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Deep Neural Networks for Classifying Nutrient Deficiencies in Rice Plants Using Leaf Images

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Abstract: Nutrients are vital in ensuring expected crop growth and yield quality. Accurate identification of nutrient deficiencies in plants is essential to provide appropriate supplements of fertilizers. Manual inspection of symptoms and identifying nutrient deficiencies is a tiresome task requiring higher expertise. This paper aims to design and develop a computationally efficient deep-learning model to classify plant nutrient deficiencies accurately. This paper presents an image-based deep-learning framework for nutrient deficiency identification. Three deep learning models, namely the Xception model, vision transformer, and multi-layer perceptron-based (MLP) mixer model, were trained to identify nitrogen (N), phosphorous (P), and potassium (K) deficiencies in rice plants from red-green-blue (RGB) images. The model performance is tested on nutrient deficiency symptoms in rice plants dataset available publicly on Kaggle. All three models achieved nutrient deficiency classification accuracy greater than 92%. The Xception model achieved the highest average accuracy of 95.14% at the cost of approximately 1.2 million total trainable parameters, much less than the vision transformer and MLP mixer model. The Xception model performs better than the other two models in classifying nutrient deficiencies with the least number of total trainable parameters. In the future, these neural networks can be trained and extended to accurately detect and segment nutrient-deficient crop areas in large fields to supply precise fertilizer supplements.

Keywords: Deep learning, MLP mixer model, Plant nutrient deficiency classification, Vision transformer, Xception model

1. INTRODUCTION

Food security, quality food production, and increase in crop yield are the major global challenges in the agricultural sector [1], [2]. Plant or crop growth is highly dependent on several nutrients. The nutrients are essential for the growth and overall development of the plants [3]. If these nutrients are low in plants, plant growth is stunted, and plants may die. Therefore, it is essential to identify plant nutrient deficiencies to sustain healthy and productive plants [4], [5]. The vital nutrients are classified as macro-and micro-nutrients based on their requirements [6]. Each nutrient deficiency has unique consequences and symptoms for each plant. For instance, leaf chlorosis or browning of leaves, poor growth, decreased rates of elongation or dwarfing, and eventual wilting are characteristic signs of various nutrient deficiencies [7], [8]. Another instance is yellowing leaves that develop from the roots and move upward, a possible symptom of nitrogen deficiency [9]. From the literature, it is evident that nitrogen contributes to growth, chlorosis, and crop yield [10], [11], while phosphorous acts in energy metabolism, root development, and flowering [12]. There are three effects of potassium in the body: promoting the regulation of water, activation of enzymes, and growth; thus, it plays a critical role in the fruit development process [13]. Other essential micro-nutrients like iron and boron can significantly affect chlorosis, cell division, and root elongation [14]. To understand how nutrient-deficient plants are, it is necessary to look at which part of the plant is affected and which symptoms of deficiency are seen. After the deficiency becomes apparent, the plant should be treated with fertilizer or other means to produce the anticipated healthy growth.

Techniques for diagnosing nutritional deficiencies in plants are soil testing, analysis of plant tissue, and visual observation of plant symptoms [15], [16]. Determining plant nutrient deficiency is usually possible by manual observation of symptoms as this method is simple and identifies the source of nutrient deficiency. Still, this approach is highly subjective since people might interpret the same signs differently. Also, checking long fields or crops can be tiring

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and demands much effort. Thus, automated mechanisms are required to detect vascular plants with nutrient deficiencies precisely and timely. Image-based plant nutrient deficiency identification is a promising and efficient solution as it is a non-invasive, efficient, and accurate method that can be applied over large fields [17], [18], [19].

2. RELATED WORK

Plant nutrient deficiency literature includes studies that analyze the effects, symptoms, and management of nutrient deficiencies in various plants. Li et al. [20] provides an overview of modern imaging methods used for plant nutrient analysis. Red-green-blue (RGB) imaging, fluorescence imaging, and imaging spectroscopy are the currently used imaging techniques for nutrient deficiency identification. RGB imaging is the simplest and most commonly used imaging method for classifying plant nutrient deficiencies [21]. Kamelia et al. [22] reviewed image processing techniques for detecting nutrient deficiencies using RGB images. The image processing methods mainly involve image acquisition, enhancement, segmentation, and feature extraction to detect nutrient deficiencies [23]. In one of the studies, hyper-spectral imaging is used to detect nutrient concentrations in hydroponic lettuce [24]. Another study uses multi-spectral satellite imaging to detect nutrient deficiencies in spruce forests [25].

