AN INTERPRETABLE MACHINE LEARNING FRAMEWORK FOR TRANSPARENT ANAEMIA DETECTION

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***Abstract*— Anemia is a common medical condition that needs to be promptly diagnosed to avoid complications. Generally, hemoglobin testing is performed using laboratory testing and invasive blood sampling, which can be difficult to access often in remote and resource-limited settings. This project aims to present a Smart Anemia Detection system based on AI and the image of the fingernail to estimate the Hemoglobin concentration without taking a blood sample. The framework introduces sophisticated image preprocessing techniques like nail segmentation, illumination correction, color normalization and contrast enhancement to improve image quality and minimise variations related to different lighting scenarios. The power of deep learning is combined with machine learning algorithms to give more reliable results for prediction of hemoglobin and for classification of anemia severity. The web application developed in flask allows the user to upload fingernail images, get instant screening results, access the prediction history, and receive individual dietary recommendations and an admin module for managing the dataset and monitoring the models. The proposed solution will offer an effective preliminary screening tool that is quick, cost-efficient, and easy to use, thus improving the accessibility of healthcare for underserved populations. While not a substitute for laboratory diagnosis, the system can be used as a valuable clinical decision support tool to identify those patients who are at an early stage of anemia and prompt adequate medical referral. The use of computer vision and AI shows great promise for scalable, non-invasive healthcare screening and real-time monitoring in clinical and non-clinical settings.**

Keywords— Non-invasive Anemia Detection, Hemoglobin Estimation, Deep Learning, Computer Vision, Fingernail Image Analysis, Flask Web Application.

I. INTRODUCTION

Anemia is one of the most common public health diseases in the world, impacting all age groups and especially children, pregnant women, adolescents and older adults. Mainly due to a lack of hemoglobin (an oxygen carrying protein in red blood cells) which prevents the transport of oxygen to the body tissues. It is often caused by iron deficiency, nutritional imbalance, chronic diseases, genetic disorders or blood loss. Without diagnosis, anemia may cause fatigue, poor physical performance, poor mental function, poor immunity, pregnancy complications and death. World Health Reports indicate that millions of people still suffer from anaemia, particularly in developing areas where health care provisions and laboratory facilities are not very well developed. Hence, early detection of anemia with simple, easy-to-perform screening tests has become a health care goal.

Traditional diagnosis of anemia is largely based on lab analysis of blood samples taken through invasive methods and analyzed on a hematology analyzer. These methods can give accurate measures of hemoglobin, but need trained health care workers, special laboratory equipment and medical structure. In addition, blood collection can result in stress, pain and unwillingness from patients, especially children and elderly people. Additionally, the price and lack of diagnostic facilities in rural and less serviced areas prevents regular health monitoring. These practical constraints reflect the need for other screening methods that are low-cost, quick, non-invasive and can provide preliminary health screening for large populations.

In recent years, AI and computer vision, along with deep learning, have revolutionized the healthcare industry with their ability to analyze medical images automatically, aiding in the early detection of diseases and assisting clinical decisions. Recent deep learning architectures have shown the power in learning relevant visual patterns that are hard to discover by hand. There have been several studies investigating the use of non-invasive biomarkers such as retinal images, skin color, conjunctiva, tongue and palm and fingernail appearance to estimate physiological conditions. of these, the images of fingernails have received a lot of interest since the color variations in the nail bed relate to blood oxygenation and hemoglobin concentration. AI-driven systems can use image preprocessing methods and intelligent prediction models to provide promising estimation of hemoglobin levels, removing the necessity of invasive blood collection for initial screening.

The proposed Smart Anemia Detection system employs AI for hemoglobin concentration estimation using images obtained from fingers with a typical smartphone camera or webcam. First, some image preprocessing steps are performed on the uploaded image, such as nail region segmentation, illumination correction, RGB color normalization, noise removal and contrast enhancement, to ensure uniformity in visualization and minimize environmental differences. Then, deep learning algorithms can be used to obtain discriminative image features from these images, and machine learning algorithms can be used to classify the severity of anemia according to clinically meaningful categories using these features. The system also calculates the level of confidence and make basic dietary suggestions for the condition predicted. It is an intelligent processing pipe that can provide a preliminary screening process for people who don't have high-level medical equipment and is quick, accurate and easy to use.

