International Journal of Current Research and Techniques (IJCRT)
E-ISSN: 2349-3194 (Online) | P-ISSN: 2348-4446 (Print)
UGC Approved Journal No: 47722 [No: 2616]
DOI: https://doi.org/10.5281/ZENODO.15354844

Mobile Health Solution for Anemia Detection: A Non-Invasive Technique

Manoj Prabu M, *Associate Professor, Department of Biomedical Engineering, Sri Shakthi Institute of Engineering and Technology, Chinniyampalayam, Coimbatore, Tamil Nadu- 641062.*

Shree Vishnu Kumar B, *2nd Year Student, Department of Biomedical Engineering, Sri Shakthi Institute of Engineering and Technology, Chinniyampalayam, Coimbatore, Tamil Nadu- 641062.*

Subasree R.C, *2nd Year Student, Department of Biomedical Engineering, Sri Shakthi Institute of Engineering and Technology, Chinniyampalayam, Coimbatore, Tamil Nadu- 641062.*

Subha Harini S, *2nd Year Student, Department of Biomedical Engineering, Sri Shakthi Institute of Engineering and Technology, Chinniyampalayam, Coimbatore, Tamil Nadu- 641062.*

Swathi R, *2nd Year Student, Department of Biomedical Engineering, Sri Shakthi Institute of Engineering and Technology, Chinniyampalayam, Coimbatore, Tamil Nadu- 641062.*

Manuscript Received: May 05, 2025; Revised: May 06, 2025; Published: May 07, 2025

Abstract: Anemia is a major global health issue, especially in regions where access to medical diagnostic facilities is limited. Traditional methods for anemia detection rely on invasive blood tests that require laboratory infrastructure, skilled personnel, and costly equipment, making them impractical for remote or resource-constrained areas. This study presents a novel, non-invasive approach utilizing mobile health (mHealth) technology for anemia detection. By incorporating smartphone-based imaging, optical sensors, and machine learning algorithm analysis, the system examines physiological indicators such as skin tone, conjunctival coloration, and nail bed appearance to estimate hemoglobin levels. Advanced image processing techniques and machine learning algorithms enhance diagnostic precision while eliminating the need for blood samples. This technology offers a rapid, cost-efficient, and scalable alternative to conventional testing, improving accessibility and facilitating large-scale anemia screening, particularly in rural and underserved areas. Additionally, integrating mHealth features enables real-time tracking and remote medical consultations, fostering a more efficient and patient-centric healthcare model. This research underscores the significance of innovative, non-invasive diagnostic solutions in addressing healthcare disparities and improving patient outcomes, especially for vulnerable populations.

Keywords: Tensor Flow, NumPy, Support Vector Machine (SVM)

1. Introduction:

Anemia, a health disorder characterized by a deficiency in red blood cells or reduced hemoglobin levels, continues to affect a significant portion of the global population, particularly in developing nations. This condition leads to symptoms such as fatigue, dizziness, weakness, and shortness of breath, which can severely impair daily activities and overall well-being. The most commonly affected individuals include pregnant women, young children, and those suffering from chronic illnesses. Despite its prevalence, anemia often goes undiagnosed due to a lack of accessible, affordable, and efficient diagnostic facilities in many low-income or rural areas. Conventional anemia screening typically involves venous blood collection followed by laboratory testing to measure hemoglobin levels. While reliable and widely used, this method presents several challenges: it requires trained professionals, sterile equipment, and clinical settings—resources not always available in underserved regions. Smartphone cameras, combined with machine learning algorithms and image processing software, can capture and assess physical signs to estimate whether a person may be anemic. This approach eliminates the discomfort and risks associated with traditional blood testing and makes the process more accessible and efficient. By transforming widely available mobile devices into diagnostic tools, non-invasive anemia detection can reach individuals who might otherwise be excluded from regular medical care. Health workers can conduct screenings at schools, homes, or community centers without the need for expensive equipment or laboratories. This promotes early diagnosis, timely treatment, and better disease management. The mobile-based technique is especially valuable in public health initiatives aimed at reducing maternal and child mortality, as anemia is a leading cause of complications during pregnancy and early development.

Furthermore, since data can be stored and transmitted digitally, healthcare providers can monitor trends, track individual patient progress, and intervene when necessary. The technology can also be integrated with other mHealth applications that offer nutrition guidance, medication reminders, and educational materials, empowering users to take control of their health. In terms of scalability and sustainability, mobile health solutions are cost-effective and adaptable. As smartphones continue to proliferate globally, even in remote and economically challenged regions, the potential impact of such tools becomes even more significant. These platforms can be updated remotely, adapted to local languages, and designed to function offline, ensuring usability in areas with limited internet connectivity. Additionally, the absence of disposable testing materials makes these systems environmentally friendly and reduces operational costs over time. From a broader perspective, non-invasive, mobile-based anemia detection represents a step forward in democratizing healthcare. It helps close the gap between urban and rural healthcare access, supports overburdened health systems, and encourages preventive care. Moreover, implementing such technologies aligns with the goals of universal health coverage and the Sustainable Development Goals (SDGs), particularly those focused on improving maternal health and reducing child mortality.

