

# Human Face Classification based on Gender, Age and Race

By

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# Introduction

Our project predicts the age, gender and race for an input human face. We have based our project the paper “Age and Gender Classification using Convolutional Neural Networks” by Gil Levi and Tal Hassner. To classify, we used a Convolutional Neural Network (CNN) and pytorch libraries.

## Dataset

For our dataset, we used the UTKDataset<sup>1</sup>. We used the pre-aligned and cropped faces. The dataset consists of about 23000 images but because of memory and speed issues we randomly selected 10000 images with a split of 8000 training images and 2000 validation images.

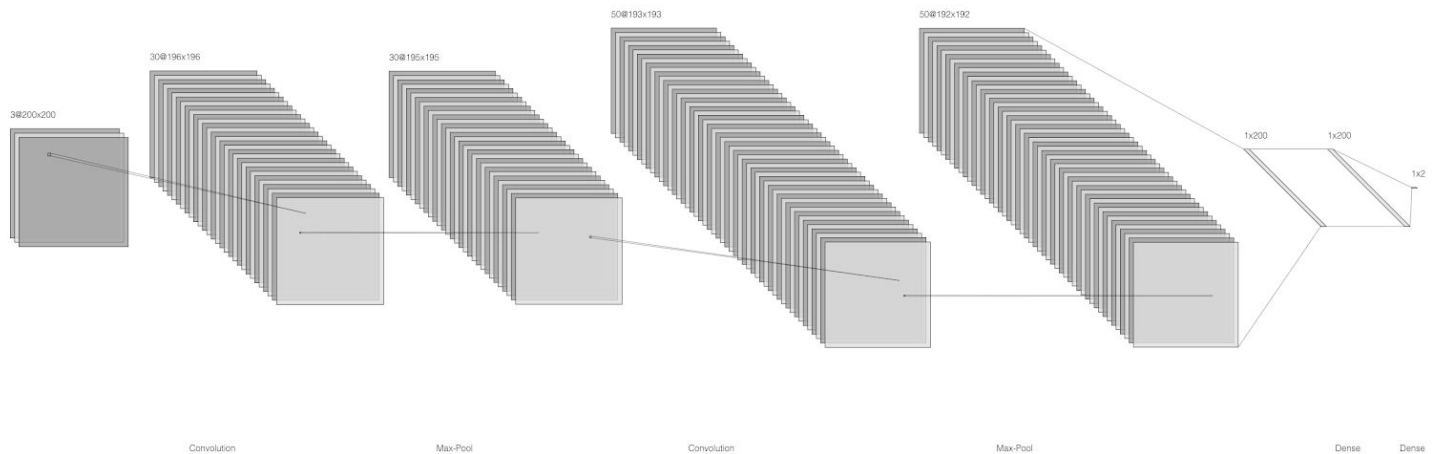
For every picture, every image has the following label:

- **Age:** an integer varying from 1 to 116. We divided the age data into 12 different labels starting from 1-10 years old until 111-120 years old.
- **Gender:** either 0 (male) or 1 (female)
- **Race:** an integer from 0 to 4 indicating the following races respectively: White, Balck, Asian, Indian, Others

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<sup>1</sup> <https://susanqq.github.io/UTKFace/>

