



Review article

Performance of an open source facial recognition system for unique patient matching in a resource-limited setting[★]Sight Ampamya^{a,*}, John M. Kitayimbwa^b, Martin C. Were^{c,d,a}^a Institute of Biomedical Informatics, Moi University, Eldoret, Kenya^b Centre for Computational Biology, Uganda Christian University, Mukono, Uganda^c Department of Biomedical Informatics, Vanderbilt University Medical Center, Nashville, TN, USA^d Vanderbilt Institute for Global Health, Vanderbilt University Medical Center, Nashville, TN, USA

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ABSTRACT

Background: The lack of unique patient identifiers is a challenge to patient care in developing countries. Probabilistic and deterministic matching approaches remain sub-optimal. However, affordable and scalable biometric solutions have not been rigorously evaluated in these settings.

Methods: We implemented and evaluated performance of an open-source facial recognition system, OpenFace, integrated within a nationally-endorsed electronic health record system in Western Kenya. Patients were first enrolled via facial images, and later matched via the system. Accuracy of facial recognition was evaluated using Sensitivity; False Acceptance Rate (FAR); False Rejection Rate (FRR); Failure to Capture Rate (FTC) and Failure to Enroll Rate (FTE). 103 patients (mean age 37.8, 49.5% female) were enrolled. Results: The system had a sensitivity of 99.0%, FAR < 1%, FRR 0.00, FTC 0.00 and FTE 0.00. Wearing spectacles did not affect performance.

Conclusion: An open source facial recognition system correctly and accurately identified almost all patients during the first match.

1. Introduction

Unique patient identification and patient matching procedures remain key challenges to providing high quality, personalized and efficient care in low- and middle-income countries (LMICs) [2]. In these countries, national personal identification systems do not cover all individuals, often not being available to children and foreign citizens. Care institutions tend to have sub-optimal and inefficient procedures for uniquely identifying individuals or providing them with unique identification numbers that can be used across departments and across care institutions.

Without unique patient identification, quality of care can be compromised, diagnostic studies duplicated, and patient safety put at risk. In the United States, it is reported that about 195,000 deaths occur yearly as a result of medical errors, with 10–17% being a result of identification errors [3]. Similar identification errors are not uncommon in LMICs, as was evident in the case of a March 2018 neurosurgical mis-identification case resulting in brain surgery performed on the wrong patient in Kenya. Unique patient identification also forms a

core component for health information exchange and continuity of care.

When national unique identifiers do not exist, care institutions largely rely on deterministic or probabilistic algorithms and other statistical matching procedures for patient identity management [3]. This is the case in most LMICs. Deterministic matching algorithms use exact match or comparisons between two fields. Probabilistic matching, by far the most widely implemented technique for record matching, compares values between two records across several fields, with weights assigned based on how close the values in the corresponding fields are. Unfortunately, deterministic and probabilistic matching mechanisms do not work as well in LMICs for other reasons beyond the simple lack of unique identifiers. Deterministic matching is generally not reliable in these settings since in most cases no single field can provide a reliable match between two records for all patients. Probabilistic matching mechanisms also fall short given the prevalence of transposition of first, middle and last names, misspellings, unknown dates of birth, and non-standard ways of representing addresses.

Approaches for unique patient identification are sorely needed in

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LMIC settings, and a potential solution can be found in biometric approaches. Biometrics is a technique for identifying people using individual's unique physiological characteristic, such as face, iris, fingerprint, eye, or behavioral characteristics, like voice and signature [6]. Among the biometric techniques, facial recognition offers a potential solution given the ubiquitous nature of cameras integrated to computers and mobile devices now widely available within LMIC settings. In fact, many electronic systems already allow capture of patient images as part of the registration process, and these are widely accepted by patients. Facial recognition has advantages primarily because of its non-intrusive nature by not requiring physical contact with an image capturing device (camera) or advanced hardware components.

While facial recognition technologies have received wide attention in areas such as banking (for user authentication), law enforcement, and immigration services with LMICs, the use of this technology for unique patient identification remains quite low in healthcare settings. A key barrier to adoption of this technology is the lack of robust evidence of its performance within these care settings, and more evidence is needed to help convince care settings and national care programs about the feasibility of this technology as an option for national unique patient identification. A second key barrier is the cost of implementing proprietary facial recognition systems, with many LMIC settings unable to afford these systems.

The objective of our study was to evaluate an open source 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 the facial recognition solution integrated to an Electronic Health Record system within an HIV care in a care setting in Western Kenya.

2. Methods

2.1. Study setting

This study was conducted at the adult care clinics affiliated with the Academic Model Providing Access to Healthcare (AMPATH) program in Western Kenya. The program provides HIV care to over 95,000 HIV positive patients in partnership with the MoH and with support from the United States Agency for International Development.

