2025 IEEE 12th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON) | 979-8-3315-0325-3/25/$31.00 ©2025 IEEE | DOI: 10.1109/UPCON66414.2025.11454042

Non-Invasive Automated Anaemia Detection Framework from Eye Conjunctiva Images Using YOLOv8

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***Abstract*—In the present work, a non-invasive method of anaemia detection using deep learning is proposed using images captured from eye conjunctiva. To this end, eye conjunctiva images captured from anaemic and non-anaemic patients were obtained from an online dataset. The obtained eye conjunctiva images were initially pre-processed through contrast limited adaptive histogram enhancement (CLAHE) algorithm. Subsequently, the CLAHE preprocessed conjunctiva images were fed to a you only look once (YOLOv8) algorithm for accurate detection of anaemia and non-anaemia patients. It has been observed that the proposed method can detection anaemia and non-anaemic patients with 99% accuracy. The performance of the proposed method when compared with existing methods was found to be better. The method proposed in this study is non-invasive in nature which can be used for rapid screening of anaemia and non-anaemic patients.**

Keywords*—*Anaemia, YOLOv8, segmentation, conjunctiva, CLAHE, deep learning.

I. Introduction

Anaemia is a health condition that occurs primarily due to the deficiency of either red-blood cells (RBC) or haemoglobin in the blood stream [1]. In recent literature, it has been found that children and pregnant women are more prone to anaemia [2]. [3] According to the world health organization (WHO) 24.8% of the world's total population is affected with anaemia ,out of which, it is estimated that 42% children (below 6 years) and almost 40% pregnant women are being diagnosed with anaemia worldwide [4]. Conventionally, experienced medical professionals use invasive techniques such as blood tests, followed by expert inference. However, the process is invasive and time consuming [5]. Apart from that, the existing method is primitive and also depend on human intervention. Therefore, it can be beneficial if anaemia detection can be done through non-invasive technique, without compromising on time and accuracy.

Anaemia detection can be performed through various non-invasive techniques such as eye-conjunctiva, tongue, nail beds etc. [5-7]. Such non-invasive methods are fast and don't require much physical interactions. In this context, a method for a non-invasive technique using fingernail image analysis for automated anaemia detection has been reported in [5]. Detection of anaemia through palm pallor image analysis have been reported in [6]. But the major limitation of detecting anaemia through palmer pallor is the skin color and the palmer coloration may be different for different countries. So, it can't be used as a generalized way for detection of anaemia. Application of machine learning algorithms like k-Nearest Neighbor (KNN), Naïve Bayes (NB), Random Forest (RF), Support Vector Machine (SVM) using visionary approach has been reported in [7]. In [8] a method for anaemia detection using photos of the anterior conjunctiva of the eye and RGB thresholding was proposed. However, the method is not generalized and may show inconsistency for different shapes of eyes. In [9], a mobile application was developed for non-invasive anaemia detection using patient sourced photos. Application of deep learning methods such as joint neural network for non-invasive anaemia classification using medical images have been reported in [10]. In [11], a method based on red light and Near-IR Spectroscopy (NIRS), can be used to measure the haemoglobin level and then detect anaemia. But, the NIRS is expensive and cannot be used for rapid screening of anaemia quickly. In [12], a deep learning model YOLOv5 has been implemented on an embedded platform to develop an anaemia detection model which yielded considerable accurate results. But it can be enhanced using higher versions of YOLO which may provide more accuracy in model detection or segmentation. In [13], a mobile application named HemaApp, has been developed that uses smartphones camera and lightning sources to measure the haemoglobin level for anaemia detection. But, this process has its own limitations, as its inability to synchronize with the different lightning conditions and hence degrading the performance of the model. Thus, it is evident from above literature survey that different non-invasive methods have already proposed by different researchers for anaemia detection. However, the accuracy of detection is not satisfactory for all cases which indicates the need for further improvement.

