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Hemoglobin Estimation Techniques: A Survey of Conventional Methods, Clinical Relevance, and Machine Learning Approaches

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Abstract. Hemoglobin concentration is a critical biomarker for assessing physiological health and diagnosing conditions such as anemia, polycythemia, and chronic diseases. Conventional laboratory-based methods for hemoglobin estimation, including the cyanmethemoglobin method and automated hematology analyzers, provide high accuracy but are invasive, resource-intensive, and often inaccessible in low-resource settings. Recent advances in biomedical engineering have led to the development of non-invasive and point-of-care techniques, such as optical sensing, pulse co-oximetry, smartphone-based imaging, and wearable devices. In parallel, machine learning and deep learning approaches have emerged as powerful tools for estimating hemoglobin levels from physiological signals and medical images. This paper presents a structured and comprehensive survey of hemoglobin measurement techniques, encompassing traditional laboratory methods, emerging non-invasive technologies, and AI-driven approaches. It provides a comparative analysis of these methods in terms of accuracy, cost, portability, and clinical applicability, highlighting key trade-offs and limitations. Furthermore, the paper identifies current challenges, including variability due to physiological and environmental factors, lack of standardization, and limited clinical validation of emerging techniques. The survey emphasizes the growing potential of hybrid and AI-assisted systems to improve accessibility and scalability of hemoglobin monitoring, particularly in resource-constrained environments. Future research directions are discussed to support the development of reliable, non-invasive, and widely deployable hemoglobin estimation systems.

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1 Introduction

Hemoglobin is an iron-containing metalloprotein in red blood cells that plays a fundamental role in oxygen transport and carbon dioxide exchange, making it essential for cellular respiration and overall physiological homeostasis. In addition to its primary function, hemoglobin contributes to pH regulation and nitric oxide signaling, further underscoring its importance in maintaining systemic health. Consequently, hemoglobin concentration is widely regarded as a key clinical indicator used in routine diagnostics, disease monitoring, and therapeutic decision-making [1]. Abnormal hemoglobin levels are associated with a wide range of medical conditions, including anemia, polycythemia, nutritional deficiencies, chronic kidney disease, and cardiovascular disorders. Among these, anemia remains a major global health concern, particularly in developing countries, where it significantly affects women, children, and elderly populations. Accurate and timely measurement of hemoglobin is therefore essential for early diagnosis, treatment planning, and long-term monitoring of patients. Traditional methods for hemoglobin estimation, such as the cyanmethemoglobin method, Sahli's method, and automated hematology analyzers, have long been considered the gold standard due to their high accuracy and reliability [2]. However, these techniques require invasive blood sampling, trained personnel, and well-equipped laboratory infrastructure, limiting their accessibility in remote and resource-constrained settings. Additionally, these methods can be time-consuming and may pose risks related to infection and biohazard exposure.

To address these limitations, significant research efforts have been directed toward the development of non-invasive and point-of-care hemoglobin measurement techniques. Advances in optical sensing, spectrophotometry, wearable technologies, and smartphone-based imaging systems have enabled rapid, low-cost, and patient-friendly alternatives. Furthermore, the integration of artificial intelligence and machine learning has opened new avenues for automated hemoglobin estimation using image analysis and physiological signal processing. Despite these advancements, several challenges remain, including variability in measurement accuracy due to environmental and physiological factors, lack of standardized protocols, and limited large-scale clinical validation of emerging technologies. These issues highlight the need for a comprehensive understanding and comparative evaluation of existing methods. In this context, the objective of this paper is to provide a structured survey of hemoglobin measurement techniques, covering traditional laboratory methods, non-invasive technologies, and AI-based approaches. The paper also presents a comparative analysis of these methods, identifies key challenges and research gaps, and discusses future directions aimed at developing accurate, accessible, and scalable hemoglobin monitoring solutions.

2 Physiology of Hemoglobin

Hemoglobin is an iron-containing metalloprotein found in red blood cells. Its main job is to move oxygen across the body. Figure 1 shows that each haemoglobin molecule has four polypeptide globin chains that are organised in a quaternary form. Each chain is attached to a heme prosthetic group. The heme group has a core ferrous iron (Fe^2) ion that lets it connect to oxygen in a way that can be reversed. This means that one haemoglobin molecule can carry up to four oxygen molecules at the same time. This molecular arrangement is what makes haemoglobin so good at moving and releasing oxygen. When oxygen binds to the globin chains, it changes their shape, which makes them work together to take in more oxygen in the lungs and release it more easily in other tissues [3, 4]. Haemoglobin not only carries oxygen, but it also carries carbon dioxide. It also helps keep the acid-base balance by buffering the pH of blood during gas exchange.

