Estimate Clinical Signs of Anemia and Noninvasive Hemoglobin Level Measurement in a Mobile Phone Environment

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1- INTRODUCTION

There is worldwide demand for an affordable hemoglobin measurement solution, which is a particularly urgent need in developing countries. The smartphone, which is the most penetrated device in both rich and resource-constrained areas, would be a suitable choice to build this solution. Consideration of a smartphone-based hemoglobin measurement tool is compelling because of the possibilities for an affordable, portable, and reliable point-of-care tool by leveraging the camera capacity, computing power, and lighting sources of the smartphone. However, several smartphone-based hemoglobin measurement techniques have encountered significant challenges with respect to data collection methods, sensor selection, signal analysis processes, and machine-learning algorithms. Therefore, a comprehensive analysis of invasive, minimally invasive, and noninvasive methods is required to recommend a hemoglobin measurement process using a smartphone device. Low Hemoglobin (Hb) level in the blood leads to many chronic health problems, including heart attack, stroke, and pregnancy complications. Anemia, a common Hb disorder, may be caused by blood loss , decreased red blood cell (RBC).

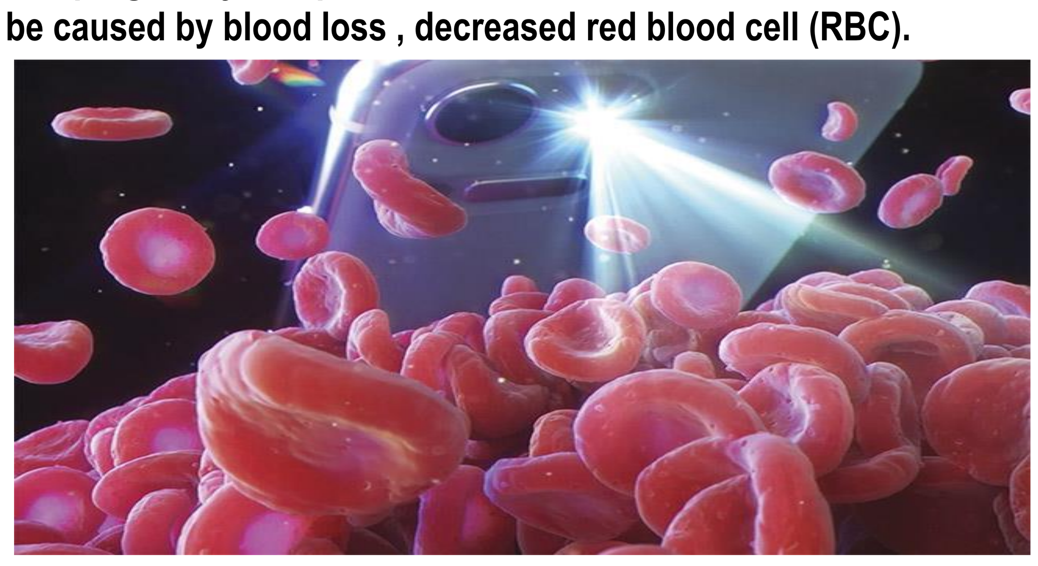

Figure 1. Blood hemoglobin levels can be estimated noninvasively using a smartphone camera.

2- OBJECTIVE

In this study, we analyzed existing invasive, minimally invasive, and noninvasive approaches for blood hemoglobin level measurement with the goal of recommending data collection techniques, signal extraction processes, feature calculation strategies, theoretical foundation, and machine-learning algorithms for developing a noninvasive hemoglobin level estimation point-of-care tool using a smartphone.

