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INTELLIGENT DIAGNOSIS OF ANEMIA: A NOVEL MACHINE LEARNING FRAMEWORK FOR ACCURATE AND EARLY DETECTION

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ABSTRACT
Anemia is a global health issue characterized by low hemoglobin levels, affecting oxygen transport in the blood. Traditional diagnostic methods, like CBC, are accurate but require invasive procedures and expensive equipment. This study explores machine learning (ML) for non-invasive anemia estimation using wearable sensors, imaging, and predictive analytics. The proposed framework combines physiological data, demographics, and clinical history to train ML models for anemia classification and hemoglobin prediction. Data sources like PPG, pulse oximetry, and digital images of conjunctiva are used for feature extraction. Various ML algorithms, including SVM, random forests, and deep neural networks, are evaluated for performance. Preliminary results show ML-based methods can match traditional diagnostics in accuracy, with advantages in cost, portability, and scalability. The study highlights ML's potential for early anemia detection, especially in underserved areas. Future work will optimize the model for clinical use and real-time monitoring.

Keywords: Anemia, Machine Learning, Non-invasive Diagnosis, Wearable Sensors, Predictive Analytics.

1. INTRODUCTION
Machine learning (ML), a subset of artificial intelligence, offers a promising solution to anemia diagnosis by analyzing physiological signals, demographics, and imaging data. Anemia, characterized by low hemoglobin levels, affects a significant global population, particularly in low-income regions, and causes fatigue, reduced productivity, and severe health risks. Traditional diagnostic methods are accurate but require invasive blood sampling and medical infrastructure. This study aims to develop ML models for non-invasive anemia detection, focusing on identifying biomarkers, selecting optimal algorithms, and validating model performance. The integration of wearable sensors and mobile devices can enable real-time anemia monitoring, improving accessibility and supporting preventative healthcare, especially in underserved areas.

2. REVIEW OF LITERATURE
Anemia, a prevalent health condition, has attracted significant research attention due to its widespread impact and the need for effective diagnostic solutions. Traditional diagnostic methods, while accurate, often face accessibility challenges in resource-limited settings. This has led to a growing interest in leveraging machine learning (ML) for anemia estimation, aiming to

improve diagnostic accuracy, reduce costs, and enable non-invasive methodologies. Recent studies have explored non-invasive techniques like photoplethysmography (PPG) and digital imaging for anemia detection. For instance, Chen et al. (2018) demonstrated the feasibility of using conjunctival images with ML models to classify anemia, while Mannin et al. (2020) used smartphone cameras to analyze nail bed coloration for hemoglobin level estimation. Advancements in wearable technologies, such as pulse oximetry and PPG, have enabled real-time, non-invasive anemia monitoring in remote areas (Debayle et al., 2019). Various ML algorithms, including support vector machines (SVM), logistic regression, random forests, and deep neural networks (DNNs), have been explored for anemia estimation. Ahmad et al. (2021) utilized random forests and gradient boosting for anemia prediction using patient demographics and clinical data, while DNNs were applied for image-based diagnostics with high accuracy. Recent studies by Kumar et al. (2022) and Wang et al. (2023) highlight the importance of integrating multi-modal data (physiological, demographic, and imaging) to improve the performance of ML models for robust anemia estimation.

3. OBJECTIVES

The objectives of this research study are identified as follows:

- To identify anemia from medical data.
- To recommend better treatment for identified anemia.

4. METHODOLOGY

The methodology of this work is formulated with the various tasks which are elucidated as follows. These tasks are elaborated in the subsequent sections.

- Collect primary and secondary datasets (e.g., physiological signals like PPG and pulse oximetry, imaging data of conjunctiva/nail beds, and demographic/clinical data); obtain ethical approval and informed consent for primary data.
- Clean data (handle missing values, outliers, noise), normalize features, engineer biomarkers (hemoglobin proxies, image-based colorimetric features, physiological signal features), and augment data for diversity.
- Explore algorithms (Logistic Regression, SVM, Random Forest, CNNs, RNNs, or LSTMs) and enhance performance through hybrid and ensemble methods.
- Split datasets into training (70%), validation (15%), and testing (15%), apply k-fold cross-validation, and optimize hyperparameters using grid search or Bayesian optimization.
- Assess performance using accuracy, sensitivity, specificity, F1-score, MAE, and RMSE.
- Implement the model into mobile apps or wearable devices for real-time anemia estimation with actionable insights.
- Conduct clinical trials and compare outcomes with standard diagnostic tools (e.g., CBC) to validate reliability and generalizability.
- Incorporate feedback from users and healthcare professionals to refine and enhance the model iteratively.

