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Mobile Application to Collect Data and Measure Blood Component Level in a Non-Invasive Way

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***Abstract*—The increasing advancement in mobile technology has led to many smartphone-based technologies being widely accepted in various research fields. In recent years, promising smartphone-based technologies have been developed for activity recognition, gait analysis, telemedicine, and fitness tracking. However, some invasive methods are used for measuring blood components (hemoglobin, glucose, bilirubin, etc.). This invasive method involves drawing blood from patients and then analyzing the blood sample. This process is painful, and the time delay between the blood collection and analysis can be a significant disadvantage. Extensive research is being conducted to introduce a noninvasive method of measuring blood components. However, these methods may be expensive and inconvenient for people with little literacy. To deal with these issues, we have developed a mobile application that any group of people can use conveniently and quickly. Furthermore, this application can collect data without causing inconvenience and output blood glucose and hemoglobin levels, allowing for real-time data monitoring. A study evaluated the system's performance, comparing invasive and noninvasive hemoglobin measurements on 15 subjects (11 male, 4 female) using this app. It was also tested on Samsung, Realme, Vivo, and Redmi phones, showing compatibility with diverse brands.**

***Index Terms*—Smartphone; FPS; NIR LED; ISO; Exposure; Glucose; Hemoglobin; Photoplethysmogram.**

I. Introduction

Smartphone sensing has brought a revolutionary change in the medical sector and has become a faithful medical attendant for us. It has changed the perspective of many benignant data mining medical applications like activity (sleeping, running, sitting, etc.) recognition, elder care, fitness monitoring, and diet monitoring. etc. Nowadays, different kinds of sensors, including accelerometers, gyroscopes, light sensors, proximity sensors, fingerprint sensors, magnetometers, infrared sensors, GPS, barometers, temperature sensors, etc., are available inside mainstream smartphones. Different motion activities, including walking, running, sitting, cycling, jogging, driving, etc., and gait patterns are recognized by smartphone sensors like camera, GPS, wifi, and accelerometer [1].

An Android-based mobile application has been developed to collect data from different mobile sensors for gait pattern recognition [2]. Research is going on to detect Neurological disease non-Alzheimer dementia, which is related to abnormal gait patterns by video games. By collecting data from the camera and then analyzing it by image processing, fall prediction can be done [3]. Heart rate can be measured by analyzing the Photoplethysmography (PPG) signal obtained by the subject's fingertip placed over the smartphone camera [4]. But we are still dependent on the old invasive version in the case of blood component-related measurements, including hemoglobin (Hb), arterial oxygen saturation(SpO2), and glucose measurement. In this process, first, the identification of the vein, preferably a median cubital vein, is carried out. Then, blood is drawn from the patient by venipuncture for analysis using a spectrophotometer. This process is painful as the needle is inserted into the body. There is also a considerable time delay between blood collection and its analysis. Besides, for this process, a skilled workforce is needed. Most importantly, if necessary, precautions are not adopted, there will be a considerable risk of deadly infections. But recently, several kinds of research have been going on to measure these blood components by the non-invasive method. This method is painless and doesn't require venipuncture, which means real-time data can be monitored without any risk of infection. It also provides quick results. Vega Pradana Rachim et al. developed a biosensor sensor attached to the back of a wristband during glucose level measurement [5]. Jessica Hanna et al. have developed a system with two EM-based sensors: a multiband slot antenna and a multiband-reject filter [6]. But, these sensors or devices are hard to carry and costly. Moreover, one should have a minimum of knowledge about the sensor/device.

