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Literature Review on Non-Invasive Haemoglobin Detection and Anemia Diagnosis Using Optical, Smartphone, and AI-Based Techniques

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Abstract - non-invasive haemoglobin (Hb) detection has emerged as a critical field of study because it circumvents the drawbacks of conventional invasive technologies, which necessitate painful blood draws, take a long time, cause discomfort for patients, and prohibit continuous monitoring. Recent developments use state-of-the-art technologies including optical sensing, photoplethysmography (PPG), smartphone-based imaging, and artificial intelligence (AI) to provide accurate, real-time, and economical Hb estimates suitable for a variety of clinical scenarios. This comprehensive review gathers research from around the globe on optical imaging techniques, wearable sensors for ambulatory use, deep learning algorithms for signal processing, and rigorous clinical validations, including postpartum anemia screening protocols. Key findings show that AI-enhanced optical systems provide scalability for point-of-care applications in resource-constrained contexts and provide improved predictive accuracy, frequently surpassing 90% correlation with gold-standard lab data. For example, PPG combined with convolutional neural networks has demonstrated resilience to motion artifacts and different skin tones. However, ongoing issues include inter-device variability, signal noise from external factors, population-specific calibration discrepancies, and the lack of universal clinical standardization. By overcoming these obstacles using multimodal sensor fusion and extensive trials, non-invasive hemoglobin monitoring will become widely used, transforming the treatment of anemia and the monitoring of chronic illnesses.

Keywords - Hemoglobin (Hb), Artificial intelligence (AI), Smartphone-based diagnosis, Point-of-care diagnostics, Photoplethysmography (PPG), Telemedicine, Model accuracy, Convolutional Neural Networks (CNN), Image segmentation (EGE-UNet), Retinal image analysis component, Raman spectroscopy, Pulse CO-oximetr.

I. INTRODUCTION

A key biomarker for assessing oxygen-carrying capacity and diagnosing a range of hematological disorders, such as iron-deficiency anemia, acute blood loss, polycythaemia, and cardiovascular complications like heart failure, is hemoglobin (Hb), the iron-rich protein in erythrocytes that carries oxygen from lungs to tissues.[3] Over 1.9 billion people worldwide suffer from anemia, which is defined by the World Health Organization as Hb <13 g/dL in men, <12 g/dL in non-pregnant women, and <11 g/dL in pregnancy. It disproportionately affects women of reproductive age (30–40% prevalence) and children under five (40%), causing significant morbidity through fatigue, cognitive impairment, and maternal/neonatal mortality; in low-resource regions like sub-Saharan Africa and South Asia.[8] Conventional invasive haemoglobin measurement involves venous or capillary blood collection, followed by laboratory analysis using spectrophotometry or automated haematology analyzers. These procedures cause discomfort during the procedure, require skilled phlebotomists, cause delays (often 30 to 60 minutes for results), increase the risk of biohazards, and are not practical for frequent or real-time monitoring in critical situations like trauma bays, postoperative wards, rural clinics, or ambulatory pediatrics.[3] These limitations worsen diagnostic disparities, especially in situations requiring long-term monitoring or in crises where quick triage is essential. [3, 7, 14]

In order to overcome these obstacles, non-invasive methods have proliferated. These methods use sophisticated computational models such as machine learning regressions on photoplethysmography (PPG), diffuse reflectance spectroscopy, and Raman spectroscopy in conjunction with haemoglobin's unique optical absorbance spectra in visible and near-infrared wavelengths (such as the Soret band at 415 nm and Q-bands at 540/577 nm) to determine Hb concentrations from skin-surface signals without venipuncture. [1, 6, 13, 15] Although continuous improvements in algorithm robustness and clinical validation are necessary for equitable deployment, these approaches promise painless, instantaneous point-of-care assessment. [2, 4, 9, 11, 12]

