Phone Application For Health Monitoring And Diagnostics

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ABSTRACT

There is a pressing need for low-cost physiological monitoring solutions that are not only easy to use but also accurate and can be used at home or on the go (ambulatory) settings. Current mobile phone technology goes beyond monitoring and measuring the patient; it can also be used to convey information to medical professionals anytime, anywhere. By attaching minimal hardware to any user-grade mobile phone, we can provide the masses the ability to perform precise physical monitoring of the patient anywhere. Mobile phones, with their many inbuilt sensors, can be used to create and develop applications to collect various biomedical signals. This project accomplishes the task of not only monitoring but also predicting certain health diseases. The application developed is able to calculate the heart rate and oxygen levels using the camera and flashlight by image processing techniques, the blood pressure and temperature with the help of a specially designed PCB, and can detect whether a patient has arrhythmia and anemia to some degree of accuracy. The method proposed is non-invasive, easy-to-use, and easily accessible to everyone while also providing essential data.

Digital image processing is an important facet of biomedical imaging. Using the inbuilt Matlab image processing toolkit and openCV for android studio, the working of these sensors has been mimicked in this project. The use of these techniques effectively; however, requires facing several challenges in both design and computational efficiency. Smartphones are made for everyday life, and many users prefer a minimalistic design that conveys only important information, rather than being bombarded with data. For an assisted-living smartphone app, the user should not be swamped with data but monitored/supervised and assisted/supported as needed.

CONTENTS

1. INTRODUCTION

Smartphones are becoming increasingly popular and powerful while also having a wide variety of sensors that are available and capable of capturing information from the outside world, processing the data in real-time, and transferring all the information remotely using wireless communication technologies. Extensive research is being conducted to monitor various physiological parameters without any need for additional hardware using smartphones [38]. These factors make smartphones an ideal choice, and their potential has been explored for many medical applications (few of which are explored here) [1]. Utilizing these features, an app has been developed to measure and detect the following six parameters related to health:

- Heart-rate
- Oxygen Levels
- Temperature
- Blood Pressure
- Arrhythmia
- Anemia

Other than temperature and blood pressure, the remaining are calculated using image processing techniques. A brief insight into the methods of each is as follows:

1. Heart-rate Monitor

The phone's ability to record and detect variations in colour signals on the fingertip placed in contact with its optical sensor, i.e., the camera, can be used to measure the intensity variations caused by blood flow. The information related to the subtle colour changes caused by a cardiac signal as blood flows in and out can then be extracted (containing a pulsatile signal) by taking the average of all the pixel intensities [2]. The rate at which this colour change occurs can be used to calculate the person's heart rate. This type of imaging is known as reflection photoplethysmographic (PPG) imaging, in which we make calculations based on the illumination of the area with a white LED mobile phone flash. [3], [4].

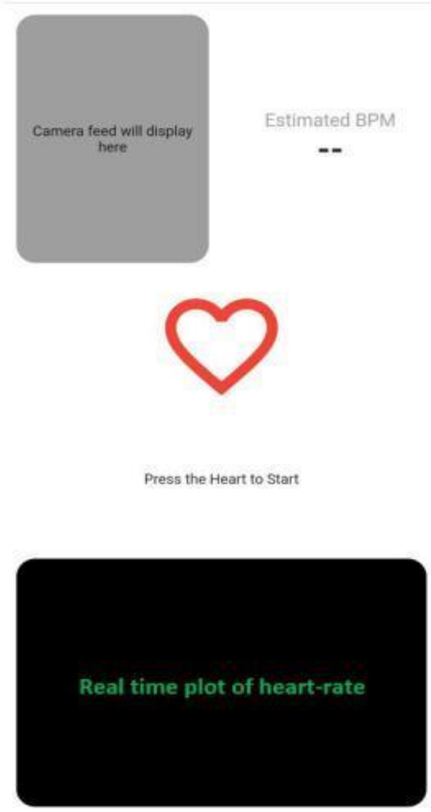

Fig. 1: Interface

The detection is made by analyzing the average red component values of the camera's frames, or portions of frames [5]. Periodic fluctuations in the received DC light on the receiver can be used to estimate the heartbeat very easily. Each heartbeat corresponds to a period of increased brightness (red DC level) followed by a period of decreased brightness. If we know the number of peaks of DC light in a given sampling period, we can use the formula below to calculate the beats per minute. [6], [7].

Heartrate = (No. of peaks in DC Red Level in a sampling period *60/Sampling period)

Fig. 2: Conversion Formula

Every valid image is processed, and the most interesting parameters are stored. Only the number of red pixels from the image is analyzed. If the number is higher than in the previous image, then we can assume that the heart is now beating. Because of the flashlight, the frame is slightly red rather than black. The ambient light passes through the tissues of the fingers and reaches the camera sensor. The image may appear to be a nearly static red frame, but periodic oscillations of blood flow in the vessels cause weak brightness variations that are undetectable with the naked eye but can be discovered using signal processing methods and algorithms. [8].

2. Arrhythmia

Cardiovascular disease is one of the main causes of death worldwide, and one of the most promising techniques to deal with this issue is preventive cardiology. Knowing your heart rate aids in the detection of disorders such as tachycardia and bradycardia. Heartbeat irregularities can be noted, such as when it is excessively rapid or too sluggish. A fast heart rate (consistently above 100 beats per minute in adults) is referred to as tachycardia, whereas a slow heart rate (consistently below 60 beats per minute) is referred to as bradycardia. We can forecast whether the user has Arrhythmia using the heart rate monitor's algorithm, which calculates the average heart rate and variance over the time of the measurement.

3. Oxygen Level

The concepts of spectrophotometry, which is the relative absorption of red (absorbed by deoxygenated blood) and infrared light, are used in oximeters (absorbed by oxygenated blood). The light of the absorption waveform's systolic component corresponds to arterial blood oxygen saturation. Multiple measurements of relative light absorption are taken every second, and the system processes them to produce a value every 0.5-1 second, which averages out the results from the previous three seconds to get a new reading. The oxygen saturation level should always be between 95% and 100%. It may be lower for persons with long-term respiratory disease or congenital cardiac disease, depending on the severity of the disease. We can compute oxygen levels by using the same algorithm as the heart-rate monitor and adding IR detection.

4. Temperature

The measurement of body temperature is done using the specially designed PCB which uses the LMT87 thermal sensor to detect the temperature (from the finger inserted) and the data is sent to the phone via a Bluetooth module.

5. Blood Pressure

The measurement of body temperature is done using the specially designed PCB which uses the TTP223 pressure sensor to detect the temperature (from the finger inserted) and the data is sent to the phone via a Bluetooth module. The model prepared; however, uses **BMP280** temperature and pressure sensor to make the readings till the PCB is available.

6. Anemia

Anemia is a condition in which people have low levels of hemoglobin or not enough healthy red blood cells. One reliable indicator of how anemic a person is; is to check the paleness in some body tissues, especially the fingernail beds. The skin beneath fingernails does not contain pigmentation, so hemoglobin – the oxygen-carrying pigment of the blood – is the main source of color. The application developed allows people to obtain a hemoglobin measurement in seconds by photographing their fingernails. Leukonychia, or white nails, is normally not a cause for concern, although it can occasionally signal a number of serious systemic diseases or congenital abnormalities. The aberrant color could be caused by a variety of factors, ranging from basic manicure habits to life-threatening liver, kidney, or iron deficiency anemia. [40].

2. METHOD

The methodology and implementation of each of the diagnostics is different and is explained in as much detail as possible in this section.

Heart-rate Monitor

The average time series of the frames' red component values are used as input signals for heart rate measurement. Each of the signal's "sharp" local maxima, known as peaks, corresponds to a single pulse. To determine the heart rate, all that is required is the number of heartbeats and the length of the measurement. Unfortunately, the original signal obtained is too noisy and may contain fake peaks or data loss as a result of the movement of the finger above the camera lens or even changes in the surrounding light level during the measurement, so we cannot rely on the number of raw signal peaks for heart rate calculation [5]. We need to use algorithms that receive signals as input and give calculated heart rate as the output [9]–[11].

The function **_scanImage** in the application's code calculates the average of the red channel of the camera image and adds the value to a data list, which is subsequently displayed on the chart. The data list's number of points has been limited to 50 values [12].

Because we do not need to process every frame, we can choose a sample rate. A sampling rate of 30 samples per second was employed in the code. This is done with **_boolean** processing, which turns true when the **_scanImage** function is invoked, stays true for 1/30 seconds, and then turns back to false. If the **_boolean** processing is false, the **_scanImage** function will be called [13]–[15].

The average and maximum values of our window data are used to calculate heart rate, which is the frequency of the depicted signal. We then set a threshold equal to the mean of these values and look for peaks over it. We also use an attenuation coefficient to update the BPM value, so there are no abrupt fluctuations [16].

The result is a real-time plot of the image's red DC mean data. The values depict a change in the received red colour intensity over time, which is used to determine the heart rate [5].