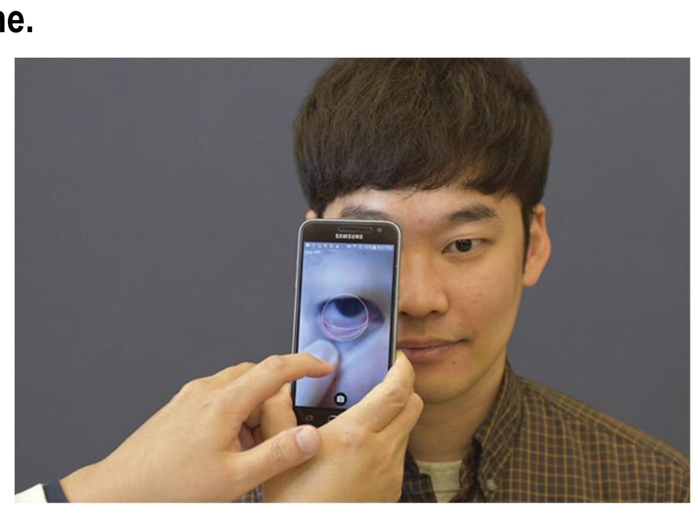

Figure 2. The mobile application for noninvasive blood hemoglobin quantification.

It aims to use blood hemoglobin testing by portable spectroscopy instead of traditional hemoglobin testing such as complete blood count (CBC) in hospitals by converting a smartphone's built-in camera into an imaging device, early detection of anemia and limiting the spread of infection by reducing the risk of infection. Reducing overcrowding in hospitals, providing health care at home instead of going to the hospital, creating an algorithm that works at any time, analyzing the digital image in the eye, increasing the concept of health among people, knowing blood hemoglobin through fingertips, reducing the cost of expensive medical devices, and monitoring follow-up From home without the need to go to the hospital for measurement, and we aim to reduce the error rate and increase accuracy.

3- METHODS

We explored research papers related to invasive, minimally invasive, and noninvasive hemoglobin level measurement processes. We investigated the challenges and opportunities of each technique. We compared the variation in data collection sites, bio signal processing techniques, theoretical foundations, photoplethysmogram (PPG) signal and features extraction process, machine-learning algorithms, and prediction models to calculate hemoglobin levels.

This analysis was then used to recommend realistic approaches to build a smartphone-based point-of-care tool for hemoglobin measurement in a noninvasive manner.

Our systems are usually composed of the three main functional components shown in Figure 3.

(1) Data acquisition sensor that captures a raw biological (e.g., image or video) signal.

(2) Feature engineering unit that preprocesses the signal and calculates features from the signals.

(3) Hb level estimation system, which generally incorporates different layers of user authentication, data storage, prediction model usage, machine learning, and result validation.

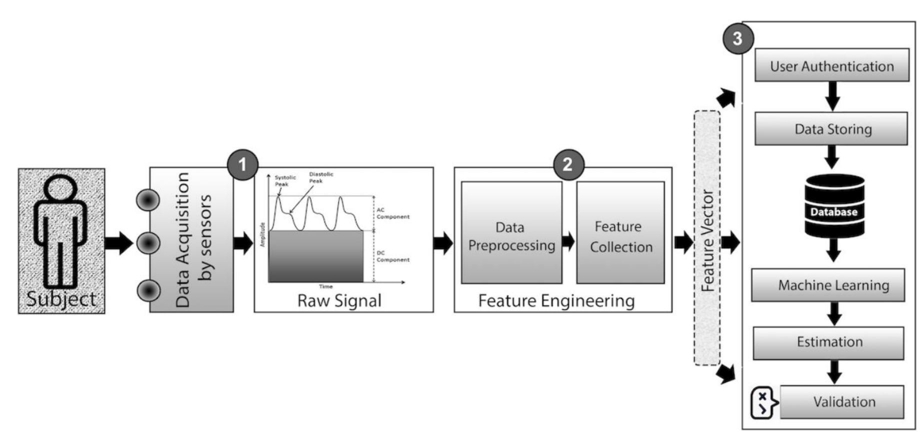

Figure 3. Phases involved in a noninvasive hemoglobin measurement system.

