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DETECTION OF NUTRIENT DEFICIENCY IN CROP PLANTS USING DEEP LEARNING MODEL

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ABSTRACT

Nutrient deficiency significantly affects plants growth and crop productivity. Hence, early detection is essential for effective agricultural management. This study aimed to develop a deep learning model for automated detection of healthy, potassium deficient (K) and nitrogen-potassium deficient (N-K) status in crop plants using leaf images. EfficientNetB0 architecture was used to build the model which was then trained and tested. The final model achieved 85.80% training accuracy and 76.61% test accuracy. Precision, recall and F1 score for test set was 76.03%, 76.49% and 75.93%%, respectively, indicating highly reliable prediction performance. Confusion matrix analysis for test set showed correct detection of 91 healthy, 72 potassium deficient and 122 nitrogen-potassium deficient crop leaves. Overall, the findings of the study indicate that the proposed model is effective for identifying nutrient deficiency in crop plants from leaf images.

KEYWORDS: Nutrient deficiency detection, Deep learning, EfficientNetB0, Crop leaf analysis.

INTRODUCTION

The world population is increasing rapidly and projected to reach nearly 9.7 billion by 2050. According to the Food and Agriculture Organization (FAO), food production may need to increase by approximately 60-70% to meet the nutritional requirements of the growing population.[1] To address the growing food demand, crop plant cultivation must significantly increase in productivity and efficiency. However, crop yields are greatly reduced by different stresses from various biotic (pests, disease) and abiotic (drought, salt, nutrient imbalance and shortage) causes, with losses ranging from 26.3% to 40% and nutrient deficiencies can lower yields by up to 70%, endangering food security.[2] As a result, ensuring sustainable crop cultivation has become one of the greatest global priorities.

Among different nutrient deficiencies, nitrogen and potassium deficiencies are two of the most common abiotic stresses that can severely decrease productivity and quality of many economically valuable crops. Nitrogen deficiency generally causes chlorosis, pale green leaves, reduced growth and poor photosynthetic activity while potassium deficiency leads to leaf margin scorching, curling, weak stems and reduced fruit quality.[3-5]

The impact of nutrient deficiencies on crop productivity have created a need for rapid and accurate plant health monitoring systems. Recent advances in artificial intelligence and deep learning have emerged as powerful tools for smart agriculture and precision farming. By integrating feature extraction from leaf images and classification into a single pipeline, deep convolutional neural networks (CNNs) have significantly improved image identification and CNNs are frequently employed in plant stress diagnosis and categorization.[6-9]

In this study, we utilized an available leaf image dataset containing potassium-deficient, nitrogen-potassium-deficient and healthy plant leaf images to develop a convolutional neural network (CNN)-based classification model. The proposed model aims to accurately detect nutrient deficiency conditions from leaf images, which may help support early diagnosis and precision agricultural practices. This study focuses on using transfer learning to classify potassium and nitrogen deficiencies in vegetable crop plants.

MATERIALS AND METHODS

This section describes the research methodology for the development of the proposed transfer learning-based framework for crop plants nutrient deficiency classification. The overall workflow is clearly presented in Figure 1, illustrating the stages involved in the proposed system. The methodology comprises plant leaf image collection, dataset preparation, data pre-processing, deep learning-based CNN model development, model training and evaluation, parameter optimization and final prediction of nutrient deficiency conditions. Furthermore, model performance was evaluated using standard classification metrics (Accuracy, precision, recall confusion matrix).

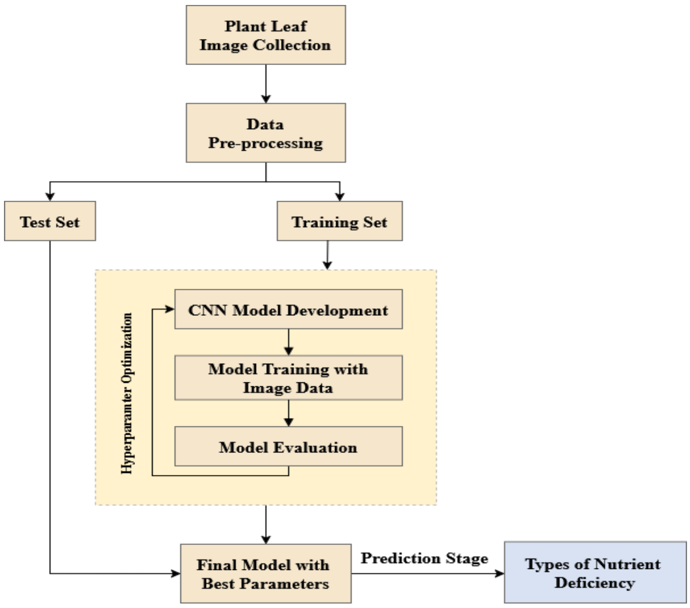

Figure 1: Overview of the proposed methodology.

Plant Leaf Image Collection

A public leaf image repository of Bangladesh's major crops containing leaf images of healthy and nutritionally deficient was used in this work. Based on image availability, healthy, potassium and nitrogen-potassium deficient leaf images were selected. Table 2 presents the number of images per group taken from the dataset. Figure 2 displays leaf image having potassium deficiency and nitrogen-potassium deficiency.

Table 1: Brief overview of the plant leaf image data.

Crop	Number of images
Healthy	786
Potassium deficient	626
Nitrogen-potassium deficient	1044

(a) (b)

Figure 2: Two types of leaf image, (a) nitrogen-potassium deficient and (b) potassium deficient.