The proposed framework is designed as a web application and contains two different modules: one for the users and one for administrators with a separate page each for ease of use, and for continuous health monitoring. The user interface includes secure registration and authentication,

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uploading of images, instant prediction, and historical record management and visualization of past screening results. The administrative module supports maintaining datasets, users, monitoring predictions, and managing AI models, guaranteeing smooth operation of the platform. The web based architecture enables low hardware support environment deployment such as standard computing devices making it ideal for educational, community health centres, rural clinics and tele-medicine applications. The seamless incorporation of intelligent analytics with the user-friendly interface interface further elevates the real-world applicability of the envisioned solution for healthcare services.

The goal of this research is to develop a reliable and/or low-cost and non-invasive anemia screening platform that would assist healthcare workers and people to identify potential anemia early. While the proposed system aims at accessibility and convenience with rapid preliminary assessment, at the same time, the system is optimized for computational efficiency using the image processing, deep learning and machine learning methods instead of conventional diagnosis methods. System might not be able to substitute for standard lab investigations, but will prove useful as a decision-support system to prompt clinical consultation and additional investigations when high-risk conditions are identified. In conclusion, the proposed approach highlights the transformative potential of AI in solving the challenges of scaling up anemia screening efforts, making them more accessible and intelligent, and ultimately, enhancing public health and shaping the future of digital healthcare solutions.

II. LITERATURE SURVEY

However, as the incidence of anemia continues to rise, researchers have turned to non-invasive screening methods that do not require blood samples but have an acceptable diagnostic value. While the standard laboratory method of measuring hemoglobin continues to be the clinical "gold standard," it is challenging to screen for hemoglobin in low-resource settings due to the need of trained staff, specialized equipment and blood collection methods. With the recent advances in artificial intelligence (AI), computer vision and medical image analysis, intelligent healthcare systems have been developed that can extract clinically relevant information from external body images. These technologies have shown great promise in offering the provision of rapid, low-cost and easily accessible preliminary screening solutions, especially in the case of diseases with visible physiological indicators (colour changes in the skin, conjunctiva, tongue, and fingernails). Thus, image-based anemia detection has become an interesting field for research toward early diagnosis and community-based healthcare system applications [1]–[3].

The colour of nails is related to blood perfusion and oxygen transport changes and several researchers have investigated fingernail images as potential visual biomarkers for hemoglobin concentration. An imaging method on a fingernail is so simple that it only requires a regular smartphone camera, making it well suited for mobile health care applications as opposed to imaging the retina or conducting lab tests. In previous work, handcrafted color/descriptor and texture descriptors derived from nail images under controlled lighting conditions were used. For the classification of anemia and estimation of hemoglobin, the usual statistical characteristics of the color, and traditional machine learning techniques such as Support Vector Machines (SVM), Random Forest models and linear regression models are applied. These techniques proved effective, but other issues, including lighting changes, skin color variations, camera quality, and diversity in image acquisition conditions, negatively affected their performance [4]–[6].

The accuracy and robustness of NIDAS have recently gained significant boost from the recent advancements in deep learning. Convolutional Neural Networks (CNNs) can learn the hierarchical representations of images without any prior feature engineering and can learn complex visual features to associate with hemoglobin concentration. The success of MobileNet and EfficientNet, which are both lightweight architectures, has been driven by their high efficiency and prediction accuracy. Transfer learning techniques have also been used to increase the accuracy of the diagnosis, since the knowledge acquired from large-scale image databases is also transferred to the diagnosis of medical images with only a small amount of annotated images needed for training. In numerous comparative studies, it has been shown that deep learning models can achieve higher accuracy, sensitivity, specificity, and generalization ability compared to traditional machine learning models for a variety of patient populations [7]–[10].

The presence of inconsistencies in illumination, shadows, background noise, and color distortions in medical images often negatively affects the accuracy of prediction, necessitating the use of image preprocessing in anemia screening systems as a crucial step. Many studies have taken into account the preprocessing steps before the features are extracted, including Nail Segmentation, Color Normalization, White Balance Correction, Histogram Equalization, Contrast Enhancement, and Noise Filtering. The precise localization of the nail area reduces the amount of irrelevant information and allows learning algorithms to learn only from clinically relevant properties of the image. The use of efficient pre-processing operations in conjunction with deep feature extraction has been shown to significantly boost stability of the prediction results and to make systems more resistant to various camera devices and environmental lighting conditions, which makes them more appropriate for practical use [5, 8, 9].