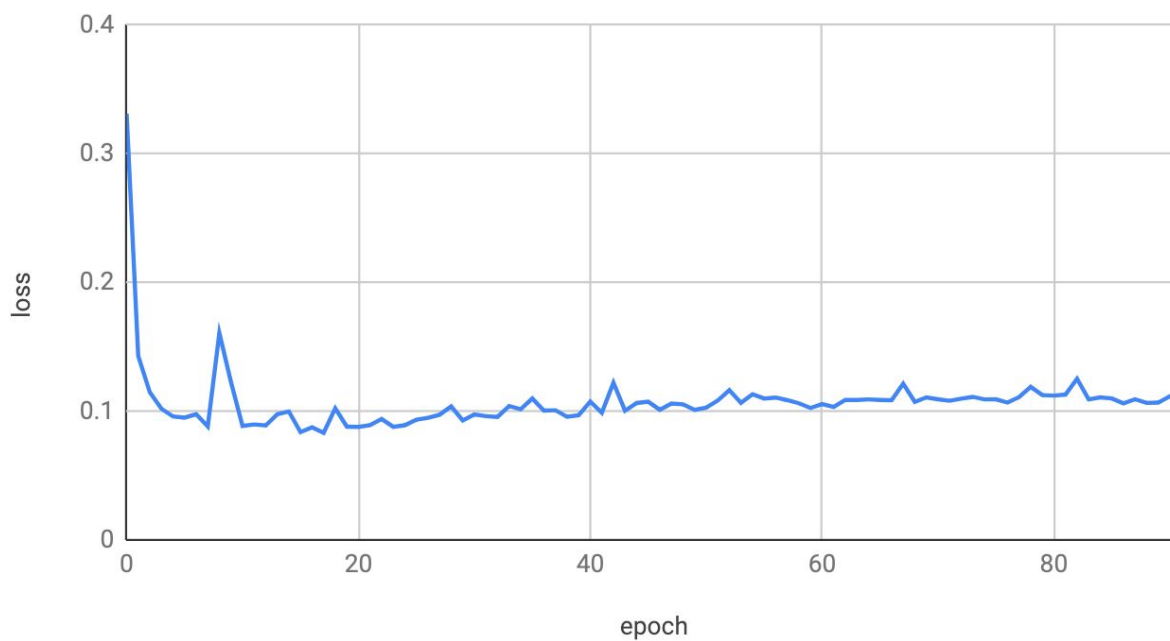
# Neural Network Architecture



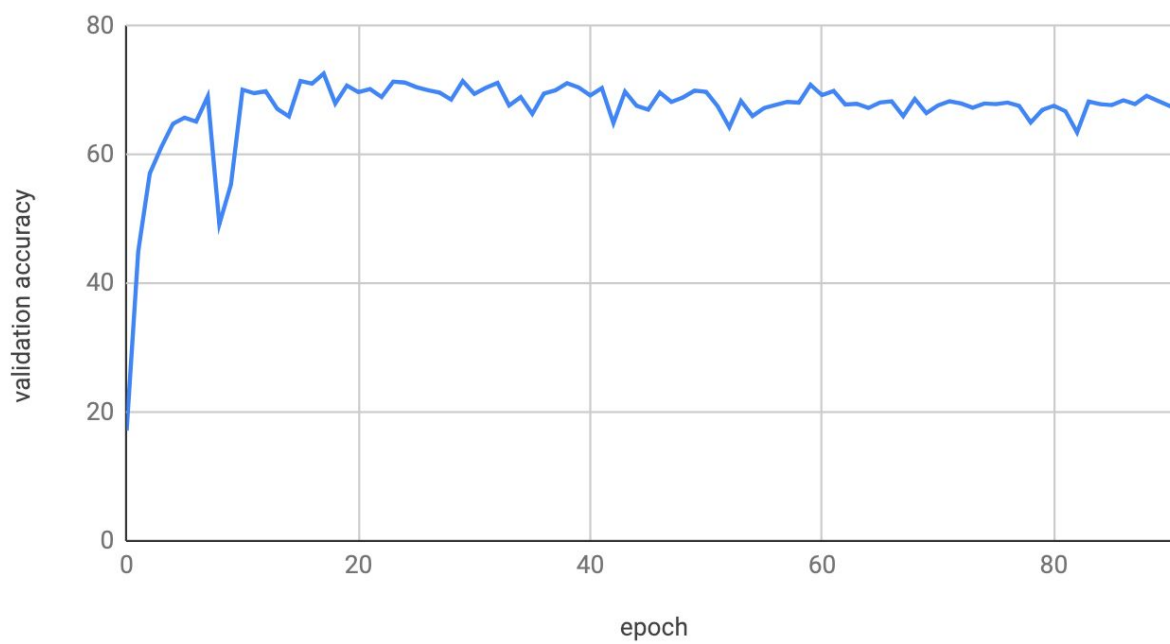
We had two convolution layers and two fully connected layers for all the three networks. Only the number of neurons in the output layer was the difference for each network. The number of output labels were 2, 5, 12 for gender, race and age respectively. The first convolutional layer extracts 30 feature maps and uses a kernel size of 5 x 5. The second convolutional layer extracts 50 feature maps and uses a kernel size of 3 x 3. In the end, there are two fully connected layers with 200 vector size for each layer.

