Open-Eye: An Open Platform to Study Human Performance on Identifying AI-Synthesized Faces

Hui Guo¹, Shu Hu², Xin Wang², Ming-Ching Chang¹, Siwei Lyu²
¹University at Albany, SUNY, USA ²University at Buffalo, SUNY, USA
{hguo, mchang2}@albany.edu, {shuhu, xwang264, siweilyu}@buffalo.edu

Abstract

AI-synthesized faces are visually challenging to discern from real ones. They have been used as profile images for fake social media accounts, which leads to high negative social impacts. Although progress has been made in developing automatic methods to detect AI-synthesized faces, there is no open platform to study the human performance of AI-synthesized faces detection. In this work, we develop an online platform called Open-eye to study the human performance of AI-synthesized faces detection. We describe the design and workflow of the Open-eye in this paper.

1. Introduction

The rapid development of Artificial intelligence (AI) technologies, called Deep Fakes, has made it possible to synthesize highly realistic images, audio, and video that are difficult to discern from real ones. In particular, AI-synthesized faces have been misused for malicious purposes. Recent years have seen an increasing number of reports of these synthesized faces have led to the development of methods aiming to distinguish GAN-generated images from real ones. Many of those methods are based on deep neural network (DNN) models due to their high detection accuracy [22, 29, 9]. Although they have achieved high accuracy and the models are end-to-end, the DNN-based methods suffer from several limitations. The models lack interpretability to the detection results, and they usually have a low capability to generalize across different synthesis methods [12, 13].

As the existing methods are either less efficient or not accurate enough to handle the torrent of daily uploads of the public content [30], the users must be able to recognize the fake faces from the real ones. Recently, the studies investigating the human performance of AI-synthesized faces detection have been conducted [19, 26]. For example, [26] examined people’s ability to discriminate GAN faces from real faces. Specifically, 400 StyleGAN2 faces and 400 real faces from the FFHQ dataset are selected with large diversity across the genders, ages, races, etc., and two sets of experiments are conducted. In the first set of experiments, 315 participants were shown a few examples of GAN faces and real faces, and around 50% of accuracy was obtained. In the second set of experiments, 170 new participants were given a tutorial consisting of examples of specific artifacts in the GAN faces. Participants were also given feedback afterward. However, it was found that such training and feedback only improve a little bit of average accuracy. Therefore, this work concluded that the StyleGAN2 faces are realistic enough to fool naive and trained human observers. However, this study provides no information on what synthesis artifacts are provided for participant training. There is no open platform for public use to test.

To overcome the above limitations, we propose an open platform, Open-eye. The Open-eye consists of several steps (See Figure 1). In Stage 1, the participants are given feedback afterward. However, it was found that such training and feedback only improve a little bit of average accuracy. Therefore, this work concluded that the StyleGAN2 faces are realistic enough to fool naive and trained human observers. However, this study provides no information on what synthesis artifacts are provided for participant training. There is no open platform for public use to test.

To overcome the above limitations, we propose an open platform, Open-eye. The Open-eye consists of several steps (See Figure 1). In Stage 1, the participants are given feedback afterward. However, it was found that such training and feedback only improve a little bit of average accuracy. Therefore, this work concluded that the StyleGAN2 faces are realistic enough to fool naive and trained human observers. However, this study provides no information on what synthesis artifacts are provided for participant training. There is no open platform for public use to test.

The main contributions of this work are two-fold:

- We are the first to propose an open platform to study whether human participants can distinguish state-of-the-art AI-synthesized faces from real faces visually.
- The proposed platform is flexible to incorporate any AI-synthesized faces and provides quick training to the participants to recognize the fake faces. An example
Figure 1: The workflow of Open-eye. The participants test 20 face images, including the same amount of real and fake. A quick tutorial is demonstrated to participants to learn how to recognize the specific artifacts in the eye. The same test will be used again to show the human performance of the AI-synthesized faces detection.

shows that the platform is simple, effective, and efficient for participants.

2. Background

AI-synthesized faces. One of the most popular AI-synthesized faces techniques is based on GAN models. A GAN model includes two neural networks (generator and discriminator) trained in tandem. The generator takes random noises as input and can effectively encode rich semantic information in the intermediate features and latent space for high-quality face image generation. The discriminator aims to distinguish synthesized images from the real ones. Generator and discriminator compete with each other during the training. A series of GAN models (e.g., PGGAN [15], BigGAN [5], StyleGAN [17], StyleGAN2 [18], StyleGAN3 [16]) have been developed and demonstrated superior capacity in generating or synthesizing realistic human faces. In some early works such as [31], they find that faces generated by the early StyleGAN model [17] have considerable artifacts such as fingerprints [22, 32], inconsistent iris colors [20, 25], etc. However, just one year later, StyleGAN2 is proposed by Karras et al. in [18], and it has greatly improved the visual quality and pixel resolution, with largely-reduced or undetectable artifacts in the generated faces.

