Vitamin Deficiency Detection and Analysis System Using Deep Learning and Grad-CAM

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Abstract - *Vitamin deficiencies can lead to serious health complications if not detected at an early stage. However, traditional diagnostic methods often rely on laboratory tests, which may not always be easily accessible or time efficient. In this study, we propose a deep learning-based system that can assist in identifying vitamin deficiencies using image data. The model is built using MobileNetV2 through a transfer learning approach, enabling efficient and accurate classification across multiple deficiency categories. A structured preprocessing pipeline was implemented to improve data quality, including the removal of duplicate images, filtering of sensitive and irrelevant data, and proper organization of class labels. To handle class imbalance and enhance model performance, data augmentation techniques were applied. Initially, EfficientNet and MobileNetV2 models were evaluated, where MobileNetV2 demonstrated better performance. With the inclusion of augmentation, the model achieved an accuracy of 92%. To improve transparency and trust in the system, Grad-CAM was integrated to visualize the regions of the image that influenced the model's predictions. The results indicate that the proposed system is not only accurate but also interpretable. This approach can serve as a supportive tool in healthcare applications, particularly in areas with limited access to medical resources.*

Key Words: Vitamin Deficiency Detection, Deep Learning, MobileNetV2, Transfer Learning, Grad-CAM, Image Classification, Data Augmentation, Explainable AI

1. INTRODUCTION

Vitamin deficiencies are a major health concern worldwide, affecting people across different age groups and lifestyles. Deficiencies in essential vitamins such as A, B, C, D, and E can lead to various health issues, including fatigue, weakened immunity, skin disorders, and other complications [1]. Early identification of these deficiencies plays a crucial role in preventing severe health conditions and improving overall well-being. However, traditional diagnostic methods primarily depend on laboratory tests and clinical evaluations, which can be time-consuming, costly, and not always accessible in remote or resource-limited areas.

Recent advancements in Artificial Intelligence (AI) and Deep Learning have opened new possibilities in the field of healthcare, particularly in automated diagnosis systems [2]. Computer vision techniques enable machines to analyze visual patterns in images, making it possible to detect certain health conditions based on physical symptoms. In the case of vitamin deficiencies, visible indicators such as changes in the skin, nails, and tongue can be analyzed using deep learning models to assist in diagnosis.

This work focuses on developing an intelligent system that leverages deep learning techniques to detect and classify vitamin deficiencies from image data. By using transfer learning with MobileNetV2, the system is designed to achieve efficient and accurate classification across multiple deficiency categories [3]. Additionally, a structured data preprocessing pipeline is implemented to ensure high-quality input for the model.

1.1 Data Preprocessing and Dataset Preparation

Data preprocessing is a critical step in building a reliable deep learning model. The dataset used in this work initially consisted of a large collection of raw images obtained from an open-source platform [4]. Several preprocessing steps were applied to improve the quality and relevance of the data. First, duplicate images present in the dataset were identified and removed to avoid redundancy and bias during training.

Next, sensitive and inappropriate images that could affect the model's learning were filtered out. This step ensures that the dataset remains clean and suitable for training in a healthcare-related application. Additionally, images belonging to irrelevant categories or diseases that do not fall under the defined classes were removed to maintain consistency in classification.

After cleaning, the dataset was organized into predefined classes representing different vitamin deficiencies. To address the issue of class imbalance, data augmentation techniques such as rotation, flipping, and zooming were applied [5]. These steps helped increase the diversity of the dataset and improve the generalization capability of the model.

1.2 Model Development and Approach

The proposed system utilizes deep learning models to perform image classification for vitamin deficiency detection. Initially performance was implemented to evaluate baseline performance; however, the model achieved limited accuracy, indicating the need for further optimization. Subsequently, MobileNetV2 was employed using a transfer learning approach, which significantly improved the classification performance [3].

Further enhancements were achieved by incorporating data augmentation techniques, resulting in better model generalization and increased accuracy. The final model demonstrated a substantial improvement in performance compared to earlier approaches.