Considering the aforesaid facts, in this paper, a novel anaemia detection framework is proposed using YOLOv8 algorithm. For this purpose, the conjunctiva images obtained from an online dataset were initially pre-processed and then segmented, so as to localize the region of interest (ROI) to make the detection much more accurate. The segmented image is then fed to YOLOv8 for image processing and

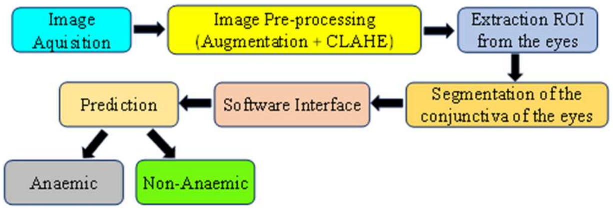

Fig. 1. Flowchart of anaemia detection framework

detection. The salient contributions of the proposed model are as follows.

i. The YOLOv8 model is lightweight and compatible for running inference on mobile applications. YOLOv8 model is used here as this version supports both image classification and detection.

ii. Image segmentation is performed manually on the image collected so as to select the region of interest. This is done generally to extract only the part of the eye which will be required for the prediction.

iii. After the segmentation is done, CLAHE is applied to the image. The basic purpose of using CLAHE is to make the image look more prominent and distinctive which in terms also increases the predicting accuracy of the model.

iv. Software and smartphone application is also developed. It is used to capture photos of the eyes where manual segmentation is done and then its fed to the YOLOv8 model for processing and predicting whether the image is anaemic or non-anaemic.

II. DATABASE DESCRPTION

A. Image Aquisition

In this study, the anaemic and non-anaemic images have been acquired from an online available benchmark dataset [14]. The anaemic and non-anaemic image dataset comprises of 183 red-green-blue (RGB)-coloured images of the conjunctiva of the eyes out of which 82 pictures are labelled as anaemic and 101 are labelled as non-anaemic. Following that, the eye conjunctiva images from the online dataset have been filtered carefully to extract the prominent and distinguishable ones to construct a custom dataset in order to establish an accurate and efficient anaemia detection model. Finally, the custom dataset utilized in the current study consists of 144 eye conjunctiva images out of which 87 are anaemic images and the rest 57 images belong to the non-anaemic category. Finally, after careful inspection, the acquired images are subjected to the following image pre-processing stage. A schematic of the research carried out in this study is described in Fig. 1

B. Image pre-processing

On the image acquired from the online database, at first, the images are being augmented by 10 images per class to form a large dataset consisting of 1440 images. The augmented images were then annotated with either of the two class labels : anaemic or non-anaemic. Further manual image segmentation is done, so as to select the region of interest (ROI). Then, on the segmented images CLAHE is applied to enhance the contrast and image quality with improved intensity. It is integrated to make the segmented image look more prominent and distinctive, which in terms also increases the accuracy of the model by a considerable margin.. At last, the pre-processed images with their respective annotations are fed to YOLOv8 segmentation model for further training

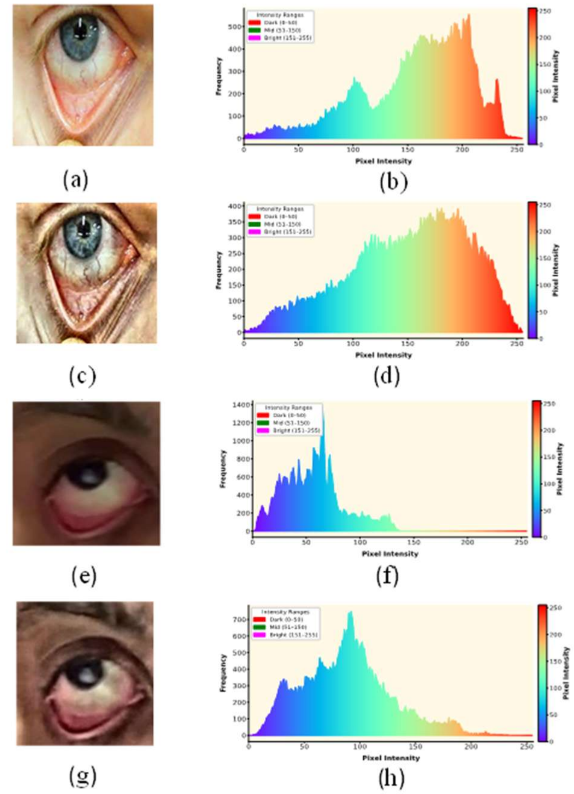

Fig. 2. Histograms of CLAHE adjusted anaemic and non anaemic images

and prediction. Fig. 1 represents a comparative study of the raw RGB coloured anaemic and non-anaemic images with the CLAHE applied RGB coloured anaemic and non-anaemic images. Taking inference from the histogram plot, it is evident that after applying CLAHE, the histogram plots appears much more spread out and the intensities are also fully distributed over the intensity range offering greater detailing of the low contrast image areas. The image labelled as (a) is the raw RGB coloured anaemia image of the eye and the histogram computed from that image, is mentioned in label (b). The raw anaemic image is then applied to CLAHE which is mentioned as (c), following that again the histogram is computed, which is labelled as (d). The same procedure was adopted for the non-anaemic images also and the labels are placed accordingly.