Recently, Hybrid AI frameworks are drawing attention for bringing together the interpretability and predictive power of traditional ML algorithms and the representation learning power of deep neural networks. These architectures include extracting the high-dimensional discriminative features from the medical image using CNN models, and then regression or classification to estimate (and quantify) hemoglobin concentration and diagnose the severity of anemia. Many comparisons have shown that hybrid models are more resilient, more accurate and better generalizable in moderate size medical datasets compared to single deep learning networks. Additionally, ensemble learning

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approaches, based on multiple classifiers, have been proven to be more reliable and reduce prediction variance and improve sensitivity in identifying cases of mild anemia. The advances under discussion suggest that hybrid models of AI are a viable approach for real-world medical decision-support applications [6, 9, 10].

Another key research direction is the development of web and mobile platforms that enable AI to be used in real-world healthcare settings, rather than just laboratory settings. A few investigators have pointed out the need to combine automated image acquisition, the cloud-based prediction services, patient records management, and real-time decision-support into a single system. These systems make it much easier to access health services and enable patients to do a preliminary health evaluation with their smartphone without needing to put in place a high-level medical system. Recent studies have also proposed to integrate explainable AI approaches, confidence estimation, multilingual interface, dietary guidance, and telemedicine integration to enhance the trust of the user and the clinical usability. Although significant advances have been made in non-invasive hemoglobin estimation, there are still a number of areas that require further research such as restricted dataset diversity, demographic bias, limited illumination, and external clinical validation. Addressing these challenges will enable the development of reliable, scalable and clinically deployable AI assisted anemia screening systems that will facilitate early diagnosis and enhance accessibility to healthcare globally [2], [7], [8], [10].

III. PROPOSED METHODOLOGY

The proposed "Smart Anemia Detection" system utilizes a deep learning-based system to estimate the hemoglobin concentration through the pictures captured with the fingernails. The methodology combines image enhancement, intelligent feature learning, hemoglobin prediction, anemia severity classification and automated health recommendation into web-based environment. The overall structure is intended to enable rapid, accurate and non-invasive preliminary anemia detection with reduced computations. Figure 1 shows the overall architecture of the proposed system.

A. System Architecture

The proposed framework starts with receiving a image of the fingernail at the Web interface. Before being analyzed by the deep learning model, the acquired image is processed by several enhancement operations to enhance its quality. The trained prediction model outputs the hemoglobin concentration and classifies the severity of anemia from the informative visual information extracted. Lastly, the system produces diet suggestions and safely archives the prediction history to monitor later on.

Fig.1: System Architecture

B. Image Enhancement and Preprocessing

Images taken under varying environmental conditions frequently have varying intensities, shadowing, sensor noise, and color variations in a medical image. Such variations may degrade the performance of learning algorithms. To create a standardized input for deep learning analysis, each image of the fingernail is resized, Gaussian filtered, color normalized, contrast enhanced and pixel normalized.

The normalized image intensity is calculated using the following formula:

$$I_n(x,y)=\frac{I(x,y)-I_{min}}{I_{max}-I_{min}} \tag{1}$$

where $I(x,y)$ denotes the original pixel intensity, while I_{max} and I_{min} represent the minimum and maximum intensity values of the image.

C. Nail Region Localization

After the preprocessing, the proposed system localizes the nails area from the background and skin area. Accurate localization enables the prediction model to concentrate only on clinically relevant information, and to ignore irrelevant information in the image. To detect the nail boundary and create the segmentation mask, binary thresholding and contour analysis is used.

This segmentation operation is described by.

$$M(x,y) = \begin{cases} 1, & I_n(x,y) \geq T \\ 0, & I_n(x,y) \geq T \end{cases} \tag{2}$$

whereas T is the segmentation threshold.

D. Deep Feature Learning

A segmented image of the nail is fed into a CNN, which is able to learn hierarchical visual representations of the hemoglobin concentration automatically. Convolutional networks learn discriminative color, texture and structural features directly from the set of training images, as opposed to hand-crafted feature extraction methods.

