DEVELOPMENT AND EVALUATION OF FACIAL RECOGNITION FOR UNIQUE PATIENT MATCHING IN A RESOURCE-LIMITED SETTING

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Declaration

This thesis is my original work and has not been presented for a degree in any other University. No part of this thesis may be reproduced without prior written permission of the author and or Moi University.

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I would like to dedicate this thesis to my loving parents ...who have been my constant source of inspiration. They have given me the drive and discipline to handle life with enthusiasm and determination. Without their love and support this master's project would not have been possible.

Abstract

Proper patient identification is pivotal for day-to-day operations of health care organizations. In low-and-middle-income countries (LMICs), the lack of unique patient identifiers remains challenging. Patients often have multiple IDs, with national IDs not readily available for younger populations or foreigners. Further, the identification system for patients varies between healthcare facilities. Even when patients have identification numbers, there are numerous cases where individuals present to care without identifying documents. Patient misidentification often results in misdiagnosis and sometimes sentinel events. Historical probabilistic and deterministic matching approaches based on patient demographics have also proven suboptimal in LMIC settings. Biometric solutions offer a potential approach for unique patient identification, but these have not been rigorously evaluated within health care settings in LMICs.

The study objective was to evaluate facial recognition biometric approach for unique patient identification and matching in a resource-limited setting. The specific objectives were to develop, implement, and evaluate the performance of a facial recognition solution integrated to an Electronic Health Record system within an HIV care clinic in the Academic Model Providing Access to Healthcare (AMPATH) program in Western Kenya.

A facial recognition module, employing deep neural networks to match facial images stored in a patient demographic database, was developed within the AMPATH medical record system (AMRS). The system was programmed to take between 10 and 14 training facial images at the time of registration. The performance of the facial recognition system to identify a patient and retrieve their medical record, was evaluated using a convenient sample of adult consenting patients presenting for routine care at the AMPATH outpatient clinic. At registration, patient facial images were captured and stored in a database. At a different station within the clinic (akin to a next visit or presentation at a distinct part of the care institution), facial images for the patients were then matched against those in the database. Accuracy of facial recognition was evaluated using standard measures, namely: Sensitivity; False Acceptance Rate (FAR); False Rejection Rate (FRR); Failure to Capture Rate (FTC) and Failure to enroll rate (FTE).

A total of 103 patients (mean age 37.8; SD 13.6; 49.5% female; 7% with spectacles) were enrolled. On average 13.0 training images (SD 1.1) per participant were captured. For all participants, the system had a sensitivity of 99.0% at accurately identifying a patient. FAR for the system was <1% (0.0097), FRR was 0.00, FTC was 0.00 and FTE was 0.00. Wearing spectacles did not affect performance.

The facial recognition system correctly and accurately identified almost all patients during the first match. Care systems needing to match patients accurately should strongly consider facial recognition as a potential approach for adults, in settings without unique patient identifiers.

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Abbreviations and Acronyms

AMPATH	Academic Model Providing Access to Healthcare
AMRS	AMPATH Medical Record System
API	Application Programming Interface
ATM	Automated Teller Machine
CHIME	College of Healthcare Information Management Executives
CIO	Chief Information Officer
CPR	Computer-based Patient Record
DCT	Discrete Cosine Transform
DNN	Deep Neural Network
EHR	Electronic Health Record
FAR	False Acceptance Rate
FRR	False Rejection Rate
FTC	Failure to Capture
FTE	Failure to Enroll
HI-TRAIN	Health Informatics Training and Research in East Africa for Improved Health Care
HIE	Health Information Exchange
HIT	Health Information Technology
HIV	Human Immunodeficiency Virus
IBMI	Institute of Biomedical Informatics
ID	Identifier
IDE	Integrated Development Environment
IEEE	Institute of Electrical and Electronics Engineers
IP	Internet Protocol

LDA Linear Discriminant Analysis

LMIC Low and Middle Income Country

MPI Master Patient Index

MTRH Moi Teaching and Referral Hospital

NORHED Norwegian Programme for Capacity Development in Higher Education and Research for Development

OCR Optical Character Recognition

OpenMRS Open Medical Record System

PCA Principle Component Analysis

PIN Personal Identification Number

ROC Receiver Operating Characteristic

TSNE t-Distributed Stochastic Neighbor Embedding

UPI Unique Patient Identification

Definition of Terms

1. **Unique Patient Identification.** Refers to approaches that are in place to ascertain to a certain degree that a patient is truly who they say they are.
2. **Biometrics** Automated recognition of individuals based on their biological and behavioural characteristics.
3. **Neural Network.** A neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates.
4. **Machine Learning.** Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed.
5. **Deep Neural Network.** A deep neural network (DNN) is an artificial neural network (ANN) with multiple layers between the input and output layers.
6. **OpenMRS.** OpenMRS is a software platform and a reference application which enables design of a customized medical records system with no programming knowledge (although medical and systems analysis knowledge is required).

Chapter 1

Introduction

1.1 Unique Patient Identification

Patient Identification is important for health care organizations' day to day operations.(Robert Wood Johnson Foundation, 2012; Sweeney, 2013; Waruhari et al., 2017) It forms the basis of operations such as the delivery of care to patients, administrative processes and decisions, support services, record keeping, health care information management, and follow-up and preventive care.(Grissinger, 2008; Harris and General, 2013) Recent changes taking place in our global and national health care delivery systems and in the computer and telecommunication technologies have presented numerous application options and expanded the scope of these functions across multiple organizations.(Uddin et al., 2018; United States Government, 2011)

Given that patients visit multiple providers and are treated by multiple organizations, it is necessary to uniquely identify patients across multiple institutions, to ensure appropriate information can be availed for care.(CHIME, 2012; Joffe et al., 2012; Scott, 2013) Unique Health Identifiers establish a comprehensive framework to facilitate exchange of information, access to healthcare, continuity of care, evaluation of quality improvement, outcome measurements and population-based healthcare.

Most providers in the LMIC health care setup are faced with uniquely identifying patients for care, as not all individuals have the existing identification methods, like, national IDs, lack of a cross-cutting identifier from one provider to another, and the inadequacies of probabilistic and deterministic methods used in matching. This research aimed at making an input in the ever-growing research area of Unique Patient Identification.

1.2 Biometric Technology

Biometrics is a technique that uses computers for identifying people by using a unique physiological characteristic, such as face, iris, fingerprint, eye, *etc.* or behavioural characteristics, like voice and signature.(Kasar et al., 2016) Today, in a fully digital era, a number of applications use individual recognition techniques that have a basis on the identification of these unique physiological and behavioral characteristics including justice, civil as well as military applications. In fact, the way to conclusively identify an individual is to recognize the personal characteristics of that individual.(Daleno et al., 2012)

In comparison to conventional methods that base on "what we own" (such as a card) or "what we know" *(such as a pass phrase)*, biometrics continue to offer promise in the area of Unique Patient Identification. Primarily based on "what we are" *(like in the case of facial recognition, fingerprint)* and "how we behave", biometric authentication provide better security because individual characteristics are usually difficult to copy in comparison to methods like passwords.(Abed et al., 2012) Facial recognition's non-invasive nature puts the technology among the top behavioural characteristics used.

The most common approaches evaluate the following features:

1. Fingerprints: The oldest and most widely used approach due to somewhat low implementation and maintenance costs.(Miller, 1994)

2. Iris: supports remove noninvasive identification. Iris recognition hinges mainly on the highly distinctive spatial patterns of an individual human iris for verification and identification of people.(Shen and Khanna, 1997)

3. Retina Vasculature: Also unique to the human eye is the layer of blood vessels situated at the back of the eye, the retina. Generally regarded as the most secure biometric method(Cavoukian, 1999). These methods use scanners to compare the blood vessels in the eye.

4. Hand Geometry: Currently among the most widely used and they measure and analyze the overall structure, shape and proportions of the hand including length, width and thickness of the hand, fingers and joints. It may also include characteristics of the skin surface area such as creases and ridges.(Holmes et al., 1991)

5. Vocal Timbre: Known also as "speaker recognition" and uses an individual's voice for verification and recognition. It is based on the unique individual acoustic features of speech.(Adeoye, 2010)

This research focused on the biometric application using the human face for recognition. Face recognition is one of the biometric approaches that combines the advantages of both high accuracy and low intrusiveness. The accuracy is due to the physiological approach and its low intrusive nature has drawn attention of researchers in different fields including security, psychology, computer vision, and now health care.(Kasar et al., 2016)

1.3 Face Biometrics

As an important alternative for selecting and developing an optimal biometric system, facial recognition that bases on the human face is considered because of its non-intrusive nature. It does not require physical contact with an image capturing device (camera) or advanced hardware components. Research further highlights that facial biometrics should be considered as a serious alternative in the development of biometric or multimodal/multi-biometric systems.(Adeoye, 2010)

1.4 Facial Recognition

Facial recognition, which involves recognition of facial features, remains perhaps one of biometric technologies more fascinating and psychologically considered by users as less hideous.(Adeoye, 2010; Salter, 2010) Facial recognition systems are based on physical characteristics of the face and remain the closest, in theory, to the human concept of "personal recognition".

The user's acceptance of the feature-based recognition is generally high, because the non-invasive nature of the acquisition method is maintained.(Adeoye, 2010; Uddin et al., 2018) Figure 1.1 shows a screen shot portraying the non intrusiveness of facial recognition of a human user. As suggested by Marques(O'Toole et al., 2007), overall face recognition techniques and the emerging methods can see use in other application fields. Therefore, it is not just an unresolved problem but also the source of new applications and challenges.

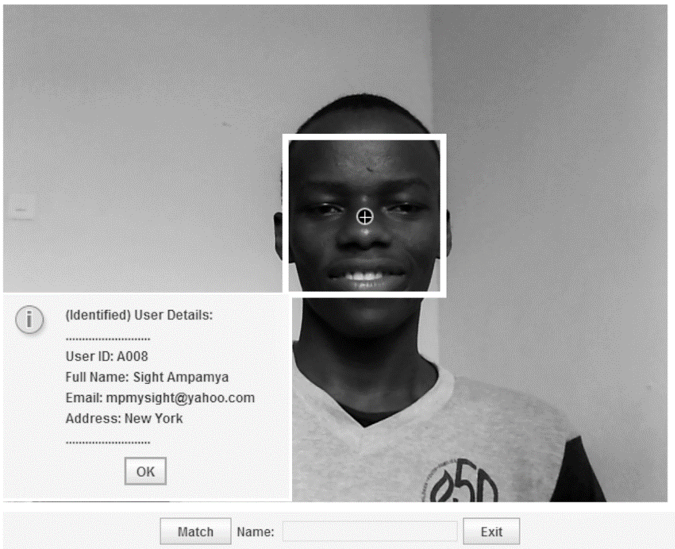


Figure 1.1 A computer recognized human face screenshot

1.5 Problem Statement

Throughout the health-care industry, correctly identifying patients continues to be a challenging problem.(Appavu, 1997; Morris et al., 2014; Reporting and Service, 2005; Robert Wood Johnson Foundation, 2012) With the increasing need for devolution of care in Low-and-middle-income settings (LMICs) to ensure affordable, suitable, and efficient care to the common man, there is need to correctly identify the Low-and-middle-income settings (LMICs) patient.(Parisi, 2003) A solution that befits the qualities: affordable, suitable and efficient would be a great addition in ensuring a generally healthy local population.

UPIs do not exist in most health settings especially Low-and-middle-income settings (LMICs). In countries such as Uganda and Kenya, not everyone has a national ID as a result of restrictions on issuing of these IDs for example they are only given after one is 18 years of age and sometimes not given to foreigners, among other issues. This is a major challenge to Unique Patient Identification.(Parisi, 2003)

Additionally, health care institutions often use different ID systems and sometimes multiple types of IDs for their patients. As a major threat to Health Information Technology (health-IT) integration, this, poses redundancy risk in form of duplicate records, and difficulty to link patient health information across the health care continuum. Probabilistic and deterministic data matching methods that are also used, fall short because of their inadequacies. In deterministic matching, either unique identifiers for each record are compared to determine a match or an exact comparison between fields. It is generally not reliable since in some cases no single field can provide a reliable match between two records. Probabilistic matching, in which several weighted field values are compared between two records falls short on its key component where achieving accurate matching depends greatly on linking together user profiles that contain the same highly specific pieces of information. It is, therefore, not a solution to Unique Patient Identification since UPI aims at providing the highest specific piece of information about the patient.

The percentage consequences of such approaches in our health care systems set ground for irrevocable future prompt drawbacks. In his final report, Analysis of Unique Patient Identifier Options, *Soloman I. Appavu*, argues, “The necessary technology and processes to issue, maintain and use the Biometric Identifiers are available but, considered expensive, time consuming and cumbersome.”(Appavu, 1997) This notion is only but a misrepresentation, and half representation of what biometric technology actually offers even in resource limited settings. Fortunately, recent technological interventions, research, and strategies have combined effort to address these inconsistencies.

While there is renewed promise of biometric identification approaches, there is lack of evidence of their application in health care settings within Low-and-middle-income settings (LMICs). There is also need for low cost, secure, efficient, accurate biometric identification systems. The study, therefore, focused on addressing this gap.

1.6 Objectives

1.6.1 Main Objective

The main objective was to develop and evaluate the use of facial recognition for patient matching in a resource limited setting.

1.6.2 Specific Objectives

1. Development and Implementation of a facial recognition solution integrated to an Electronic Health Record system for use within clinical settings in Low-and-middle-income settings (LMICs).

2. Assessment of performance of the facial recognition technology within an LMIC clinical setting.

1.7 Scope

Early facial recognition algorithms used simple generic models but the recognition process has now matured into a science of sophisticated mathematical representations and matching processes. In its implementation this research focuses on the following highlighted areas.

1.7.1 Adaptation of existing techniques

Most health care settings in LMICs still use methods like Patient IDs to uniquely identify patients. Implementation of these methods that employ methods like Name Comparison Techniques and UPIs continue to suffer drawbacks in scalability and interoperability(Waruhari et al., 2017). However, these methods are still reliable in organizational information handling and reporting purposes. The research therefore adapts existing techniques seeking to strengthen them with an additional approach.

1.7.2 Integration into OpenMRS

The research also recognizes that a Unique Patient Identifier plays an indispensable role as interoperability key.(Appavu, 1997; Erin, 2013) The research developed and used an OpenMRS module to explore integration advantages of the open-source system whose implementation in LMICs has shown promise.

1.7.3 Implementation within an LMIC clinical setting

The results of the research were conducted within a Low-and-middle-income setting. This was aimed at the initial objective of the research which is to evaluate the performance of the Biometric system in a low-resource setting.

1.8 Justification

There is a big problem with uniquely identifying and matching patients in the health sector.(Appavu, 1997; Morris et al., 2014; Robert Wood Johnson Foundation, 2012) Current patient matching approaches are suboptimal given the need to rightly identify and match patient data including their electronically protected health information (e-PHI). There is, therefore, need for a patient matching approach that is non-intrusive, affordable, and accurate. Such an approach would fit the health sector in low-resource settings.

Furthermore, facial recognition approaches have not been broadly tested within the healthcare setting and little research points to implementations of facial recognition systems that fit well within the clinical work-flow of Low-and-middle-income country settings. Performance of facial recognition systems within LMIC setting clinical work-flows is also not well known.