TABLE I: Heart-rate Measurement using App and Mobile Phone

Sno.	Average Heart-rate Value		
	Application	Smart Watch	Activity
1.	76 BPM	72 BPM	Resting
2.	103 BPM	100 BPM	Workout

Fig. 3: Comparing values between conventional sensors and our application

Fig. 4: Values Observed

The logical flow of data can be summarized from the flowchart below:

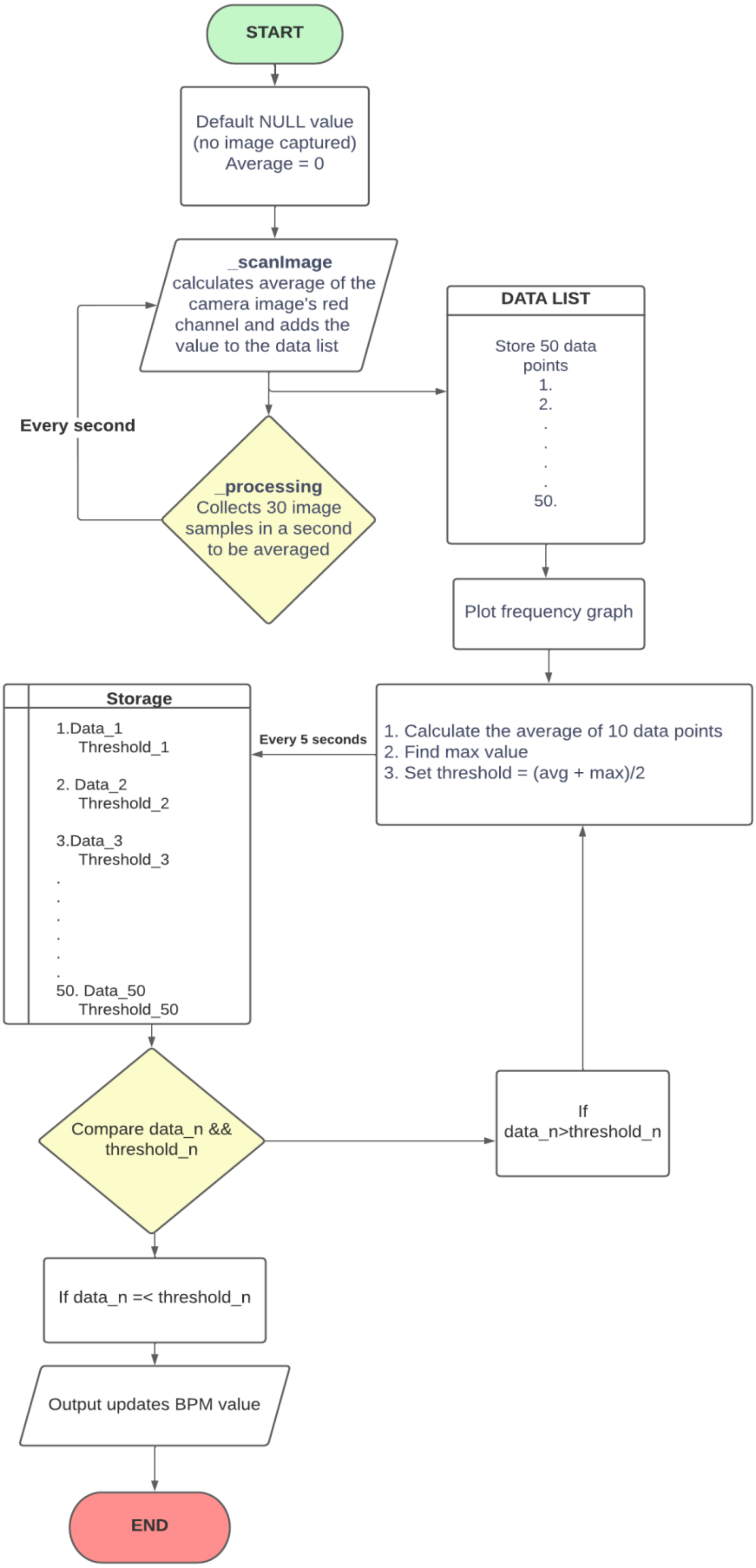

Fig. 5: Algorithm

Oximeter

The proposed application for SpO2 percent monitoring makes use of the smartphone's LED and flashlight as a wide spectrum light source, the camera as a light detector and image recorder, and a suitable image-processing algorithm for the extraction of the PPG signals [9], [17], [37]. A user-friendly interface permits the use of the application by non-expert patients.

SpO2% is evaluated according to the following equation:

$$SpO_2\% = K_1 + K_2 \frac{V_{ppR} * V_{offIR}}{V_{offR} * V_{ppIR}}$$

Fig. 6: Formula implemented

where VppR and VoffR are the peak to peak and offset amplitudes of the PPG(red) obtained with the RED wavelength, respectively. The amplitude of the peak to peak and offset of the PPG(IR) obtained with the infrared wavelength are denoted by VppIR and VoffR, respectively. K1 and K2 are calibration factors derived from data curve fitting [18]–[20].

Each pixel on the smartphone contains information about three different light wavelength bands: Channels for red, green, and blue (RGB) [37].

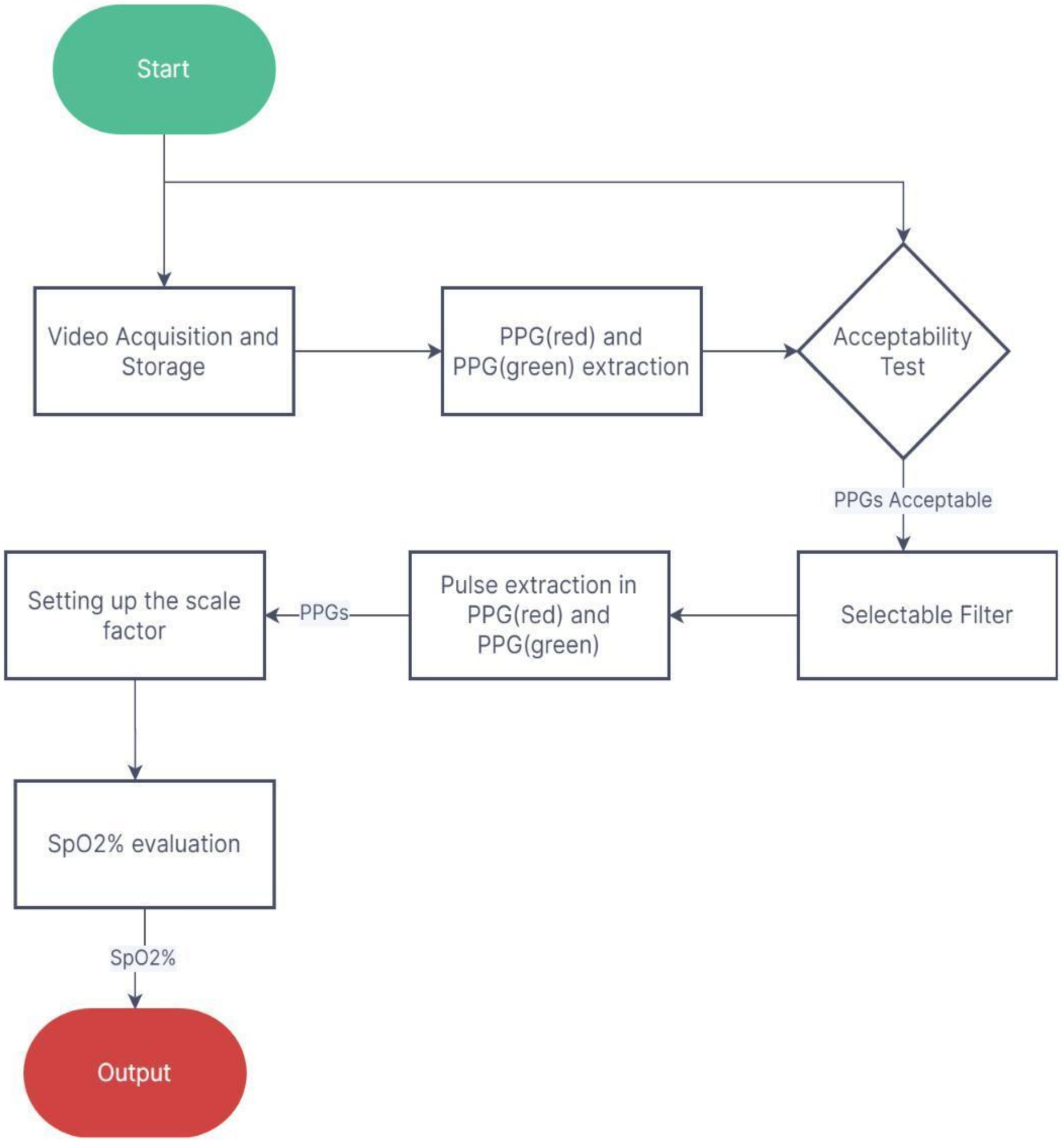

Fig. 7: Flow of data collection for oxygen level calculation

PPGRed and PPGGreen signals are produced using a broad spectrum of light as well as the reflected light rather than the transmitted light through the skin and tissue. Because the PPG signals represent a color band rather than a specific wavelength as required for SpO2 percent evaluation, the first step is to scale the PPG(Red) extracted on the red channel to evaluate the equivalent PPG that would be obtained with monochromatic light and the PPG(Green) extracted on the green channel to evaluate the equivalent PPG that would be obtained. The pulses in each scaled PPG(Red) and PPG(Green) signal are extracted by an algorithm for the detection of peaks and troughs. The extraction algorithm considers the maximum peak value to be associated with a single pulse, and the previous minimum trough value is assumed to be the start of the pulse. [21].

