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Classification of Nutrient Deficiencies Based on Leaf Image in Hydroponic Lettuce using MobileNet Architecture

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ABSTRAK

Saat ini sektor industri di Indonesia tumbuh semakin pesat yang menggeser lahan pertanian menjadi sempit. Hal tersebut mengakibatkan para petani perlu mencari lahan lain untuk tetap dapat memproduksi bahan pangannya. Hidroponik merupakan teknik bertanam menggunakan media air yang memanfaatkan lahan sempit. Salah satu tanaman yang sering diterapkan ialah tanaman selada. Namun, dengan penerapan teknik hidroponik ini masih terdapat kualitas tanaman selada yang kurang baik karena kurang memperhatikan pemeliharaannya sehingga mengakibatkan kurangnya nutrisi pada tanaman selada. Maka dari itu, pada penelitian ini akan membuat sistem klasifikasi defisiensi nutrisi pada tanaman hidroponik selada melalui citra daun dengan menggunakan Convolutional Neural Network (CNN) berbasis arsitektur MobileNetV2. Hasil dalam skenario uji penelitian ini memperoleh akurasi sebesar 88%. Dengan begitu, diharapkan dapat membantu para petani untuk mengetahui defisiensi nutrisi pada tanaman selada agar tetap dapat menjaga kualitas produksi tanaman selada.

Kata kunci*: CNN, hidroponik, MobileNetV2, nutrisi, selada*

ABSTRACT

Currently the industrial sector in Indonesia is growing rapidly which shifts agricultural land to narrow. This resulted in farmers needing to look for other land to continue to be able to produce their food. Hydroponics is a farming technique using water media that utilizes narrow land. One of the plants that is often used is lettuce. However, with the application of this hydroponic technique, the quality of lettuce plants is still not good due to lack of attention to maintenance, resulting in a lack of nutrition in lettuce plants. Therefore, this research will create a nutritional deficiency classification system in hydroponic lettuce through leaf images using a Convolutional Neural Network (CNN) based on the MobileNetV2 architecture. The results in this research test scenario obtained an accuracy of 88%. That way, it is hoped that it can help farmers to find out nutritional deficiencies in lettuce plants so that they can maintain the quality of lettuce production.

Keywords*: CNN, hydroponic, lettuce, MobileNetV2, nutrition*

1. INTRODUCTION

Agriculture is a very important sector for humans because it is directly related to food production. This proves that the majority of Indonesian people work as farmers to maintain their food security. But as technology develops, the industrial sector in Indonesia grows rapidly which then shifts agricultural land to narrow. Hydroponics is a farming technique using water media as a substitute for soil used to grow vegetables by emphasizing the fulfillment of nutrients for plants while utilizing narrow land **(Kannan et al., 2022)**.The nutrients contained in hydroponics are substances needed by hydroponic plants so that the quality of the plants is maintained **(Sulmi, 2022)**. One of the plants that is often applied using hydroponic techniques is lettuce (*Lactuva Sativa L.*). Lettuce plants are known for their rich nutrition and content, including fiber, vitamin A and high mineral content **(Shatilov et al., 2019)**. The natural fiber content in lettuce can also maintain the health of the digestive tract. Therefore, lettuce is often used as a complementary vegetable that is eaten raw, in salads and served in a variety of other dishes. With the increase in population and public awareness of nutritional value, public interest in lettuce production is increasing **(Romalasari & Sobari, 2019)**.

Even though lettuce plants are known to be rich in natural nutrients, it is not uncommon for farmers or people who apply this hydroponic technique to still get poor quality lettuce plants because they pay less attention to their maintenance resulting in a lack of nutrients in lettuce plants. This is a record for farmers and the community that lettuce plants need regular maintenance properly to get nutritional input from outside. Nutritional deficiencies in lettuce consist of Nitrogen Deficiency (minN), Phosphorus Deficiency (minPH) and Potassium Deficiency (minPO), which are similar to one another, so manual classification tends to be subjective. Several studies have proposed a nutritional classification based on leaves. Lili Ayu Wulandhari et al., detected nutritional deficiencies in okra plants using the Inception-ResNetV2 architecture **(Wulandhari et al., 2019)**. To help farmers and the community, needed a classification using the right technology to find out the nutritional deficiencies that exist in these hydroponic lettuce plants. One method of deep learning is the Convolutional Neural Network (CNN) which functions to detect and process data of an object in images. CNN is a development of Multilayer Perceptron (MLP), which is a type of neural network used for processing image data. The ability of the CNN method has been recognized as the best model for analyzing a problem in object detection and object recognition **(Ren et al., 2018)**. This CNN method can have tens to hundreds of layers, each layer detecting various images. Thus, CNN has a good performance value in agriculture for the detection, classification and identification of a disease in plants. MobileNet is one of the CNN architectures that is often used to detect objects in an image. The advantages of MobileNet include low cost, stability, and high precision **(Michele et al., 2019).**

