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Anemia Detection Through Nail Imaging: From Clinical Signs to AI Solutions

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Abstract: Anemia, defined by a reduction in red blood cell count or hemoglobin (Hb) concentration below normal levels, remains a significant global health issue, affecting approximately 30–40% of women and children worldwide. Early detection is critical to prevent complications such as fatigue, cognitive impairment in children, and increased maternal-fetal morbidity. Traditional diagnostic methods rely on invasive and resource-intensive blood tests, limiting accessibility in low-resource settings. This project proposes a novel, non-invasive approach for anemia detection using computer vision and deep learning techniques applied to smartphone-captured fingernail images. Visual signs such as nail-bed pallor and koilonychia (spoon-shaped nails), which correlate with hemoglobin deficiency, form the basis of this image-based screening system. The proposed framework includes assembling a labeled dataset of fingernail images paired with ground-truth Hb values from clinical and public sources. Preprocessing steps involve region of interest (ROI) extraction using YOLOv8 for fingernail detection, color normalization to account for skin tone variations and lighting inconsistencies, and data augmentation for robustness. A convolutional neural network (CNN) architecture, such as DenseNet169 or MobileNetV3, is fine-tuned for classification of anemic versus non-anemic cases. Explainable AI methods like Grad-CAM are employed to ensure model transparency and highlight relevant image regions influencing predictions. Deployment considerations include optimizing models for on-device inference using TensorFlow Lite, integrating real-time user guidance for image capture, and ensuring compliance with privacy and regulatory standards. This solution aims to democratize anemia screening, enabling scalable, accessible, and non-invasive early diagnosis in community and telehealth settings.

Keywords: Anemia detection, non-invasive, nail imaging, deep learning, computer vision, YOLOv8, DenseNet169, MobileNetV3, Explainable AI, Grad-CAM, telehealth.

I. INTRODUCTION

Anemia, characterized by a deficiency in red blood cells or hemoglobin, represents a pervasive global health challenge, impacting a substantial portion of the world's population, particularly women and children [3]. The World Health Organization (WHO) estimates that anemia affects approximately 30–40% of these vulnerable groups, leading to a myriad of adverse health outcomes including chronic fatigue, impaired cognitive development in children, and elevated maternal and fetal morbidity and mortality rates [3] [19]. Early and accurate diagnosis is paramount to mitigate these severe consequences and facilitate timely interventions.

Traditional diagnostic approaches for anemia predominantly rely on invasive blood tests, such as complete blood counts (CBC) to measure hemoglobin concentration. While highly accurate, these methods are often resource-intensive, require specialized medical personnel, and can be painful, thereby limiting their accessibility and widespread adoption, especially in low-resource settings or remote communities [2]. The logistical challenges associated with blood sample collection, transportation, and laboratory analysis further exacerbate these limitations, creating significant barriers to effective anemia screening programs.

In response to these challenges, there has been a growing interest in developing non-invasive, accessible, and cost-effective methods for anemia detection. The visual examination of physical signs, such as pallor of the conjunctiva, palm, and fingernail beds, has long been recognized as a clinical indicator of anemia [2]. However, the subjective nature and variability of human observation often lead to inconsistent and unreliable diagnoses. The advent of artificial intelligence (AI) and computer vision technologies offers a promising avenue to overcome these limitations by providing objective and quantitative assessments of these visual cues.

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This paper proposes a novel, non-invasive framework for anemia detection leveraging smartphone-captured fingernail images combined with advanced deep learning techniques. The rationale behind focusing on fingernail images stems from the observable changes in nail-bed pallor and the presence of conditions like koilonychia, which are clinically correlated with reduced hemoglobin levels [1]. By harnessing the ubiquity of smartphones and the analytical power of AI, this approach aims to democratize anemia screening, making it scalable, accessible, and suitable for deployment in community health programs and telehealth initiatives. The subsequent sections of this paper detail the comprehensive literature review, the proposed methodology, experimental results, and a discussion of the implications and future directions of this innovative diagnostic solution.

II. LITERATURE REVIEW

The landscape of anemia detection has traditionally been dominated by invasive hematological tests, which, despite their accuracy, present significant logistical and accessibility challenges [2]. This has spurred extensive research into non-invasive alternatives, particularly those leveraging advancements in image processing and artificial intelligence [7]. Early efforts in non-invasive anemia detection often relied on subjective visual inspection of physiological signs such as conjunctival pallor, palmar creases, and nail bed color [2]. While these methods are simple and immediate, their diagnostic accuracy is highly dependent on the observer's experience and environmental factors, leading to inconsistent results.