To address these challenges, Some researchers have proposed using smartphones to make this process affordable, portable, and compact. These researches are concentrated on utilizing the smartphone's camera sensor to collect fingertip video data, which is then analyzed by different mechanisms. Some of the mechanisms include Pulse Transmission Time(PTT) analysis [7], chromatic analysis [8], pixel intensity analysis [9] and Photoplethysmography(PPG) signal analysis [10]. Research is going on to improve the accuracy of these mechanisms. In addition to improving these mechanisms, proper video data acquisition also influences the system's accuracy. Acquisition of fingertip video requires a light source and a camera sensor to capture the variation in blood volume. Some studies have used IR sensors, NIR LED, etc. Research has shown that NIR LED could be used as the light source for this purpose. However, there are some areas for improvement in this research. There are numerous smartphones available with different configuration facilities. This could lead to compatibility problems. For example, some device supports capturing video at only 30 frames per second. However, if the target device supports 60 frames per second, capturing video at 60 frames per second is preferable to enhance information extraction. Again, because ambient light can alter the video's brightness, it can be challenging to record while maintaining the same quality in various lighting situations.

To address the abovementioned issues, We have developed a mobile application to simplify collecting fingertip video data using the camera sensor. This application enables capturing video using an external NIR LED as the light source, as shown in Fig. 1. In conjunction with NIR LED, the application also supports capturing video using white LED, as almost every smartphone has a flashlight.

Fig. 1: NIR LED Board Device.

We employed a deep learning approach in this study based on the research done by [10]. The authors proposed a novel non-invasive technique based on PPG signal using Deep Neural Networks (DNN) to measure blood hemoglobin, glucose, and creatinine levels. According to the research, the application developed in this study initially collects personal data from users, including name, gender, age, height, and weight. Then, it contains a video of the index finger placed on top of the flashlight or a NIR LED device. The system then extracts frames from the video and saves them as raw images. A PPG signal is generated by analyzing these frames, and several features are extracted from the signal. Finally, these features are fed into the machine learning model to predict the glucose and hemoglobin levels. Finally, the predicted measurement is displayed on the mobile application.

The main contributions of the study are as follows:

- Construction of a cost-effective, user-friendly mobile application system for fingertip video data collection.
- Setting up the system to ease the data collection process from the users and. Keeping track of users' video data by renaming files.
- Automating the process of capturing video data of 15-second duration and saving the data locally in the target device.
- Manipulating Brightness, ISO, Exposure, and Focusing parameters to capture video in different wavelengths of light.
- Controlling Frames Per Second (FPS) of recorded video.
- Measuring blood component level from the collected data.

The remaining parts are organized as follows: We present some related works in Section II. Section III describes our proposed system and how we developed it. In Section IV, the paper concludes with the experimental results.

II. Related Works

Several techniques have been applied for monitoring health non-invasively using mobile applications. E. Jonathan Et al. [11] present a study where the authors demonstrate the use of a smartphone's video unit, which includes a camera and white light emitting diode (WLED) as an illumination source, for reflection-mode photoplethysmographic (PPG) imaging [11]. The study records videos of a human finger using a smartphone. It successfully detects usable PPG signals, such as changes in heart rate, indicating promising results for personal and home-based care applications. However, the study was conducted on the index finger of a single male volunteer. A larger and more diverse sample size would be needed to establish the generalizability of the results. Moreover, the paper needs to address the capability of continuous monitoring using the smartphone-based system.

Edward Jay Wang et al. have introduced HemaApp, a smartphone application that utilizes the smartphone's camera and various lighting sources to monitor blood hemoglobin concentration [8] noninvasively. HemaApp performs chromatic analysis by analyzing the colour of the blood when a light source shines through a patient's finger to estimate hemoglobin levels. However, the limitation of the proposed system is the requirement of using a custom array of LEDs as a phone case, which is not convenient for real-life applications.

Shantanu Sen Gupta et al. have developed an all-purpose photoplethysmography (PPG) system design for non-invasive blood glucose measurement using machine learning [12]. The system design includes an LED, a photodiode, a signal conditioning circuit, and a microcontroller for data acquisition and analysis. The collected PPG data is processed and analyzed using machine learning algorithms to estimate the blood glucose level. The paper briefly mentions that PPG devices are subject to motion artifacts. However, the mitigation or handling of these artifacts needs to be discussed. This is vital for accurate and reliable measurements, especially in daily-life scenarios where individuals may be moving or active.

