ENEL 610 Project (2021 Winter)

Implementation and Doddington Zoo Analysis of a Facial Recognition System

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Abstract

This paper provides an overview of the implementation and Doddington Zoo Analysis of a Facial recognition system. The facial recognition technology that will be specifically utilized for our project is based on a face recognition library known as Dlib [1]. This library was created and currently maintained by the software engineer Davis King [1]. This library has been widely used by both "industry and academia" in a wide range of fields such as "robotics, embedded devices, mobile phones, and large high-performance computing environments" [1].

While researching on the subject area of Facial Recognition Technology, our team decided to focus on two important aspects:

- Study and Implement a Facial Recognition Model
- Apply Dodington Zoo analysis on the model to test its effectiveness.

The report initially explores the key components of the model in a step-by-step fashion. This will be followed by an overview and application of the Doddington Zoo classification on the dataset. For the coding implementation of the model, Python programming language was utilized in both PyCharm as well as Google collab IDE.

Most modern-day Facial Recognition technology models have significant overlaps when it comes to Mathematical and Statistical concepts that are integral to the foundation of the model. It was crucially important to gain a thorough understanding of the functioning and implementation of one of these models. Developing a thorough understanding of one of these models will be a great starting point in terms of future exploration of other models in this field. The implementation of Doddington zoo analysis was a great way to test the effectiveness of the model, and it allowed us to apply biometric concepts in real-world settings [2] [3].

All the citations and references have been formatted in the IEEE format

Keywords: Biometric, Facial Recognition, Dlib, Doddington Zoo, Histogram of Oriented Gradients (HOG)

1. Introduction

1.1 Background

Facial recognition systems are one of the most important Biometric technologies that are currently in use along with fingerprint and iris recognition [4]. It is classified as a biometric technology as it utilizes templates that are generated by locating and measuring attributes or feature points such as "location of the eyes, eyebrows, nose, mouth, chin, and ears [5]. The technology compares two templates and generates a match score that helps determine if the images belong to the same individual [5].

Facial recognition technology has come a long way since its humble origins as a form of computer application in the 1960s [6]. Furthermore, significant advances in the field of artificial intelligence in particular deep learning models have greatly contributed to the advancements in the field of biometric technologies and Facial recognition is no exception [5]. Today, it is utilized by law enforcement, academia, and civilian application [5]. Law enforcement agencies utilize the technology to track and search for criminals amongst the civilian population [5]. The facial recognition technology trains on a database of images that have been enrolled. The system extracts relevant features and creates a template [5]. These templates are in turn compared with templates from other people to find a match [5]. In an increasingly, globalized world, it is a norm for all individuals to possess a picture ID that will be contained in passports or other picture identification documentation. These picture IDs will be authenticated using biometric technologies and they are an essential requirement when it comes to Job applications, International travel, and Banking/financial formalities. Also, over the past decade, facial recognition systems have been integrated into mobile and tablet technology [5]. Therefore, facial recognition technology is a crucial part of our everyday lives.

Just like other biometrics, facial recognition technologies come with their own set of advantages and disadvantages. The advantages include the following [5]:

- **The abundance of facial image data:** The existence of billions of digital facial images sourced from numerous databases are convenient for training machine learning models that have become integrated into most facial recognition technologies. The existence of a huge training dataset will result in better accuracy for machine learning models
- **Enhancement of manual facial recognition:** Often, we may have image data that are not good quality due to varying reasons such as poor lighting conditions or facial occlusions (people wearing sunglasses or masks). The technologies behind facial recognition can greatly aid in enhancing image quality.
- **Integration of advanced camera technology into mobile devices:** Most people have mobile devices with social networking apps such as Facebook, Instagram, Snapchat, and tik-tok that have advanced recognition technology. These applications are widely popular amongst youngsters.
- **Commonly utilized authentication tool for mobile devices:** Along with fingerprint and iris scanner, face recognition is a commonly utilized authentication mechanism in most mobile devices.

Face recognition technology also comes with its own set of challenges [5]:

- The abundance of facial data may sometimes have a collection of datasets that might favor quantity over quality. These images may be affected by poor lighting and face occlusions. Those set of images will not be good training data for the face recognition model
- Contrary to the previous point, there is also an abundance of good-quality images of people online, especially on social media websites. These images can be utilized by fraudsters to perform identity thefts thereby compromising the face recognition system.

1.2 Objective

Our main goal is to study a facial recognition model and study its effectiveness by applying the Doddington Zoo Analysis. It is important to understand the mathematical and statistical foundations of the existing model and build our own implementation of it that caters to achieving the functionality of facial recognition on a diverse dataset (race, gender, unique facial features). Implementing Doddington zoo analysis on the model will quantify the measure of effectiveness of the facial recognition model.

2. Approach and Algorithm

2.1 Face Recognition Model

The following steps are implemented as part of the implementation and analysis of the Face Recognition Model. These steps include:

1. Face Detection
2. Landmark detection on faces
3. Face Encodings
4. Application of Doddington Zoo Analysis

2.1.1 Face Detection

The very first course of action is to identify all the faces in each image. The model utilized a method known as **Histogram of Oriented Gradients (HOG)** [7]. This descriptor has a wide range of applications in areas such as computer vision and image processing to perform the functionality of face detection [7]. It was originally conceptualized by Robert K. McConnell of Wayland Research Inc [8]. However, the adaptation of the term HOG and its widespread application came to the forefront after researchers from the French National Institute of Research in Computer Science and Automation (INRIA), Navneet Dalal, and Bill Triggs presented their work on HOG descriptors in the year 2005 [8].

The following presents an overview of the generation of a HOG image given an input image [9] [10]:

1. The color image is first converted to greyscale
2. Each image can be represented as a discrete function of x and y i.e. f(x,y)
3. Given a function f(x,y), the corresponding gradient can be represented by the (fx,fy).
4. A set of horizontal(x-direction) and vertical gradient(y-direction) components are calculated corresponding to each pixel.
5. The horizontal and vertical components that are generated from the previous step can be utilized to generate the resultant gradient magnitude and angle ($arctan\left(\frac{f_x}{f_y}\right)$)
6. The resultant gradient values will be mapped on a range of 0-255. The pixels that display a largely positive change will be white and the ones that have a large negative change will be black. The pixel values that are in between will possess little or no change, and they will be colored gray (varying intensities).

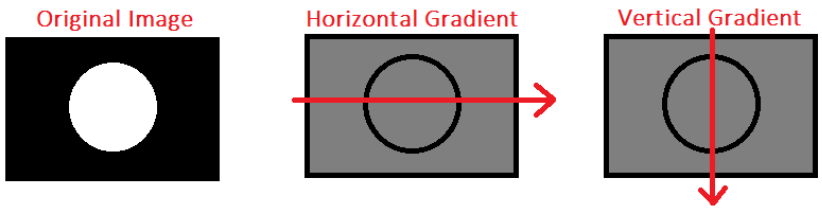


Figure 1 Histogram of Oriented Gradients Mechanism. The diagram was adapted from another drawing that was originally referenced by Dr. Ryan Ahmed [9]

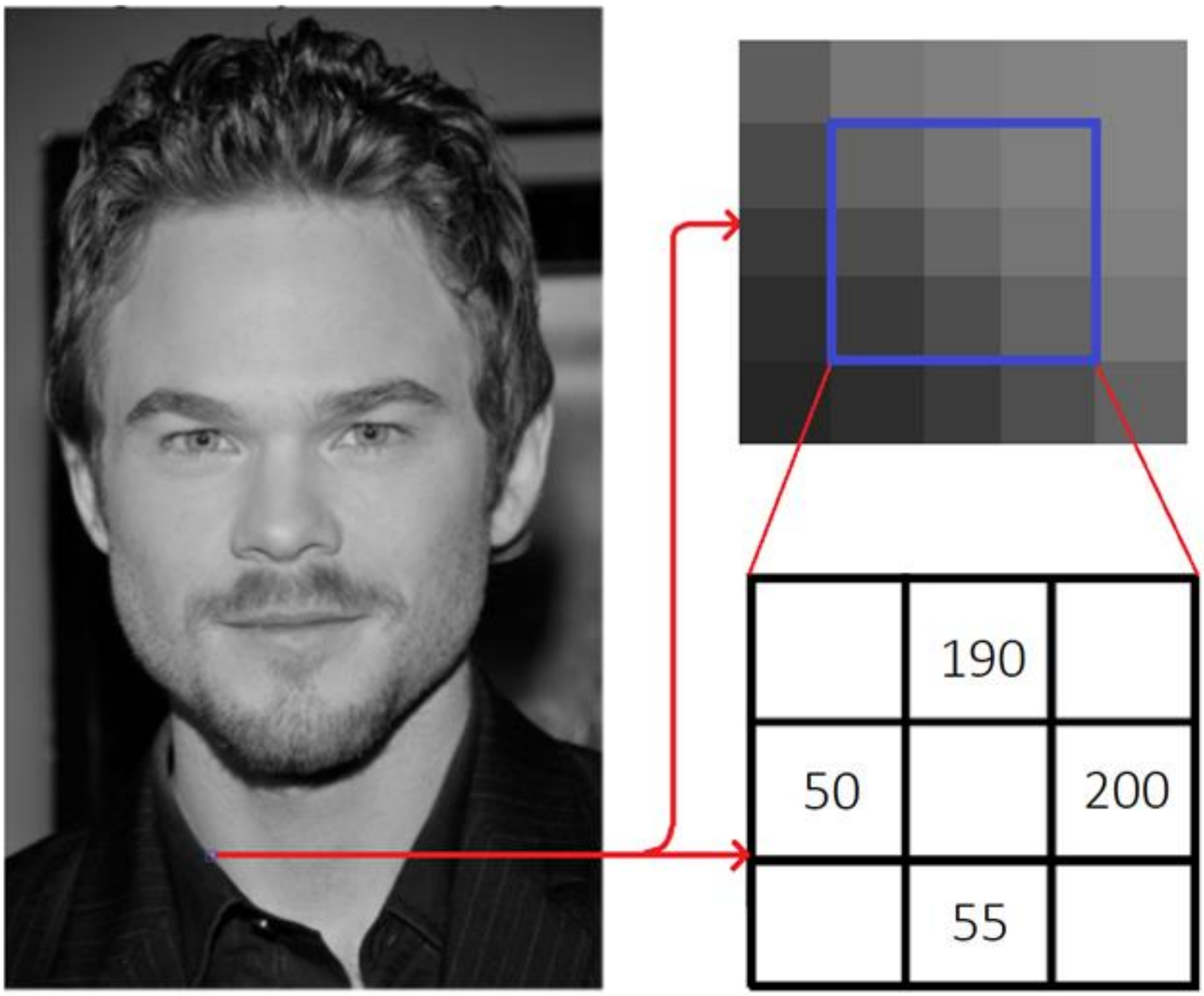


Figure 2 Demonstration of HOG process. Adapted and inspired from the works of Dr. Ryan Ahmed and Adam Geitgey [7][8][9][10][25]

- The gradient value for X-direction $f_x = 200 - 50 = 150$
- The gradient value for Y-direction $f_y = 190 - 55 = 135$
- Total Gradient Magnitude = 201.804
- Gradient Angle = $arctan\left(\frac{f_x}{f_y}\right) = arctan\left(\frac{135}{150}\right) = 41.987^0$

Now that we have obtained the value of gradients for every pixel, it would be more practical to observe the transition from lightness to darkness at a higher level. This will in turn generate an interesting pattern for the image. The process for generating the pattern is as follows [9]:

1. The entire image is divided into smaller squares that are of size 16x16 pixels.
2. A count of the orientation of each gradient point (Number of point ups, point left, point right etc.) are considered for each one of the 16x16 pixel size square components of the image
3. The orientation (represented as an arrow direction) that yielded that majority in terms of count replaces the existing image present in the 16x16 pixel box.
4. The previous steps will in turn generate a HOG image corresponding to the input image.

While performing image detection, the HOG pattern for the unknown face is compared with that of the known face. If the program were to train on multiple images, then the HOG face pattern will be extracted on all the training images and assigned to the corresponding individual. The resulting HOG face pattern belonging to the individual will be compared to the HOG pattern of the unknown individual once the face is detected [11].

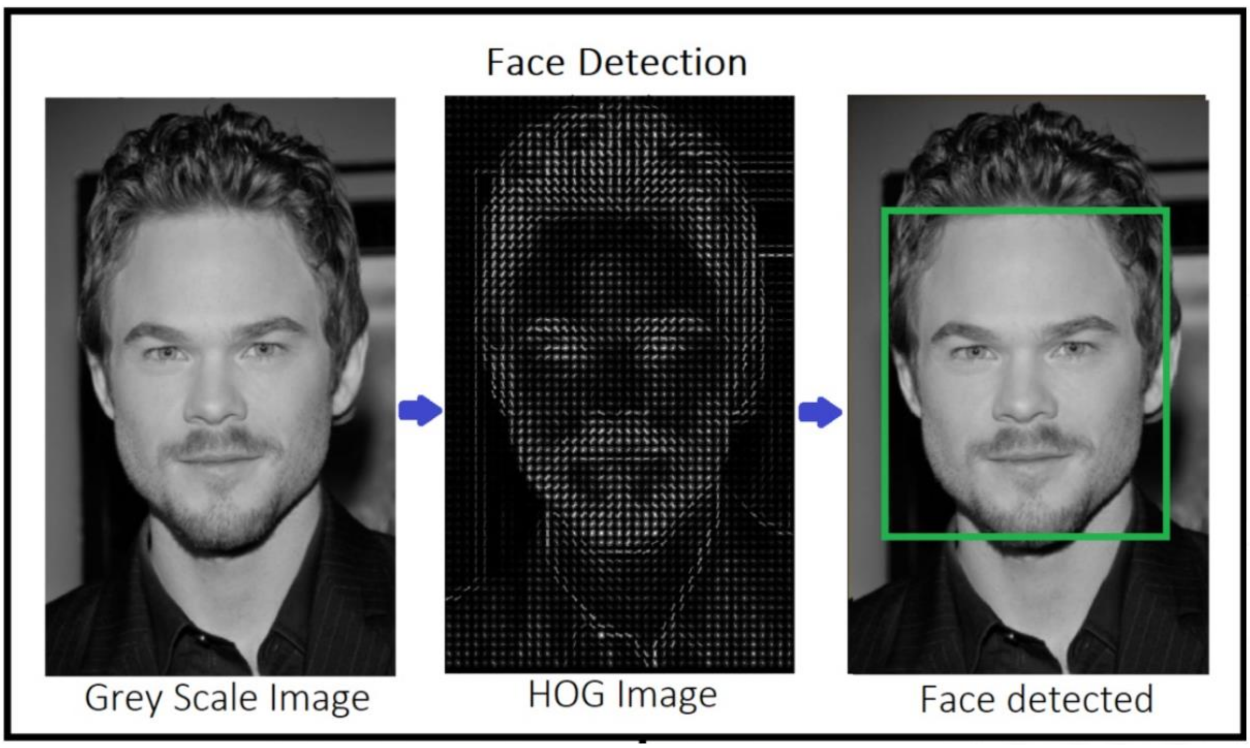


Figure 3 Face Detection Process that generates HOG Image and detects the face

2.1.2 Landmark detection on faces

Once the faces have been identified and isolated in an image, we are confronted with the problem of face projections (posing in directions other than straight to the camera such as sideways), emotional variability (happy, sad, angry), and facial occlusions (such as individuals wearing sunglasses or masks) [7]. Regardless of facial orientation or pose, the algorithm is expected to detect and identify the location of key features (location of eyes, lips, and nose) of the detected face in an image [12]. To address this challenge, the model utilizes an algorithm known as face landmark estimation. It was invented in the year 2004 by Vahid Kazemi and Josephine Sullivan [11].