Recently, machine learning (ML) approaches are also used to identify plant nutrient deficiencies. Barbedo et al. [26] present a review that explains using proximal images of plants to detect nutrient deficiencies using ML models. Jose et al. [27] proposed an ML-based approach in which statistical and gray-level co-occurrence matrix features are obtained, and a neural network is trained on these features to classify nutrient deficiencies. In one of the studies, the authors used color and shape features along with an artificial neural network, k-nearest neighbor (k-NN), and support vector machine (SVM) to classify macro-nutrient deficiency in maize plants [28]. In another study, the authors used an unmanned aerial vehicle to capture multi-spectral images of citrus plants and gradient boost regression to determine citrus plant nutrient concentrations in plant leaves [29]. Recently, machine learning models were used to identify Soybean genotypes from macro-nutrient contents to develop efficient genotypes. Multi-spectral data was used as input to ML classifiers such as decision tree, SVM, and random forest [30].

Recently, many papers have reported using deep neural networks to classify plant nutrient deficiencies [31], [32], [33]. Sudhakar et al. [34] presented an extensive survey about machine and deep learning (DL) methods for identifying plant nutrient deficiencies based on plant images. Convolutional neural networks (CNN) are beneficial for image-related tasks and are used in many image-based plant nutrient deficiency classification studies [35]. In one of the studies, the black gram plant leaf image is split into different sections of pixels, and each of these sections is checked for nutrient deficiencies. Then, the response is combined using a multi-layer perceptron (MLP) [36]. In another paper, the authors applied a transfer learning approach to train the Inception-ResNet model to determine nutrition deficiencies in okra plants [37]. Another study uses CNN to identify nutritional deficiencies in tomato plants using leaf images [38]. Xu et al. [39] used deep CNNs like ResNet50, InceptionV3, DenseNet, and NasNet to detect nutrition deficiency symptoms in rice plants, where DenseNet with 121 layers performed better than other networks. In another study, Taha et al. [40] used DCNN to detect the nutritional level of plants grown in aquaponics. The study compares DCNN with ML models like SVM, k-means clustering, and k-NN. DCNN outperformed all the machine learning models and achieved around 96% classification accuracy.

This paper identifies macro-nutrient deficiency in rice plants, as rice is an essential staple food for a large population. Identifying nutrient deficiencies and providing necessary fertilizer supplements requires knowledge and expertise in botany [41]. One way to detect nutrient deficiency symptoms is using visual symptoms evident from leaf phenotypes [42]. This paper uses RGB images to detect nutritional deficiencies in rice plants. Three deep learning models are built and implemented in this paper to classify macro-nutrient deficiencies, such as nitrogen (N), phosphorous (P), and potassium (K). This paper aims to increase the accuracy of nutrient deficiency classification by implementing the latest and computationally efficient deep learning models.

3. METHOD

The deep-learning models identify nutritional deficiencies from RGB images of rice plants. The nutrient-deficient plant image dataset, three deep-learning models, and train and test parameters are explained in this section.

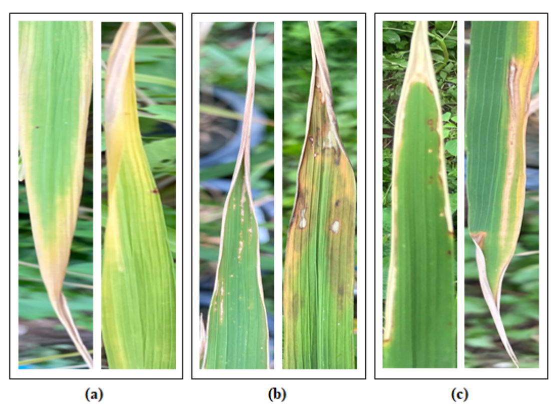

Figure 1. Sample images in nutrient deficiency dataset (a) Nitrogen-deficient plant image (b) Phosphorous-deficient plant image (c) Potassium-deficient plant image

A. Dataset Description

The nutrient deficiency symptoms in rice plants image dataset is publicly available on Kaggle [43]. The dataset