II. CLINICAL IMPORTANCE OF HEMOGLOBIN MONITORING

Measurement of hemoglobin (Hb) is an essential metric for patient assessment and treatment in a variety of therapeutic applications. It is frequently used to guide transfusion decisions, monitor intraoperative blood loss, diagnose anemia, and assess preoperative risk. [4, 14] Notably, real-time detection of anemic trends and prompt, evidence-based decision-making have been made possible by the use of continuous, non-invasive Hb monitoring during surgical procedures, which has shown substantial clinical utility. [14]

The treatment of postpartum anemia, a disorder with significant consequences for mother health, is a particularly significant use of hemoglobin monitoring. More over half of the 670 postpartum women in the study were found to be anemic after giving birth, highlighting the urgent need for routine hemoglobin testing in this population. [5] With a stated sensitivity of 95.69% and a significant correlation (r = 0.87) with standard laboratory data, emerging non-invasive technologies like the Eze Check gadget have demonstrated promising diagnostic performance. These results demonstrate

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the promise of low-cost, non-invasive, and user-friendly screening methods to improve anemia early identification and treatment, especially in maternal healthcare settings with limited resources. [5]

III. NON-INVASIVE OPTICAL AND SIGNAL-BASED METHODS

A. Systems Based on Photoplethysmography (PPG)

Because of its ease of use, affordability, and compatibility with wearable technology, photoplethysmography (PPG) has become one of the most popular methods for non-invasive hemoglobin (Hb) assessment. PPG uses light absorption properties at various wavelengths to detect changes in blood volume. Multi-wavelength techniques have been the focus of recent developments to improve measuring precision and dependability. For example, a multi-wavelength PPG system created and showed high agreement confirmed by Bland-Altman analysis and a moderate but substantial correlation with invasive Hb readings ($r = 0.61–0.62$).

By combining PPG systems with machine learning algorithms, additional advancements have been made. With a root mean square error (RMSE) of 0.762 g/L and a coefficient of determination (R^2) of 0.997, a four-wavelength PPG-based model demonstrated remarkably good predictive accuracy (Chen et al., 2023). These findings suggest that the accuracy of non-invasive Hb estimation could be greatly increased by combining optical detection with sophisticated computer models.[14]

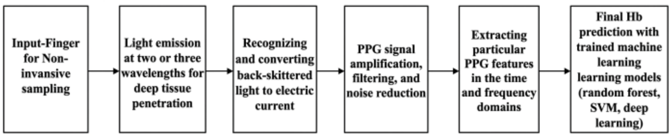

Fig. 1 PPG-Based Hb Detection System

The diagram illustrates a complete workflow:

PPG-based Hb detection system illustrating the complete workflow: finger placement → multi-wavelength LED emission → photodiode signal acquisition → signal processing → feature extraction → machine learning model → Hb prediction.

The non-invasive and continuous monitoring capabilities of PPG-based systems is one of their main advantages, which makes them especially well-suited for incorporation into wearable technology. These systems are nonetheless vulnerable to motion artifacts, background noise, and changes in tissue characteristics, all of which can have an impact on measurement precision.

B. Optical Imaging and Spectroscopy

By utilizing hemoglobin's ability to absorb light at particular wavelengths, optical spectroscopy and imaging techniques offer a different non-invasive method for estimating hemoglobin. Diffuse optical imaging, spectrophotometry, and pulse CO-oximetry are common modalities. These techniques have been extensively investigated in clinical settings and allow for real-time monitoring.

Despite their benefits, optical methods are frequently constrained by things like sensitivity to the environment, difficulties with calibration, and decreased accuracy in different physiological and external situations. [14] As a result, further research attempts to increase resilience and reliability, especially for application in contexts that are dynamic and resource-constrained.

