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PLANT NUTRIENT DEFICIENCY DETECTION USING DEEP CONVOLUTIONAL NEURAL NETWORK

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Abstract. *Nutrient deficiency is a common condition that can spread and affect plants, if it is not handled quickly. For this time, deficiency surveillance is carried on manually which needs more effort especially for large area. With rapid growth of technology, it is possible to build a system via smartphone to detect the nutrient deficiency of plants. In this paper, we propose a deep convolutional neural network to diagnose condition based on image of plants. Inception-Resnet architecture with transfer learning and fine tuning from model that is previously trained using ImageNet dataset is applied in the experiments. We trained the model further with image of okra plants. The dataset consists of 184 images for the training process and 47 images for testing. Image augmentation method is also used to increase the variation of the dataset. The experimental results show that fine tuning approach achieves the best accuracy, namely 96% and 86% for training and testing respectively.*
Keywords: Macronutrient deficiency, Deficiency detection, Machine learning, Deep learning

1. **Introduction.** Agriculture system is highly dependent on sufficient of water, sunlight and nutrients intake in a plant. Different plants need different amount of nutrient which are distinguished as macronutrient and micronutrient. Macronutrients are nutrients whose higher amount compare to micronutrients since these substances are required in cell and tissue development of plants [10]. Macronutrients consist of Nitrogen (N), Phosporus (P), Pottasium (K), Calcium (Ca), Sulfur (S) and Magnesium (Mg), while micronutrients are Ferrum (Fe), Zinc (Zn), Cuprum (Cu) and Manganese (Mn). Deficiency of macronutrients is affected to leaves growth which causes disruption on food formation. Insufficient food formed has role in growth disorder such as dwarf plans, poor flowering and fruiting. Symptomps of nutrient deficiency immadiately appearing on colour of leaves and foliage growth with details of symtomps are presented in Table 1.

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Table 1. Macronutrients deficiency symptomps

Macronutrients	Symptoms
Nitrogen (N)	Light green of upper leaves and yellow of lower leaves.
Pottasium (K)	Yellow and purple leaves with brown at leaves edge and poor flower and fruit.
Phosporus (P)	Slow growth and yellow folliage.
Magnesium (Mg)	Yellow between the leaf veins with red brown tints and early leaves fall.

All this time, deficiency surveillance is conducted using manual observation. The growers inspect condition of plants regularly whether nutrients of plant are fulfilled well. However, the obstacle of this method is if the agricultural field is quite large. It needs more effort to observe whole field intensively. Previous researchers proposed various techniques to monitor and control soil nutrient of crops automatically. Lettuce calcium deficiency in greeenhouse is detected using machine vision technique based on temporal, colour and morphological changes of the plants [15]. This method was successful to identify calcium deficeincy earlier compared to human vision. In other types of crops, potato yield and sulfur deficiency are predicted based on optical sensor data [13]. Hengl et al. used spatial data to predict macronutrient and micronutrient in Sub Saharan Africa (SSA) with Principal Component Analysis (PCA) approach [7].

Machine learning in agriculture field is not a new thing, and several approaches of machine learning had been implemented to support agriculture process, control or monitoring task. Deep learning as part of machine learning is widely used, for instance, in maize color image segmentation for 3D reconstruction [3]. The 3D reconstruction is useful to measure the effects on growth. It uses camera to capture maize plant from six different sides with angle of view around 30° apart and also from a top-view. Another work uses deep learning for leaf vein pattern identification for three legume species namely white bean, red bean and soy bean. This identification has beneficial to reduce classification time and human expert intervention when building a huge catalogues of plant species [5].

Besides in leaf pattern identification, deep learning is also used extensively for plant disesase detection. Northern Leaf Blight (NLB) is an indication of disease in maize plant which is identified efficiently using Convolutional Neural Networks (CNN) [2]. The experimental result showed that CNN is able to identify 1796 images consisting of 1028 NLB-infected and 768 non infected images with accuracy 96.7%. Mohanty et al. [11] applied AlexNet and GoogleNet architecture to identifying disease or healthy condition from plant leaves using 54,306 image dataset to identify 14 crop species and 26 disease with 99.35% accuracy. While Hanson et al. [6] used deep learning, in this case CNN to identify leaf disease which is affected by pests. This research achieves 95% accuracy as the performance evaluation. An improvement was carried out by Ferentinos [4] in plant disease detection. The 87,848 images data containing 25 different plants with 58 classes of disease and health was detected using CNN approach. The researcher compared five CNN techniques: AlexNet [9], AlexNetOWTBn [8], GoogleNet [16], Overfeat [12] and VGG [14]. It is obtained that VGG has the highest accuracy 99.48% followed by AlexNetOWTBn 99.44%, AlexNet 99.06%, Overfeat 98.96% and GoogleNet 97.27%.

