Nutrient Deficiency Detection In Paddy Crop Using Leaf Images

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Abstract- *The early detection of nutrient deficiencies in paddy crops is essential for improving crop yield and ensuring sustainable agricultural practices. Traditional methods rely on manual observation and expert knowledge, which can be time-consuming, costly, and prone to errors. This paper presents a deep learning based approach to detect Nitrogen (N), Phosphorus (P), and Potassium (K) deficiencies using paddy leaf images. The proposed system utilizes a MobileNetV2 transfer learning model for accurate image classification. Image pre-processing techniques such as resizing, normalisation, and data augmentation are applied to enhance model performance. The system is implemented as a web-based application using HTML, CSS, JavaScript, and Python Flask, allowing users to upload leaf images and receive real-time predictions along with confidence scores. Additionally, the system provides fertilizer recommendations and generates PDF reports for future reference. The model achieves high classification accuracy, demonstrating its effectiveness in identifying nutrient deficiencies and supporting precision agriculture.*

Keywords: Deep Learning, MobileNetV2, NPK Deficiency, Paddy Crops, Image Processing, Precision Agriculture

I. INTRODUCTION

Agriculture remains a fundamental sector in the global economy, particularly in countries like India where a large portion of the population depends on farming for their livelihood. Paddy cultivation is one of the most significant agricultural activities, and its productivity is highly influenced by proper nutrient management. Essential nutrients such as Nitrogen (N), Phosphorus (P), and Potassium (K) play a crucial role in plant growth, and their deficiency can lead to poor crop health, reduced yield, and economic loss.

Traditionally, the detection of nutrient deficiencies in paddy crops is carried out through manual observation or laboratory testing. These methods are often time-consuming, expensive, and require expert knowledge, making them less accessible to small-scale farmers [1]. Additionally, visual inspection can sometimes lead to incorrect diagnosis due to the similarity of symptoms among different deficiencies [2].
To address these challenges, this paper proposes an automated system that:

1. Detects nutrient deficiencies (Nitrogen, Phosphorus, Potassium) in paddy leaves using deep learning techniques.
2. Provides real-time predictions and confidence scores through a user-friendly web application.
3. Recommends appropriate fertilizers based on the detected deficiency to assist farmers in corrective action.

The proposed system utilizes the MobileNetV2 transfer learning model for efficient and accurate classification of leaf images [3]. The system is integrated into a web-based platform that allows users to upload images and receive instant results. This approach ensures early detection, reduces dependency on experts, and supports precision agriculture practices.

II. PROBLEM STATEMENT

Farmers cultivating paddy crops often face significant challenges in accurately identifying deficiencies of essential nutrients such as Nitrogen (N), Phosphorus (P), and Potassium (K) at an early stage. Early detection is crucial for maintaining crop health and ensuring optimal yield.

Traditional methods of nutrient deficiency detection suffer from the following major limitations:

- Dependence on manual observation: Identification relies heavily on farmer experience and visual inspection, which is subjective and inconsistent.
- High chances of human error: Similar visual symptoms among different nutrient deficiencies often lead to misdiagnosis and incorrect treatment.
- Time-consuming process: Manual inspection and expert consultation delay the detection and corrective action.

- Costly laboratory testing: Soil and plant analysis methods are expensive and not affordable for small and marginal farmers [5].
- Lack of accessibility: Advanced diagnostic facilities are not easily available in rural and remote farming areas.
- Delayed decision-making: Absence of real-time detection results in late intervention, affecting crop growth.

Therefore, there is a strong need for an automated, cost-effective, and efficient system that can detect NPK nutrient deficiencies in paddy crops using leaf images and provide accurate, real-time results to support farmers in making informed decisions.

III. LITERATURE SURVEY

Research has shown that Convolutional Neural Networks (CNNs) are superior to traditional machine learning for handling complex visual patterns in plant disease and nutrient deficiency detection.

A. Key Findings from Existing Research

Sabri and Kassim [1] demonstrated that CNN-based models achieved 96.67% accuracy for leaf-based nutrient deficiency detection in maize crops, focusing on colour, shape, and texture features with data augmentation.

