TESTING THE MATCHING CAPABILITIES OF MEGVII'S FACE++ FACIAL RECOGNITION USING AGE-PROGRESSED AND REAL-LIFE IMAGES

by

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A Research Project
Submitted to the
Forensic Science Forensic Research Committee
George Mason University
in Partial Fulfillment of
The Requirements for the Degree
of
Master of Science
Forensic Science

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Spring Semester 2020
George Mason University
Fairfax, VA

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Definitions

Artificial Intelligence (AI)	The simulation, development, and programming of human intelligence in machines to perform tasks related to the human mind such as speech recognition and decision-making.
Algorithm	A series of steps to be followed in order to complete a task or calculation.
AP	Age progression
API	Application Platform Interface – an interface between parts of a computer; set of protocols or definitions describing how software applications must interact with one another.
Confidence Score	The score given to indicate the similarity between two faces; the higher, the greater the chance that the face belongs to the same person; generated as a numerical value out of 100.
FaceSet	Gallery of images to be searched against; all images in the FaceSet are assigned a unique face token.
Identification (1:N matching)	Facial recognition use case where a biometric sample, such as an image, is searched against a database or gallery of images to generate a candidate list of potential matches. 1:N stands for one-to-many.
Python	Programming language used to write code. Python coding was used to connect to and interact with Face++ APIs.
Verification (1:1 matching)	Facial recognition use case where a biometric sample, such as an image, is compared to a previously stored biometric template (image) in order to verify and authenticate a person's identity.
Visual Studio Code	Software editor used to store, write, and execute code.

Abstract

The National Center for Missing & Exploited Children (NCMEC) assisted law enforcement with over 29,000 missing children cases in 2019 and has completed more than 6,800 age-progressed images in its history of working on long-term missing children cases. There is currently little research on the topic of age progressions and their impact on facial recognition algorithms specifically when comparing real-life images and digitally produced age-progressed images of the same individuals. The goal of this study was to determine if a facial recognition algorithm could accurately match and generate a missing child's age-progressed image in a list of top 5 candidates when using the child's real-life image as the probe image for the search. Another goal of this research was to determine if there were any differences in the likelihood of matching based on the age of the missing child and the age variation between the child's real-life image and his or her respective age-progressed images.

The age-progressed and real-life images of 347 children who went missing between the ages of 1 to 20 were included in the study. A gallery of images (called a FaceSet) was created and included the age-progressed images of all 347 missing children. The missing children's real-life images were searched against the FaceSet using Face++'s Search API and the top 5 matches for each person were generated. Every child was categorized as being in the 'older' group (>=13 – 20 years old) or 'younger' group (<13 years old) based on the age the child was when he or she went missing. The results of the study showed that the confidence scores of matches are higher for older children and there is a greater likelihood of matching for older children. The results of the study also demonstrated that the age-progressed images closest in age to the age of the missing child have a greater chance of being matched as compared to the age-progressed images with more age variation.

Introduction

The use of facial recognition has increased significantly over the past decade and only continues to be utilized by law enforcement for identification purposes and criminal investigations. As the technology evolves and is used for multiple purposes by law enforcement, it is essential to conduct research by testing the matching capabilities of facial recognition algorithms in ways that could benefit law enforcement. One potential use case for law enforcement and area of research that needs to be further studied is age progression and how aging can impact the matching capabilities of a facial recognition algorithm. Testing an algorithm by comparing real-life images and digitally produced age-progressed images is a specific method that has not been greatly researched and has generated the following questions which will be addressed in this research:

1. Can Face++ detect an age-progressed image and accurately match it with the same child's real-life image?
2. Will the confidence scores of matches be higher for older children (ages >=13 – 20)?
3. Will there be a difference in Face++'s ability to match images based on the age of the missing child (and real-life image) when he or she went missing?
4. Will there be a difference in Face++'s ability to match images based on the age variation between real-life and age-progressed images?

Based off of these questions, three hypotheses were formed and are listed below.

1. The older the child is at the age of missing, the greater the confidence score will be when there is a match between the child's real-life image and age-progressed image.
2. The older the child is at the age of missing, the more likely there will be a match between the child's real-life and age-progressed image(s).

3. The closer in age the age-progressed image is to the age of the child when he or she went missing (less age variation), the greater the likelihood there will be a match.

Objectives

Based off of the questions and hypotheses, there were four main objectives to be determined through this research.

1. Determine if conducting searches with age-progressed images would be useful for law enforcement to use as investigative leads and help solve long-term missing children cases.
2. Determine if Megvii's Face++ facial recognition algorithm can accurately match a real-life image and an age-progressed image of the same child.
3. Determine if there is any difference in confidence scores and the likelihood of matching for older (>=13-20 years) versus younger (<13 years) children.
4. Determine if there is a greater likelihood of matching a child's real-life image and age-progressed image(s) when the age-progressed image(s) are closer in age to the child at the time he or she went missing (less age variation).

Importance of Research

There has not been a lot of research completed using age-progressed images to test the accuracy and matching capabilities of a facial recognition algorithm. There has been research completed which looks at the impacts of aging on algorithms for verification (1:1 matching) and identification (1:N matching), but the majority of these studies used real-life photos of the same people over time. There has not been any research completed to test the 1:N matching capabilities of a facial recognition algorithm using digitally produced age-progressed images completed by Forensic Artists. Testing facial recognition algorithms with age-progressed and real-life images could greatly benefit law enforcement and investigators in long-term missing children cases especially with the increase in the use of facial recognition by law enforcement. Some of the specific types of long-term missing children cases that this research could help with are family abductions, kidnappings, and runaways. Additionally, this research could assist with the identification of previously unidentified children and could serve as investigative leads in cases. It could also provide insights into an algorithm's ability to detect changes in an individual's face over time and determine how much aging affects performance accuracy. If an age-progressed image can be linked to a missing child using facial recognition then it could help save lives and bring long-term missing children back to their families.

Background Information

Age Progression

The digital age progression of a person's face is a combination of art, science, anthropology, and technology. Synthetic age-progressed images can be created in two ways – Forensic Artists can sketch and draw them either digitally or they can be produced by software and algorithms. Over the past few years, there has more interest in the automation of age progression and researchers have used multiple methods and modeling techniques to age progress facial images using technology. Researchers at the University of Bradford conducted a study using an active appearance model (AAM) and sparse partial least squares regression model (sPLS) to age progress Ben Needham's face, who is a child that went missing at age 21 months on the Greek Island, Kos (Bukar &Ugail 2017). Another group of researchers at Michigan State

University used the approach of a Generative Adversarial Network (GAN) to age progress facial images and they used this method to study the accuracy and durability of people's faces as they age. For law enforcement purposes, age progressions are usually created by Forensic Artists because the artists are able to take other factors into account such as a person's genetics, family history, diseases, and environment. Some of the most widespread and well-known age-progressed images are those created by the National Center for Missing & Exploited Children (NCMEC).

Age progressions (or age-progressed images) were first created at NCMEC when the Forensic Imaging Unit was formed in 1989 and they were completed in black and white by slow, proprietary software. An age-progressed image is essentially a digital image of a missing person that is used to show what the person may look like at a specific age and at the time the image is created. Advancements in technology over the past 30 years have been instrumental in improving the quality of the images and the speed at which they are completed. NCMEC Forensic Artists have used Adobe Photoshop to complete all age progressions for years now and the images are in color, are extremely detailed and realistic, and can be completed in about one day.

Age progressions at NCMEC are only completed for long-term missing children cases and will only be created once a child has been missing for at least two years. The main reason for the two-year limit is because children's faces change so much especially when they are very young so Forensic artists need to be able to account for the drastic changes in facial features once the original images have become outdated. The age-progressed images are then updated every two years for missing children under the age of 18 and every five years once they are over the age of 18. In the images, artists try to keep the expression and pose the same as the original real-life picture of the missing child and if there is something unique about the child, such as missing teeth, the artist will showcase the unique feature. When creating an age progression, Forensic artists will reference photos of the missing child's family members to help with aging effects on the face and they will take genetics, diseases, and other biological or environmental factors into account when creating the image. For example, if a child goes missing at age 7 and has been missing for two years, the artist would ideally want to see pictures of both parents at age 7 and at age 9. There is some subjectivity that goes into an age progression, such as the individual's hairstyle, but for the most part, artists try to keep facial features consistent and accurate as the child ages. The figure below shows a NCMEC Forensic artist completing an age progression using Adobe Photoshop. The artist uses pictures of the missing child's family members as reference and to assist with the age progression.

Figure 1: *NCMEC Forensic Artist completing an age progression*
Image retrieved from https://www.fbi.gov/video-repository/asha-charlotte-ncmec-013120a.mp4/view

Once an age progression is completed, NCMEC will send the image to law enforcement agencies and it will become available to the public. The image will also appear on the poster for the missing child which can be located online in the long-term missing children section of the

NCMEC website. If a child has more than one age-progressed image as part of his or her case, the most recent age-progressed image is the one that will appear on the poster. NCMEC Forensic artists usually only create age progressions for children and teenagers who are 18 years old and younger at the time they go missing, but there are some cases where age progressions have been completed for individuals who went missing at ages 18 – 22 years old.

