## **Private Neural Portraits**

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### **Abstract**

1	Facial recognition systems learn from datasets whose data subjects have not con-
2	sented to being subjects. To preserve the privacy of these individuals, researchers
3	have designed systems like LowKey[1] and Fawkes[2] that add adversarial pertur-
4	bations to images containing faces. These adversarial perturbations make it difficult
5	for facial recognition models to correctly label faces in an image. This work pro-
6	poses a strategy in which the artistic stylizing of an image containing a face makes
7	it difficult for a facial recognition model to correctly label the face in the image.

### 8 1 Motivation

- Facial recognition datasets can contain images of individuals who have not consented to being a data
   subject. Corporations regularly scrape the Internet to increase the size of their facial recognition
   datasets[3].
- The ImageNet dataset originally contained faces that were not obfuscated. ImageNet curators later obfuscated the faces of data subjects out of concern for the privacy of the data subjects[4].
- Systems like Fawkes[2] and LowKey[1] let potential data subjects concerned about their privacy
- obfuscate personal images. However, defenses applied to facial recognition systems like adversarial
- training[3] and image super-resolution[5] make it difficult for LowKey[1] and Fawkes[2] to protect
- 17 privacy-concerned users from facial recognition models in the long term.
- We propose the use of a Paint Transformer[6] for obfuscating faces in natural images.
- 19 We demonstrate the performance of our strategy in a case study. In our case study, Fawkes applies
- 20 adversarial perturbations to an image. A Paint Transformer stylizes this image. ESRGAN [7] then
- 21 upscales the image.
- 22 MTCNN[8] is a model that detects faces. Face detection is required for face recognition. Facial
- 23 recognition systems cannot label faces that have not been detected first.
- For our experiment, we test the ability of MTCNN[8] to detect faces in the upscaled image.

### 25 **Methodology**

- 26 The code and data needed to reproduce these results is contained in a Jupyter notebook on GitHub at
- 27 this url: https://github.com/enderminyard/private-neural-portraits
- 28 The data used for our case study is an image of a celebrity from Wikipedia [9]. In our case study,
- Fawkes obfuscates this image of a celebrity[9]. A Paint Transformer[6] stylizes the image.
- 30 ESRGAN[7] upscales both the stylized and unstylized images. MTCNN[8] tries to detect faces in
- both the stylized and unstylized images.
- This experiment was run using an NVIDIA Tesla T4 GPU.

### 33 Results

### Original Image



MTCNN detects facial landmarks such as the nose and mouth.

# Fawkes + Paint Transformer

Image perturbed with

MTCNN does not detect a face.

Table 1: MTCNN evalution of perturbed and upscaled images

	Fawkes	Fawkes + Paint Transformer
Confidence	0.9934871196746826	none
Bounding box	[1609, 859, 1039, 1164]	N/A

- 35 In our case study, we find that MTCNN[8] does not detect a face in the upscaled image stylized with
- 36 the Paint Transformer.

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- MTCNN[8] is able to detect a face in the upscaled image that is not stylized with a confidence score of 0.9934871196746826.
- 39 Fawkes applied perturbations to both images before the image super-resolution process.

### 40 4 Discussion

- 41 Our results suggest that the Paint Transformer [6] is effective for defeating super-resolution defenses [5]
- against adversarial perturbations applied to images of faces.

### 43 4.1 Further Work

- 44 The ability of MTCNN to detect faces in stylized images could change depending on the image being
- evaluated. In order to conduct a more comprehensive experiment, we need to test the performance
- 46 of facial recognition systems using a dataset whose subjects have actively consented to being data
- subjects or consider how to evaluate the performance of a facial detection system without a dataset.
- 48 Further work in this area may require research in the direction of participatory AI [10].

### 49 4.2 Broader Impact

- 50 Privacy-concerned individuals aware of becoming potential data subjects without their expressed
- 51 consent may consider using the strategy described within this work to decrease the probability of
- being labeled correctly by facial detection systems.

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