This work, therefore, aimed at providing research based answers to one of health care's biggest challenges - Unique Patient Identification within a resource-limited setting.

1.9 Significance

“If you cannot uniquely identify your patients within whatever data you’re analyzing, you’re going to misread and therefore make executive decisions that are not spot-on.”(Scott, 2013) Patient misidentification further leads to big strategic and grave mistakes.

Unique Patient Identification is necessary to facilitate accurate and comprehensive care. The critical barrier in the health care setting is lack thereof of a crosscutting Unique Patient Identifier. Different health care providers use organization-specific identifiers and IDs to treat patients and this makes interoperability and sharing of patient information across organizations a challenge.

The research focused on minimizing the costs involved in implementation of such systems and provided scientific insight into the challenges of implementing facial biometrics in resource-limited settings. The non-intrusive nature of the research approach was also a major highlight making privacy, which is a major health concern, addressable.

1.10 Research Questions

Patient matching is a complex problem; therefore, improvements will be multifaceted and incremental with no single solution or step that is final. There is, as yet, no silver bullet, no one-size-fits-all solution for the patient identification matching problem. Research into improvements of this solution or more so adaptation to better solutions are an area future research could focus on.

1. Can the current Identity Crisis in the medical sector be better addressed?
2. Statistical versus Unique Patient Identifier (UPI) matching approaches comparing:
   - Potential for errors
   - Operating Issues i.e. ambiguity, dis-ambiguity
   - Costs
3. Can this approach provide additional knowledge in terms of implementation detail analysis in the field of Unique Patient Identification especially in a resource limited setting?

Chapter 2

Review of Literature

2.1 Introduction

Accurate identification and matching of patient records is pivotal for ensuring patient safety as records are stored and exchanged electronically. For instance, one fifth of CIOs surveyed by College of Health care Information Management Executives (CHIME) indicated that at least one patient in the last year suffered an adverse event, due to mismatched records.(CHIME, 2012) Other studies have found an association between duplicate patient records and lab results not being reported to patients to receive adequate follow-up care.(Joffe et al., 2012) As the use of EHRs and electronic exchange of patient data has increased and accurately identifying and matching patient records has been recognized as a major challenge to the industry, many organizations (both public and private) and industry leaders have researched and evaluated patient record matching challenges. The result is a growing body of research on the subject.

Facial recognition is one of the most relevant applications of image processing(Brodsky et al., 2012). Reliable facial recognition has long been an attractive goal. "The strong demand for user friendly systems which can secure our assets and protect our privacy without losing our identity in a sea of numbers is obvious. At present, one needs a PIN to get cash from an ATM, a password for a computer, and other to access the Internet and so on."(Brodsky et al., 2012) A personal identification system based on images of the face is non-intrusive as compared to fingerprint scans or retinal analysis and thus makes face recognition user friendly. It should be noted that with the advances in multimedia use even in the health sector, as well as Internet Protocol (IP) technologies, the possibility and need for applying face recognition technology has been long imminent.

Dealing with faces presents loads of difficulties that come with the several facial shapes due to the different social expressions of human beings. Face recognition comes with problems of large computation complexity and memory storage(Jamil et al., 2001; Kasar et al., 2016). Face recognition involves face detection, classification and feature extraction.(O'Toole et al., 2007) The question first asked is how the brain is even able to detect that people are different thus looking for design inspiration. This knowledge would then be applied to the design of such and more programs.

2.2 Background

Information technology has changed the way medical record information is stored and retrieved. Computer-based Patient Records (CPRs) have the unique potential to improve the care and well-being of both the individual and the population as a whole. They link an individual's clinical records created by different providers, sites of care and episodes. Computer and communication technologies enable aggregation of information from CPRs across organizational boundaries to facilitate population-based research, planning and improvement. In order to facilitate the linkage of various clinical records from different care settings and times, and across institutional boundaries, health care organizations and computer systems, a valid and reliable patient identification method is required. An identifier that uniquely identifies an individual is a Unique Patient Identifier (UPI).

The African health care setting continues to suffer major drawbacks resulting from its inefficiency of delivering the right care to the right patient. While the system continues to steadily embrace technology use in the health care setting, its lack of a more organized approach from the leading shareholders in the industry continues to leave both the local health care providers and the common man in a dilemma.

Because patient misidentification is identified as a root cause of many errors, the Joint Commission, in the United States of America, listed improving patient identification accuracy as the first of its National Patient Safety Goals introduced in 2003, and this continues to be an accreditation requirement.(Parisi, 2003)

Compared to the western system, the African health care system and setting continues to operate in a resource limited, remote setup. The typical African patient does not always have reliable access to medical care and therefore government initiatives through mass population exercises continue to be a common trend to provide affordable health care to the common man. This has led to more research on how to solve the unique patient identification puzzle.

Technology has caught up, with recent trends in the field presenting exploration into areas like bar coding and finger print technology that are aimed at improving patient identification. Some of these have proved to be cost-effective. Regardless of the technology or approach used for accurately identifying patients, careful planning for the processes of care will ensure proper patient identification prior to any medical intervention and proper, safer care with significantly fewer errors.

2.2.1 Historical Background

Patient identifiers are vital for health care organization's day to day operations such as the delivery of care, administrative processes, support services, record keeping, information management, and follow-up and preventive care. The recent revolution, taking place in our national health care delivery system and in the computer and telecommunication technologies, has expanded the scope of these functions across multiple organizations spread around the nation. In addition, patients are mobile, visit multiple providers and are treated by multiple organizations. This, and many other reasons, have created the need to ensure the right care is given the right patient. Therefore, to support the continuum of care, it is necessary to uniquely identify patients across multiple providers and access their information from multiple locations.

The current method of patient identification involves use of a medical record number, issued and maintained by a practitioner or a provider organization. This number is based on an institutional Master Patient Index (MPI) and the numbering system is specific to the issuing organization. Different provider organizations use different numbering systems. Patients receive multiple Medical Record Numbers, each issued by the organization that provided them care. These numbers provide unique identification only within the issuing organization. A Patient Identifier that is unique only within a provider organization or a single enterprise is inadequate to support the national health care system. In order to uniquely identify an individual across multiple organizations, a reliable Unique Patient Identifier is required. It is this gap that this research aimed to make an input.

2.2.2 Conceptual Background

Like almost everything associated with the human body - the brain, perceptive abilities, cognition and consciousness, facial recognition in humans remains a marvel. One such task is how the brain handles identification and recognition. This research work focused on the use of digital facial recognition to improve health care administration.

The human face changes with respect to internal factors like facial expression, beard, mustache, glasses and is sensitive to external factors like scale, lighting conditions, and contrast between face, background and orientation of face. This makes face detection and identification a challenge to enable on a computer, mobile phone or even an ordinary personal digital assistant. It is with this background knowledge that face detection and identification remains an open challenge.

As earlier noted, to uniquely identify an individual across multiple organizations, a reliable unique patient identifier is a requirement. The Unique Patient Identifier will at minimum be expected to perform and support four basic functionalities:(Appavu, 1997)

1. Positive identification of the individual:
    - For delivery of care (e.g. diagnosis, treatment, blood transfusion and medication)
    - For administrative functions (e.g. eligibility, reimbursement, billing and payment)
2. Identification of information:
    - Identification to access patient information for prompt delivery of care, coordination of multi-disciplinary patient care services during current encounters and communication of orders, results, supplies, etc.
    - Organization of patient care information into a manual medical record chart or an automated electronic medical record for both current and future use

- Manual and automated linkage of various clinical records pertaining to a patient from different practitioners, sites of care and times to form a lifelong view of the patient's record and facilitate continuity of care in the future
- Aggregation of information across institutional boundaries for population-based research and planning

3. Support the protection of privacy and confidentiality through, accurate identification (explicit identification of patient information) and dis-identification (mask/encrypt/hide patient information)
4. Reduce healthcare operational cost and enhance the health status of the nation by supporting both automated and manual patient record management, access to care and information sharing.

These functionalities will provide the research ground work for analysis of the facial recognition approach as a method for Unique Patient Identification in a resource limited setting.

2.2.3 Contextual Background

The proposed invention would relate to a system and method for unique facial patient identification and adaptable transformative clinical care. More particularly, the presented invention relates to a patient identification system and method providing for accurate identification of a patient and for relating items to a patient and ensuring that patient specific items do properly correspond to a patient, thereby providing for accurate medical treatment, billing and inventory and cost control.

Medical institutions are presently faced with a competitive environment in which they must improve profitability and yet simultaneously improve patient care. There are several factors which contribute to the ever increasing costs of hospital care. In the current system, for example, there is an ever increasing amount of paperwork required by nurses, pharmacists and laboratory personnel. Additionally, inaccurate recording of drugs, supplies and tests involved in patient care results in decreasing revenues by a failure to fully capture billing opportunities of these actual costs. Inadequate management also results in a failure to provide an accurate report of all costs involved in treating a particular illness.

In most advanced hospitals and clinical laboratories, a bracelet device containing the patient's name is permanently affixed around the arm of an incoming patient. This is done so as to identify the patient during his or her entire stay. Despite this, numerous situations arise which result in errors in patient identification. But even then, this solution is not perfect. Between November 2003 and July 2005, the United Kingdom National Patient Safety Agency reported 236 incidents and near misses related to missing wristbands or wristbands with incorrect information.(Reporting and Service, 2005) Other facilities still rely entirely on the memory of the attendant and a simple recall mistake will cause devastating results.

For example, when a blood sample is taken from a patient, the blood sample must be identified by the name on the patient's bracelet. In transferring the patient's name, a nurse or technician may miscopy the name or may rely on memory or a different data source, rather than actually reading the patient's bracelet.

Moreover, the lack of accurate and rapid transfer of patient information often reduces the accuracy and/or effectiveness of drug administration and patient care, thereby increasing the duration of hospital stay. In our limited resource setting - East Africa to be specific - this continues to be a main challenge in health care delivery.

In addition, hospitals and other institutions must continuously strive to provide quality patient care. Medical errors, where the wrong patient receives the wrong drug at the wrong time, in the wrong dosage or even the wrong surgery, are a significant problem for all health care facilities. Many prescription drugs and injections are identified merely by slips of paper on which the patient's name and identification number have been handwritten by a nurse or technician who is to administer the treatment. For a variety of reasons, such as the transfer of patients to different beds and errors in marking the slips of paper, a patient may be given an incorrect treatment. Further, as health care facilities continue to decrease the number of staff personnel as a cost cutting measure, as is the case in Uganda and Kenya, the possibility of personnel errors will most likely increase.

The present invention offers a system which attempts to bridge the impact gap of the above-identified problems and other problems associated with health care facilities. The malady of Unique Patient Identification is an area into which further research remains open.

2.3 Development Through History

Face recognition remains one of the most relevant applications in the image analysis field. An automated system that can emulate the human capability to recognize faces is desirable but continues to challenge researchers and implementers. Although humans are quite good at identifying known faces, we are not very skilled when we must deal with data that involves a large amount of unknown faces. Conversely, computers are well equipped for this particular task; with their almost limitless memory and computational speed, they overcome this among other human limitations.

Face recognition remains an unsolved problem and demanded technology(O'Toole et al., 2007) - see Table 2.1. A simple search with the phrase "face recognition" in the IEEE Digital Library throws 23,526 results. 2,128 articles in only the year - 2015. It is evident that the different industry application areas interested in what the biometric technology could offer have risen over time.

Information technology has changed the way medical record information is stored and retrieved. Computer-based Patient Records (CPRs) have the unique potential to improve the care and well-being of both the individual and the population as a whole. They link an individual's clinical record created by different providers, sites of care and episodes. Computer and communication technologies enable aggregation of information from CPRs across organizational boundaries to facilitate population-based research, planning and improvement. In order to facilitate the linkage of various clinical records from these different care settings and times, across institutional boundaries, health care organizations

Areas	**Applications**
Information Security	Access security (OS, data bases) Data privacy (e.g. medical records) User authentication (trading, online banking)
Access Management	Secure access authentication (restricted facilities) Permission based systems Access log or audit trails
Biometrics	Personal identification (national IDs, Passports, voter registrations, driver licenses) Automated identity verification (border controls)
Law Enforcement	Video surveillance Suspect identification Suspect tracking (investigation) Simulated aging Forensic Reconstruction of faces from remains
Personal Security	Home video surveillance systems Expression interpretation (driver monitoring system)
Entertainment - Leisure	Home video game systems Photo camera applications

Table 2.1 Applications of facial recognition *(Carrera, P., 2010, p. 5)*

and computer systems, a valid and reliable patient identification method is required. An identifier that uniquely identifies an individual patient is what is referred to as a Unique Patient Identifier (UPI).

2.4 Face Recognition System Structure

2.4.1 A Generic Face Recognition System

The input of a face recognition system is always an image or video stream. The output involves identification or in some cases verification of the subject or subjects that appear in the image or video. Some approaches(Zhao et al., 2003) define a face recognition system that involves a three step process - see Figure 2.1.

Figure 2.1 A generic face recognition system

Face detection is defined as the process of extracting faces from scenes and therefore involves identification of a certain given image region as a face. This procedure has many applications like face tracking, pose estimation or compression.

Feature extraction involves obtaining relevant facial features from the data. These features could be certain face regions, variations, angles or measures, which are human relevant (for example, eye spacing). Facial feature recognition and emotion tracking are some of the applications of feature extraction. The final step is recognizing the face. In an identification setup, the system reports a matching identity from a database. This particular phase involves a comparison method, a classification algorithm and a corresponding accuracy measure.

2.5 Face Detection

In recent times some applications of Face Recognition do not require face detection as an initial step. In some cases, face images are stored in the data bases in an already normalized form. There is a standard image input format, hence no need for a detection step. However, in a health care setting but also as noted, the conventional input image of computer vision systems are not that suitable and contain many items or faces.(O'Toole et al., 2007) So it is only reasonable to assume face detection as part of the more ample face recognition problem.

Face detection remains a very challenging step of the process. It must deal with several well know challenges.(Zhao et al., 2003) These usually come about as a result of images captured in uncontrolled environments, such as surveillance video systems. These challenges can be attributed to some well-known factors:

- **Pose variation**. The ideal case scenario for facial detection would be one in which only frontal images were involved. But, in practical cases, this is only another challenge because of the generally uncontrolled nature of the conditions. It is key to note that this severely drops the performance of face detection algorithms in cases of large pose variations. Pose variations are majorly due to the subject's movements or camera's angle. More research is needed in this area.

- **Feature occlusion**. This refers to the presence of elements like beards, glasses or hats that in turn introduce high variability in the images. In addition, faces can also be partially covered by objects or even other faces.

- **Facial expression**. Human beings tend to express their moods sometimes by expressing their faces in varying ways. Facial features can vary greatly because of different facial expressions.

- **Imaging conditions**. Different cameras give different image outputs. Ambient conditions can also affect the quality of an image, which affects the appearance of a face.

There are some problems that relate closely to face detection besides feature extraction and face classification. An example that aims at determining the location of a face in an image where there is only one face is face location. Facial feature detection hinges generally on detecting and locating some relevant features, such as the nose, eyebrow, lips, ears etc. Another problem that comes about as a result of face detection is face tracking. Many systems focus not only to detect a face, but to be able to locate this same face in real time.