This algorithm generates a total of 68 landmark points that are commonly found in all human faces [12]. They localize and represent salient features such as Eyes, Eyebrows, Nose, Mouth, and Jawline. These landmarks are unique to every individual [12].

Figure 4 Face Landmark Sample [7]

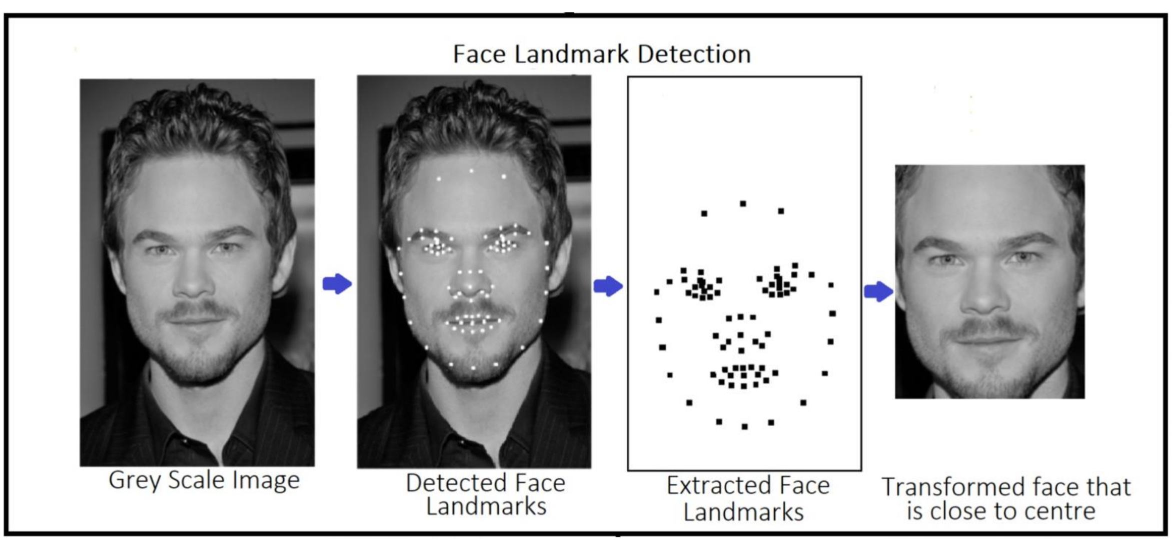


Figure 5 Face Landmark Detection Process

2.1.3 Generation of Face Encodings

In this step, the algorithm generates a total of 128 measurements for each face [7]. These encodings/embeddings are generated by the algorithm through the process of training a convolutional neural network. It utilizes pre-trained models from dlib or OpenCV [7]. This component of the model was developed by Brandon Amos and his team from “OpenFace” in the year 2015 [7]. The pioneers of this model originally trained it using a “single triplet training” step. In this setup, three pictures are taken into consideration. Two of the images are from the same individual and a third individual is a different person from that individual [7]. The model is trained by generating 128 embeddings from all three pictures [7]. Adjustments are made to the neural network to ensure the measurements generated for the images belonging to the same individual are closer to each other while the measurements generated from the image of the unknown individual are slightly further apart [7].

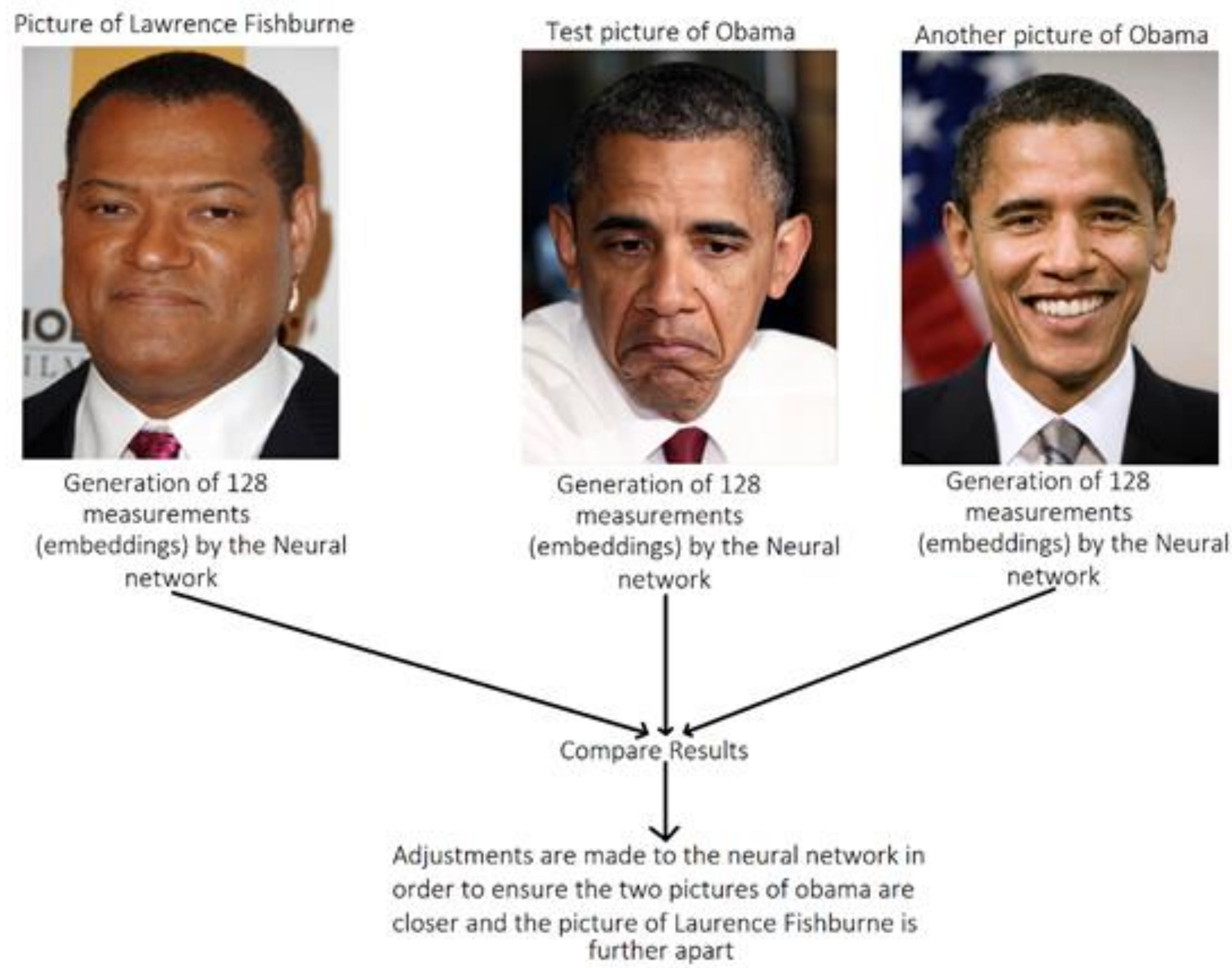


Figure 6 "Single triplet" Model. Adapted and inspired from the work of Adam Geitgey [7][53][45]

Once the input image has been input into the "Single triplet" trained model, it generates an array of 128 embeddings. These numbers are unique to every individual facial image [7].

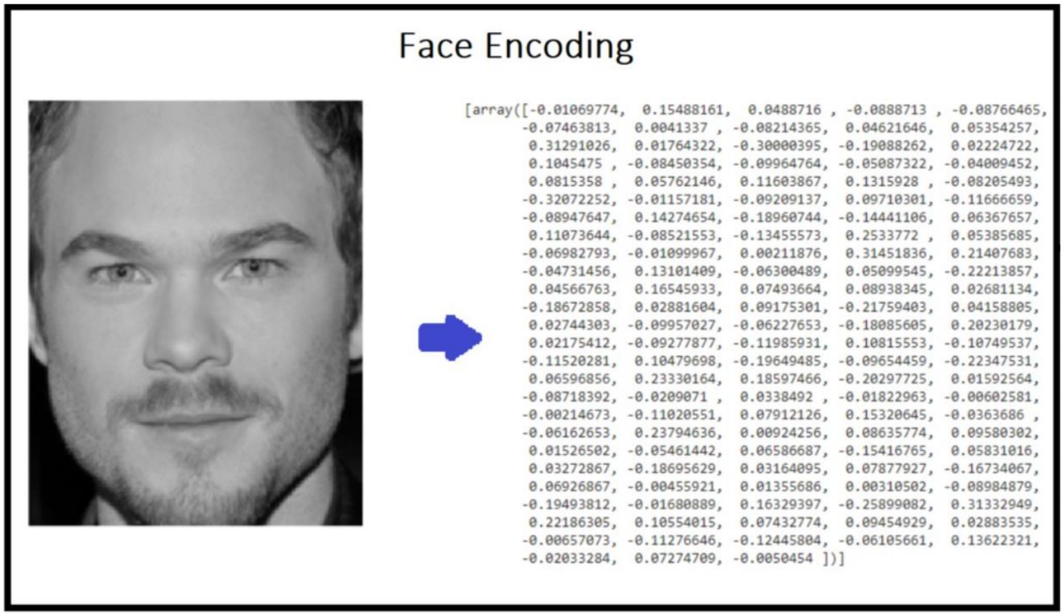


Figure 7 Face Encoding Sample

The face encodings for one individual can be compared with the encodings for another person using the Euclidean distance [7]. The lower the distance the more similar the images and the more likely the chance the images may belong to the same individual [7]. Similarly, the larger the distance the less similar the image and it is a good indication that the image belongs to a different individual when compared to the reference image [7].

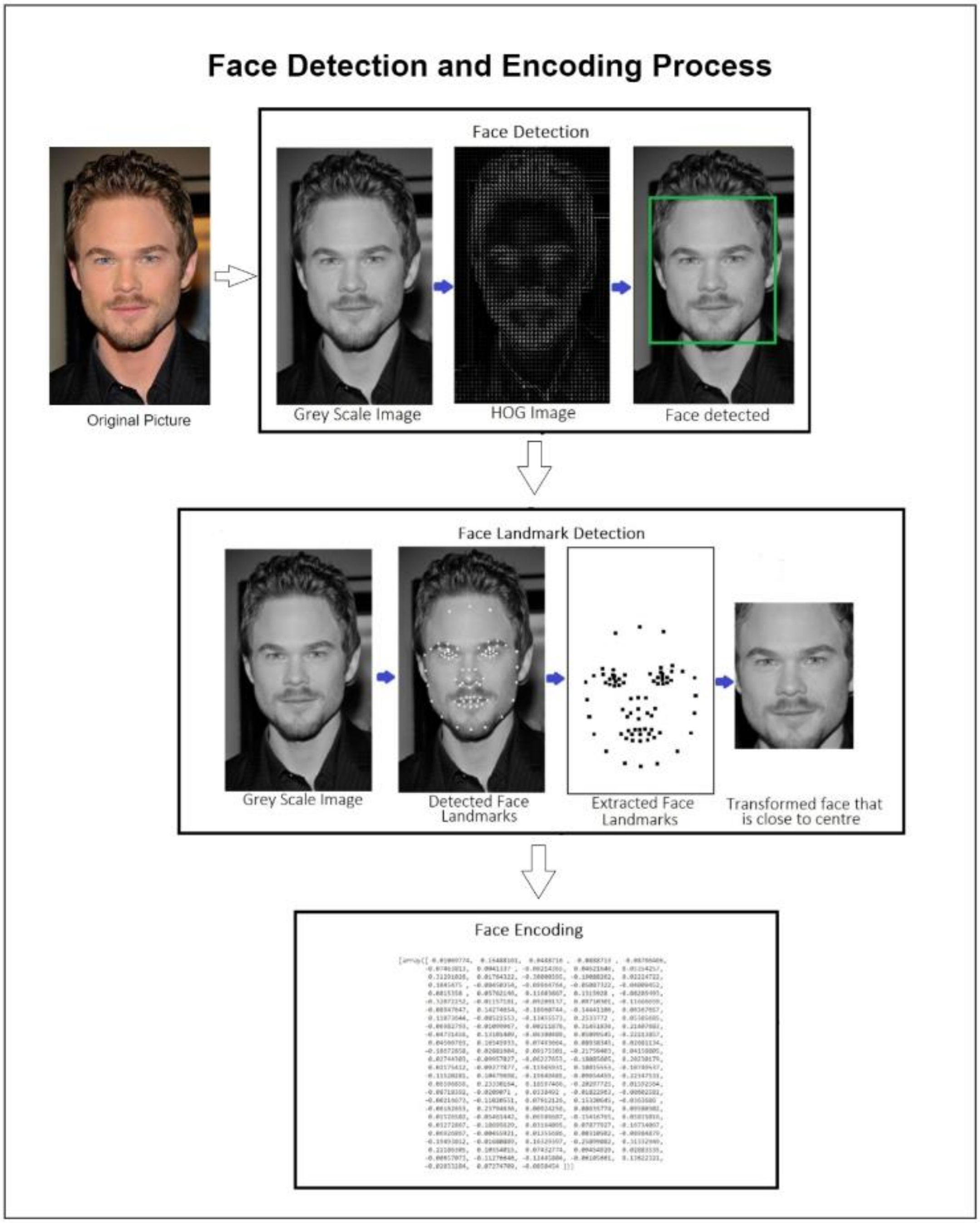


Figure 8 Overview of Face Detection and Encoding Process

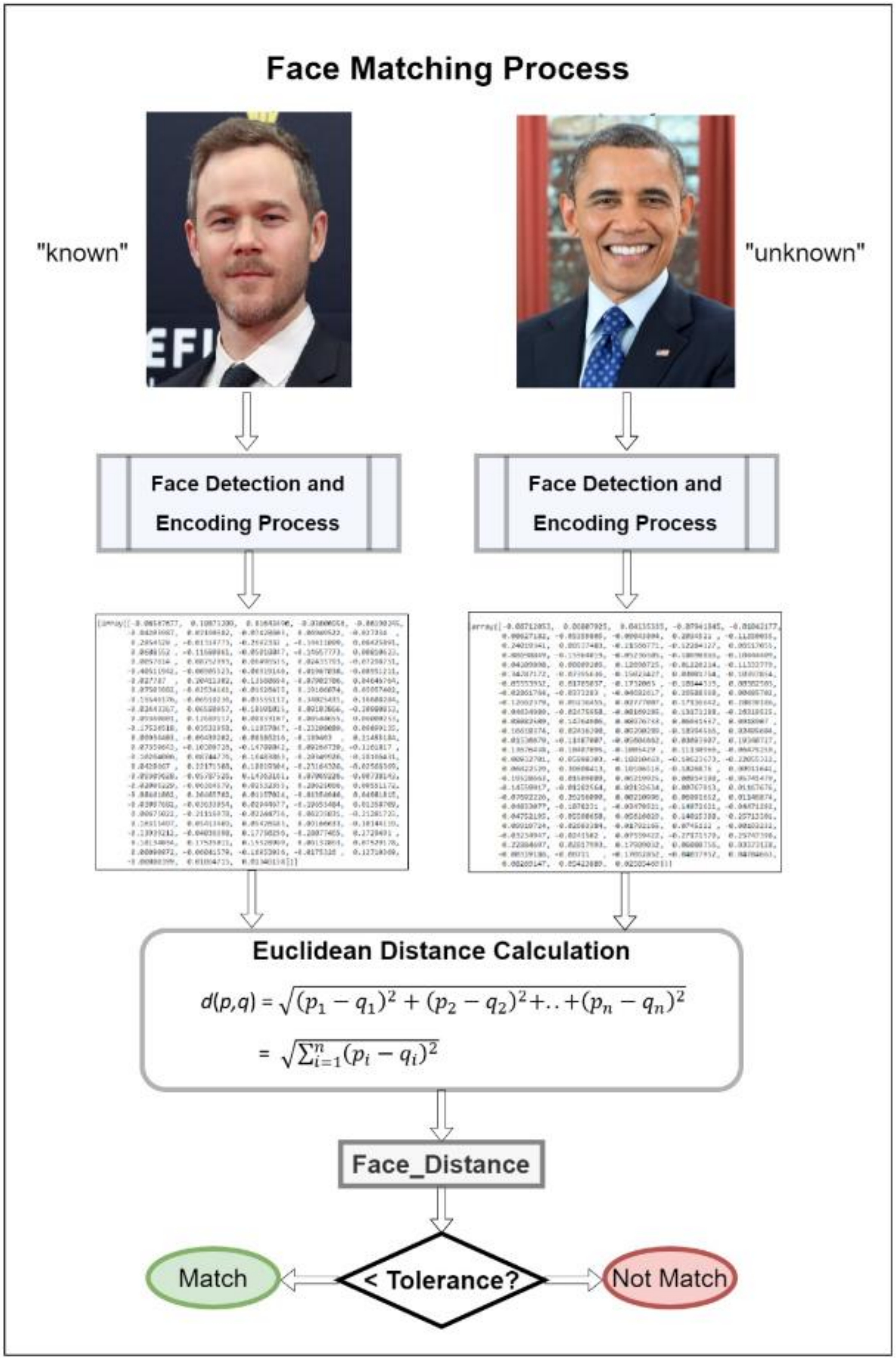


Figure 9 Face Matching Process between different pictures [49][45]

