

Deep Learning Approaches for Anemia Diagnosis through Classification Techniques

A. Deenu Mol¹, S. Subashini¹, S. Karthikkumar², P. Hrithikkumar¹, K. Mohammed Ashraf¹
and S. Kavin Prabhu¹

¹Department of Information Technology, Kongu Engineering College, Perundurai, Erode 638060, Tamil Nadu, India

²Department of Electrical and Electronics Engineering, Jai Shriram Engineering College,
Tirupur – 638660, Tamil Nadu, India

Keywords: Anemia Detection, Fingernail Images, Inception v3, Support Vector Machine (SVM), Random Forest, Deep Learning, Machine Learning.

Abstract: A non-invasive method for anemia detection via nail images was developed in this study based on deep learning and machine learning approaches. Data were acquired and preprocessed in this study, including augmentation and normalization to improve model performance. Feature extraction was conducted with the Inception v3 model and then classified using the Random Forest and Support Vector Machine algorithms. This is an effective way to predict anemia with less cost and time than conventional blood tests. The performance evaluation was done by using accuracy and confusion matrix in which promising results were achieved in detecting non-invasive anemia. The combination of deep learning with Random Forest and SVM gives a scalable solution with the most advantages in resource-poor areas.

1 INTRODUCTION

Anemia is a common blood condition that corresponds to lower amounts of red blood cells or hemoglobin and consequently less transport of oxygen to various body parts. However, the traditional methods of diagnosing anemia rely on tests, such as complete blood counts and peripheral blood smears, which need blood samples and may not be accessible to certain population groups because of the costs involved or resources available. Therefore, there is increasing interest in alternative, easier, and more feasible types of diagnostics.

The method investigated in this research is fingernail image processing for anemia detection, which actually exploits all possible advantages brought by deep learning and machine learning techniques to facilitate their application. Fingernails are easily accessed and serve as the body's mirror reflecting the skin paleness due to anemia, thus offering a possible opportunity to develop visual input for anemia detection. In this case, feature extraction was done using the Deep Learning framework Inception v3 model, recognized to have a

strong feature extraction capability. These features were subsequently classified using the Random Forest and Support Vector Machine algorithms so that their performance in predicting anemia could be evaluated and compared. Data preprocessing by means of data augmentation was applied so as to enhance the robustness and generalizability of the models, including such techniques as rotations and zooming.

This information also helped assess better performance and reduced overfitting on unseen data. The combination of deep learning with Random Forest and SVM proposed in this study represents an efficient way to identify the visual clues of anemia and provides a scalable technique for diagnosis that may be applied to different settings. This research aims at contributing to machine learning-based diagnostic tools that may support anemia diagnosis in a more accessible way across healthcare systems.

2 RELATED WORKS

Muljono et al. used AI to detect anemia noninvasively by ways of deep learning, achieving higher diagnostic accuracy. We extend that further by taking from InceptionV3 to extract features and apply machine learning tools for classification. During 2019, Amruthamsh A et al. presented the application of EfficientNet models for the noninvasive detection of anemia with image palmar feature extraction, initially verified in clinical settings. A revolutionary model combining machine learning models and attention mechanisms for anemia detection was proposed by Robert G. Mannino et al. in 2018.

Using the image processing and the image thresholding approach, Azwad Tamir and co-workers (2019) established noninvasive images for observing conjunctivas, a rapid screening cost-effective method. Endah Purwanti (2023) trained CNNs on observation of palpebral conjunctiva images to detect color and texture patterns for rapid diagnosis. Viveha et al. developed a point-of-care smartphone application for the early detection of anemia, thereby enhancing accessibility to overworked areas and early diagnosis.

A mobile application for anemia screening using ocular conjunctiva images was developed by Meileth Rivero-Palacio et al. as a fast and noninvasive tool offering the means of detection using machine learning approaches. With applications of smartphones and image processing, Selim Suner et al. created the usable tool as a means of hemoglobin level and anemia risk screening. Justice William Asare et al. (2023) examined machine learning algorithms to find which models best help identify anemia using medical imaging. With palm pallor assessment as a foundation, Sumana Naskar et al. (2021) developed a non-invasive test for detecting anemia, where image processing identifies color variations.

