# A Noninvasive Computerized Technique to Detect Anemia Using Images of Eye Conjunctiva

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**Abstract**—Anemia is the blood disorder which develops in the condition of lack of healthy red blood cells or hemoglobin. According to the World Health Organization (WHO) nearly quarter of the human population suffers from anemia moreover, invasive detection of anemia is tedious and expensive. Initial screening for noninvasive detection of anemia is done by examining the color of eye conjunctiva and after that by accommodating the outcomes with an intrusive blood test. This paper aims to resolve this issues along with providing an optimal and fast solution for detecting the anemia using noninvasive methods. This process includes capturing the image of eyes and then manually extracting the eye conjunctiva and obtaining the region of interest (ROI). Once ROI is extracted, these images are processed to obtain the mean intensity values of red and green components of image pixels corresponding to ROI. Then a tuned machine learning algorithm is used to predict whether the patient is anemic or not. The model employed is run over 99 test subjects using k-Fold cross-validation and had achieved an accuracy of 93 percent. This study aims to develop an automated and cost-effective noninvasive technique.

*Keywords:* anemia, conjunctiva, hemoglobin, support vector machine, threshold triangle

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## 1. INTRODUCTION

Anemia is the most common disorder of the blood. There are various factors which may result in anemia such as nutrition deficiency or due to excessive blood loss during surgery, delivery, and accidents or it can also be caused by the formation of sickle red blood cells, yet the most well-known reason of anemia is due to lack of enough hemoglobin and healthy erythrocytes (red blood cells) which delivers oxygen throughout the body tissues. Hemoglobin (Hb) is a protein-based component and is the main part of the red blood cells. Thus the concentration of the Hb in the blood is the most suitable indicator for determining the presence of anemia. Table 1 shows the normal hemoglobin ranges in the human.

The exact number of people who have anemia cannot be determined accurately. According to the World Health Organization (WHO), global anemia prevalence counts to 24.8 percentage of the entire world population which accounts for nearly two billion people [1]. Anemia goes undetected in many people and symptoms can be minor. In many underdeveloped areas, it even goes undetected due to wanting healthcare and medical facilities. The hemoglobin concentration in the blood is the most preferred way for determining if the person has anemia or not. This process includes taking the blood sample of the patient and then determining the concentration of the hemoglobin using Hematocrit (Hct) test which determines the volume percentage of red blood cells. Since the detection is an intravenous process requiring lab testing which requires time and may even expose the workers to bloodborne infections [10], efficient noninvasive techniques are thus needed for anemia detection.

Another noninvasive technique used to quickly screen for anemia is through examination of the conjunctiva pallor of the eye. Physicians generally pull the

**Table 1.** Normal Hemoglobin Ranges in Human

| Age/Sex | Threshold/Hb |
|---|---|
| Children (<2 years) | 10.5 to 13.5 g/dL (mean 12.0 g/dL) |
| Children (<2–6 years) | 11.5 to 13.5 g/dL (mean 12.5 g/dL) |
| Children (<6–12 years) | 11.5 to 15.5 g/dL (mean 13.5 g/dL) |
| Female (12–18 years) | 12.0 to 16.0 g/dL (mean 14.0 g/dL) |
| Female (>18 years) | 12.1 to 15.1 g/dL (mean 14.0 g/dL) |
| Male (12–18 years) | 13.0 to 16.0 g/dL (mean 14.5 g/dL) |
| Male (>18 years) | 13.6 to 17.7 g/dL (mean 15.5 g/dL) |

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eyelid and subjectively examine the coloring of the eye conjunctiva membrane. This method for detecting anemia proved to be quite useful in many cases but the low sensitivity of anterior conjunctiva's color can undermine the authenticity of the visual detection process [2, 3], by using color scale cards which consists of the color spectrum and corresponding hemoglobin levels can mitigate the problem and reduce human errors.

Hemoglobin is the main component which contributes to the pigmentation of the blood. It posses bias in reflecting the red component of light falling on its surface as compared to green component of light which is absorbed more than the red component, this is the main reason which leads to deep reddish color of hemoglobin. Hence by comparing the intensities of red and green component of the RGB spectrum of conjunctiva's pallor, it is possible to estimate the hemoglobin concentration in human and further predict whether the patient has anemia or not.