Facial Recognition

The use of facial recognition has increased drastically over the past decade by companies, law enforcement, homeland security, social media, and businesses. From unlocking an iPhone to attending a large concert, facial recognition use is widespread and over the last few years, has been more frequently utilized by law enforcement for criminal investigations. The primary uses of facial recognition are for verification (one-to-one matching), identification (one-to-many matching), and screening. Verification (1:1 matching) is when a biometric sample, such as a photo, is compared to a previously stored biometric template in order to verify an individual's identity. Identification (1:N matching) is when a biometric sample, such as a photo, is compared to a gallery of biometric samples (photos) and a candidate list of top matches is generated to help identify the individual. Once the list of matches is produced, a human examiner visually reviews all matches and makes the final determination. Screening is used to confirm that a person is not on a list of identified individuals, such as terrorists on a watchlist. Law enforcement's primary use of facial recognition is identifying suspects through identification (1:N matching) where a mugshot or an image of the suspect from the crime scene is compared to a large database of previously enrolled images, such as a database with driver's licenses and passport images. It is primarily for this reason that identification (1:N matching) was used in this study since it is much more likely that law enforcement would use one image and search it against a database of images to generate matches in a missing person's case.

For the 1:N matching process, a biometric template is created when a person first enrolls a biometric sample, such as a photo, and features of the sample are extracted to create a numerical representation of the sample. This numerical representation (or template) is then added to the database along with all of the other previously enrolled templates and is used when any photos are searched against the database. All of the previously enrolled images in a database for example, would have templates that the probe (or input) photos would be compared to in order to establish a person's identity. Some of the distinct features that a facial recognition algorithm extracts for comparisons are the distance between a person's eyes and the location of the nose and mouth. It is from these facial features that the system creates a template or numerical representation of the person's face. Below is an example of the process where a person's face is converted into a numerical template.

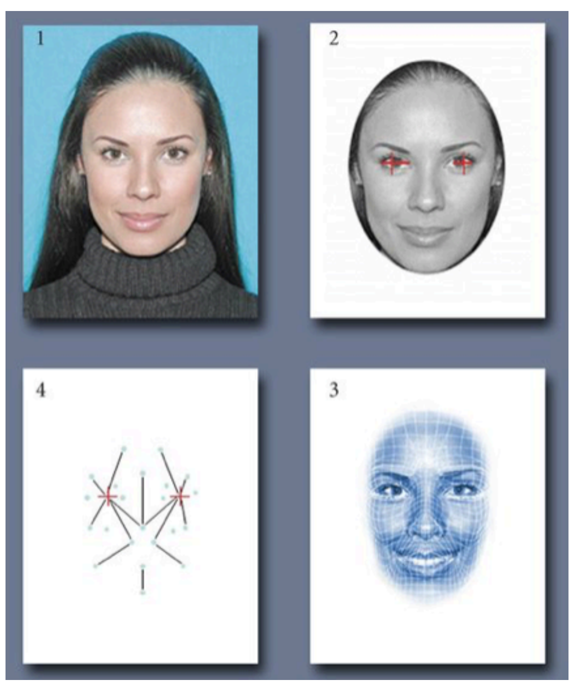

Figure 2: *Facial Recognition Template Process*
Image retrieved from https://www.eff.org/pages/face-recognition

There are multiple facial recognition algorithms that have been tested by the National Institute of Standards and Technology (NIST) for accuracy as part of the Face Recognition Vendor Test (FRVT) and one of these algorithms, Face++, is a product of the Chinese technology company, Megvii. Face++ uses APIs to conduct facial recognition and the APIs perform tasks such as detecting a person's face in an image, searching for a person's face in a gallery of images, and comparing two facial images. Face++ was used as the facial recognition algorithm in this research based on its ability to conduct identification (1:N) matching, utilization of APIs, and proven accuracy testing by NIST.

Previous Research

Over the past few years, there has been significant research looking at the effects of aging on facial recognition algorithms. In the 2018 NIST "Ongoing Face Recognition Vendor Test (FRVT) Part 2: Identification", researchers studied the performance of multiple facial recognition algorithms and how they were impacted by certain factors, such as aging. For the study, they enrolled the images of 3.1 million adults and then conducted a search with 10.3 million more recent images of the same adults, which had an age difference of up to 18 years when compared to the original images (Grother, Ngan, & Hanaoka 2018). They found that aging over time causes the accuracy of the algorithms to decrease and led to more errors. This suggests that changes in facial appearance due to aging can impact similarity or confidence scores, which can then affect the likelihood of the correct images appearing as matches.

"The Impact of Age Related Variables on Facial Comparisons with Images of Children: Algorithm and Practitioner Performance" was a study that compared images of children to those of adults and tested how algorithms and practitioners performed (with the algorithm performance being of greater relevance to this study). In one part of the study, six algorithms were tested for accuracy when comparing images of children to images of adults and in another part of the study, images of the same children were compared at various ages with different age variations between images. The researcher found that when using images of children for comparisons, algorithm performance was lower for all algorithms. The false match rate and the false non-match rate were higher for images of children across all algorithms. Additionally, the researcher found that when there was greater age variation between images, the algorithm performance was lower. The results of the study suggest that algorithms are less accurate when comparing images of children to image of adults and when there is greater age variation between images, which is information that was very pertinent to how this research was conducted.

The 2014 NIST Face Recognition Vendor Test (FRVT) looked at aging as a factor that impacts algorithm performance. To test the accuracy of an algorithm as a person ages, the researchers created seven different age groups starting with 'baby' (ages 0 – 3 years) and going up to 'Older' (ages 55 – 101 years). They created these groups based on the ages where there are similarities among facial features and where there is agreement that facial changes take place and are the most drastic. The study found that algorithm performance accuracy was higher for the older groups and lower for younger groups. For example, the baby group (ages 0 – 3 years) had a false negative identification rate (FNIR) of 0.7 whereas the older group (ages 55 – 101) had a FNIR of 0.008. FNIR is when a biometric sample, such as an image, is enrolled in the system but the correct identity is not returned as a match. The results of the baby group suggest that it is very difficult to properly identify infants and young toddlers because their identifications were incorrect more often than they were correct (FNIR greater than 50%). The younger groups also had a higher false positive identification rate (FPIR) where their images were more frequently incorrectly matched when they did not have prior enrollments. These results indicate how it is more difficult to recognize and differentiate infants and young toddlers as compared to adults. Both this study and the previously mentioned research on algorithm performance with children demonstrate how facial recognition algorithms are overall not as accurate with children's faces as compared to the faces of adults especially in terms of performance. The results from all of these studies were taken into account when formulating the questions and hypotheses for this research especially when looking at differences between younger and older children as well as the age variation between images.

Experimental Design

This study was designed for identification (1:N matching) so that each image could be compared to a database (or gallery) of images. A total of 347 children who went missing between the ages of 1 to 20 years old were included in the study. Every missing child had at least two age-progressed images that were included in the FaceSet (database of images to be searched against); missing children with only one age-progressed image were not included in the study. The reason for this was so that comparisons could be made for matches with multiple age-progressed images to see if there are differences in the likelihood of matching based on the age variation between images.

All of the age-progressed images used in this study were created by Forensic Artists at NCMEC. There were two age groups that were created based on the ages of the children when they went missing – individuals were either in the 'younger' group which represented children less than 13 years old at time of missing or the 'older' group which represented children greater than or equal to 13 years old at time of missing. Out of the 347 missing children, 212 were in the older age group and 135 were in the younger age group; 240 were female and 107 were male.

In order to use Face++ APIs for facial recognition, some coding needed to be completed for this research and it was done using the programming language, Python. All of the code was written, executed, and stored in Visual Studio Code, which is a code editor. There were three Face++ APIs that were used: the 'Detect' API was used first to detect a face in each image. The 'AddFace' API was used to add each image to the FaceSet and lastly, the 'Search' API was used to search each real-life image against the FaceSet. Once the program ran, the results could be viewed in Visual Studio Code as well as an Excel file that included all matches and non-matches and their confidence scores.

Methods & Materials

All of the images used in this study were frontal-facing images and were collected from the NCMEC missing children's database and the National Missing and Unidentified Persons System (NamUs) missing persons' database. Both databases were used because the NamUs missing persons' database usually had more than one NCMEC age progression for each person involved in the study. The NCMEC Long Term Missing & Unidentified Child Map was also used to track missing individuals. All images are publicly available and approval to use them for this study was granted by NCMEC.

The first step in the study was to collect all of the images from the databases and store them in one place. The two figures below show examples of real-life and age-progressed images used in this study. In figure 3, the image on the left side of the poster is the real-life image of the missing girl and the image on the right side is her most recent age-progressed image. Names have been blurred to maintain confidentiality.

Figure 3: *Example of images from NCMEC missing child poster*

In figure 4, the individual's real-life image is on the left, and the two age progressions at different ages are in the middle and on the right.

