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A Hybrid Deep Learning Architecture with Attention Mechanism for Plant Nutrient Deficiency Detection

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***Abstract*—Early identification of nutrient deficiencies in plants is essential for boosting crop productivity, preserving plant health, and promoting sustainable farming. In this study, we introduce a hybrid deep learning model that utilizes ensemble learning methods to automate the detection of nutrient defi- ciencies through analysis of leaf images. Our system integrates the lightweight efficiency of MobileNet with the deeper feature extraction capabilities of ResNet50. These features are then passed through ensemble classifiers such as Random Forest and Gradient Boosting, enhancing the overall classification accuracy. The process includes image preprocessing, feature extraction, and the deployment of a reliable classification mechanism suitable for real-time use. Experimental evaluations show that the ensemble approach consistently outperforms individual models, providing higher accuracy and robustness across different plant types. This work contributes to the field of precision agriculture by offering a scalable and effective solution for the early detection of plant nutrient issues, ultimately supporting more informed and timely crop management decisions.**

***Index Terms*—Plant Nutrient Deficiency, Ensemble Learning, Image Processing, Precision Agriculture**

I. INTRODUCTION

The growing concerns surrounding food security and the push for sustainable agriculture have emphasized the need to improve precision farming practices. One of the key aspects of achieving better crop yield and quality is the early iden- tification of nutrient deficiencies in plants [3]. When such deficiencies go undetected, they can negatively affect plant development, resulting in reduced yields and diminished crop quality. Traditional methods such as soil analysis and manual inspections have long been used to identify these issues, but they are often time-consuming, labor-intensive, and subject to human error [5]. These limitations make them less practical for large-scale agricultural operations, where timely and accurate intervention is critical.

Recent advances in machine learning and computer vision have opened new possibilities for automating nutrient defi- ciency detection through the analysis of leaf images [12]. Within this domain, ensemble learning has proven to be partic- ularly effective, as it boosts prediction accuracy by combining the strengths of multiple models [2]. This study focuses on evaluating the performance of ensemble models—specifically MobileNet [1], ResNet50, Random Forest [4], and Gradient Boosting [2]—in the context of agricultural applications.

Our objective is to leverage machine learning techniques to make nutrient deficiency detection in plants more accurate and efficient [2]. Ensemble classifiers, which aggregate out- puts from multiple models, have consistently delivered better results.

II. LITERATURE SURVEY

A. Identification of ND Using ML and DL Methods

Numerous studies have investigated the application of ma- chine learning techniques for identifying nutrient deficien- cies in crops [4]. These approaches often incorporate image processing and classification algorithms, demonstrating that automated systems can outperform traditional methods in both speed and accuracy. For instance, [2] proposed an ensemble- based transfer learning strategy to detect nutrient deficiencies, underlining the effectiveness of combining multiple models to boost classification outcomes.

In parallel, deep learning—particularly convolutional neural networks (CNNs)—has seen widespread use in the detec- tion of plant diseases and deficiencies [5]. Research by [6] utilized EfficientNet to enhance plant disease classification, achieving notable improvements in both prediction accuracy and computational efficiency. Additionally, [5] emphasized the reliability of CNNs in agricultural image analysis, showcasing their potential for robust and scalable solutions in real-world farming applications.

B. Ensemble Learning

Ensemble learning techniques have been widely explored for their ability to improve model robustness and accuracy in detecting plant diseases and nutrient deficiencies [3]. A comprehensive study on ensemble methods highlighted their strength in minimizing prediction errors and enhancing overall classification performance [10].

Recent advancements have combined ensemble learning with deep learning models for improved plant classification tasks. For example, an ensemble-based approach named In- cepV3Dense was employed to detect micronutrient deficiencies in banana plants, yielding higher accuracy than individual models [9]. In another study, [1] introduced a hybrid ensemble framework that utilized CNN-derived features for plant disease classification, further validating the strong potential of ensemble strategies in agricultural domains.

