Single to Multiple Profile Generation Of A Face Using Conditional GANs

CS 543 Fall 2022 Project-2 Report for Group 5

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***Abstract*—The aim of this project is solely to aid the police in searching for the missing or wanted people, or maybe have some fun among our peers. The basic idea of this project to implement an image translation model for generating multiple profiles (0°, 45°, 135°, 180°) of a face given a single profile (center profile) using Conditional Generative Adversarial Networks (CGANs). This project is an implementation and application of the work presented in pix2pix [1]. The methodology, architecture and hyperparameters of [1] have been used to train the model on an entirely new dataset with an entirely new aim. We utilize the KDEF and CVL Face Database for training, evaluation and testing purposes.**

***Index Terms*—Conditional GANs, Generative Adversarial Networks, Computer Vision**

I. Introduction

Our main motivation behind this project was to help the police and other private security firms in searching for wanted criminals or missing people. As we all know whenever a person is convicted of a crime and taken into custody, the police capture their mugshot photos from all their profiles (i.e., left, center and right). This is done so that it's easier for them to identify that person if they do anything in the future, as it's always easier to identify that person if we have all their profiles rather than just one. In case the criminal hasn't been caught yet by the police and they are looking for the said criminal using some CCTV footage they found. The CCTV footage might not have all the profiles of the face of the said criminal making it harder for the police to find them. In a similar scenario if a person goes missing the family of the said person might only have their photos from a single profile making it harder for the police to find the person. This is where our project comes in handy.

Our project aims to generate all the profiles of a face of a person given only a single profile view image. We aim to do this using CGANs. CGANs gives us the ability to map image to image as described by the authors in their original paper [1]. Given one image as input we can generate another image as its corresponding output image. So in this case we wish to train 4 models for generating images of different angles (i.e., 0°, 45°, 135°, 180°), given the center profile image (i.e., 90°). We aggregate and align the KDEF and CVL Faces Database consisting of images of faces of different individuals from 5 different angles (0°, 45°, 90°, 135°, 180°), with different facial expressions for training, evaluation, and testing purposes.

II. Dataset

For this project we'll be combining 2 datasets i.e., KDEF and CVL Face Database as these are all the datasets we could get permission to use and would fit for the purpose of our project.

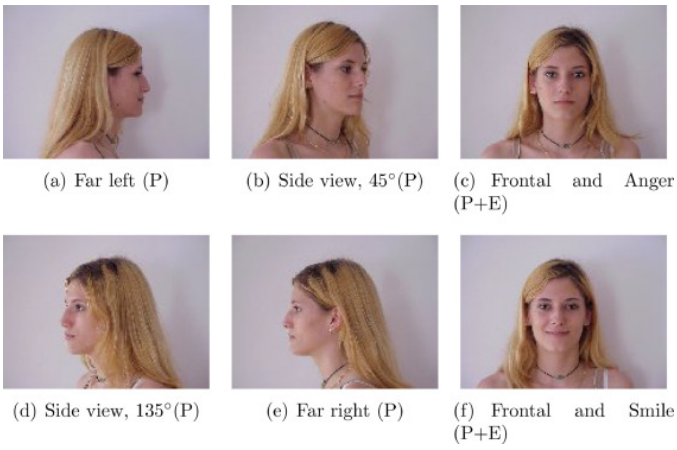
A. KDEF

This dataset has 4900 images of 70 individuals, having 7 different facial expressions from 5 different angles. All the images are of 562 x 762 pixels.

Fig. 1. KDEF dataset

B. CVL Face Database

This dataset has 798 images of 114 individuals, having 3 different expressions from 5 different angles. All the images are of 640 x 480 pixels.



(a) Far left (P) (b) Side view, 45°(P) (c) Frontal and Anger (P+E)

(d) Side view, 135°(P) (e) Far right (P) (f) Frontal and Smile (P+E)

Fig. 2. CVL Faces dataset

When combined and preprocessed it gives us a total of 1094 sets of images with each set containing 5 images (i.e., 0°, 45°, 90°, 135°, 180°), making a total of 5470 images occupying 1.28 GB memory. After processing all these images using Photoshop to change the background to white the dataset folder size reduced to 1.07 GB.

