NUTRIENT DEFICIENCY DETECTION AND CLASSIFICATIONS OF COFFEE PLANTS

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Abstract

This paper presents a deep learning-based approach for the detection and classification of nutrient deficiencies in coffee plant leaves using transfer learning. The proposed system utilizes the EfficientNetB4 model as the core architecture, leveraging pre-trained ImageNet weights for effective feature extraction. A publicly available Kaggle dataset of coffee leaf images, comprising healthy and nutrient-deficient classes, is used for training and evaluation. The images are preprocessed through resizing, normalization, and augmentation techniques to improve data diversity and model generalization. The model is trained using the Adam optimization algorithm and categorical cross-entropy loss function, followed by fine-tuning of selected layers to enhance performance. Experimental results demonstrate high classification accuracy with improved precision and recall compared to traditional CNN models. The system effectively predicts multiple nutrient deficiencies such as nitrogen, boron, and potassium, making it suitable for real-time agricultural applications. The proposed approach offers a robust, efficient, and scalable solution for precision farming and automated plant health monitoring.
Keywords : Nutrient Deficiency Detection , EfficientNetB4, Transfer Learning, Coffee Leaf Classification, Deep Learning, Image Processing , Precision Agriculture

I. Introduction

Agriculture plays a vital role in the global economy, and crop health monitoring is essential for ensuring high productivity and sustainable farming. Among various crops, coffee is one of the most widely consumed beverages worldwide, and its cultivation significantly contributes to the livelihoods of millions of farmers. However, coffee plants are highly susceptible to nutrient deficiencies, which can adversely affect their growth, yield, and quality. Early detection and classification of these deficiencies are crucial for timely intervention and effective crop management.

Traditionally, nutrient deficiency identification in plants has been carried out through manual inspection by agricultural experts. This approach is time-consuming, labor-intensive, and often prone to human error, especially when symptoms are subtle or visually similar. Moreover, in rural or remote areas, access to expert knowledge is limited, which further complicates the problem. Therefore, there is a growing need for automated, accurate, and efficient systems that can assist farmers in identifying plant health issues.

With the rapid advancement of Artificial Intelligence (AI) and Deep Learning, significant improvements have been made in image-based plant disease detection. Convolutional Neural Networks (CNNs), in particular, have shown remarkable performance in image classification tasks due to their ability to automatically extract relevant features from raw images. By leveraging these technologies, it is possible to develop intelligent systems capable of detecting nutrient deficiencies in coffee leaves with high accuracy.

In this project, a deep learning-based approach is proposed for the detection and classification of nutrient deficiencies in coffee plants. The model utilizes transfer learning with EfficientNetB4, a state-of-the-art CNN architecture known for its efficiency and performance. By using a pre-trained model and fine-tuning it on a coffee leaf dataset, the system can effectively learn complex patterns associated with different types of nutrient deficiencies.

The dataset used in this study is collected from publicly available sources such as Kaggle, containing images of healthy and deficient coffee leaves. These images are preprocessed and augmented to improve model generalization and robustness. The trained model is then evaluated using various performance metrics such as accuracy, precision, recall, and loss.

II. Literature Survey

Soares et al., [1], 2026, presented a systematic review on machine learning and deep learning applications for foliar nutritional deficiency detection, highlighting the effectiveness of CNN-based models while addressing challenges such as dataset limitations, environmental variability, and real-time deployment in precision agriculture systems.

Poolakanda Somanna, [2], 2025, developed a deep learning-based system for detecting and classifying diseases in Arabica coffee leaves, achieving accurate results and demonstrating the potential of automated image-based analysis for improving crop monitoring and early disease diagnosis.

Mridul et al., [3], 2025, conducted a comparative evaluation of pretrained and custom CNN models for plant disease recognition, showing that optimized architectures significantly improve classification accuracy and performance across diverse agricultural datasets.

