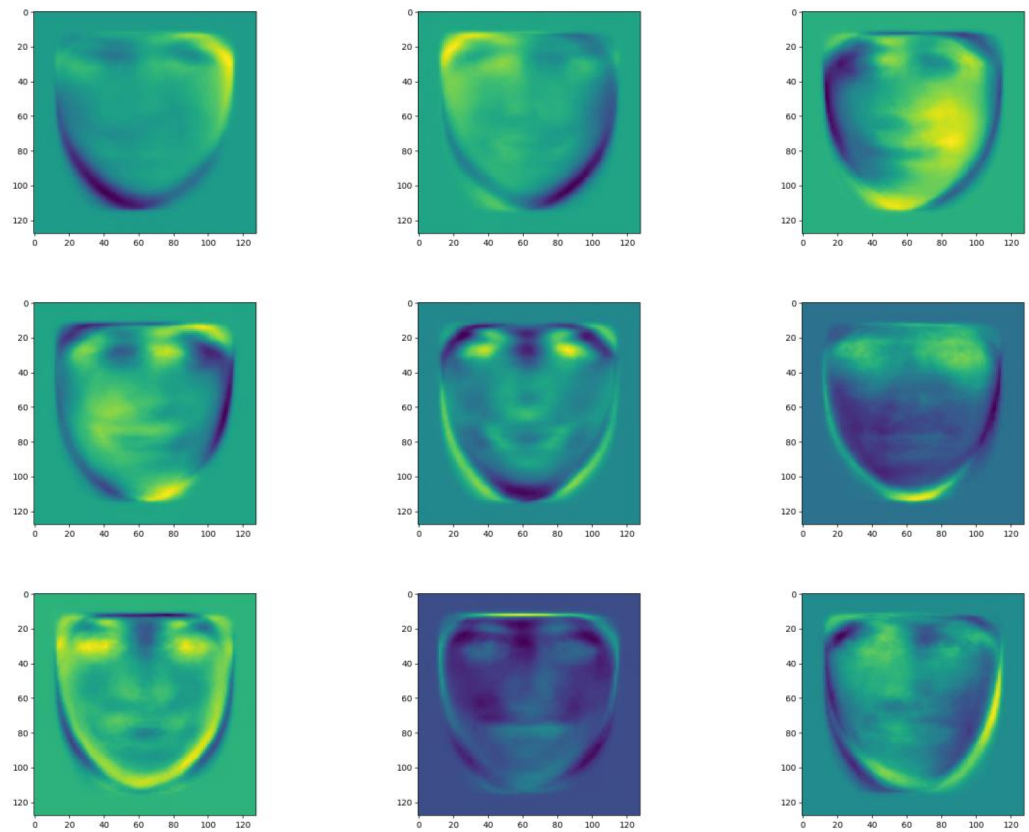
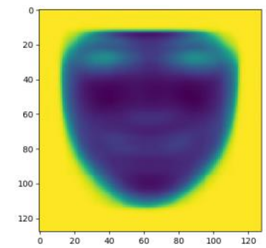
PROJECT REPORT
PROJECT 1

Anurag Pant
UID: 705085298

2.1 PCA: a non-linear method

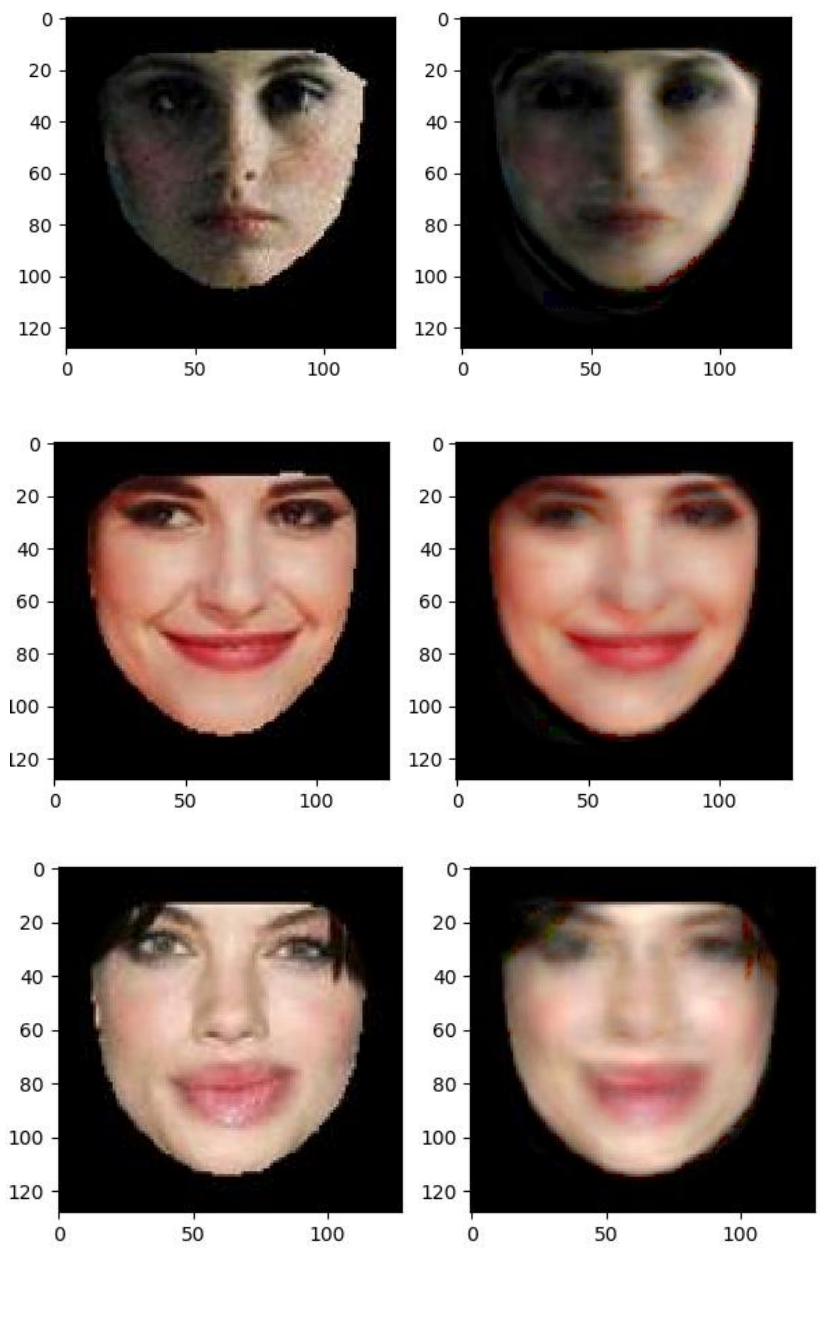
1. Principal Component Analysis is used to reduce the dimensionality of the image to make it easier to transmit images from the sender to the receiver. The only pre-requisite for this is that both the sender and the receiver must possess the codebook which consists of the mean image and the eigen vectors of the images (calculated from the image database).
   In the first part of the question, we reduced the two-dimensional human faces (testing data) of 128x128 pixels into 50 features by making use of the mean image and the eigen vectors. We calculated the mean image and the eigen vectors over the training data.

