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Palm leaf nutrient deficiency detection using convolutional neural network (CNN)

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Abstract

Palm oil, scientifically known as Elaeis guineensis, is a rapidly growing commercial sector in Southeast Asia with a diverse economic composition. Palm oil plantations are crucial in economic activities and growth, as they generate employment in managing the palm oil quality. However, the lack of nutrients can affect the growth and quality of the crops. The manual detection of palm leaf nutrient deficiency can be one of the challenges as the visual symptoms of the deficiency demonstrate a similar representation. Thus, in this study, the palm leaf nutrient deficiency detection using Convolutional Neural Network (CNN) is proposed. CNN or ConvNet is a branch of deep neural networks in Deep Learning that is commonly used in analysing images and has proven to produce better feature extraction from dataset. A total of 350 images of healthy leaf and six types of palm leaf nutrient deficiency are Nitrogen, Potassium, Magnesium, Boron, Zinc, and Manganese were tested. The application of CNN to a variety of testing datasets returned good detection accuracy at 94.29%. It can be deduced that the proposed implementation of CNN for palm leaf nutrient deficiency detection is found to be successful. Nonetheless, the number of datasets could be increased in the future to improve the detection performance.

Keywords: Palm leaf, Nutrient deficiency, Detection, Convolutional Neural Network (CNN).

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1. Introduction

Palm oil is marketed with a variety of names, including palmate, palmitate, and glyceryl. Palm oil is derived primarily from the tropical African palm species named Elaesis guineensis. Oil palm is the most cost-effective of all vegetable oil crops. It has the ability to produce five times the amount of soybean oil. Palm oil contains nutritional advantages such as carotenoids [20]. Numerous criteria need to be considered when planting a plant . A plant's ability to grow is dependent on its ability to obtain sufficient nutrients. One of the most critical factors in maintaining a plant's health and quality is nutrient. Plant quality is related to physical features that define the appearance of the plant, as well as chemistry, including nutrient balance [12].

A plant with a natural deficiency exhibits a variety of symptoms. The palm oil leaves change colour, which is one of the plant's apparent symptoms. Nutrient deficiencies and toxicities can be seen first on the leaves [13]. The plant leaves exhibit characteristic changes when suffering from deficiencies [7]. Shraddha et al. [16] determined that it serves additional purpose in addition to bettering growth. Nitrogen, for example, seems to be an essential element in maintaining a clean environment.

The traditional method of manual nutrient deficiency detection and diagnosis has significant drawbacks. A farmer must have a basic theoretical understanding of nutritional deficiencies as well as practical knowledge in recognizing symptoms in the field [11]. Only the experts could identify a nutrient like phosphorus through observation of morphological changes of leaves, making observations by local residents or those without knowledge difficult [9]. One of the difficulties is detecting and diagnosing nutritional deficiency based on leaf appearance. Although each nutrient deficiency has its own set of symptoms, certain nutrients have visually comparable signs [6]. An experienced farmer can easily diagnose the leaf, but a novice farmer may need to acquire an expert to monitor the plant's deficiency on a constant monitoring [5].

The agriculturists could diagnose the nutrient deficiency in plants based on their experience. They are capable of detecting and distinguishing plant diseases and deficiencies using visual information such as leaf colour. However, it requires a lot of time since the expert needs to examine the leaf's pattern in determining whether the leaf possesses nutrient deficiency symptoms before a diagnosis could be made. Furthermore, hiring an expert to monitor plant deficiencies on a constant basis is incredibly expensive [5]. As a result, an automated approach for detecting nutrient deficiency through the leaf is gaining an attention.

Image processing, on the other hand, is used to improve, modify, compress, extract information, and transform images into multivariate signals [19]. It is employed in a variety of applications, such as improving the appearance of an image to a human observer or preparing the measurement of structure and features revealed by the image [14]. Digital image processing is widely used in various of fields and has become cost-effective in research, industry, and military applications [2].