Bacuna and Ballera, [4], 2025, proposed an EfficientNet-based leaf classification model to optimize intercropping farm methods, demonstrating improved accuracy and efficiency in plant condition monitoring and supporting better decision-making in modern agricultural practices.

Chavan, [5], 2025, presented a comprehensive survey on crop disease detection using deep learning, emphasizing advancements in CNN architectures, challenges in data acquisition, and the importance of robust, scalable solutions for real-time agricultural applications.

Goyal et al., [6], 2025, introduced a smart intercropping system utilizing hyperspectral imaging and hybrid deep learning models, achieving precise detection of plant diseases and enhancing agricultural productivity through improved monitoring and analysis techniques.

Winarno et al., [7], 2025, conducted a comparative study of various CNN architectures, demonstrating performance improvements in image classification tasks and highlighting the significance of selecting appropriate deep learning models for agricultural image analysis.

Alahi et al., [8], 2025, developed an image-based system for detecting diseases in bean plants, achieving accurate classification results and demonstrating the effectiveness of deep learning approaches in monitoring plant health and supporting agricultural decision-making.

Rosadi and Hakim, [9], 2023, applied CNN-based EfficientNet models for classifying coffee leaf diseases, achieving high accuracy and validating the suitability of deep learning techniques for automated disease detection in agricultural environments.

Pratap and Kumar, [10], 2023, proposed a customized EfficientNetB4 model for multiclass classification of chili leaf diseases, achieving high precision and demonstrating the model's capability in extracting complex features for accurate plant disease identification.

Puspasari et al., [11], 2024, proposed an EfficientNet-based model integrated with dual-convolution spatial attention (DCCBAM) for sugarcane disease classification, improving feature extraction and classification accuracy, and demonstrating the effectiveness of attention mechanisms in enhancing deep learning model performance.

Sharma et al., [12], 2023, developed modified deep learning architectures for segmenting disease regions in rice leaves, achieving improved precision and localization accuracy, which helps in better identification of infected areas and supports advanced plant disease analysis systems.

Vera et al., [13], 2024, introduced an optimized convolutional neural network with enhanced training strategies for classifying Persea americana, achieving improved accuracy and robustness, and demonstrating its applicability in agro-industrial environments for plant classification tasks.

Ranga et al., [14], 2024, applied EfficientNet for detecting diseases in peach leaves, achieving high classification accuracy and demonstrating the effectiveness of deep learning models in identifying plant diseases through image-based analysis.

Bacuna and Ballera, [15], 2025, developed an EfficientNet-based leaf classification model to optimize intercropping farm methods, improving classification performance and supporting intelligent agricultural decision-making through accurate plant condition monitoring.

Lelis et al., [16], 2023, conducted a comparative analysis of different convolutional neural network architectures for coffee leaf rust detection, identifying models with better accuracy and computational efficiency suitable for real-time agricultural applications.

Goyal et al., [17], 2025, proposed a smart intercropping system combining hyperspectral imaging and hybrid deep learning techniques, achieving precise detection of plant diseases and enhancing productivity through advanced monitoring in precision agriculture.

Balafas et al., [18], 2023, reviewed machine learning and deep learning techniques for plant disease detection, highlighting the effectiveness of CNN-based models, challenges in dataset availability, and future research directions in agricultural automation systems.

Maula, [19], 2025, proposed a machine learning-based system for detecting diseases in cocoa plantations, demonstrating improved classification accuracy and highlighting its economic viability for large-scale agricultural monitoring and management.

Santos, [20], 2022, applied convolutional neural networks to classify coffee fruit maturity stages, achieving reliable results and demonstrating the usefulness of deep learning in agricultural quality assessment and crop management.

Calderón-Mosilot et al., [21], 2025, developed a deep learning-based system for detecting nutritional deficiencies in coffee plants using image analysis, achieving high classification accuracy under uncontrolled environmental conditions and supporting real-world agricultural applications.