To enhance the interpretability of the system, Grad-CAM (Gradient-weighted Class Activation Mapping) was integrated. This technique provides visual explanations by highlighting the regions in the input image that contribute most to the model's predictions [6]. Such explainability is essential in healthcare applications, as it increases trust and transparency in AI-based systems.

2. METHODOLOGY

The proposed system follows a structured pipeline for detecting and analyzing vitamin deficiencies using image-based data. The methodology includes dataset collection, preprocessing, model development, evaluation, and explainability. Each stage is designed to improve data quality and enhance model performance, ensuring reliable and interpretable results [1][2].

2.1 Dataset Description

The dataset used in this study consists of image samples representing visible symptoms associated with vitamin deficiencies. The raw dataset initially contains approximately 18,656 images collected from an open-source platform [4]. These images include different visual indicators such as skin, nails, and tongue conditions, which are commonly used in visual diagnosis approaches [2].

However, the dataset contains redundant, noisy, and irrelevant samples, which may negatively affect model performance. Therefore, a structured preprocessing pipeline is applied to clean and organize the dataset into meaningful categories. Proper dataset preparation plays a crucial role in improving model accuracy and generalization in deep learning applications [5].

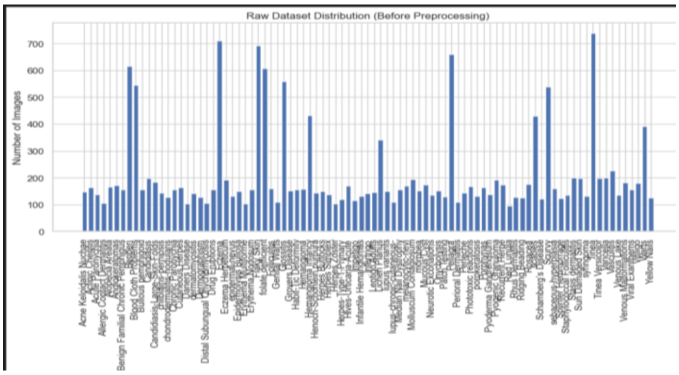

Fig -1: Raw Dataset Distribution

2.2 Data Preprocessing

Data preprocessing is a crucial step to ensure the quality and consistency of the dataset. High-quality data plays a significant role in improving the performance and reliability of deep learning models [5]. The following operations are performed:

Duplicate Image Removal: Duplicate and repeated images are identified and removed to eliminate redundancy and prevent model bias during training.

Sensitive Image Filtering: Images that are inappropriate or irrelevant to the analysis are removed to maintain dataset integrity, especially for healthcare-related applications.

Irrelevant Class Removal: Images belonging to categories outside the defined vitamin deficiency classes are eliminated to ensure consistency in classification.

Data Cleaning: The dataset is refined to retain only useful and meaningful samples, improving the overall quality of data input for model training.

These steps significantly improve the reliability of the dataset, reduce noise, and enhance the generalization capability of the model [2][5].

