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Application of pest detection on vegetable crops using the cnn algorithm as a smart farm innovation to realize food security in the 4.0 era

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ABSTRACT

Pests and diseases are one of the factors that become obstacles in the cultivation of vegetables because they can cause a decrease in the quality and quantity of production. The more varied types of pests have different impacts on crops, so if farmers incorrectly identify the class of pests, the treatment will be ineffective. Therefore, we need a technology that can classify the types of pests on vegetable crops to maintain the quality and quality of the product as well as the abundant harvest. The classification model of pests on vegetables using the deep learning method using the Convolutional Neural Network (CNN) algorithm with a high level of accuracy is the solution to this problem. The application of artificial intelligence in the agricultural sector also supports smart agriculture in Indonesia. Based on the research that has been carried out, the application of pest classification on vegetable crops made by applying the CNN model using the Inception V3 - k-fold cross validation method has a test accuracy rate of 99%, meaning that the application can perform pest classification correctly.

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1. INTRODUCTION

Vegetable crops are one of the essential commodities in Indonesia, with a relatively high production level. In 2018, Indonesia's most significant vegetable production reached 1.5 million tons of shallots, 1.42 million tons of cabbage, 1.34 for cayenne pepper, 1.28 for potatoes, and 1.21 million tons of large chilies [1]. However, pest and disease attacks are still one of the factors that become obstacles in the cultivation of vegetable crops because they can cause a decrease in production yields. Conventional pest classification methods make the process of classifying pests and diseases by farmers very complex, inefficient, and prone to errors, so the results are inaccurate [2]. The more varied types of pests have different impacts on crops, so if farmers incorrectly identify the class of pests, the treatment will be ineffective [2]. The practical and timely detection, identification, and localization of pests is a real challenge associated with precision agriculture. Addressing these challenges will allow appropriate action to be taken to contain the damage caused while helping to reduce the need for pesticides [3], [4]. Therefore, we need a technology that can classify the types of pests on vegetable crops to maintain the quality and quality of the product as well as an abundant harvest.

Technological developments in the 4.0 era gave birth to great potential for more advanced technological developments in agriculture, one of which is smart farming (smart agriculture). Agriculture 4.0 develops with several innovative technologies such as big data, machine learning, deep learning, intelligence swarm, internet-of-things, blockchain, Generative Adversarial Network (GAN), robotics and autonomous systems, cyber-physical systems, and cloud-fog computing edge [5], [6]. Several techniques should be integrated to develop intelligent farming systems, such as crop production, food sharing, mass farming, real-time data collection, and processing. Therefore, the transformation of intelligent agriculture will lead to the development of the whole ecosystem with modern agricultural management. In real-time, decision support systems can improve productivity, resource allocation, climate change adaptability, food supply chains, and computer vision [7]–[9].

The agricultural industry is one sector that can implement artificial intelligence technology. This technology offers various conveniences for users through various learning and optimization techniques with the concepts of machine learning and swarms intelligence [10]. Therefore, creating an artificial intelligence system that can detect various types of pests is considered very helpful for farmers to identify pests on vegetable crops through leaf imagery and classify them into several categories. Techniques that use image-based systems and artificial intelligence are starting to be applied due to the considerable visual changes caused by most diseases in plants' leaves, fruit, and stems [11], [12].

Computer vision is a field of artificial intelligence that aims to offer machine vision capabilities. The field of computer vision has presented solutions and applications relevant to agriculture, offering an independent and effective method for cultivating various crops [13]. Researchers have studied pest control extensively, and it is possible to find in the literature several applications using computer vision for pest and disease detection [14]. One artificial intelligence system that can classify images is a deep learning technique with the Convolutional Neural Network (CNN) algorithm. The use of the CNN method is considered suitable in the case of pest identification because the process becomes more effective in feature extraction and produces a significant level of accuracy because it is devoted to unstructured data such as images and has been widely implemented in image data [15], [16].

Research on the diagnosis of pests and diseases in plants has previously been carried out using the CNN algorithm by Rezk et al [17] in his research entitled "An Efficient Plant Disease Recognition System Using Hybrid Convolutional Neural Networks (CNNs) and Conditional Random Fields (CRFs) for Smart IoT Applications in Agriculture". This study proposes an efficient IoT-based plant disease recognition system using semantic segmentation methods such as FCN-8 s, CED-Net, SegNet, DeepLabv3, and U-Net with the CRF method to allocate disease parts in leaf plants. Evaluation of this network and comparison with other state art networks. The experimental results and comparisons state the F1 score, sensitivity, and intersection over union (IoU). The proposed system with SegNet and CRF gives a high yield compared to other methods, which is 79%. These results indicate the development of a disease classification system using the CNN algorithm to help farmers.

