Point of Care Noninvasive Screening Tool for Early Detection of Anemia using Smartphone

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Abstract— **Hemoglobin, a crucial protein situated in red blood cells, plays a vital role in the identification and diagnosis of various conditions, including Anemia, through blood examinations. Anemia is a prevalent ailment affecting billions of individuals globally. The conventional means of diagnosing anemia typically entail invasive blood tests, which can be inconvenient, expensive, and challenging to access, especially in remote or underserved areas. Therefore, the innovative project aims to create a noninvasive point-of-care screening tool for early anemia detection utilizing a smartphone. Smartphone-based tools offer widespread accessibility, enabling the prediction and monitoring of anemia for a broad population, including those in remote or underserved regions. This research focuses on the development of AI-enabled models for precise estimation of hemoglobin levels using noninvasive data captured by smartphones. The primary objective is to facilitate early detection and prediction of anemia, enabling timely intervention and treatment to enhance patient outcomes. The proposed system introduces a unique approach to predict hemoglobin levels noninvasively by analyzing the appearance of fingernails. Hemoglobin levels are forecasted by extracting RGB values from nail images, which are then applied to various regression models for hemoglobin level determination. The machine learning models employed encompass Random Forest Regression, K-Nearest Neighbors Regression, Bayesian Ridge Regression, Ridge Regression, and Multiple Linear Regressions. Among the diverse machine learning techniques, Ridge Regression exhibits a low root mean square error rate of 2.07 and a mean absolute error of 1.51. Additionally, the deep learning model EfficientNet demonstrates a reduced root mean square error rate of 0.6591 and a mean absolute error of 0.624. These outcomes highlight the efficacy of the proposed approach in predicting hemoglobin levels accurately.**

Keywords- ***Anemia, Hemoglobin, Noninvasive, Machine Learning, Deep Learning.***

I. INTRODUCTION

Anemia, characterized by a deficiency of red blood cells or hemoglobin, is a global health concern. According to World Health Organization (WHO) data, 42% of children under 5 and 40% of pregnant women worldwide are affected by anemia. Notably, India has the highest prevalence, with 57% experiencing moderate anemia and 41% severe anemia. Over the past decade, iron deficiency anemia has consistently been identified as the primary health challenge in India, as evidenced by previous evaluations in the Global Burden of Disease (GBD) surveys. Contributing factors to the prevalence of anemia in India encompass issues such as poverty, caste-related disparities, and insufficient sanitation. According to the Global Nutrition Assessment 2016, India is positioned at 170th out of 180 countries in terms of women's anemia, underscoring its elevated rates of iron deficiency. In 2018, the Anemia Mukt Bharat (AMB) initiative was inaugurated as part of the Strengthened Nationwide Iron Plus Initiative Project. The objective of AMB is to systematically decrease anemia rates by one to three percentage points annually[1]. The negative impact of anemia extends to the health of women of reproductive age and children, leading to heightened morbidity, maternal mortality, and hindrance to socio-economic development [2]. Early detection and intervention are crucial to preventing complications and improving health outcomes. Traditional invasive diagnostic methods for anemia screening involve procedures that penetrate the skin or use instruments inside the body. Thus, there is a need for a non-invasive solution. Nails, often overlooked yet easily accessible, can provide essential insights into one's well-being, especially regarding anemia. This study utilizes nail images to train a model for predicting hemoglobin levels.

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A. Impact of Anemia

Anemia is a condition characterized by a decrease in the number of red blood cells or a deficiency of hemoglobin in the blood. Various factors contribute to anemia in India, including nutritional deficiencies, particularly iron-deficiency anemia. Anemia leads to a decrease in the number of red blood cells or the amount of hemoglobin, both of which are essential for transporting oxygen from the lungs to the rest of the body. This results in reduced oxygen delivery to tissues and organs.

Insufficient oxygen supply to cells can cause fatigue, weakness, and a general feeling of tiredness. Individuals with anemia often experience low energy levels, affecting their daily activities and quality of life. Inadequate oxygenation of the brain due to anemia can lead to cognitive difficulties, including poor concentration, memory problems, and reduced overall cognitive function.