2.2. Electronic record system at AMPATH

AMPATH clinics have since 2006 implemented the AMPATH Medical Record System (AMRS) to record and store patient information. AMRS is an implementation of the widely available and nationally-endorsed OpenMRS medical record system [5]. OpenMRS is currently in use in Tanzania, Uganda and in over 30 others countries around the globe, ensuring that findings from this evaluation will be translatable to other LMIC settings. At the time of this study, AMRS was using OpenMRS Version 1.11.6, with the providers using the system for direct data entry as a point-of-care system to enter patient demographics, clinical encounter information, diagnostic studies and pharmacy information are captured. 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 x8.

2.3. Clinic patient flow

Within the AMPATH study clinics, patients coming for a clinic visit usually present to the registration desk. For new patients, several pieces of demographic information are usually captured into the AMRS including: (a) first, middle and last name, (b) date of birth or age, (c) national ID number, (d) phone number, (e) address information. The AMRS then performs a probabilistic match on these demographics to see if the individual was already registered in the system. AMPATH

currently uses the Felligi Sunter matching algorithm. If a match is found, the system notifies the registration team, but if no match is found, the new patient can be registered. All registered patients receive an AMRS ID, which is number-based with a check digit. Returning patients are usually matched based on their AMRS IDs but if the patient does not have this ID, as is often the case, demographic information is used to identify them within the system. Once a patient is registered and checked-in, they can go to the various stations for care, with re-identification needed at each station.

Patient matching and identification at the AMPATH continues to be a challenge. The Felligi Sunter matching algorithm used has previously had a matching accuracy between 50 and 70%, when data from HIV home-based counseling and testing was matched against those within AMRS for active HIV patients, highlighting challenges to probabilistic-based matching using demographic information in this setting.

2.4. Integrating facial recognition into AMRS

To integrate facial recognition within the AMRS EHRs, we developed a module within AMRS. This module had the ability to perform standard facial recognition functions, namely: (a) *image capture* – using a standard camera integrated into the computing device; (b) *face detection* – the process of extracting faces from scenes and involves identification of a certain given image region as a face; (c) *feature extraction* – involving obtaining relevant facial features such certain face regions, variations, angles or measures, which are human relevant (for example, eye spacing) and (d) *face recognition* – this involves an identification set up and subsequent matching of the identity from a database using a comparison method, a classification algorithm and a corresponding accuracy measure (Fig. 1).

2.5. Face recognition approach

Face recognition is an evolving field with a diversity of recognition approaches that are affected by and incorporate computer vision, optics, pattern recognition, neural networks, machine learning, and psychology among others. As a field under Machine learning, face recognition employs both *supervised* (where instances are given with known labels to the corresponding correct outputs) and *unsupervised* learning (where the instances are unlabeled).

Methods like Eigenfaces [7] employing Principal Component Analysis (PCA) which computes the maximum variations in data while converting from high dimensional image space to low dimensional image space fall under supervised learning [4]. Face recognition using Neural network, especially Deep Neural Networks (DNN) draw inference from unlabeled data using regression and classification methods. Because of their trainable nature, artificial neural networks are a popular tool in facial recognition and have been used in pattern recognition and classification. The topic of what the best neural network structure for a particular task is, remains an unsolved and thriving

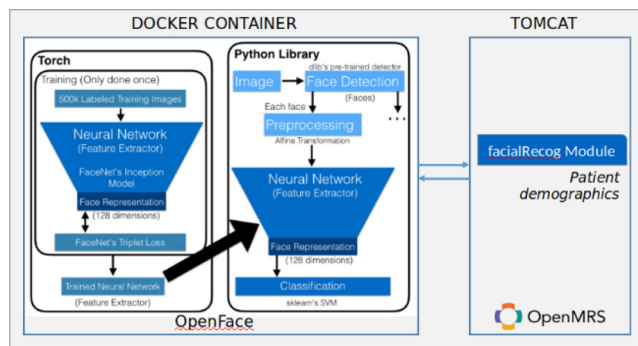


Fig. 1. OpenFace logic flow.

research topic in the field of computer vision.

Emerging open source deep neural network facial recognition systems now exist. One such system is OpenFace, implemented using Python and Torch to ensure that it can run on Central Processing Units or Graphics Processing Units [1,9]. OpenFace has demonstrated levels of accuracy similar to proprietary facial recognition models witnessed in private state-of-the-art systems like Google's FaceNet and Facebook's DeepFace [11]. OpenFace provides the logic flow as shown in Fig. 1 to obtain low-dimensional face representations for the faces in an image.

2.6. Study population

The participant population in this study included adult patients (18 years of age or older) receiving care at the different clinics within AMPATH. Convenience sampling was used to select participants as they presented for registration and check-in during a routine outpatient clinic visit. Patients below 18 years of age and those who did not consent to the participate were excluded from the study. The study was approved by the Institutional Review and Ethics committee at Moi University, Kenya.