1-Finger-Based Analysis

Our system uses smartphone camera sensors to capture image or videos, and each video frame was analyzed pixelwise by separating the red, green, and blue (RGB) pixel intensities, and generating timeseries information on each block over all frames. Then an artificial neural network is applied to estimate Hb levels based on training data. The most significant region of interest was determined to be close to the smartphone's flashlight. Although RGB pixels were explored in this study, only the red pixel information was employed for development of the prediction model.

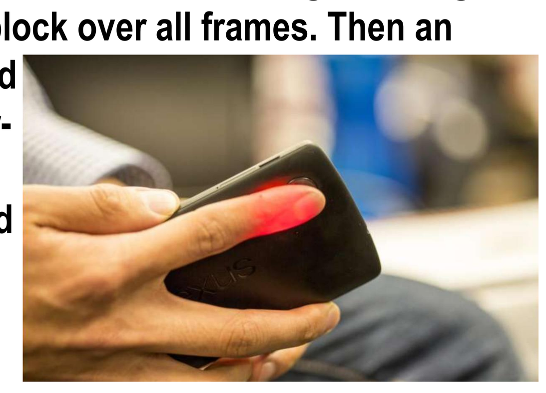

Figure 4. noninvasive hemoglobin measurement using fingertip.

2-Fingernail

A human fingernail, with about 1 mm thickness on average, is comprised of keratin protein, which is translucent. Fingernails have been studied since they allow for easy data capture, and they are relatively easy to control. The images of a fingernail bed captured by a smartphone-based app with the camera flash both on and off and analyzed to investigate critical information for noninvasive Hb level measurement. Multilinear regression with a bisquare weighting algorithm was applied to build a prediction model from the nail bed's image parameters and standard laboratory reports.

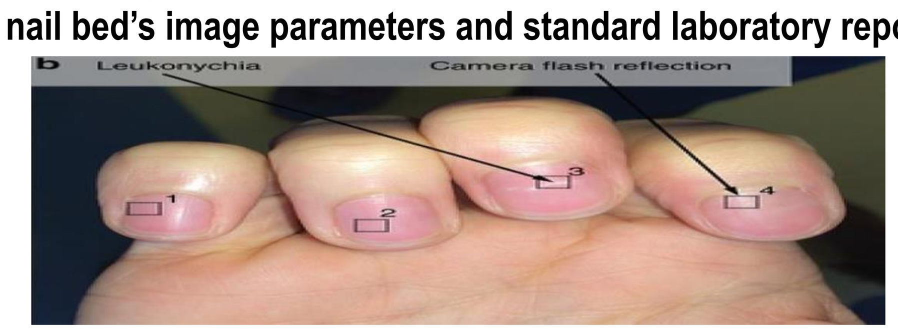

Figure 5. Smartphone-based for noninvasive hemoglobin measurement using fingernail

3-Palpebral Conjunctiva

The palpebral conjunctiva, the lower eyelid area of the eye, has received considerable attention as a measurement site because the micro vessels in this area are clearly visible and melanocytes are not present. Reflectance spectroscopy has been applied to capture data from the eyelid area. Digital photography and spectral data of lower eyelid images or spectral data converted from an RGB image to measure Hb levels in a noninvasive manner. We introduced a smartphone-based solution that converts an RGB image captured by a smartphone's camera sensor into a virtual hyperspectral image using SLIC super pixel (figure 6) method for assisted selection of the area of the palpebral conjunctiva. The need for additional equipment such as an attachment with a smartphone to capture the spectral response was avoided by generating a conversion matrix (T) to transfer a regular image to a spectral image. The generated spectral image was defined as virtual spectra, which were used to train an Hb prediction model.

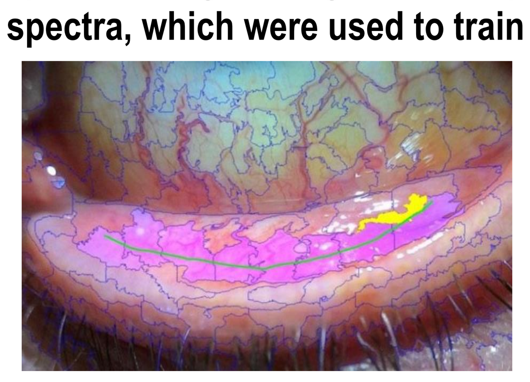

Figure 6. Example of supervised selection of the palpebral conjunctiva using the SLIC super pixel.