A convolutional neural network, often known as CNN or ConvNet, is a kind of deep neural network that is frequently used in image analysis [21]. The rationale seems to be due to the enormous model capacity and complex information, CNN's basic structural characteristics enable it to have an advantage in image recognition. CNNs may recognise visual patterns from images with minimal processing [17]. The architecture of CNNs differs from other neural networks. CNNs are employed in a variety of applications, including object detection, speech recognition, language translation, to name a few [18]. CNNs are made up of an input and an output with a number of hidden layers in between. Convolutional layer, ReLU layer, pooling layer, fully connected layer, and normalisation layer are the hidden layers [22]. The ability to solve the image's ruggedness to shifts and distortion is one of the CNN's advantages. However, the CNN's drawbacks is the consistently increased network size as a result of the substantially increased consumption of computational resources [15].

Recent advancements in agricultural technology have prompted a call for a new era of automated, non-destructive plant disease detection technologies. As a result, a variety of approaches have focused on computer vision and machine learning techniques to develop a quick way for detecting plant diseases at the onset of symptoms. A study on tomato leaf disease classification based on the condition of the leaf presentation was conducted by Ashqar and Abu-Naser [4], employing the CNN. There were two types of models used: a full-color model and a grey-scale model. The tomato leaf dataset were derived from the well-known plantVillage dataset. A total of 9,000 images of healthy and diseased tomato leaves were used in the study. The research achieves 99.84% for the full-color model and 95.54% of accuracy for the grey-scale model.

Nachtigall and Araujo [10] presented their research on the detection and classification of apple tree disorders in three different apple tree species: Maxigala, Fuji Suprema, and Pink Lady. They used labelled images of five different types of disorders that commonly affect apple orchards. The CNN was used, and the data was divided into three categories: training, validation, and testing. The CNN was built, trained, and tested with the use of the Caffe and DIGITS tools. The AlexNet architecture produced the greatest results over the validation set. They employed three strategies in order to correctly diagnose each problem. The first is image data consisting of 100 images with chemical analysis in order to measure the number of nutrient concentrations. The chemical analysis was also applied to disease damage and herbicide damage. The CNN was monitored to return a strong accuracy at 97.3%.

Amara et al. [3] implemented a deep learning-based strategy to identify and classify image data to detect banana leaf disease. They classified the image data set using LeNet architecture, as a convolutional neural network, and stored the data in either global or local repositories comprising a large number of images of healthy and diseased leaves. A total of 3700 images were collected, including 1643 healthy leaf images, 240 images of black sigatoka illness, and 1817 images of black speckle disease. The experimental results returned 98.61% of accuracy for 80:20 data separation.

Several deep learning-based plant disease and pest detection technologies have been used in real-world agriculture, and some domestic and international enterprises have produced a variety of deep learning-based plant disease and pest detection software [8]. As a result, a deep learning-based system for detecting plant diseases and pests offers significant academic research value as well as a large business application potential. Therefore, in this research, CNN is proposed for detecting the palm leaf nutrient deficiency. The study is expected to contribute in agriculture field for faster and cheaper way of palm leaf nutrient deficiency detection. The remainder of this paper is organized as follows: Section 2 describes our research method, as well as the image datasets and the CNN structure. Our findings and discussions are presented in Section 3. Finally, in Section 4, we present our conclusions.

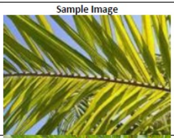
2. METHODS

The in-depth process flowchart for palm leaf nutrient deficiency detection using CNN technique begins with input image which is the palm leaf nutrient deficiency. The image will then go through the pre-processing which involved the training of data. The CNN detection process is then carried out, which consists of three layer processes: convolutional, pooling, and fully connected layer processes. The third step is performance evaluation, which is used to assess how well the CNN detects nutrient deficiency in palm leaves.

2.1. Palm Leaf Nutrient Deficiency Image

A total of 350 images of palm leaf nutrient deficiency were collected. The healthy leaf and six types of palm leaf nutrient deficiency are Nitrogen, Potassium, Magnesium, Boron, Zinc, and Manganese. Table 1 tabulates the sample images of the palm leaf nutrient deficiency as mentioned.

