Bachelor of Science in Computer Science & Engineering

Automatic Region of Interest Extraction from Finger Nail Images for Measuring Blood Hemoglobin Level

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Submitted in partial fulfilment of the requirements for
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The thesis titled '**Automatic Region of Interest Extraction from Finger Nail Images for Measuring Blood Hemoglobin Level'** submitted by ID: **1504040,** Session 2019-2020 has been accepted as satisfactory in fulfilment of the requirement for the degree of Bachelor of Science in Computer Science & Engineering to be awarded by the Chittagong University of Engineering & Technology (CUET).

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Abstract

Point-of-care medical diagnosis has gained popularity for rapid diagnosis in medical field. Historically Blood Hemoglobin test was confined to the medical laboratory but cell phone-based telehealth has empowered remote diagnosis. Researches on hemoglobin measurement by colorimetric analysis of user image taken from a smartphone are adding new dimension to medical diagnosis. Images of body feature like fingertip and fingernail are mostly used. Colorimetric analysis requires selection of perfect region of interest which has uniform color. In this thesis work, the main focus is to extract region of interest automatically from fingernail images to detect blood hemoglobin level. A contour detection based process was introduced to separate user hand from the background, from which fingernails were detected. Our system can successfully subtract background if user hand is the closest object to the camera. By analyzing the color of fingernail data from smartphone images, our system calculates hemoglobin levels. Our application enables anyone with a smartphone to immediately detect blood hemoglobin level from anywhere, anytime. We used a simple linear regression model to measure blood hemoglobin level. Our application is able to measure blood hemoglobin level with MAE value of 0.79, MSE value of 0.93, RMSE value of 0.97 and R^2 of 0.65 .

Keywords: Point-of-care, Blood Hemoglobin, Contour detection, Background subtraction, Linear regression model

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Chapter 1

Introduction

1.1 Introduction

A Region of Interest (ROI) is a portion of an image that we want to filter or perform some other operation on. The concept of ROI is used in many application areas. One of the area is medical imaging[1]. Here ROI is the finger nail area from an input hand image. The color of ROI will be used for analysis for measurement of blood hemoglobin level.

Hemoglobin is a protein in our red blood cells. It is a component which makes our blood color red, it carries oxygen to our body's organs and tissues and transports carbon dioxide from our organs and tissues back to our lungs. If a hemoglobin test of a person reveals its lower than the normal blood hemoglobin count then it is a cause for concern as it is described as anemia [2].

Despite advancement of medical science blood based testing still can't be done non-invasively. We still have to do a blood test by breaking the skin and taking blood for test. This lab based testing is not an instantaneous process. There have been few research on non-invasive blood hemoglobin level calculation such as one by Robert G. Mannino et al. [3].Their app estimates hemoglobin levels by analyzing color and metadata of fingernail bed smartphone photos and detects anemia. But on their app they select the region of interest manually, here in my process we will do it automatically.

In this chapter, overview of Region of Interest extraction framework will be described, also the difficulties faced, applications, motivation, contribution will be covered in this chapter.

1.2 Region of Interest Extraction Framework

In the field of image processing background removal is one of the most popular image pre-processing techniques. To extract region of interest from hand images at first we have to remove the background of our input picture. After that we will get a blank foreground and the foreground will only include the whole hand. Next step is to detect finger nails region from the foreground. These finger nails are are our desired region from which we have to extract the part of it or the whole of it for our final region of interest. The final extraction will based on properties like if our selected area is free of leukonychia or if our image is burned out due to camera flash. Finally based on the color of our region of interest our system will calculate a hemoglobin level.

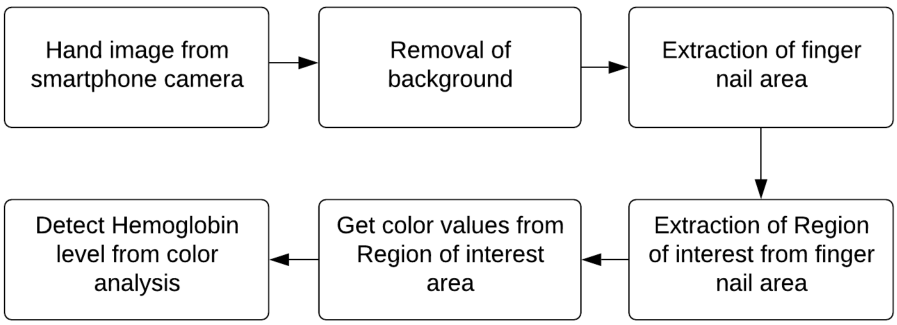


Figure 1.1: Block diagram of Region of Interest Extraction Framework

1.3 Difficulties

Image quality depends on lots of factors like level of lighting, camera quality, absence of camera flash, due to this this variation hand image from a same person may display different level of brightness and colors. Also background can be of any values or environment, it is difficult to extract background of variable environment, due to working with images the major encountered difficulties are:

- **Absence of light uniformity:** It was difficult to maintain uniform light in the data collection process as it varies depending on room light and camera focus, also user of the system will take pictures in different environment so uniform lighting won't maintained there too.

- **Varying background:** Background will not be same for every picture as each user will take hand picture from different environment as a result background will different for each picture. Extracting background consisting of different colors and object is a very complex process.

1.4 Applications

Hemoglobin test is necessary for several reasons. Hemoglobin test is done for checking overall health condition. A hemoglobin test help diagnose anemia or polycythemia vera. But traditional methods are not non-invasive and they require time for a verdict, as a result a non-invasive and quick solution is necessary. The range of applications are:

1. Assistive system for old and sick users who needs regular hemoglobin level monitoring.
2. Automated system for blood hemoglobin level measurement.
3. Gives a verdict regarding the possibility of user having anemia.
4. An alternative system instead of traditional blood based hemoglobin count test.

1.5 Motivation

Despite the fact that cell phone-based telehealth can possibly change how medicinal services is conveyed by empowering remote diagnosis, these advances still can't seem to non-invasively supplant blood-based testing, which remains a major cornerstone of disease diagnosis in modern medicine. Indeed, while custom-designed smartphone attachments may allow for blood based, point-of-care diagnosis and analysis, the burden of blood sampling combined with the additional cost and need for equipment external to the smartphone prevents broader adoption of these potentially disruptive technologies.

Blood hemoglobin level measurement is necessary for various disease detection as it is a symptom of Cancer, kidney disease, Leukemia. Although there are some non-invasive process to measure blood hemoglobin level, the Region of area extraction process is not automatic in the method developed by Robert G. Mannino et al [3].

1.6 Contribution of the Thesis

Thesis or Research work is performed for contributing in the field of science, it may be via developing a new methodology or by improving the existing ones. The main purpose is to achieve a specific set of goals. In this thesis, the main focus was given to automate the Region of Interest extraction from hand image to make it simpler. The primary contribution of this thesis is the following:

1. Extraction of Region of Interest from hand images to analysis blood hemoglobin level.
2. Collection of real life image data with tested hemoglobin level.
3. Development of an android application to predict blood hemoglobin level.

1.7 Thesis Organization

The rest of this thesis report is organized as follows:

- Chapter 2 gives a brief summary of previous research works based on non invasive blood hemoglobin measurement and finger nail area extraction from hand images.
- Chapter 3 describes the proposed methodology for blood hemoglobin measurement from hand images. First step is extraction of Region of Interest which is done by removing the background and applying our proposed algorithm for detecting Region of Interest, We inspect the color values from region and use a linear regression model to measure blood hemoglobin level.
- Chapter 4 discusses about the dataset and analysis the performance and accuracy of our system.