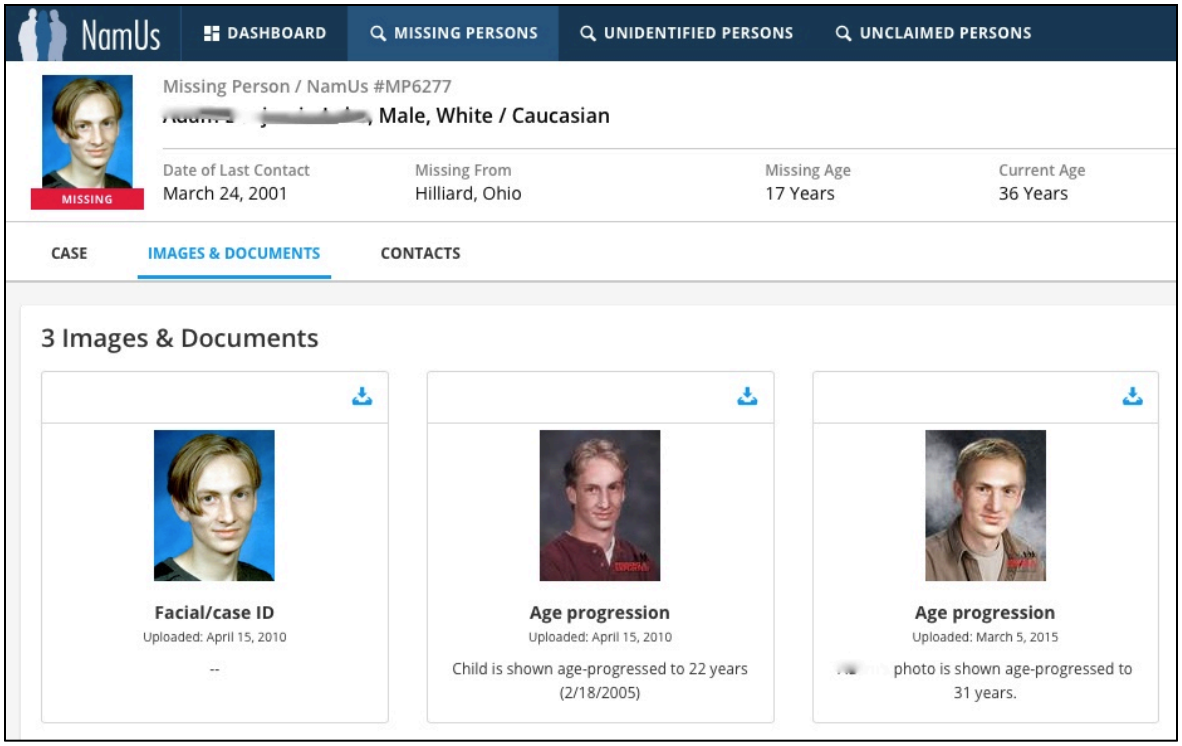

Figure 4: *Images from NamUs Database*

Since NCMEC tries to get the most recent real-life facial images of children for the missing posters posted online, an assumption going into the study was that the age of the child at the time he or she went missing was the same age as the child's real-life image on his or her missing poster. For example, the person in figure 4 went missing at age 17 so the age assigned to his real-life image on the left was 17. All of the age progressions had an age assigned which was the age the missing child would have been at the time the artist created the image. Once all of the images were collected and stored in folders in iPhoto, they were then exported to folders on the desktop so that their file paths could be accessed in Visual Studio Code. Below is a diagram showing the flow of images from each application.

Figure 5: *Process flow of image collection and storage*

Once the images were added to the folders, the images and their file paths could be accessed in Visual Studio Code and the FaceSet could be created. The figure below shows a list some of the images that were used in Visual Studio Code.

Figure 6: *Images in Visual Studio Code*

The FaceSet had to be created first so that the real-life images could be searched against it. Both the ‘Detect’ API and the ‘FaceSet AddFace’ API were used to create the FaceSet and the URLs for both APIs can be seen in the figure below.

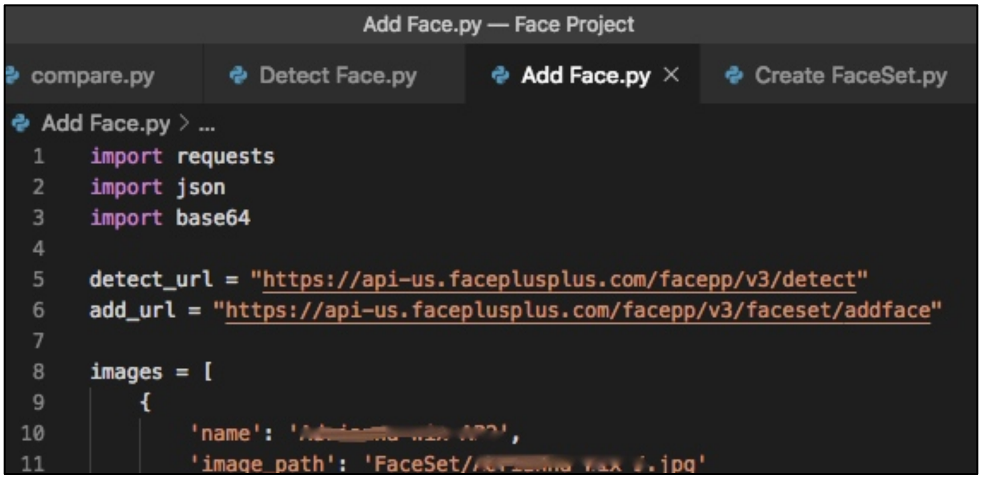

Figure 7: URLs of *Detect API and FaceSet AddFace API*

After pointing to specific URLs, the images that needed to be added to the FaceSet were written out in the code. Below is an example of what the code looked like in order to add an image to the FaceSet. The first line of code was to identify the person by name for tracking purposes and the second line of code provided the image path where the image could be found and retrieved.

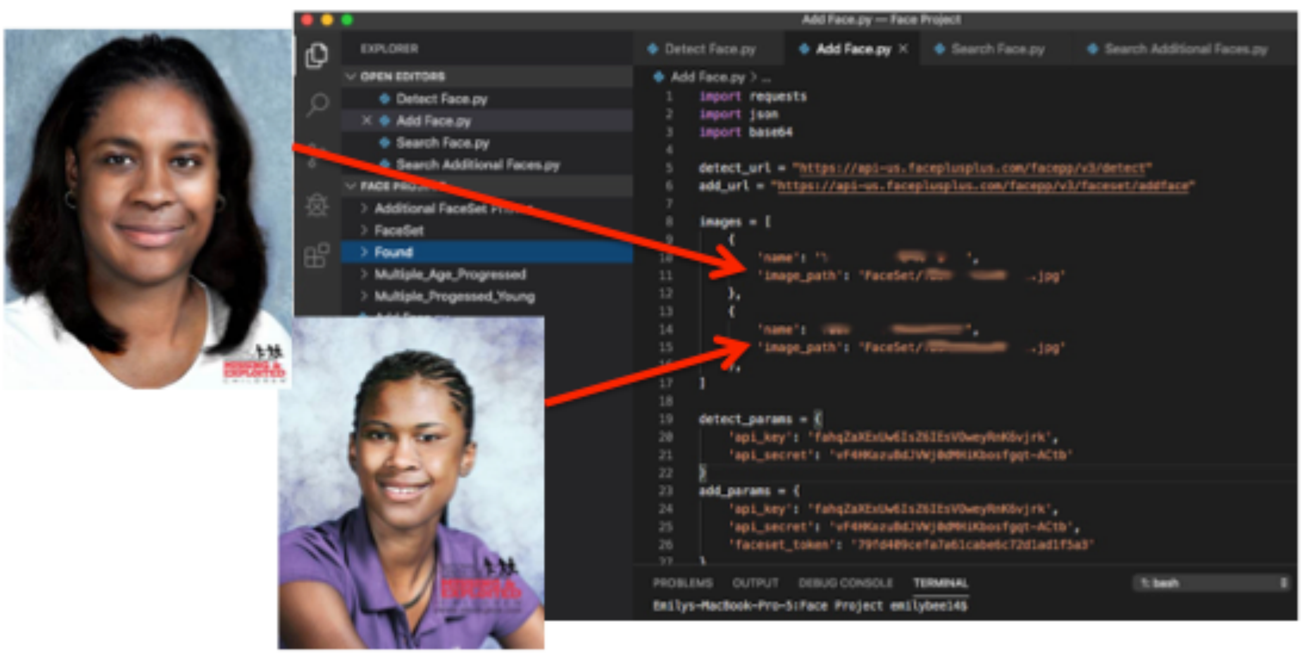

Figure 8: *Python code used to create FaceSet*
*Note: Name and file path were blurred to maintain confidentiality.

The FaceSet included a total of 978 images – 872 age-progressed images from the 347 missing children that were part of the study and 106 additional real-life images of missing people who were not part of the study.

Once the code was written, the program ran and detected the faces in the images and then added the images to the FaceSet. Below is an example of what the output looked like once the program was executed and faces were added to the FaceSet. The results are in white under 'Terminal' and provide information for each image added to the FaceSet.

