Iranian Journal of Blood & Cancer

Iran J Blood Cancer, 2026, 18(1),49-63
https://ijbc.ir

Original Article

Intelligent Clinical Support System for Anemia Detection and Diagnosis

Abhishek Rao[1], Rohit Kumar Tiwari[1*], Sushil Kumar Saroj[1]

[1]Department of Computer Science & Engineering Madan Mohan Malaviya University of Technology, Gorakhpur Uttar Pradesh 273010 India.

Scan and read the article online

Citation Rao A, Kumar Tiwari R, Kumar Saroj S.Intelligent Clinical Support System for Anemia Detection and Diagnosis. Iran J Blood Cancer. 2026 March 31;18(1): 49-63.

doi 0

Article info:
Received: 09 Dec 2025
Accepted: 18 Feb 2026
Published: 31 Mar 2026

Keywords:
Anemia
Machine Learning
Haar Wavelet
k-NN
Non-Invasive Technique
Iron Deficiency

Abstract

Anemia is a common worldwide health concern affecting almost 25% of people, including 37% of pregnant women, 40% of children between the age of 6 and 59 months, and 30% of women between the age of 15 and 49 years. Anemia is primarily diagnosed through blood tests that measure hemoglobin levels. However, these conventional diagnostic methods rely on invasive blood sampling, which is costly, time-consuming and inaccessible in resource-limited areas. To address these challenges, this study proposes a non-invasive method for anemia detection using Haar Wavelet Transform for feature extraction from conjunctiva images of patients. The essential statistical features are extracted from the conjunctiva images using Haar Wavelet Transform that captures the crucial information indicating anemia. These extracted Haar features are used for training various machine learning methods like k-Nearest Neighbour, Decision Tree, XGBoost, Gradient Boosting, Random Subspace, and Random Forest. The accuracy achieved through k-Nearest Neighbour, Decision Tree, XGBoost, Gradient Boosting, Random Subspace and Random Forest are 99.18%, 97.66%, 95.08%, 79.25%, 95.55%, and 98.24% respectively. The k-NN method outperformed the others with an accuracy of 99.18%. This remarkable performance suggests that non-invasive machine learning techniques based on conjunctiva image analysis could serve as a promising alternative for anemia detection.

* Corresponding Author:
Rohit Kumar Tiwari
Affiliation: Department of Computer Science & Engineering Madan Mohan Malaviya University of Technology, Gorakhpur Uttar Pradesh 273010 India.
E-mail: rohitkushinagar@gmail.com

1. INTRODUCTION

Anemia is a significant health problem around the world which impacts around 25% of the global population, characterized by decrease in the red blood cells (RBC) count or the hemoglobin levels in blood below normal. Anemia develops when the blood's hemoglobin levels are insufficient to provide oxygen to the organs and tissues due to one or more of the reasons like decreased red blood cell counts, blood loss, insufficient cell formation or increased red cell breakdown [1, 2]. Anemia mostly affects children and pregnant women. Anemia affects 37% of pregnant women, 40% of all kids having age between 6 to 59 months and 30% of women between age 15 to 49 years as per a study by the World Health Organization [1, 3].

Anemia can lead to a range of symptoms including fatigue, reduced physical performance, and shortness of breath called dyspnea. The common symptoms of anemia include headaches, fatigue, lightheadedness or vertigo, shortness of breath during physical activity as well as feeling cold in hand and feet [4]. More severe symptoms can occur in cases of significant anemia such as pale mucous membranes in the mouth and nose. Other signs of severe anemia may include a pale complexion, fast breathing, increased heart rate, dizziness while standing and easy bruising under the fingernails [5]. The complications from mild iron deficiency anemia are rare, but if left untreated can lead to several significant issues such as rapid or irregular heartbeat because the heart has to work more rigorously to deliver oxygen. This increased workload on the heart can potentially lead to heart failure or an enlarged heart. Severe anemia in pregnant women arises due to low birth weight or premature births [6]. Severe iron deficiency in children and newborns can lead to anemia and can be problematic for normal growth and development. Anemia exists in several forms, mainly thalassemia, aplastic, sickle cell and iron or vitamin deficiency [7, 8]. Every type of anemia has a unique origin, ranges from moderate to severe, and can be either short-term or long-term.

The detection of anemia using clinical methods typically involves blood tests, which present several challenges, such as discomfort from the procedure, the need for frequent testing, and emotional strain, especially for young patients. Regular blood tests can also lead to excessive blood loss, and there are risks of complications such as infection, bruising, or hematoma. Furthermore, in rural or low-resource settings, accessibility to adequate testing is often limited due to a lack of necessary infrastructure and qualified personnel. The non-invasive approach, particularly the application of machine learning algorithms has emerged as a significant method for detecting clinical diseases like cancer [9, 10], retinal disease [11, 12] and anemia [13, 14] in recent times. In contrast to traditional invasive methods for diagnosing anemia are often time-consuming, costly, and can be painful for patients due to blood extraction, which also poses a risk of injury to clinicians. The non-invasive techniques offer a cost-effective solution that requires less time and is more reliable. These techniques evaluate the palm, conjunctiva, tongue, and fingernails of the patient [15]. Medical professionals can assess the pallor of these areas to detect anemia, such evaluations are often left to their discretion.

This study seeks to advance the non-invasive way of diagnosing anemia by analyzing images of the conjunctiva in the eye through machine learning techniques. The proposed method extracts Haar features from the conjunctiva images of a patient to extract important information related to anemia disease of the patient. The extracted Haar features are further used to train and validate the several machine learning methods like k-Nearest Neighbour (k-NN), Decision Tree, XGBoost, Gradient Boosting, Random Subspace and Random Forest. The test result of above machine learning techniques is further evaluated with sample test conjunctiva images to find the efficiency of above methods on different evaluation parameters. The k-NN algorithm demonstrates the highest accuracy which promises to contribute meaningfully to the field of medical diagnostics. The major contribution of this study for diagnosing anemia is given below.

- A detailed literature review is carried out for exploring anemia detection using machine learning techniques.
- Haar wavelet-based feature extraction technique is used to extract features from the conjunctiva images.
- Various machine learning methods are trained and tested to check the efficiency of machine learning techniques for anemia detection from the conjunctiva of a patient.
- The effectiveness of various machine learning techniques is evaluated on various evaluation metrics and compared with state-of-the-art techniques for detecting anemia using machine learning.

The remaining part of the study is structured as follows. The detailed literature survey for diagnosing anemia using machine learning is carried out in section 2. Section 3 discusses the methodology used for diagnosing anemia along with Haar Wavelet transform and machine learning methods used for detection. Section 4 explains the system details for performing experiments as well as results obtained for anemia diagnosis through various machine learning methods. It also discusses the comparison of proposed method with state-of-the-art methods available in literature. Finally, the conclusion of the study and future directions have been explained in section 5.

2. LITERATURE REVIEW

Several studies have been carried out to identify anemia using non-invasive methods based on machine learning. The anemia detection methods based on machine learning have used conjunctiva of the eye, fingernails and palm images of the patient and have been effective in its diagnostics. Recent developments in medical imaging technology have made it possible for researchers to build machine learning models and procedures for using medical imaging to identify iron deficiency. The various works reviewed for exploring anemia detection using machine learning techniques are discussed below.

Zhang et al. [16] proposed an automated system to detect anemia by analyzing images of the conjunctiva of the eye. They compared the classification results of five convolutional neural networks like InceptionV3, EfficientNetB0, ResNet50, DenseNet121 and MobileNet and ultimately selected InceptionV3 as the best model for detecting anemia. They used a dataset of conjunctiva images for the training purpose to identify visual indicators of anemia and their best model has an accuracy of 82.37%. Asare et al. [13] utilized datasets of fingernail, palpable palm and conjunctiva images and applied various deep learning and machine learning methods such as convolutional neural networks (CNN), k-NN, Naïve Bayes, decision tree and Support Vector Machine (SVM) to detect anemia. The convolutional neural networks attained remarkable result with an accuracy of 99.12% and an F1 score of 99.89% for the palpable palm dataset. The accuracy was achieved 98.45% with an F1 score of 97.63% for the conjunctiva dataset, while the accuracy reached 98.33% with an F1 score of 97.54% found for the fingernail dataset.