IV. SMARTPHONE-BASED HEMOGLOBIN IDENTIFICATION

Because mobile devices are widely available and have sophisticated computational capabilities, smartphone-based hemoglobin (Hb) detection systems are becoming more widely acknowledged as scalable and accessible solutions. Without the need for specific external hardware, these systems provide non-invasive, real-time Hb estimate through the use of built-in cameras and artificial intelligence. The performance of these methods has been greatly enhanced by recent developments in deep learning. For instance, a smartphone-based system using eyelid (conjunctival) image analysis maintained a lightweight architecture with only 1.08 million parameters while achieving an accuracy of 97% with a mean absolute error (MAE) of 1.34. [4] Because of these features, the system is especially well-suited for implementation in point-of-care and resource-constrained environments.

These systems eliminate the need for external devices and enable real-time point-of-care diagnostics.

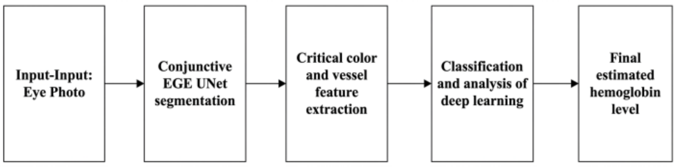

Fig. 2 Smartphone Deep Learning Pipeline

Smartphone-based deep learning pipeline for Hb estimation: eye image acquisition → segmentation using EGE-UNet → feature extraction → prediction using DHA-C3AE model → Hb output.

The first step in the processing pipeline is to take an image of the eye, which is the raw input. The conjunctiva and other clinically significant areas are then isolated using an EGE-UNet segmentation model. Discriminative features, like vascular patterns and colour intensity, are extracted after segmentation and converted into a numerical feature vector. A specific deep learning architecture (DHA-C3AE) then analyzes this vector and predicts the hemoglobin level as a quantitative output (g/dL).

Practically speaking, smartphone-based systems have many benefits, such as portability, affordability, and quick real-time analysis, which makes them ideal for telemedicine and large-scale screening applications. However, outside variables like lighting, camera quality, and user variability might affect how well they function.

V. AI-POWERED METHODS FOR IMAGE PROCESSING

AI has greatly enhanced non-invasive hemoglobin detection.

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A. *Image-Based Retinal Detection*

The accuracy and dependability of non-invasive hemoglobin (Hb) measurement have been greatly improved by artificial intelligence (AI), especially when it comes to the interpretation of medical imaging modalities. Using retinal fundus images to extract tiny vascular characteristics linked to hemoglobin levels using deep learning models is one of the most promising methods. With an accuracy of 98%, sensitivity of 99%, and mean absolute error (MAE) of 0.58 g/dL, a recent study showed exceptional performance utilizing this method. Clinically significant biomarkers, such as vascular tortuosity and decreased vessel density, which are suggestive of physiological alterations linked to anemia, were successfully detected by the model. [8]

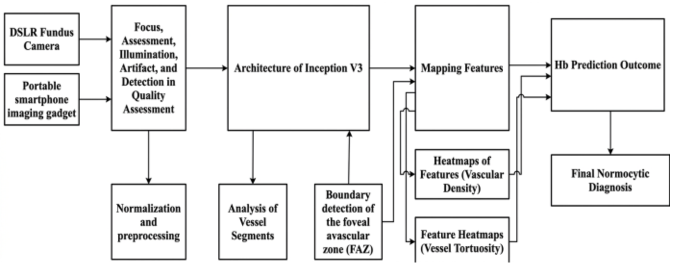

Fig. 3 Retinal AI-Based Detection

Retinal AI-based Hb detection pipeline: image acquisition → preprocessing → convolutional neural network (InceptionV3) → feature mapping → Hb prediction and classification.