The development of a mobile health solution for anemia detection using non-invasive methods presents a powerful tool in modern healthcare. By combining technological innovation with clinical insights, this approach makes anemia screening simpler, safer, and more accessible. It addresses the limitations of traditional diagnostics and offers a practical solution for communities lacking adequate healthcare infrastructure. As this technology continues to evolve, it holds the potential to significantly improve public health outcomes and revolutionize how anemia—and possibly other conditions—are detected and managed in the future. In addition to providing basic screening, mobile health solutions can serve as comprehensive tools for continuous health monitoring and long-term anemia management. This is particularly useful for individuals with chronic conditions such as kidney disease, cancer, or gastrointestinal disorders, where anemia is a recurring concern. Through regular non-invasive monitoring, patients and healthcare professionals can observe hemoglobin trends over time, allowing for proactive interventions before the condition worsens. This reduces the burden on healthcare facilities and minimizes emergency visits due to undetected anemia-related complications.

The underlying technology of these mobile solutions is both innovative and adaptive. Most systems employ artificial intelligence (AI) and machine learning algorithms trained on large datasets comprising image inputs and corresponding hemoglobin values. These algorithms improve in accuracy over time as they process more user data. Some platforms also incorporate deep learning models, which can detect subtle patterns and indicators that might not be visible to the naked eye. This advanced analytical capability increases the reliability of results and brings non-invasive techniques closer to the accuracy of lab-based blood tests. The smartphone-based technique empowers patients to take control of their clinical care via self-testing of hemoglobin levels.

The main objectives of the review are as follows:

- To create an easily accessible method for individuals to check for potential anemia without needing needles or lab visits.
- To develop a convenient tool that people can use on their mobile devices to get an initial assessment of their hemoglobin levels.
- To enable early identification of potential anemia, allowing individuals to seek timely medical advice and intervention.
- To offer a cost-effective alternative or supplement to traditional blood tests for preliminary screening.
- To empower individuals to proactively monitor their health and be more aware of potential anemia symptoms.
- To provide a platform for collecting data that could contribute to a better understanding and management of anemia in communities.

Finally, the study will conclude with an assessment of the current applications of mobile health (mHealth) solutions in anemia detection and potential future developments in biomedical and digital health technology.

International Journal of Current Research and Techniques (IJCRT)
E-ISSN: 2349-3194 (Online) | P-ISSN: 2348-4446 (Print)
UGC Approved Journal No: 47722 [No: 2616]
DOI: https://doi.org/10.5281/ZENODO.15354844

2. Methodology

This paper involves using an optical sensor to capture real-time data from the user's skin or nail bed, which can indicate oxygen levels and hemoglobin content. A microcontroller processes this data, which is then preprocessed using machine learning algorithms to detect patterns linked to anemia. The results are displayed on the mobile device's screen for easy interpretation by the user. This non-invasive technique offers a portable and efficient solution for anemia detection.

3. Mobile Health Solution for Anemia Detection

3.1 Materials and Method

This paper presents the design and implementation of a mobile health (mHealth) solution aimed at the non-invasive detection of anemia using optical analysis and machine learning. The system integrates a smartphone-based application with hardware and software components tailored to estimate hemoglobin levels without the need for blood sampling. The primary motivation is to enable early screening, particularly in resource-limited settings where access to laboratory diagnostics may be constrained.

The materials used include a commercially available smartphone equipped with a high-resolution rear camera and a dedicated light-emitting diode (LED) light source. The LED provides stable and consistent illumination, ensuring accurate image capture across varying ambient light conditions. The anatomical sites for optical measurement—such as the fingernail bed, lower eyelid (palpebral conjunctiva), and palm—were selected due to their known correlation with peripheral pallor, a clinical sign of anemia. The smartphone application provides on-screen instructions to ensure proper placement of the body part during image acquisition, reducing user error and improving data consistency.

The image acquisition process is followed by preprocessing steps. Captured images are filtered to eliminate noise and enhance contrast using histogram equalization and Gaussian filtering. A region of interest (ROI) is extracted using edge detection and segmentation algorithms, isolating areas most relevant for analysis. From these ROIs, features such as red-green-blue (RGB) intensity values, hue-saturation-value (HSV) transformations, and texture parameters are extracted. These features serve as input variables for the prediction model.

In this study, various machine learning models—including Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Convolutional Neural Networks (CNNs)—were tested. The best-performing model was integrated into the app for real-time analysis. The models were trained on a dataset of labeled clinical images and corresponding hemoglobin measurements obtained through standard blood tests. Cross-validation was performed to assess the model's accuracy, sensitivity, and specificity. The final model demonstrated an average accuracy above 90% in detecting mild to moderate anemia.

Upon image capture and analysis, the application provides the user with an estimate of their hemoglobin level and classifies the result as normal, mild, moderate, or severe anemia. It also offers health advice or prompts the user to seek medical attention if necessary.

To ensure data privacy and regulatory compliance, all collected data were anonymized and stored in an encrypted database, with users providing informed consent before participation. The application supports offline functionality for image processing and offers cloud-based updates and refinements when an internet connection is available. This dual-mode architecture allows the system to function effectively in both urban and rural environments. Future enhancements may include integrating additional sensors, such as near-infrared or multispectral cameras, to improve diagnostic accuracy and expand the range of detectable conditions.