Chen et al. [17] developed a priori causal knowledge-based deep neural semantic segmentation and a convolutional network to estimate hemoglobin level using conjunctival images to identify iron deficiency. The system attained a 95% confidence interval. Sarsam et al. [18] suggested a unique method for identifying patients with iron deficiency by examining the correlation between the patients' emotions expressed on Twitter and the symptoms of the condition using Sequential Minimal Optimization (SMO), k-means and Latent Dirichlet Allocation (LDA). They attained a prediction accuracy of 98.96%. To predict the severity of iron insufficiency, Shahzad et al. [19] suggested a three-tier deep convolutional fused network (3-TierDCFNet) to extract the best morphological characteristics from images of the disease. There are two modules in the suggested model. The first module divides the input images into two groups like non-iron and iron deficient while the second module evaluates the degree of iron deficiency and labels it as either moderate or chronic. The training, validation, and test accuracy achieved for their proposed model were 91.37%, 88.85%, and 86.06%, with corresponding F1-Scores of 98.95%, 98.12%, and 98.12%.

D'Souza et al. [20] were able to attain accuracy of 90%, precision of 90.8%, recall of 90.6% and F1 score of 90.6% using Naïve Bayes method on the Kaggle dataset. Jain et al. [14] utilized datasets of 99 images to classify iron deficiency based on a non-invasive technique that examines conjunctival images. The Artificial Neural Network (ANN) approach yielded a 97% accuracy rate, demonstrating the study's impressive accomplishment. Magdalena et al. [21] utilized CNN to detect anemia using conjunctiva of eye images. They successfully attained an accuracy of 94%. Dimauro et al. [22] developed a mobile phone application that employed the k-NN classification algorithm to detect anemia using conjunctiva eye images. The application produced substantial results when tested on non-anemic individuals, showing a strong correlation with their actual hemoglobin values. Additionally, they used a deep-learning algorithm to identify anemia by using retinal fundus images and hemoglobin level. Their model attained a confidence interval of 90.5%. Tamir et al. [23] proposed a method to diagnose anemia using a thresholding algorithm as part of an automated anemia detection. In their study, they extracted the RGB color components from the conjunctival eye images as measured by a camera. They attained an accuracy of 78.90%.

Dimauro et al. [24] used the Eyes-defy-anemia dataset, which consists of conjunctiva images of people in Italy and India. Using the Italian dataset of palpebral conjunctiva, the method attained an accuracy of 88%, sensitivity of 0.66, and specificity of 0.91. In contrast, on the Indian dataset, it attained an accuracy of 75%, sensitivity of 0.79, and specificity of 0.74. Appiahene et al. [25] utilized several machine learning methods like CNN, SVM, Naïve Bayes and decision tree for the detection of anemia using the images of palpable palm. They augmented these images for training, testing and validation of their proposed models. During model evaluation, the CNN achieved a remarkable accuracy of 99.96%, while the SVM achieved the lowest accuracy of 96.34%. Noor et al. [26] conducted a comparative analysis to assess the performance of SVM, decision tree, Naïve Bayes, and k-NN in detecting anemia using 104 conjunctival eye images. They evaluated each model's performance using a confusion matrix and found that the decision tree outperformed the others with the greatest accuracy of 82.61%.

Dhalla et al. [27] employed five pre-trained segmentation architectures to analyze conjunctival eye images from pediatric patients for the detection of anemia. The models used are UNet, FPN, UNet++, LinkNet and PSPNet. They separated the conjunctiva's visible images from the eye image to train the model. Their results show that the LinkNet model performed the best at segmenting the conjunctiva images with an accuracy of 94.17%. Ramzan et al. [28] used the conjunctiva images of the patients with their EHRs (Electronic Health Records) to detect anemia by using multi modal fusion. They attained an accuracy of 95%. Salma et al. [29] used characteristics related to parents like the children's fathers' education, child's age, water source, mother's age, breastfeeding status, mother's toilet type, education, and the number of children under five years old for the forecasting of anemia in children. They used different machine learning algorithms like k-NN, SVM, NB, Gradient Boosting, Bagging, RF and XGBoost and attained the accuracies 72.72%, 84.46%, 78.89%, 87.46%, 78.29%, 83.13% and 75.99% respectively. The summary of various works reviewed in the literature review is given in **Table 1**.

3.METHODOLOGY

The proposed methodology for anemia detection consists of several sequential steps like image acquisition, region of interest (ROI) extraction, feature extraction using Haar Wavelet Transform, model selection, training, testing and performance evaluation. The entire process is shown in **Figure 1** and is described in detail below.

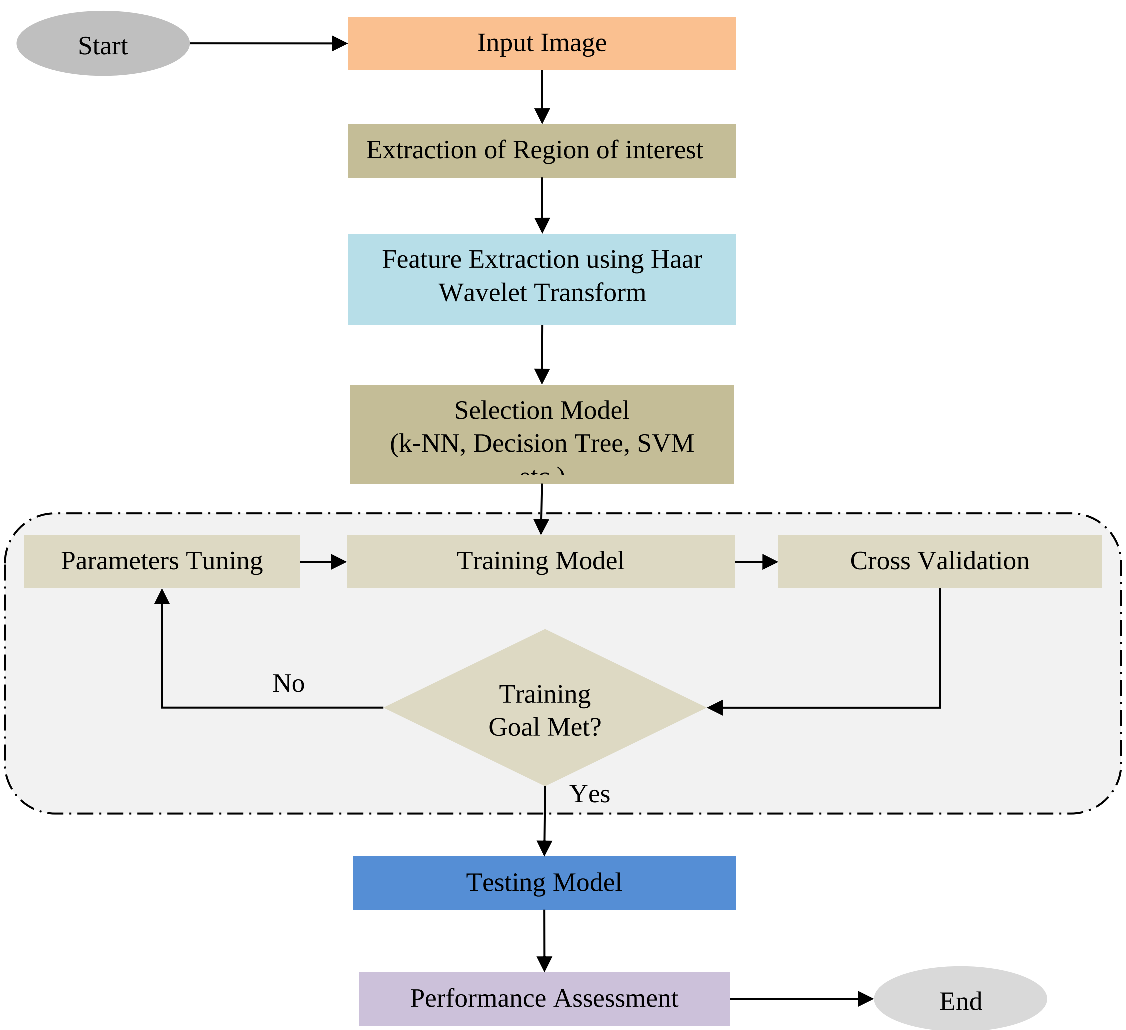


Figure 1. The Flowchart of Proposed Method for Anemia Detection.