AI-synthesized faces detection. With the development of the GAN models for face generation/synthesis, methods for distinguishing GAN-generated faces have progressed accordingly. Most of these methods are Deep Learning-based [23, 14, 29, 7, 21]. Notably, several methods exploit the physiological cues (which suggest inconsistency in the physical world) to distinguish GAN-generated faces from the real ones [24]. In [31], GAN-generated faces are identified by analyzing the distributions of the facial landmarks. The work of [11] analyzes the light source directions from the perspective distortion of the locations of the specular highlights of the two eyes. Such physiological/physical-based methods come with intuitive interpretations and are more robust to adversarial attacks [27, 10].

3 Platform Design

This section describes the design of the Open-eye platform. Our platform is composed of three stages:

In Stage 1, the participants are tested with real and AI-synthesized faces from a given dataset. In Stage 2, the participants are trained with the artifacts to identify AI-synthesized faces reliably. Our participants’ training method is motivated by observing that GAN-generated faces exhibit a common artifact. For example, Iris and pupil Analysis is a critical task in biometric identification that has been studied well. The pupils appear with irregular shapes or boundaries, other than a smooth circle or ellipse. This artifact is universal for all known GAN models (at least for now, e.g., PGGAN [15], Alias-Free GAN [16], and SofGAN [6]), as shown in Figure 2. In Stage 3, the participants will repeat the test using the same data in Stage 1. The overview of the platform workflow is illustrated in Figure 1.

In the next section, we describe the use of the Open-eye platform with the above example.

4 An Example

In this section, we use irregular pupil shapes to reveal GAN-generated faces [8] as a tutorial example to further explain the platform. In general, we can incorporate more methods and datatypes into our platform.

Datasets. We use the real human faces from the Flickr-Faces-HQ (FFHQ) dataset [17]. Since StyleGAN2 [18] 1

1http://thispersondoesnotexist.com
is currently the state-of-the-art GAN face generation model with the best synthesis quality, we collect GAN-generated faces from it. We only use images where the eyes and pupils can be successfully extracted.

In Stage 1, 20 images are shown to the participants. Note that 20 is only a predefined number. We can adjust it as the demand need. 10 real images are randomly selected from the Flickr-Faces-HQ (FFHQ) dataset [17], and 10 fake images are randomly selected from StyleGAN2 [18]. The participants are requested to click the real or fake button for each image based on their cognition. After the test, the system will output the human performance, including accuracy, precision, recall, and F-score.

In Stage 2, three courses are provided to the participants that can be learned to recognize the fake images from real ones, including introducing human eye anatomy, comparing pupils from real human faces and AI-synthesized faces, and presenting more iris examples to show the difference between the real and fake pupils (see Fig. 3 for more details). Specifically, the participants will be taught to identify the pupil outer boundary, iris outer boundary, sclera, iris, and pupil in an eye. Then, the participants will learn the difference between real and fake pupils, e.g., fake pupils may contain unclear boundaries, and the shapes stretch up or toward the width. This stage mainly brings an awareness of how fake and real pupils are distinguished in shapes.

In Stage 3, the participants will do the test again using the same 20 images from Stage 1. We will also output the new human performance. By comparing two results (in Stage 1 and Stage 3) from the same data set, we can get a cognition of whether human participants can distinguish state-of-the-art AI-synthesized faces from real faces visually after learning from the tutorial.

The proposed pupil shape-based tutorial contains several limitations. Since the method is based on the simple assumption of pupil shape regularity, false positives may occur when the pupil shapes are non-elliptical in the real faces. This may happen for infected eyes with certain diseases. Also, poor imaging conditions, including lighting variations, largely skewed views, and occlusions, can cause errors in
pupil segmentation or thresholding errors. To make our system more useful and educational, we can add more tutorials according to existing research. For example, [11] uses the inconsistency of the corneal specular highlights between the two synthesized eyes to identify GAN-generated faces, and [24] discerns the GAN-generated faces by different iris [28] colors of the left and right eye.

5 Conclusion

In this work, we describe an open platform known as Open-eye, for investigating the human performance of AI face detection. This platform provides interfaces for training participants that may further improve forensic detection effectiveness. For future works, we will continue to integrate more AI faces into the platform that can further expand the impact in addressing issues in social media forensics. And investigate the human performance with this open platform.