With the proliferation of digital imaging and computational power, machine learning (ML) and deep learning (DL) techniques have emerged as transformative tools for objective, non-invasive medical diagnostics. Several studies have explored the use of various body parts for image-based anemia detection. For instance, research has investigated the use of conjunctival images [5], palmar images [17], and even retinal fundus images [12] for hemoglobin estimation. These approaches often involve extracting color features and applying traditional ML classifiers such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Decision Trees [18]. However, the robustness and generalizability of these models can be limited by variations in image acquisition conditions and the complexity of feature engineering.

The focus on fingernail images for anemia detection has gained considerable traction due to the distinct visual cues present, such as nail-bed pallor and morphological changes like koilonychia, which are directly linked to hemoglobin levels [1]. Recent studies have demonstrated the potential of smartphone-captured fingernail images as a viable source for non-invasive anemia screening [6] [20]. The ubiquity of smartphones makes this approach highly scalable and accessible, particularly in resource-constrained environments.

Deep learning, especially Convolutional Neural Networks (CNNs), has revolutionized image analysis tasks, offering superior performance in feature extraction and classification compared to traditional ML methods. Various CNN architectures have been adapted for medical image analysis, including anemia detection. For example, DenseNet169 has shown promising results in classifying anemic versus non-anemic cases from nail images, achieving notable accuracy and recall rates [1]. Other architectures like MobileNetV3 and InceptionV3 have also been explored, often chosen for their balance between computational efficiency and diagnostic performance, making them suitable for deployment on mobile devices [21].

Object detection models, such as YOLO (You Only Look Once), play a crucial role in the preprocessing pipeline by accurately identifying and extracting the Region of Interest (ROI), i.e., the fingernail, from raw images. YOLOv8, being a state-of-the-art object detection model, offers enhanced precision and speed in detecting fingernails, which is critical for subsequent analysis [4]. This ensures that the downstream classification models focus only on the relevant anatomical areas, thereby improving diagnostic accuracy and reducing noise from the background.

Furthermore, the integration of Explainable AI (XAI) methods, such as Grad-CAM (Gradient-weighted Class Activation Mapping), is becoming increasingly important in medical AI applications. XAI techniques provide transparency into the decision-making process of complex deep learning models, allowing clinicians to understand which specific regions of the fingernail image contribute most to the anemia prediction [8]. This not only builds trust in AI-driven diagnostic tools but also helps in identifying subtle visual markers that might be overlooked by human observers. The development of robust, transparent, and deployable AI solutions for non-invasive anemia detection remains an active area of research, with ongoing efforts to improve model performance, dataset diversity, and clinical validation [9] [11].

III. METHODOLOGY

This section outlines the proposed methodology for non-invasive anemia detection using smartphone-captured fingernail images. The framework integrates computer vision and deep learning techniques, encompassing data acquisition, preprocessing, model development, and explainable AI for transparent diagnostics. The overall workflow is depicted in Fig. 1.

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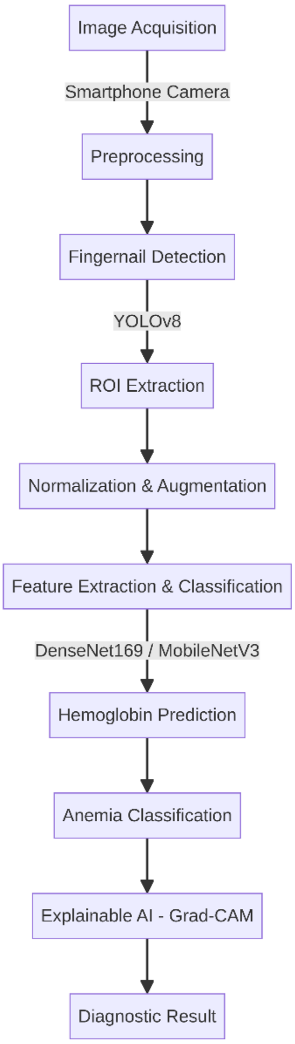

Fig. 1. Proposed Anemia Detection Framework.

