

Fake Face Detection and Fairness

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Abstract

In this study we investigate whether it is still feasible to automatically discern AI-generated human face images from genuine photographic ones, by training a convolutional neural network on a labeled dataset of 70,000 real and 70,000 fake face images. We use the fake face classification problem to further explore the topic of model fairness, by evaluating the model's performance across age, gender and race groups on a demographically labeled face dataset. To achieve this, we propose a method of utilizing an autoencoder network to translate demographically labeled real face images into an approximation of their latent space code representations and then reconstruct them back into images, creating a dataset of matching fake face images with the same demographic labels. This allows us to assess whether our fake face detection model works equally well for human faces of different age, gender and race groups, or whether it even generalizes to a dataset that is demographically diverse and balanced.

Introduction

Generative Adversarial Networks (GANs) have created the ability to encode photographic images into a latent space representation and automatically generate many images that can appear to be genuine photographs, to the human eye. NVIDIA's StyleGAN [1] model, trained on a dataset of human face images, is capable of generating extremely photo-realistic images of people who do not exist. StyleGAN is an example of a generative adversarial network (GAN), a type of network that consists of two models, a *generator*, which learns a data distribution from a training set and draws from it, and a *discriminator*, which learns to estimate the probability that a sample came from the training data or from the generator [2].

The application of GANs to generating realistic human faces has garnered much media attention in recent years. The well-known website This Person Does Not Exist serves random, high-resolution fake face images drawn from StyleGAN. Many models have been created for exploring the latent space of StyleGAN to discover vectors that correspond to semantic directions in which the latent codes can be perturbed in order to make semantic edits to human face photos, such as making the face look older vs. younger, more masculine vs. more feminine [3], or thinner vs. heavier [4]. The popular mobile applica-

tion FaceApp utilizes this method to allow users to transform images of themselves in this manner and share them on social media for humor. Two different people's face images can also be blended together by encoding both images and interpolating some point between them in the latent space, which can be used for applications like visualizing what a couple's children might look like, a concept that has been implemented in the project FamilyGAN.

It is also easy to imagine nefarious applications of fake face generation, some of which have already been realized, such as swapping faces of celebrities onto pornographic actors or falsifying speeches by political leaders [5]. Because such applications of this technology can unfairly damage people's reputations and erode trust in society, there is a public interest in retaining the ability to effectively discern real human face images and video from fake ones and detect "deep fake" tampering, which requires training more deep learning models to distinguish them.

A problem with the available open datasets of human faces used in training deep learning models, is bias in the demographic composition of the pictured individuals. The machine learning community has recently been struggling with the issue of model fairness—it is important that models perform equitably for users and data subjects of different backgrounds, and also very difficult to enumerate and

quantify the sources of bias in training data that can contribute to biased model performance.

The FairFace [6] study introduced a new dataset of human face images collected from public datasets with manually verified, crowdsourced age, gender and race labels. The FairFace paper demonstrates that because existing public datasets of human faces contain a majority of white faces, models trained on them fail to generalize well to datasets where more non-white faces are present. We suspected that this might also be the case for the 70k real and fake faces dataset that we utilized for model training, and sought to test this by evaluating it on a demographically labeled dataset.

While the FairFace dataset provides real human face images that can be used to assess disparities in a fake face detector’s true negative and false positive rates, a second, similarly labeled dataset of fake face images is needed to compute true positive and false negative rates for specific age, gender and race groups. To address this gap, we investigated methods for “falsifying” a real face image by autoencoding it via the StyleGAN latent space. A research team at Tel Aviv University recently developed a novel encoder network [7] called *pixel2style2pixel*, that is capable of approximately reconstructing StyleGAN’s latent code representation of a face image and then decoding it back into an image. This yields a fake face output image that very closely resembles the real face input image, implying that the original demographic labels would remain valid, and giving us a dataset of matching real and fake faces for scoring our models and calculating classifier fairness metrics.

Methods

Data Preprocessing and Augmentation

We tested several methods for preprocessing and augmenting the image data before feeding it into the CNN model.

- 3-color (RGB) images vs. grayscale
- Pre-cropping and centering faces using pre-trained face detection models
- Random horizontal flips, rotations, and shears

Before training our CNN models we pre-cropped the images to center and align the faces with eyes,

nose and mouth level. We utilized two different pre-trained face detection models. The first model we used was the Multi-Task Cascaded Convolutional Neural Network (MTCNN) [8]. Later, we switched to utilizing the Dlib package implementation of the Shape Predictor 68 Face Landmarks model [9] because the *pixel2style2pixel* model was trained on face images that were aligned with this model and expects such as input.

Model Training

To solve the binary classification task of distinguishing between real and fake human face images, we trained several variations of deep Convolutional Neural Networks (CNN), varying the number of convolution layers as well as several model hyperparameters and image preprocessing steps.

Our initial baseline model was a CNN with three convolution layers using a 3x3 element kernel. We trained it on grayscale images from the 70k fair and fake faces dataset, cropped using MTCNN, with no image augmentations applied. The baseline model’s learning curves over training 20 epochs are pictured in Figure 1.