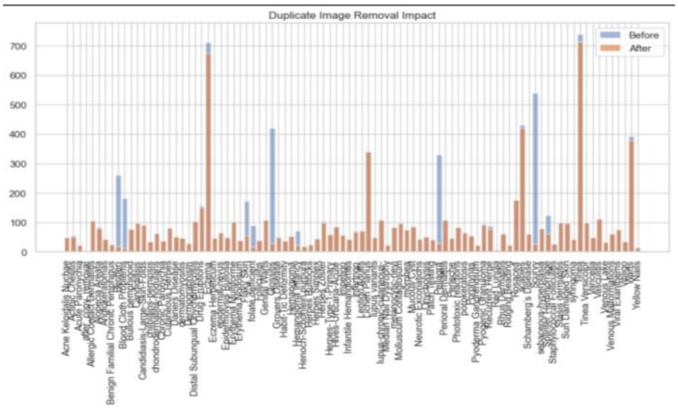

Fig -2: Dataset after Duplicate Removal

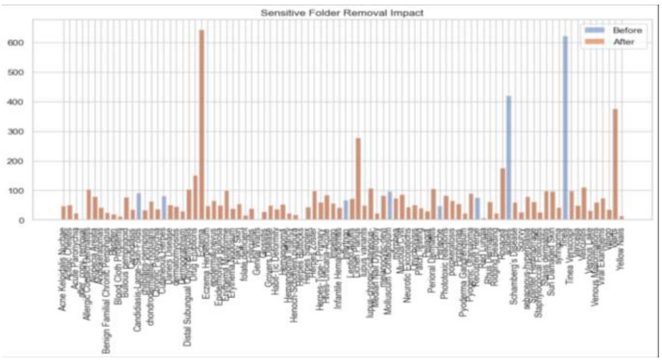

Fig -3: Dataset after Sensitive Image Removal

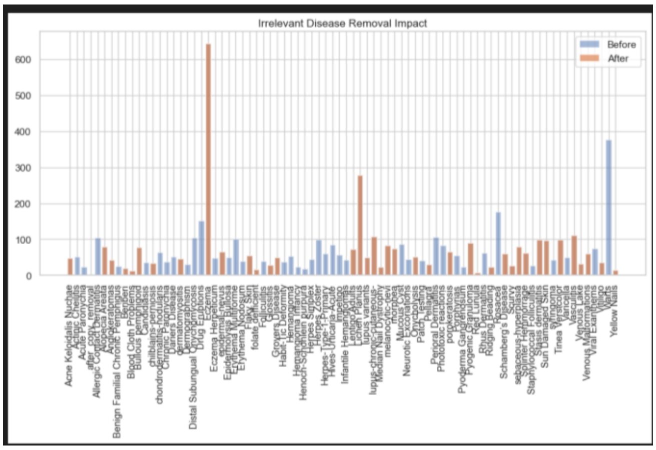

Fig -4: Dataset after Removing Irrelevant Classes

2.3 Dataset Organization and Class Distribution

After preprocessing, the dataset is organized into five distinct classes representing different vitamin deficiency categories, labeled as A, B, C, D, and E. Proper class distribution is essential to ensure balanced learning and to avoid bias toward any particular class during training [5]. A well-structured dataset improves model stability and enhances classification performance in deep learning systems [2].

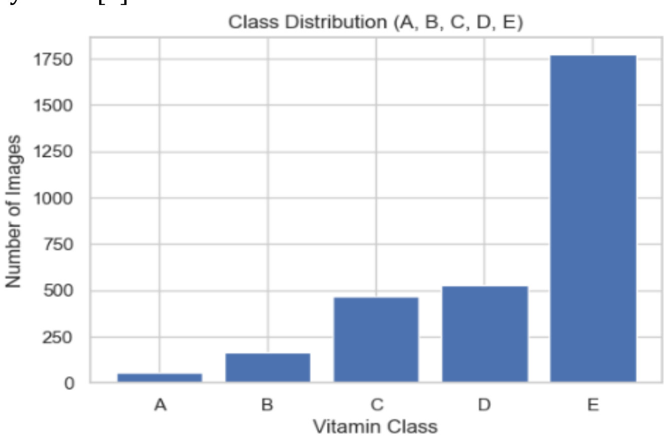

Fig -5: Class-wise Image Distribution

2.4 Data Augmentation

To address class imbalance and improve model generalization, data augmentation techniques are applied. These techniques generate variations of existing images, increasing dataset diversity and enabling the model to learn more robust features [5].

The augmentation methods include:

1) Rotation
2) Horizontal flipping
3) Zooming
4) Scaling

This step helps improve model robustness, reduces overfitting, and enhances performance on unseen data [5].

