STANDARDIZING IMAGE CAPTURE FOR MACHINE LEARNING ALGORITHMS IN LOW-RESOURCE SETTINGS CONFERENCE SUBMISSIONS

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ABSTRACT

Image-based machine learning (ML) could address health diagnostic gaps in low- and middle-income countries (LMICs). However, images must be standardized and high-quality to develop and deploy such image-based algorithms. We describe here our experience in developing tools to collect images of post-cesarean section (c-section) wounds in rural Rwanda to predict surgical site infection (SSI) diagnosis. We developed a mobile application suite called WoundScreener to standardize the collection of c-section wound images using a smartphone camera. Automatic tracking, scaling, alignment, and color calibration of the image is made possible through the use of a printed optical pattern, known as a computer vision "target." In our case, the target is in the form of a printed frame with a square hole cut-out that is placed and centered over the patient's surgical wound. The mobile app uses this target frame to automatically detect and capture the wound image. From September 2019 through January 2020, we prospectively enrolled all women delivering via c-section at Kirehe District Hospital (KDH) in rural Rwanda. Our study team used WoundScreener and the target for wound image capture at the hospital and trained community health workers to use these tools for image capture in the patient's home. To date, 653 women have enrolled in the study. We have captured 1,160 images in the hospital at approximately postoperative days 3 and 11, and 571 images in the home at approximately postoperative day 10. After implementation, the target required several adjustments to be the appropriate size and durable enough to withstand long travel, severe weather conditions, and sanitization. All challenges arising with the application have been resolved but resolution was complicated by the distance between the development team, located in Boston, and the study location in Rwanda. In conclusion, we demonstrate the feasibility of capturing standardized c-section wound images for SSI diagnostic algorithms, after resolving issues with WoundScreener and the target. The tools and accompanying training should be tailored to the trainees' experience with such technology. Ideally, developers and implementing teams are located in close proximity to maximize troubleshooting efficiency of new technical challenges. Finally, regular monitoring of image quality is crucial to ensure timely adjustments and retraining.

1 INTRODUCTION

Using mobile health (mHealth) technologies in a variety of clinical settings presents a novel opportunity to improve clinical care, especially in low-resource settings. These mHealth technologies utilize machine learning (ML) algorithms, which are programs (math and logic) that are developed based on existing data, such as images, and adjust themselves to perform better as they are exposed to feedback on their previous performance. For supervised learning, the data must be labeled and ML algorithms must be trained, which means that for a given dataset, input objects are paired with desired output beforehand (Venkatasalam, 2012). However, to be useful for ML, data must be cleaned. For images, this process often requires manual editing to scale, crop, and rotate the images, as well as to adjust the brightness and contrast. This process is often the most time consuming and laborious step in a ML project, thus preventing these algorithms from being used in real-time in the field. Furthermore, in global health, data collection is often complicated by a lack of training, skilled personnel, and mentors (Fletcher et al., 2016). To date in sub-Saharan Africa, only one study has been carried out to investigate the potential of using ML and wound images to predict the diagnosis of SSI, which our research team conducted in the Kirehe district of Rwanda (Fletcher et al., 2019). Therefore, there still exists a need to develop appropriate mobile applications to capture these images in a standardized way (Fletcher et al., 2019). Here we describe our experience in developing a mobile application, targets, and machine recognizable patterns to collect images of post-c-section wounds in rural Rwanda to predict SSI.

2 BACKGROUND

2.1 CESAREAN SECTIONS AND SURGICAL SITE INFECTIONS IN LMICS

Thanks to coordinated efforts to improve maternal health and decrease mortality during childbirth, access to c-sections has substantially increased worldwide over the last two decades, particularly in low- and middle-income countries (LMICs). With this increase in c-sections, however, comes an increase in associated complications including SSIs. In Sub-Saharan Africa, the SSI rate after c-section ranges from 7 to 48 per cent (Mivumbi et al., 2014; Mpogoro et al., 2014; Chu et al., 2015; De Nardo et al., 2016; Kaboré et al., 2016). If not detected early, they can cause significant morbidity and can even be fatal. Development of an image-based ML algorithm for SSI detection has the potential to aid in early diagnosis of this complication while eliminating the costs for transportation and wages lost to go for hospital follow up, significantly relieving the financial burden on these women and their families.

