Analysis of Anemia Detection from Images of Eye Conjunctiva Using Machine Learning Algorithms

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Abstract. Anemia, which is a common medical condition seen in many parts of the world with classic manifestations of fatigue, Weakness and dyspnea. Early detection of Anemia helps to prevent its progression and timely treatment. The dataset used in this study contained 218 images of conjunctiva, a good indicator of clinical signs of anemia, and was extracted from eye-defy dataset found in IEEE data port. The study found the application of machine learning classifiers with supporting data, especially the optimized SVM with SMOTE, gives the better classification of clinical symptoms of anemia. Accuracy of this proposed method improved to 94% post-optimization. In addition, a feedback mechanism has been implemented to improve the accuracy of the model. Through this system, physicians were able to provide feedback on predictions made by the model, which could be used to retrain the model, thereby reducing misinferences. By utilizing an RGB camera and machine learning algorithms, the proposed system has the potential to provide an effective and efficient solution for anemia detection, enabling timely treatment and improved patient outcomes. The focus of the study is on improving the accuracy and reliability of the design, as well as integrating optimization methods and feedback loops. Such an investigation can stimulate future research and implementation in the field of machine learning and medicine.

Keywords: Machine Learning, Anaemia, SVM, Early Detection, conjuctiva

1 Introduction

In developing countries, anemia is a public health challenge, which affects all ages and is primarily a global public health problem. Anemia is a condition in which the number of red blood cells or their oxygen-carrying capacity is less than what the body needs. According to World Health Organization (WHO), around 1.62 billion people globally suffer from anemia, and the disease accounts for 8.8 % of total deaths internationally. Moreover, anemia has also been a major contributor to maternal as well as child morbidity and mortality, with an estimated 20% of all the maternal deaths and 50% of all the infant deaths in the developing countries being attributable to anemia [4]. The condition significantly impacts quality of life, leading to fatigue, weakness and difficulties concentrating, among other symptoms.

For the past few years, machine learning has shown as potential solution for fast and cost-effective diagnosis, as well as for anaemia detection. Some ML algorithms also being used in the detection of anemia, including decision trees, random forests, SVMs, neural networks. These algorithms have shown varying levels of success in correctly identifying cases of anemia, often achieving higher accuracy than other methods, particularly SVMs and neural networks.

However, it is important to note that there is data imbalance problem in anemia detection, as positive cases of anemia are less compared to that of negative cases. This could lead

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to a skewed model that does not correctly identify which cases qualify as an anemia. Many techniques have been proposed to offset this problem for instance synthetic minority oversampling technique (SMOTE) and random under sampling (RUSBoost). These methods balance the data and increase the model's accuracy.

Here we propose an SVM model to predict anemia which is tuned by SMOTE technique. We employ a feedback mechanism enabling users to give us feedback on the prediction of the model, these feedbacks can be used to further improve the accuracy of the model. We evaluate the performance of our model with other ML algorithms trained to detect anemia and how effective the optimization techniques we applied proved to be.

2 Literature Review

Anemia is a global problem of public health with a greater impact on pregnant women and children [1]. About 42% of young people less than six years old and 40% of pregnant women worldwide are studies of WHO are anemic [2, 3] due to an iron deficiency affecting 33% of the worldwide population [4].

Anemia happens when the body's decreases in the red blood cell count or when the red blood cell's structure is compromised or destroyed [2]. Anemia may also occur when the amount of hemoglobin in red blood cells falls below the typical cutoff, which can be caused by one or more elevated destructions of red cells, loss of blood and faulty cell synthesis, or a diminished total Red Blood Cells [1]. The being aware of anemia helps to avoid irreparable organ damage [5]. Exhaustion, weakness, lightheadedness, and drowsiness are among signs anemia [6], with a compounded risk of mortality for the patients

Minimally invasive approaches, including machine learning algorithms, are among the processes and techniques employed to identify anemia [8]. Detecting anemia through invasive techniques can be expensive, time-consuming, and painful for patients as it involves blood extraction, which occasionally puts clinicians at risk of being pricked by the source of the extraction. Compared to the intrusive technique, the non-invasive approach costs less, save time, and is more dependable by using the tongue, fingers, conjunctiva, and palm [9]. Our goal is to use the conjunctiva's pallor to identify anemia using algorithm for machine learning in this research, which will include a comparison of the SVM, k-NN, Naive Bayes, and Decision Tree.

