Non-invasive Way to Detect Anemia using Machine Learning

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The challenge of anemia significantly impacts children and pregnant women worldwide. In recent times, there has been growing interest in using machine learning algorithms to tackle this issue. In this study, two machine learning methods were employed to identify iron-deficiency anemia by analyzing images of the conjunctiva, showing promising results. The process involves collection of data and converting the color space from RGB to CIELAB in preprocessing and developing their models. So, the abstract talks a lot about critical considerations in this field, like dataset quality and the pesky issue of model interpretability. We need more research to refine and validate these models across diverse populations and healthcare settings. It's advocating for collaboration between data scientists, medical professionals, and policymakers. Using machine learning to facilitate non-invasive techniques for anemia detection is a new technique in healthcare. It's like an advancement in human life. It's all about revolutionizing the way we diagnose, manage, and monitor anemia. And as technology keeps progressing and we get more and more data, itis going to make millions of lives better. Early detection, personalized treatment, efficient healthcare delivery becomes easy. As a result of our efforts, we have designed a computerized screening test that is noninvasive, easy to use, and affordable. This innovative test is portable and user-friendly, making it accessible for widespread use in developing nations. By offering a practical substitute to invasive techniques for detecting anemia, this screening test has the potential to significantly improve the quality of life for individuals in these regions. Its simplicity and affordability make it a valuable tool in addressing healthcare challenges faced by populations in resource-limited settings. This advancement represents a step forward in providing essential healthcare solutions tailored to the needs of underserved communities.

Keywords: Iron deficiency, anemia, non-invasive, machine learning, image processing, detect, user friendly, healthcare.

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1 Introduction

Anemia, a common worldwide health condition, disproportionately affects vulnerable groups including children and pregnant women. According to the World Health Organization (WHO), anemia affects approximately 37 % of pregnant women and an alarming 40% of children under six years old globally [1]. It is a real problem for approximately 33% of the entire population due to iron deficiency. Early and correct identification of anemia is critical for successful intervention and therapy.

The traditional approach to detecting anemia involves drawing blood to measure hemoglobin levels, an invasive method that can act as a deterrent for individuals seeking regular checkups. Given the severity of anemia and the need for frequent monitoring, developing an accurate and reliable non-invasive method for detecting anemia is essential.

In recent years, the use of machine learning [2] has emerged as a significant tool in healthcare, with promising outcomes in illness detection. This study employs convolutional neural networks (CNN) and Random Forest algorithms for the development of a non-invasive screening test to identify anemia. The application of CNN enables effective extraction of features from conjunctiva pictures, which aids in the detection of anemia-related abnormalities. Random Forest, noted for its collaborative learning technique, exceptional handling when it comes to various datasets and its reliable predictions. By integrating these methods, we hope to improve both the precision and dependability of anemia detection

Studies on non-invasive methods for anemia detection often use mobile phone cameras to capture images of the conjunctiva, which can introduce noise due to varying lighting conditions. In contrast, we adopted a different approach by creating a VR headset-type enclosure device equipped with a camera, LED lights, and a microcontroller. Our aim was to reduce external noise and create a controlled environment, resulting in images with minimal noise and a standardized appearance. This controlled environment will facilitate our algorithm in accurately determining which images indicate anemia and which do not.

The goal of this study was to identify the most effective algorithms for anemia detection and evaluate the effectiveness of the VR headset-like enclosure. Our aim is to integrate both elements to create a device that is accurate and easy to use, thereby contributing to healthcare, promoting awareness about anemia, and eliminating barriers between patients and their checkups. If the study shows positive results, this device could remove the need for syringes, alleviating the fear associated with traditional anemia testing.

The unique contribution of our study lies in our comprehensive approach to anemia detection, which goes beyond merely comparing the accuracy of different algorithms. While existing research predominantly focuses on identifying the most effective algorithms and methods for anemia detection, we took a significant step forward by integrating both software and hardware components to develop a practical, non-invasive device. This device, which we named "HemoScope," leverages machine learning capabilities to analyze images of the ocular palpebral conjunctiva, achieving an accuracy of 98.44%. Our approach not only addresses the limitations of traditional methods but also enhances the reliability and consistency of non-invasive techniques by creating a controlled, noise-free environment for image capture. This integration of hardware and software in a cohesive system represents a novel advancement in the field, providing a tangible solution that bridges the gap between theoretical research and practical application.