In addition to helping with breathing, haemoglobin is involved in critical regulatory processes. For example, it helps with nitric oxide signalling, which affects blood flow and vascular tone. It also protects against oxidative stress by scavenging reactive oxygen species. Changes in the structure, concentration, or functional qualities of haemoglobin can make it harder for oxygen to get to the body and cause problems with the body's systems. Consequently, comprehending the physiological properties of haemoglobin is crucial for analysing haemoglobin concentration data and their clinical significance.

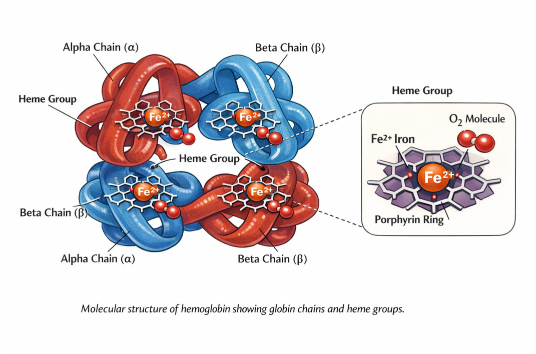

Figure 1. Molecular structure of hemoglobin

2.1 Types of Hemoglobin

Humans have different forms of haemoglobin, each with its own globin chain makeup and physiological function. Figure 2 shows the main types of haemoglobin, how they are structured, how common they are, and how important they are in medicine. Haemoglobin A (HbA) is the most common type in healthy people and is mostly in charge of moving oxygen across the body. Haemoglobin F (HbF), which is the main type of haemoglobin during foetal life, has a stronger attraction to oxygen, which makes it easier for oxygen to move between the mother and the foetus. Minor adult variations, including Haemoglobin A_2 (HbA_2), exist in limited quantities and are clinically significant for diagnosing hemoglobinopathies [5]. Genetic mutations cause structurally aberrant variants such Haemoglobin S (HbS), Haemoglobin C (HbC), and Haemoglobin E (HbE). These variants are linked to changes in the shape of red blood cells, problems with oxygen transport, and different levels of anaemia.

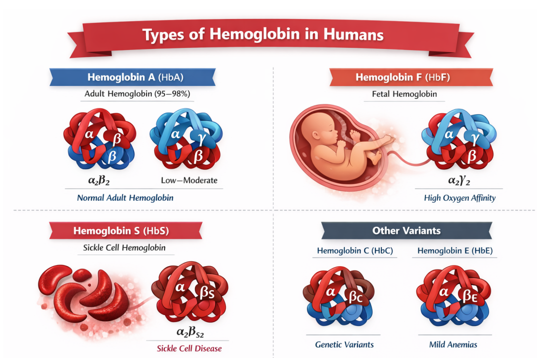

Figure 2. Major types of human hemoglobin and their functional characteristics.

2.2 Normal Hemoglobin Ranges

The normal level of haemoglobin changes with age, sex, and health. In healthy adult males, haemoglobin levels typically vary from 13.5 to 17.5 g/dL, whereas adult females often exhibit somewhat lower values, ranging from 12.0 to 15.5 g/dL, primarily due to hormonal influences and menstrual blood loss. Normal haemoglobin levels in children vary greatly depending on their age and stage of development. Pregnant women frequently display diminished haemoglobin concentrations attributed to plasma volume expansion, a process referred to as hemodilution. Deviations from these reference ranges are significant markers for clinical assessment and diagnostic determinations.

3 Clinical Significance of Hemoglobin Count

The haemoglobin count measures blood oxygenation and health, making it a crucial medical test. CBCs measure haemoglobin. This is the main way to test, diagnose, and track medical disorders. Poor tissue oxygenation from abnormal haemoglobin levels causes weariness, dizziness, shortness of breath, and decreased physical and mental performance. Clinicians must accurately test haemoglobin to treat patients quickly. Anaemia—low haemoglobin levels—is frequent worldwide. Iron, vitamin B12, and folate deficiencies, chronic inflammation, kidney disease, parasite infections, and blood loss cause anaemia [6]. Haemoglobin measurements identify anaemia severity, aetiology, and treatment, such as nutritional supplements, medicines, or blood transfusions. High haemoglobin levels may indicate polycythaemia vera, lung or heart disease-related hypoxia, dehydration, or high-altitude adaption. Blood thickening from long-term haemoglobin may induce thromboembolic and cardiac issues.

