Face, Age and Genre Detection with Convolutional Neural Network

Chriss Jordan Oboa
Computer Science Department
Hood College
Frederick, Maryland, USA
cfo2@hood.edu

1 ABSTRACT

Facial detection is a difficult computer vision task that involves detecting and locating faces in images.
This process is based on machine learning in which we used, accompanied by the addition of deep learning to extract, and provide more features when detecting Age and Genre during the process. This project is based on the Face, Age, and Gender detection of a human being using some pre-trained deep learning model to reach the final goal of this project's execution.
In the process, face detection was performed using the classical feature-based cascade classifier using the OpenCV library, which is a Machine learning tool, with the addition of Deep Learning Convolution Neural Network used for classification tasks due to their excellent performance in facial analysis.
Additionally, we use the two-level CNN architecture which includes feature extraction and classification itself which is in the pre-trained phase of this project. The feature extraction process extracts feature that correspond to Age and Gender, while the classification process assigns the face images to the appropriate age and gender groups. Numerous real unfiltered face images were used with a robust image preprocessing algorithm to be prepared and processed into the CNN model.
The results were satisfying and provided accurate results based on certain factors as the quality of the image used for the testing.

CCS CONCEPTS
• Computing methodologies → Artificial intelligence; Computer vision; Computer vision tasks; Activity recognition and understanding; Artificial intelligence; Computer vision; Computer vision tasks
KEYWORDS
Deep Learning, Computer Vision, Convolutional Neural Network, Transfer Learning, Feature Extraction, Fine-tuning, Deep Neural Network, Image Augmentation, Batch Normalization, Age & Genre detection, Facial recognition.

2 INTRODUCTION

What is Face, Age, and Gender detection? Well, it is a program that can take an image of a person, understanding the face of the person, and then passing it through a Machine learning and Deep learning algorithm to detect the gender and the approximate age of that person; it's as simple as that. In this project, we provided a simple application that can detect the gender and age of the person right there in front of you. We employ accurate face detection with OpenCV in this project, using a pre-trained CNN Deep learning face detector model that comes with the library.

However, this project is not only used for fun but can also be used to enhance safety across the world. "Those features as Age and Gender classification can be helpful in several real-life situations including security and video surveillance, electronic customer relationship management, biometrics, electronic vending machines, human-computer interaction, entertainment, cosmetology, forensic art, and more." (NCBI)
Nevertheless, several issues could be faced due to the imperfection of technology that is still in need of major improvements. "Age and gender predictions of unfiltered real-life faces are yet to meet the requirements of commercial and real-world applications despite the progress the computer vision community keeps making with the continuous improvement of the new techniques that improve the state of the art." (NCBI)

3 BACKGROUND

In our Deep Learning Class at Hood College, hosted by Professor Liu Xinlian, we were attracted by how we could detect and identify an object using Deep Learning. This was fascinating, so we decided to give it a try, to work on a project-based Detection and Identification/Classification. The goal was to learn as much as possible about this area without forgetting to have fun while learning.

4 IMPLEMENTATIONS /EXPERIMENTS

This project was done using Google collab.

4.1 Dataset Description

For the dataset, we used two developed models one based on Age and one on Genre found on YouTube provided by Misbah Mohammed. They were developed by researchers who deployed or made these models, shipped through different types of images which they collected, and they also had their database. Those images collected are completely different. They had a different brightness, different profile, were taken on a different day, different saturation, different person and more which make those images have different property levels. Those models were pre-trained and have proven to be efficient during the process of this project.

On the other hand, a good alternative for a database could be found on Kaggle. We first used Kaggle before we found a more efficient way to enhance the efficiency to execute the project according to the time frame given.