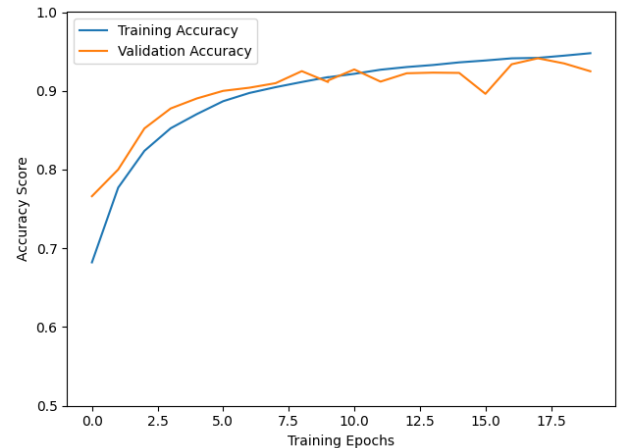


Figure 1: Learning curve for baseline model trained on fake faces grayscale images

Figure 2 and Figure 3 depict the learning curves for our best VGG-10 model, trained on the combined dataset in grayscale and RGB, respectively. Using RGB color images did not appear to offer a significant benefit, as both models were able to exceed 98% validation accuracy within fewer than 20 training epochs.

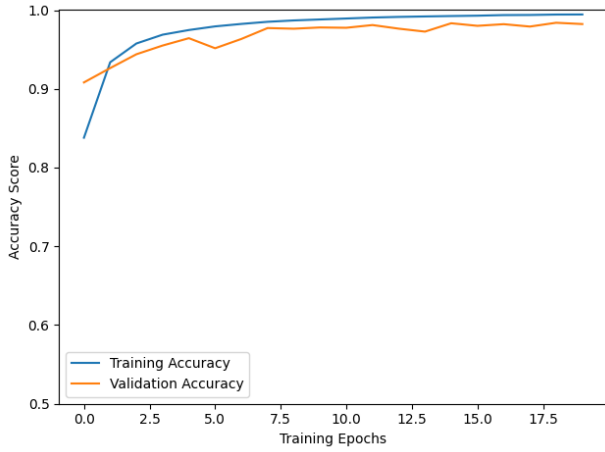


Figure 2: Learning curve for VGG-10 model trained on combined grayscale images

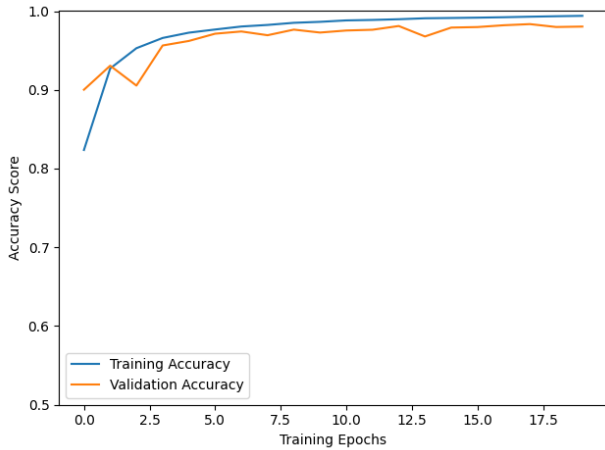


Figure 3: Learning curve for VGG-10 model trained on combined RGB images

Model Serving

TODO: Details and screenshots of web application here

Model Explainability

TODO: Explanation and screenshot of eli5 highlighted image, possibly CNN activation map

Model Evaluation

Our primary metric for performance assessment during training and model selection was validation set accuracy, because the balanced classes of the input dataset made accuracy straightforward to interpret. For final model performance on out-of-sample

test data, we report performance using F1 score, precision score and recall score in addition to accuracy score, to communicate how well the model performed across a variety of standard binary classifier metrics.

For fairness metrics, we selected two standard binary classifier metrics to evaluate our classifier on: disparate impact ratio, given by the ratio of the rate of positive predictions for the unprivileged class to that of the privileged class [10], given by:

$$\frac{P(\hat{y}|\text{unprivileged})}{P(\hat{y}|\text{privileged})}$$

and average odds difference, given by:

$$\frac{(FPR_{unpriv} - FPR_{priv}) + (TPR_{unpriv} - TPR_{priv})}{2}$$

for the following binary group definitions taken from the FairFace labels:

1. Gender = “male” vs Gender = “female”
2. Race = “white” vs all other races
3. Race = “black” vs all other races
4. Age = “0-2” vs all other ages
5. Age = “3-9” vs all other ages
6. Age = “more than 70” vs all other ages

We examine the model fairness for children and senior citizens as a recent study [11] found that the popular face recognition model Face++ disproportionately fails to recognize children’s faces in images collected from social media.

Results

We determined that the fake face classification task is still achievable with a relatively simple CNN model, but that model also failed to generalize to the unseen FairFace dataset.

Preprocessing Results

We utilized two pre-trained face recognition models to locate the human face in the image, align it so that the eyes, nose and mouth are level and centered, and crop to a margin around the face. Because these preprocessing models are themselves probabilistic machine learning models, they sometimes fail to recognize a human face at all (false negative) or incorrectly recognize some other object as a human face

(false positive). We examined the images for which face detection failed.