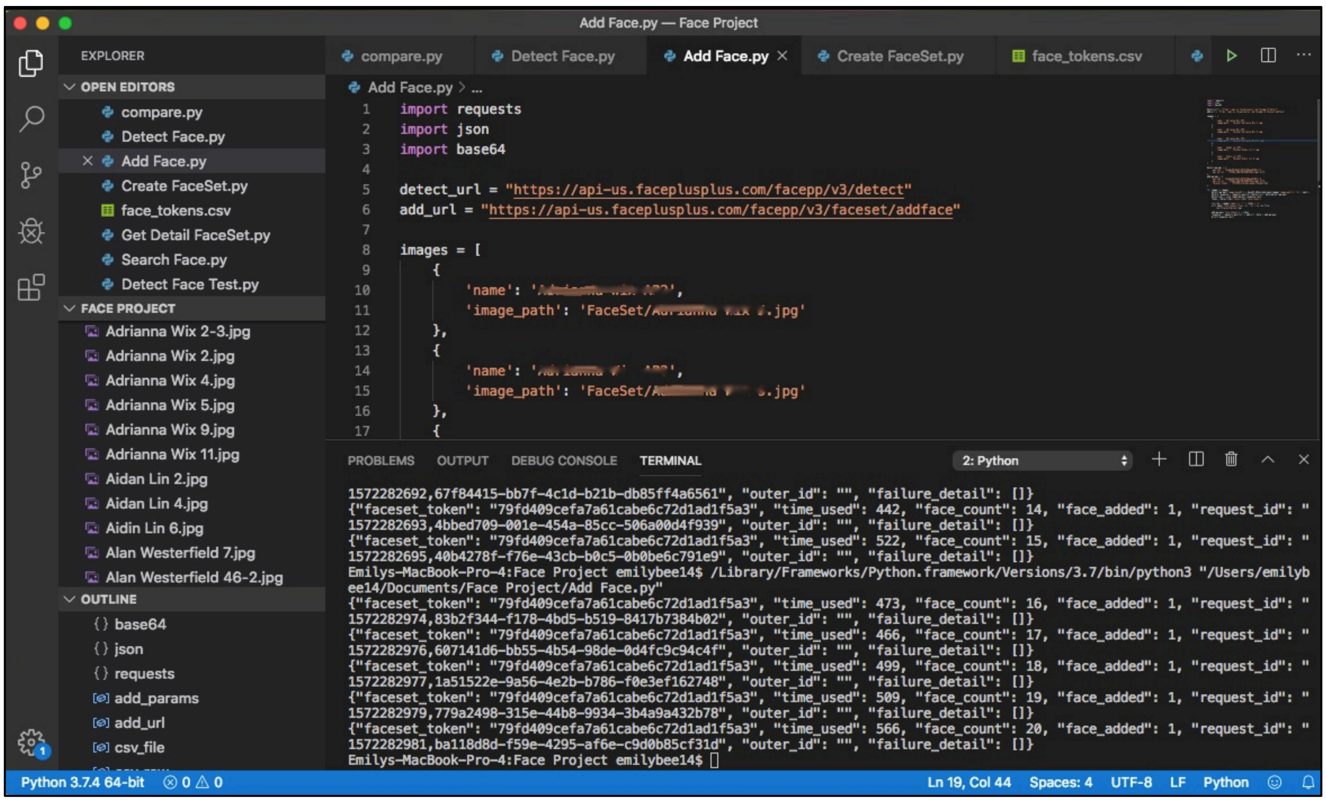

Figure 9: *Results of images added to FaceSet*

In addition to the results under 'Terminal', every image added to the FaceSet was tracked in an Excel spreadsheet that included the image name in Column A and its associated token ID in Column B. Figure 10 below provides a view of the FaceSet Excel file.

	A	B
1	[redacted] AP1	5411b383e8c2562782b627f0a1876742
2	[redacted] AP2	38c2b610ae05b5e53937a31f54ac9046
3	[redacted] AP1	b8f782e3b79eaf40a1ad0adc73d334e8
4	[redacted] AP2	d595ae14f419f424a39e7e7c5774d9e5
5	[redacted] AP3	f6d110ed98a754417d130484005370fb
6	[redacted] AP1	09cf231242e87cc32e0bf398ed2d1166
7	[redacted] AP2	ebcd40390ab184d6ab53bb2f18dcc15c
8	[redacted] AP1	146b265c86728f90aac8e1e39745c528
9	[redacted] AP2	0466991ecab89584f9a8a5c2162318b9
10	[redacted] AP3	0ee8dd783be8f0c8e71ec0e757612565
11	[redacted] AP1	dd77d7e6f7b78d97e04669141393e672
12	[redacted] AP2	36d5ed111655aa3d16bf881f1025618f
13	[redacted] AP1	8bc8e55d889dd7bae5a49e80c4d38b4f
14	[redacted] AP2	cb08fe09f184de50c63b4a8d8764e35b
15	[redacted] AP1	63406887ebf1165ebb00f0c45d0e56d2
16	[redacted] AP2	e643e57af0afe47a0f1ecb3447590fae
17	[redacted] AP1	2ce9da5e1ab26796c2dfd8c6169baed7
18	[redacted] AP2	fbce3fd4d1bb55b5c0c2a2c86e2dc0dc

Figure 10: *List of FaceSet images in Excel spreadsheet*
*Note: Image names in Column A were blurred to maintain confidentiality.

After all 978 images were added to the FaceSet, searches against the FaceSet could begin.

The 347 missing children who were included in the study each had one real-life image that was searched against the FaceSet to produce a candidate list of the top 5 matches, ranked by confidence score. The real-life images that were searched against the FaceSet were considered the probe or ‘input’ images. The figure below shows how the code was written in Visual Studio Code and how each real-life photo was represented by two lines of code – one line with the name of the individual and the second line with the file path of the image.

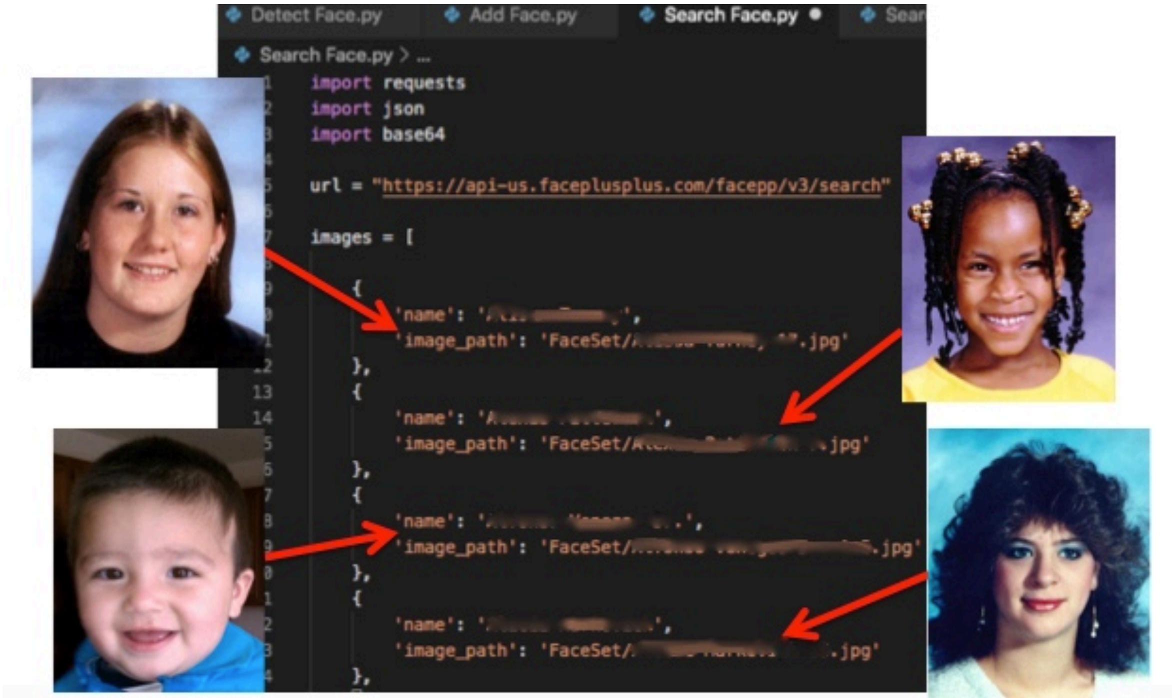

Figure 11: *Python code used for real-life images in searches*
*Note: Names and file paths have been blurred to maintain confidentiality.

Once the code was executed, each individual real-life photo was searched against the FaceSet using the Search API. The figure below is an example of the search process with results for one of the children from the figure above. The real-life image of this person was searched against the FaceSet and the results with the top 5 matches are below. For this case, all three of the girl's age progressions appeared in the top 5 matches and were actually ranked 1st, 2nd, and 3rd.