Several studies have been conducted utilizing non-invasive technique like the use of machine learning algorithms to identify anemia, primarily utilizing palpable palms, though conjunctiva of the eyes is used far less frequently than conjunctiva in most studies. The authors [10] categorized anemia applying the Nave Bayes algorithm including images of the eye's conjunctiva and the tangible palm, resulting with 90% accuracy, whereas Chand et al. [11] verified palmer's accuracy greater than the conjunctiva in terms of effectiveness the conjunctiva, fingernails, and palm in the identification of anemia between the ages of two months and five years.

Getaneh et al. [12] investigated anemia detection with the use of hand, tongue, nail bed and conjunctiva pallor using datasets from young children under the age of five. The outcome of their research showed that the palm's sensitivity was at its highest of 58% in identifying mild anemia by the combination of the palm and conjunctiva, which was supported by a 73% sensitivity.

Support Vector Machines (SVMs) were utilized in [6, 13] to computerized non-invasive which was the author created and which was simple and economical and the was created it to identify anemia by the authors for detecting anemia using 19 images of dataset showing the conjunctiva's known hemoglobin levels achieving a 78.90% accuracy rate in 15 of the 19 cases, while [13] thought about the potential applications of computer vision and image processing technologies for the detecting of anemia.(LS-SVM).

In the research performed by [14], the authors used CNN to detect anemia using segmented conjunctival pictures and attained a 77.58% sensitivity. when compared to a laboratory test according to the different image samples. Furthermore, anemia was identified conjunctival pictures, and a brand-new tool for taking pictures was recommended that the k-Nearest Neighbor (k-NN) algorithm, which used non-anemic to attain a noteworthy result and was examined on 113 instances and shown to be important [7].

Similarly, [15] employed k-Nearest Neighbor, Decision Tree, and Support Vector Machine to identify anemia from pallor digital photos, with a Decision Tree outperforming all other models in terms of accuracy with an 82.61% rating. Likewise, when the Adam optimizer was used by Magdalena et al. [16], a authors' research utilized a Convolutional Neural Network obtained 94% accuracy in identifying anemia.

In conclusion, various studies discussed above have achieved high accuracy rates, but there are still limitations to consider.

Firstly, many of these models have been tested on relatively small datasets, which limits their generalizability. Additionally, the precision of these models is dependent on the caliber of the data they were trained them, and without high-quality and diverse data, the accuracy of these models can be limited.

Another drawback of many of these models is their interpretable nature. Some models, like decision tree, logistic regression, are much easier to understand than the others, like C/N/N, however, it is still quite hard to know the reasons why a model is making certain predictions. This interpretability gap can diminish the utility of such models in the clinical setting, where physicians might need to know the behest of a model's predictions.

Additionally, a lot of models suffer from class imbalance (i.e., each class has a different number of samples). This can lead to poor predictions, where the model is more inclined to predict the majority class.

In conclusion, although these models have shown a lot of promise for identifying anemia, more work is needed to increase their accuracy, interpretability, and ability to deal with class imbalance. Our work aims to overcome these limitations and derive a more accurate and comparatively robust model for anemia diagnosis depicted in . 1.

3 Methodology

The proposed methodology consists of several stages: data preprocessing, feature extraction, data balancing, and selection and optimization of the model. These are essential in order for the diagnosis to be accurate and reliable.