3.1 Input Image Acquisition

The input images are obtained from a conjunctiva image database collected from subjects with varying anemia conditions. These images capture the inner lower eyelid, which is a known region for assessing anemia-related pallor. Image acquisition is performed under standardized lighting conditions to minimize variability and enhance reproducibility.

3.2 Region of Interest Extraction

After acquiring the images, the next step is to extract the Region of Interest (ROI), specifically targeting the conjunctival area. The ROI is chosen to eliminate any unrelated background areas and to concentrate on the conjunctival region where pallor is most visible.

3.3 Feature Extraction

The extracted ROI undergoes feature extraction using the Haar Wavelet Transform (HWT) [30], which is particularly effective for capturing texture and frequency-based features essential for anemia detection. Saadatmorad et. al. [31] has used discrete wavelet transform for crack detection. The Haar wavelet transform decomposes an image into different frequency components by applying a set of basis functions. The scaling function $\phi(t)$ and the wavelet function $\psi(t)$ define the Haar wavelet basis for the one-dimensional signal is given in Eq. 1 and Eq. 2.

The Haar wavelet coefficients for a given one-dimensional signal $f(t)$ is computed using Eq. 3 given below.

$$W_{j,k} = \int_{-\infty}^{\infty} f(t)\psi_{j,k}(t)dt \qquad (3)$$

where $\psi_{j,k}(t)$ represents the scaled and translated versions of the Haar wavelet given in Eq. 4.

$$\psi_{j,k}(t) = 2^{\frac{j}{2}}\psi(2^j t - k) \qquad (4)$$

In the case of images, the transformation is applied separately along the rows and columns, resulting in four sub-bands at each decomposition level. In the 2D Haar wavelet transform [32], the basis functions are constructed as the tensor product of the one-dimensional scaling and wavelet functions which are given below.

- **Approximation (LL) sub-band:** This component represents the coarse approximation of the image which is computed using Eq. 5.

$$\Phi(t_1, t_2) = \phi(t_1)\phi(t_2) \qquad (5)$$

$$\phi(t) = \begin{cases} 1, & 0 \le t < 1 \\ 0, & otherwise \end{cases} \qquad (1)$$

$$\psi(t) = \begin{cases} 1, & 0 \le t < \frac{1}{2} \\ -1, & \frac{1}{2} \le t < 1 \\ 0, & otherwise \end{cases} \qquad (2)$$

Table 1. **Summary of Studies on Anemia Detection using Machine Learning.**

Author	Patient Image	Method Used	Accuracy (%)
Zhang et al. [16]	Conjunctiva	MobileNet	79.90
		ResNet50	78.26
		DenseNet121	78.47
		EfficientNetB0	69.98
		InceptionV3	82.37
Asare et al. [13]	Palpable palm	Decision Tree	98.29
		k-NN	98.92
		CNN	99.12
		Naïve Bayes	98.96
		SVM	95.34
	Fingernail	Decision Tree	97.18
		k-NN	97.89
		CNN	98.33
		Naïve Bayes	94.94
		SVM	92.69
	Conjunctiva	Decision Tree	97.32
		k-NN	97.96
		CNN	98.45
		Naïve Bayes	94.94
		SVM	89.45
Chen et al. [17]	Conjunctiva	CNN	95%
Shahzad et al. [19]	Conjunctiva	3-TierDCFNet	91.37
Jain et al. [14]	Conjunctiva	Artificial Neural Network	97.00
Tamir et al. [23]	Conjunctiva	Thresholding Method	78.90
Magdalena et al. [21]	Conjunctiva	CNN	94.00
Dimauro et al. [22]	Conjunctiva and retinal fundus	k-NN	90.00
Dimauro et al. [24]	Conjunctiva	RUSBoost	88.00
Appiahene et al. [25]	Palpable palm	CNN	99.92
		SVM	96.34
		DT	99.29
		Naïve Bayes	99.96
		k-NN	99.92
Noor et al. [26]	Conjunctiva	SVM	73.91
		k-NN	73.91
		DT	82.61
Dhalla et al. [27]	Conjunctiva	UNet	94.12
		LinkNet	94.17
		UNet++	94.15
		FPN	93.34
		PSPNet	91.85

- **Horizontal (LH) sub-band:** It captures horizontal edge details of an image and is extracted using Eq. 6.

$$\Psi_H(t_1,t_2) = \psi(t_1)\phi(t_2) \quad (6)$$

- **Vertical (HL) sub-band:** It captures vertical edge details of an image and is extracted using Eq. 7.

$$\Psi_V(t_1,t_2) = \phi(t_1)\psi(t_2) \quad (7)$$

- **Diagonal (HH) sub-band:** It captures diagonal patterns of an image and is extracted using Eq. 8.

$$\Psi_D(t_1,t_2) = \psi(t_1)\psi(t_2) \quad (8)$$

Thus, the two-dimensional Haar transform basis functions are written using the tensor product notation shown below using Eq. 9-12.

$$\Phi_{ij}(t_1,t_2) = \phi_i(t_1) \otimes \phi_j(t_2) \quad (9)$$

$$\Psi_{H,ij}(t_1,t_2) = \psi_i(t_1) \otimes \phi_j(t_2) \quad (10)$$

$$\Psi_{V,ij}(t_1,t_2) = \phi_i(t_1) \otimes \psi_j(t_2) \quad (11)$$

$$\Psi_{D,ij}(t_1,t_2) = \psi_i(t_1) \otimes \psi_j(t_2) \quad (12)$$

where i, j correspond to different levels of decomposition.

Given an image represented by a matrix $I(x,y)$ of size $M \times N$, the two-dimensional Haar Wavelet transform coefficients are computed using Eq. 13.

$$W = HIH^T \quad (11)$$

where H is the Haar matrix of size $N \times N$ and W represents the transformed coefficients. **Figure 2** shows a sample conjunctiva image and its Haar wavelet transform at level one. By recursively applying the Haar transform on the approximation (LL) sub-band, multi-level decomposition [33] is achieved as follows.

$$I \rightarrow (LL_1, LH_1, HL_1, HH_1) \rightarrow (LL_2, LH_2, HL_2, HH_2) \rightarrow \cdots \quad (12)$$

where LH_j, HL_j, HH_j are wavelet coefficients at level j. At each level j, the wavelet coefficients are obtained using Eq. 15.

$$LL_j = H^j I (H^T)^j \quad (13)$$

From the decomposed sub-bands, statistical features like mean, standard deviation and median are extracted to serve as distinguishing features for anemia detection. The mean and standard deviation of Haar wavelet coefficients is computed using Eq. 16-17

$$Mean\ (\mu) = \frac{1}{N}\sum_{i=1}^{N} x_i \quad (14)$$

$$Standard\ Deviation\ (\sigma) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \quad (15)$$

where x_i is the i^{th} wavelet coefficient at decomposition level and N is the length of wavelet coefficients. The median is the middle value of the sorted wavelet features. These extracted features form the input image are used to train the classification models.

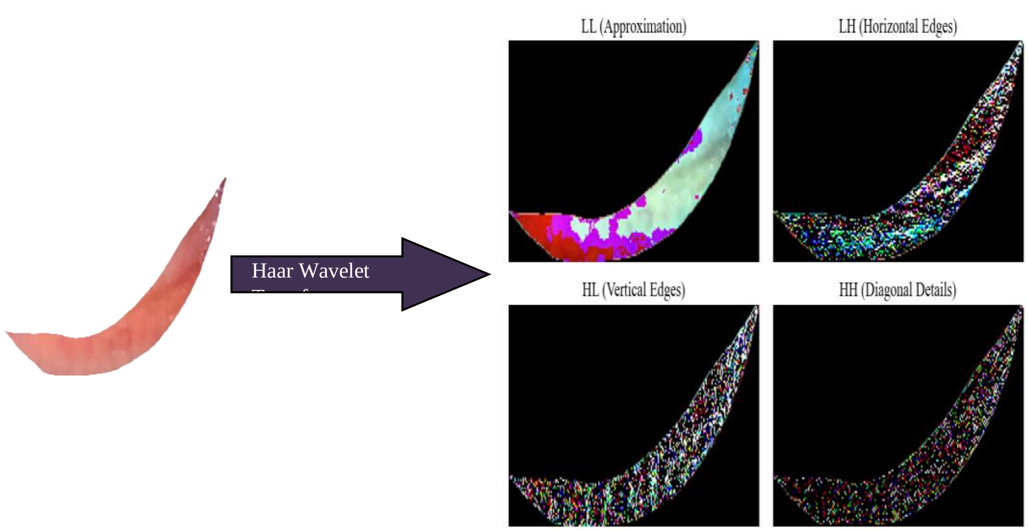


Figure 2. A sample conjunctiva image and its Haar Wavelet Transform

3.4 Machine Learning Model Training

After feature extraction, various classification models are trained to distinguish between non-anemic and anemic based on features extracted from conjunctiva image of the patient. The various machine learning methods used in our study for diagnosing anemia are discussed below.

