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Plant Nutrient Deficiency Detection Using Ensemble Learning

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Abstract: *Early detection of plant nutrient deficiencies is a critical aspect of precision agriculture, as it enables timely intervention to prevent negative impacts on crop health, yield, and soil fertility. Undetected nutrient imbalances can significantly reduce agricultural productivity and compromise the quality of the produce. This research proposes an image-based detection system that leverages advanced machine learning techniques for automated identification of nutrient deficiencies in plants. A hybrid deep learning framework combining MobileNet and ResNet50 is used for efficient and robust feature extraction from leaf images. These features are then processed using ensemble classifiers such as Random Forest and Gradient Boosting, which offer improved accuracy and generalization by aggregating predictions from multiple learners. Experimental results show that this ensemble-based approach consistently outperforms individual classifiers in terms of performance metrics like accuracy and precision. MobileNet's lightweight architecture ensures compatibility with mobile and edge devices, while ResNet50 adds depth to feature representation, making the model suitable for real-time deployment in agricultural settings. By providing early and accurate insights into plant health, this system supports informed decision-making, reduces reliance on manual inspection, and optimizes the use of fertilizers. Ultimately, it contributes to sustainable farming by enhancing crop management practices, minimizing environmental impact, and supporting food security through increased efficiency and productivity*.

Keywords: Ensemble Learning, MobileNet, ResNet50, Precision Agriculture, Sustainable Farming, Feature Extraction

I. INTRODUCTION

The increasing demands of food security and sustainable agriculture have underscored the importance of enhancing precision farming techniques. A critical factor in achieving optimal crop yield and quality is the early and accurate detection of nutrient deficiencies in plants. If these deficiencies are not addressed promptly, they can lead to deteriorated plant health, reduced crop yields, and diminished crop quality. Traditional methods for identifying nutrient deficiencies, such as soil testing and manual inspection, have been widely employed. However, these approaches are often resource-intensive, time-consuming, and susceptible to human error. These limitations render them impractical for large-scale agricultural systems, where timely intervention is crucial.

The advancement of machine learning and computer vision has opened up new possibilities for automated and efficient nutrient deficiency detection through the analysis of leaf images. Among these techniques, ensemble learning has emerged as a highly effective method for minimizing classification errors by integrating multiple models to enhance predictive accuracy. This study investigates the effectiveness of ensemble learning models, specifically MobileNet, ResNet50, Random Forest, and Gradient Boosting, in agriculture-related applications. Our research aims to leverage machine learning techniques to improve the efficiency and precision of plant nutrient deficiency detection.

Ensemble-based classifiers, which combine predictions from various models, have consistently demonstrated superior performance compared to standalone classifiers. This improved performance is attributed to their ability to reduce bias and variance. This characteristic makes them particularly well-suited for handling the inherent variability found in agricultural datasets, where subtle nutrient deficiency symptoms may not be easily discernible by conventional single-model classifiers. By integrating multiple feature extraction techniques and utilizing advanced leaf imaging in conjunction with ensemble learning, this research seeks to significantly improve classification accuracy and provide valuable insights for farmers.

This paper presents an analysis of the techniques employed in plant nutrient deficiency detection, emphasizing the potential of cutting-edge machine learning methods to overcome the drawbacks of traditional approaches. Beyond enhancing classification accuracy, this study explores avenues to advance precision agriculture by demonstrating how intelligent machine learning solutions can improve decision-making processes and optimize overall agricultural productivity.

II. RELATED WORK

Recent research has focused heavily on enhancing agricultural productivity through the automated detection and classification of plant diseases. One such study introduces an ensemble deep learning framework that integrates pre-trained models, hybrid preprocessing techniques, texture analysis, and CNN feature optimization using metaheuristic algorithms like Binary Dragonfly, Ant Colony Optimization, and Moth Flame Optimization. This method, applied to apple and maize plants, achieves a notable accuracy of 99.8%, showcasing its potential to significantly improve disease detection and sustainable crop management [1].

In a similar line of work, Muthusamy and Ramu (2024) designed an ensemble-based convolutional neural network (E-CNN) aimed at identifying micronutrient deficiencies in banana leaves. They employed six pre-trained models, including VGG-19, InceptionResNetV2, Inception V3, Xception, DenseNet169, and DenseNet201. The DenseNet169 model delivered the highest individual performance, and among various ensemble combinations, the Inception V3 + DenseNet169 ensemble achieved the best results, with a validation accuracy of 98.62% and an F1 score of 93% [2].