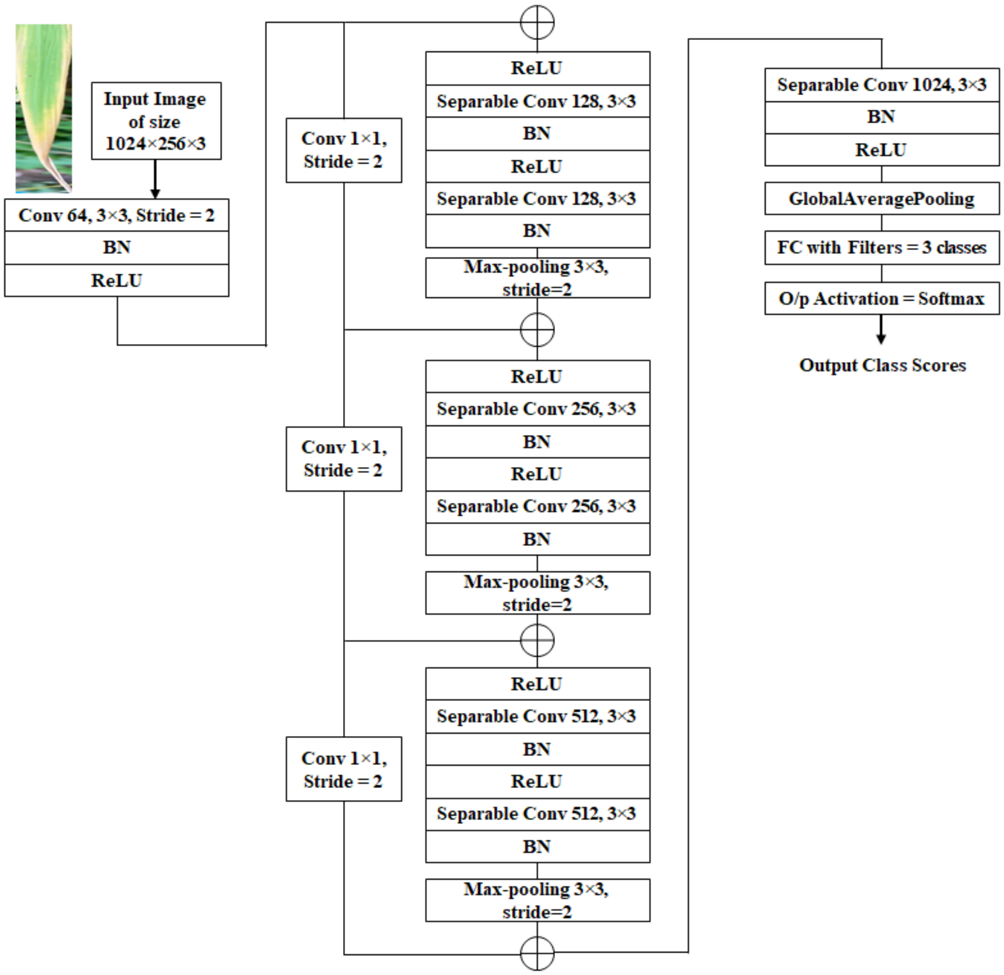

Figure 2. Xception model

TABLE I. Number of train and test images per class for each fold

Fold	Training Set			Test Set		
	N	P	K	N	P	K
1	363	256	305	77	77	78
2	342	269	311	98	61	72
3	344	272	306	96	58	77
4	362	259	301	78	71	82
5	349	264	309	91	66	74

includes rice plants deficient in three macro-nutrients: nitrogen, phosphorous, and potassium. Nutrient deficiencies were created by feeding plants a controlled amount of nutrients and then observing the visual changes in the plants. The dataset aims to classify these nutrient deficiencies in the rice crop from the RGB images of plant leaves. Two sample images from each class in the dataset are shown in Figure 1. The dataset comprises 1,156 rice plant leaf images, of which 440 images belong to nitrogen-deficient plants, 333 to phosphorous-deficient, and 383 to potassium-deficient plants. Data reprocessing and data augmentation are used to improve the dataset overall. The orientation and image size vary throughout the dataset. Therefore, the images are resized to the dimensions of 1024×256, where height is 1024 and width is 256. Then, the images are normalized, and various image augmentation techniques like random flip, rotate, and zoom are used to increase the variations in the dataset. Keras image augmentation layers generate augmented images, which are directly fed into the deep learning model. Data augmentation increases variations in the dataset and helps deep learning models to generalize. Since this is an imbalanced dataset, using five-fold cross-validation helps avoid over-fitting models to the dataset. Table I indicates the number of train and test images per class for each fold.