- K-Nearest Neighbours (k-NN)

k-NN uses the concept of nearness from existing labelled data points to predict the class of a new data point by analysing the labels of its k closest neighbours in the data space. In other words, it uses proximity to find the class of a new data point by determining its proximity from cluster centres. The value of k has a important role on the performance of the algorithm. Here we have used k=1 as it gives the best performance [34]. In this study, the Euclidean distance has been used to measure similarity between instances which is computed using below Eq. 18.

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \qquad (16)$$

where x and y are feature vectors. As a lazy learning technique, k-NN creates predictions at runtime by storing all training examples rather than explicitly creating a model during training.

- Decision Tree

The decision tree algorithm based on the C4.5 algorithm is a tree-based model that recursively partitions the dataset into subsets based on feature values to maximize the class separation. It selects the optimal feature for splitting by utilizing measures such as entropy and information gain. Entropy $H(X)$ quantifies the uncertainty or impurity in a dataset and is mathematically defined as:

$$H(X) = -\sum_{i} p_i(x) log_2 p_i(x) \qquad (17)$$

where $p_i(x)$ represents the probability of class i in the dataset. A lower entropy value indicates a more homogeneous subset. Information Gain (IG) measures the reduction in entropy after a split and helps determine the best feature for partitioning. It is computed using Eq. 20.

$$IG(S,A) = H(S) - \sum \frac{|S_v|}{|S|} H(S_v) \qquad (20)$$

where S is the original dataset, A is the feature being evaluated, and S_v are the subsets formed after the split. A feature with higher information gain is preferred, as it maximizes class separation and improves decision-making. The tree structure consists of decision nodes that represent features, branches represent decisions, and leaf nodes contain class labels. Decision trees provide interpretability. They are also efficient for handling both numerical and categorical data.

- Random Forest

Random Forest partitions the dataset in different subsets and creates a decision tree based on each subset. Each tree is trained on a random subset of features and samples using bootstrapping. It aggregates the output of each decision tree to predict accurate and robust outcomes. The final prediction is made by a voting method for classification or averaging for regression. It is a type of ensemble learning technique. The strength of Random Forest lies in its ability to reduce overfitting and provide better generalization compared to individual decision trees. The prediction of the random forest is computed using Eq. 21.

$$\hat{y} = \frac{1}{n}\sum_{i=1}^{n} h_i(x) \qquad (21)$$

where $h_i(x)$ represents the prediction value of individual tree i and n represent the number of decision trees in random forest.

- Gradient Boosting

Gradient Boosting is an iterative boosting algorithm that builds models one by one, each correcting the errors of its predecessor by minimizing a differentiable loss function. The loss function is optimized using gradient descent that is expressed using Eq. 22.

$$F_m(x) = F_{m-1}(x) + \eta \sum_{i=1}^{N} \nabla \mathrm{L}(y_i, F_{m-1}(x_i)) \qquad (22)$$

where $F_m(x)$ is the updated model L is the loss function and η is the learning rate. Unlike Random Forest, Gradient Boosting builds trees adaptively, focusing more on difficult-to-classify instances, leading to higher predictive accuracy but at the cost of increased training time.

- Random Subspace Algorithm

The Random Subspace method is an ensemble learning technique that improves classification performance by training multiple base learners on randomly selected subsets of features. Unlike traditional ensemble methods that focus on bootstrapping samples, the Random Subspace method focuses on feature randomness, which enhances diversity among the base models. Typically, decision trees are used as the base learners. Mathematically, if X is the original feature space with n features, and m features are randomly selected such that $m < n$, the classifier h_i is trained on the reduced feature space X_i, and the final prediction is obtained through majority voting represented using Eq. 23.

$$H(x) = majority\ vote\{h_1(x), h_2(x), \ldots, h_k(x)\} \quad (23)$$

where k represents the number of base learners.

- Extreme Gradient Boosting (XGBoost)

XGBoost is an advanced ensemble learning algorithm based on gradient boosting that optimizes model performance through regularization and efficient computation. It forms a number of weak learners (typically decision trees) one by one, with each new tree correcting the residual errors of the previous ones. XGBoost uses both first order and second order gradient information for minimizing the loss function more effectively. A regularization term is used in objective function in XGBoost to prevent overfitting which is given in Eq. 24.

$$\mathcal{L}(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{j=1}^{T} \Omega(f_j) \quad (24)$$

where $l(y_i, \hat{y}_i)$ is the loss function like squared error in case regression or log loss in case classification, and $\Omega(f_j)$is a regularization term that controls the complexity of the trees. The prediction of a new input x is obtained by summing the outputs of all trees shown using Eq. 25.

$$\hat{y} = \sum_{k=1}^{K} f_k(x) \quad (25)$$

The training process of all the machine learning methods used in this study consists of following steps.

- The dataset is divided into 70%, 20% and 10% for training, test and validation respectively to ensure proper evaluation.
- Cross-validation with k=10 folds is performed to prevent overfitting.
- Hyperparameters like tree depth, number of neighbours etc. are tuned using grid search for optimization of the model performance.

4. EXPERIMENTAL SETUP AND RESULT

In this study, we have used six machine learning algorithms like k-NN, Decision Tree, XGBoost, Gradient Boosting, Random Subspace and Random Forest to detect anemia using conjunctival eye images. All experiments were conducted using Python 3.8 on a system with an Intel i7 processor and 8 GB of RAM. The dataset used, evaluation metrics used for measuring the effectiveness of machine learning models and results obtained are discussed below.

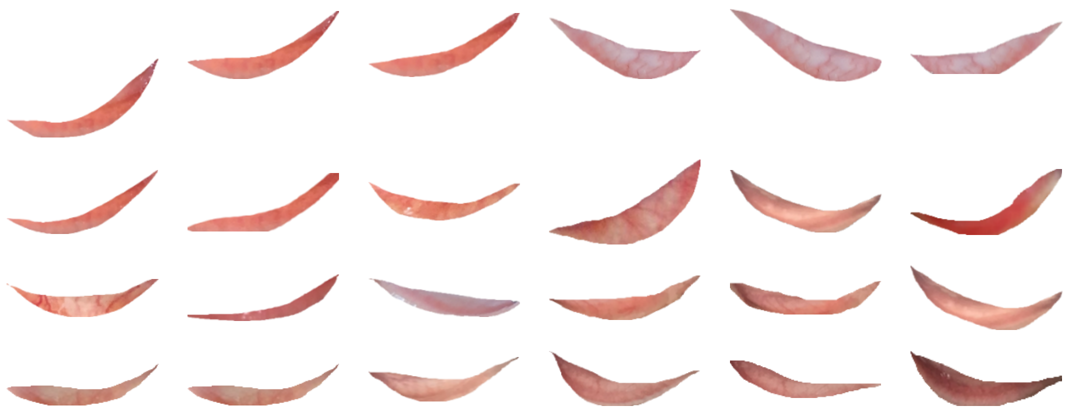
4.1 Dataset

The conjunctiva image dataset that we used in this study was taken from the Mendeley Data repository and came from research done by Appiahene et al. [35]. The dataset comprises conjunctival eye images captured by skilled lab workers using top-notch cameras with a minimum resolution of 12 megapixels. Relevant patient data, including hemoglobin (Hb) values, sex, age, and anemia diagnosis (whether non-anemic or anemic), were recorded by medical laboratory officers. To ensure accurate image capture, the lower eyelid was gently drawn back with index finger and thumb. In order to avoid excessive glare during image collecting, which could compromise the precision of machine learning models, spotlights were switched off. Data collection was conducted at several healthcare facilities across Ghana, including Holy Family Hospital at Berekum, Nkawie-Toase Government Hospital at Nkawie-Toase, SDA Hospital at Sunyani, Ejusu Government Hospital at Ejusu, Manhyia District Hospital at Kumasi, Sunyani Municipal Hospital at Sunyani, Ahmadiyya Muslim Hospital at Techiman, Kintampo Municipal Hospital at Kintampo, Bolgatanga Regional Hospital at Bolgatanga, Komfo Anokye Teaching Hospital at Kumasi. The dataset primarily focuses on children aged five years and below, a demographic identified by the World Health Organization (WHO) as highly vulnerable to anemia, with approximately 42% of children under five and 40% of pregnant women [1].