Retinal image acquisition using a DSLR-based fundus camera or a portable imaging device is the first step in the workflow. Quality evaluation and preprocessing procedures like scaling and normalization come next. A convolutional neural network (CNN), usually built on the InceptionV3 architecture, receives the processed fundus image and uses multi-scale convolutional filters to extract hierarchical features. By using activation maps to highlight important areas, the feature mapping stage makes it possible to identify vascular properties. The prediction power of the model is further improved by additional diagnostic sub-analyses including micro-aneurysm identification and vessel diameter assessment. In order to facilitate diagnostic interpretation, the system's final output is a quantitative Hb prediction that may also be classified into clinical classifications (such as normocytic or microcytic disorders). [8]

Clinically speaking, retinal imaging-based hemoglobin detection can be easily incorporated into current ocular screening programs and provides good diagnostic accuracy. Despite its excellent predictive accuracy, its application is hampered by the need for specialized imaging equipment and restricted accessibility in low-resource areas, which may prevent widespread use. [8]

VI. CONTINUOUS AND WEARABLE MONITORING SYSTEMS

A useful development in non-invasive hemoglobin (Hb) measurement, continuous monitoring systems based on pulse CO-oximetry allow for real-time tracking of Hb levels in dynamic clinical settings. By continually estimating Hb levels via multi-wavelength spectrophotometry, these systems lessen the need for sporadic intrusive blood sample. The predictive accuracy of 93.3% for identifying drops in Hb levels was shown in a randomized clinical trial, demonstrating the dependability of this technology in detecting clinically relevant changes. Additionally, it has been demonstrated that the availability of continuous Hb data improves clinical decision-making by offering prompt patient status information. [14]

The use of pulse CO-oximetry systems has a number of significant advantages from a clinical standpoint. These include better blood test scheduling and optimization since doctors are better able to identify when more laboratory testing is required. Additionally, by enabling more accurate monitoring of Hb trends, these devices help reduce needless blood transfusions, hence lowering associated hazards and healthcare expenses. Crucially, in both surgical and critical care situations, ongoing monitoring facilitates a more proactive approach to patient management, enabling early intervention and better overall results. [14]

VII. COMPARATIVE EVALUATION OF METHODS

TABLE 1. Comparative Assessment of Approaches

Technique	*Accuracy*	*Cost*	*Portability*	*Clinical Use*
PPG Systems	r ≈ 0.60–0.99, RMSE ≈ 0.7–2.0 g/dL	Medium (£160 – £1,600 depending on device)	High (wearable sensors, finger probes, compact devices)	Permits ongoing, real-time hemoglobin monitoring, particularly in ICU and surgical settings. helpful in identifying trends, detecting anemia early, and directing transfusion choices without the need for frequent intrusive sample.
Smartphone AI	Accuracy ≈ 90–97%, MAE ≈ 1.0–1.5 g/dL	Low (£0 – £80, uses existing smartphones)	Very High (fully mobile, no external hardware required)	Perfect for large-scale screening and point-of-care, particularly in distant or resource-constrained settings. facilitates self-evaluation, telemedicine, and quick anemic case triaging.

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Technique	*Accuracy*	*Cost*	*Portability*	*Clinical Use*
Retinal AI	Accuracy ≈ 95–98%, Sensitivity ≈ 95–99%, MAE ≈ 0.5–0.8 g/dL	Medium (£800 – £4,000 for fundus devices)	Medium (requires portable or tabletop fundus cameras)	Utilized mostly for diagnostic assistance and clinical screening. can be combined with eye exams to detect retinal disorders and anemia at the same time.
Optical Imaging	Accuracy ≈ 85–95% depending on conditions	High (£2,400 – £8,000+)	Low (bulky hospital-based systems)	Extensively utilized for ongoing intraoperative monitoring in hospital and surgical settings. helps make decisions about critical care, but it needs controlled environments.
Spectroscopy	Moderate accuracy (r ≈ 0.5–0.85, variable with environment)	Low (£80 – £400)	High (portable handheld devices possible)	Ideal for field screening and rural healthcare. allows for the basic identification of anemia, while physiological and environmental factors may have an impact on accuracy.