B. *Deep-learning Models*

This paper implements three deep learning models, namely the Xception model, vision transformer, and multi-layer perceptron-based mixer model, to classify the images of nutrient-deficient plants.

1) Xception Model

The Xception model consists of eight convolution layers, including depth-wise separable and regular spatial convolutions, as shown in Figure 2. The depth-wise separable convolution includes applying convolution for each channel separately and then point-wise convolution [46]. The point-wise 1×1 convolution combines the output of the depth-wise convolution. The model comprises a standard convolution layer with 64 filters at the input of the model, followed by three blocks, each with two repeated implementations of depth-wise separable convolution layers with 128, 256, and 512 filters, respectively.

Each block consists of two repeated implementations of rectified linear unit (ReLU), separable convolution, and batch normalization (BN). At the end of each block, a max-pooling layer down samples the features feature maps, which helps reduce the size of feature maps. The output side of the model consists of a depth-wise separable convolution layer with 1024 filters, BN, and ReLU. A global average pooling layer is used to flatten the output. A fully connected (FC) layer, having three filters that are the same as nutrient deficiency classes, is used with the softmax output activation function to provide class scores.

2) Vision Transformer Model

The model contains a transformer encoder having multi-headed self-attention and MLP layers. The transformer model needs a one-dimensional (1-D) input called a token. Therefore, the input image of size 1024×256×3 is split into 256 equal patches of size 32×32. These patches of the image are converted to 1-D fixed-size vectors with learnable linear projections called patch embeddings. The position of patches is stored by inserting 1-D position embedding. A learnable class embedding is prepended to each patch embedding sequence. The output layer is implemented using an MLP head and dense layer with nodes equal to a number of categories [44]. The overview of the vision transformer model is shown in Figure 3.

3) Multi-layer Perceptron (MLP) Mixer Model

The MLP mixer model is entirely based on MLP layers instead of convolutions or self-attention [45]. MLP mixer model consists of a per-patch input dense layer, mixer layer, and dense layer as classifier head, as seen in Figure 4. The input image of size 1024×256×3 is split into 256 patches of size 32×32. These patches are converted to 1-D tokens. The input is shaped as a table with dimensions as number of patches×number of channels, and this dimensionality is maintained. Two MLP layers are used, namely channel-mixer and token-mixer. The channel-mixer MLPs allow interaction between various channels, treat each token separately, and take in table rows as input. The token-mixer MLPs allow interaction between tokens, work independently for each channel, and accept the table's columns as input. These two MLP layers are combined to enable the interaction of both input dimensions.

In this paper, we have implemented three different models for comparative analysis. The Xception model represents the convolutional model, the vision transformer based on transformer encoder-decoder blocks, and the MLP mixer model with multi-layer perceptrons. These models differ in architecture and how they process images. The Xception model used depth-wise separable convolutions instead of regular convolutions that act along the channels. This helps achieve a rise in performance due to the efficient parameter use without an increase in the number of parameters compared to the Inception model. The Xception model depends on convolution operations, exploits local connections, and is shift invariant. On the contrary, in the case of a vision transformer, every image is split into small patches, and these image patches are treated in parallel. Self-attention is a crucial mechanism in the vision transformer that determines the dependencies and contextual information in the images. The MLP mixer model is similar to the vision transformer in that the image is divided into patches and mapped to an embedding vector in both models. However, the MLP mixer model slightly differs from the vision transformer in handling images and image patches. Vision transformer uses a self-attention layer, whereas the MLP mixer model relies on multi-layer perceptrons and uses two MLP layers: channel-mixer and token-mixer. Vision transformers perform better than MLP mixer models but are more complex than MLP mixer models.

The models are built on Google Colab using Python, Keras 2.14.0, and Tensorflow libraries. NVIDIA Tesla T4 GPU by Google Colab is used to train and test the networks.