Anemic individuals may experience decreased exercise tolerance, reduced stamina, and impaired physical performance due to the limited oxygen-carrying capacity of the blood. Severe or chronic anemia can lead to complications such as heart problems, increased susceptibility to infections, and difficulties in pregnancy (if present in women). In children, anemia can affect growth and development, leading to delayed milestones, cognitive impairments, and a higher risk of infections. Anemia can result from various underlying conditions, such as nutritional deficiencies, chronic diseases, or genetic disorders.

Early detection allows for prompt intervention, which may include dietary changes, iron supplementation, or other targeted treatments. This can prevent the progression of anemia and its associated complications.

B. Objectives

The objectives of the proposed system include:

- Developing AI-enabled models capable of accurately estimating hemoglobin levels from noninvasive smartphone-captured data.
- Enabling early detection and prediction of anemia for timely intervention and treatment to prevent complications and enhance patient outcomes.
- Designing a user-friendly smartphone application or interface to simplify the process of capturing and analyzing data.
- Creating a method accessible to a wide range of individuals, including those in remote or resource-limited areas where traditional blood tests may be challenging.
- Developing and implementing robust privacy and data security measures to protect sensitive health information.

This approach aims to address the challenges associated with anemia diagnosis, providing a convenient, accessible, and secure solution for a diverse population, ultimately contributing to improved healthcare outcomes.

II. Literature Review

Numerous non-invasive methods have been explored in the literature to predict hemoglobin levels, each with its limitations. Some lack smartphone integration, while others, particularly image processing-based techniques, require manual selection of the region of interest, leading to less accurate outcomes. Recent studies have demonstrated successful detection of total hemoglobin using biosensors coupled with smartphones, achieving enhanced accuracy [3]. Additionally, an automated Artificial Intelligence (AI) method has been employed for anemia detection [4]. Point-of-care devices have been designed to monitor hemoglobin levels, offering individuals the ability to proactively assess their health conditions [5].

Smartphone images have been leveraged for anemia prediction [6], and another innovative approach involves using smartphone-captured nail images based on pressure changes [7], [8]. Smartphone spectroscopy has been suggested for non-invasive hemoglobin level detection [9], [10] and a combination of principal component analysis and AI has been utilized for accurate estimation [11]. Some methods propose point-of-care support using ultra-low volume whole blood samples and spectrometry [12]. A multi-model regressor has been recommended for estimating hemoglobin levels [13]. Furthermore, a comprehensive research study has been proposed for detecting anemia from medical images [14].

Despite these advancements, many existing techniques have limitations. Some rely on a single image, which may lead to accuracy issues if the image is damaged or of poor quality. Additionally, methods utilizing photoplethysmography (PPG) signals for hemoglobin estimation may require substantial resources and be cost-sensitive. To address these challenges, our innovative project aims to develop a point-of-care, non-invasive screening tool for early anemia detection using a smartphone. The proposed system introduces a novel approach by analyzing fingernail appearance, capitalizing on the widespread accessibility of smartphone-based tools, particularly beneficial for individuals in remote or underserved areas. This innovative approach seeks to overcome the limitations associated with existing methods and enhance the accuracy and accessibility of non-invasive hemoglobin level prediction.

III. Methodology

Anemia, characterized by a deficiency of red blood cells or hemoglobin, is marked by physiological changes, including variations in nail bed color and structure [7]. This project addresses a significant healthcare challenge in dermatology by focusing on the automated detection of anemia using nail images. The timely and precise identification of anemia through nail images holds the potential to facilitate early diagnosis and effective medical intervention. The proposed project involves the creation of a user-friendly smartphone application or interface, simplifying the process of data capture and analysis. This approach aims to make the method accessible to a diverse population, including individuals in remote or resource-limited areas where traditional blood tests pose challenges. Additionally, robust privacy and data security measures are being developed and implemented to safeguard sensitive health information. The integration of artificial intelligence into hemoglobin level estimation not only offers a technological advancement but also holds the potential to revolutionize healthcare by providing a convenient and effective means of monitoring and addressing anemia.

The primary objective is to create a model capable of analyzing digital nail images and accurately classifying them as indicative of anemia or non-anemic conditions. Traditional diagnostic methods often rely on clinical observations, and incorporating automation can enhance efficiency and provide a more objective assessment. The classification task is complex due to variations in nail color, shape, and texture, as well as potential confounding factors such as different skin tones. The model must exhibit robust performance across diverse demographic groups to ensure effectiveness for a broad range of individuals.