Amtul Haq Ayesha et al. have proposed that heart rate (HR) can be estimated without the usage-specific sensor technology [4]. Instead, it applies photoplethysmography (PPG) technology using a smartphone camera and recordings of the fingertip. Their method is to observe slight colour alterations in the skin by cardiovascular activity. It enables heart rate measurement using a commonly available smartphone camera. However, their method accuracy is limited to camera quality, light conditions, and skin tone variations.

To overcome these limitations, we intend to build a system that can be used for real-time monitoring of patients and is cost-free with very little or no integration of external hardware.

III. Proposed Methodology

A. Proposed System

In the field of noninvasive blood component measurement research, fingertip video data holds significant importance in the accuracy of measurement. When this data is collected manually, there are several issues to mention. Among them include applying appropriate camera settings manually to get the proper video in different light conditions, changing the video file name after every fingertip video is recorded for later access, keeping track of the patient, waiting for the video recording stop time, and many more. The proposed system offers several advantages and solutions to the issues encountered during manual data collection. The flowchart of the proposed method is shown in Fig. 2.

This research introduces a smartphone application to streamline the data collection process for noninvasive blood component measurement. The system includes a user registration activity, where essential user details such as name, gender, age, height, and weight are collected. Once these details are provided, users are directed to the next activity, which facilitates fingertip video recording using the application's camera feature.

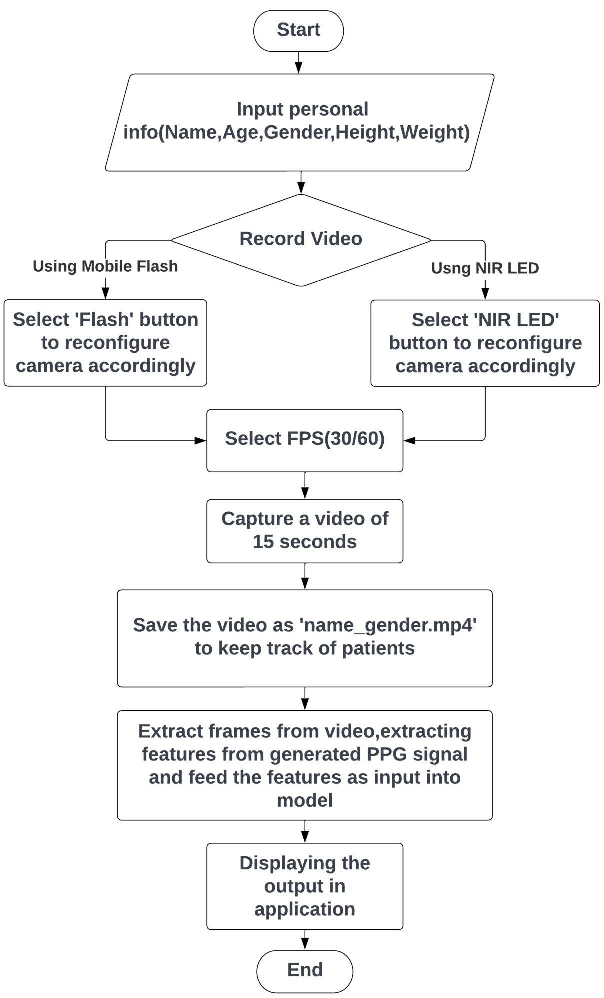
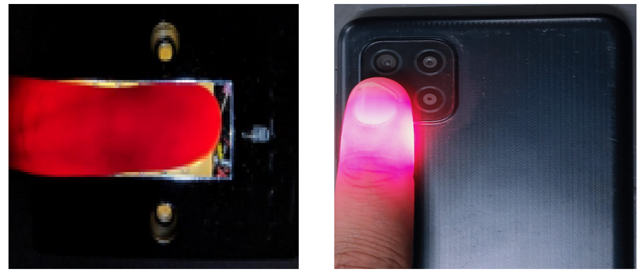


Fig. 2: Flowchart of the system.



