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A Systematic Approach to Predict Anemia from Eye Conjunctiva Images

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***Abstract*—Anemia is a health condition that occurs when there is insufficient hemoglobin (Hb) in the bloodstream. Although not usually lethal in mild cases, in severe cases, it can be life-threatening, especially for women, as it can lead to premature birth during pregnancy, heart problems, and multi-organ failure resulting in death. Anemia is a disease that can be easily cured if caught early, however, patients often ignore symptoms like fatigue, headache, or shortness of breath. Diagnosis of anemia requires a CBC blood test or a physical examination done by a healthcare professional, which can be both costly and time-consuming. The main aim of the current study is to propose a non-invasive and efficient method to diagnose anemia, which can be done by taking images of the eye conjunctiva. The raw image data corresponding to anemic conditions and blood hemoglobin levels (BHL) were collected from three distinct clinical sources. After preprocessing and cleaning the images, 18 features in 3 different color spaces were extracted. Using those features, anemia was predicted by various machine learning algorithms. The highest detection accuracies of 92% were observed with an ensemble of Support Vector Classifier, Random Forest, Logistic Regression, and XGBoost.**

***Clinical Relevance*- Anemia affects approximately 25% of the world's population. This study suggests a non-invasive method for predicting anemia using images of the eye conjunctiva, which eliminates the need for any blood tests.**

I. INTRODUCTION

Anemia occurs when the Red Blood Cell (RBC) count falls below the optimum level or there are not enough healthy RBCs in the bloodstream. RBCs contain hemoglobin, an iron-based protein that forms an unstable bond with oxygen and carries it to every cell in the human body. When the cells do not receive the required amount of oxygen, the organs cannot function properly, resulting in tiredness and fatigue. Other common symptoms of anemia include headaches, chest pain, dizziness, shortness of breath, irregular heartbeats, and cold hands and feet [1]. The leading cause of anemia is iron deficiency, but a lack of micronutrients such as Vitamin B12, Vitamin A, folate, and Zinc can also cause anemia.

A blood test can usually determine the amount of Hb in blood, and anemia is diagnosed when the hemoglobin(Hb) level is below 13.5 g/dL in males or less than 12.0 g/dL in females. Anemia can be classified as mild, moderate, and severe. Mild anemia corresponds to a level of hemoglobin concentration of 10.0-10.9 g/dL for pregnant women and children under age 5 and 10.0-11.9 g/dL for nonpregnant women. For all the tested groups, moderate anemia corresponds to a 7.0-9.9 g/dL, while severe anemia corresponds to a level less than 7.0 g/dL [1]. In some other sources, [2], [3], hemoglobin (hb) concentrations of $<$12.0 g/dL for women who are not pregnant, $<$13.0 g/dL for men, $<$11.0 g/dL for women who are pregnant in the first or third trimester, and $<$10.5 g/dL for women who are pregnant in the second trimester were considered anemia. Considering these data, the threshold of the Hb level selected for the detection of anemia in this paper is 10.9 g/dL.

World Health Organization (WHO) has predicted that 24.8% of the world's population suffers from anemia, which is around 2 billion people [4]. As the symptoms are usually mild, they are often ignored and it goes undetected, especially in underdeveloped countries with improper and/or non-functioning healthcare systems. As detecting the disease requires an invasive procedure like drawing blood and then culturing it in the lab, many underprivileged people are reluctant and sometimes cannot afford to go through this process. Also, laboratory procedures take up much time and human interactions.

Physical examinations of anatomical sites like eye conjunctiva, tongue, palmar crease pallor and nail beds [5]–[7] are also performed by healthcare professionals to detect anemia; these are non-invasive procedures, however, they are less accurate and results vary when checked by different examiners, hence the results are sometimes disputable. On the contrary, digital technology can be used to diagnose the disease early to alert patients and prevent its severity in later stages. In that case, it is worthwhile to invest in and develop a reliable technology, which this paper aims to do.

II. BACKGROUND AND RELATED WORKS

In this era of technological boom, machine learning and digital image processing play a huge role in research related to the medical and healthcare fields. For example, Machine Learning is used to classify breast cancer, which determines if a tumor is benign or malignant using classifiers like Decision Tree, SVM, Random Forest and KNN [8]. As discussed earlier, there are several clinical methods to detect anemia, such as HomoCue, which is a portable hemoglobin photometer, but it is very expensive [9]. In contrast, there is a WHO color scale, which is much cheaper but unreliable; although these are both invasive methods [10].