III. Programming Tools

A. Programming Language

Python

B. Library

Pytorch, OpenCV, Mediapipe, Numpy, Matplotlib and Tkinter

C. Tools

Rutgers iLab, Jupyter Notebook and Adobe Photoshop

IV. Methodology

A. Stage 1: Data Preprocessing

1) KDEF Dataset: For all the individuals in this dataset there were a total of 5 images in the correct angles as needed for the purpose and scope of this project per expression. There were a total of 7 expressions per person making it total of 35 images per person. These images were also renamed and kept into correct folder structure. No extra pixel space was observed in these images so no cropping was done.

Apart from this while going over the dataset, we found that some of the images were missing, so as all the missing images were luckily of a side profile rather than center profile, we were able to generate those images using Photoshop by simply flipping the image of the other side angle.

2) CVL Faces Dataset: For all the individuals in this dataset there were a total of 7 images. 5 Images were in different angles with neutral expressions and 2 other images were with other expressions from the center profile. So for the purpose and scope of this project we discarded those extra facial expression images and renamed and saved the remaining 5 images in correct folder structure optimal for training.

Apart from this it was observed that all the images in this dataset had a lot of extra pixel space in the sides which wasn't necessary, and was different from the first dataset, so we cropped the images from the sides to convert the images from 640 x 480 pixels to 354 × 480 pixels. This was also done to make the image's height and width proportional to the first dataset.

3) Common preprocessing: After the initial preprocessing of both the datasets, to generalize our dataset, we changed the background of all the images of both the datasets to white. We did this so that our model could ignore the background and learn more important aspects of the face. We implemented this process first through selfie segmentation model of Mediapipe, though it gave us pretty quick results but we saw that its segmentation wasn't that good. On a lot of images some parts of the person were also turned white, so then we used Photoshop to complete this process. We automated a transformation for all our images, taking much more time to process as compared to Mediapipe but giving excellent results. We could even notice different strands of hair of all the individuals.

Since the aim of our project is to help the police in searching for wanted criminals and missing people, therefore turning the background to white doesn't really matter as the face is all that we're interested in. It doesn't matter what the background is. So we can do the similar process to the test images we're going to download from the web. As we don't need to retain their background as we're only interested in the face part.

B. Stage 2: Creating four dataloaders

As we trained 4 models, one for each output angle image (i.e., 0°, 45°, 135°, 180°), 4 data loaders were made from scratch. These data loaders would use opencv to read the input and target images and resize them to a uniform 256 x 256 pixel images. As we had RGB images and opencv reads the images in BGR format, we had to split the read images and then merge in the correct format. After this we used transpose to change the 256 x 256 x 3 image arrays to 3 x 256 x 256 image arrays as that is the shape in which the images will go into the model to train. Lastly we normalized all the images from the range between 0-255 (pixel value range) to between -1 to 1, as this is mentioned in [1] to give better results. The batch size was also kept at 16 again as mentioned in [1].

C. Stage 3: Algorithm - Generative Adversarial Networks (GANs) and CGANs

GANs are generative models that learn a mapping from random noise vector z to output image y, G:z $\rightarrow$ y.

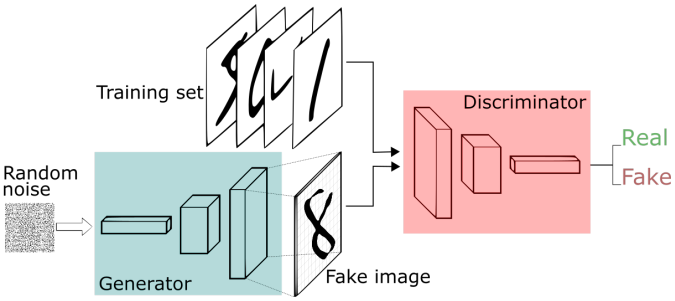


Fig. 3. GANs Framweork (Image Credit: Thalles Silva)

In contrast, CGANs learn a mapping from observed image x and random vector z to y, G:x, z $\rightarrow$ y.

