

Detection of Anaemia using Image Processing

Ms Radhika Ravikrindi¹, N Sharanya², K Srividya³, T Srujana⁴

¹Assistant Professor Bhoj Reddy Engineering College for Women Department of Electronics and Communication Engineering, Hyderabad, India.

^{2,3,4}B Tech Students Bhoj Reddy Engineering College for Women Department of Electronics and Communication Engineering, Hyderabad, India.

nakkasharanya72@gmail.com, kappalasrividya@gmail.com, tulasisrujana2004@gmail.com

Abstract

Anaemia is a widespread hematological condition characterized by a reduction in the number of red blood cells (RBCs) or a decrease in haemoglobin concentration, which leads to insufficient oxygen transport to body tissues. Early and accessible screening is particularly important in rural and resource-limited regions where conventional laboratory infrastructure such as automated haematology analysers is unavailable. This paper presents an automated image-processing-based system for detecting anaemia from peripheral blood smear images and a simple graphical user interface (GUI) to facilitate practical clinical use. High-resolution microscopic images acquired at 400× magnification are processed using a two-stage preprocessing approach consisting of gamma correction for contrast enhancement and Wiener filtering for noise suppression. Red blood cells are segmented and detected using the Circular Hough Transform (CHT). The total number of detected RBCs within a field of view is calculated and compared with a clinically motivated threshold of 500 cells per image. Images with RBC counts below this threshold are classified as anaemic, while higher counts are labelled as normal. A Python-based Tkinter GUI enables users to load images, visualize detected cells, and obtain diagnostic results in a single step. The proposed system offers a low-cost, portable, and user-friendly solution suitable for rural health centres, mobile diagnostic units, and telemedicine services. The framework can be further extended with machine learning methods and advanced feature analysis for improved diagnostic accuracy and classification of anaemia subtypes.

Keywords: Red blood cell counting, Image processing, Anaemia detection, Peripheral blood smear, Automated diagnosis, Tkinter GUI, Python.

Introduction

Anaemia is a major global public health concern affecting populations in both developed and developing countries and has significant consequences for human health and socioeconomic development. It is clinically characterized by a reduction in the number of red blood cells (RBCs) or a decrease in the haemoglobin concentration

within the blood, resulting in inadequate oxygen transport to body tissues. Among the various contributing factors, nutritional deficiencies—particularly iron deficiency—remain the most common cause, especially in low-income and resource-limited regions. Early identification and continuous monitoring of anaemia are therefore essential for effective disease management and for preventing severe complications, particularly among vulnerable groups such as pregnant women, children, and the elderly.

Conventional diagnostic procedures for anaemia include complete blood count (CBC) testing, manual haemocytometer-based counting, and automated haematology analysers. Although these methods provide reliable and accurate results, they require expensive equipment, trained laboratory personnel, and well-established clinical infrastructure. Such requirements often limit their availability in rural and remote healthcare settings, thereby restricting access to timely diagnosis and large-scale screening programmes.

Recent advancements in digital microscopy and image acquisition technologies have enabled the use of image processing techniques for automating medical diagnostic tasks. Peripheral blood smear examination remains a low-cost and widely adopted laboratory practice for haematological analysis. By integrating digital image processing algorithms with microscopic blood smear imaging, it is possible to develop affordable and portable tools to assist healthcare professionals in preliminary screening.

This project presents an automated image-processing-based approach for anaemia detection using peripheral blood smear images. The proposed system identifies and counts red blood cells from microscopic images and determines the anaemic condition based on the number of RBCs detected per field of view. A graphical user interface (GUI) is also developed to ensure ease of use and accessibility in real clinical and field environments. The primary objective is to deliver a cost-effective, scalable, and efficient anaemia screening tool suitable for deployment in primary healthcare centres, mobile diagnostic units, and community health programmes.

The aim of this project is to design and implement an automated anaemia detection system using digital image processing techniques to improve the accuracy, accessibility, and efficiency of anaemia screening. The proposed system provides a user-friendly solution for timely diagnosis, particularly in resource-constrained regions, by accurately counting red blood cells and classifying samples as either normal or anaemic.