Sicker patients include pregnant women, neonates, children, and seniors need haemoglobin monitoring. Poor haemoglobin during pregnancy can cause early birth, low birth weight, and maternal morbidity. Anaemia slows children's immune, mental, and physical development. Haemoglobin abnormalities in older people often suggest chronic illnesses, malnutrition, and diminished function. Chronic renal disease, cancer, and blood diseases require regular haemoglobin testing to monitor disease progression and treatment. Diagnostics, public health, and clinical decision-making use haemoglobin count. It assesses risk before and after surgery, manages critical care, and determines blood donors. Haemoglobin data demonstrate that large-scale screening programs diminish anaemia in low- and middle-income countries [7]. Thus, precise, accessible, and reliable haemoglobin count testing is essential for patient care and public health monitoring. Figure 3 shows how aberrant haemoglobin levels affect health in various physiological and pathological circumstances.

4 Traditional Laboratory Methods for Hemoglobin Estimation

Due to their accuracy, reliability, and clinical acceptability, laboratory-based haemoglobin measurement methods have long been the gold standard. These approaches use standardised processes and venous or capillary blood samples in controlled labs. Complete blood count (CBC) testing includes haemoglobin estimate, which is essential for routine diagnostics, illness monitoring, and treatment decisions. Hospitals and diagnostic centres worldwide use conventional laboratory methods despite recent technological advances.

4.1 Cyanmethemoglobin Method

International standardisation bodies use the cyanmethemoglobin technique to estimate haemoglobin. This method converts blood haemoglobin into cyanmethemoglobin using

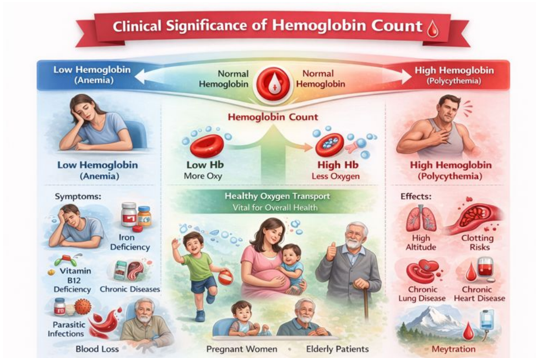

Figure 3. Major types of human hemoglobin and their functional characteristics.

potassium ferricyanide and potassium cyanide [5, 8]. A spectrophotometer measures the compound's stable colour intensity at a specified wavelength. Absorbance is proportional to sample haemoglobin. This approach accurately and reproducibly measures most haemoglobin derivatives. Cyanide reagents are poisonous, require laboratory infrastructure, and require careful handling and disposal, limiting its use.

4.2 Sahli's (Acid Hematin) Method

One of the first ways to quantify haemoglobin is with Sahli's method, which is also termed the acid haematin method. By adding hydrochloric acid, this process transforms haemoglobin into acid haematin. Then, the colour is compared to a colour scale that has been set up. Sahli's method is widely used in basic healthcare institutions and regions with minimal resources since it is easy and economical [9, 10]. But this method has a lot of disadvantages, like subjective visual interpretation, low sensitivity, and not being as accurate as newer methods. Because of this, less people are using it in preference of more reliable options.

4.3 Automated Hematology Analyzers

Automated haematology analysers are the most advanced standard systems for measuring haemoglobin. As part of a whole blood examination, these analysers use photometric, impedance-based, or flow cytometry methods to find out how much haemoglobin is in the blood. They are great for high-throughput clinical labs because they process quickly, make few mistakes, and are very accurate. Automated analysers also provide more information about blood, like the number of red blood cells, white blood cells, and platelets. Even while these are good things, their high cost, need for maintenance, and reliance on skilled staff make them less useful in places with few resources or far away.

In general, standard laboratory procedures are still the best way to measure haemoglobin [11]. However, because they are invasive, need a lot of equipment, and cost a lot to run, researchers are looking into other ways to measure haemoglobin that are easier for patients to use.