The evolution of non-invasive methods to detect anemic conditions was pioneered by S. Suner et al., who used digital pictures of the palpebral conjunctiva [11]. Another approach was taken by Mannino et al., who developed a smartphone application that utilizes photos of the fingernail bed, analyzing color and metadata to estimate hemoglobin levels and effectively detects anemia, indicated by hemoglobin levels below 12.5 g dL-1, with a high level of accuracy at approximately ±2.4 g dL-1 and a sensitivity rate of 97% [12]. Another non-invasive technique for hemoglobin detection based on a specific conjunctiva region image was proposed by Bevilacqua et al., they designed an easily wearable device to be used by patients. The authors used only 77 individuals to train their model with a detection accuracy of 84.4% [13]. Smartphone-based anemia prediction from eye images is commonly practiced nowadays. Wightman et al. developed a prototype where 64 tongue and 64 eye conjunctiva images were used to diagnose anemia. The result showed 91.89% sensitivity and 85.18% specificity for tongue images and 91.89% sensitivity and 70.34% specificity for eye conjunctiva images [14].

Another smartphone-based anemia detection study was reported by G. Dimauro et al., where only eye conjunctiva images from 102 people were used [15]. As the dataset was initially unbalanced, SMOTE and ROSE algorithms were used to balance the dataset. The accuracy of this work was 98.2% with SMOTE and 98% with the ROSE algorithm. In another research study, the authors used 113 images and classified them into three classes. If a blood hemoglobin value ¡ 10.5 g/dL was found, the person was judged at a high risk of anemia; a level between 10.5 g/dL to 11.5 g/dL was considered as doubtful but otherwise high risk. In that case, almost 100% detection accuracy was achieved [16]. A similar study was done by N.B Noor et al., where the authors collected 104 images of eye conjunctiva with an anemic condition [17]. The highest 82.61% detection accuracy was achieved using the Decision Tree algorithm.

A very distinct approach was adopted by P. Jain et al., Artificial Neural Networks (ANN) were used to predict anemia from eye conjunctiva images [18]. Though the total number of images where 99, data augmentation was used to generate a total of 3,103 images. The features were extracted in RGB color space and authors achieved 97% accuracy with 99.21% sensitivity and 95.42% specificity. Numerous research studies have been done on anemia detection using conjunctiva images with machine learning and deep learning. Among them, machine learning-based works are more successful. For deep learning, we need thousands of images without data augmentation, which would be a daunting task.

In this study, the three different datasets from three different research works were combined to get 421 conjunctive image entries with their corresponding anemic condition. Combined together, we curated a collection of 130 images for the anemic data and 291 for nonanemic data. The images were analyzed into three different color spaces: RGB, HSV and CIE LAB. A total of 18 features were collected from those images. Using those features, the dataset was trained and tested using Machine Learning algorithms like Logistic Regression, Support Vector Classifier, Random Forest, XGBoost and Ensemble learning. In the final analysis, we obtained the highest 92% accuracy with an ensemble of Logistic Regression, Support Vector Classifier Random Forest and XGBoost.

III. DATA DESCRIPTION

In this work, a new dataset was created from three different sources [19], [18], [20], to aid research in anemia detection using images of eye conjunctiva. All the data were curated for this purpose and processed using the methods described below. The image data were collected from three different datasets from three different countries, Bangladesh, India and Italy. The combined dataset contains a total of 421 entries, 130 of which are anemic data, and 291 are non-anemic data. The image data were combined before being further processed, including cropping and ROI selection. Finally, 18 features were extracted from them by image processing, which includes percentage and average of color information for RGB (Red, Green, Blue), HSV (Hue, Saturation, Value) and CIELAB (Lightness, *a (Red/Green Value) and *b (Blue/Yellow)) color spaces. Fig. 1 shows the percentage of data distribution in the collected images based on gender and anemic condition and Fig. 2 demonstrates images of ROIs (Region of Interest).