Based on these problems, this research will create a system to classify nutrient deficiencies in hydroponic lettuce plants using CNN with MobileNetV2 architecture. MobileNetV2 was chosen because it produces high accuracy as reported in a study by Viet Dang **(Dang, 2022)**. The classification of lettuce deficiency is divided into 2 scenarios, including 4 deficiency categories: Full Nutrition (FN), minN, minPH and minPO as well as 2 deficiency categories, namely: Healthy (FN) and Unhealthy (minN, minPH, minPO). This classification is carried out to identify nutritional deficiency problems that occur in lettuce plants. The purpose of this study is to be able to determine nutritional deficiencies in hydroponic lettuce plants in 2 scenarios and to help farmers or the public in the process of classifying nutrient deficiencies found in hydroponic lettuce plants through leaf images and maintain the quality of hydroponic lettuce production.

2. METHODS

In this study, a design was carried out regarding the application of the CNN method based on the MobileNetV2 architecture for the classification of nutritional deficiencies in hydroponic lettuce plants based on leaf images. The performance of this system is measured based on measuring parameters which include precision, recall, F1 – score and accuracy. The design flow of this system can be seen in Figure 1.

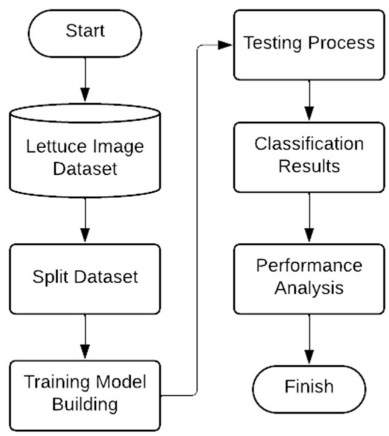

Figure 1. Flowchart of The Proposed System

Based on Figure 1, the following is an explanation of the several stages carried out in this study:

2.1 Lettuce Image Dataset

The data collection for this study was taken from the Kaggle website created by Rami Malik **(Malik, 2022)** and Kritik Seth **(Seth, 2022)**, as well as from the Roboflow website created by Adam Dika Lazuardi **(Lazuardi, 2021)**. Data is grouped into 2 comparison scenarios between 4 deficiency categories: Full Nutrition (FN), Nitrogen Deficiency (minN), Phosphorus Deficiency (minPH) and Potassium Deficiency (minPO) with each class totaling 66 images, so the total data is 264 images with 2 deficiency categories, namely: Healthy (H) and Unhealthy (NH) with each class totaling 66 images, so that the total data is 132 images. The example images of the nutritional deficiency categories can be seen in Figure 2, Figure 3, and Figure 4.

(a) **(b)** **(c)** **(d)**

Figure 2. Lettuce Plant Nutrient; (a) Full Nutrition, (b) Nitrogen Deficiency, (c) Phosphorus Deficiency and (d) Potassium Deficiency

Figure 3. Nutrition Deficiencies of Healthy Lettuce Plants

Figure 4. Nutrient Deficiencies of Unhealthy Lettuce Plants

The dataset is entered into Google Drive by creating a folder according to the contents of the dataset class. The dataset on Google Drive is linked to Google Collab as the platform that is used in this research. Google Collab runs program code more flexibly and the GPU is free, so it can collaborate with other users **(Carneiro et al., 2018).**

2.2 Split Dataset

The dataset that has been entered in Google Collab will carry out the process of splitting data on the system randomly divided into 3 stages, namely training data, validation data and random testing data. The training data is used for the model training process on the dataset. Validation data is used to evaluate and optimize model performance from datasets during the training process. While the test data is used for the last test using separate data and is not used during the training or validation process.

2.3 Training Model Building

After the dataset has been divided into 3 stages randomly, the dataset will go through training process. This training model is used to perform the model training process using CNN-based MobileNetV2 architecture. The model training process goes through convolution stages, non-linear activation functions, full connection layer, average pooling, and classification **(Altim et al., 2022).** The stages of data processing are shown in Table 1.