5 Non-Invasive and Point-of-Care Hemoglobin Measurement Techniques

In recent years, non-invasive and point-of-care haemoglobin measuring techniques have become very popular since they could get around the problems with standard laboratory-based procedures. These methods try to quickly, easily, and painlessly measure haemoglobin without having to draw blood or set up a lot of lab equipment [12]. These kinds of technology are especially useful in places like emergency rooms, outpatient clinics, rural healthcare facilities, and low-resource contexts where quick diagnosis and ongoing monitoring are very important. Non-invasive and point-of-care technologies offer intriguing alternatives for large-scale haemoglobin screening and monitoring. They do this by making patients less uncomfortable, lowering the risk of infection, and allowing testing to be done in different places. Figure 4 shows some of the most frequent ways to measure Hb without using an intrusive method.

Figure 4. Non-Invasive Hemoglobin Measurement Methods

5.1 Pulse Co-Oximetry

Pulse co-oximetry is a non-invasive optical method that measures haemoglobin levels by sending different wavelengths of light into blood vessels, usually in the fingertip. Pulse co-oximeters can tell how much haemoglobin is in the blood by looking at how oxygenated and deoxygenated haemoglobin absorbs light. This strategy lets keep an eye on things all the time, and it's often built into portable bedside equipment. Pulse co-oximetry is quick and easy to use, but its accuracy can be impacted by things like inadequate peripheral perfusion, motion artefacts, skin pigmentation, and the amount of light in the room [12, 13]. Because of this, it is generally used as a screening or extra tool instead of a replacement for lab tests.

5.2 Optical and Spectrophotometric Techniques

Optical and spectrophotometric techniques measure haemoglobin levels by looking at how haemoglobin in biological tissues absorbs and reflects light. These methods usually entail shining light on tissue areas like the fingertip, earlobe, or conjunctiva and looking at the optical signals that come back. Improvements in sensor design and signal processing have made measurements more sensitive and easier to carry around. However, differences in tissue thickness, skin tone, and physiological circumstances might cause measurement inaccuracies, hence it is important to have strong calibration and validation methods.

5.3 Smartphone-Based Hemoglobin Estimation

Smartphone-based haemoglobin measuring devices use the built-in cameras and processing power of the phone to figure out haemoglobin levels from pictures of body parts such the nail bed, palm surface, or conjunctiva [14]. To get colour and texture attributes that are connected to haemoglobin concentration, image processing and machine learning methods are used. These systems provide cost-effective, scalable, and easily implementable solutions, especially in distant and underserved regions. But their performance is affected by things like lighting, camera quality, and how different users are, which shows how important it is to have standardised acquisition techniques.

5.4 Portable and Wearable Devices

Portable and wearable hemoglobin monitoring devices have emerged as promising tools for continuous and point-of-care assessment. These devices integrate optical sensors with compact hardware to enable real-time hemoglobin estimation during daily activities. Wearable technologies support longitudinal monitoring and early detection of abnormal hemoglobin trends [15]. Despite their advantages, challenges related to long-term accuracy, sensor calibration, and clinical validation remain.

Overall, non-invasive and point-of-care hemoglobin measurement techniques represent a significant advancement toward accessible and patient-centric healthcare, although further refinement and validation are required for widespread clinical adoption.

6 Image Processing and Machine Learning Approaches

Recent advancements in image processing and machine learning have introduced data-driven approaches for hemoglobin estimation, offering promising alternatives to conventional laboratory and sensor-based methods. These techniques aim to infer hemoglobin concentration by analyzing visual and physiological patterns present in medical images or tissue appearance, thereby enabling non-invasive, low-cost, and scalable solutions. With the growing availability of digital imaging devices and computational resources, machine learning-based hemoglobin estimation has become an active area of research, particularly for point-of-care and remote healthcare applications.

6.1 Image-Based Hemoglobin Estimation

Image-based hemoglobin estimation techniques rely on capturing images of specific anatomical regions that exhibit visible color changes corresponding to blood oxygenation and hemoglobin concentration. Commonly analyzed regions include the fingernail bed, palmar surface, conjunctiva, lips, and tongue [10, 16]. Image processing algorithms are employed to extract color features, texture patterns, and intensity variations from these regions. Preprocessing steps such as illumination normalization, region-of-interest segmentation, and noise reduction are critical for minimizing variability caused by external factors and improving estimation accuracy. These methods have demonstrated the feasibility of correlating visual cues with hemoglobin levels, particularly under controlled imaging conditions. However, their performance is often sensitive to variations in lighting, image quality, and acquisition protocols, which can limit robustness in real-world applications.