In [4], a noninvasive method has been used for the detection of anemia. The authors have achieved an accuracy of 78.9% with a sparse data set of 19 images using histogram thresholding. In [5], the authors have designed a noninvasive device and method for the detection of anemia. k-Nearest neighbors (kNN) classifier has been used by the author for the prediction of anemic or nonanemic class. kNN is a supervised machine learning algorithm in which the class of the object is predicted using the majority votes of its neighbor, the class to which the object would belong to is the most frequent among its k nearest neighbor [9]. In [6], the segmentation of the anterior conjunctiva has been dealt with showing the correlation between a* axis, i.e., red–green axis against Hemoglobin (Hb) which has been used in this paper for detection of anemia using the red-green color intensities.

This paper similarly deals with the prediction of class labels of given images of eye conjunctiva (i.e. whether it belongs to anemic patient or nonanemic patient) by constructing a noninvasive method. A tuned model of SVM is developed for prediction purposes. SVM is a supervised machine learning algorithm which analyses the training dataset to predict the class labels of test object in this way SVM is a non-probabilistic binary linear classifier, This algorithm plots the input data points on $n$-dimensional space (where n is the number of features) with the value of each feature is the value of a particular coordinate, this algorithm performs classification by finding the hyperplane that differentiates the two classes very well. There is a clear demarcation between anemic and nonanemic people as can be seen in Fig. 4 due to the mean color intensities of red and green components of ROI. Our findings suggest that noninvasive methods are friendly, reliable and it provides good accuracy and cost affordability in comparison to an invasive method. This will make it easier to detect anemia as a substitute in place of invasive methods.

## 2. PROPOSED METHODOLOGY

The flowchart of the proposed method of the entire process for determining whether the patient is suffering from anemia or not, from the image of the eye conjunctiva of the patient is presented in Fig. 1. This flowchart captures the major part of the developed algorithm and each segment of the flowchart is described in later sections.

### *2.1. Dataset*

The process starts with taking the images of interior eye conjunctiva of anemic and nonanemic patients for generating the dataset on which the modified classifier can be trained and later on can be tested for computing the accuracy, sensitivity, and specificity of the model. All the images were taken using standard camera. This is done by slightly pulling the lower eyelid with the index finger and taking the photograph, so that the eye conjunctiva is in the focus and can be as magnified as possible. Further while taking the images, the flashlight was off in order to avoid excessive glare effect because the quality of images largely affects the accuracy of the prediction algorithm. It was observed that some images are too bright whereas some images are too dark due to uneven lighting effect while capturing the images, such images were manually removed before performing preprocessing on images. Finally, the dataset consists of 99 images out of which 51 belong to the nonanemic patients and 48 belongs to the anemic patients, thus the dataset is balanced so that the classifier model remains unbiased.

### *2.2. Image Preprocessing*

In order to extract the region of interest (ROI) from the image of eye conjunctiva of the patient. This paper uses a threshold triangle (which uses triangle algorithm for thresholding) for binary differentiation between the ROI as shown in Fig. 2 (i.e., palpebral conjunctiva) and background. Once the contour for the ROI is formed (i.e., the patient's palpebral conjunctiva), the following steps were performed for predicting whether the patient is anemic or nonanemic these steps are explained in the next subsection.

### *2.3. Model for Predicting Class Labels*

After the image preprocessing was done and the dataset was constructed, for each image the ROI which was extracted in earlier part is converted in CIELAB (or La*b*) color space model. Lab color is designed to approximate human vision. It is repre-