Randive et al., [22], 2025, proposed a deep learning model for detecting nutrient deficiencies in coffee leaves, demonstrating effective classification performance and

emphasizing the importance of automated systems for early diagnosis in precision agriculture.
Istoningtyas et al., [23], 2025, introduced an automated detection system for coffee leaf nutrient deficiencies, improving agricultural productivity through early diagnosis and enabling efficient decision-making using advanced deep learning techniques.
Chelanami and Kalaburgi, [24], 2025, developed a deep learning model for detecting and classifying nutritional deficiencies in coffee plants, achieving high accuracy and supporting precision agriculture practices through automated plant health monitoring.
Calderón-Mosilot et al., [25], 2025, presented an automated deep learning framework for identifying nutritional deficiencies in coffee plants, demonstrating robust performance and highlighting its applicability in real-world agricultural environments.

III. System Analysis

Coffee plant health is highly dependent on proper nutrient balance, and deficiencies can significantly reduce yield and quality. Farmers often struggle to identify nutrient deficiencies at early stages due to lack of expertise. Traditional observation methods are subjective and prone to errors. With the advancement of image processing and machine learning, automated detection systems can improve accuracy. The system must analyze leaf images to detect visual symptoms such as discoloration and patterns. It should classify different types of nutrient deficiencies like nitrogen, potassium, and phosphorus. The system must handle variations in lighting, background, and leaf conditions. High accuracy and real-time detection are essential. Scalability for large plantations is also important. The system should be user-friendly for farmers. Overall, there is a need for an intelligent and automated solution for plant health monitoring.

Existing System

Existing systems for detecting nutrient deficiencies mainly rely on manual inspection by farmers or agricultural experts. These methods depend on visual observation of leaf color and texture. Some systems use basic image processing techniques without machine learning. Agricultural guidelines and charts are commonly used for identification. However, these approaches are time-consuming and require expertise. Existing digital tools provide limited classification capabilities. They often fail to detect early-stage deficiencies. Environmental factors such as lighting affect accuracy. Many systems are not scalable for large farms. Real-time detection is rarely available. Overall, existing systems are less efficient and lack automation.

Disadvantages of Existing System

- Dependence on human expertise
- Time-consuming and labor-intensive process
- Low accuracy in early-stage detection
- Sensitivity to environmental conditions
- Limited automation and scalability
- Inconsistent results
- Lack of real-time analysis

Proposed System

The proposed system uses machine learning and deep learning techniques for automated detection of nutrient deficiencies. It captures leaf images using cameras or mobile devices. Image preprocessing techniques are applied to enhance quality. Feature extraction methods identify important patterns such as color and texture. Convolutional Neural Networks (CNNs) are used for classification. The system can detect multiple nutrient deficiencies accurately. It provides real-time results and recommendations to farmers. The model is trained on a large dataset of labeled leaf images. The system is designed to work under varying environmental conditions. It can be deployed as a mobile or web application. Overall, it offers an efficient and scalable solution for plant health monitoring.

