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Anaemia Detection using Deep Learning by processing Conjunctiva, Fingernails, Palm and Tongue Images

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Abstract
Anemia poses a significant global public health challenge, particularly impacting children and pregnant women. According to the WHO, anemia is a highly prevalent condition, especially among patients in the emergency department. It occurs when the hemoglobin level falls below its normal threshold or when red blood cells are weakened or destroyed. This decreased number of red blood cells will lead to the paleness of the skin especially in the conjunctiva, palpable palm & fingernails. In current scenario anemia is being diagnosed by using invasive method. In this project, we propose the use of non-invasive techniques employing deep learning algorithms to aid in the diagnosis and detection of clinical diseases, specifically focusing on anemia detection. This approach aims to simplify the process of detection by analyzing images of specific areas such as the conjunctiva of the eye, palpable palm, fingernails, and tongue from diverse individuals. The processing and classification of these images are conducted using various deep learning algorithms including Convolutional Neural Networks (CNN), Mobilenet, and others. Our project paves way to identify the best algorithm that gives greatest accuracy rate and minimum time consumption for the detection of anemia. We have got the maximum accuracy rate of 99% in mobilenet and 83% in CNN.

Keywords: *Anemia; CNN; Deep learning; Mobilenet.*

1. Introduction
1.1. Anemia
Anemia is characterized as a blood disorder where the blood's capacity to carry oxygen is diminished. This can result from a lower than typical count of red blood cells, a decrease in the amount of hemoglobin available for oxygen transport, or abnormalities in hemoglobin that hinder its function. Anemia is a widespread blood disorder affecting a significant portion of the global population, estimated to be between one-fifth and one-third. The most prevalent form of anemia worldwide is iron-deficiency anemia, impacting more than 1 billion people. In 2013, iron deficiency anemia was associated with approximately 183,000 deaths, a decrease from 213,000 deaths reported in 1990. This scenario is particularly prevalent among children, as well as among elderly individuals and women of childbearing age, particularly during pregnancy. These demographic groups experience higher rates and risks of developing this condition compared to the general population. This study is focused on identifying anemia through a non-invasive approach using images of the visible palm, fingernail color, and eye conjunctiva. Timely detection and treatment of anemia have a positive impact on public health, physical well-being, and economic growth. [1-5]

1.1.1. Causes of Anemia
Anemia can be categorized based on its causes into several main types:

1. **Impaired Red Blood Cell (RBC) Fabrication:** This type of anemia occurs when the bone marrow doesn't produce enough red blood cells. marrow disorders, chronic diseases, or genetic conditions affecting red blood cell synthesis.
2. **Increased RBC Destruction (Hemolytic Anemia):** Hemolytic anemia results from the premature destruction of red blood cells either

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within the blood vessels (intravascular hemolysis) or in the spleen or liver (extravascular hemolysis). Causes include autoimmune disorders, infections, certain medications, and inherited conditions like sickle cell disease or thalassemia.

3. **Blood Loss:** Anemia due to blood loss can occur from acute or chronic bleeding, such as gastrointestinal bleeding (ulcers, colorectal cancer), menstrual bleeding (in women with heavy periods), or trauma.
4. **Fluid Overload (Hypervolemia):** This type of anemia is less common and occurs when the volume of plasma (the liquid portion of blood) increases relative to the number of red blood cells, diluting their concentration in the blood.

1.1.2. Signs and Symptoms

An individual with anemia may not exhibit symptoms initially, depending on the underlying cause and the severity of the condition. Symptoms may only become noticeable as the anemia progresses. Common symptoms reported by patients with anemia include fatigue, weakness, difficulty concentrating, and occasionally, shortness of breath during physical exertion. [6-10]

1.1.3. Possible Symptoms of Anemia Include

Tiredness, weakness, shortness of breath, pale or yellolike skin, which might be more obvious on white skin than on Black or brown skin, irregular heartbeat, dizziness or light headedness, chest pain, cold hands and feet, headaches are some of the common symptoms mojorly noticed in anemia. It's important to note that the visibility of certain symptoms, such as pale or yellowish skin, may vary based on an individual's skin tone, being more noticeable on lighter skin compared to darker skin tones. These symptoms can vary in severity depending on the type and severity of anemia, and individuals experiencing these symptoms should seek medical evaluation for proper diagnosis and treatment. Having a pale complexion is a common symptom in all types of anemia due to the decreased number of red blood cells affecting blood flow. Reduced red blood cells results in less blood reaching the skin's surface, causing a loss of skin color. Paleness in the inner eyelids(conjunctiva) is a telltale sign of anemia, regardless of race. It is considered as a sensitive indicator of severe anemia. (Refer Figure 1)

