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Implementation Of Deep Learning Approach For Anemia Detection Using Palpebral Conjunctival Images

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Abstract
Anemia is a prevalent health condition normally diagnosed using invasive blood tests. This work presents a deep learning-based, non-invasive approach to anemia detection using conjunctival images. A convolutional neural network (CNN) learns deep features after preprocessing methods such as normalization and contrast stretching are applied. The model is trained and tested on labeled conjunctival images with related haemoglobin (Hb) values. Performance is assessed by means of metrics such as mean absolute error (MAE), root mean square error (RMSE), and Pearson correlation coefficient (R^2). High accuracy in Hb estimation is revealed through results, showing high correlation with laboratory findings. The method provides a quick, low-cost option for standard blood testing, especially in resource-constrained environments. Early anemia diagnosis is facilitated without the use of specialized laboratory facilities. Future studies will concentrate on increasing the dataset, enhancing model generalization, and incorporating the system into a mobile-based diagnostic application to make it more accessible.
Keywords: Anemia; Deep learning; Non-invasive diagnosis; Palpebral conjunctiva

1. INTRODUCTION
Anemia is a widespread haematological disorder affecting billions of people worldwide, particularly in low-income and developing countries where healthcare infrastructure is limited. It is primarily characterized by a deficiency in red blood cells (RBCs) or a reduced Hb concentration, leading to impaired oxygen transport and systemic fatigue, weakness, and cognitive impairments. The condition disproportionately affects pregnant women, young children, and individuals suffering from chronic diseases [1]. Hb estimation is critical for diagnosing anemia, with traditional methods relying on invasive blood tests conducted in well-equipped laboratories. However, these methods pose significant challenges, including high costs, time delays, requirement of skilled personnel, and limited accessibility in remote areas. The increasing adoption of artificial intelligence in healthcare has paved the way for novel, non-invasive diagnostic techniques that can offer rapid, cost-effective, and accessible solutions. By leveraging deep learning techniques, it is possible to develop a robust system for anemia detection and Hb level estimation using medical images, such as conjunctiva images [2].
Despite the growing prevalence of anemia, its diagnosis remains reliant on invasive and resource-intensive blood tests, which are not readily available to underserved populations. Traditional methods such as complete blood count (CBC) analysis require venipuncture, specialized equipment, and trained personnel, creating barriers to frequent screening and early detection. In resource-limited settings, delays in diagnosis often lead to severe health complications, including increased morbidity and mortality rates, particularly among vulnerable groups [3]. Recent advancements in computer vision and deep learning provide a unique opportunity to address these challenges by automating anemia detection using medical images. However, existing studies on AI-based anemia

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detection often suffer from limitations such as small datasets, lack of standardization, and inadequate validation in diverse populations [4]. This study aims to bridge this gap by developing an accurate, scalable, and non-invasive deep learning model for detecting anemia and estimating Hb levels from conjunctival images, thereby improving accessibility to early diagnosis and treatment. Figure 1 illustrates the causes of anemia listed by the World Health Organization (WHO).

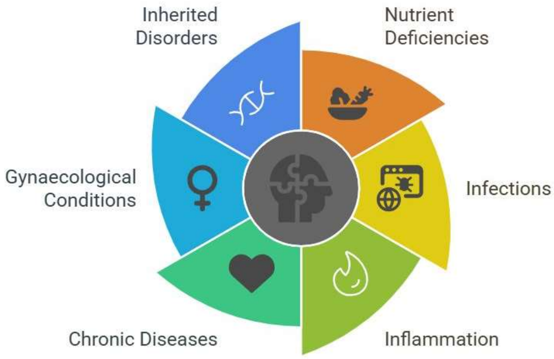

FIGURE 1. Causes of anemia listed by WHO

The overall goal of this research work is to develop and implement a deep learning-based system capable of detecting anemia and estimating Hb levels from conjunctival images. To do so, the study targets a few primary goals: (1) acquiring and preprocessing a multiclass dataset of medical images such as conjunctiva, fingernail bed, and retinal images; (2) constructing a deep learning model in the form of CNN to classify anemic and non-anemic cases from image features; (3) creating a regression-based deep learning model to estimate Hb levels with negligible errors; (4) measuring the performance of the model by applying conventional parameters such as accuracy, sensitivity, specificity, and mean absolute error (MAE); and (5) comparing various deep learning architectures to identify the most efficient method for practical implementation [5]. This study seeks to offer an affordable and scalable diagnostic solution that can be adapted for use in mobile health apps, telemedicine, and medical workflows.