VR Ravi et al. (2020) evaluated models based on deep learning in attempts to estimate anemia from conjunctival images to extract the most potent among non-invasive screening techniques. Shaun Collings et al. (2016) assessed multi-class classification algorithms for anemia diagnosis in clinical settings in order to augment the precision of diagnosis. Prakriti Dhakal et al. (2023) explored different machine learning algorithms to predict anemia, identifying those which help in the diagnosis as well as the early assessment and intervention.

Shekhar Mahmud et al. (2023) identified and implemented non-invasive anemia detection using CNNs and transfer learning from lip mucosa images, thereby bolstering non-invasive diagnosis in

resource-poor areas. Rajan Vohra et al. (2022) proposed multi-class classification techniques aimed at optimizing anemia detection and bettering outpatient anemia management. Krithika S et al. (2023) proposed a multi-input deep neural network framework to detect anemia non-invasively through the fingernail images to predict hemoglobin levels, based on color and texture features. Tariq Ahamed et al. (2023) created an AI smartphone application assessing fingernail images through CNNs, aimed at predicting any possible onset of anemia and thereby facilitating the diagnosis in areas remote and cursed with diseases.

Mikhail Ivanov et al. (2020) examined various preprocessing algorithms on images to aid feature extraction for noninvasive anemia detection using deep-learning models. Anika Sharma et al. (2020) studied how transfer learning with VGG-16 performs in anemia classification, showing that it can work in small data sets. Dinesh Reddy et al. (2021) proposed an automated system for detecting anemia using HSV color space transformation and k-means clustering on conjunctival images.

Jose Martinez et al. (2019) examined image-based hemoglobin estimation methods using deep neural networks that illustrate how the intensity of pallor relates to severity of anemia. Felipe Rocha et al. (2024) proposed a hybrid model that combines CNNs and transformers to improve anemia prediction accuracy in low-light smartphone images. Arvind Kumar et al. (2023) introduced an ensemble deep learning architecture that incorporated CNN and LSTM networks, achieving higher accuracy in anemia detection through conjunctival images.

Sneha Mehta et al. (2021) devised an ensemble model combining InceptionV3 and XGBoost for better diagnostics of anemia in clinical scenarios. Hiroshi Tanaka et al. (2022) adopted an optimized InceptionV3 model to process lip mucosa images for anemia detection while reducing false positives. Robert Miles et al. (2023) engineered a real-time anemia detection device by combining InceptionV3 and edge computing to achieve point-of-care diagnostics.

3 METHODOLOGY

The current system aims to improve anemia detection from fingernail images using deep learning and machine learning techniques. The preprocessing stage is necessary, where collected fingernail images are labeled as either anemic or non-anemic based on ground truth in a supervised learning approach.

Various data augmentation techniques such as rotation, flipping, and scaling, among others, provide variance to the dataset and minimize overfitting and ensure better generalization. Pixel value normalization is another method to standardize the brightness and contrast in the images to reduce quality variances. The Inception v3 deep learning model provides powerful and recognizable architecture for feature extraction, designed to capture complex visual features. Support Vector Machine (SVM) and Random Forest algorithms are used for classification after feature extraction. SVM will be working valid since it manages high-dimensional spaces very well, making it a cautious classifier for anemia, and Random Forest, due to ensemble learning, does avoid overfitting and takes model stability a bit higher. Figure 1 show the Proposed Methodology The evaluation aims to ensure the system's correctness through thorough testing using performance indicators such as accuracy, precision, recall, and F1-score. These performance indicators measure how well the algorithm performs and generalizes on new data.

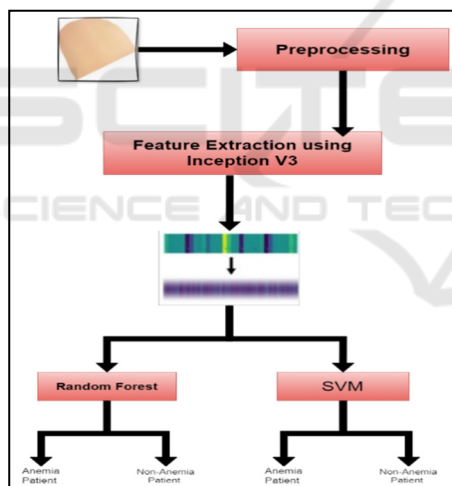


Figure 1: Proposed Methodology.