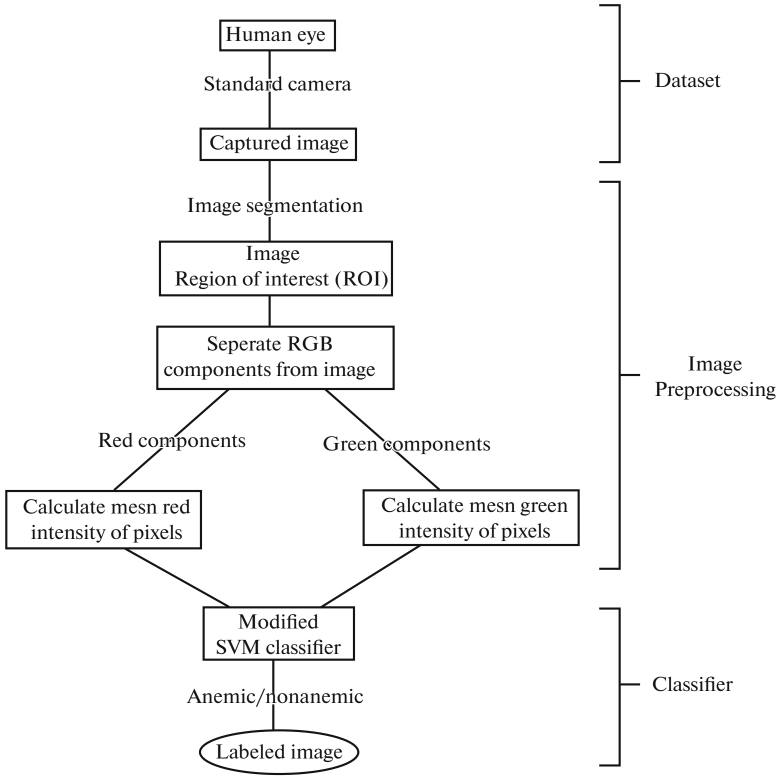


**Fig. 1.** Flowchart of proposed methodology.

sented by the mean value of a* components of ROI. a* components includes red component (a* > 0) and green component (a* < 0). In order to establish the relationship between the a* components of the ROI and the Hb levels of the patient, previous work done in this area shows there exists a strong relationship between a* components and Hb levels when calculated using Pearson correlation index, various experiments done in this area shows that patient with higher Hb values tend to have average value of a* greater than 160 and the patients with lower Hb values tend to have average value of a* less than 142 [6]. Thus the average values of a* components are more discriminating (i.e. the mean intensity of red components and green components best discriminates the anemic and nonanemic patients, this detailed study is described in the Section 3.2).

### *2.4. Classifier*

Modified and tuned support vector machine (SVM) is used for classification into anemic or nonanemic labels. It has been tuned on the following parameters i.e. the kernel and the regularization parameter (C). It also involves the tuning of the degree in the case when the kernel has been set to poly.

• Kernel tells the type of algorithm to be used for deducing the separating hyperplane. The following kernels i.e. linear, radial basis function (rbf), polynomial (poly) and sigmoid, have been used while tuning on different kernels.

• Regularization parameter controls the trade-off between the slack variable penalty (misclassifications) and width of the margin. Small C makes the constraints easy to ignore which leads to a large margin, while large C allows the constraints hard to be ignored which leads to a small margin [8]. It was evaluated on values including 0.1, 1, 10, 100 etc.

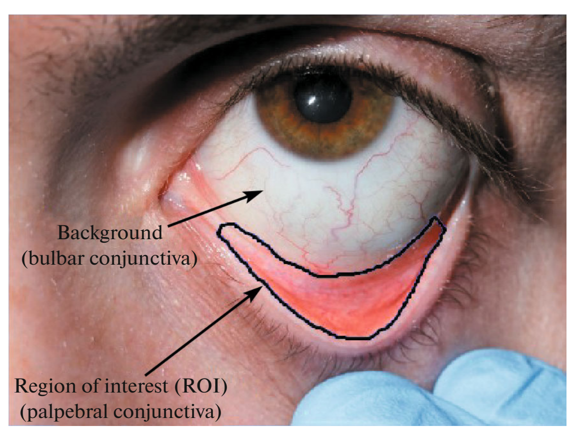


**Fig. 2.** (Color online) Region of interest.

(a)

(b)

**Fig. 3.** (Color online) (a) anemic conjunctiva, (b) nonanemic conjunctiva.

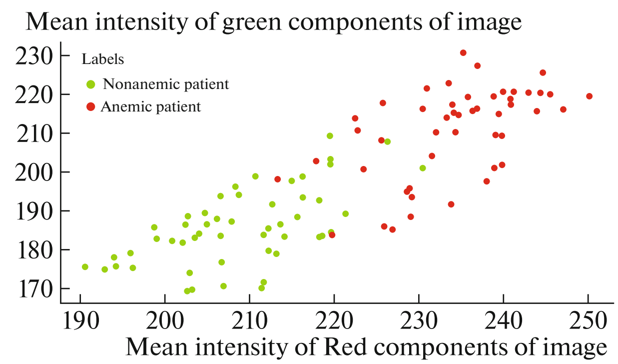


**Fig. 4.** (Color online) Mean intensity of red component of image vs mean intensity of green components of images.

According to *no free lunch* (NFL) theorem, there is no model which works best for every given problem so by iterating through all possible combinations of SVM parameters then only we can find out which possible combination provides best results. Thus, the tuning has been done to get the hyperplanes that have the largest margin in a high-dimensional space to separate given data into classes, i.e., anemic and nonanemic. This tuning helped in achieving the best figures for accuracy, specificity, and sensitivity. The values were varied with every possible permutation for the dataset and then fixed upon after getting better results in either of the permutations for kernel and C. The results obtained are discussed in Section III presenting the conclusions of the tuned and modified SVM.