This paper consists of V sections. Section II consists of a literature survey. Section III describes the materials and methodology. Section IV consists of results and future scope. We have concluded the research in Section V.

2 Literature Survey

There are multiple research papers demonstrating the effectiveness of machine learning algorithms in detecting anemia.

In a study published in 2023 by Appiahene, P. et al [3] , non- invasive methods utilizing machine learning (ML) algorithms were explored for anemia detection, focusing on palm images as an alternative to conjunctiva images. The methodology consisted of three phases: dataset collection involving palm images, preprocessing including image extraction, augmentation, ROI segmentation, and analysis in the CIELAB color space, and model development using Convolutional Neural Networks (CNN), K-Nearest Neighbors (K-NN), Naive Bayes, Sum, and Decision Tree algorithms. The CNN model was configured with AlexNet architecture, optimized with Stochastic Gradient Descent (SGD), ReLU activation function, regularization (a coefficient of 0.0001), and 10 iterations. Data processing involved converting the ROI into the CIELAB Color space to mimic human visual perception, with criteria set for high ($a^* > 160$) and low ($a^* < 142$) hemoglobin values. Results showed high accuracy with Naive Bayes achieving 99.66%, Sum algorithm 96.39%, and CNN the highest at 99.92%. Image augmentation was highlighted as a key technique, increasing the dataset size from 527 to 2635 images, enhancing model robustness for anemia detection.

Asare, J. W. et al. [4] proposed a study which evaluated machine learning models for iron- deficiency anemia detection using the accuracy, F1-score, AUC, precision, recall, and machine learning models for anemia due to iron deficiency identification were assessed in this work. With an accuracy of 98.96% on the palpable palm, the Naïve Bayes model outperformed the Convolutional Neural Network (CNN) at 99.12%. The Support Vector Machine (SVM) produced the least accurate findings, with 95.34% accuracy. The models' results on the dataset of nail color were comparable. For this purpose, the palm is a reliable anatomical feature of the human body, and the CNN model outperforms Naïve Bayes. To diagnose iron deficiency anemia, the outcome of machine learning models (k-NN, Naïve Bayes Decision Tree, CNN, and SVM) was examined in this study. To train, validate, and test the system, images of the ocular conjunctiva, palpable palms, and nail color were employed. When tested on the photos of the Conjunctiva, palpable palm, and fingernails, the CNN outperformed all the other models in terms of accuracy. Furthermore, when tested using the data set, the palm models performed more accurately than the fingernails and conjunctiva models. As proven by the models' outcomes the palpable palm is one of the most reliable human warning signs of anemia, and CNN is resilient and beats Naïve Bayes, Decision Tree, k- NN, and SVM in this domain.

The authors Jayakody, J. A. D. C. A. et al. [5] used a methodology to train a machine learning algorithm for anemia diagnosis. They used training data from patients diagnosed with anemia and healthy individuals to train the algorithm. The server played a significant captured role in obtaining inputs from these data sets, increasing the chances of accurate results. The algorithm was trained using supervised machine learning, initially feeding the output to the system. After being sorted, the gathered data was utilized to create the algorithm. After that, the computer evaluated the photos of the fingertip and a questionnaire from a mobile app to produce results relating to anemia. By comparing the non-invasive measures with traditional blood samples, HemoSmart was able to demonstrate a linear link between hemoglobin concentration and Hb coefficients. The sampled data's percentage average relative deviation was 0.43%.

In their experiment, Dalvi, P. T. et al. [6] suggested an Ensemble Learning Technique and evaluated classification performance using 10-fold cross- validation. 50 subsets of the dataset were created, with one subset being used for testing and the other 49 for training. Based on the results, it was shown that Artificial Neural Network (ANN) outperformed Decision Tree, Naïve Bayes, and K-NN in the classification of red blood cells (RBCs). The best accuracy, specificity, recall, and precision were notably shown by a stacked classifier that included K-NN and Decision Tree. The classifier ensemble using Decision Tree, K-NN, Naïve Bayes, and ANN combined yielded the best accuracy in voting. In general, stacking performed the best, followed by voting, bagging, Bayesian boosting, and boosting. ANN frequently generated superior outcomes than all other ensemble approaches, followed by Decision Tree and Naïve Bayes, and K-NN.