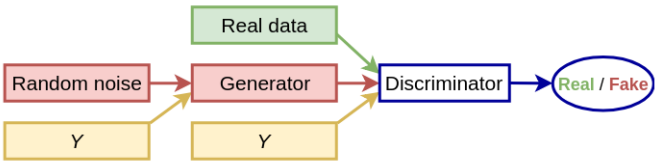


Fig. 4. CGANs Framweork (Image Credit: Manish Nayak)

GANs are algorithmic architectures that uses two neural networks, that compete against each other ("thus the "adversarial") in order to generate new, synthetic instances of data that can be passed for real data. These two neural networks are called Generator and Discriminator. Generator's job is to artificially generate fake images in an attempt to fool the Discriminator for real images. The Discriminator's job is to identify which outputs it receives have been artificially created and which are real. Both models are trained in tandem and follow a cooperative zero-sum game framework to learn. In other words, they play a min max game in order to make each other better. The CGANs is one of the first GAN innovations that made targeted data generation possible as it works on the paired data. It also adds labels to the Discriminator input to distinguish data better.

D. Stage 4: Architecture

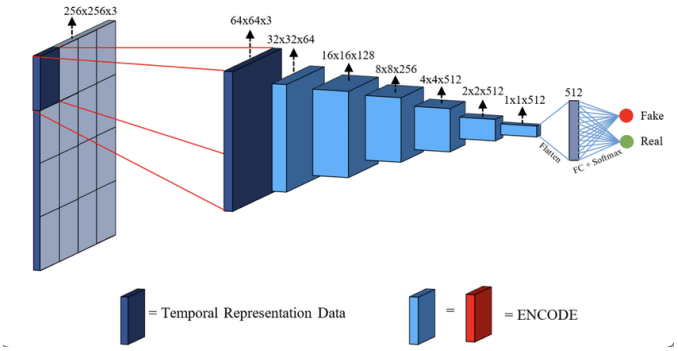


Fig. 5. Convolutional PatchGAN Architecture (Image Credit: ResearchGate)

We have used a 286 x 286 convolutional PatchGAN for the Discriminator, as mentioned in [1].

Let Ck denote a Convolution-BatchNorm-ReLU layer with k filters. CDK denotes a Convolution-BatchNorm-Dropout-ReLU layer with a dropout rate of 50%. All convolutions are 4 x 4 spatial filters applied with stride 2. Convolutions in the encoder, and in the discriminator, downsample by a factor of 2, whereas in the decoder they upsample by a factor of 2.

286 x 286 Discriminator:
C64-C128-C256-C512-C512-C512

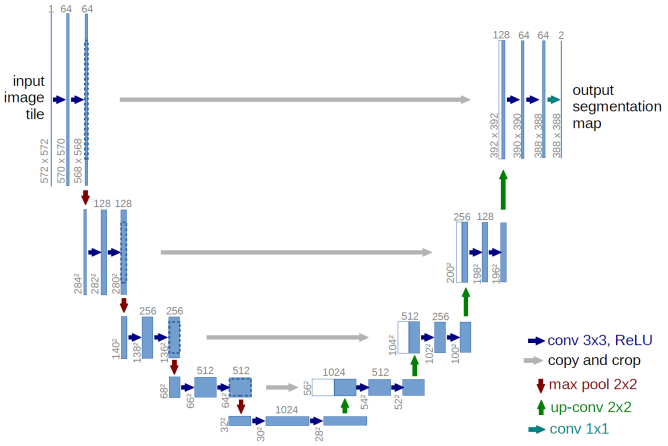


Fig. 6. U-net Architecture (Image Credit: Computer Vision Group)

For the Generator we have used the U-net architecture as again mentioned in [1], that is a convolutional network architecture for fast and precise segmentation of images. As named, it is a U-shaped architecture consisting of a specific encoder-decoder scheme. A U-Net architecture allows low-level information to shortcut across the network by serving the skip connections.

Encoder:
C64-C128-C256-C512-C512-C512-C512-C512

Decoder:
CD512-CD512-CD512-C512-C256-C128-C64

The objective of a GANs can be expressed as:

$$\mathcal{L}_{GAN}(G,D) = \mathbb{E}_y[logD(y)] + \mathbb{E}_{x,z}[log(1 - D(G(x,z))] \quad (1)$$

As opposed to this, the objective for CGANs can be expressed as:

$$\mathcal{L}_{cGAN}(G,D) = \mathbb{E}_{x,y}[logD(x,y)] + \mathbb{E}_{x,z}[log(1 - D(x,G(x,z))] \quad (2)$$

