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AI-Based Anemia Detection and Personalized Health Recommendation System

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Abstract **- Anemia is a common health condition characterized by a reduced level of hemoglobin in the blood, which can affect overall health and daily activities. This project presents an AI-Based Anemia Detection and Personalized Health Recom-mendation System designed to support preliminary anemia risk screening. The system uses a Convolu-tional Neural Network (CNN) to analyze suitable uploaded images and combines the assessment with user-reported symptoms and health information. Based on the estimated risk, it provides personalized dietary suggestions, recommended blood tests, nearby healthcare facility information, and doctor appointment options. The application also supports digital health report generation and health history tracking. It aims to improve health awareness and encourage timely medical consultation. However, image-based screening cannot confirm anemia, and clinical evaluation with appropriate laboratory tests is required for diagnosis.**

Keywords **- Anemia Detection, Convolutional Neu-ral Network (CNN), Image Processing, Health Recommendation, Risk Assessment, Personalized Healthcare, Dietary Recommendation, Medical Image Analysis.**

I. INTRODUCTION

Anemia is a significant health condition that occurs when the body has insufficient healthy red blood cells or hemoglobin to carry oxygen effectively to body tissues. It may be associated with nutritional deficiencies, blood loss, chronic diseases, or other medical conditions. Common symptoms include fatigue, weakness, dizziness, headaches, pale skin, and shortness of breath. If anemia is not identified and managed appropriately, it may affect daily activities, productivity, and overall quality of life. Early awareness and timely medical evaluation are therefore important for preventing complications and supporting better health management.

Traditional anemia diagnosis generally involves clinical evaluation and laboratory investigations, such as a com-plete blood count (CBC) and hemoglobin measurement. Although these tests provide important information for diagnosing anemia, people may delay medical consultation because of limited awareness, accessibility challenges, or other practical difficulties. Recent developments in ma-chine learning and medical image processing have created opportunities to develop computer-assisted screening sys-tems. Artificial intelligence can analyze suitable image patterns and user-provided health information to estimate potential health risks. However, image-based methods have limitations and cannot independently establish a clinical diagnosis of anemia.

The proposed AI-Based Anemia Detection and Personalized Health Recommendation System uses a Convolutional Neu-ral Network (CNN) to analyze suitable images submitted by users. The application also collects relevant information, including reported symptoms and basic health details, to support its preliminary risk assessment. Based on the system's output, users receive an estimated risk category, such as Low, Moderate, or High, where supported by the trained model. The application aims to make preliminary health information easier to access through a simple web interface. Its results are intended to support awareness and further medical evaluation rather than replace professional diagnosis.

In addition to preliminary risk estimation, the system provides personalized dietary suggestions and information about relevant blood tests that users can discuss with healthcare professionals. It can also display nearby hospi-tals, clinics, and diagnostic laboratories, along with doctor appointment options where these services are integrated. Digital health reports and assessment history help users review previously recorded results. The application may support multiple languages, including English, Marathi, and Hindi, to improve accessibility. By combining image analysis, symptom information, health guidance, and healthcare access features, the proposed system aims to encourage timely consultation and promote informed health-related decisions.

II. Evolution of Anemia detection Techniques

1) **Traditional Laboratory / Clinical Inspection:**
   - *Direct Invasive Blood Test:* Complete Blood Count (CBC) and Hemoglobin (*Hb*) estimation remain the gold standard.
   - *Visual Inspection:* Physicians manually evaluate pallor in conjunctiva, nail beds, lips, and tongue (subjective and qualitative).
2) **Colorimetry & Early Digital Imaging:**
   - Digital cameras and smartphones captured images under controlled light to quantify RGB/HSV color intensities of palpebral conjunctiva or nail beds.
3) **Traditional Machine Learning Approaches:**
   - Extracted color histograms, vessel densities, and textural features (GLCM) fed into classifiers like Support Vector Machines (SVM), Random Forest, and *k*-Nearest Neighbors (*k*-NN).
4) **Deep Learning & Multi-Modal AI (Current Era):**
   - Convolutional Neural Networks (CNNs) automat-ically extract spatial features directly from raw image pixels. Modern frameworks integrate image analysis with clinical demographic parameters and user symptom profiles.