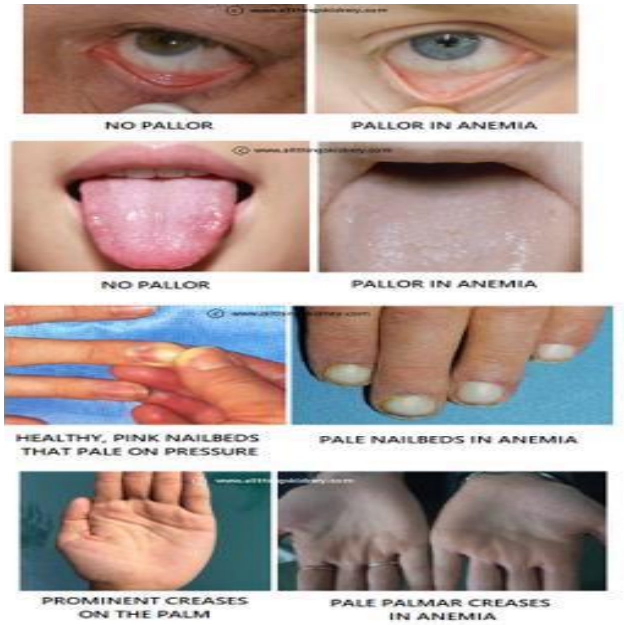

Figure 1 Pallor and Non-Pallor Images of Conjunctiva, Tongue, Fingernails, Palm

1.2. Deep Learning

The Deep Neural Network (DNN) mimics the neural networks in the human brain, utilizing complex layers that define input and output through a composition of neurons and nonlinear functions. Unlike traditional machine learning methods, DNNs excel in learning directly from raw data, leveraging multiple hidden layers to extract abstract features and achieve high accuracy and performance. This capability has made deep learning a preferred choice among researchers in the medical field for tasks such as medical image analysis, disease diagnosis, outcome prediction, and personalized treatment planning. Its ability to process vast amounts of data and discern complex patterns contributes significantly to advancing healthcare practices and improving patient outcomes. [11-15]

1.2.1. Mobilenet

MobileNet is a model that performs image convolution similar to CNN, but utilizes Depth and point convolutions in a unique manner compared to traditional CNNs. This innovative approach enhances the efficiency of predicting images, enabling it to be competitive in mobile systems as well. MobileNet is TensorFlow's first mobile computer vision model. It

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utilizes depthwise separable convolutions to drastically reduce the number of parameters in comparison to conventional networks with regular convolutions of the same depth. This leads to the development of lightweight deep neural networks.

1.2.2. Convolutional Neural Network

A Convolutional Neural Network (CNN or ConvNet) is a deep learning model specially crafted for tasks where object identification is critical, like image classification, detection, and segmentation. The convolution layers in CNNs are translation invariant, enabling them to identify patterns within data and extract features regardless of their orientation, size, or position changes. Besides imagerelated tasks, CNNs can be applied to various non-image classification challenges, including natural language processing, time series analysis, and speech recognition.

2. Literature Review

[1] Yang B., Yu M., Zhang J., Li Y., & Wang Z (2019) introduced the nailbed color analysis for anemia detection. This study proposed a method for anemia detection by analyzing the color images of fingernails. They utilized machine learning techniques for feature extraction and classification. [2] Teng, C., Zhu, Y., & Zhang, D. (2017) published the palm color image-based anemia detection using convolutional neural networks. The researchers investigated the feasibility of using palm color images for anemia detection.They employed convolutional neural networks (CNNs) toautomatically extract features from palm images and achieved satisfactory accuracy in identifying anemic conditions. [3] Li, X., & Wang, Y. (2020) proposed the Conjunctival color image analysis for anemia detection using deep learning. This research explored the potential of conjunctival color image analysis for diagnosing anemia. It uses the Deep learning techniques to extract discriminative features from conjunctival images, showing promising results in anemia detection. [4]Chen, H., Liu, J., & Yin, F. (2018). Proposed the multimodality for detecting anemia using various parameters like fingernails, palm, conjunctiva. This study proposed a multi-modal machine learning approach that combines information from multiple sources, including fingernail,palm, and conjunctiva images, for enhanced anemia detection. The fusion of information from different modalities improved the accuracy of anemia diagnosis significantly. [5] Zhang, L., Liu, Y., & Zhang, D. (2019). Studied the different body parts for anemia diagnosis with the help of deep learning. This research conducted a comparative analysis of using different body parts, including fingernails, palms, and conjunctiva, for anemia detection. Machine learning models were employed to evaluate the effectiveness of each modality, providing insights into their respective strengths and limitations. The above mentioned literatures were used for better understanding of our work.