Table 1: Sample of Datasets

Type of Nutrient Deficiencies	Sample Image	Total no. of images
Nitrogen		50
Potassium		50
Magnesium		50
Boron		50
Zinc		50
Manganese		50
Healthy		50

2.2. Training Data

The training data process was carried out using a pre-trained CNN called Resnet-50. The ResNet-50 is a CNN network contain 50 layers deep. Figure 1 shows the first layer in the ResNet-50.

2.3. Convolutional Layer

In the convolutional layer, the features of images were extracted. The dot product between the filter pixel and the input pixel using the image that has previously been filtered to the raw pixel value in the red, green, and blue colour channels were then calculated. The convolutional layers encode numerous lower-level features in a spatially context aware manner for better discriminate features. Convolutional layers comprise filters that transform an image into a different pattern. The network learning filters were activated when the comparable features in the input were discovered. The CNN

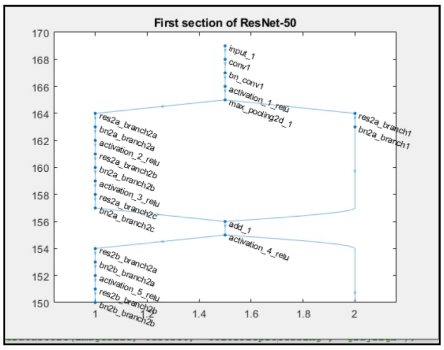


Figure 1: First layer of ResNet-50

learned the value of these filters during the training process. After the convolutional layer, a non-linearity layer was applied. It was utilised to modify and cut-off the output that was generated. This layer was used to saturate or limit the output of the generator. The Rectified Linear Unit (ReLU) was chosen as it has a more straightforward function and gradient formulation.

2.4. Pooling Layer

The dimensionality of image data from a leaf image was reduced using a pooling layer. Pooling is often used to improve the feature position invariance. On the other hand, the maximum pooling was used in most CNN subsampling strategies to separate the convolutional layer output data into a small grid. Then it builds a small image matrix using the maximum number from each grid. The CNN pooling layer was specifically used in reducing image size and could also be used to improve the efficiency with the usage of non-equal filters and strides.

2.5. Fully Connected Layer

The neuron was set up in a traditional neural network, with intentions to adjust the information measurement such that the data may be classified linearly. Each node in the preceding and subsequent layers was linked to each other. From the fully connected layer, every node in the pooling layer is connected as a vector to the main layer. These were the most commonly used CNN parameters inside these layers, despite took a long time to prepare. As this process allows spatial information loss and is not reversible, the fully connected layer must be updated towards the end of the network.

2.6. Performance Evaluation

The data is split into two categories: training, and testing. The training and testing datasets are split in a 75:25 ratio as in [1], with each dataset weighing in at 40 and 10 respectively. The palm leaf nutrient deficiency detection testing results were presented using confusion matrix. Based on the confusion matrix obtained, the classification accuracy, sensitivity and specificity rate for each palm leaf nutrient deficiency were computed using Eq. (2.1), Eq. (2.2), and Eq. (2.3) respectively. The accuracy is used to measure both true positive (TP) and true negative (TN) over the total values of TP, false positive (FP), false negative (FN), and TN rate. The sensitivity rate was calculated using the TP, whereas the specificity rate was computed by the TN rate.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{2.1}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{2.2}$$

$$Specificity = \frac{TN}{TN + FP} \tag{2.3}$$

3. Results

A total of 70 palm leaf nutrient deficiency images for healthy leaf and six types of palm leaf nutrient deficiency which are Nitrogen, Potassium, Magnesium, Boron, Zinc, and Manganese were tested. The confusion matrix constructed from the results of accuracy testing is tabulated in Table 2.