Figure 1 represents the proposed system architecture. Machine learning and deep learning offer automated, precise hemoglobin estimation from nail images, providing non-invasive, adaptable, and continuously monitoring methods. The potential for personalization enhances accessibility and efficiency in predicting hemoglobin levels, revolutionizing healthcare diagnostics.

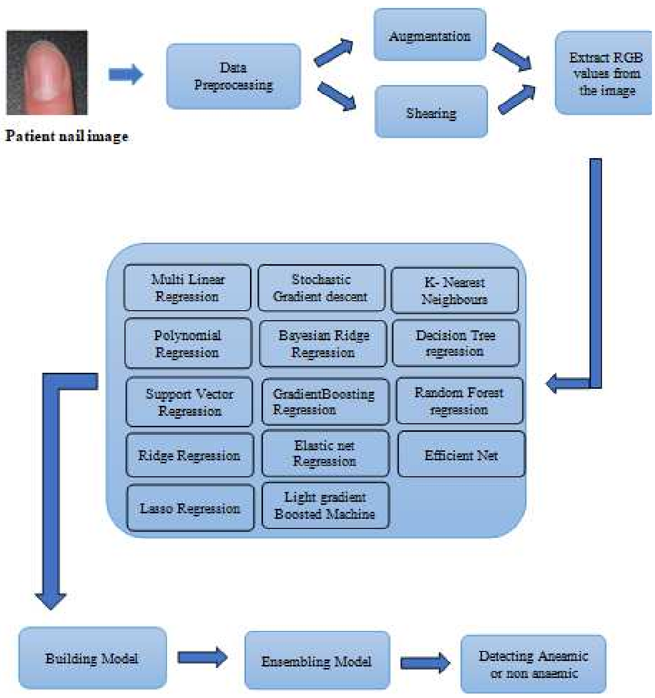

Fig 1 Proposed System Architecture

TABLE I DATASET DESCRIPTION

Dataset name	Fingernails
Dataset Link	https://data.mendeley.com/datasets/2xx4j3kjg2/1
Number of anemic images	2564
Number of nonanemic images	754
Total number of images	3318

Table I describes the details of the dataset used for the proposed system. The model will be trained on a diverse dataset, encompassing a variety of anemic and non-anemic cases, allowing it to learn nuanced patterns indicative of the condition. Various machine learning models, including ridge regression, multi-linear regression, and lasso regression, are employed, along with the deep learning model EfficientNet, to forecast anemia from provided nail photos. RGB values are extracted from the nail photos, serving as input for these models to determine hemoglobin values. Different assessment measures are employed to guarantee the correctness of anticipated models. Among these models, the EfficientNet model and Ridge regression produced the lowest error rate and maximum accuracy, emphasizing the system's ability to identify anemia through nail pallor.

Developing an AI-enabled methodology for predicting anemia by measuring hemoglobin levels using smartphone-captured data is a structured yet complex process. The proposed system architecture involves key steps:

A. Data Collection:

Collect a diverse dataset of high-resolution fingernail images from individuals, ensuring representation across various demographics.

B. Data Preprocessing:

Improve image quality by adjusting contrast, reducing noise, and aligning images. Normalize hemoglobin level measurements for consistency.

C. Feature Extraction:

Extract relevant features, including color analysis, texture analysis, shape measurements, and capillary pattern analysis, creating a feature vector for each image.

D. AI Model Development:

Utilize machine learning and deep learning models on the dataset, optimizing them to predict hemoglobin levels from fingernail features. Experiment with hyperparameters for optimal performance.

E. User Interface Development:

Create a user-friendly smartphone application for capturing fingernail images, integrating the trained model for real-time hemoglobin level predictions.

These steps form the foundation for an innovative system aiming to provide accurate and accessible anemia detection through smartphone-based nail image analysis.