Previous researches have given general overview of technology utilization to detect disease and monitor plant condition automatically. However, macronutrient deficiency monitoring always misses to be noticed whereas it has essential impact on plant quality. Therefore, this research proposes a technique with deep learning based to detect macronutrient deficiency of plant based on image input data. Deep learning approach is utilized to detect gradation color of leaves as effect of nutrient deficiency as a monitoring process to avoid severe condition.

This paper is arranged as follows. In Section 2, data collection and analysis are conducted to be input in deficiency detection algorithm which is explained in Section 2.2. The experimental result and conclusion will be presented in Section 3 and Section 4 respectively.

2. Materials and Methods.

2.1. Plant image data. This paper uses okra *(Abelmoschus Esculentus)* as the data input. Okra is one of medicinal plants which are useful for diabetes and high cholesterol patient. Health okra has appeareance of dark green with width of leaves around 10 cm, while deficiency plant has light yellowish green and width of leaves around 3 cm (See Figure 1). The challenge in deficiency detection is that in the early stage, transformation of leaves colour cannot be distinguished visually, so that early detection and treatment is quite difficult to be executed.

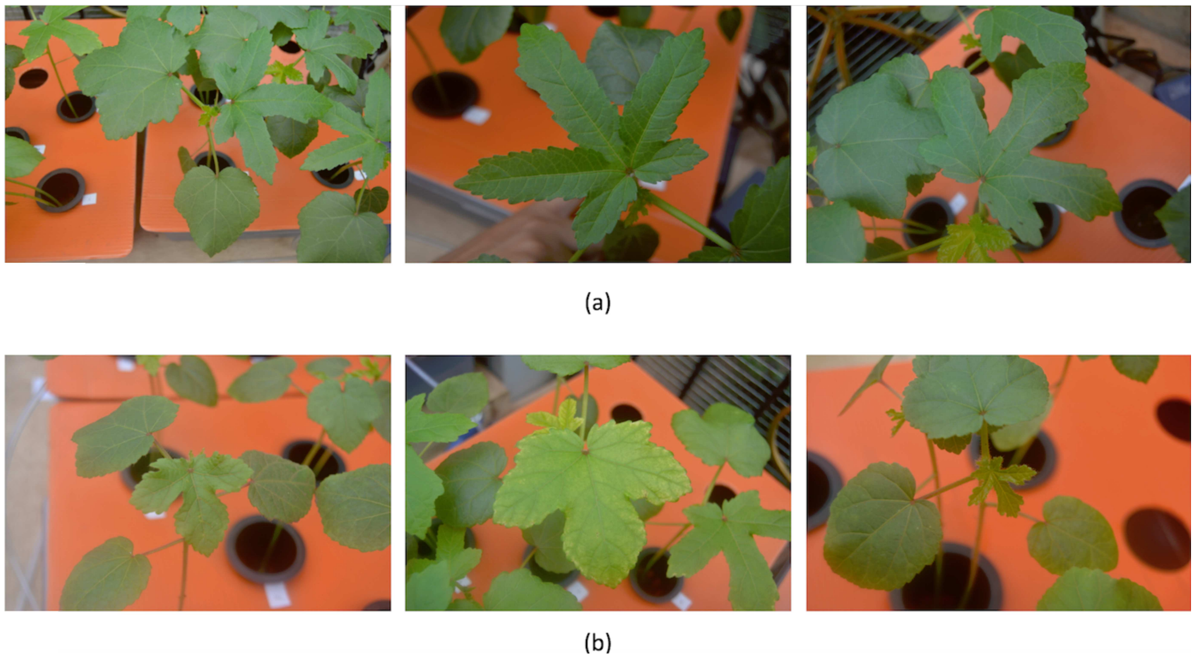

Figure 1. Sample of plant image data: health plant (a) and deficiency plant (b)

Plant image data is acquired using phone camera with standard specification (12 MP) in plantation laboratory. This image data is resized into 299×299 pixel and then image augmentation is applied as process of artificial increasing size of dataset via transformations. For the implementation of image augmentation, we use ImageDataGenerator class provided by Keras, and the transformation consists of rotation, width and height shift, shear, zooming, and horizontal flip. These image data become inputs in convolutional neural network algorithm.