III. METHODOLOGY

A. YOLOv8 Architechture

The YOLOv8 architecture model consists of 3 parts which includes the backbone, neck and head [15]. For the backbone of the architecture, custom DarkNet53 is used, in which cross-stage partial connections is implemented to improve the information flow. Moreover, based on CSP idea, C3 module which was introduced by YOLOv5, is replaced with C2f module for making it lightweight for providing enriched gradient flow [16]. It also uses a spatial pyramid pooling fast (SPPF) to capture the features from multiple scales with maintaining its computational speed. The neck, which is known for feature extraction uses PAN-FPN, which follows a top-down and bottom-up network, can extract feature information at different scales [14-16]. The PAN-FPN feature is implemented to eliminate the convolutional layers

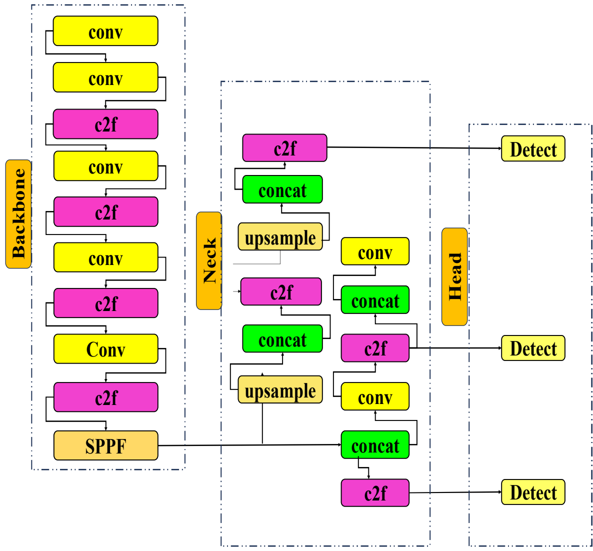

Fig. 3. Architecture of the YOLOv8 model.

in the up-sampling stage. This feature also enhances a suitable transfer of semantic and localized features. So, with the use of PAN-FPN, the object detection can be done more accurately as features are captured from various scales. The head part generally deals with decision making. The head part is responsible for conversion of the captured feature map to the detecting bounding boxes with the help of three layers, detection layer, up-sampling and root layer [17]. YOLOv8 version abandons the existing anchor-base and implements anchor-free which increases the detection speed [18]. The Head part involves bounding boxes and loss calculation. Regression and classification are taken under loss calculation. With some major improvements in certain parameters such as predicting bounding boxes, objectness score, the accuracy of detection is increased by a significant margin. The YOLOv8 model architecture is given below:

B. *Implementation of YOLO model in this paper*

In this paper, we used you only look once model, the version 8 (YOLOv8) variant. A major advantage of this YOLO version is, it supports sort and segmentation at the same time making it much more efficient and real-time. Also, this version is extendible i.e. it can support all versions of YOLO and is highly compatible for running inferences in mobile applications.

IV. RESULTS AND DISCUSSIONS

A. *Training Hyperprameters*

The YOLOv8 algorithm was implemented to classify anaemia and non anaemia by only taking the image of the conjunctiva of the eyes and then extracting the ROI. In our model, we have implemented k-fold validation (k=5 fold, in our model). It works by dividing the dataset in k equal folds, which ensures that each of the data is being trained and validated. In every iteration, one fold is kept for validation and the other 4 folds are used for training. The process continues till the end of the iteration and at the end of each iteration the performance of the model is evaluated. The final performance result is calculated by taking the mean of all the performance results after each iteration. k-fold validation can be used to reduce overfitting and also helps to increase the robustness and efficiency of the model.