The specific objectives of the proposed work are as follows:

1. Image acquisition and preprocessing of high-resolution peripheral blood smear images captured at 400× magnification using gamma correction for contrast enhancement and Wiener filtering for noise suppression.
2. Segmentation of red blood cells using Otsu's thresholding method to suppress white blood cells and background regions, followed by the application of the Watershed algorithm to separate overlapping red blood cells.
3. Detection of individual red blood cells using the Circular Hough Transform and computation of the total RBC count per field of view.
4. Classification of blood smear images as normal or anaemic using a clinically informed threshold of 500 red blood cells per field.
5. Development of a user-friendly graphical user interface using Python's Tkinter framework to enable image loading, automated processing, and visual display of detected cells and diagnostic results.
6. Evaluation of the accuracy, efficiency, and reliability of the proposed system for potential deployment in rural health centres, mobile diagnostic units, and telemedicine environments.

The remainder of this report is organised as follows. Chapter 2 presents a review of related work in the field of automated blood smear analysis and anaemia detection. Chapter 3 describes the overall system architecture and workflow of the proposed method. Chapter 4 explains the detailed methodology, including image preprocessing, segmentation, red blood cell detection, and classification procedures. Chapter 5 introduces the graphical user interface and its functional components. Chapter 6 discusses the experimental results and performance analysis of the system. Chapter 7 presents a discussion of the obtained results and limitations of the proposed approach. Finally, Chapter 8 concludes the work and outlines directions for future research.

2. Related Work

Several studies have investigated the use of digital image processing techniques for analysing peripheral blood smears. Common approaches include colour space transformation,

threshold-based segmentation, morphological operations, and feature extraction for detecting and classifying blood cells. Circular and shape-based detection methods have been widely adopted for red blood cell identification because RBCs exhibit approximately circular morphology under normal conditions.

Recent research has also explored machine learning and deep learning models for blood cell classification and disease detection. Although such methods provide high accuracy, they require large labelled datasets and high computational resources, which may not be suitable for low-resource clinical environments. In contrast, classical image processing approaches remain attractive for low-cost and real-time applications due to their simplicity, interpretability, and reduced hardware requirements.

The present work focuses on a lightweight and transparent image-based pipeline using contrast enhancement, noise reduction, and Circular Hough Transform-based detection to estimate RBC counts for anaemia screening.

3. System Overview

The proposed system is composed of three major components:

1. Image acquisition and preprocessing,
2. Red blood cell segmentation and detection,
3. Classification and graphical user interface.

Figure-based illustrations are omitted in this text version, but the overall workflow begins with loading a microscopic blood smear image and ends with the display of the anaemia classification result to the user.

4. Materials and Methods

Image Acquisition

Peripheral blood smear images are captured using a digital microscope at 400× magnification. The images are assumed to be in high-resolution RGB format. The proposed system processes a single field of view at a time.

Preprocessing

To improve the reliability of red blood cell detection, a two-stage preprocessing strategy is adopted.

Gamma Correction

Gamma correction is applied to enhance the contrast between red blood cells and the background. This step improves the visibility of cell boundaries and reduces the impact of uneven illumination.

Wiener Filtering

A Wiener filter is employed to suppress noise while preserving important structural information such as cell edges. This adaptive filtering technique helps in improving segmentation performance under varying image quality conditions.

Red Blood Cell Segmentation

Following preprocessing, the enhanced image is converted into a grayscale representation to facilitate segmentation. Otsu's global thresholding technique is applied to distinguish red blood cells from the background and to suppress regions corresponding to white blood cells and staining artefacts. This step provides an initial binary mask of candidate red blood cell regions.

Due to the frequent occurrence of touching and overlapping cells in peripheral blood smear images, the Watershed segmentation algorithm is subsequently employed to separate adjacent red blood cells into distinct regions. Distance transform and marker-based watershed processing are used to minimise over-segmentation and improve the delineation of individual cells. The resulting segmented regions are forwarded to the detection stage for precise localisation and counting.

Red Blood Cell Detection Using Circular Hough Transform

Red blood cell detection is performed using the Circular Hough Transform. This method is well suited for identifying circular objects in an image and is robust to partial occlusions and moderate shape variations. The algorithm searches for circular patterns within

Literature Survey

Early studies focused on detecting red blood cells using shape-based approaches. Venkatalakshmi and Thilagavathi introduced a method based on the Circular Hough Transform for identifying RBCs in microscopic images. Their results demonstrated that circular structures in blood smears can be detected reliably, forming a foundation for automated cell counting systems.