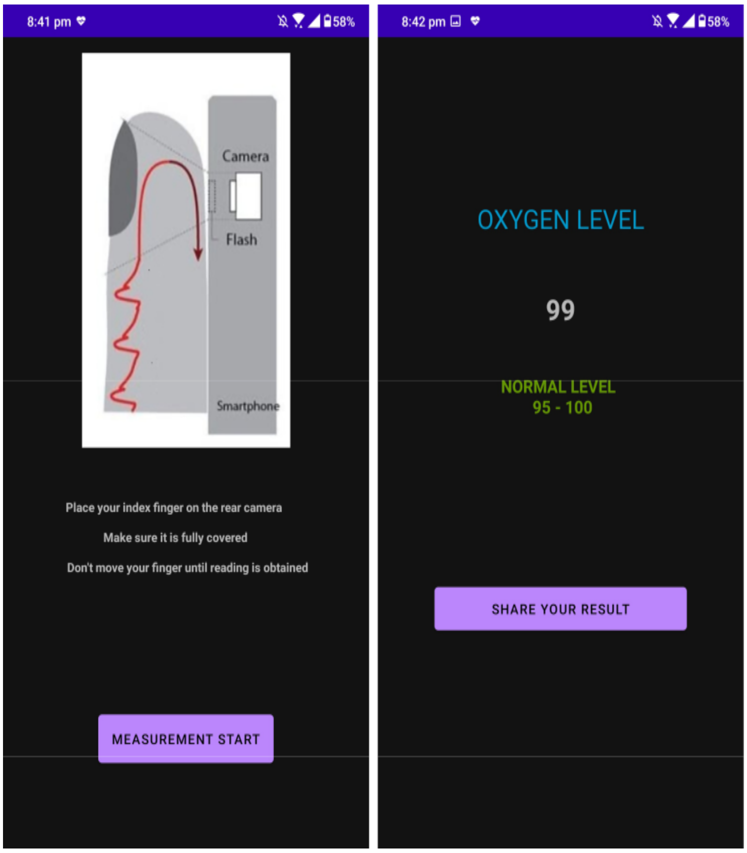

Fig. 8: The interface is first shown and then the output reading after image processing

Temperature and Blood Pressure

The temperature and blood pressure are detected using the sensors LMT87 and TTP223 respectively embedded in the PCB.

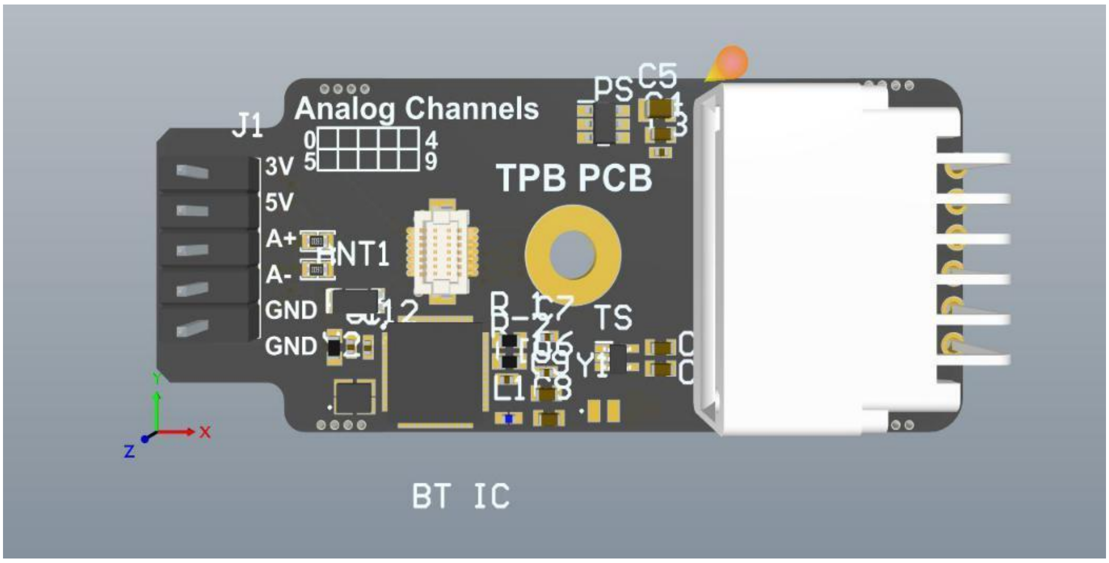

Fig. 9: PCB Module

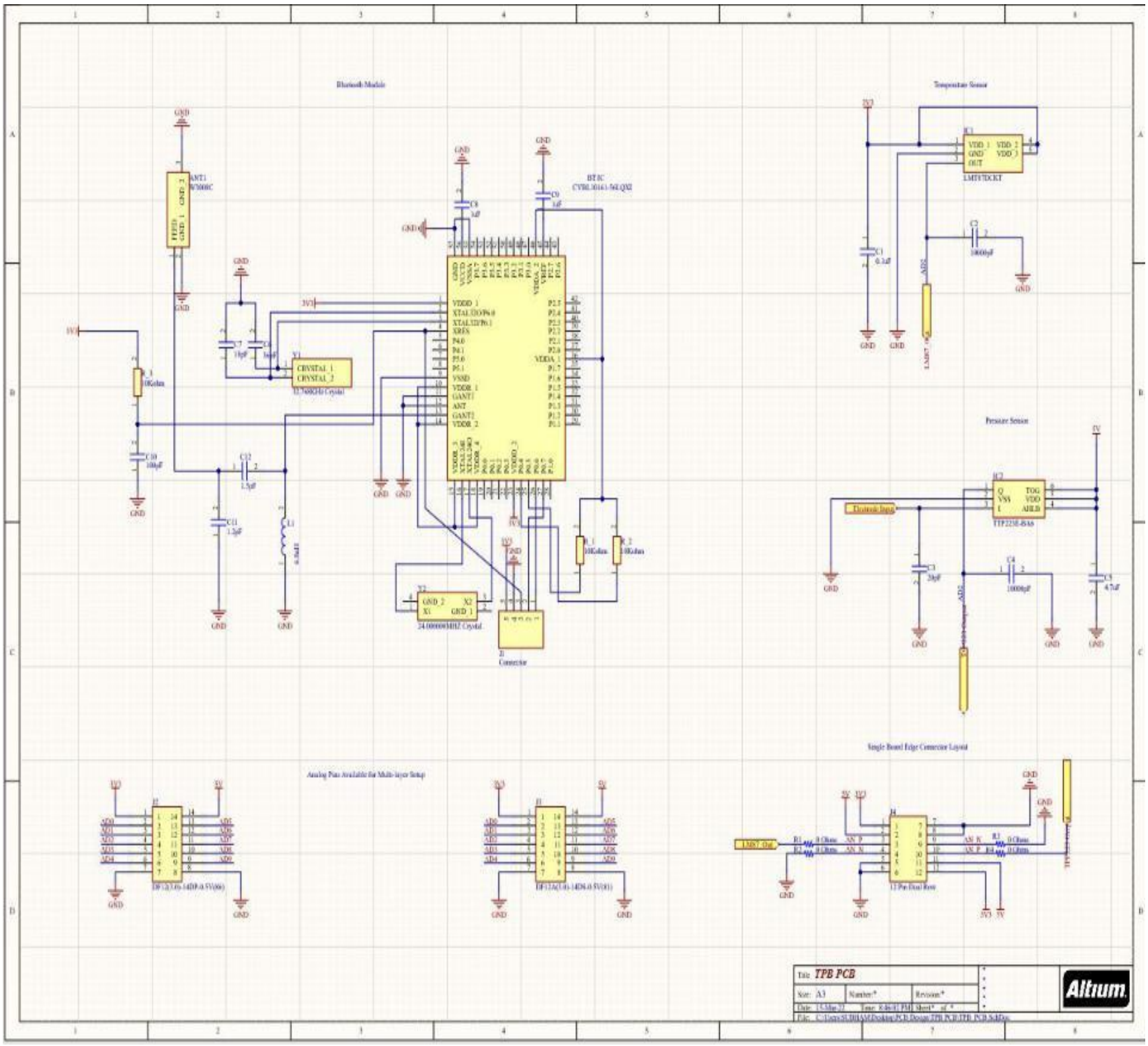

Fig. 10: Schematic of PCB

Blood pressure trend (BPT) is NOT the same as absolute blood pressure measurement normally used. BPT uses an algorithm to look at changes in the shape of the PPG signal and then correlates them to changes in BP from a given calibrated baseline. The temperature is calculated based on the changes in voltage. LMT87 device is a precision CMOS temperature sensor with a linear analog output voltage that is shown to be inversely proportional to temperature [22].