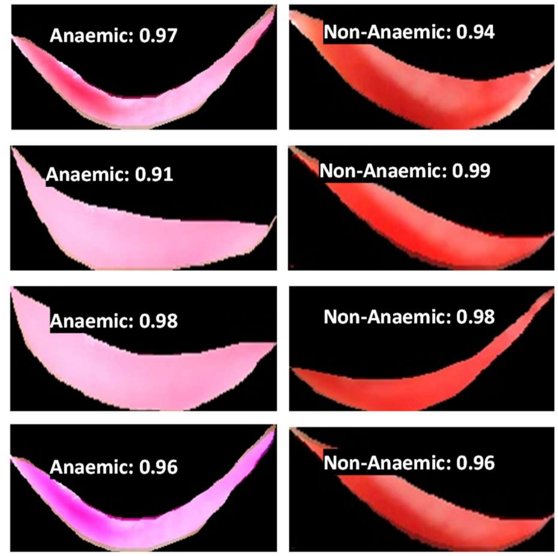

Fig. 4. Prediction of the conjunctiva images of the eyes with confidence scores.

B. *Performance Evaluation*

Certain parameters through which the performance of the model can be evaluated are:

1. Accuracy is the ratio of the total correct predictions to the total number of images in the dataset.
$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$
2. Precision is the ratio of the true positives to the total positive predictions.
$$Precision = \frac{TP}{TP + FP}$$
3. Specificity is the ratio of the true negatives to all actual negatives.
$$Specificity = \frac{TN}{TN + FP}$$
4. Sensitivity is the ratio of the true positives to the actual positives.
$$Sensitivity = \frac{TP}{TP + FN}$$
5. F1 is the harmonic mean of recall and precision.
$$F1\ Score = \frac{2 \times TP}{2 \times TP + FP + FN}$$

where, TP indicates true positives, FP indicates false positives, TN indicates true negatives and FN indicates false negatives.

C. *Performance Analysis:*

The model was trained with YOLOv8 version and based on the aforesaid parameters, the performance analysis was evaluated. The tabular representations of the performance of the model is hereby mentioned in Table I. It can be observed from Table I that the performance of the proposed YOLOv8 model in classifying anaemia and non-anaemia patients is satisfactory. The proposed model can hence be implemented for non-invasive aneamia screening in practice. Fig. 4 shows the confidence score obtained in anaemia prediction which indicate very high confidence scores. The training graph of YOLOv8 is shown in Fig. 6.

D. *Comparative study*

Table II presents a comparative study for detection of anaemia with previous literatures. Tamir et al. [8] in their

TABLE I. PERFORMANCE ANALYSIS

Accuracy	Precision	Sensitivity	Specificity	F1 Score
99%	98%	100%	98.04%	98.99%

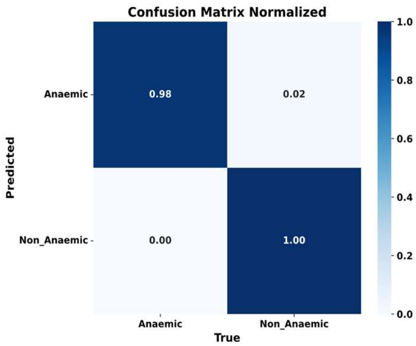

Fig. 5. Confusion matrix of the model

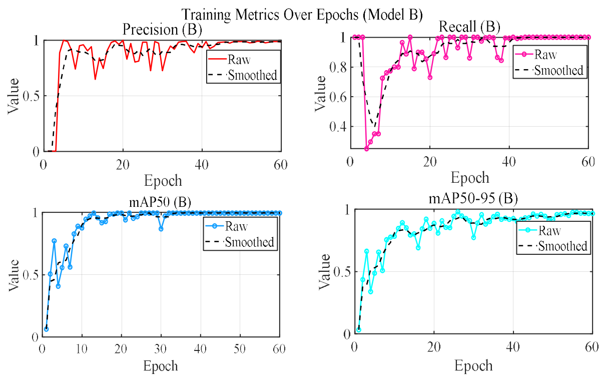

Fig. 6. Results of YOLOv8 over different epochs.

work has developed a smartphone application where the photos of the anterior conjunctiva were taken and then processed the pictures using MATLAB. Through this process, the model gained an accuracy of 79.8%. Rivero-Palacio et al. [12] in their work has designed a smartphone application with the implementation of YOLOv8 algorithm, where the conjunctiva images of children less than 5 years of age were used and an an accuracy of 80% was achieved. Noor et al. [19] in their work has done a comparative study of predicting anaemia using Decision Tree, SVM and k-NN where the images of the palpebral conjunctiva of the eyes have been used. Out of the three mechanisms decision tree was found to give the best accuracy which is 82.61%. Appiahene et al. [10] implemented CNN, where the images of the conjunctiva of the eyes are taken from children between 6 to 59 months of age. Through the aforesaid model an accuracy of 84.79% has been obtained. Our model has outperformed the existing models in terms of accuracy which indicates the superiority of the proposed method. The next step is to design the software for automated detection of anaemia.