The triangle thresholding algorithm [36] was applied to distinguish the Region of Interest from the image contours, ensuring that the relevant area for anemia diagnosis was correctly isolated. Depending on the matching laboratory Hb levels supplied during data collection, the images were classified as either Non-Anemic or Anemic. To increase the size of dataset and diversity, data augmentation techniques were employed, increasing the number of samples from an initial 710 images (284 non-anemic and 426 anemic) to 4,262 images. Each augmented image retained the original classification label ensuring consistency across the expanded dataset. Considering the young age of the participants, special attention was given to handling the smaller size of conjunctival regions in comparison to adult subjects. The dataset thus provides a unique and valuable resource for developing and evaluating machine learning models aimed at non-invasive anemia detection in young children. The detail of the dataset is given in **Table 2.** The sample conjunctiva image of anemic and non-anemic patient of original dataset is shown in **Figure 3.** The dataset is divided into 70%, 20% and 10% for training, testing and validation purpose respectively.

Table 2. Statistics of original Dataset

	Non-anemic	Anemic	Total
Patients	286 (40%)	424 (60%)	710 (100%)
Male	154 (38%)	250 (62%)	404 (57%)
Female	132 (43%)	174 (57%)	306 (43%)



(a) (b)

Figure 3. (a) Anemic Conjunctiva images (b) Non-Anemic Conjunctiva images

4.2 Performance Evaluation Matrices

The assessment of a model in classification problems is based on how well it predicts results. Following are the four fundamental metrics that are mostly used to measure the effectiveness of a classification model. These components establish the basis for evaluating the model's ability to classify between negative and positive classes.

- True Positive

The True Positive (TP) represents the number of times the model correctly predicts the positive class like identifying an anemic patient as anemic.

- False Positive

The False Positive (FP) represents the cases where the model wrongly predicts the positive class for an instance that in reality belongs to the negative class like diagnosing a non-anemic patient as anemic.

- True Negative

The True Negative (TN) refers the number of times when the model correctly predicts the negative class as negative like identifying a non-anemic patient as non-anemic.

- False Negative

The False Negative (FN) refers the number of times the model predicts the negative class for an instance that actually belongs to the positive class like predicting an anemic patient as non-anemic.

- Accuracy

It is one of the most widely applied metrics in classification. It determines the percentage of cases that were correctly classified out of all the instances. In terms of mathematics, it is stated using Eq. 26.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (26)$$

- Precision

Precision, sometimes called Positive Predictive Value, quantifies the percentage of actual positive predictions among all positive forecasts. It is computed using Eq. 27.

$$Precision = \frac{TP}{TP + FP} \quad (27)$$

- Recall

Recall also known as genuine Positive Rate or Sensitivity, determines the percentage of genuine positives among all positive occurrences. It is computed using Eq. 28.

$$Recall = \frac{TP}{TP + FN} \quad (28)$$

- F1-Score

The F1 Score is an essential metric that offers a fair assessment of a model's recall and precision. The precision recall F1 score framework relies heavily on the F1 Score formula, which is derived from the harmonic mean of precision and recall. This measure is especially helpful when there is an imbalance in the distribution of classes. It is computed using Eq. 29.

$$F1 = 2 \cdot \frac{Precision\ \cdot Recall}{Precision + Recall} \quad (29)$$

- ROC Curve and AUC

The Receiver Operating Characteristic (ROC) curve represents how well the model performs at different classification criteria. It is the plot that displays the False Positive Rate (FPR) against the True Positive Rate FPR and TPR is computed using below equations.

$$FPR = \frac{FP}{FP + TN} \quad (30)$$

$$TPR = \frac{TP}{TP + FN} \quad (31)$$

The model's overall capacity to discriminate between positive and negative classes is measured by the Area Under the Curve (AUC). The perfect classification is shown by an AUC of 1.0, random guessing is suggested by an AUC of 0.5, and performance that is lower than random is indicated by values less than 0.5. The ROC-AUC curve is particularly helpful in comparing different models, as it considers the model's performance at all thresholds, rather than relying on a fixed threshold.

4.3. Results

The various machine learning models were evaluated on different performance metrics to assess their effectiveness in anemia detection. **Figure 4** shows the confusion matrix of all the machine learning models like k-NN, gradient boosting, decision tree, random subspace, random forest and XGBoost used for anemia detection using conjunctiva image of a patient. **Table 3** shows the accuracy, recall, precision, F1-score and AUC value all the machine learning methods used to diagnose anemia. It can be observed from **Table 3** that the k-NN model has attained 99.18% accuracy, while the Random Forest has attained accuracy of 98.24%. The decision tree and Random Subspace have accuracy of 97.66% and 95.55% respectively while XGBoost and Gradient Boosting have attained accuracy of 95.08% and 79.25% respectively. It can be observed that k-NN has outperformed all the models in terms of recall, accuracy, precision and F1-score with value of 99.18%, 99.11%, 98.82% and 98.97% respectively. The random forest has outperformed all other methods with AUC value of 99.86%.

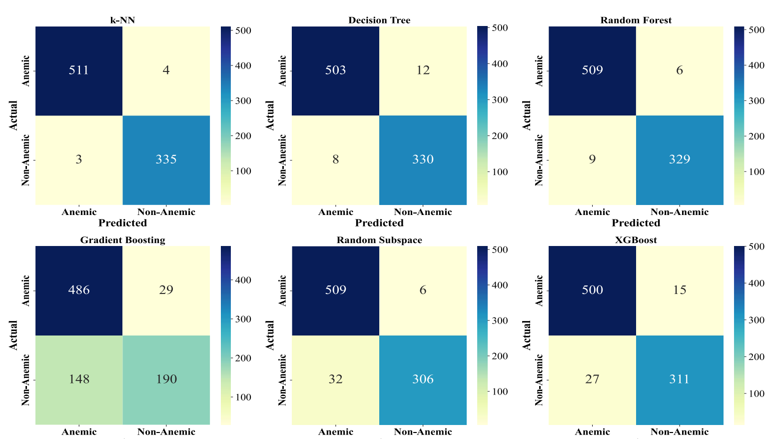


Figure 4. Confusion Matrix for all the machine learning models used in the study.

Table 3. Accuracy, Recall, Precision, F1-Score and AUC of machine learning models used in the study.

