



ANEMIA DETECTION USING CNN AND FINGERNAIL IMAGE

Mr. VJ. Rajakumar¹, Dr. A. Somasundaram², V.Pratheeksha³

¹Research Scholar & Assistant Professor, Sri Krishna Arts and Science College, Tamil Nadu

²Assistant Professor, Sri Krishna Arts and Science College, Tamil Nadu

³UG Student, Sri Krishna Arts and Science College, Tamil Nadu

Abstract - Anemia is a common blood disorder characterized by a decrease in hemoglobin concentration or red blood cells, reducing the oxygen-carrying capacity of blood. Conventional diagnostic methods rely on invasive blood tests, which require laboratory facilities and trained medical personnel. This paper proposes a non-invasive approach for anemia detection using fingernail image analysis and deep learning techniques. Fingernail images are captured using smartphone cameras and processed through image preprocessing and segmentation techniques to extract the region of interest. A MobileNetV2-based Convolutional Neural Network (CNN) is employed to automatically learn discriminative features from the fingernail images and classify them into anemic and non-anemic categories. The proposed model achieved a test accuracy of 82.77% and an Area Under Curve (AUC) score of 0.7091.

The system provides a rapid, low-cost, and accessible screening method that can support early anemia detection, particularly in remote and resource-limited healthcare environments.

Key words: Anemia Detection, Convolutional Neural Network, Non-Invasive Diagnosis.

1. INTRODUCTION

Anemia is one of the most common blood disorders worldwide and occurs when the body lacks sufficient healthy red blood cells or hemoglobin to transport oxygen efficiently. According to the World Health Organization (WHO), anemia affects millions of people, particularly women and children. Common symptoms include fatigue, weakness, dizziness, and pale skin and fingernails. Early diagnosis is essential to prevent serious health complications and improve patient outcomes.

The conventional diagnosis of anemia primarily relies on blood tests, such as hemoglobin measurement and Complete Blood Count (CBC). Although these methods provide accurate results, they are invasive, time-consuming, and require laboratory facilities and trained medical professionals. In many rural and resource-limited regions, access to such healthcare services is limited, resulting in delayed diagnosis and treatment.

Recent advancements in image processing and deep learning have enabled the development of non-invasive medical diagnostic systems. Fingernails exhibit visible color changes when hemoglobin levels decrease and can therefore serve as an important indicator of anemia. This paper proposes a non-invasive anemia detection system using fingernail image analysis and a MobileNetV2-based Convolutional Neural Network (CNN). The proposed approach aims to provide a rapid, low-cost, and accessible screening method for preliminary anemia detection.

2. LITERATURE REVIEW

Anemia is one of the most prevalent hematological disorders worldwide, affecting individuals across all age groups. Early diagnosis is essential to prevent severe health complications; however, conventional diagnostic methods require invasive blood tests, laboratory infrastructure, and trained healthcare professionals. These limitations have encouraged researchers to develop non-invasive, cost-effective, and rapid screening techniques based on medical image analysis. Among various approaches, the analysis of fingernail images has gained significant attention because changes in nail color and texture are closely associated with variations in hemoglobin concentration.

Recent advancements in artificial intelligence, computer vision, and deep learning have significantly improved the performance of medical image classification systems. Convolutional Neural Networks (CNNs) have emerged as one of the most effective deep

learning models for automatically extracting complex image features without requiring manual feature engineering. Several studies have demonstrated that CNN-based approaches outperform conventional machine learning techniques in disease detection tasks due to their ability to learn hierarchical visual representations.

Researchers have also investigated the use of conjunctiva, palm, tongue, and fingernail images for anemia detection. These methods generally involve image acquisition, preprocessing, feature extraction, and classification. While traditional approaches rely on handcrafted color and texture features combined with machine learning classifiers such as Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), and K-Nearest Neighbor (KNN), recent studies have shifted toward deep learning models capable of end-to-end learning. Despite these advancements, challenges such as varying illumination conditions, image quality, skin tone diversity, and limited annotated datasets continue to affect classification performance. Consequently, robust preprocessing techniques and efficient CNN architectures remain active areas of research.

2.1 Anemia and Fingernail Pallor

Anemia is characterized by a reduction in hemoglobin concentration or red blood cell count, resulting in decreased oxygen transport throughout the body. Common symptoms include fatigue, dizziness, weakness, shortness of breath, and pale skin. One of the clinically observable signs of anemia is fingernail pallor,

where the nail bed loses its normal pink coloration due to reduced blood oxygenation and hemoglobin levels.

Medical practitioners often examine nail color during preliminary physical examinations because fingernails provide a convenient and easily accessible region for visual assessment. Healthy individuals typically exhibit pinkish nail beds, whereas anemic patients often show pale or whitish nails. The degree of pallor generally correlates with the severity of anemia, making fingernail appearance an important visual indicator for early screening.