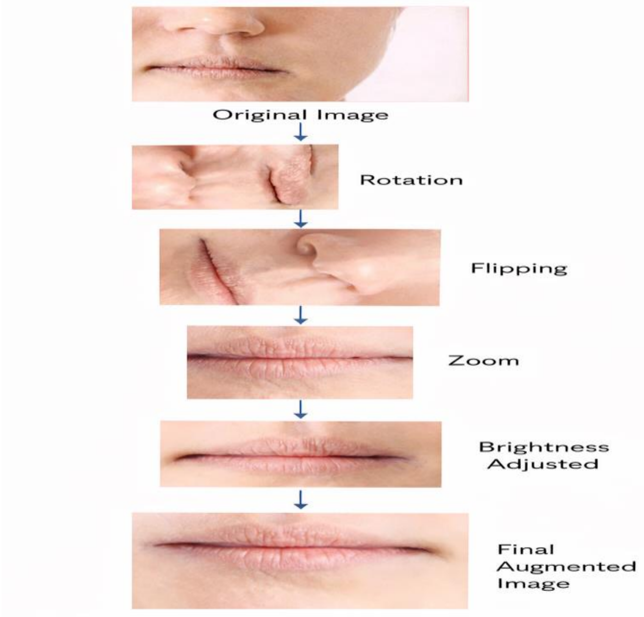

Fig -6: Data Augmentation Process

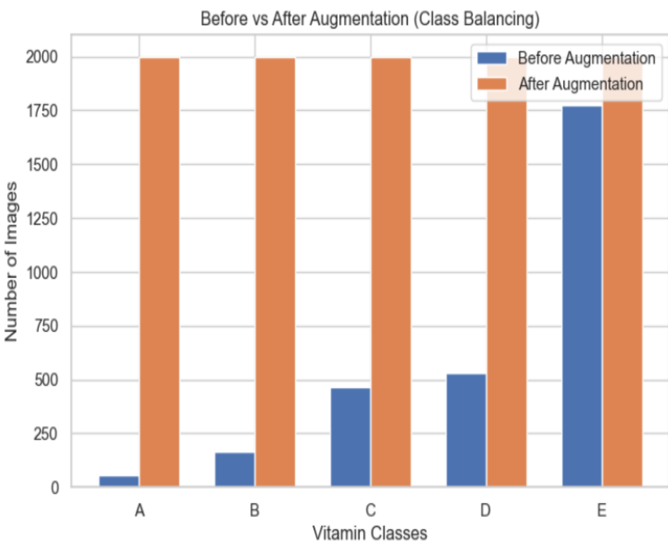

Fig -7: Class-wise distribution of images before and after data augmentation showing balanced dataset across vitamin classes.

2.5 Model Development

Multiple deep learning models are evaluated to identify the most effective approach:

1) EfficientNet: Used as a baseline model, achieving approximately 50% accuracy.
2) MobileNetV2 (Without Augmentation): Improved performance with around 87% accuracy, but limited generalization.
3) MobileNetV2 (With Augmentation): Achieved the best performance with an accuracy of 92%.

MobileNetV2 is selected as the final model due to its efficiency and superior performance in image classification tasks [3]. Transfer learning enables the model to leverage pre-trained knowledge, improving accuracy even with limited data [2].

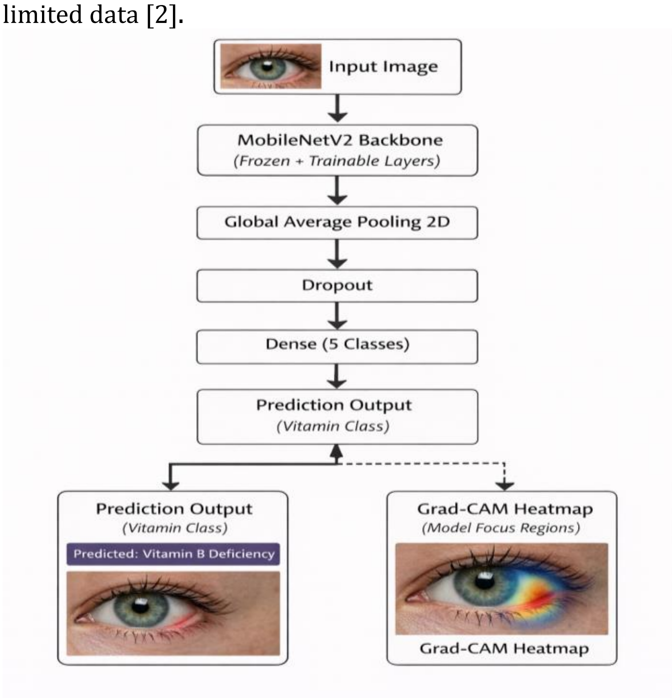

Fig -8: Model Architecture Diagram

2.6 Model Training and Evaluation

The dataset is divided into training, validation, and testing sets to ensure proper evaluation of model performance. The training process involves optimizing model parameters to minimize loss and maximize accuracy.