- Chapter 5 contains the overall summary of this thesis work and also provide some recommendations.

1.8 Conclusion

In this chapter, an overview of Region of Interest and Blood hemoglobin is provided. The overview of Region of Interest extraction and blood hemoglobin level measurement was also provide in this chapter. A brief about the challenges and difficulties were given along with the motivation behind this work and contributions are also stated here. In the next chapter, background about the problem will be provided.

Chapter 2

Literature Review

2.1 Introduction

We have found that various approaches of measurement of hemoglobin level has already been done. Traditional ways to measure hemoglobin level methods requires blood and extra devices to calculate blood hemoglobin level. These ways require physical presence of patient but not all patients can be physically present when require ,so then comes point of care method. Point of care [4] method helps to accurately achieve real time diagnostic result within minutes rather than hours. It is playing an increasingly important role in public health monitoring. It can be of two types smartphone based point of care diagnostics with built in sensors or without built in sensors [4]. One of the most challenging factor in these methods are background subtraction as background may vary depending on the environment on which image was taken. Another challenging factor in measurement of blood hemoglobin in a non-invasive way using smartphone is to not involve any external hardware as the system should be able to function fully based on the facilities provided by the smartphone. In order to fully understand these challenges we must have a clear understanding of the previous research works.

In this chapter we will discuss about various hemoglobin measurement techniques in non-invasive way using smartphone. All of them are point of care. But some of them require external sensors and some can be done with only built in sensors of smartphone. A brief overview will also be given about the techniques used, what problems they solved, their limitations, accuracy.

2.2 Related Work on Measurement of Blood Hemoglobin Level

2.2.1 Hemoglobin Level Detection from Fingernail Color Analysis

Mannino et al. [3] introduced a non-invasive paradigm to estimate hemoglobin levels by analyzing color and metadata of fingernail bed smartphone photos. By this method they detected anemia. According to WHO lower limit of blood hemoglobin concentration for anemia in men is 13 g/dL for women it is 12 g/dL [5]. In their method, a patient obtains a smartphone photo of his/her fingernail beds. The patient first takes an image of their fingernails and is then prompted by the app to tap on the screen to select regions of interest corresponding to the nailbeds, and a result is then displayed. But result maybe wrong by a large margin because of fingernail irregularities like camera flash reflections or leukonychia. Regions of interest, from which fingernail and skin color data were extracted, were manually selected to ensure that fingernail irregularities were excluded from analysis. Fingernail data, skin color data and image metadata were extracted from fingernail bed smartphone images . They used robust multilinear regression to measure blood hemoglobin level.

One of the point of care method [6] gives good accuracy but ultimately it requires a PDMS light diffuser which is quietly costly and it is not easy to use for every age of people. In [7] Fujishima et al. introduced a method to detect fingernail from hand images but their method sometimes detect skin area too.

Edward Jay Wang et al. [8] presented a smartphone application that non-invasively monitors blood hemoglobin concentration using the smartphone's camera and various lighting sources. But their procedure require additional light sources. Their application achieve a sensitivity and precision of 85.7% and 76.5%. Their current results are based on data collected on a Nexus 5 device and using only one brand of incandescent light bulb. Their data collection focuses on a range of 8-16 g/dL. Building upon the prior work they again demonstrated in [9] a system with only the built-in RGB camera and white LED without modification.

2.2.2 Hemoglobin Level detection from Fingertip Video Images

In a laboratory setting hemoglobin level is detected by shining light through a small volume of blood and using a colorimetric electronic particle counting algorithm. It is process which requires much time, so researches are being done make blood hemoglobin detection process non-invasive and more accurate. In [10] Golam M T Ahsan et al. used e video images collected from the fingertip of a person. They hypothesized that there is a significant relation between the fingertip mini-video images and the hemoglobin level by laboratory "gold standard". Frames were extracted from the video data. Red, green and blue (RGB) pixels were separated from each frame. From the RGB values, different statistical parameters and feature variables were calculated. Feature variables were matched with hemoglobin values to create a mathematical model for future detection. In their reasearch patient had to take videos for 30 seconds in such a way that the finger tip covers the flash and camera sensor but pressure put on the camera sensors were not uniform during this 30 seconds.

Md Kamrul Hasan et al. used an artificial neural network and video imaging for measurement of blood hemoglobin [11]. They recorded 10 second-300 frame fingertip videos using a smartphone in 75 adults. They identified specific regions of interest in the video images. They subdivided an image into multiple regions and color-mapped each region averaging pixels intensities. Their average R2 (goodness-of-fit measure) value is 0.90.

2.2.3 Hemoglobin Level Detection Using Palpebral Conjunctiva Image

Anggraeni and Fatoni aim to develop a non-invasive self-care anemia detection based on the palpebral color observation and using a smartphone camera [12]. In their work they measure color intensity (Red, Green, Blue) using a Colorgrab software and analyzed compared to the hemoglobin concentration of the samples, measured using standard Spectrophotometer method. The result showed that the red color intensity had a high correlation ($R2=0.814$) with a linear regression of $y=14.486x + 50.228$. Many factors have been reported to make a variation of the hemoglobin level, such as body mass index (BMI), parity and geographical altitude.

2.3 Conclusion

In this chapter, a detailed overview of related work on measurement of blood hemoglobin level in a non-invasive way based on colorimetric analysis by using smartphone was given. Different techniques based on image or video analysis of fingertip, fingernail bed or Palpebral conjunctiva was discussed. The next chapter will contain detailed explanation of the proposed methodology of automatic region of interest extraction from fingernail images for measuring blood hemoglobin level.

2.3.1 Implementation Challenges

Some of the implementation challenges are discussed below:

- As this thesis work has image processing work, it is very difficult to achieve desired image processing using java which is official supported programming language of Android Studio. Image processing work in this project is done with Python programming language, so in order to used python programming language we had to use a plugin named chaquopy, we also required licensing to use chaquopy.
- The collected image data from hospital needed to be pre processed one by one, which was a time consuming task.

Chapter 3

Methodology

3.1 Introduction

Hemoglobin test helps to check the level of red blood cell. The function of the red blood cells is to deliver oxygen to the different parts of the body. Hemoglobin test is done as part of regular checkup or when a person is not feeling well. Low hemoglobin level indicates the patient might have anemia and high hemoglobin level indicates to polycythemia [13]. So it is beneficial to have non-invasive means to predict blood hemoglobin level from anywhere, anytime. In this research work, the purpose is to facilitate this process by implementing automatic region of interest extraction. Here region of interest is fingernail beds.

In this chapter we will discuss about the implementation process to detect region of interest and in turn to predict blood hemoglobin level of user.

3.2 Steps of Region of Interest Extraction Framework from User Hand Image

Figure 3.1 shows the basic steps of the proposed methodology to extract region of interest from user hand image and in turn predict blood hemoglobin level. In the pre-processing step edge detection is used which also makes the image grayscale from color image. Then dilation and erosion is used to remove noise make the image processed enough for contour detection. After this, we use contour detection to detect largest contour, here largest contour is our foreground area.We can use the pixels from largest contour to filter out the unnecessary background from the image. This detected largest contour is user hand without the background. The next step is to detect finger nails from this image and draw bounding box around the finger nail. Now finally comes the region of interest extraction part, we can extract the region of interest by monitoring sharp change in image brightness as image brightness changes sharply on edge points [14]. From the pixel points of our desired region of interest we calculate the mean red color intensity as blood color is red because of presence of iron in hemoglobin [15]. This mean red pixel intensity level is the input feature for a simple linear regression model. We trained the regression model on pre-processed image data and hemoglobin data. We can use this regression model t predict blood hemoglobin level of the user.