The entire PCB is housed in a 3D printed module which would also have a slot to place a finger. Simultaneous reading of all parameters will be taken.

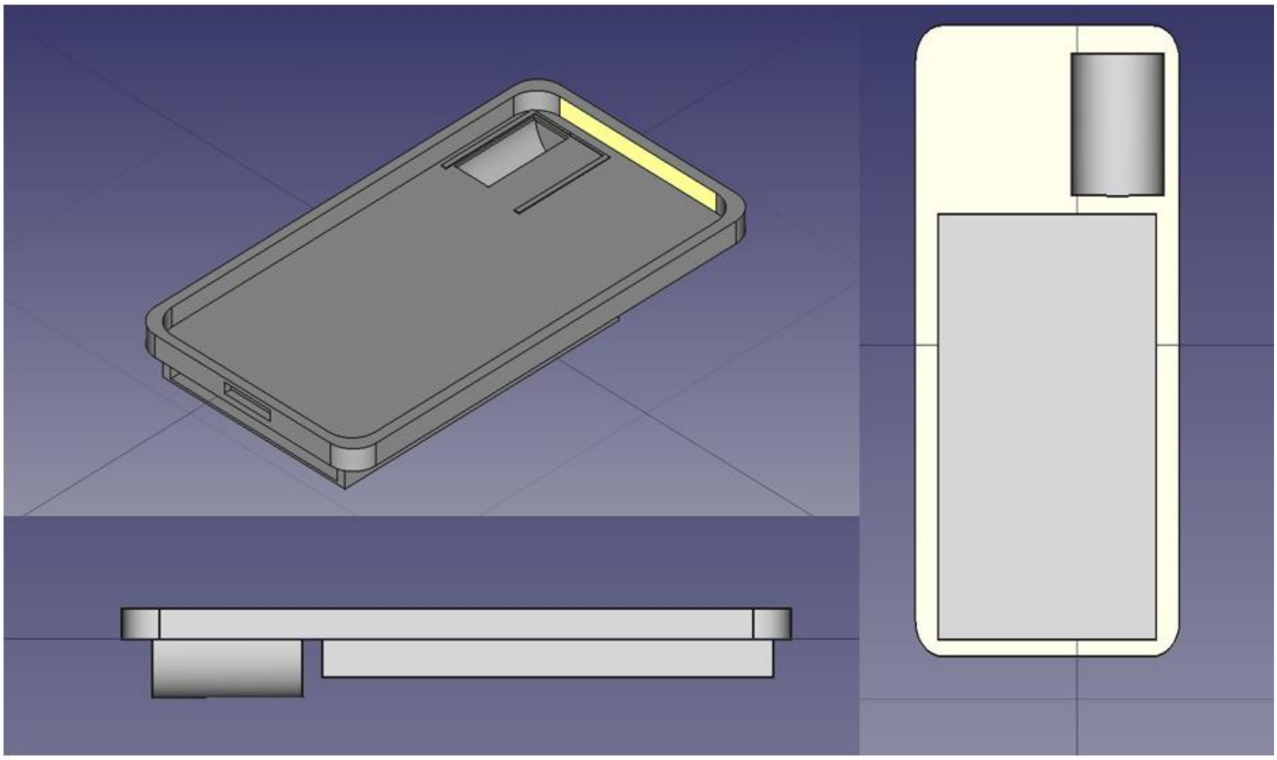

Fig. 11: 3D model of finger housing module - Top view, back view, and side view

To test the arrangement a circuit was designed using an ESP32 module and BMP280 pressure and temperature sensor. The data was sent to a phone application allowing the user to see the reading. After uploading the code on the microcontroller, subsequent readings are taken by powering it up using the phone itself (through an OTG cable).

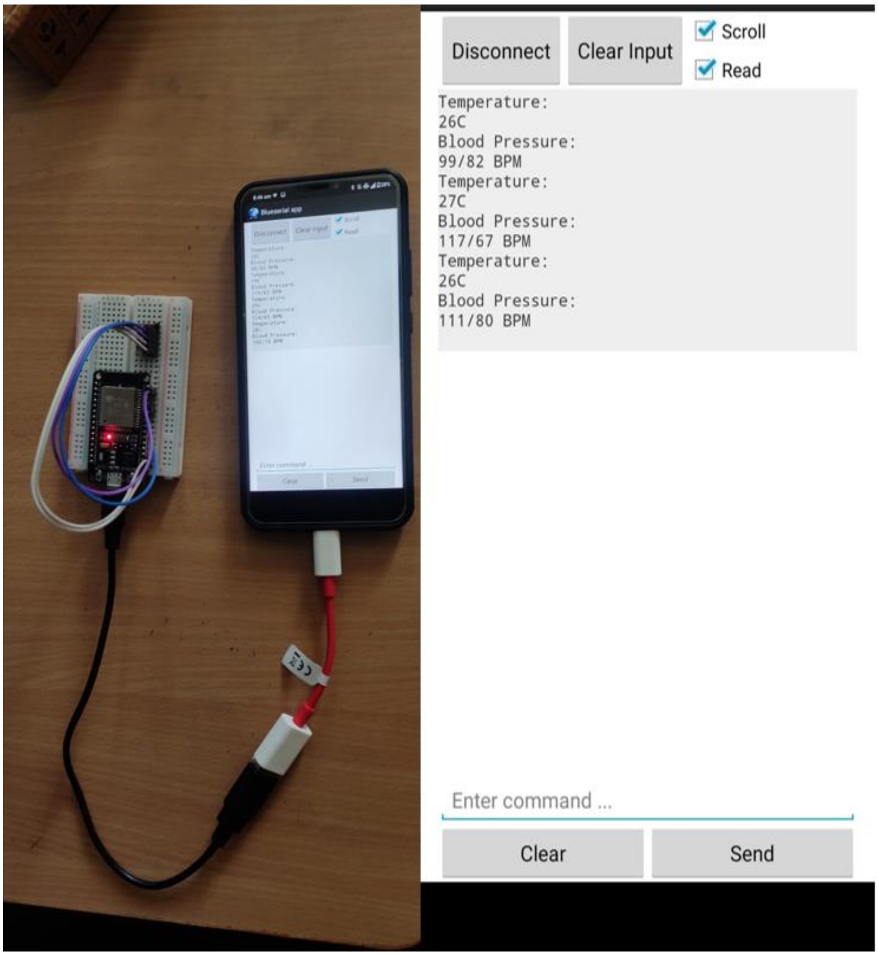

Fig. 12: Sensor and module setup along with output

However, there lies a large margin of error in the calculation of blood pressure. BMP280 is a sensor to detect atmospheric pressure and not tactile pressure. When a finger is placed on the sensor it does not calculate the beat in the finger but rather the difference in atmospheric pressure and the point of contact. The formula used to convert the pressure change to beats per minute (BPM) requires lots of approximations and assumptions making the reading not only highly erroneous but also very unstable. This can be corrected by isolating the sensor in a rubber film and placing a finger on top of the film [23]. This would ensure that the pressure change detected is more accurate. Implementation and testing of the method would be done once the 3D printed case is ready.

Arrhythmia and Anemia Detection

Arrhythmia is detected based on the definition of the ailment that irregularities in heartbeat is observed such as when it is too fast or too slow. A heart rate that is too fast (consistently above 100 beats per minute in adults) – is called tachycardia, and a heart rate that is too slow (consistently below 60 beats per minute) – is called bradycardia [24]–[26]. The readings over a duration of 30 seconds is stored and analyzed. If the average is above 100 or below 60 with a signification variance during the duration of reading, then it can be said that the user of Arrhythmia [27], [28].