Where G tries to minimize this objective against adversarial D that tries to maximize it. In addition, the most important part

of CGANs which differentiates it from vanilla GANs is the L1 loss, which makes the pairing of images possible. We use L1 loss as opposed to L2 loss as it offers less blurring.

$$\mathcal{L}_{L1}(G) = \mathbb{E}_{x,y,z}[||y - G(x,z)||_1] \tag{3}$$

Final objective thus becomes:

$$G^* = arg \min_G \max_D \mathcal{L}_{cGAN}(G,D) + \lambda \mathcal{L}_{L1}(G) \tag{4}$$

The weight initialization was again done according to [1]. Weights were initialized from a Gaussian distribution with mean 0 and standard deviation 0.02. For Batchnorm layers the weights were initialized with mean = 1 and standard deviation 0.02.

E. Stage 5: Training

As mentioned in [1], to train the model, BCE with logits loss and L1 loss was used to calculate the loss and Adam optimizer was used with learning rate 0.0002 with betas (0.5, 0.999). Alpha (the multiplying factor for the L1 loss) was set to 100. All the models were trained for 200 epochs with batch size 16, while saving the results of the second last batch into files and logging the loss as well. We had the train test split as 1089 set of images for the training purpose and 5 set of images for the testing purpose. We included more data in training than normal convention because of the nature of the problem statement of this project. As we can't really calculate the accuracy for the image generation problems but can only judge the results from our human eyes, also having limited data, plus we're anyway going to test our model on images from the web, so we decided to put more data in the training set so as to train our models better.

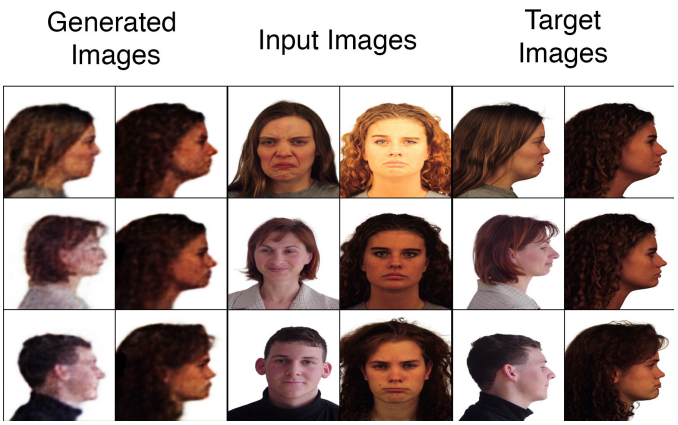


Fig. 7. 200th epoch training images for 0°model

V. Evaluation

All the 4 models were evaluated based on their Generator and Discriminator loss.