TABLE II. COMPARISON WITH EXISTING STUDIES

References	Method	Accuracy (%)
Tamir et al. [8]	MATLAB with android application	79.80
Rivero-Palacio [12]	YOLOv5 Algorithm	80.00
Noor et al. [19]	Decision Trees	82.61
Appiahene et al. [10]	CNN(ResNet50)	84.79
This study	YOLOv8 with software application	99.00

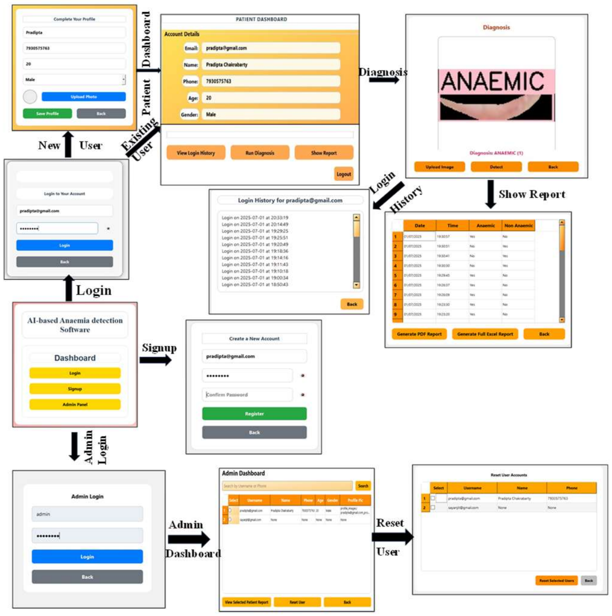

Fig. 7. Flowchart of the developed anaemia detection software application

E. *Software and smartphone application*

A novel anaemia detection software with an interactive graphical user interface (GUI) and artificial intelligence (AI) based expert prediction is developed in the current study, which is currently compatible with windows operating system based PCs. The software was designed in such a way that it should be user-friendly and at the same time, produces accurate and reliable inference. Moreover, they can also be used for early screening of the patients without using advanced technical equipment, removing the obstruction of high. Both of them can be highly useful for the people residing in the rural areas as they are still deprived of advanced technical assistance. The working of the software is described in the following steps followed by a flowchart for better understanding and convenience:

Steps for Software Implementation

Step 1	**Login, if you already have an account else Signup.**
Step 2	**Fill the patient details part carefully and then click on Register to go to the Home page.**
Step 3	**In the Home page, select the Diagnosis option.**
Step 4	**In the Diagnosis option, either select the option which opens the camera and capture the image of the conjunctiva of the eyes or open the gallery and upload picture from it.**
Step 5	**After selecting the picture, manual segmentation is done to extract the ROI for better prediction.**
Step 6	**After extraction, click on Process to feed the image to YOLO model.**
Step 7	**Following that along with the image, the results are displayed with proper class labels and confidence scores.**
Step 8	**The results along with the patient details are automatically stored under Show Report section, in the Home page.**

V. CONLUSION

In this paper, we have proposed a non-invasive method for anaemia detection using deep learning applied on eye conjunctiva images. The process involves either by taking the picture of the conjunctiva of the eye using any image sensor or by uploading a pre-captured image of the conjunctiva of the eye. The image taken or uploaded was then pre-processed by segmenting to select the ROI and finally the image was processed with YOLOv8 model to detect the anaemic or non-anaemic status. It has been observed that the proposed model can classify anaemia and non-anaemic patients achieving very high accuracy. The novelty in this work is the development of a software with the YOLOv8 model and running the inference on it. The deployed model can be easily deployed on a smartphone which will aid in fast and rapid screening of anaemia. The method is a one step forward for development of remote health monitoring especially in rural areas.

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