(a) (b)

Fig. 3: Placement of fingertip: (a) NIR LED device and (b) mobile flash.

The video recording activity incorporates a camera preview surface and interactive buttons that enable users to configure camera settings for different lighting conditions, including using NIR LED and a flashlight. Furthermore, the application offers an automated 15-second video recording option, eliminating the need for manual intervention to stop recording. To simplify data organization, the recorded videos are saved on the device with a filename format of 'username_age.mp4', aiding in patient data tracking.

To accommodate devices that do not support 60 frames per second (FPS), the proposed system allows video recording at both 30 FPS and 60 FPS. Recording at 60 FPS enhances data richness by generating a more significant number of frames. The system employs a standardized approach to set parameters like brightness, ISO, exposure, and focusing to capture video effectively in various lighting conditions, whether using a flashlight or NIR LED, as depicted in Fig. 3.

After video recording, the system analyses the video data to extract frames and generate a photoplethysmogram (PPG) signal from these frames. Feature extraction from the structures follows, and these features serve as input for a locally embedded DNN-based model. This model is employed in this application for blood component prediction based on the approach presented in [10]. A complete flow diagram of the system is depicted in Fig. 4.

B. System Development

This application is mainly developed targeting anemia and diabetic patients. In Bangladesh, most anaemia patients are not well educated and accustomed to smartphone applications. To simplify the user experience, we initiated by gathering the requirements of target users and then designed an interactive user interface focusing on ease of use,

This application is structured into three phases:

1) Inital Data Collection : The initial activity of the application is designed for collecting personal data from users, including their name, gender, age, height, and weight, as illustrated in Fig. 4(a). For age and weight, numerical input fields are provided. Gender and height information is collected