2.2 OVERVIEW OF MHEALTH AND TELEMEDICINE STUDIES IN RWANDA

In 2016, through a partnership between Harvard Medical School and Partners In Health - Rwanda, a prospective study analyzing the rates and predictors of SSI in women who undergo c-section was implemented at Kirehe District Hospital (KDH), located in the Eastern province of Rwanda (Nkurunziza et al., 2017; Sonderman et al., 2018).Women enrolled in this study were randomized into three arms for follow-up, and one of these arms consisted of home follow-up visits performed by study community health workers (sCHWs). Five sCHWs performed home visits, which included taking photos of the patients' wounds, and a total of 553 images were captured. A second study was developed and implemented in 2019 and is currently enrolling. In this study, all women were visited at home by sCHWs, and it was for this phase that the mobile health application and accompanying target, which will be discussed below, were developed. To date, 653 women have been enrolled in the study. Using the WoundScreener application, we have captured 1,160 images in the hospital at approximately postoperative days (PODs) 3 and 11, and 571 images in the home at approximately POD 10.

2.3 IMAGE CAPTURE OVERVIEW AND CHALLENGES IN PHASE ONE

The 553 images from the first study were used to develop a ML algorithm for predicting GP SSI diagnosis. However, given that there was no mechanism for standardization of these photographs, they varied widely and required significant pre-processing in order to be used for development of the algorithm. Photographs varied widely in a number of ways, including angle of view, distance from the incision, and lighting. Manual cropping of these images was required prior to use for algorithm development. Given the wide variation of all of these image characteristics, tools and methods were developed to standardize the image capturing process in the subsequent study.

3 STUDY METHODS OF IMAGE CAPTURE

3.1 DESCRIPTION OF TOOLS

The WoundScreener application is a mobile container application for screening for post c-section SSI that guides the user through the process of collecting and inputting the data. The application was implemented in Android using a low-cost Samsung J8 smartphone. The application was developed in English and then translated into Kinyarwanda for ease of use by sCHWs, who have limited English proficiency. The WoundScreener application was used together with an external printed optical pattern, known as a computer vision "target", made of flexible, glossy poster board material. The target was used for tracking, alignment, scaling, and color calibration of the image. Image capture occurs only when the application recognizes the wound by detecting a frame on the border of the target. Finally, a rechargeable natural light lamp was used to increase the luminosity at the incision. This was used in place of the camera flash to prevent overexposure of the image.

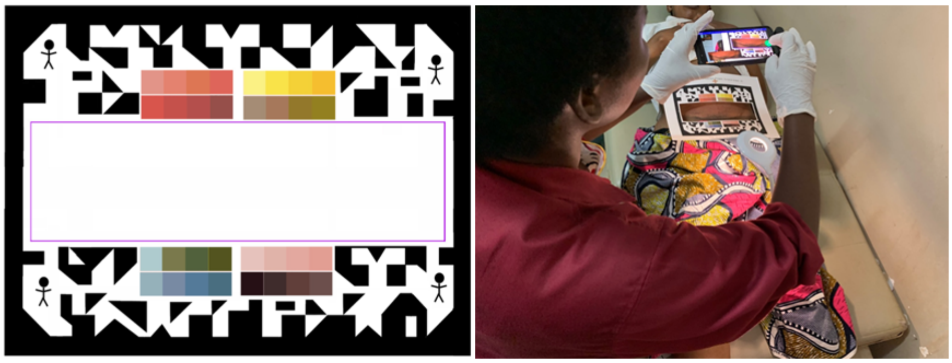

Figure 1: **(left) Final target used in conjunction with WoundScreener application; (right) A study team member capturing c-section wound image on POD 3**

3.2 Overview of photo taking process

See **Figure 2** for an overview of the image capturing process. Photographs were taken by seven sCHWs and six study team data collectors, each of whom had a unique ID for logging in to the WoundScreener application. Empty profiles had been uploaded into WoundScreener prior to the start of the study, and users would select the profile which corresponded to the patient's study enrollment ID. The visible light image is captured when the application recognizes the target and that the resulting image includes the entire area of interest. Images and related data were stored on a password-protected study computer and on a cloud server.