C. Training of the Networks

The dataset is divided into five folds, and cross-validation is used to train the deep learning models. As the dataset has a comparatively small number of images and the dataset is imbalanced, cross-validation helps detect over-fitting. Also, image augmentation techniques like vertical and horizontal flipping, random rotation, and zoom were used to avoid class imbalance problems and introduce variations in the dataset. For the learning algorithm, an Adam optimizer is chosen, and the rate of learning is set to 0.001. As this is a multi-class classification, categorical cross-entropy is selected as the loss function. The batch size of 8 images is set, and the model training is carried out over 200 epochs. Categorical accuracy is used as an evaluation metric to examine the model performance.

4. RESULTS AND DISCUSSION

Four metrics, namely average classification accuracy, precision, recall, F1-score, and average miss-classification rate, were used to assess the performance of the Xception model, vision transformer, and MLP mixer model in classifying plant nutrient deficiencies. Five-fold cross-validation is used to avoid model over-fitting to the dataset. Figures 5, 6, and 7 depict the classification performance

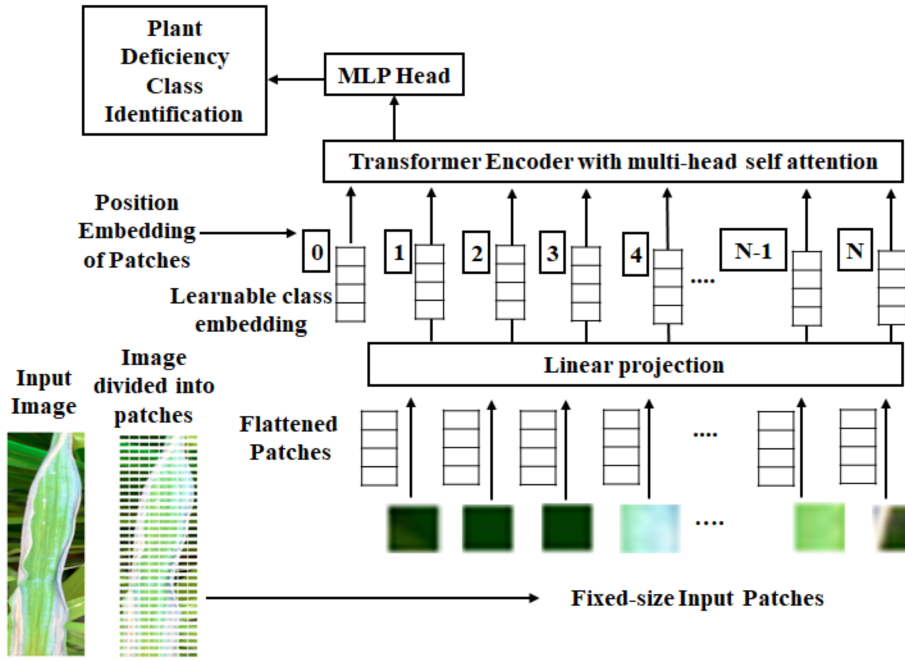

Figure 3. Vision transformer model [44]