Unsupervised learning methods have also been explored for RBC analysis. Abdurraheem and colleagues employed clustering techniques, including k-means and fuzzy c-means, to separate normal red blood cells from sickle cells. Geometric and texture-based features were extracted and subsequently supplied to classification models such as neural networks. Their work showed that clustering-based segmentation can support the discrimination of abnormal cell morphology.

Feature-based classification approaches were presented by Deb et al., who utilized Fourier descriptors to represent the shapes of RBCs and applied Euclidean distance for classification between normal and anaemic cells. This work highlighted the usefulness of compact shape representations in hematological image analysis.

A broader evaluation of automatic cell counting techniques was conducted in studies that analyzed the advantages and drawbacks of Circular Hough Transform-based detection. These studies noted that while the method performs well for isolated cells, overlapping structures and non-uniform staining significantly degrade detection accuracy.

A comprehensive review of image processing methods for RBC and white blood cell counting was compiled by Akshaya P. Sahastrabudhe. The study compared various segmentation and feature extraction strategies and discussed the relevance of shape, texture, and color descriptors in blood smear analysis.

More recently, Hasani and Hanani proposed an automated framework for iron deficiency anaemia detection using multiple classifiers combined through a voting strategy. Their experimental results indicated that ensemble-based classification improves accuracy while reducing the number of required features.

Despite these encouraging developments, several limitations persist across existing methods. The majority of studies focus primarily on algorithmic performance and often neglect practical usability. Issues such as overlapping cells, illumination variations, and image noise remain unresolved in many systems. Furthermore, very few implementations provide user-oriented interfaces suitable for routine clinical use.

In addition to microscopic image analysis, non-invasive optical methods have been investigated. Techniques based on hemoglobin absorption spectra in visible and near-infrared wavelengths were introduced for estimating hemoglobin concentration. Diffuse reflectance spectroscopy has also been applied to estimate melanin and hemoglobin levels in skin. Although these approaches are non-invasive, they require specialized sensors, controlled acquisition conditions, and trained personnel, which restrict their applicability in rural healthcare settings.

Clinical examination of pallor at various anatomical sites, such as the conjunctiva, nail beds, and palms, has been evaluated as a low-cost screening method. Several studies have shown that conjunctival pallor correlates well with hemoglobin concentration, particularly for severe anaemia. However, the diagnostic accuracy of pallor-based assessment is limited by subjective interpretation and poor inter-observer agreement, especially for moderate anaemia.

Recent literature suggests that integrating traditional visual assessment with digital image processing and classification techniques may lead to faster and more reliable anaemia screening tools. Automated systems have the potential to reduce observer bias, support high-throughput analysis, and facilitate population-level screening programs, particularly for vulnerable groups.

Research Gap and Motivation

From the existing literature, it is evident that substantial progress has been made in RBC detection and classification. However, most studies

are constrained by one or more of the following factors:

- sensitivity to overlapping and clustered cells,
- lack of robustness to staining and illumination variations,
- limited focus on real-time processing, and
- absence of practical graphical interfaces for clinical deployment.

Furthermore, non-invasive and pallor-based diagnostic approaches, although promising, either require specialized hardware or suffer from subjectivity and limited accuracy. These limitations motivate the development of an automated, image-based screening system that is both technically robust and practically usable.

5. Proposed Methodology

The proposed system aims to develop an automated anaemia screening tool based on microscopic blood smear images, integrated within a graphical user interface for user-friendly operation.

The major stages of the proposed framework include:

1. **Image Acquisition and Preprocessing**
Blood smear images are acquired using a digital microscope. Preprocessing operations such as noise filtering, contrast enhancement, and color normalization are applied to improve image quality and minimize variations due to illumination and staining.
2. **Segmentation of Red Blood Cells**
Segmentation techniques are used to isolate RBC regions from the background. Filtering and thresholding methods are combined with morphological operations to reduce noise and separate cell clusters.
3. **Cell Detection using Circular Hough Transform**
Circular Hough Transform is employed to detect individual RBCs based on their approximate circular shape. This step assists in cell localization and counting while improving robustness against partial occlusion.
4. **Feature Extraction**
Morphological features such as area, perimeter, radius, and circularity, along with texture and color descriptors, are extracted from each detected cell.
5. **Classification and Anaemia Screening**
The extracted features are supplied to a classification module to determine whether the observed cell patterns indicate normal or anaemic conditions. Ensemble or hybrid classification strategies may be employed to enhance reliability.
6. **Graphical User Interface**
A GUI is incorporated to allow clinicians or technicians to upload images, visualize segmentation results, and obtain automated screening outputs in real time.