## Training Graphs

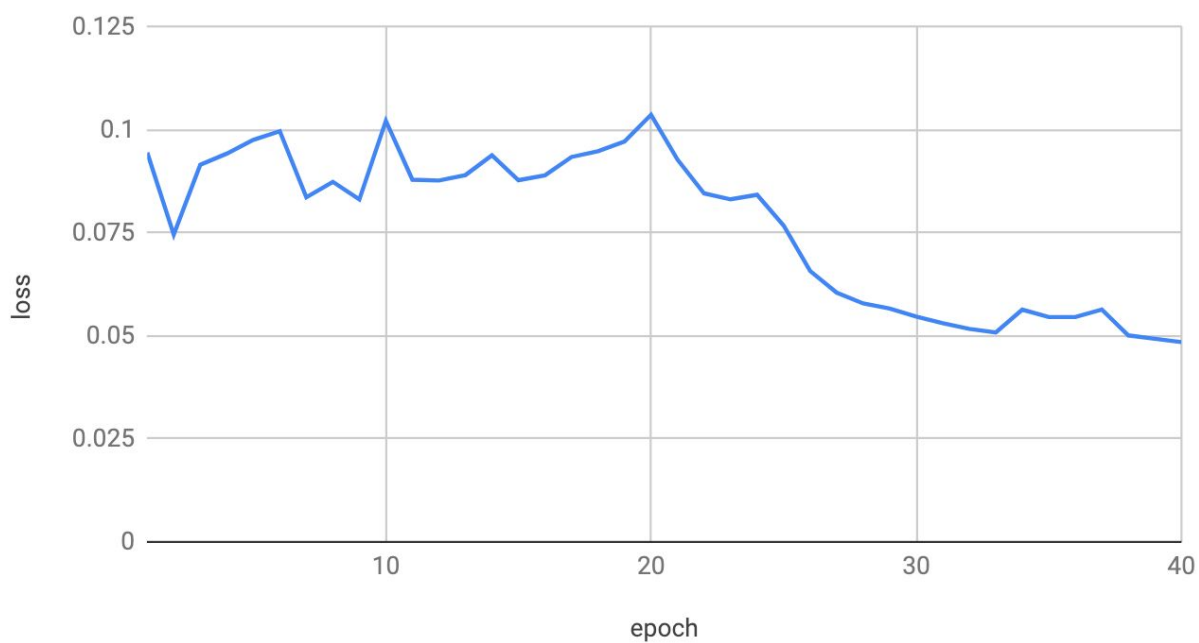
Race Classification: Loss vs. Epoch



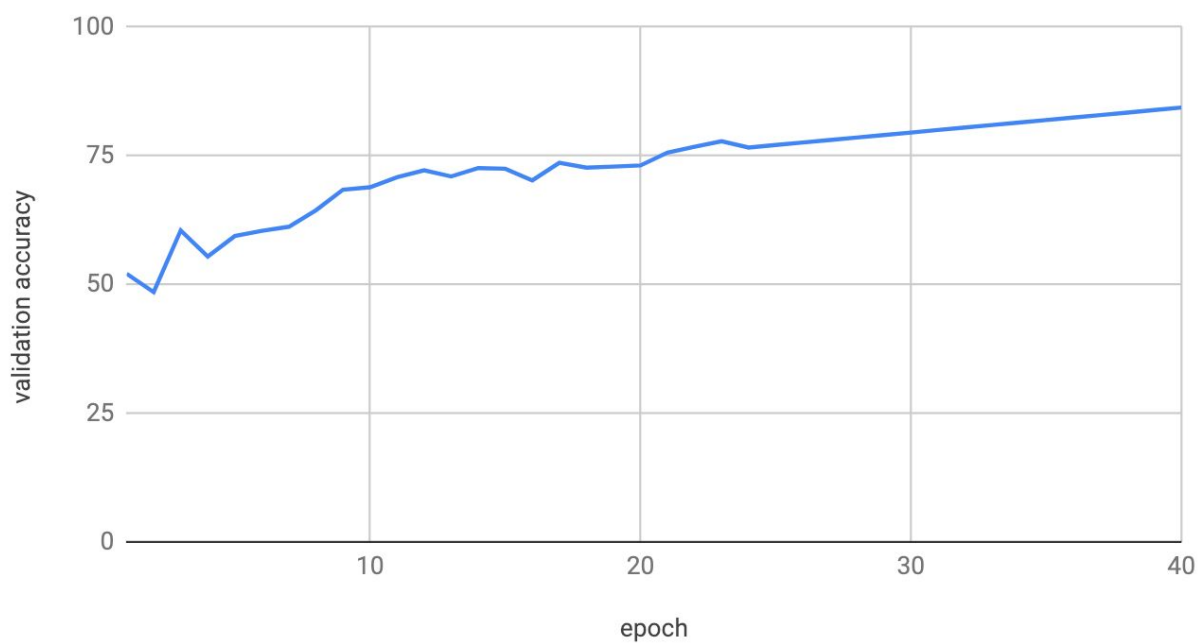