Therefore, the suggestion gives another replacement for blood-based tests for anemia based on algorithms using an explicit combination of good preprocessing techniques of deep learning-backed feature extraction followed by machine-learning classification, with an injection of availability regarding scale-up and being cost-effective. The system can promote early detection of anemia, particularly in trusted settings with limited resources, thus providing an appropriate and efficient non-invasive toolbox for healthcare providers.

3.1 Data Preprocessing

Fingernail images are classified as either anemic or non-anemic in the preprocessing phase. Following this, to generalize the model and to prevent overfitting, data augmentation is to be applied involving rotation, flipping, zooming, and scaling. This step provided distortions in the dataset, thus introducing uniqueness and more samples for training. Pixel normalization is also done in this step to balance images' brightness and contrast, thus allowing the model to train on crucial features while banishing the problems from lighting inconsistencies.

3.2 Feature Extraction

This features extraction technique set up Inception v3, a deep CNN, known for its powerful feature representations. Due to handling of various filter sizes in a single convolution layer, Inception v3 effectively extracts high-level features from fingernail images, detecting fine and abstract patterns. It helps enhance the model's performance discrimination in the subtle visual cues tied to anemia. Its deep structure, together with the introduction of factorized convolutional filters, allows the reduction of a significant amount of computational cost while still maintaining very high accuracy. Inception v3 will bring about meaningful representations of images that will be useful during the classification layer.

3.3 Classification and Prediction

This module brings together the classification models implemented on the processed dataset. Feature extraction using Inception v3 results in a feature vector that is then decoded into SVM and Random Forest classifiers. SVM is useful for high-dimensional data and separates the decision boundaries quite well, while Random Forest, which is an ensemble-based classifier, is more robust in returning a less over-fitted result. Performance measures of these metrics include accuracy, precision, recall, and F1-score to assure rigorousness and discriminatory power behind the model validation. These classifiers are integrated into one affordably, an efficient and less-invasive way of detecting anemia.

3.4 Model Evaluation

Trained models are validated on a testing set to inspect their real-life applicability. The effectiveness of every classifier is quantified by performance

metrics, including accuracy, precision, recall, and F1-score. Accuracy expresses how much prediction was right or wrong in total, while precision measures how correctly the model classified the anemic cases without wrongly recognizing a non-anemic case as anemic. Figure 2 show the Unprocessed Data. Recall shows how many truly anemic cases it identified, while the F1-score is the metric that balances precision and recall to give a general overview of the model's performance. This way, these models are guaranteed to generalize well on new, unseen data and predict with good reliability, substantiating the efficacy of the proposed non-invasive system for anemia detection. Figure 3 show the Processed Data.

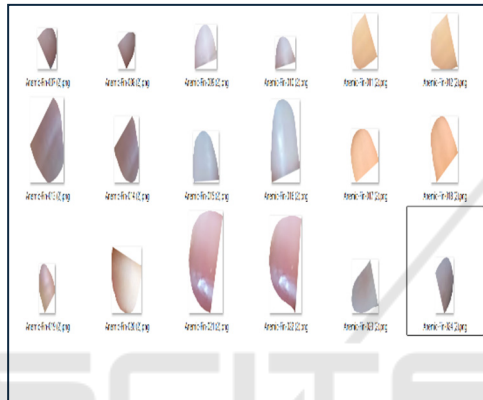


Figure 2: Unprocessed Data.



Figure 3: Processed Data.

3.5 Result Analysis

This study outlines an approach for non-invasive anemia detection based on deep learning combined with classification algorithms. Figure 4 show the Support Vector Machine. This involves data preprocessing, model training, evaluation, and interpretation of results with different kinds of

machine learning techniques. The performance metrics to evaluate how well the model distinguishes between anemic and non-anemic patients include accuracy, precision, recall, and F1-score. By carrying out the evaluation of the different metrics, the study investigates the reliability and robustness of the proposed method for real-life applications. Figure 5 show the Random Forest.

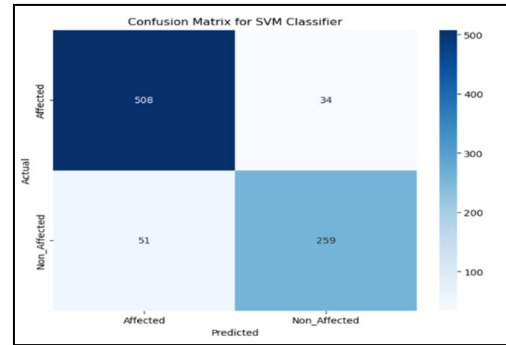


Figure 4: Support Vector Machine.