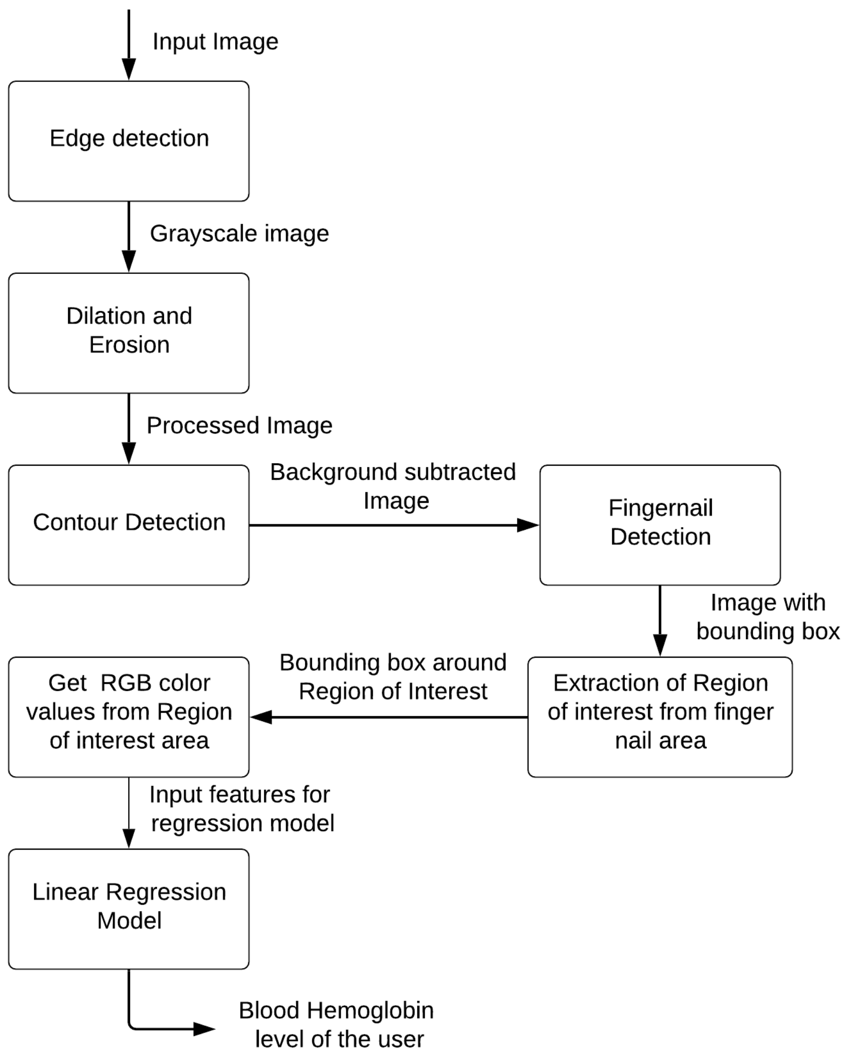


Figure 3.1: Steps of the proposed framework.

3.3 Implementation Details

3.3.1 Edge Detection

For edge detection we used canny edge detection algorithm. It is multistage algorithm. The steps are Noise Reduction, Finding Intensity Gradient of the Image, Non-maximum Suppression, Hysteresis Thresholding [16]. Canny edge detection best works for gray images. So first we convert our input hand image to grayscale image. Then we need two threshold values for edge detection, they are minVal, maxVal. Any edges with an intensity gradient greater than maxVal are certain to be edges, whereas those with an intensity gradient less than minVal are certain to be non-edges, and should be discarded. Based on their connectivity, those that fall between these two levels are known as edges or non-edges. For the type of input image data we will be using we settled on 10 as minVal and 40 as maxVal. We can see from fig. 3.2 that, because of careful choosing of minVal

Figure 3.2: Input image and Grayscale image after edge detection

and maxVal after edge detection process is completed, our edge detection process ignored some edges of background.

3.3.2 Dilation and Erosion

From fig. 3.2 we can see that most of the edges are inside of hand, so we will apply dilation to the grayscale image so that edges inside the hand becomes more congested. The purpose of this to make the background completely black and foreground white. So it will be like finding white object from black background. It can be observed from fig. 3.3 edges in our foreground have become more congested which will facilitate background removal process. Now erosion will be applied, it

Figure 3.3: Changes in grayscale image after applying dilation

will erode away the boundary of the foreground. Depending on the kernel size, all pixels near the boundary will be discarded. Here kernel [17] is small matrix. It's used for a variety of things, including blurring, sharpening, embossing, and edge detection.It is achieved by doing a convolution between a kernel and an image. Convolution is a method of producing a third array of numbers of the same dimensionality by multiplying together two arrays of numbers, usually of different sizes but of the same dimensionality [18]. Erosion is also useful for removing small white noises.