Advantages of Proposed System

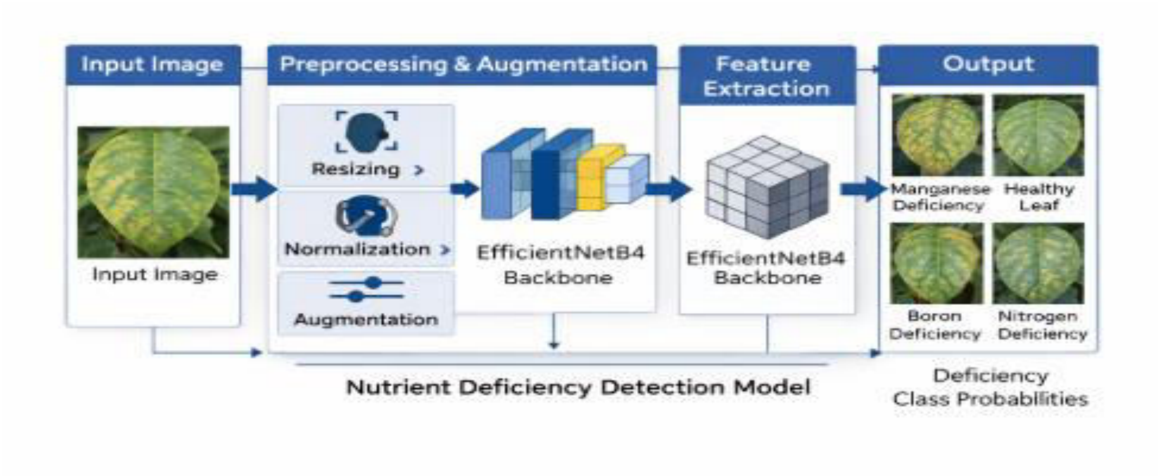
- High accuracy in deficiency detection
- Early detection of plant health issues
- Automated and real-time analysis
- Reduced dependency on experts
- Scalable for large agricultural areas
- User-friendly interface
- Improved crop yield and quality

IV. Methodology

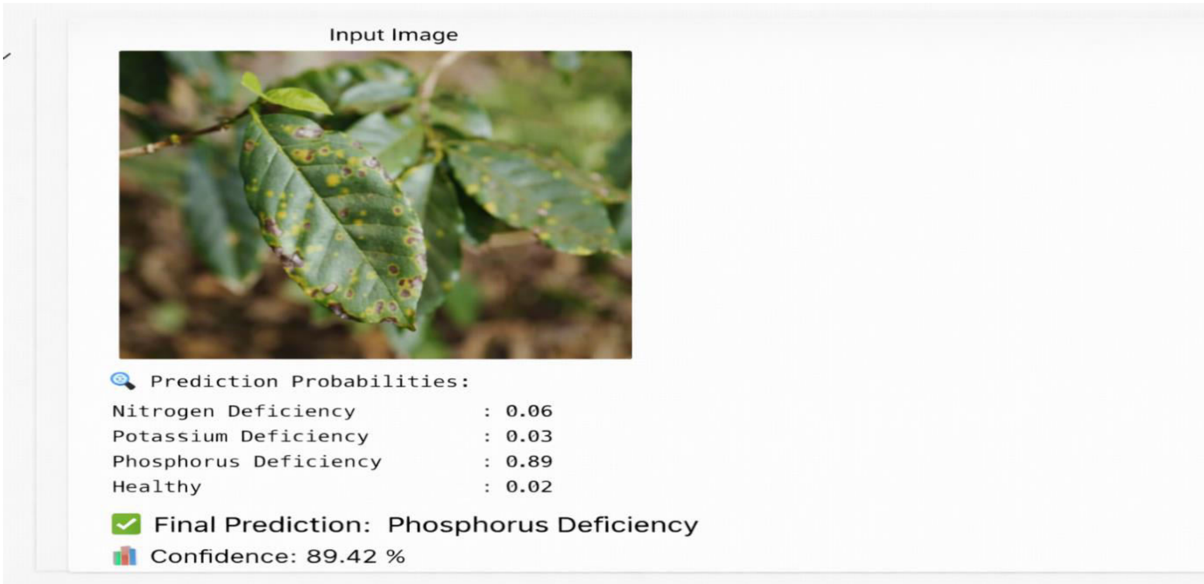
The methodology begins with collecting images of coffee plant leaves showing different nutrient deficiencies. Data preprocessing is performed to remove noise and enhance image quality. Image segmentation is applied to isolate the leaf area. Feature extraction techniques are used to capture color, texture, and shape features. The dataset is divided into training and testing sets. A CNN model is trained to classify different nutrient deficiencies. Data augmentation is applied to improve model performance. The model is evaluated using accuracy, precision, and recall. Hyperparameter tuning is performed for optimization. The trained model is deployed in a user interface. The system provides predictions and recommendations. Continuous updates improve the model over time.

