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EAMBER SCAN: FACE RECOGNITION FOR MISSING CHILDREN IN THE NATIONAL
AMBER ALERT SYSTEM

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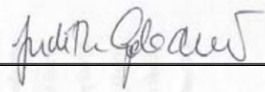
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ABSTRACT

Data published by the National Center for Missing and Exploited Children (NCMEC) shows how hundreds of thousands of children are reported missing every year. The Amber Alert system was designed and implemented to address this problem but has failed to stay current with technological advancements. By utilizing mobile platforms, e.g. mobile phones, tablets, etc., and breaking technological improvements in computer vision and machine learning via deep artificial neural networks, the biometric modality face, can be leveraged to demonstrably reduce the painstaking manual process of triaging sightings. This work details a framework to implement face recognition into the current sighting process.

The Amber Alert system can be modernized with the use of an intelligent mobile application that leverages ubiquitous mobile platforms to generate actionable leads via biometrically confirmed sightings. The mobile application will employ a RESTful architecture, which enables cross compatibility with many different front interfaces. Sightings are then analyzed through commercial-off-the-shelf (COTS) face recognition solutions and open source software to generate enhanced leads. An enhanced lead is demonstrably more informative than the current process comprised of emails, SMS, or phone calls reporting a physical sighting. The solution proposed in this work will provide an iOS application that will secure a photography of the suspected missing child complete with geolocation data, time stamp information, etc. and a face recognition match report to law enforcement. The proposed solution will provide officials with tools that will help to quickly and efficiently comb through hundreds of reportings/sightings to find actionable intelligence. Officials will be able to use the reports to view images of suspected sightings and focus location efforts.

This proposed solution is codified in an IOS mobile application with a set of actual missing child cases to demonstrate the efficacy of this solution over the current process.

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Chapter 1. Introduction

Roughly 800,000 children are reported missing each year in the United States according to the National Center for Missing and Exploited Children [18]. The US solution to this problem is the Amber Alert program. The Amber Alert program is a collaborative effort between law enforcement agencies, broadcast companies, transportation agencies, and the wireless industry to disseminate an urgent message to the US population in the event of a child abduction. AMBER is officially a contrived acronym for America's Missing: Broadcast Emergency Response.

The Amber Alert systems current functionality has failed to keep up with the rapid state of technological advancement in the United States. In its current form, the system relies upon the observations of community members to spot missing children. This form of crowd sourcing of manual subject identification is ill-suited for the twenty first century where camera enabled mobile devices are ubiquitous and computing power pricing is at all-time low. Communication with law enforcement agencies is done through one to one communication methods such as email and phone calls. Alerts are available online in mobile friendly webpages but do not offer any additional functionality besides displaying information about the missing child. Potential sightings are not filtered or pre-processed but are turned over to the law enforcement agency responsible for further analysis.

Technological advancements have opened opportunities to expand the amber alert system to become more effective. One such approach to improving the effectiveness of the current system is to integrate biometric technologies such as face recognition within the system.

The goal of this work is to create an additional interface to assist law enforcement agents in their search for missing children. The proposed interface is known as the Amber Scan system. The Amber Scan system acts as a communication portal between the public and law enforcement

agencies. The Amber Scan system has two main functionalities, one is that it acts as a communication portal between the public and law enforcement agencies. Secondly, the Amber Scan system has a built in flexible framework to perform face recognition. For example, if an Amber Alert is issued, users can view active alerts and submit information of sightings along with an image of the child in question. Next, the system will compare the image submitted by the public user against a set of images of missing children and return match scores to the relevant law enforcement agency autonomously. Integrating biometric technologies into the reporting process can help reduce the response times of law enforcement by augmenting the flow of information from the public to law enforcement officials.

1.1 Proposed Framework

The goal of this project is to present a innovative solution to expand the capabilities of the current Amber Alert system by considering that 91% of US adults now have mobile phones of which 61% have smartphones [17]. Smartphones can allow for greater functionality of this system by allowing the general population to have missing children info available at their fingertips while providing a method to report a potential sighting within the framework of an app. The thesis focuses on creating a smartphone application that links into National Center for Missing or Exploited Children's (NCMEC) ¹ database of missing children and allows for users to submit interactive reports to improve the current systems abilities and allow law enforcement officials to respond quicker. Facial recognition algorithms are implemented into the system to help filter potential sightings by using confidence scores from face matches.

Although facial recognition technology has improved significantly over the past decade, it is still in its infancy stages with respect to children [1,12,14,43,44]. To understand why there is a gap

¹ <http://www.missingkids.com/home>

in solutions for child face technologies, we will look at the essentials of sub-adult facial morphology and review prior work in face recognition for this demographic. In chapter two, we will provide a primer on face recognition and discussion of the challenges of child face recognition. We will also look at how an automated system can help filter out the most likely sightings to minimize the time it takes for law enforcement officials to respond.

Currently, missing children reports come into local law enforcement entities with insufficient data to perform effective execution of a recovery procedure immediately. Incoming reports can lack much of the information needed to find the missing child, e.g. precise location, incorrect vehicle reported, inaccurate direction of travel/speed. Conflicting reports of the child being sighted requires that law-enforcement prioritize requests and since these reports may lack sufficient data to make a real-time decision, improper prioritization can lead to random selection delaying recovery efforts. Multiple reports from many various locations can cause law enforcement officers to divide resources to cover more ground exposing units to greater risk if confrontation was to occur. The Amber Scan system will give law enforcement officials the ability to prioritize accurate reports of potential sightings and allow them to follow up on the most promising leads first. These reports will consist of the following:

1. GPS based location information of potential sightings
2. Detailed reports of sightings from the public with location information generated by user
3. Submission of photographic evidence
4. Face recognition analysis of suspected missing child with corresponding matches.
5. Geotagged photograph provides location and time/date information.

The Amber Scan application and accompanying framework supplement the current system by expanding into a new technical domain. Multiple face recognition algorithms can be integrated

inside the framework to give law enforcement agencies more reliable data resulting in an effective approach to prioritizing searches . Although this work demonstrates an Apple iOS device application, the RESTful application programming interface underlying the system is ecosystem independent and can be used on any platform that uses the internet for communication.

1.2 Goals and Contributions

This thesis has two main contributions. The first is will be to establish a framework in which the Amber Alert system can be brought to smart phones taking advantage of the changing lifestyle of the American Population. By establishing a framework for submitting images of children for analysis, others will be able to build upon this work to create new and innovative technologies to improve recognition rates and establish accurate location coordinates. The framework's flexibility will allow it to accept different face recognition algorithms independent of technological ecosystem.

The second goal is to create an innovative solution for the child face recognition problem. Since child face recognition technologies are still in the initial stages of development, this research project will allow for testing of multiple algorithms to compare performances. The results from this study can be used to further improve this niche of facial recognition. Depending on the application context, facial recognition systems can be configured for verification, a system which confirms the claimed identity of a subject presented to it, and identification, a system identifies an unknown subject by matching to a set (gallery) of known subjects. To meet our objectives, we will investigate the current state-of-art commercial systems in the identification scenario.

This project also allows for incorporating modern technologies in a public service area that is in major need of improvement. This body of work is not limited to missing children, but can be applied to other problems facing society when looking at children, such as keeping track of

vaccinations. Child identification would also be beneficial for civil ID programs such as India's Aadhaar program, which has already enrolled over 600 million individuals and their biometric modalities [15]. As of this writing, the author is not aware of any currently implemented applications of face recognition specifically targeted at children.

The remainder of this thesis is organized as follows: Chapter two details the background information on child face recognition and the current state of research on the topic. We also compare currently available applications on the mobile app marketplace that try to expand the systems capabilities. Chapter three describes the proposed Amber Scan application and the flexible framework created. Chapter four looks at the results of preliminary testing of the system on a small dataset consisting of current missing children. Chapter Five summarizes the work contributed, conclusions drawn from the experiments and future work that can be pursued.

Chapter 2: Review of literature and analysis

2.1 Amber Alert

The United States Amber Alert program was created in the Dallas-Fort Worth area when broadcasters teamed up with local police to develop an early warning system to help find abducted children [16]. Amber alert has now grown into a nationwide program at both state and federal levels. The latest version of the system allows for amber alerts to be transmitted to cell phones directly through the Wireless Emergency Alert System [16]. As of August 1st, 2016, there have been 830 successful recoveries of children by the Amber Alert Program. [16].

The amber alert system has strict guidelines set by the Department of justice on how amber alerts can be issued. These guidelines are [16]:

- There is reasonable belief by law enforcement an abduction/runaway has occurred.
- The missing child is of age 17 or younger.

- The law enforcement agency believes the child is in imminent danger of serious bodily injury or death.
- There is enough descriptive information about the victim and abduction for law enforcement to issue an AMBER Alert to assist in the recovery of the child.
- The child's name and other critical data elements, including the Child Abduction flag, have been entered into the National Crime Information Center, known as NCIC, database

Establishment of these guidelines prevents desensitization by the public for repeated alerts. By constricting the alerts to only the most severe of cases; amber alerts are rare events focusing the attention of the public to the missing adolescent. An amber alert is distributed via two systems, primary distribution system and the secondary distribution system [18]. The primary distribution system encompasses cooperation between law enforcement agencies, broadcasters, and transportation agencies. The AMBER Alert Secondary Distribution system, known as AASD, is comprised of wireless carriers, Internet service providers, digital signage, social networking websites, content providers and major retailers who distribute AMBER Alerts to a geographically targeted audience in support of the AMBER Alert coordinator [19]. These alerts assist in notifying the public about recently reported missing children with information to help in the search for the missing child, suspected abductor and/or suspected vehicle. Research on the amber alert has focused on the effectiveness of the program in assisting law enforcement officials to locate missing children.

The Wireless alert system attempts to use mobile devices to display urgent messages. This system links amber alerts to a notification system within most smart phones to display a brief message to the user. Messages are typically short 1- 2 sentence descriptions of the missing child

and the last known location/direction of travel. Users can then call/text the Amber Alert hot line with tips on sighted missing children.