Although visual examination is simple and inexpensive, manual assessment is subjective and depends heavily on clinical experience. Factors such as lighting conditions, skin pigmentation, camera quality, and observer variability can influence diagnosis. Therefore, automated image analysis systems capable of objectively evaluating fingernail color have become an important research direction. Such systems can assist healthcare professionals in performing quick, non-invasive, and reliable anemia screening, particularly in remote and resource-limited settings.

2.2 Image Processing Techniques

Image preprocessing plays a critical role in improving the quality and consistency of medical images before they are analyzed by machine learning or deep learning models. Since fingernail images are captured under different environmental conditions, variations in illumination, shadows, camera resolution, and

background can introduce noise and reduce classification accuracy.

The preprocessing stage generally begins with image resizing, which standardizes all images to a fixed resolution suitable for CNN architectures. This ensures consistent input dimensions and reduces computational complexity during training. Noise removal techniques, including median filtering and Gaussian filtering, are commonly applied to eliminate unwanted artifacts while preserving important structural information.

Another important preprocessing step is brightness and contrast normalization, which compensates for illumination differences across images. Color normalization techniques reduce variations caused by different lighting environments and improve the consistency of color-based features. In many studies, the Region of Interest (ROI), corresponding to the fingernail area, is segmented from the background to eliminate irrelevant information and focus the analysis on clinically significant regions.

Image enhancement methods such as histogram equalization, adaptive histogram equalization (CLAHE), and contrast stretching further improve the visibility of subtle color differences associated with anemia. Data augmentation techniques—including rotation, horizontal flipping, zooming, shifting, and brightness adjustment—are also widely employed to increase dataset diversity, reduce overfitting, and improve model generalization. Together, these preprocessing techniques provide cleaner

and more informative images, enabling CNN models to learn robust and discriminative features for accurate anemia detection.

2.3 Deep Learning for Medical Image Classification

Deep learning has transformed medical image analysis by enabling automatic feature extraction and high-accuracy disease classification. Unlike traditional machine learning methods, which require manually designed features, deep learning models learn relevant representations directly from raw image data through multiple hierarchical layers.

Among various deep learning architectures, Convolutional Neural Networks (CNNs) have become the dominant approach for medical image classification due to their exceptional ability to capture spatial patterns, edges, textures, and color variations. A typical CNN consists of convolutional layers, activation functions, pooling layers, and fully connected layers that progressively learn increasingly abstract image features. This hierarchical learning capability allows CNNs to distinguish subtle visual differences between healthy and diseased tissues.

In recent years, several CNN architectures—including AlexNet, VGGNet, ResNet, DenseNet, MobileNet, EfficientNet, and InceptionNet—have been successfully applied to medical imaging tasks such as diabetic retinopathy detection, skin cancer classification, pneumonia diagnosis, breast cancer detection, malaria identification, and anemia screening. Transfer learning has

become particularly popular because pretrained CNN models leverage knowledge learned from large image datasets, allowing effective training even when limited medical datasets are available.

For anemia detection using fingernail images, CNN models automatically learn discriminative color distributions, texture characteristics, and intensity variations associated with hemoglobin deficiency. Their ability to perform end-to-end learning minimizes the need for manual feature engineering and often results in higher classification accuracy compared to conventional machine learning techniques. Nevertheless, challenges such as limited annotated datasets, class imbalance, computational complexity, and model interpretability remain active research areas. Ongoing research focuses on lightweight CNN architectures, explainable artificial intelligence (XAI), attention mechanisms, and hybrid deep learning models to improve diagnostic performance and support clinical decision-making.

3. METHODOLOGY

3.1 Dataset Description

The proposed system uses a dataset consisting of **1,881 fingernail images**, including **300 anemic** and **1,581 non-anemic** samples. Images were collected under different lighting conditions and resized to **224 × 224 pixels**. Data augmentation techniques such as rotation, zooming, brightness adjustment, and horizontal

flipping were applied to improve model generalization and reduce overfitting.

3.2 Image Acquisition

Users capture fingernail images using smartphone cameras under proper lighting conditions. The uploaded image is received through the Streamlit web application and stored for further analysis.

3.3 Image Preprocessing

Image preprocessing includes resizing the uploaded image to **224 × 224 pixels**, brightness

Metric	Value
Test Accuracy	82.77%
Test AUC	0.7091
Precision (Non-Anemic)	0.83
Recall (Non-Anemic)	1.00
F1-score (Non-Anemic)	0.91

normalization, contrast enhancement, and noise reduction. These operations improve image quality and provide consistent input for the deep learning model.

3.4 Fingernail Segmentation

MediaPipe Hand Landmark Detection is employed to detect fingertips automatically. The fingernail region is segmented from the hand image and extracted as the Region of Interest (ROI), eliminating unnecessary background information.