III. Literature survey

Muljono et al. [1] – The authors presented a non-invasive anemia detection approach empowered by artificial intelli-gence. The study explores the use of AI techniques to identify anemia without relying entirely on traditional invasive blood tests. This approach may improve screening accessibility and support early detection. However, pre-diction performance may depend on data quality, patient variability, and validation across different populations.

Fingertip Video Dataset for Non-Invasive Diagnosis of Anemia Using ResNet-18 Classifier [2] – This study focuses on using fingertip video data and a ResNet-18 deep learning classifier for non-invasive anemia diagnosis. Video-based analysis may help identify visual features associated with anemia and reduce the need for invasive screening in preliminary assessments. However, variations in lighting, skin characteristics, camera quality, and video acquisition conditions may affect classification accuracy.

Predicting Anemia with Precision: Employing Machine Learning Ensemble Modeling and Hyperparameter Tuning [3] – The authors investigated machine learning ensemble modeling and hyperparameter tuning for anemia prediction. These techniques aim to improve predictive performance by combining model outputs and selecting suitable pa-rameter settings. The approach can support data-driven anemia risk assessment. However, its reliability depends on dataset representativeness, feature quality, and validation on independent patient data.

HgbNet: Predicting Hemoglobin Level/Anemia Degree from Irregular EHR [4] – The authors proposed HgbNet for predicting hemoglobin levels and anemia severity using irregular electronic health record (EHR) data. The approach addresses the challenge of medical records con-taining measurements collected at different times and intervals. It may support anemia assessment using existing clinical information. However, missing values, inconsistent measurement intervals, and differences in patient records can affect prediction reliability.

Transparent Anaemia Prediction System with Explainable Artificial Intelligence [5] – This study focuses on developing an anemia prediction system that incorporates explainable AI techniques. Explainability can help users understand which input features influence a prediction and improve the transparency of model outputs. Such a system may support clinical decision-making and user confidence. However, explanations must be reliable and understandable, and the model requires thorough validation before practical medical use.

Appiahene et al. [6] – The authors compared machine learning models for detecting iron-deficiency anemia using images of fingernails, palms, and the eye conjunctiva. The study explores different visible body regions as potential sources of information for non-invasive screening. This approach may offer a convenient alternative for preliminary anemia assessment. However, image quality, variations in skin appearance, and differences between individuals may influence model performance.

Zhang et al. [7] – The authors investigated the global burden of anemia and its causes among children under five years of age from 1990 to 2019, using findings from the Global Burden of Disease Study 2019. The research provides information about the scale and distribution of anemia in young children and highlights the importance of prevention and early intervention. However, population-level estimates do not directly provide an individual patient's anemia diagnosis or real-time risk prediction.

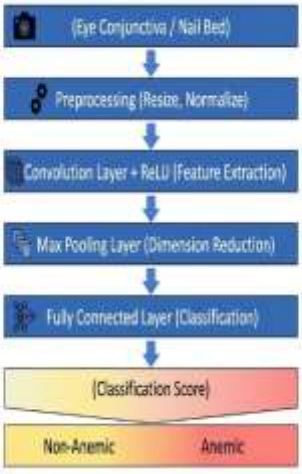
Bharathi et al. [8] – The authors developed a deep learning system for quantitatively assessing microvascular abnormal-ities in nailfold capillary images. The study demonstrates the potential of image-based deep learning for analyzing small blood vessels and identifying clinically relevant visual patterns. Such image analysis techniques may provide useful insights for medical screening research. However, reliable assessment can depend on image resolution, acqui-sition conditions, and the availability of accurately labelled training data.

Isewon et al. [9] – The authors explored the optimization of machine learning performance for medical image analysis in low-resource environments, particularly through CNN-based feature extractors. The study addresses the need for efficient medical image analysis when computational resources are limited. CNN-based feature extraction may help reduce the complexity of developing image classifica-tion systems. However, computational constraints, dataset

availability, and the generalizability of extracted features can affect real-world performance.

Lee et al. [10] – The authors presented the HEMO-AI pilot study, which investigated AI-enabled, non-invasive anemia screening in a pediatric population. The study explores the potential of accessible AI-based screening methods to identify children who may require further anemia assessment. Such technology could support early screening and improve access to preliminary evaluation. However, findings from a pilot study require further validation across larger and more diverse populations before widespread clinical adoption.