Race Classification: Validation Accuracy vs. Epoch



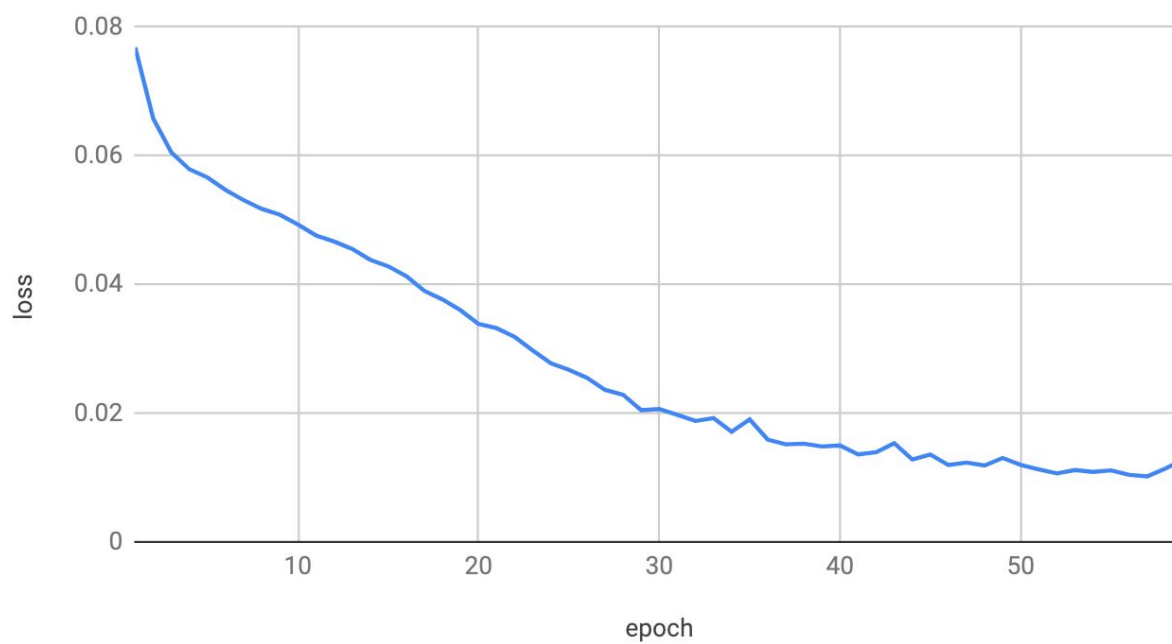
### Gender Classification: Loss vs. Epoch