2.5.1 Face Detection Problem Structure

The face detection concept includes many sub-problems. Some systems detect and locate faces at the same time, while others first perform a detection routine and then, if positive, they try to locate the face. At this point face tracking algorithms may be deployed - see Figure 2.2.

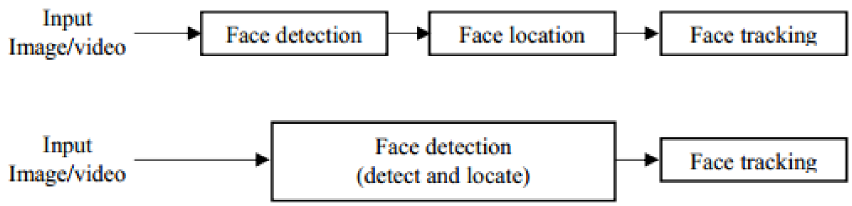


Figure 2.2 Face Detection Processes *(Carrera, P., 2010, p. 10)*

Face detection algorithms share some common operational steps. First of all, some data dimension reduction is done, in order to achieve an admissible response time. Pre-processing can also be done at this stage to adapt the input image to the algorithm prerequisites. Other parts of the algorithm analyze the image in its current state while other parts try to extract certain relevant facial regions to be used in the process.

2.5.2 Approaches to Face Detection

There are no globally acceptable grouping criteria of face detection methods. This in part is due to the face that they usually mix, overlap or do both. Ion(O'Toole et al., 2007) presents two classification criteria that is one that differentiates between distinct scenarios; which given the different scenarios applies varying approaches, and another criteria that divides the detection algorithms into four categories as highlighted below.

Detection depending on the scenario.

1. Controlled environment. It is the most straightforward case. Photographs are taken under controlled light, background, etc. Simple edge detection techniques are then used to detect faces.

2. Color images. The typical skin colors can be used to find faces. These are usually weakened whenever light conditions alter. Human skin color changes a lot, from nearly white to almost black. But, several studies show that the major difference between the two extremes lies between their intensity, making chrominance a good feature.

3. Images in motion. Real time video gives the chance to use motion detection to localize faces. Most commercial systems of late must locate faces in videos. The challenge continues to be achieving best detection results with the best possible performance.

Detection methods divided into categories
Yang, Kriegman and Ahuja(O'Toole et al., 2007) presented a well-accepted classification. Methods are divided into four categories which may overlap hence an algorithm may belong to two or more categories.

1. Knowledge-based methods. Rule-based methods that encode our knowledge of human faces.

2. Feature-invariant methods. Algorithms that try to find invariant features of a face despite its angle or even position.

3. Template matching methods. These are algorithms that compare input images with already stored patterns of faces or features to find a best match.

4. Appearance-based methods. This category describes a template matching algorithm whose pattern is learnt from a set of training methods.

2.6 Feature Extraction

Humans can easily recognize faces from as early as about five years of age. More fascinatingly, we are able to recognize people we know, even with some slight changes like wearing glasses or hats. We still can recognize men who have grown beards or even recognize a younger photo of a person who is now older despite the visible changes. While humans can do this with very little or no effort, this seemingly trivial process continues to be a challenge in the computing arena. In fact, face recognition's core problem is to extract information from photographs.(O'Toole et al., 2007) The feature extraction process can be defined as the procedure of extracting relevant information from a face image. This information obtained in this stage is invaluable to the later step of identifying the subject with an acceptable error rate. The feature extraction process must be efficient in terms of computing time and memory usage. The output should further be optimized for the classification step.

Feature extraction involves several steps - *dimensionality reduction*, which is an essential task in any pattern recognition system. Additionally, *extraction* involves feature extraction and feature selection steps. These steps may overlap, and dimensionality reduction could sometimes be looked at as a consequence of the feature extraction and selection algorithms.

2.6.1 Feature Extraction Methods

Researchers in face recognition have used, modified and adapted many algorithms and methods for feature extraction. In fact, most of them are used in other areas rather than face recognition. Marques,(O'Toole et al., 2007) presents a summary of the methods.

2.6.2 Feature Selection Methods

Feature selection algorithms aim at being able to select a subset of the extracted features that cause the smallest classification error. The importance of this error is what makes feature selection dependent on the prior classification method used. The viable solution and approach to this problem would be to examine every possible subset and choose the one that fulfills the criterion function. This approach, however, can become an expensive one in terms of algorithm computational time. As this is a research problem, researchers usually opt for a satisfactory algorithm rather than an optimum one which involves creating

Method	Notes
Principal Component Analysis (PCA)	Eigenvector-based, linear map
Kernel PCA	Eigenvector-based, non-linear map, uses kernel methods
Weighted PCA	PCA using weighted coefficients
Linear Discriminant Analysis (LDA)	Eigenvector-based, supervised linear map
Kernel LDA	LDA-based, uses kernel methods
Semi-supervised Discriminant Analysis (SDA)	Semi-supervised adaptation of LDA
Independent Component Analysis (ICA)	Linear map, separates non-Gaussian distributed features
Neural Network based methods	Diverse neural networks using PCA, etc.
Multidimensional Scaling (MDS)	Nonlinear map, sample size limited, noise sensitive.
Self-organizing map (SOM)	Nonlinear, based on a grid of neurons in the feature space
Active Shape Models (ASM)	Statistical method, searches boundaries
Active Appearance Models (AAM)	Evolution of ASM, uses shape and texture
Gavor wavelet transforms	Biologically motivated, linear filter
Discrete Cosine Transform (DCT)	Linear function, Fourier-related transform, usually used 2D-DCT
MMSD, SMSD	Methods using maximum scatter difference criterion.

Table 2.2 Summary of Feature Extraction Methods

an algorithm that selects the most satisfying feature subset, minimizing the dimensionality and complexity.

2.7 Face Classification

Once the features are extracted and selected, the next step involves classification of the image. Algorithms that make a basis on appearance are mostly used in a variety of classification methods. In some instances, two or more classifiers are combined to achieve better results. However, most model-based algorithms match the given samples with the model or template. A learning method is then used to improve the algorithm's efficiency. Face recognition is largely affected by classifiers.

Classification algorithms usually involve some learning - they can be, supervised, unsupervised or semi-supervised in nature. The most difficult approach to implement is the unsupervised learning, as there are no tagged examples. In layman's terms, in unsupervised learning no datasets are provided, instead the data is clustered into different classes. This is contrary to most face recognition applications which include a tagged set of subjects. To this effect, most face recognition systems implement supervised learning methods. In this research a set of training images of the patient was used, hence unsupervised learning.

2.7.1 Classifiers

According to Jain, Duin and Mao,(Matas et al., 2002) there are three concepts that are key in building a classifier - similarity, probability and decision boundaries. A brief overview of these concepts is presented below.

Similarity
This approach is instinctive and simple. Basically patterns that are similar should belong to the same class. Late implementations of face recognition algorithms employ this approach. The idea is to establish a metric that defines similarity and a representation of the same-class samples. For example, the metric used can be the euclidean distance. The representation of a class can be the mean vector of all the patterns belonging to this class. It's classification performance is usually good. This approach is similar to the *k-means* clustering algorithm(Ng et al., 2006) in unsupervised learning.

Probability
Some classifiers are built based on a probabilistic approach. Bayes decision rule is often used. The rule can be modified to take into account different factors that could lead to mis-classification. Bayesian decision rules can give an optimal classifier, and the Bayes error can be the best criterion to evaluate features.

Decision Boundaries
This approach can become equivalent to a Bayesian classifier. It depends on the chosen metric. The main idea behind this approach is to minimize a criterion (a measurement of error) between the candidate pattern and the testing patterns.

2.7.2 Classifier Combination

The classifier combination problem can be defined as a problem of finding the combination function accepting N-dimensional score vectors from M-classifiers and outputting N final classification scores.(Tulyakov et al., 2008) There can be several different reasons to combine classifiers in a face recognition implementation.(O'Toole et al., 2007)

1. The designer has some classifiers, each developed with a different approach. An example is a classifier designed to recognize faces using iris templates. This could be combined with another classifier that uses another recognition approach. In most cases, this leads to better recognition performance.

2. There are instances which deploy different training sets, collected in different conditions and representing different features. A different classifier could be used on a certain training set or the classifiers combined.

3. A single training set could also show different results when using different classifiers and a combination of classifiers could be used for best results.

4. Some classifiers differ in their performance even computational performance. This is as a result of dependencies on certain initializations. Instead of choosing one classifier, a combination of some of them could be used. This usually boosts performance.

Several combination schemes exist and while they may differ from each other in their architectures and the selection of the combiner, in pattern recognition, combiners usually use a fixed number of classifiers.

2.8 Face Recognition: Neural Network Approach

Face recognition is an evolving, and promising area, changing and improving constantly. The diversity of recognition approaches bases on the many implementations that are affected by face recognition - computer vision, optics, pattern recognition, neural networks, machine learning, psychology, etcetera. This research focused on the deep neural network implementation approach to the facial recognition problem.

Because of their trainable nature, artificial neural networks are a popular tool in facial recognition. They have been used in pattern recognition and classification. Kohonen(Kohonen, 1988) was the first to demonstrate that a neuron network could be used to recognize aligned and normalized faces. And researchers have since proposed many and different methods based on the neural network approach. Some other implementations use neural networks just for classification.

2.8.1 Deep Neural Networks

In today's top-notch applications of facial recognition techniques, two convolutional approaches of neural networks stand out. Facebook's DeepFace(Taigman et al., 2014) and Google's FaceNet(Schroff et al., 2015) systems continue to yield the highest accuracies.

Because of their trainable nature, Neural Networks offer acceptable options in this researchable area. Deep neural networks, though often harder to train than shallow neural networks have proved their worth in areas like cognitive applications where they are used to recognize handwritten digits as seen in Optical Character Recognition (OCR) applications.

The ever-changing nature of the health care sector needs, including patient problems like loss to follow up, will require an approach like the thriving field of neural network-based face recognition. This approach suggests such a solution that combines the advantages of open source technology to provide a solution that will not burden the intended low-resource setting where it is intended for use.

2.9 Important Concepts

2.9.1 Unique Patient Identifier

In the absence of work toward an official national patient identification number, some research has continued to explore the possibilities of a voluntary patient identifier, largely at the local or regional level. Global Patient Identifier, Inc. (GPII) has been working on the voluntary universal healthcare identification (VUHID) project, whose goal is to make unique healthcare identifiers available to any patient who uses the services of a regional health information organization (RHIO) or health information exchange (HIE). The project issues a unique identifier to patients in the form of a token (such as a smart card). Patients can then choose to use the identifier at each point of care.

Additionally, small research projects have studied identifier cards that patients can use to positively identify themselves at multiple provider sites, and found that the cards can accommodate providers' workflow and are technologically feasible.(Robert Wood Johnson Foundation, 2012) In 2011, the White House launched the *National Strategy for Trusted Identities in Cyberspace* (NSTIC), the goal of which is to decrease identity theft caused by the multiple passwords and identities individuals must maintain across websites. NSTIC intends to allow individuals to create voluntary trusted identities or credentials that can be used across the internet for sensitive information. Individuals maintain control of the credential(s) and choose the amount of personal information to share with each site. In 2013, NSTIC launched a number pilots, that included use of the credentials for healthcare.(United States Government, 2011)

2.9.2 Privacy, Confidentiality and Security Considerations

Privacy, in the healthcare context, amounts to the freedom and ability to share an individual's personal and health information in confidence. Confidentiality is the actual protection such information receives from the provider organizations. An individual's personal and health information include those that were supplied by the individual and those observed by the care giver during the course of the delivery of care.

Security is the measure that an organization has employed to protect the confidentiality of the patient information. In essence, privacy of an individual's health information depends on the level of confidentiality maintained by organizations which in turn, depends on the security measures implemented by the same organization.

Respect for the privacy and confidentiality of patient information must be adopted and fostered as an essential organizational policy and culture. Security measures that are failsafe must be utilized. Yet, the organizational security measures can work only within the walls of the organization and among its employees. Protection outside the provider organization will require federal legislative measure in addition to an organization's security measures. Therefore, protecting the privacy of patient information is a joint responsibility of individuals, organizations and the nation as a whole; appropriate effort must be put forth by all of them.

The Privacy and Confidentiality Challenge

The privacy and confidentiality of patient care information is a difficult challenge facing the entire healthcare industry and cannot be ignored. The following measures as suggested(Appavu, 1997) are necessary to overcome this challenge:

1. A judicious design of the identifier
2. Organizational security measures to control access
3. Uniform federal/state legislation
4. Developing security policies and instilling responsibility among individuals

Judicious Design

Identifier design should separate the identification function from the access control function. The identifier's capability must be limited to identification only and the access control function must handle access to all information. The access control will verify the authentication of the system user, check the access privileges of the requestor and maintain an audit trail of all activities. The identifier must be designed to be unique and supported by a set of standard/uniform identification information. The design must also include the capability to store as well as communicate the identifier in an encrypted format.

Organizational Security Measures to Control Access

Appropriate organizational policies and procedures to protect the patient care information must be maintained by healthcare organizations. A failsafe access control mechanism including software access security, physical access security, encryption protection and an authentication mechanism must be in place to prevent unauthorized access and ensure legitimate access. The security measures include audit trails for tracking inappropriate access and preventive steps against possible misuse. These protective measures must be evaluated on an ongoing basis and improved continuously.

Uniform Federal/State Legislation

Uniform federal and state privacy and confidentiality legislation is required to assure the privacy and confidentiality of patient care information beyond the organizational boundaries. Such legislation must protect the Unique Patient Identifier from misuse, and prevent unauthorized access to patient information and illegal linkages of confidential information to cause harm.

Developing Security Policies and Instilling Responsibility among Individuals

Employees and others who use patient care information have a responsibility for its security. Therefore, individual responsibility for the privacy and confidentiality of patient information must be instilled through staff and user training, education and reinforcement among the users and consumers.

Much of the patient matching literature also recognizes the risk of exposing patient information inadvertently in an effort to make a correct identification. The ONC Power Team stated, “Responses to patient queries should not return any patient attributes that were not included in the original query, though it may be appropriate for the response to indicate other data that could be useful in matching the patient.” The group also suggested additional research on specific metrics that should be returned in response to a query, and recommended that a query response provide a Uniform Resource Locator (URL) link, explaining the matching approach used and providing a point of contact for more information. One study also reached the conclusion that patients who are concerned about the exposure of their personal health information may be more likely to withhold information from their physician.(Agaku et al., 2014) Health care organizations are increasingly concerned about patient identification from the perspective of fraudulent use of individuals’ medical identity.(Harris and General, 2013) Meanwhile, privacy advocates are concerned about the use of patient data without the express permission of the individual patient access to their electronic health information,(Erin, 2013) and about potential security risks around the increased use of databases for research and public health.(Sweeney, 2013)

2.9.3 Private Industry Work on Patient Identification and Matching

Various efforts and industry collaborations are now geared toward health IT issues among which is the enthusing research area of approaches to unique patient identification and matching.

AMPATH

Here is an excerpt of the AMPATH data migration project that explains the challenges in this case caused by different databases that are alleged to have various duplicated patient records.