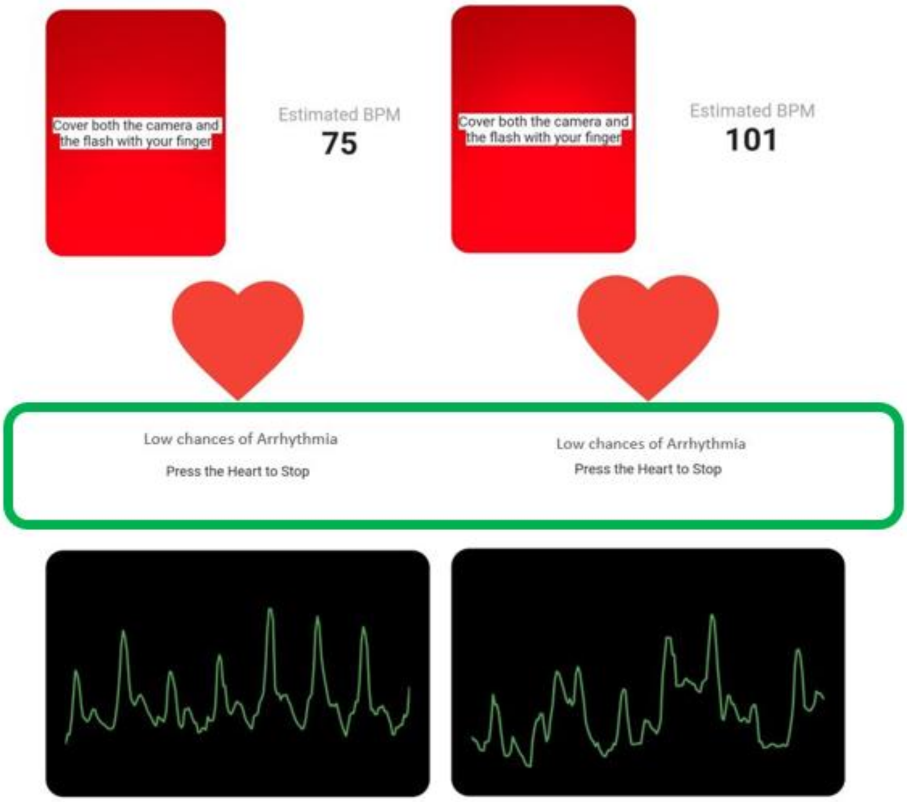

Fig. 13: The prediction of arrhythmia is displayed once the reading is done

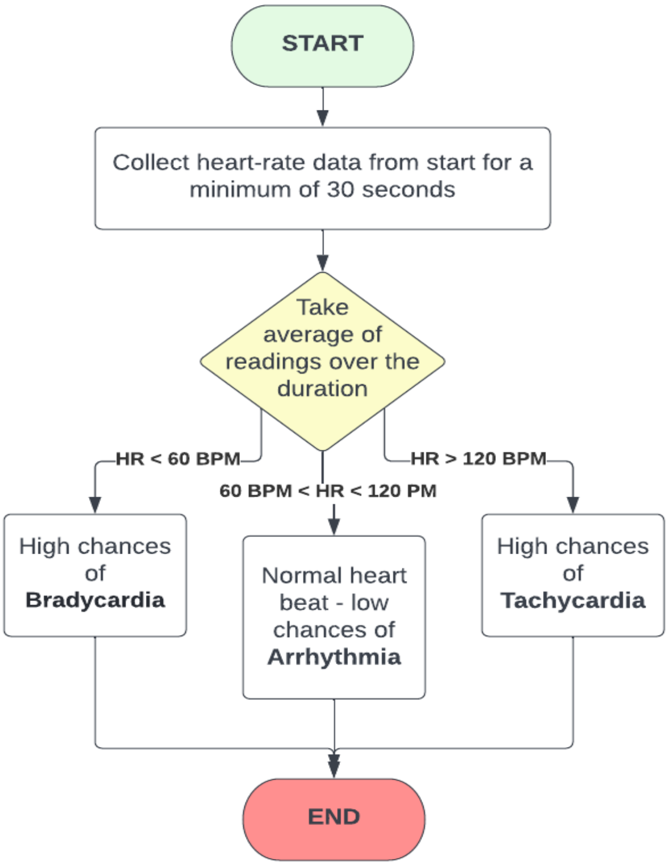

Fig. 14: Algorithm of Arrhythmia detection

Anemia is linked to pallor and a sickly pale appearance. We developed a method that uses image processing algorithms to quantitatively examine pallor, allowing for a non-invasive, accurate quantitative application for identifying anemia [29], [30]. It is well known that fingernail beds have very little melanin in comparison to other regions of the skin, making this procedure indifferent to skin tone. A blob detection algorithm is used to choose regions of interest from each finger. Each person's color data is collected from each location and averaged across all of their fingers. Due to the limited color diversity between different fingers, this method was found to be acceptable [31], [32].

The image is first converted to grayscale to differentiate the white spots from the rest of the image. A histogram is plotted for the entire dataset and a threshold grey level is observed (>240 in this case) in all the pictures. This value is used to make a mask around all points that exceed the threshold. The resulting image is then processed by edge detection and blob detection techniques to identify the number of white spots. Five is taken as the threshold blob count value. Any image with a blob count greater than 5 can be considered a possible case of anemia.