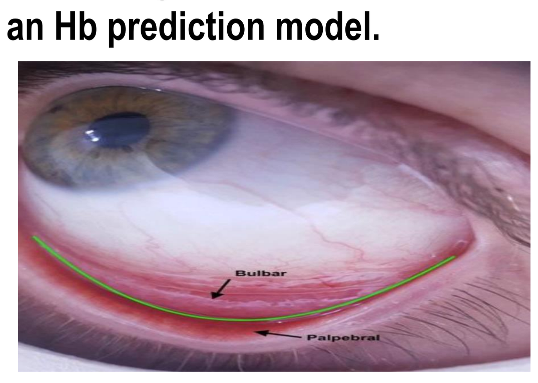

Figure 7. Bulbar and palpebral conjunctiva.

The technology is based on spectral super resolution (SSR), which virtually transforms a built-in smartphone camera into an imaging device for spectroscopic quantification of blood hemoglobin content. SSR enables mathematical reconstruction of high-resolution reflectance spectra from the three-color values of the RGB channels acquired by the camera (Figure 8a). Super resolution is defined as a high-resolution reconstruction of the digital signals acquired by low-resolution systems. This concept was extended to the frequency domain for purposes of the Purdue study.

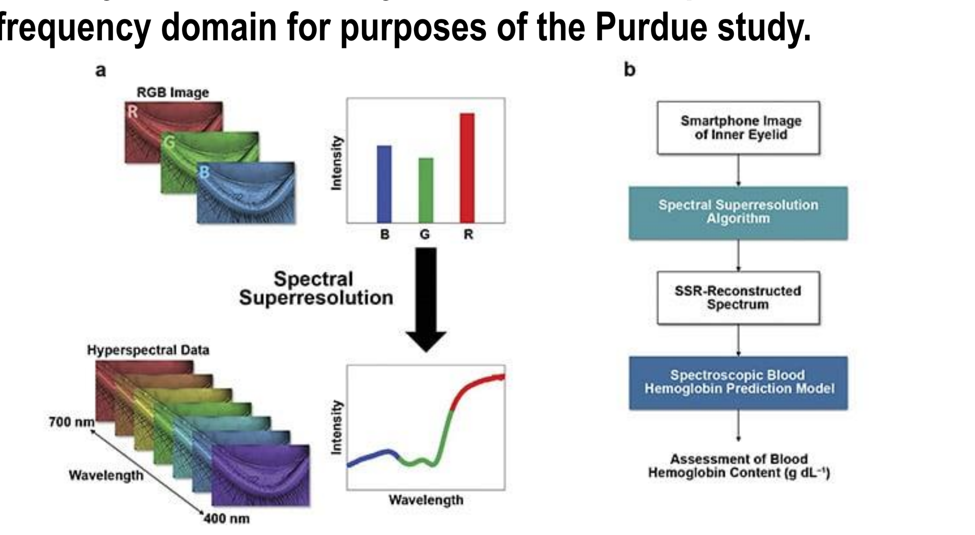

Figure 8. Statistical learning framework blood hemoglobin analysis using a Vitalism algorithm.

4- RESULTS

The fingertip area is one of the best data collection sites from the body, followed by the lower eye conjunctival area. Near-infrared (NIR) light-emitting diode (LED) light with wavelengths of 850 nm, 940 nm, and 1070 nm were identified as potential light sources to receive a hemoglobin response from living tissue. PPG signals from fingertip videos, captured under various light sources, can provide critical physiological clues. The features of PPG signals captured under 1070 nm and 850 nm NIR LED are considered to be the best signal combinations following a dual-wavelength theoretical foundation. For error metrics presentation, we recommend the mean absolute percentage error, mean squared error, correlation coefficient, and Bland-Altman plot. In the visible wavelength range, the reconstructed spectra aligned well with the original data that was measured by a spectroscopic imaging system. More importantly, the reconstructed spectra show the consistent performance in a broad range of clinical laboratory hemoglobin levels, reflecting varying levels of anemia (Figure 9).