Table 1. MobileNetV2 Architecture

Input	Operator	*t*	*c*	*n*	*s*
$224^2 \times 3$	conv2d	-	32	1	2
$112^2 \times 32$	bottleneck	1	16	1	1
$112^2 \times 16$	bottleneck	6	24	2	2
$56^2 \times 24$	bottleneck	6	32	3	2
$28^2 \times 32$	bottleneck	6	64	4	2
$14^2 \times 64$	bottleneck	6	96	3	1
$14^2 \times 96$	bottleneck	6	160	3	2
$7^2 \times 160$	bottleneck	6	320	1	1
$7^2 \times 320$	conv2d 1x1	-	1280	1	1
$7^2 \times 1280$	avgpool 7x7	-	-	1	-
$1 \times 1 \times 1280$	conv2d 1x1	-	k	-	-

Based on Table 1, the model training process has several stages. In this training process, the model will perform a convolution operation on two-dimensional input to process input features by studying relevant patterns in the data. This process helps the model to understand and extract the required essential features. Then enter the bottleneck layer or inverted residual block to reduce the channel dimensions and computational complexity in the residual block resulting in a lighter and more efficient model without sacrificing important feature representation. Then the process of merging the average with the kernel size 7 x 7 scanned on the input features and the average value in the kernel is taken as the output values. This training process takes a long time to obtain an identification model because of the large number of images that must be processed **(Ramaidani et al., 2022).**

2.4 Testing Process

After the training process is carried out, the model then enters the testing process. Before entering the testing process, the model has gone through a validation process to evaluate and optimize the performance of the model from the dataset during the training process. The results of the model pattern on training will be tested to measure accuracy. If the test results show a high loss value, then the training will be run again. The results of this training and testing process will result in a classification of nutrient deficiencies in lettuce plants **(Nasrullah & Annur, 2023).**

2.5 Performance Analysis

After the data is trained, validated and tested, the data can be analyzed to determine the final result of the classification of lettuce plant nutritional deficiencies. The results of this analysis can show a fairly high accuracy in classifying nutrient deficiencies in lettuce plants. However, if it turns out that the results of the analysis show that the accuracy results are not good, then the model needs to be tested again starting from the data processing stage by changing the change in value.

3. RESULTS AND DISCUSSION

In this research, 80% of the dataset was used for the training process and 20% for the testing process with 66 images for each class, so the total amount of the data is 264 images. The use of this number of datasets is sufficient for the process of classifying nutrient deficiencies in hydroponic lettuce plants with the availability of existing data and resources. A dataset with a similar number of images in each class serves to prevent bias in the model. The input dimensions of the dataset are adjusted to an image measuring 224 x 224 pixels and 3 RGB color channels in jpg format. The results of the accuracy of the testing process on the dataset using the model that has been built can be seen in Table 2.

Table 2. Data Accuracy Test Results

No.	Categories	Valid	Fault	Total
1.	Full Nutrition (FN)	13	2	15
2.	Nitrogen Deficiency (minN)	13	2	15
3.	Phosphorus Deficiency (minPH)	10	5	15
4.	Potassium Deficiency (minPO)	15	0	15
	Total	**51**	**9**	**60**
	Accuracy		**85%**	

Based on Table 2, the results of the accuracy of the model that has been tested is 85%. Then it can also be seen in Figure 5, that the system can classify nutrient deficiency in lettuce plants well and show an accuracy percentage result of 34.01% along with the category of nutrient deficiency detected is FN.

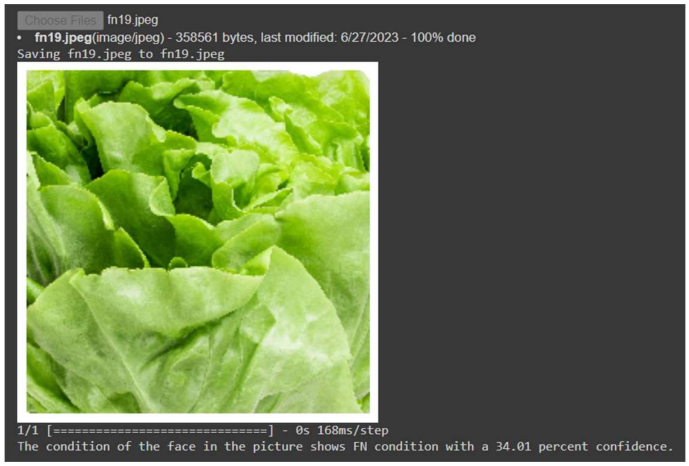

Figure 5. Results of The Classification of Nutrient Deficiencies in Lettuce Plants

However, sometimes the system can misclassify nutritional deficiencies in the dataset because they have almost the same characteristics or patterns. But the system can still distinguish them because the datasets provided are numerous and specific. This can be seen in Figure 6.