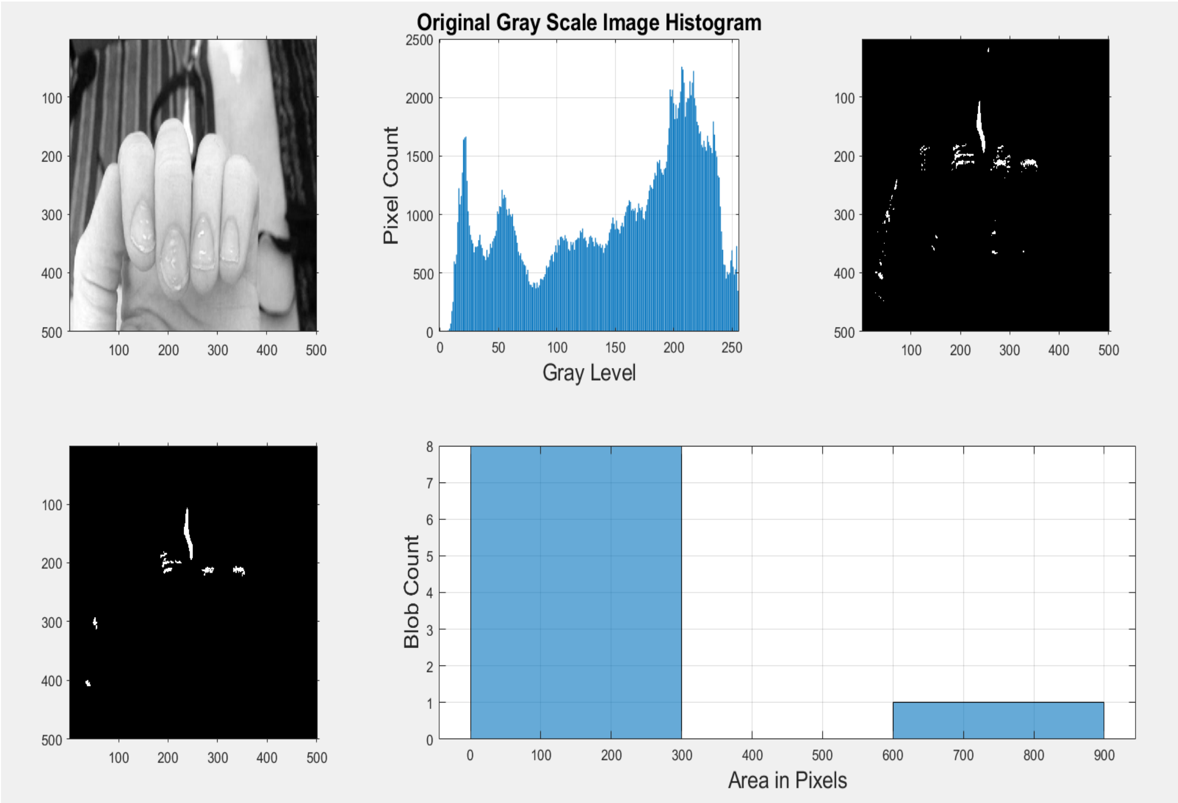

Fig. 15: Output of algorithm - Anemia detected

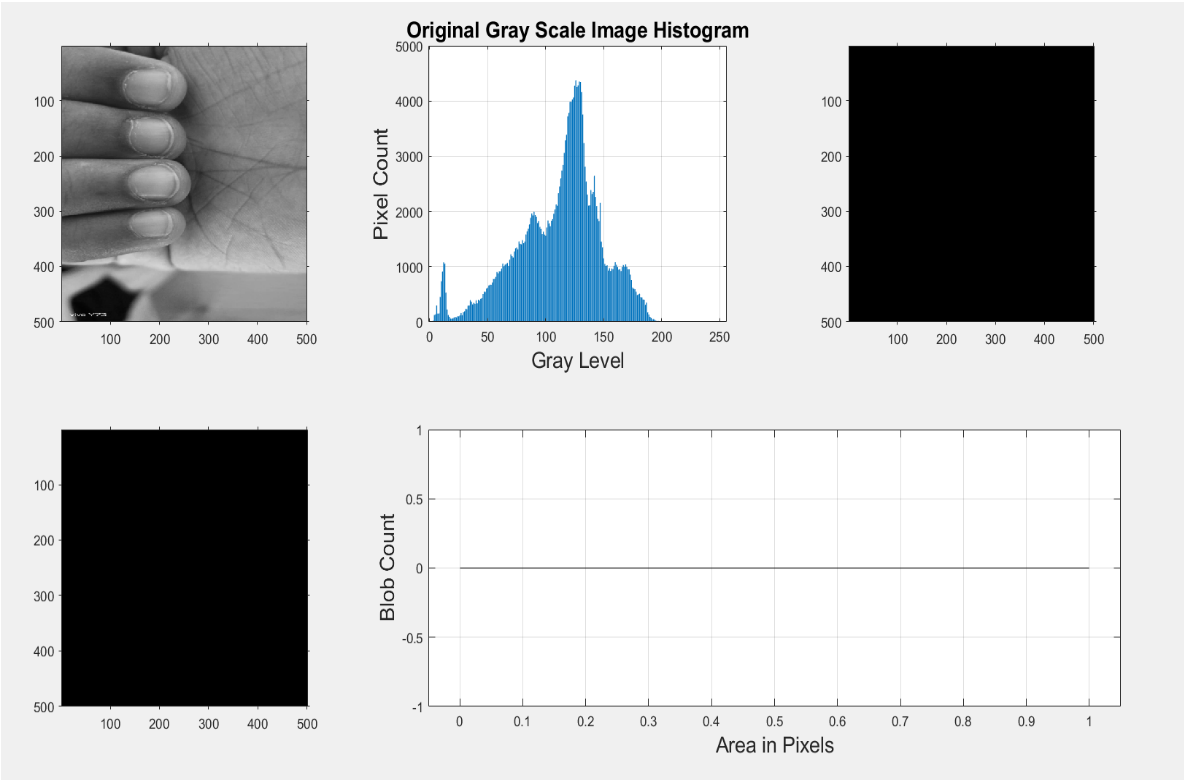

Fig. 16: Output of algorithm - Normal case detected

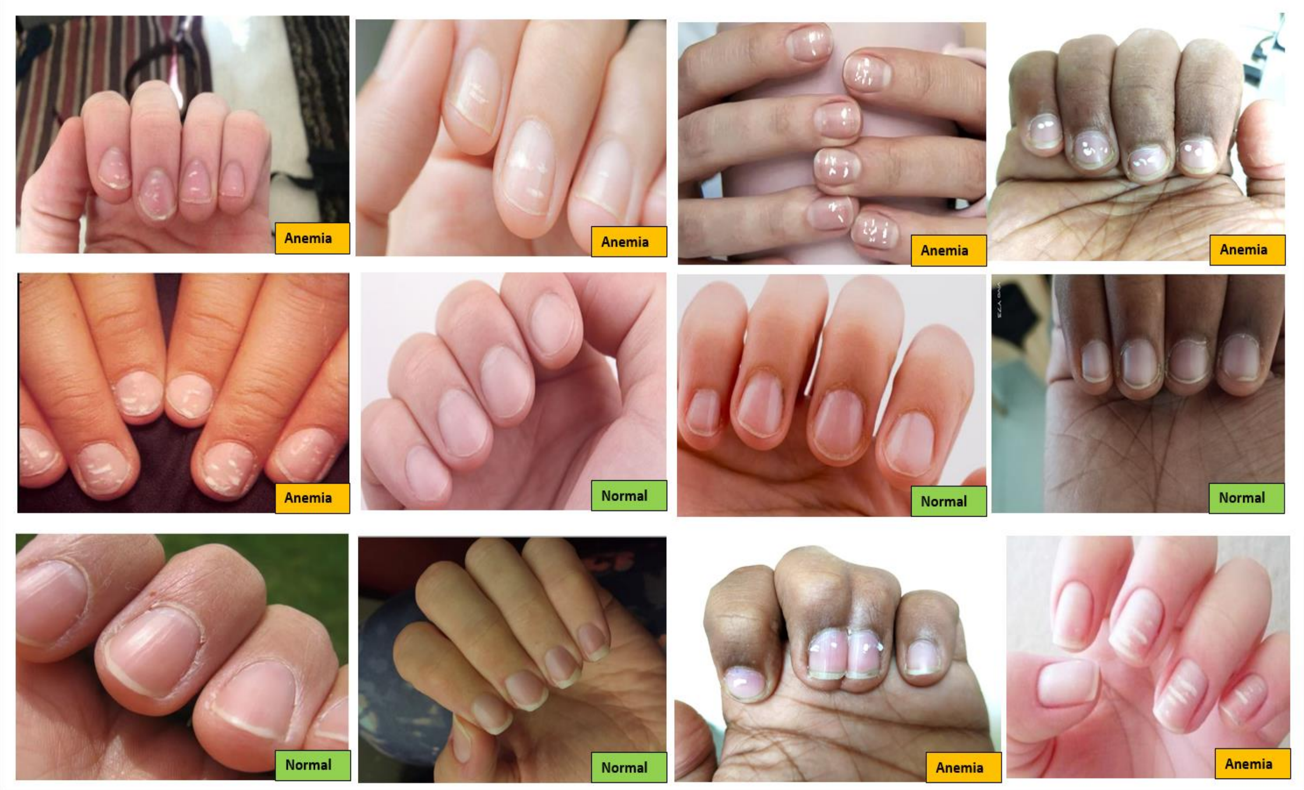

Fig. 17: The dataset of 12 images used to test the accuracy of the algorithm

Using the procedure above the algorithm correctly detected (100% accuracy) all twelve images taken from both google images and a personal phone camera. A caveat in the process is that the image should have a certain level of brightness to successfully identify the white spots [33]. This can be ensured by using the camera flash when taking the image.

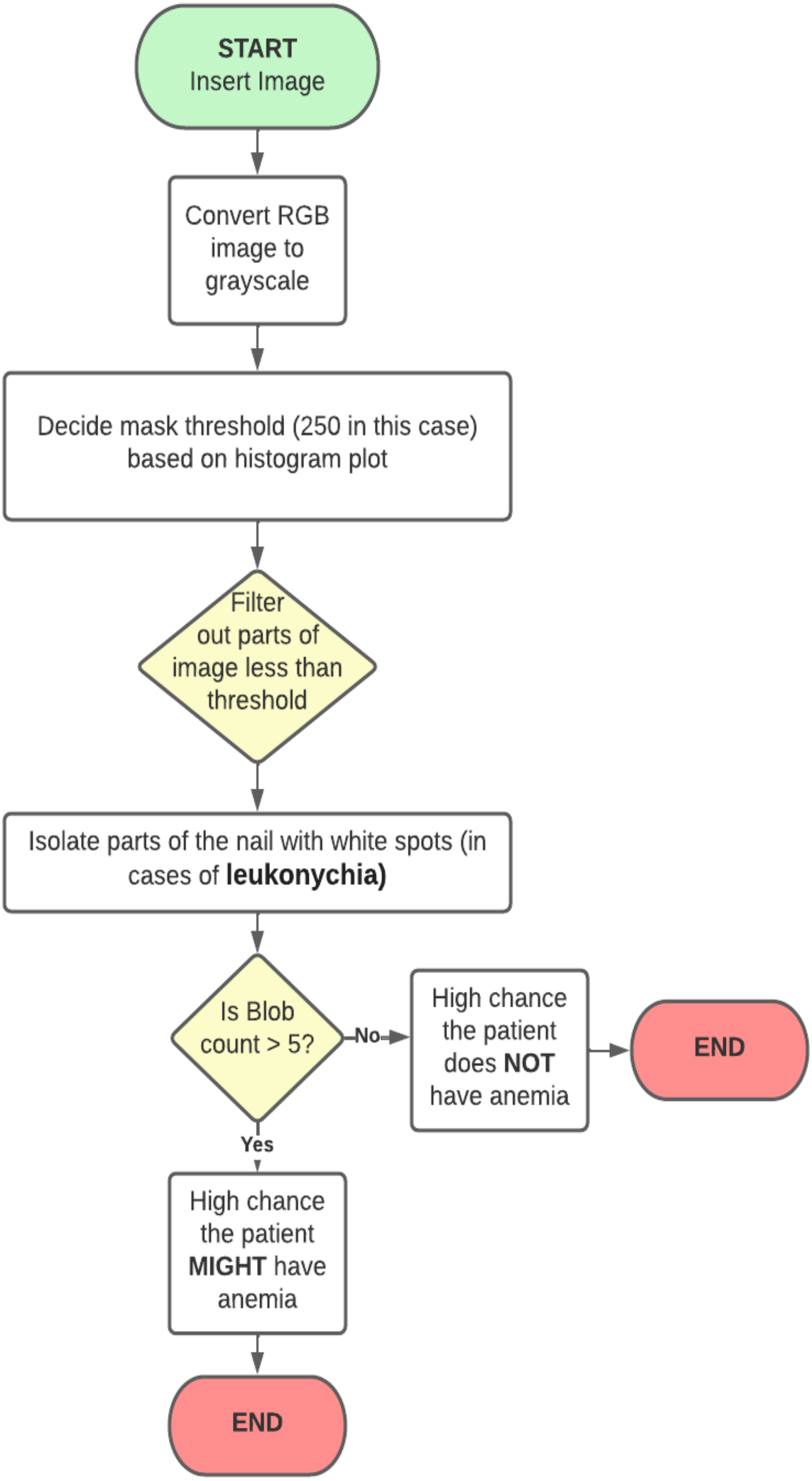

Fig. 18: Algorithm of Anemia detection

3. RESULTS AND DISCUSSION

A high Signal-to-Noise Ratio (SNR) is required to identify heart rate and oxygen level signals accurately. There are numerous places where the implementation can be improved, such as reducing the noise or improving signal power. The noise impacting the measurement in our scenario originates from three major sources:

- Image noise: The camera sensor is the source of this. We are filtering away a large chunk of the spatial component of the brightness computation by averaging all the pixels. As a result, there will always be some noise in the band of interest.