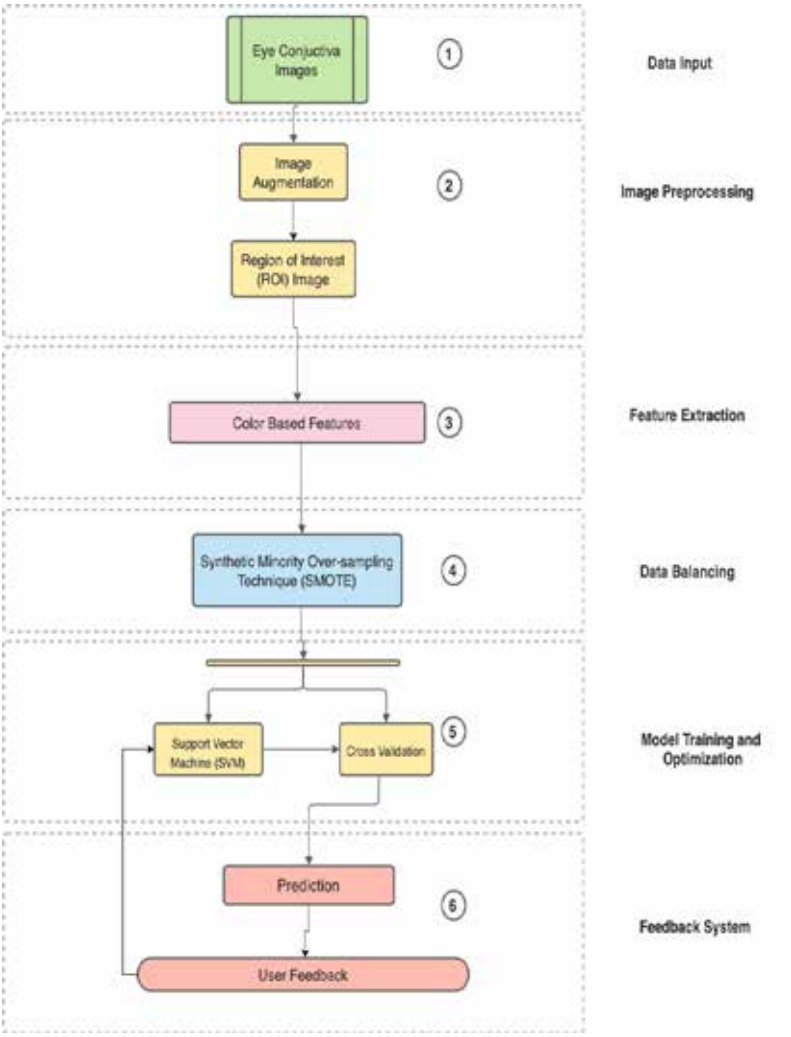

Fig. 1. System Architecture.

3.1 Dataset

The Eye-defy-anemia dataset includes 218 pictures of eyes namely the conjunctiva, which researchers can use to diagnose or estimate anemia based on conjunctival pallor, as indicated in Table1.

Conjunctivas or exposed areas of the sclera and iris may be successfully studied using the same photos to examine segmentation algorithms. Every image in the collection has segmented elements (palpebral, forniceal, and palpebral+forniceal conjunctivas) that prove helpful for evaluating the effectiveness of segmentation algorithms and also for correlated the pallor with the Hb value. Included in xlsx files are vital details about each image, including the patient's age, sex, and the laboratory-measured Hb value. A Samsung s6 smartphone that has a specific gadget that enlarges photos, standardized lighting, and reduces the impact of ambient light was used to take the pictures. As a result, the identical white LED light and distance were used to take each picture. [17,18]

Table 1. Statistics on the original dataset and the Hemoglobin concentration level (g/dL).

Category	Patient Class		
	Anemic	*Non-Anemic*	*Total*
Patients	40(India)+15(Italy) = 55 (25.23%)	55(India)+108(Italy) = 163 (74.77%)	218 (100%)
Female	35(India)+8(Italy) = 43 (50%)	11(India)+32 (Italy) = 43 (50%)	86 (39.45%)
Male	5(India)+7(Italy) = 12 (0.09%)	44(India)+76 (Italy) = 120 (90.9%)	132 (60.55%)
Hgb Levels	<11 g/dL	>=11g/dL	

3.2 Data Preprocessing

Image processing constitutes one of the fundamental steps in the proposed system to diagnose anemia via eye conjunctiva images. The first stage is the data processing and filtering, such that noise or unwanted data cannot reach diagnosis. The Gaussian blur algorithm is applied to denoise the image, as it reduces the noise present in the images [19]. Such an undertaking is of utmost importance, for the images obtained in clinical settings may have a lot of noise due to camera and lighting conditions, leading to a missed diagnosis.