The idea of creating a mobile phone application for the Amber Alert system is one that has been looked at before. Several applications exist on the market which serve some functions to help locate missing children. Table 1 outlines these apps and their features from the Apple app store and Android Marketplace. The goal of this work will be to fill in the gaps from other solutions and create one system which can serve all these functions. The only current official application, AMBER Alert, by Jonathan Zdziarski, was created in conjunction with NCMEC to display alerts on the iPhone [16]. After being published on the app store in 2009 it has only been updated in 2014 for iOS 7 compliance and a legacy bug fix.

Table 1: Comparison of current mobile phone applications on Amber Alert system. No system, inclusive of those identified below, are actively being managed by the publisher or NCMEC.

Application Name	Publisher	Official	Face Recognition	Reporting	Real Time	OS
Amber Alert	Jonathan Zdziarski	Yes	No	Yes	Yes	iOS
All Hands Alert	Lee Cassar	No	No	No	Yes	iOS
Unknown Alert System	UNKNOWN Plan Prep	No	No	No	Yes	iOS
Amber Alert	Agilus	No	No	No	No	Android
Missing Kids Android	Irick James	No	No	No	Yes	Android

Although applications exist on the Android marketplace, there is no official NCMEC app, and those that do, have minimal functionality by displaying a web browser in-app which re-directs users to the NCMEC webpage or retrieving current alerts and placing them in a list format. As of this writing, no application support face recognition capabilities in any capacity and only one allows for reporting of missing children from within the application. The one instance in which reporting capabilities are available, reporting is done through a shortcut which initiates a phone call to the missing children sighting hotline.

The current systems in place for locating missing children lack recent advancements in technology. This work aims to re-invigorate the crowd sourcing of potential sighting information

by leveraging today's technology in a safe and effective manner. By exploiting the increasing availability of smart devices in most America people, we hope to successfully find missing children and act as a deterrence for criminal behavior.

2.2 Biometrics

Biometrics have been used by humans for much of our evolution. Humans evolved an ability to recognize patterns in the natural world as a defense mechanism to defend themselves from predators [4]. These pattern recognition abilities extend to recognize the faces of other human beings. The importance of face recognition for humans becomes evident when analyzing the information that can be extracted from a single glance. Humans can distinguish the ethnicity (both race and culture), sex, age, health state, emotional state (happiness, sadness, anger, frustration, attraction, etc.), and the direction of attention of the individual from a single glance of a face[4]. Biometrics as a characteristic is defined as a measurable biological (anatomical and physiological) or behavioral characteristic. A biological characteristic is a unique and inherent physical attribute of an individual that can be used for identification purposes like fingerprint, iris, vein, face etc. Behavioral biometric characteristics include signature, gait, voice recordings, keystroke, rhythms, etc. [42]. Figure 1 presents examples of the different biometrics [46]. As a process, biometric is defined as a system that is used to identify individuals based on their biological or behavioral characteristics. Biometric characteristics are also known as biometric modalities. It is commonly accepted that the oldest recorded use of a modality was in 1879 when Alphonse Bertillon invented a method using detailed measurements and classification of unique features using frontal and profile pictures of suspected criminals. [47].

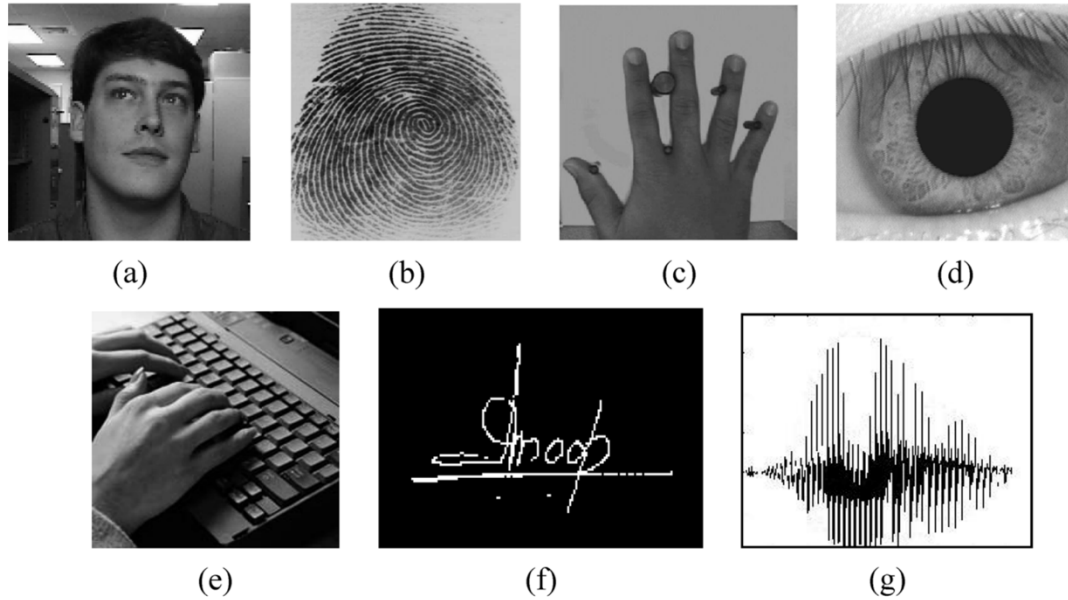


Figure 1: Examples of biometric characteristics. (A)Face, (B) fingerprint, (C) hand geometry, (D) iris, (E) keystroke, (F)signature, (G)voice [46].

2.3 Face Recognition

Face recognition is the process of identifying a subject based upon their facial features. The face modality is used in this work for several reasons as identified by the seven traits of a functional biometric:

- Universality: Every individual has a face
- Semi-permanence: permanence is necessary for longitudinal work, and it is important that the biometric feature is sufficiently consistent over a period, or how the biometric system can incorporate the changes in the trait. With the advancement in facial recognition technology, it is possible to recognize an adult over more than ten years of time lapse [12,49].

- Access: The face metric is easily accessible from media sources. Faces can be extracted from social media systems, CCTV footage, or scanned in from physical photos.
- Performance/Accuracy: Face recognition is accurate as humans. In Face Recognition Vendor Test 2006, an experiment comparing human and algorithm performance, demonstrated the best-performing face recognition algorithms like Tsinghua (Ts2-norm) were more accurate than humans [12, 27].
- Problem Domain: Since this work is focused on improving the amber alert system, a sub-adult face is often the only modality available for law-enforcement officials. The face is also the easiest modality to capture by the public for search purposes.

The face modality has proven itself to be one of the best metrics for identification of individuals. Typical applications of face recognition systems have yielded robustness in identification of subjects through the face even with poor image quality. The National Institute of Standards and Technology (NIST) has been tracking improvements in facial recognition to present through Face Recognition Grand Challenges (FRGC), which contain face recognition vendor tests, fostered improvements in the field [51]. The 2014 FRVT, sponsored by NIST, showed how proficient Commercial Vendors have become in creating solutions for face recognition. According to the 2014 FRVT report, face recognition accuracy has improved in all evaluated scenarios since 2010. The latest report reflects a rank-one miss rate for recognition in a population size of 1.6 million at 4.1% for the commercial vendor NEC [52]. A rank-one miss rate in lay terms is how often do as the FR system choose the wrong candidate (imposter) as the highest match to the input face. Increasing enrollment rates raise the possibility of false positives due to lookalike faces but at an approximate power law rate of aN^b where N is the population, b for mugshot searches, and a , the previous error rate. This means that a large 10-fold increase in N yields only a 1.2 -1.4-fold

increase in error [52]. Similar studies on the most popular modality, fingerprinting, led to false negative identification rates of 0.27% on a similar gallery of 1.6 million subjects [53]. Although not as accurate as fingerprinting, face recognition low increase in error rate with respect to large datasets makes it better suited for large scale scenarios. Further, fingerprint requires the subject to present the finger to a fingerprint device, i.e. place the finger on a sensor in a prescribed manner. FR (face recognition) is often used in a non-cooperative or non-habituated fashion. It can easily be used without anyone noticing that a photograph is being taken thus making this ideal for the propose case, Amber Alert.

Automatic face recognition systems have been gaining attention in the scientific community for the last 50 years. The first semi-automatic face recognition system was developed by Woody Bledsoe in the 1960's for the US Government [6]. Since then, many different techniques have been applied to face recognition to create a “lights out” automatic face recognition system capable of running fully autonomously with little to no errors.

Recognizing a face within an image is a multi-step process in which a machine must process individual components of the image to create a set of features that correspond with the target object. A simplified process of how an automated recognition system could work is by starting out with detection of the face, arguably the most difficult part of the process. Once an object is detected in the image, feature extraction on the object yields usable data points. Facial features vary on the classification method used but can encompass certain biological components such as the nose, eyes, and mouth; to abstract features such as lines and fiducial points [8]. Figure 2 shows the steps in the Face Aging groups face recognition system.

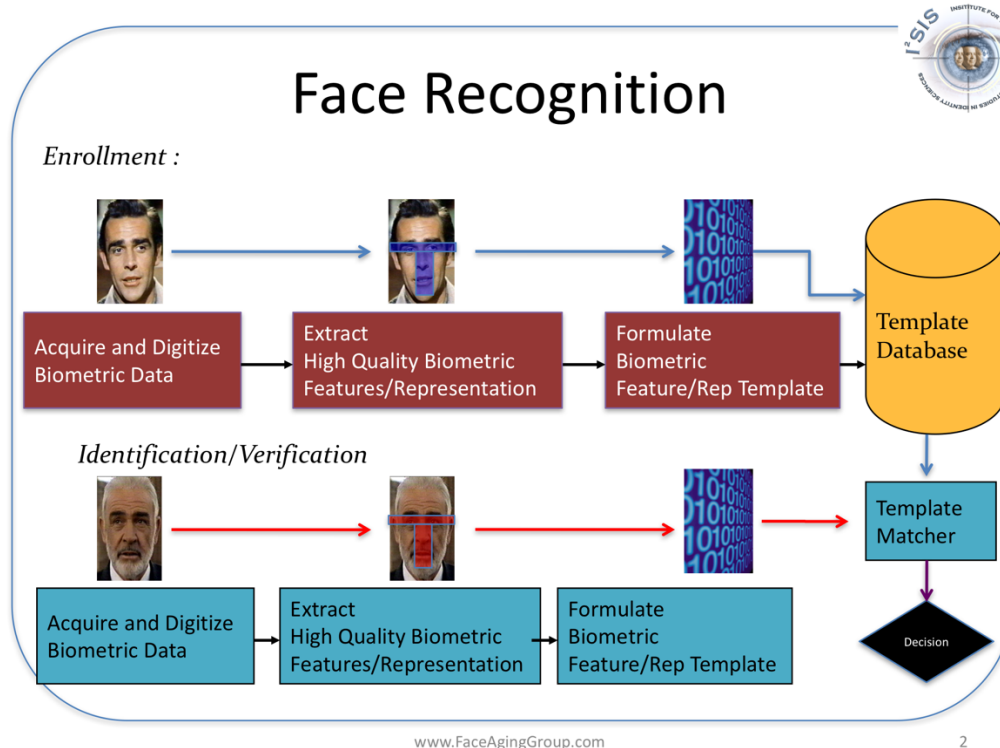


Figure 2: The face aging groups face recognition system.