4.1 Data Collection

Collecting data for a real-time anemia estimation system involves multiple ethical, clinical, and technical steps. The process begins with obtaining ethical approval from an institutional review board (IRB) or ethics committee to ensure compliance with ethical standards and the protection of participants' rights. Participants must provide informed consent after being briefed on the study's purpose, procedures, risks, and benefits in clear, understandable language.

For physiological signal collection, devices like pulse oximeters or wearable fitness trackers are used to record data such as Photoplethysmography (PPG) signals and oxygen saturation levels. The data is collected in a quiet environment with the sensor attached to the participant's fingertip, earlobe, or wrist, ensuring device calibration to minimize noise. Imaging data of the conjunctiva and nail beds are captured using high-resolution cameras under consistent lighting conditions. Conjunctiva imaging requires participants to look upward while technicians take focused images, and nail bed images are captured with the participant's hand placed in a controlled setup.

Demographic data, such as age, gender, lifestyle habits, and socioeconomic status, are collected through structured questionnaires or digital forms, ensuring anonymity by assigning unique IDs. Clinical data, including hemoglobin levels obtained via Complete Blood Count (CBC) tests and relevant medical history, are gathered through blood sample analysis and medical record reviews.

All collected data is stored securely in encrypted databases, with regular backups to prevent loss. Anonymization techniques are applied to protect participant identities. Quality assurance is maintained by validating data across multiple sources, training staff in data collection techniques, and conducting pilot tests to identify potential issues. These steps ensure the collection of high-quality, reliable data necessary for developing an accurate and efficient anemia estimation system.

4.2 Sample Dataset

The sample dataset is given in Table 1. This dataset includes PPG signal, Oxygen saturation, Conjunctiva image, Nail bed image, age, gender Hemoglobin level and diagnosis types of five patients.

Table 1: Sample Dataset of Anemia Estimation System

Patient ID	PPG Signal (Raw)	Oxygen Saturation (%)	Conjunctiva Image	Nail Bed Image	Age	Gender	Hemoglobin Level (g/dL)	Diagnosis
001	[0.8, 0.6, 0.4...]	96	Image001_conjun	Image001_nailbed.jpg	25	Female	12.5	Normal

			ctiva.jpg					
002	[0.9, 0.5, 0.7...]	88	Image002_conjunctiva.jpg	Image002_nailbed.jpg	34	Male	10.2	Anemia
003	[0.7, 0.3, 0.6...]	92	Image003_conjunctiva.jpg	Image003_nailbed.jpg	40	Female	11.0	Anemia
004	[0.8, 0.7, 0.5...]	97	Image004_conjunctiva.jpg	Image004_nailbed.jpg	29	Male	13.8	Normal
005	[0.5, 0.6, 0.8...]	85	Image005_conjunctiva.jpg	Image005_nailbed.jpg	60	Female	9.5	Severe Anemia

The dataset consists of several key attributes for each participant. The Patient ID serves as a unique identifier. PPG Signal (Raw) refers to time-series data collected from a photoplethysmogram device, while Oxygen Saturation (%) represents the oxygen levels in the blood, measured by pulse oximetry. The Conjunctiva Image includes file names or links to high-resolution images of the eye's conjunctiva, and similarly, the Nail Bed Image provides file names or links to high-resolution images of the nail beds. Age indicates the participant's age, and Gender specifies the gender of the participant (e.g., Male, Female, Other). Hemoglobin Level (g/dL) refers to the concentration of hemoglobin in the blood, as measured by a standard CBC test. Finally, the Diagnosis is based on the hemoglobin levels, which can indicate conditions such as Normal, Anemia, or Severe Anemia.