2.7. Study procedures

Adult patients presenting for routine clinical visits at the study site were recruited by a trained research assistant, and those who agreed to participate received written informed consent. Participants were provided standard information on enrolling in the study, and made aware of the voluntary nature of participation. Participants who agreed to the study had their facial images captured, processed and used in the training process to register the face, with the system configured to take 10–14 training images as part of the facial image registration process. A logic model is shown in Fig. 2

At a different station within the clinic (akin to a patient revisit or re-identification at another location within the facility), patient's facial images were also captured and used for unique patient identification and patient matching against the stored registration images.

2.8. Statistical analysis

To identify the open-source facial recognition method to use, we performed Receiver Operating Characteristics (ROC) for the two common open face approaches, EigenFace and OpenFace. The better performing open-source recognition system, OpenFace, was selected for integration into AMRS and for subsequent analysis.

The developed system captured data in a log file and these were uploaded into the R statistical package for analysis. Data on participant age, sex and use of spectacles during image capture was also captured and used for analysis. Age was summarized using mean and standard deviation. Gender was summarized using frequencies and the

Table 1
Performance metrics for facial recognition.

Performance metric	Formula
Sensitivity	$\frac{\text{True Positives}}{\text{True Positives} + \text{True Negatives}}$
Specificity	$\frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}}$
False Acceptance Rate (FAR)	$\frac{\text{No. of false acceptances}}{\text{No. of identification attempts}}$
False Rejection Rate (FRR)	$\frac{\text{No. of false rejections}}{\text{No. of identification attempts}}$
Failure to enroll rate (FER)	$\frac{\text{No. of failed enrollments}}{\text{No. of total enrollments}}$
Failure to capture rate (FCR)	$\frac{\text{No. of failed input detections}}{\text{No. of total detections}}$

corresponding percentages. Performance calculations of the OpenFace facial recognition system were performed using standard biometric measures including (Table 1):

- *Participants correctly identified*: Total number of identification attempts minus total wrongly or not identified.
- *Sensitivity*: Proportion of patients with registered facial images correctly matched.
- *Specificity*: Proportion of patients without registered facial images that are correctly identified as not having matching facial images in system.
- *False Accept Rate (FAR)*: Probability that the system incorrectly matches the input patient face to a non-matching face template in the database. FAR is also known as *False Match Rate*.
- *False Reject Rate (FRR)*: 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. FRR is also sometimes known as *False non-match rate*.
- *Failure to enroll rate (FER)*: The rate at which attempts to create a template from an input is unsuccessful. This is most commonly caused by low quality inputs.
- *Failure to capture rate (FCR)*: Within automatic systems, the probability that the system fails to detect a biometric input when presented correctly.

Specificity is calculated based on the number of times a patient being registered for the first time was matched against those in the databases. We also applied T-distributed Stochastic Neighbor Embedding (t-SNE) dimensionality reduction algorithm to downsize the image data for better management within a real-world implementation setting and to ensure efficient response times.

3. Results

3.1. Implementation

A comparison of open-source facial recognition libraries using ROC curves demonstrated that OpenFace performed better than EigenFace as shown in Fig. 3.

Today's top-performing face recognition techniques are based on convolutional neural networks. Facebook's DeepFace and Google's FaceNet systems yield the highest accuracy. However, in the past, these deep neural network-based techniques were trained with private data sets containing millions of social media images that are orders of magnitude larger than available data sets for research.[1] Recently many pre-trained face recognition models continue to be publicly available.

3.2. Performance of the facial recognition system

A total of 103 patients were consented and enrolled in the study.

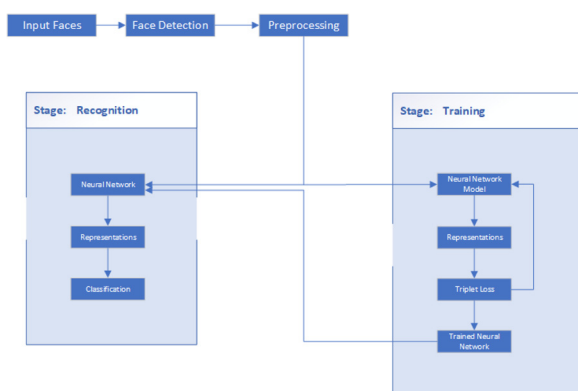


Fig. 2. OpenFace logic flow model.