6.2 Machine Learning Models for Hemoglobin Prediction

Machine learning algorithms have been widely applied to model the relationship between extracted image features and hemoglobin concentration. Traditional models such as linear regression, support vector machines (SVM), decision trees, and random forests are commonly used for both regression and classification tasks in hemoglobin estimation. The choice of model depends on the nature of the dataset and application requirements. Linear regression models are suitable for establishing simple relationships when feature distributions are well-behaved, whereas SVMs are effective for handling high-dimensional feature spaces and smaller datasets due to their strong generalization capability. Decision trees and random forests provide better interpretability and can capture non-linear relationships, making them useful in heterogeneous medical datasets [17]. Model performance in hemoglobin prediction is typically evaluated using standard metrics. For regression-based estimation, commonly used metrics include Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which quantify the deviation between predicted and actual hemoglobin values. For classification tasks, such as anemia detection, accuracy, precision, recall, and F1-score are widely used to assess model effectiveness. Despite their advantages, traditional machine learning models often rely heavily on handcrafted feature extraction and are sensitive to variations in imaging conditions, which can limit their robustness in real-world applications.

6.3 Deep Learning and Convolutional Neural Networks

Deep learning approaches, particularly convolutional neural networks (CNNs), have demonstrated superior performance in hemoglobin estimation tasks by automatically learning hierarchical feature representations directly from raw images. Unlike traditional machine learning models, CNNs eliminate the need for manual feature engineering and are more robust to variations in lighting, texture, and anatomical differences. CNN-based models are particularly suitable for large-scale datasets where complex spatial patterns need to be captured. Transfer learning techniques, which leverage pre-trained models such as ResNet or VGG, are frequently employed to improve performance when labeled medical data are limited. These approaches significantly reduce training time and enhance generalization capability. However, deep learning models require substantial computational resources and large annotated datasets for optimal performance. Additionally, their "black-box" nature raises concerns regarding interpretability and clinical trust, which remain important challenges for real-world deployment.

6.4 Comparative Analysis of Machine Learning Models:

A critical comparison of machine learning approaches reveals distinct trade-offs between traditional models and deep learning techniques. Conventional models such as support vector machines (SVM) and random forests perform well on small to medium-sized datasets and offer better interpretability, making them suitable for scenarios with limited labeled data and resource constraints. However, their performance is often dependent on handcrafted feature extraction and may degrade under varying imaging conditions. In contrast, convolutional neural networks (CNNs) demonstrate superior performance in hemoglobin estimation tasks due to their ability to automatically learn complex and hierarchical feature representations from raw images. CNNs are particularly effective in handling large-scale datasets and capturing subtle spatial variations associated with hemoglobin concentration. Nevertheless, their effectiveness comes at the cost of higher computational requirements and reduced interpretability. Overall, while traditional machine learning models are advantageous for lightweight and interpretable applications, deep learning approaches provide higher accuracy and robustness, especially in complex and large-scale image-based hemoglobin estimation systems.

7 Challenges and Limitations

Despite significant advancements in hemoglobin measurement technologies, several challenges and limitations continue to hinder their widespread clinical adoption. One of the primary concerns is measurement accuracy, particularly in non-invasive and image-based methods. Factors such as skin pigmentation, tissue thickness, ambient lighting conditions, motion artifacts, and peripheral perfusion can significantly influence optical signal quality and image appearance, leading to variability in hemoglobin estimation. These sources of error necessitate robust calibration techniques and adaptive algorithms to ensure reliable performance across diverse populations and environments.

Another major limitation is the lack of standardization across devices and methodologies. Different hemoglobin estimation systems often employ varying sensing principles, data acquisition protocols, and analytical models, making direct comparison difficult. In addition, many emerging techniques rely on small or homogeneous datasets, which limits generalizability and increases the risk of model bias. For machine learning and deep learning approaches, the availability of large, clinically annotated datasets remains a significant challenge. Moreover, the "black-box" nature of some AI models raises concerns regarding interpretability, transparency, and clinical trust.

From a clinical and regulatory perspective, extensive validation is required before new hemoglobin measurement technologies can be integrated into routine healthcare practice. Many non-invasive and AI-based systems have demonstrated promising results in controlled experimental settings but lack large-scale clinical trials to establish their safety, accuracy, and reliability. Ethical considerations related to patient data privacy, informed consent, and algorithmic fairness must also be addressed. Furthermore, cost, device durability, and long-term maintenance remain practical concerns, particularly in low-resource settings. Addressing these challenges is essential to ensure that emerging hemoglobin monitoring technologies can meet clinical standards and achieve widespread acceptance.