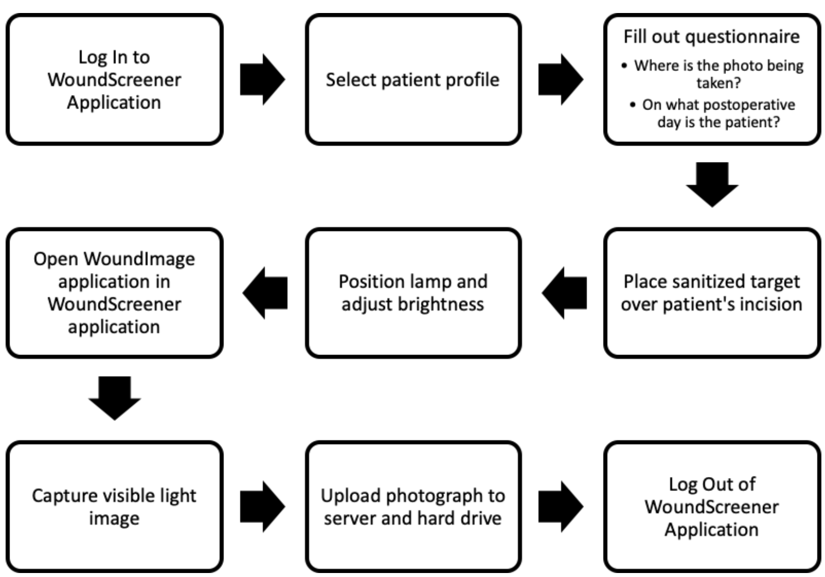

Figure 2: **Overview of the image capturing process and example of the target and mobile application being used for image capture**

3.3 TRAINING

In order to standardize operating procedures for image capturing, extensive training was held for all team members involved. Additionally, images were continuously assessed throughout the course of the study, and modification of the study procedures and additional retraining with study team members was performed as necessary.

A. Study team member training
All study team members who were involved in image capturing were English speaking, and all had extensive experience with using smartphones. Prior to the start of the second study, two study team members who would be based in Rwanda during data collection met with the application development team in Boston, MA, USA. Over one week, these study team members learned how to use the WoundScreener application, practiced image capture, developed standard protocols for image capture, and learned how to troubleshoot and update the applications. These two team members then trained the remainder of the study data collectors. Training took approximately eight hours over the course of two days and involved orientation to the application, explanation of image capturing procedures, and practice using the application.

B. sCHW training
In order to be able to capture the images at the homes of the patients, sCHWs were given extensive training in image capture and use of the image capture tools. Five of the seven sCHWs had prior knowledge on using smartphones and tablets to capture images, as they participated in the first study. As part of the initial training, sCHWs simulated an actual home visit with image capturing, and retraining was done as appropriate. The duration of training for each of the first five sCHWs is estimated to be 20 hours, while approximately 35 hours of training were required for the two new sCHWs to gain the necessary skills and confidence with the image capturing tools to obtain high-quality images.

4 CHALLENGES IN DEVELOPMENT AND IMPLEMENTATION

4.1 1. TECHNICAL CHALLENGES

A. Lighting and Image Clarity
Initially, the camera flash of the phone was automatically turned on by the application, which led to overexposure of the image. The application was adjusted so that the phone camera flash was turned off by default and only the natural light lamp was used. Furthermore, the lamp intensity needed to be decreased to improve image clarity. Given the location of the c-section incision, it was difficult to light the entire incision without casting a shadow over one edge. Sometimes, the application user needed an assistant or assistance of the patient to ensure that the incision was well-lit and well-positioned in the target.