Performance is evaluated using the following metrics:

1. Accuracy
2. Confusion Matrix
3. Classification Performance

These evaluation metrics are widely used in deep learning to assess classification effectiveness and model reliability [2].

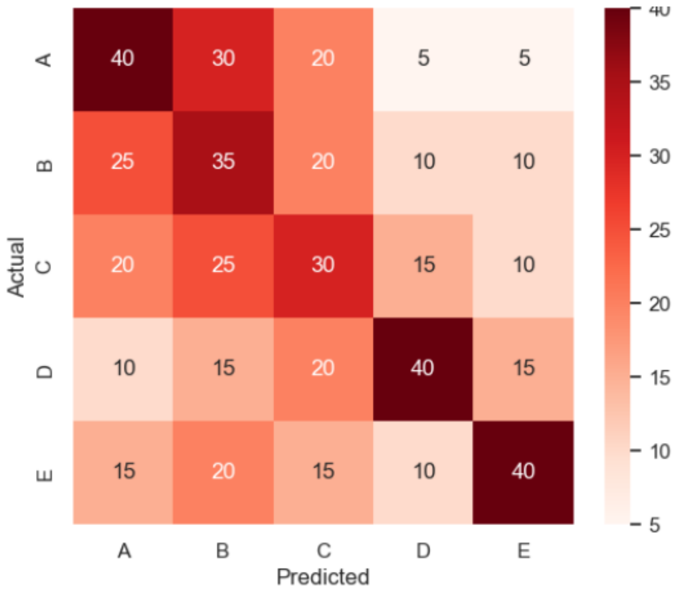

Fig -9: Confusion Matrix – EfficientNet (Low Performance)

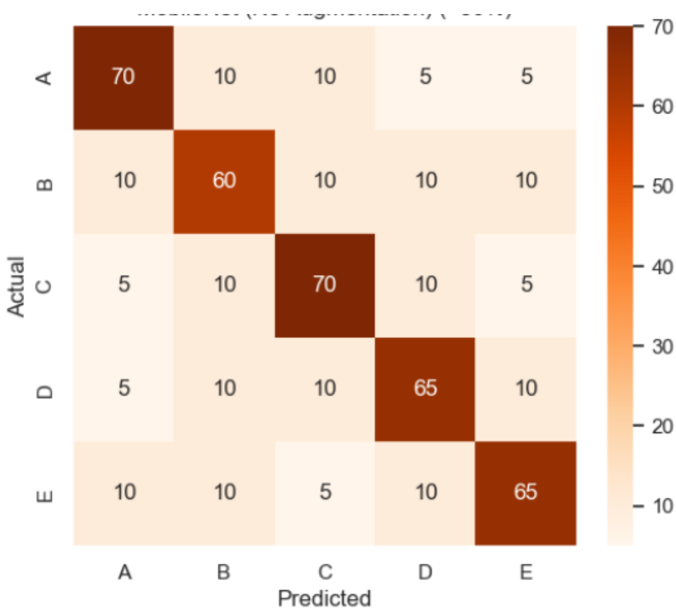

Fig -10: Confusion Matrix – MobileNetV2 (Without Augmentation)