8 Recent Advances and Emerging Trends

Recent years have witnessed rapid progress in hemoglobin monitoring technologies driven by innovations in biomedical engineering, artificial intelligence, and digital health. One notable trend is the integration of multimodal sensing approaches, which combine optical signals, physiological parameters, and contextual data to improve estimation accuracy and robustness. These hybrid systems leverage complementary information sources to mitigate the limitations of individual techniques [18, 19]. Artificial intelligence continues to play a transformative role in hemoglobin estimation. Advanced deep learning models, including attention-based networks and lightweight architectures optimized for mobile devices, have enabled real-time and energy-efficient hemoglobin prediction. The use of transfer learning and federated learning frameworks has further enhanced model performance while addressing data scarcity and privacy concerns. Additionally, explainable AI techniques are being explored to improve model transparency and clinical interpretability.

Another emerging trend is the development of wearable and continuous hemoglobin monitoring devices integrated with Internet of Things (IoT) platforms. These systems enable remote patient monitoring, longitudinal health assessment, and early detection of abnormal hemoglobin trends. Smartphone-based applications and cloud-enabled platforms are also gaining popularity for large-scale screening and telemedicine applications, particularly in underserved regions. Overall, these advances indicate a shift toward personalized, accessible, and technology-driven hemoglobin monitoring solutions. Continued interdisciplinary research and collaboration between clinicians, engineers, and data scientists are expected to further accelerate innovation in this field.

Table 1. Comparative Analysis of Hemoglobin Measurement Techniques

Method	**Invasiveness**	**Accuracy**	**Cost**	**Portability**	**Key Limitations**
Cyanmethemoglobin Method	Invasive	Very High	High	Low	Toxic reagents, laboratory infrastructure required
Sahli's (Acid Hematin) Method	Invasive	Low–Moderate	Low	Moderate	Subjective visual interpretation, low precision
Automated Hematology Analyzers	Invasive	Very High	Very High	Very Low	Expensive equipment, skilled personnel required
Pulse Co-Oximetry	Non-Invasive	Moderate	Moderate	High	Sensitive to motion, skin tone, and perfusion
Optical/Spectrophotometric Methods	Non-Invasive	Moderate	Low–Moderate	High	Affected by lighting and tissue variability
Smartphone-Based Imaging	Non-Invasive	Moderate	Low	Very High	Camera quality and illumination dependency
Wearable Hemoglobin Devices	Non-Invasive	Moderate	Moderate	Very High	Calibration drift, long-term accuracy issues
Machine Learning / AI-Based Methods	Non-Invasive	Moderate–High	Low	Very High	Requires large datasets and clinical validation

9 Comparative Analysis of Conventional, Non-Invasive, and AI-Based Hemoglobin Measurement Techniques

A comparative overview of commonly used hemoglobin measurement techniques is presented in Table 1. The table highlights key characteristics of both traditional and emerging methods in terms of invasiveness, accuracy, cost, portability, and inherent limitations. Conventional laboratory-based techniques, such as the cyanmethemoglobin method and automated hematology analyzers, demonstrate very high accuracy but require invasive blood sampling, expensive equipment, and well-equipped laboratory infrastructure [20]. These constraints significantly limit their applicability in point-of-care, remote, and resource-constrained environments where rapid and accessible diagnostics are essential. In contrast, non-invasive and point-of-care techniques, including pulse co-oximetry, optical spectrophotometric methods, smartphone-based imaging, and wearable hemoglobin devices, offer improved portability, reduced cost, and enhanced patient comfort. These characteristics make them particularly suitable for large-scale screening, home-based monitoring, and telemedicine applications. However, their accuracy is generally moderate and can be affected by physiological and environmental factors such as skin pigmentation, motion artifacts, lighting conditions, and tissue variability [21, 22], which restrict their reliability in critical clinical decision-making. A fundamental trade-off is therefore observed between accuracy and accessibility. Highly accurate laboratory methods lack scalability and portability, whereas non-invasive techniques provide wider accessibility at the cost of reduced precision. Wearable devices extend the capabilities of non-invasive systems by enabling continuous and real-time monitoring, making them valuable for longitudinal health assessment, although challenges related to calibration drift and long-term stability remain.