Hugar and Waheed [2] employed CNNs specifically for identifying NPK deficiencies in paddy fields using the IJISAE framework, confirming the effectiveness of deep learning for multi-class classification in rice crop analysis.

Amudha and Brindha [3] proposed the CAR-Capsule Network, which improved spatial feature learning and achieved 97.1% accuracy, effectively detecting subtle visual symptoms of nutrient stress in rice leaves.Han and Watchareeruetai [4] classified nutrient deficiency in black gram using deep convolutional neural networks, further validating the applicability of CNNs across multiple crop varieties.Kavitha [5] explored machine learning techniques, showing that traditional methods like Random Forest showed moderate performance but were sensitive to overlapping symptoms and image quality variations.Ensemble and image fusion techniques reported by Sirsat and Cernadas [6] achieved the highest accuracy (98.17%) but required significant computational resources, limiting real-time applicability.Farzizadeh and Mardanqom [7] proposed smart detection methods combining machine learning with sensor data, expanding the scope of precision agriculture beyond image-only approaches.

B. Drawbacks in Existing Systems

- High computational complexity in advanced models such as Capsule Networks and Ensemble methods.
- Limited suitability for real-time and mobile-based applications due to heavy architectures.
- Sensitivity to environmental variations such as lighting conditions and image quality.
- Requirement of large, diverse datasets for better generalisation across different crop varieties.
- Reduced interpretability in complex deep learning models, making decision support challenging.

C. Improvements in Proposed Work

The proposed system addresses the above limitations by:

- Using MobileNetV2, a lightweight and efficient model suitable for real-time applications.
- Providing a web-based system for easy accessibility and user interaction.
- Enabling real-time prediction with confidence scores.
- Offering fertilizer recommendations for corrective action based on predicted deficiency class.
- Reducing computational cost while maintaining high accuracy.

IV. PROPOSED SYSTEM AND METHODOLOGY

1. System Architecture

The proposed diagnostic framework is structured as a cohesive, multi-layered architecture that seamlessly integrates data acquisition, deep learning-based classification, and web deployment, as illustrated in the System Architecture (Fig. 1). At the primary interface, the Input Layer facilitates user interaction through a responsive front-end developed using HTML, CSS, and JavaScript, where paddy leaf images are securely uploaded and transmitted to the server. These images are immediately processed within the Pre-processing Layer, which performs critical operations such as RGB normalization and resizing to a uniform 224 × 224 pixel resolution to ensure compatibility with the neural network's requirements.

The computational core resides in the Deep Learning Model Layer, where a fine-tuned MobileNetV2 model executes multi-class classification to identify Nitrogen (N), Phosphorus (P), or Potassium (K) deficiencies. Upon successful inference, the Recommendation and Output Layer cross-references the result with an agricultural knowledge base to provide tailored fertilizer advice. To ensure data persistence, the Storage and Reporting Layer utilizes an SQLite database to archive prediction history while generating automated PDF reports. This modular approach, detailed in Fig. 1, ensures high operational efficiency and provides the scalability necessary for future integration with broader smart farming ecosystems.

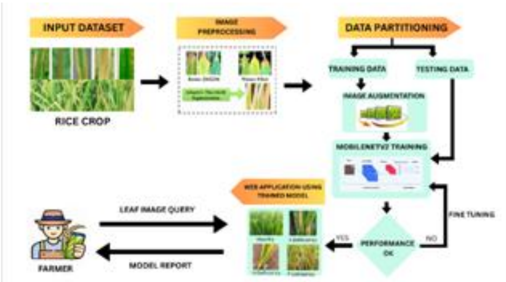

Fig. 1: System Architecture

2. Methodology

This section presents a comprehensive description of the methodology adopted for the detection and classification of nutrient deficiencies in paddy crops using leaf images. The system integrates image processing, deep learning, and web-based deployment to provide accurate and real-time predictions.