3. Methodology

The steps that was being carried out is depicted in the form of flow chart as shown in Figure 2

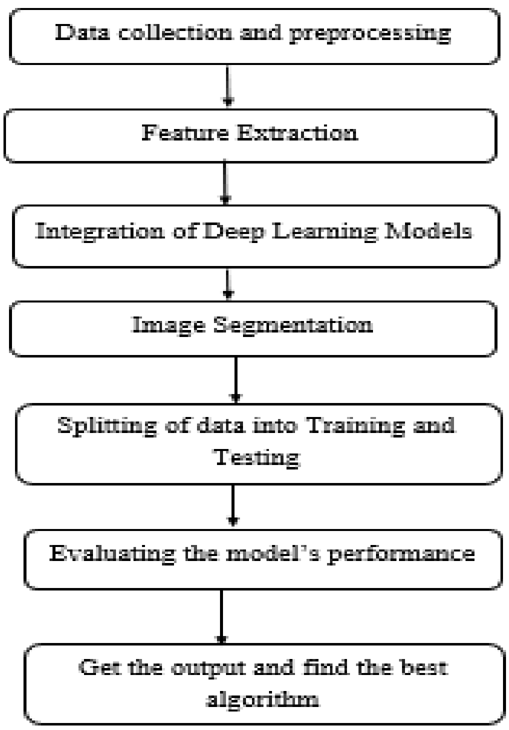

Figure 2 Work Flow

3.1. Data Collection

The data utilized to identify anemia through deep learning was being collected from the platform of Kaggle which consists of data of medical images of conjunctiva of the eye, palpable palm, fingernails of various individual. It consists of over 4000 images which has both anemic and non anemic category. (Refer Figure 3-6)

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Figure 3 Anemic and Non-Anemic Conjunctiva

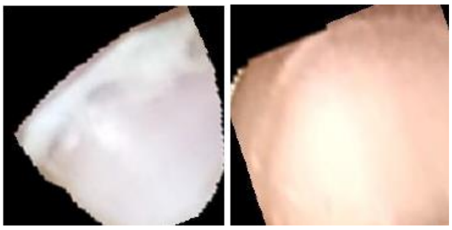

Figure 4 Anemic and Non-Anemic Fingernail

Figure 5 Anemic and Non-Anemic Palpable Palm

Figure 6 Anemic and Non-Anemic Tongue Images

3.2. Data Prepocessing

Prior to model training, extensive preprocessing of the images was conducted to ensure data quality and consistency. This involved noise removal, resizing to standardized dimensions, and enhancement of relevant features to improve the model's ability to extract meaningful information.

3.3. Model Selection

A Convolutional Neural Network (CNN) architecture was chosen as the foundation for the deep learning model due to its effectiveness in image classification tasks. The specific architecture and configuration were determined through empirical evaluation and experimentation. Then Mobilenet model was chosen due to its greater accuracy rate and less time consumption. These both models paved way for a easier detection of anemia by giving a greater accuracy.

3.4. Model Training

The annotated dataset was splitted into training, validation, and testing sets using stratified sampling to ensure representative distributions of anemic and non-anemic cases across the sets. The model was trained using the training set, while also monitoring its performance on the validation set to avoid overfitting. Hyperparameters were fine-tuned iteratively to optimize performance. We have considered 60% of the data for training and 40% data for testing.

3.5. Epochs and Batching

Train the model over a defined number of epochs with a specified batch size. Smaller batch sizes may be suitable for MobileNet due to memory constraints, while larger CNNs might benefit from larger batches.

$$\begin{aligned} &Total\ number\ of\ iterations(Epoch)\\ &= Total\ number\ of\ training\ samples\\ &/Batch\ size \end{aligned}$$

3.6. Accuracy function

The performance of a CNN in image categorization tasks can be assessed using different criteria.This metric indicates the percentage of test images correctly classified by the CNN. Among the most widely used metrics accuracy is the proportion of test images correctly classified by the CNN.

$$Accuracy = (TP + TN)/(TP + TN + FN + FP)$$

3.7. Loss Function

Use an appropriate loss function for the task. For binary classification (like anemia detection), Binary Cross-Entropy Loss is common. For multi-class tasks, Categorical Cross-Entropy is used.