> AMPATH has been collecting patient/person identifying data through various programs such as AMPATH HIV Program and HCT Program which the patient/person identifying data is stored in more than one database. It’s likely that the same person would have more than one record created/collected among different programs. Even for the data collected in the same program, it’s likely that the same person might have more than one record in the same database due to different reasons (e.g. misspelled patient names, interchanging patient three names, inaccurate date of birth data, data entry errors, or patients provide different information in multiple registrations). These errors can result in

duplicate patient records even within the same database.

Since we have been collecting HCT data with individual standalone databases, as of today (March 25, 2011), we have seven standalone databases for collecting seven HCT catchment areas. The first three HCT data collection were done through standalone MS Access database.

Starting from the fourth HCT data collection, it's been stored in individual OpenMRS instances. The plan is to look at those HCT data collections through OpenMRS instances and evaluate their data quality before migrating into AMRS. There are two main steps to evaluate the HCT data quality. First is to evaluate the observations data quality. A series of data quality evaluation will be done through data management methods. Next is to identify any patient/person records which belong to the same person which we will use the RecMatch/Patient Matching Program created by Dr. Shaun Grannis.

2.9.4 Conclusion

Work on patient identity and matching has accelerated in the past few years, with all sectors of the industry working to develop a better understanding of the root problems and identifying potential solutions. Much of the work has demonstrated that there is no single solution that will ensure patients' health information is accurately matched 100 percent of the time, with zero false positives and false negatives. While a universal patient identifier has been discussed by many in the industry as a solution, they acknowledge that many of the matching mechanisms and data quality methods that are in practice today would still be required. Emerging technologies such as biometrics and smart cards have some stakeholders optimistic that they could reduce reliance on complicated statistical analyses of demographics in data sets. Yet, veteran health information management professionals point out that improving the accuracy of data entry and maintenance will always be needed, and they offer a number of fundamental best practices in patient identity integrity and registration training.

Chapter 3

Research Design and Methodology

3.1 Introduction

The quantitative research implementation was done at AMPATH specifically on its current OpenMRS implementation among its modules. Design and Implementation of the facial registration implementation was introduced alongside other works like the ongoing fingerprint work and the under use, Felligi-Sunter probabilistic matching algorithms, as a module under the OpenMRS implementation. Comparison was done on the patient registration with an added component of taking the patients facial images, matching and identification areas, with the existing technologies. Duration of these tasks especially identification was logged by the prototype and computer resource usage also noted for evaluation purposes.

3.2 Site of Research

The Academic Model Providing Access to Healthcare (AMPATH), is a Moi University, Moi Teaching and Referral Hospital (MTRH) and a consortium of North American academic health centers led by Indiana University working in partnership with the Government of Kenya. Figure 3.1 shows the location of the Eldoret AMPATH centre as of the time this paper was written.

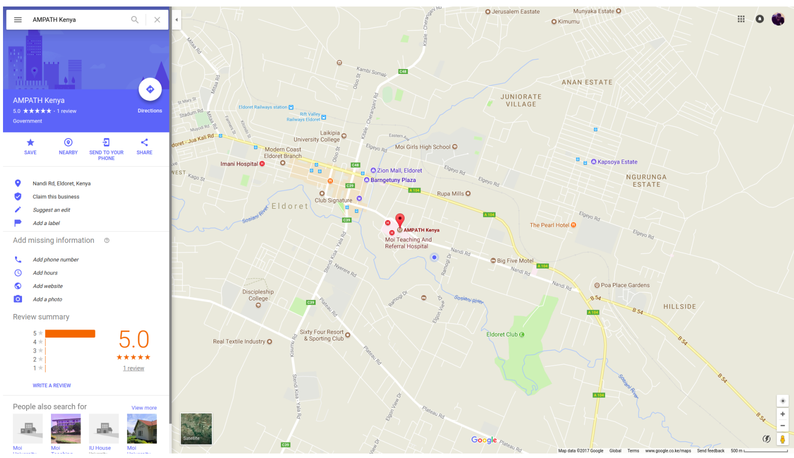


Figure 3.1 A 2017 Google Map screenshot showing the location of AMPATH

3.3 Design and Implementation

In building the design of OpenFace for health, the focus of this proposal is in Unique Patient Identification scenarios where a provider is able to recognize, in real-time, a patient depending on their context and are able to link this recognition to pull up the right patient related health information.

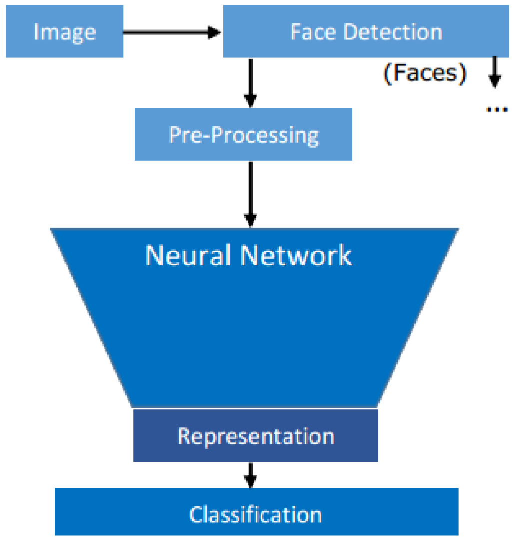


Figure 3.2 Logic flow for face recognition with a neural network

3.3.1 openmrs-module-facialRecog

An OpenMRS module is simply packaged java code which can be additionally installed on a running OpenMRS instance and has the ability to modify all aspects of the instance. The **openmrs-module-facialRecog** that was used in this research is an example of the Community module type. The open-source module code is available at https://github.com/mpmysight/openmrs-module-facialRecog

The setup of the module was done using the Module Maven Archetype wizard. In latest versions, this has now been deprecated and the tool has been replaced by the OpenMRS SDK. As a prerequisite, Maven should be installed on the environment.

The following maven plugin command listing was used to generate an initial layout of the module: `mvn module-wizard:generate`.

Module File Structure

If viewed as a single maven module project, the default OpenMRS module structure is as follows:(OpenMRS, 2013; Seebregts et al., 2009)

- **.settings** - Eclipse specific folder containing preferences for your environment
- **api** - non web specific 'maven module' project

  - **src**
    - **main** - Java files in the module that are not web-specific. These will be compiled into a distributable mymodule.jar
    - **test** - contains the unit test java files for the generic java classes
  - **target** - folder built at runtime that will contain the distributable jar file for the module
- **omod**
  - **src**
    - **main**
      - **java** - web specific java files like controllers, servlets, and filters
      - **resources** -
        - config.xml
        - *.hbm.xml files
        - liquibase.xml (or the old sqldiff.xml)
        - messages_*.properties files
        - modulesApplicationContext.xml
        - log4j.xml - optional file to control logging in your module
      - **webapp** - jsp and html files included in the omod
        - portlets -
        - resources -image, js, and css files that your jsp files reference
        - **tags** -
        - **taglibs** -
    - **test** - contains java unit test classes that test the controllers in omod/src/main/java
  - **target** - Contains the distributable omod file
- **.classpath** - Eclipse specific file that points to the files necessary for building the omod and jar files on the fly
- **.project** - Eclipse specific file containing the name and properties of your eclipse project
- **pom.xml** - Maven build file. Delegates to pom.xml files in the omod and api project

Figures 3.3 and 3.4 show the package and class design break down used for the Facial Recognition OpenMRS module used in this research.

3.3.2 OpenFace

OpenFace(Amos et al., 2016) provides the logic flow as shown in Figure 3.2 to obtain low-dimensional face representations for the faces in an image. Figure 3.5 further highlights OpenFace's implementation. The base neural network training and corollary portions use Torch(Collobert et al., 2011) Lua(Ierusalimschy et al., 1996) and luajit. The Python(van Rossum and Drake, 2003) library uses numphy(Gold et al., 2015) for arrays and linear algebra operations, OpenCV for computer vision primitives, and scikit-learn(, 2014) for classification are also used. OpenFace also uses dlib's(E. King, 2009) pre-trained face detector for higher accuracy than OpenCV's detector.

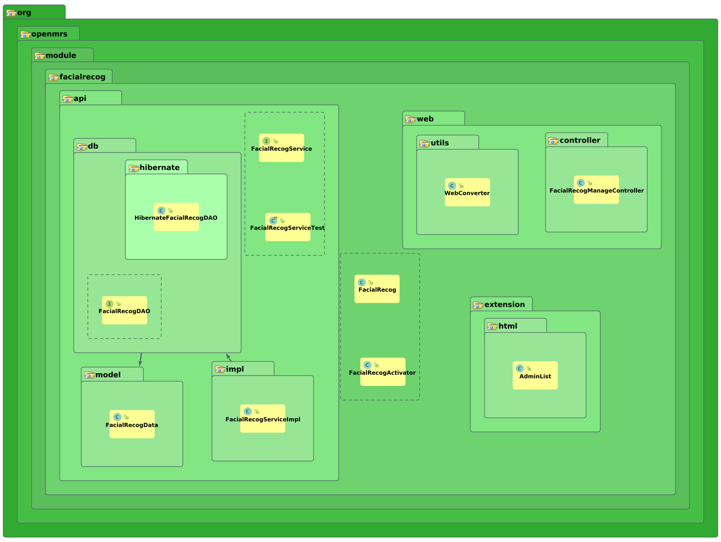


Figure 3.3 openmrs-module-facialRecog Package Design View

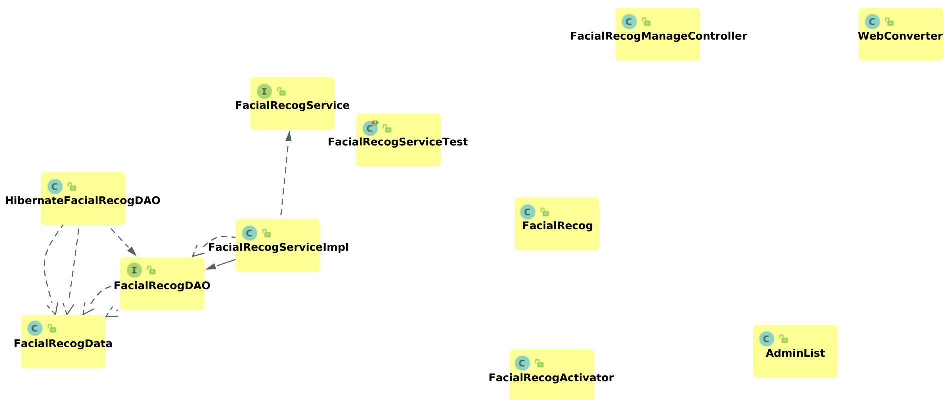


Figure 3.4 openmrs-module-facialRecog Class Design View

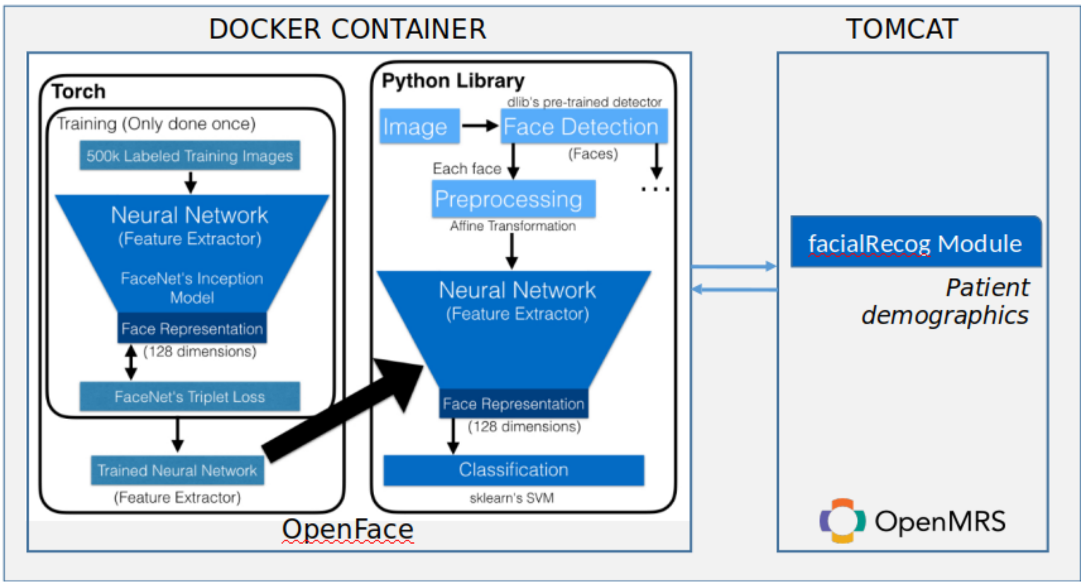


Figure 3.5 OpenFace's Project Structure showing the integration

3.3.3 Training the Face Representation Neural Network

This process is resource and data-intensive. Reference systems like FaceNet(Schroff et al., 2015) use a private dataset with 100M-200M images while DeepFace(Taigman et al., 2014) uses one with 4.4M images. The research OpenFace prototype tests included training with about 500k images that were a result of combining two of the largest labeled face recognition datasets for research, CASIA-WebFace(Yi et al., 2014) and FaceScrub(Ng and Winkler, 2014). These were downloaded for this particular training task.

The neural network component as shown in Figure 3.5 maps a preprocessed or aligned image to a low-dimensional representation of the same. The topic of what the best neural network structure for a particular task is, remains an unsolved and thriving research topic in the field of computer vision. OpenFace uses a modified version of FaceNet's nn4 network presented in this research report in *Appendix D*. nn4 is based on the GoogLeNet(Szegedy et al., 2015) architecture and the modified nn4.small2 variant reduces the number of parameters for smaller datasets as was used in this research implementation.

A total of 103 subjects were used in the final study with an average of 13 images used for each subject. These pre-captured images were used in the training of the deep neural networks for the particular patient and a live stream video of the patient face was used for identification. Deep neural networks present a classification accuracy of 0.9292 ± 0.0134 against methods like wavelets at a classification accuracy of 77.8%. The research sought to utilize this sort of classification accuracy to ensure a high identification rate of the study subjects.

3.4 Methods

The proposed solution aimed at using Deep Neural Networks for best results to achieve a trainable and improved facial recognition system that would meet the Unique Patient

Recognition gap currently faced by the growing field of Health Informatics in Low-and-Middle-Income Countries.

3.4.1 Deep Neural Networks

The proposed solution aimed at using facial recognition in a hospital setup to Uniquely Identify Patients implemented deep neural networks under an OpenFace, Python and OpenMRS Java based implementation to improve efficiency, reliability and delivery of health to people in low resource settings. The implementation was further boosted by the advantages of the open-source world by implementing OpenFace. The superior nature of the Python language, which is a powerful, flexible, open source language that is easy to learn, easy to use, and has powerful libraries for data manipulation and analysis made this implementation not only easy but also fit for a low resource setup.

A feed-forward neural network consists of many function compositions, or layers, followed by a loss function. The loss function measures how well the neural network models the data, for example gives a picture of how accurately the neural network classifies an image. Each layer i is parameterized by θ_i, which can be a vector or matrix. Common layer operations are:

1. **Spatial convolutions** that slide a kernel over the input feature maps,
2. **Linear** or fully connected layers that take a weighted sum of all the input units, and
3. **Pooling** that take the max, average, or Euclidean norm over spatial regions.