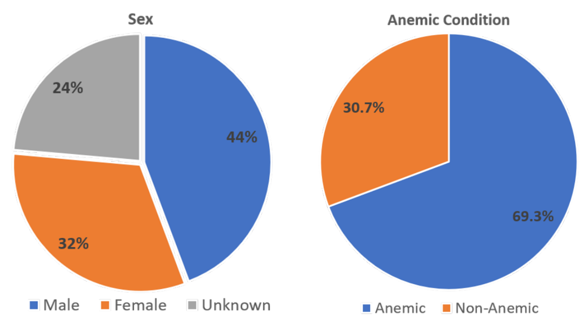

Fig. 1. Data distribution percentages based on gender and anemic condition

Fig. 2. Image of the ROI

IV. DETECTION METHODOLOGY

Figure 3 depicts the methodology used to create the dataset with 421 images. The data that was collected from primary sources were scattered. The data consisted of some images with their corresponding Hb value. Based on the Hb value, those images are separated into two classes: Anemic and Non-anemic for the first two data sources. The threshold Hb value was 10.9 g/dL to classify [1]. In the third source, the images are already classified into two classes. After that, the Region of Interest (ROI) was selected by removing unwanted portions.

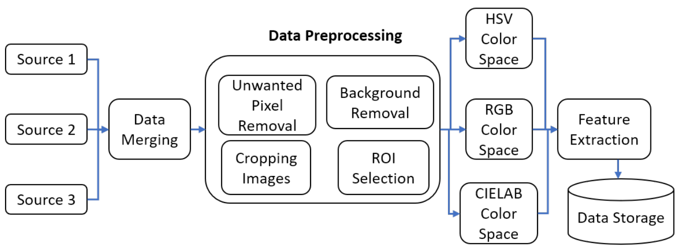

Fig. 3. Dataset Construction Flow

Oftentimes, unwanted pixels showed up due to light reflection while capturing the images. Those pixels were set to zero in all three red, green, and blue channels. Those images were analyzed in three different color spaces (RGB, HSV, CIE LAB). For all cases, percentage and average values were extracted by the following equations (1-6) and for this purpose image processing techniques were utilized.

$$\%RedPixel = \frac{RedPixels * 100}{\sum(RedPixels, GreenPixel, BluePixel)} \tag{1}$$

$$\%GreenPixel = \frac{RedPixels * 100}{\sum(RedPixels, GreenPixel, BluePixel)} \tag{2}$$

$$\%BluePixel = \frac{RedPixels * 100}{\sum(RedPixels, GreenPixel, BluePixel)} \tag{3}$$

$$Average\ Red\ Pixel = \frac{Total\ Red\ Pixel}{Total\ Channels} \tag{4}$$

$$Average\ Green\ Pixel = \frac{Total\ Green\ Pixel}{Total\ Channels} \tag{5}$$

$$Average\ Blue\ Pixel = \frac{Total\ Blue\ Pixel}{Total\ Channels} \tag{6}$$

Eq. (1) to (6) are shown only for RGB color spaces. The same analysis was done for the other two-color spaces (HSV and CIELAB). Finally, all features were exported into a CSV file.

Figure 4 depicts the methodology of training and testing the dataset which contains 18 features extracted from the collected 421 images in three different color spaces, different machine learning algorithms were applied to get the Anemic Condition. Logistic Regression, KNN, Support Vector Classifier (SVC), Random Forest, Decision Tree, XGBoost. Ensemble Learning is also used to determine the anemic condition by combining Support Vector Classifier (SVC), Logistic Regression, Random Forest, and XGBoost.

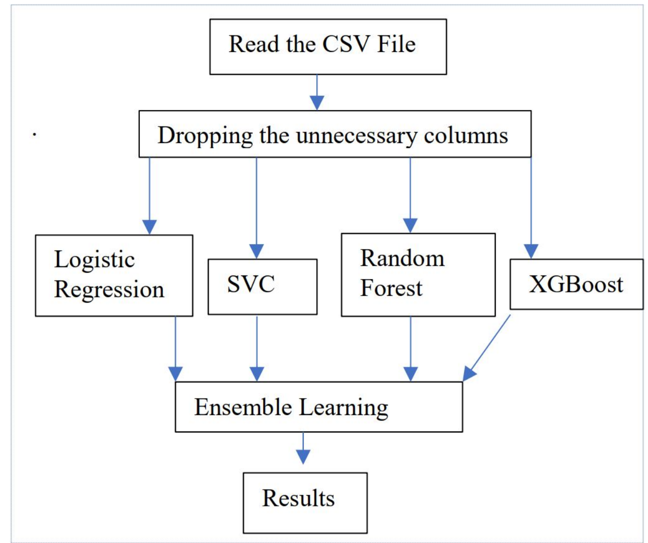

Fig. 4. Flowchart of the methodology used to process images in the database.