3.8. Validation

After every epoch, assess the model's performance on the validation set to track progress and identify overfitting. Adjustments to learning rate or other hyperparameters may be required.

3.9. Evaluation

The model that was trained underwent evaluation on the separate testing set to assess its effectiveness in detecting anemia. Performance metrics such as accuracy, Epoch, Loss, Time taken were computed to

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quantify the model's performance and compare it against baseline methods.

3.10. Deployment

Upon achieving satisfactory performance, the trained model was deployed for real-world use, either integrated into existing medical diagnostic systems or as a standalone application for healthcare professionals. Rigorous testing and validation were conducted prior to deployment to ensure the model's reliability and safety in clinical settings.

3.11. Monitoring and Maintenance

Continuous monitoring of the deployed model's performance was carried out post deployment, with periodic updates and maintenance to adapt to changes in data distribution or medical practices. Collaboration with healthcare professionals and domain experts facilitated ongoing improvement and refinement of the model. These are the steps involved for achieving the expected results and outcome of our work.

4. Results and Discussion

On comparing to CNN we got greater rate of accuracy by using mobilenet model. (Refer Table 1, 2) The accuracy rate was to the maximum of 99% while using mobilenet model. (Refer Figure 7-15)

Table 1 Various Metrices Observed From the Output (CNN)

Parameter	Epoch	Accuracy (%)	Loss (%)	Time Taken(sec)
Conjunctiva	10	52	61	30.58
Palm	10	44	70	27.95
Fingernail	10	83	56	44.32
Tongue	10	62	45	35.23

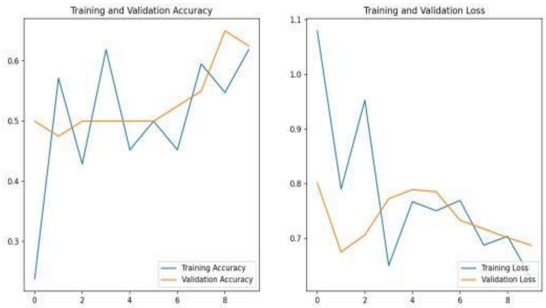

Figure 7 Output of CNN (Conjunctiva)

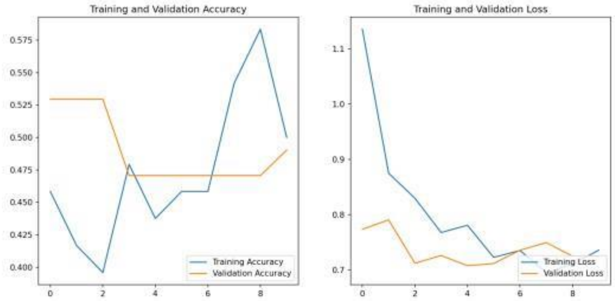

Figure 8 Output of CNN (Palm)

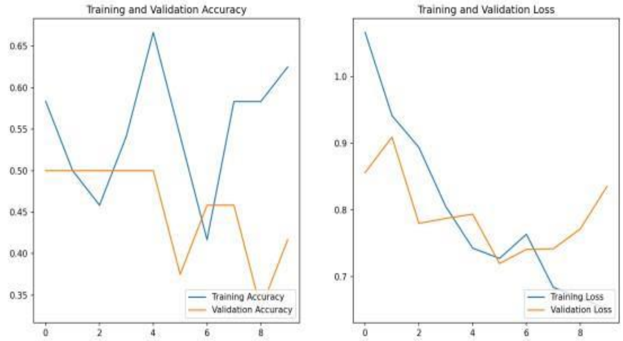

Figure 9 Output of CNN (Fingernail)

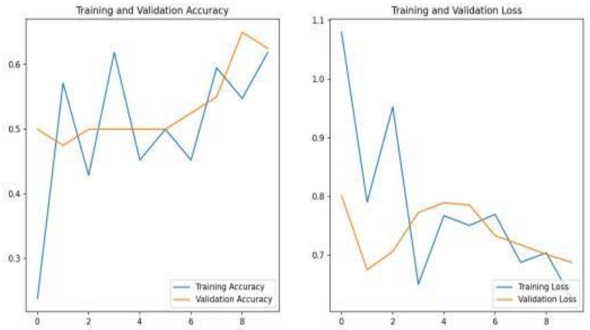

Figure 10 Output of CNN (Tongue)

Table 2 Various Metrices Observed from the Output (Mobilenet)

Parameter	Epoch	Accuracy (%)	Loss (%)	Time Taken(sec)
Conjunctiva	15	99	1	18.24
Palm	15	97	3	21.30
Fingernail	15	98	2	20.93
Tongue	15	96	4	21.68