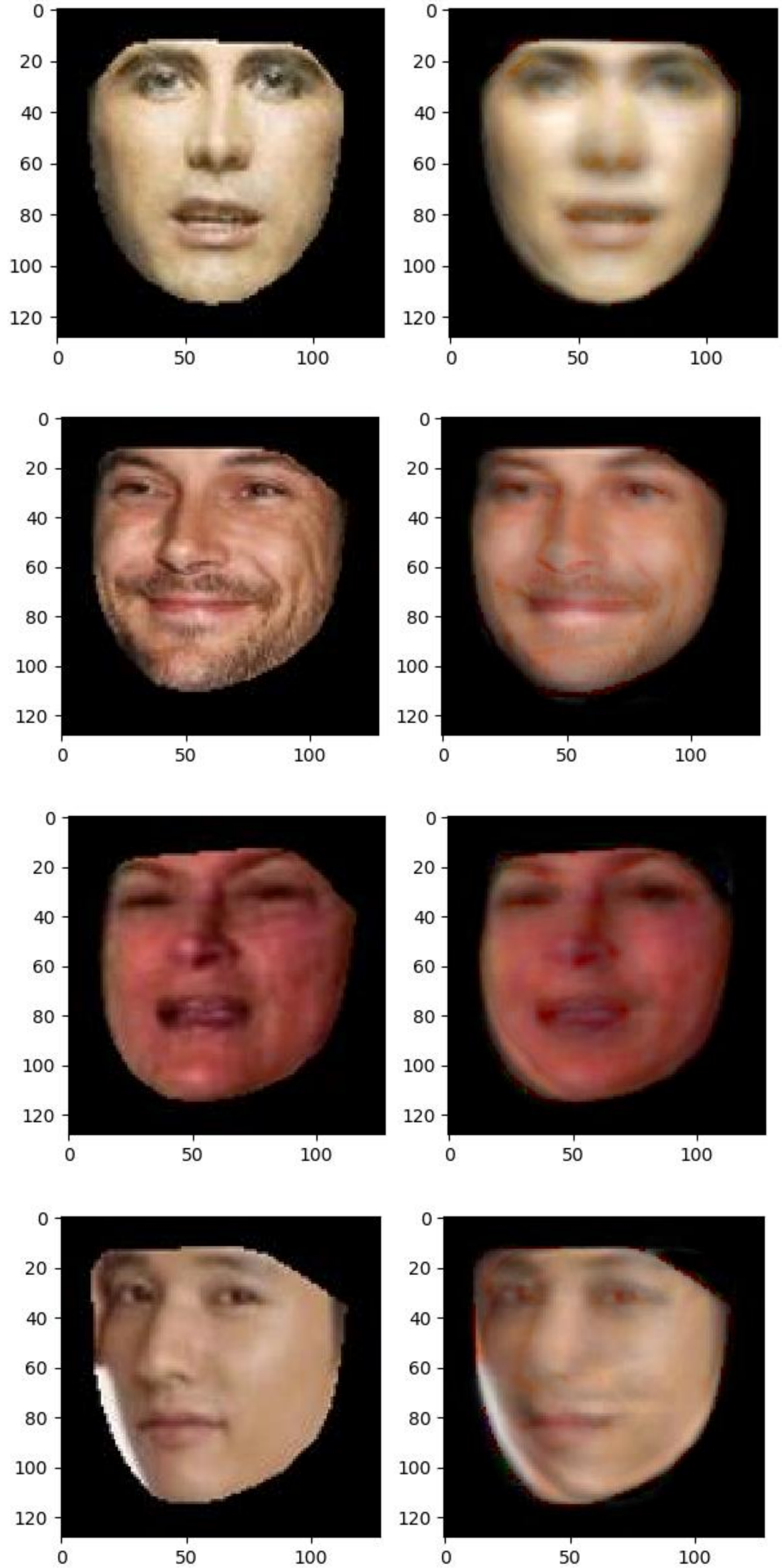


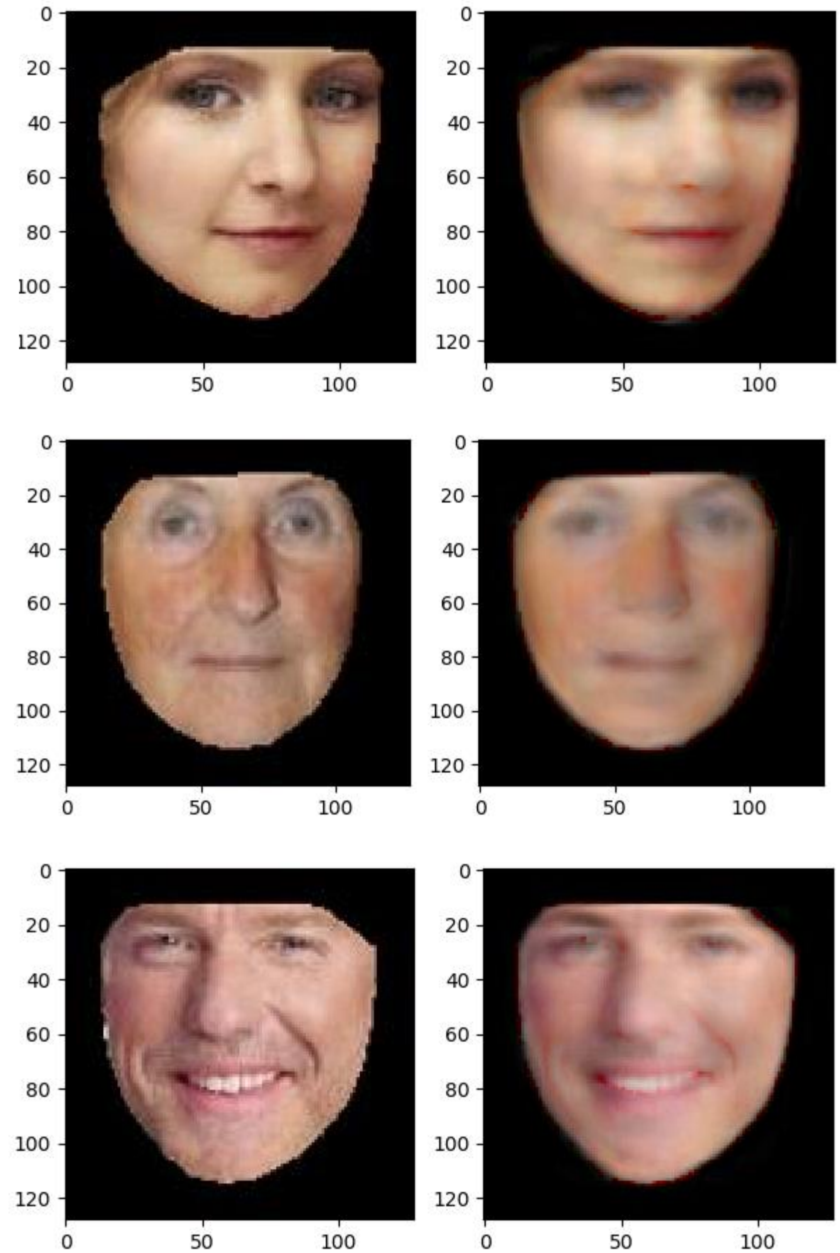


<u>Eigen Faces</u>

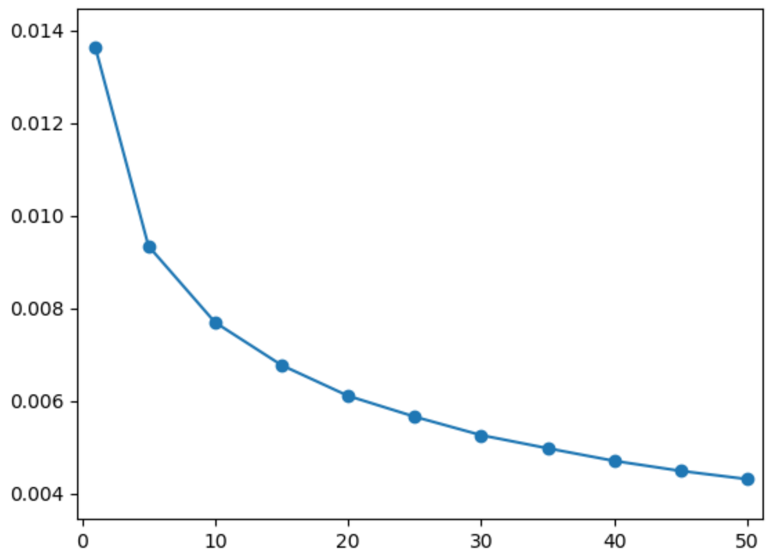
After reducing the testing images into 50 features, we proceeded to reconstruct the images and then plotted the error (mean squared intensity of the difference between the reconstructed image and the input image) on a graph. The reconstructed faces are given below (on the right) with the original image (on the left):