The integration of these components is intended to address both technical and practical limitations identified in previous studies.

Expected Impact and Applications

The proposed system is expected to improve screening efficiency by enabling rapid and automated analysis of blood smear images. By reducing dependence on manual counting and subjective interpretation, the system can minimize inter-observer variability and diagnostic delays. Such a framework can support large-scale screening initiatives, particularly in rural and resource-constrained regions where laboratory infrastructure is limited. The system may also serve as a decision-support tool for healthcare workers and aid in early identification of anaemic conditions in high-risk populations.

6. Problem Statement

Anaemia is a highly prevalent hematological disorder caused by insufficient red blood cells or hemoglobin, leading to reduced oxygen delivery to body tissues. Although laboratory-based diagnostic tests are reliable, their dependence on expensive equipment, skilled personnel, and centralized facilities restricts accessibility, particularly in remote and economically disadvantaged regions.

OpenCV

OpenCV is a cross-platform computer vision library that supports image processing, feature extraction, object detection and video analysis. It provides optimized routines for filtering, segmentation, transformation and geometric operations. OpenCV supports multiple programming languages, including Java and Python, and runs on major operating systems such as Windows, Linux and macOS.

The system utilizes OpenCV modules related to:

- Core data structures and matrix handling,
- Image processing operations such as filtering and color conversion,
- Feature detection and object detection.

These components form the foundation for RBC localization and segmentation.

3.2 NumPy

NumPy is the fundamental numerical computing library in Python. It provides efficient multidimensional arrays and mathematical operations required for scientific applications.

In the proposed framework, NumPy is employed for:

- Pixel-level array manipulation,
- Mathematical operations during preprocessing and segmentation,
- Supporting linear algebra routines used by OpenCV internally.

Its compatibility with scientific libraries such as SciPy and Matplotlib further strengthens its role in medical image analysis systems.

Python Pillow

Pillow is the actively maintained successor of the original Python Imaging Library (PIL). It supports a wide range of image formats such as PNG, JPEG, BMP and TIFF.

In this system, Pillow is mainly used for:

- Loading and saving image files,
 - Basic image manipulation operations,
 - Displaying images during testing and debugging.
- Although Pillow offers convenient visualization through the show() function, it is primarily used for development and verification rather than clinical deployment.

Tkinter

Tkinter is Python's standard graphical user interface toolkit. It enables rapid development of desktop applications using widgets such as buttons, labels and text fields.

The system interface is developed using Tkinter and includes:

- Image selection and loading controls,
- Display panels for processed images,
- Output fields for RBC count and diagnostic messages.

The event-driven programming model of Tkinter allows seamless interaction between the user and the image analysis pipeline.

System Architecture

The proposed framework follows a modular design that integrates image acquisition, preprocessing, segmentation and result presentation. The major components of the system are:

Input Module – Loads microscopic blood smear images using Pillow and OpenCV.

Preprocessing Module – Performs noise reduction, contrast enhancement and color conversion.

Segmentation Module – Separates red blood cells from the background using thresholding and morphological operations.

Feature Analysis Module – Estimates the number of RBCs based on connected component analysis and contour detection.

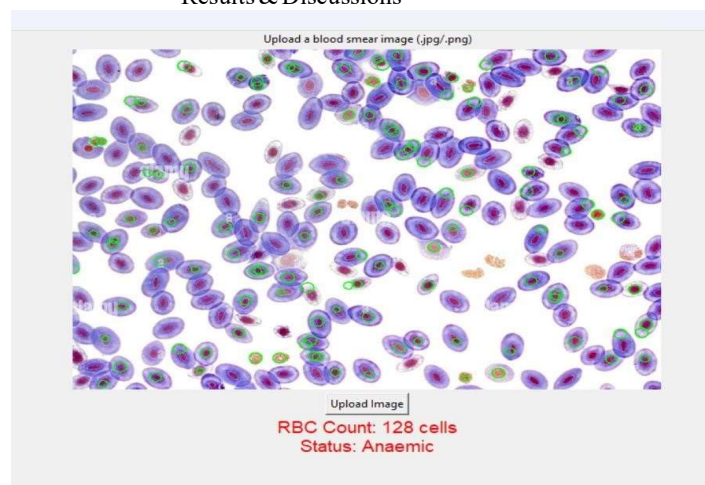
Graphical User Interface Module – Displays the results and processed images to the user through a Tkinter interface.