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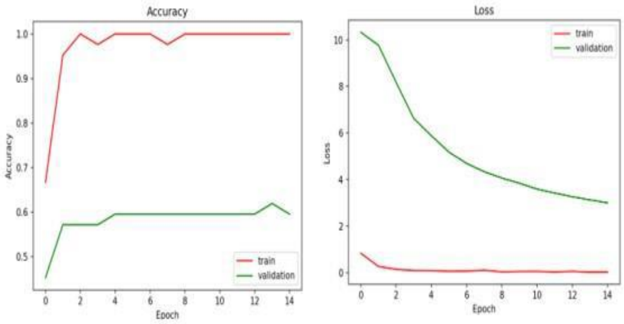

Figure 11 Output of Mobilenet (Conjunctiva)

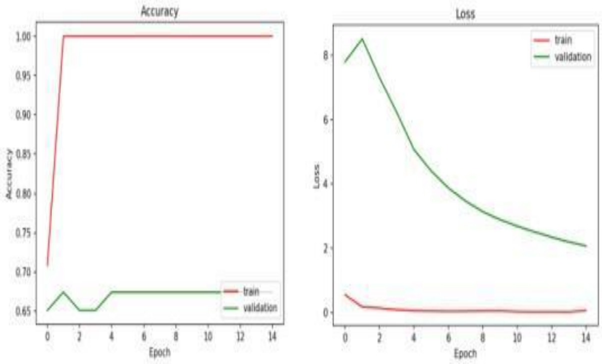

Figure 12 Output of Mobilenet (Palm)

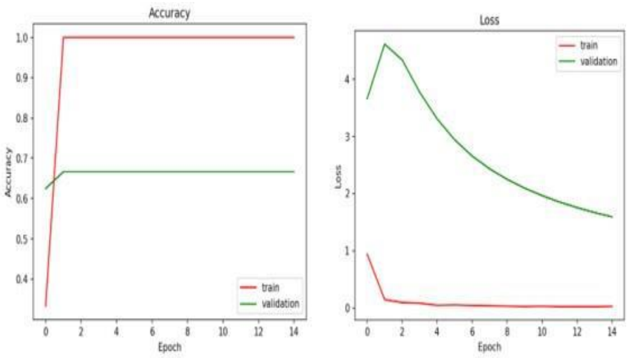

Figure 13 Output of Mobilenet (Fingernail)

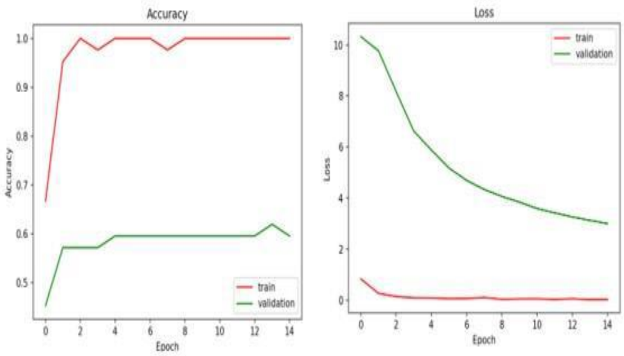

Figure 14 Output of Mobilenet (Tongue)

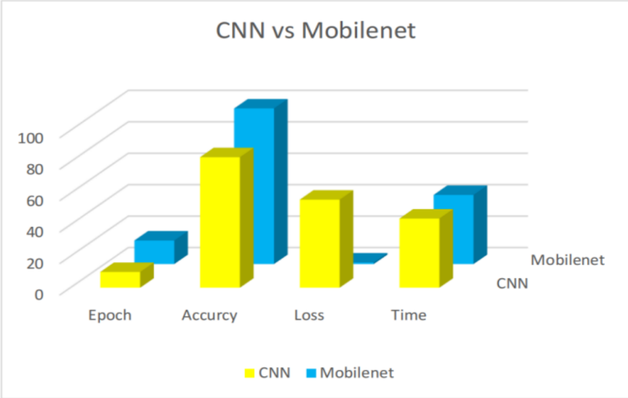

Figure 15 Comparison between CNN and Mobilenet

Conclusion

On comparing to CNN we got greater rate of accuracy by using mobilenet model. The accuracy rate was to the maximum of 99% while using mobilenet model whereas in CNN the maximum accuracy rate was 83%. Therefore we could infer that mobilenet model paves way for the higher accuracy and helps us to gain the expected outcome. Therefore we could infer that mobilenet model paves way for the higher accuracy and helps us to gain the expected outcome.

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