IV. RESULTS AND DISCUSSION

To evaluate the precision and effectiveness of the proposed models, crucial performance metrics such as root mean square error (RMSE) and mean absolute error (MAE) are utilized. These metrics collectively provide valuable insights into the model's accuracy and reliability concerning anemia detection through nail images. In Figure 2, a comparison is presented, illustrating the root mean square error and mean absolute error for all the proposed models. During the evaluation of the models for accuracy and error rate, distinct patterns become evident. Notably, Random Forest Regression and Support Vector Regression exhibit identical error rates, highlighting their comparable performance. Similarly, Stochastic Gradient Descent (SGD) Regression and Lasso Regression yield identical error values. Conversely, Decision Tree Regression and Elastic Net Regression demonstrate the highest error rates. Ridge Regression emerges as the most accurate among the suggested regression models. The Elastic Net Deep Learning model, with the lowest error rate, stands out as the most proficient predictive model. The results of the regression models evaluated in this proposed study provide valuable insights into their performance for the given task. The CNN-EfficientNet model emerged as the top-performing model, exhibiting the lowest RMSE and MAE. This suggests that the combination of CNN architecture and the EfficientNet backbone is well-suited for capturing intricate patterns in the data, leading to highly accurate predictions.

Fig 2 Comparative Results of Proposed Models

TABLE II PROPOSED MODELS RESULTS

S. No	Proposed Model	Root Mean Square	Mean Absolute Error
1	Convolutional Neural Network-EfficientNet	0.6591	0.624
2	Ridge Regression	2.09	1.51
3	Linear Regression	2.22	1.61
4	Support Vector Regression	2.11	1.55
5	Stochastic Gradient Descent Regression	1.82	1.47
6	Lasso Regression	1.82	1.47
7	Gradient Boosting Regression	1.89	1.40
8	Decision Tree Regression	2.32	1.72
9	Elastic-net Regression	2.32	1.72

Traditional linear models, including Ridge Regression, Linear Regression, and Support Vector Regression, displayed comparable performance but with higher errors than the CNN-EfficientNet model. These models may have limitations in capturing the complex relationships present in the data, especially when compared to more sophisticated non-linear models.SGD Regression and Lasso Regression demonstrated similar and improved performance compared to traditional linear models. The use of optimization techniques and regularization mechanisms contributed to their ability to provide more accurate predictions. Gradient Boosting Regression showed competitive performance with lower errors, highlighting the effectiveness of ensemble methods in improving predictive accuracy. Decision Tree Regression, a non-linear model, exhibited higher errors, indicating a potential challenge with over fitting. Elastic-net Regression, combining L1 and L2 regularization, showed results similar to Decision Tree Regression. The balance between the two regularization techniques may not have significantly influenced predictive accuracy in this context. Over all obtained results, the CNN-EfficientNet model outperformed traditional regression models, emphasizing the effectiveness of deep learning architectures for regression tasks. The choice of model should consider the trade-off between predictive accuracy and model complexity.

The advancement in early anemia detection and related health conditions becomes more attainable, allowing for timely interventions and improved patient outcomes. This method enhances accessibility to hemoglobin level assessment, particularly in resource-limited or remote areas where traditional blood tests may pose challenges. The creation of a user-friendly smartphone application empowers individuals to actively participate in their health management, facilitating informed decision-making. The Blynk app incorporates a button function facilitating the activation and deactivation of the relay module.

V. CONCLUSION

Detecting anemia early is pivotal for intervening and preventing health complications. Early identification enables targeted treatments, mitigating the risks associated with low hemoglobin levels, such as fatigue, weakness, and more severe conditions. Various machine learning techniques, including ridge regression, multilinear regression, and lasso regression, are employed for anemia prediction. Additionally, a deep learning model called EfficientNet is utilized to forecast anemia from given nail pictures. Initially, RGB data is extracted from the nail photographs. Using these RGB values as input, the machine learning and deep learning models discussed earlier are employed to determine hemoglobin values, serving as indicators of anemia. Various evaluation metrics are applied to ensure the precision of the predicted models.

The models demonstrating the lowest error rate and maximum accuracy are the EfficientNet model and Ridge regression. The ridge regression machine learning model achieves a root mean square error and mean absolute error of 2.09 and 1.51, respectively. On the other hand, the EfficientNet deep learning model achieves a RMSE and MAE of 0.65 and 0.624, respectively. The choice of the appropriate regression model depends on the specific characteristics of the data and the trade-off between model complexity and predictive accuracy. The CNN-EfficientNet model stands out as the preferred choice for this particular task, emphasizing the importance of leveraging deep learning architectures when dealing with complex regression problems. The validation on an independent test set underscores the robustness and generalization capability of the chosen model. To enhance precision and advancement, the model can undergo training and assessment alongside additional deep learning models, such as transfer learning and other CNN models.

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