These operators are often followed by a nonlinear activation function, such as Rectified Linear Units (ReLUs), which are defined by $f(x) = max\{0,x\}$. Neural network training is a nonconvex optimization problem that finds a θ that minimizes (or even maximizes) L. With differentiable layers, $\delta L/\delta\theta_i$ can be computed with backpropagation. The optimization problem is then solved with a first-order method, which iteratively progress towards the optimal value based on $\delta L/\delta\theta_i$. There are many face detection methods to choose from as discussed in the literature review section but once a face is detected, the system pre-processes each face in the image to create a normalized and fixed-size input to the neural network. The preprocessed images are too high dimensional for the classifier to take directly into input. The neural network is used as a feature extractor to produce a low-dimensional representation that characterizes a person or subject's face. The low dimensional representation is key so it can be efficiently used in classifiers or clustering techniques.

DNN Models and Accuracies

This section gives an overview of the different OpenFace neural network models. Models can basically be described as forecasting methods that are based on simple mathematical models of the brain. They, further, allow complex nonlinear relationships between the response variable and its predictors.

Model	Number of Parameters
nn4.small2	3733968
nn4.small1	5579520
nn4	6959088
nn2	7472144

Table 3.1 Parameters are with 128-dimensional embedding

Model	alignment landmarkIndices
nn4.v1	openface.AlignDlib.INNER_EYES_AND_BOTTOM_LIP
nn4.v2	openface.AlignDlib.OUTER_EYES_AND_NOSE
nn4.small1.v1	openface.AlignDlib.OUTER_EYES_AND_NOSE
nn4.small2.v1	openface.AlignDlib.OUTER_EYES_AND_NOSE

Table 3.2 API differences between the models

Model Definitions

The number of parameters are with 128-dimensional embedding and do not include the batch normalization running means and variances. Table 3.1 shows a summary.

Pre-Trained Models

A model is the final result of training that has been done on a dataset. Different datasets result in different models. When training has been done on a dataset, the dataset model is versioned and should be released with a corresponding model definition. Switching between models should be with caution because the embeddings are not compatible with each other. The current OpenFace models are trained with a combination of the two largest publicly-available face recognition datasets based on names: FaceScrub(Ng and Winkler, 2014) and CASIA-WebFace(Yi et al., 2014).

The models used in this research were downloaded from the OpenFace storage servers and incorporated as part of the `docker hub` project at `mpmysight/openface`. The table below summarizes the API differences between the models.

Preprocessing: Alignment with an Affine Transformation

Faces in an image that can be under different pose and illumination conditions are returned as a list of bounding boxes during face detection. A potential issue with using the bounding boxes directly as an input into the neural network as noted by Brandon et.al(Amos et al., 2016) is that faces could be looking in different directions or under different illumination conditions. The FaceNet application is able to handle this issue by using a large training dataset, but the workaround for smaller datasets like was used in this research is to reduce the size of the input space by normalizing the faces so that the eyes, nose, and mouth appear at similar locations in each image. The normalization of faces in computer vision remains an open research area and most modern approaches like DeepFace(Taigman et al., 2014) frontalize the face to a 3D model so the image appears as if the face is looking directly toward the camera.

OpenFace, however, uses a simple 2D affine transformation to make the eyes and nose appear in similar locations for the neural network input. This means that for every input image even if the face is tilted to an angle, the affine transformation is applied to make the input for the neural networks similar in each patient record. This highly increases the chances of true recognition.

Figure 3.6 summarizes the workflow of the affine transformation to normalize input faces. The indicated 68 landmarks are detected with dlib's face landmark detector(E. King, 2009). Given an input image the affine transformation makes the eye corners of each image and the nose close to the mean locations. It also resizes and crops the image to the edges of the landmarks so the input image to the neural network is 96 x 96 pixels.

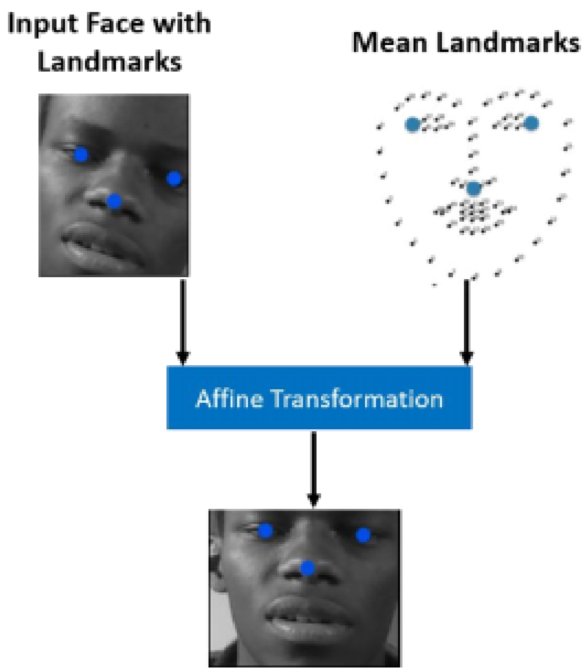


Figure 3.6 OpenFace's Affine Transformation.

3.5 Data Management Plan

3.5.1 Sampling

Convenience sampling that bases its sample on the convenience and proximity of the subject to the researcher was used for this study. The sampling frame involved no knowledge of subjects in the sample of the 103 patients used in this study. Studies have shown that a sample of 40 patients with a minimum of 10 training images can have sufficient results.(Bicego et al., 2003; Etemad and Chellappa, 1997) The patients were from:

1. AMPATH Module One
2. AMPATH Module Two
3. AMPATH Module Three
4. AMPATH Pharmacy
5. AMPATH Registration Center
6. Revolving Fund Pharmacy

All subjects that visited AMPATH, therefore, had an equal chance of being chosen to take part in the research.

3.5.2 Inclusion Criteria

All adult patients visiting and receiving care at the facility during the *data collection* time of study were suitable candidates for enrollment/inclusion in the research undertaking. Adults were considered because their facial features are well developed as opposed to children.

3.5.3 Exclusion Criteria

A registered participant who opted out of the study after initial registration (capturing of facial images) was excluded. A patient who further was unwilling to sign the consent to allow use of their information in the study, was also not included.

3.5.4 Data Collection

The study aimed at the performance of facial recognition in a health care setting, and much emphasis and focus was put on this cause. Facial images of the study subjects, who consented were captured, processed and used in the training process of the Deep Neural Network algorithm and then stored temporarily in the browser Websocket. The collection was done over a period of two weeks. The temporary storage was also used to ensure privacy and confidentiality of the captured face information of the study participants.

The prototype system used for purposes of this research implemented a docker component that was used to record and keep track of the time that spent on the recognition process. A `5 MB` log file was recorded.

3.5.5 Data Cleaning

With minimal human interaction, except for registering patients in the OpenMRS instance, there was, as expected, very little if any need to check for completeness and consistency of the captured data. This approach was aimed at minimizing subsequent human errors in the results of the research study.

3.5.6 Data Entry

Captured system data was stored in a log file and additional information would be entered into R statistical package for analysis. Double data entry and validity checks like default values would emphasize clean, and quality data from the collection exercise.

3.5.7 Data Protection and Security

A host of services were lined up and further implemented to ensure the security of the collected patient data. These included but were not limited to:

1. log and key in cases of storage and transfer
2. passwords on top of a Linux-based implementation
3. backups of key information
4. AMPATH research department also ensured that I had little access to the production environments of the current environments. A local instance was therefore used
5. encryption of the data for sharing purposes and removal of patient identifiable variables
6. keep the collected research study data for up to 5-7 years as evidence or even legal implications on this research.

3.5.8 Ethical Considerations

To ensure quality and integrity of the research, a number of ethical principles were considered:

1. Sought approval from IREC for the research study. A copy of the approval is shown in Appendix A of this report
2. Sought informed consent to ensure that participants participated in the study voluntarily
3. Permission was sought from the AMPATH Chief of Party to conduct the study at the various modules under the facility
4. The confidentiality and anonymity of the research respondents was respected

3.6 Research Design Instrument

3.6.1 Materials that were used

The basis for the OpenMRS module development was done in the Java language. The language offers many advantages in addition to its easy way of getting things done. Furthermore, my background and familiarity of the language were an added advantage as a major consideration in choice of the ideal language for the module development.

IDE: Eclipse and IntelliJ IDEA

A brief look at its origins made Eclipse stand out as the choice Integrated Development Environment. *Eclipse* was created by IBM. In the ranks of old-line corporations, those three letters carry a lot of weight. Back in the 1960's, a common term for what's now known as the IT department was "IBM Department". Before there was Microsoft, IBM was basically Alpha and Omega for what they called "Data Processing".

Eclipse is also more than just a Java IDE. Unlike most of its competitors, Eclipse is a general purpose framework, and not even specifically an IDE - although the various Java IDE versions of it are the most popular. It's also capable of serving as an application framework, and as a development platform for non-Java languages such as C/C++, Python, Perl, and Shell Scripting.

For my case like many others which involve developing systems or prototypes with multiple components interacting in complex ways and non-Java components, *Eclipse* and later *IntelliJ IDEA* remained the cutting edge solutions and choice.

None of the major IDEs is really all that bad, and each has its own particular set of virtues. To a certain degree, it is just a matter of figuring out which horse you want to place your bet on. As the saying goes, "Nothing succeeds like success", and Eclipse with the latest entrant IntelliJ IDEA have been successful.

MySQL

OpenMRS runs on a relational MySQL database for its functions. Patient information is generally stored and retrieved in and from the installed MySQL instance. Instead of reinventing the wheel and implementing my own system of storing and retrieving data, this implementation will simply use the already implemented OpenMRS MySQL database. Its list of advantages in addition to being free software made it an ideal choice for this research.

Maven and OpenMRS

OpenMRS and in essence the Facial Recognition module are implemented in Java.

Apache project, *Maven*, is a build automation tool for Java projects. Maven, a Yiddish word meaning "accumulator of knowledge," was originally started as an attempt to simplify the build processes in the Jakarta Turbine project. There were several projects each with their own Ant build files that were all slightly different and JARs were checked into CVS. An effort was fronted for a standard way to build the projects, a clear definition of what the project consisted of, an easy way to publish project information and a way to share JARs across several projects.

The result was a tool that can now be used for building and managing any Java-based project. The Maven development team hoped to create something that would make the day-to-day work of Java developers easier and generally help with the comprehension of any Java-based project. This explained Maven as a choice for this research.

Docker

Docker is an open platform for developers and sysadmins to build, ship, and run distributed applications. It is furthermore an open framework to assemble specialized container systems without reinventing the wheel. Its futuristic advantages bring on board exciting advantages.
Its ability and focus to eliminate the “it works on my machine" problem once and for all, made Docker the perfect candidate for the job. The new technology also offers better team collaboration and with additional tools like GitHub and Docker hub involved, it makes the future of this project bright with anticipation for future additional and collaborative implementations and improvements. Docker hub, additionally, made compilation of the submitted github changes seamless as all and any submitted GitHub code was automatically compiled into a Docker Image for use at the hub `mpmysight/openface`.

3.7 Installation

Installation was done on an `Ubuntu 16.04 LTS` system running with 16 GB of RAM and a Soldered Quad Core (HQ) processor with specifications: `Intel® Core™ i7-6700HQ CPU @ 2.60GHz ×8`. The figure 3.7 shows a screen shot summary of the system that was used during the research implementation at AMPATH.

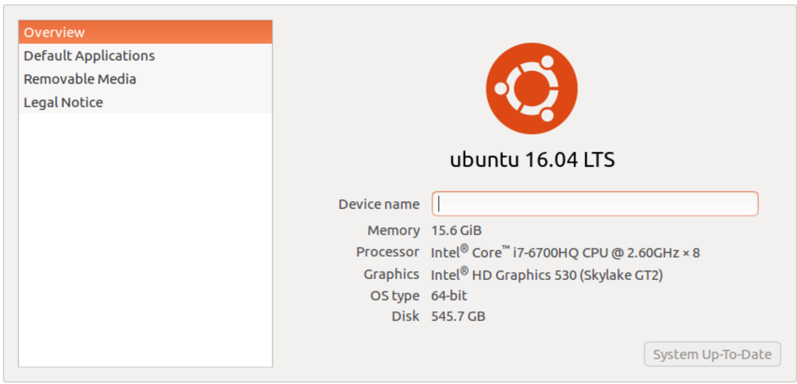


Figure 3.7 Implementation Machine Details Summary

3.7.1 Docker pulling container

The following shows the Terminal code used to make a copy of the docker container on the installation machine. The last `command` makes a clone copy of the container in `/Projects/openface/` directory which is used to make changes to the container files. This directory is a git repository clone and any submission or upload is synced to the docker hub and the code automatically generated into a docker image.

```
docker pull mpmysight/openface
docker run -p 9000:9000 -p 8000:8000 -t -i bamos/openface /bin/bash
docker run --rm -p 9000:9000 -p 8000:8000 --name openface -t -i mpmysight/openface /bin/bash
sudo docker cp openface:/root/openface ~/Projects/openface
sudo docker stop openface
docker run -d -p 9000:9000 -p 8000:8000 -v ~/Projects/openface:/root/openface --name openface -t -i
    mpmysight/openface /bin/bash
```

3.7.2 Getting Docker IP Address

```
##get IP Address
docker inspect -f '{{.Name}} - {{.NetworkSettings.IPAddress }}' $(docker ps -aq)
##log into container
docker exec -it openface /bin/bash
```

3.7.3 Setting up the Docker Container

```
##setup
cd /root/openface
./demos/compare.py images/examples/{lennon*,clapton*}
./demos/classifier.py infer models/openface/celeb-classifier.nn4.small2.v1.pkl
    ./images/examples/carell.jpg
./demos/web/start-servers.sh
```

3.8 Evaluating Performance

The following standard performance metrics were used to evaluate the prototype system as summarized by Table 3.3.

Performance Metric	Method
False Acceptance Rate (FAR) False Match Rate (FMR)	$\frac{no.offalseacceptances}{no.ofidentificationattempts}$
False Rejection Rate (FRR) False Non-Match Rate (FNMR)	$\frac{no.offalserejections}{no.ofidentificationattempts}$
Failure to enroll rate (FTE/FER)	$\frac{no.offailedenrolls}{no.oftotalenrolls}$
Failure to capture rate	$\frac{no.offailedinputdetections}{no.oftotaldetections}$
Sensitivity	$\frac{TP}{TP+FN}$

Table 3.3 Performance metrics for Biometric systems

1. **False match rate (FMR)**, also called False Accept Rate(FAR): refers to the probability that the system incorrectly matches the input patient face to a non-matching face template in the database. FMR measures the percent of invalid inputs that are incorrectly accepted. In the health care setting, this has to be kept to a very low value. The ultimate goal would be to eventually build systems that keep this value at zero as its effects can be diverse in hospitals from wrong drugs, procedures or even disabling injury due to wrong treatment of the wrong person.

2. **False non-match rate (FNMR)**, also called False Reject Rate(FRR): the probability that the system fails to detect a match between the input pattern and a matching template in the database. It measures the percent of valid inputs that are incorrectly rejected.