Furthermore, as the model was pre-trained and developed by researchers, we did expect that the models provided to be efficient and well-coordinated, and well documented.
It was expected by us that the model used for the age group and gender classification, method as OIU-Adience dataset, but also IMDb-WIKI and MORPH-II datasets in which can be also employed to pre-train our network when evaluating the classifiers on OIU-Adience dataset. (NCBI)

IMDb-WIKI is the world's largest publicly available dataset for estimating people's ages in the field, with over half a million photos with precise age labels ranging from 0 to 100 years.
(NCBI)

MORPH-II is the most widely used dataset for estimating true age. It's a publicly accessible face aging benchmark that includes over 55,000 facial photos from over 13,000 people. (HINDAWI)

OIU-Adience is a collection of facial photographs taken in natural, unrestricted settings. It has all the characteristics that one would expect from a photograph gathered from difficult real-world settings. (HINDAWI)

Figure 3

Sample face images from IMDb-WIKI, MORPH-II, and OIU-Adience datasets.

Table 3

The details of the datasets used in our experiments.

Dataset	Dataset size	No. of subjects	Age type	Age range
IMDb-WIKI [2]	523,051	20,284	Real age	0–100
MORPH-II [58]	55,134	13,618	Real age	16–77
OIU-Adience [12]	26,580	2284	Age group	0–60+

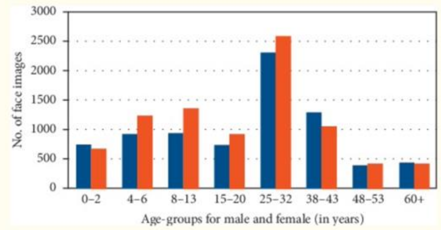


Figure 4

The number of image samples for age group and gender in OIU-Adience dataset.

4.2 How does it work?

What is this Face, Age, and Gender detection program doing? This program takes the image and goes through a face detection system. Then, there is this function called “face box” implemented that has the role of opening and reading through the face detector file and getting the dimensions or the director the location of the face in the image and it takes that information and supplies it to the pre-trained Gender and Age detection module.

4.3 Dataset Pre-Processing

There are three steps present in this process:
So, this is how it goes in a simple explanation.

4.4 Step one

Step one is simply doing face reduction. This step is reading the image and passing it to the face detectors. Once the face is detected and there's a small pre-processing stage in which localize and lock the face in to start pre-processing.

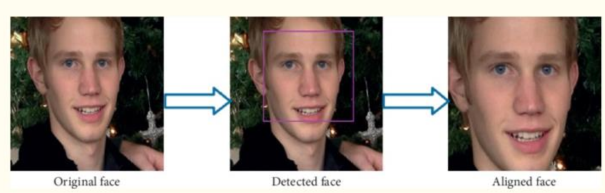


Figure 2

The image preprocessing phase.

4.5 Step two

Step two is the pre-processing stage: some sort of processing on the image and once that is done then you're sending it to the detector module which is going to detect the age and gender of the person.
Step two uses a **blob** from the image. What does this function do? This tries to bring your image, the image that you have on your file that you want to test and bring that image onto the same level as the original image where this model was trained.
By using blob frame images, it brings our image to that same property level as those images collected by researchers who deployed or made these models. So, a **blob** frame image will take an image and remove all the variables, all the external features, all the extraneous information like the brightness, the saturation, the hue, and all these things that define an image. Then, it takes this information out and brings the image to its bare minimum.
The blob from the image just brings that image into that basic property so that when you send it to the gender or the age detection model it will give you the right output without much error.
Once this process is done, it uses that pre-processed image for our detection and sends it to the age and gender detection (not the original image).
P.S: Step one and Step uses the OpenCV library.

4.6 Step Three

This step is the part where Age and Gender detection receives the pre-processed image, then runs it into the age and detector frame in which uses the pre-trained model based on Convolution Neural Network made by researchers, provided to us by Misbah Mohammed.
This step uses a three-line snippet to read an image, send it to the agent detector function and give us the output in the Collab.

4.7 Issues Encountered

During the process of this project, we have encountered several issues before being capable of fully executing this project.
The first issue we ran into was based on the training of the model via CNN in which we couldn't have satisfied and efficient enough results to fully accommodate it to the detection part of the project. As a result, we opt to use a great alternative suggestion from Misbah Mohammed, which was to use the deployed model made by researchers shipped through different types of images which they collected, and they also had their database. These were truly important in setting the program and fully executing it.