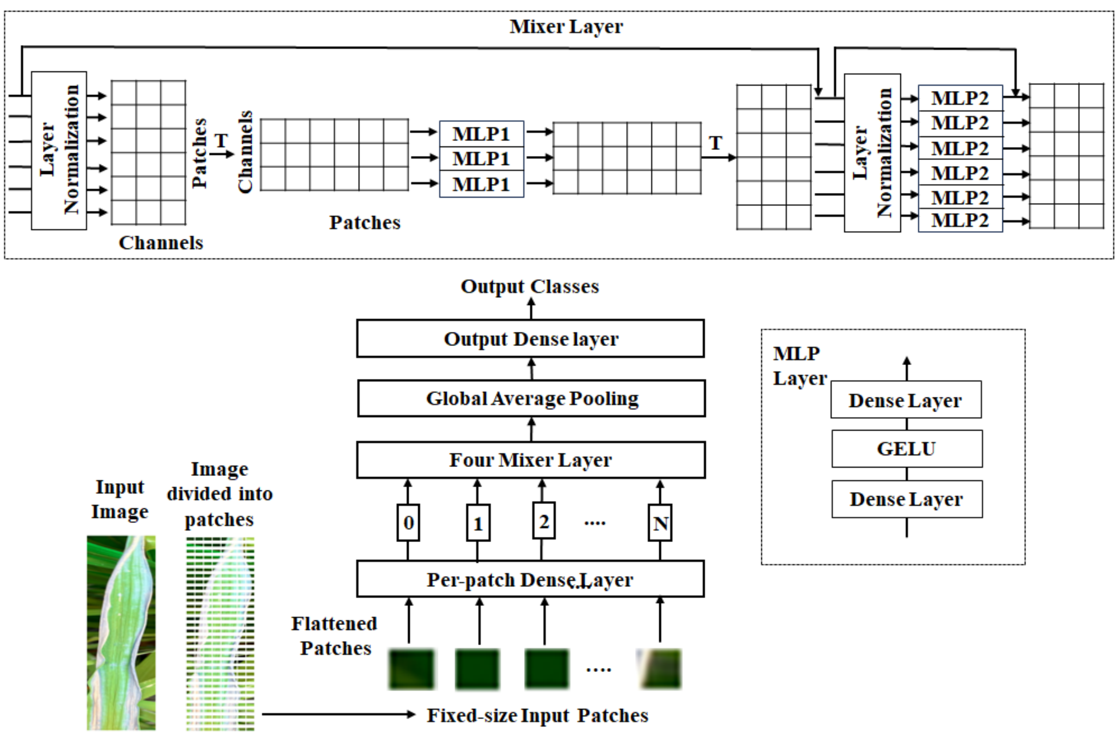

Figure 4. MLP Mixer model [45]

of the three models using confusion matrices. Out of five folds, fold 1 and 4 confusion matrices are shown only for demonstration purposes. The confusion matrix provides values of evaluation metrics for the models in terms of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). These values determine the accuracy,

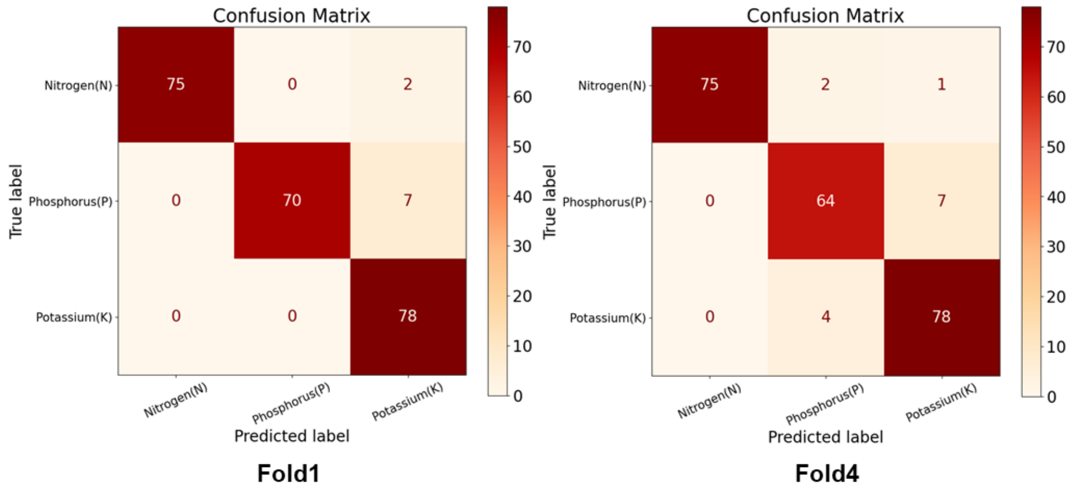

Figure 5. Sample confusion matrices for fold 1 and 4 presenting classification performance of the Xception model