Ngugi et al. (2024) provided a detailed review of deep learning applications for crop disease detection, classification, and severity estimation. Their work highlights the transition from traditional digital image processing to deep learning approaches, noting how these models convert input images into actionable insights. The study also contrasts the strengths and limitations of both machine learning and deep learning techniques, and outlines potential areas for future research [3].

Mienye and Sun (2022) examined the foundations and advancements in ensemble learning, discussing key algorithms like bagging, boosting, and stacking. Their survey covers various ensemble methods including Random Forest, AdaBoost, Gradient Boosting, XGBoost, LightGBM, and CatBoost, offering both mathematical explanations and algorithmic insights. This comprehensive overview supports the growing interest in ensemble techniques for diverse applications [4].

Focusing on beans, Elfatimi et al. (2021) employed the MobileNet architecture to identify and classify bean leaf diseases. They compared MobileNet with MobileNetV2, training both on a dataset containing images of healthy and diseased leaves. The MobileNet model demonstrated strong performance, achieving over 97% accuracy on the training set and 92% on the testing set, highlighting its suitability for lightweight yet accurate disease detection tasks [5].

Chen et al. (2021) explored lightweight deep learning solutions for pest detection in real-world agricultural settings. They used a MobileNetV2-based model enhanced with attention mechanisms and Classification Activation Maps (CAMs) to focus on relevant pest features within cluttered backgrounds. The model was trained using a two-stage transfer learning approach with an optimized loss function, effectively improving detection in field conditions [6].

Addressing the issue of nutrient deficiency, Amirtha et al. (2020) proposed a robotic vehicle-based system equipped with CNNs to identify and diagnose deficiencies from captured leaf images. The model compares new images with a reference dataset, providing output that includes the nutrient name and recommended fertilizer amount on an LCD. This approach not only reduces manual labor but also increases diagnostic accuracy compared to traditional methods [7].

Bahtiar and Santoso (2020) explored deep learning for identifying nutrient deficiencies in chili plants. Using the RCNN model on a dataset of 270 images across four chili categories, their system demonstrated promising results, with an accuracy of 82.61% and a mean average precision of 15.57%. The study underscores the applicability of AI in supporting farmers with real-time diagnostic tools [8].

Watchareeruetai et al. (2018) introduced an innovative method where leaf images are segmented into blocks, and each block is analyzed using CNNs specifically trained to detect individual nutrient deficiencies. The responses from each CNN are combined using a multi-layer perceptron to yield a final classification for the entire leaf, offering a fine-grained and accurate detection mechanism [9].

Lastly, Choi et al. (2018) implemented a deep learning-based model for detecting nutrient deficiencies in tomato plants under greenhouse conditions. Their method used the Inception-ResNet v2 CNN architecture to differentiate between various mineral deficiencies, demonstrating the power of deep learning in enhancing greenhouse crop management and monitoring systems [10].

III. PROPOSED METHODOLOGY

The creation of the proposed model involves several systematic steps, including:

1. Data Collection
2. Data Preprocessing
3. Feature Extraction
4. Model Evaluation and Performance Monitoring
5. Model Inference and Deployment

Dataset Collection and Preparation

Raw images of coffee and banana plant leaves were manually collected from various plantations using mobile cameras under diverse lighting conditions. An agricultural expert classified these images into eight distinct nutrient deficiency categories, and the data was organized into separate folders based on these classes.

To ensure the dataset was clean and consistent, it was processed through a detailed preprocessing pipeline, which involved:

Removing the background using an online tool

Manually cropping the images to isolate the leaf regions

Resizing all images to a fixed size of 256×256 pixels

Standardizing the background color to black for uniformity across samples

To enhance the model's generalization ability and maintain balanced class representation, data augmentation techniques were applied. These included rotation, flipping, zooming, and brightness adjustments. As a result, the dataset was expanded to over 7,000 images, evenly distributed across all eight nutrient classes.

Feature Extraction

At the heart of the proposed system lies a hybrid deep learning model that combines two powerful pre-trained architectures: MobileNetV3Large and ResNet50. MobileNetV3Large provides efficiency and speed, while ResNet50 contributes its depth and strong feature extraction capabilities.

Both models were fine-tuned using pre-trained ImageNet weights and used to extract high-level features from the input images. The extracted features were then:

Pooled using Global Average Pooling

Concatenated to merge information from both models

Passed through Dense layers equipped with ReLU activation and Dropout layers for regularization

Finally, a softmax output layer was used to classify the input into one of the eight nutrient deficiency categories.

Model Training and Evaluation

The model was trained using the Adam optimizer with categorical cross-entropy as the loss function, and accuracy as the primary performance metric. Throughout the training process, metrics such as training loss and accuracy were monitored to evaluate learning progress.