2.2 Doddington Zoo Theory

To test the effectiveness of the face recognition algorithm we implemented Doddington Zoo Analysis. This algorithm will categorize individuals into sheep, wolves, goats, and lambs [2] [3]. Here is a quick overview of each one of the categories [2] [3]:

- **Sheep:** These individuals are correctly recognized. They are rarely mistaken for someone else.
- **Goat:** These individuals are extremely hard to identify as they produce low genuine match score distribution resulting in false rejections.
- **Lambs:** These individuals are easily susceptible to being impersonated when they are matched with other individuals. They produce high matching scores which correspond to high imposter distribution resulting in false acceptances.
- **Wolves:** These individuals are the most successful at impersonations when compared with other individuals. They have high matching scores resulting in false acceptances.

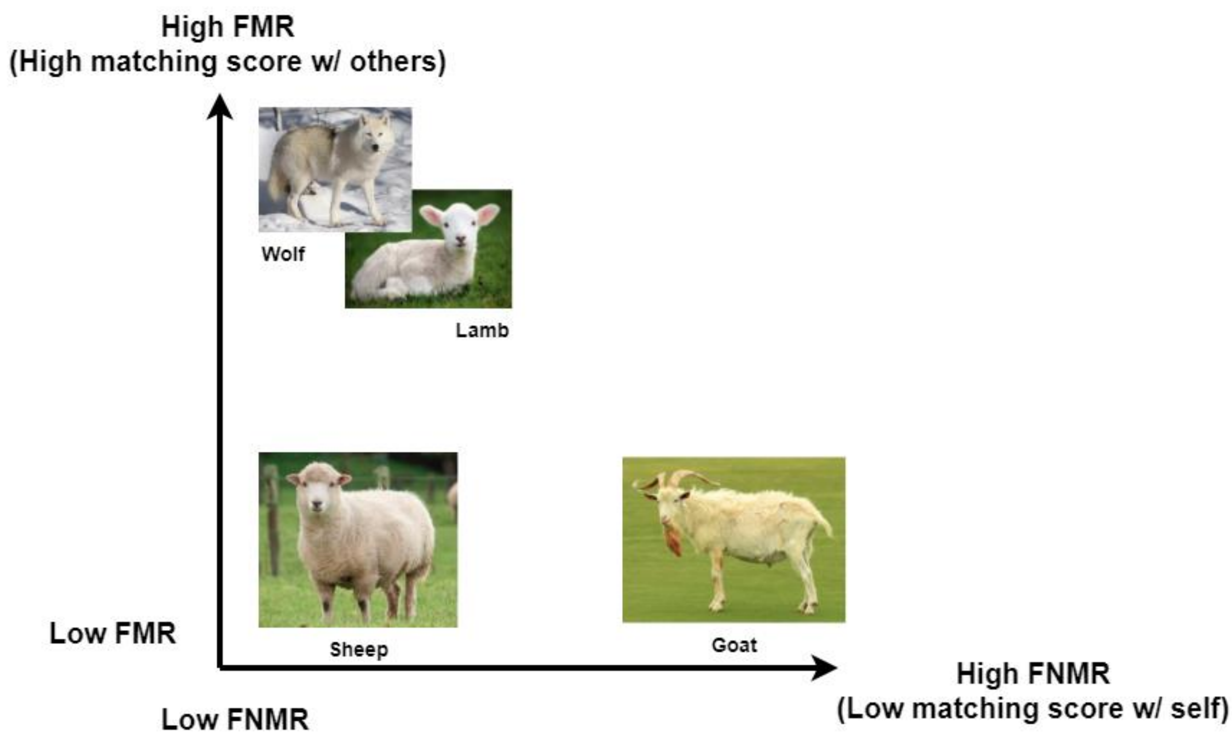


Figure 10 Doddington Zoo Categories

While implementing the Doddington zoo analysis on the face recognition model both lambs and wolves are classified as one category as there was no planned effort to implement a spoof attack on the system.

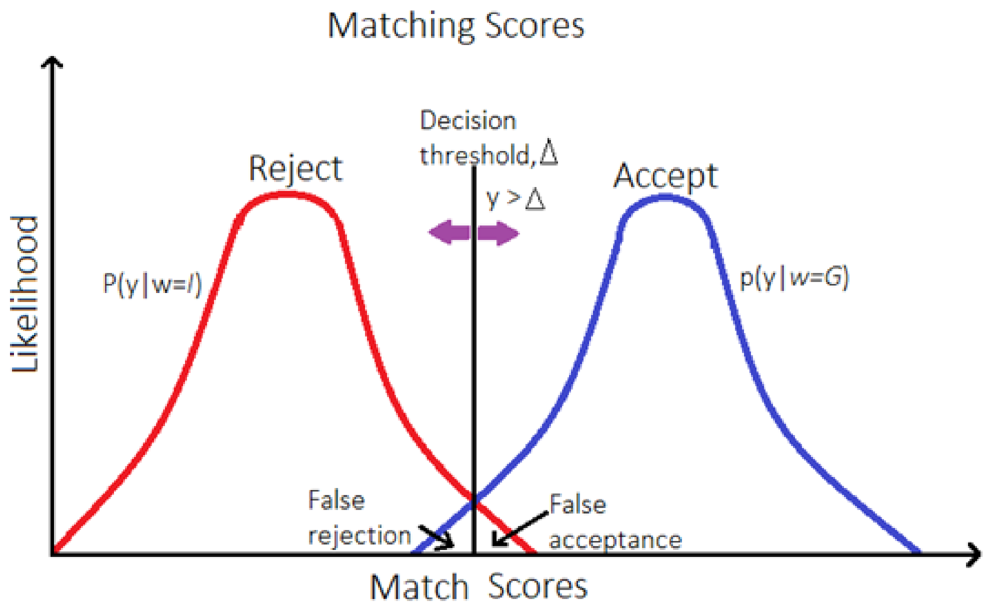


Figure 11 Matching Score and FMR/FNMR Analysis [2]

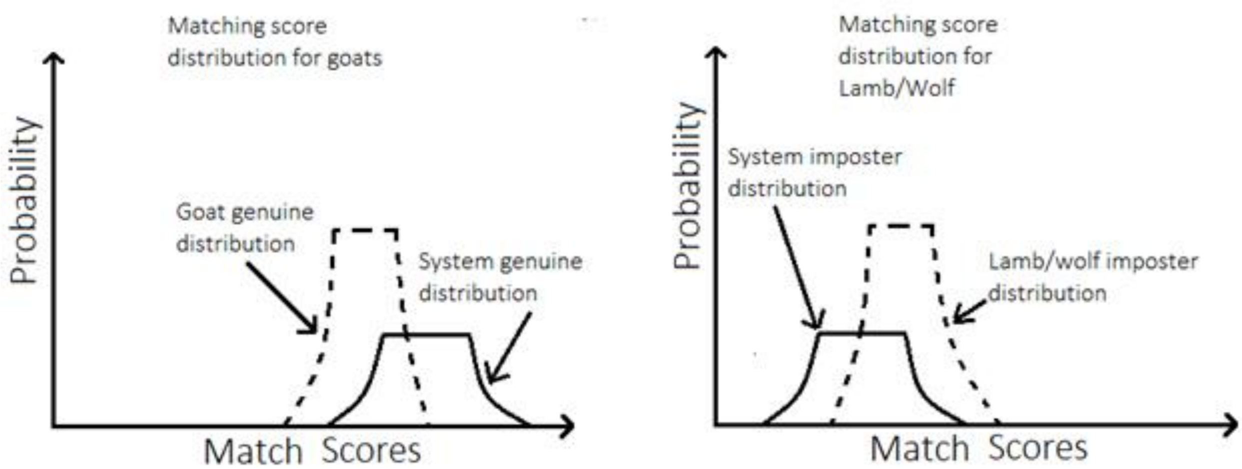


Figure 12 Doddington Zoo Samples Match Scores [2]

It was important for the model to best utilize the tool of Doddington Zoo Analysis. To improve system performance, the users were selected from a pool of diverse criteria which include people from different races, skin color, gender, specific facial features(beard), and faces subjected to artificial modifications (facelifts). Ideally, the effectiveness of a facial recognition model can be determined by its ability to correctly identify people regardless of the criteria. Therefore, Doddington zoo analysis is a crucial part of the decision-making support process for the facial recognition model.

3. Face Recognition Result Analysis

To analyze the distribution feature, a photo collection of 8 persons was selected as the test sample, including different genders and ethnicities. Each person has 21 photos, of which 1 for "genuine" and 20 for "trial". An assumption was made for Doddington Zoo Categories based on observation and to be verified by the test. The assumption does not impact the testing result.

Table 1 List of Selected Samples

No.	Name	Photo	Category Assumption
1	Shawn Ashmore		Wolf/Lamb Reason: identical twins
2	Aaron Ashmore		Wolf/Lamb Reason: identical twins
3	Chris Pratt		Wolf/Lamb or Sheep Reason: highly similar to the twins
4	Scarlett Johansson		Sheep Reason: highly distinguishable
5	Barack Obama		Goat or Sheep Reason: highly distinguishable but photos with exaggerated facial expression were intentionally selected for testing

6	Laurence Fishburne		Sheep Reason: highly distinguishable
7	Angela Yang		Goat Reason: facelift surgery history
8	Eddie Peng		Sheep Reason: highly distinguishable

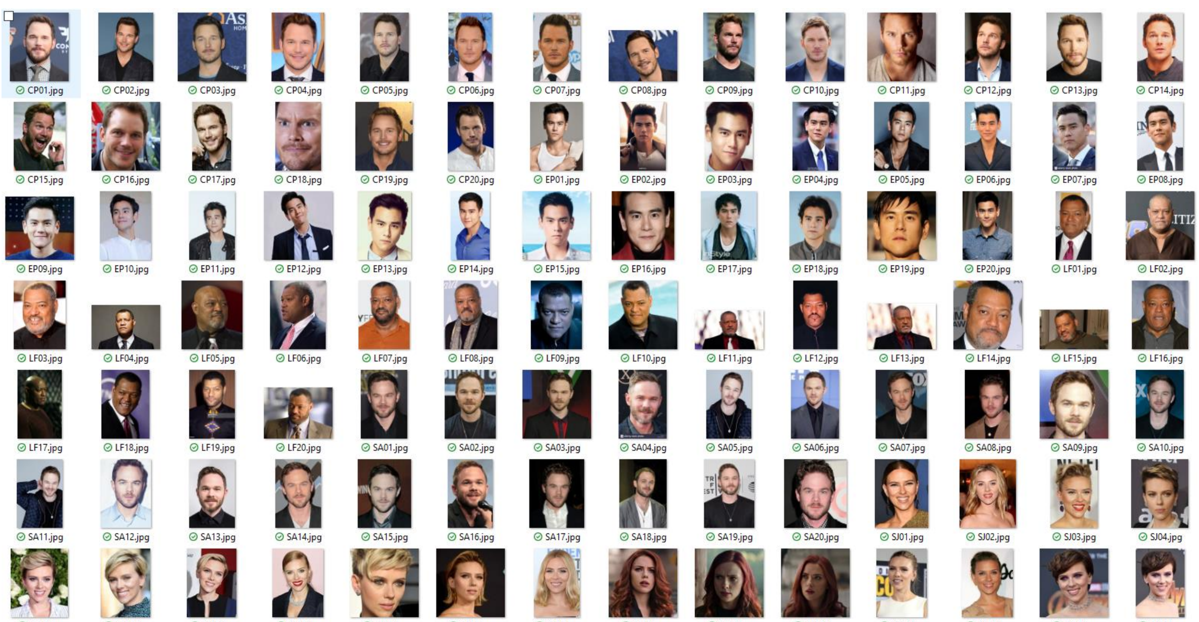


Figure 13 Sample Photos Demonstration

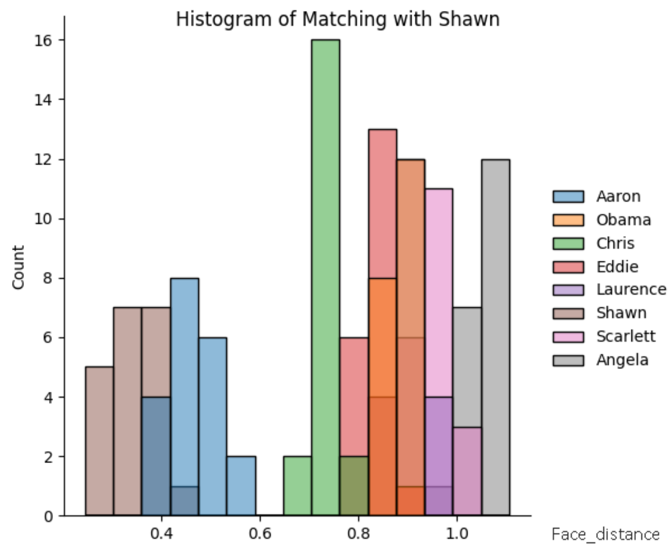
3.1 Face-Distance Result Analysis of 1:N Match

In this process the system distinguishes each person from others and verify the previous assumption of Doddington Zoo categories. We use one photo of each person as the genuine faces, and perform comparisons with all the testing photos, which means we will get a 20*8*8 = 1280 face-distance values.