3. **Receiver operating characteristic or relative operating characteristic (ROC)**: The ROC plot is a visual characterization of the trade-off between the FMR and the FNMR. In general, the matching algorithm performs a decision based on a threshold that determines how close to a template the input needs to be for it to be considered a match. If the threshold is reduced, there will be fewer false non-matches but more false accepts. Conversely, a higher threshold will reduce the FMR but increase the FNMR. A common variation is the Detection error trade-off (DET),

which is obtained using normal deviation scales on both axes. This more linear graph illuminates the differences for higher performances (rarer errors).

4. **Failure to enroll rate (FTE or FER)**: the rate at which attempts to create a template from an input is unsuccessful. This is most commonly caused by low quality inputs.
5. **Failure to capture rate (FTC)**: Within automatic systems, the probability that the system fails to detect a biometric input when presented correctly.
6. **Sensitivity**: how well the system is able to identify positively captured people. It is calculated using the formula $\frac{TP}{TP+FN}$.

Chapter 4

Results

4.1 Introduction

The purpose of this study was to develop and evaluate the use of facial technology for patient matching in a resource limited setting. It further implemented the developed prototype solution and assessed its performance ability, focusing mainly on accuracy, in a financially constrained, developing country setting. This evaluation was done in an implemented OpenMRS environment.

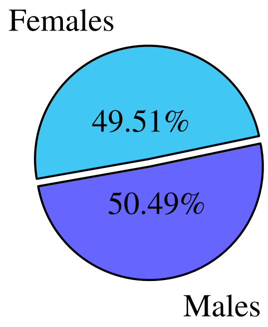
4.2 Demographic Analysis

The study sample comprised of a total of 103 patients with *mean* age of 37.8 and *standard deviation* of 13.6. 50.49% of the total enrolled were males as shown in Table 4.1 and the corresponding pie chart. The study also further had 7% of the total subjects wearing spectacles. All of these subjects who participated wearing spectacles, were positively identified.

A total of 103 patients (mean age 37.8; SD 13.6) maintaining an average of 13.0 training images with *SD* of 1.1. The total unique training images used in the study were **1347**. Table 4.2 shows a summary of the data with the full table in Appendix E.

Demographic Variable	**N**	**Percentage (%)**
Gender		
Male	52	50.49
Female	51	49.51
Total	**103**	100.0

Table 4.1 Study Participants Gender Summary



No.	Unique Patient_ID	Sex	Age	Train. Images	Total Train. Images	Spects	Identified?
First Phase							
1	100-1	M	38	11	11	N	✓
2	100-2	M	24	12	23	N	✓
3	100-3	F	29	11	34	N	✓
4	100-4	F	41	12	46	N	✓
5	100-5	M	42	13	59	N	✓
6	100-6	M	32	13	72	N	✓
7	100-7	F	56	15	87	Y	✓

Table 4.2 Study Participants' Redacted Demographics Summary

The research registered an increased power of the test of the prototype system. An increased workload in terms of computational resources that included the workload on the `7-core` machine used for the training of the images, would also better inform the research for future or further related implementations.

Of the total **103** study patients, with a total average training image database of **1347** images, 99.029% were *correctly* identified during the *"first match"*! This is also the sensitivity of the system - how well the system was able to positively identify captured people. The increased workload on the processor due to the resources needed to train the now large database of images and run a live-video stream through the algorithm, was the recorded reason for the resulting "first trial" mismatch. The remaining 0.971% were also correctly identified on the "second trial".

4.3 Factor Analysis

4.3.1 FAR, FRR and Failure to Enroll

False Acceptance Rate (FAR), False Rejection Rate (FRR) and 'Failure to enroll' values are standard measures used to determine the accuracy of biometric identification systems. FAR refers to the measure of the likelihood that the biometric security system will incorrectly **accept** an access attempt by an unauthorized user. The research prototype system's FAR was given by the ratio of the number of **false** acceptances divided by the number of identification attempts.

On the other hand, the FRR refers to the measure of the likelihood that the biometric system will incorrectly reject an access attempt by authorized user. It is given by the ratio of the number of **false** recognitions divided by the number of identification attempts.

The Table 4.3 shows a summary of accuracy results of performance metrics as used in measuring standard performance among biometric systems.

Performance Metric	**Study**	**Result**
False Acceptance Rate (FAR) False Match Rate (FMR)	$\frac{1}{103}$	0.0097087379
False Rejection Rate (FRR) False Non-Match Rate (FNMR)	$\frac{0}{103}$	0.00
Failure to enroll rate (FTE/FER)	0.0	0.00
Failure to capture rate	0.0	0.00
Sensitivity	$\frac{102}{102+1}$	99.03

Table 4.3 Performance metrics for Biometric systems

The major research finding was to do with the accuracy of the system. With a near 99% identification accuracy, Deep Neural Networks offer very improved Biometric Results for the field of Unique Patient Identification. As shown by the results, this implementation can be run on a very low initial cost for setup with resulting low maintenance costs in a health care setup.

4.3.2 Receiver Operating Characteristic (ROC) Curve

In statistics, a receiver operating characteristic curve, i.e. ROC curve, is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied. Figure 4.1 shows a comparison of OpenFace and EigenFaces ROC curves.

A Receiver/Relative Operating Characteristic (ROC) curve demonstrates several things:

1. Shows the trade-off between the sensitivity and specificity. An increase in sensitivity will be accompanied by a decrease in specificity.

2. The closer a curve follows the left-hand border and the top border of the plot space, the more accurate the test is.

3. The closer the curve comes to the 45-degree diagonal of the area under the curve (AUC) space, the less accurate the test.

4. The slope of the tangent line at a cutpoint gives the likelihood ratio (LR) for the value of the test.

5. The area under the curve (AUC) is a measure of accuracy. As seen in Figure 4.1, Deep Neural Networks have a better accuracy of approximately 97% compared to the earlier used Eigenfaces option that show a mere 65%.

The ROC curve was created by plotting the true positive rate (TPR) against the false positive rate (FPR) at various threshold settings. The true-positive rate is also known as sensitivity, recall or probability of detection in machine learning. The false-positive

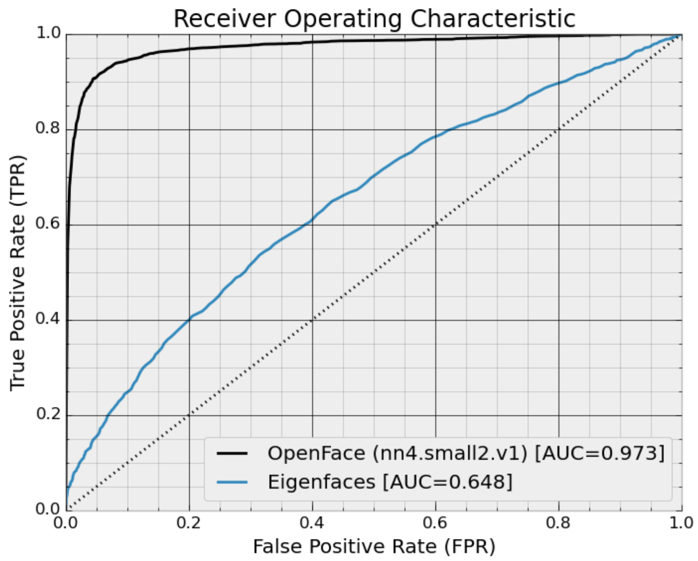


Figure 4.1 Receiver Operating Characteristic (ROC) Curve Representation

rate is also known as the fall-out or probability of false alarm and can be calculated as (1-Specificity). The ROC curve is thus the sensitivity as a function of fall-out of the Biometric system.

It is also key to note that the ROC analysis which relates in a direct and natural way to cost/benefit analysis provides decision makers with optimal information in case a choice is to be made on which of the two approaches to use in a low resource patient setup as was used in the study.

4.3.3 Lighting Conditions

A Logitech `3 MP C270 HD` WEBCAM was used in the capturing of the face images that were used in the identification process. During day-time hours, with natural light, the lighting was not controlled at all. Figure 4.2 shows a grid of some of the images that were captured and used in the training and identification processes of the study subjects.

4.3.4 Algorithm Computational Speed

The implementation displayed a noticeable time lag as the number of `training images` increased beyond 500. Most of the computer resources were dedicated to running the different resource-intensive components of the setup, including:

1. Tomcat
2. Docker
3. OpenMRS
4. Camera Live Stream

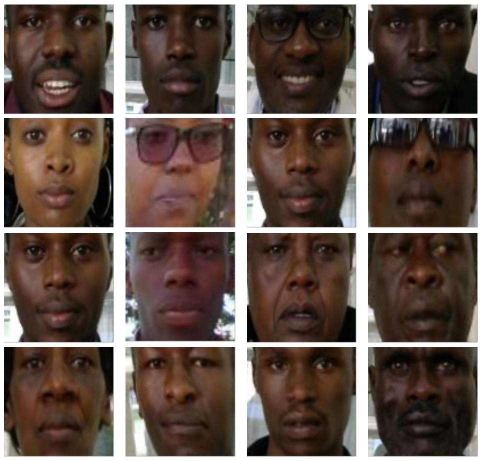
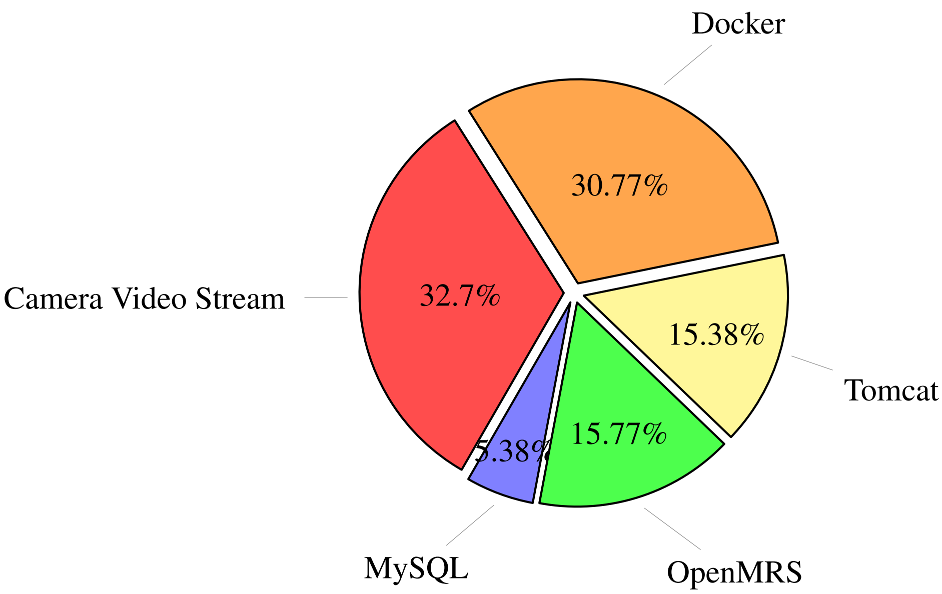


Figure 4.2 Sample images showing the lighting of the images used in the identification process

Component	**Running**	**iCore 7 CPU (%) Usage**	**15.7 GB RAM (%) Usage**
MySQL	✓	14	15.7
Tomcat	✓	40	17.0
OpenMRS	✓	41	17.1
Docker	✓	80	43.4
Camera Video Stream	✓	85	45.7

Table 4.4 A summary of the computational performance of an i-Core7 laptop

The following chart better displays the cumulative i-Core 7 Central Processing Unit (CPU) computer resource usage according to the setup components.



This was the only problem that would need to be solved by increasing the number of computational resources available to future implementations of the system in the health care sector. Further technologies like parallel computing and parallel processing would also offer better results.

The following is an excerpt from the `log file` to show the difference in workload as the number of training images increases.

```
2017-10-02 12:27:56+0000 [-] Received FRAME message of length 12798.
2017-10-02 12:27:56+0000 [-] Received FRAME message of length 12918.
2017-10-02 12:27:56+0000 [-] Received FRAME message of length 13142.
2017-10-02 12:27:57+0000 [-]
    /root/.local/lib/python2.7/site-packages/sklearn/utils/validation.py:386:
    exceptions.DeprecationWarning: Passing 1d arrays as data is deprecated
    in 0.17 and willraise ValueError in 0.19. Reshape your data either
    using X.reshape(-1, 1) if your data has a single feature or
    X.reshape(1, -1) if it contains a single sample.
2017-10-02 12:27:57+0000 [-] Received FRAME message of length 13402.
2017-10-02 12:27:57+0000 [-]
    /root/.local/lib/python2.7/site-packages/sklearn/utils/validation.py:386:
    exceptions.DeprecationWarning: Passing 1d arrays as data is deprecated
    in 0.17 and willraise ValueError in 0.19. Reshape your data either
    using X.reshape(-1, 1) if your data has a single feature or
    X.reshape(1, -1) if it contains a single sample.
2017-10-02 12:27:57+0000 [-] Received FRAME message of length 13558.
2017-10-02 12:27:58+0000 [-]
    /root/.local/lib/python2.7/site-packages/sklearn/utils/validation.py:386:
    exceptions.DeprecationWarning: Passing 1d arrays as data is deprecated
    in 0.17 and willraise ValueError in 0.19. Reshape your data either
    using X.reshape(-1, 1) if your data has a single feature or
    X.reshape(1, -1) if it contains a single sample.
2017-10-02 12:27:58+0000 [-] Received FRAME message of length 13418.
2017-10-02 12:27:58+0000 [-]
    /root/.local/lib/python2.7/site-packages/sklearn/utils/validation.py:386:
    exceptions.DeprecationWarning: Passing 1d arrays as data is deprecated
    in 0.17 and willraise ValueError in 0.19. Reshape your data either
    using X.reshape(-1, 1) if your data has a single feature or
    X.reshape(1, -1) if it contains a single sample.
2017-10-02 12:27:58+0000 [-] Received FRAME message of length 13446.
2017-10-02 12:27:59+0000 [-]
    /root/.local/lib/python2.7/site-packages/sklearn/utils/validation.py:386:
    exceptions.DeprecationWarning: Passing 1d arrays as data is deprecated
    in 0.17 and willraise ValueError in 0.19. Reshape your data either
```

```
    using X.reshape(-1, 1) if your data has a single feature or
    X.reshape(1, -1) if it contains a single sample.
13 2017-10-02 12:27:59+0000 [-] Received FRAME message of length 13422.
14 2017-10-02 12:27:59+0000 [-] Received FRAME message of length 13402.
15 2017-10-02 12:27:59+0000 [-] Received FRAME message of length 13418.
```

The LaTeX listing above shows an excerpt of the `log file` that highlights this important challenge. In `lines 7 and 8; and also lines 11 and 12`, the one (1) second difference presented in the recognition process was due to the lag in the video stream caused by over-used computer processor and RAM resources. In other identifications, the process took milliseconds to return a true positive match as earlier highlighted in Table 4.2.

4.4 Implementation Detail Additional Knowledge

Can this approach provide additional knowledge in terms of implementation detail analysis in the field of Unique Patient Identification especially in a resource limited setting? Care has been taken to ensure that the research findings of this study inform the emerging field of *Implementation science* which aims to publish research relevant to the scientific study of methods to promote the uptake of research findings into routine health-care in clinical, organizational or policy contexts.