Previous research on pest detection using the CNN algorithm has also been carried out by Mondal et al. [18] with the research title "Deep learning-based approach to detect and classify signs of crop leaf diseases and pest damage". The best level of accuracy was obtained at 99.62% for the image of tomato leaves and 91.63% for the image of rice leaves. In the identification and classification of tomato leaf diseases, convolutional recurrent neural network architecture with a gated recurrent unit is used. Meanwhile, to classify pest and disease attacks on rice leaves, the concept of transfer learning uses the same model that was trained with the tomato leaf dataset because the rice leaf dataset used is insufficient and unbalanced. Furthermore, it can be concluded that the accuracy value obtained is quite good and can classify nine classes of tomato leaf disease and mite infection along with healthy leaves and two types of each rice leaf disease and pest attack along with healthy leaves.

Based on the results obtained from the two studies above, it can be concluded that the CNN algorithm can be implemented to classify the types of diseases and pests in oil palm and rice plants. Research on the classification of pests and diseases still needs to be improved and expanded the scope of plant variations so that in this paper, research is proposed with the title "Application of pest detection on vegetable crops using the CNN Algorithm as a smart farm innovation to realize food security in the 4.0 era". This study aims to obtain a model for classifying types of pests on vegetable crops with a deep learning method using the CNN algorithm with a high level of accuracy. Through this research, it is hoped that it can help the community determine the types of pests on vegetable crops based on images quickly and accurately. Furthermore, the results of research regarding the exploration of the potential of the CNN algorithm as an image classifier in general can open and broaden horizons for the public and in particular can be used as a basis for researchers in the technology industry to develop an artificial intelligence-based system to support smart agriculture in Indonesia as one of the one of the SDGs goals by 2030.

2. METHOD

Research and prototype development was carried out at the Artificial Intelligence Laboratory, D5 Building, Semarang State University, for two months. The method used in this research is CNN with Inception v3 and VGG16 architecture and applies the k-fold cross-validation procedure. The dataset used is the vegetable pest image dataset which consists of 10 types of pest samples, including armyworm (pest 0), stem borer (pest 1), fruit fly pest (pest 2), soybean pod sucking pest (pest 3), yellow beetles (pest 4), mealybugs (pest 5), green hornworms (pest 6), leaf beetles (pest 7), weevils (pest 8), and brinjal beetles (pest 9). A sampling of the dataset is done online by downloading the data on the www.kaggle.com page.

The data analysis process uses google collaboratory, which applies the python programming language with several libraries, including pandas, scikit-learn, keras, and tensorflow. The pandas library is used to handle a collection of data [19]. The Scikit-learn library was used to analyze experimental data [20]. keras library [21], on top of tensorflow, is used to implement CNN [22].

In this study, 8-fold cross-validation was adopted for the CNN model construction, meaning that 8 data partitioning schemes were used to model the same input data set. A general illustration of the CNN architecture can be seen in Figure 1.

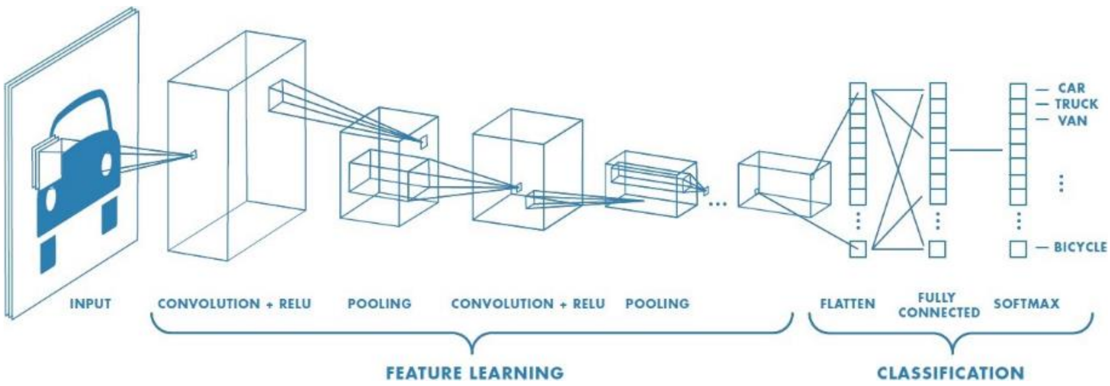

Figure 1. Illustration of CNN architecture in general (source: www.medium.com, 2017)

Based on the picture above, the first stage in the CNN architecture is the convolution stage. Then proceed to the activation function, usually using the Rectifier Linear Unit (ReLU) activation function. After exiting the activation function process, then through the pooling process. This process is repeated several times until a sufficient feature map is obtained to proceed to the fully connected neural network. The output class is from the fully connected network.