The results are listed as follows:

Table 2 Face-distance with Shawn Ashmore

	Name	Max	Min	Average
Matching with	Shawn Ashmore (Self)	0.4321	0.2467	0.3475
	Aaron Ashmore	0.5519	0.3684	0.4606
	Chris Pratt	0.7688	0.6848	0.7342
	Scarlett Johansson	0.9965	0.8942	0.9511
	Barack Obama	0.9327	0.8199	0.8782
	Laurence Fishburne	0.9666	0.8588	0.9003
	Angela Yang	1.1058	0.9839	1.0526
	Eddie Peng	0.8851	0.7876	0.8289



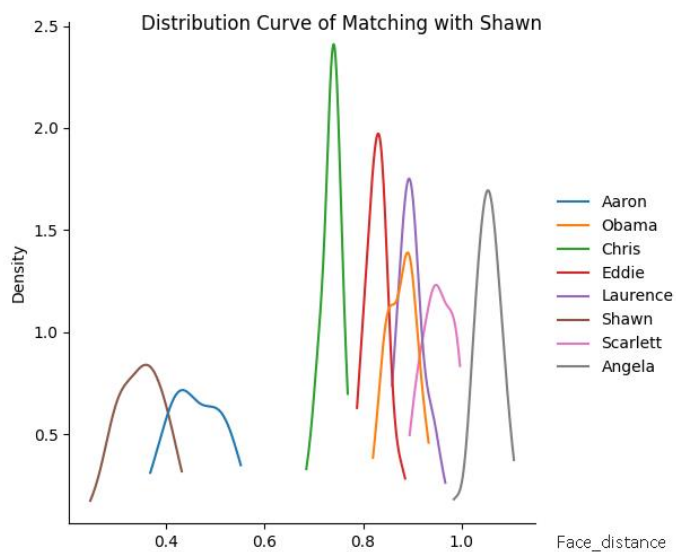


Figure 14 Distribution of Face-Distance matching with Shawn Ashmore

Analysis: A large overlap is produced by the distribution curves of Shawn and Aaron Ashmore, which categorizes them into “lamb/wolf”.

Table 3 Face-distance with Aaron Ashmore

	Name	Max	Min	Average
Matching with	Shawn Ashmore	0.5236	0.4468	0.4842
	Aaron Ashmore (Self)	0.5203	0.3239	0.4340
	Chris Pratt	0.7134	0.5872	0.6569
	Scarlett Johansson	1.0066	0.8668	0.9177
	Barack Obama	0.8401	0.7843	0.8183
	Laurence Fishburne	0.9186	0.7505	0.8579
	Angela Yang	0.9897	0.9033	0.9415
	Eddie Peng	0.8107	0.7239	0.7738

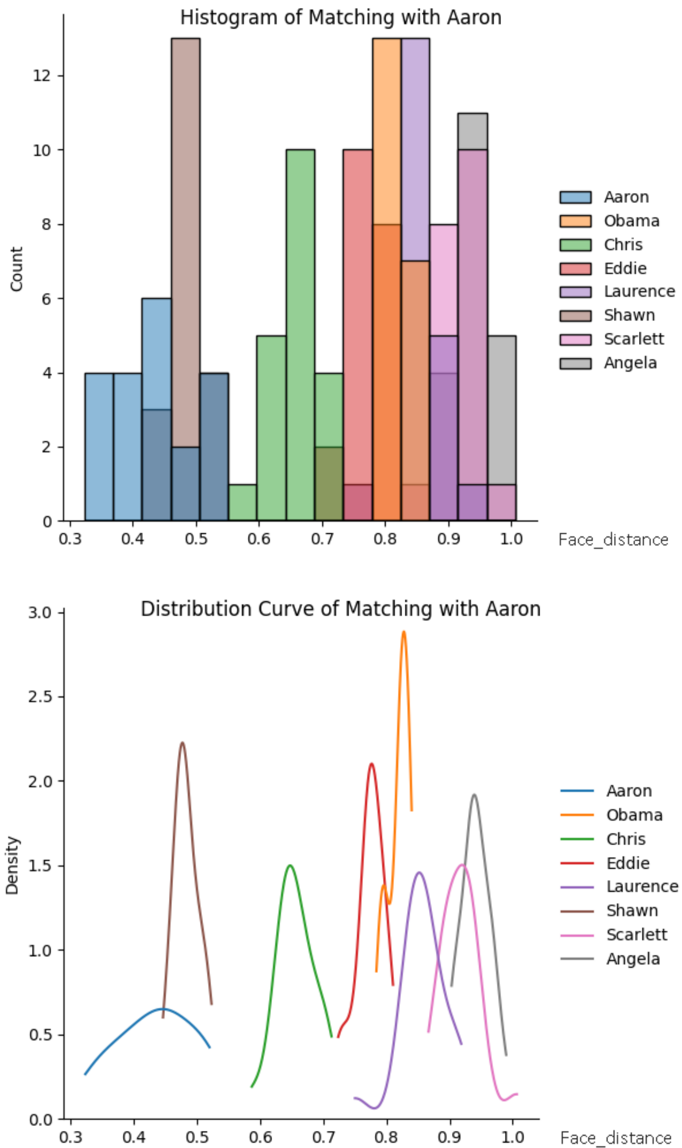


Figure 15 Distribution of Face-Distance matching with Aaron Ashmore

Analysis: Same as the previous analysis on Shawn Ashmore.

Table 4 Face-distance with Chris Pratt

	Name	Max	Min	Average
Matching with	Shawn Ashmore	0.7251	0.6587	0.6932
	Aaron Ashmore	0.7365	0.5821	0.6656
	Chris Pratt (Self)	0.5294	0.3076	0.3909
	Scarlett Johansson	1.0668	0.9470	1.0043
	Barack Obama	0.9823	0.8657	0.9325
	Laurence Fishburne	1.0474	0.8818	0.9535
	Angela Yang	1.1002	0.9862	1.0483
	Eddie Peng	0.9259	0.8198	0.8736

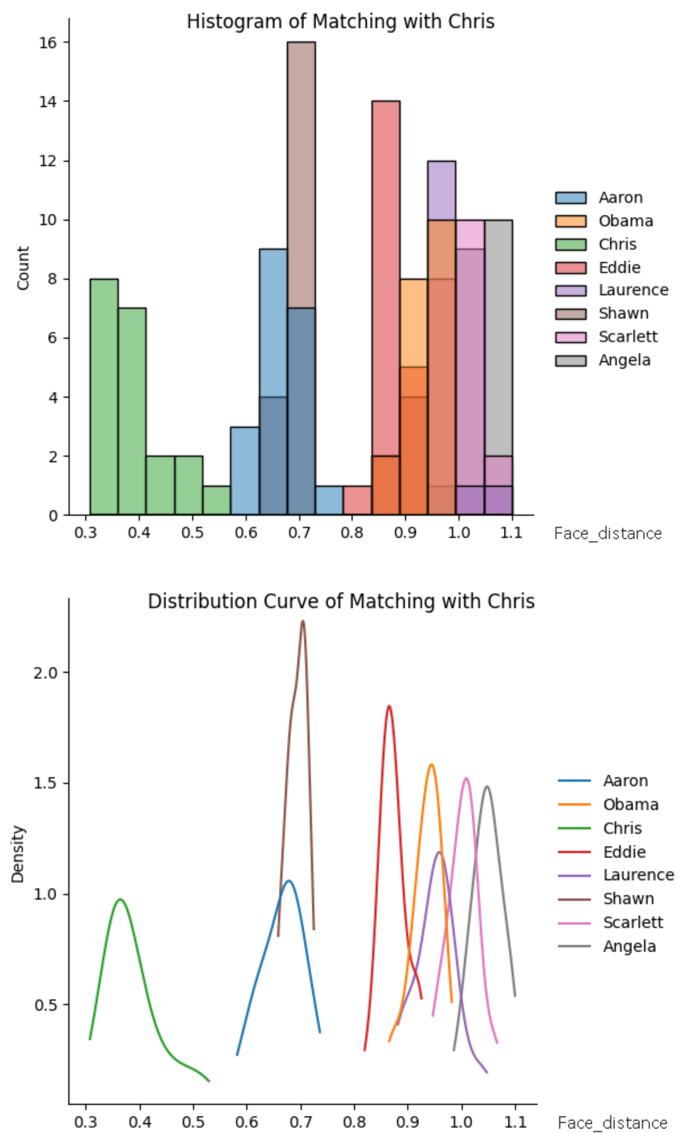
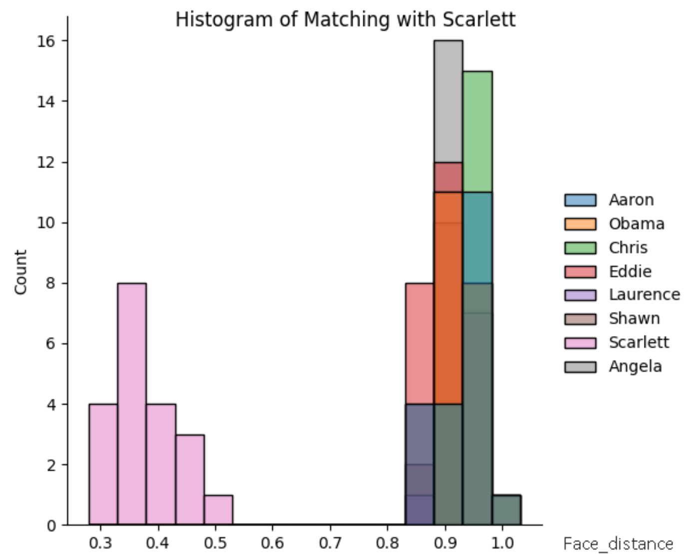


Figure 16 Distribution of Face-Distance matching with Chris Pratt

Analysis: Even though Chris's face looks similar to Ashmore brothers, the algorithm could tell the difference and distinguish them well. The distinction is large enough to categorize Chris into "sheep".

Table 5 Face-distance with Scarlett Johansson

	Name	Max	Min	Average
Matching with	Shawn Ashmore	0.9611	0.8746	0.9205
	Aaron Ashmore	1.0011	0.8519	0.9247
	Chris Pratt	1.0031	0.8850	0.9500
	Scarlett Johansson (Self)	0.5262	0.2799	0.3732
	Barack Obama	1.0313	0.8899	0.9324
	Laurence Fishburne	0.9864	0.8684	0.9263
	Angela Yang	0.9276	0.8361	0.8904
	Eddie Peng	0.9263	0.8481	0.8908



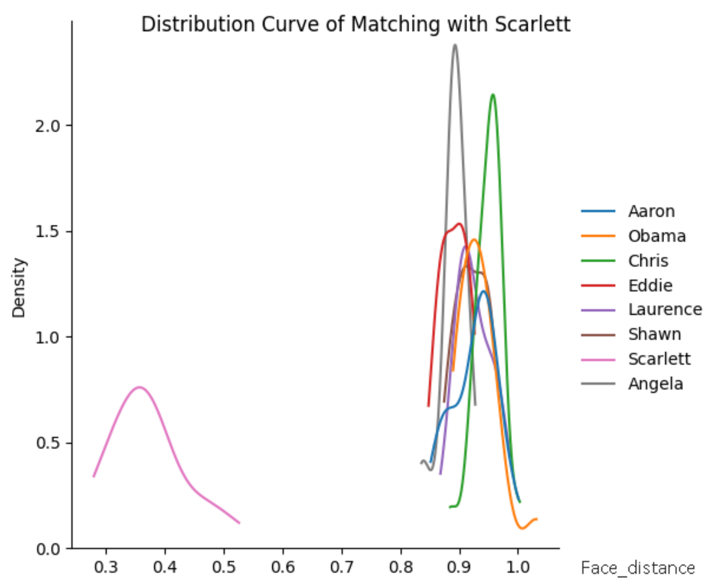


Figure 17 Distribution of Face-Distance matching with Scarlett Johansson

Analysis: Scarlett is quite distinguishable among the samples, which makes her a “sheep”.

Table 6 Face-distance with Barack Obama

	Name	Max	Min	Average
Matching with	Shawn Ashmore	0.9550	0.8593	0.9239
	Aaron Ashmore	0.9328	0.8045	0.8781
	Chris Pratt	0.9507	0.8753	0.9211
	Scarlett Johansson	1.0109	0.9231	0.9587
	Barack Obama (Self)	0.4768	0.3269	0.3983
	Laurence Fishburne	0.8568	0.7469	0.8058
	Angela Yang	0.9902	0.8850	0.9251
	Eddie Peng	0.8365	0.7681	0.8027

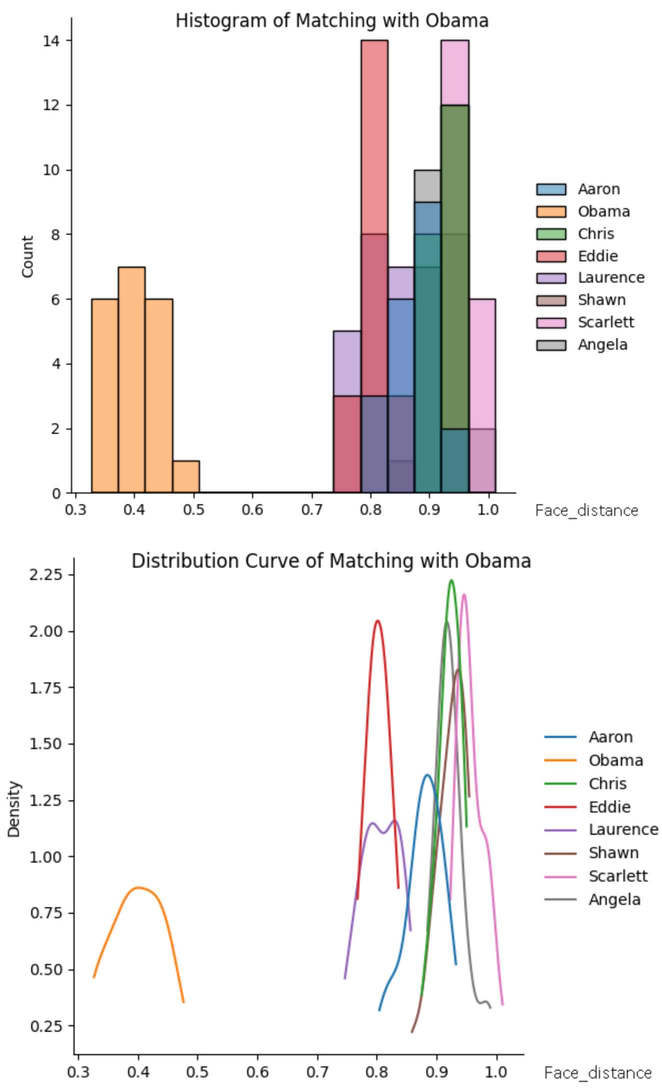
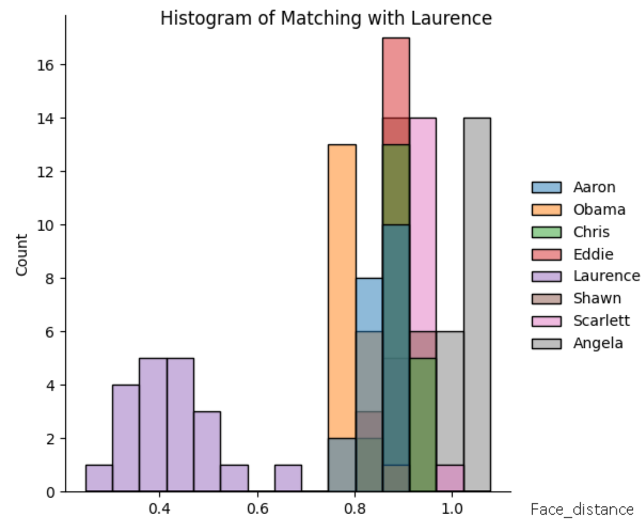


Figure 18 Distribution of Face-Distance matching with Barack Obama

Analysis: Even though we intentionally select some distorted face with exaggerated expression for testing, the recognition is not influenced. The self-matching face-distance are still distributed within a low range, which makes Obama a “sheep” as well.