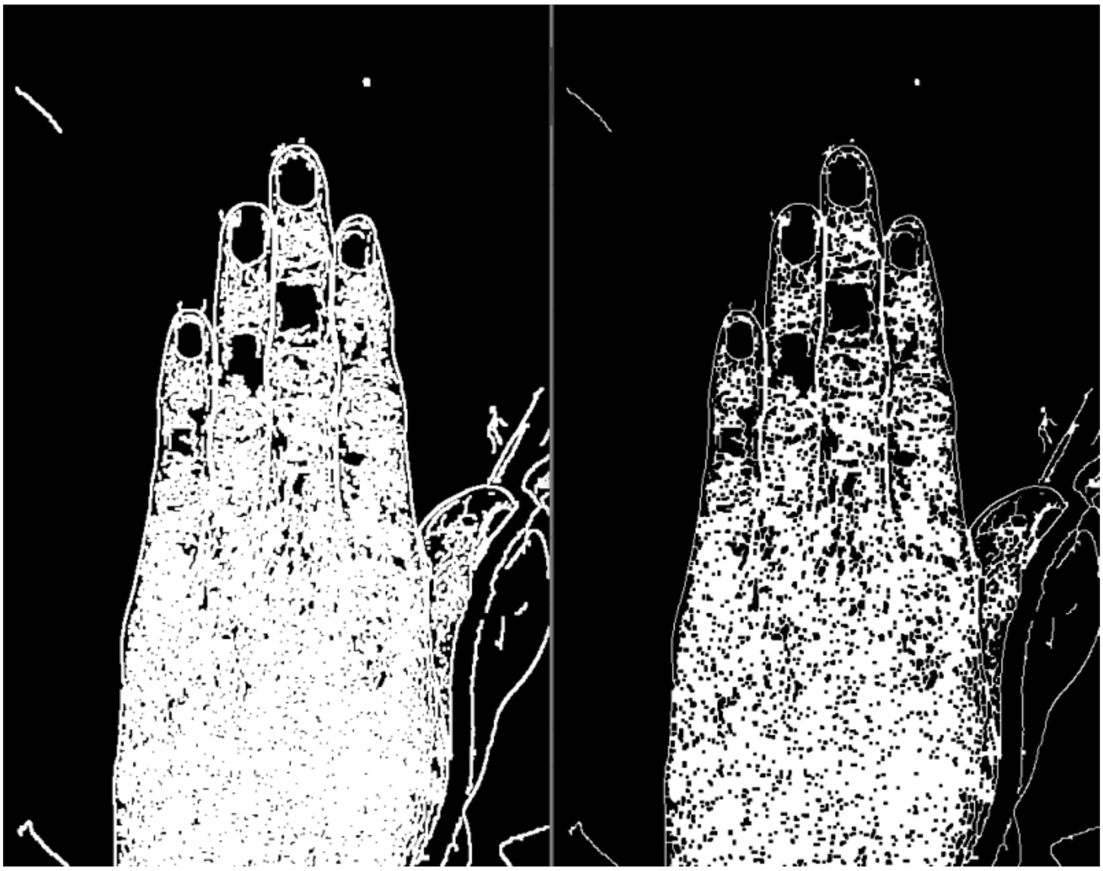


Figure 3.4: Dilation and Erosion

3.3.3 Contour Detection

As described in [19], A contour is an outline that represents or confines an object's shape or form. Contours are essentially a curve that connects all of the continuous points (along the boundary) that are the same color or intensity. For this work our desired object is hand portion which is the largest contour, largest contour is the contour with the largest area. So contour detection will detect all the contours from which largest contour contains our desired object which is hand portion. By detecting the largest contour we get the boundary points of our desired object, now we can draw a boundary on the original input image to detect hand. From fig. 3.5 it is observed that a boundary line which is of color red is draw around the hand. By detecting the largest contour we have detected user hand from input images. Now subtracting the background has become easy, we can just change the RGB values of the pixels which are outside of this boundary. We can do so by changing the pixel values to (0,0,0). As a result pixels outside of the red colored boundary will display black color, so only the foreground will remain. fig. 3.6

shows the image after background is removed.

Figure 3.5: Largest contour detection

Figure 3.6: Background subtraction after largest contour detection

3.3.4 Fingernail Detection and Region of Interest Extraction

Now that background is subtracted and we also have the boundary pixels of our largest contour, by observing fig. 3.6 it can be said that the extreme top coordinate of the contour resides on top of the middle finger. This point is an intensive to detect fingernail of the middle finger. In Python programming language a contour is simply a NumPy array of (x, y)-coordinates [20]. We can use NumPy functions to help us find the extreme coordinates. In fig. 3.7 blue

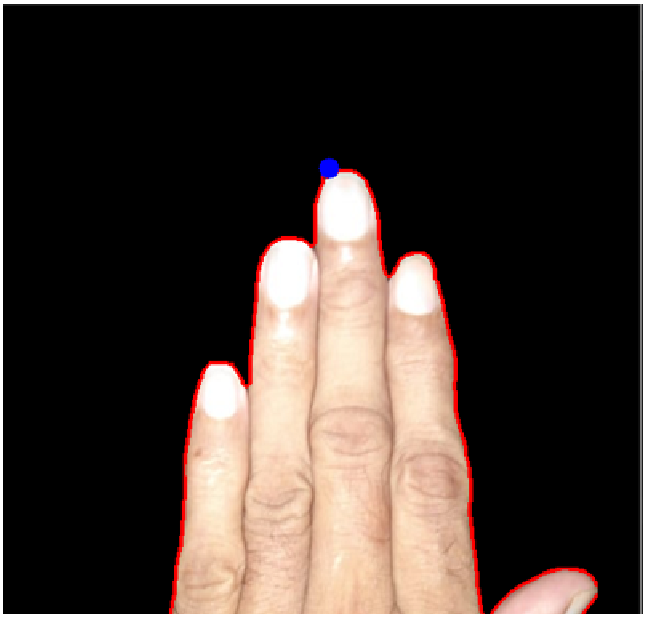


Figure 3.7: Extreme top coordinate in the contour

circle indicates the extreme top point in the contour boundary. Now that we have got the top point of a finger, we need the left point,right point and bottom point of finger nail to detect fingernail of the middle finger. So in order to find the left and right edge of the fingernail we can apply a trick. We can iterate left and right and check if the pixel coordinate reside inside the contour boundary, when we find a coordinate which reside outside the contour boundary, those two coordinates in the left and right are our desired left point and right point of finger nail. In order to detect to bottom point we observe sharp change in brightness value of pixels from the extreme top point, because the point at which there is a sharp change of pixel brightness values there resides the edge separating fingernail and skin [21].

RGB values of the pixels were converted to HSV(hue, saturation, brightness) to check for sharp increase in brightness.

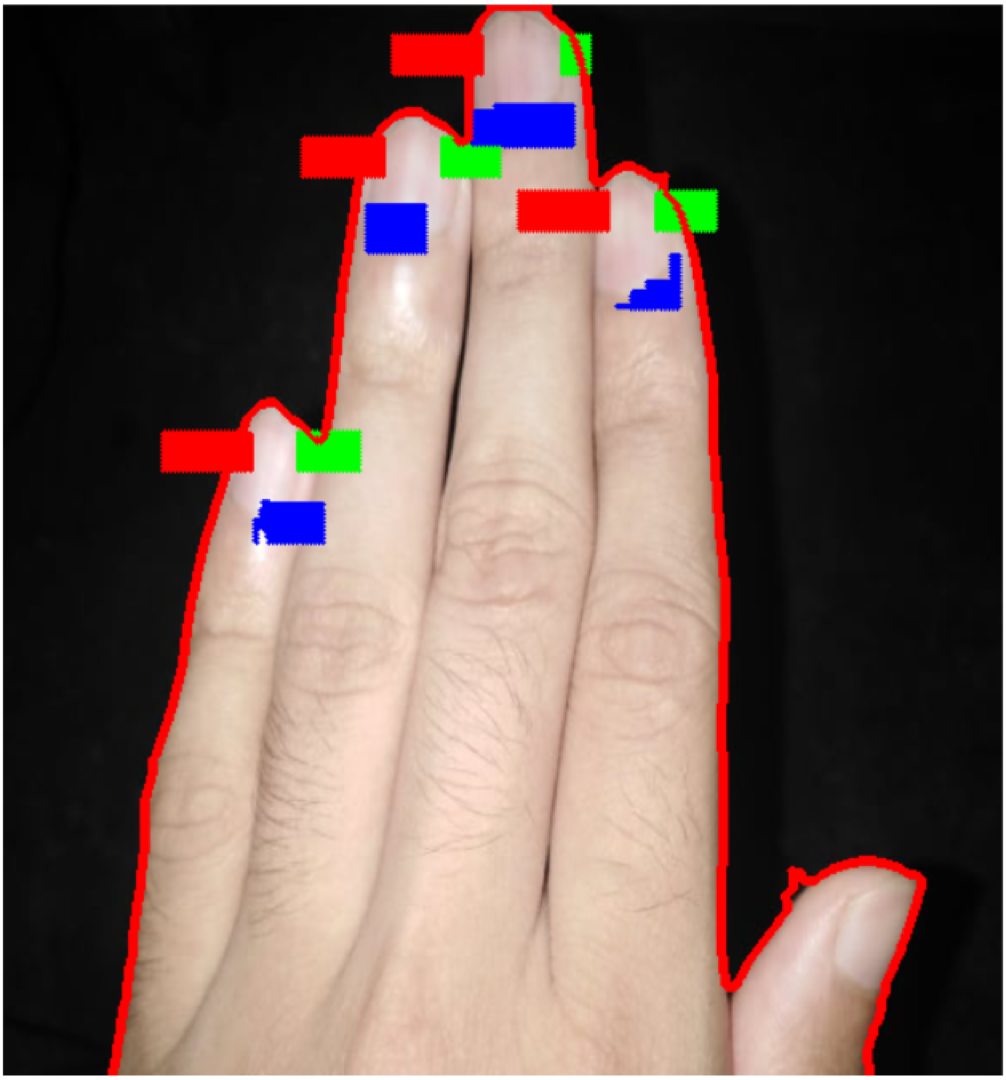


Figure 3.8: Extreme point detection for fingernail boundary

For this work, to find the bottom point we used a brightness threshold of 3, if there is sudden brightness change of more than 3 than there is a discontinuity and that is our bottom point. In fig. 3.8 red colors indicate found left boundary point after finding points where there is a sharp change of brightness, green indicates right boundary point and blue for bottom points, we take the closer points for our boundary points to detect fingernail. We can see in fig. 3.9 image after a fingernail was detected.