3.5 Feature Extraction

Color-based features including RGB values, redness ratio, brightness, and pallor score are

extracted from the segmented fingernail image. These features represent changes in nail color associated with reduced hemoglobin levels.

3.6 MobileNetV2 Architecture

Transfer learning is performed using the MobileNetV2 architecture pretrained on ImageNet. The original classification layer is replaced with a Global Average Pooling layer, Dropout layer, and Dense output layer with sigmoid activation for binary classification. The architecture enables efficient feature extraction while maintaining low computational complexity.

3.7 Classification and Prediction

The processed fingernail image is classified into one of two categories:

- Anemic
- Non-Anemic

Table-1: Metric

The prediction result is displayed in the Streamlit application along with a confidence score. A PDF report containing patient information and prediction results is automatically generated.

4. DATASET

The Mendely website provided the dataset. The dataset includes pictures of both anemic and non-anemic people's fingernails. There are 1695 non-anemic fingernails and 2565 anemic fingernails in the sample. The collection contains segmented and enhanced photos. The pictures have labels.



Fig-1: Anemia Fingernails

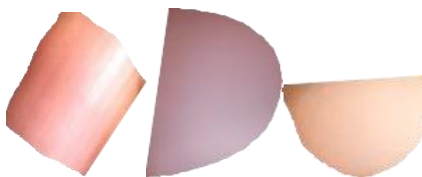


Fig-2: Non-Anemia Fingernails

5. RESULTS AND DISCUSSION

The proposed MobileNetV2 model was evaluated using the test dataset. The model achieved a test accuracy of 82.77% and an AUC score of 0.7091.

The experimental results demonstrate that MobileNetV2 effectively extracts visual features from fingernail images and achieves good overall classification performance. The high recall for the non-anemic class indicates that the model accurately identifies healthy individuals. However, lower performance for the anemic class is mainly due to dataset imbalance, where non-anemic images significantly outnumber anemic samples. Collecting additional real-world anemic images and applying class-balancing techniques can further improve model performance. Despite these limitations, the proposed system provides a rapid, affordable, and non-invasive screening tool suitable for preliminary anemia detection.

6. COMPARISON WITH TRADITIONAL METHODS

Traditional anemia diagnosis primarily relies on blood tests such as the Complete Blood Count (CBC) and hemoglobin measurements performed in laboratories. Although these methods provide highly accurate results, they are invasive, time-consuming, and require trained healthcare professionals and specialized medical equipment. In contrast, the proposed fingernail image analysis system offers a non-invasive, low-cost, and rapid screening approach using smartphone images and deep learning techniques. While the proposed system is intended for preliminary screening and cannot replace laboratory diagnosis, it has the potential to improve early detection and accessibility, especially in rural and resource-limited areas.

7. CONCLUSION

This paper presented a non-invasive approach for anemia detection using fingernail image analysis and deep learning techniques. The proposed system utilizes image preprocessing, fingernail segmentation, color feature extraction, and a MobileNetV2-based Convolutional Neural Network (CNN) to classify fingernail images as anemic or non-anemic. Experimental results demonstrated an overall accuracy of 82.77% with an AUC score of 0.7091. The proposed method provides a rapid, low-cost, and accessible preliminary screening solution for anemia detection without requiring invasive blood tests.

Future work will focus on improving the performance and reliability of the proposed

system. A larger and more balanced fingernail image dataset will be collected to enhance model generalization. Advanced deep learning architectures and data augmentation techniques can be employed to improve anemia detection accuracy. Additionally, the system can be integrated into a mobile application for real-time anemia screening and remote healthcare monitoring, making it more accessible in rural and resource-limited areas.

REFERENCES

- [1] World Health Organization (WHO), *Anaemia*. Geneva, Switzerland: WHO, 2023.
- [2] S. H. Mannino and M. D. Myers, "Smartphone-Based Non-Invasive Detection of Anemia Using Image Processing," *Nature Communications*, vol. 9, no. 1, pp. 1-10, 2018.
- [3] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 4th ed. New York, NY, USA: Pearson, 2018.
- [4] Y. LeCun, Y. Bengio, and G. Hinton, "Deep Learning," *Nature*, vol. 521, no. 7553, pp. 436-444, May 2015.
- [5] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," in *Advances in Neural Information Processing Systems (NIPS)*, 2012, pp. 1097-1105.
- [6] A. G. Howard et al., "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," arXiv:1704.04861, 2017.
- [7] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. C. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, Salt Lake City, UT, USA, 2018, pp. 4510-4520.
- [8] F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, Honolulu, HI, USA, 2017, pp. 1251-1258.
- [9] D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," in *Proc. International Conference on Learning Representations (ICLR)*, San Diego, CA, USA, 2015.
- [10] T. F. Chan and L. A. Vese, "Active Contours Without Edges," *IEEE Transactions on Image Processing*, vol. 10, no. 2, pp. 266-277, Feb. 2001.