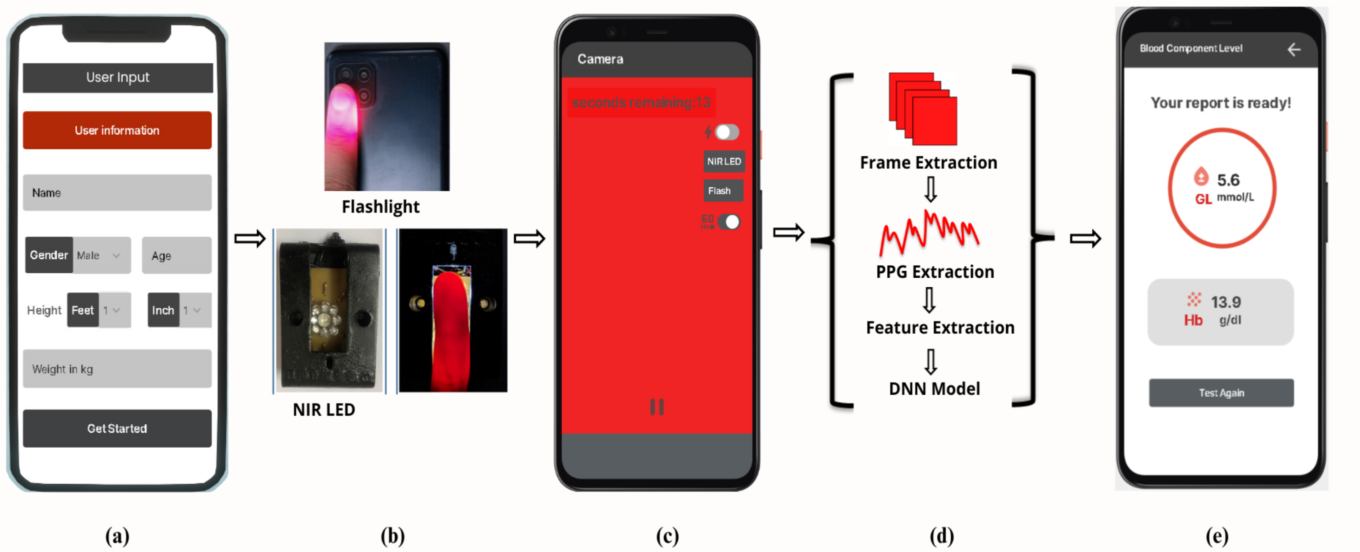


Fig. 4: Overview of our proposed system. (a) Initially, information about the user is collected. (b) The user then places the fingertip on the flashlight or the external NIR LED device. (c) After properly placing the fingertip, the user clicks the start recording button. A 15-second video is then automatically recorded and saved on the local storage. (d) The video is then analyzed, and frames are extracted, followed by ppg signal generation. Then, necessary features are extracted and fed to the DNN model as proposed in [10]. (e) Finally, the prediction of blood components such as glucose and hemoglobin level is displayed on the screen.

using dropdown menus. Users are required to input their gender and age for validation.

2) Fingertip Video Data Acquisition : The second activity of the application is designed for collecting fingertip video, as shown in Fig. 4(b). It includes a live camera preview incorporating the camera view, a button for initiating video recording, a toggle button to turn the camera flash on or off during video capture, an option for selecting frames per second (fps), and two buttons to allow video capture using either a NIR LED or a flashlight. The functionality is abstractly managed by adjusting camera settings such as ISO, exposure, and brightness based on the user's choice of using a NIR LED or flashlight. These adjustments help optimize video quality and visibility in different lighting conditions. We have used the CameraX application programming interface (API) to record video. CameraX API is a modern library that is based on Camera2 API. It is compatible with devices running API level 21 (Lollipop) or higher. This API also supports several Camera2 functionalities through the Camera2 interop API.

We opted for CameraX API because it provides various use cases such as Preview, Image Analysis, Image Capture, and Video Capture. Since our application involves video recording, we have used the preview and Video Capture use cases. The preview use case allows setting the resolution of the preview camera surface. We have configured it to a resolution of 1920 x 1080. The video capture use case provides additional features such as video quality selection, audio control enable/disable, pause/resume, and starting and stopping recording, which we have integrated into our application. We have extended the Camera2 features using Camera2 Interop API to control the camera's sensitivity, frame duration, and exposure time. This allowed us to adjust ISO, exposure, and brightness to achieve optimal video quality regardless of the lighting conditions and whether a mobile flash or an NIR LED device is utilized as the light source. We have configured the camera settings (ISO, Exposure, Brightness) required to capture the video using a mobile flash or NIR LED device. CameraX API also allows focusing automatically while video recording.

We have also implemented the feature of recording a 15-second video automatically when the user clicks the record button. Once the recording is completed, the video is saved locally on the user's device in the format 'name_age.mp4'.

3) Blood Component Level Analysis : The final activity is designed to display the glucose and hb level of the user once the analysis is done, as depicted in Fig. 4(e). The glucose level is calculated as per the unit of mmol/L and Hemoglobin level is calculated as per the unit of g/dL .

IV. EXPERIMENTAL ANALYSIS

A comparative study between an invasive and noninvasive measurement of hemoglobin level using this application is discussed in this section. A total of 15 subjects (11 male and four female) were studied, ranging in age from 20 – 25 years. The range of reference hemoglobin levels varies from 9.4 g/dl to 16.0 g/dl for this targeted study. The Cyanmethemoglobin (CM) method was used for the invasive procedure to measure the reference hemoglobin concentration in blood samples collected from patients. This method releases hemoglobin from red blood cells by adding a reagent. Then, methemoglobin is formed from hemoglobin. The spectrophotometer that measured the colour intensity of the methemoglobin solution used light at a wavelength of 545 nm. Then, hemoglobin level was measured using the proposed system to compare the obtained value from this system with the reference value obtained from the invasive method. The flashlight was used as the light source to conduct this experiment through our application.

A. Evaluation Metrices

The performance of the proposed system is measured using coefficient of determination (R^2) and mean absolute error (MAE). The higher value of (R^2) indicates a better model fit. The mathematical formulas are as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{1}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

where y_i is the ith reference value, $\hat{y}_i$ is the corresponding measurement, and n is the total sample.