To detect our first finger first we had to find the top extreme point, a similar

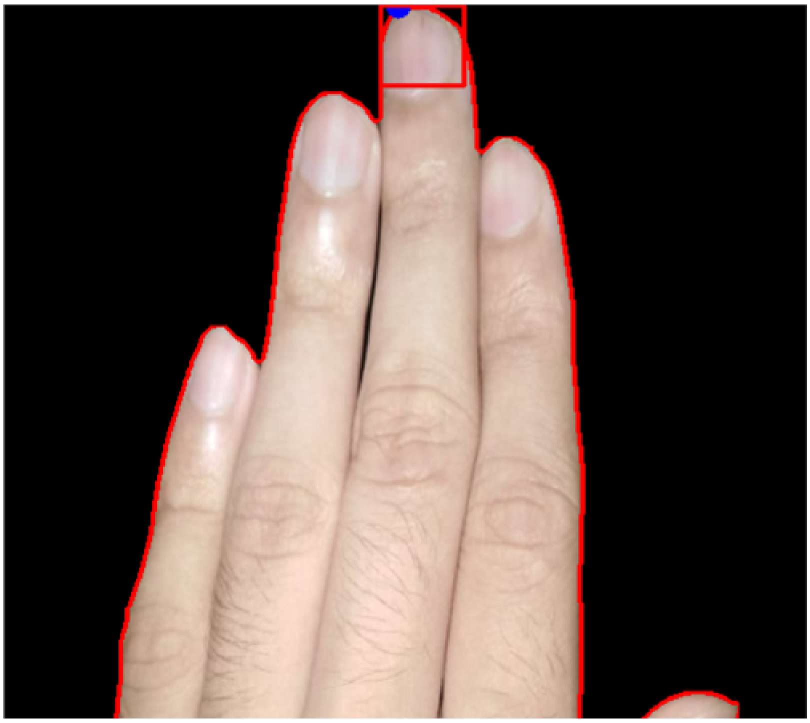


Figure 3.9: Image after one fingernail was detected

approach will be followed to detect other fingernails but now that we have detected one fingernail we need to apply some modifications to the image so that our contour top point resides on top of the next fingernail to be detected. We will remove our detected finger from foreground. It will be done by making the half of the detected finger part of the background as a result contour top point will no longer reside on top of middle finger in our image, so a new contour will be detected. We can see from fig. 3.10 that our extreme top point has now moved on to next finger top as we now have a different contour after we have made the first finger part of our background. We have removed the first finger by drawing a rectangle over the first finger and filling the rectangle with black color. We have already found out the top point, left and right point when we detected fingernail for drawing the rectangle, we have calculated the bottom boundary for rectangle by calculating contour center. fig. 3.11 shows top points of the remaining fingernails. Now that we have all the top points of our finger, we can use the same procedure by which we detected the first fingernail to detect all the fingernails. fig. 3.12 shows the image after all the fingernails are detected.

Now to extract region of interest from fingernail beds we will have to choose an area where there is no image area burned out due to flash light and there is

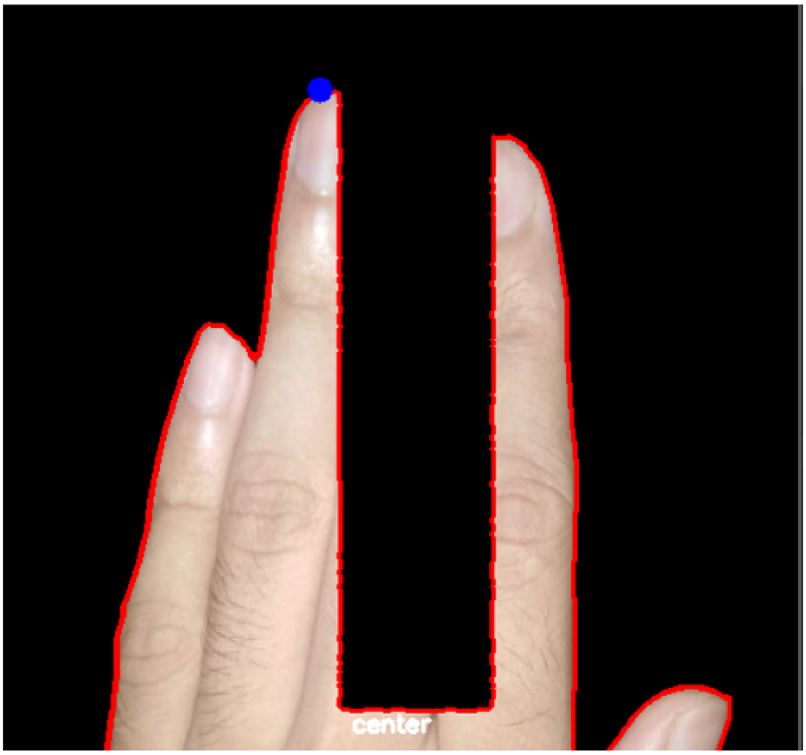
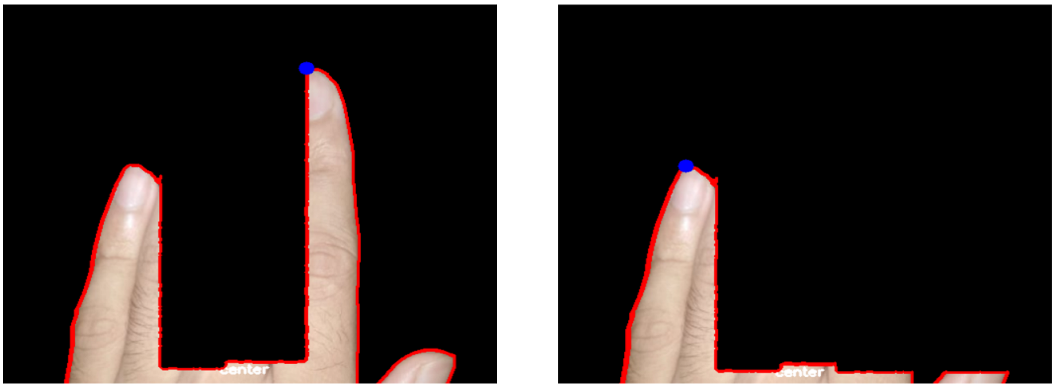


Figure 3.10: New top extreme point for detecting second fingernail



(a) Extreme top point for third fingernail

(b) Extreme top point for fourth fingernail

Figure 3.11: Extreme Top Points for Detecting Remaining Fingernail

no leukonychia. To crop out area that satisfy these requirement we will detect the largest area whose average brightness value is lower than fingernail mean brightness. In doing so we will not consider this area if there is pixels in area which shows sharp increase in brightness, then we will consider the next best area.

The approach is discussed below-

Approach:

Figure 3.12: Image after all the fingernails detected

1. **Step 1:** For the acquired matrix **nail**[][] which contains the pixel brightness of nail area,create a prefix average matrix(say **average**[][]) such that **average**[][]) stores the average brightness of all the elements of the matrix of size **i x j**.