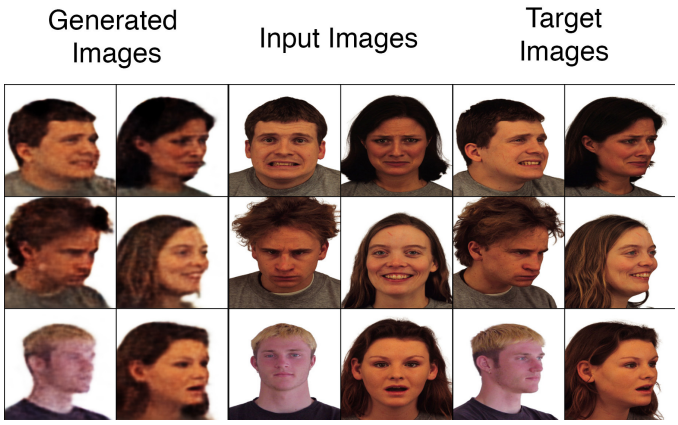


Fig. 8. 200th epoch training images for 45°model

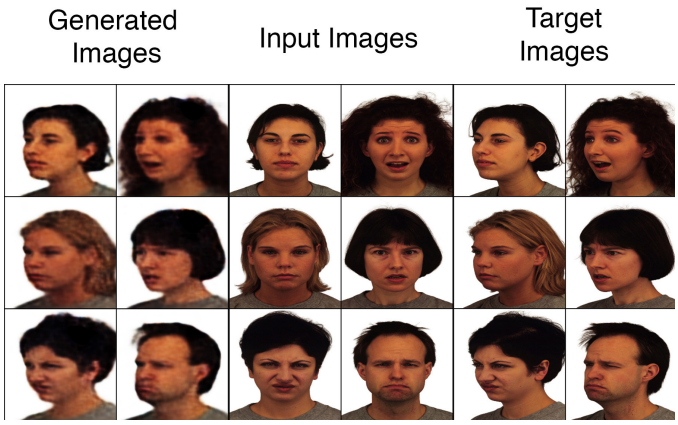


Fig. 9. 200th epoch training images for 135°model

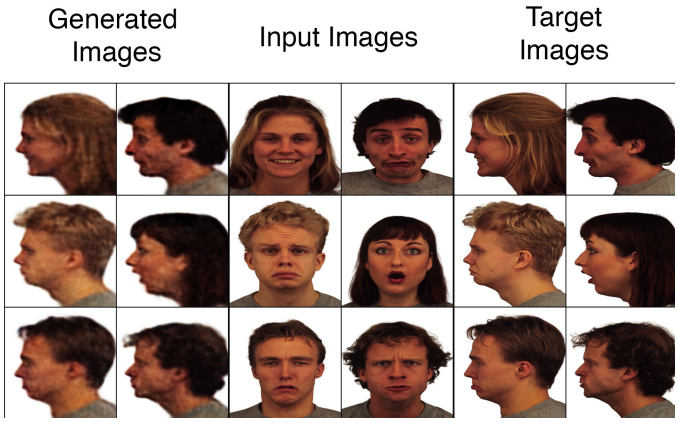


Fig. 10. 200th epoch training images for 180°model

As can be clearly seen from the loss graphs, loss of Discriminators have some oscillations in the beginning but afterwords it starts to become constant. As for the loss of Generators, for all the models it steadily decreases across the

200 epochs which again is a good thing certifying that our models trained well.