Tamir, A. et al. [7] proposed a study using RGB thresholding to detect anemia in anemic patients. The white sclera and anterior conjunctiva are extracted, and the RGB spectrum is standardized using the white sclera part's brightness. The red and green color intensities are compared to determine anemia. A threshold value of 1.5 is selected based on previous eye images, indicating a small difference between anemic and non- anemic patients. A Redmi Note 3 pro cell phone was used to take pictures of 19 patients, and the blood report was used to extract the patients' hemoglobin levels. The system accurately anticipated 15 out of 19 values, resulting in an accuracy of almost 78.9%, according to the data. The patients' anterior conjunctival pallor red and green spectrums were then evaluated by the algorithm. The findings demonstrated that non-anemic individuals had a greater intensity of the red spectrum while anemic patients had a greater intensity of the green spectrum relative to red. The patient's condition is then ascertained by the algorithm by averaging the two numbers and comparing them. The patient is classified as non- anemic if there is a difference between the two spectrums that is more than the threshold value.

The study proposed by Prakriti, D. et al. [8] aims to predict anemia in children under 5 years using classifier algorithms. Experiments were conducted on unbalanced and balanced datasets. Random Forest achieved 98.4% accuracy for unbalanced data. Ensemble learning methods like Stacking and Bagging improved accuracy to 98.8%. Stacking Random Forest with SVM, Naïve Bayes, Logistic Regression achieved accuracy of 98.7% and Extreme Gradient Boosting led to 99% accuracy. Other ensemble methods did not show significant improvement.

Roychowdhury, S. et al. [9] conducted a study utilizing concentrated facial pallor site photos. Their research focuses on employing image-based techniques for feature extraction, categorization, and data modelling to screen and classify anemia-like pallor. The research highlights the significance of spatial Regions with Interest (ROIs) and features based on picture intensity in differentiating between normal and aberrant images. The inner tongue and conjunctiva regions of the eye are important for distinguishing between normal and aberrant images. The technique can test anemia severity utilizing face pallor site photos, as evidenced by its 86% screening accuracy for eye images and 98% screening accuracy for tongue images.

Mahmud, S. et al. [10] proposed a study evaluating machine learning models for iron-deficiency anemia detection using various metrics, including accuracy, F1-score, AUC, precision, and recall. The study assessed models like Naïve Bayes, Convolutional Neural Network (CNN), and Support Vector Machine (SVM) for identifying anemia due to iron deficiency. The Naïve Bayes model achieved 98.96% accuracy on palpable palm images, slightly lower than the CNN at 99.12%, while the SVM had the lowest accuracy at 95.34%. The models showed similar results on the nail color dataset, with the palm being a reliable anatomical feature. The CNN model outperformed Naïve Bayes in terms of accuracy on conjunctiva, palpable palm, and fingernail images. The study concluded that the palpable palm is a reliable indicator of anemia, and CNN outperforms Naïve Bayes, Decision Tree, k-NN, and SVM in this domain.

In the study "Estimate of Anemia with New Non-Invasive Systems—A Moment of Reflection," [11] various non-invasive methods for anemia detection were evaluated. These methods included imaging techniques and machine learning models. The study emphasized the need for non- invasive, accessible, and reliable anemia detection methods due to the limitations and discomfort associated with traditional invasive techniques. The authors highlighted the potential of using imaging techniques, such as analyzing the palpebral conjunctiva and nail bed, combined with machine learning algorithms to improve the accuracy and efficiency of anemia detection. The study concluded that further research is necessary to refine these non-invasive techniques and validate their effectiveness in diverse populations.