Detected faces are then stored in a template database known as the gallery. A gallery is the set of faces which will be used to run face detection against. A face is detected from the input image and extraction of the face takes place by using a template matching classification technique such as Viola-Jones [7]. The Viola Jones algorithm is one of the most popular open source systems and has been used in the development of many face recognition solutions such as the Open Source Computer Vision (OpenCV) development suite [9]. OpenCV is used in many algorithms for preprocessing, including the algorithm used in this work.

For the Identification verification of query (probe) faces, a similar process is followed. The image is acquired and digitized for face detection. After the subject's face has been identified, features are extracted and used for comparison using the desired template matching approach.

Returned result are typically a score matrix used to determine similarity scores between the gallery images and the query image

Standard approaches to face recognition include:

- Principal Component Analysis (PCA): A reduced parametrization, and consequent data reduction, for 2-D digital images of faces. Here, faces are represented by the appropriate superposition of macro-features which are objectively generated on a statistical basis. Facial components are encoded in a vector format known as EigenVectors [62].
- Linear Discriminant Analysis (LDA): A classification method that projects high-dimensional data onto a line and performs classification in a one-dimensional space. The goal of which is to maximize between class variance and minimize in class variances [63].
- Elastic Bunch Graph Matching: A method to address non-linear characteristics such as illumination, pose, expression. A Gabor wavelet transform creates a dynamic link architecture that projects the face onto an elastic grid [64]. It is the result of a convolution of the image with a Gabor filter, which is used to detect shapes and to extract features using image processing. Recognition is based on the similarity of the Gabor filter response at each Gabor node

Each method has been more efficient than the prior method at face recognition. Current trends in the computer vision space have led to the maturation of machine learning systems such as convolutional neural networks. These types of system's show promise to solve problems once thought to be too difficult for computers to handle. Deep learning is an extension of the field of machine learning that attempts to model elevated level abstractions in data by using a deep graph with multiple processing layers with both linear and non-linear transformations.

The possibility of implementing biomechanical mechanisms such as the human brains neural physiology has been studied since the early 1940's [20]. It wasn't until 1954 when Farley and Clark created an actual implementation of neurons on a digital computer [21,22]. Soon after came the first artificial neural networks (ANN) with the advent of the perceptron [23]. Rosenblatt's perceptron is a probabilistic model for information storage and organization in the brain. The perceptron as described by Rosenblatt is one layer of model neurons projecting to another layer of model neurons by way of parallel bundles of connections. The perceptron originally was a three-layer device [23]. When comparing the perceptron, modern ANNs share this architecture. The perceptron was designed with the goal of image recognition, a theme that is common when looking at this field.

Deep learning neural networks are a term used for ANN that consist of many layers of neurons. Shallow neural network like models with few such stages have been around for many decades. A deep neural network (DNN) will contain many multiple layers in between the input layer and output layer. DNN may also have linear functions, such as filters, to preform preprocessing for layers.

Convolutional neural networks (CNNs) are deep neural networks which are inspired by the organization of animal visual cortexes. Hubel and Wiesel's early work on cat visual cortexes showed how complex arrangements of neurons can work together in identifying special pattern recognition [25]. Sensory neurons (also known as cortical neurons) respond to stimuli in restricted areas of space. These receptive fields overlap to create a tiling effect on the overall visual field (Figure 3). The responses of individual neurons to subsequent neurons is transmitted to post-neurons where the mathematical convolution operation is used [26], hence the name Convolutional

Neural Network. By analyzing parts of the input image, CNN's can recognize patterns similar to how the visual cortex processes images.

Typical convolutional neural networks consist of a set of layers, each of which contains one or more planes. A typical convolutional network is shown in Figure 3. Normalized images (faces which have been rotated and centered) enter in the input layer of the CNN. Each unit in a plane receives input from a small neighborhood in the planes of the previous layer [27]. The weights forming the receptive field for a plane are forced to be equal at all points in the plane and are passed to subsequent layers. Each plane can be considered a feature map which has a fixed feature detector that is convolved with a local window which is scanned over the planes in the previous layer [27]. Convolutional neural networks can contain a number of planes in each layer to capture multiple features. These layers are known as the convolutional layers. Following convolutional layers are subsampling layers which perform a pooling function. Pooling shrinks, the size of the plane to simplify computations while maintaining the features located within the plane. Subsampling also functions to desensitize the location of the feature and emphasize the presence instead. With each subsequent plane, the feature map size shrinks. The Fully connected layer serves to take in all data from prior layers and combine the results to form an output for the CNN. Training a CNN can take place by different training algorithms such as the backpropagation gradient-descent procedure.

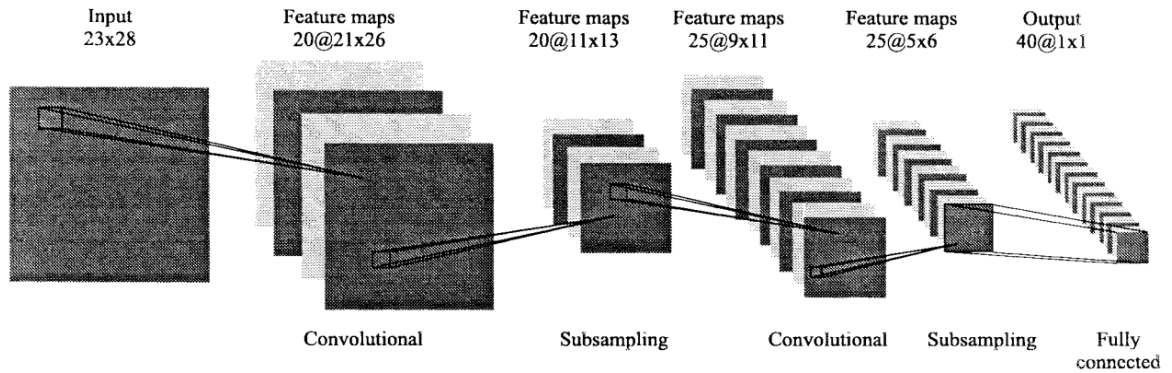


Figure 3: A typical convolutional neural network.

CNN's have been used in numerous studies for face detection [27,28,30-34]. Comparisons of CNN performance to more traditional recognition approaches, such as Turk and Pentland's [35], has shown a marked improvement in face recognition. For this research, two algorithms utilizing DNN trained on open data sets was used: *Open Biometrics 4SF* and *Rank One Face Recognition*. The reasoning behind using these two face recognition algorithms were based partially on previous research regarding child face recognition.

2.3 Child Face Recognition

Although much research has been conducted on face recognition for adults, research on face recognition for children is sparse. Of the published work [1,12,14] the focus has been on establishing Child FR as a hard problem by evaluating commercial solutions specifically on child faces. This body of work will extend previous research on evaluation and understanding the difficulty of the problem and attempt to create a new solution to child face recognition.

Lack of data has been the primary limiting factor in child face recognition. The very nature of the problem creates a roadblock for researchers to effectively analyze the problem and develop solutions. Prior work on automated systems for child face recognition is limited due to two primarily reasons. The first being the difficulty in collecting longitudinal child face data. In the

United States, certain laws restrict the usage of children in research projects. Any such proposals have to be approved by an Institutional Review board (IRB). IRBs strictly vet proposals to ensure maximum protections are afforded to the participants. The second being the general perception that face recognition of children is infeasible because of rapid growth rates.

To the best of my knowledge, the only publicly available datasets containing children faces are FG-NET [56], FaceTracer [57], and the Cross-Age Reference Coding (CACD). FG-NET contains face images of 82 persons with ages ranging from 0 to 69. Although FG-Net does contain faces of children, the dataset is focused on adult faces and not enough data on child faces exists. The FaceTracer database contains 15,000 faces with 5,000 hand labels including demographic information such as age, race, facial features, and hair color. [56]. Unfortunately, each child face has only one image and is not suitable for face recognition. The CACD dataset contains more than 160,000 images of 2,000 celebrities with age ranging from 16 to 62 [57]. This limited age range restricts the application of this dataset to the child face recognition problem.

The first such dataset designed specifically for the evaluation of craniofacial morphological changes due to natural aging of sub-adults was developed by Michael Sodomsky et etc. [1] with the creation of the In The Wild Child Celebrity (ITWCC) Dataset. The ITWCC dataset was created to assist the evaluation of facial recognition tools over a longitudinal span. ITWCC contains images of child celebrities over the span of their careers [1]. Sodomsky compares several standard open source and COTS to demonstrate face recognition performance degradation when the enrolled face is temporally displaced by the probe face. ITWCC contains 301 subjects with 1705 images. Subject ages range from 5 months to 32 years. The dataset contains 872 female images and 846 male images with an average age of 13.418 and a standard deviation of 3.432 years [1]. Sodomsky's results showed the comparison of 6 algorithms to test the effectiveness on child face

recognition. The most accurate algorithm according to his findings gave a 37% true accept rate at 1% false accept rate [1]. Comparison of performance at different age groups found a direct relationship between decreasing performance and decreasing age. Sodomsky’s findings agree with another study performed by NIST on face recognition algorithms on multiple age groups [52].