- User behavior: The signal may reflect the fluctuation in pressure applied by the fingertip to the camera lens. If the user has moderate to severe shaking hands, it is suggested that they utilise a finger from the hand that is holding the phone to lessen variability.

- Lighting changes: Any change in the light sources or the scene that reflects light towards the camera can produce noise. Moving the phone in the air while recording a video sequence, for example, could introduce a variety of aspects. The light intensities of these scene elements in the area of view are extremely diverse.

There are a few other factors that can cause a wrong reading that cannot be mitigated by the software or algorithm itself.

Such factors include:

1) Contact area may change continuously affecting the average reading.

2) Unexpected pulse amplitude variations.

3) The ambiguity involved in the conversion of light intensity values to RGB measurement of the camera.

The experiment was done over a period of 30 minutes, taking a reading every minute and subsequently checking the readings on a standard heart rate monitor. The heart rate observed is that for a patient in a resting and seated position [39].

1) **Covering only the camera:** This reduces the amount of light falling on the finger placed, thereby making the image darker than it needs to be. A darker image results in an overall higher value, as observed in the table below. Since the torch is always on (by default), some amount of light is shone on the finger.

Sno.	Reading from Application	Reading from Smart Watch	% Error
1	141	82	72%
2	142	88	61%
3	146	84	74%
4	117	86	36%
5	104	84	24%
6	78	85	8%
7	132	88	50%
8	140	83	69%
9	124	81	53%
10	118	87	36%
Average	124.2	84.8	48%
Standard Deviation	21.12818023	2.440400696	22%

Table 1: Data Obtained on Covering only the Camera

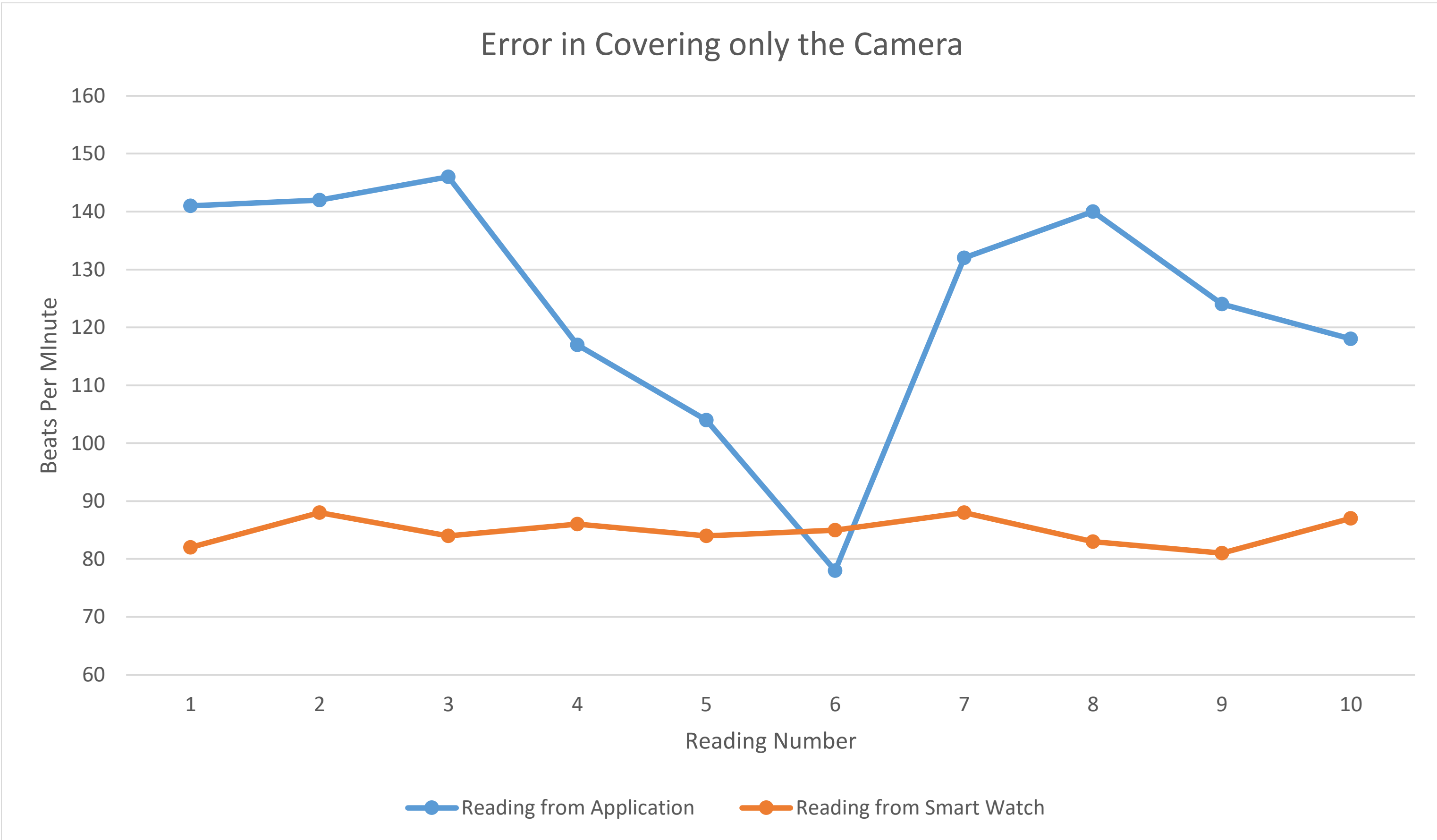

Fig. 19: Covering only camera

The average reading of 39 BPM is more than the required average value obtained from a standard heart rate monitor, which is an error of almost 46%, and hence should be avoided.

2) **Partially covering the camera:** By partially covering the camera, the algorithm takes into account the colors present in the background while calculating the average. In order to find out the range of error, ten readings have been taken simulating different cases, i.e., placing a tiny part of the finger all the way to leaving out only a small part of the required region. Depending on the situation, the readings could be as low as 77 BPM or as high as 133 BPM.

Sno.	Reading from Application	Reading from Smart Watch	% Error
1	95	85	12%
2	102	81	26%
3	130	87	49%
4	102	86	19%
5	77	83	7%
6	108	89	21%
7	96	88	9%
8	133	84	58%
9	130	82	59%
10	111	89	25%
Average	108.4	85.4	28%
Standard Deviation	18.09358388	2.875181154	20%