This research is important because it fills a vital gap in anemia screening by offering a non-invasive, AI-based diagnostic tool that can be made widely available, especially in resource-poor environments. By avoiding the requirement for invasive blood draws, this method improves patient comfort, lowers healthcare expenses, and allows for large-scale screening initiatives. The use of deep learning models in anemia detection has numerous benefits, such as quick diagnosis, high accuracy, and analysis of large amounts of data with minimal human interference [6]. The study also makes a significant contribution to AI in healthcare at large by propelling the use of deep learning in medical image analysis. Moreover, the creation of a precise and effective Hb estimation model can assist healthcare workers in tracking anemia development and treatment efficacy, ultimately enhancing patient outcomes and lowering anemia-related mortality rates.

2. RELATED WORKS

In this study focuses on image-based modalities for anemia detection, utilizing deep learning techniques for analysis. As a result, we have reviewed existing research that explores non-invasive, image-based methods for diagnosing anemia. Previous studies have explored different anatomical regions, such as conjunctiva, palm, fingernails and lips for anemia prediction and Hb level estimation. These approaches have incorporated machine learning and deep learning models, including CNN, ResNet, MobileNet and transfer learning-based models to improve predictive accuracy. Here, we mention some existing works related to image-based anemia detection.

Jain et al. (2020) explored non-invasive anemia detection through conjunctiva image analysis. The study utilized ANN for classification, incorporating computer vision techniques for preprocessing and feature extraction. Data augmentation was applied to enhance model generalization and

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improve performance. The ANN model was refined using backpropagation and hyperparameter tuning [7].

Rahatara Ferdousil et al. (2022) used CNN and Local Interpretable Model-agnostic Explanations (LIME) to classify anemia using conjunctiva pallor images from real subjects. The model employed convolutional and pooling layers with specified kernel size, utilizing categorical cross-entropy as the loss function. The challenges included an insufficient dataset, reliance on transfer learning (YOLO) due to limited original data and the absence of bounding box labeling which could affect the prediction accuracy. Future improvements should focus on enhancing dataset quality and refining model optimization [8].

Endah Purwanti et al. (2023) developed the CNN models to classify anemia using eye, palpebral conjunctiva and forniceal conjunctival images with ResNet50 that model achieved F1- score of 0.52 for anemia condition and 0.54 for the normal condition. The authors suggested that future work should explore image enhancement techniques to improve classification performance [9].

Peter Appiahene et al. (2023) conducted a comparative study of anemia detection using medical images of the palm. The study utilized multiple ML and DL models like CNN, Naïve Bayes, KNN, SVM and Decision Tree. And also, this analysis evaluated classification performance to determine the most effective approach. However, the results were indicating the importance of palm image analysis for anemia detection [10].

Shekhar Mahmud et al. (2023) utilized anemia detection using lip mucosa images with transfer learning and CNN models including VGG16, Xception, MobileNet and ResNet50. The dataset categorized into healthy and anemic with preprocessing and data augmentation applied before classification. The Xception model achieved high accuracy of 99.28% then the future work will focus on implement online classification and anemia detection via mobile application [11].

Justice et al. (2023) analyzed non-invasive anemia detection using images of the conjunctiva, palm and fingernails. The study compared various ML models such as CNN, SVM, Naïve Bayes, KNN and Decision Tree to assess their classification performance. The results finding the effectiveness of image-based methods for identifying iron deficiency anemia. Future work may focus on enhancing model accuracy and reliability [12].

Xiao-yan Hu et al. (2023) proposed a model integrating with Mask R-CNN and MobileNetv3 to estimate Hb concentration from smartphone-captured eye images. The model achieved an R^2 of 0.503 and an MAE of 1.6 g/dL, demonstrating reliable accuracy without requiring manual image selection. However, its applicability may be limited due to a small dataset of 1065 images. The reliance on controlled lighting conditions and a specific smartphone may also limit broader applicability [13].

3.METHODOLOGY AND EXPERIMENTAL DESIGN

3.1 Overview of Methodology

Loading image data is the initial process in the deep learning approach to anemia detection. Pre-processing techniques like scaling and normalization are employed to enhance the quality of the images. Data augmentation is employed to increase the dataset and improve model generalization. Subsequently, features are extracted using a trained deep learning model and labelled data. Accuracy and precision are some of the performance measures that are utilized to evaluate the trained model. Finally, the prediction model provides a non-invasive way of identifying anemia by predicting Hb (Hb) levels and categorizing individuals as normal or anemic [14]. The Figure 2 represents the block diagram of deep learning model which is used for Hb estimation.