Model	Accuracy (%)	Recall (%)	Precision (%)	F1-score (%)	AUC (%)
k-NN	99.18	99.11	98.82	98.97	99.17
Random Forest	98.24	97.34	98.21	97.77	99.86
Decision Tree	97.66	97.63	96.49	97.06	97.65
Random Subspace	95.55	90.53	98.08	94.15	98.97
XGBoost	95.08	92.01	95.40	93.67	98.74
Gradient Boosting	79.25	56.21	86.76	68.22	89.18

Figure 5 compares the accuracy, recall, precision, F1-score and AUC of the different machine learning algorithms that have been used to diagnose anemia. It can be observed from it that the k-NN performance is best among all the other machine learning methods. **Figure 6** shows a lift curve that represents a machine learning model classification ability to identify positive instances compared to random selection. The x-axis displays the population proportion while the y-axis

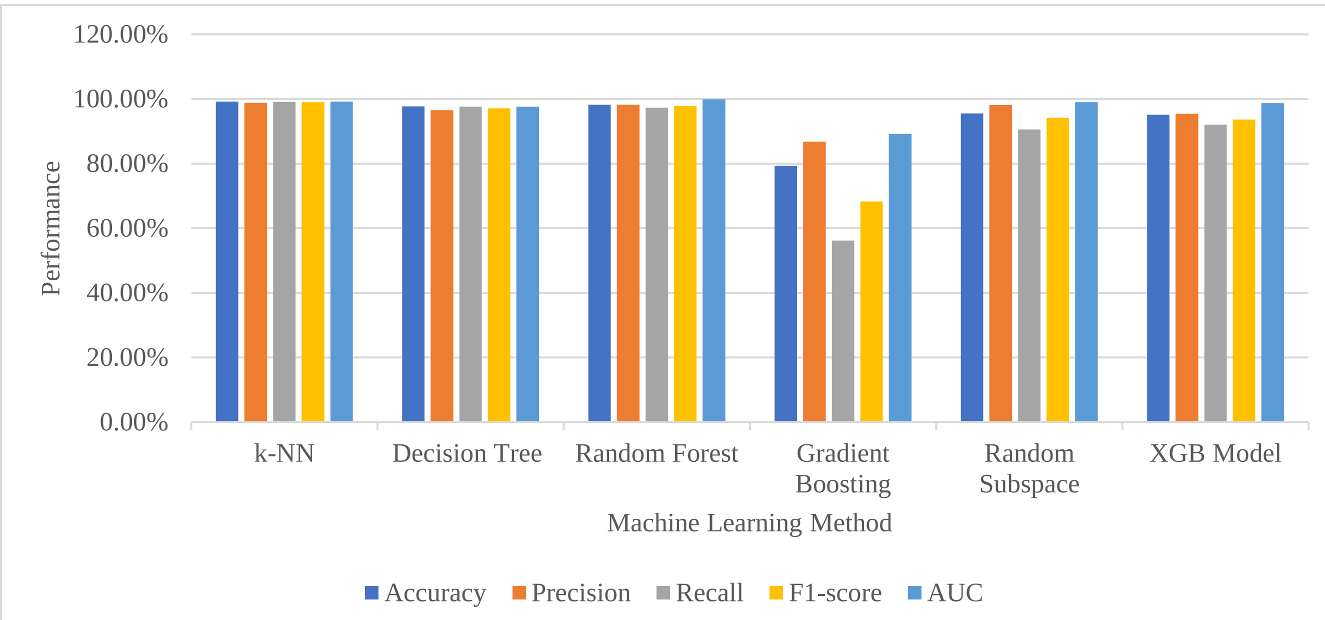


Figure 5. Accuracy, Precision, Recall, F1-Score and AUC of Machine Learning Models.

shows the lift value. A higher lift indicates better performance in finding relevant cases within a population segment. **Figure 7** shows a ROC curve which is a graph that demonstrates the performance of a model across different thresholds. It is utilized to evaluate the accuracy of a test or it can be used to compare the performances of multiple tests. Here we are comparing the performance of different models using this ROC curve. **Table 4** shows the comparison of proposed machine learning models with various state-of-the-art studies available in literature to detect anemia using conjunctiva images. It can be observed that the use of Haar wavelet transform with k-NN machine learning technique has outperformed all of them. The proposed k-NN based model has the highest accuracy of 99.18% among all the state-of-the-art works used for comparison. So, our study confirms that machine learning-based anemia detection using conjunctiva images is a viable alternative to traditional methods, offering higher accuracy, efficiency, and ease of deployment in clinical and remote healthcare settings. Our findings align with previous research in the field and further validate the importance of using medical imaging and AI-driven techniques for early diagnosis.

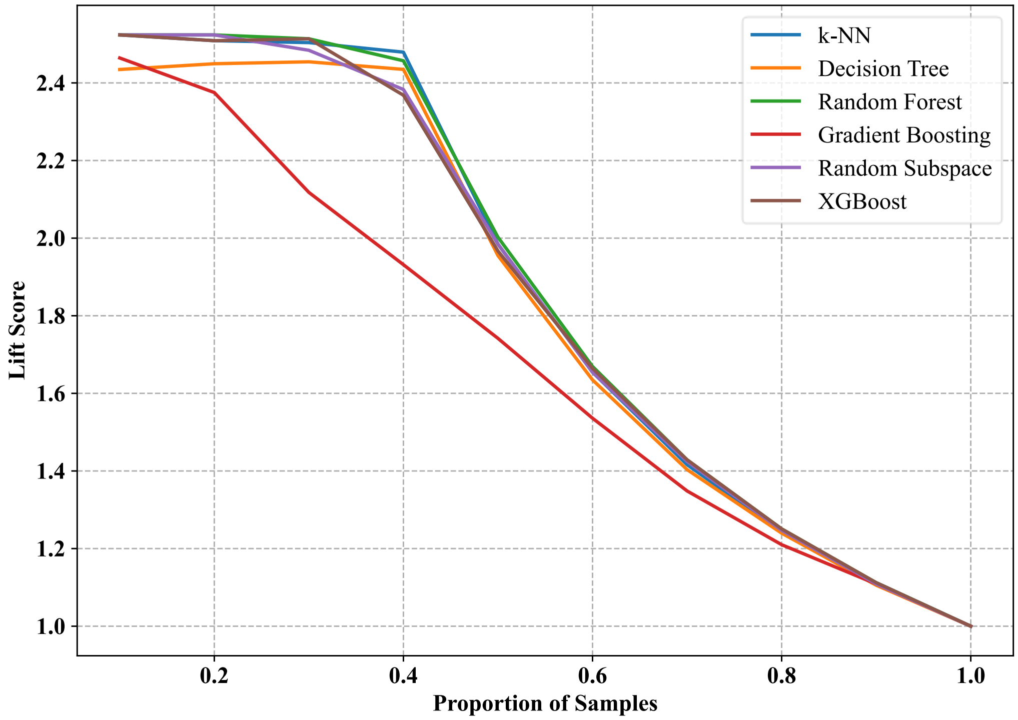
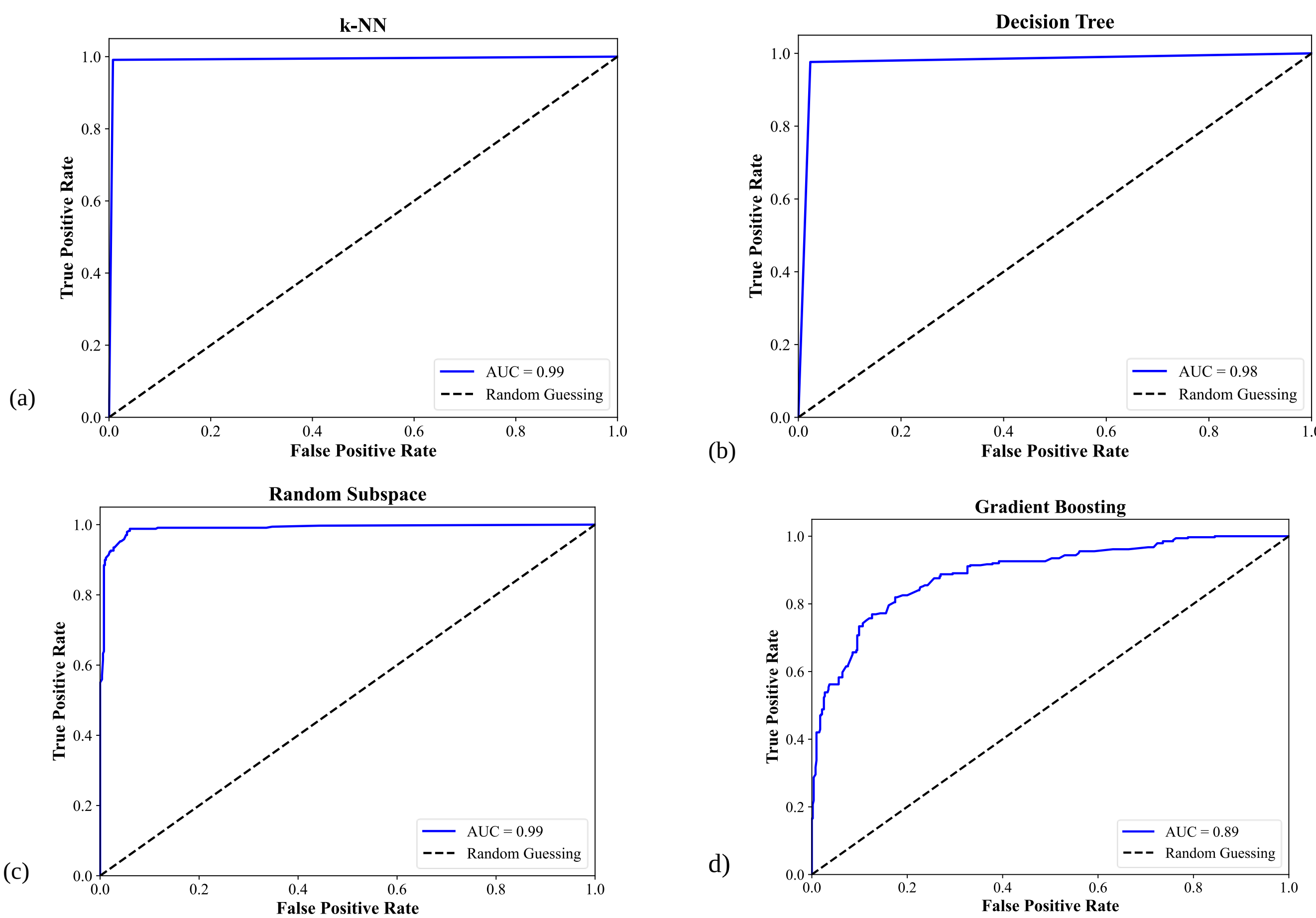