B. Target size and materials
Targets were developed with the help of clinicians in the US with knowledge on the size of the c-section incision. However, this initial estimate was based on American patients, who are on average larger than the Rwandan patients enrolled in the study. The initial target cut-out window was too large (26cm wide by 8cm tall) and could include patients' clothes, bedsheets, etc. The large size also caused the target to fold, especially given the location of the incision under the patient's pannus. The target window was subsequently reduced in size (19.5cm wide by 5.5cm tall), producing much more standardized images. The target material was revised several times to improve target stability and durability for transport over long distances and often through the rain. The material also needed to be easy to sanitize without washing off the machine recognizable frame and flexible enough to sit well over incision while still allowing the app to recognize the target.

4.2 REMOTE TROUBLESHOOTING OF APPLICATION

The application development team was based in Boston, and the study was implemented in Rwanda, with a six to seven hour time difference depending on the month. Thus, if any issues with the application arose, the study coordinators would often need to wait up to seven hours before being able to consult with the development team. Additionally, some issues encountered in the field were difficult to communicate, due to both the language difference as well as to the inability to demonstrate the problem. Most issues could be resolved based on the training that the two study team members received in Boston. The remaining issues were solved through frequent communication between the two teams, including sending images to the application developers for review and feedback to address potential problems.

4.3 Differences in skill level amongst those taking photos

As previously described, a total of 13 study team members were involved in image capturing, and their levels of experience with this type of technology varied widely. This introduced variations in the images themselves. For example, sCHWs and study data collectors who had more experience with this type of technology felt more comfortable holding the phones and taking images, which led to increased camera stability and image clarity. While the large number of people taking images led to increased variability, it is important to note that, should this intervention be translated into a real-world SSI screening program, an even larger number of users would be involved in image capture. Thus, the conditions of our study replicate this variability on a smaller scale, and the images taken by our study team members can help train the ML algorithm to interpret images taken by users with a wide range of skill and experience with this technology.

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5 Recommendations

Based on our experience, we have developed several recommendations for improving standardization of image capturing for ML algorithms in low-resource settings. First, when developing tools to standardize image capture, it is important to keep in mind the patient population that will benefit from the ML algorithm and the setting in which the algorithm will be used. In our study, the patients studied were of smaller stature and thus required smaller targets. Furthermore, targets and smartphones needed to be durable to withstand long travel times and severe weather conditions. Secondly, training programs are essential prior to implementation of image collection. These programs must be tailored to the skill levels of each of the data collectors and must also include training on the use of image capturing tools and image capture techniques. Third, regular monitoring of image quality is essential so that appropriate retraining and adjustment to tools or the image capturing process can be made quickly. Finally, troubleshooting of any of the tools would be much faster and smoother if development teams and data collectors worked together in person, which would require close collaboration with in-country institutions. These institutions are familiar with the local context in which the images are captured and the ML algorithm would be used, and thus they are best positioned to recommend future directions for the tools and ML algorithms developed. Frequent and open communication between development teams and data collectors is essential to ensure timely resolution of any issues and to prevent major problems during the image capturing process.

6 Conclusion

There is a growing need for mobile applications for clinical care delivery in developing countries, particularly in rural areas. The described mobile screening tool can be a feasible approach to reduce the number of undiagnosed SSI in rural areas. This approach can also be used for other clinical conditions, such as sepsis or other types of infections. Future application development would seek to include a way of having the supporting natural light as an augmented tool that can be attached to the micro USB port of the phone, and other similar developments to reduce the amount of external support needed to capture images. However, there is a need to have a close collaboration with in-country institutions during the development of tools and processes for image capturing. This would facilitate selection of resources, such as smartphones and targets, which are appropriate and convenient for the setting.

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