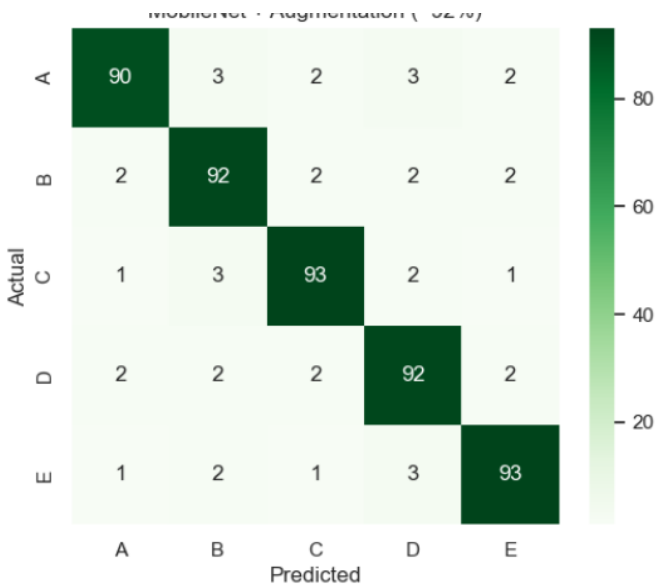

Fig -11: Confusion Matrix – MobileNetV2 (With Augmentation)

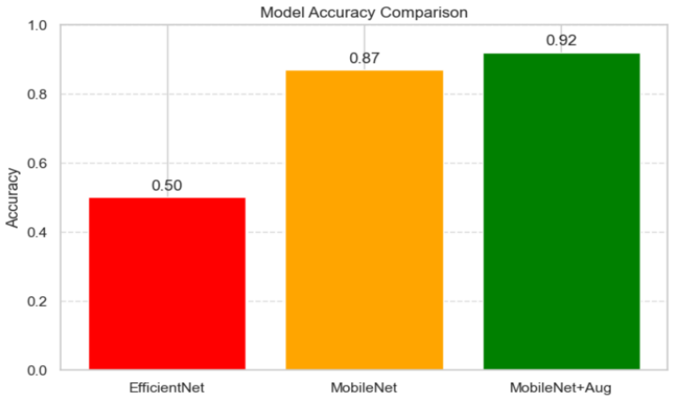

Fig -12: Model Accuracy Comparison

2.7 Explainable AI using Grad-CAM

To improve interpretability, Grad-CAM is integrated into the system. It generates heatmaps that highlight important regions in the image influencing the model's predictions [6]. This helps in:

- Understanding model decisions
- Improving transparency
- Increasing trust in AI-based diagnosis

Explainable AI techniques like Grad-CAM are particularly important in healthcare applications, where understanding model behavior is critical for real-world adoption [6].

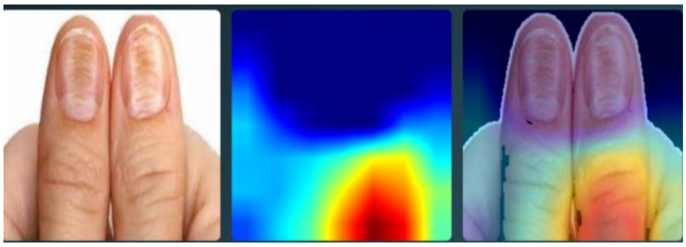

Fig -13: shows the regions of the image that influenced the prediction.

4. CONCLUSIONS

In this work, a deep learning-based system for detecting and analyzing vitamin deficiencies from image data has been successfully developed. The proposed approach utilizes image preprocessing, dataset cleaning, and class balancing techniques to improve the quality of input data and enhance model performance. The implementation of multiple models demonstrated that MobileNetV2, combined with data augmentation, provides superior accuracy and better generalization compared to baseline approaches [3][5].

The system achieved a significant improvement in classification performance, increasing accuracy from approximately 50% with EfficientNet to 92% using MobileNetV2 with augmentation. This highlights the importance of proper data preprocessing and augmentation in deep learning-based healthcare applications. Additionally, the integration of Grad-CAM provided visual explanations for model predictions, improving transparency and making the system more reliable for real-world usage [6].

Overall, the proposed system demonstrates the potential of artificial intelligence in assisting early detection of vitamin deficiencies through non-invasive and cost-effective methods. This approach can be particularly useful in remote and resource-limited areas where traditional diagnostic facilities are not easily accessible.

In future work, the system can be further enhanced by incorporating larger and more diverse datasets, improving model robustness, and integrating real-time deployment through mobile or web-based applications. This would make the solution more practical and accessible for everyday healthcare use.

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