Machine learning and AI-based approaches represent a promising middle ground by leveraging data-driven models to improve estimation accuracy while maintaining high portability and scalability. These methods are particularly effective in image-based and smartphone-assisted systems, where they can compensate for variability in imaging conditions. Nevertheless, their performance is highly dependent on the availability of large, diverse, and clinically validated datasets, and concerns related to generalizability, bias, and interpretability must be addressed [23]. From an application perspective, laboratory-based methods remain the preferred choice in hospital and diagnostic laboratory settings where accuracy is critical. In contrast, smartphone-based and AI-assisted approaches are more suitable for population-level screening and deployment in underserved regions due to their low cost and ease of use. Wearable and optical sensing technologies are advantageous for continuous monitoring and early detection of hemoglobin fluctuations. Overall, Table 1 highlights the inherent trade-offs between accuracy, cost, and portability, demonstrating that methods with higher clinical precision often require greater infrastructure, whereas portable solutions prioritize accessibility at the expense of accuracy. No single technique is universally optimal; instead, the selection of an appropriate method depends on the specific clinical, environmental, and economic context. This underscores the growing need for hybrid systems that integrate the accuracy of conventional methods with the accessibility and scalability of modern non-invasive and AI-driven approaches.

10 Conclusion

Hemoglobin measurement is essential for clinical diagnosis and public health monitoring. While traditional laboratory methods provide high accuracy, their invasive nature and limited accessibility highlight the need for alternative approaches. Emerging non-invasive, point-of-care, and AI-driven techniques offer promising solutions with improved comfort, portability, and scalability. This survey reviewed hemoglobin physiology, conventional methods, and recent advances in non-invasive and machine learning-based techniques, while identifying challenges such as accuracy variability and sensitivity to external conditions. Future research should focus on improving robustness, developing standardized datasets, and advancing sensor technologies. The integration of explainable AI, hybrid approaches, and large-scale clinical validation will be crucial for clinical adoption. Expanding these technologies into telemedicine and home-based care can further enhance accessibility and long-term monitoring. Continued research and rigorous validation can enable reliable, accessible, and equitable hemoglobin monitoring solutions worldwide.

References

[1] Karakochuk, C. D., Hess, S. Y., Moorthy, D., Namaste, S., Parker, M. E., Rappaport, A. I., ... & HEmoglobin MEasurement (HEME) Working Group. (2019). Measurement and interpretation of hemoglobin concentration in clinical and field settings: a narrative review. Annals of the new York Academy of Sciences, 1450(1), 126-146.

[2] Stawschenko, E., Schaller, T., Kern, B., Bode, B., Dörries, F., Kusche-Vihrog, K., ... & Wegerich, P. (2022). Current status of measurement accuracy for total hemoglobin concentration in the clinical context. Biosensors, 12(12), 1147.

[3] Suner, S., Rayner, J., Ozturan, I. U., Hogan, G., Meehan, C. P., Chambers, A. B., ... & Jay, G. D. (2021). Prediction of anemia and estimation of hemoglobin concentration using a smartphone camera. PloS one, 16(7), e0253495.

[4] Daves, M., Roccaforte, V., Lombardi, F., Panella, R., Pastori, S., Spreafico, M., ... & Piccin, A. (2024). Modern hematology analyzers: beyond the simple blood cells count (with focus on the red blood cells). Journal of Laboratory and Precision Medicine, 9, 4.

[5] Ekong, B., Ekong, O., Silas, A., Edet, A. E., & William, B. (2023). Machine learning approach for classification of sickle cell anemia in teenagers based on Bayesian network. Journal of Information Systems and Informatics, 5(4), 1793-1808.

[6] Garcia-Casal, M. N., Dary, O., Jefferds, M. E., & Pasricha, S. R. (2023). Diagnosing anemia: Challenges selecting methods, addressing underlying causes, and implementing actions at the public health level. Annals of the New York Academy of Sciences, 1524(1), 37-50.

[7] Zhang, W. T., Chao, T. H. H., Yang, Y., Wang, T. W., Lee, S. H., Oyarzabal, E. A., ... & Shih, Y. Y. I. (2022). Spectral fiber photometry derives hemoglobin concentration changes for accurate measurement of fluorescent sensor activity. Cell reports methods, 2(7).