The models tested are Inception v3 and VGG16, which are the models found in the Keras application [21]. Inception v3 is a deep learning model with small convolutions, accelerated training speed, and lower computational costs [23]. VGG16 is a CNN model that performs better, consisting of 16 layers [24]. The two deep learning models were trained to classify the types of pests on vegetables using a manually labeled image data set. The image dataset is divided into 50% training data and 50% testing data.

3. RESULTS AND DISCUSSIONS

The CNN algorithm training process to produce a classification model of pest types on vegetable crops involves the vegetable pest image dataset, which is downloaded from the www.kaggle.com page, containing 1,000 data consisting of 100 data on the category of armyworm pests, 100 data on the category of stem borer pests, 100 data for fruit fly pest categories, 100 data for soybean pod sucking pests, 100 data for yellow beetles, 100 for mealybugs, 100 for green hornworms, 100 for leaf beetles, 100 for driving beetles, 100 data for the category of brinjal beetle pests. The CNN model was developed by dividing the dataset into training data and testing data with a training data percentage of 50% and testing data at 50%. The training was carried out using the k-fold cross validation – VGG 16 method and the Inception V3 – k-fold cross validation method with 50 epochs, resulting in training data accuracy reaching 92% and validation data reaching 96%, as shown in Figure 2.

```
Epoch 6/50
14/14 - 5s - loss: 0.7879 - accuracy: 0.8086 - val_loss: 0.4850 - val_accuracy: 0.8600 - 5s/epoch - 360ms/step
Epoch 7/50
14/14 - 6s - loss: 0.6189 - accuracy: 0.8486 - val_loss: 0.4382 - val_accuracy: 0.8600 - 6s/epoch - 416ms/step
Epoch 8/50
14/14 - 7s - loss: 0.5968 - accuracy: 0.8371 - val_loss: 0.3649 - val_accuracy: 0.8600 - 7s/epoch - 470ms/step
Epoch 9/50
14/14 - 5s - loss: 0.4935 - accuracy: 0.8886 - val_loss: 0.2754 - val_accuracy: 0.9000 - 5s/epoch - 357ms/step
Epoch 10/50
14/14 - 5s - loss: 0.4296 - accuracy: 0.8943 - val_loss: 0.3014 - val_accuracy: 0.9000 - 5s/epoch - 353ms/step
Epoch 11/50
14/14 - 5s - loss: 0.3525 - accuracy: 0.9114 - val_loss: 0.2056 - val_accuracy: 0.9600 - 5s/epoch - 357ms/step
Epoch 12/50
14/14 - 5s - loss: 0.3216 - accuracy: 0.9286 - val_loss: 0.2177 - val_accuracy: 0.9600 - 5s/epoch - 354ms/step
Epoch 13/50
14/14 - 5s - loss: 0.3001 - accuracy: 0.9200 - val_loss: 0.1937 - val_accuracy: 0.9600 - 5s/epoch - 359ms/step
Epoch 14/50
```

Figure 2. Data training and data validation

Based on the training process, the highest accuracy results obtained are 100% in the 6th to 8th iterations of the Inception V3 – k-fold cross validation method and 76% in the 3rd iteration of the k-fold cross validation – VGG method. 16. The results of the training dataset in more detail can be seen in Table 1 and Table 2.

Table 1. Results of training with inception v3 method – k-fold cross validation

Fold	Loss	Accuracy
1	0.0306	1.0000
2	0.0286	1.0000
3	0.0299	0.9900
4	0.0514	0.9900
5	0.0400	0.9900
6	0.0261	1.0000
7	0.0286	1.0000
8	0.0225	1.0000

Table 2. Results of training with the k-fold cross validation method – vgg 16

Fold	Loss	Accuracy
1	1.6908	0.6200
2	1.6248	0.6300
3	1.3087	0.7600
4	1.6755	0.6000
5	1.5487	0.6800
6	1.3578	0.7500
7	1.2942	0.7000
8	1.7247	0.6000

Based on the data in the two tables, the Inception V3 – k-fold cross validation method produces better accuracy than the k-fold cross validation – VGG 16 method. Therefore, the Inception V3 – k-fold cross validation method is then applied to pest classification application made. The information on the dashboard of the application consists of variable names of vegetables, types of pests, and pest information. In this system, the user will upload the image that he wants to classify, and the user also needs to input the name of the vegetable into the system for further processing and output according to the available variables.

4. CONCLUSION

Based on the research that has been done, it can be concluded that in making the application of pest classification on vegetable crops using the CNN algorithm, the highest accuracy is 99%, meaning that from 50 samples of the dataset tested on each pest, almost all samples can be classified correctly. By the system. This accuracy result is obtained through modeling using the Inception V3 – k-fold cross validation method, which consists of 8 iterations.

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