GMPI Conference Series, Vol.2, 2023, pp. 52-57
e-ISSN 2829-0747 DOI. 10.53889/gmpics.v2.173

Smart Plant: A Mobile Application for Plant Disease Detection

Submitted 1 May 2022, Revised 30 May 2022, Accepted 30 May 2022

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Abstract

Indonesia is one of the big producers of agricultural products in the world. Agriculture sector plays an important role in the national economic development structure. However, the proportion of young farmers (ages 20 to 30 years old) is only 8% of the farmer population (BPS, 2019). Majority proportion comes from old people with age interval from 50 to 60 years old. (Taufik & Leoni, 2020). Based on our case study in Purwokerto, the problem that is often found by old age farmers is the reduced ability to see and recognize plant diseases. Furthermore, they also face the difficulty to follow the development of agricultural science so that some of their knowledge is outdated. That encourages us to make a mobile application to identify plant disease and connect them with scientists. Since the majority of farmers in Purwokerto plant tomatoes, we limit this research for tomato disease only. After studying some related previous research, we found most of them used a deep structure of Convolutional Neural Network (CNN) to reach a high accuracy. However, since our aim is to make daily use technology for old people, a high complexity model does not fit for this case. Therefore, we proposed our own CNN model with less complexity but got 89% accuracy. For future works, we plan to develop it for the other plants and hope it will help all farmers to do quality control, especially for the old age farmers.

Keywords: Plant Disease; CNN; Image Processing

1. Introduction

The agricultural sector is one of the pillars of our society's economic activities. It is not only as a source of food, but also for foreign exchange (Kusumaningrum, 2019). One of the agricultural sub-sectors that has a strategic role is horticulture which includes vegetables, fruits, ornamental plants, and biopharmaceutical plants. Based on the Survey of Survei Pertanian Antar Sensus (SUTAS), the number of agricultural business households (RTUP) in horticulture is 10,104,683 households and is the fourth largest after households in the food crops, livestock and plantation. However, the number of households is not proportional to the contribution of the horticulture to the 2019 Quarter I Gross Domestic Product (GDP) which is only 1.36 percent or Rp. 126,060.6 billion. This condition indicates that the potential of horticulture has not been optimized, so it is necessary to measure production for several strategic commodities. Horticultural crops have been widely cultivated in Indonesia, but the harvest is still not satisfactory. It is caused by lack of knowledge in cultivation techniques, environmental conditions and pest and disease disturbances. Some people think they do not need a specific high skill or knowledge to be a farmer (Kusumaningrum, 2019). Therefore, some farmers do not know the updated knowledge in agriculture.

Based on data from the Central Statistics Agency (BPS), the number of farmers in Indonesia reached 33.4 million people in 2019. However, only 8% of them come from a young age (20-30 years old) or equivalent to 2.7 million people. Around 30.4 million people or 91% are over 40 years old, with the majority of them approaching 50-60 years old (Hidayatullah and Alvionita, 2020). We studied the effect of this number in

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Purwokerto and found that old farmers have a low ability of vision to notice a plant disease. As a result, they did not get the best quality harvest. Moreover, it is hard for them as old people to learn and follow the updated knowledge and technology in agriculture. This problem motivated us to make an easily used technology that can help old farmers to recognize plant disease and make their knowledge in agriculture no longer outdated.

2. Materials and Method

2.1. Related Works

Plant disease detection is one of the most interesting topics for artificial intelligence engineers in agriculture. There are many kinds of models developed to check whether it could detect the disease correctly and give an early warning for farmers. Ramesh et al (2018) compared 6 traditional machine learning algorithms to classify the healthy and diseased papaya leaves. The advantage of using traditional machine learning is we could identify the important features of each model easily. However, the accuracy of each model is quite low. The highest accuracy reached by Random Forests with only about 70.14%.

Deep learning is a machine learning approach that uses artificial neural networks modeled on the human brain. Many experiments show that deep learning, especially Convolutional Neural Networks (CNN), can reach a higher accuracy than traditional machine learning in image classification. However, this model is not interpretable since the feature selected by the model on the blackbox system (LeCun et al., 2015). Since interpretability is not too important in this case, some researchers prefer to choose deep learning to detect plant disease. Moreover, Liu and Wang reviewed some previous research and found most authors used a deep structure of neural networks to get a very high accuracy. Some of them proposed their own Deep CNN (DCNN) structure and got accuracy more than 95% (Liu and Wang, 2021).