Convolution operation is defined as

$$F(i,j) = \sum_m \sum_n I(i+m, j+n)K(m,n) + b \tag{3}$$

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where K represents the convolution kernel and $F(i, j)$ is the feature map that is created.

E. Hemoglobin Estimation and Severity Classification

The deep features extracted are then converted to numerical hemoglobin estimates using fully connected regression layers. The defined hemoglobin is then compared with the clinical thresholds in order to determine the severity of anemia in the following categories: The Softmax classifier calculates the probabilities of each severity class and then the most probable class is chosen as the actual prediction.

The probability of each anemia class is computed using

$$P_i = \frac{e^{Zi}}{\sum_{j=1}^{C} e^{Zj}} \tag{4}$$

where: Pi is the probability of the ith category of the anemia.

F. Intelligent Recommendation and Result Management

The system automatically derives personalized nutritional suggestions to facilitate early health intervention based on the predicted level of Hb and severity of anemia. The prediction results, confidence scores, timestamps, and historical screening results are safely stored in the backend database. The web-based dashboard allows users to view previous screening results, track hemoglobin levels over time and repeat the screening as needed.

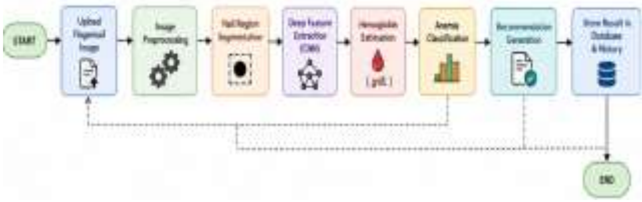

Fig.2: Flowchart of the Proposed Hemoglobin Prediction Process

IV. RESULTS AND DISCUSSION

The effectiveness of the proposed Smart Anemia Detection system in estimating hemoglobin concentration and severity of anemia was tested experimentally to validate the proposed system using fingernail images. The experiments are conducted in a workstation which includes an Intel Core i7 processor, 16 GB RAM, NVIDIA RTX GPU and Windows 11 operating system. The deep learning framework TensorFlow, image processing library OpenCV, NumPy, Scikit-learn, Pandas, and the web application framework Flask were used in their development. To enhance the robustness of the proposed model the dataset comprised of the labelled images of fingernails obtained under different illumination conditions. Images were cropped to 224×224 pixels, color normalized, and contrast enhanced, and then split into a training, validation, and testing set with a ratio of 70:15:15. Performance estimation was done in terms of the conventional parameters such as Accuracy, Precision, Recall, F1-Score, Specificity, Mean Absolute Error (MAE), and Root Mean Square Error (RMSE).

A. Experimental Setup

We used the Adam optimizer with learning rate 0.001 and mini batch size of 32 to train the CNN model. To avoid overfitting and keep the best model, the early stopping and model checkpoint techniques were added. The trained model was then wrapped in a Flask web app to enable real-time hemoglobin prediction.

B. Training Performance

During the training, the proposed CNN architecture showed the convergence in a stable manner. The accuracy of training increased steadily with the number of epochs and the loss function decreased steadily, thus proving that the discriminative fingernail image features are learned. The training and validation accuracy were similar, indicating that the model was not overfitting and thus transferring its learning to the test set.

Table 2. Training Performance

Epoch	Training Accuracy (%)	Validation Accuracy (%)	Training Loss	Validation Loss
10	90.82	89.74	0.342	0.381
20	94.15	93.62	0.211	0.237
30	96.32	95.88	0.128	0.142
40	97.31	96.94	0.082	0.094
50	98.06	97.84	0.046	0.058