The ITWCC dataset’s longitudinal data was extended by Bhardwaj et al. [12] with the ITWCC-2 dataset. ITWCC-2 extended the number subjects to 501 over 32,515 images. Bhardwaj evaluated the performance of the COTS Rank One [2] v1.20 (at that time, the latest COTS), Neurotechnology’s Verilook v6.0 [59], and Cognitec v 8.5 [60]. Bhardwaj was able to achieve a true accept rate of 76.9% at a false accept rate of 1% using the extended ITWCC-2 dataset and Rank One COTS. Although this is an improvement from Sodomsky’s findings, the results indicate these algorithm which were designed for adult face recognition, do not perform as well when used on child faces (Figure 4). More research is needed in creating a solution for better results.

FAR	Rank One Computing v1.20		Cognitec v8.50		Verilook v6.0	
	ITWCC-2 (sub-adult)	LFW (adult)	ITWCC-2 (sub-adult)	LFW (adult)	ITWCC-2 (sub-adult)	LFW (adult)
1e ⁻⁰⁶	2.4%	12.2%	1.8%	2%	1.04%	0%
1e ⁻⁰⁵	6.4%	33.8%	4.5%	16.5%	04.1%	9.5%
1e ⁻⁰⁴	13%	52.2%	7.5%	26.7%	7.0%	16.4%
1e ⁻⁰³	25.4%	71.6%	13.1%	37.9%	12.3%	23.3%
1e ⁻⁰²	46.8%	87.6%	24.7%	53.1%	23.7%	32.1%
1e ⁻⁰¹	76.9%	96.5%	49.8%	74.7%	33.0%	48.4%

Figure 4: TAR comparisons for adult and sub-adult faces by Bhardwaj [12].

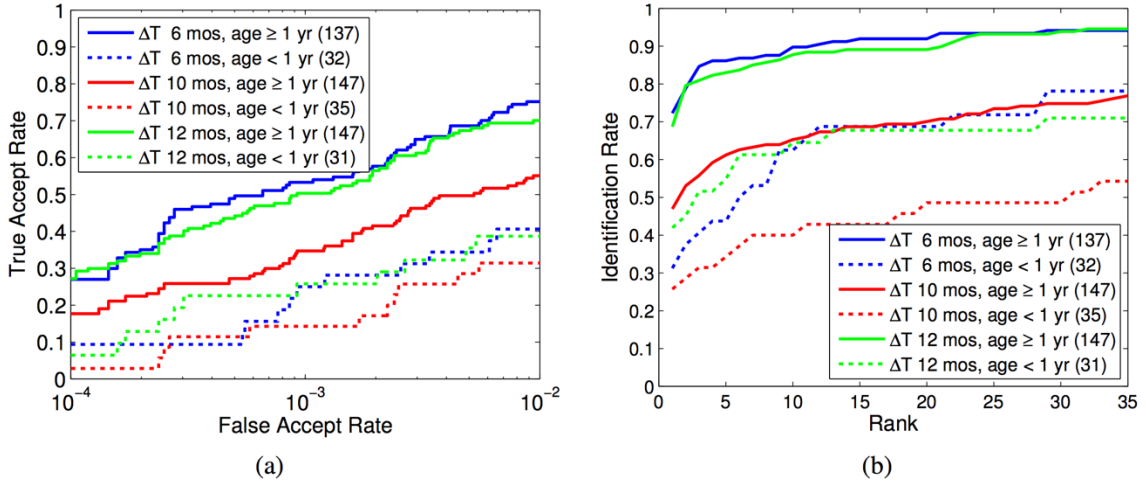


Figure 5: Longitudinal performance of COTS for (A) verification and (B) identification experiments of the 206 total subjects in the NIT-S1 subset of the NITL face image database. The gallery for these experiments consists of face images from session 1 of the study.

Another child specific dataset has been developed by Lacey Best-Rowden et al. [14]. Through a longitudinal capture study in which photographs of young children were taken at the Saran Ashram Hospital in Dayalbagh, India; known as Newborns, Infants, and Toddlers (NITL) dataset. Three sessions were conducted to gather images of the same subject at 6 month intervals. The dataset contains 314 subjects in the age range of 0-4 years old. As of this writing, this dataset has not been made available to the public. Testing of the dataset through one of the top-3 performers in the NIST FRVT [52], although which was used, is not specified. Application of the COTS was performed for both absolute age and longitudinal aging factors. Results from the study are shown in in Figure 5 [14]. Lacey demonstrated the performance of the COTS on faces younger than 6 months of age yielded a true accept rate of 26% at a false accept rate of .01%. Subjects which were greater than 6 months of age had a true accept rate of 53% at a .01% false accept rate [14]. In summary, the research showed the deficiencies of COTSs when confronted with as little as 6 months of adolescence growth.

Chapter 3: Methodology

3.1 System Overview

To create a system to meet the targeted goals, a two-part approach was selected. A mobile phone application to serve as the user-interface for child face identification, and an application programming interface through a web portal to allow for data analysis and reporting to take place on. Most large-scale applications consist of a server-client setup in which most of processing takes place on the server, similarly, the Amber Scan system is based upon the same methodology.

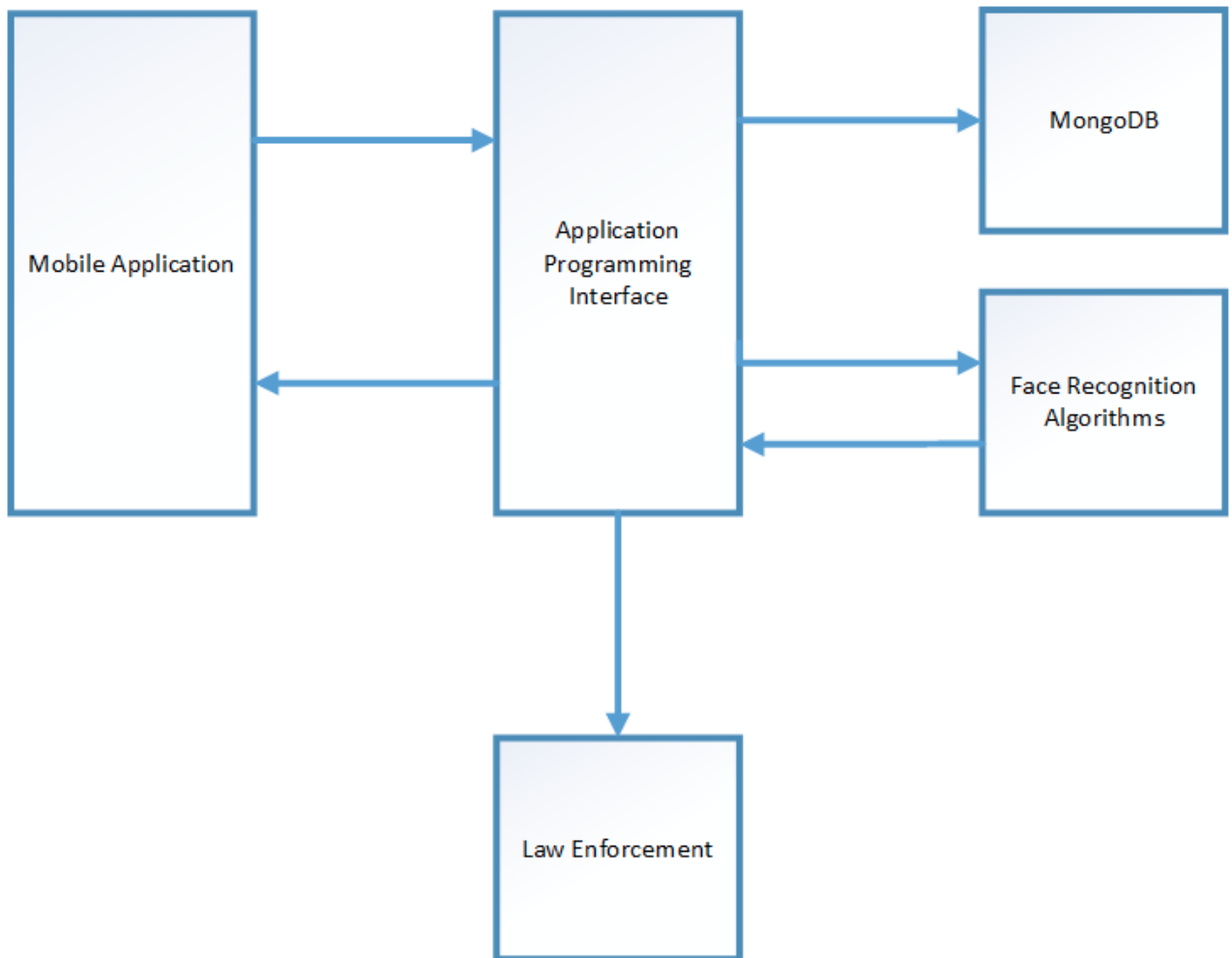


Figure 6: Overview of the Amber Scan system with arrows depicting the flow of data.

The iOS mobile application serves as the primary way of interfacing with the system and takes place through the RESTful communications protocol [40]. Server-side logic consists of the application programming interface, a database, face recognition algorithms, and an email system used to communicate with law enforcement officials as shown in figure 6. In future efforts, capabilities of this system will be cross platform. Our hope is that NCMEC will implement this system alongside the current sighting system.

3.2 Amber Scan Application

To improve the Amber Alert system, this body of work creates a mobile phone application to serve as the user-interface for child face identification called Amber Scan. The proliferation of cellular phones into the American lifestyle allows for an immediate communication channel to be available at any given time. Smart phones have taken this ability one step further and enabled the population to access data transmission through applications utilizing mobile data.

Smart phone application design is a heavily researched topic. In the United States, smartphones apps are being used as the gateways to internet services more than traditional web browsers [36]. The type of smart phone app influences the usage level. Native and cross-platform web-based applications are the primary types found in the major software app stores.