B. Result Analysis

1) Measurement Verification: To verify the accuracy of the measured hemoglobin levels using the proposed system with respect to the reference values obtained from the invasive blood drawing method, the coefficient of determination (R^2) and mean absolute error (MAE) was calculated using equation (2) and (3). The estimated accuracies of the application are R^2= 0.81 and MAE = 0.68 g/dl. Fig. 5 shows a correlation between reference hemoglobin and estimated hemoglobin level.

2) Reference Model: The incorporated model in this system was proposed by the work done in [10]. The authors of [10] evaluated the performance of their proposed model. They employed seven performance measurement indices: R, (R^2), MAE, MSE, RMSE, MAPE, and IA. Their study involved 93 participants, ranging in age from 0 to 79 years, including 59 males and 34 females. The clinically measured Hb levels (Reference Hemoglobin) for this group of individuals ranged from 7.90 g/dL to 21.49 g/dL.The authors used the NIR Led device for fingertip video. According to their study [10], their approach provides the highest estimated accuracy of R^2 = 0.922 for Hb.

3) Choice of Light Source: Since NIR light within a wavelength range of 700-2500 nm penetrates the finger more efficiently than white LED, the NIR LED is the best choice for this purpose. NIR LED was identified as the potential light source to receive a hemoglobin response from living tissue. [13].

C. Compatibility Testing Results

This application has been tested on various smartphones, including Samsung, Realme, Vivo, and Redmi. This indicates that this application is compatible with these diverse smartphone brands.

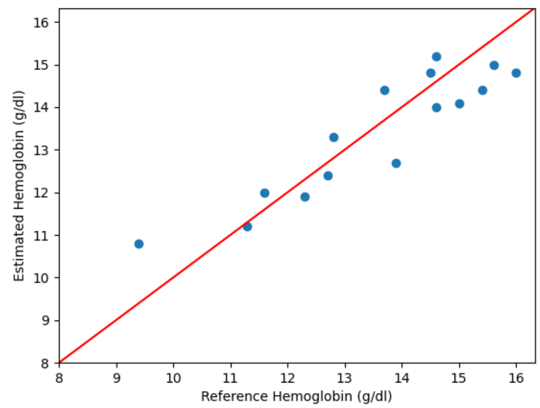


Fig. 5: Correlation plot of reference values and estimated values.

D. Discussion

Throughout the development process of this application, we faced several challenges. Bangladesh has a notable population of anemia and diabetic patients who may not be well-educated or accustomed to smartphone applications. So, simplicity in the user interface to ensure ease of use was the priority. The user interface was designed to be intuitive and user-friendly, ensuring that even individuals with limited smartphone experience could easily use the application. It was also challenging to harness the full potential of CameraX API due to the limited availability of comprehensive documentation. CameraX was successfully integrated into the application to provide a smooth and efficient user experience despite these challenges. One of the remarkable aspects of this application is its multi-functionality. This multi-functionality allows the application to serve as a research tool. Researchers and healthcare professionals can use the application to collect fingertip video datasets, which are valuable for medical research, analysis, and studies. Along with collecting video data, this application also serves as a self-controlled hemoglobinometer, allowing users to capture their fingertip video and measure their hemoglobin levels effortlessly.

V. Conclusions

A smartphone-based blood component measurement system has been presented in this paper. The proposed system overcomes the difficulties of manual data collection and has the potential to make non-invasive blood component measurement more effortless, more efficient, and more accessible for patients. The intuitive interface allows individuals to measure their blood component levels easily, promoting proactive health management. This system not only streamlines the blood component level measurement process painless and convenient for users but also has the potential to serve as a tool for researchers and healthcare professionals.

Furthermore, this mobile application can be extended to aid other medical conditions that require frequent blood testing, such as cardiovascular diseases, anaemia, and thyroid disorders. Integrating a cloud-based platform can facilitate easier data management, sharing among healthcare professionals and patients, and collaboration with healthcare providers for a more comprehensive health monitoring approach.

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