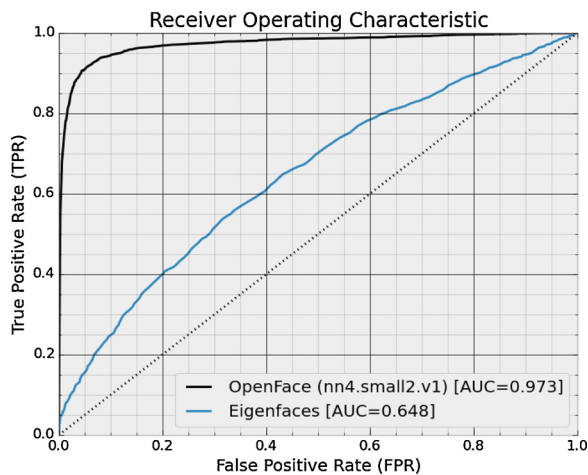


Fig. 3. Performance comparison using a ROC curve.

Table 2
Results of the performance metrics.

Performance metric	Calculation	Value
Sensitivity	$\frac{102}{102 + 1}$	99.03%
Specificity	$\frac{103}{103 + 0}$	100%
False acceptance rate (FAR)	$\frac{1}{103}$	0.0097
False rejection rate (FRR)	$\frac{0}{103}$	0.0
Failure to enroll rate (FER)	0	0.0
Failure to capture rate (FER)	0	0.0

Mean age of participants was 37.8 (SD 13.6), 51 (49.5%) were female, and seven (7%) wore spectacles. For initial registration, an average of 13.0 (SD 1.1) training images were needed. Table 2 shows results of the performance metrics of the implemented patient recognition system for all patients. Of the 103 patients, 102 were correctly identified during the first try, for a sensitivity of 99.03%. The one participant who was not identified on the first try was identified correctly on the second attempt. Wearing of spectacles did not affect performance, with all patients wearing spectacles correctly identified.

4. Discussion

The results of our study confirm that an open source-based facial recognition system integrated within a widely available EHRs is a highly accurate modality for unique patient identification within a

resource-limited setting in Kenya. The performance of the facial recognition system, with a sensitivity of 99% is much better than the existing Felligi-Sunter probabilistic matching algorithm that was previously evaluated to perform at 50–70% within the same patient population [10]. Further, performance of the facial recognition system was not affected by whether the patients wore glasses or by the site specific lighting conditions. In practice, however, lighting conditions are one of the main causes of bad performance of facial recognition systems.

With the accuracy observed of the facial recognition system, it likely performs better than other potential biometric matching modalities. The non-intrusive nature of facial recognition, hygienic nature in view of recent concerns with touch-sensitive methods, coupled with availability of additional sensors, support selection of the methodology. The ubiquitous nature of cameras, the open-source nature of the systems used, and the ability to integrate with an open-source EHRs demonstrate the cost-feasibility of this system, negating the need for use of expensive and proprietary facial recognition technologies.

Our study offers a potential solution to the problem of unique patient identification within resource-limited LMIC settings. The OpenFace library is available for use within mobile devices and for integration with other digital health systems, providing a core component towards ensuring health information exchange through a robust unique patient identification system.

Limitations in our study involved the fact that the evaluation was performed at one site, with a limited number of patients. Future evaluations need to look at performance with a larger patient population, taking into consideration processing speed as the number of images increases. The ethical and cultural aspects of use and acceptability of facial recognition technologies within LMIC settings also need to be evaluated rigorously.

5. Conclusions

An opensource-based facial recognition system demonstrated a high level of accuracy when used within a resource-limited LMIC setting and offers a potentially robust solution for unique patient identification. Further research, however, is needed for comparisons of some of the most recent algorithms.

CRedit author contribution statement

Sight Ampamya: Study concept, method, design, and collection of data.

John M. Kitayimbwa: Data analysis, Curation, Original draft revision, Interpretation of data.

Martin C. Were: Original draft preparation, Critical revision of the manuscript for intellectual content.

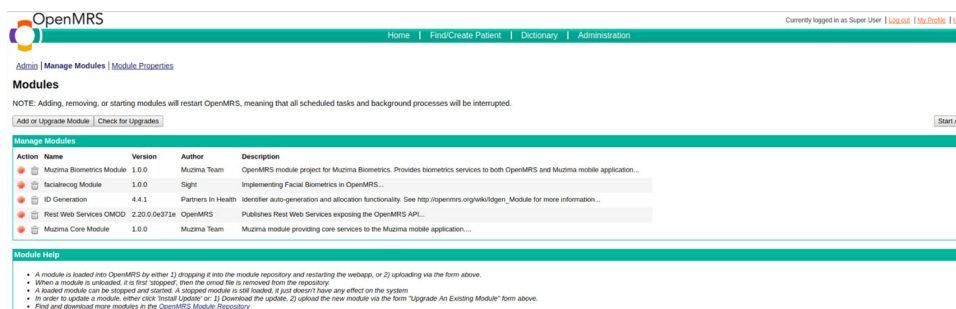


Fig. 4. Developed OpenMRS facial recognition module running.

Conflicts of interest

All authors report no conflicts of interest.

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