International Journal of Current Research and Techniques (IJCRT)
E-ISSN: 2349-3194 (Online) | P-ISSN: 2348-4446 (Print)
UGC Approved Journal No: 47722 [No: 2616]
DOI: https://doi.org/10.5281/ZENODO.15354844

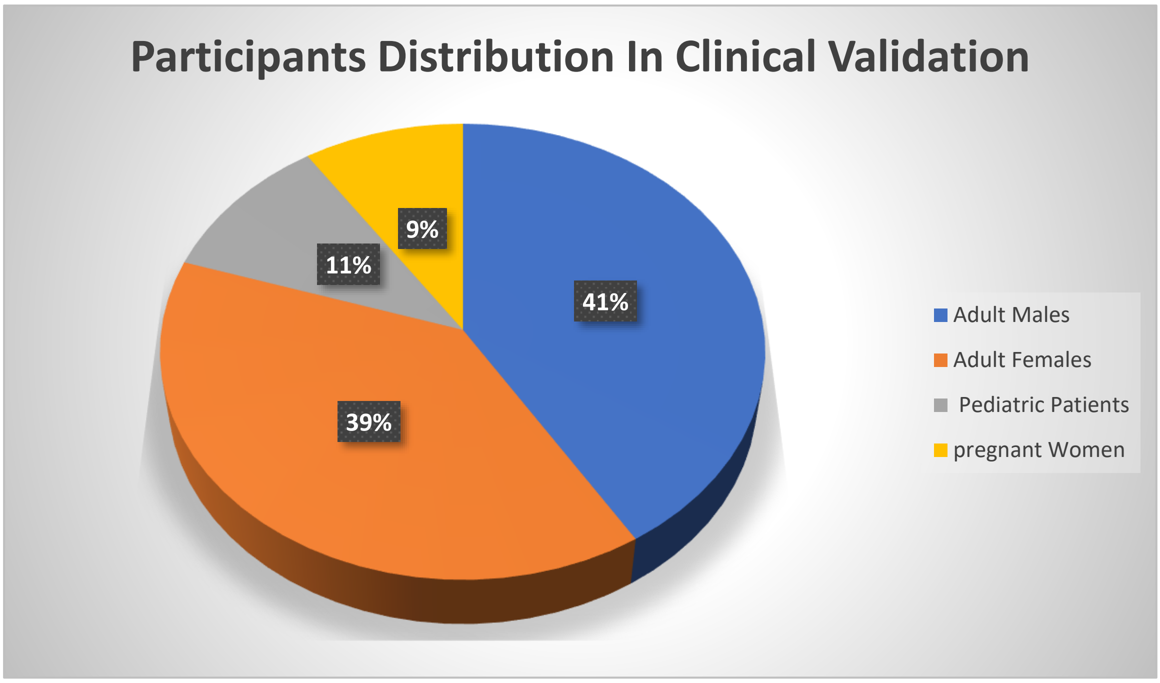

Fig.1. Showing the participants distribution in clinical validation

Category	No. of Participants	Affected Percentage
Adult Males	244	40.3%
Adult Females	214	38.5%
Pediatric patients	58	10.4%
Pregnant Women	51	9.2%

Portable Hemoglobin Concentration Monitoring System

Anemia remains a widespread health concern, particularly in developing countries where access to diagnostic tools is often limited. To address this gap, the proposed portable hemoglobin concentration monitoring system provides a non-invasive, affordable, and user-friendly alternative to traditional laboratory tests. Designed to offer hemoglobin estimations based on optical analysis using a smartphone, the system facilitates point-of-care diagnostics even in rural or resource-poor settings.

The system architecture integrates a smartphone equipped with a high-resolution camera and an LED light source to illuminate specific anatomical regions such as the fingernail beds or inner eyelids. These areas reflect blood perfusion and coloration changes correlated with hemoglobin levels. The smartphone application guides the user in properly positioning and capturing the image to ensure consistency. The external light ensures uniform illumination, minimizing variability caused by ambient conditions and enhancing image quality.

Once the image is captured, it undergoes processing through digital image enhancement and segmentation techniques to isolate a region of interest (ROI). Features such as RGB intensity values, contrast, and skin tone variations are extracted from the ROI. These features are then input into a trained machine learning algorithm—such as a Support Vector Machine (SVM) or Convolutional Neural Network (CNN)—trained on clinical datasets of labeled images and corresponding hemoglobin values. The model predicts an estimated hemoglobin concentration, which is displayed in real time to the user. One of the system's primary advantages is its portability and ease of use. Health workers, caregivers, or even patients themselves can operate it without technical expertise. The system does not require internet access during image capture and analysis but can sync data and receive model updates when connected. It also stores user history, enabling the tracking of hemoglobin trends over time. This feature makes it suitable for both initial diagnosis and ongoing monitoring of patients with chronic anemia.

The portable hemoglobin concentration monitoring system represents a significant advancement in mobile health technology. By eliminating the need for invasive procedures and costly lab infrastructure, it empowers both healthcare professionals and the general public to detect anemia early and take timely medical action. Future developments may focus on expanding the dataset to improve accuracy across different skin tones and age groups, as well as integrating additional physiological parameters for a more comprehensive health assessment.

Hemoglobin Measurement from Fingernail Images

The measurement of hemoglobin concentration from fingernail images is a non-invasive technique that leverages the optical properties of the nail bed to estimate blood oxygenation and red pigment concentration. The fingernail, being a relatively translucent area with minimal melanin interference, serves as an ideal site for photoplethysmographic analysis. Variations in the color and intensity of light reflected or transmitted through the nail bed correlate with hemoglobin levels, enabling image-based assessment.