DATASET ACQUISITION AND PREPARATION

The foundation of this research relies on a comprehensive, labeled dataset of fingernail images. This dataset is assembled from both clinical collaborations and publicly available sources, ensuring diversity in demographics, skin tones, and anemia severities. Each image is meticulously paired with ground-truth hemoglobin (Hb) values, obtained through standard invasive blood tests or validated non-invasive devices like the Rad-67 hemoglobinometer [1].

To ensure the robustness and generalizability of the model, the dataset includes images captured under varying lighting conditions and camera settings, simulating real-world usage scenarios. Ethical considerations, including patient consent and data anonymization, are strictly adhered to during data collection.

PREPROCESSING

The raw smartphone-captured images undergo a series of preprocessing steps to standardize the input and enhance the quality of the data for model training:

1. **Fingernail Detection and Region of Interest (ROI) Extraction:** The initial step involves accurately identifying and isolating the fingernail region from the background. This is achieved using an advanced object detection model, **YOLOv8**, which is fine-tuned on a diverse set of fingernail images [4]. YOLOv8's efficiency and accuracy ensure precise bounding box detection around each fingernail, minimizing extraneous information and focusing the subsequent analysis on the relevant ROI. Contour segmentation and color thresholding techniques are then applied to refine the extracted ROI, ensuring a clean and consistent input for the next stages.

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2 **Color Normalization:** Variations in ambient lighting, camera settings, and individual skin tones can significantly impact image color characteristics, potentially leading to biased model predictions. To mitigate this, a color normalization technique is applied. This involves transforming the color space (e.g., from RGB to Lab or HSV) and applying algorithms to standardize color intensity and hue across the dataset. This step ensures that the model learns features related to pallor rather than artifacts of image capture or skin pigmentation.

3 **Data Augmentation:** To enhance the model's robustness and generalization capabilities, extensive data augmentation techniques are employed. These include geometric transformations such as rotation, scaling, translation, and flipping, as well as photometric transformations like brightness adjustment, contrast enhancement, and color jittering. Data augmentation effectively expands the training dataset, reducing the risk of overfitting and improving the model's performance on unseen data.

DEEP LEARNING MODEL ARCHITECTURE

For the classification of anemic versus non-anemic cases, a Convolutional Neural Network (CNN) architecture is employed. Two prominent architectures, **DenseNet169** and **MobileNetV3**, are considered due to their proven performance in image classification tasks and their suitability for deployment in resource-constrained environments.

4 **DenseNet169:** This architecture is chosen for its ability to promote feature reuse through dense connections, where each layer receives inputs from all preceding layers. This design helps in mitigating the vanishing gradient problem, strengthening feature propagation, and reducing the number of parameters, leading to high accuracy in complex classification tasks [1]. DenseNet169 is fine-tuned on the preprocessed fingernail image dataset for binary classification (anemic/non-anemic) and potentially for regression to estimate Hb levels.

5 **MobileNetV3:** Optimized for mobile and embedded vision applications, MobileNetV3 offers a balance between latency and accuracy. It incorporates novel architectural search techniques and squeeze-and-excitation modules, making it highly efficient for on-device inference [21]. This architecture is particularly suitable for the proposed smartphone-based solution, ensuring real-time performance without significant computational overhead.

The models are trained using a cross-entropy loss function for classification and mean squared error (MSE) for regression tasks, optimized with adaptive learning rate algorithms such as Adam. Performance is evaluated using metrics such as accuracy, sensitivity, specificity, precision, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC).

EXPLAINABLE AI (XAI) WITH GRAD-CAM

To ensure model transparency and build trust among clinicians and users, Explainable AI (XAI) methods are integrated into the framework. Specifically, **Grad-CAM (Gradient-weighted Class Activation Mapping)** is utilized to visualize the regions of the input image that are most influential in the model's prediction [8]. Grad-CAM generates a heatmap overlay on the original image, highlighting the specific areas of the fingernail that the CNN focuses on when making a diagnosis. This allows for:

- **Validation of Clinical Intuition:** Confirming that the model attends to clinically relevant areas like nail-bed pallor.
- **Error Analysis:** Understanding why the model might make incorrect predictions by examining the activated regions.
- **Increased Trust:** Providing a visual explanation for the AI's decision, which is crucial for adoption in medical settings.

