Deep Learning-Based Estimation of Micronutrient Deficiency in Crops

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Abstract- Plant health is a critical factor in agricultural productivity, and nutrient deficiencies can lead to significant reductions in crop yield and quality. Early detection of such deficiencies is essential for effective crop management and sustainable farming practices. This paper presents an automated deep learning–based approach for detecting nutrient deficiencies in plants through leaf image analysis. The proposed system focuses on economically important crops, namely banana, bottle gourd, cucumber, maize, and rice.

In the proposed methodology, the input leaf image is divided into smaller blocks, each of which is processed using a set of Convolutional Neural Networks (CNNs) trained to detect specific nutrient deficiencies. A winner-take-all strategy is employed to determine the dominant deficiency at the block level, and these outputs are subsequently combined using a Multi-Layer Perceptron (MLP) to generate a final classification for the entire leaf. The system identifies deficiencies of key nutrients such as nitrogen (N), phosphorus (P), potassium (K), magnesium (Mg), iron (Fe), and calcium (Ca) based on visible symptom patterns.

To improve robustness and adaptability across different crops and environmental conditions, transfer learning techniques are incorporated. Experimental results demonstrate that the proposed CNN-based model outperforms traditional Artificial Neural Networks (ANNs) and other deep learning architectures, including DenseNet-121, in terms of classification accuracy. The proposed system provides a fast, accurate, and cost-effective solution for nutrient deficiency detection, reducing reliance on manual inspection and supporting precision fertilizer management for sustainable agriculture.

Keywords: Plant Nutrient Deficiency Detection, Leaf Image Analysis, Convolutional Neural Networks, Deep Learning, Transfer Learning, Precision Agriculture, Computer Vision, Sustainable Agriculture

I. INTRODUCTION

In the developing world, technology plays a vital role in all sectors, and agriculture is no exception. The Indian economy mainly depends on agriculture. However, traditional methods are still being used widely in agricultural practices. One major challenge faced by farmers today is the identification of nutrient deficiencies in plants. This process is often time-consuming, labor-intensive, and costly. If the deficiency is incorrectly diagnosed, it may result in a significant loss of yield, resources, and time. Currently, nutrient deficiencies in plants are identified through agricultural laboratories and the experience of seasoned farmers. However, manual prediction can often go wrong due to varying environmental conditions and human error. Typically, nutrient deficiencies manifest in plant leaves, stems, flowers, or fruits. In this project, we focus on analyzing leaves to identify such deficiencies. A healthy plant requires around twelve essential nutrients for optimal growth—namely Nitrogen, Phosphorus, Potassium, Magnesium, Sulphur, Molybdenum, Zinc, Boron, Copper, Calcium, Iron, and Chloride. Nutrient deficiency symptoms in leaves include changes such as reduction in leaf size, discoloration, distorted edges, necrosis, and black spots. In conventional methods, farmers may need to uproot the entire plant and send it for laboratory testing, which is not only time-intensive but also cost-heavy. This project aims to provide an efficient solution by automatically identifying and analyzing specific nutrient deficiencies from leaf images, thereby helping plants recover faster and improving crop management decisions. Agriculture is a critical pillar of global food security and economic development, especially in countries where a large portion of the population depends on farming. However, plant diseases and nutrient-related disorders are significant issues that greatly affect crop productivity, food security, and sustainable agricultural practices. These issues can spread rapidly and often go unnoticed until the damage becomes irreversible, leading to heavy losses and food shortages. With the rise of modern technologies, Artificial Intelligence (AI) and Machine Learning (ML) have emerged as powerful tools in the agricultural sector. Among these, Deep Learning, and particularly Convolutional Neural Networks (CNNs), has shown great promise in improving image-based classification tasks. Using CNNs, images of plant leaves can be analyzed with high accuracy to detect diseases and nutrient deficiencies. This capability is further enhanced by Transfer Learning, which leverages pre-trained models to achieve better performance with limited data—making the solution more scalable and accessible. Additionally, Artificial Neural Networks (ANNs) play a crucial role in modelling complex patterns and relationships between features in plant health data.

II. LITERATURE SURVEY

Recent studies have explored the use of deep learning techniques for plant nutrient deficiency detection using leaf images. Makka et al. [1] proposed a transfer learning–based CNN framework trained on more than 9,000 images, achieving an accuracy of 93.1%. The study also highlighted the potential integration of IoT and cloud platforms for real-time diagnosis, but reported challenges related to dataset imbalance and performance under field conditions. Kolhar et al. [2] investigated advanced architectures such as Xception, Vision Transformer (ViT), and MLP-Mixer for rice nutrient deficiency classification. Among them, the Xception model achieved the highest accuracy of 95.1%. However, the dataset size was limited and collected under controlled conditions, which may affect real-world generalization. Katari Hemanth [3] developed a custom CNN model for detecting nutrient deficiencies across multiple crops and achieved approximately 90% accuracy. Although the system demonstrated practical feasibility, the limited dataset increased the risk of overfitting and reduced robustness.