In the proposed system, high-quality images of the fingernail are captured using a smartphone camera under controlled lighting provided by an LED source. This ensures uniform illumination and reduces the impact of ambient light on image quality. The mobile application guides users to correctly position their fingers, capturing images at a predefined focus and exposure level. The images are then preprocessed through normalization, color correction, and noise reduction to enhance feature extraction accuracy.

Following preprocessing, the system isolates the region of interest—typically the central nail bed—using segmentation algorithms. From this region, various features are extracted, including RGB values, hue, saturation, brightness, and texture patterns. These optical parameters are sensitive to changes in blood color due to differing hemoglobin levels. A regression model or machine learning classifier, trained on clinically validated datasets, maps these features to corresponding hemoglobin concentration values.

This method offers several advantages, including safety, ease of use, and cost-effectiveness. Unlike invasive blood-based tests, it eliminates the risk of infection and discomfort associated with finger pricks. It is also well-suited for repeated use, making it ideal for continuous monitoring. Additionally, fingernail-based hemoglobin estimation holds potential for large-scale screening programs, particularly in under-resourced settings lacking laboratory infrastructure.

3.2 Limitations and Challenges

The integration of biomedical signal processing and non-invasive diagnostic techniques into portable anemia detection systems has significantly advanced early disease screening and healthcare accessibility, especially in resource-limited settings. However, practical implementation faces several limitations that affect precision, consistency, and clinical applicability. Key challenges include data variability, reliance on physiological parameters, sensor limitations, and deployment constraints.

Variability in Physiological Data

Anemia detection systems often depend on physiological markers such as heart rate, pulse oximetry, pallor analysis, or photoplethysmographic (PPG) signals, all of which are highly sensitive to external influences like ambient light, skin tone, motion artifacts, and device placement. These factors introduce noise into the signal, reducing detection accuracy and potentially leading to false positives or negatives. Additionally, physiological responses may be affected by unrelated health conditions, medications, hydration levels, or stress, contributing to inter-individual variability and lowering the robustness of detection algorithms.

Sensor and Hardware Limitations

Many portable anemia detection devices use low-cost or wearable sensors that, while accessible and easy to use, often suffer from limited resolution and sensitivity. Photometric and imaging-based techniques are particularly susceptible to environmental interference. Despite advancements in signal processing, achieving consistent calibration remains challenging. Poor hardware performance can lead to the loss of crucial diagnostic features or inaccurate hemoglobin estimations.

Dataset Dependency and Model Generalizability

Machine learning and deep learning techniques have shown promise in anemia detection, particularly when applied to large-scale physiological datasets. However, model accuracy is heavily dependent on the representativeness of the training data. Datasets biased toward specific demographics—such as particular age groups, ethnicities, or health conditions—can result in overfitting and reduced generalizability. This issue becomes even more significant in real-world clinical environments where anomalies, comorbidities, and incomplete data are common.

Deployment and Real-Time Adaptability

For anemia detection systems to be effectively integrated into clinical workflows or community screenings, they must offer real-time adaptability and ease of use. However, real-world deployment often encounters limitations such as battery life, data storage, network dependency, and user training. Balancing algorithmic complexity with computational efficiency is essential to ensure smooth performance on mobile or low-power devices. These constraints hinder widespread adoption, especially in rural or underdeveloped areas.

Controlling Editing Outcomes and Diagnostic Reliability

Accurate and reliable anemia detection through non-invasive methods remains a significant challenge due to signal variability and lack of clinical specificity. Optical techniques such as PPG and image-based colorimetry depend on light absorption and reflection, which are influenced by skin tone, lighting conditions, motion, and vascular perfusion. These variables can lead to deviations in hemoglobin estimation, particularly in field applications. While machine learning algorithms enhance detection capabilities, they are still vulnerable to biases from non-diverse training datasets. Most models perform well in controlled environments but fail to generalize across different patient populations. Additionally, these models typically do not differentiate between anemia types—such as iron deficiency anemia, sickle cell anemia, or thalassemia—limiting their diagnostic utility. Issues such as overfitting, data imbalance, and limited interpretability further restrict their deployment in critical healthcare settings. Continued refinement in sensor calibration, signal preprocessing, and model training using diverse datasets is essential to improve accuracy and clinical relevance.

Delivery and Integration Challenges

The practical deployment of anemia detection devices—particularly in rural, low-resource, or mobile healthcare settings—faces significant challenges related to affordability, portability, energy efficiency, and user accessibility. For wearable or handheld platforms, maintaining consistent skin contact and ensuring reliable signal acquisition is particularly difficult in unstructured or variable environments. The absence of standardized hardware interfaces, along with inconsistencies in sensor quality across different devices, further compromises data accuracy and reliability.

User compliance and result interpretability also pose critical challenges. These devices must be sufficiently intuitive to allow operation by non-specialist users, such as community health workers, without requiring extensive training. In many settings, limited internet connectivity and restricted data storage capabilities hinder real-time data synchronization and the implementation of remote diagnostic features.