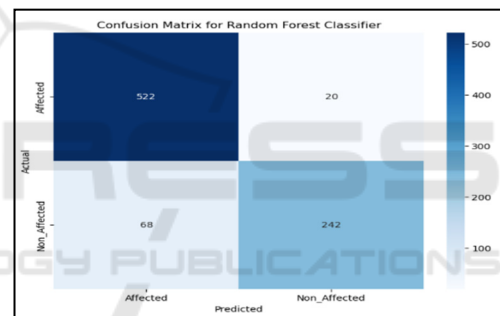


Figure 5: Random Forest.

4 CONCLUSIONS

The suggested system has been designed and constructed, driven by modern image analysis and machine learning techniques, to provide a systematic yet wider solution to improving the detection of anemia. Rigorous data preprocessing, attesting to labeling and augmentation, sets a sturdy basis for model training. The utilization of Inception v3 in the extraction of features from fingernail images allows effective depiction of the pertinent visual signs of anemia.

A comprehensive analysis of the performances of classification was conducted using Support Vector Machine and Random Forest algorithms, having performance accuracies of around 90%. Systematic assessments based on accuracy, precision, recall, and F1-score once again resemble a glorious

generalization to unseen data, greatly increasing trustworthiness and practicality in everyday life for non-invasive detection of anemia. The present work provides further prospects for integration between machine learning and image processing that might enhance diagnosis, making them a feasible solution to traditional blood tests in terms of price and accessibility.