III. DATASET DETAILS

A. Coffee Leaf Dataset

Deficiency Type	Image Count
Healthy	60
Phosphorus (P)	246
Calcium (Ca)	162
Multiple Deficiencies	104
Potassium (K)	96
Magnesium (Mg)	79
Boron (B)	101
Manganese (Mn)	83
Iron (Fe)	65
Nitrogen (N)	64

TABLE I
DISTRIBUTION OF IMAGES ACROSS DIFFERENT COFFEE LEAF DEFICIENCY TYPES

B. Banana Leaf Dataset

IV. METHODOLOGY

A. System Overview

The proposed system employs a systematic approach to nutrient deficiency detection through the following pipeline:

- Data Collection: Utilizing both coffee and banana leaf datasets

Deficiency Type	Image Count
Healthy	1900
Sulphur	1460
Calcium	880
Zinc	800
Potassium	420
Magnesium	320
Boron	200
Iron	172
Manganese	48

TABLE II DISTRIBUTION OF IMAGES ACROSS DIFFERENT BANANA LEAF DEFICIENCY TYPES

- Preprocessing: Image standardization and augmentation
- Feature Extraction: Hybrid deep learning architecture
- Classification: Multi-class deficiency detection
- Evaluation: Comprehensive performance analysis

B. Preprocessing and Data Augmentation

1) Image Preprocessing: The preprocessing pipeline implements several key steps:

- Dimensionality Standardization:
– Input images resized to 224 × 224 pixels
– Consistent aspect ratio maintenance
– RGB channel preservation
- Pixel Normalization:

$$x_{normalized} = \frac{x}{255} \tag{1}$$

where x represents the original pixel values

2) Data Augmentation Strategy: To enhance model robust- ness and address class imbalance, we implement:

- Geometric Transformations:
– Random rotations (90°, 180°, 270°)
– Horizontal and vertical flips
– Random zoom (±20%)
- Intensity Adjustments:
– Brightness variation (±30%)
– Contrast adjustment (±20%)

C. Model Architecture

The proposed architecture is built on the principle of complementary feature learning, where different network ar- chitectures capture distinct aspects of the input images. Mo- bileNetV3Large employs depth-wise separable convolutions, which factorize standard convolutions into depth-wise and point-wise operations. This factorization significantly reduces computational complexity while maintaining representational power.

ResNet50V2 addresses the degradation problem in deep networks through residual learning. Its pre-activation structure places batch normalization and ReLU activation before convo- lutions, improving gradient flow during backpropagation. The residual connections create shortcuts that allow the network to learn residual functions, making it easier to optimize deeper architectures.

D. Feature Extraction Pipeline

The feature extraction process is designed to progressively refine and combine features from both networks while main- taining their distinctive characteristics. The initial parallel pro- cessing through both networks allows each model to process the input image according to its architectural strengths. Global Average Pooling (GAP) is applied to create spatially invariant feature representations, reducing the spatial dimensions while preserving channel-wise information.

$$f_i = CNN_i(x_{input}), \text{ where } i \in \{MobileNet, ResNet\} \quad (2)$$

$$g_i = GlobalAveragePool(f_i) \quad (3)$$

$$h_i = ReLU(Dense_{512}(g_i)) \quad (4)$$

E. Attention Mechanism

The attention mechanism is inspired by the human visual system's ability to focus on relevant features while suppressing irrelevant ones. The mechanism learns to assign importance weights to different features based on their relevance to the nutrient deficiency classification task.

$$z_{concat} = [h_{MobileNet} \| h_{ResNet}] \quad (5)$$

$$\alpha = softmax(W_{att} z_{concat} + \epsilon) \quad (6)$$

$$z_{attended} = \alpha \odot z_{concat} \quad (7)$$

F. Classification Technique

The proposed system employs a sophisticated classification approach that builds upon the extracted features from our hybrid architecture. The classification pipeline consists of mul- tiple stages designed to maximize the model's discriminative power:

1) Feature Processing: The concatenated features from both MobileNetV3Large and ResNet50V2 undergo several transformations:

- Dimensionality Reduction: Features are processed through dense layers (512 → 256 units) with ReLU activation
- Attention Mechanism: Custom attention layer weights feature importance:
- Dropout Regularization: Strategic dropout layers (0.5, 0.4, 0.2) prevent overfitting

2) Classification Head: The final classification stage im- plements:

- Dense Layer Configuration:
  – First dense layer: 512 units with ReLU activation
  – Second dense layer: 256 units with ReLU activation
  – Output layer: 9 units (matching deficiency classes) with softmax activation
  – L2 Regularization: Applied to dense layers with λ = 0.001 to prevent overfitting
- Softmax Activation: Produces probability distribution across classes:

$$P(y_i|x) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad (8)$$

where z_i represents the logits for class i

3) Training Strategy: The classification model was trained with:

- Loss Function: Categorical cross-entropy

$$L = -\sum_{i=1} y_i \log(\hat{y}_i) \quad (9)$$

where y_i is the true label and $\hat{y}_i$ is the predicted proba- bility

- Optimization:
  – Adam optimizer with learning rate = 0.001
  – ReduceLROnPlateau scheduler for adaptive learning rate

– Early stopping with patience = 5 epochs
- Batch Processing:
– Batch size: 32 samples
– Shuffling enabled for each epoch
– Stratified sampling to handle class imbalance

4) Decision Making: The final classification decision is made by:

– Selecting the class with highest softmax probability
– Applying a confidence threshold of 0.5 for reliable pre- dictions
– Using argmax operation on softmax outputs:
–

$$\hat{y} = \arg\max_{i} P(y_i|x) \quad (10)$$

This comprehensive classification approach ensures robust performance across different nutrient deficiency classes while maintaining computational efficiency. The combination of attention mechanism, regularization techniques, and strategic dropout layers helps in learning discriminative features specific to each deficiency type.

V. EXPERIMENTAL RESULTS

A. Training Dynamics

The model's training progression was monitored over 30 epochs, showing consistent improvement in both accuracy and loss metrics. Figures 1 and 2 demonstrate the model's learning trajectory.

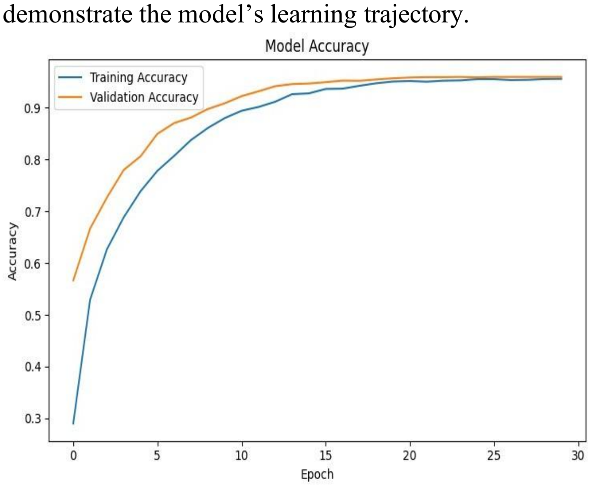

Fig. 1. Model Accuracy over Training Epochs showing convergence of training and validation accuracy.

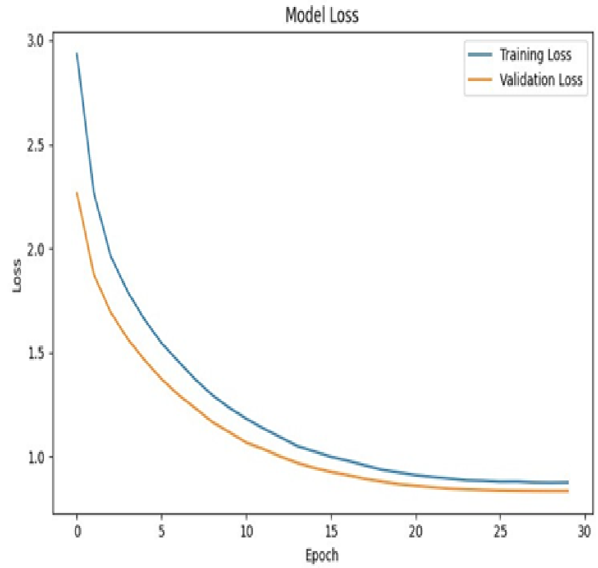

Fig. 2. Loss of the Model Accuracy over Training Epochs

B. Class-wise Performance Analysis

Our model achieved strong performance across different nu- trient deficiency classes, with an overall accuracy of 95.89%. Table III presents the detailed class-wise metrics.