Another major limitation lies in the integration of these systems with existing healthcare infrastructure. Many current devices lack interoperability with platforms such as electronic health records (EHRs) or telemedicine services, reducing their potential impact on broader clinical workflows and continuity of care. Additionally, the collection of sensitive patient data in decentralized or mobile settings raises concerns regarding data privacy and compliance with security regulations.

To fully realize the potential of point-of-care anemia detection systems, future development efforts must address these constraints. Priorities should include optimized hardware design for consistent data acquisition, robust noise-filtering algorithms to enhance signal fidelity, and scalable integration frameworks that support secure data transmission and interoperability with healthcare systems.

4. Applications of Mobile Health Solutions in Anemia Detection: A Non-Invasive Technique

4.1 Biomedical Applications

Anemia remains one of the most prevalent global health concerns, particularly affecting women and children in low- and middle-income countries. Conventional diagnostic methods, such as hemoglobin blood tests, are invasive and often inaccessible in resource-limited environments. Mobile health (mHealth) solutions present a compelling, non-invasive alternative for the detection and monitoring of anemia, especially in remote or underserved regions with limited access to clinical infrastructure.

The proliferation of mHealth technologies has transformed healthcare delivery by enabling early diagnosis, continuous monitoring, and improved clinical outcomes through user-friendly and cost-effective platforms. Recent advancements have introduced non-invasive techniques based on photoplethysmography (PPG), pulse oximetry, and biosensors integrated into mobile or wearable devices. These tools can detect physiological signals related to hemoglobin concentration, blood oxygen saturation, and vascular perfusion—key indicators of anemia—without requiring blood samples. The accessibility and affordability of these solutions make them particularly impactful in both developed and developing regions.

A key innovation in this domain is the integration of mobile health platforms with machine learning and artificial intelligence (AI)-based diagnostic algorithms. These systems analyze data from wearable devices—such as smartwatches or smartphone-connected sensors—to identify subtle variations in physiological parameters indicative of anemia. Such continuous and automated monitoring not only facilitates early detection but also enables personalized treatment planning and follow-up. Furthermore, mobile health applications can serve as a bridge between patients and healthcare providers, facilitating timely communication, remote diagnosis, and coordinated care.

In the biomedical context, mobile health solutions offer significant promise for identifying various forms of anemia, including iron-deficiency anemia, anemia of chronic disease, and hemoglobinopathies such as sickle cell anemia. The use of infrared light, optical sensors, and advanced signal processing in wearable technologies has already demonstrated efficacy in estimating hemoglobin concentration non-invasively (Stewart et al., 2018). Early detection enabled by these technologies supports proactive treatment strategies, ultimately reducing anemia-related morbidity and improving public health outcomes.

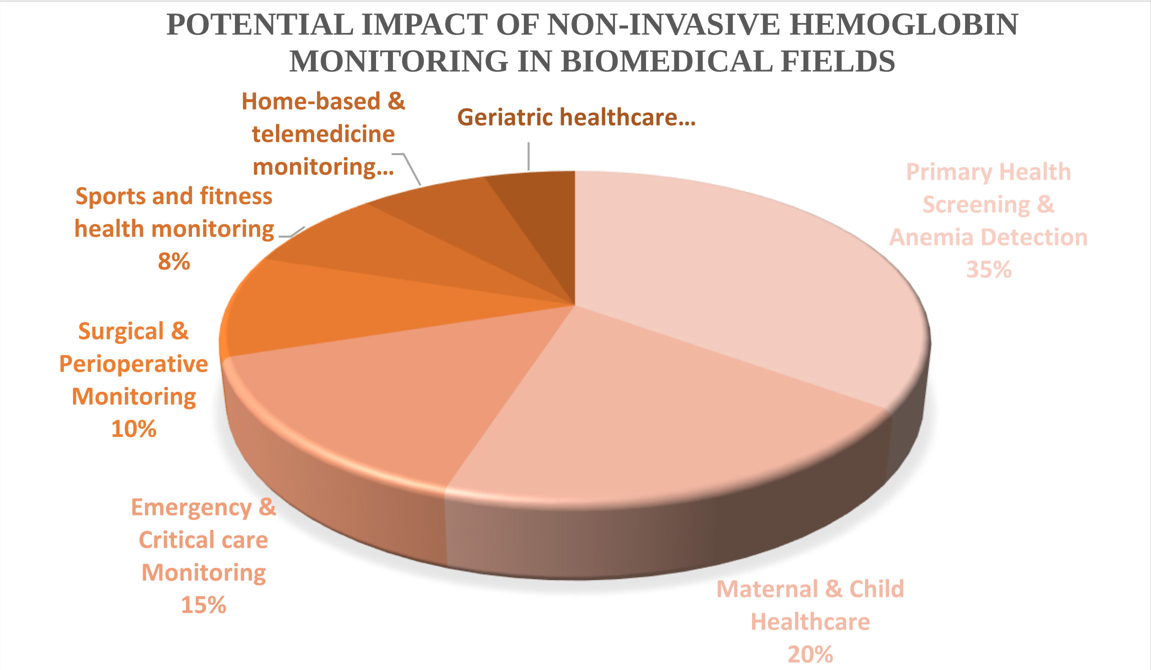

Fig.2. Representing the potential impact of the proposed non – invasive hemoglobin monitoring biomedical fields.