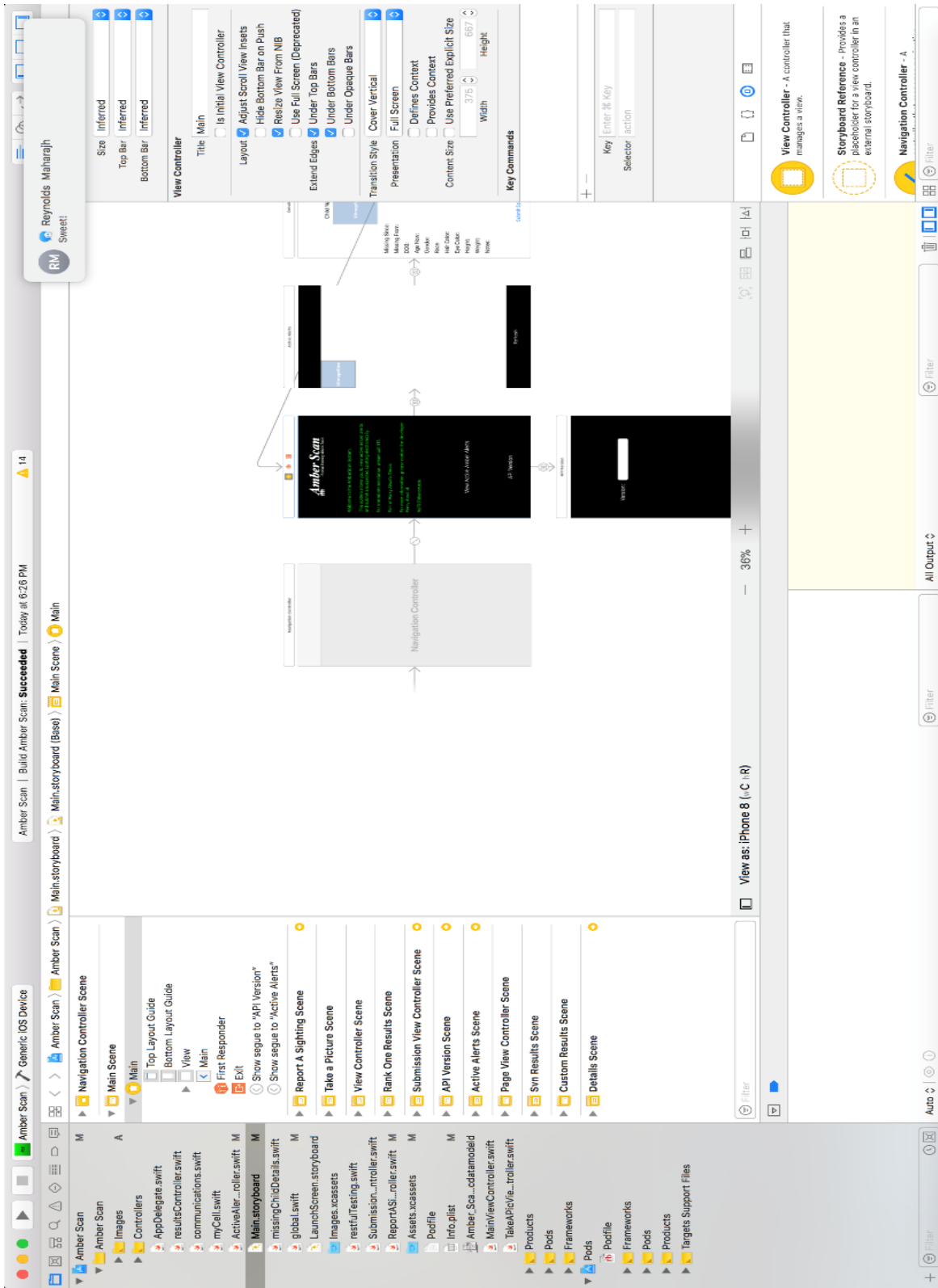


Figure 7: The Xcode Integrated Development Environment

Native operating system applications have the best experience for the users due to the ability to more completely tie into the operating system of the device [38]. Core software links which connect application functionality to the mobile phones hardware can be absent; affecting the functionality of cross platform applications. Such applications will then often fail to replicate the same experience as a native application would have. For this project, Apple Inc's Xcode software is used to create an native iOS mobile application (Figure 7). Architectural systems such as Xamarian [40] allows for a single code repository to be utilized on multiple platforms but failed to provide the same level of access to the iOS device as the native system. Xamarian relies upon the open C# language to establish one common code base which is then translated to the destination device's native language. Xcode allows developers to utilize either Objective C or Swift, Apple's proprietary language, to program devices². Previous research by Stroud et al. [68] demonstrates deficiencies with cross platform development tools. To facilitate rapid design and prototyping, we chose to focus on using the Swift language using Xcode to create the Amber Scan iOS application.

Apples design guidelines use a Model View Controller (MVC) architectural pattern for developers (Figure 8). Developers are given a story board to design views and assign controllers to. Views are used to show data to the user and accept interaction. Resulting actions are relayed to the Controller for logic processing. The Controller may then choose to update the model if needed. Modifications to the model are relayed to the view by notifying the controller to update content on the specified view. The Amber Scan application uses individual view controllers for each view.

² Amber Scan uses the opensource Alamofire library for HTTP communications [65].

Participants follow a step by step tutorial that takes them through selecting a child, submitting information about the sighting, and taking a candid picture of the child for analysis.

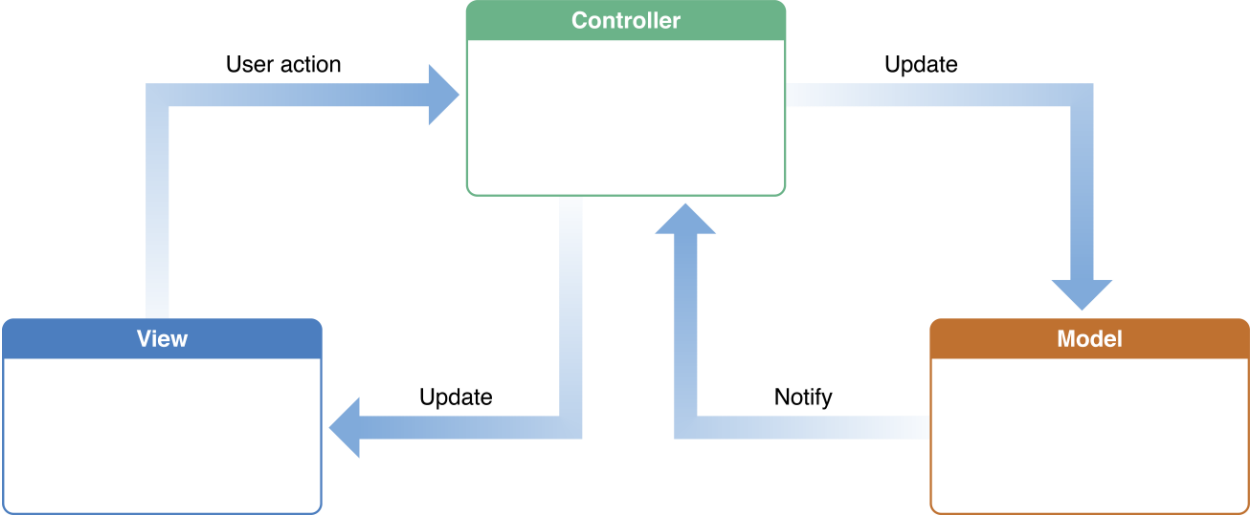


Figure 8: Apple’s model view controller design pattern in Xcode. [69]

After clicking on the Amber scan icon on the device, the user is prompted by a loading screen displaying the name off the system as well some graphical art depicting a family (figure 9). During this phase, images are being loaded from the system as well as connecting to the application programming interface to retrieve the latest version. After the application has been fully initialized, core variables are set for application use in the persistent data area of the device. Persistent data is used to ensure the version of the API being accessed is the most recent version as well as allotting space for future implementation of encryption codes for communication.

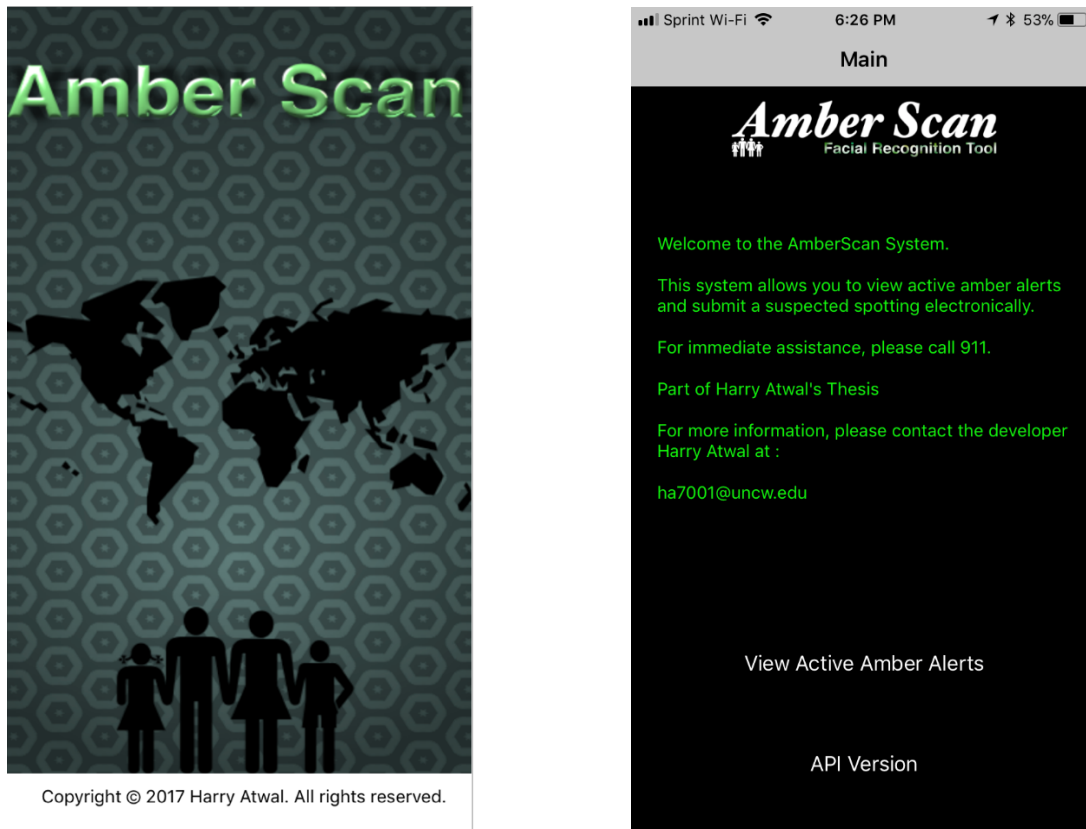


Figure 9: LOADING SCREEN AND HOME PAGE OF AMBER SCAN SYSTEM

A clean distraction free interface was chosen to minimize the time it would take for a user to familiarize themselves with the program. The initial welcome screen provides the user with information on the purpose of the application, the creator, as well as a disclaimer stating the user should call 911 for immediate assistance in the event of an actual sighting. The user is then prompted with two options. The “View Active Amber Alerts” button, and an “API Version” button (figure 9). The API version button is only displayed if debug mode on the application is set to be on and displays a numeric code corresponding to the current API version being communicated with.