Aggarwal, A. K. et al. (2014) [12] conducted a study to validate the use of palmar pallor for diagnosing anemia among children aged 6-59 months in North India. The study aimed to test the accuracy and interobserver reliability of this clinical sign in a different setting than previous studies, which were mostly conducted in Africa. In a sample of 80 children, hemoglobin levels were measured, and two examiners assessed palmar pallor. The results showed that the sensitivity of palmar pallor for detecting anemia was low, ranging from 30.8% to 47%, while the specificity ranged from 60% to 89%. The interobserver agreement was moderate (Kappa = 0.48), improving slightly when severe and mild pallor were combined (Kappa = 0.51). The study concluded that while palmar pallor has moderate specificity, its low sensitivity necessitates further follow-up for accurate anemia detection. This suggests that palmar pallor can be a useful initial screening tool but should not be solely relied upon for diagnosing anemia in children.

3 Materials and Methodology

3.1 Schematic Design

Following is the functional schematic of the complete Project:

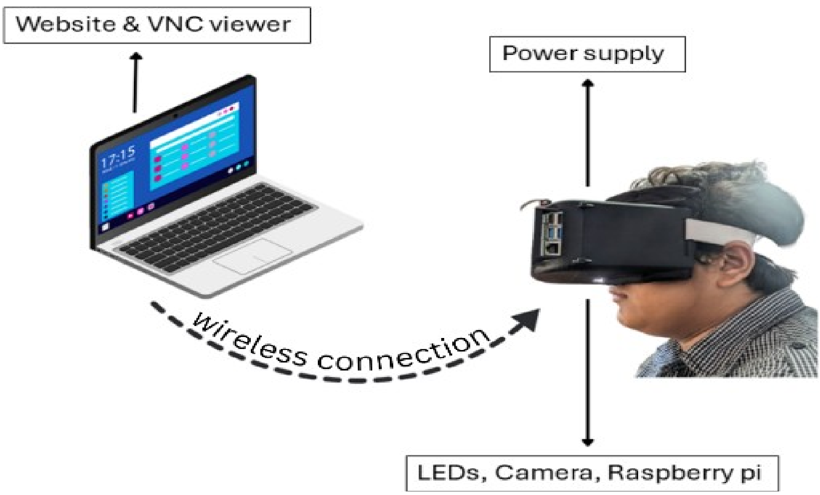

Figure 1. Schematic Design

In this setup (Figure 1), the camera is connected to the microcontroller to capture the image when needed. The microcontroller is connected to the laptop through VNC viewer. VNC viewer is used to wirelessly connect to the microcontroller. After capturing the image of the conjunctiva, Image gets saved in the local storage. To test whether its anemic or not, the image must be uploaded on the website, which we named “HemoScope”, after which the machine learning algorithms classifies and gives the result.

3.2 System Architecture

The proposed system architecture (Figure 2) for improving anemia detection is divided into two sections: hardware and software.