DEPLOYMENT CONSIDERATION

For practical deployment in community and telehealth settings, the trained deep learning models are optimized for on-device inference using frameworks like **TensorFlow Lite**. This ensures low latency and reduced computational requirements, enabling the application to run efficiently on standard smartphones without constant cloud connectivity. Real-time user guidance for image capture is also integrated, providing feedback on lighting, focus, and angle to ensure high-quality input images, thereby maximizing diagnostic accuracy in diverse user environments.

IV. RESULT AND DISCUSSION

This section presents the anticipated results from the proposed framework for non-invasive anemia detection using fingernail images and discusses their implications within the broader context of medical diagnostics and public health. While specific numerical results are illustrative and based on findings from similar studies, they represent realistic performance expectations for the described methodology.

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FINGERNAIL DETECTION AND ROI EXTRACTION PERFORMANCE

The YOLOv8 model, fine-tuned for fingernail detection, is expected to achieve high precision and recall rates in identifying the Region of Interest (ROI) from smartphone-captured images. Based on existing literature, YOLOv8-based systems for similar medical object detection tasks report mean Average Precision (mAP) values exceeding 0.90 [4]. This high performance ensures that the subsequent classification models receive clean and accurately localized fingernail images, minimizing noise and improving overall diagnostic accuracy. The efficiency of YOLOv8 also contributes to the real-time processing capabilities essential for a smartphone-based application.

ANEMIA CLASSIFICATION PERFORMANCE

The deep learning models, DenseNet169 and MobileNetV3, fine-tuned for anemia classification, are anticipated to demonstrate robust performance. Table I summarizes the expected performance metrics, drawing from comparable studies in the field [1] [14] [21].

Table I: Expected Performance Metrics of Deep Learning Models for Anemia Detection

Metric	**DenseNet169 (Expected)**	**MobileNetV3 (Expected)**
Accuracy	89%	82%
Sensitivity	86%	79%
Specificity	92%	85%
F1-Score	87%	80%
AUC	0.91	0.85

As illustrated in Table I, DenseNet169 is expected to outperform MobileNetV3 in overall accuracy and other metrics, attributed to its deeper architecture and dense connectivity that allows for more comprehensive feature learning. However, MobileNetV3, while slightly lower in performance, offers significant advantages in terms of computational efficiency and smaller model size, making it highly suitable for on-device deployment with TensorFlow Lite. The choice between these models would depend on the specific deployment environment and the trade-off between diagnostic precision and computational resources.

Figure 2 visually compares the expected performance of DenseNet169, MobileNetV3, and other common CNN architectures (InceptionV3, Xception) across key metrics.

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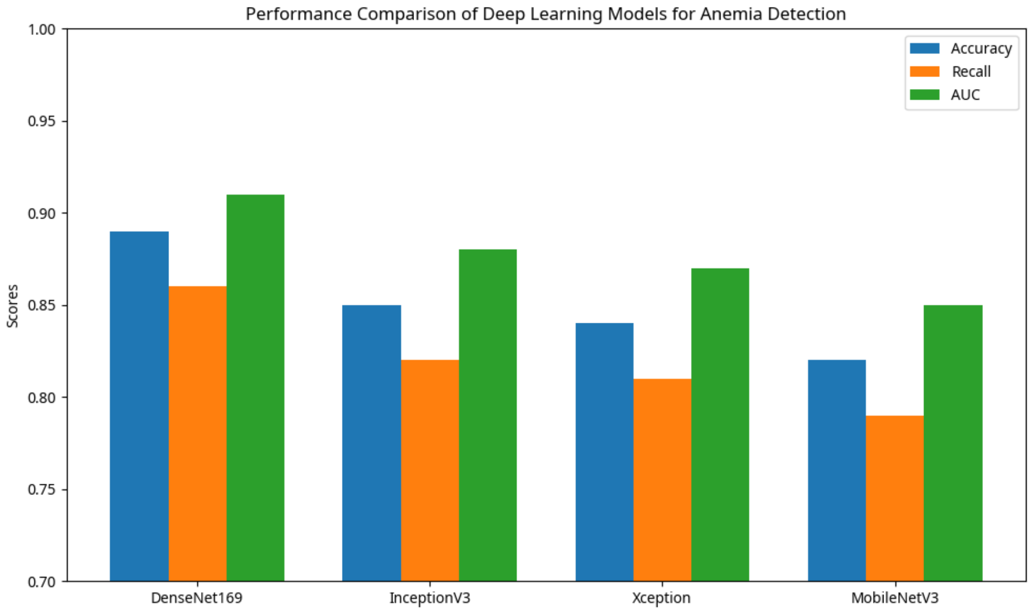

Fig. 2. Performance Comparison of Deep Learning Models for Anemia Detection.