2.2. Proposed Method

In previous research, most researchers prefer a high complexity model to reach a high accuracy of plant disease detection. However, sometimes a high accuracy is not the only one requirement to implement an AI model. In this project, since the goal is to make an easy daily used technology for old people, we also need a low complexity model. Because a high complexity model will increase the computational load and require a high memory capacity so that it will be hard to deploy it on mobile application for daily use. Therefore, we tried to make a model that is quite different from previous research. We propose our own CNN model with less complexity structure but high enough accuracy so that it fits our objective.

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```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape
=================================================================
conv2d_5 (Conv2D)            (None, 98, 98, 32)
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 49, 49, 32)
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 47, 47, 32)
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 23, 23, 32)
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 21, 21, 64)
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 19, 19, 64)
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 9, 9, 64)
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 7, 7, 128)
_________________________________________________________________
max_pooling2d_7 (MaxPooling2 (None, 3, 3, 128)
_________________________________________________________________
flatten_1 (Flatten)          (None, 1152)
_________________________________________________________________
dense_2 (Dense)              (None, 128)
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)
_________________________________________________________________
dense_3 (Dense)              (None, 10)
=================================================================
Total params: 288,298
Trainable params: 288,298
Non-trainable params: 0
```

Figure 1. Structure of neural network

Our proposed model consists of 5 convolutional layers with ReLU activation function, 4 max-pooling layers, fully connected layer, and softmax as the classifier. Here we also add dropout to prevent overfitting on the model [8]. We can see the complete structure and number of parameters of this model on Figure 1.

2.3. Dataset

There are 10 classes of tomato leaves in this experiment that consist of 9 kinds of diseases and healthy leaves. Here we used a public dataset from kaggle (https://www.kaggle.com/saroz014/plant-disease). Table 1 describes the detailed information of class and dataset size per class.

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Table 1. Dataset

Class	For Training	For Testing
Bacterial spot	1702	425
Early blight	800	200
Late blight	1528	381
Leaf Mold	762	190
Septoria leaf spot	1417	354
Two spotted spider mite	1341	335
Target Spot	1124	280
Yellow Leaf Curl Virus	4286	1071
Mosaic Virus	299	74
Healthy	1273	318
Total	14532 (80%)	3628 (20%)

3. Results and Discussion

3.1. Image preprocessing