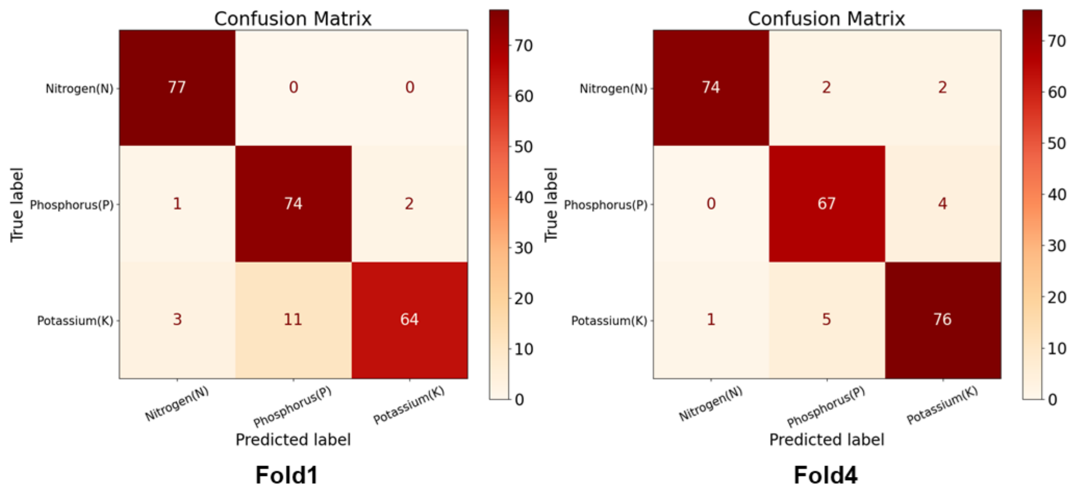

Figure 6. Sample confusion matrices for fold 1 and 4 presenting classification performance of the vision transformer model

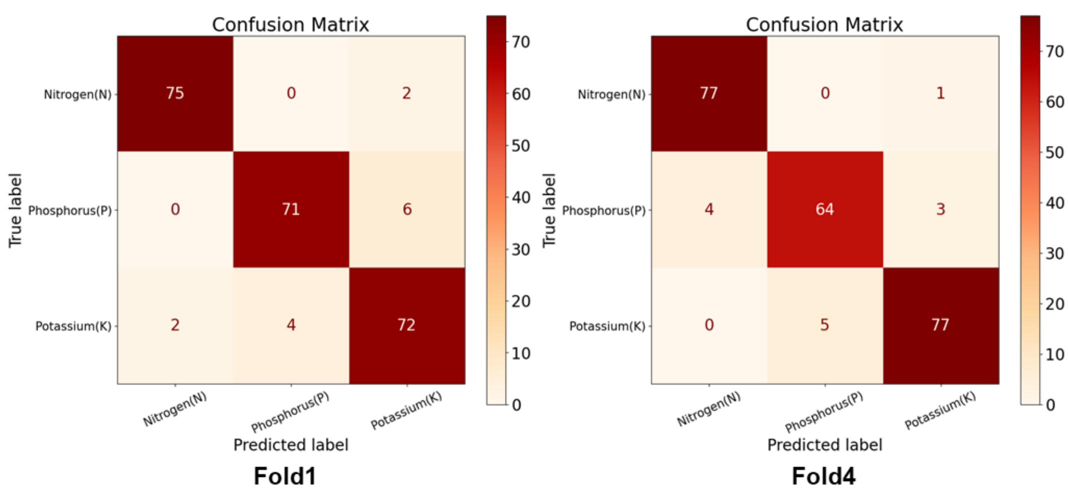

Figure 7. Sample confusion matrices for fold 1 and 4 presenting classification performance of the MLP mixer model

TABLE II. Nutrient deficiency classification results for Xception model on the test set for five folds in terms of evaluation metrics

Fold	Accuracy			Precision			Recall			F1-score		
	N	P	K	N	P	K	N	P	K	N	P	K
1	0.97	0.90	0.99	0.99	0.99	0.90	0.97	0.91	0.99	0.99	0.95	0.95
2	0.99	0.96	0.91	0.99	0.91	0.99	0.99	0.97	0.92	0.99	0.94	0.95
3	0.94	0.77	0.99	0.99	0.99	0.81	0.95	0.78	0.99	0.97	0.87	0.90
4	0.96	0.90	0.95	0.99	0.91	0.91	0.96	0.90	0.95	0.98	0.91	0.93
5	0.99	0.92	0.97	0.94	0.99	0.99	0.99	0.92	0.97	0.97	0.96	0.98

TABLE III. Nutrient deficiency classification results for vision transformer model on the test set for five folds in terms of evaluation metrics