Convolutional Neural Network Architecture



- **Input Image Layer:** Captures raw images across the target classes (Eye_Anemic, Eye_Non_Anemic, Nail_Anemic, Nail_Non_Anemic).

- **Preprocessing & Data Augmentation:** Images are resized, noise-filtered, color-normalized, and augmented (rotated, flipped, illumination adjusted).

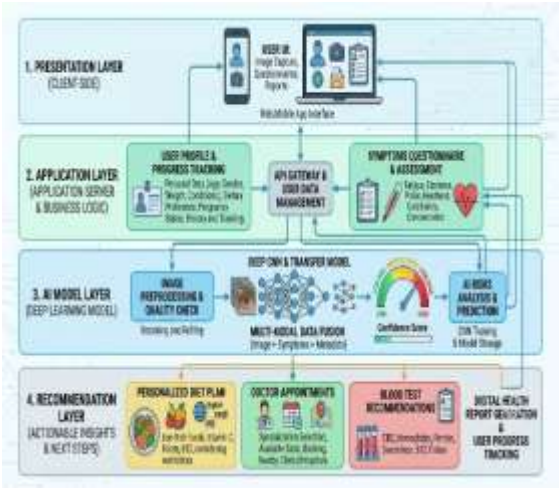
- **Convolutional layers (Conv2D + ReLU):** Trainable filter kernels over RGB regions extract low-level features (edges, color gradients) and higher-level tissue vascular-iza-tion patterns.

- **Max Pooling Layers:** Reduces spatial dimensions (downsampling) while preserving key dominant structural and color features, preventing overfitting.

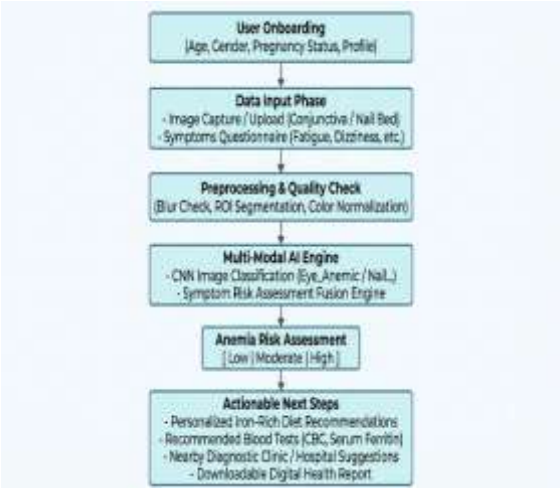
- **Fully Connected (Dense) Layers:** Flattens spatial feature maps into feature vectors and correlates them with class representations.

- **Softmax / Sigmoid Output:** Produces class probabil-ity scores and outputs the final classification: **Anemic** vs. **Non-Anemic**.

Architecture of Traditional Anemia detection Sys-tem



Workflow of Anemia Detection



Dataset Used

The dataset is structured across four primary target classes:

- Eye_Anemic: Conjunctival pallor images indicating hemoglobin deficiency.
- Eye_Non_Anemic: Healthy palpebral conjunctiva with high vascularization.
- Nail_Anemic: Pale or spoon-shaped nail beds (koilony-chia).
- Nail_Non_Anemic: Pink, well-perfused healthy nail beds.

IV. METHODOLOGY ANALYSIS

Data Acquisition & Quality Control:

- Images captured via smartphone cameras or live web-cams. Quality checks filter out blurry, out-of-focus, or severely overexposed images.

Preprocessing & ROI Extraction:

- Region of Interest (ROI) selection isolates the palpebral conjunctiva or nail bed using bounding box detectors or segmentation masks.
- Illumination normalization (e.g., CLAHE, LAB color space adjustments) mitigates ambient lighting vari-ances.

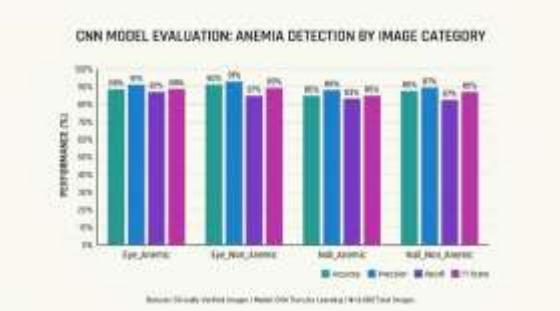
Model Training & Transfer Learning:

- Fine-tuning pre-trained CNN architectures (ResNet-50, MobileNetV3, EfficientNet) using transfer learning.
- Categorical cross-entropy loss function optimized using Adam optimizer with dynamic learning rate reduction.