The second issue was based on the efficacy of detecting the face which was a little bit off in some cases. We fixed it via tweaking the blob

However, here below are a few result we wanted to reach:
The most wanted accuracy while training that we failed to achieve, is 90% or over as this great trained model below demonstrate:

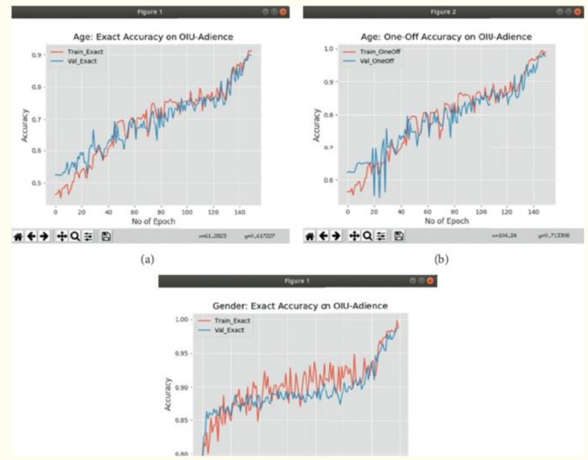


Figure 5 Open in a separate window

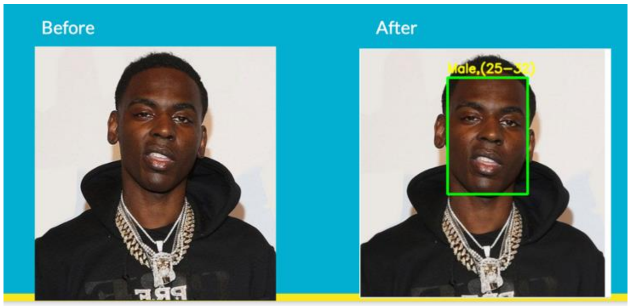
The details of experimental results of our model on OIU-Adience dataset.

Pretraining on IMDb-WIKI	Fine-tuning on MORPH-II	Image preprocessing	Data augmentation	Batch normalization	Exact acc. (age)	One-off (age)	Exact acc, (gender)
Yes	No	No	No	No	71.2	84.8	91.3
Yes	Yes	No	No	No	76.1	88.3	93.8
Yes	Yes	Yes	No	No	79.3	90.6	94.5
Yes	Yes	Yes	Yes	No	81.2	91.8	95.9
Yes	Yes	Yes	Yes	Yes	**83.1**	**93.8**	**96.2**

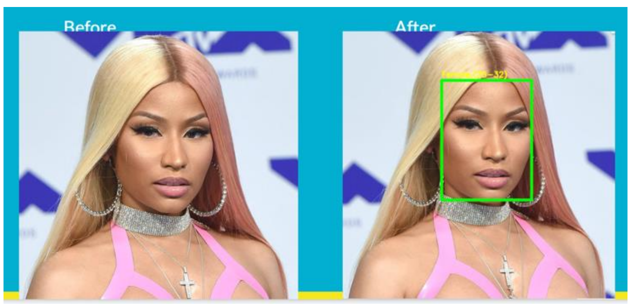
And as we know, by failing to result in great training, validation will also be tremendously affected. When well-trained the result will be most satisfying like represented below:

1. RESULTS

Via using the method we used, we came to achieve a good result as shown below:

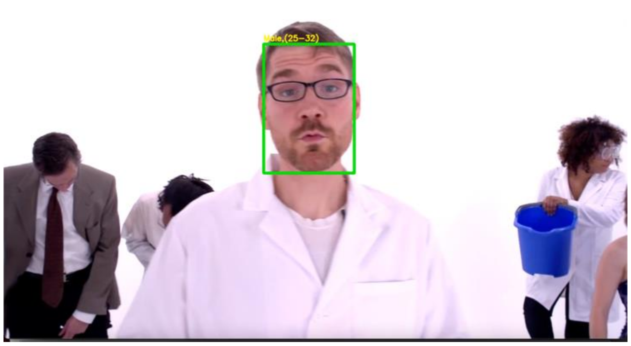


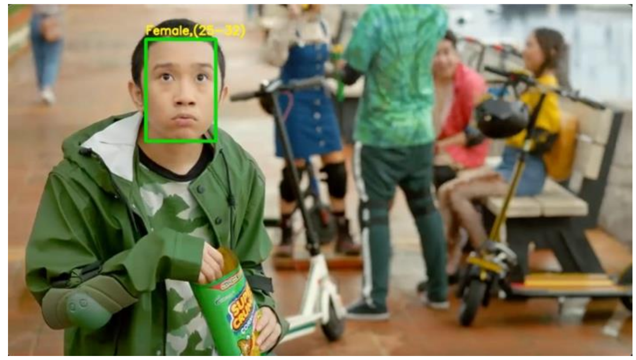
Young Dolph: American Rap Artist, was between 30-34 at that time.