Fold	Accuracy			Precision			Recall			F1-score		
	N	P	K	N	P	K	N	P	K	N	P	K
1	0.99	0.96	0.82	0.95	0.87	0.97	0.99	0.96	0.82	0.97	0.91	0.89
2	0.94	0.95	0.86	0.98	0.83	0.94	0.95	0.95	0.86	0.96	0.89	0.90
3	0.91	0.87	0.90	0.95	0.89	0.86	0.92	0.88	0.91	0.93	0.89	0.89
4	0.94	0.94	0.92	0.99	0.91	0.93	0.95	0.94	0.93	0.97	0.92	0.93
5	0.97	0.90	0.98	0.99	0.98	0.90	0.98	0.91	0.99	0.99	0.94	0.94

TABLE IV. Nutrient deficiency classification results for MLP mixer model on test set for five folds in terms of evaluation metrics

Fold	Accuracy			Precision			Recall			F1-score		
	N	P	K	N	P	K	N	P	K	N	P	K
1	0.97	0.92	0.92	0.97	0.95	0.90	0.97	0.92	0.92	0.97	0.93	0.91
2	0.94	0.91	0.95	0.98	0.90	0.93	0.95	0.92	0.96	0.96	0.91	0.95
3	0.80	0.96	0.93	0.99	0.80	0.87	0.80	0.97	0.94	0.89	0.88	0.90
4	0.98	0.90	0.93	0.95	0.93	0.95	0.99	0.90	0.94	0.97	0.91	0.94
5	0.93	0.89	0.97	0.97	0.92	0.91	0.93	0.89	0.97	0.95	0.91	0.94

TABLE V. Comparative performance of the models in terms of average classification accuracy, average miss-classification rate, and total number of trainable parameters

Model name	Average accuracy (%)	Miss-classification rate	Total trainable parameters in million (M)
Xception model	95.14	0.048	1,243,459 (1.2 M)
Vision transformer	93.07	0.069	36,536,515 (36 M)
MLP mixer model	92.98	0.070	1,842,179 (1.8 M)

TABLE VI. Performance comparison of the Xception model, vision transformer, and MLP mixer model with methods available in the literature

Model name	Accuracy (%)
Ensemble approach [47]	92.00
Modified InceptionResNetV2 [48]	91.66
Modified DensNet-201 [48]	95.00
MLP mixer model	92.98
Vision transformer model	93.07
Xception model	95.14

precision, recall, F1-score, and miss-classification rate as shown in (1), (2), (3), (4), and (5).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (4)$$

$$Miss - classification\ rate = \frac{FP + FN}{TP + TN + FP + FN} \quad (5)$$

Tables II, III, and IV present the classification report of the three models in evaluation metrics for five-fold cross-validation. Table V compares the three models in terms of average classification accuracies, average miss-classification rate, and the total trainable parameters of the models. The Xception model achieves the highest average classification accuracy of 95.14%, followed by the vision transformer and MLP mixer models, with accuracies of 93.07% and 92.98%, respectively. Also, the average miss-classification rate is 0.048 for the Xception model, much less than the vision transformer and MLP mixer model.

Besides achieving the highest classification accuracy and lowest miss-classification rate, the Xception model needs approximately 1.2 million total trainable parameters, 35 times less than the vision transformer. Compared with the MLP mixer model, the Xception model achieves a rise of 3% in average accuracy with slightly fewer total trainable parameters, as seen in Table V.

Table VI compares the implemented models with the methods implemented in the literature on the same dataset used in this paper. The methods available in the literature use transfer learning and ensemble averaging methods [47], [48]. All three models implemented in this paper achieve better accuracy results than the methods available in the literature. Notably, the Xception model outperforms the methods available in the literature in accuracy and total trainable parameters.

5. Conclusions and Future Work

In this paper, three deep learning models, namely the Xception model, vision transformer, and MLP mixer model, are trained and tested for plant nutrient deficiency classification using leaf images. These three models differ in architecture and how they process and interpret images. Out of these three models, the Xception model achieves the highest average classification accuracy and lowest miss-classification rate at the cost of significantly fewer total trainable parameters. The Xception model achieved a 3% rise in the average plant nutrient deficiency classification accuracy with 35 times fewer trainable parameters than the vision transformer and approximately the same number of parameters as the MLP mixer model. Also, the Xception model outperforms methods implemented in the literature in accuracy and total trainable parameters by using depth-wise separable convolutions. Accurate prediction of plant nutrient deficiencies will help farmers determine the right type and quantity of fertilizers to be supplied to plants for expected growth. In the future, the study aims to determine the exact areas of plants affected due to nutrient deficiencies.

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