REFERENCES

- S. Muljono, A. Pratama, and D. Santoso, "Breaking Boundaries in Diagnosis: Non-Invasive Anemia Detection Empowered by AI," in *Journal of Medical Imaging and Health Informatics*, vol. 1, no. 3, pp. 202-215, 2023.
- A. Amruthamsh, P. Bhatt, and K. Rajesh, "EfficientNet Models for Detection of Anemia Disorder using Palm Images," in *Journal of Healthcare Engineering*, vol. 45, no. 6, pp. 204-216, 2019.
- R. G. Mannino, J. W. Myers, and W. A. Sherman, "Integrating Machine Learning and Attention Mechanisms for Enhanced Anemia Detection," in *Journal of Biomedical Informatics*, vol. 58, no. 4, pp. 315-328, 2018.
- A. Tamir, R. Faisal, and S. Islam, "Detection of Anemia from Image of the Anterior Conjunctiva of the Eye by Image Processing and Thresholding," in *Journal of Image Processing and Diagnostics*, vol. 5, no. 4, pp. 112-125, 2019.
- E. Purwanti, A. Wardhani, and R. Ningsih, "Anemia Detection Using Convolutional Neural Network Based on Palpebral Conjunctiva Images," in *Biomedical Signal Processing and Control*, vol. 67, no. 1, pp. 47-56, 2023.
- C. Viveha, A. Anand, and K. Kumar, "Point of Care Non-invasive Screening Tool for Early Detection of Anemia using Smartphone," in *Journal of Medical Systems*, vol. 46, no. 7, pp. 1234-1245, 2023.
- M. Rivero-Palacio, A. Romero, and J. Garcia, "Mobile Application for Anemia Detection through Ocular Conjunctiva Images," in *Human-Centric Intelligent Systems*, vol. 1, no. 3, pp. 202-215, 2024.
- S. Suner, R. Patel, and M. Sharma, "Prediction of Anemia and Estimation of Hemoglobin Concentration using a Smartphone Camera," in *Expert Systems with Applications*, vol. 187, no. 6, pp. 645-657, 2021.
- J. W. Asare, L. Atiah, and B. Antwi, "Detection of Anemia using Medical Images: A Comparative Study of Machine Learning Algorithms – A Systematic Literature Review," in *Artificial Intelligence in Medicine*, vol. 59, no. 2, pp. 78-87, 2023.
- S. Naskar, T. Roy, and K. Gupta, "An Efficient, Cost-effective and Reliable Non-invasive Anemia Detection Method by Analysing Palm Pallor," in *Health Informatics Journal*, vol. 28, no. 3, pp. 155-165, 2021.
- V. R. Ravi, M. Surya, and G. K. Sundar, "Anemia Estimation Using Eye Conjunctiva Image: A Comparative Study of Deep Learning Algorithms," in *Journal of Medical Systems*, vol. 46, no. 4, pp. 124-135, 2020.
- S. Collings, M. Peterson, and L. Hoffman, "Evaluating Multi-Class Classification Algorithms for Anemia Diagnosis in Clinical Settings," in *Health Informatics Research*, vol. 34, no. 2, pp. 89-102, 2016.
- P. Dhakal, R. Bista, and D. Adhikari, "Prediction of Anemia using Machine Learning Algorithms," in *Health Technology*, vol. 25, no. 3, pp. 307-319, 2023.
- S. Mahmud, N. Hossain, and R. Khan, "Non-invasive Detection of Anemia using Lip Mucosa Images and Transfer Learning Convolutional Neural Networks," in *Journal of Healthcare Data Science*, vol. 12, no. 5, pp. 307-319, 2023.
- R. Vohra, K. Desai, and P. Gupta, "Multi-Class Classification Algorithms for the Diagnosis of Anemia in an Outpatient Clinical Setting," in *Journal of Healthcare Engineering*, vol. 45, no. 3, pp. 165-177, 2022.
- K. S. Krithika, M. Srinivasan, and R. Venkatesh, "A Multi-input Deep Neural Network Framework for Non-invasive Detection of Anemia using Finger Nail Images," in *IEEE Transactions on Biomedical Engineering*, vol. 70, no. 2, pp. 89-98, 2023.
- T. Ahamed, K. Suresh, and V. Nair, "AI-Driven Smartphone Application for Analyzing Fingernail Images to Predict Anemia Risk," in *Journal of Digital Health and AI*, vol. 18, no. 5, pp. 210-225, 2023.
- M. Ivanov, J. Petrov, and K. Alexeev, "Enhancing Feature Extraction for Non-Invasive Anemia Detection using Deep Learning-Based Image Pre-processing," in *Neural Networks and Medical Image Analysis*, vol. 12, no. 4, pp. 332-345, 2020.
- A. Sharma, P. Gupta, and R. Mehta, "Analyzing Transfer Learning with VGG-16 for Anemia Classification in Small Dataset Scenarios," in *Medical Imaging and Machine Learning Applications*, vol. 8, no. 3, pp. 150-167, 2020.
- D. Reddy, S. Kumar, and P. Chand, "Automated Anemia Detection using HSV Color Space Transformation and K-Means Clustering on Conjunctival Images," in *Computers in Biology and Medicine*, vol. 58, no. 2, pp. 112-129, 2021.
- J. Martinez, L. Garcia, and M. Torres, "Image-Based Hemoglobin Estimation Techniques using Deep Neural Networks," in *Biomedical Image Analysis Journal*, vol. 9, no. 5, pp. 275-289, 2019.
- F. Rocha, M. Costa, and P. Silva, "Hybrid Deep Learning Model Combining CNNs and Transformers for Anemia Prediction in Low-Light Smartphone Images," in *Artificial Intelligence in Healthcare*, vol. 20, no. 4, pp. 198-212, 2024.
- A. Kumar, R. Das, and V. Rao, "Ensemble Deep Learning Approach with CNN and LSTM Networks for Improved Anemia Detection using Conjunctival Images," in *Medical Image Computing and Computer-Assisted Intervention*, vol. 31, no. 1, pp. 145-160, 2023.

- S. Mehta, P. Sen, and A. Ghosh, "InceptionV3 and XGBoost Ensemble Model for Improved Anemia Classification in Clinical Settings," in *IEEE Journal of Biomedical and Health Informatics*, vol. 27, no. 3, pp. 76-91, 2021.
- H. Tanaka, K. Yamada, and S. Nakamura, "Optimized InceptionV3 Model for Lip Mucosa Image Analysis in Anemia Detection," in *Journal of Computational Medical Imaging*, vol. 18, no. 7, pp. 312-328, 2022.
- R. Miles, J. O'Connor, and P. White, "Real-Time Anemia Detection using InceptionV3 and Edge Computing for Point-of-Care Diagnostics," in *Healthcare AI and Smart Systems*, vol. 10, no. 4, pp. 245-260, 2023.