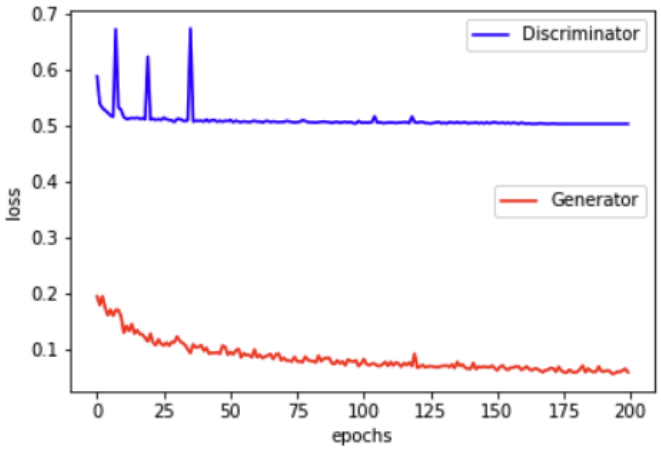


Fig. 11. Loss graph for 0°model

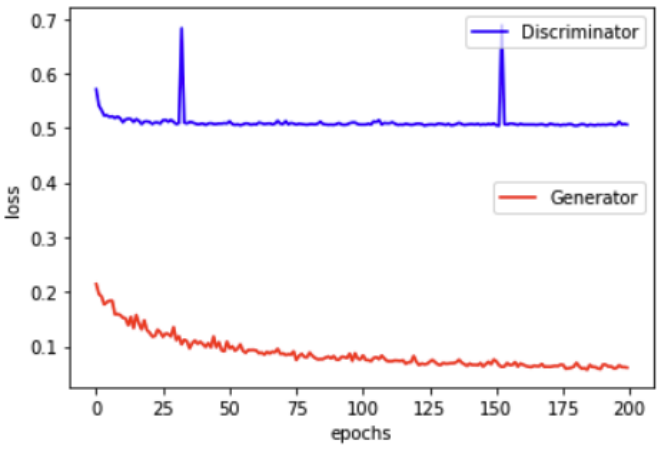


Fig. 12. Loss graph for 45°model

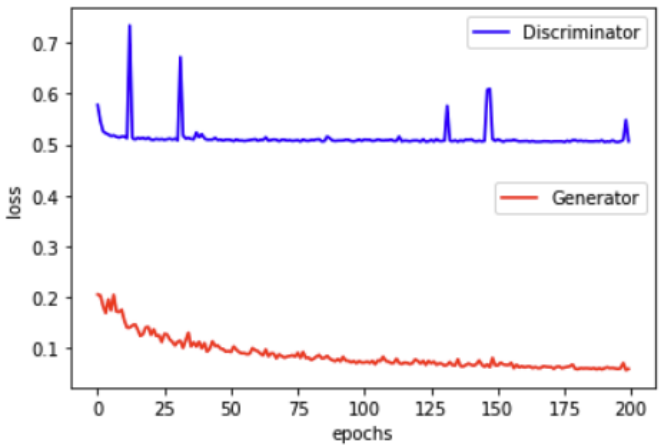


Fig. 13. Loss graph for 135°model

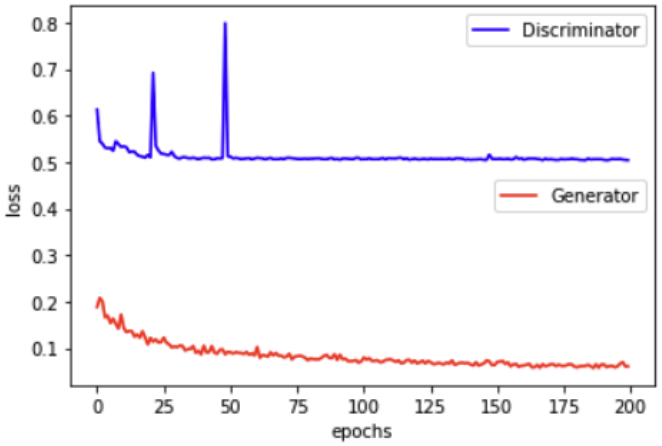


Fig. 14. Loss graph for 180°model

VI. Testing and Results

The performance of our models has been tested using two categories of data.

A. Test Category 1

In this category we test our model on the images from the test set of the dataset. As these images are part of the dataset they have a lot of features similar to the other images in the training set of the dataset, such as camera, lighting, background, person's ethnicity etc. But at the same time since these are the test images and not included to train the models, our models have never seen the faces that are in these images. So keeping that in mind we think that our models have done a good job in generating the different profiles for these images as we can clearly see that our model has been able to learn and generate facial features such as hair, nose, ears, mouth, eyes etc very similar to the target images. There's still a long way to go as we can observe that the generated images are a bit pixelated, but I believe this has been the case because of limited dataset. If we could've have gotten bigger datasets with more diversity and ethnicity in their subjects, then this probably wouldn't have been the case.

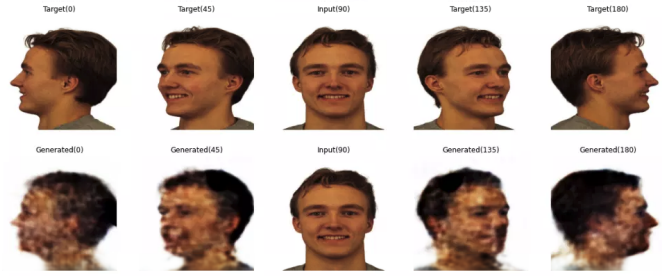


Fig. 15. Test image 1 from the test set of the Dataset

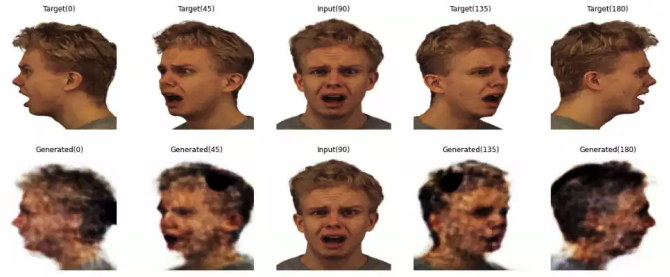


Fig. 16. Test image 2 from the test set of the Dataset

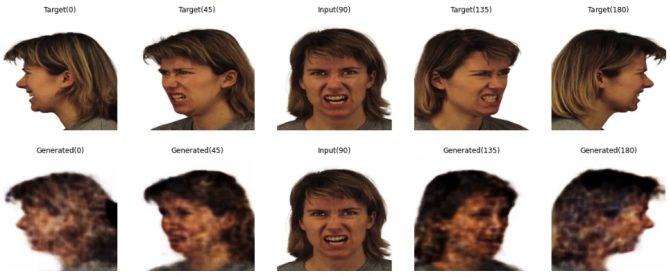


Fig. 17. Test image 3 from the test set of the Dataset

B. Test Category 2

In this category we test our model on the images obtained from the Web. This is a more difficult category for our models as these images have nothing similar to the images from our dataset. As our datasets were very limited with very little diversity and ethnicity in them, its reasonable that our model didn't quite perform as well on the web images as it did on the test images. But again there were some positives that we can take. We can see that our model has been able to learn and generate facial features like hair and nose quite correctly. The angle of the generated facial images are also correct, but I can agree that these images could have been much better.