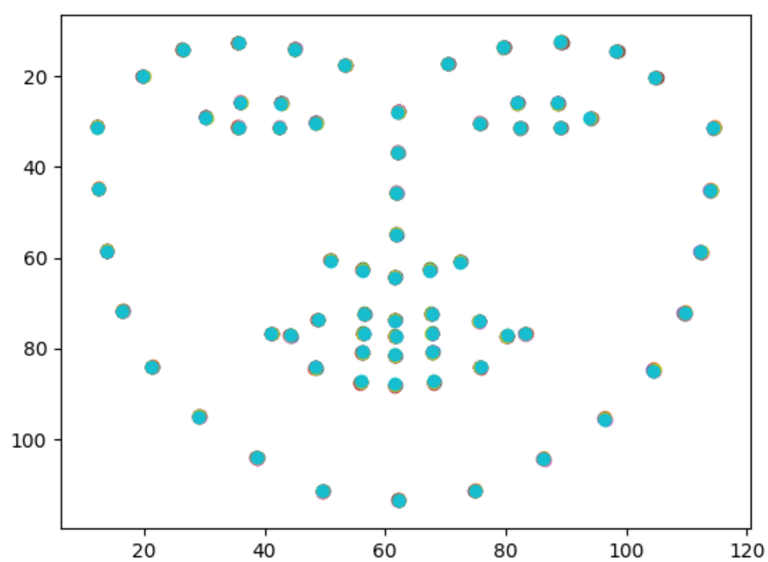

0
20
40
60
80
100
120
0
50
100



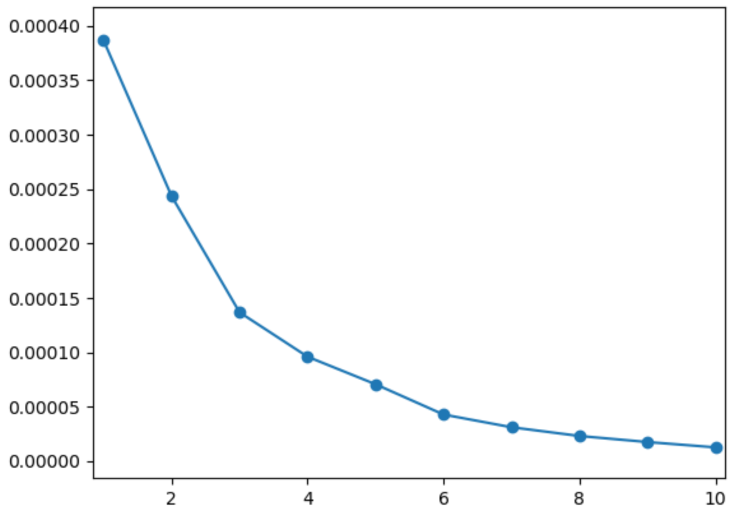
The plotted error is given below:



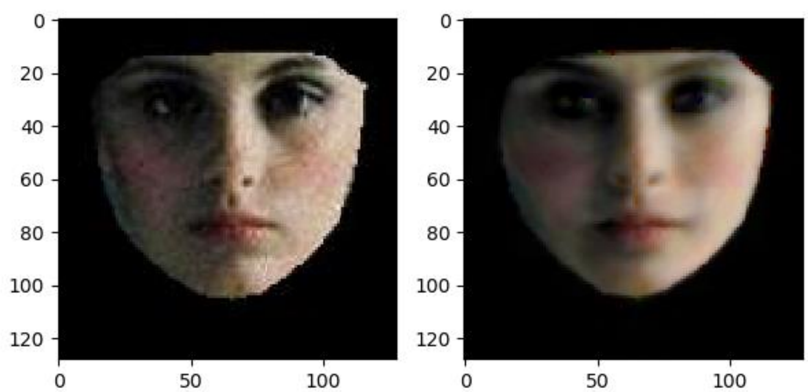
2. In the second part of this exercise, we did the same exact thing as we did in the first part. The only difference is that we now use the landmarks of the human faces instead of using the two-dimensional human faces. The eigen landmarks are plotted below:

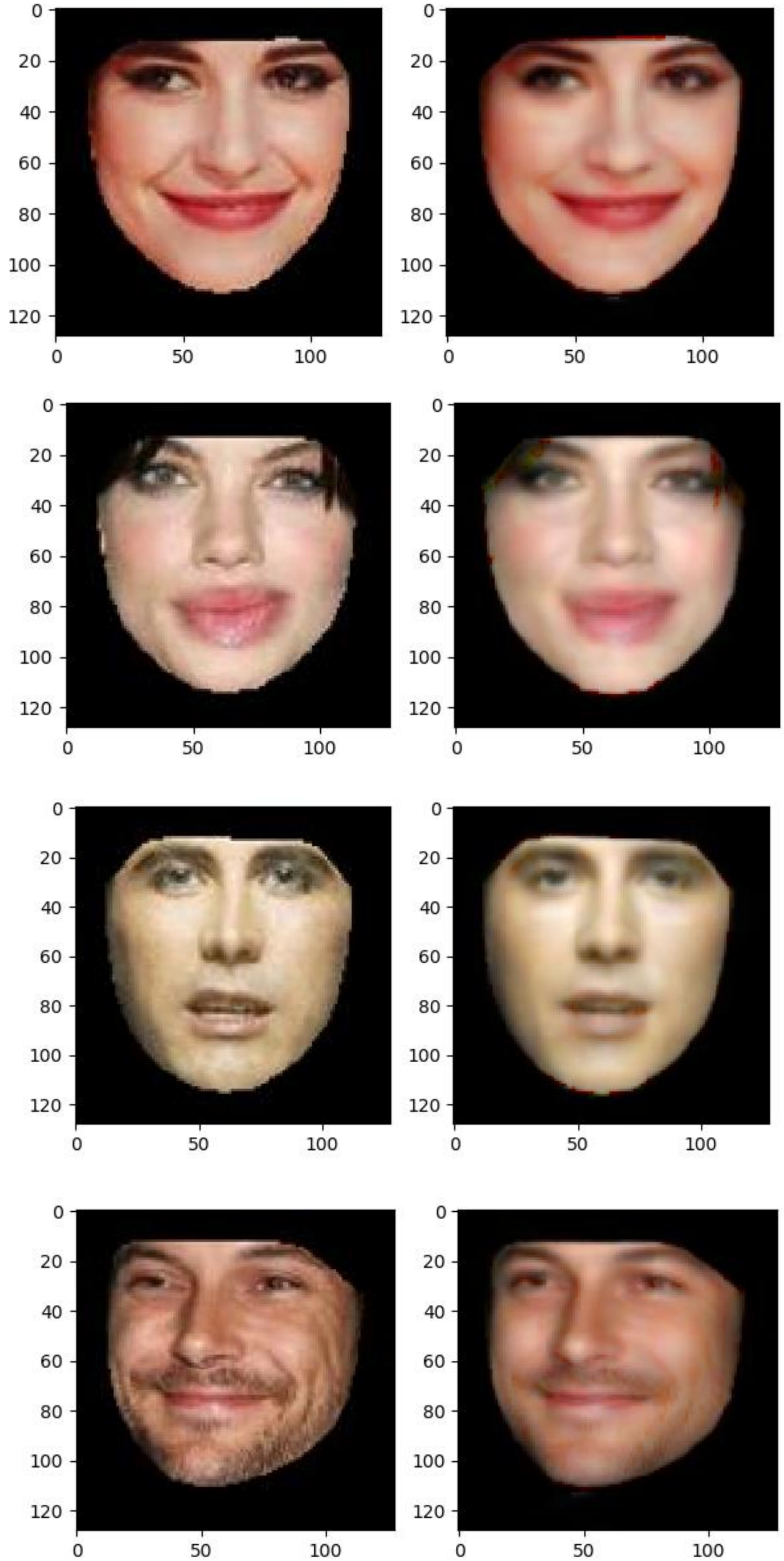


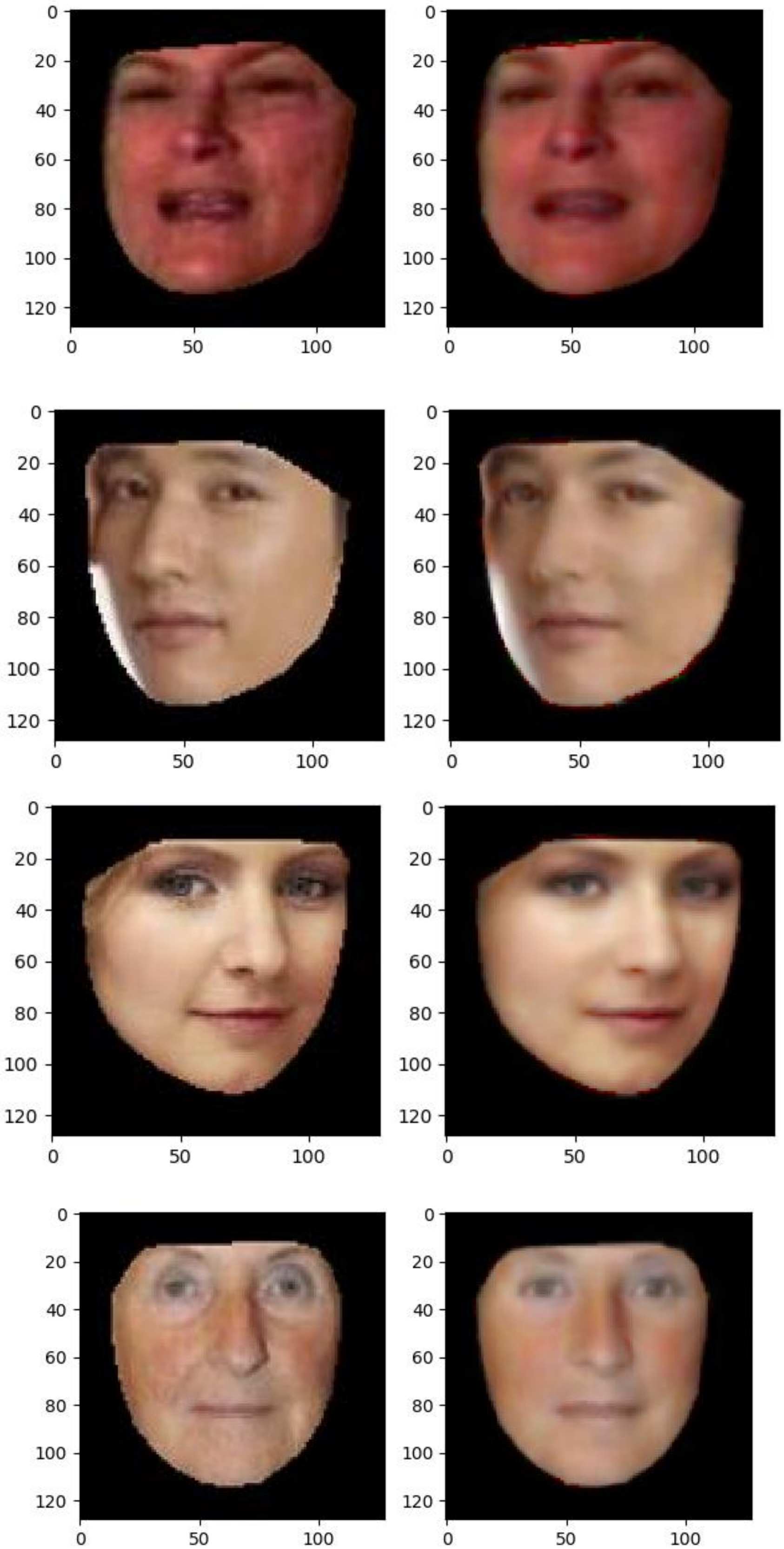
The plotted error is given below:



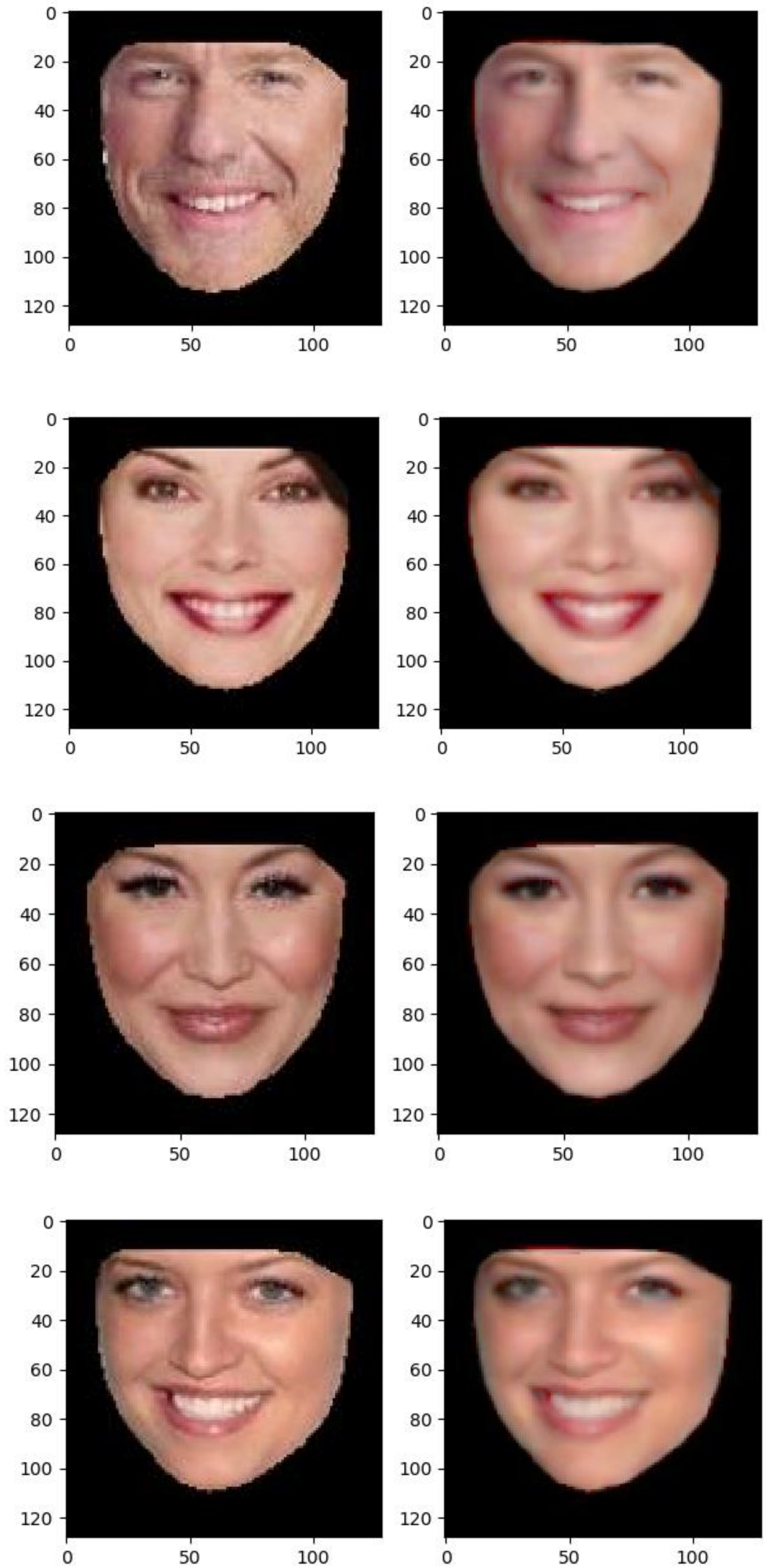
3. In the third part of this question, we combined what we did in the first and the second part of the question. First, we warped all the two-dimensional images to their mean landmarks. Then using these warped images, we followed the procedure of the first part, wherein we calculated the eigen vectors and the mean image using the training images and then, reduced the dimensionality of each testing image to 50 features. After this, we reconstructed the testing images. Then we followed the procedure of the second part, wherein we calculated the eigen vectors and the mean landmarks using the training landmarks and then, reduced the dimensionality of each testing landmark to 10 features. After that, we reconstructed the testing landmarks. Finally, we warped the reconstructed images to the reconstructed landmarks and plotted the error. The reconstructed faces are shown below (on the right) alongside the original faces (on the left):