After selecting the view active alerts button, the user is sent to the active alerts view. Alerts are organized in a collection view with small squares displaying an image of a missing child

(Figure 10). This view does not provide any detailed information and attempts to place as many children in the view as possible. This design was chosen to consider a usage scenario where the user needs to quickly scan the list of missing children and locate the suspected victim.

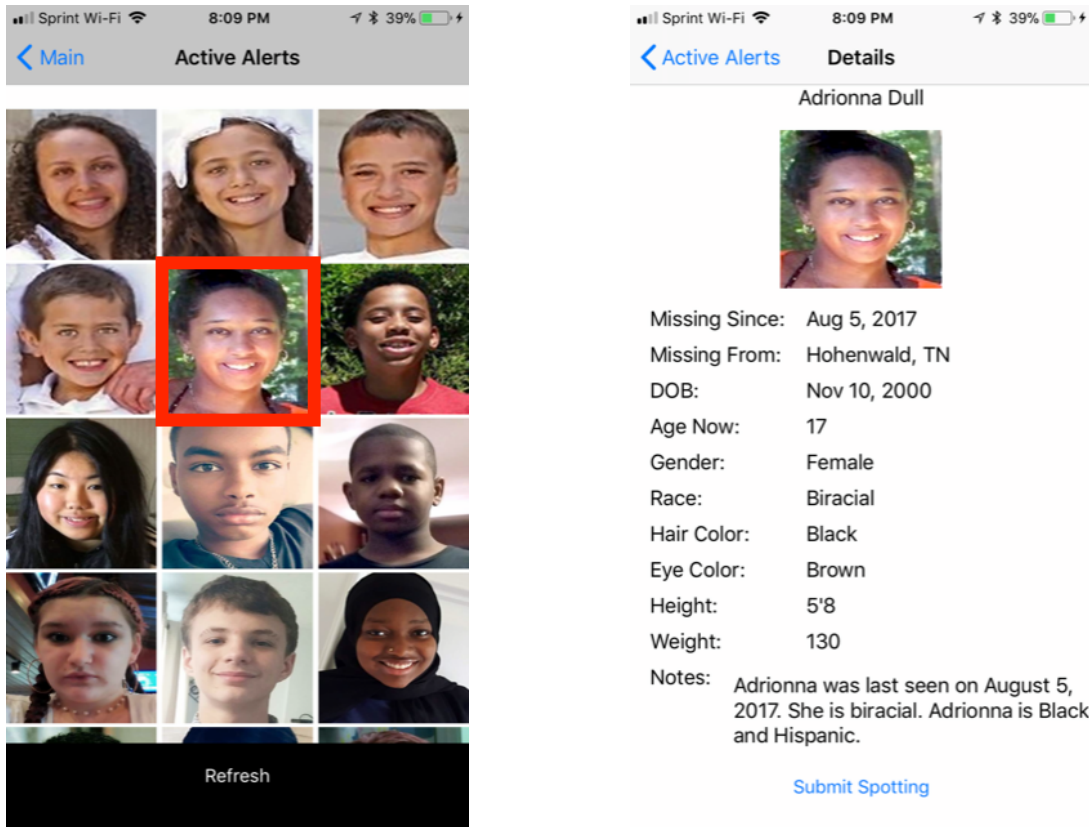
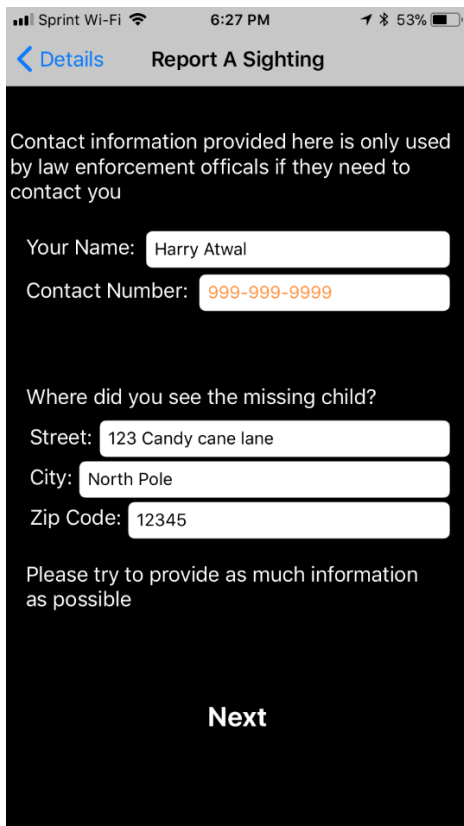


Figure 10: Active alerts page and details of missing child selected in red.

By clicking on the image of the child, the user is taken to a detailed information screen displaying an enlarged image of the child, the date they went missing, the last known location, as well as other identifiable information (Figure. 10). Each alert also comes with a notes section where additional details regarding who the missing child is with, what vehicle they were last spotted in, and the condition of the missing child are listed. The information presented on this page is the same provided by NCMEC. The user can then either opt to continue with the sighting or to return to the subject selection page to choose a different missing child.

After the user has selected a missing child, they are taken to a report page which asks them to fill out some basic information about the sighting (Figure 11). The information requested is:

1. Name of user submitting information
2. Contact number of user
3. Street where sighting occurred
4. City where sighting occurred
5. Zip code where sighting occurred



The screenshot shows a mobile application interface for reporting a sighting. At the top, the status bar shows 'Sprint Wi-Fi', '6:27 PM', and '53%' battery. The app header includes a back arrow and the text 'Details Report A Sighting'. Below the header, a disclaimer states: 'Contact information provided here is only used by law enforcement officials if they need to contact you'. The form contains several input fields: 'Your Name' with the value 'Harry Atwal', 'Contact Number' with the value '999-999-9999', 'Where did you see the missing child?' section with sub-fields for 'Street' (123 Candy cane lane), 'City' (North Pole), and 'Zip Code' (12345). A note at the bottom of the form says 'Please try to provide as much information as possible'. A large 'Next' button is positioned at the bottom center.



Figure 11: Submit information about the sighting page, submit image of target image page.

The user has the option of opting out not to provide any information he/she feels uncomfortable with providing but is encouraged to provide as much information as possible. An additional prompt asks the user for location information. If the user opts in, the application utilizes the built in GPS

system to retrieve relevant Latitude and Longitude of the user at the time of the sighting. This information is immediately submitted to the API server for processing. Immediate submission occurs in case the sighting process is not completed on the user's device. This allows for every reported sighting, even incomplete sightings to be analyzed by law enforcement agencies. An Id number is returned with each sighting to be used in the next phase of the application.

After the user has submitted details of the sighting, he/she is asked to submit a photo of the sighted subject (Figure 11). Pictures can be uploaded from the user device photo library or by opening the device camera module and allowing them to immediately take a picture. Selected images are shown on the screen for the user to review before clicking the submit button. The image is then uploaded to the same secure server, using the returned id number, for face recognition and communication with law enforcement. The user is provided with a status bar indicated the upload progress. After a successful upload, the user is prompted with a thank you message indicated their sighting was a success (Figure 12).

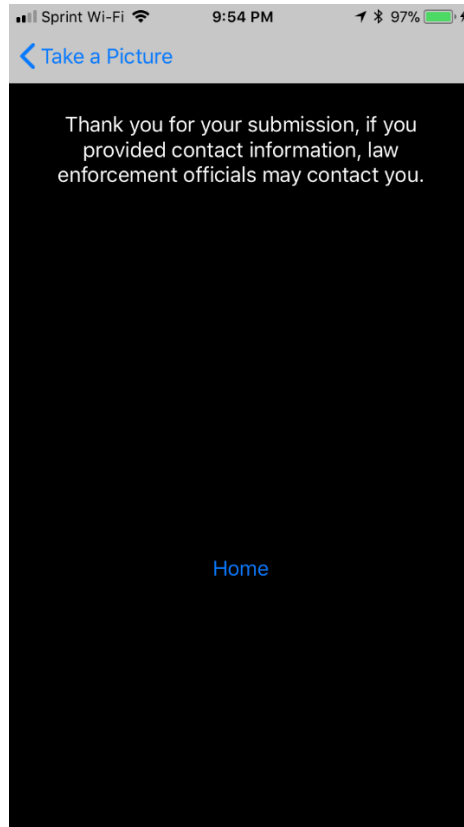


Figure 12: Thank you screen to user after uploading image.

3.3 Application Programming Interface

To accommodate communication between the law enforcement officials and the mobile phone application, an Application Programming Interface (API) was developed. This API is based on a Representational State Transfer (REST) architecture [40]. A REST architecture allows maximum compatibility with third party systems and the greatest flexibility incorporating external modules. In addition, this framework can handle multiple asynchronous communication requests from users submitting sightings simultaneously. The API is located on a Faceaging lab computer system located at the University, but can be deployed anywhere in the world through a simple Domain Name System (DNS) entry modification.

Communication between user devices and the logic server are performed via HTML GET and HTML POST requests [41]. Utilizing the HTML protocol also facilitates compatibility and flexibility in development. Submissions of data are done using ‘POST’ requests. Retrieval of data from the API server are done via ‘GET’ requests. The API has the ability to run scripts locally on the machine to allow for additional flexibility with respect to plugin use. Use of the established frameworks NodeJS allowed us to implement the API behind UNCW’s security mechanisms and lab data protection system.