Fig. 18. Test image 1 from the Web

Fig. 19. Test image 2 from the Web

VII. Building the GUI using Tkinter

We finally built a seamless and user-friendly GUI using Tkinter as given the nature of our project, it seemed a good choice to build a GUI, so that people form both CS and non CS backgrounds could benefit from our project. This GUI will ask you to select the image file you need to generate more profiles of. Once the image is selected, you can see the results displayed on the GUI within matter of seconds. The GUI even shows a "Loading…" text while processing the image just to let the user know that the program is working . As our project is training and using 4 models to predict the different profiles, one for every profile. Choosing the path of all the 4 models in the GUI did not seem very user-friendly, so it was removed and now the user only needs to select the image that they want to generate the multiple profiles for. But in order to run the GUI successfully the user needs to change the path of all the 4 models. We have shown this part in the Demo for more clarity.

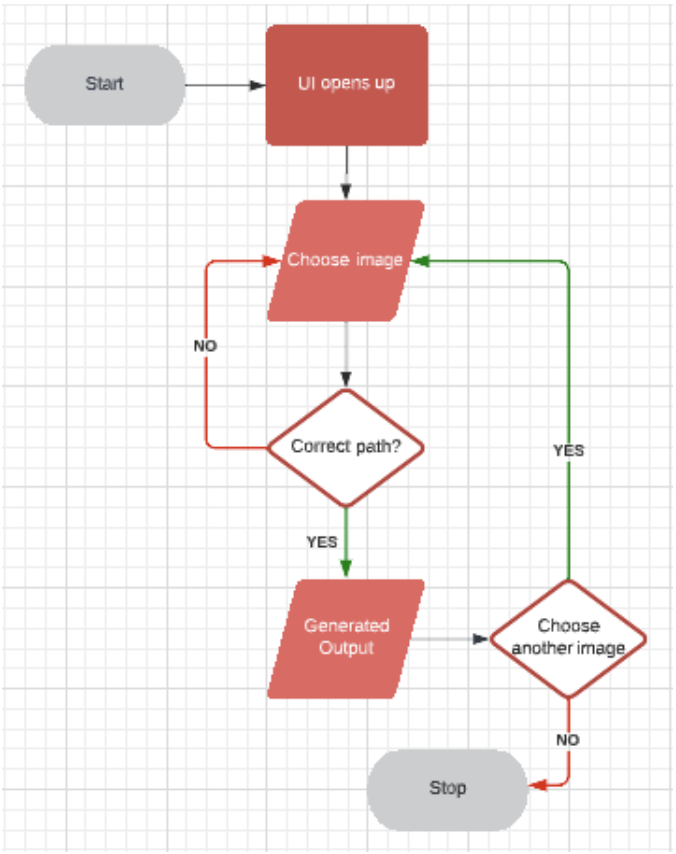


Fig. 20. Flowchart of the GUI Application

Fig. 21. Initial screen of the GUI

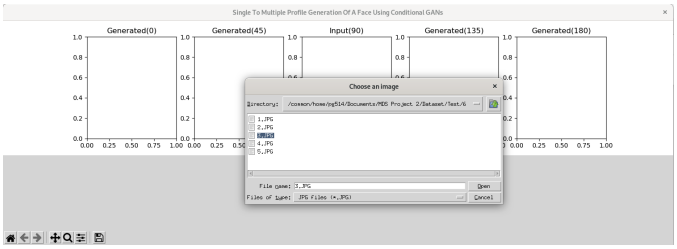


Fig. 22. Dialog box opens up to choose the test image on the press of the button

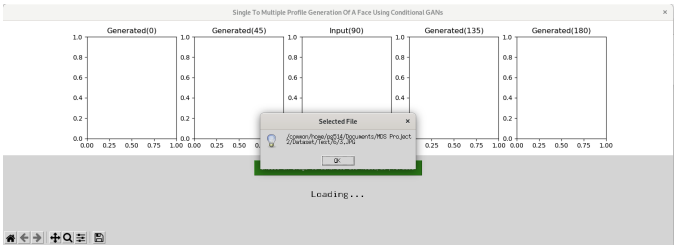


Fig. 23. On choosing an image the GUI asks the user to make sure if the chosen image path is correct