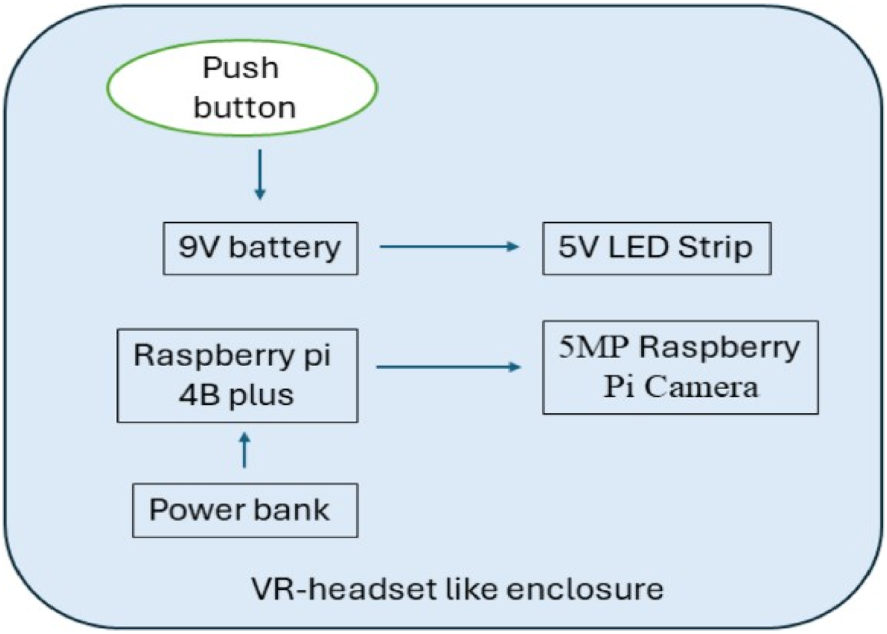

Figure 2. Hardware Section

Hardware Section

- **3D Printed VR-like Headset:** Designed to provide a stable and controlled environment for capturing images.
- **Raspberry Pi 4B Plus:** Used as the microcontroller for processing and control tasks.
- **5MP Raspberry Pi Camera:** Utilized for capturing high-quality images of the eye conjunctiva.
- **5V LED Strip:** Ensures proper illumination during image capture to improve image quality and consistency.
- **9V battery:** Used as a power supply for LED strip.
- **Push switch:** To turn on and off the LED when required.

Software Section

The software used for image analysis, as detailed in Figure 3, played a crucial role in processing the conjunctival images for our study.

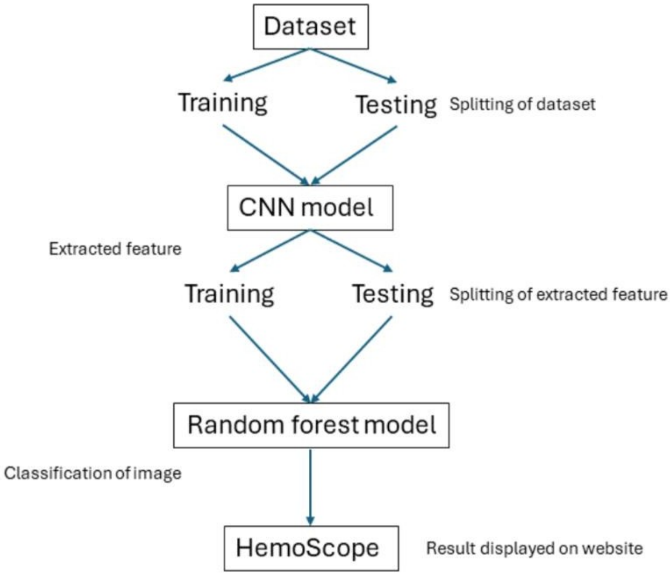

Figure 3. Software section

- **Dataset:** Contains images of anemic and non- anemic eye conjunctiva, which are used for training and testing machine learning models.
- **CNN Model:** Employed for feature extraction from the captured images, leveraging its ability to automatically learn and identify relevant features.
- **Random Forest Classifier:** Used for classification, distinguishing between anemic and non-anemic images based on the features extracted by the CNN model.
- **HemoScope:** Website hosted locally, where our model was deployed, to provide a front end for user to upload image, to test whether they're anemic or not.

3.3 Design Considerations of VR-Headset

In this section, the process of creating a VR-headset type enclosure device, specifically to detect anemia, is discussed. The following parts will elaborate on the technique, technological concerns and design complexities of the same.

- **Selecting Microcontroller for Headset:** It was important to take aspects like availability, connectivity, processing power and compatibility of the microcontroller into consideration. After going through multiple options, we chose Raspberry pi 4B plus which was easily available for us, wireless connection and control was possible using VNC viewer, high performance and camera module was also easily available for this microcontroller.

- **Camera Selection:** The main goal in selecting a camera, which is to be installed into the VR-headset, is to capturean accurate and clear image of conjunctiva, to be portable and flexible enough for installationand compatible with the microcontroller. Following is the list of the types of camera modulesthat were considered:
  a) Infrared camera
  b) Cell Phone camera
  c) Web camera
  d) Raspberry pi 4B plus camera module

As our dataset contained images from a normal camera, and not infrared camera, the first option was rejected. The second option was not compatible with the aim of our project and thus it was rejected. Normal web cameras are not portable enough to be installed in a VR- headset type device.
Finally, the fourth option, i.e. Raspberry pi 4B plus, was chosen to be installed on our device.