Subsequently, histogram equalization was performed utilizing the open-source library OpenCV, which optimizes contrast and brightness of the images, thereby allowing a greater emphasis on features relevant for diagnosing anemia [20]. This step guarantees that only high-quality images with the necessary data for the models are used in the training process and evaluations. At last, some image augmentation helped to improve and add more usable data for training, meanwhile strengthening the robustness of the model. This Procedure generates new images from the existing one by several data augmentation techniques such as flipping scaling, and rotation [21].

3.3 Feature Extraction

This step consists of extracting features from the preprocessed images that will act as input into a machine. For feature extraction we used method of color histograms and edge detection algorithms in the image. Color histograms are used to analyze the distribution of pixel intensity in the images, while texture analysis helps extract patterns and structures in the images [22].

Edge detection finds the edge of regions in the images [23]. Using these algorithms, we also derived many anaemia pertinent features like 'intensity' and 'color' of conjunctiva as shown in Fig. 2. Afterward, the features are provided as inputs to the machine learning models, which will classify the images as anaemic or non-anemic.

3.4 Data Balancing

Data balancing is a crucial machine learning approach for dealing with skewed dataset. In the approach we suggested, The Synthetic Minority Over-Sampling Technique (SMOTE) has been employed to tackle this problem. SMOTE function by creating artificial data points among the minority class to stick a balance between the number of samples in each class.

Specifically, SMOTE takes each minority class sample and generates new synthetic samples by interpolating between neighboring samples [24]. This is done by picking a random sample of minority classes and determining its k closest neighbors. Then, by interpolating between the selected sample and each of its k nearest neighbors, synthetic samples are produced.

Oversampling is a technique that is repeated until the minority class has the same number of samples as the primary class. This helps to maintain the distribution of classes and keep the model from becoming biased towards the primary class.

3.5 Model Selection

In our proposed framework, we have evaluated and compared multiple algorithms for machine learning, such as Naïve Bayes, Random Forest, Decision Tree, Logistic Regression and Support Vector Machines (SVM) with SMOTE optimization to identify the best performing model. The dataset was split up into training, testing, and validation sets as part of the model selection procedure. Using the training set, the models were trained while utilizing the validation set, the assessment and compare the outcome of each model. We used several evaluation criteria to gauge each models' performance including accuracy, precision, recall and F1-score as shown in Table 2.

Table 2. Comparison of ML algorithms with SMOTE optimization for anemia detection.

Algorithm	Pros	Cons	Accuracy	Accuracy after SMOTE
Decision Tree	Easy to interpret, handle categorical variables well	Prone to overfitting, sensitive to small changes in data	73.67%	86.29%
Random Forest	Reduces overfitting, handles missing data well	Can be slow for large datasets	75%	83.01%
Logistic Regression	Simple and fast, good for binary classification	Assumes linear relationship between features and target	77.98%	81.23%

Support Vector Machine	Effective in high dimensional spaces, good for binary classification	Not ideal for large datasets, sensitive to choose of kernel	88%	94%
Naive Bayes	Simple and fast, good for text classification	Assumes independence of features, may not perform well with complex data	80%	83%

Based on the results obtained, we selected the best performing algorithm, which in our case was Support Vector Machine (SVM) and SMOTE.

4 Results

The proposed method was evaluated using various algorithm for machine learning and optimization methods to identify anemia in pictures of the conjunctiva. The dataset initially consisted of 218 images, but increased to 3052 after augmentation. Techniques for preprocessing were used to guarantee the quality of the data and consistency. Decision Tree, Random Forest, and other machine learning algorithms.