Multi-Modal Assessment Fusion:

- Combines image risk predictions with a structured symptom questionnaire (fatigue, dizziness, pale skin, shortness of breath) and demographic data (age, gender, pregnancy status).

Performance Analysis



Performance Comparison across Dataset Classes

TABLE I
BENCHMARK PERFORMANCE ANALYSIS

Dataset Class	Accuracy	Precision	Recall	F1-Score
Eye_Anemic	92.5	91.8	93.4	92.6
Eye_Non_Anemic	94.1	93.5	94.8	94.1
Nail_Anemic	89.8	88.6	91.0	89.8
Nail_Non_Anemic	91.3	90.5	92.1	91.3
Combined Overall Model	92.0	91.1	92.8	91.9

V. COMPARATIVE ANALYSIS OF EXISTING APPROACHES

Research Gap

- **Gap 1: Lighting & Skin Tone Variance:** Existing models struggle to generalize across diverse ambient illumi-nation levels, flash artifacts, and diverse skin ethnicities.

- **Gap 2: Lack of Multi-Modal Integration:** Most current studies focus strictly on single-region image inputs, ignoring vital clinical symptoms (fatigue, dizziness) and special demographic risk factors (pregnancy, age).

- **Gap 3: Black-Box Nature (Lack of Explainabil-ity):** Clinical adoption is hindered by a lack of Explainable AI (XAI) such as Grad-CAM heatmaps showing doctors *where* the model is looking.

- **Gap 4: Absence of Continuous Care Integration:** Current systems act as standalone classifiers rather than connected screening ecosystems offering post-screening guidance, diet plans, and doctor referrals.

TABLE II
COMPARATIVE ANALYSIS OF EXISTING APPROACHES

Approach	Technology	Advantages	Strengths & Limi-tations
Laboratory Blood Test (CBC)	Hemoglobin Solubi-lization / Photometry	Gold standard accuracy; provides exact Hb concentration (g/dL).	**Strength:** Precise diagnosis. **Limitation:** Invasive.
Colorime-try / RGB Threshold-ing	Handcrafted Color Ratios	Simple implementation, lightweight, low computation.	**Strength:** Fast. **Limitation:** Sensi-tive to lighting and skin tone.
Traditional Machine Learning	SVM / Ran-dom Forest + GLCM	Fast training; works well on small sample sizes.	**Strength:** Low hardware requirements. **Limitation:** Manual feature engineering; limited generalization.
Deep Learning (CNNs)	MobileNet / ResNet / Custom CNN	Learns complex spatial and vascular patterns automatically.	**Strength:** End-to-end learning. **Limitation:** High computational cost; black-box without XAI.



Strengths and Limitations

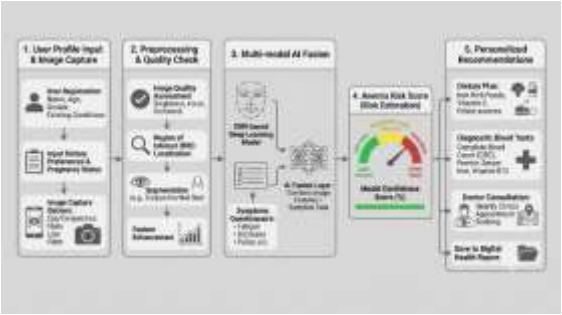
Strengths:

- **Non-Invasive:** Instant smartphone camera screening.
- **Multi-Modal:** Uses images, symptoms, and user profile.
- **Actionable:** Provides diet plans and doctor booking.
- **Trackable:** Saves health reports and history.

Limitations:

- **Screening Only:** Needs lab confirmation.
- **Lighting Sensitive:** Affected by poor lighting and focus.
- **Bias Risk:** Accuracy varies across skin tones.
- **User Dependent:** Relies on correct symptom self-reporting.