Pawade et al. [4] addressed class imbalance issues by proposing a hybrid approach combining CNNs with autoencoders and precision-aware learning. The work emphasized improving performance for minority classes and suggested future research on multimodal data and explainable AI.

Aleksandrov [5] introduced a different approach based on chlorophyll fluorescence parameters instead of RGB images, enabling early deficiency detection. However, the requirement for specialized equipment limits its practical field application.

A recent IJNRD study [6] presented a transfer learning–based CNN model with 88–91% accuracy and a user-oriented web/mobile interface. The study was limited by a small dataset and lack of validation under diverse environmental conditions.

While CNNs are specialized for image-based tasks, ANNs can be integrated to interpret additional plant growth parameters, environmental data, or to support decision-making models that complement image analysis. This research proposes a robust, scalable, and automated system for plant disease and nutrient deficiency detection using a transfer learning-based CNN model, supported by deep learning and ANN techniques. The aim is to assist farmers in diagnosing issues early, taking timely action, and ultimately enhancing productivity, sustainability, and food security through smart agricultural solutions.

III. METHODOLOGY

The proposed system is designed to develop an automated framework for detecting nutrient deficiencies in plants using image analysis and deep learning techniques. A dataset of plant leaf images exhibiting various nutrient deficiencies, including nitrogen (N), phosphorus (P), potassium (K), magnesium (Mg), iron (Fe), and calcium (Ca), is collected from reliable sources and manually labelled according to the type of deficiency. The dataset includes multiple crop types to improve the generalization ability of the model. Several preprocessing operations are applied to standardize the input data, including image resizing, normalization, and grayscale conversion. In addition, data augmentation techniques such as rotation, flipping, and brightness adjustment are used to increase dataset diversity and enhance model robustness.

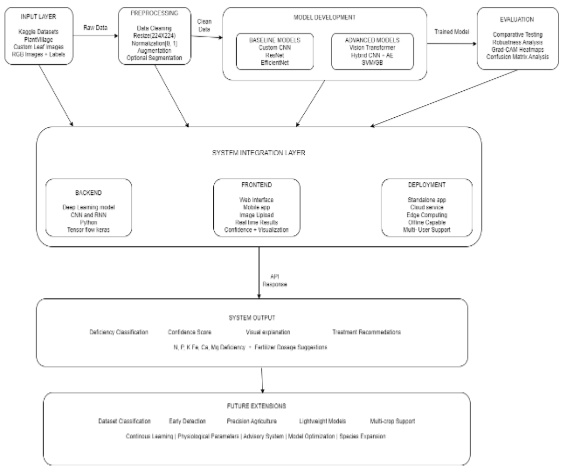

Fig 1. Architecture

A Convolutional Neural Network (CNN) is employed as the primary model due to its effectiveness in extracting spatial features from images. The network architecture consists of multiple convolutional layers followed by pooling layers for feature extraction and dimensionality reduction. These layers are connected to fully connected dense layers for classification. The Rectified Linear Unit (ReLU) activation function is used in the hidden layers to introduce non-linearity, while a Softmax activation function is applied in the output layer to classify the leaf image into the corresponding nutrient deficiency category. An Artificial Neural Network (ANN) may also be considered for comparative analysis and deeper pattern recognition.

The dataset is divided into training, validation, and testing sets in a 70:20:10 ratio to ensure proper model learning and unbiased evaluation. The model is trained over multiple epochs using appropriate batch sizes to learn visual patterns associated with different nutrient deficiencies. Efficient data handling techniques such as caching and prefetching are implemented to improve training performance. The Adam optimizer is used to update model parameters and minimize the categorical cross-entropy loss function, which measures the difference between predicted and actual class labels.

The trained model is evaluated using performance metrics such as accuracy, precision, recall, and F1-score to assess its effectiveness and reliability. The predicted outputs are compared with actual labels, and visualization tools such as confusion matrices and classification reports are used to analyze class-wise performance and identify misclassifications. The results may also be compared with other models such as ANN or DenseNet to evaluate performance improvements.