2.2. Convolutional neural network for nutrient deficiency detection. Convolutional Neural Network (CNN) is one of deep learning methods which is used to obtain spatial information in an image. CNN has several architectures which were introduced by previous researchers to reach better performance in image recognition. This research applies Inception Resnet as the algorithm to detecting nutrient deficiency based on plant images. Plant images including health and deficiency conditions are captured by handphone camera to be collected as input data. This input data is applied to CNN method to being classified as health or deficiency plant (See Figure 2).

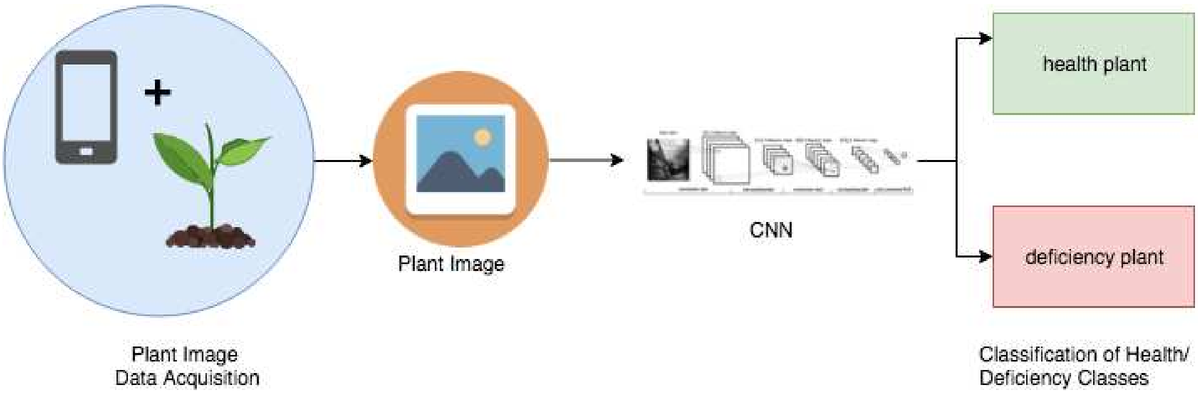

FIGURE 2. Research methodology

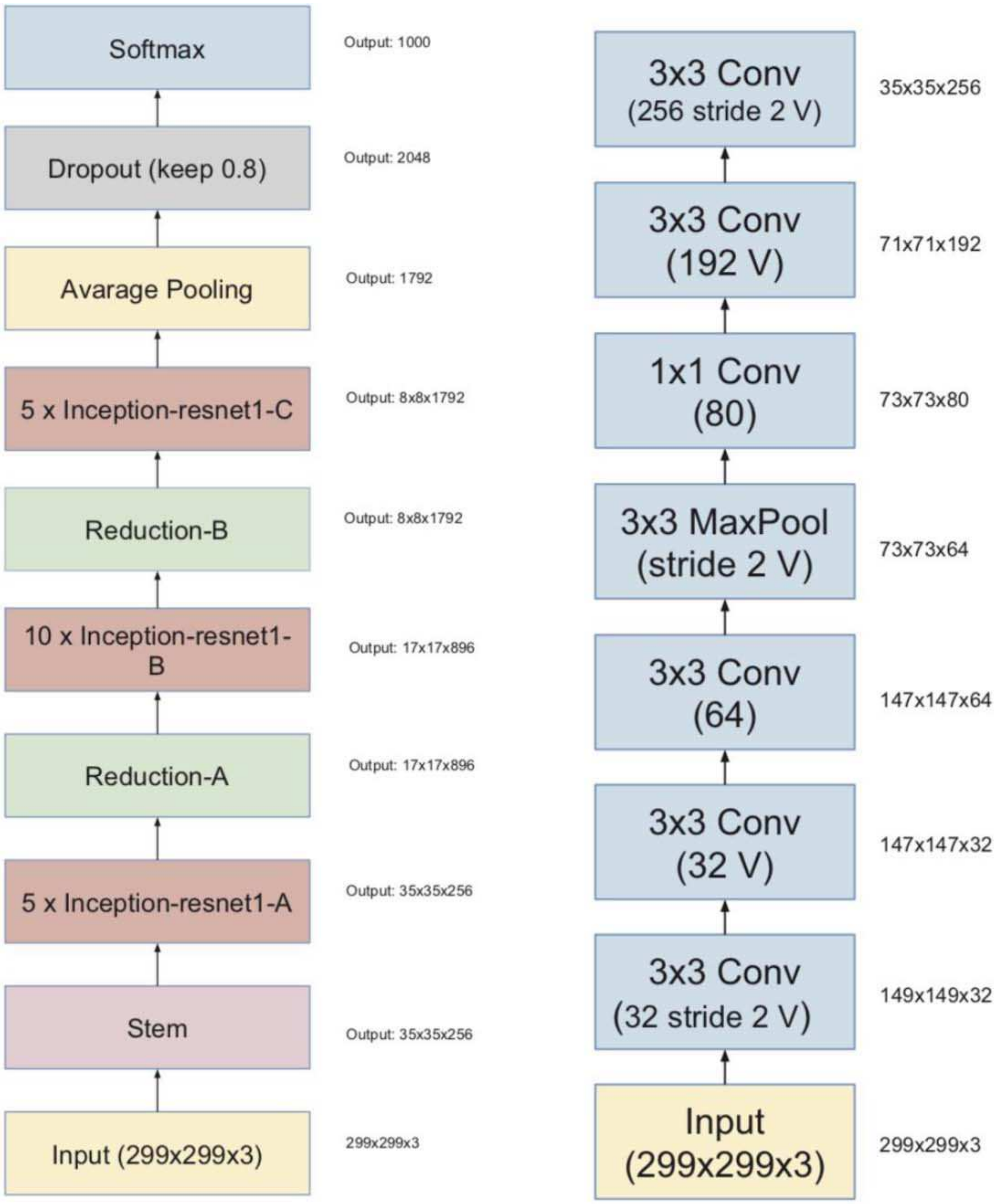

FIGURE 3. Inception ResNet-v2 architecture [16]

This research applies Inception ResNet-v2 to classifying normal and deficiency classes whose architecture consists of stem, Inception Resnet1, Reduction and Fully connected as shown in Figure 3. ResNet-v2 is the improvement form of Inception-v4, which has objective to reduce computational process by using 1×1 convolution without activation function [16].

3. **Experimental Result and Analysis.** Two methods of training are conducted, specifically transfer learning and fine tuning approach. Transfer learning uses trained weights from ImageNet dataset, excluding the top layer and adding our own softmax layer based on image classes. Fine tuning freezes the first 249 layer and trains the rest of the network. Doing both approaches will ensure training achieves stable and consistent condition. Without frozen layer, large gradient updates are triggered by random initialized weights and it could wreck the learned weights in the convolutional base [1].

The 231 data is divided into 184 training and 47 testing data. The first training uses learning rate 0.0001 in 100 epoch with Adam optimizer and it is able to perform well with accuracy above 95%. However, in the testing phase the accuracy is unstable and only yields in the range between 56% and 63%. In next trial, we try to reduce the number of epochs and also increase the learning rate from 0.0001 to 0.001 and it also yields an unstable result, with the training accuracy in range of 83% to 100% while the testing only achieves approximately 56% to 62% of accuracy.