For a resource limited setting which was the focus of this research as we tried to get a system ready and running with limited resources, the research has beyond doubt proven that Biometrics can be implemented in our low resource settings with low or mediocre budget figures.

Additionally, this system does not threaten a great principle of Health Informatics, that is interoperability. Existing systems, policies and implementations would need to be expanded a bit to cater for use of Biometrics. Most health providers in these settings are already using systems like OpenMRS, DHIS-2, Kenya EMR, Uganda EMR, mUzima which already run on hardware and software that would work well and support additional functionality as seen in this research. This reduces any erroneous re-configurations and major system upgrades.

4.5 Other Analyses

4.5.1 TSNE Visualization

The varying dimensional nature of the facial images call for dimensionality reduction techniques like the "t-SNE" which shows a very normal graph of the captured images despite the differences in lighting, posture, facial features and the likes that affect the representation of the high-dimensional representation of the captures faces used in this research. Figure 4.3 show a graph of this representation of the faces for some of the different patient IDs used in this research.

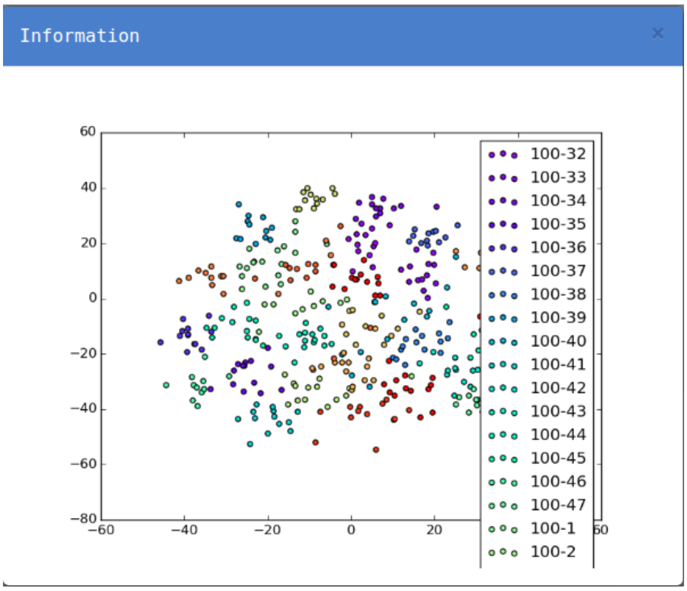


Figure 4.3 A “t-SNE” high-dimensional 2D visualization of the data

4.6 Summary

In summary, the study results provided research ground for further expansion of implementation and use of facial recognition technology in resource constrained environments. A picture of what is expected in and with such an implementation was derived to inform such future intentions. The results were more than we expected and further beyond what the research had anticipated in the following ways:

1. The Deep Neural Networks Python implementation was very fast. Compared to an earlier *dropped* implementation using Eigen-faces, the used research implementation exhibited credible, improved, and consistent facial recognition results.

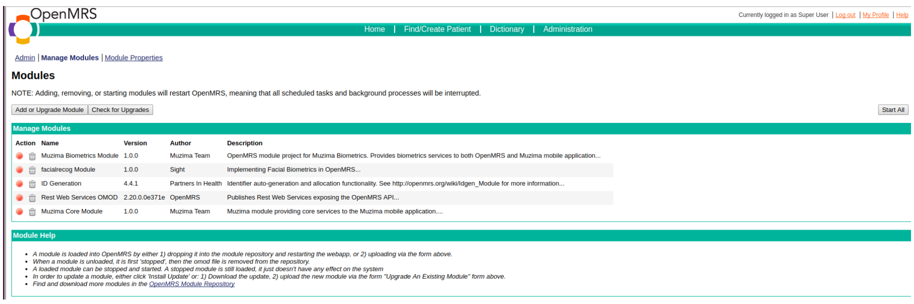


Figure 4.4 System screenshot showing the created module

2. Despite the poor lighting conditions at the AMPATH collection site, the results of the identification process were and remained unaltered. Figure 4.5 shows a screen shot of a correctly matched patient and the patient’s OpenMRS detail page which can now be used to dispense drugs or any other hospital routine as needed by the system user.

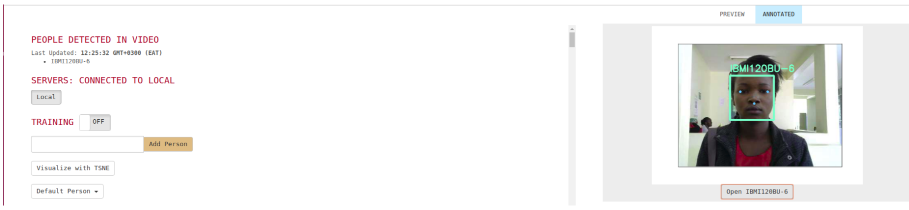


Figure 4.5 Screenshot showing a detected and recognized patient

3. There is renewed promise to combat through research the problem of Unique Patient Identification. As biometrics get better, and bi-modal systems are put in place, health care providers will soon identify the patient with near-human accuracy.

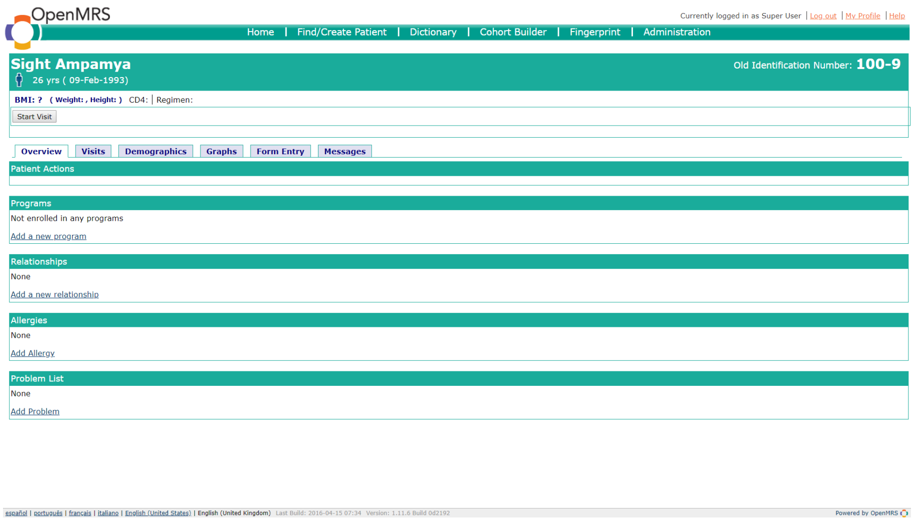


Figure 4.6 Screenshot showing identified patient record in OpenMRS

Chapter 5

Summary, Discussion, Conclusion, and Implications

5.1 Introduction

This section seeks to set the record straight as to why this OpenFace implementation and/or better facial recognition methods should be adopted into the health care sector. Results are further interpreted in light of the research questions and discussed in conjunction with other literature. Limitations of the interpretation and study are also presented. Further research recommendations are suggested and conclusions drawn.

5.2 Summary

The performance of biometric identification systems is mostly assessed using the system's accuracy, speed, storage, cost and ease of use.(Moon, 2004; Waruhari et al., 2017) This particular research focuses of accuracy, with mention of speed and cost in the discussion.

As earlier mentioned, Deep Neural Networks offer an improved solution to earlier considered and developed trial methods like EigenFaces. A comparison of the classification accuracy of these implementations are shown in Figure 5.1. Further improvements like multi-modal biometric methods and the latest entrant 3D based implementations being tested will further improve these results with parallel implementations in the health care setup.

5.3 Results Discussion

The results confirm that facial recognition is very efficient for Unique Patient Identification in Low-and-Middle-Income Country settings. The ability to embed the technology within an EMR system makes facial recognition efficient and cost effective within these LMIC settings.

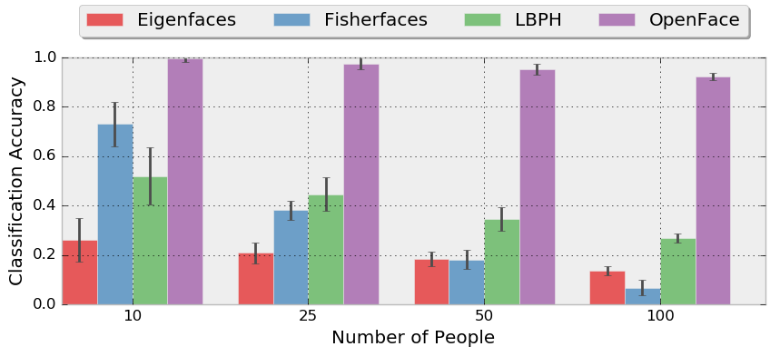


Figure 5.1 OpenFace Accuracy against number of people, comparison

The results confirm that facial recognition is highly accurate for Unique Patient Identification in a low-resource settings with sensitivity of 99.03% This performs better than probabilistic approaches in the same setting. Wawira et.al registers probabilistic methods in a similar setting at 50-79% accuracy(Sonak et al., 2014)

In low-resource settings where patient mis-identification has often led to "never events" this approach shows great promise in minimizing patient mis-identification. The health care sector continues to suffer overwhelmingly the effects of mis-identification ranging from misdiagnosis to losses in millions of dollars. The results of the study show that progress can be made in this critical area to minimize these.

With an accuracy of 97.%, facial recognition coupled with its ease of use perform better than a fingerprint implementation accuracy by Afsar et al,(Afsar and Hussain, 1994) that put fingerprint performance at 92%. Certainly, differences in the biometric implementation choice and especially the environment could contribute to the accuracy differences between the present study and that of Afsar et al.

The results also take into consideration the differences in the number of test subjects used for the different studies and the current one. The differences in the computer processing power capability of the machines used could also account for the differences in results.

The clinically important measurements, for accuracy of the facial recognition system, was a sensitivity result (of 99.03%). The technology will greatly reduce wait times in hospital queues, minimize patient mis-identification, reduce costs of health systems while upholding efficiency to get the work done.

It is also key to note that the lack of routine uptake of IT research findings is strategically important for the development of Health Information Technology (HIT) because it clearly places an invisible ceiling on the potential for IT research to enhance health. This makes these research results a foundation to improving Unique Patient Identification results in low resource health setups.

5.4 Limitations of the Study

The system was tested on a quite small database of 1347 images due to time limitations. It is also key to note that performance against a larger database is recommended for future improvements and testing.

The implementation did not involve testing with children mainly due to consent and ethical reasons. Additionally, the facial features of children are also still developing and not fully defined hence testing was not done with children.

5.4.1 Known Challenges of Face Recognition

Even though current machine recognition systems have reached a certain level of maturity, their success is limited by the conditions imposed by many real applications. For example, recognition of face images acquired in an outdoor environment, like in this research, with changes in illumination and/or pose remains a largely unsolved problem. In other words, current systems are still far away from the capability of the human perception system.(Zhao et al., 2003) Despite this variety, face recognition faces some issues inherent to the problem definition, environmental conditions and hardware constraints.

Illumination

Most algorithms rely on color information to recognize faces. Features are extracted from color images, although most implementations use gray-scale images. In nature, the color we perceive from a given surface depends not only on the surface's nature, but also on the light upon it. This is where the illumination challenge stems up. Furthermore, color derives from the perception of our light receptors of the spectrum of light-distribution of light energy versus wavelength.(O'Toole et al., 2007) while it is essential to try and control the conditions under which the images to be used for recognition will be taken, it is key to note that there can be relevant illumination variations on images taken under uncontrolled environment.

It is not only the value of the pixels that varies with light changes, the relation or variations between pixels may also vary. As many feature extraction methods rely on color and its intensity variability measures between pixels to obtain relevant data, they show an important dependency on lighting changes. The big problem is that given two faces of the same subject but with illumination variations may show more differences between them than compared to another subject. There is still more research in this area if automated face recognition systems are to keep the promising delivery they bring.

Pose

Researchers in the area of facial recognition face two main problems of pose variation and illumination. Many face recognition methods are based on frontal face images because of the solid research base these images can provide. These databases of frontal faces provide a good test for image representation methods, dimension reduction algorithms, basic recognition techniques, and illumination invariant methods.

Several approaches are used to face pose variations that include: multi-image based approaches - which require multiple images for training, single-model based approaches - which uses several data of a subject on training, but only one image at recognition. 3D morphable model methods are a self-explanatory example of this category. Geometric approaches try to build a sub-layer of pose-variant information of faces. The input images are transformed depending on geometric measures of these models.

Other Problems Related To Face Recognition

There are other problems that automated face recognition research must face sooner than later. Some of them have no relation between each other. They include, *occlusion* - or the state of being obstructed which involves cases where some parts of the face cannot be obtained, *optical technology* - which describes issues that deal with which format the input images are provided, *expression* - which is another variability provider, and algorithm evaluation. The effectiveness of an algorithm is not easy to evaluate as several core factors are unavoidable. These include: the hit ratio, error rate, memory usage, and computational speed of the algorithm.

5.5 Recommendations for Future Research

As educative and challenging as this transformative research was, the positives, and challenges that were faced along the way were very informative in making future recommendations for further research in this area of Biometrics use in Health care delivery. It would be erroneous to assume this research as very conclusive for an African limited resource health care setting. The recommendations for future research are highlighted below:

1. **Further module and mobile development**
   Further development is needed to make sure there is adequate integration between the Docker element of the research implementation and the OpenMRS implementation. Further development should also focus on a permanent storage solution for the face images. Secure methods like encryption and SecSDLC methodologies should be followed to ensure that the patient identifiable information remains secure. A mobile implementation of the system would also ensure portability and versatility of the technology. The research time-line did not allow for most of these to be fully developed and implemented.

2. **Multimodal Biometric Approaches**
   Research continues to show that there is no silver bullet, no one-size-fits-all solution for the UPI problem. There is not yet an “all conclusive” solution to the Unique Patient Matching problem. While the ideal would be the ability to identify the patient fully and at all times and in so doing minimize chances of medication errors, and the resulting problems.

   The research has continued to prove the need for all ways in which the patient can be truly identified. The study recommends immediate integration of facial recognition in the health care sector to mitigate on the Unique Patient Identification problem. With further facial matching and recognition algorithms including Face

3D methods in the research pipeline, the UPI problem will continue to be addressed.

This implementation should be done with backup methods like fingerprint in place to cater for any unforeseen challenges that might arise. This is also to increase the chances of true identification.

3. **Longer periods before "second" identification**
The research has shown that the system will be stable with patients whose follow up period is not very long - two to three weeks as was used in this case. However, the system should further be tested over longer periods of time including up to two (2) years when there will be significant and noticeable changes over the appearance of a person's face.

   This, however, should not be used as a replacement to the patient database update process so that the system is able to keep track of changes that result due to accidents on a patient's face. After an estimated time frame, most preferably, six months, a patient's facial profile should be updated with new images. This is also a functionality that should be further developed in the research module.

5.5.1 Conclusion

In their book, Karen A. Wager, et al,(Harsanyi et al., 2000) argue that there is a renewed promise that IT investments can help a country to not only improve the quality of care provided to the population but also lower the cost (or at least moderate the rate of increase in that cost).