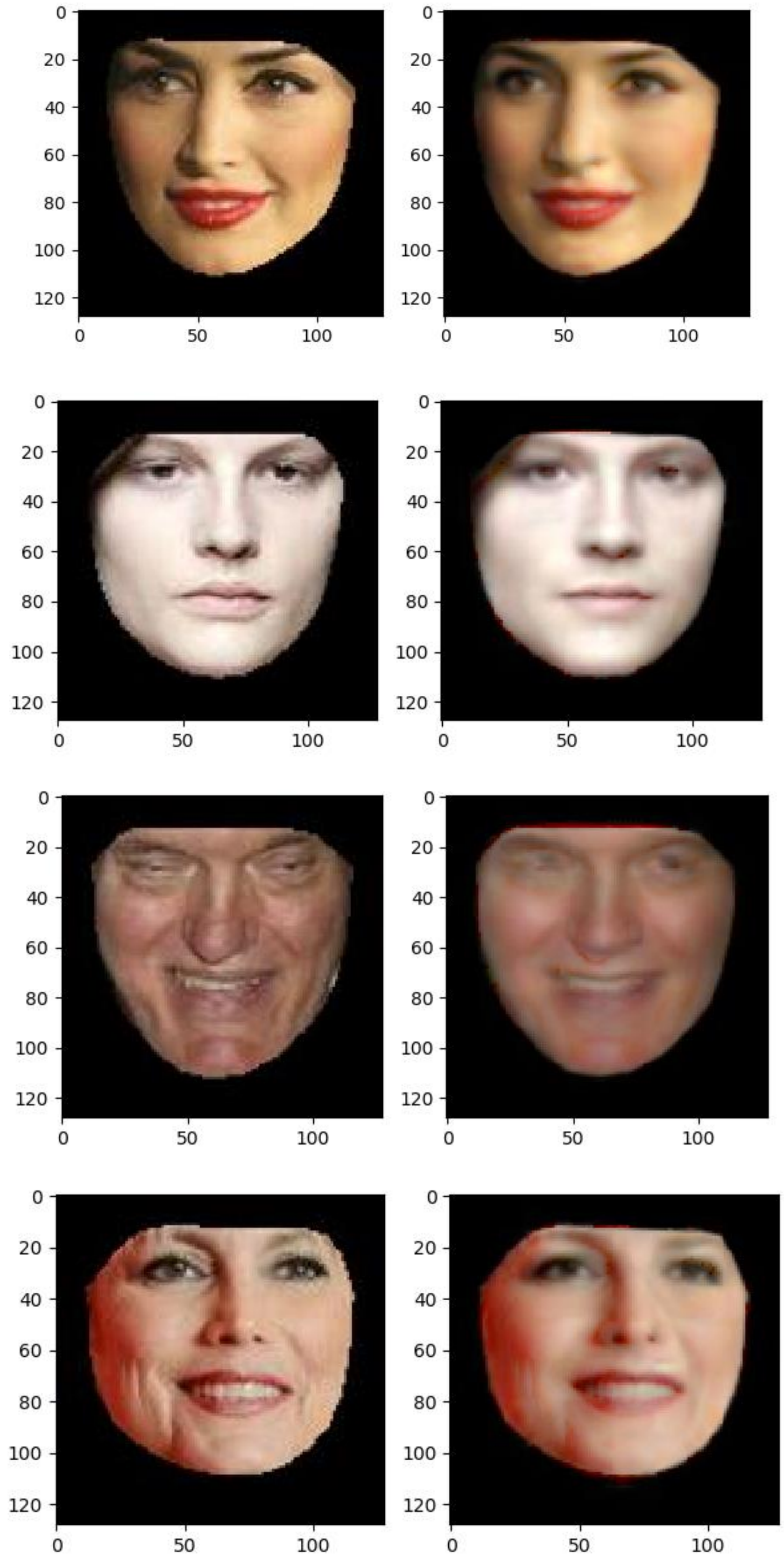


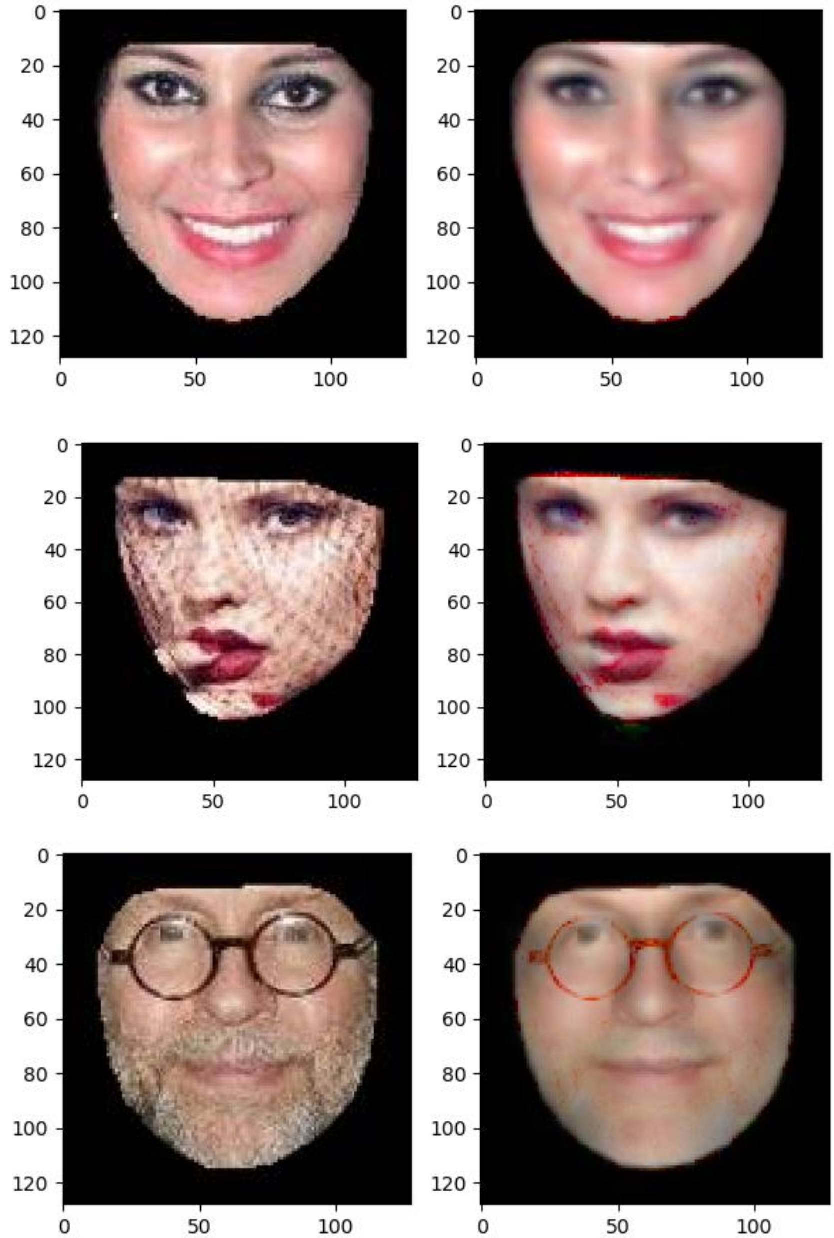




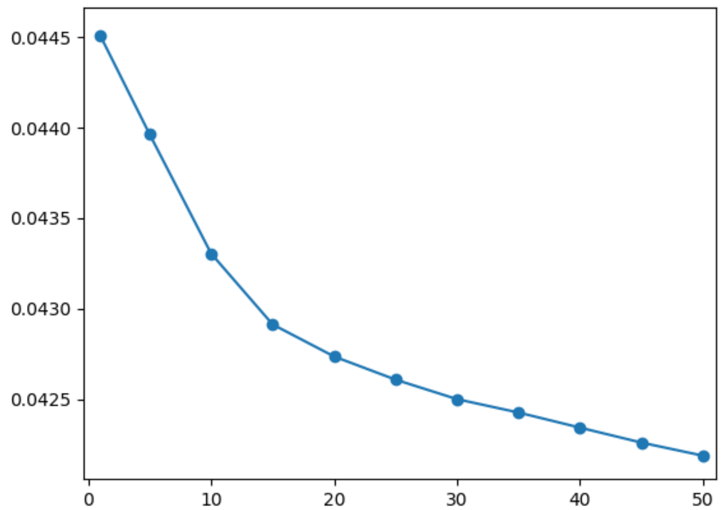
0 20 40 60 80 100 120
0 50 100
0 20 40 60 80 100 120
0 50 100
0 20 40 60 80 100 120
0 50 100
0 20 40 60 80 100 120
0 50 100
0 20 40 60 80 100 120
0 50 100
0 20 40 60 80 100 120
0 50 100
0 20 40 60 80 100 120
0 50 100
0 20 40 60 80 100 120
0 50 100




0
20
40
60
80
100
120
0
50
100
0
20
40
60
80
100
120
0
50
100
0
20
40
60
80
100
120
0
50
100
0
20
40
60
80
100
120
0
50
100
0
20
40
60
80
100
120
0
50
100
0
20
40
60
80
100
120
0
50
100
0
20
40
60
80
100
120
0
50
100
0
20
40
60
80
100
120
0
50
100