It is indeed important to note that the values in Table 2 with the diagonal pattern show the correct palm leaf nutrient deficiency detection. It can be observed that eight Nitrogen images were

Table 2: Confusion matrix of CNN Detection

		CNN palm leaf nutrient deficiency						
		Nitrogen	Potassium	Magnesium	Boron	Zinc	Manganese	Healthy
Actual palm leaf nutrient deficiency	Nitrogen	8 (TRUE)	0	2 (FALSE)	0	0	0	0
	Potassium	0	8 (TRUE)	0	0	0	0	2 (FALSE)
	Magnesium	3 (FALSE)	0	7 (TRUE)	0	0	0	0
	Boron	0	0	0	7 (TRUE)	0	0	3 (FALSE)
	Zinc	0	0	0	1 (FALSE)	8 (TRUE)	0	1 (FALSE)
	Manganese	0	0	0	2 (FALSE)	0	8 (TRUE)	0
	Healthy	0	0	0	0	0	0	10 (TRUE)

Table 3: Confusion matrix summary of CNN Detection

	Nitrogen	**Potassium**	**Magnesium**	**Boron**	**Zinc**	**Manganese**	**Healthy**
True Positive	8	8	7	7	8	8	10
True Negative	57	60	58	57	60	60	54
False Positive	3	0	2	3	0	0	6
False Negative	2	2	3	3	2	2	0

correctly detected as Nitrogen, whereas two images were incorrectly detected as Magnesium. Next, eight Potassium images were accurately identified as Potassium, while two images were wrongly labelled as Healthy. The Magnesium, on the other hand, detected seven times correctly and three times incorrectly detected as Nitrogen. The Boron yielded seven correct detections and three were incorrectly detected as Healthy. Zinc then returned eight correct and one incorrect detection as Boron and Healthy, respectively. Manganese yielded eight valid detections, whereas two images were incorrectly detected as Boron. Finally, the healthy leaf was monitored to produce an excellent detection of all 10 testing images. As a result, Table 3 tabulates the confusion matrix summary for each nutrient deficiency in palm leaves. The computed percentages of accuracy, sensitivity, and specificity are then presented in Table 4.

From Table 4, the Potassium, Zinc, and Manganese were monitored to return the highest percentages for accuracy at 97.14%. It was then followed by the Nitrogen and Magnesium which returned 92.86% of accuracy. The Boron and Healthy produced the lowest percentages of accuracy at 91.43% respectively. This is due to the high number of incorrect detections for both False Positive and False negative rates. The Healthy was observed to produce an excellent percentage of sensitivity at 100%. The Nitrogen, Potassium, Zinc, and Manganese produced good detection results at 80% of sensitivity. However, the Magnesium and Boron were found to return slightly lower percentages of

Table 4: Summary of Accuracy, Sensitivity, and Specificity Result

Palm leaf nutrient deficiency	**Accuracy (%)**	**Sensitivity (%)**	**Specificity (%)**
Nitrogen	92.86	80	95
Potassiumt	97.14	80	100
Magnesium	92.86	70	96.7
Boron	91.43	70	95
Zinc	97.14	80	100
Manganese	97.14	80	100
Healthy	91.43	100	90
MEAN	**94.29**	**80**	**96.67**

sensitivity at 70% correspondingly. This could be caused by the wrong detection of the Magnesium and Boron with the other similar presentation of nutrient deficiency such as Nitrogen. For specificity, the Potassium, Zinc, and Manganese recorded excellent percentage at 100%. It was followed by the Magnesium (96.7%), Nitrogen (95%), Boron (95%), and Healthy (90%). The overall mean percentage of accuracy, sensitivity, and specificity demonstrated a very strong accuracy which are 94.29%, 80%, and 96.67% correspondingly.

4. Conclusion

A study on palm leaf nutrient deficiency detection using the Convolutional Neural Network (CNN) technique was presented. The Nitrogen, Potassium, Magnesium, Boron, Zinc, and Manganese are the six categories of nutritional deficiency in palm leaves investigated in this research. The application was successful on 350 different image datasets. A confusion matrix was used to evaluate the performance of palm leaf nutrient deficiency detection. The overall mean percentages of accuracy, sensitivity, and specificity indicated promising performance at 94.29%, 80%, and 96.67%, correspondingly. It could therefore be concluded that the proposed palm leaf nutrient deficiency detection using CNN is reliable.

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