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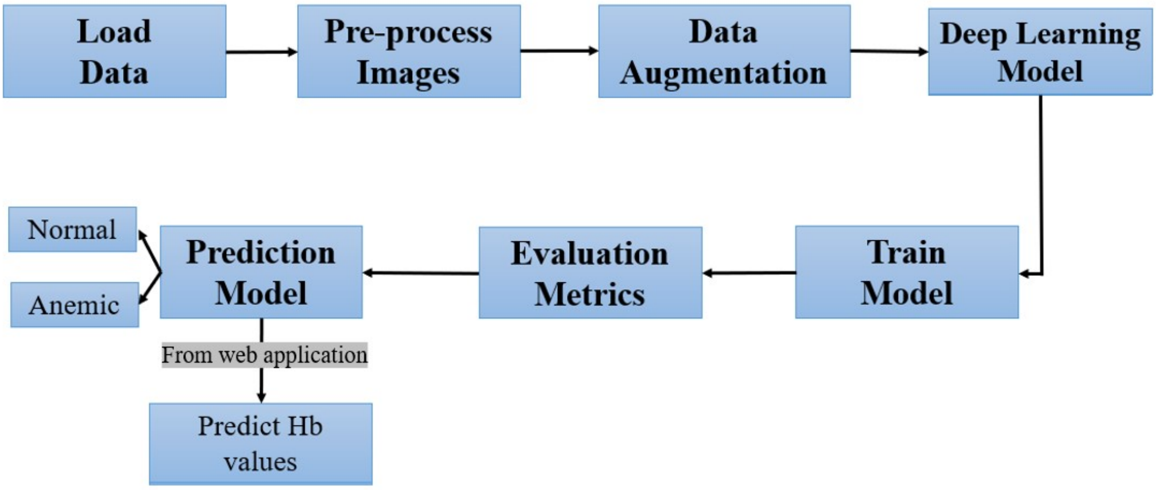

FIGURE 2. Block diagram of the Proposed Methodology

3.2 Dataset Description

The research dataset consisted of 217 photos of the palpebral conjunctiva from both anemic and non-anemic patients, which were openly accessible on Kaggle. The dataset was divided into two folders: Italy and India, containing 122 and 95 images, respectively. Each dataset was accompanied by an Excel file that included patient information, such as demographic details (age and sex) and medical data, including Hb (Hb) concentration levels measured in g/dL based on blood count. Additionally, 20 conjunctival images, along with their corresponding Hb values, were collected from subjects by obtaining ethical consent. These images were manually segmented and used for validating the deep learning model. The data collection process was carried out using an iPhone, which served as the primary device for capturing relevant data [15]. The iPhone 15 Pro was chosen due to its high-resolution camera, advanced image processing capabilities, and consistent performance, ensuring reliable and accurate data acquisition. We used a value of Hb concentration of 10.5 g/dL to determine whether a patient was anemic or not. Specifically, we considered individuals as being anemic when their Hb concentrations were <= 10.5 g/dL, and as nonanemic when their values were >= 10.5 g/dL. According to that, 65 and 111 anemic patients and 30 and 12 non-anemic patients, respectively, were added to Indian and Italian patient eye image datasets.

3.3 Image Augmentation

To achieve higher accuracy, deep learning model requires large amount of data. The images available are augmented by various techniques such as flipping, rotation, zooming, translation and shifting. Table 1 corresponds to the number of images present before and after applying augmentation techniques.

Table 1. Dataset before and after applying augmentation techniques

Dataset	Normal	Anemic	Total
Images before Augmentation	175	42	217
Images after Augmentation	1050	252	1302

Post image augmentation, the dataset is split randomly into training and testing. Out of which 80% of the total data is included in training dataset and 20% of the total dataset is included in testing dataset.

3.4 Implementing Deep Learning Frameworks

To develop a dependable and accurate method for non-invasive anemia detection, we used Xception as a basis model and an ensemble deep learning approach that combined ResNet50 and

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DenseNet121. By using the benefits of many CNN models, this architecture aimed to enhance feature extraction and predictive performance. By combining these models, our approach ensures a more comprehensive analysis of conjunctival images, improving the accuracy of Hb level estimation and classification. Figure 3 represents a DL based architecture for Hb level prediction from conjunctiva images.

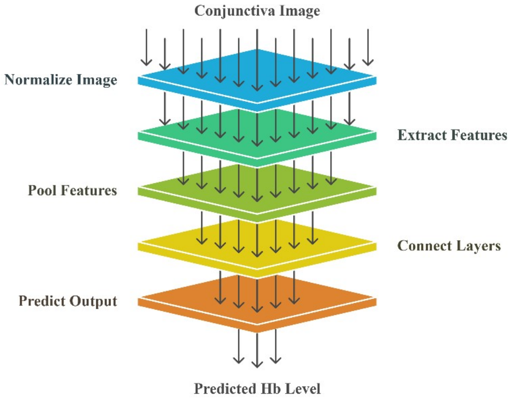

FIGURE 3. Information Network Architecture for Hb Level Prediction

In order to learn high-level patterns in conjunctival pictures, Xception was used as the basic model for the feature extraction procedure. For medical picture analysis, Xception was the best option because of its depthwise separable convolutions, which reduced computational cost and enabled effective feature learning. As a result, the model was better able to discern between anemic and non-anemic cases by capturing fine-grained information from input photos.