Discussion

The proposed methodology emphasizes simplicity, computational efficiency and practical deployment. By combining classical image processing techniques with shape-based detection, the system avoids the need for complex training procedures or large annotated datasets. The hybrid segmentation strategy improves the separation of overlapping cells, which is a common challenge in microscopic blood smear analysis.

Although the current implementation focuses solely on red blood cell count, the system can be extended to incorporate morphological features, colour-based descriptors or machine learning classifiers for more detailed haematological analysis. Integration with real-time microscopy systems, mobile platforms and telemedicine services may further enhance its applicability in remote healthcare environments

Results & Discussions



5.1 GUI for Anemia image

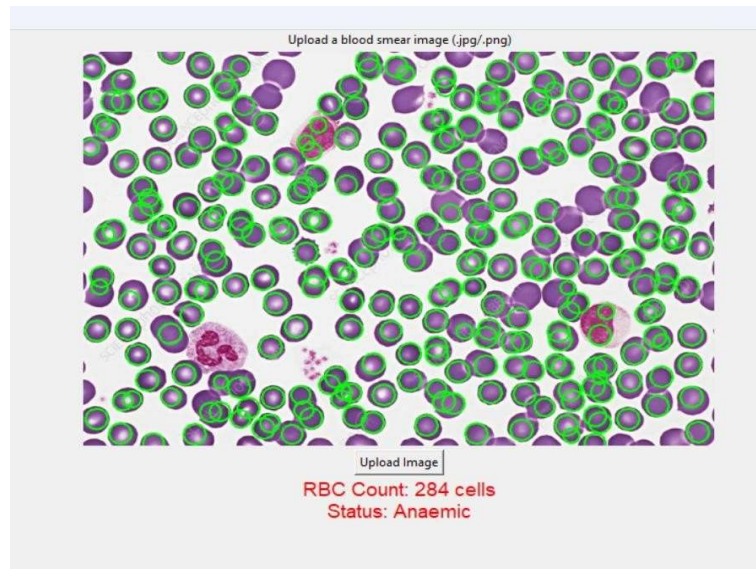
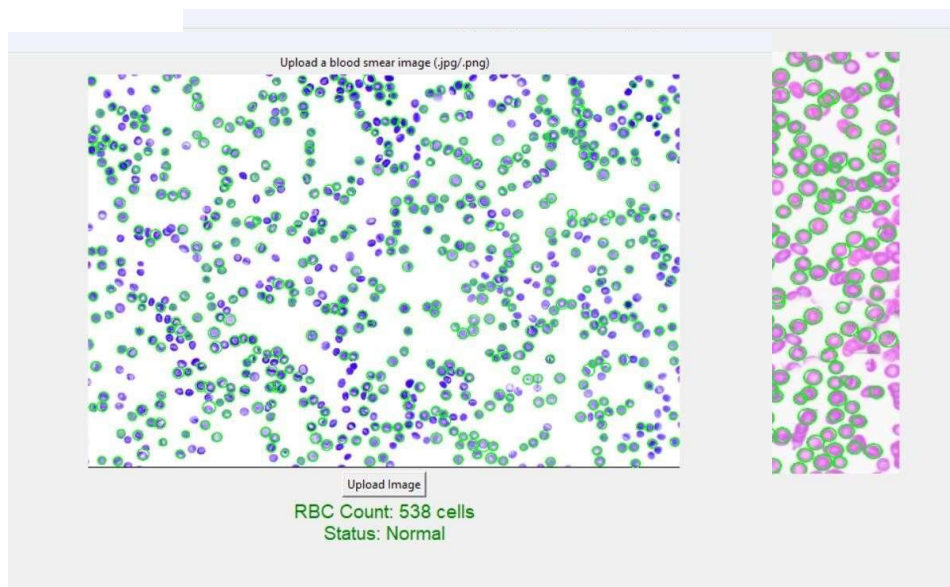


Fig 5.2 GUI for Anemia image

This image displays a blood smear of a person with anemia. The red blood cell (RBC) count is less than 500, indicating a deficiency in RBCs.