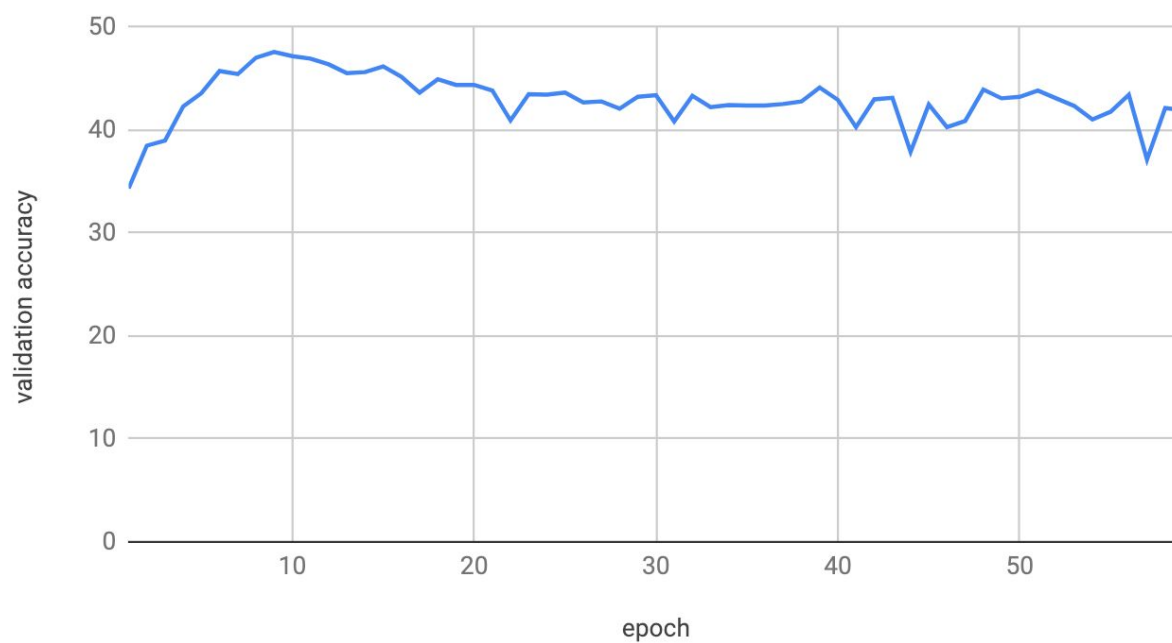
### Gender Classification: Validation Accuracy vs. Epoch



### Age Classification: Loss vs. Epoch





### Age Classification: Validation Accuracy vs. Epoch



## Results

We ran the trained model with examples and the following was the output:

Image	Expected Output	Our Output
	Gender: Female Race: Black Age: 21-30	Gender: Female Race: Black Age: 31-40
	Gender: Male Race: Asian Age: 21-30	Gender: Female Race: Asian Age: 21-30



## Discussion

We initially decided to train a convolutional neural network to be able to detect a face and put a bounded box around it in a given image and then predict that person's age and gender. We pivoted from this idea to do this. We at first, found it rather difficult to find a comprehensive dataset that had labels for a person's age, gender and race. We then found the UTKFace dataset that has roughly 22000 images of people around the world. We split the images into 18000 for the training dataset and 4000 for the validation set of images. This led to problems while training as we did not have the hardware to run the large batch sizes of the training or validation dataset. We also have three different models for each of the category we predict. This is because we were not able to incorporate the multi-label architecture provided by pytorch.

## Github Link

<https://github.com/pkenkere/BME-595>

## Youtube Video

<https://youtu.be/bYZTLMZ07Iq>

## Future Work

Now that we have the trained model for classification of age, gender and race, we plan on to expanding this project to replicate the paper "Age Progression/Regression by Conditional Adversarial Autoencoder" by Zhifei Zhang, Yang Song, Hairong Qi.

## References

- Levi, G., & Hassner, T. (2015). Age and gender classification using convolutional neural networks. *2015 IEEE Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*. doi:10.1109/cvprw.2015.7301352
- Zhang, Z., Song, Y., & Qi, H. (2017). Age Progression/Regression by Conditional Adversarial Autoencoder. *2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. doi:10.1109/cvpr.2017.463