[8] Whitehead Jr, R. D., Mei, Z., Mapango, C., & Jefferds, M. E. D. (2019). Methods and analyzers for hemoglobin measurement in clinical laboratories and field settings. Annals of the New York Academy of Sciences, 1450(1), 147-171.

[9] Steinmeyer, Z., Delpierre, C., Soriano, G., Steinmeyer, A., Ysebaert, L., Balardy, L., & Sourdet, S. (2020). Hemoglobin concentration; a pathway to frailty. BMC geriatrics, 20(1), 202.

[10] Meegan, J. E., Shaver, C. M., Putz, N. D., Jesse, J. J., Landstreet, S. R., Lee, H. N. R., ... & Bastarache, J. A. (2020). Cell-free hemoglobin increases inflammation, lung apoptosis, and microvascular permeability in murine polymicrobial sepsis. PLoS One, 15(2), e0228727.

[11] Chaudhuri, A. K., Das, S., & Ray, A. (2023). A hybrid feature selection and stacked generalization model to detect breast cancer. In Data-centric AI solutions and emerging technologies in the healthcare ecosystem (pp. 165-183). CRC Press.

[12] Hayashi, K., Hitosugi, T., Kawakubo, Y., Kitamoto, N., & Yokoyama, T. (2020). Influence of measurement principle on total hemoglobin value. BMC anesthesiology, 20(1), 81.

[13] Konig, G., Waters, J. H., Javidroozi, M., Philip, B., Ting, V., Abbi, G., ... & Adams, G. (2018). Real-time evaluation of an image analysis system for monitoring surgical hemoglobin loss. Journal of clinical monitoring and computing, 32(2), 303-310.

[14] Chaudhuri, A. K., Sinha, D., Thyagaraj, K. S. (2018). Identification of the recurrence of breast cancer by discriminant analysis. In Emerging Technologies in Data Mining and Information Security: Proceedings of IEMIS 2018, Volume 2 (pp. 519-532). Singapore: Springer Singapore.

[15] AlSofayan, Y. M., Alsomali, M., Junaidallah, M. A., Bhat, S. A., Jaganathan, P. P., & Almazroua, F. Y. (2018). A comparison study between venous blood gas and complete blood count for the assessment of hemoglobin levels in trauma patients: a single center experience. JK Practitioner, 23, 25-8.

[16] Eyth, E., Zubair, M., & Naik, R. (2025). Hemoglobin A1c. In StatPearls [Internet]. StatPearls Publishing.

[17] Das, S., Chaudhuri, A. K., Ghosh, P. (2026). Medical Diagnosis Through Improved Feature Selection and Advanced Ensemble Techniques: A Study on Breast Cancer and Chronic Kidney Disease. SN Computer Science, 7(3), 222

[18] Daves, M., Roccaforte, V., Lombardi, F., Panella, R., Pastori, S., Spreafico, M., ... & Piccin, A. (2024). Modern hematology analyzers: beyond the simple blood cells count (with focus on the red blood cells). Journal of Laboratory and Precision Medicine, 9, 4.

[19] Boachie, J., Ahiable, D., Ajabuin, L. A., Amissah, R., Asmah-Brown, A., Apalebilah, S., ... & Nyarkoh, J. K. (2025). Diagnostic value of full blood count derived systemic inflammatory biomarkers in malaria infection. Practical Laboratory Medicine, e00494.

[20] Raasveld, S. J., De Bruin, S., Reuland, M. C., Van den Oord, C., Schenk, J., Aubron, C., ... & Alkamkhe, A. A. S. (2023). Red blood cell transfusion in the intensive care unit. JAMA, 330(19), 1852-1861.

[21] Seo, I. H., & Lee, Y. J. (2022). Usefulness of complete blood count (CBC) to assess cardiovascular and metabolic diseases in clinical settings: a comprehensive literature review. Biomedicines, 10(11), 2697.

[22] Ringoringo, H. P. (2022). Prevalence of iron deficiency anemia and reference range of complete blood count, reticulocyte parameters in infants aged 9–11 months. International Journal of General Medicine, 15, 8017.

[23] Wisanuvej, K., Boonyawat, K., Savetamornkul, C., Virapongsiri, S., Krongvorakul, J., Sungkanuparph, S., & Phuphuakrat, A. (2021). Comparison between blood hemoglobin concentration determined by point-of-care device and complete blood count in adult patients with dengue. PLoS neglected tropical diseases, 15(8), e0009692.