest* and *lowest manipulation intensity*, along with the *occurrence time stamps*. The user can utilize this information to take informed decisions and actions during the virtual meeting.

In the background, *FakeBuster* initiates imposter detection on the selected face by learning the appearance around the face position. Further, it performs face tracking, face-frame segmentation and deepfake prediction on each video segment in the background. The prediction scores are aggregated, and the time-series graph is updated over time.

2.2 Deepfake Detection

For segment-wise deepfake prediction, we train a 3D ResNet deep learning model [11] based visual stream architecture (Fig. 3), followed by the state-of-the-art deepfake detection proposed by Chugh et al. [8]. The input to the network is a segment of 30 face frames, and the output is the probability of the input chunk being *real*/*fake*. A number of large deepfake datasets with accompanying annotations exist such as DFDC [9], Deeperforensics [12] and FakeET [10] consisting of fake videos generated via face-swapping techniques that generate good quality deepfakes.

However, one of the successful online deepfake creator tools- *Avatarify* [5] performs face swapping in video conferencing apps using First Order Motion Model (FOMM) proposed by Siarohin et al.

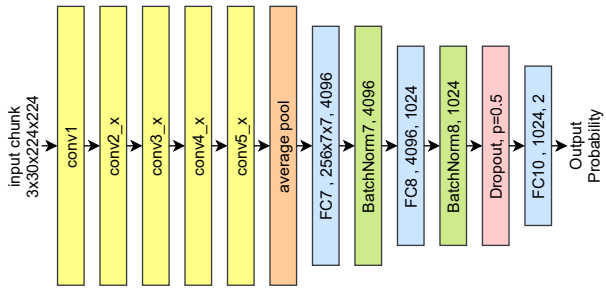


Figure 3: Deepfake detection network architecture.

[17]. These online generated deepfake image content are relatively low in resolution. Moreover, the video conferencing scenario introduces different types of perturbations due to diversity in camera quality, network bandwidth, and video compression-related artifacts. Therefore, we created a novel dataset comprising 10K real + 10K fake videos to account for the above variations.

Dataset: To generate facial performance transfer videos we used FOMM [17] to swap faces. At first, we manually selected (to ensure frontal face position) 100 face videos from the pre-processed VoxCeleb [15] dataset. We collected 25 images from 25 subjects, which are captured using the mobile cameras or webcams to mimic the low image quality and face pose as found during video calls. Moreover, we also selected 75 front-facing high-quality face images with plain background from Flickr-Faces-HQ Dataset (FFHQ) [13]. By swapping every image's face with the one in every video, we generated 10,000 fake videos. To get an equal number of real videos, we selected 4105 face videos from the pre-processed VoxCeleb [15] dataset. The remaining 5895 face videos are obtained by processing frontal face videos chosen from the Deeperforensics [12] dataset.

Training and Results: We created a subject-independent 3:1 train/test split from the synthesized dataset. For a better generalization of the network, we also performed a 3:1 train/test split of a balanced subset from DFDC [9] consisting of distinct 10,000 fake and corresponding real video pairs. We mixed both the sets and trained the model for 20 epochs with a batch size of 8 and a learning rate of 0.001, with Adam [14] optimizer for back-propogation. The Area Under the ROC Curve for this model is 90.61 on the test set.

2.3 Ethical Use and Privacy

FakeBuster performs screen recording, which offers the feasibility to test any face video that appears on screen. However, screen recording may breach the subjects' privacy in a video conference meeting. Therefore, it is important that all meeting participants be made aware beforehand regarding use the tool. *FakeBuster* is designed in such a way that it does not record any image or video in the file system. Moreover, the captured face images are buffered and removed immediately upon inference. We are currently investigating if biases in the training videos impact imposter detection performance for faces of different ethnicities.

3 CONCLUSION AND FUTURE WORKS

To the best of our knowledge, *FakeBuster* is one of the first tools for detecting impostors during video conferencing using deepfake detection technology. It is noted that the standalone tool works well with different video conferencing solutions such as *Zoom* and *Skype*. The tool can also be used for checking if an online video is fake or not in close to real-time. The real-time aspect is dependent on the GPU capabilities of the machine on which *FakeBuster* is installed.

At present, *FakeBuster* can evaluate only one face at a time, as part of the future work, multiple face processing will be implemented. This will help in reducing user effort in validation of multiple faces. *FakeBuster* uses 3D convolutions, which are computationally expensive. In this regard, we will aim to make the network smaller and lighter to enable *FakeBuster* to run on mobile devices as well. Another important direction is to add more training data so that the solution can generalize better to unseen scenarios. *FakeBuster* analytics is currently only video-based; we will experiment with multimodal deep learning based networks [8] by adding audio information in future.

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