Table 2: Data Obtained on Partially Covering the Camera

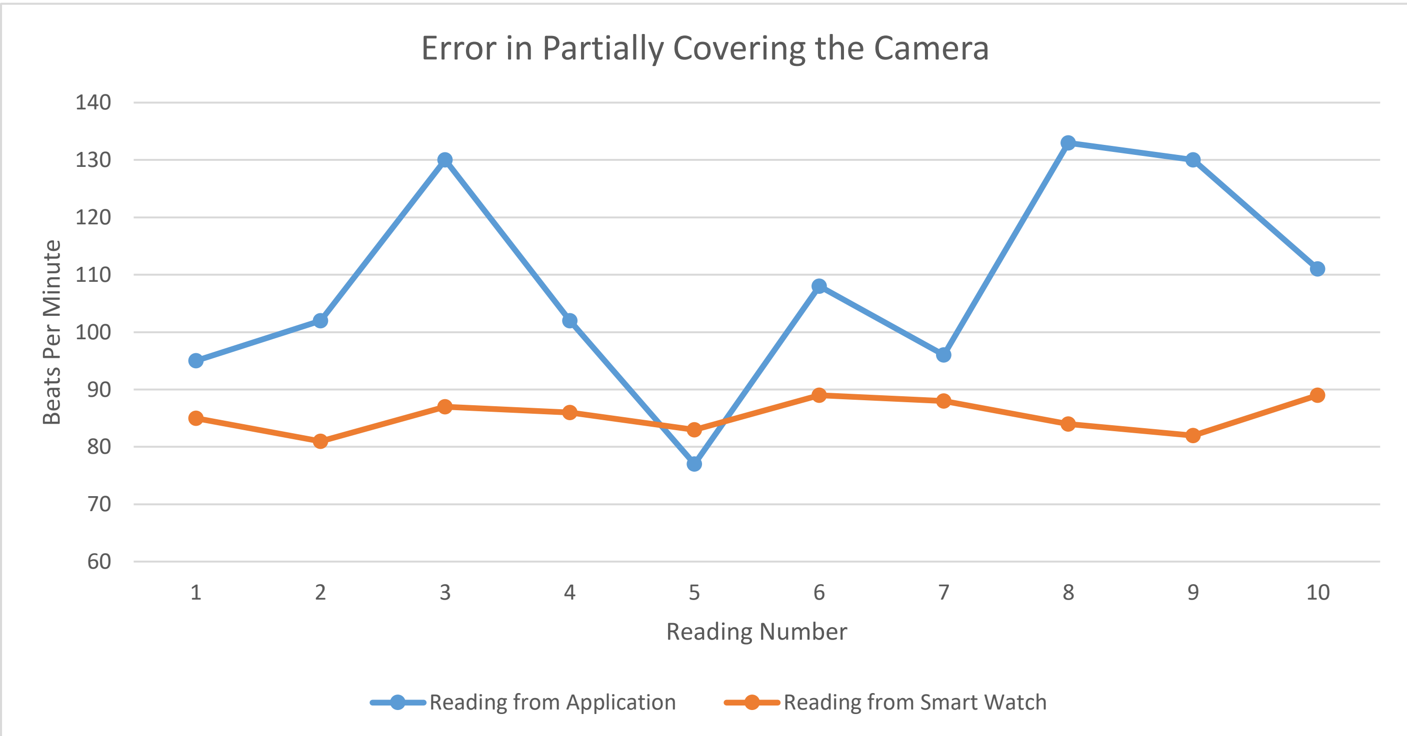

Fig. 20: Partially covering camera

Since the algorithm takes the average value of colors present and also takes into account the previous reading, there is no particular trend that can be observed. The average reading, in this case, is 23 BPM more than the average value obtained from a standard heart rate monitor, which is an error of almost 28%, while lower than the previous case, the range observed is extremely high despite the algorithm taking into account such changes.

Covering only the flashlight would have no effect as the algorithm is such that it requires a minimum amount of red to start taking a reading which would not be possible unless the finger is placed on the camera up to some degree or there are lots of red elements in the background.

3) **Applying improper pressure:** Constantly changing the pressure applied by the finger can also affect the final reading. To observe the changes, we first applied high pressure and obtained five readings, then substantially reduced the applied pressure and took five more readings. While there are no observable trends that can be observed, we notice that the subsequent readings are not stable and have significant variations. However, the effect due to this type of error is considerably low as compared to the above two cases, as finger placement and lighting on the finger are optimal.

Sno.	Reading from Application	Reading from Smart Watch	% Error
1	71	88	19%
2	83	87	5%
3	71	89	20%
4	70	84	17%
5	79	83	5%
6	77	87	11%
7	73	85	14%
8	76	81	6%
9	87	86	1%
10	83	87	5%
Average	77	85.7	10%
Standard Deviation	5.906681716	2.45175674	7%

Table 3: Data Obtained on Applying Different Pressure

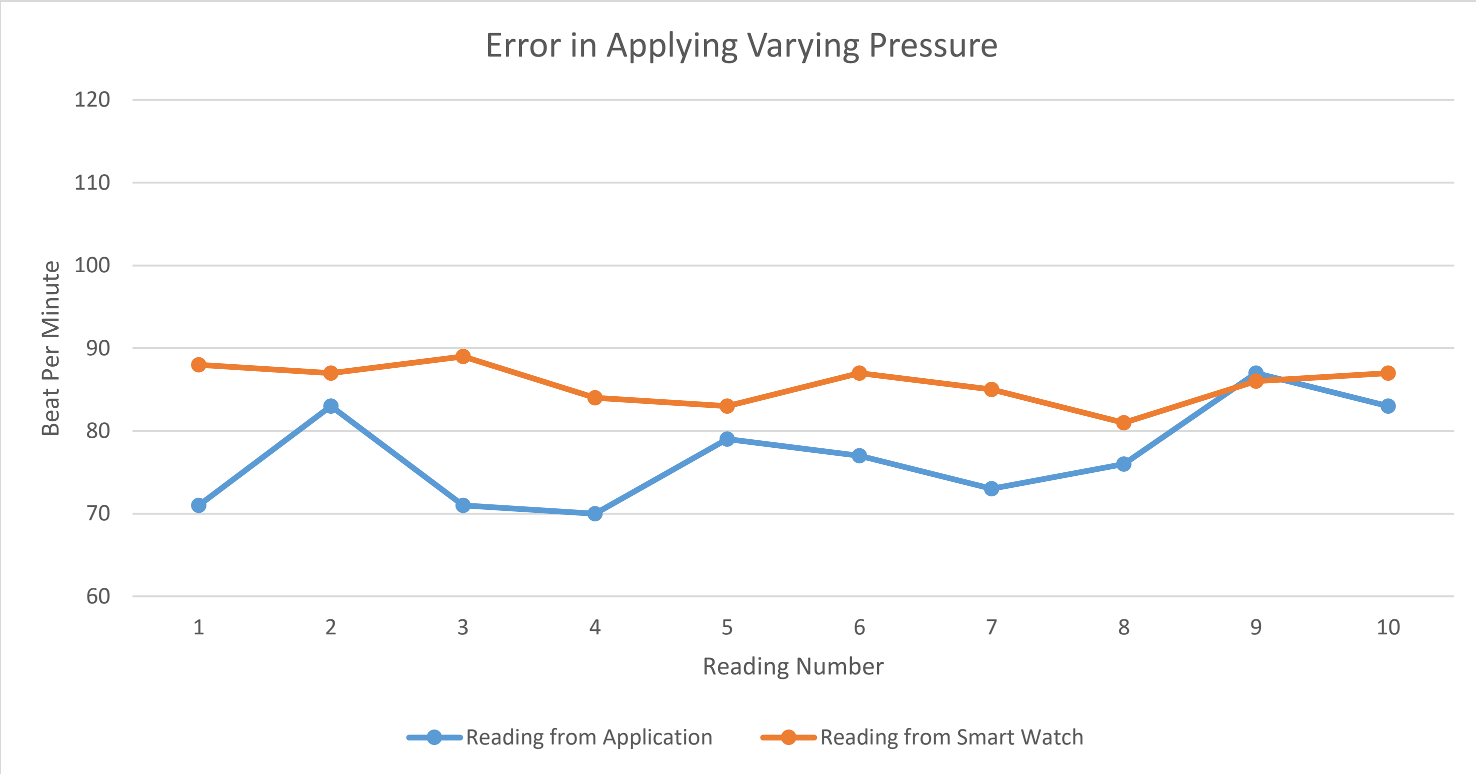

Fig.21: Applying different pressure

The average reading, in this case, is 8.7 BPM more than the average value obtained from a standard heart rate monitor, which is an error of almost 10%, which is much lower than the above two errors. While the effect is low, a better and more stable value may be obtained by mitigating this sort of error.

We observe that any type of reading with the above three abnormalities will lead to a very different reading from the actual value. These errors cannot be taken into account by changes in the algorithm. So, it is advisable to get the heart rate checked by a standard heart rate monitor in case the patient feels that the reading is not normal, as in some cases it may be due to an actual heart-related issue, but it could also be because of taking an incorrect reading. The same is also applicable for oxygen level detection.

Measurement of temperature and pressure is quite robust; however, the issue lies in the area from which detection is being done. The fingertip is not an ideal location to take readings for temperature and pressure as the blood vessels are not very close to the skin and environmental factors also play a role. Changes can be made to the code of these sensors after the PCB has been printed and cross-checked with conventional sensors to obtain a factor by which the measurements need to be corrected.

In the project, we have used a placeholder arrangement to check the nature of the output. Since the sensor used, BMP280, is an atmospheric sensor as compared to the tactile sensor TTP223, further modifications need to be made to ensure reading is accurate to a certain extent. The inbuilt temperature sensor of BMP280 has a different range and sensitivity compared to LMT87 so their calibrations will be different [23].

The data with which we can check the anemia detection feature is currently limited as we are working on MATLAB and using google images/camera images as our dataset which is also very small (only twelve images). To test the robustness of the application a bigger dataset would be required. Additionally, extensive real-life testing should also be done.

4. CONCLUSIONS

More work can be done to incorporate other factors to calculate the parameters more accurately. The diagnostics in the android app works similar to conventional sensors with an error of ±7-20% (not always). Arrhythmia detection has also been implemented; however, on-field testing with a positive and negative dataset would be required to check the accuracy of the algorithm [34]–[36].

The module which is 3D printed allows the user to put their finger inside (eliminating improper placement as a type of error). The PCB and 3D printed module will be integrated with the smartphone to be able to take all readings simultaneously. Currently we are working with the ESP32 module and BMP280 sensor to simulate the conditions and output of PCB.

The anemia detection is currently being done in MATLAB but will be converted to a mobile application by the end of the project. The algorithm for the same has been modified and tested to the extent that the code provides an accuracy of 100% with the dataset prepared.

Finally, all the apps which are currently standalone will be integrated into a single application under different tabs making it easier for the user to download and take readings.

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