2. **Step 2:** For each row in prefix sum matrix **average**[][]) using Binary Search do the following:

   - Perform Binary search with the lower limit as 0 end the upper limit as to maximum size of square matrix.

- Find the middle index (say mid).
- If the average of elements of all possible square matrix of size mid is less than or equals to mean brightness of fingernail, then update the lower limit as mid + 1 to find the maximum sum with size greater than mid.
- Else Update the upper limit as mid – 1 to find the maximum sum with size less than mid.

3. **Step 3:** Keep updating the maximum size of square matrix in each iteration for the given valid condition above.

3.3.5 Get RGB Color Values from Region of Interest Area

fig. 3.12 shows final image after extracting region of interest. It also gives a bounding box to our region of interest. The next step is to extract RGB values of the pixels which reside in this detected region. The RGB color model is an additive color model that combines red, green, and blue light in different ways to create a wide range of colors [22]. So color of each pixel of our image can be divide into red,green and blue parts. As blood color is red because of presence of hemoglobin we will only work with RED color. Hemoglobin contains iron because of which blood color is red. So red color intensity varies based on level of hemoglobin. We will iterate through the region of interest and calculate mean red value of the pixels within the boundary of region of interest. This mean value is the input feature for our regression model, based on this value our model will predict user blood hemoglobin level.

3.3.6 Linear Regression Model

Linear regression is a straightforward approach that has proved to be extremely useful in a variety of circumstances. There is one independent variable and one dependent variable in simple linear regression. For a given independent, we can estimate the average value of dependent variable [23]. Linear regression is very fast. It doesn't require any parameter tuning. It is easy to understand and highly interpretable. A simple linear regression model resembles a equation of straight line which is $y = mx + c$. For linear regression x is the input feature value and y is the predicted value and m and c are the coefficients. We can get those values from statistical method. But most of the machine learning libraries in python has built-in function to calculate these coefficient values from analysing a given dataset. eq. (3.1) explains linear regression modeling.

$$\hat{y} = \theta_0 + \theta_1 x_i \tag{3.1}$$

Here θ_0,θ_1 is are coefficients. For this work, x_i is the mean red color intensity from the region of interest and $\hat{y}$ is predicted blood hemoglobin level of the user. θ_1 can be defined by eq. (3.2).

$$\theta_1 = \frac{\sum_{i=1}^{i=S}(x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^{i=S}(x_i - \bar{x})^2} \tag{3.2}$$

θ_0 is defined by eq. (3.3)

$$\theta_2 = \bar{y} - \theta_1 \bar{x} \tag{3.3}$$

fig. 3.13 shows simple linear regression model for blood hemoglobin prediction. For our work, we find θ_1 after training the model on dataset of 118 collections.

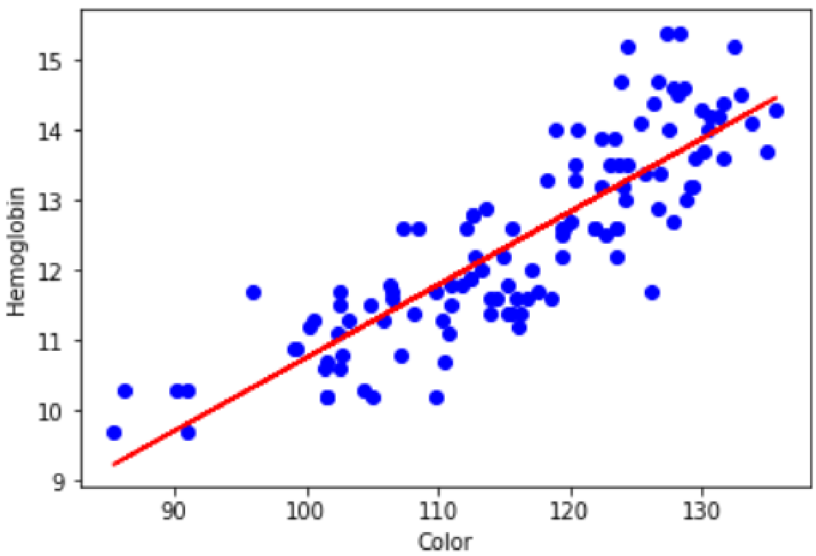


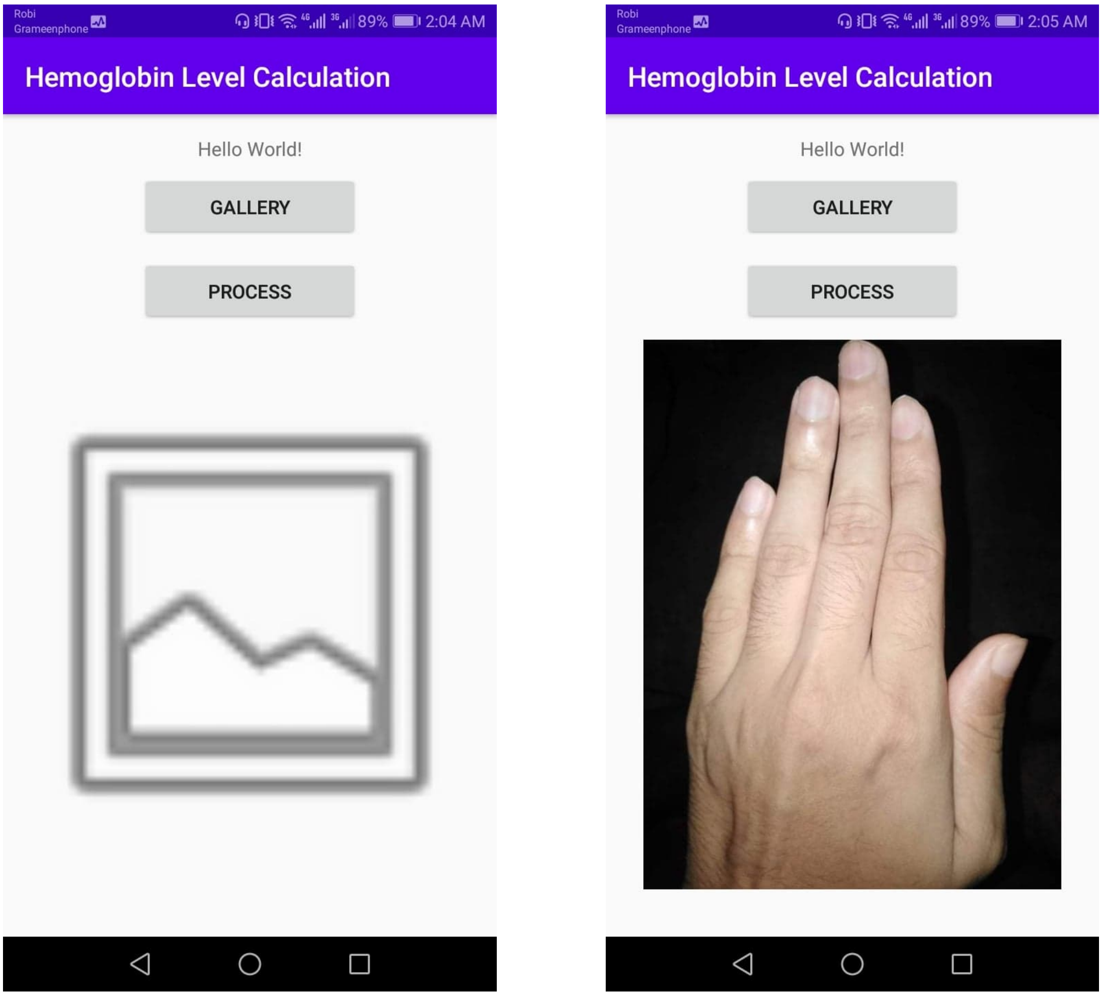
Figure 3.13: Simple Linear Regression Model