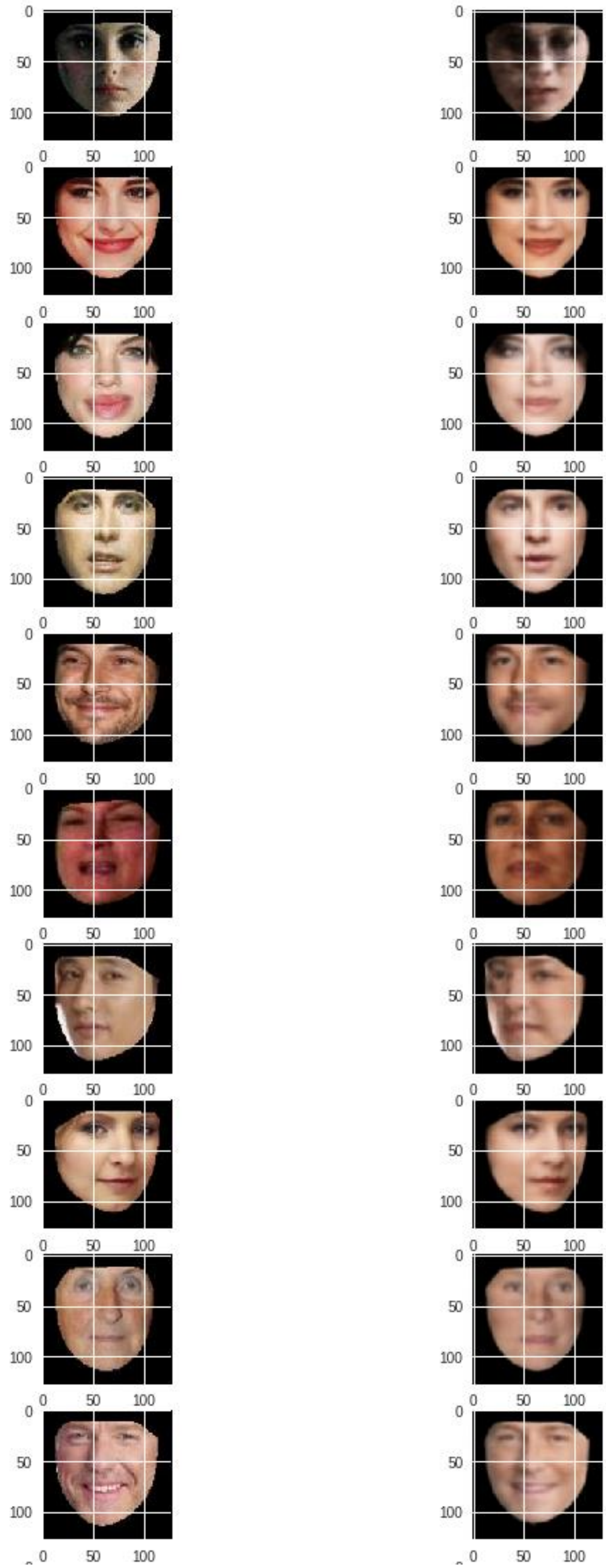
The plotted error is given below:

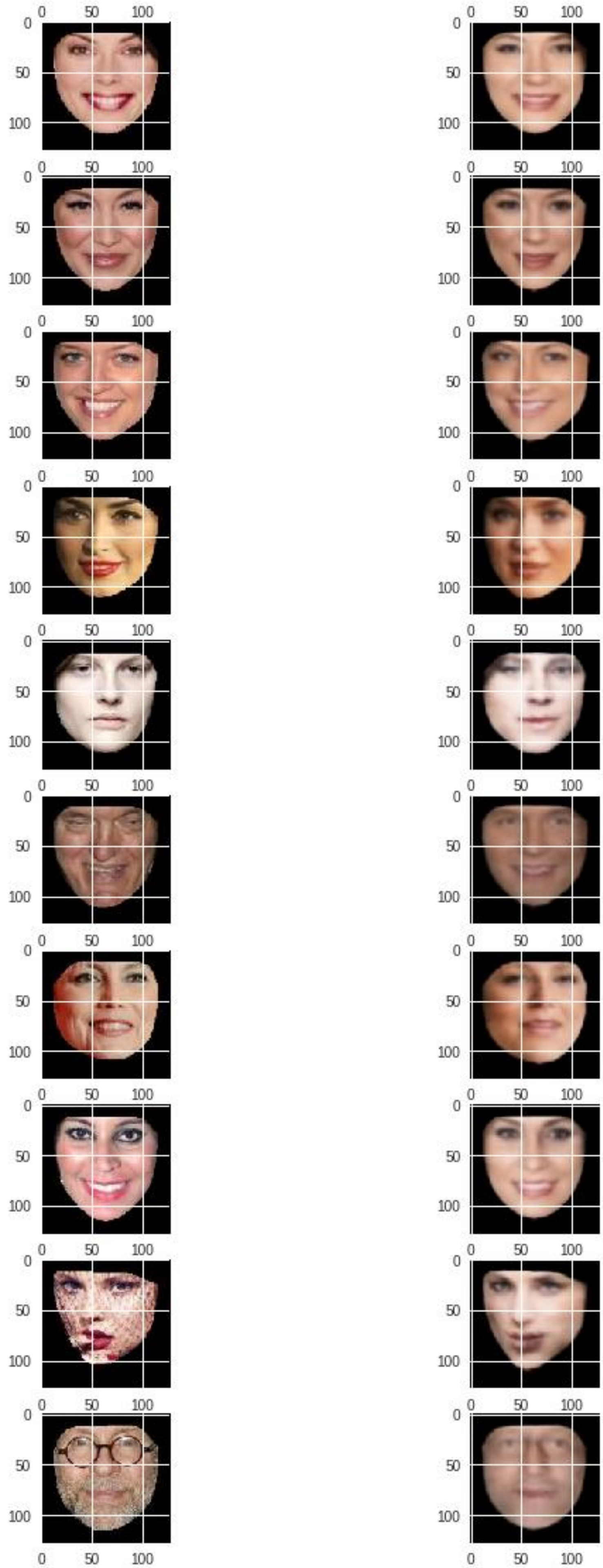


4. In the last part of the PCA question, we worked on synthesizing new images. To do this we made use of the eigen vectors of the two-dimensional human faces and the landmarks from the last part of the question. Furthermore, we calculate the eigenvalues of the human faces and the landmarks. Now we use the normal distribution to find the newly synthesized images by taking mean as 0 and the square root of the eigen values as the standard deviation. We create the images by randomly sampling to find the 50 features that can make the reduced dimensionality form of an image. Similarly, we also find the 10 features for the landmarks of each image. Then we reconstruct the images and the landmarks using the eigen vectors. Finally, we warp the reconstructed images to the reconstructed eigen vectors. The synthesized images are given below:

2.2 Autoencoder: a non-linear method

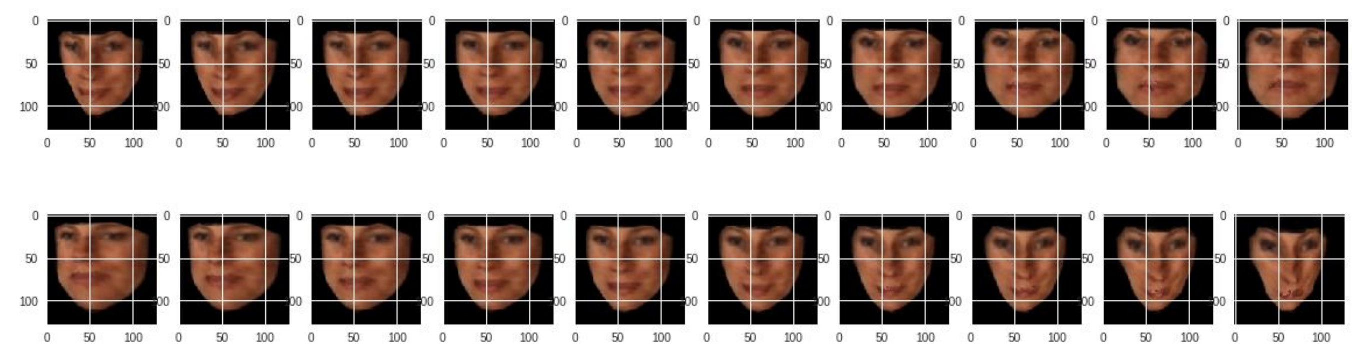
1. In the first part of this question, we had to make use of two auto-encoders to reduce and then reconstruct the image. We first warped the two-dimensional face images to their mean landmarks. We then set the learning rate to 7e-4, the training epochs to 300 and the batch size to 100. Then, we used the first auto-encoder to reduce the dimensionality of the two-dimensional face images by making use of a convolutional architecture. After that, we reconstructed the original images from the reduced images using the decoder part of the auto-encoder. Similarly, the second auto-encoder reduced the dimensionality of the landmarks of the images by making use of a fully-connected architecture, after which we reconstructed the landmarks by making use of the decoder part of the second auto-encoder. The reconstructed two-dimensional face images were then warped to their respective reconstructed landmarks. The 20 reconstructed images can be seen on the next page (on the right) alongside the original images (on the left).





2. In the second part of this question, we had to demonstrate image interpolation. To achieve this, we first reduced the two-dimensional face images using the auto-encoder we had created above. Then making use of this image of reduced dimensionality, we found the 4 features with maximal variance and showed the interpolation results of each dimension while keeping the other dimensions fixed on any one image. The results were as follows:

We also worked on interpolation of the landmarks in a similar manner, by first reducing the landmarks using the auto-encoder and then finding the 2 features with maximal variance. We then selected any one image to show the results of landmark interpolation, which were as follows:



3. <u>Fisher faces for gender discrimination</u>

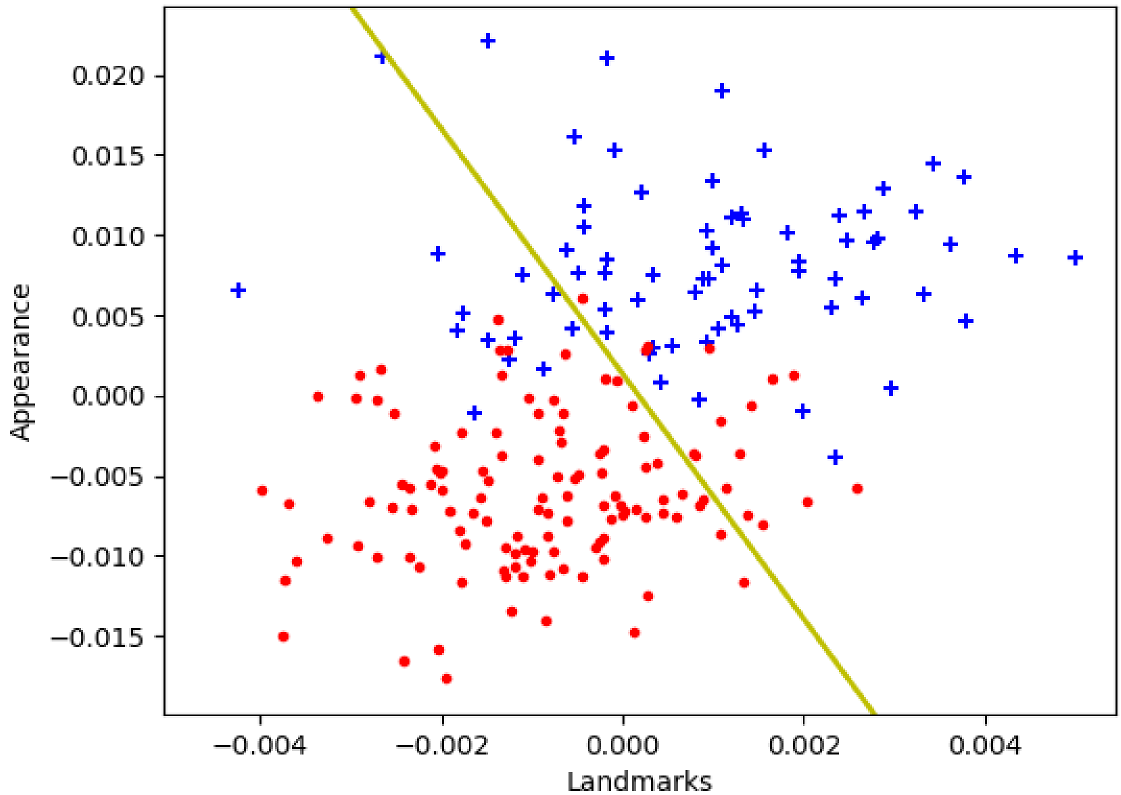
1. The Fisher face is a discriminative model of the face that allows us to extract the key features belonging to different classes (in this case male and female) to allow us to separate them. In the first part of the question, we created a Fisher face out of the training data (which is a randomized combination of male and female images) by first performing PCA to reduce the dimensionality of the data and then used the reduced data to create a Fisher face. In the process of creating a Fisher face, we combined the 50 features from the two-dimensional face images (that have been warped to their mean from their original landmarks) and the 10 features obtained from the landmarks.

   Using these 60 features, we proceeded to first find the mean male face (m_m) and the mean female face (m_f) from the training data. Then we calculated the Fisher face by applying the formula: $W = S_w^{-1} (m_m - m_f)$. Once we have the Fisher face, we calculated the threshold value that separates the male and the female images. We then projected the faces in the testing data to the Fisher space (after calculating their reduced dimensionality form using PCA). Using the values we got from the projection of the test data, we were able to differentiate between the male faces and the female faces using the threshold value.

   Using our Fisher face, we get a **testing accuracy of 94%**.

   However, if we use un-warped images instead of warped images and then reduced those to get the 50 features, we wind up with a **testing accuracy of 85%.**

2. In the second part of this question, we created two Fisher faces: one from the 50 features taken from two-dimensional human faces and the second from the 10 features taken from the landmarks. After calculating the threshold for both the Fisher faces respectively, we proceeded to project our reduced test data onto the Fisher space for both the Fisher faces. Now once we have 2 values for each point (one from each Fisher face), we can proceed to plot it on a graph to show the separability of the points in 2D space. Also, we can plot a line that connects both the threshold points to show how well they are separated based on the threshold values respectively.


0.020
0.015
0.010
0.005
0.000
−0.005
−0.010
−0.015
Appearance
−0.004
−0.002
0.000
0.002
0.004
Landmarks