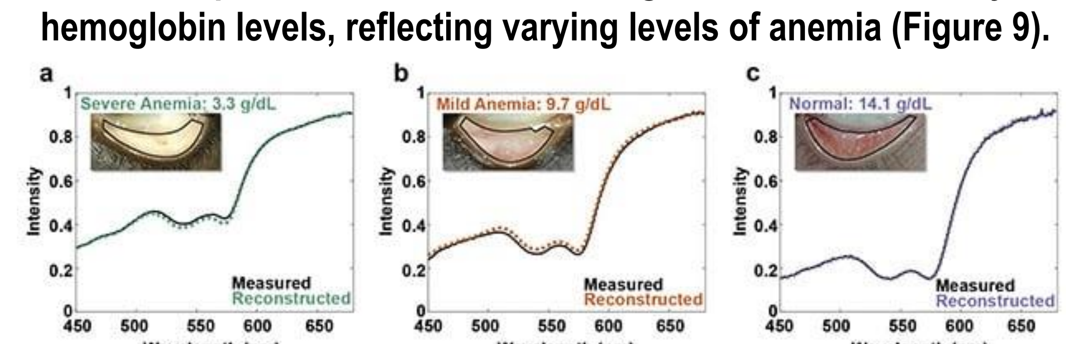

Figure 9. Representative SSR hyperspectral reconstruction for severe anemia, mild anemia, and normal condition.

Using the RGB data acquired by the mobile app, the computed blood hemoglobin levels of the validation data set show a high coefficient of determination R2 value of 0.912 and a narrow 95% limits of agreement of −2.20, 2.29 g/dL with a bias of 0.04 g/dL in the Bland-Altman plot (Figure 5), which analyzes agreement between two assays. These results suggest that the mHealth blood hemoglobin prediction algorithm could offer reliable assessments.

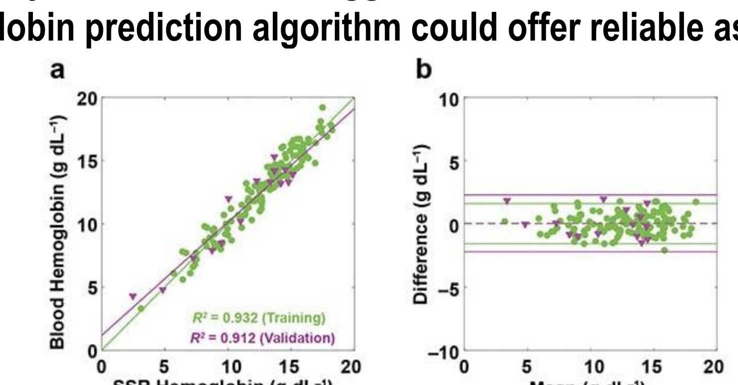

Figure 10. Performance of SSR hemoglobin assessments using the mHealth algorithm. Correlations between clinical lab blood hemoglobin levels and computed levels of the training (138 individuals) and validation (15 individuals) data sets (a). Bland-Altman analyses between measured and computed levels (b).

5- CONCLUSIONS

We addressed the challenges of developing an affordable, portable, and reliable point-of-care tool for hemoglobin measurement using a smartphone. Leveraging the smartphone's camera capacity, computing power, and lighting sources, we define specific recommendations for practical point-of-care solution development. We further provide recommendations to resolve several long-standing research questions, including how to capture a signal using a smartphone camera, select the best body site. We also will make a moving robot scan faces of children and measure vital signs moreover send alerts when detect a health problem and send it to their parents ,and also to monitor the health of the elderly.