Table 7 Face-distance with Laurence Fishburne

	Name	Max	Min	Average
Matching with	Shawn Ashmore	0.9329	0.8611	0.8985
	Aaron Ashmore	0.9038	0.7882	0.8495
	Chris Pratt	0.9458	0.8448	0.8951
	Scarlett Johansson	0.9949	0.8751	0.9282
	Barack Obama	0.8673	0.7472	0.7935
	Laurence Fishburne (Self)	0.6465	0.2483	0.4181
	Angela Yang	1.0779	0.9766	1.0296
	Eddie Peng	0.9088	0.8344	0.8734



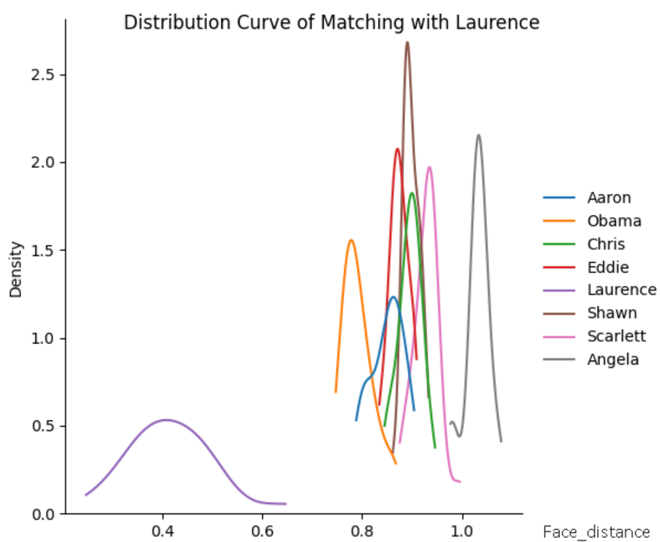
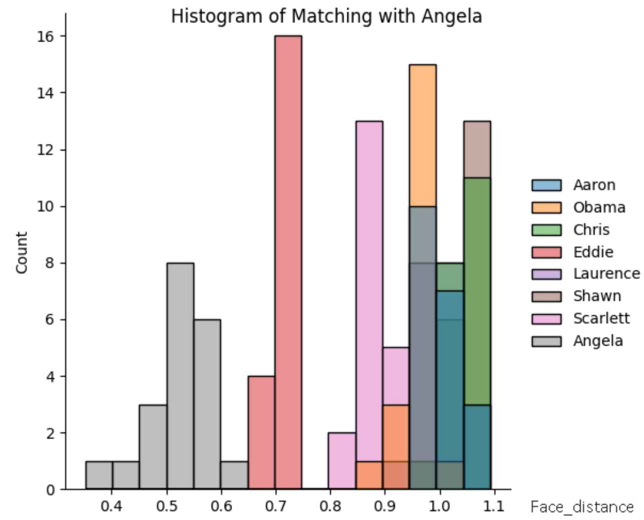


Figure 19 Distribution of Face-Distance matching with Laurence Fishburne

Analysis: Laurance is distinguishable among the samples, which makes him a “sheep”. However, there is a discrete high value, which may be an abnormal data and further analysis need to be performed on it.

Table 8 Face-distance with Angela Yang

	Name	Max	Min	Average
Matching with	Shawn Ashmore	1.0927	0.9909	1.0513
	Aaron Ashmore	1.0648	0.9538	1.0019
	Chris Pratt	1.0901	0.9928	1.0464
	Scarlett Johansson	0.9436	0.8314	0.8803
	Barack Obama	1.0174	0.8898	0.9600
	Laurence Fishburne	1.0601	0.9296	1.0073
	Angela Yang (Self)	0.6152	0.3522	0.5244
	Eddie Peng	0.7460	0.6603	0.7198



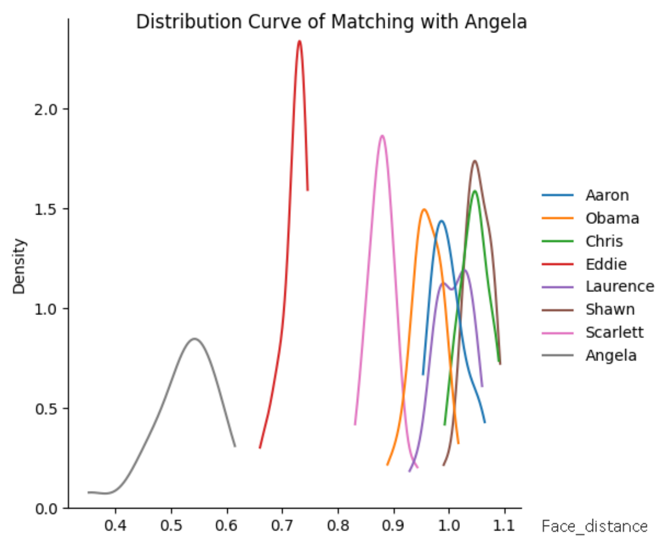


Figure 20 Distribution of Face-Distance matching with Angela Yang

Analysis: Even though Angela is distinguishable from others, her self-matching face-distance is significantly higher than others due to the facelift surgery, which leads to high False Not Match Rate, making her a “goat”.

Table 9 Face-distance with Eddie Peng

	Name	Max	Min	Average
Matching with	Shawn Ashmore	0.8821	0.8135	0.8589
	Aaron Ashmore	0.8608	0.7855	0.8239
	Chris Pratt	0.9075	0.8331	0.8685
	Scarlett Johansson	0.9027	0.8080	0.8541
	Barack Obama	0.8539	0.7277	0.7913
	Laurence Fishburne	0.9123	0.8064	0.8520
	Angela Yang	0.8222	0.6714	0.7521
	Eddie Peng (Self)	0.4615	0.3008	0.3599

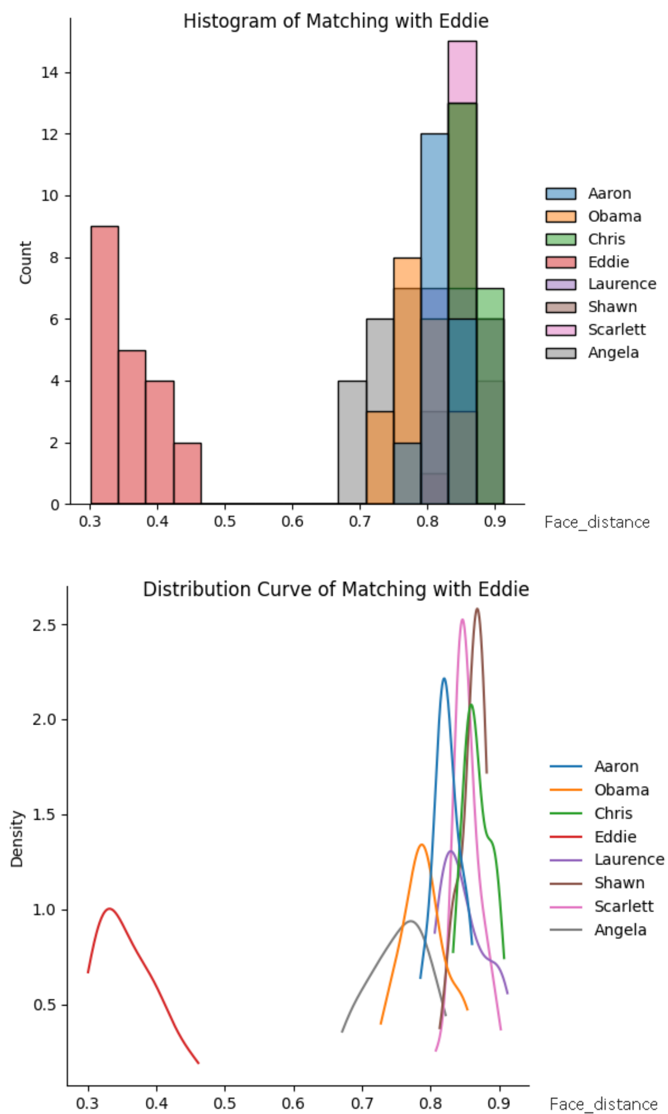


Figure 21 Distribution of Face-Distance matching with Eddie Peng

Analysis: Eddie is quite distinguishable among the samples, which categorizes him into “sheep”.

3.2 Face-Distance Result Analysis by Categories

3.2.1 “Sheep” Category

The statistics of face-distance results of 5 people in “sheep” category are listed as follows.

Table 10 Face-Distance Statistics of "Sheep" Category

Matching	Max.	Min.	Avg.	Matching	Max.	Min.	Avg.
Chris Pratt (vs Self)	0.5294	0.3076	0.3909	Chris Pratt (vs Others)	1.1002	0.5821	0.8815
Scarlett Johansson (vs Self)	0.5262	0.2799	0.3732	Scarlett Johansson (vs Others)	1.0313	0.8361	0.9193
Barack Obama (vs Self)	0.4768	0.3269	0.3983	Barack Obama (vs Others)	1.0109	0.7469	0.8879
Laurence Fishburne (vs Self)	0.6465	0.2483	0.4181	Laurence Fishburne (vs Others)	1.0779	0.7472	0.8991
Eddie Peng (vs Self)	0.4615	0.3008	0.3599	Eddie Peng (vs Others)	0.9123	0.6714	0.8287
Overall Average (vs Self)	-	-	0.3881	Overall Average (vs Others)	-	-	0.8833

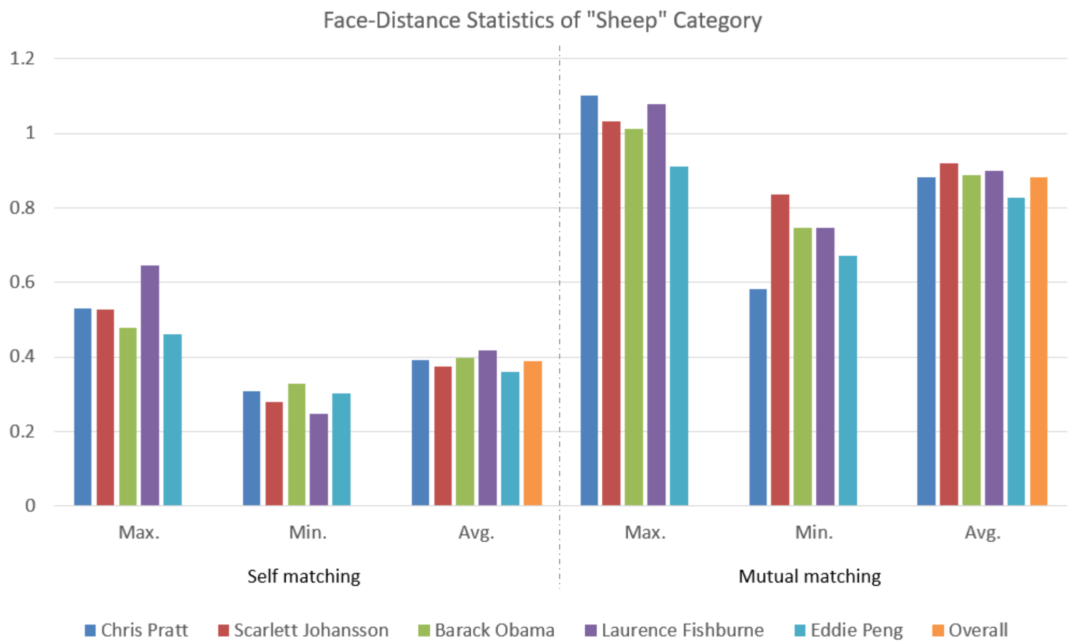


Figure 22 Bar chart of Face-Distance Statistics of "Sheep" Category

The data indicates that:

1) The self-matching face-distances of a sample in “sheep” category mainly falls in 0.3-0.5 interval, with an average of 0.4 approximately.

2) The minimum face-distance value of matching between two different individuals is higher than the maximum value of self-matching. Hence there is no overlap of distribution. Under this circumstance, the system is able to achieve a very low False Match Rate and False Not Match Rate.

3.2.2 “Lamb / Wolf” Category

The statistics of face-distance results of 2 people in “lamb/wolf” category are listed as follows.

Table 11 Face-Distance Statistics of "Lamb/Wolf" Category

Matching	Max.	Min.	Avg.	Matching	Max.	Min.	Avg.
Shawn Ashmore (vs Self)	0.4321	0.2467	0.3475	Shawn Ashmore (vs Aaron)	0.5519	0.3684	0.4606
Aaron Ashmore (vs Self)	0.5203	0.3239	0.4340	Aaron Ashmore (vs Shawn)	0.5236	0.4468	0.4842

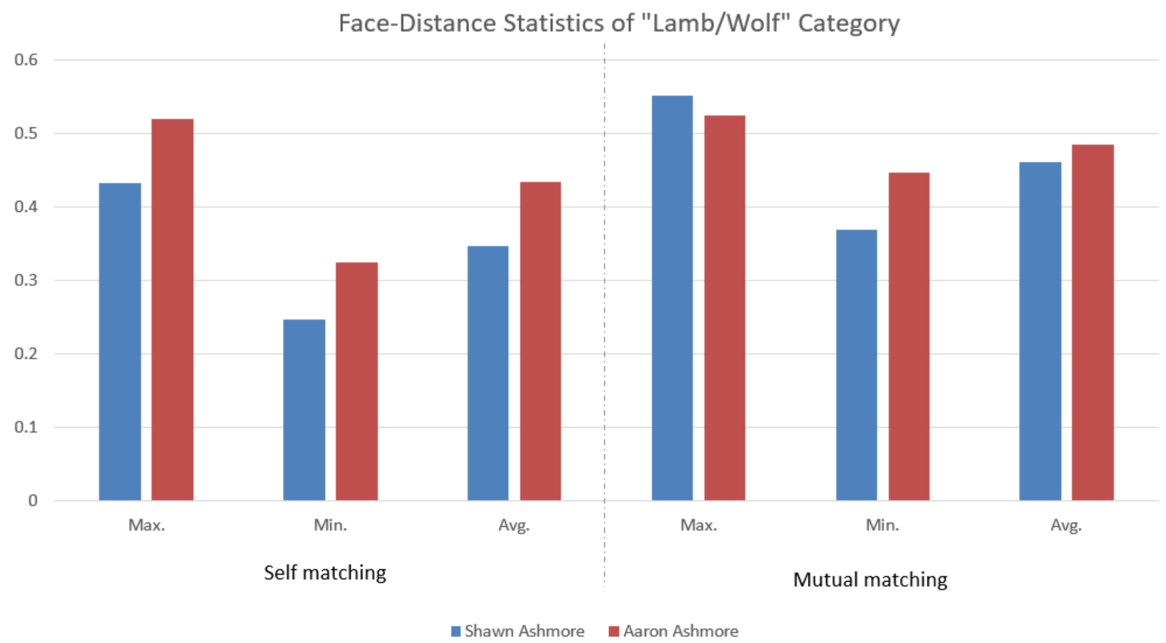


Figure 23 Bar Chart of Face-Distance Statistics of "Lamb/Wolf" Category

The data indicates that:

1) The self-matching face-distances of a sample in “lamb/wolf” category are similar to “sheep” samples, which means they can be well recognized by the system regardless of other samples.
2) When a pair of “lamb/wolf” samples matching with each other, the face-distance is very close to self-matching, which leads to a large overlap, or a high False Match Rate.

In addition, since both Shawn and Aaron are considered as “known” to the system, they are a pair of coupled “lamb/wolf” samples here, which means any one of them would be considered as an imposter to the other one. In other scenarios, for example, Shawn is registered while Aaron is not. Then we will call Shawn the “lamb” and Aaron is the “wolf”.