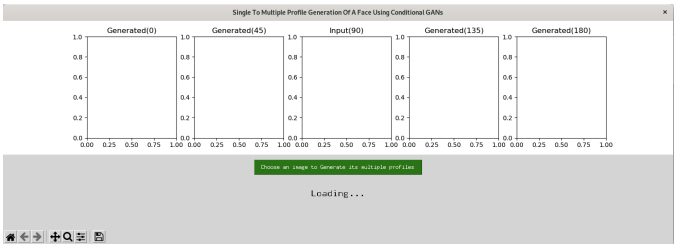


Fig. 24. While the image is processing the GUI shows Loading message

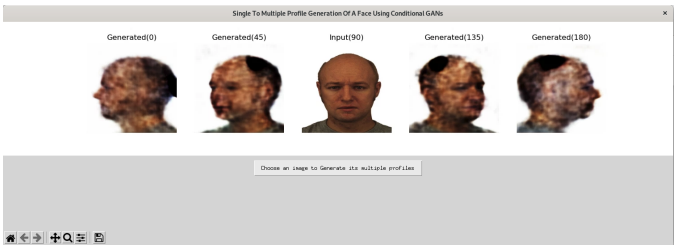


Fig. 25. Final generated output in the GUI

VIII. Challenges Faced

Getting the dataset was the first challenge that we faced for this project. All the relevant good datasets we found for the purpose of this project are open-source but require approval from their owners. They are not openly available as it's not allowed to use them for commercial purposes. So the owners need to check our background affiliation with Rutgers in order to grant us the approval to use their datasets.

Secondly, the datasets that we acquired were primarily for facial expression recognition, plus there were some missing images in the dataset, so I had to manually go over the dataset to generate the images using Photoshop, and clean the data to make it usable for our purpose. Also, CGANs algorithm is latest research with few online resources to understand it, so we had to read the original paper in order to understand and implement this algorithm. Since we're working with a custom dataset, we also had to make a custom dataloader to cater to the needs of this project.

We initially trained the models using 70 x 70 PatchGAN Discriminator architecture but then evaluating the results had to re-train the models using 286 x 286 PatchGAN Discriminator architecture. These models were giving good results on the test set from the dataset but when we used it for testing on the images from the web, it gave poor results. We figured it was because all the images in the dataset had the same background, so our model was uneccessarily learning the background and when getting an image with a different color background getting confused. So to fix this we used Photoshop script to remove the background from all the images and then train all the 4 models again.

Lastly we built a GUI using Tkinter which was our first time using that library. Learning a new library from scratch is always a challenge, but given the nature of our project it seemed a good choice to build a GUI, so that people from both CS and non CS backgrounds could use our project.

IX. Division of Work and Timeline

Fig. 26. Gantt Chart

Working as the sole member of this group, I was responsible for gathering, cleaning and combining the datasets. I automated the background removal process using Photoshop. I read [1], to get myself familiar with the training methodology and architecture used in the paper. I fed this data to the CGANs model that I created from scratch. I then evaluated the models

using Matplotlib plots and finally tested the model by building a seamless and user-friendly GUI using Tkinter and sending many test images from the dataset test set and the web.

X. Conclusion and Future Work

In conclusion our project did a good job being a prototype. We can see from the evaluation plots that the losses of both the Generators and Discriminators are exactly as they as supposed to be. In addition to that we saw good results on the test images from the Dataset meaning that our model learnt pretty well given the small diversity in our dataset. For the images from the web we can see that the results are not that good as compared to the dataset test images but they are still quite reasonable.

For future work we would like to get a bigger dataset which has more diversity, meaning it has people from different ethnicity, currently one of our datasets only consists of Caucasian people and the other dataset only has White people. Therefore training our model on a dataset with people from different ethnicities would give even better results.

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