A. Data Collection

The paddy leaf image dataset was sourced from GitHub. The dataset encompasses four categories: Healthy Leaves, Nitrogen Deficiency (N), Phosphorus Deficiency (P), and Potassium Deficiency (K). Images exhibit visible symptoms such as yellowing, discoloration, and leaf damage specific to each deficiency class.

Images are organized into three subsets: (i) Training Dataset – used to train the model; (ii) Validation Dataset – used to tune model parameters; and (iii) Testing Dataset – used to evaluate model performance. The structured dataset ensures balanced learning and reliable evaluation.

B. Data Preprocessing

To improve model performance and ensure consistency, several preprocessing techniques are applied to the input images before training:

Image Resizing: All images are resized to a uniform dimension of 224 × 224 pixels, which is required for MobileNetV2 input.

Normalization: Pixel values are scaled to the range [0, 1], enabling faster convergence and stable training.

Data Augmentation: Applied only to the training dataset to increase diversity and reduce overfitting — horizontal flipping, random rotation, and zoom transformations.

Dataset Optimization: Techniques such as caching, shuffling, and prefetching are used to improve training efficiency and reduce loading time.

Batch Processing: Images are processed in batches to optimize memory usage and speed up training.

C. Feature Extraction

In deep learning architectures, the transformation of raw imagery into structured numerical descriptors is essential for automated analysis. This process begins with **pixel normalization**, which rescales input data into a consistent range (typically [1,0])to ensure numerical stability during training:

$$X_{no^{r}m} = X / 255$$

where **X** denotes the initial pixel intensity.

The core of spatial understanding is achieved via **convolutional operations**. Here, a specialized filter or kernel (K) slides across the input image (X) to detect edges, textures, and complex patterns:

$$S(i,j) = \Sigma_m \Sigma_n X(i+m, j+n) \cdot K(m,n)$$

To introduce non-linearity—allowing the network to learn intricate, non-proportional relationships—the **Rectified Linear Unit (ReLU)** activation is applied:

$$f(x) = max(0, x)$$

Finally, **Global Average Pooling (GAP)** is utilized to condense the spatial dimensions of the feature maps (F_k) into a singular, representative vector. This reduces the parameter count and mitigates the risk of overfitting:

$$G_k = (1/H\times W)\ \Sigma^i \Sigma_j F_k(i,j)$$

D. Model Training

The classification model is built using MobileNetV2 with transfer learning, which significantly improves performance while reducing training time. The model architecture consists of a pre-trained MobileNetV2 base (ImageNet weights) with frozen base layers, followed by custom classification layers including Global Average

Pooling, a Dropout layer to prevent overfitting, and a Dense layer with Softmax activation.

Training Configuration: Optimizer: Adam; Loss Function: Sparse Categorical Crossentropy; Epochs: 20; Batch Size: 32.

The base model is initially frozen to leverage pre-trained knowledge. Only top layers are trained for classification. Early stopping is applied to prevent overfitting and restore the best model weights.

MobileNetV2 was selected due to its lightweight architecture, faster computation, and suitability for real-time web-based applications. It provides an excellent balance between accuracy and computational speed compared to heavier architectures such as VGG-16 and ResNet-50 [4].

E. Model Evaluation

After training, the model is evaluated using the test dataset using the following metrics:

- Accuracy: Measures overall prediction correctness.
- Loss: Indicates model error during training and testing.
- Precision: Measures correctness of positive predictions.
- Recall: Measures ability to identify actual positives.
- F1-Score: Balance between precision and recall.
- Confusion Matrix: Visual representation of classification performance.

Evaluation results are visualized using accuracy/loss graphs and confusion matrix plots to highlight model performance and generalization capability.

F. Prediction and Recommendation System

The trained model is deployed within a Flask-based web application. The prediction workflow involves: (1) Image Upload by the user; (2) Input Validation to ensure format and quality; (3) Image Preprocessing — resizing to 224×224, RGB conversion, and normalization; (4) Model Prediction via the trained MobileNetV2 model; (5) Classification Output into Healthy, Nitrogen, Phosphorus, or Potassium Deficiency class; and (6) Confidence Score Calculation indicating prediction probability.