We used an ensemble learning approach, combining ResNet50 and DenseNet121, to further hone the extracted features. The vanishing gradient issue was lessened by ResNet50's residual learning methodology, which guaranteed consistent training across deep networks. On the other hand, DenseNet121's densely connected layers boosted gradient flow and feature reuse, which improved model performance and generalization.

3.5 Evaluation metrics

The performance of this regression model is evaluated by metrics such as Mean Square Error (MSE), Root Mean Square Error (RMSE) and Pearson's Correlation Coefficient (PCC).

MSE: MSE is a metric that measures the average squared difference between actual and predicted values in a regression model. Smaller MSE value indicates better model performance. Since it squares the errors, it gives more weight to large errors, making it sensitive to outliers. It is commonly used as a loss function in regression models for both ML and DL. $MSE = \frac{1}{m}\left(\sum(y-\hat{y})^2\right)$ Eq. (1)

where y is the actual Hb value, $\hat{y}$ is the predicted Hb value and m refers to the number of samples.

RMSE: RMSE is the square root of MSE, providing an error measure in the same unit as the target variable. It evaluates the model's accuracy by penalizing large errors more than small ones. RMSE penalizes large errors more than MSE, making it more sensitive to significant deviations. It is easier to interpret than MSE since it has the same unit as the target variable. A lower RMSE indicates a more accurate and better-performing model.

$$RMSE = \sqrt{\frac{1}{m}\left(\sum(y-\hat{y})^2\right)} \qquad \text{Eq. (2)}$$

PCC: PCC measures the linear correlation between actual and predicted Hb values, ranging from -1 to 1. A value closer to ±1 indicates a strong correlation, while 0 means no correlation. Higher absolute values of PCC (closer to ±1) indicate better model performance and it is commonly used in regression tasks and time series forecasting.

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4. RESULTS AND DISCUSSION

The proposed deep learning for non-invasive anemia detection was assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Pearson Correlation Coefficient (PCC). Table 2 provides analysis of the results obtained by the ensembled deep learning model. MAE is 0.72g/dL, this value indicates the predicted Hb values are deviate by an average of 1.43g/dL from actual values. The RMSE of 0.93g/dL suggests a moderate level of prediction errors, while a PCC of 0.93 demonstrates the strong positive linear relationship between the predicted and actual Hb values. The model was trained using ensemble learning approach integrating ResNet50 and DenseNet121 with Xception as the base model for the purpose of feature extraction. The dataset initially contains 217 conjunctival images but after using the data augmentation techniques we expanded into 1302 images for enhancing generalization and model robustness. The model was trained for 10 epochs, during the validation loss decreased from 13.66 to 6.62 it indicates the stable learning and accurate prediction. These results highlight the model effectiveness as a non-invasive tool for anemia detection that is used to alternate method for traditional blood tests.

A web-based application was designed to facilitate non-invasive anemia detection using the trained deep learning model. The platform allows users to upload eye conjunctiva images and the system accurately estimates Hb levels in real time. This implementation enhances remote healthcare and telemedicine offering a convenient approach to anemia screening. Figure 4. represents the images of the webpage which is developed for the visualization of the Hb value.

Table 2. Evaluation metrics of ensemble model

Metrics	Training	Testing
Mean Absolute Error (MAE)	0.72	1.43
Root Mean Squared Error (RMSE)	0.93	1.81
Pearson Correlation Coefficient (PCC)	0.93	0.28

FIGURE 4. Result produced by the user-friendly webpage

5. CONCLUSION

Anemia is a widespread global health issue caused by nutritional deficiencies, chronic diseases, and genetic disorders, affecting millions of people worldwide. This study presented an ensemble deep learning model for Hb level prediction, demonstrating strong training performance but facing challenges in generalization. The observed performance gap between training and validation highlights the issue of overfitting, which needs to be mitigated through techniques such as enhanced regularization, improved data augmentation, and leveraging transfer learning. Additionally, addressing dataset imbalances and refining feature extraction can help enhance model robustness. This research encounters few challenges, including overfitting as indicated by the performance gap

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between training and validation, which affects the model's generalizability. The limited dataset size restricts the model's performance to capture diverse features, while the imbalance between anemia and non-anemia datasets may introduce biases in classification. Furthermore, the lack of comprehensive clinical validation using real-time patient data raises concerns about the model's applicability and reliability in healthcare settings. Advanced image preprocessing techniques should be added to improve image quality, minimize inconsistencies caused by lighting fluctuations, and improve feature extraction for more accurate detection.

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