Finally, we try to train in two steps, in the first step only last fully connected layers are trained with the learning rate of 0.001 then in the second step we fine tune the network by freezing the first 249 layers of the network and train the remaining layers, and both steps used 50 epochs. This approach improves the results quite significantly and it produces a more stable and consistent result. In the second step of the training, the accuracy reaches 96% for 5 times experiments while testing accuracy achieves approximately 86%. Comparison performance is presented in Figure 4 according to detail of parameter in Table 2.

FIGURE 4. Comparison of training and testing from transfer learning and fine tuning approach

Table 2. Parameter of experimental process

Experiment	Method	Learning rate	Epoch
Exp 1	Transfer Learning	0.0001	100
Exp 2	Transfer Learning	0.001	50
Exp 3	Fine Tuning	0.001	50

4. **Conclusion.** We implement the Inception ResNet-v2 network using transfer learning where the network has already trained using ImageNet dataset. Then the model is retrained using okra plant images data. A few experiments are conducted by changing the hyperparameter such as learning rate and epochs. It is found that training performance at first does not yield a stable result and we suspect it is because of the large differences between ImageNet data and okra dataset. In order to achieve a better result, fine tuning is conducted by freezing some early layers. Three designs of training have been executed and achieve 96% and 86% for training and testing respectively, with fine tuning approach as the best results. Improvement of this work is conducted by applying simpler architecture such as Mobilenet to be easier implemented in Mobile platform.

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