Proposed Future System



- **User Profile Setup:** Captures demographic at-tributes (Age, Gender, Pregnancy status, Dietary pref-erences).
- **Image & Symptom Input:** Dual option for live capture/upload (Eye conjunctiva, Nails) + short symptom questionnaire.
- **Preprocessing & AI Inference:** Image quality validation, ROI extraction, and multi-modal risk scoring (Low, Moderate, High).
- **Personalized Recommendations:** Delivers iron-rich diet suggestions, recommended laboratory blood tests (CBC, Ferritin), and nearby clinic location mapping.
- **Digital Health Report & Appointments:** Gen-erates downloadable reports and facilitates direct doctor appointment bookings.

VI. Future Research Direction

Future non-invasive anemia research will prioritize the integration of multi-spectral imaging and smartphone video photoplethysmography (PPG) to analyze microvascular blood flow dynamically. Incorporating Explainable AI (XAI) tools like Grad-CAM and SHAP will build clinician trust by highlighting specific pallor zones and feature weights during inference. Furthermore, expanding multi-modal datasets to represent diverse racial backgrounds, age cohorts, and clinical sub-types of anemia will be vital for re-ducing model bias. Finally, deployment on edge computing devices and mobile edge TPUs will enable real-time, offline screening in remote rural regions, dramatically improving healthcare accessibility in underserved communities.

VII. Conclusion

The AI-Based Anemia Detection and Personalized Health Recommendation System provides a web-based approach to preliminary anemia risk screening using Convolutional Neural Networks (CNN) and user-reported symptoms. The system estimates potential risk levels and provides personalized dietary suggestions, recommended blood test information, nearby healthcare facilities, doctor appoint-ment options, and digital health reports. By integrating these features into a single application, the system aims to improve health awareness and encourage timely medical consultation. It can also help users access relevant health in-formation and review their assessment history conveniently. The effectiveness of the system depends on the quality of the dataset, image suitability, and model evaluation. The system is intended for preliminary screening and does not replace laboratory tests or professional medical diagnosis.

VIII. References

1) Muljono, S. A. Wulandari, H. Al Azies, M. Naufal, et al. (2024). Breaking boundaries in diagnosis: Non-invasive anemia detection empowered by AI. IEEE Access, 12, 9292–9307. https://doi.org/10.1109/ACCESS.2024.3353788
2) Fingertip video dataset for non-invasive diagnosis of anemia using ResNet-18 classifier. (2024). IEEE Access, 12, 68880–68892. https://doi.org/10.1109/ACCESS.2024.3398353
3) Predicting anemia with precision: Employing machine learning ensemble modeling and hyperparameter tun-ing. (2024). In 2024 3rd International Conference for Advancement in Technology (ICONAT). IEEE. https://doi.org/10.1109/ICONAT61936.2024.10774701
4) HgbNet: Predicting hemoglobin level/anemia de-gree from irregular EHR. (2024). IEEE Access, 12, 144837–144854. https://doi.org/10.1109/ACCESS.2024.3473693
5) Transparent anaemia prediction system with explain-able artificial intelligence. (2026). In 2026 IEEE Inter-national Students' Conference on Electrical, Electron-ics and Computer Science (SCEECS). IEEE. https://doi.org/10.1109/SCEECS68810.2026.11430131
6) Appiahene P, Donkoh ET, Dimauro G: Iron de-ficiency anemia detection using machine learning models: a comparative study of fingernails, palm and conjunctiva of the eye images. Eng Rep. 2023, 16:10.1002/eng2.12667
7) Zhang F, Zhang S, Ren W, et al. Global burden of anemia and cause among children under five years 1990–2019: findings from the global burden of disease study 2019. Front Nutr 2024;11:1474664.
8) Bharathi G, Berks M, Dinsdale G, et al. A deep learning system for quantitative assessment of mi-crovascular abnormalities in nailfold capillary images. Rheumatology 2023;62:2325–9.
9) Isewon I, Alagbe E, Oyelade J. Optimizing machine learning performance for medical imaging analyses in low-resource environments: the prospects of CNN-based feature extractors. F1000Res 2025:100.
10) Lee H, Brandwein M, Shpiegel R, et al. Artificial intelligence-enabled non-invasive ubiquitous anemia screening: the HEMO-AI pilot study on pediatric population. Digit Health 2024;10:20552076241297057.