Nicki Minaj: American HipHop/R&B/Rap Artist, was between 28-32 at that time

Video results

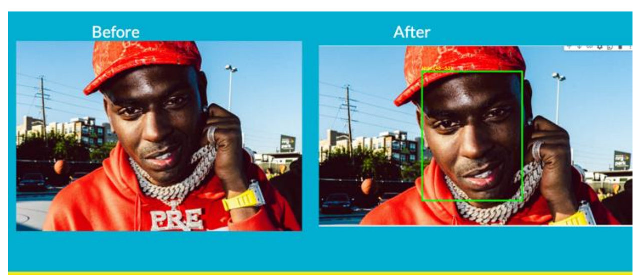




2. IMPROVEMENT NEEDED

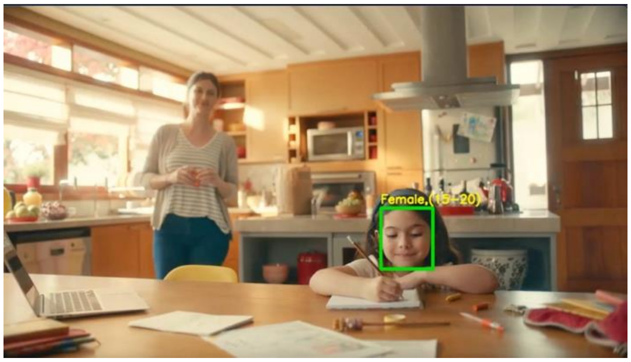
Some of the results were not quite satisfying and are often due to the image quality or even the angle and the shadow of the images which tend to affect the results when detecting.

Professor Liu Xinlian



This picture is another picture from the American Rap Artist Young Dolph in which gave different results that were way off compared to his age at the time.

Video results issue



The predictions were not accurate in all the videos. Some factors as makeup could be the reason why this little girl in this video was classified in the age range of 15-20.

5 CONCLUSION & LESSONS LEARNED

5.1 Conclusion

We conclude that convolutional neural networks can be used for Face, Age, and Gender Detection. The accuracy of these predictions can be increased by adding more layers into the CNN or by resizing the blob function that processes facial recognition.

5.2 Lessons Learned

Throughout this project, we came to learn a little bit more about Machine Learning in which we have never learned before, but also deeper our Knowledge of Deep Learning. Moreover, we also came to better understand the difference between Machine learning and Deep Learning and how those two can relate and be useful to each other. Moreover, we also came to learn about pre-trained datasets in which I was never taught beforehand.

In addition, even with a pre-trained dataset to ensure more efficiency, there is still improvement to make to achieve a program that can be strongly reliable in the domain it could be employed or used.

6 FUTURE WORK

Based on the outcome of this project, there is an improvement that should be made based on the imperfection of some of the results.

On the Age classification, the prediction did not acknowledge the facts that some of the people could maybe look older or younger than they are due to genetics, stress, diseases, and all other factors. So, being able to proceed and more accurate results should be the first step.

On the Genre classification, knowing that the human Genre has been a huge debate throughout the past years with the LGBTQ community, we should be able to provide a better Genre identification based on the now-society point of view.

In addition, we should also provide a way to train the images to reduce wrong results sometimes due to the image quality or even the angle and the shadow of the images which tend to affect the results when detecting.

Furthermore, the next step of this project would be to incorporate a detection feature to identify humans by race, and humans and animals at the same and estimate both their genre and age if possible.

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It was an honor for us to learn about this interesting field of Deep Learning and to be able to build something that we never thought of building and learning throughout this life journey.

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