Here, $\theta_1 = 0.10427298$ and $\theta_0 = 0.3249128$. Our final equation to detect blood hemoglobin level of user-

$$\hat{y} = 0.3249128 + 0.10427298x_i \tag{3.4}$$

3.3.7 Android App Implementation

To convert our blood hemoglobin detection system to an android application we used Android Studio which is the official integrated development environment for Google's Android operating system. We used programming languages Python and Java. Java was used in main Activity whereas Python was used in background to apply image processing steps in our selected image which was captured by our smartphone. We used Chaquopy to include python components in our android app. Chaquopy is a plugin for standard Android build system. Figure 3.14 shows

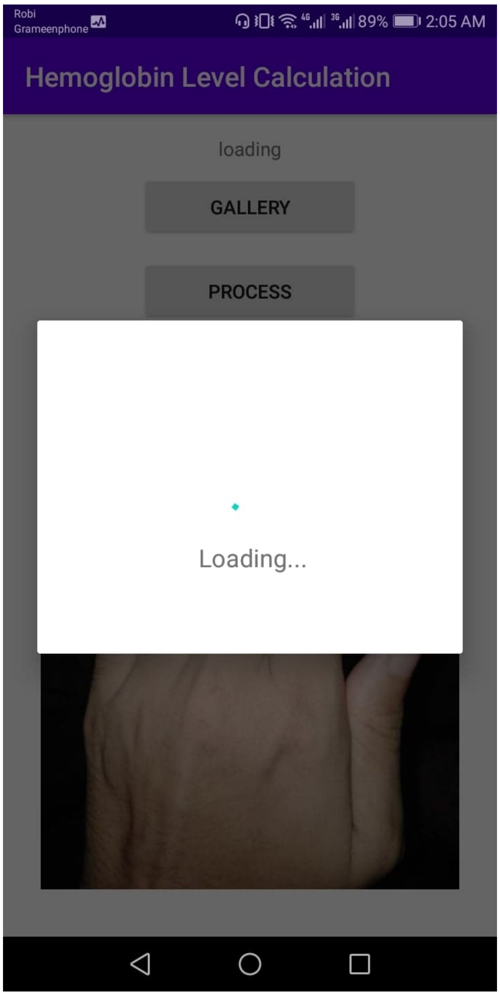


(a) Initial interface (b) Selection of image

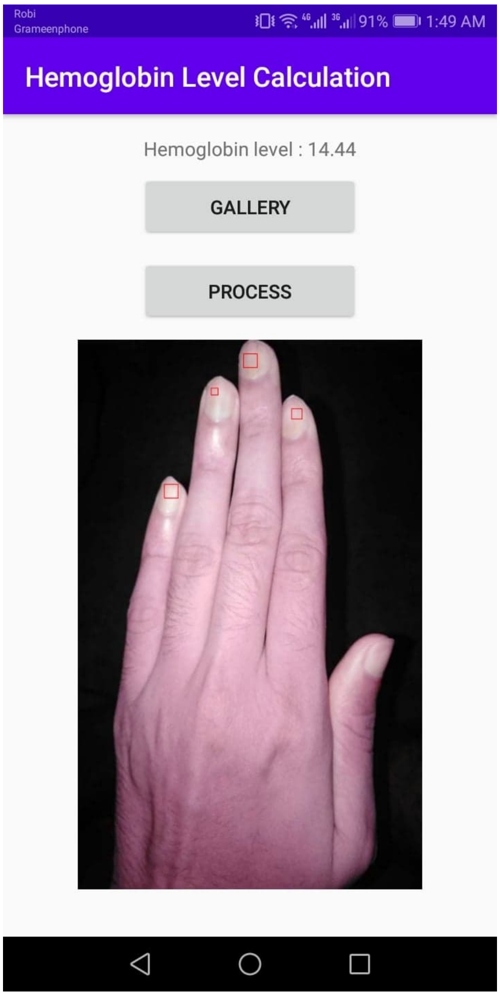
Figure 3.14: Image selection from gallery

the process of selecting picture in our android app. We converted our input image to arrays of pixel containing RGB values then we send this to our Python component. The instructions in the Python component will regenerate the image and apply all the steps discussed in this chapter and convert it back to arrays of pixels and send this array to Java main activity. Main Java Activity rebuilds the image.

When we press GALLERY button of fig. 3.14a we can choose our input image from gallery and in fig. 3.14b we can see that input picture was selected. If we press the PROCESS button of fig. 3.14b we transition to loading screen in fig. 3.15a. After the app finishes processing it finally shows modified image with blood hemoglobin level detected in fig. 3.15b. We can see from fig. 3.15b there are some bounding boxes in fingernails, the area bounded by these 4 red boxes are our desired region of interest.



(a) Loading state



(b) Final output

Figure 3.15: Blood hemoglobin level detection

3.4 Conclusion

In this chapter, the whole implementation details of the system was discussed including Android application implementation. A combined approach of edge detection and contour detection was used for background subtraction. An iterative mean approach was followed to extract region of interest. For predicting blood hemoglobin level a simple linear regression model was used with mean red color intensity of region of interest as input feature. In the next chapter, result and performance of the system will be discussed.

Chapter 4

Results and Discussions

4.1 Introduction

In the previous chapter a detailed explanation on region of interest extraction framework from user hand image was given. This chapter discusses about the datasets used for model training and the performance evaluation of the framework. The model will be evaluated based on various performance metrics like Mean absolute error, Residual sum of squares (MSE), R2-score, Variance score.

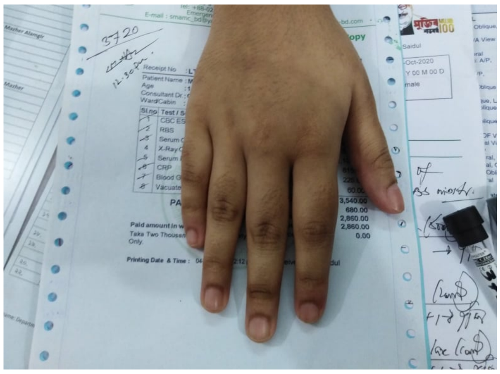
This framework was first implemented in PyCharm environment with Intel Core i5 processor and 8GB RAM, then in Android Studio environment for creation of our android application. The dataset used for linear regression was self developed as the data required for this work was not publicly available.

4.2 Dataset Description

The dataset was colleccted from Shaheed Monsur Ali Medical College and Hospital. Address of the hospital is Road 10, Sector 11, Uttara Model Town. Data collection duration was 1 week. Active data collection took place from 1st of November 2020 to 5th of November 2020. Figure 4.1a shows some sample image data which was taken from the hospital. We also acquired blood hemoglobin level from hospital. In total we collected 138 images from both male and female patient, from which we separated pictures of 20 patient with varying blood hemoglobin for testing purpose. The rest 118 images were pre-processed to create our data set for testing.

We will process image data from fig. 4.1 to create data set like table 4.1. From table 4.1 we can see in each record we will have information like redlevel, which

(a)



(b)

Figure 4.1: Some sample image data

indicates mean red color intensity of region of interest pixels and it is also the input feature for our regression model. Here serial number is the serial at which blood was collected for testing in the hospital.