k-Fold cross validation has been used over SVM in order to alleviate the problems associated with limited data-sample. Cross-validation is a resampling procedure used to evaluate machine learning models on a skimpy data set and is also popular because the results are less biased than the other methods such as train-test split. The parameter "k" defines the number of groups the given data set is to be split. The lower value of "k" is usually cheaper in terms of computation but are more biased whereas the larger value of 'k' is more expensive in terms of computation and less biased, but can suffer from large variability.

It is usually the best choice to select the moderate value of "k," i.e., in range 10–20.

## 3. RESULTS

### *3.1. Data Collection*

Dataset consists of images of eye conjunctiva for preliminary detection of anemia. It consists of 99 images out of which 51 images belong to the nonanemic patients and 48 images belong to the anemic patients. So the dataset is quite balanced (i.e., not weighted more for either of the class). Dataset was collected from students at Maulana Azad National Institute of Technology, Bhopal and also from internet services and was labeled by a pathologist in two classes "anemic" and "nonanemic". Standard camera is used for the acquisition of all images in the dataset.

Figures 3a and 3b shows the sample of the anemic and nonanemic conjunctiva respectively. It is clearly differentiated that the images of eye conjunctiva of anemic patient posses less redness (i.e., tending towards brighter region) and images of eye conjunctiva of nonanemic patient posses more redness (i.e., tending towards darker region).

### *3.2. Detailed Analysis*

Different analysis was done on data set by converting the images into different dimensions, but there was not much significant change in the performance metrics because the model uses the mean intensity values of the red and green components of an image for predicting the class label. Best results were obtained when original images were used and then by plotting the graph between the mean intensity values of red components and green components of the images, it was found that nonanemic patients correspond to the lower section in the graph (closer to the origin, towards darker region) whereas anemic patients correspond to the upper section of the graph (away from the origin, towards brighter region). Thus by examining the mean intensity values of red and green components of the

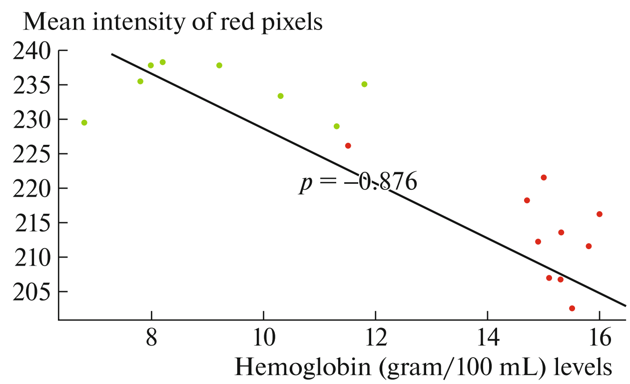


**Fig. 5.** (Color online) Mean intensity value of red pixels vs hemoglobin (Hb) and pearson coefficient ρ (μr, Hb)

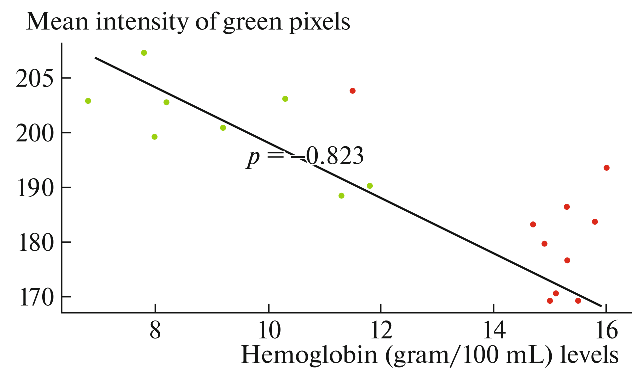


**Fig. 6.** (Color online) mean intensity value of green pixels vs hemoglobin (Hb) and pearson coefficient ρ (μg, Hb)

image of eye conjunctiva of the patient in this way, this paper expects to anticipate whether the patient is suffering from iron deficiency (anemia) or not. Figure 4 shows the graph distribution of dataset.