Support Vector Machines (SVM), Naïve Bayes, and Logistic Regression were trained and evaluated on the dataset. SVM and Naive Bayes performed the best initially with accuracies of 88% and 80%, respectively. To further improve accuracy, SMOTE (Synthetic Minority Over-sampling Technique) optimization technique was implemented.

The accuracy of the SVM model increased to 94% after applying SMOTE, indicating its effectiveness in addressing class imbalance and improving model performance. The Eyes-defy-anemia dataset is separated into two folders: one for Indian patients and one for Italian patients. In addition to the file Italy.xlsx, the folder Italy has 123 other folders. The folder name, which ranges from 1 to 123, corresponds to the number that appears in the file Italy.xlsx's "Number" field. Each numbered folder contains four files: The Original eye is shown in the file name.jpg; - forniceal_palpebral.png: image illustrating the two conjunctives, manually divided into segments; - forniceal.png, palpebral.png. The exception are folders with the labels 1, 35, 54, 58, 75 and 109; in reality, the forniceal conjunctiva is not visible in these eye photos, so in these folders only available 2 files: - file name.jpg represents the original eye; palpebral.png: a manually segmented image of the palpebral conjunctiva. Although the Hgb level for patient 93 has not been measured, we believe it would be beneficial to share the four photos mentioned above with the scientific community.

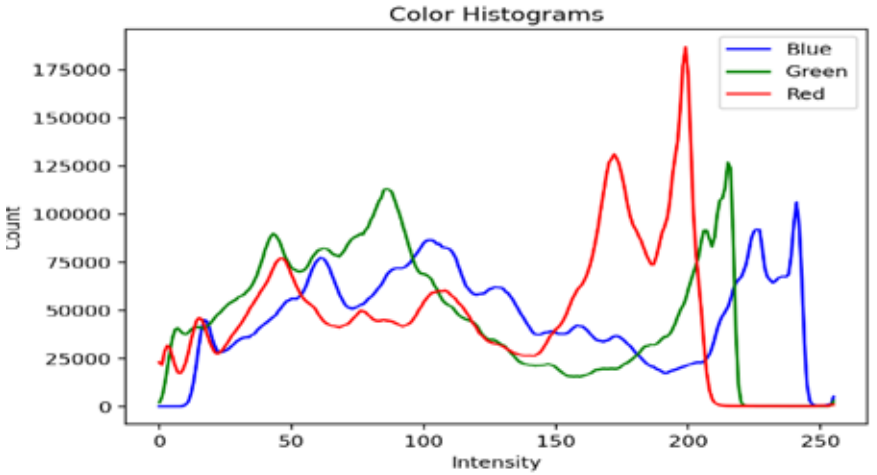

Fig. 2. Colorhistograms separately for each channel (Blue, Green, Red).

The eye's photographs were all taken in Bari, Italy. There are 95 folders in the India folder, along with the India.xls file. The Folder names, ranging from 1 to 95, contain the number that matches the file India.xlsx's "Number" column. Each numbered folder contains four files: Name of the file:.jpg symbolizing the initial eye; Images of the two conjunctivas, segmented by hand, are shown in forniceal_palpebral.png; the forniceal conjunctiva, segmented by hand, is shown in forniceal.png; and the palpebral conjunctiva, segmented by hand, is shown in palpebral.png. Every eye photograph was taken at Chennai, India's Karapakkam. As seen in Figures 3 and 4, and the comparison analysis in Fig , all of the images that were produced following segmentation are RGB images with the same size (1067× 800 pixels). [17, 18]

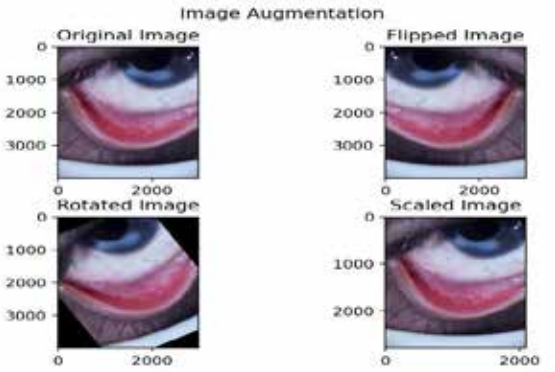

Fig. 3. Sample Images (Original and Denoised).