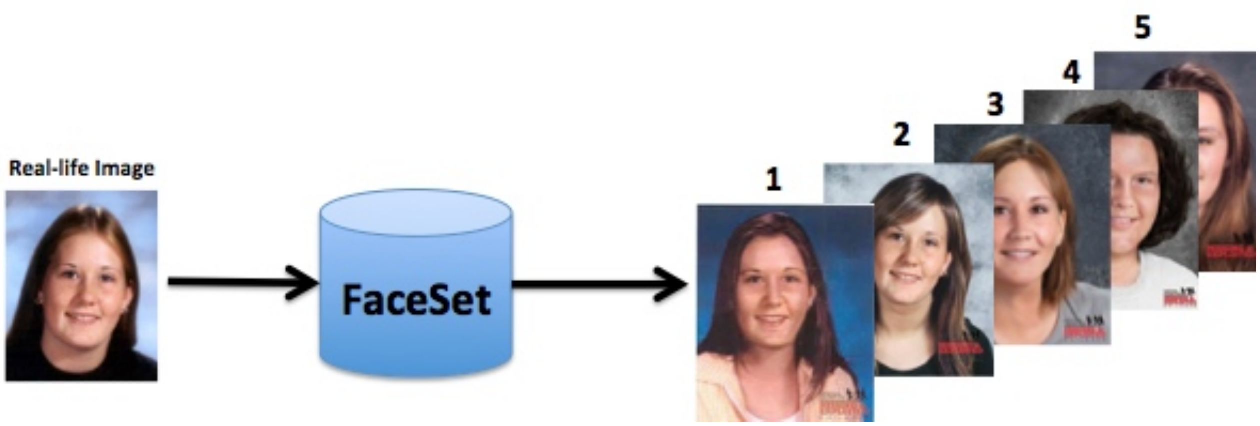

Figure 12: *Search process diagram*

Figure 12 is a visual representation of the results that were generated in Excel and can be seen in figure 13. The Excel file contained the name of the person, the person's top 5 matches ranked by confidence score, and the token ID that was assigned to each image from the FaceSet. Below are the actual results in Excel from the person in the search process diagram above and her top 5 matches with the confidence scores.

	A	B	C	D
1	Name	FaceSet Image Name	Confidence Score	Token
2	[illegible]	[illegible]	96.263	37b167768fbf6397e1e35464215c1da3
3	[illegible]	[illegible]	93.279	7d51722ae1ce7534426b0629b2da21b2
4	[illegible]	[illegible]	83.789	c050ce7dfbf1b61d97a9684f71e691b8
5	[illegible]	[illegible]	80.774	898dc7daddd43153cf1a29235843268d
6	[illegible]	[illegible]	79.013	8ce8a27faa25a62d999670f8a9ff740e

Figure 13: *List of top 5 matches*

*Note: Name and FaceSet image names have been blurred to maintain confidentiality.

A final data file was created to track each person in the study and whether or not the person had any matches. A column was created in this file to track a match with a 1 and a non-match with a 0. The file included additional information for each individual such as gender, ethnicity, the age of the child when he or she went missing, and the age of the person in the age-progressed image. Below is a screenshot of the final data file.

	A	B	C	D	E	F	G	H	I
1	ID	Age when Missing	Confidence Score	Older or Younger	Gender	Ethnicity	Matched	Age-Progressed Age	Token
2	1	2	0	Younger	M	White	0	0	102a6303456b969c6ade5fc690829565
3	2	1	81.144	Younger	F	White	1	5	b8f782e3b79eaf40a1ad0adc73d334e8
4	3	12	0	Younger	M	White	0	0	c5165857e446fc536c4e730d2dd8cbfc
5	4	17	92.04	Older	M	White	1	22	146b265c86728f90aac8e1e39745c528
6	4	17	89.747	Older	M	White	1	31	0ee8dd783be8f0c8e71ec0e757612565
7	4	17	82.6	Older	M	White	1	27	0466991ecab89584f9a8a5c2162318b9
8	5	6	79.46	Younger	M	Black	1	10	dd77d7e6f7b78d97e04669141393e672
9	6	17	89.45	Older	F	Hispanic	1	26	8bc8e55d889dd7bae5a49e80c4d38b4f
10	7	2	0	Younger	F	White	0	0	4bfe3f0d37352a90694d65349e8e4026
11	8	2	69.908	Younger	M	Asian	1	4	63406887ebf1165ebb00f0c45d0e56d2
12	9	16	82.902	Older	F	White	1	19	2ce9da5e1ab26796c2dfd8c6169baed7
13	10	16	0	Older	F	White	0	0	2f2f876e423b69d541cda8faa16a52d2
14	11	7	87.943	Younger	F	Black	1	9	2136aaea452f6e5d39bba7c882a6e93d
15	11	7	78.532	Younger	F	Black	1	14	a3d2eb0c11ffdb6f62ba04b5a4bc0a66
16	12	1	0	Younger	M	Asian	0	0	4bfe3f0d37352a90694d65349e8e4026
17	13	15	78.945	Older	F	White	1	38	2afb96e559ca640b7eb17a3222c949a4
18	13	15	76.311	Older	F	White	1	38	f5365a9f6b5c0949fcaec79a26e14210
19	14	15	84.242	Older	F	White	1	24	0d24bad59eee605780fb7f93447f11e9
20	14	15	82.145	Older	F	White	1	19	9572235042ea56ca13dc5fdcddfd4320

Figure 14: *View of final data file*

Data Analysis and Interpretation

Once the data was updated in the final Excel file, the spreadsheet was uploaded into STATA so that the statistical analysis could be completed. For Hypothesis 1, a t-test was conducted because the confidence scores of two age groups (the older and younger groups) were being compared and a t-test would show what the mean confidence score was for each group. The results of the t-test are below.

*Hypothesis 1: *The older a child is at the age of missing, the higher the confidence score will be when there is a match between the child's real-life image and age-progressed image.*

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
Older	309	72.24374	1.491237	26.21355	69.30944	75.17804
Younger	158	47.22416	3.253176	40.89179	40.79852	53.6498
combined	467	63.77887	1.574667	34.02884	60.68455	66.8732
diff		25.01959	3.123132		18.88239	31.15679

diff = mean(Older) - mean(Younger) t = 8.0111

Ho: diff = 0 degrees of freedom = 465

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
Pr(T < t) = 1.0000	Pr(|T| > |t|) = 0.0000	Pr(T > t) = 0.0000

Table 1: *T-test for mean confidence score by age group*

As shown in the table above, the mean confidence score of the older age group was 72.24% and the younger group was 47.22% so the difference was 25.02%. The difference in the mean scores shows that Hypothesis 1 is supported. The p-value is <0.05 so the results are statistically significant at 5% and the Null hypothesis (the means for both groups being similar) could be rejected. The three tables below show the distribution of confidence scores for all matches and the distribution of scores by each age group. The scores of 0 represent non-matches since non-matches did not generate a confidence score.