5.3 GUI for Non anaemia image



5.4 GUI for Non anaemia image

This image shows a blood smear of a healthy individual. The red blood cell (RBC) count is greater than 500, indicating a normal and sufficient presence of RBCs in the blood.

Conclusion

The project successfully demonstrates the feasibility of using image processing techniques to automate the detection of anaemia based on peripheral blood smear analysis. Through a structured pipeline that includes preprocessing, segmentation, and RBC detection, the system effectively analyzes images to determine the red blood cell count. The integration of algorithms such as gamma correction, Wiener filtering, Otsu thresholding, Watershed segmentation, and Circular Hough Transform ensures reliable and consistent detection of RBCs, even in challenging image conditions.

The inclusion of a GUI significantly enhances the system's usability, enabling non-expert users to operate the software with ease. By simply uploading a blood smear image, users receive instant results along with visual feedback. The system categorizes images as "Normal" or "Anaemic" based on a clinically accepted threshold, making it a practical alternative to manual and lab-based methods.

This automated solution provides a significant step forward in bridging the healthcare gap in underprivileged areas. It reduces reliance on costly lab equipment and highly skilled personnel while offering a scalable, repeatable, and portable system for anaemia screening.

In summary, the system delivers on its objective of providing an efficient, low-cost, and accurate tool for anaemia detection and sets a foundation for future enhancements in computer-aided medical diagnostics.

Future Scope

While the current system effectively detects anaemia based on RBC count, there is considerable scope for further enhancement and expansion of functionality:

References

1. Deep Learning Integration: Incorporating deep learning models such as U-Net or ResNet can improve segmentation accuracy, particularly in poor-quality or highly overlapped images. AI could also help classify RBC morphology and detect subtypes of anaemia (e.g., microcytic, macrocytic).
2. Live Video Processing: Future versions could process live video feeds from digital microscopes, enabling real-time RBC tracking and analysis.
3. Multi-parameter Detection: Expanding beyond RBC count, future systems could simultaneously analyze hemoglobin density (via color features), white blood

cell count, and platelet detection for comprehensive CBC analysis.

4. Cloud-Based Reporting: Integrating with cloud platforms would allow remote experts to review results, enabling a collaborative telemedicine model and data storage for long-term patient monitoring.
5. Mobile App Development: Porting the system to smartphones with camera attachments could create a fully portable diagnostic tool suitable for field workers and rapid deployment in emergencies.
6. Multilingual GUI: Adding support for regional languages in the GUI would increase accessibility and adoption in diverse communities.
7. Regulatory Compliance and Deployment: With proper clinical validation and regulatory approvals, the system could be deployed in government health programs for widespread anaemia screening. By addressing these future directions, the system could evolve into a complete, AI-driven digital pathology assistant for hematology diagnostics in the near future

References

1. Venkatalakshmi, B., and Thilagavathi, K., "Detection and counting of red blood cells using Circular Hough Transform," 2013.
2. Abdulraheem Fadhel, M., Humaidi, A. J., and Oleiwi, B. K., "Image processing based diagnosis of sickle cell anemia in erythrocytes," *Proceedings of the Conference on New Trends in Information and Communications Technology Applications*, 2017, p. 203.
3. Deb, S., and Saptarshi, D., "A novel technique for detecting anemia through classification of red blood cells in blood smear," *Proceedings of the International Conference on Recent Advances and Innovations in Engineering*, 2014, pp. 1–9.
4. Hanani, A., "Automated diagnosis of iron deficiency anemia and thalassemia using data mining techniques," *International Journal of Computer Science and Network Security*, vol. 17, 2017, p. 326.
5. Sahastrabuddhe, A., "Counting of RBC and WBC using image processing: A review," *International Journal of Research in Engineering and Technology*, vol. 5, 2016, pp. 356–360.
6. Hasani, H., et al., "Automated iron deficiency anemia detection using hybrid classification and voting strategies," 2016.
7. Kuenster, J. T., "Automated detection and counting of red blood cells using image processing techniques," *International Journal of Scientific Research and Management*, vol. 3, 2015, pp. 2692–2695.
8. Zonios, G., "Estimation of skin melanin and hemoglobin concentrations using diffuse reflectance spectroscopy," 2001.

9. Kalantri, A., "Accuracy and reliability of pallor for anemia detection," 2010.
10. Stoltzfus, R. J., "Clinical pallor and hemoglobin concentration: Assessment of conjunctival pallor for detection of severe anemia," 1999.