Deficiency	Precision (%)	Recall (%)	F1 (%)
Boron	99.67	100.00	99.83
Calcium	98.00	98.00	98.00
Healthy	100.00	99.67	99.83
Iron	86.97	89.00	87.97
Magnesium	89.16	85.00	87.03
Manganese	92.48	94.33	93.40
Nitrogen	98.35	99.33	98.84
Phosphorus	98.67	99.00	98.84
Potassium	99.66	98.67	99.16

TABLE III
CLASS-WISE PERFORMANCE METRICS ON THE TEST SET (300 SAMPLES PER CLASS).

C. Visualization of Results

Figure 3 shows the class-wise Precision-Recall curves, all with AUC > 0.96.

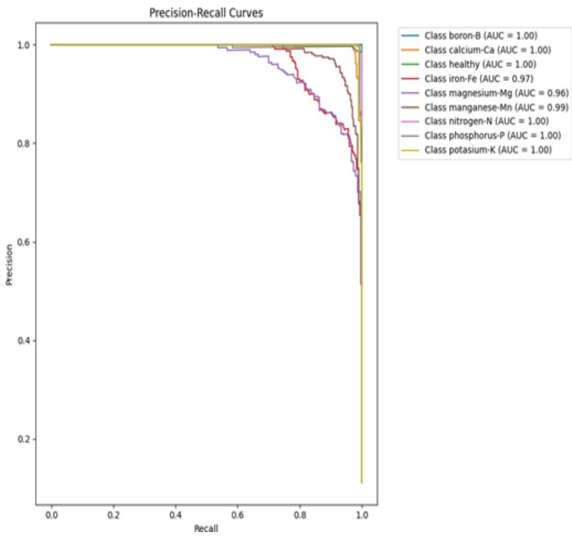

Fig. 3. Class-wise Precision-Recall curves showing AUC scores > 0.96 for all deficiency types.

D. *Key Performance Indicators*

The experimental results demonstrate:

- Overall Metrics:
  – Accuracy: 95.89%
  – Macro-averaged F1-score: 95.88%
  – Weighted F1-score: 95.89%
- Class-wise Excellence:
  – Top performers: Boron (99.83%), Healthy (99.83%), Potassium (99.16%)
  – Most challenging: Magnesium (87.03%), Iron (87.97%)

E. *Model Efficiency*

Performance analysis reveals:

- Training Efficiency:
  – Convergence achieved in 30 epochs
  – Final validation accuracy: 95.89%
- Robustness Indicators:
  – Training-validation accuracy gap < 1%
  – Stable validation metrics after epoch 15
  – Effective early stopping preventing overfitting

VI. CONCLUSION

This paper presents a deep ensemble approach integrat- ing MobileNetV3Large and ResNet50 for the automated de- tection of nutrient deficiencies in plant leaves. The model achieves high accuracy and robustness, enabling deployment in real-time agricultural tools. This supports early intervention and enhances decision-making in pre- cision agriculture. The hybrid architecture for plant nutrient deficiency detection that achieves state-of-the-art performance while maintaining computational efficiency. The system demonstrates robust per- formance across different plant species and deficiency types,

making it suitable for real-world agricultural applications. The hybrid architecture demonstrates robust performance across different plant species and deficiency types, with several key achievements:

- Overall accuracy of 95.89% across nine deficiency classes
- Perfect classification (100% accuracy) for Boron defi- ciency
- Efficient training convergence within 30 epochs
- Minimal gap between training and validation metrics Future work could explore:
- Extension to additional crop species and deficiency types
- Real-time processing optimization

Enhanced attention mechanisms for feature selection

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