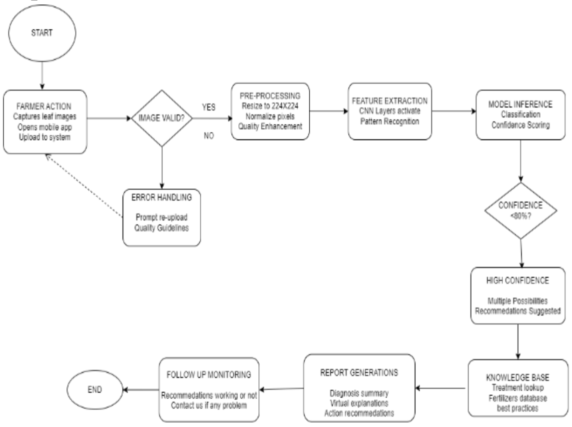

Fig 2. Methodology

Once the training and evaluation phases are completed, the system is capable of identifying the specific nutrient deficiency present in a given leaf image by classifying it into the appropriate category. Based on the predicted deficiency, the system generates recommendations for corrective measures, such as the appropriate fertilizer or nutrient application. This functionality assists farmers and users in making timely decisions to improve plant health and enhance crop productivity.

IV. IMPLEMENTATION

he implementation of the proposed system was carried out in a phased manner, with primary focus on preparing a high-quality dataset and developing a deployable deep learning framework for nutrient deficiency detection. Since the performance of deep learning models largely depends on the quality and consistency of input data, the initial stage involved comprehensive image preprocessing and dataset preparation.

The dataset consists of crop leaf images captured using smartphone and digital cameras under natural field conditions. The collected data includes both healthy leaves and leaves exhibiting visible nutrient deficiency symptoms across multiple crops. The images vary in size, orientation, lighting conditions, and background, making preprocessing essential to ensure uniformity and reliability for model training. All images were resized to a fixed resolution of 224 × 224 pixels to maintain consistency across the dataset and to match the input requirements of standard deep learning architectures. Pixel normalization was applied to scale values between 0 and 1, improving computational efficiency and stabilizing the training process. To further enhance dataset diversity and reduce the risk of overfitting, data augmentation techniques such as random rotation, horizontal and vertical flipping, zooming, brightness adjustment, and cropping were applied. These transformations simulate real-world variations in leaf orientation and environmental conditions.

After preprocessing, the dataset was divided into training, validation, and testing sets in a 70:15:15 ratio. This structured partitioning ensures effective model learning, hyperparameter tuning, and unbiased performance evaluation.

For classification, transfer learning was implemented using the EfficientNetB0 architecture, which was fine-tuned to detect specific nutrient deficiencies. Transfer learning enabled the model to leverage pre-trained feature representations, improving accuracy while reducing training time and computational requirements.

The trained model was deployed using a Flask-based web application. The Flask server hosts the model and provides a RESTful API endpoint for inference. Users can upload leaf images through a web interface, and the images are processed and sent asynchronously to the backend using AJAX and the Fetch API. The server returns prediction results in JSON format, enabling real-time nutrient deficiency detection without requiring page reloads. This implementation provides a practical and user-friendly solution for field-level agricultural applications.

V. RESULT ANALYSIS

The performance of the proposed nutrient deficiency detection system was evaluated using the test dataset after the training phase. The model was assessed using standard performance metrics such as accuracy, precision, recall, and F1-score to measure its effectiveness in classifying different nutrient deficiencies.

During training, the model showed a steady improvement in accuracy while the loss decreased across epochs, indicating effective learning without significant overfitting. The validation accuracy closely followed the training accuracy, demonstrating good generalization capability of the model on unseen data.

To further analyze the classification performance, a confusion matrix was generated. The confusion matrix provides a detailed view of correct and incorrect predictions for each nutrient class. The results indicate that the model performed well in identifying major deficiencies such as nitrogen and potassium, while slight misclassification was observed between visually similar deficiency symptoms. This behavior is expected due to the similarity in leaf discoloration patterns among certain nutrient deficiencies.

Precision, recall, and F1-score values for each class confirmed the reliability of the model across different nutrient categories. Most classes achieved high precision and recall, indicating that the model is capable of accurately detecting deficiencies with minimal false predictions.

The trained model was also tested through the web application by uploading sample leaf images. The system successfully provided real-time predictions along with appropriate deficiency labels, demonstrating its practical usability.

VI. CONCLUSION

This research presented an automated deep learning–based system for detecting nutrient deficiencies in plants using leaf image analysis. The proposed approach utilizes image preprocessing, data augmentation, and transfer learning to develop a robust classification model capable of identifying multiple nutrient deficiencies across different crop types. The use of EfficientNetB0 enabled effective feature extraction and improved classification performance while reducing training time and computational complexity.

The experimental results demonstrated that the model achieved reliable performance with good accuracy, precision, and recall across different nutrient categories. The integration of the trained model into a Flask-based web application further enhanced the practical usability of the system by enabling real-time prediction through a user-friendly interface. The system can assist farmers and agricultural practitioners in early diagnosis of nutrient deficiencies and provide appropriate recommendations for corrective actions.

Overall, the proposed solution offers a fast, cost-effective, and scalable approach for plant nutrient deficiency detection. By reducing dependency on manual inspection and supporting timely fertilizer management, the system contributes to improved crop health, increased productivity, and sustainable agricultural practices.

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