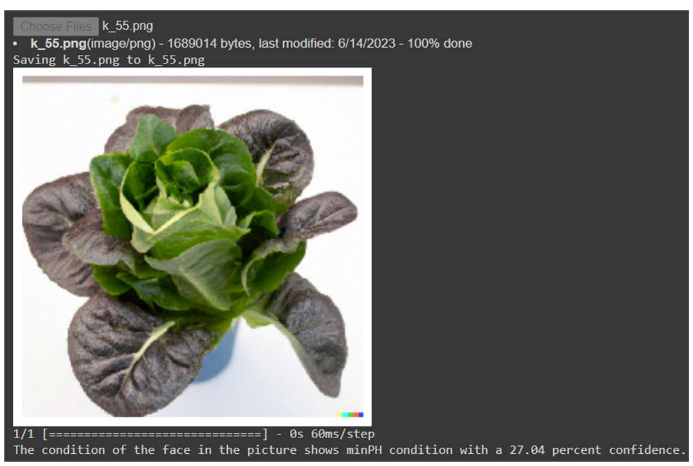

Figure 6. Incorrect Results of Lettuce Plant Nutrient Deficiency Classification

It can be seen in Figure 6, that the system for classifying uploaded data images shows the result of the deficiency category is minPH with an accuracy percentage of 27.04%. In this test case, the system misclassifies nutritional deficiencies in lettuce because the pattern in the uploaded data image has the same pattern as the minPH deficiency category pattern.

In this study, a comparison scenario was also made between 4 classes of nutritional deficiencies of lettuce (FN, minN, minPH, minPO) and 2 classes of nutritional deficiencies of lettuce (Healthy and Unhealthy). The purpose of this comparative study between the 2 classes is to see which class data images have more accurate accuracy. The results of testing the classification of nutritional deficiencies in lettuce in 2 classes can be seen in Table 3.

Table 3. Accuracy Test Results in 2 Classes

No.	Categories	Valid	Fault	Total
1.	Healthy (H)	11	2	15
2.	Unhealthy (NH)	14	1	15
	Total	**25**	**3**	**30**
	Accuracy		**88%**	

Based on Table 3, the results of the accuracy of the classification of nutritional deficiencies in lettuce in 2 classes is 88%. Then in Figure 7, the system for classifying uploaded data images shows the results of the NH deficiency category with an accuracy percentage of 52.42%. This shows that the system can classify nutritional deficiencies in lettuce plants more accurately because the patterns in the 2 classes of deficiencies are more easily recognized.

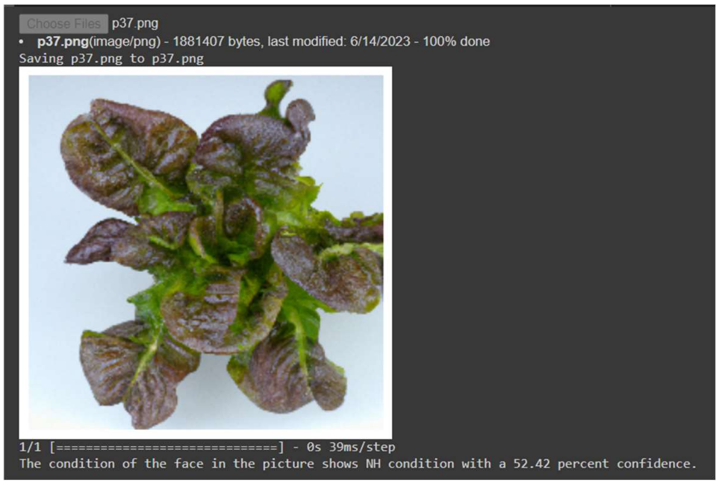

Figure 7. Results of the Classification of Unhealthy Lettuce Nutrient Deficiencies

After the data has gone through the stages of training, validation and testing, the resulting data will become a model that will be used to classify nutritional deficiencies in lettuce plants. A good classification result is when the system can recognize and classify nutrient deficiencies with high accuracy and is relevant to the state of the plant **(Felix et al., 2020)**. This can be seen from the results of measuring parameters such as precision, recall, F1 – score and accuracy.