Before training the model, we did some image augmentation such as zooming, both horizontal and vertical flipping to add the variability of data and prevent the overfitting. Furthermore, in order to make computation easier and faster since we plan to deploy this model to a mobile application we did normalization. Here we added rescale 1./255 function that transforms every pixel of image from [0, 255] to [0, 1]. Then, we divide our dataset into 80% for training, and 20% for testing.

3.2. Model Evaluation

After preprocessing the image, we trained the model with batch size = 32, learning rate = 0.001, categorical cross entropy as loss function. For optimizer, RMSprop was chosen since it performs very well based on the review of Zaheer and Shaziya (Zaheer and Shaziya, 2019). After 13 iterations, we evaluate the model based on the accuracy and loss function graph. As we can see on the figure 2, our model reached accuracy 89% with no overfitting. So, with low complexity and good accuracy, we conclude that the model is ready to be deployed.

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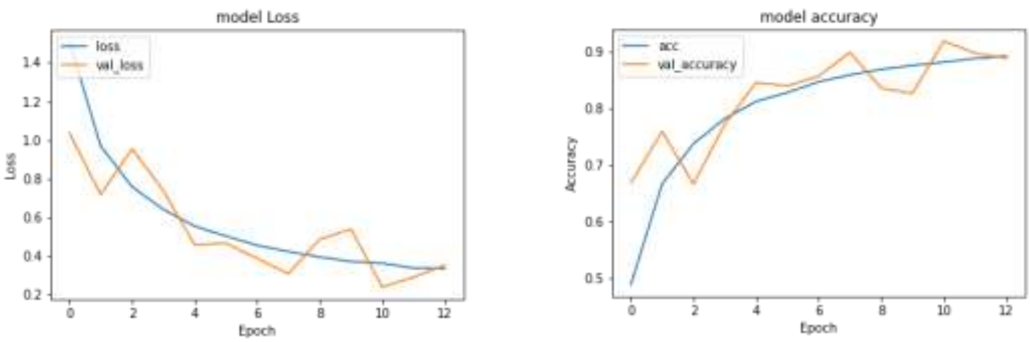

Figure 2. Accuracy and Loss Function Graph

3.3. Model Deployment and Consultation Feature

The model is deployed in an android mobile application using Flask that called "Smart Plant" to detect the disease of the plant, especially tomato. Furthermore, this application also links users to the scientist and plant expert so that they can do consultation and prevent the lack of knowledge in agriculture. In addition, we add some updated articles and tips about farming on the app. Therefore, all users can benefit from the current development of AI and update their knowledge for farming. Here the design of the mobile application (Figure 3).

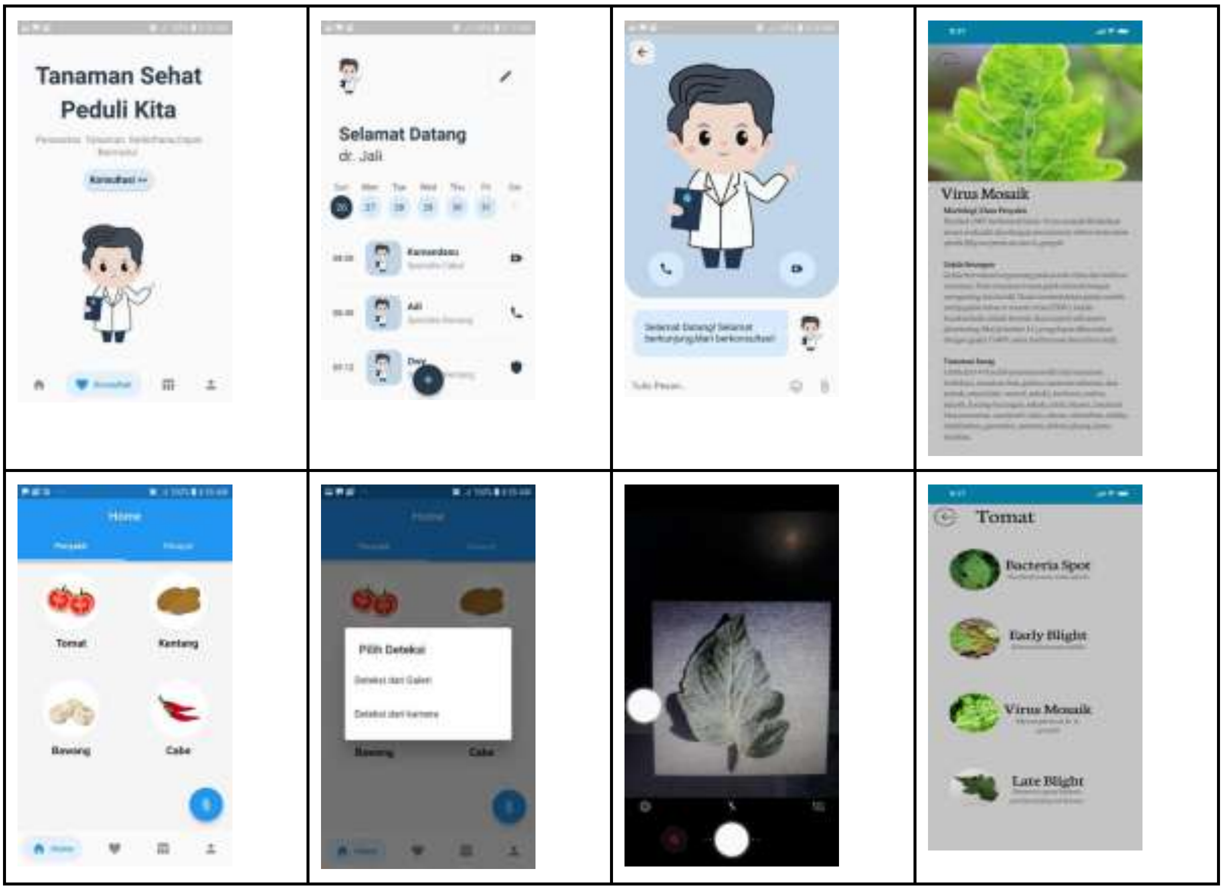

Figure 3. Design of Application

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4. Conclusion and Future Work

Old farmers face the problem of plant disease detection since the low ability of vision they have. Furthermore, their knowledge about agriculture is outdated so that they do not know how to prevent crop failure based on current knowledge and technology. Most previous researchers proposed a deep CNN (DCNN) model to get a high accuracy of plant disease detection. However, this project requires an easy-to-use technology for old people so that a high complexity model that needs high memory capacity does not fit our objective. Therefore, we proposed our own CNN model with high enough accuracy but low complexity to detect the disease on tomatoes. Then, we deployed the model using Flask and added some features to connect farmers with scientists and useful articles about plants. Furthermore, in order to make this application widely-used, we have to add more detection models for the other plants. Thus, we plan to establish the cooperation with some plant experts for not only being a consultant for users but also for the development of this application. We hope this application can help many farmers, especially in Indonesia and contribute to the developing economy.

5. Acknowledgements

We want to thank the Ministry of Education of Indonesia for the Kampus Merdeka program and Orbit Future Academy as the partner institution of Artificial Intelligence training for Start-up.

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