Table 2 shows the analysis between anemia detection using computerized method (proposed model) vs blood analysis report provided by the pathologists.

This paper uses Pearson coefficient [11] to show the relationship between mean intensity values of red and green pixels of ROI with hemoglobin.

The results are as follows: mean intensity value of red pixels of ROI vs hemoglobin $\rho$ ($\mu_r$, Hb) = –0.876.

Mean intensity value of green pixels of ROI vs hemoglobin $\rho$ ($\mu_g$, Hb) = –0.823.

Figure 5 shows the plot of the mean intensity value of red pixels of ROI with hemoglobin.

Figure 6 shows the plot of the mean intensity value of green pixels of ROI with hemoglobin.

Thus, it could be strongly concluded that hemoglobin holds a strong correlation with the mean intensity value of red and green pixels for predicting whether the patient is anemic or nonanemic.

The model used for predicting whether the patients are anemic or nonanemic:

A modified version of SVM has been used and also hyperparameters (kernel type, regularization parameter) tuning has been performed over the original SVM model in order to increase the accuracy of prediction.

### *3.3. Performance Metrics*

To evaluate the performance of the algorithm, various evaluation metrics can be used. This paper uses the most widely used metrics with the following classification:

• True positive (TP): when predicted anemic person is actually anemic.

• True negative (TN): when predicted nonanemic is actually annotated as nonanemic.

• False negative (FN): when predicted nonanemic is actually annotated as anemic.

• False positive (FP): when predicted anemic is actually annotated as nonanemic.

The performance metrics are defined as follows:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}, \quad (1)$$

$$Specificity = \frac{TN}{TN + FP}, \quad (2)$$

$$Sensitivity = \frac{TP}{TP + FN}. \quad (3)$$

This metrics are usually used to evaluate the performance of machine learning models or classifiers from different perspective. The outcomes obtained on different combinations of kernels and regularization parameter are as shown in Tables 3–5.

• Table 3 shows the performance metrics for different regularization parameters (C) when the kernel type is *sigmoid*.

• Table 4 shows the performance metrics for different regularization parameters (C) when the kernel type is *rbf*.

If the training data objects are not linearly separable and if the *rbf* kernel is used for classification then it will choose a nonlinear decision boundary and perform a nonlinear classification. Also the value of regularization parameter should not be too large or too small, as the above performance metric for *rbf* kernel shows that accuracy is highest for C = 1 and the accuracy decrease as the value of C increases or decreases, so for the best results C value should neither be too large nor be too small.

• Table 5 shows the performance metrics for different regularization parameters (C) when the kernel type is *linear*.

The *linear* kernel is the simplest kernel of SVM and it takes less time to train as compared to other

**Table 2.** Analysis between anemia detection using computerized method (proposed model) vs blood analysis report provided by the pathologists

| # | Region of interest (ROI) extracted from images | Mean intensity of red pixel ($\mu_r$) | Mean intensity of green pixel ($\mu_g$) | Blood report hemoglobin level, g/100 mL | Pathologists prediction | Proposed model prediction |
|---|---|---|---|---|---|---|
| 1 |  | 233.42 | 206.15 | 10.3 | Anemia | Anemia |
| 2 |  | 229.55 | 205.77 | 6.8 | Anemia | Anemia |
| 3 |  | 235.51 | 214.54 | 7.8 | Anemia | Anemia |
| 4 |  | 235.15 | 190.23 | 11.8 | Anemia | Anemia |
| 5 |  | 238.32 | 205.48 | 8.2 | Anemia | Anemia |
| 6 |  | 237.90 | 200.85 | 9.2 | Anemia | Anemia |
| 7 |  | 237.89 | 199.24 | 8.0 | Anemia | Anemia |
| 8 |  | 229.05 | 188.53 | 11.3 | Anemia | Anemia |
| 9 |  | 212.22 | 179.72 | 14.9 | Nonanemia | Nonanemia |
| 10 |  | 221.59 | 169.38 | 15 | Nonanemia | Nonanemia |
| 11 |  | 202.59 | 169.38 | 15.5 | Nonanemia | Nonanemia |
| 12 |  | 206.97 | 170.74 | 15.1 | Nonanemia | Nonanemia |