- **Considerations for Appropriate Lighting:** To obtain an accurate picture of the conjunctiva for detailed imaging, key considerations when selecting a light strip for the VR-headset included flexibility, luminosity, hue accuracy, visibility, eliminating discomfort, delivering accurate illumination, compatibility with VR environment, and convenience of integration. Following are the considerations:
  a) Luminosity of light
  b) Hue of light
  c) The separation between the eyes and light strip
  d) Low heat emission

  In applications such as conjunctiva examination, cold white LEDs provide a high temperature of color and produce a bright, crisp illumination that facilitates the visibility of minor physiological indications. These LEDs' cold white light helps to accurately show color fluctuations, which is important for identifying any anemia indications. Their capacity to adjust to different color temperatures guarantees that the lighting may be adjusted to maximize the accuracy of the diagnostics. LEDs' efficient and low-heat properties enhance users' overall comfort during prolonged test session, which is crucial for applications in healthcare vital for medical applications requiring in-depth, targeted analysis.

  The strategic integration of cool white LEDs was in line with our objectives. Thus, a 12V Cold White LED strip was selected after taking these variables into account.

- **Construction of the Headset:** To create a headset (Figure 4), that is suitable for Our task of housing Raspberry pi, camera and LED light, no prebuilt VR or similar headset would've worked so we had to opt for a custom 3D-printed headset. The printing was done in a local shop with payment based on weight and the material used was PLA. The final product was a sturdy and reliable enclosure, which was able to house all our hardware components. The filament used was white in color and hence we had to spray paint it black so that there was no external interference.

Figure 4. 3D printed headset

- **Algorithm to detect anemia:** The step-by-step process of our anemia detection algorithm is illustrated in Figure 5, highlighting the key stages from image preprocessing to final diagnosis.

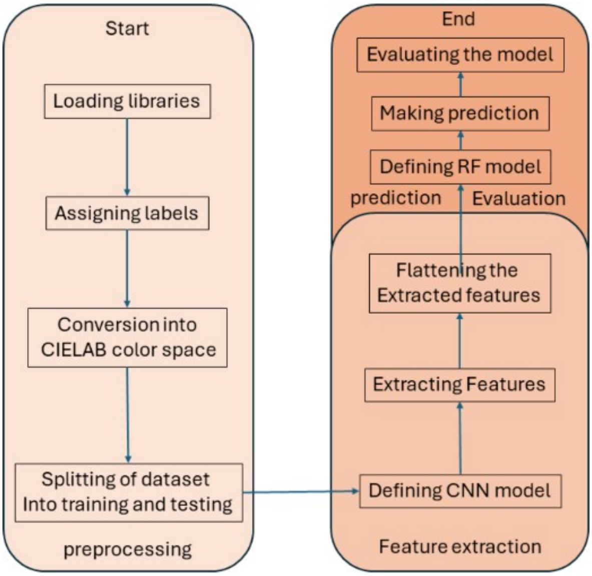

Figure 5. Algorithm to detect anemia

a) **Dataset Acquisition:** To train our algorithm, we first needed a dataset containing eye conjunctiva images. We obtained through Mendeley [13], trained Biomedical scientists in Ghana captured conjunctival images from children aged 6-59 months using electronic instruments and mobile tablets.
The images were taken in ambient natural light, with spotlights turned off to prevent excessive shine effects. The ROI of the conjunctiva was extracted using the triangle thresholding algorithm and entropy grayscale image algorithm.

b) **Preprocessing:** While we were going through all the research papers that we collected from various online journals, we came across a paper by Appiahene, P. et al. [3], and other co-authors. In their paper they achieved high accuracy with their algorithms, which they attributed to the fact that they converted their image from RGB color space to CIELAB color space. Of the total of 10 papers that we researched only these two papers, from same authors, had this step in their preprocessing stage. While we tried running our algorithm without changing the color space, the best result was obtained after we added this in our preprocessing stage (and after integration of two models).