References

[1] A high school student created a fake 2020 US candidate. Twitter verified it. https://www.cnn.com/2020/02/28/tech/fake-twitter-candidate-2020/index.html.
[2] How fake faces are being weaponized online. https://www.cnn.com/2020/02/20/tech/fake-faces-deepfake/index.html.
[3] A spy reportedly used an AI-generated profile picture to connect with sources on LinkedIn. https://bit.ly/35BU215.
[4] These faces are not real. https://graphics.reuters.com/CYBER-DEEPFAKE/ACTIVIST/nmovajgnxpa/index.html.
[5] A. Brock, J. Donahue, and K. Simonyan. Large scale gan training for high fidelity natural image synthesis. arXiv:1809.11096, 2018.
[6] A. Chen, R. Liu, L. Xie, Z. Chen, H. Su, and J. Yu. SoGAN: A portrait image generator with dynamic styling. ACM transactions on graphics, 2021.
[7] M. Goebel, L. Nataraj, and etc. Detection, attribution and localization of GAN generated images. arXiv:2007.10466, 2020.
[8] H. Guo, S. Hu, X. Wang, M.-C. Chang, and S. Lyu. Eyes tell all: Irregular pupil shapes reveal GAN-generated faces. ICASSP, 2022.
[9] H. Guo, S. Hu, X. Wang, M.-C. Chang, and S. Lyu. Robust attentive deep neural network for exposing gan-generated faces. IEEE Access, 2022.
[10] S. Hu, L. Ke, X. Wang, and S. Lyu. Tkml-ap: Adversarial attacks to top-k multi-label learning. In ICCV, pages 7649–7657, 2021.
[11] S. Hu, Y. Li, and S. Lyu. Exposing GAN-generated faces using inconsistent corneal specular highlights. In ICASSP, 2021.
[12] S. Hu, Y. Ying, X. Wang, and S. Lyu. Learning by minimizing the sum of ranked range. NeurIPS, 33, 2020.
[13] S. Hu, Y. Ying, X. Wang, and S. Lyu. Sum of ranked range loss for supervised learning. JMLR, 2022.
[14] N. Hulzebosch, S. Ibrahim, and M. Worring. Detecting CNN-generated facial images in real-world scenarios. In CVPR Workshops, pages 642–643, 2020.
[15] T. Karras, T. Aila, S. Laine, and J. Lehtinen. Progressive growing of GANs for improved quality, stability, and variation. ICLR, 2018.
[16] T. Karras, M. Aittala, S. Laine, E. Härkönen, J. Hellsten, J. Lehtinen, and T. Aila. Alias-free generative adversarial networks. arXiv:2106.12423, 2021.
[17] T. Karras, S. Laine, and T. Aila. A style-based generator architecture for generative adversarial networks. In CVPR, 2019.
[18] T. Karras, S. Laine, M. Aittala, J. Hellsten, J. Lehtinen, and T. Aila. Analyzing and improving the image quality of StyleGAN. In CVPR, 2020.
[19] F. Lago, C. Pasquini, R. Böhme, et al. More real than real: A study on human visual perception of synthetic faces. arXiv:2106.07226, 2021.
[20] H. Li, B. Li, S. Tan, and J. Huang. Detection of deep network generated images using disparities in color components. arXiv:1808.07276, 2018.
[21] Z. Liu, X. Qi, and P. H. Torr. Global texture enhancement for fake face detection in the wild. In CVPR, 2020.
[22] F. Marra, D. Gragnaniello, L. Verdoliva, and G. Poggi. Do GANs leave artificial fingerprints? In MIPR, 2019.
[23] F. Marra, C. Saltori, G. Boato, and L. Verdoliva. Incremental learning for the detection and classification of GAN-generated images. In IEEE WIFS, 2019.
[24] F. Matern, C. Riess, and M. Stamminger. Exploiting visual artifacts to expose Deepfakes and face manipulations. In IEEE WACV Workshop, pages 83–92. IEEE, 2019.
[25] S. McCloskey and M. Albright. Detecting GAN-generated imagery using color cues. arXiv:1812.08247, 2018.
[26] S. Nightingale, S.agarwal, E. Härkönen, J. Lehtinen, and H. Farid. Synthetic faces: how perceptually convincing are they? Journal of Vision, 2021.
[27] L. Verdoliva. Media forensics and DeepFakes: an overview. arXiv:2001.06564, 2020.
[28] C. Wang et al. Nir iris challenge evaluation in non-cooperative environments: Segmentation and localization. In IJCB, pages 1–10. IEEE, 2021.
[29] S.-Y. Wang, O. Wang, R. Zhang, A. Owens, and A. A. Efros. CNN-generated images are surprisingly easy to spot... for now. In CVPR, pages 8695–8704, 2020.
[30] X. Wang, H. Guo, S. Hu, M.-C. Chang, and S. Lyu. GAN-generated faces detection: A survey and new perspectives. arXiv:2202.07145, 2022.
[31] X. Yang, Y. Li, H. Qi, and S. Lyu. Exposing GAN-synthesized faces using landmark locations. In ACM Workshop on IHMMSec, 2019.
[32] N. Yu, L. S. Davis, and M. Fritz. Attributing fake images to GANs: Learning and analyzing GAN fingerprints. In ICCV, 2019.