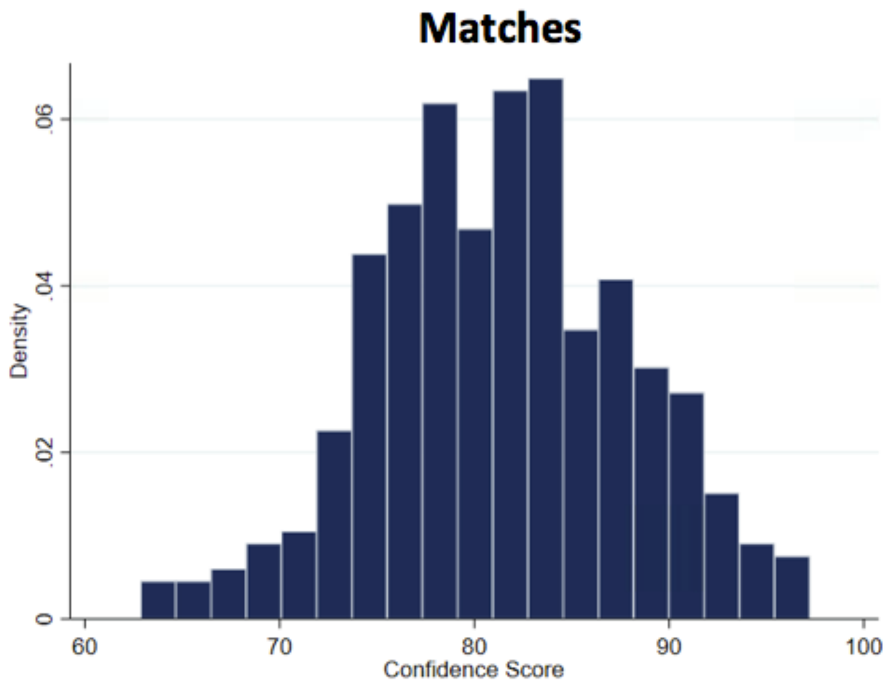

Figure 15: *Histogram of confidence scores for matches*

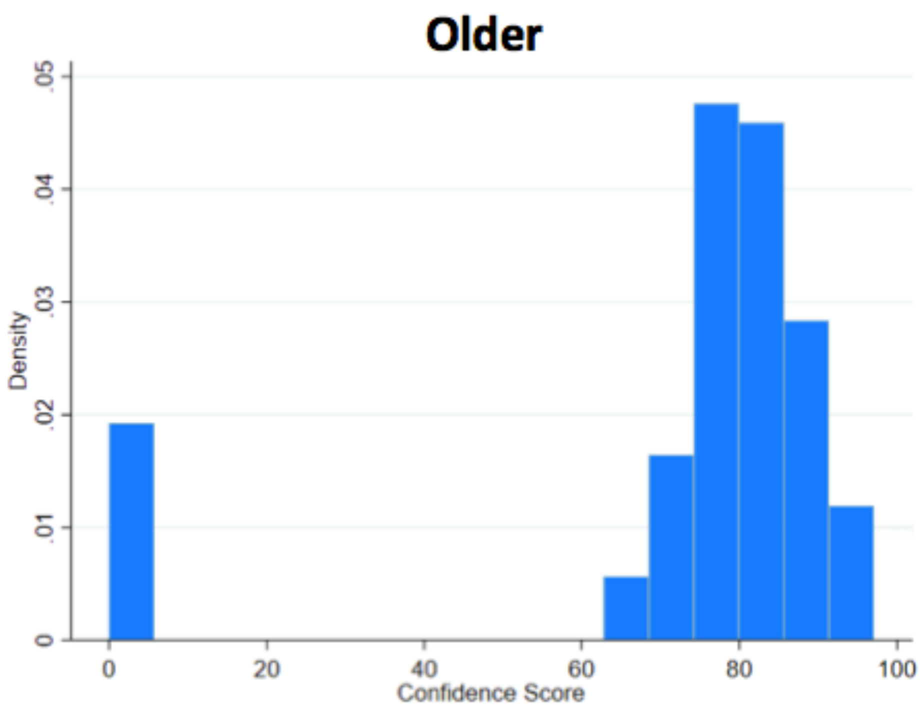

Figure 16: *Histogram of confidence scores for matches in older age group*

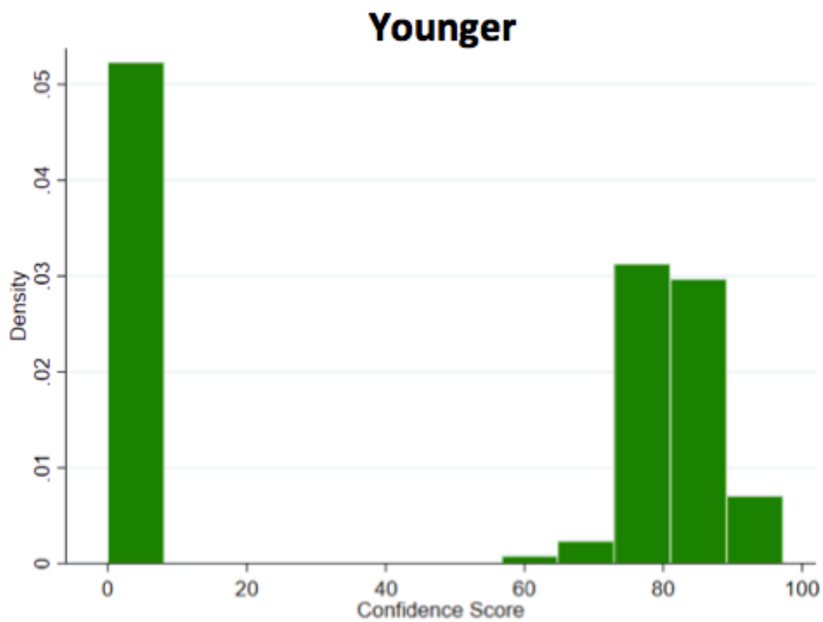

Figure 17: *Histogram of confidence scores for matches in younger age group*

*Hypothesis 2: *The older the child is at the age of missing, the more likely there will be a match between the child's real-life and age-progressed image(s).*

For hypothesis 2, an analysis was completed to determine the number of matches for the older and younger age groups. The table below provides an overview of the number of matches, the number of non-matches, and percentage of matches by both age groups. The higher percentage of matches in the older group compared to the lower percentage of matches in the younger group supports hypothesis 2.

Age Grouping	Total	Match	No Match	% Match
Older	309	275	34	**89.00%**
Younger	158	91	67	57.59%
Total	467	366	101	78.37%

Table 2: *Matches and non-matches by age group*

A t-test was conducted to determine the average age at the time of missing for matches and non-matches and the results are below. Group 0 represents non-matches and Group 1 represents matches.

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
0	101	8.792079	.5347928	5.374601	7.731066	9.853093
1	366	13.59836	.2222714	4.252303	13.16127	14.03545
combined	467	12.55889	.228043	4.928051	12.11077	13.00701
diff		-4.806281	.5077286		-5.804008	-3.808555

diff = mean(0) - mean(1) t = -9.4662
Ho: diff = 0 degrees of freedom = 465

Ha: diff < 0 Ha: diff != 0 Ha: diff > 0
Pr(T < t) = 0.0000 Pr(|T| > |t|) = 0.0000 Pr(T > t) = 1.0000

Table 3: *T-test to determine mean age for matches and non-matches*

The results of the t-test show that the mean missing age for non-matches was 8.79 years and the mean age for matches was 13.60 years, which are results that also support hypothesis 2.

In addition to the t-test, a regression analysis was conducted for hypothesis 2 in order to see if there was a greater probability of matching for children who went missing at older ages as compared to younger ages and to be able to analyze other variables, such as gender and ethnicity. The linear probability model used was y = b0 + b1x1 + …+ which would be represented as Matched (0/1) = b0 + b1*(Age when missing). This model was used to calculate the probability of matches based on the ages the children were when went missing.

Source	SS	df	MS			
				Number of obs	=	467
				F(1, 465)	=	89.61
Model	12.78949	1	12.78949	Prob > F	=	0.0000
Residual	66.3668269	465	.142724359	R-squared	=	0.1616
				Adj R-squared	=	0.1598
Total	79.1563169	466	.169863341	Root MSE	=	.37779

matched	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
agewhenmissing	.033617	.0035512	9.47	0.000	.0266385	.0405954
_cons	.3615343	.0479036	7.55	0.000	.2674	.4556686

Table 4: *Regression analysis for age when missing*

The results of the regression analysis show that the p-value is very small so the null hypothesis of b1=0 was rejected. The data shows that when a missing child's age is one year older, the probability of matching is 0.0336 percentage points higher. The results suggest a statistically significant positive correlation between missing age and the probability of matching so as the child's age at the time of missing increases, the probability of matching increases. Adding gender as an additional factor to the linear probability model produced the following results.

Source	SS	df	MS			
				Number of obs	=	467
				F(2, 464)	=	46.40
Model	13.1923061	2	6.59615305	Prob > F	=	0.0000
Residual	65.9640108	464	.142163816	R-squared	=	0.1667
				Adj R-squared	=	0.1631
Total	79.1563169	466	.169863341	Root MSE	=	.37705

matched	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
agewhenmissing	.034411	.0035755	9.62	0.000	.0273848	.0414372
female	-.063914	.0379697	-1.68	0.093	-.1385278	.0106999
_cons	.3954945	.0518919	7.62	0.000	.2935223	.4974667

Table 5: *Regression analysis for age when missing and gender (female)*

In the interpretation of the coefficient for age when missing, the coefficient is statistically significant at 1% and the data again suggests a positive correlation between matching age and probability of matching. When the missing person's age is one year older, the probability of matching images is 0.034 percentage points higher. In the interpretation of the coefficient for gender (female), the coefficient is statistically significant at 10% and the results of -0.064 suggest that if the missing child is female then the probability of matching decreases by 0.064 percentage points. This means that when missing age is held constant, a girl is less likely to be matched than a boy. These results are consistent with real life because as girls get older, they are more likely to have extra changes in facial appearance with make-up or accessories, which could impact matching capabilities between images. The three tables below add in ethnicity as an additional factor to the regression analysis.

Source	SS	df	MS			
				Number of obs	=	467
				F(5, 461)	=	22.14
Model	15.3256384	5	3.06512769	Prob > F	=	0.0000
Residual	63.8306785	461	.138461342	R-squared	=	0.1936
				Adj R-squared	=	0.1849
Total	79.1563169	466	.169863341	Root MSE	=	.3721

matched	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
agewhenmissing	.0367972	.0035822	10.27	0.000	.0297577	.0438368
female	-.045396	.0378856	-1.20	0.231	-.119846	.0290539
white	-.2332838	.0683497	-3.41	0.001	-.3675994	-.0989681
black	-.1265678	.0779502	-1.62	0.105	-.2797496	.026614
hispanic	-.135149	.0840756	-1.61	0.109	-.300368	.0300699
_cons	.5429957	.0749422	7.25	0.000	.3957251	.6902662

Table 6: *Regression analysis for age when missing, gender (female), and White, Black, and Hispanic ethnicities*

Source	SS	df	MS			
				Number of obs	=	467
				F(5, 461)	=	22.14
Model	15.3256384	5	3.06512769	Prob > F	=	0.0000
Residual	63.8306785	461	.138461342	R-squared	=	0.1936
				Adj R-squared	=	0.1849
Total	79.1563169	466	.169863341	Root MSE	=	.3721

matched	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
agewhenmissing	.0367972	.0035822	10.27	0.000	.0297577	.0438368
female	-.045396	.0378856	-1.20	0.231	-.119846	.0290539
white	-.106716	.0495076	-2.16	0.032	-.2040046	-.0094274
hispanic	-.0085813	.0701081	-0.12	0.903	-.1463523	.1291898
other	.1265678	.0779502	1.62	0.105	-.026614	.2797496
_cons	.4164279	.0633906	6.57	0.000	.2918575	.5409983

Table 7: *Regression analysis for age when missing, gender (female), and White, Hispanic, and Other ethnicities*