The total loss that appears on the system also needs to be considered. So when the training process takes place, try to lose the loss value less than one. Because according to previous research **(Ilahiyah & Nilogiri, 2018).** During the training process, the total loss or error value must be less than one because it will affect the detection accuracy. The total loss in the classification of nutritional deficiencies in lettuce can be seen in Figure 8.

```
5/5 [==============================] - 5s 1s/step - loss: 0.4118 - accuracy: 0.9655
Train Loss: 0.41175857186317444
Train Accuracy: 0.9655172228813171
3/3 [==============================] - 2s 600ms/step - loss: 0.6186 - accuracy: 0.8462
Val Loss: 0.6185849905014038
Val Accuracy: 0.8461538553237915
2/2 [==============================] - 2s 830ms/step - loss: 0.6769 - accuracy: 0.8519
Test Loss: 0.6768553256988525
Test Accuracy: 0.8518518805503845
```

Figure 8. Total Loss Classification of Nutrient Deficiencies in Lettuce Plants

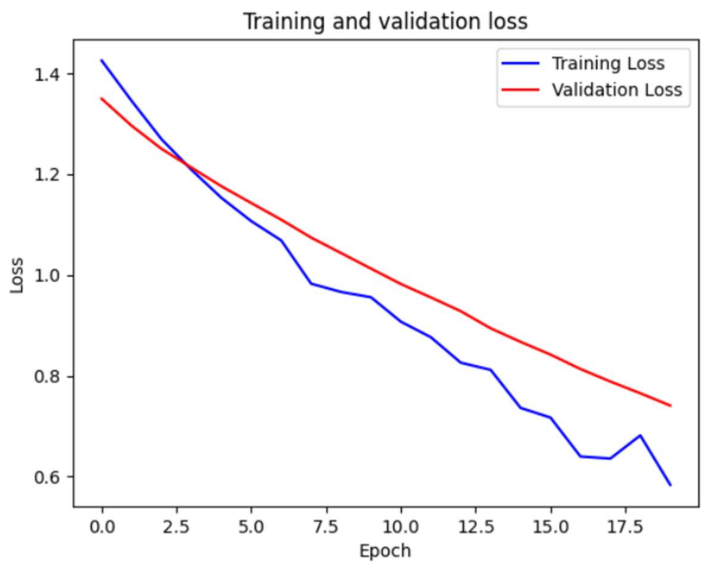

Figure 9. Total Loss Chart

Based on Figure 9, the training process is carried out in 20 epochs and takes 4 minutes using the GPU as a place to process data. The smaller the loss value, the more accurate the system is in detecting an object **(Riswandi et al., 2021)**. The graph results show that in the first step it shows a very high loss value. But the more steps are used, the value of the loss decreases. This shows that the system can recognize object patterns in lettuce nutrient deficiencies.

Table 4. Performance Comparison with Previous Study

Data Train	Data Test	Class	Accuracy	Methods
412	53	2	69.81%	Faster R-CNN with Inception V2 **(Pratama et al, 2020)**
412	53	2	75,47%	Faster R-CNN YOLO **(Pratama et al, 2020)**
184	47	2	86.00%	Inception ResNet-v2 **(Wulandhari et al, 2019)**
72	27	2	88.00%	**MobileNetV2 (proposed)**
145	54	4	85.00%	**MobileNetV2 (proposed)**

In this study, a comparison of method performance with previous research was also carried out as shown in Table 4. It can be analyzed that in this study by having the same number of classes, namely 2 classes and less training data, it can show higher accuracy results by 88% using the MobileNetV2 architecture.

4. CONCLUSION

In this study the system has succeeded in classifying nutrient deficiencies in hydroponic lettuce plants. Research on the classification of nutritional deficiencies in lettuce plants is divided into 2 scenarios for comparison of which class data images have more accurate accuracy. The first scenario is divided into 4 nutritional deficiency categories, namely Full Nutrition (FN), Nitrogen Deficiency (minN), Phosphorus Deficiency (minPH) and Potassium Deficiency (minPO) with the results of its testing accuracy of 85%. Then the second scenario is divided into 2 nutritional deficiency categories, namely Healthy (H) and Unhealthy (NH) with the result of the accuracy of the test that is owned by 88%. The classification of nutritional deficiencies in 2 classes shows higher accuracy results compared to the classification of nutritional deficiencies in 4 classes. Theres 80% of the dataset was used for the training process and 20% for the testing process. The use of this number of datasets is sufficient for the process of classifying nutrient deficiencies in hydroponic lettuce plants with the availability of existing data and resources. A dataset with a similar number of images in each class serves to prevent bias in the model. The implementation of the MobileNetV2 architecture can detect nutritional deficiencies quite accurately. This research was conducted in 20 epochs with a batch size of 32 and the activation function used was ReLU. It is hoped that the system that has been built can help farmers and the public to find out nutritional deficiencies in hydroponic lettuce plants and maintain the quality of hydroponic lettuce production.

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