Figure 6. Lift Curve Performance of Machine Learning Models.



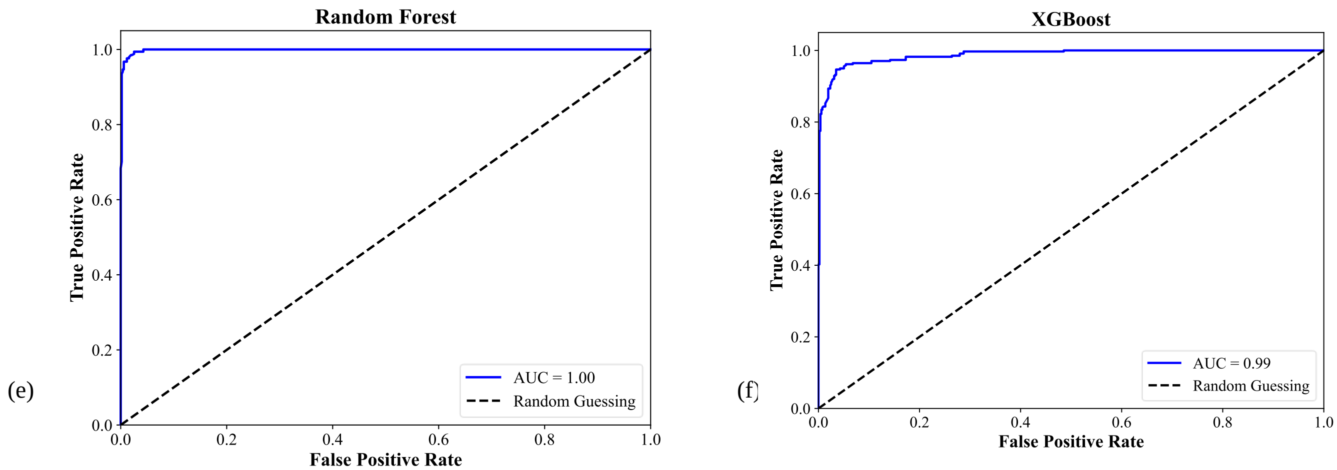


Figure 7. The ROC curves of k-NN, Decision Tree, Random Subspace, Gradient Boosting, Random Forest and XGBoost Machine Learning Models.

Table 4. Comparison of proposed work with state-of-artworks.

Authors	Algorithm	Accuracy
Asare et al. [13] [2024]	CNN	98.45%
Jain et al. [14] [2019]	ANN	97.00%
Tamir et al. [23] [2017]	Thresholding Algorithm	78.90%
Magdalena et al. [21] [2022]	CNN	94.00%
Noor et al. [26] [2019]	Decision Tree	82.61%
Dhalla et al. [27] [2023]	LinkNet	94.17%
Dimauro et al. [22] [2018]	k-NN	90.26%
Proposed Method	**k-NN**	**99.18%**

5. CONCLUSION AND FUTURE WORK

Anemia is a major concern worldwide among children and women. It arises due to deficiency of iron or blood loss. The diagnostics techniques used to detect anemia are invasive based which involve the collection of blood from the patients and its laboratory test to find vitals to blood to detect the anemia. The above method causes discomfort to patients and becomes a source of infection also. To address the above issue, this study presents a non-invasive approach for detecting anemia using machine learning algorithms applied to conjunctiva images. By leveraging the Haar Wavelet Transform for feature extraction and utilizing various classification models like k-NN, Decision Tree, XGBoost, Gradient Boosting, Random Subspace and Random Forest, the proposed method effectively distinguishes non-anemic and anemic cases among patients. The accuracy achieved in the detection of anemia using conjunctiva of a patient using k-NN, Decision Tree, XGBoost, Gradient Boosting, Random Subspace and Random Forest is 99.18%, 97.66%, 95.08%, 79.25%, 95.55%, and 98.24% respectively. The k-NN algorithm demonstrated the highest accuracy of 99.18% outperforming other models and has been proposed for the detection of anemia. The proposed method is compared with state-of-art-works available in literature and found that using Haar features with k-NN method outperforms all of them. The other performance metrics results highlight the potential of proposed non-invasive method of anemia detection reducing the dependency on traditional blood test, which is time-consuming, invasive and costly.

Despite the promising results, the proposed approach can be further improved by expanding the dataset by incorporating a larger and more diverse collection from multiple geographic locations as well as multi-modal data integration where conjunctiva images are combined with clinical parameters like hemoglobin levels and patient history, which could significantly improve its predictive power. Further advancements in data quality, deep learning models, and real-time deployment can make this approach an essential tool for early anemia detection and global healthcare improvement.

Acknowledgment

We acknowledge Madan Mohan Malaviya University of Technology for providing the research facilities

Conflict of interest

The authors have no relevant financial or non-financial interests to disclose.

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Ethical statement

This study has used data collected from a hospital for training and testing of models that is publicly available. Hence no Human Participants or Animals are involved in the study.

References

1. World Health Organization, "Anaemia," WHO, 1 May 2023. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/anaemia. [Accessed 28 January 2025].

2. Ernest Beutler and Jill Waalen , "The definition of anemia: what is the lower limit of normal of the blood hemoglobin concentration?," *Blood,* vol. 107, no. 5, pp. 1747-1750, March 2006.

3. Al-alimi, Abdullah Ahmed, Bashanfer, Salem, Morish, Mohammed Abdo, "Prevalence of Iron Deficiency Anemia among University Students in Hodeida Province, Yemen," *Anemia,* vol. 2018, no. 4157876, p. 7, 2018.

4. Sivachandar Kasiviswanathan, Thulasi Bai Vijayan, Lorenzo Simone and Giovanni Dimauro, "Semantic Segmentation of Conjunctiva Region for Non-Invasive Anemia Detection Applications," *Electronics,* vol. 9, no. 8, p. 1309, 2020.

5. Mohammed Sami MOHAMMED, Arshed A. AHMAD and Murat SARI, "Analysis of Anemia Using Data Mining Techniques with Risk Factors Specification," in *2020 International Conference for Emerging Technology (INCET)*, Belgaum, India, 2020.

6. Ana C. M. G. Figueiredo, Isaac S. Gomes-Filho, Roberta B. Silva, Priscilla P. S. Pereira, Fabiana A. F. Da Mata, Amanda O. Lyrio, Elivan S. Souza, Elivan S. Souza and Mauricio G. Pereira , "Maternal Anemia and Low Birth Weight: A Systematic Review and Meta-Analysis," *Nutrients,* vol. 10, no. 5, p. 601, 2018.

7. D.A. Newhall, R. Oliver, S. Lugthart, "Anaemia: A disease or symptom?," *The Netherlands Journal of Medicine,* vol. 78, no. 3, pp. 104-110, 2020.