Facial recognition has a major advantage of not requiring any physical contact with an image capturing device (camera)(Adeoye, 2010). Face identification systems do not require any advanced hardware, as they can be used with minimal capturing devices like webcams, and security cameras. It is on this basis that we recommend consideration of this technology as a serious alternative in development of Unique Patient Identification biometric or multimodal systems. Additionally, the one-to-many identification offered by multi-biometric systems should be a highlight of the next research in the area for higher accuracy and reliability(Choudhari et al., 2014) results.

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Appendix A

Consent Form

INSTITUTIONAL RESEARCH AND ETHICS COMMITTEE (IREC)

MOI TEACHING AND REFERRAL HOSPITAL
P.O. BOX 3
ELDORET
Tel: 33471//2/3

MOI UNIVERSITY
SCHOOL OF MEDICINE
P.O. BOX 4606
ELDORET

Reference: IREC/2016/219
Approval Number: 0001821

2nd February, 2017

Mr. Sight Ampamya,
Moi University,
School of Medicine,
P.O. Box 4606-30100,
ELDORET-KENYA.

INSTITUTIONAL RESEARCH & ETHICS COMMITTEE
02 FEB 2017
APPROVED
P. O. Box 4606-30100 ELDORET

Dear Mr. Ampamya,

RE: FORMAL APPROVAL

The Institutional Research and Ethics Committee has reviewed your research proposal titled: -

"Evaluating Facial Recognition for Unique Patient Matching in a Resource Limited Setting".

Your proposal has been granted a Formal Approval Number: ***FAN: IREC 1821*** on 2nd February, 2017. You are therefore permitted to begin your investigations.

Note that this approval is for 1 year; it will thus expire on 1st February, 2018. If it is necessary to continue with this research beyond the expiry date, a request for continuation should be made in writing to IREC Secretariat two months prior to the expiry date.

You are required to submit progress report(s) regularly as dictated by your proposal. Furthermore, you must notify the Committee of any proposal change (s) or amendment (s), serious or unexpected outcomes related to the conduct of the study, or study termination for any reason. The Committee expects to receive a final report at the end of the study.

Sincerely,

PROF. E. WERE
CHAIRMAN
INSTITUTIONAL RESEARCH AND ETHICS COMMITTEE

cc	CEO	-	MTRH	Dean	-	SOP	Dean	-	SOM
	Principal	-	CHS	Dean	-	SON	Dean	-	SOD

Appendix B

Thesis Schedule

#	Activity	Timeline/Dateline
1	1^{st} Proposal Draft	by 19^{th} Feb. 2016
2	Departmental Proposal Presentations	22^{nd} - 25^{th} Feb. 2016
3	2^{nd} Draft & Final submission of Proposal to Supervisors for Review	by 11^{th} Mar. 2016
4	Submission to IREC	by 1st Feb. 2017
5	Corrections as per IREC & Re-submission	2^{nd} to 13^{th} May 2017
6	Approval from IREC to conduct study	by 20^{th} May 2017
7	Data Collection	1^{st} Jun to Nov 2017
8	Data Cleaning & Analysis	December 2017
9	Thesis 1^{st} Draft	by 27^{th} April 2018
10	Departmental Defense	30^{th} Jan - 10^{th} Aug 2017
11	Submission to GSC (letter of intent & abstract)	13^{th} - 24^{th} Aug 2018
12	Senate Approval	by 19^{th} Sept 2018
13	Submit 6 Copies to SGC for External Examiner	by 20^{th} September 2018
14	Books Received from External Examiners	by 7^{th} Nov 2018
15	Final Thesis Defense	November 2018

Table B.1 Thesis Proposal and Research Time lines

Appendix C

Budget

Total estimated expenses for this proposed research are **KES 176,254.46** as shown in Table C.1. These funds were used to cover direct out-of-pocket expenses associated with the study, including questionnaire production, printing, and distribution, participant incentives, and funding for a research assistant. I have not received any prior funding for this project.

Table C.1 Research and Study Budget

Category	Quantity	Unit Cost (KSH)	Total Cost (KSH)	Justification
Direct Expenses				
Proposal Development				This part of funding will be used to cover direct out-of- pocket expenses, including questionnaire production, printing, distribution, and collection
Printing and Binding	4	600	2400	
IREC Fees	1	1000	1000	
Labour				
Participant Incentives	70	100	7000	High rates of participation are needed across all three waves of study over a six-month period. Prior research suggests that these kinds of incentives are effective at eliciting participation.
Field Assistant	1	10000	10000	This comprehensive study requires significant effort in survey administration (e.g., distribution and collection), data management (e.g., data input and analysis), and feedback report writing. Significant time has already been invested in conducting the extensive literature review and survey design.

Category	Quantity	Unit Cost (KSH)	Total Cost (KSH)	Justification
Expenses				
Travel				Traveling to Uganda to see supervisor
Airfare to Uganda	2	2500	5000	
Research Equipment				
Programming Laptop	1	132354.46	132354.46	The system requires a lot of computing power both to develop and to run.
Mobile Internet Modem	1	1500	1500	
Portable Hard Drive	1	8000	8000	
Research Materials				
Cell Phone Usage Charges	1	1000	1000	
Mobile Internet	2	1500	3000	
8 GB Pen Drive	2	1000	2000	
Subtotal Expenses		**161,054.46**		
Total Expenses			**176,254.46**	

Appendix D

FaceNet's nn4 network

```
-- Model: nn4.small2.def.lua
-- Description: FaceNet's NN4 network with 4b, 4c, and 4d layers removed
--   and smaller 5 layers.
-- Input size: 3x96x96
-- Number of Parameters from net:getParameters() with embSize=128: 3733968
-- Components: Mostly `nn`
-- Devices: CPU and CUDA
--
-- Brandon Amos <http://bamos.github.io>
-- 2016-01-08
--
-- Copyright 2015-2016 Carnegie Mellon University
--
-- Licensed under the Apache License, Version 2.0 (the "License");
-- you may not use this file except in compliance with the License.
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-- Unless required by applicable law or agreed to in writing, software
-- distributed under the License is distributed on an "AS IS" BASIS,
-- WITHOUT WARRANTIES OR CONDITIONS OF ANY KIND, either express or implied.
-- See the License for the specific language governing permissions and
-- limitations under the License.

imgDim = 96

function createModel()
local net = nn.Sequential()
```

```
net:add(nn.SpatialConvolutionMM(3, 64, 7, 7, 2, 2, 3, 3))
net:add(nn.SpatialBatchNormalization(64))
net:add(nn.ReLU())

-- The FaceNet paper just says 'norm' and that the models are based
-- heavily on the inception paper (http://arxiv.org/pdf/1409.4842.pdf),
-- which uses pooling and normalization in the same way in the early
    layers.
--
-- The Caffe and official versions of this network both use LRN:
--
--   + https://github.com/BVLC/caffe/tree/master/models/bvlc_googlenet
--   + https://github.com/google/inception/blob/master/inception.ipynb
--
-- The Caffe docs at http://caffe.berkeleyvision.org/tutorial/layers.html
-- define LRN to be across channels.
net:add(nn.SpatialMaxPooling(3, 3, 2, 2, 1, 1))
net:add(nn.SpatialCrossMapLRN(5, 0.0001, 0.75))

-- Inception (2)
net:add(nn.SpatialConvolutionMM(64, 64, 1, 1))
net:add(nn.SpatialBatchNormalization(64))
net:add(nn.ReLU())
net:add(nn.SpatialConvolutionMM(64, 192, 3, 3, 1, 1, 1))
net:add(nn.SpatialBatchNormalization(192))
net:add(nn.ReLU())

net:add(nn.SpatialCrossMapLRN(5, 0.0001, 0.75))
net:add(nn.SpatialMaxPooling(3, 3, 2, 2, 1, 1))

-- Inception (3a)
net:add(nn.Inception{
inputSize = 192,
kernelSize = {3, 5},
kernelStride = {1, 1},
outputSize = {128, 32},
reduceSize = {96, 16, 32, 64},
pool = nn.SpatialMaxPooling(3, 3, 1, 1, 1, 1),
batchNorm = true
})
```

```

-- Inception (3b)
net:add(nn.Inception{
inputSize = 256,
kernelSize = {3, 5},
kernelStride = {1, 1},
outputSize = {128, 64},
reduceSize = {96, 32, 64, 64},
pool = nn.SpatialLPPooling(256, 2, 3, 3, 1, 1),
batchNorm = true
})

-- Inception (3c)
net:add(nn.Inception{
inputSize = 320,
kernelSize = {3, 5},
kernelStride = {2, 2},
outputSize = {256, 64},
reduceSize = {128, 32, nil, nil},
pool = nn.SpatialMaxPooling(3, 3, 2, 2, 1, 1),
batchNorm = true
})

-- Inception (4a)
net:add(nn.Inception{
inputSize = 640,
kernelSize = {3, 5},
kernelStride = {1, 1},
outputSize = {192, 64},
reduceSize = {96, 32, 128, 256},
pool = nn.SpatialLPPooling(640, 2, 3, 3, 1, 1),
batchNorm = true
})

-- Inception (4e)
net:add(nn.Inception{
inputSize = 640,
kernelSize = {3, 5},
kernelStride = {2, 2},
outputSize = {256, 128},
reduceSize = {160, 64, nil, nil},
```

```lua
pool = nn.SpatialMaxPooling(3, 3, 2, 2, 1, 1),
batchNorm = true
})

-- Inception (5a)
net:add(nn.Inception{
inputSize = 1024,
kernelSize = {3},
kernelStride = {1},
outputSize = {384},
reduceSize = {96, 96, 256},
pool = nn.SpatialLPPooling(960, 2, 3, 3, 1, 1),
batchNorm = true
})
-- net:add(nn.Reshape(736,3,3))

-- Inception (5b)
net:add(nn.Inception{
inputSize = 736,
kernelSize = {3},
kernelStride = {1},
outputSize = {384},
reduceSize = {96, 96, 256},
pool = nn.SpatialMaxPooling(3, 3, 1, 1, 1, 1),
batchNorm = true
})

net:add(nn.SpatialAveragePooling(3, 3))

-- Validate shape with:
-- net:add(nn.Reshape(736))

net:add(nn.View(736))
net:add(nn.Linear(736, opt.embSize))
net:add(nn.Normalize(2))

return net
end
```

Appendix E

Demographic Results

No.	Unique Patient_ID	Sex	Age	Train. Images	Total Train. Images	Spects	Identified?
First Phase							
1	100-1	M	38	11	11	N	✓
2	100-2	M	24	12	23	N	✓
3	100-3	F	29	11	34	N	✓
4	100-4	F	41	12	46	N	✓
5	100-5	M	42	13	59	N	✓
6	100-6	M	32	13	72	N	✓
7	100-7	F	56	15	87	Y	✓
8	100-8	F	43	13	100	N	✓
9	100-9	M	56	13	113	N	✓
10	100-10	M	25	14	127	N	✓
11	100-11	F	18	14	141	N	✓
12	100-12	M	56	13	154	N	✓
13	100-13	F	36	11	165	N	✓
14	100-14	M	40	12	177	N	✓
15	100-15	M	55	11	188	N	✓
16	100-16	M	50	12	200	N	✓
17	100-17	F	38	12	212	N	✓
18	100-18	M	21	12	224	N	✓
19	100-19	F	21	14	238	N	✓
20	100-20	M	22	10	248	N	✓

21	100-21	F	38	12	260	N	✓
22	100-22	M	33	13	273	N	✓
23	100-23	M	44	13	286	N	✓
24	100-24	M	39	12	298	N	✓
25	100-25	F	31	12	310	N	✓
26	100-26	M	30	12	322	N	✓
27	100-27	M	35	13	335	Y	✓
28	100-28	F	52	13	348	N	✓
29	100-29	F	36	12	360	N	✓
30	100-30	F	23	12	372	N	✓
31	100-31	M	45	11	383	N	✓
32	100-32	F	23	13	396	N	✓
33	100-33	M	60	13	409	N	✓
34	100-34	F	40	12	421	N	✓
35	100-35	M	54	14	435	N	✓
36	100-36	M	29	13	448	N	✓
37	100-37	M	18	12	460	N	✓
38	100-38	M	29	15	475	Y	✓
39	100-39	M	31	13	488	N	✓
40	100-40	F	64	14	502	N	✓
41	100-41	F	32	13	515	N	✓
42	100-42	F	27	15	530	N	✓
43	100-43	F	63	14	544	N	✓
44	100-44	M	38	15	559	N	✓
45	100-45	M	41	15	574	N	✓
46	100-46	M	40	11	585	N	✓
47	100-47	F	39	13	598	N	✓
48	100-48	M	39	13	611	N	✓
49	100-49	F	38	12	623	N	✓
50	100-50	M	42	13	636	N	✓
51	100-51	M	35	14	650	N	✓
52	100-52	M	57	14	664	N	✓
53	100-53	M	25	13	677	N	✓

54	100-54	F	21	13	690	N	✓
55	100-55	M	23	13	703	N	✓
56	100-56	M	27	13	716	N	✓
57	100-57	F	51	13	729	N	✓
58	100-58	M	39	13	742	N	✓
59	100-59	M	27	13	755	N	✓
60	100-60	F	32	12	**767**	N	✓
Second Phase							
61	100-61	M	29	13	780	N	✓
62	100-62	M	73	12	792	N	✓
63	100-63	F	34	12	804	N	✓
64	100-64	F	35	13	817	N	✓
65	100-65	F	44	13	830	N	✓
66	100-66	M	22	14	844	Y	✓
67	100-67	F	47	13	857	N	✓
68	100-68	M	27	13	870	N	✓
69	100-69	F	46	15	885	N	✓
70	100-70	F	57	14	899	N	✓
71	100-71	M	22	14	913	Y	✓
72	100-72	F	28	14	927	N	✓
73	100-73	F	30	14	941	N	✓
74	100-74	F	48	13	954	N	✓
75	100-75	M	21	13	967	N	✓
76	100-76	M	22	14	981	N	✓
77	100-77	F	21	13	994	N	✓
78	100-78	M	21	18	1012	N	✓
79	100-79	F	19	13	1025	N	✓
80	100-80	F	71	13	1038	N	✓
81	100-81	F	20	14	1052	Y	✓
82	100-82	F	18	14	1066	N	✓
83	100-83	F	40	13	1079	N	✓
84	100-84	F	51	13	1092	N	✓
85	100-85	M	48	13	1105	Y	✓

86	100-86	F	65	13	1118	N	✓
87	100-87	M	37	14	1132	N	✓
88	100-88	F	23	14	1146	N	✓
89	100-89	M	48	14	1160	N	✓
90	100-90	F	58	14	1174	N	✓
91	100-91	F	52	13	1187	N	✓
92	100-92	M	42	14	1201	N	✓
93	100-93	F	48	14	1215	N	✓
94	100-94	M	44	13	1228	N	✓
95	100-95	M	20	14	1242	N	✓
96	100-96	F	26	13	1255	N	✓
97	100-97	F	32	13	1268	N	✓
98	100-98	F	61	12	1280	N	✓
99	100-99	F	39	13	1293	N	✓
100	100-100	F	41	13	1306	N	✓
101	100-101	M	60	14	1320	N	✓
102	100-102	F	55	14	1334	N	×
103	100-103	F	22	13	**1347**	N	✓

Table E.1 Study Participants' Full Demographics Summary