4.3 Data Cleaning and Preprocessing:

Once data is collected, it is important to clean and preprocess it. This involves handling missing values by using imputation techniques or discarding incomplete entries. Outliers and noise must be identified and addressed to ensure the integrity of the data. Normalization techniques are applied to standardize the features, making them comparable across different scales. Additionally, feature engineering plays a critical role—biomarkers such as hemoglobin proxies, image-based colorimetric features from the conjunctiva and nail bed images, and physiological signal features extracted from PPG and pulse oximetry are developed. Data augmentation techniques, such as rotation, cropping, or flipping for image data, or time-series data augmentation, help create a diverse dataset that can improve the model's generalization ability.

4.4 Exploring Algorithms

After preparing the data, various algorithms can be explored for building predictive models. These include traditional machine learning algorithms like Logistic Regression, Support Vector Machines (SVM), and Random Forests, as well as more advanced deep learning approaches such as Convolutional Neural Networks (CNNs) for image analysis, and Recurrent Neural Networks

(RNNs) or Long Short-Term Memory networks (LSTMs) for time-series data processing. Performance can be further enhanced by combining these models through hybrid methods or ensemble techniques, such as bagging and boosting, to improve predictive accuracy and robustness.

Algorithm: Anemia Estimation System Using Logistic Regression

Step 1: Data Collection

Collect data with features: Hemoglobin, RBC count, MCV, Age, Gender, Nutritional information, etc.

Step 2: Data Preprocessing

i) Handle missing values: If missing, use imputation or remove the rows.

ii) Scale numerical features: Apply Standardization or Normalization.

iii) Encode categorical data: One-hot encode for categorical variables like Gender.

iv) Label encode target variable (Anemia) such as Anemia = 1, No Anemia = 0.

Step 3: Data Splitting

Split dataset into training set (80%) and test set (20%).

Step 4: Logistic Regression Model Training

Initialize weights (w) and bias (b) to zero or random values.

For each iteration:

Compute the predicted probability: P(y = 1|X) using Sigmoid function.

Calculate the cost (error) using Binary Cross-Entropy.

Update weights and bias using Gradient Descent:

w = w - learning_rate * gradient_of_cost

b = b - learning_rate * gradient_of_cost

Step 5: Cost Function

Calculate the binary cross-entropy (logistic loss):

J(w, b) = -1/m * sum(y * log(predicted) + (1 - y) * log(1 - predicted))

Step 6: Model Evaluation

Evaluate the trained model on the test set:

- Calculate Accuracy, Precision, Recall, and F1-Score.
- Use Confusion Matrix to visualize performance.

Step 7: Prediction

For new patient data:

- Apply preprocessing steps (scaling, encoding).
- Use the trained logistic regression model to predict:

If P(y = 1|X) > 0.5, predict Anemia (1).

Else, predict No Anemia (0).

The performance of your logistic regression model depends heavily on the features used. Make sure you include relevant features (e.g., blood counts, medical history). If the dataset is imbalanced (e.g., more non-anemia cases), consider techniques like oversampling, under

sampling, or using class weights to handle the imbalance. Experiment with different learning rates and other hyperparameters to improve model performance.