8. Tuba Karagül Yıldız, Nilüfer Yurtay and Birgül Öneç, "Classifying anemia types using artificial learning methods," *Engineering Science and Technology, an International Journal,* vol. 24, no. 1, pp. 50-70, 2021.

9. Nazir, A., Hussain, A., Singh, M., & Assad, A., "A novel approach in cancer diagnosis: integrating holography microscopic medical imaging and deep learning techniques—challenges and future trends," *Biomedical Physics & Engineering Express,* vol. 11, no. 2, 2025.

10. Swathypriyadharsini, P., Rupashini, P. R., & Premalatha, K., "Feature selection for classification based on machine learning algorithms for prostate cancer," *Biomedical Physics & Engineering Express,* vol. 11, no. 3, p. 035023, 2025.

11. Pan, H., Miao, J., Yu, J., Li, J., Wang, X., & Feng, J., "Multi-modal Classification of Retinal Disease Based On Convolutional Neural Network," *Biomedical Physics & Engineering Express,* 2025.

12. Latha, G., "Optimized glaucoma detection using HCCNN with PSO-driven hyperparameter tuning," *Biomedical Physics & Engineering Express,* vol. 11, no. 3, p. 035018, 2025.

13. Justice Williams Asare, William Leslie Brown-Acquaye, Martin Mabeifam Ujakpa, Emmanuel Freeman and Peter Appiahene , "Application of machine learning approach for iron defciency anaemia detection in children using conjunctiva images," *Informatics in Medicine Unlocked,* vol. 45, no. 2352-9148, p. 101451, 2024.

14. PrakharJain, Shubham Bauskar and Manasi Gyanchandani, "Neural network based non-invasive method to detect anemia from images of eye conjunctiva," *International Journal of Imaging Systems and Technology,* vol. 30, no. 1, pp. 1-265, 2019.

15. Giovanni Dimauro, Attilio Guarini, Danilo Caivano, Francesco Girardi, Crescenza Pasciolla and Angela Iacobazzi, "Detecting Clinical Signs of Anaemia From Digital Images of the Palpebral Conjunctiva," *IEEE Access,* vol. 7, pp. 113488-113498, 2019.

16. Aixian Zhang, Jingjiao Lou, Zijie Pan, Jiaqi Luo, Xiaomeng Zhang, Han Zhang, Jianpeng Li, Lili Wang, Xiang Cui, Bing Ji and Li Chen, "Prediction of anemia using facial images and deep learning technology in the emergency department," *Front. Public Health,* vol. 10, no. 964385, 2022.

17. Yuwen Chen, Kunhua Zhong, Yiziting Zhu and Qilong Sun, "Two-stage hemoglobin prediction based on prior causality," *Front Public Health,* vol. 10, no. 1079389, 2022.

18. Samer Muthana Sarsam, Hosam Al-Samarraie, Ahmed Ibrahim AlzahraniI and Abdul Samad Shibghatullah, "A non-invasive machine learning mechanism for early disease recognition on Twitter: the case of anemia," *Artificial Intelligence in Medicine,* vol. 134, no. 1873-2860, p. 102428, 2022.

19. Muhammad Shahzad, Arif Iqbal Umar, Syed Hamad Shirazi, Zakir Khan, Asfandyar Khan, Muhammad Assam, Abdullah Mohamed and El-Awady Attia, "Identification of anemia and its severity level in a peripheral blood smear using 3-tier deep neural network.," *Applied Sciences,* vol. 12, no. 10, p. 5030, 2022.

20. Pearl D'Souza and Ritu Bhargava, "Prediction of Anemia Using Naïve-Bayes Classification Algorithm in Machine Learning," in *Emerging Trends in Expert Applications and Security (ICETEAS)*, Singapore, 2023.

21. Rita Magdalena, Sofia Saidah, Ibnu Da'wan Salim Ubaidah, Yunendah Nur Fuadah, Nabila Herman and Nur Ibrahim, "Convolutional neural network for ANEMIA detection based on conjunctiva palpebral images," *Jurnal Teknik Informatika (JUTIF),* vol. 3, no. 2, pp. 349-354, 2022.

22. Giovanni Dimauro, Danilo Caivano and Francesco Girardi, "A New Method and a Non-Invasive Device to Estimate Anemia Based on Digital Images of the Conjunctiva," *IEEE Access,* vol. 6, no. 2169-3536, pp. 46968 - 46975, 2018.

23. Azwad Tamir, "Detection of anemia from image of the anterior conjunctiva of the eye by image processing and thresholding," in *IEEE Region 10 Humanitarian Technology Conference (R10-HTC)*, Dhaka, Bangladesh, 2017.

24. Giovanni Dimauro, Maria Elena Griseta, Mauro Giuseppe Camporeale, Felice Clemente, Attilio Guarini and Rosalia Maglietta, "An intelligent non-invasive system for automated diagnosis of anemia exploiting a novel dataset," *Artificial Intelligence in Medicine,* vol. 136, no. 1873-2860, p. 102477, 2023.

25. Peter Appiahene, Justice Williams Asare, Emmanuel Timmy Donkoh, Giovanni Dimauro and Rosalia Maglietta, "Detection of iron deficiency anemia by medical images: a comparative study of machine learning algorithms," *BioData Mining,* vol. 16, no. 1, 2023.

26. Nahiyan Bin Noor, Mohammad Saeid Anwar and Mrinmoy Dey, "Comparative Study Between Decision Tree, SVM and KNN to Predict Anaemic Condition," in *IEEE International Conference on Biomedical*

Engineering, Computer and Information Technology for Health (BECITHCON), Dhaka, Bangladesh, 2019.

27. Sabrina Dhalla, Junaid Maqbool, Tanvir Singh Mann, Aastha Gupta, Ajay Mittal, Preeti Aggarwal, Krishan Saluja, Munish Kumar and Shiv Sajan Saini , "Semantic segmentation of palpebral conjunctiva using predefined deep neural architectures for anemia detection," *Procedia Computer Science,* vol. 218, pp. 328-337, 2023.

28. Muhammad Ramzan, Muhammad Usman Saeed and Ghulam Ali, "Enhancing anemia detection through multimodal data fusion: a non-invasive approach using EHRs and conjunctiva images," *Discover Artifcial Intelligence,* vol. 4, no. 100, 2024.

29. Nahid Salma and Majid Khan Majahar Ali, "Evaluating the Factors and Forecasting Childhood Anemia Through Machine Learning Algorithms," *Malaysian Journal of Fundamental and Applied Sciences,* vol. 21, no. 1, pp. 1529-1541, 2025.

30. Muhammad S. Mandisha, Mohamed A. Hussien, Amr K. Shalaby and Omar M. Fahmy, "Wavelet Transform-based Methods for Forensic Analysis of Digital Images," *Journal of Advanced Research in Applied Sciences and Engineering Technology,* vol. 44, no. 1, pp. 46-54, 2024.

31. Morteza Saadatmorad and Bochra Khatir, "Crack detection in concrete structures using standard deviation of discrete wavelet transform," *HCMCOU Journal of Science – Advances in Computational Structures,* vol. 15, no. 1, 2024.

32. Kamarul Hawari Ghazali, Mohd Fais Mansor, Mohd. Marzuki Mustafa and Aini Hussain , "Feature Extraction Technique using Discrete Wavelet Transform for Image Classification," in *2007 5th Student Conference on Research and Development*, Selangor, Malaysia, 2007.

33. Contributors, Wikipedia, "Haar wavelet," Wikipedia, [Online]. Available: https://en.wikipedia.org/wiki/Haar_wavelet. [Accessed 10 February 2025].

34. Emrullah ACAR, "Extraction of Texture Features From Local Iris Areas by GLCM and Iris Recognition System Based on KNN," *European Journal of Technic,* vol. 6, no. 1, 2016.

35. Peter Appiahene, Justice Williams Asare, Emmanuel Donkoh, "Application of Machine Learning in Detecting Iron Deficiency Anemia Using Conjunctiva image Dataset from Ghana," Mendeley Data, 2022.

36. Samer Sawalha and Arafat Awajan, "Blank Background Image lossless Compression Technique," *International Journal of Image Processing (IJIP),* vol. 8, no. 1, pp. 9-16, 2014.