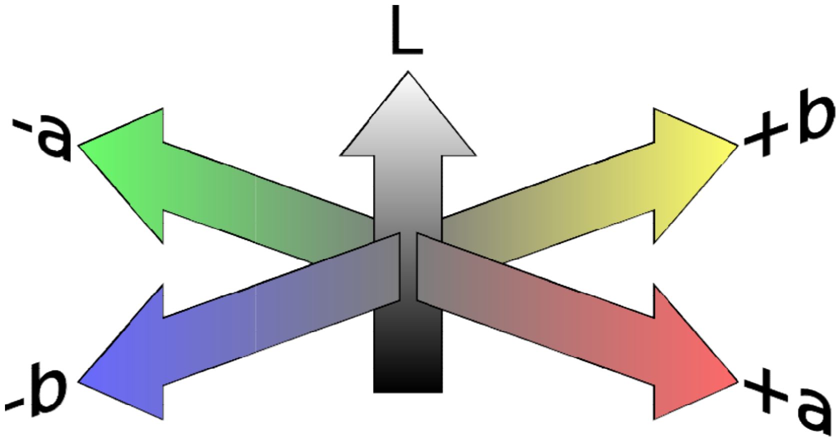

Figure 6. Representation of CIELAB color space

The CIELAB (Figure 6) and RGB color spaces serve different purposes in color representation and manipulation. The RGB color space is an additive model using red, green, and blue light to create colors, primarily for digital displays and imaging devices. Each color is defined by a triplet value indicating the intensity of the red, green, and blue components. In contrast, the CIELAB color space, which is perceptually uniform, is designed to be more aligned with human vision. It includesthree components: L* (lightness), a* (green to red), and b* (blue to yellow). Unlike RGB, CIELAB is device-independent, meaning it provides consistent color representation across different devices and lighting conditions. This makes CIELABparticularly useful in industries requiring precise color matching, such as printing and textile manufacturing.

c) **Feature extraction, prediction and evaluation:** During our research we came across many papers discussing the effectiveness of various algorithms for detection of anemia. Even after converting our color space the result was not satisfactory. Until we came across the paper from P.T. Dalvi, and other coauthors, the idea of utilizing ensemble learning to improve the accuracy ofthe model came into picture. Upon learning about this approach, we tried different combinations of algorithms to see which combination works best in our case. Whichturned out to be the combination of Convolutional neural network and Random Forest.

1) **Feature Extraction:** algorithms for detection of anemia. Even after converting our color space the result was not satisfactory. Until we came across the paper from P.T. Dalvi, and other coauthors, the idea of utilizing ensemble learning to improve the accuracy of the model came into picture. Upon learning about this approach, we tried different combinations of algorithms to see which combination works best in our case. Which turned out to be the combination of Convolutional neural network and Random Forest.

2) **Prediction:** The Random Forest algorithm was selected for classification because of its robustness and effectiveness in handling high- dimensional data. RF is an ensemble learning method that combines multiple decision trees to improve predictive accuracy and control over-fitting. By integrating CNN for feature extractionand RF for classification, we leverage the strengths of both models.

3) **Evaluation:** To further enhance the reliability of our classification results, we employed 10-fold cross-validation. This technique ensures that the model is evaluated on different subsets of the data, providing a more comprehensive assessment of its performance and reducing the risk of overfitting.

4 Results & Future Scope

A dataset containing 4000 images of the ocular Palpebral conjunctiva from Ghana was fed into our machine learning algorithms. The proportion was: 60% of the images were labelled anemia and the remaining 40% was non anemic. Following is the list of machine learning algorithms we compared:

- CNN
- VGG16 & RF
- XGBoost
- Logistic regression
- CNN & RF

The performance comparison of the different machine learning algorithms we used, including CNN, VGG16 & RF, XGBoost, Logistic Regression, and CNN & RF, (is illustrated in Figure 7).