For comprehensive evaluation, additional metrics were considered, including:

Precision

Recall
F1-Score
Confusion Matrix
ROC Curves
These metrics helped assess the model's effectiveness and robustness in real-world scenarios.

Integration into Mobile Application

Once the model was trained and validated, the next step was to integrate it into a mobile application to provide real-time predictions for end users. To make the model suitable for mobile environments, it was converted into the TensorFlow Lite (TFLite) format. This format significantly reduces the model size and improves inference speed, all while maintaining high accuracy.

TFLite is specifically designed for mobile and edge devices, allowing the app to function efficiently even without internet connectivity or on devices with limited computational resources. The converted model file, typically named model.tflite, is added to the app's assets directory. Using the TensorFlow Lite Interpreter, the mobile application can load the model and perform real-time predictions based on images captured by users.

Within the app, users interact with a built-in camera interface to capture images of plant leaves. Once captured, the image undergoes the same preprocessing steps as used during training: resizing to 256×256 pixels, normalizing the pixel values, and converting the image into a tensor format compatible with model inference.

This preprocessed image is then fed into the TFLite model, which returns a set of probabilities for each nutrient class. The nutrient deficiency with the highest prediction probability is chosen as the final result. The app displays this result to the user along with additional helpful information such as the name of the deficiency, a brief description, and practical recommendations. Suggested remedies may include the application of specific fertilizers, changes in watering schedules, or the use of soil enhancers.

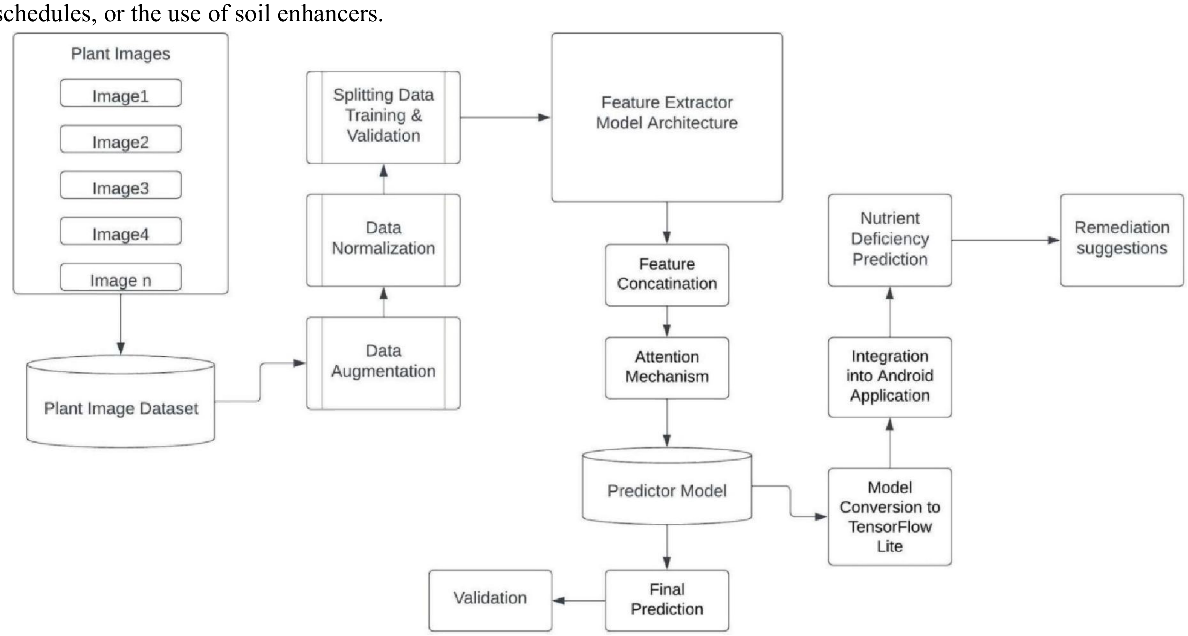

Fig. 1. Proposed System

IV. CONCLUSION

This research presents a robust and efficient approach for the early detection of plant nutrient deficiencies through the integration of ensemble learning and deep learning techniques. By combining the feature extraction capabilities of MobileNetV3Large and ResNet50, and employing ensemble classifiers, the proposed system achieves high classification accuracy while maintaining lightweight performance suitable for real-time mobile deployment. The model was trained on a carefully curated and augmented dataset of coffee and banana leaf images, ensuring class balance and generalization across various environmental conditions. The successful conversion of the trained model into TensorFlow Lite and its integration into a mobile application demonstrates the system's potential for practical use by farmers and agricultural professionals. The app provides instant, on-device predictions along with informative suggestions for remedying deficiencies, thereby supporting precision agriculture

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