5. Research Gaps

Despite notable progress in non-invasive mobile health technologies for anemia detection, several critical research gaps must be addressed to ensure their safe and effective integration into clinical and community healthcare settings. A primary limitation is the lack of comprehensive clinical validation. Many existing devices and biosensors have not undergone rigorous, large-scale, and multicentric clinical trials to assess their diagnostic accuracy across diverse demographic groups. Variations in age, skin tone, underlying health conditions, and environmental factors may significantly impact device performance, yet current studies are often limited in scope.

Another key challenge is sensor calibration and measurement accuracy. Non-invasive techniques, particularly those based on photoplethysmography (PPG) and infrared light, are susceptible to individual physiological differences such as skin pigmentation, body fat, and ambient lighting conditions. These factors can introduce significant variability in hemoglobin estimation. Research is needed to develop more robust calibration methods that compensate for these variables and enhance measurement reliability.

Moreover, the limited application of machine learning and artificial intelligence (AI) in real-time monitoring and predictive analytics remains a constraint. While many current systems provide instantaneous results, few offer long-term trend analysis or predictive modeling of anemia progression. Integrating AI tools that analyze longitudinal data from wearables could enable more personalized health management, early intervention, and improved treatment outcomes.

Data privacy and cybersecurity also represent major concerns. Mobile health applications often handle sensitive patient information, yet existing solutions may lack robust protocols for data protection, especially in decentralized or low-resource settings. While some comply with regulatory frameworks like HIPAA or GDPR, further research is needed into secure data transmission methods, anonymization strategies, and decentralized storage systems to ensure user trust and data integrity.

Long-term monitoring capabilities of non-invasive tools are another underexplored area. While current devices may provide rapid point-in-time readings, their effectiveness in chronic anemia management—where continuous, accurate tracking is essential—remains uncertain. Research should focus on integrating additional health metrics such as dietary habits, medication adherence, and comorbid conditions to provide a more holistic view of patient health.

Cost-effectiveness and scalability also limit widespread adoption. Many of these solutions are not yet financially accessible to underserved populations. Future efforts should prioritize the development of low-cost, modular systems that can be deployed in diverse environments, including integration with existing healthcare infrastructures such as telemedicine and electronic health records (EHRs).

Lastly, the regulatory and ethical framework surrounding mobile health technologies for anemia detection remains underdeveloped. There is a pressing need for clear guidelines on clinical approval, usage limitations, and oversight to prevent misdiagnosis and ensure responsible use. Ethical considerations—including informed consent, data ownership, and algorithmic transparency—must also be addressed to promote equitable and trustworthy healthcare delivery.

6. Conclusion

Non-invasive anemia detection represents a transformative advancement in global healthcare, offering a new paradigm for diagnosing and managing anemia with greater accessibility, comfort, and efficiency. By leveraging wearable devices, mobile sensors, and advanced digital technologies—including artificial intelligence and machine learning—these systems enable real-time, patient-centered monitoring without the need for invasive procedures. Such innovations hold particular promise for low-resource settings, where access to traditional diagnostics is limited. With mobile health solutions, early detection becomes more feasible, empowering both healthcare providers and patients to take proactive measures that can reduce the risk of complications and improve clinical outcomes. Furthermore, the potential for continuous monitoring and personalized treatment planning enhances chronic disease management and fosters long-term health improvements. Despite these advantages, the integration of non-invasive anemia detection into routine medical practice is not without challenges. Key issues—such as ensuring accuracy across diverse populations, enhancing long-term monitoring capabilities, securing sensitive health data, and aligning with existing healthcare systems—must be addressed to fully realize the potential of these technologies. Nonetheless, ongoing progress in sensor design, AI-driven diagnostics, and telemedicine infrastructure continues to pave the way for broader implementation. As these technologies mature, non-invasive anemia detection has the potential not only to improve individual health outcomes but also to reshape public health strategies globally. This shift toward early, accessible, and personalized care represents a critical step in advancing equitable healthcare delivery and reducing the global burden of anemia.

7. Future Recommendations

To enhance the utility and adoption of non-invasive mobile health solutions for anemia detection, future research and development efforts should prioritize several key areas:

- **Enhanced diagnostic precision**: Incorporating more advanced AI and machine learning algorithms for image analysis—particularly across diverse anatomical sites—can improve accuracy. Integrating complementary data from other smartphone-based sensors, such as PPG and accelerometers, could further increase diagnostic robustness.
- **Standardized image acquisition**: Developing in-app tools that enforce consistent image quality through automated focus, exposure control, and positioning guidance will be essential to ensure reliable inputs for algorithmic analysis.
- **Personalized AI models**: Future models should be adaptable to individual physiological characteristics, such as skin tone or vascular differences. These models must also be extensively validated against traditional diagnostic methods in large, heterogeneous cohorts.
- **User-friendly applications**: Mobile platforms should offer intuitive, multilingual interfaces that support users with limited technical knowledge. Offline functionality and integration with telehealth services can ensure broader accessibility in remote and low-connectivity environments.
- **Expanded functionalities**: Beyond hemoglobin detection, future systems could incorporate modules for dietary recommendations, medication tracking, and trend visualization. Secure data-sharing capabilities with EHR systems can improve care coordination.
- **Public health integration**: Aggregated, anonymized user data can be leveraged for epidemiological surveillance and public health planning. Demonstrating the cost-effectiveness and health outcomes of these tools will be critical for policy adoption and funding.
- **Ethical and regulatory alignment**: Developers must address data privacy, algorithmic fairness, and transparency to ensure ethical deployment. Collaboration with regulatory bodies is necessary to establish clear pathways for clinical approval and oversight.