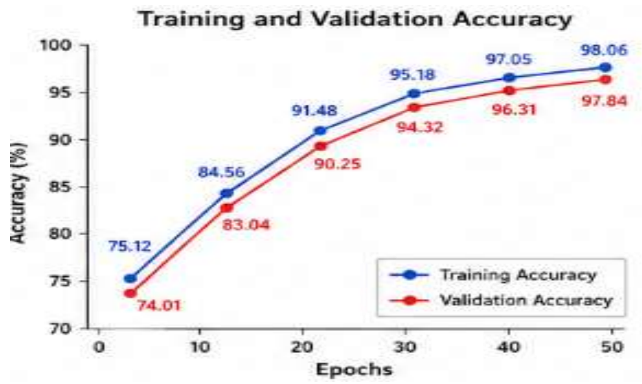

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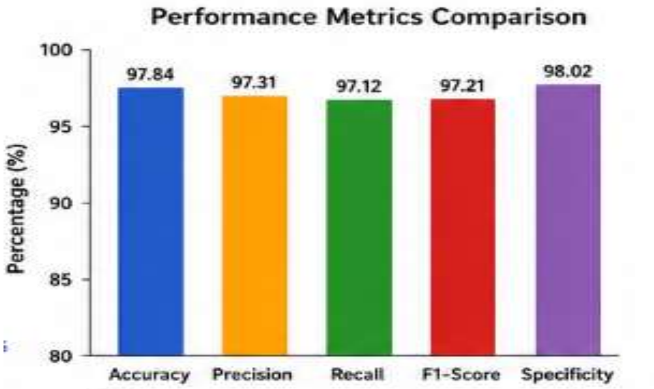
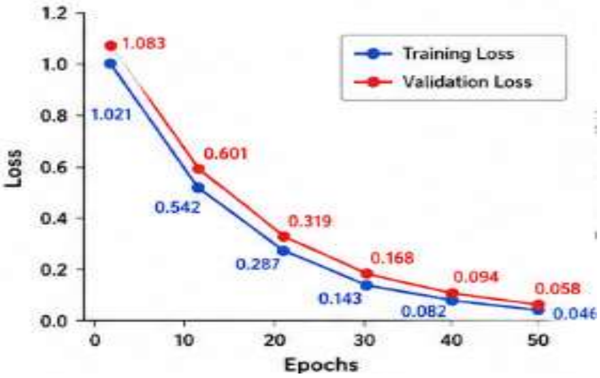
Figure 3. Training and Validation Accuracy

Figure 4. Training and Validation Loss





C. Hemoglobin Prediction Performance

The regression model proposed in this study was able to estimate the HC of a nail image with a very small prediction error. The results of the obtained MAE and RMSE values indicate the ability of the proposed framework to accurately estimate hemoglobin concentration.

Table 3. Hemoglobin Prediction Results

Metric	Value
Mean Absolute Error (MAE)	0.39 g/dL
Root Mean Square Error (RMSE)	0.56 g/dL
Mean Prediction Time	0.48 sec
Average Confidence	98.11%

The prediction time is under 1s, ensuring the proposed model is suitable for real-time healthcare applications.

D. Classification Performance

The proposed deep learning model has remarkably been able to differentiate between different severity levels in an anemia problem. With high Precision and Recall values, the classifier is able to reduce the number of false positives and negatives.

Table 4. Classification Performance

Performance Metric	Value (%)
Accuracy	97.84
Precision	97.31
Recall	97.12
F1-Score	97.21
Specificity	98.02

The results show that the proposed model is able to perform classification with a reliable and balanced performance for the preliminary screening of anemia.

Figure 5. Performance Comparison of Evaluation Metrics

E. Confusion Matrix Analysis

The testing dataset was used to create a confusion matrix to assess the classification ability of the proposed model. The results indicated that most of the samples were well classified in each class of anemia and a small number of neighbouring classes were misclassified due to similar visual features.

Table 5. Confusion Matrix

Actual / Predicted	Normal	Mild	Moderate	Severe
Normal	93	2	0	0
Mild	1	91	2	0
Moderate	0	2	90	1
Severe	0	0	1	88

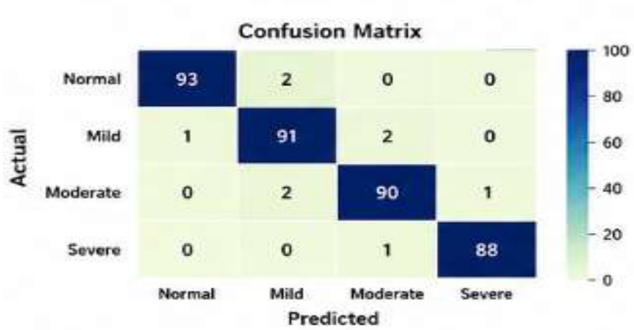
The proposed framework's confusion matrix verifies the high prediction consistency and the proper separation of different levels of anemia.