3.2.3 “Goat” Category

The statistics of face-distance results of 1 people in “goat” category are listed as follows.

Table 12 Face-Distance Statistics of "Goat" Category

Matching	Max.	Min.	Avg.	Matching	Max.	Min.	Avg.
Angela Yang (vs Self)	0.6152	0.3522	0.5244	Angela Yang (vs Others)	1.0926	0.6603	0.9524

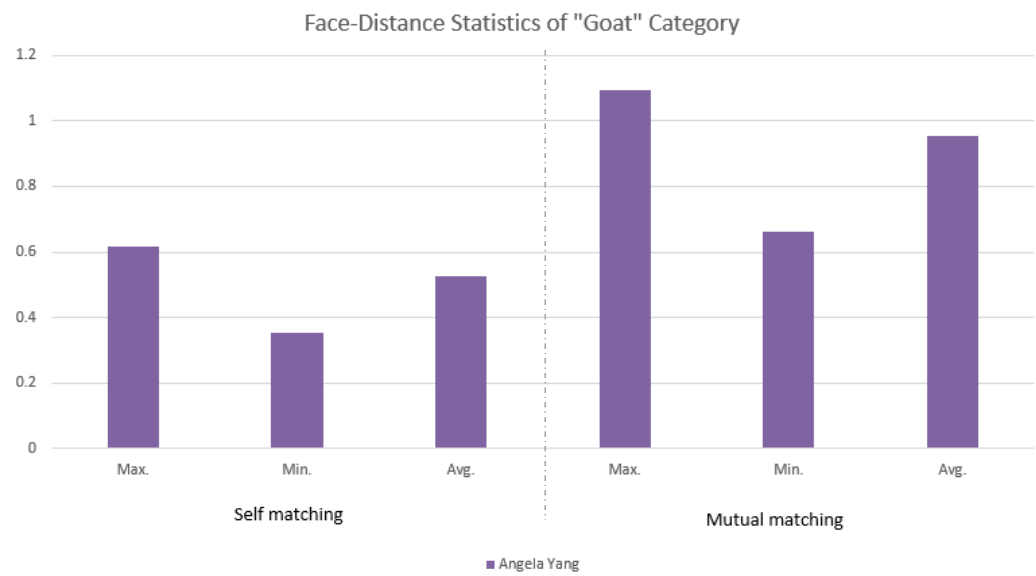


Figure 24 Face-Distance Statistics of "Goat" Category

The data indicates that:

1) When a sample in “goat” category is checked against others, and if the face-distance is higher than normal, which means it can be clearly distinguished from others.
2) The self-matching face-distance is significantly higher than “sheep” and “lamb” samples. Under this circumstance, the “goat” samples could cause a high False Not Match Rate.

3.3 Tolerance and FMR/FNMR Analysis

The tolerance value means the recognition threshold for each matching. A self-matching with a face-distance higher than tolerance leads to a False Not Match. If comparing two different faces produces a face-distance lower than the tolerance value, then it results in a False Match. The statistics of FMR and FNMR by different categories are listed as follows.

Table 13 FMR and FNMR for different tolerance values

Category	Genuine Sample	Tolerance=0.4		Tolerance=0.5		Tolerance=0.6	
		FMR	FNMR	FMR	FNMR	FMR	FNMR
Sheep	Chris Pratt	0%	35%	0%	10%	0.71%	0%
	Scarlett Johansson	0%	20%	0%	5%	0%	0%
	Barack Obama	0%	45%	0%	0%	0%	0%
	Laurence Fishburne	0%	55%	0%	10%	0%	5%
	Eddie Peng	0%	20%	0%	0%	0%	0%
Lamb/ Wolf	Shawn Ashmore	1.42%	20%	8.57%	0%	14.29%	0%
	Aaron Ashmore	0%	70%	10.7%	25%	15%	0%
Goat	Angela Yang	0%	95%	0%	75%	0%	5%
Overall Average		0.18%	45%	2.41%	15.63%	3.75%	1.25%

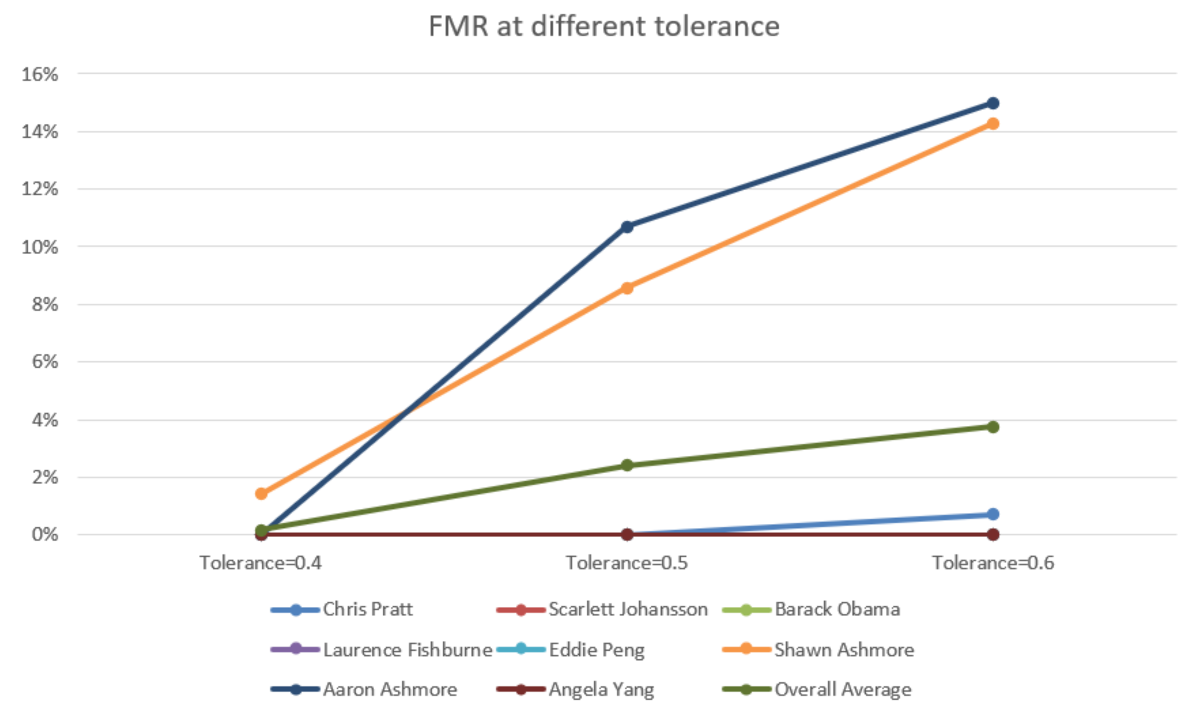


Figure 25 FMR at different tolerance

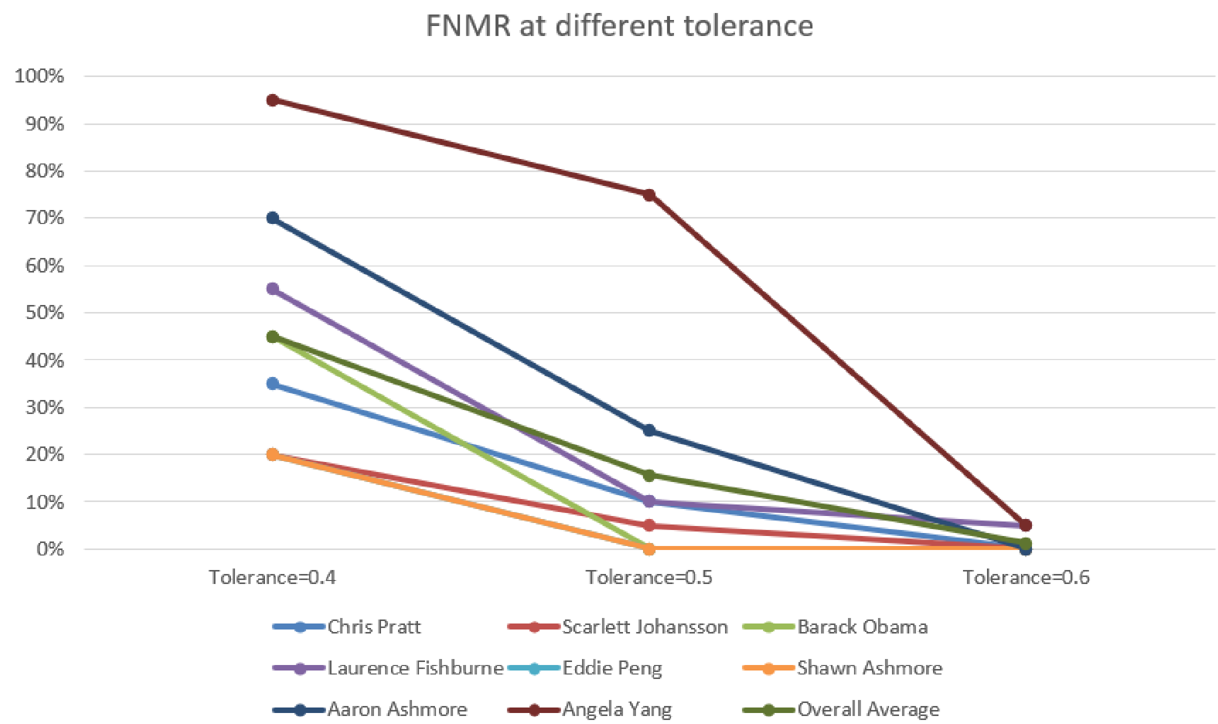


Figure 26 FNMR at different tolerance

As the tolerance goes higher, the FMR increases and the FNMR decreases. The result suggests that, for higher security, a tolerance between 0.4-0.5 would be recommended to achieve a low FMR, so that imposters could be rejected. For higher convenience, a tolerance value within 0.5-0.6 range would be recommended in order to achieve a low FNMR, so that the registered persons could access the system smoothly.

However, for samples in lamb/wolf category, it would be a dilemma. It is difficult to achieve an acceptable FMR and FNMR at the same time. The system designer must find a balance between the security and convenience that is subject to the major demand of the application.

3.4 Foreground Output of Recognition

For samples not matching with any known faces, i.e. the samples of which face_distance with all "genuine" faces are higher than the tolerance, the system will respond with a prompt that states that "Unknown face(s)" detected.

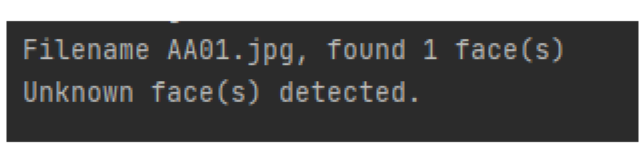


Figure 27 Unknown face detected Prompt

For recognized faces, the system will show the picture with a naming label.

Figure 28 Labeled Recognized Faces[49][45]

3.5 Outliers Analysis

In certain scenarios, image quality may impact the recognition due to compromised face features.

In previous analysis, we noticed that there are some high face_distance values in “sheep” samples, which is abnormal. To find the outliers, we did a full cross-match with 20 test set pictures of one person and obtained a 20*20 symmetrical face_distance array. With “color scales” function of Microsoft Excel, the outliers are outstanding, such as LF06.jpg in the following sample.

	LF01.jpg	LF02.jpg	LF03.jpg	LF04.jpg	LF05.jpg	LF06.jpg	LF07.jpg	LF08.jpg	LF09.jpg	LF10.jpg	LF11.jpg	LF12.jpg	LF13.jpg	LF14.jpg	LF15.jpg	LF16.jpg	LF17.jpg	LF18.jpg	LF19.jpg	LF20.jpg
LF01.jpg	0	0.38352	0.44257	0.39613	0.52661	0.60182	0.42979	0.36256	0.40773	0.36857	0.41676	0.36227	0.43617	0.39008	0.47688	0.34636	0.49146	0.43958	0.41291	0.48482
LF02.jpg	0.38352	0	0.52544	0.3807	0.5024	0.65636	0.47562	0.36469	0.40416	0.40652	0.36342	0.47482	0.40634	0.3858	0.45024	0.34758	0.49817	0.43694	0.50721	0.49252
LF03.jpg	0.44257	0.52544	0	0.5594	0.44481	0.69794	0.38609	0.4044	0.54016	0.42638	0.42444	0.43778	0.41645	0.38418	0.34723	0.46935	0.59187	0.45768	0.51022	0.52093
LF04.jpg	0.39613	0.3807	0.5594	0	0.58603	0.60701	0.53245	0.4579	0.30651	0.38053	0.40421	0.44265	0.44005	0.43011	0.51472	0.3747	0.41106	0.42457	0.49978	0.4801
LF05.jpg	0.52661	0.5024	0.44481	0.58603	0	0.67709	0.44085	0.44813	0.56502	0.47606	0.43443	0.48206	0.45514	0.45706	0.45095	0.48854	0.57549	0.49882	0.49574	0.48862
LF06.jpg	0.60182	0.65636	0.69794	0.60701	0.67709	0	0.65564	0.64889	0.64001	0.68251	0.58947	0.57803	0.61991	0.59867	0.66927	0.63443	0.5721	0.70355	0.58809	0.64979
LF07.jpg	0.42979	0.47562	0.38609	0.53245	0.44085	0.65564	0	0.32233	0.47699	0.43547	0.40563	0.41368	0.39641	0.342	0.3371	0.42905	0.55775	0.50777	0.37524	0.44898
LF08.jpg	0.36256	0.36469	0.4044	0.4579	0.44813	0.64889	0.32233	0	0.44072	0.4098	0.31994	0.41515	0.36932	0.29179	0.32752	0.33137	0.54456	0.48273	0.43379	0.45598
LF09.jpg	0.40773	0.40416	0.54016	0.30651	0.56502	0.64001	0.47699	0.44072	0	0.40048	0.39126	0.43946	0.42604	0.40665	0.4638	0.35766	0.43892	0.42301	0.48545	0.49504
LF10.jpg	0.36857	0.40652	0.42638	0.38053	0.47606	0.68251	0.43547	0.4098	0.40048	0	0.40313	0.41451	0.39963	0.38057	0.44541	0.34056	0.4684	0.38227	0.44444	0.41671
LF11.jpg	0.41676	0.36342	0.42444	0.40421	0.43443	0.58947	0.40563	0.31994	0.39126	0.40313	0	0.43916	0.21357	0.31852	0.36934	0.32944	0.47819	0.43411	0.49579	0.49551
LF12.jpg	0.36227	0.47482	0.43778	0.44265	0.48206	0.57803	0.41368	0.41515	0.43946	0.41451	0.43916	0	0.4259	0.41146	0.45332	0.43799	0.51123	0.42148	0.32679	0.3953
LF13.jpg	0.43617	0.40634	0.41645	0.44005	0.45514	0.61991	0.39641	0.36932	0.42604	0.39963	0.21357	0.4259	0	0.32736	0.36668	0.35276	0.48408	0.39365	0.46615	0.49974
LF14.jpg	0.39008	0.3858	0.38418	0.43011	0.45706	0.59867	0.342	0.29179	0.40665	0.38057	0.31852	0.41146	0.32736	0	0.3628	0.36063	0.45948	0.47671	0.42092	0.43685
LF15.jpg	0.47688	0.45024	0.34723	0.51472	0.45095	0.66927	0.3371	0.32752	0.4638	0.44541	0.36934	0.45332	0.36668	0.3628	0	0.38149	0.57653	0.44164	0.45702	0.48336
LF16.jpg	0.34636	0.34758	0.46935	0.3747	0.48854	0.63443	0.42905	0.33137	0.35766	0.34056	0.32944	0.43799	0.35276	0.36063	0.38149	0	0.44802	0.3976	0.46355	0.48298
LF17.jpg	0.49146	0.49817	0.59187	0.41106	0.57549	0.5721	0.55775	0.54456	0.43892	0.4684	0.47819	0.51123	0.48408	0.45948	0.57653	0.44802	0	0.50771	0.50768	0.4813
LF18.jpg	0.43958	0.43694	0.45768	0.42457	0.49882	0.70355	0.50777	0.48273	0.42301	0.38227	0.43411	0.42148	0.39365	0.47671	0.44164	0.3976	0.50771	0	0.48016	0.48253
LF19.jpg	0.41291	0.50721	0.51022	0.49978	0.49574	0.58809	0.37524	0.43379	0.48545	0.44444	0.49579	0.32679	0.46615	0.42092	0.45702	0.46355	0.50768	0.48016	0	0.36453
LF20.jpg	0.48482	0.49252	0.52093	0.4801	0.48862	0.64979	0.44898	0.45598	0.49504	0.41671	0.49551	0.3953	0.49974	0.43685	0.48336	0.48298	0.4813	0.48253	0.36453	0