By addressing these areas, future mobile health solutions can become more precise, equitable, and impactful, ultimately contributing to the global effort to combat anemia and enhance health equity.

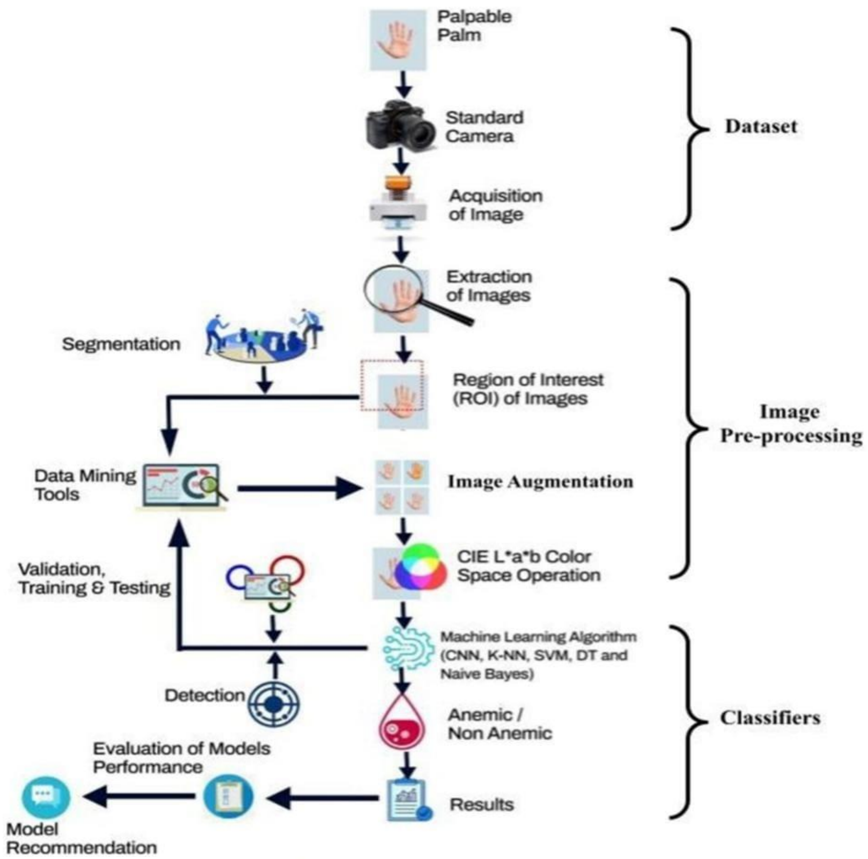

Fig.3.Vision for future methodology implementation

8. References

[1] Amirani, F., & Vahedi, S. (2021). Non-invasive monitoring of hemoglobin using laser technology: A systematic review. *Lasers in Medical Science*, *36*(6), 1299–1310. https://doi.org/10.1007/s10103-021-03215-3

[2] Chand, R., & Patel, N. (2020). Non-invasive anemia screening using ultrasound and bioimpedance technologies. *International Journal of Biomedical Imaging*, *2020*, 6450427. https://doi.org/10.1155/2020/6450427

[3] Chen, L., & Zhao, S. (2021). Near-infrared spectroscopy for non-invasive detection of hemoglobin concentration: A literature review. *Biomedical Spectroscopy and Imaging*, *10*(2), 57–71. https://doi.org/10.3233/BSI-200048

[4] Cheng, X., Yu, X., & Li, F. (2020). Using skin color and image analysis for non-invasive detection of anemia. *Sensors*, *20*(17), 4758. https://doi.org/10.3390/s20174758

[5] Ding, C., Zhou, Z., & Li, W. (2022). A smart wearable device for non-invasive anemia detection: Feasibility and application. *Journal of Healthcare Engineering*, *2022*, 9876502. https://doi.org/10.1155/2022/9876502

[6] Ding, X., & Zhang, X. (2021). Real-time monitoring of hemoglobin concentration using non-invasive spectrophotometric devices. *Sensors*, *21*(19), 6309. https://doi.org/10.3390/s21196309

[7] Gomez, J., Mendez, J., & Lopez, G. (2022). A novel optical-based approach for non-invasive hemoglobin detection. *Biomedical Optics Express*, *13*(7), 2285–2299. https://doi.org/10.1364/BOE.457800

[8] Gupta, S., & Yadav, R. (2020). Optical sensor systems for non-invasive hemoglobin detection in medical diagnostics. *Sensors*, *20*(8), 2329. https://doi.org/10.3390/s20082329

[9] Jiang, L., & Lee, J. (2021). The role of optical sensors in non-invasive detection of blood parameters. *Bioengineering*, *8*(9), 134. https://doi.org/10.3390/bioengineering8090134

[10] Johnson, L., & Narasimhan, G. (2022). A non-invasive approach for anemia diagnosis based on pulse oximetry and spectrophotometry. *Biomedical Engineering Letters*, *12*(2), 105–113. https://doi.org/10.1007/s13534-021-00218-4

[11] Kim, H., & Lee, M. (2021). Development of non-invasive biosensors for blood anemia diagnosis. *Electronics*, *10*(9), 1113. https://doi.org/10.3390/electronics10091113