**Table 2.** (Contd.)

| # | Region of interest (ROI) extracted from images | Mean intensity of red pixel ($\mu_r$) | Mean intensity of green pixel ($\mu_g$) | Blood report hemoglobin level, g/100 mL | Pathologists prediction | Proposed model prediction |
|---|---|---|---|---|---|---|
| 13 |  | 211.63 | 183.77 | 15.8 | Nonanemia | Nonanemia |
| 14 |  | 216.27 | 193.59 | 16 | Nonanemia | Nonanemia |
| 15 |  | 218.27 | 183.28 | 14.7 | Nonanemia | Nonanemia |
| 16 |  | 206.74 | 176.80 | 15.3 | Nonanemia | Nonanemia |
| 17 |  | 226.25 | 207.76 | 11.5 | Nonanemia | Anemia |
| 18 |  | 213.63 | 186.60 | 15.3 | Nonanemia | Nonanemia |

**Table 3.** Performance metrics for *sigmoid* kernel

| C | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| 0.001 | 0.5 | 0.5 | 0.0 |
| 0.01 | 0.5 | 0.5 | 0.0 |
| 0.1 | 0.5 | 0.5 | 0.0 |
| 1 | 0.5 | 0.5 | 0.0 |
| 10 | 0.5 | 0.5 | 0.0 |
| 100 | 0.5 | 0.5 | 0.0 |
| 1000 | 0.5 | 0.5 | 0.0 |

**Table 4.** Performance metrics for *rbf* kernel

| C | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| 0.001 | 0.5 | 0.5 | 0.00 |
| 0.01 | 0.5 | 0.5 | 0.00 |
| 0.1 | 0.5 | 0.5 | 0.00 |
| 1 | 0.7 | 0.64 | 0.88 |
| 10 | 0.67 | 0.62 | 0.78 |
| 100 | 0.67 | 0.62 | 0.78 |
| 1000 | 0.67 | 0.62 | 0.78 |

kernels of SVM because it tries to find a linear hyperplane which can best differentiate the objects, whereas other kernel uses nonlinear hyperplanes which takes more time to train.

The plot of mean intensity values of a* components of images of eye conjunctiva of patients shown in Fig. 4 shows that the linear hyperplane can best discriminates the anemic and nonanemic patients, due to

**Table 5.** Performance metrics for *linear* kernel

| C | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| 0.001 | 0.93 | 1 | 0.88 |
| 0.01 | 0.93 | 1 | 0.88 |
| 0.1 | 0.93 | 1 | 0.88 |
| 1 | 0.93 | 1 | 0.88 |
| 10 | 0.93 | 1 | 0.88 |
| 100 | 0.93 | 1 | 0.88 |
| 1000 | 0.93 | 1 | 0.88 |

this reason the *linear* kernel has outperformed all other nonlinear kernels of SVM.

## 4. CONCLUSIONS

The aim of this study is to build a modification of the existing classifier for detecting anemia based on a noninvasive method which can provide a more accurate estimation of the concentration of Hb in blood by analyzing the image of eye conjunctiva. Results were achieved without any sample selection and are impartial with respect to the gender of the patient. Modified SVM is used by tuning the parameters of SVM. Then, this tuned SVM is used to predict whether the patient is anemic or not. Thus the result obtained from this model can be utilized together with the data of other examinations to further reduce the number of patients that are required to undergo an invasive blood test. In this work, the modified SVM was tested on 99 test samples using k-Fold cross-validation that resulted in the best accuracy obtained among all possible combinations of the parameters of SVM is 93%. In addition, future development will include more emphasis on the preprocessing step which will automatically discard all the images that are not suitable for analysis (i.e. due to acquisition error) in this paper such images that are either too bright or too dark has been removed manually and also the process of extracting ROI can be automated using the various filter and computer vision algorithms.

## COMPLIANCE WITH ETHICAL STANDARDS

### ETHICAL STATEMENT

All studies were conducted in accordance with principles for human experimentation as defined in the Declaration of Helsinki and International Conference on Harmonization Good Clinical Practice guidelines, and approved by the relevant institutional review boards.

### INFORMED CONSENT

Informed consent was obtained from each study participant after they were told of the potential risks and benefits as well as the investigational nature of the study.

## CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

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