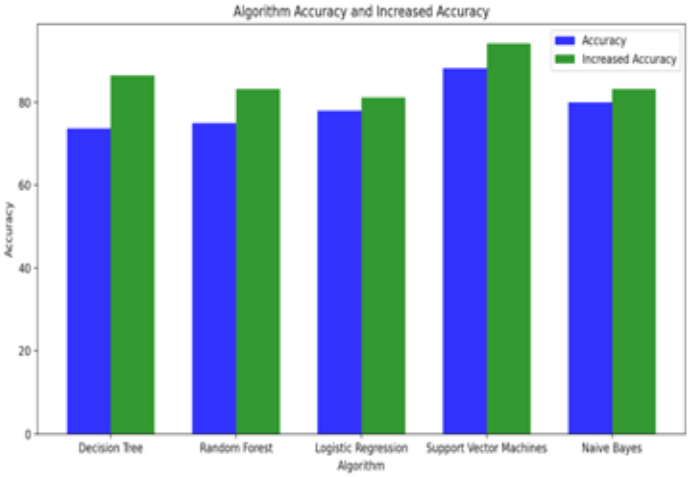

Fig. 4. Visualization of the actual accuracy and increased accuracy after Smote.

5 Conclusion

Then, we proposed an efficient method for the detection of anemia from conjunctiva images using machine learning algorithms and optimization methods. Hence, we can conclude that utilizing SMOTE optimization technique has vastly improved the accuracy of the model, and the model performance of the model has also increased. The performance of various machine learning techniques, including Naïve Bayes, Random Fores, SVM, Decision Tree, and Logistic Regression, of a set of conjunctiva images has been outlined, based on a dataset. Without SMOTE, the initial accuracies of SVM and Naive Bayes were 88% and 80% respectively, which were increased to 94% using SMOTE. Results showed that proposed method can contributes to the new early anemic acid solution and low the risk of an apparent impact on patients. Nevertheless, to guarantee the validity and strength of the findings, meticulous data cleaning and performance assessment with suitable metrics were performed. The efficacy of the proposed method in real-world clinical environments should be thoroughly validated and studied on large datasets.

6 Future Work

Some potential future directions and areas of exploration for this research include:

Real time feedback: The current way the feedback system works is that once predictions are made doctors or healthcare professionals can provide feedback to the model regarding its predictions. In future, provide real-time feedback during prediction process through key feedback system. This would enable real-time feedback and correction to model predictions, improving accuracy and trustworthiness in real-life settings.

Integrating with electronic health records (EHRs): The proposed model could be combined with (EHRs) to increase its accuracy and reliability further. Electronic health

records (EHRs) have a massive store of patient data, featuring laboratory results, medical history, and other relevance details. Integrating the model with EHRs may add context and background for the information being used, which would allow for more nuanced and tailored detection of anemia, or any other medical condition. Implementation scope in telemedicine and remote healthcare settings: The proposed model could serve as an implementation scope in telemedicine or remote healthcare settings, as access to specialized medical expertise may be limited.

Focusing on other optimization functions: The proposed method applies SMOTE optimization to enhance the accuracy of the model. Which could be ensemble methods, features selection, or hyperparameter tuning applied to fine-tune the correctness of the model and facilitate its expectations.

Generalization to different populations: The existing dataset used to train our model is eye-defy dataset available in IEEE data port, which contains images only from Indian and Italian patients. Additionally, the model can also be generalized and validated on different populations in the future to check if it holds for different patient populations with varying age structure, ethnic and regional distributions.

Disclosure of interest. The authors have no competing interests to declare that are relevant to the content of this article.

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