Figure 29 Full Cross-Match Face_distance Array in Microsoft Excel

Outliers found:

The following images from the dataset are the outliers. These images contain people faces that are oriented outside the norm (Straight facing image). These outlier’s yield abnormally high Full Cross-Match Face_distance values that are significantly higher than any of the preset threshold value. Figure 30 lists the images that are classified as outliers. Each one of the above images have certain unique features that generate outliers(Left to right: Facial Orientation, Facial Orientation, Facial Orientation and abnormal expression, shadow, close up and abnormal expression)

Figure 30 Outlier in Previous Data Set[46][49][45][44][41]

It is important to make note of these observations and understand the reasoning behind it. We will elaborate on each one of the outliers as follows:

- Influence of Shadows
- Close ups
- Facial Orientation
- Other Factors(Facial Occlusions)

3.5.1 Influence of shadows

The lighting quality of an image heavily influences the generation of HOG image that is responsible for face detection[7][8][9][10][11]. In addition, it also has an influence on landmark detection. Shadows heavily influences pixel intensities thereby the gradient components of a HOG image[7][11]. Figure 31 demonstrates the generation of a HOG image from a heavily shadowed input image. It seems the HOG image is unable to generate the gradient pattern of the entire face. The entirety of the left side of the individuals image does not generate any gradient on the HOG image since that part is heavily shadowed and there is no transition of pixel gradient intensity.

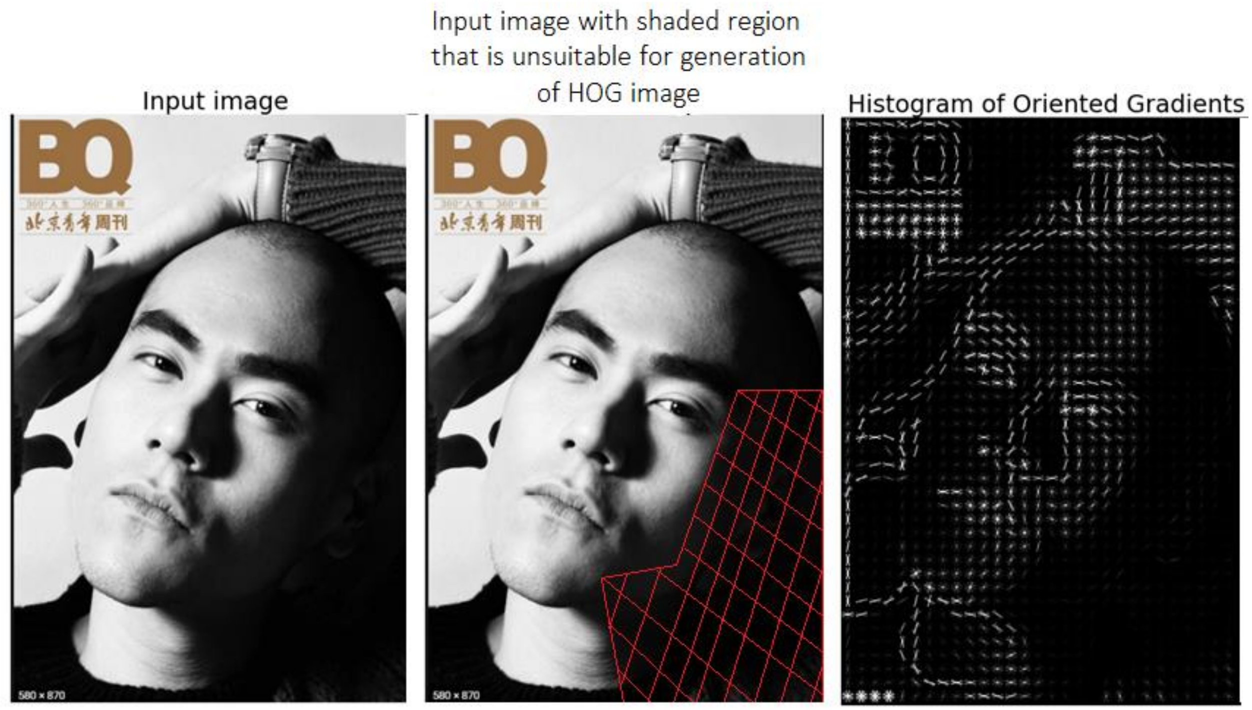


Figure 31 Genration of HOG image of a heavily shadowed image [42]

Upon experimenting with the above image a corresponding HOG is generated but the program could not generate facial landmarks.

3.5.2 Close ups

For the case of close ups, the program can generate the HOG image and detect the face. However, when it came to landmark detection, it is unable to generate all the 68 landmark points. A normal image is supposed to generate landmark points that map various facial features(outline of jaw, eyebrow, eyes, lips, nose etc.). However, the close up images of faces are clearly missing some of these landmarks. This clearly affects the generation of facial encodings thereby face distance.

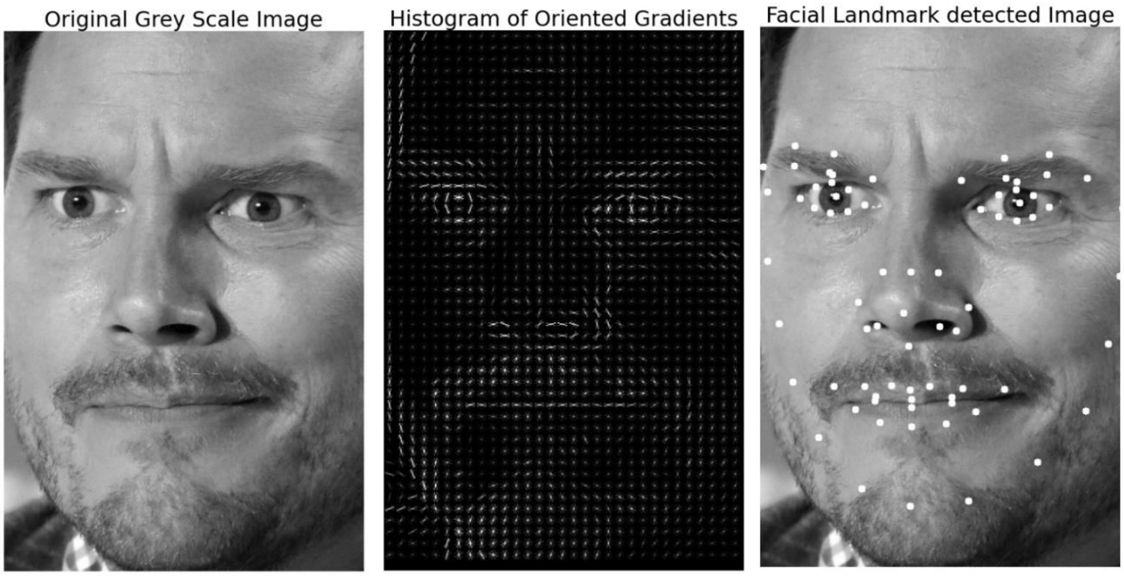


Figure 32 Genration of HOG image and facial landmarks of a close up image [41]

The landmark image above seems to be missing landmarks on the forehead and left side of the jaw close to the year. This image generates a relatively high value for face distance.

3.5.3 Facial Orientation

These images have a similar issue as with the case of "close ups" in that there are problems with generation of facial landmarks. Figure 33 shows an image of an individual oriented sideways. In this image significant number of landmarks are mapped outside the face. This will imapct the generation of facial encodings thereby face distance[7][11]. However, if the image were rotated at about 90 degrees(left and right) then facial encodings are not all generated. For those images certain important facial features(one eye, half of nose, half of jaw etc) are missing. Landmarks cannot be generated for such images. These faces will yield a relatively higher value for face distance. It will perform the task of face detection but it will most likely have trouble identifying the individual.

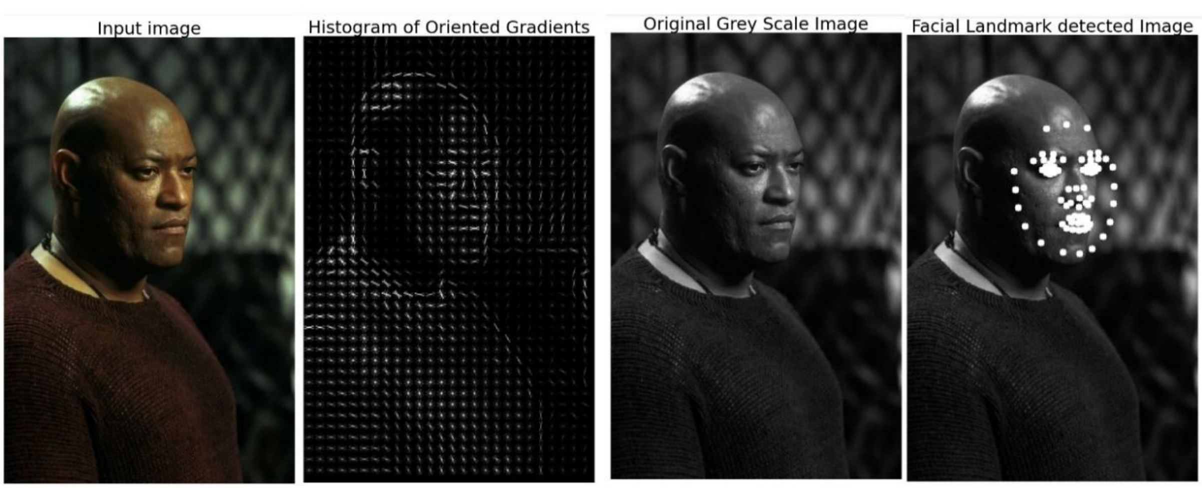


Figure 33 Genration of HOG image and facial landmarks of a side-face image [46]

3.5.4 Other factors

An experiment was conducted to test images of varying qualities(expression, shadow, close ups, facial orientation, Facial Occlusions(faces covered by mask, shades)) and measure the face distance. Based on the experiment and results, facial occlusions do not have as much of an impact as shadows and facial orientation. The facial recognition model is very much accustomed to recognizing images that contain upright images[7][11]. Regardless of facial orientation the program can be trained to orient each one of the images in the upright position as long as the detected face contains most of the facial features on which the landmark points can be mapped. However, based on experiments and simulations, it seems the position of the eye and the surrounding features(eyebrows) seem to have the most impact when it comes to mapping landmark detection. If there are faces oriented sideways in a 90 degree fashion with only one eye visible in the image then the face distance is relatively higher than the images that contain front facing faces and it would most likely yield non-match.

Figure 34 Experiment for performing face recognition on images that are subjected various outliers

Table 14 Results of the experiment displaying values for face distance

Factor Tested	Face_distance Value
Regular	0.1581
Facial expression	0.2889
Glasses	0.2989
Shades	0.3874
Shadowed face	0.4033
Mask	0.4997
Side face	0.5122

3.5.5 Verifying experiment

Another experiment was conducted with one of the individuals that was originally used with the facial recognition dataset, in order to verify the previous conclusion. We selected the actor Eddie Peng who was verified to be a sheep with the lowest face distance. Hence, he was the best canditate on whom the outlier test can be formed.

Figure 35 Probe images for Eddie Peng that are all outliers [43]

Figure 36 Images for Eddie Peng that will be compared with the outlier probe images [43]

	EP01.jpg	EP02.jpg	EP03.jpg	EP04.jpg	EP05.jpg	EP06.jpg	EP07.jpg	EP08.jpg	EP09.jpg	EP10.jpg	EP11.jpg	EP12.jpg	EP13.jpg	EP14.jpg	EP15.jpg	EP16.jpg	EP17.jpg	EP18.jpg	EP19.jpg	EP20.jpg
Eddie_shadow1.jpg	0.49155	0.38359	0.43087	0.42998	0.47143	0.42283	0.44044	0.4443	0.45184	0.48069	0.49402	0.46364	0.42027	0.44462	0.46498	0.46402	0.42495	0.48824	0.47197	0.44726
Eddie_shadow2.jpg	0.50294	0.46398	0.47819	0.4744	0.45675	0.46704	0.44507	0.44202	0.48561	0.47865	0.52633	0.47039	0.47801	0.45537	0.4921	0.4651	0.47363	0.466	0.49409	0.47131
Eddie_shadow3.jpg	0.47517	0.35929	0.49535	0.44438	0.48512	0.45131	0.43217	0.47116	0.44707	0.45135	0.48237	0.4722	0.46118	0.39911	0.47223	0.43535	0.41116	0.42527	0.51956	0.46106
Eddie_side1.jpg	0.466	0.43172	0.46423	0.47364	0.49748	0.41609	0.46046	0.43065	0.4674	0.45393	0.44035	0.44808	0.4405	0.46697	0.45667	0.4671	0.42664	0.46266	0.43859	0.43166
Eddie_side2.jpg	0.66668	0.63778	0.66699	0.65218	0.65601	0.62145	0.64042	0.66265	0.64033	0.59123	0.6343	0.65021	0.65701	0.65513	0.65005	0.6127	0.67326	0.60256	0.70647	0.63951
Eddie_side3.jpg	0.50188	0.45107	0.49356	0.50109	0.52202	0.48121	0.50153	0.47054	0.45216	0.50277	0.50109	0.4637	0.49275	0.50851	0.4605	0.49492	0.45911	0.51026	0.53603	0.4625

Figure 37 Results for facial analysis on outlier images

The experiment yielded some interesting observations. Both shadows and facial orientation have a profound impact on face distance. Based on the results sideways facial orientation seem to have a bigger impact than shadows. The picture “Eddie_side2” yielded the highest face distance thereby making it the most unsuitable for facial recognition system. However, one exception to this particular trend was the picture “Eddie_side1” which performed fairly well with the facial recognition system. This particular one performs better than atleast two of the shadow images(“Eddie_shadow2” and “Eddie_shadow3”). We speculate the reason the image “Eddie_side1” performs better than the aforementioned shadow images, is that the side view image seems to have the right amount of shadows, which may work against the the two shadow images. This is surprising considering the sideview images may seem problematic for facial recognition system.