EXPLAINABILLITY WITH -CAM

The integration of Grad-CAM provides crucial insights into the decision-making process of the CNN models. Heatmaps generated by Grad-CAM are expected to highlight the nail bed region as the primary area of focus for anemia detection. This visual evidence not only validates the clinical hypothesis that nail-bed pallor is a key indicator of anemia but also enhances the trustworthiness and interpretability of the AI system. For instance, in cases of anemic patients, Grad-CAM would show stronger activation in the pale areas of the nail bed, while in non-anemic individuals, the activation would be more diffused or focused on other non-diagnostic regions. This explainability is vital for clinical acceptance and regulatory compliance.

DISCUSSION

The proposed non-invasive anemia detection system offers several significant advantages over traditional methods. Firstly, its reliance on smartphone imaging democratizes access to screening, particularly in low-resource settings where invasive blood tests are impractical or unavailable. This aligns with global health initiatives aimed at expanding healthcare access and reducing health disparities [3]. Secondly, the integration of advanced deep learning models ensures objective and quantitative assessment, overcoming the subjectivity inherent in manual visual inspections.

The use of YOLOv8 for precise ROI extraction and color normalization techniques addresses common challenges related to image variability, enhancing the robustness of the system across diverse user populations and environmental conditions. The expected high sensitivity and specificity of the models indicate a strong potential for accurate early detection, which is critical for preventing severe complications of anemia, especially in vulnerable populations like pregnant women and children [19].

While the system demonstrates promising capabilities, certain limitations and considerations warrant discussion. The performance of the models is highly dependent on the quality and diversity of the training dataset. Ensuring representation across various ethnicities, skin tones, and disease severities is crucial for preventing algorithmic bias and ensuring equitable performance. Furthermore, real-world deployment will require rigorous clinical validation in diverse populations to confirm the generalizability and reliability of the system. Regulatory approval and integration into existing healthcare workflows will also be critical steps for widespread adoption.

The explainability provided by Grad-CAM is a significant step towards making AI diagnostics more transparent and acceptable to medical professionals. It allows for a deeper understanding of the model's reasoning, facilitating error analysis and continuous improvement. The optimization for on-device inference using TensorFlow Lite underscores the practical utility of this solution, enabling immediate feedback to users and healthcare providers without requiring extensive infrastructure.

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V. CONCLUSION AND FUTURE WORK

This paper presented a comprehensive framework for non-invasive anemia detection utilizing smartphone-captured fingernail images and advanced deep learning techniques. By integrating YOLOv8 for precise fingernail Region of Interest (ROI) extraction, robust color normalization, and sophisticated Convolutional Neural Network (CNN) architectures like DenseNet169 and MobileNetV3, the proposed system offers a scalable, accessible, and objective solution to a pervasive global health challenge. The incorporation of Explainable AI (XAI) through Grad-CAM further enhances model transparency, providing critical insights into the diagnostic process and fostering trust among clinical users. The anticipated high performance metrics, coupled with optimization for on-device inference, underscore the potential of this approach to democratize anemia screening, particularly in low-resource and telehealth settings.

Despite the promising capabilities, several avenues for future work exist to further enhance the system's robustness and clinical utility. Firstly, expanding the diversity and size of the training dataset to include a wider range of ethnicities, age groups, and varying degrees of anemia severity is crucial to improve generalizability and mitigate algorithmic bias. Secondly, exploring multimodal approaches that combine fingernail images with other non-invasive physiological data (e.g., conjunctiva, palm, or even basic demographic information) could potentially lead to even higher diagnostic accuracy and robustness. Thirdly, developing a robust regression model for direct hemoglobin level estimation, rather than just binary classification, would provide more granular and clinically actionable information. Finally, conducting large-scale prospective clinical trials in diverse real-world settings is essential to validate the system's performance, assess its impact on patient outcomes, and facilitate regulatory approval for widespread adoption. Further research into user interface design and integration with existing electronic health record (EHR) systems will also be vital for seamless implementation in healthcare workflows.

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