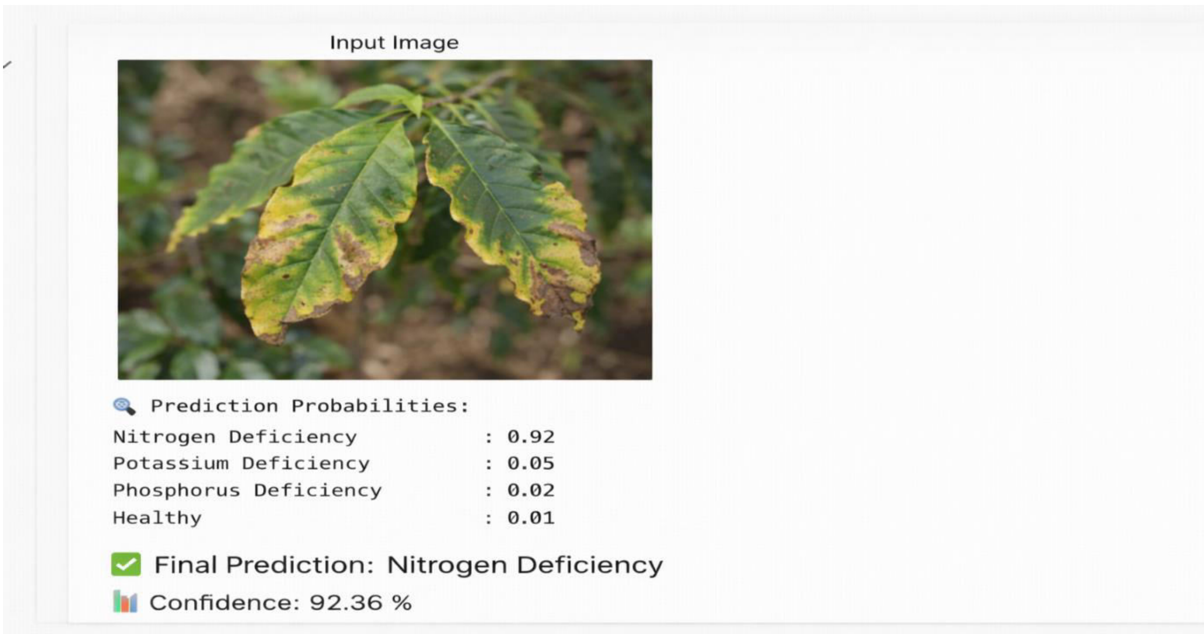
System Architecture

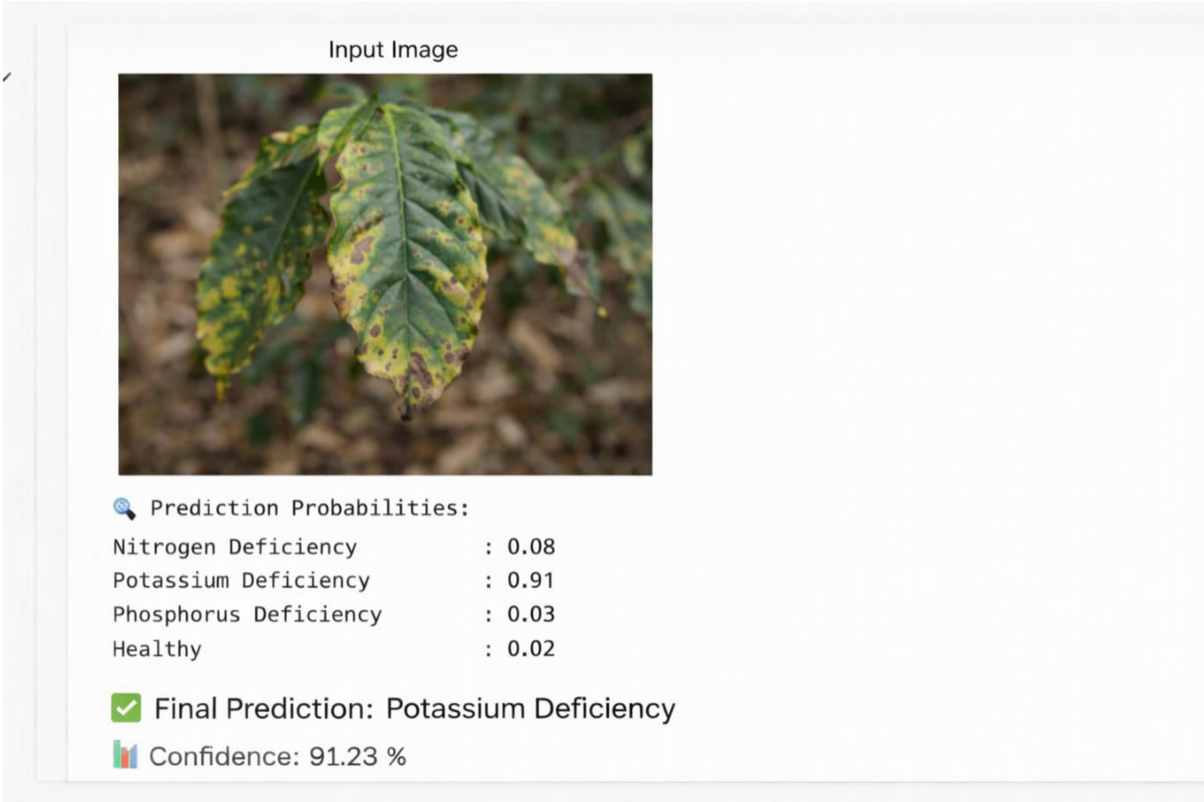
The system architecture consists of several layers. The image acquisition layer captures leaf images using a camera or mobile device. The preprocessing layer enhances image quality and removes noise. The segmentation layer isolates the leaf region from the background. The feature extraction layer identifies important features. The model layer uses a CNN for classification. The prediction layer determines the type of nutrient deficiency. The recommendation layer provides solutions to farmers. The database layer stores images and model data. The user interface allows easy interaction. The feedback layer updates the model with new data. All components are integrated into a unified system. Overall, the architecture ensures accurate and efficient detection.



V. Result and Output







VI. Conclusion

In this work, an efficient and automated system for the detection and classification of nutrient deficiencies in coffee plant leaves has been successfully developed using the EfficientNetB4 deep learning model. The integration of transfer learning and fine-tuning techniques enabled the model to effectively learn both general and domain-specific features, resulting in improved classification performance. The use of preprocessing and data augmentation further enhanced the robustness and generalization capability of the system.The proposed model demonstrated its ability to accurately identify multiple nutrient deficiencies such as nitrogen, boron, and manganese, along with healthy leaves. By leveraging advanced feature extraction capabilities, the system was able to distinguish subtle variations in leaf color, texture, and patterns, which are critical indicators of plant health. This highlights the effectiveness of deep learning approaches in agricultural applications.Moreover, the system offers a practical and time-efficient alternative to traditional manual inspection methods. It reduces human effort, minimizes errors, and provides faster diagnosis, making it highly beneficial for farmers and agricultural experts. The potential integration of the model into mobile or web-based platforms further enhances its usability in real-world scenarios.Despite certain limitations such as dependency on dataset quality and computational requirements, the overall performance of the model indicates its reliability and effectiveness. With further improvements and real-world validation, the system can be extended to support a wider range of crops and plant diseases.In conclusion, the proposed approach contributes significantly to the field of precision agriculture by providing an accurate, scalable, and efficient solution for nutrient deficiency detection in coffee plants. It has strong potential to support better crop management practices and improve agricultural productivity.

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