V. RESULTS

Figure 5 illustrates the accuracy of the individual models using which the dataset is trained and tested. The machine learning algorithms (SVC, Logistic Regression, Random Forest and XGBoost) were compared by their accuracy of anemia detection for this study. The highest accuracy of 90% was achieved using the Random Forest classifier when n_estimator value of 60 and random_state is 10 was selected. However, when the four machine learning algorithms were ensembled to predict the anemic condition and voting classifier was used to achieve the highest accuracy of 92%.

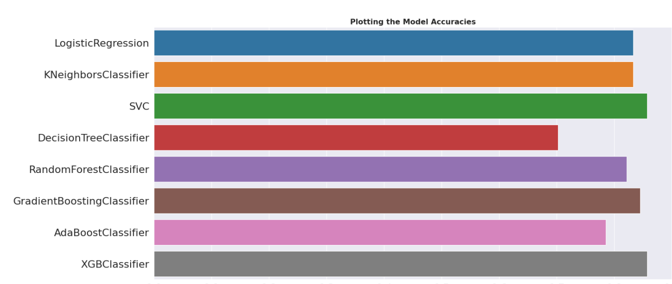

Fig. 5. Accuracy of Individual Algorithms.

Figure 6 shows the confusion matrix of ensemble learning, where 77 instances were correctly predicted and only 7 instances of incorrect prediction were reported.

To conclude, we analyze the sources from where the Conjunctiva images are obtained. Specifically, from [18], [20] and [19], a total number of 99, 219 and 104 images respectively, were collected. In Table I, an overall comparison has been

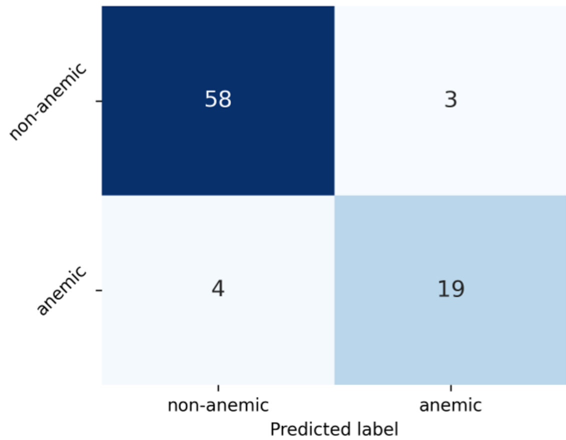

Fig. 6. Confusion Matrix of Ensemble Learning.

made among related research. In addition, the contribution of this work and its differences from the previous works has been highlighted.

TABLE I
COMPARISON BETWEEN RELATED WORKS WITH THIS WORK.

Paper	Data	Method	Result	Disadvantages
[15]	102	SMOTE AND ROSE algorithm to balance data, then KNN	98.2% (SMOTE) 98% (ROSE)	SMOTE and ROSE only provide a good result for small dataset
[16]	113	KNN Classifier	100%	Small Dataset
[19]	104	Decision Tree	82.61%	Small Dataset
[18]	99, augmented to 3103	Data Augmentation and Artificial Neural Network	97%	Generated fake and duplicate data using data augmentation
This work	421	Extracted features in all color space, the dataset has been created using all previous data, trained, and tested using Ensemble Learning.	92%	Unbalanced data with 70% and 30%, SMOTE/ ROSE algorithms are ineffective for large datasets.

VI. CONCLUSION AND FUTURE WORK

In this paper, a new image dataset was created by combining three previous image data and a total of 18 features were extracted in three different color spaces (RGB, HSV and CIE Lab). Using the prepared dataset, this paper aimed to detect anemia from eye conjunctiva images in a non-invasive way. In all previous works, anemia detection using eye conjunctiva images did not contain a large amount of original data. In this work, a total of 421 images are used to train and test the classifiers; more data are required to obtain better performance from the classifiers.

Among other challenges, the number of severely anemic patient, whose blood hemoglobin level is less than 5 is small, making those data an outlier. As a result, the dataset becomes unbalanced, influencing overall accuracy. Dataset balancing techniques like SMOTE or ROSE are only effective for a small amount of data. Thus, more images are required from patients with low blood hemoglobin for training.

The image collection process for this study is continuing; more images to the image database will be added in the future to this dataset. This will allow us to check how the accuracy changes with the increase in data. Moreover, lighting condition has an impact on the image quality. By ensuring better lighting conditions in future data collection processes, the accuracy can be improved. Deep learning can also be used once a large amount of data has been collected. Currently, the deep learning model's average accuracy with 421 images resulted below 70%, which is not very good as the models perform better on large datasets. On the other hand, data augmentation and transfer learning will hold poorly as we are using the color feature of the images instead of shapes.

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