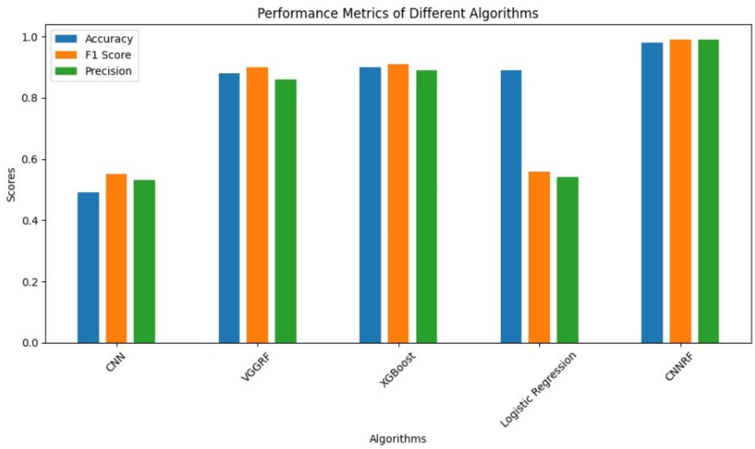

Figure 7. Comparison of different algorithm

After testing five alternative algorithms VGG16 and Random Forest, CNN, XGBoost, Logic Regression, and Convolutional Neural Network with Random Forest using the metrics of accuracy, F1 score, precision, and it was discovered that CNN in conjunction with Random Forest had the highest accuracy of 98.44 % as shown in the above graph along with the highest F1 score and precision accuracy of CNN being the lowest with 49%. Logistic Regression had accuracy of 89% but the F1 score, and Precision was relatively very low. VGG+RF had an accuracy of 88.53% and XGBoost had 90.48% both had high F1 score and precision too.

Thus, we chose CNN and RF as our model for anemia detection. Following the model development and selection process, we proceeded to hardware integration. We deployed this model locally, naming it "HemoScope," marking the completion of our product development phase.

For validation, we tested the HemoScope on 7 volunteers for anemia screening. All of them had to go through the traditional approach, namely CBC test. Later the test report was used to verify the outcome of our algorithm. Remarkably, all 7 test results were accurate, demonstrating the effectiveness and reliability of our system. The validation results, presented in the table 1 below, demonstrate that our HemoScope system accurately identified anemia in all 7 volunteers, matching the outcomes of the traditional CBC tests.

Table 1. Validation Results of the HemoScope System Compared to Traditional CBC Tests

Patient number	Age	Hemoglobin level Less than the std, Meaning 'Anemia'	Outcome of our algorithm
1	21	Non-anemic	Non-anemic
2	22	Non-anemic	Non-anemic
3	21	Non-anemic	Non-anemic
4	22	Non-anemic	Non-anemic
5	42	Non-anemic	Non-anemic
6	44	Non-anemic	Non-anemic
7	47	Anemic	Anemic

After completion of our project, we were able to deduce two shortcomings, which we propose as future scope for this project. Following are the shortcomings:

- **Lack of Indian Dataset:** As the geographical location changes so does an individual's physical features. While researching for local dataset, containing images of Indians, we found there aren't any. As such, we had no other option than to use dataset from Ghana. We propose this as a future scope for other researchers or health specialists etc. To incorporate the idea of VR- headset type device to create a dataset containing images of ocular Palpebral conjunctiva for India.

- **Lack of Validation:** We validated our proposed model and device on 7 volunteers and got 100% accurate results. But the size is too small, due to our lack of resources, as this was our final year project, we were not able to validate our project on a large and diverse set of volunteers. We propose this as a future scope for other researchers or health specialists etc. To validate this approach, after creating an Indian dataset, on large and diverse set of volunteers.

5 Conclusion

We successfully introduced a novel device-based approach that leverages machine learning capabilities to detect anemia non-invasively using images of the ocular palpebral conjunctiva, achieving an impressive accuracy of 98.44%. While numerous studies compare different algorithms and techniques to determine the most effective ones, there is a notable gap in research on integrating these algorithms with hardware components to create a practical device. Our approach not only overcomes the barriers of traditional methods but also addresses the limitations of modern non-invasive techniques by creating a controlled environment that minimizes noise in the captured images.

Despite our success, we acknowledge certain shortcomings, including the absence of a dataset of Indian origin and a relatively small validation sample size. However, our promising results highlight the potential of this novel approach and underscore the importance of developing comprehensive products that integrate advanced technologies to enhance healthcare. Our work encourages further exploration and development in this field to improve healthcare systems globally, ensuring more accurate and accessible anemia detection methods.

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