Note: 'Other' includes American Indian, Asian, Biracial, and Pacific Islander

Source	SS	df	MS			
				Number of obs	=	467
				F(5, 461)	=	22.14
Model	15.3256384	5	3.06512769	Prob > F	=	0.0000
Residual	63.8306785	461	.138461342	R-squared	=	0.1936
				Adj R-squared	=	0.1849
Total	79.1563169	466	.169863341	Root MSE	=	.3721

matched	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
agewhenmissing	.0367972	.0035822	10.27	0.000	.0297577	.0438368
female	-.045396	.0378856	-1.20	0.231	-.119846	.0290539
black	.106716	.0495076	2.16	0.032	.0094274	.2040046
hispanic	.0981347	.058449	1.68	0.094	-.0167248	.2129942
other	.2332838	.0683497	3.41	0.001	.0989681	.3675994
_cons	.3097119	.0560037	5.53	0.000	.1996578	.419766

Table 8: *Regression analysis based on age when missing, gender (female), and Black, Hispanic, and Other ethnicities*

Note: 'Other' includes American Indian, Asian, Biracial, and Pacific Islander

When adding in ethnicity as a factor, the results from the three tables above all show a statistically significant positive correlation between missing age and probability of matching, which is similar to the previous regression analyses for hypothesis 2. In terms of gender, the data does not have statistical significance for females in these three regression analyses. For ethnicity, the p-values and t-stat in tables 6 and 7 show that there is a statistically significant negative correlation between being matched and being of White ethnicity when compared to children of Other (table 6) or Black (table 7) ethnicities. This means that a child who is White is 0.233 percentage points less likely to be matched as compared to Other individuals (table 6) and 0.107 percentage points less likely to be matched as compared to Black individuals (table 7). Table 8 suggests a statistically significant positive correlation between probability of being matched and being of Black ethnicity or as a part of the Other ethnicity when compared to Whites. This is consistent with tables 6 and 7 and demonstrates how a missing child who is of the 'Other' or Black ethnicity is more likely to be matched when compared to White children.

*Hypothesis 3: *The closer in age the age-progressed image is to the age of the child when he or she went missing (less age variation), the greater the likelihood there will be a match.*

Out of the 347 missing children who were searched in this study, there were 246 children who matched with one or more than one of their age progressions creating a total of 366 matches. There were 101 children that did not match with any of their age progressions, which created a total of 101 non-matches. Below is a breakdown of the 1^{st}, 2^{nd}, 3^{rd}, and 4^{th} age progressions and the number of matches they generated.

Matched	1st AP	2nd AP	3rd AP	4th AP
Number of Images Matched	199	132	31	4
Total Available	347	347	114	14
Matched % (Number of images / Total Available)	57.35%	38.04%	27.19%	28.57%

Table 9: *Images matched by age progression*

The "1st" age progression group refers to the age progression that was closest in age to the missing child, the "2nd" age progression group refers to the age progression second closest in age, and so on up until the 4th age progression group. The "1st" age progression was not necessarily the very first age progression that was ever created of the missing child – it was just the age-progressed image closest in age to the missing child when he or she went missing that could be found in one of the databases (same for the 2nd, 3rd, and 4th). Since every child in the study had at least two age-progressed images, both the 1st and 2nd age progressions each had a total of 347. The 3rd and 4th age progressions were lower in count because fewer children had more than two age progressions. It is evident from Table 9 that the 1st age progressions generated the highest number and highest percentage of matches, which supports hypothesis 3.

The pie chart below shows the percentage breakdown by age progression based off of the 366 total matches. The data shows that the 1st age progressions have the highest percentage (54.37%) of matches out of all age progressions, which also supports hypothesis 3.

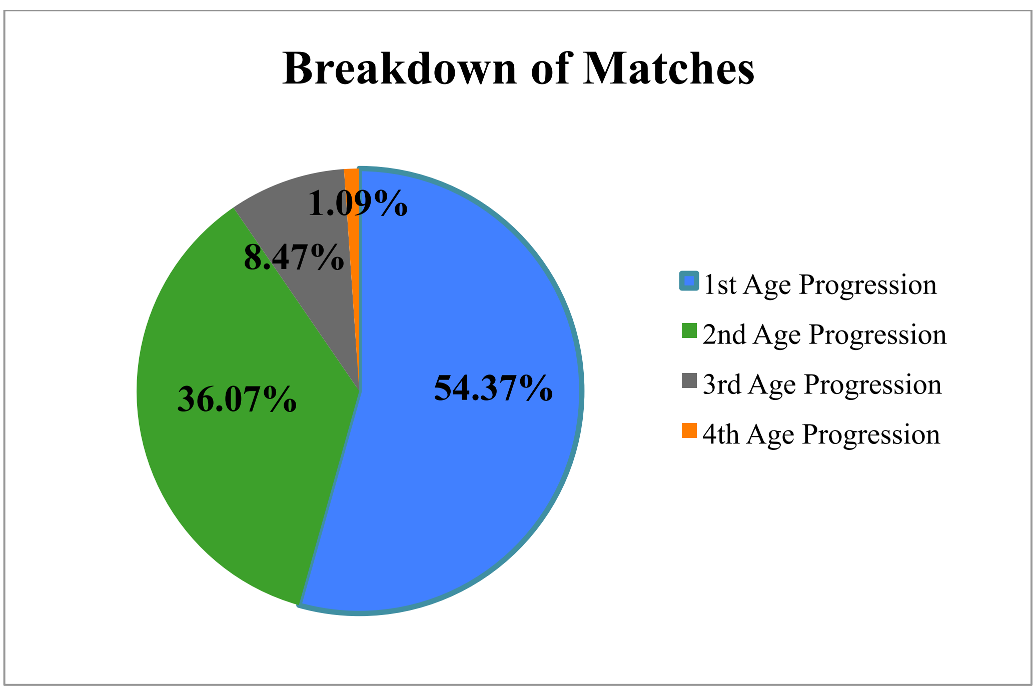

Figure 18: *Breakdown of matches by age progression group*

In terms of age groups, the chart below shows the breakdown of age progressions by age group. The fact that the younger group has an even higher percentage of matches for the 1st age progresion as compared to the older group shows how much aging can impact a younger child's face. For the younger group, 60.4% of matches were with the first age progressions and for the older group, 52.4% were matches with the first age progressions. The decrease in percentage is a lot more from the 1st to the 2nd age-progressed image for the younger group which shows how much of an impact a couple of extra years can make in an age progression.

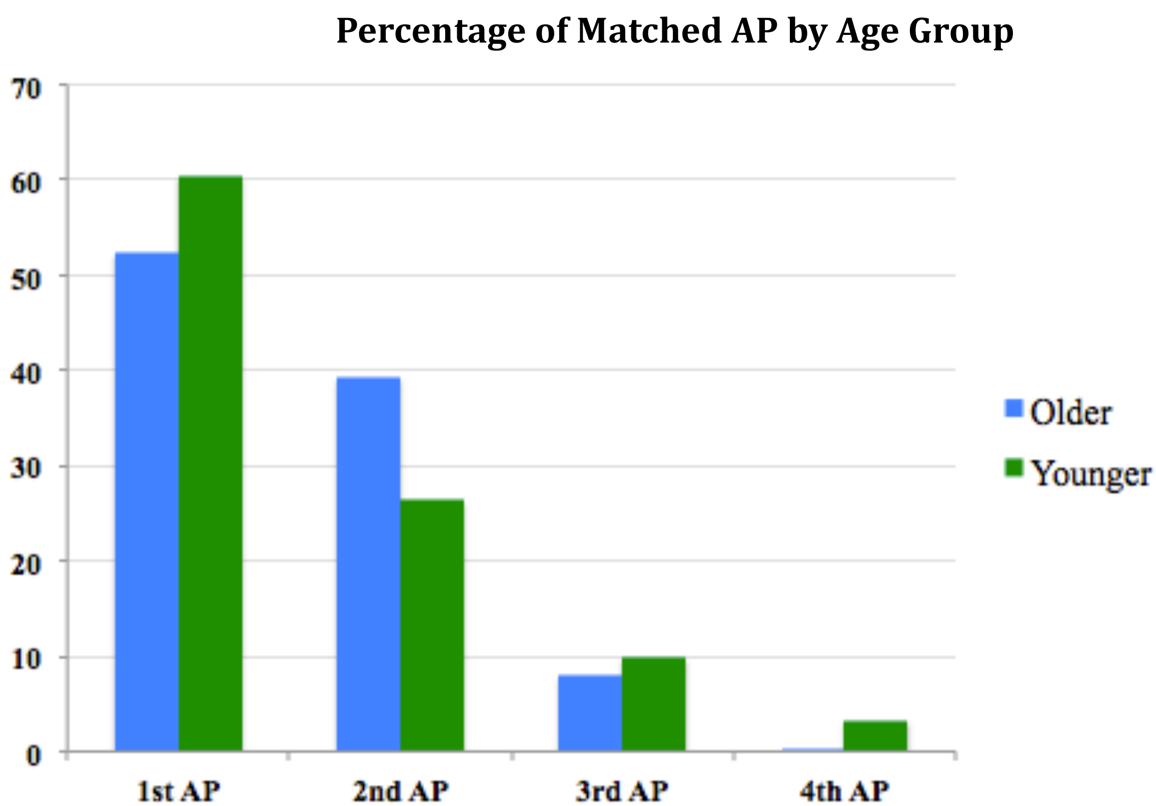

Figure 19: *Breakdown of matches by age progression for older and younger groups*

A regression analysis using the linear probability model was also completed for hypothesis 3 to determine the likelihood of matching based on the age variance between the children's real-life and age-progressed images. The equation used was Matched (0/1) = b0 +

b1*GapAge where 0 represented non-matches and 1 represented matches. 'GapAge' was a calculation created in STATA and it was the difference between the age of the age-progressed image and the age of the child when he or she went missing (Age AP image – Age when missing). For example, if the age a child went missing was age 10 and the age of one of the age-progressed images that matched was 14 then the gap age between the two images would be 4.