Table 4.1: First 5 record of in data set

SERIALNUMBER	USEDFINGER	REDLEVEL	GENDER	HEMOGLOBIN
3641	2	112.14	M	12.6
3641	3	121.90	M	12.6
3689	3	100.56	F	11.3
3689	4	103.24	F	11.3
3700	2	107.19	F	10.8

Table 4.2 shows the description of the training data set. In the data set the sample with the minimum blood hemoglobin level is 9.7 g/dL and maximum level is 15.4 g/dL. Average level is 12.43 g/dL. Minimum red color intensity 85.42 and maximum is 135.66 .

Table 4.2: Description of dataset

	SERIALNUMBER	USEDFINGER	REDLEVEL	HEMOGLOBIN
count	118.000000	118.000000	118.000000	118.000000
mean	3664.203390	2.652542	116.152119	12.436441
std	86.905741	0.788563	11.340815	1.388085
min	3520.000000	1.000000	85.420000	9.700000
25%	3564.750000	2.000000	108.252500	11.400000
50%	3689.000000	3.000000	116.895000	12.500000
75%	3727.000000	3.000000	125.092500	13.500000
max	3793.000000	4.000000	135.660000	15.400000

Figure 4.2 shows scatter plot of color vs hemoglobin.

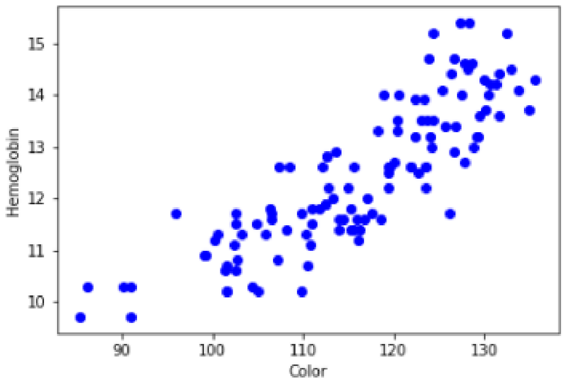


Figure 4.2: Plot of the data set for simple linear regression

4.3 Impact Analysis

4.3.1 Social and Environmental Impact

Computers and machines have only been around for a little more than 75 years. Yet, like the printing press, aircraft, television, and cars, they have had a significant influence on the world and society.

This thesis work will have a significant impact on medical field as time passes by and technology improves point of care diagnosis has become ever so important. Also this system enable automatic region of interest extraction which will help elderly people who can't point out region of interest manually.

4.3.2 Ethical Impact

When a decision, situation, or action conflicts with a society's moral values, ethical problems arise. Individuals and companies alike may be interested in these controversies, as all of their actions may be questioned on ethical grounds.

As traditional blood based hemoglobin level detection is correct and popular our system won't be trustable to every user. It is not the final product to replace tradition blood based detection.

4.4 Evaluation of Framework

For this thesis work hand image taken from a smartphone camera was taken as input. User hand needs to be close to camera lens for taking the input picture. The necessary data set was collected from Shaheed Monsur Ali Medical College and Hospital. The room was properly lighted. Patients were told to place their hand up to up to wrist in a way so that fingernail are upwards. Patients whose nails were not normally colored due to different issues like nail polish, using henna and separate diseases. Patients were told to keep their fingers closed not separated.

Different performance metrics were used for evaluation of framework. Some of the performance metrics for linear regression are MAE(mean absolute error), Residual sum of squares (MSE), Root mean squared error (RMSE), Relative squared error (RSE), R-squared(R^2)[24].

From eq. (4.1) we can calculate MAE(mean absolute error)[25], here y_j is the actual hemoglobin level and $\hat{y_j}$ is the predicted hemoglobin level for our model. From eq. (4.2) MSE can be calculated and from eq. (4.3) RMSE can be calculated. Equation (4.4) and Equation (4.5) are used for calculating Relative squared error and R-squared.

$$MAE = \frac{1}{n}\sum_{j=1}^{j=n} \mid y_j - \hat{y_j} \mid \tag{4.1}$$

$$MSE = \frac{1}{n}\sum_{j=1}^{j=n} (y_j - \hat{y_j})^2 \tag{4.2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{j=n} (y_j - \hat{y_j})^2} \tag{4.3}$$

$$RSE = \frac{\sum_{j=1}^{j=n} (y_j - \hat{y_j})^2}{\sum_{j=1}^{j=n} (y_j - \bar{y})^2} \tag{4.4}$$

$$R^2 = 1 - RSE \tag{4.5}$$

4.5 Evaluation of Performance

To evaluate the model better, we kept 20 data hidden from our whole data set of 138 record. This hidden data set was given different data of varying hemoglobin level after carefully observing. We used 118 record to train our model. First, data set was split into two portion namely train and test, train portion included 80% of the dataset randomly. We used the remainder 20% data to test the model, first row of table 4.3 indicate performance metrics more this case.

Next we used the whole whole data set to train and also the whole data set to test the model. Second row of table 4.3 indicate performance metrics more this case.

Finally we used our hidden data set consisting of 20 data to test the model. Third row of table 4.3 indicate performance metrics more this case.

Table 4.3: Performance measurement of linear regression model

	MAE	**MSE**	**RMSE**	R^2
Train and test split	0.59	0.51	0.71	0.60
Train & test using the whole data set	0.59	0.52	0.71	0.62
Test using the separate data set	0.79	0.93	0.97	0.65

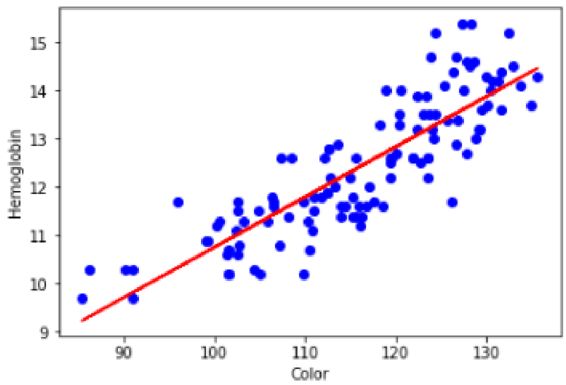


Figure 4.3: Regression model after being trained on the whole dataset

It is clear to see model performs better for known data on which it was trained on, for completely hidden data performance of the model regresses slightly. Figure 4.3 shows the model after it was trained on the whole data set.

4.6 Conclusion

This chapter shows the result of measurement of blood hemoglobin level from user hand image by detection region of interest from fingernail beds. Performance of the proposed framework is also discussed here. As shown by the results, the proposed region of interest extraction framework shows good performance. The conclusion to this thesis work is drawn in the next chapter.

Chapter 5

Conclusion

5.1 Conclusion

Extracting an optimum region of interest can ensure good performance. To detect blood hemoglobin from just user hand image, it is necessary to a lot of pre-processing, our first pre-processing task was to detect our main object from which is user hand and remove the background. It was done so by detecting the largest contour as detecting contour from a grayscale image is like detecting white object from a black background. Then we used contour top data iteratively to detect top of the finger point from hand image. This top point coordinate was used to draw bounding box over the fingernail area. Then finally our image becomes processed enough to detect ROI (region of interest). Pixel color values from coordinates residing in ROI area was calculated which is the input feature for our regression model. Here we used simple linear regression to measure blood hemoglobin level.

5.2 Future Work

There are so many challenges to extract ideal region of interest,one of the main issues is to negate smartphone camera flash effect over the whole fingernail, if a side of the finger nail is burned out due to flash it is possible to extract other side as the region of interest. So future research need to be done to completely negate brightness effect from camera flash. Also further research need to be done to subtract any form of background with multiple objects in it to make it smoother for measuring blood hemoglobin level.

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