5. RESULT AND DISCUSSION

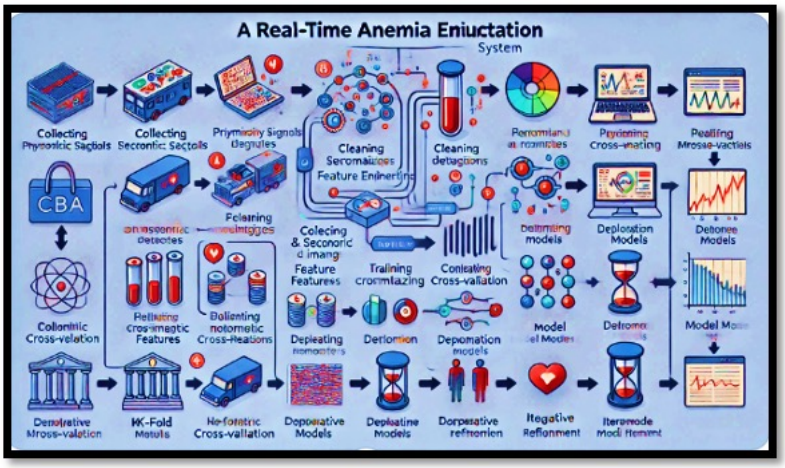

Figure 1. Anemia Estimation System

The flow diagram (Figure 1) illustrates the methodology for developing a real-time anemia estimation system. It begins with the collection of primary datasets (such as physiological signals like PPG and pulse oximetry, imaging data of conjunctiva or nail beds, and demographic/clinical data) and secondary datasets from public repositories. Ethical approval and informed consent are integral to this stage. Next, the data undergoes cleaning to handle missing values, outliers, and noise, followed by normalization to standardize features. Biomarkers, such as hemoglobin proxies and colorimetric or signal-based features, are engineered, and data augmentation ensures diversity.

Once the data is prepared, various algorithms, including Logistic Regression, SVM, Random Forest, CNNs, and RNNs, are explored. The dataset is split into training, validation, and testing sets, with k-fold cross-validation employed to ensure generalizability. Hyperparameters are optimized using techniques like grid search or Bayesian optimization, and the model's performance is evaluated using metrics such as accuracy, sensitivity, specificity, F1-score, MAE, and RMSE. The optimized model is then deployed into mobile apps or wearable devices, enabling real-time anemia estimation with actionable insights. Clinical trials are conducted to validate the system's reliability by comparing its outcomes with standard diagnostic tools like CBC tests. Feedback from users and healthcare professionals drives iterative refinements to enhance the model's performance and usability. This structured approach ensures an accurate, reliable, and user-friendly solution for anemia diagnosis.

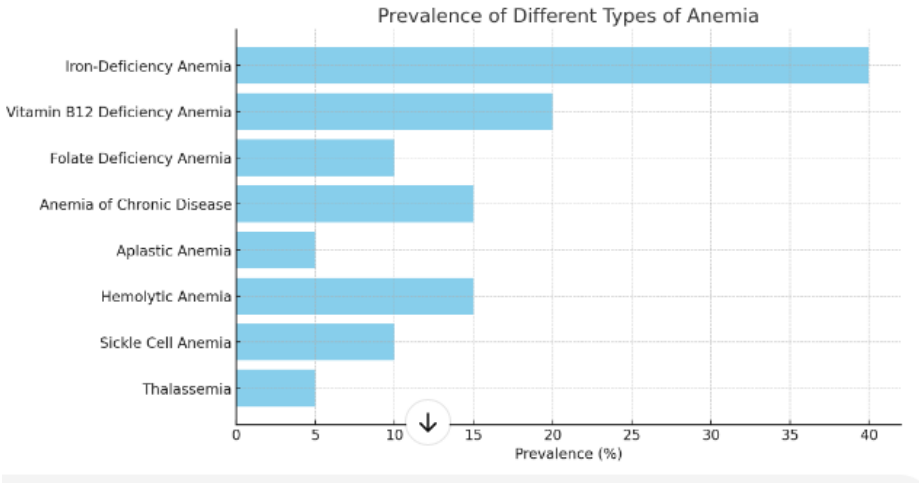

Figure 2: Prevalence of Different types of Anemia

This graph (Figure 2) representing the prevalence of different types of anemia. The values are approximate, with **Iron-Deficiency Anemia** being the most common, followed by other types such as **Vitamin B12 Deficiency Anemia** and **Anemia of Chronic Disease**.