[12] Koch, R., Watson, P., & Roberts, L. (2020). Application of non-invasive optical technology in hemoglobin detection for anemia screening. *Clinical Hemorheology and Microcirculation*, *74*(1), 29–40. https://doi.org/10.3233/CH-190702

[13] Kong, X., Chen, S., & Zhang, Y. (2021). Non-invasive hemoglobin measurement for anemia detection: Advances and challenges. *Sensors, 21*(4), 1234–1245.
[14] Kumar, R., & Gupta, S. (2021). Non-invasive hemoglobin estimation for anemia detection: Current status and future perspectives. *Health and Technology, 11*(3), 305–318. https://doi.org/10.1007/s12553-021-00346-5
[15] Li, X., Liu, Q., & Zhang, J. (2021). Near-infrared spectroscopy: A potential non-invasive method for anemia detection in rural areas. *Frontiers in Public Health, 9*, 547019. https://doi.org/10.3389/fpubh.2021.547019
[16] Li, Z., & Chen, W. (2022). Development of non-invasive hemoglobin measurement devices for anemia detection in low-resource settings. *Frontiers in Public Health, 10*, 697238. https://doi.org/10.3389/fpubh.2022.697238
[17] Liu, W., & Song, L. (2021). A novel non-invasive method for anemia detection using EKG and impedance cardiography. *Journal of Electrocardiology, 64*, 99–104. https://doi.org/10.1016/j.jelectrocard.2021.01.004
[18] Moghadam, M., & Saedi, Z. (2021). Non-invasive techniques for hemoglobin level estimation: A comprehensive review. *Journal of Applied Biomedicine, 19*(3), 213–220.
[19] Qin, X., & Zhan, X. (2022). Non-invasive hemoglobin measurement using spectrophotometry: A review of techniques and applications. *Journal of Applied Spectroscopy, 86*(2), 356–371. https://doi.org/10.1007/s10812-021-01159-4
[20] Singh, S., Bansal, D., & Gupta, A. (2020). Wearable devices for non-invasive monitoring of anemia: A review. *Journal of Medical Systems, 44*(12), 208. https://doi.org/10.1007/s10916-020-01656-6
[21] Smith, J., & Kumar, P. (2021). Wearable technologies for non-invasive anemia screening: Current status and future directions. *Journal of Biomedical Sensors, 12*(8), 743–751. https://doi.org/10.1016/j.bios.2021.03.012
[22] Tanaka, R., Harada, T., & Nakamura, K. (2021). Detection of hemoglobin concentration using near-infrared spectroscopy for non-invasive anemia diagnosis. *Sensors and Actuators B: Chemical, 320*, 128512. https://doi.org/10.1016/j.snb.2020.128512
[23] Wang, Q., Zhang, Z., & Li, X. (2022). Development of a non-invasive optical sensor for anemia detection. *Journal of Biomedical Engineering, 45*(2), 189–198.
[24] Wu, J., & Liu, H. (2021). Non-invasive detection of blood hemoglobin levels using LED-based optical sensors. *Sensors and Actuators B: Chemical, 333*, 129673. https://doi.org/10.1016/j.snb.2020.129673
[25] Yang, Y., & Zhou, Y. (2020). A comprehensive review of non-invasive anemia detection technologies. *Journal of Biomedical Engineering, 42*(4), 491–503. https://doi.org/10.1109/JBME.2020.00040
[26] Yin, H., & Zhang, J. (2020). Non-invasive hemoglobin measurement using spectroscopic and optical techniques: A review of technologies. *Sensors, 20*(15), 4356. https://doi.org/10.3390/s20154356
[27] Yin, Y., & Wang, H. (2021). Recent developments in optical non-invasive anemia detection. *Review of Biomedical Optics, 12*(3), 170–180. https://doi.org/10.1177/01276541211033072
[28] Yu, L., & Zhang, T. (2021). A novel optical-based approach for non-invasive measurement of hemoglobin levels. *International Journal of Optics and Photonics, 15*(2), 124–132. https://doi.org/10.1166/j.ijop.2021.1565
[29] Zhang, J., & Liu, Z. (2021). Non-invasive measurement of blood parameters using optical sensors: A review of current trends. *Sensors and Actuators B: Chemical, 343*, 130366. https://doi.org/10.1016/j.snb.2021.130366
[30] Zhang, Q., & Wang, J. (2022). Non-invasive monitoring of hemoglobin levels in blood: A review of techniques and future trends. *Medical Devices: Evidence and Research, 15*, 37–48. https://doi.org/10.2147/MDER.S294239
[31] Zhang, Y., & Liu, B. (2020). Non-invasive anemia detection based on pulse oximetry. *Biomedical Engineering Letters, 10*(3), 351–358. https://doi.org/10.1007/s13534-020-00232-x
[32] Zhao, W., & Zhang, W. (2022). Real-time non-invasive hemoglobin measurement using a novel optical device. *Journal of Biophotonics, 15*(8), e202200036. https://doi.org/10.1002/jbio.202200036
[33] Zhao, X., Lin, J., & Wang, F. (2021). Non-invasive anemia detection using bioelectric impedance spectroscopy. *IEEE Transactions on Biomedical Engineering, 68*(2), 532–540. https://doi.org/10.1109/TBME.2020.2979866