G. Output and Recommendation

Based on the prediction, the system generates the predicted class, confidence percentage, and appropriate fertilizer recommendation:

- Nitrogen Deficiency → Urea or Ammonium Sulfate
- Phosphorus Deficiency → DAP or Super Phosphate
- Potassium Deficiency → Muriate of Potash

H. Data Storage and Report Generation

The system uses SQLite for lightweight and serverless data management. Stored data includes user authentication details, uploaded leaf image references, prediction results, confidence scores, fertilizer recommendations, and timestamps. The system also generates downloadable PDF reports containing user details, prediction results, confidence percentage, fertilizer recommendation, and analysis timestamp.

V. RESULTS AND DISCUSSION

The MobileNetV2-based classification system was trained and evaluated on the paddy leaf dataset across four classes: Healthy, Nitrogen Deficiency, Phosphorus Deficiency, and Potassium Deficiency. The model was trained for 20 epochs with early stopping to prevent overfitting.

The model demonstrates high classification accuracy and low loss, confirming the effectiveness of the MobileNetV2 transfer learning approach for real-time nutrient deficiency detection in paddy crops.

Classification Report for mobilenetv2_transfer:

	precision	recall	f1-score	support
Healthy	1.00	1.00	1.00	374
N_Deficiency	0.97	0.94	0.96	440
P_Deficiency	0.94	0.75	0.83	333
K_Deficiency	0.79	0.96	0.86	383
accuracy			0.92	1530
macro avg	0.93	0.91	0.91	1530
weighted avg	0.93	0.92	0.92	1530

Fig. 2: Key Results Summary

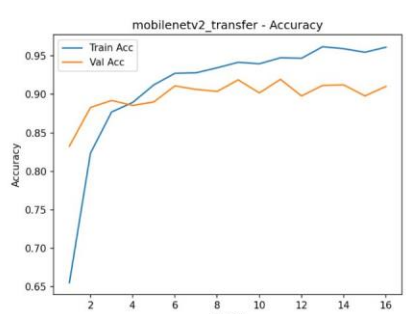

Fig. 3: Training and Validation Accuracy

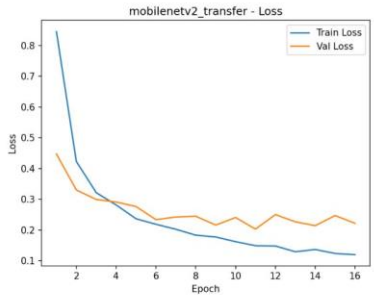

Fig. 4: Training and Validation Loss

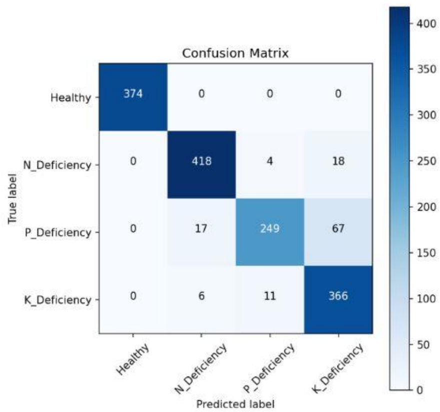

Fig. 5: Confusion Matrix

The accuracy graph (Fig. 2) confirms consistent improvement across epochs with negligible overfitting. The confusion matrix (Fig. 4) reveals high true-positive rates across all four classes, demonstrating balanced classification performance. The results validate that MobileNetV2 is effective and computationally efficient for this agricultural classification task.

Figures [6] through [9] demonstrate the end-to-end user workflow, from image upload to the generation of the nutrient deficiency report and fertilizer recommendation.