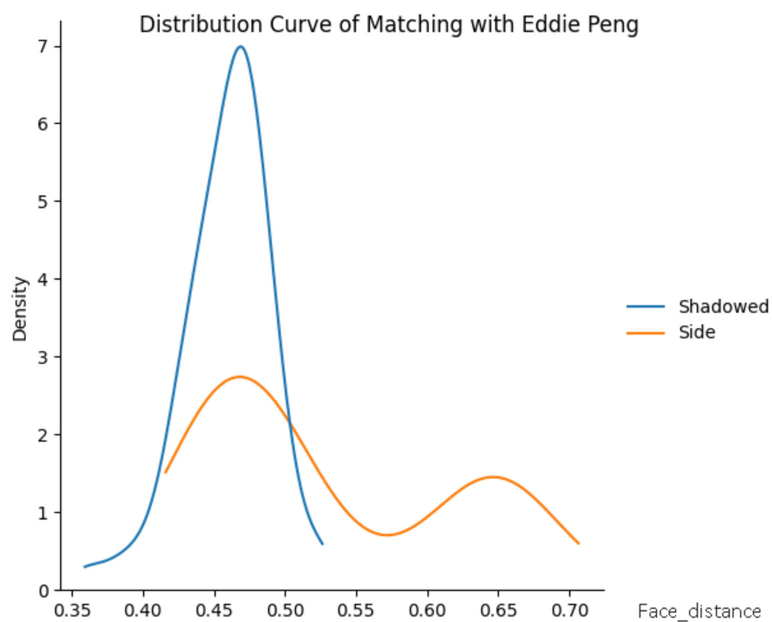


Figure 38 Distribution curves of pictures for Eddie Peng in verifying experiment

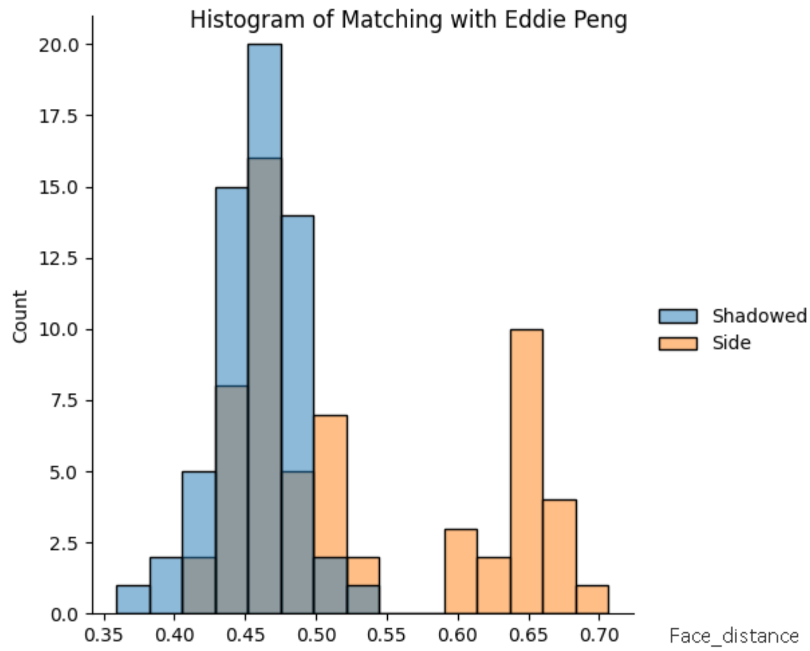


Figure 39 Histogram of pictures for Eddie Peng in verifying experiment

The distribution curve and histogram of matching are a great visual representation of results. The side view images have a far greater impact than the shadow images and the former is more suitable for facial recognition system in relative terms.

4. Future Work

The current system can perform face recognition with a 95% accuracy, which is adequate for entry-level usage. Furthermore, Doddington Zoo Theory was verified by a 160-picture dataset. However, due to the time limit, occasionality may occur. Therefore, more samples need to be collected and tested for a more convincing conclusion.

To complement the system, some future work is suggested.

1. **Training and testing the algorithm on multiple images**: The current algorithm uses only one photo as the reference. Hence, there is a high occasionality. The system is not good at recognizing side faces or faces with heavy make-ups. A CNN model is to be introduced to establish a training process to improve the accuracy.
2. **Implementation of numerous deep learning models:** Histogram of Oriented Gradients (HOG) is a good descriptor to perform the functionality of face detection. However, there are many models that perform the entire process of Facial Recognition using Deep learning techniques. Extensive research has been carried out in this field. A few good starting point models include the following [14][15][16]:
    - Face Recognition model using FaceNet in Keras
    - YOLO(You Only Look Once) Face Detector
    - MTCNN(Multi-Test Cascaded Convolutional Neural Network)

5. Conclusion

Facial Recognition is one of the most important authentication technologies that have become mainstream in today's day and age. There is always a constant demand for improvement of this biometric and extensive research is being carried on this field. It is important to have a good understanding of the statistical and mathematical foundations of these models as it will serve as a good starting point to understanding numerous face recognition models that have significant overlaps in terms of algorithm structure. Once the model is selected and built, it is important to test its effectiveness. This is accomplished by testing and training the model with a diverse data. Biometric menagerie technique such as Doddington Zoo provides a biometric system designer with useful mathematical and statistical tools to define and label user groups. The results from Doddington Zoo analysis provide the biometric system designer with useful data that serves as a good indicator of the effectiveness of the algorithm.

For further details, please visit the github repository to check the original code, dataset, and exported data: https://github.com/vamar123/ENEL-610-Project

References

[1] D. E. King, "Dlib C++ Library," Dlib C++ Library, 28 May 2021. [Online]. Available: http://dlib.net/[Accessed February 2021].

[2] D. S. Yanushkevich, "Fundamentals of Biometric Systems Design, Part 7: Doddington zoo-biometric biases," University of Calgary, Calgary, 2021.

[3] D. S. Yanushkevich, "Fundamentals of Biometric Systems Design, Part 8: Doddington and Ranking Based Matching," University of Calgary, Calgary, 2021.

[4] Y. S.K.Chen, 2014 International Conference on Artificial Intelligence and Software Engineering (AISE2014), California, USA: DEStech Publications, Inc, 2014.

[5] AWARE, "Facial Recognition," Aware, 2021. [Online]. Available: https://www.aware.com/facial-recognition/ [Accessed March 2021].

[6] J. Norman, "Woodrow Bledsoe Originates of Automated Facial Recognition," HistoryofInformation, 2021. [Online]. Available: https://www.historyofinformation.com/detail.php?entryid=2495.

[7] A. Geitgey, "Machine Learning is Fun! Part 4: Modern Face Recognition with Deep Learning," medium, 24 July 2016. [Online]. Available: https://medium.com/@ageitgey/machine-learning-is-fun-part-4-modern-face-recognition-with-deep-learning-c3cffc121d78[Accessed February 2021].

[8] N. D. a. B. Triggs, "Histograms of Oriented Gradients for Human Detection," 25 July 2005. [Online]. Available: http://lear.inrialpes.fr/people/triggs/pubs/Dalal-cvpr05.pdf[Accessed February 2021].

[9] D. R. Ahmed, "Histogram of Oriented Gradients (HOG) | By Dr. Ry @Stemplicity," youtube, 4 August 2019. [Online]. Available: https://www.youtube.com/watch?v=XmO0CSsKg88&ab_channel=Stemplicity. [Accessed February 2021].

[10] S. Mallick, "Histogram of Oriented Gradients explained using OpenCV," OpenCV, 6 December 2016. [Online]. Available: https://learnopencv.com/histogram-of-oriented-gradients/. [Accessed February 2021].

[11] A. Geitgey, "Face Recognition," Face Recognition, 2017. [Online]. Available:https://face-recognition.readthedocs.io/en/latest/readme.html. [Accessed February 2021].

[12] A. Geitgey, "Face Recogntion," github, 2021. [Online]. Available: https://github.com/ageitgey/face_recognition. [Accessed February 2021].

[13] "face_recognition package," Face Recognition, 2017. [Online]. Available: https://face-recognition.readthedocs.io/en/latest/face_recognition.html. [Accessed March 2021].

[14] J. Brownlee, "How to Perform Face Detection with Deep Learning," Machine Learning Mastery, 24 August 2020. [Online]. Available: https://machinelearningmastery.com/how-to-perform-face-detection-with-classical-and-deep-learning-methods-in-python-with-keras/. [Accessed February 2021].

[15] Z. Z. Z. L. Y. Q. Kaipeng Zhang, "arxiv," 11 April 2016. [Online]. Available: https://arxiv.org/ftp/arxiv/papers/1604/1604.02878.pdf. [Accessed 15 March 2021].

[16] I. Itzcovich, "faced: CPU Real Time face detection using Deep Learning," 26 September 2018. [Online]. Available: owardsdatascience.com/faced-cpu-real-time-face-detection-using-deep-learning-1488681c1602. [Accessed 31 March 2021].

References for Pictures

[17] Rotten tomatoes, "Aaron Ashmore," Rotten Tomatoes, [Online]. Available: https://www.rottentomatoes.com/celebrity/aaron_ashmore. [Accessed 5 March 2021].

[18] MUBI, "Aaron Ashmore," MUBI, [Online]. Available: https://mubi.com/cast/aaron-ashmore. [Accessed 5 March 2021].

[19] Locke & Key France, "Locke & Key France," Facebook, [Online]. Available: https://www.facebook.com/lockeandkeyfrance/posts/2391420857638933/. [Accessed 2021 March 5].

[20] Locke & Key Wiki, "Locke & Key Wiki," Locke & Key Wiki, [Online]. Available: 2021.

[21] zimbio, "zimbio," zimbio, 2 April 2015. [Online]. Available: https://www.zimbio.com/Aaron+Ashmore/pictures/pro. [Accessed 2021 March 5].

[22] C. Gallay, "Charley Gallay," pinterest, [Online]. Available: https://www.pinterest.ca/pin/346706871294219297/. [Accessed 5 March 2021].

[23] IMDB, "Shawn Ashmore," IMDB, [Online]. Available: https://www.imdb.com/name/nm0039162/mediaviewer/rm2643197184/. [Accessed 5 March 2021].

[24] Aaron Ashmore, "Celebrity Sizes," Celebrity Sizes, 24 January 2018. [Online]. Available: https://www.celebritysizes.com/aaron-ashmore-age-weight-height-measurements/ [Accessed 5 March 2021].

[25] ShareTV, "Shawn Ashmore," ShareTV, [Online]. Available: https://sharetv.com/person/shawn_ashmore. [Accessed 5 March 2021].

[26] Forbes, "Forbes," Amazon Studios, 10 August 2020. [Online]. Available: https://www.forbes.com/sites/robsalkowitz/2020/08/10/surprise-the-boys-adds-shawn-ashmore-as-a-missing-member-of-the-seven/?sh=bde019166e0a. [Accessed 10 March 2021].

[27] Shawn Ashmore, "Shawn Ashmore," Rotten Tomatoes, [Online]. Available: https://www.rottentomatoes.com/celebrity/shawn_ashmore. [Accessed 5 March 2021].

[28] G. Carraquillo, Getty Images, 16 February 2017. [Online]. Available: https://www.self.com/story/scarlett-johansson-monogamy. [Accessed 10 March 2021].

[29] "Plastic Surgery People," 26 May 2019. [Online]. Available: https://www.plasticsurgerypeople.com/angelababy-before-and-after/. [Accessed 5 March 2021].

[30] MyDramaList, "Angelababy," MyDramaList, [Online]. Available: https://mydramalist.com/people/1762-angela-baby. [Accessed 10 March 2021].

[31] Tabercil, "Angelababy," wikipedia, 23 October 2014. [Online]. Available: https://en.wikipedia.org/wiki/Angelababy#/media/File:Angelababy_in_2014_crop2.jpg. [Accessed 10 March 2021].

[32] P. Souza, "Barack Obama," wikipedia, 6 December 2012. [Online]. Available: https://en.wikipedia.org/wiki/Barack_Obama#/media/File:President_Barack_Obama.jpg. [Accessed 2021 March 05].

[33] D. T. Johnson, "Chris Pratt," wikipedia, 28 June 2018. [Online]. Available: https://en.wikipedia.org/wiki/Chris_Pratt#/media/File:Chris_Pratt_2018.jpg. [Accessed 10 March 2021].

[34] Pete Souza, "Barack Obama," wikipedia, 6 December 2012. [Online]. Available: https://en.wikipedia.org/wiki/Presidency_of_Barack_Obama#/media/File:President_Barack_Obama,_2012_portrait_crop.jpg. [Accessed 10 March 2021].

[35] I. Hasegawa, "Laurence Fishburne," ethniccelebs, 4 April 2019. [Online]. Available: https://ethnicelebs.com/laurence-fishburne. [Accessed 10 March 2021].

[36] 17QQ, "Eddie Peng," 17QQ, [Online]. Available: https://jbh.17qq.com/article/kmwhqgqy.html. [Accessed 10 March 2021].

[37] S. Liss, "The Life and Loves of a Young Obama," The New Republic, 21 September 2016. [Online]. Available: https://newrepublic.com/article/136974/life-loves-young-obama. [Accessed 20 March 2021].

[38] Chad J. McNeeley, "The Blacksmith' scores more key virtual Cannes deals for AGC Studios (exclusive)," screendaily, 29 June 2020. [Online]. Available: https://www.screendaily.com/news/the-blacksmith-scores-more-key-virtual-cannes-deals-for-agc-studios-exclusive/5151131.article. [Accessed 15 March 2021].

[39] SciFI Vision, SciFi Vision, [Online]. Available: Aaron
[Accessed 2021 March 10].

[40] Sarah Thomas, "5 Types of Posts i'Hoping to See from @POTUS," komyuonline, [Online]. Available: https://komyuonline.wordpress.com/2015/05/18/5-types-of-memes-im-hoping-to-see-on-obamas-official-potus-twitter-account/. [Accessed 2021 March 10].

[41] babbington, "Chris Pratt," pinterest, [Online]. Available: https://www.pinterest.ca/pin/111112315789845500/. [Accessed 10 March 2021].

[42] MUBI, "Eddie Peng," mubi, [Online]. Available: https://mubi.com/cast/eddie-peng.
[Accessed 2021 March 10].

[43] Google, "Eddie Peng," Google, [Online]. Available: Eddie Peng. [Accessed 10 March 2021].

[44] "Scarlett johansson," Google, [Online]. Available: Scarlett Johansson [Accessed 10 March 2021].

[45] Google, "obama," Google, [Online]. Available: Barack Obama [Accessed 10 March 2021].

[46] Google, "Laurence Fishburne," Google, [Online]. Available: Laurence Fishburne.
[Accessed 10 March 2021].

[47] Google, "Chris Pratt," Google, [Online]. Available: Chris Pratt. [Accessed 10 March 2021].

[48] Google, "Shawn Ashmore," Google, [Online]. Available: Shawn Ashmore. [Accessed 10 March 2021].

[49] Google, "Aaron Ashmore," Google, [Online]. Available: Aaron Ashmore1. [Accessed 10 March 2021].

[50] Google, "Angela Baby," Google, [Online]. Available: Angela Baby. [Accessed 10 March 2021].

[51] T. O.-B. T. Project, "File:Poster-sized portrait of Barack Obama.jpg," wikipedia, November 2008. [Online]. Available: https://en.wikipedia.org/wiki/File:Poster-sized_portrait_of_Barack_Obama.jpg.
[Accessed 10 March 2021].

[52] M. NGAN, "Barack Obama Says 'I Wouldn't Vote for Me' If He Watched Fox News' 'Weird' Coverage," GETTY, 12 January 2017. [Online]. Available: https://www.newsweek.com/obama-wouldnt-vote-himself-fox-news-728177. [Accessed 10 March 2021].

[53] S. Granitz, "imdb," WireImage.com, [Online]. Available:
https://www.imdb.com/name/nm0000401/mediaviewer/rm1925683200/
[Accessed 10 May 2021].