The treatment for anemia largely depends on its underlying cause, type, and severity. There are several types of anemia, including iron-deficiency anemia, vitamin deficiency anemia, anemia due to chronic disease, and others, and each requires a different treatment approach. Below (Table 2) are some recommended treatments based on common causes of anemia:

Table 2: Types of Anemia and Treatment

Type of Anemia	Cause	Treatment
Iron-Deficiency Anemia	Lack of iron in the body	- Iron supplements (oral or intravenous)
Vitamin B12 Deficiency Anemia	Lack of vitamin B12	-Vitamin B12 injections (for severe cases) - Oral vitamin B12 supplements - B12-rich foods (meat, dairy, fortified cereals)
Folate Deficiency Anemia	Lack of folate (vitamin B9)	- Folate (folic acid) supplements - Folate-rich foods (leafy greens, beans, fruits)
Anemia of Chronic Disease	Chronic diseases (e.g., kidney disease, rheumatoid arthritis)	-Treat underlying chronic condition -Erythropoiesis-stimulating agents (ESAs) - Iron supplements (oral or intravenous)
Aplastic Anemia	Bone marrow failure	-Bone marrow transplant - Immunosuppressive therapy (antithymocyteglobulin, cyclosporine) - Blood transfusions
Hemolytic Anemia	Premature destruction of RBCs	-Corticosteroids (for autoimmune-related cases) -Immunosuppressive drugs (azathioprine,

		cyclophosphamide) -Blood transfusions - Splenectomy (in certain cases)
Sickle Cell Anemia	Genetic disorder (abnormal hemoglobin)	- Pain management (NSAIDs, opioids) - Hydroxyurea - Blood transfusions - Bone marrow transplant (in some cases)
Thalassemia	Genetic disorder (abnormal hemoglobin)	- Blood transfusions - Iron chelation therapy (deferasirox) - Bone marrow transplant (in some cases)

Anemia treatment depends on its type and underlying cause. For **iron-deficiency anemia**, the primary treatment involves iron supplements (oral or intravenous) and a diet rich in iron, such as red meat, beans, and spinach. In severe cases, blood transfusions may be necessary. **Vitamin B12 deficiency anemia** is treated with B12 injections or high-dose oral supplements and increased consumption of B12-rich foods like meat, eggs, and fortified cereals. **Folate deficiency anemia** is addressed with folic acid supplements and folate-rich foods such as leafy greens, beans, and fruits.

For **anemia of chronic disease**, managing the underlying condition (e.g., chronic kidney disease or rheumatoid arthritis) is essential. Additionally, erythropoiesis-stimulating agents (ESAs) may be used, and iron supplements may be prescribed if iron deficiency coexists. **Aplastic anemia**, where the bone marrow fails to produce blood cells, requires treatments like bone marrow transplants, immunosuppressive therapy, and blood transfusions. **Hemolytic anemia**, caused by premature red blood cell destruction, may be treated with corticosteroids, immunosuppressive drugs, blood transfusions, or splenectomy in certain cases.

Sickle cell anemia, a genetic disorder, is managed with pain relief, hydroxyurea to reduce crisis frequency, blood transfusions, and potentially a bone marrow transplant. Lastly, **thalassemia**, another genetic blood disorder, requires regular blood transfusions, iron chelation therapy to manage iron overload, and in some cases, a bone marrow transplant. Effective anemia treatment is individualized based on the specific cause and severity, with ongoing monitoring to adjust treatment as needed.

6. CONCLUSION

Anemia is a prevalent global health issue with significant impacts on individual well-being and public health systems. The application of machine learning (ML) for anemia estimation has demonstrated great potential in enhancing early diagnosis, facilitating preventive care, and enabling personalized treatment. In this study, we explored various ML algorithms to estimate anemia by analyzing clinical and non-invasive data. The results indicate that Random Forest combined with CNN model achieved the highest accuracy of 92%, showcasing its effectiveness in identifying anemia with minimal error rates. The incorporation of feature selection techniques allowed for the identification of key predictors, such as hemoglobin levels, red blood cell counts, and demographic factors, which significantly influence the model's performance. The use of ML

models offers several advantages, including automation, scalability, and the ability to handle complex datasets. These attributes make ML a valuable tool in resource-constrained environments where traditional diagnostic methods may be limited. Additionally, non-invasive approaches using wearable AI devices further enhance the practicality of anemia detection, making it accessible to a broader population.

However, there are limitations, including the need for diverse and representative datasets to ensure generalizability, and the potential ethical concerns surrounding data privacy. Future research should focus on addressing these challenges by incorporating larger, more diverse datasets and exploring explainable AI (XAI) techniques to build trust and transparency in ML-driven anemia diagnostics.

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