Source	SS	df	MS			
Model	75.4032816	1	75.4032816	Number of obs	=	467
Residual	3.75303528	465	.008071044	F(1, 465)	=	9342.45
				Prob > F	=	0.0000
Total	79.1563169	466	.169863341	R-squared	=	0.9526
				Adj R-squared	=	0.9525
				Root MSE	=	.08984

matched	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
gap_age	-.0110461	.0001143	-96.66	0.000	-.0112706	-.0108215
_cons	1.141765	.0055681	205.05	0.000	1.130823	1.152707

Table 10: *Regression analysis of gap age*

The results of the regression analysis from the table above show that the Null hypothesis of Ho: b1=0 can be rejected with the p-value = 0.0001. The results suggest that there is a statistically significant negative correlation between gap age and the probability of matching which means that the closer in age the age-progressed image is to the age of the child at the time he or she went missing (less age variation), the greater the probability is that their images will match. Using this model, an assumption was made that for people who did not have a match, it took in infinite amount of time for them to get matched so their gap age was set to 100 instead of 0. This was a large number in comparison to the actual range of gap ages for matches, which was 2 to 43 years. The regression analysis for hypothesis 3 was used to include a couple of other factors such as gender and ethnicity. The table below shows the results for gap age and gender (female).

Source	SS	df	MS			
				Number of obs	=	467
				F(2, 464)	=	4721.47
Model	75.4489645	2	37.7244823	Prob > F	=	0.0000
Residual	3.70735241	464	.007989984	R-squared	=	0.9532
				Adj R-squared	=	0.9530
Total	79.1563169	466	.169863341	Root MSE	=	.08939

matched	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
gap_age	-.0110577	.0001138	-97.16	0.000	-.0112813	-.010834
female	.0213552	.008931	2.39	0.017	.003805	.0389053
_cons	1.127463	.0081528	138.29	0.000	1.111442	1.143484

Table 11: *Regression analysis of gap age and gender (female)*

The results of the negative coefficient, p-value, and t-stat suggest that there is a statistically significant negative correlation between gap age and the probability of matching. For females, the data suggests a statistically significant positive correlation between females and the probability of matching. This means that in relation to gap age and keeping the gap age constant, girls are more likely to be matched than boys. In addition to gender, the regression analysis using the linear probability model was run for ethnicity.

Source	SS	df	MS			
				Number of obs	=	467
				F(5, 461)	=	1925.77
Model	75.539705	5	15.107941	Prob > F	=	0.0000
Residual	3.61661194	461	.007845145	R-squared	=	0.9543
				Adj R-squared	=	0.9538
Total	79.1563169	466	.169863341	Root MSE	=	.08857

matched	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
gap_age	-.0111021	.0001137	-97.66	0.000	-.0113255	-.0108787
female	.0174469	.0089659	1.95	0.052	-.0001722	.035066
white	.0382137	.0138963	2.75	0.006	.0109057	.0655216
black	.0141922	.0166852	0.85	0.395	-.0185964	.0469807
other	.0103562	.0199723	0.52	0.604	-.0288918	.0496042
_cons	1.102901	.0145206	75.95	0.000	1.074366	1.131436

Table 12: *Regression analysis of gap age, gender (female), and White, Black, and Other ethnicities*

Note: 'Other' includes American Indian, Asian, Biracial, and Pacific Islander

Source	SS	df	MS			
Model	75.539705	5	15.107941	Number of obs	=	467
Residual	3.61661194	461	.007845145	F(5, 461)	=	1925.77
Total	79.1563169	466	.169863341	Prob > F	=	0.0000
				R-squared	=	0.9543
				Adj R-squared	=	0.9538
				Root MSE	=	.08857

matched	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
gap_age	-.0111021	.0001137	-97.66	0.000	-.0113255	-.0108787
female	.0174469	.0089659	1.95	0.052	-.0001722	.035066
white	.0240215	.0117974	2.04	0.042	.0008382	.0472048
hispanic	-.0141922	.0166852	-0.85	0.395	-.0469807	.0185964
other	-.0038359	.0184814	-0.21	0.836	-.0401541	.0324823
_cons	1.117093	.0119679	93.34	0.000	1.093575	1.140612

Table 13: *Regression analysis of gap age, gender (female), and White, Hispanic, and Other ethnicities*

Note: 'Other' includes American Indian, Asian, Biracial, and Pacific Islander

Source	SS	df	MS			
Model	75.539705	5	15.107941	Number of obs	=	467
Residual	3.61661194	461	.007845145	F(5, 461)	=	1925.77
Total	79.1563169	466	.169863341	Prob > F	=	0.0000
				R-squared	=	0.9543
				Adj R-squared	=	0.9538
				Root MSE	=	.08857

matched	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
gap_age	-.0111021	.0001137	-97.66	0.000	-.0113255	-.0108787
female	.0174469	.0089659	1.95	0.052	-.0001722	.035066
black	-.0240215	.0117974	-2.04	0.042	-.0472048	-.0008382
hispanic	-.0382137	.0138963	-2.75	0.006	-.0655216	-.0109057
other	-.0278574	.0161422	-1.73	0.085	-.0595789	.0038641
_cons	1.141115	.0091466	124.76	0.000	1.123141	1.159089

Table 14: *Regression analysis of gap age, gender (female), and Black, Hispanic, and Other ethnicities*

Note: 'Other' includes American Indian, Asian, Biracial, and Pacific Islander

When adding ethnicity as a variable, the results in all three tables suggest a statistically significant negative correlation for gap age and probability of matching and a statistically significant positive correlation for females and probability of matching at a significance level of 10%. The data in tables 12 and 13 suggest a statistically significant positive correlation between missing children who are White and probability of being matched when compared to children who are of Hispanic (table 12) and Black (table 13) ethnicities. In table 12, the coefficient for White individuals suggests that the probability of matching is 0.038 percentages points higher than Hispanic children. The coefficient White children in table 13 suggests that the probability of matching is 0.024 percentage points higher than Black children. The results depicted in table 14 suggest a statistically significant negative correlation for Hispanic and Black ethnicities meaning that the probability of matching either ethnicity is less than Whites – 0.038 percentage points less for Hispanic individuals and 0.024 less for Black individuals. These results support the data in tables 12 and 13.

Results & Discussion

The results from this research demonstrate that Face++ can accurately detect and match digitally produced age-progressed images to real-life images. The results suggest that children who go missing at older ages will have higher confidence scores and a greater likelihood of matching their real-life and an age-progressed image(s). The results of this study also demonstrate that age-progressed images closer in age to the age of the missing child and his or her real-life image (less age variance) will have a greater likelihood of being matched. Additionally, the age progression that is closest in age to the missing individual has the greatest likelihood of matching for both older children and especially for younger children. The best chance of matching for young children would be with the age progression that is completed two years after the child went missing, which makes sense because a child's face can change a lot within a span of two or more years.

Conclusion

The results of this study could benefit law enforcement and investigators in long-term missing children cases by knowing that the likelihood of matching real-life and age-progressed images increases for children who go missing at older ages. That is not to say that there will not be matches with younger children since children in the 'younger' age group of this study generated 91 out of 158 matches (57%), but there is a greater likelihood of matching as the age of the missing child increases. It is beneficial for investigators to know that a child's first or second age progression will have a greater chance of matching especially the first age progression for younger children. In terms of limitations of this study, one limitation was the inability to train the Face++ facial recognition algorithm with images of toddlers and young children. In general, facial recognition algorithms are trained with adult faces so if there had been the possibility to train the algorithm with younger faces prior to collecting data then there might have been different results and the algorithm may have been able to match images of younger children more accurately. Another limitation was for some cases, the very first, original age progressions were not available in the databases or the ages of the age progressions were not listed so there may have been images that would have been closer in age to the missing children that were not used in the study.

One future direction related to this research is for long-term missing children who have been found, such as Jaycee Dugard. The missing child's age-progressed images could be compared to more recent photos of them once they were found to see how accurately a facial recognition algorithm could match them. Another future direction could be through the use of digital images from facial reconstructions in order to identify previously unidentified and deceased individuals. These images could be searched against a database of real-life images with photos from driver's licenses and passports to see if there are any matches. In addition to digitally created facial reconstructions, facial images created through DNA phenotyping could also be searched against a database of images in order to identify an individual. Another future direction would be to use the same experimental design of this study and test multiple different facial recognition algorithms to see which algorithm generates the most accurate scores and matches. Lastly, age regression is another relevant area of research so age-progressed or older real-life images could be compared to a database with younger, real-life images of the same people. It would essentially be the inverse of this study's design and could test an algorithm's ability to properly identify the participants at younger ages.

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