Incoming data is split into two endpoints. One endpoint accepts sighting data in the form of a JSON packet containing all information provided by users, as well as device information and timestamp. This information is stored in a localized instance of a Mongo database[66]. MongoDB was chosen to store data because of its ability to grow and accept changing data types as the program progresses, future proofing the system on the way. MongoDB also has well documented security features to prevent unauthorized access and can be expanded in the future to have enterprise level features such as database wide encryption. Each incoming sighting is assigned a unique identification number based upon the identification number assigned by mongoID. This unique ID will be used for storing the sightings corresponding image.

The second endpoint accepts images submitted along corresponding sighting for face recognition. Each image upload is named after the Id number generated when the sighting was originally added to the database. For each image submission, a folder is created to hold the image and all corresponding analysis files of the entry. Following the file creation, the endpoint calls a series of python scripts to perform facial recognition on the uploaded image. Stored images in this folder are available to law enforcement through unique URL generated during this process.

Face recognition on the image is performed via two algorithms. One is the commercial off the shelf solution provided by Rank One Computing [2]. The second is an algorithm from an open source library Open Biometrics [11]. The raw results for each sighting is stored in the corresponding submission folder for archival and further analysis. The top three matches for each system are stored in a separate CSV file (Table 2). At the end of analysis an email is constructed with an image of the suspected victim, submission information, and results from face recognition. This email is sent to law enforcement agency listed on the originally listed bulletin from NCMEC.

Table 2: Sample top scores sent to law enforcement.

Source Image Name :		Subject 0				
Algorithm	Match 1 Name	Score	Match 2 Name	Score	Match 3 Name	Score
openBR	Subject 1	3.43859979	Subject 2	4.808234774	Subject 0	100
Rank One	Subject 0	0.995064318	Subject 3	0.452588558	Subject 4	0.417328238

Each algorithm relies upon having a gallery of missing children already created to run the probe image against. Currently the system requires manual input of new subjects to be enrolled into the gallery. In the future this ability will be automated where new missing children are added to the gallery automatically. If the user elects to not submit image data, the submission information is automatically emailed to law enforcement personnel after 15 min. All possible leads are submitted to law enforcement for human review and decision making.

The Amber Scan system also the additional functionality, where if a certain threshold is reached for match scores for non-target gallery images, the relevant agency responsible for the listing will be automatically notified of a possible sighting. Match scores for the submitted image is passed onto the responsible agency as it would be in a normal submission. The threshold feature is currently unimplemented because each algorithm has its own methodology on rating thresholds.

3.5 Rank One Face Recognition

Rank One computing is a computer vision and deep learning company founded in 2014 by researchers and engineers from the public sector [2]. Rank One computing uses the cutting-edge research performed by the community to create complete solutions in the OpenBR framework [11]. Rank One computing has two algorithms [2]:

- **ROCFR** - designed for accurate identification of unconstrained faces (i.e., faces of non-ideal quality)
- **ROCID** - designed for controlled capture frontal face recognition images (i.e., images that comply with the ISO/IEC 19794-5 and ICAO 9303 standards)

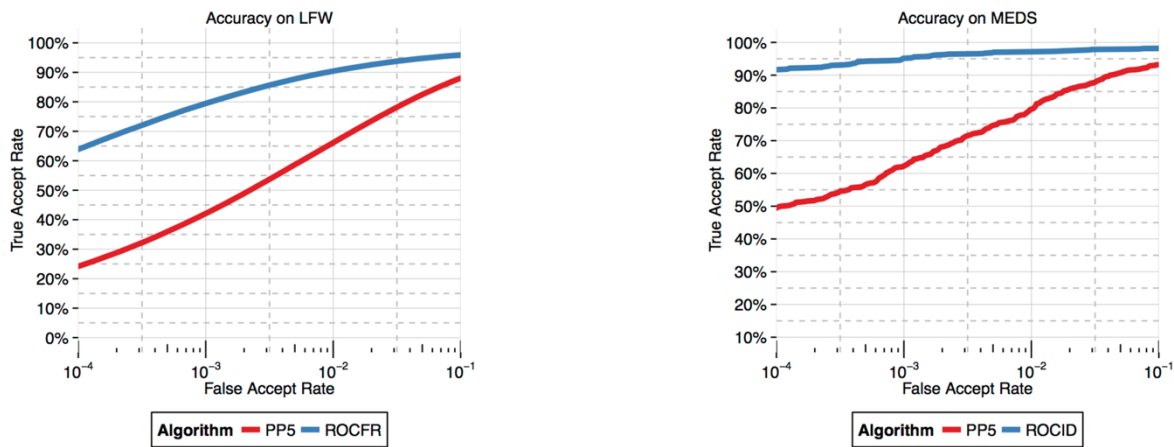


Figure 13: Rank One algorithms performance on Labeled Faces In The Wild and NIST Multiple Encounter Datasets. Both ROCFR and ROCID were use independently against PittPatt 5.2.2 SDK [2]

ROCFR will be used in this work to account for user submissions being of non ISO/IEC 19794 standards. Faces submitted will be unconstrained due to the nature of the capture, i.e. users covertly

attempting to capture images of the child in question. Although Rank One does not disclose the technical details behind their algorithms, the results published by the research community [12, 52] and documentation provided by Rank One show how effective their algorithms can be in face recognition (Figure 13). In the NIST FRVT challenge, Rank One scored higher than all other vendor submissions. Bhardwaj [12] also showed how Rank One performed better on child faces than all other algorithms tested.

3.6 Open Biometrics Face Recognition

The Open Source Biometric Recognition (OpenBR) is a series of tools and an interface to incorporate biometric tools into end user applications [11]. OpenBr has been used in many publications and research experiments due to its mature core framework, plugin availability, and support for both open and closed source development. OpenBR was developed by MITRE corporation and was later published as open source software under *Apache 2* and is free for academic and commercial use[11].

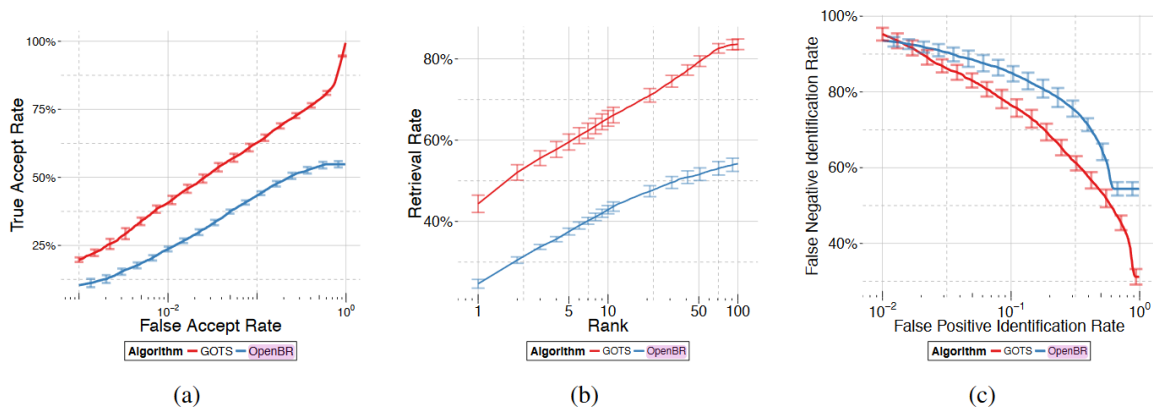


Figure 14: Benchmark recognition accuracies on the IJB-A dataset using unspecified government off the shelf face recognition algorithm and OpenBR. (A) ROC plot for the compare protocol. (B) CMC Plot for the search protocol. (C) DET Plot for the search protocol. [67]

OpenBR's face recognition algorithm is based on the Spectrally Sampled Structural Subspaces Features (4SF) algorithm [67], which is a machine learning based approach. OpenBR is designed to be a framework which could be incorporated into end products. OpenBr was tested on the IARPA Janus Benchmark A dataset which contained 500 subjects with 1,501,267 unconstrained images [67]. OpenBr had a true accept rate of 23.6% at a False accept rate of .01, underperforming against the unspecified government off the shelf solution (Figure 14). For this work, openBr was chosen for its ease of use in implementation and to compare performance against Rank One.

3.7 Testing and Evaluation

Similar to a real-world scenario, the system was tested by autonomously submitting multiple images simultaneously to the system and measuring the performance of the returned results. The dataset used for testing contained all currently missing children as of November 14th 2017 as listed on the NCMEC Amber Alert website. Twenty-four missing children were listed as of this research and were used as the gallery. All images were 500 pixels by 400 pixels with varying inter-ocular distances. Figure 15 shows some examples of enrolled gallery images.



Figure 15: Sample gallery images

Probe images were generated by taking secondary images of missing children which would sometimes be provided with each alert. The images were not of the same quality as the primary image of the sighting but often an off angle photo of the child. Out of twenty four total missing

children, only eight children had a second image provided. All images are 500 pixels by 400 pixels with varying inter-ocular distances. Inferior quality of source images meant only four of the eight probe images were usable by openBR. Rank one was able to detect six out of the 8 probe images. Figure 16 shows probe images of the same subjects as in figure eleven.

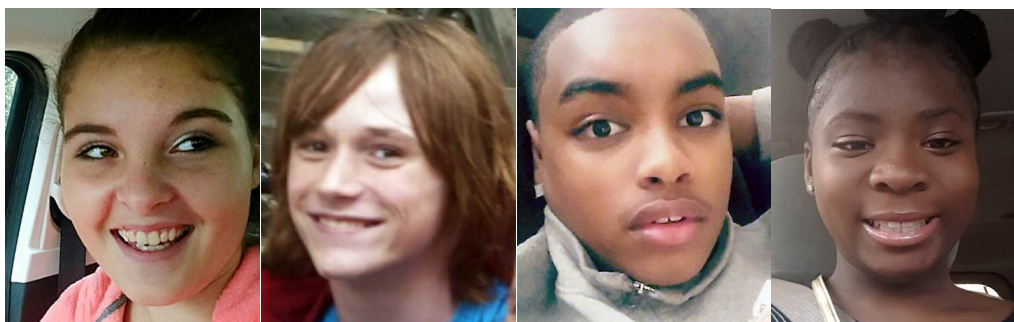


Figure 16: Sample probe images from the same subjects as the gallery images in figure 11.