Data Pre-processing

The original images had a large black background and overlapping leaves of the same or other plants, weed and soil. So, we need to preprocess the image by applying noise reduction and image enhancement technique. Unnecessary background clutter was removed to keep only the leaf region. Then, images were resized from 3024×3024×3 to 224 × 224 × 3 before feeding into the model to reduce computational complexity. Figure 3 shows the output image after performing pre-processing.

(a) (b)

Figure 3: (a) Original leaf image and (b) Output of leaf image after performing pre-processing.

Model Training and Evaluation for Nutrient Deficiency Classification

A convolutional neural network (CNN) model was developed using pre-trained EfficientNetB0 architecture with a transfer learning approach. The original classifier layer was replaced with a custom classification layer to adapt the model for health, potassium-deficient and nitrogen-potassium deficient leaf image classification. After that, the model was trained on the training dataset and parameter tuning was performed to improve model's prediction performance. To examine model's prediction performance, accuracy, precision, recall and F1 score were used along with classification report and confusion matrix.

The hyperparameters settings for the final developed model are as follows:
Number of epochs: 50
Batch size: 32
Initial learning rate: 0.0001

RESULTS AND DISCUSSION

The performance results of the developed CNN-based framework for detecting healthy, potassium deficient and nitrogen-potassium deficient crop leaf images are presented and discussed in the following section.

The pre-processed dataset was randomly split into 70% training, 15% validation and 15% test subsets, respectively. Since the image selection for each subset was performed randomly, slight variation in model performance may occur across different runs. Figure 4 shows the results of model training and validation with 50 numbers of epochs. After 50 epochs, there found 85.80% training accuracy with 78.42% validation accuracy in nutrient deficiency detection. Training and validation losses was 0.3548 and 0.5226, respectively.

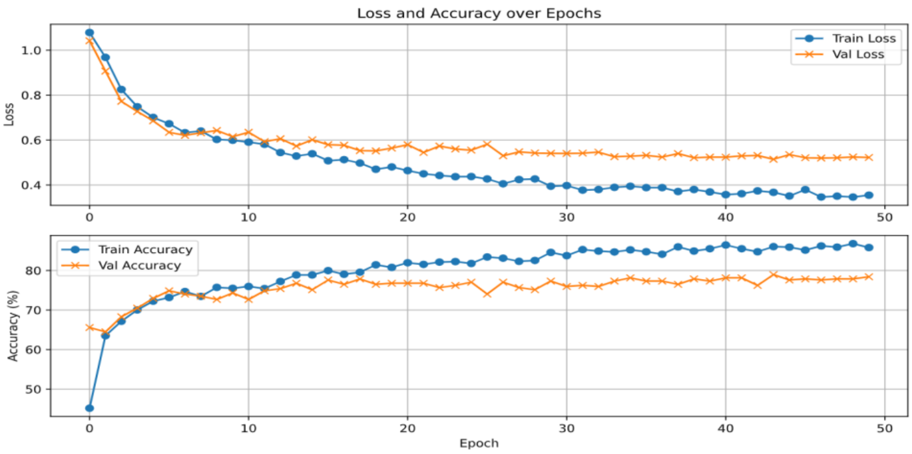

Figure 4: Results after model training and validation.

Model Testing: Performance of Nutrient Deficiency Classification

Table 2 summarizes the classification performance of the final model on the test dataset. The model achieved 76.61% accuracy, 76.03% precision, 76.49% recall and an F1 score of 75.93%%. The results suggest that overall model efficiency are satisfactory considering the difficulties of multiclass classification.

Table 2: Test results of the final model.

Evaluative Parameters	Value (%)
Accuracy	76.61
Precision	76.03
Recall	76.49
F1 Score	75.93

Table 3 displays a detailed evaluation of the final model in identifying each conditions, i.e., health, potassium deficient and nitrogen-potassium deficient. Among the three classes, the nitrogen-potassium deficient category achieved the highest performance, with 85.31% accuracy, 77.22% precision and 81.06% recall. The healthy class also showed strong predictive performance while the potassium deficient category demonstrated comparatively lower precision (61.54%), although the recall remained satisfactory (75.79%).

Model Testing: Confusion Matrix Analysis

The confusion matrix for the test set presented in Figure 5, indicates that the model correctly identified 91 health, 72 potassium deficient (K) and 122 nitrogen-potassium deficient (N-K) leaf images. Misclassification was comparatively higher between the K and N-K deficient categories, indicating slight similarity in visual symptoms among them.

Table 3: Detailed result of the model for each category.

	Precision (%)	Recall (%)	F1-score (%)	Number of Images
Healthy	81.25	76.47	78.79	119
Potassium deficient	61.54	75.79	67.92	95
Nitrogen-potassium deficient	85.31	77.22	81.06	158
Weighted average	77.94	76.61	76.98	372

Predicted

Actual	Healthy	K	N–K
Healthy	**91**	**17**	**11**
K	**13**	**72**	**10**
N–K	**8**	**28**	**122**

Figure 5: Confusion matrix for the test set.

CONCLUSION

This study demonstrated the effectiveness of a transfer learning-based deep learning model for the classification of healthy, potassium-deficient, and nitrogen-potassium- deficient crop plant leaves using digital images. The modified EfficientNet EfficientNetB0 model achieved high classification performance, with strong accuracy, specificity, precision, recall, and AUC values. Confusion matrix analysis further confirmed the robustness of the model distinguishing nutrient deficiency classes with minimal misclassification. Overall, the findings suggest that the processed model can serve as a reliable and efficient tool for automated nutrient deficiency detection in precision agriculture. Future studies may focus on expanding the dataset, evaluating different crops species under field conditions, and developing real-time monitoring systems for practical agricultural applications.

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