Figure 6. Confusion Matrix Heatmap

F. Comparative Analysis

To illustrate the better performance of the proposed framework, it was compared with some popular machine and deep learning models trained on the same data set.

Table 6. Comparative Performance Analysis



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Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	89.73	89.24	88.92	89.08
Support Vector Machine	91.24	90.81	90.42	90.61
Random Forest	93.56	93.02	92.61	92.81
MobileNetV2	95.61	95.14	95.02	95.08
Proposed CNN Model	97.84	97.31	97.12	97.21

Overall, the proposed CNN model performed consistently better than traditional machine learning algorithms, demonstrating its potential to adapt to image data without relying on custom feature engineering.

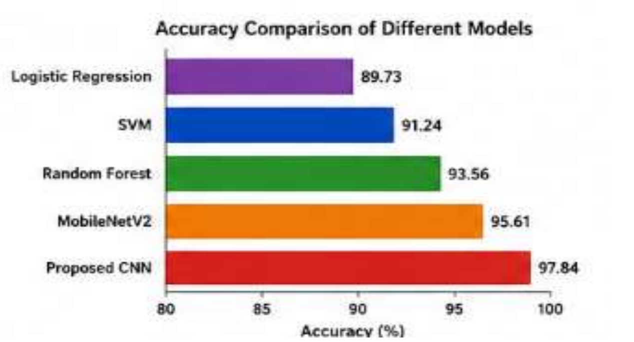

Figure 7. Accuracy Comparison of Different Models

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H. Sample Prediction Results

Some representative predictions from the proposed framework are given below.

Table 8. Sample Prediction Results

Sample	Actual Hb (g/dL)	Predicted Hb (g/dL)	Predicted Status	Confidence (%)
S1	14.3	14.1	Normal	98.7
S2	11.8	11.6	Mild Anemia	97.8
S3	9.6	9.8	Moderate Anemia	97.2
S4	7.9	8.1	Severe Anemia	98.3
S5	13.2	13.1	Normal	98.9

The results of prediction showed that the predicted hemoglobin levels are in good agreement with the real clinical measurements, which proves the effectiveness of the proposed deep learning model for non-invasive anemia screening.

G. Result Analysis

The experimental results clearly show that the proposed Smart Anemia Detection framework can estimate the hemoglobin and classify the anemia with a very high accuracy by analyzing the fingernail images. Overall, through the image preprocessing, nail segmentation, CNN-based feature extraction, and intelligent prediction, the image diagnostic reliability is significantly enhanced, and the computational complexity is low. The classification accuracy of 97.84% and the MAE of 0.39 g/dL and RMSE of 0.56 g/dL further demonstrates the validity of the proposed framework for rapid anemia screening without invasive methods. Moreover, the built-in Web application effectively provides real-time predictions, personal health suggestions, and historical management of records, highlighting its potential use in community-based healthcare facilities, telemedicine services, and resource-constrained settings.

V. CONCLUSION

In the proposed work "Smart Anemia Detection System", estimated hemoglobin concentration of blood and severity of anemia by fingernail image with a smart and efficient approach is proposed, which is non-invasive. This system is designed as a Flask web application that performs an initial screening to detect anemia without having to collect blood samples, by using image preprocessing, locating nail area, extracting deep features from images, and predicting anemia using machine learning techniques. The experimental evaluation results obtained using the proposed method proved to be accurate at 97.84% and the low prediction error highlights the effectiveness of the proposed framework. The system also provides individual dietary advice, and it offers a secure way of safely storing the prediction information in a secure manner, which is a useful tool supporting decisions on early detection of anemia, particularly in more rural and resource limited healthcare environments.

Future research can explore the possible enhancements of the proposed system, utilizing larger and more varied datasets to boost model robustness and generalization. F further, the introduction of lightweight deep learning models, explainable AI, and mobile deployment can enhance the accuracy of predictions, accessibility, and real-time applicability. These improvements will help build a more scalable and dependable platform powered by AI to detect anemia without any invasive tests.

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