Evaluation of the two recognition algorithms is measured by one of the preferred metrics for evaluating Face Recognition systems against one another with a common data corpus. Rank one scores are determined by taking the number of times the query image was returned in the top match during comparison. Rank three scores are determined by taking the number of times the query image was returned in the top three matches during comparison. The goals of these tests are to not test the effectiveness of Rank one or OpenBR, but to provide functionality testing to ensure the system is working as designed.

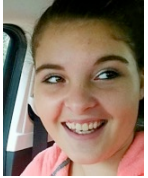

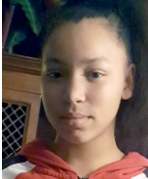

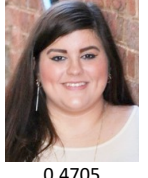



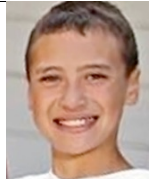





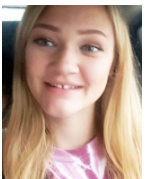



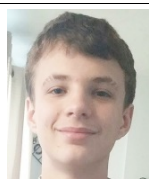



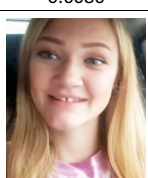
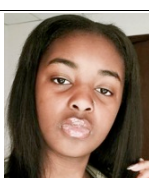

Chapter 4: Results

Table 3 displays the results of the open BR algorithm on the probe images. Five probes were able to be successfully enrolled and compare against gallery images for detection. The match scores for each match show how confident the algorithm in the match (ordered from greatest match score to least) equal to the probe subject. This table shows what a law enforcement official would use to respond to a potential sighting of a missing child. Image data is not currently emailed to the

agency due to size constraints, but the image is made available through a unique URL generated by Amber Scan during face recognition.

In a production environment, law enforcement officials would receive an email after a sighting has been submitted through the Amber Scan application. Contained in the email would be a set of scores like Table 3 where the official would have access to the names of the subjects and the match scores by each individual algorithm. They would then be able to look up the images of subjects in NCMEC's database to perform a human verification of the results if they did not have the images already. Table 3 shows what the scores would look like when matched to the corresponding image. From this table, the official may see a match score and image that warrant a response from the official.

Table 3: OpenBR results showing images used for face recognition, matches returned by OpenBRs face recognition system and corresponding match scores.

Probe Image	Correct Target Gallery Image	Match 1 + Score	Match 2 + Score	Match 3 + Score
 S1	 S1	 0.7836	 0.4962	 0.4705
 S2	 S2	 0.3046	 0.2879	 0.2442
 S3	 S3	 0.8831	 0.8068	 0.6936
 S4	 S4	 0.6086	 0.5795	 0.5193
 S5	 S5	 0.7401	 0.6906	 0.6429

To illustrate this, we can use row 1 in table 3 as an example. From the submission, the officer can see that match 1 is not the probe image submitted. However, the second match returned seems to bear some similarity to the probe image. The official uses his/her best judgement and decides the sighted missing child is indeed Subject 1 and decides to dispatch officers to the location of the sighting. This scenario illustrates the value of presenting all possible leads to law enforcement.

Even though the top match returned by the system is not correct, a secondary match with a high match score was correct.

Table 4: Rank One results showing image used for face recognition, matches returned by Rank One's face recognition system and corresponding match scores.

Probe Image	Gallery Image	Match 1 + Score	Match 2 + Score	Match 3 + Score
 S1	 S1	 0.7163	 0.3879	 0.383
 S2	 S2	 0.3743	 0.3412	 0.3393
 S3	 S3	 0.8154	 0.5158	 0.3813
 S4	 S4	 0.5921	 0.4921	 0.4873
 S5	 S5	 0.5921	 0.4941	 0.4192

During testing, Rank One's algorithm performed much better on the probe images than with OpenBR (Table 4). Four out of 5 probe images matched with the top returned gallery image. The subject that did not match with any gallery images was the same as with OpenBR indicating issues with the probe image or gallery image. Image quality was a consistent issue throughout testing and shows the issues remaining with child face recognition. OpenBR rank one score was 0.0 with Rank

One Computing rank one score of 0.80. OpenBr was not able to match the probe image as a top match in any of the test scenarios. Rank One was able to match the probe to the gallery as its top match 4 out of 5 times. Rank-three scores for OpenBR and Rank One Computing was 0.4 and 0.8 respectively. Rank three scores indicate how frequently the correct match was in the top three returned matches.

Measuring the effectiveness of the application was done by distributing the application to a small group of individuals and asking for feedback through a survey. The survey asked users to perform three tasks inside the application and rating the effectiveness of the application in two categories.

- Usefulness of the application in fulfilling the specified task.
- Ease in performing the task

Users were asked to perform three tasks in the application using the probe image of a subject. Results of the survey are shown in figure 17. The survey employed a Likert Scale from 0 to 5 with 1 defined as “Least Effective” and 5 defined as “Most Effective”. Following completion of the tasks, users were asked whether they would prefer to use the Amber Scan application or the traditional phone 911 scenario. Finally, the users were provided with a comment field to provide any feedback deemed important. Twelve users provided feedback on the application.

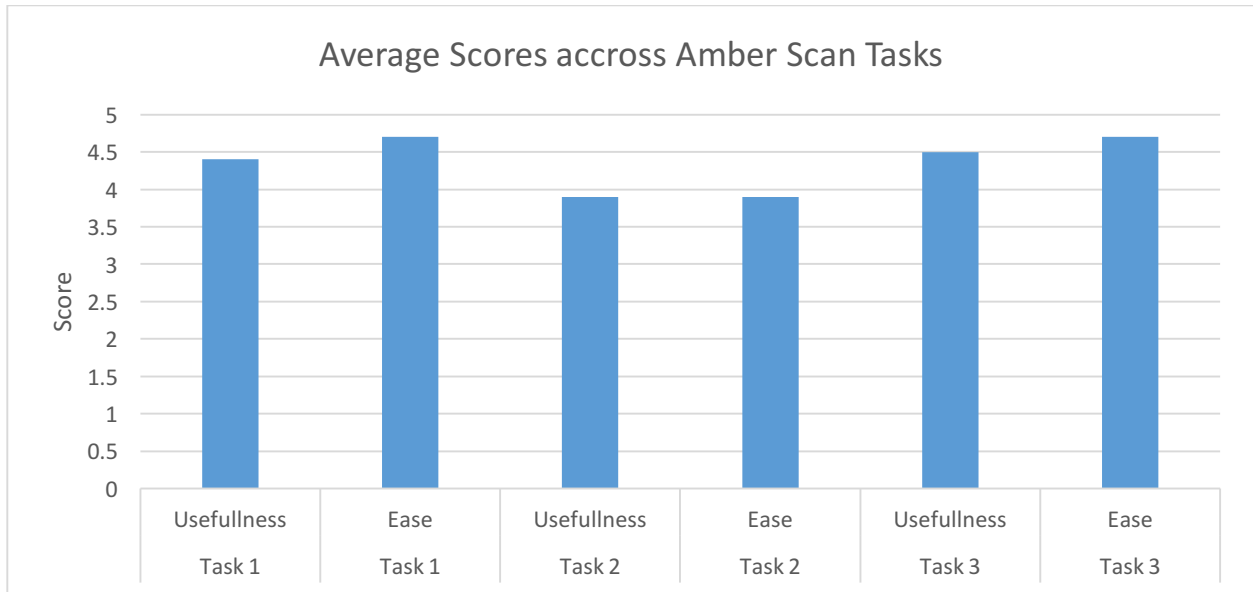


Figure 17: Results of survey measuring usefulness and ease in using Amber Scan

User comments indicated a better color scheme and control interface maybe required.

Comments such as:

- Can't click "Next" button on enter sighting information page.
- Children should be listed in "Most recent disappearance" to Oldest
- Difficulty in scrolling on missing children page
- Button to auto-fill location data based on GPS
- "It's not pretty and looks old"

All but one of the users preferred using Amber Scan to the traditional phone method of calling 911. Users expressed enthusiasm for the application and asked if it could be incorporated into their phones similar to the secondary broadcast system currently implemented.

Chapter 5: Conclusions and Future work

The goal of this work was to create a framework and application in which facial recognition technology is integrated to perform child face recognition to help locate missing children. To that

effort, the testing of the application and its parts shows a functional product that is ready for real world testing. For the small-scale testing scenario, probe faces were shown to successfully match with their gallery counter parts using one algorithm. As prior research has indicated, this algorithm may not work as well on scale and further evaluation is needed.

Feedback from users illustrated some deficiencies in the application during the completion of certain tasks. When trying to submit sighting information on the missing child, several users provided feedback illustrating difficulties in using the GUI to enter in information. This task was rated the lowest amongst all three tasks. User feedback showed the interface was clunky and would not allow the user to use the return key to submit information. Overall, the feedback was positive and indicated demand for a mobile application to submit user sightings in.

Although the system is designed to be able to incorporate any face recognition algorithm, the greatest challenge will be on the side of deployment with the user. The user will need to acquire an image of the target subject that is clear enough to perform face analysis on. Further testing needs to be performed on the viability of off angle portrait captures. Another drawback could be adoptability by the public. If the application was to be used in the real-world system, it will take a community effort to gain enough participation from the general public to make the system viable. Conversely, if enough public attention was brought to the application, it may serve as a deterrent for abductors. Potential abductors may worry about having cameras everywhere that could be used to identify the missing child.

To accommodate future work, this system creates a framework to expand the capabilities of the current Amber Alert system, a more featured application can now be developed with the capabilities to handle nation-wide emergencies. By utilizing a cloud based approach, computational servers can easily be ramped up to handle the additional load of probable thousands

of requests simultaneously. Basing the architecture on a non-synchronous RESTful system allows for easy expandability and integration of third party modules to accomplish it. Future face recognition algorithms can be easily incorporated into the analysis module and improve the quality of data delivered to law enforcement officials.

Applications in the private sector will also be possible from the development of an autonomous face recognition system specifically designed for children. In sectors where it is important to verify a child's age, this algorithm could be implemented and prevent underage viewing. An example of this is the auto-tagging feature used by many social media companies. Many of these companies have restrictions on the minimum age of its users to be able to access their systems. A reliable autonomous face recognition system can search images for under-age faces and flag them for action.

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