VIII. OBSTACLES AND RESTRICTIONS

A. Technical Difficulties

Non-invasive hemoglobin (Hb) detection devices still have a number of technological issues that compromise their robustness and dependability despite tremendous progress. Motion artifacts are one of the main problems, especially in photoplethysmography (PPG)-based systems where patient movement can add noise and distort signal quality, resulting in erroneous Hb estimation. [14] Signal acquisition and processing might also be hampered by environmental elements like temperature fluctuations, ambient light variations, and inconsistent sensor placement. These outside factors are particularly important for optical and smartphone-based systems, because uncontrolled circumstances can seriously impair performance. [4]

B. Clinical Difficulties

From a clinical standpoint, the absence of comprehensive, large-scale validation studies in a variety of healthcare settings is impeding the adoption of non-invasive Hb monitoring systems. The generalizability of many suggested models is limited because they are tested on comparatively small or homogeneous populations. Additionally, individual variances in skin tone, age, comorbidities, and vascular features can affect measurement accuracy, making universal clinical applicability difficult. [8]

C. Data Difficulties

The efficacy of AI-driven Hb estimate systems is also severely limited by data-related problems. Particularly when trained on small or non-representative datasets, machine learning models are prone to bias and overfitting. When used in practical situations, this may lead to decreased performance. Furthermore, model comparison, benchmarking, and repeatability are hampered by the lack of standardized, large-scale, and well-annotated datasets for Hb estimate, which slows the development of widely applicable and clinically reliable solutions. [2]

IX. PROSPECTIVE RESEARCH PATHS

By addressing present technological and clinical constraints, future non-invasive hemoglobin (Hb) detection research should focus on creating more reliable, accurate, and broadly applicable solutions. In order to improve measurement reliability and make up for the shortcomings of individual modalities, one interesting method is the integration of multimodal sensing systems, which combine optical, thermal, and artificial intelligence (AI)-based techniques. These hybrid systems could offer more thorough physiological insights and enhance signal quality. [11]

Designing lightweight and computationally efficient AI models that can be easily implemented on mobile and edge devices, such wearables and smartphones, is another crucial area of focus. Scalable healthcare solutions can be supported by real-time Hb estimate with high accuracy thanks to developments in model optimization and compression techniques.

Additionally, there is a great chance to increase access to healthcare services, especially in poor and distant areas, by integrating non-invasive Hb monitoring systems with telemedicine platforms. This would eliminate the need for frequent hospital visits and enable ongoing remote monitoring, early diagnosis, and prompt therapeutic action. [4]

Lastly, the standardization of assessment frameworks and measurement procedures is urgently needed. The clinical translation of non-invasive Hb detection technologies will be accelerated, reproducibility will be improved, and fair comparison across studies will be made possible by the establishment of consistent guidelines for data collecting, device calibration, and performance evaluation.

CONCLUSION

Recent years have seen tremendous improvement in non-invasive hemoglobin (Hb) detection due to advances in optical sensing technologies and the quick development of artificial intelligence (AI). [7, 9, 15] The shift from conventional invasive techniques to more patient-friendly, real-time, and scalable solutions has been made possible by these advancements. Because of its accessibility, affordability, and ease of use, wearable technology based on photoplethysmography (PPG) and AI-based smartphone systems show the most promise for mainstream healthcare application. [1, 4, 11, 13]

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Clinical studies, such as those involving intraoperative monitoring and postpartum anemia screening, have confirmed the usefulness of these devices in actual healthcare environments. [5, 14] These tools facilitate prompt clinical decision-making in addition to improving early diagnosis and ongoing monitoring. [2, 3, 10] However, there are still a number of significant obstacles to overcome in spite of these encouraging advancements. To guarantee dependability and regulatory approval, problems with measurement accuracy, a lack of established procedures, and inadequate large-scale clinical validation must be methodically resolved. [6, 7]

All things considered, non-invasive hemoglobin monitoring technologies have a great deal of potential to change the way healthcare is delivered globally, but widespread clinical adoption and integration into standard medical practice will require ongoing interdisciplinary research and thorough validation. [9, 15]

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