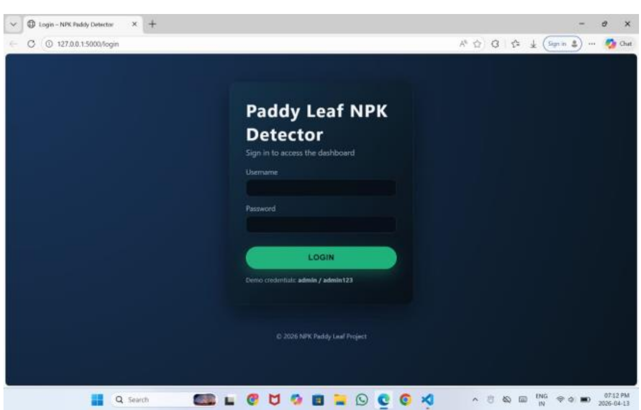

Fig. 6: User Interface - Login Page

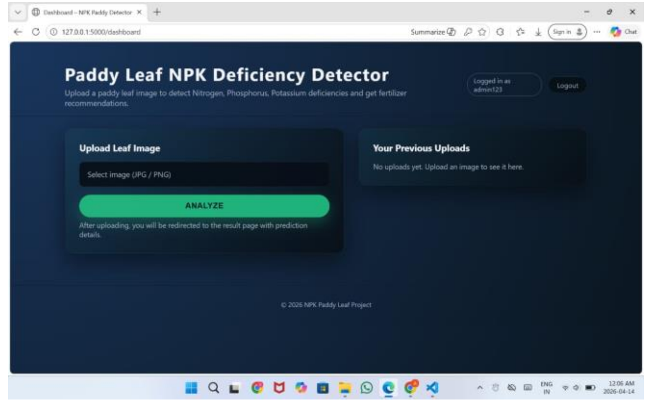

Fig. 7: Home page

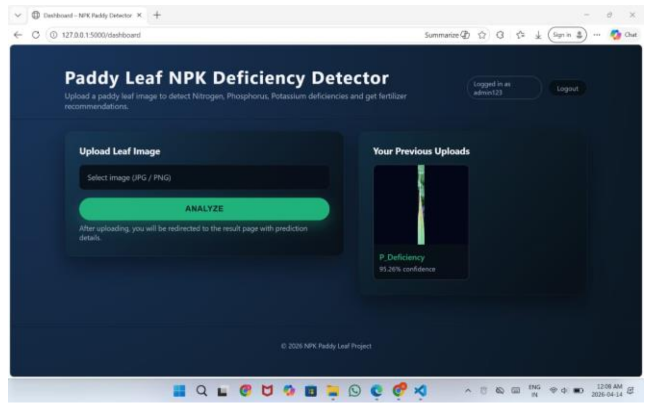

Fig. 8: Sample selection

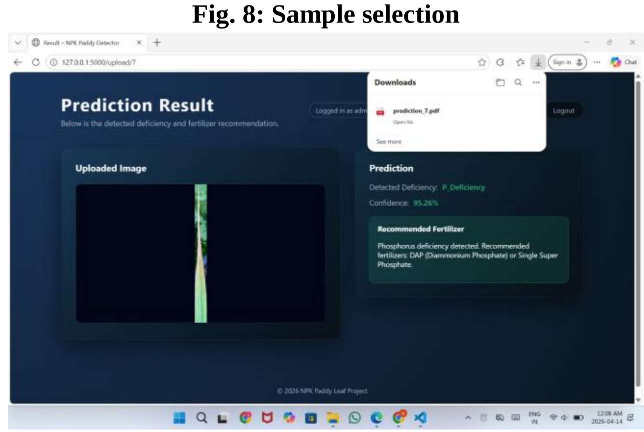

Fig. 9: Classification result display

VI. CONCLUSION

This study demonstrates an automated diagnostic framework using MobileNetV2 transfer learning to detect paddy nutrient deficiencies with high accuracy. By integrating real-time image classification with specific fertilizer recommendations and automated reporting, the system provides a scalable tool for precision agriculture, reducing dependency on manual inspection. This approach facilitates early diagnosis of N, P, and K shortfalls, ensuring timely interventions to optimize crop productivity and promote sustainable farming practices.

Future research will focus on integrating IoT sensors and real-time agricultural databases to enable multi-modal monitoring of soil and environmental conditions. Additionally, the development of a native mobile application with multilingual support and cloud integration will enhance the system's accessibility and proactive diagnostic capabilities for farmers in diverse rural regions.

VII. ACKNOWLEDGMENT

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