The Dlib frontal face detector method mistook several objects including a logo and a necklace for human faces (Figure 4), while the MTCNN face detector method failed to identify several faces with brightly colored hair or wigs and heavy makeup as faces (Figure 5)



Figure 4: Sample of false positives cropped by Dlib.



Figure 5: Sample of false negatives that MTCNN failed to crop.

By applying the pixel2style2pixel encoding algorithm to the FairFace images, we were able to successfully obtain a dataset of 79,484 matching pairs of real and fake faces with verified age, race, and gender labels.



Figure 6: Selected FairFace images before/after encoding by pixel2style2pixel

Model Performance Results

The baseline model achieved the following performance on the Fake Faces test set, after 18 training epochs (Table 1):

Table 1: Baseline model performance

Accuracy	F1	Precision	Recall
0.942197	0.941569	0.951865	0.931493

Our best model in hyperparameter tuning was a variant of the VGG architecture [12] with 10 total layers (8 convolution layers and 2 fully connected layers). This model's performance is given by (Figure 2).

Table 2: Best (VGG10) Model performance on Fake Faces test set

Accuracy	F1	Precision	Recall
0.968298	0.967689	0.986595	0.949495

Fairness Assessment Results

Our best model trained on the 70k real and fake faces dataset failed to generalize to the FairFace dataset, marking nearly all of the FairFace observations as fake faces, resulting in high recall but very low precision and accuracy scores (Figure 3).

Table 3: VGG10 model performance metrics on FairFace after training on Fake Faces

Accuracy	F1	Precision	Recall
0.54305	0.676667	0.52357	0.9563

We originally intended to perform a fairness assessment on both our baseline model and our best model trained on the fake faces dataset, but because these models completely failed to generalize to the FairFace data, we decided not to even assess their demographic fairness metrics. Rather, we retrained our best model on a combined dataset consisting of the entire training sets from both the 70k real and fake faces and the FairFace datasets.

The resulting model performed very well on the combined dataset (Figure 4), and even performed better on the 70 real and fake faces dataset than the model version that was only trained on that dataset (Figure 5), suggesting that the additional training examples from FairFace led to a general improvement.

Table 4: Model performance metrics on FairFace + Fake Faces combined dataset

Accuracy	F1	Precision	Recall
0.984457	0.984411	0.986268	0.982561

Table 5: Performance on Fake Faces test set for model trained on combined dataset

Accuracy	F1	Precision	Recall
0.971232	0.971092	0.97374	0.968458

Our best model, using the VGG10 architecture and trained on the combined dataset, achieved excellent performance by the fairness metrics, disparate impact ratio (where 1.0 is perfectly fair) and average odds difference (where 0.0 is perfectly fair).

Table 6: Model Fairness metrics

	Disparate Impact	Avg Odds Diff
Male	0.993955	-0.000031
White	1.027800	-0.001012
Non-Black	1.004817	0.000983
Non-Child	1.011344	0.000167
Non-Senior	1.003951	0.001968

Discussion

Our initial goal of detecting fake faces was quite successful, especially on the original dataset. The VGG10 model achieved accuracy of 96.8% percent on the test set. After some thorough testing and investigation, we made the decision to incorporate other fake images, and to go as far as making it more fair.

After a successfully testing our network against same set testing images, we thought that our model was doing quite well so we moved onto external datasets. Upon testing with other fake images, we noted that the accuracy took a dramatic turn in the opposite direction. While investigating, we determined that there could be several causes for this decrease:

1. The original training set had a specific pattern the our models were detecting, causing our network to look for those specific details. It could be something minute, such as the eyes having x and y coordinates that were within a specific range. Although, we determined that this was unlikely due to our randomness when pre-processing (add noise, flips, shears, rotations) our data.
2. Our method for creating a fair face dataset was flawed <talk about how we got this dataset>
3. We didn't have enough data in original dataset to allow for a higher classification rate outside of that set.

Future Work

Overall, we are quite happy with the way our model classifies, but there are several adjustments we'd love to make that could help increase accuracy. We do not believe that there were any fundamental flaws in our methods, rather an inadequate amount of time,

resources, and overall data. All of issues revolve around a lack of time, and given more, we could increase the performance of our model architecture and classification.

Time was our largest blocker throughout the entirety of our project, whether it was the time required to set up CUDA, train, or research new theories. During our models training time, we never saw a hint at over fitting, which indicated that there was still performance to be had. Given more time and compute power, we could have increased our accuracy. In addition, we could also take some images from NVIDIA's fake face dataset and add that to our train-

ing data, but once again the cost involved is more than our team could handle.

In the future, we would love to incorporate these changes and throw more compute power at the problem. Using ample amounts of training data and more computer vision techniques we believe that there is still room to improve on our model. Although, as fake faces become better in better, we wonder how our model would fare. Looking at a company like NVIDIA, who has the resources to make fake faces using GANs and enormous amounts of compute power, will it be possible to detect their fake faces?

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