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Potato Leaf Disease Classification

Using Deep Learning Approach

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Abstract— Potato is one of the staple foods that widely consumed, becoming the 4th staple food consumed throughout the world. Also, the world demand for potato is increasing significantly, primarily due to the world pandemic coronavirus. However, potato diseases are the leading cause of the decline in the quality and quantity of the harvest. Inappropriate classification and late detection of the disease's type will drastically worsen the plant conditions. Fortunately, several diseases in potato plants can be identified based on leaf conditions. Therefore, in this paper, we present a system to classify the four types of diseases in potato plants based on leaf conditions by utilizing deep learning using the VGG16 and VGG19 convolutional neural network architecture model to obtain an accurate classification system. This experiment has achieved an average accuracy of 91-93%, which indicates the feasibility of the deep neural network approach.

Keywords— Leaf Disease Classification, Deep Learning, VGG16, VGG19, Potato Plant

I. INTRODUCTION

The agricultural sector is one of the essential role holders in Indonesia, according to a survey conducted by the Indonesian statistics show that 28.79% of Indonesia's population depend on agriculture [1] [2]. Food safety and nutrition improvement are some of the significant challenges faced by the agricultural sector. Potatoes become one of the staple foods that are expected to be able to suffice these needs in terms of quantity and quality. They are rich in nutrients, most notably vitamins C and B6 and the minerals, potassium, magnesium, and iron [3]. Besides being a popular staple food in Indonesia, potatoes are the number one vegetable crop in the United States of America and became the fourth most consumed vegetable crop in the world. Potato agricultural products have developed rapidly in this decade. Every year, the amount of production can reach around 850,000 tons. The amount is produced from an area of about 60,000 hectares. The area of planting and production has increased by approximately 10% per year, making Indonesia the largest potato producing country in Southeast Asia. The presence of pests and diseases of potato plants during the growth period has reduced the quality and quantity of agricultural products. Potato pests and diseases can lead to an early harvest where the harvest is done when the potatoes are still small in size, and crop failure is caused by spoilage of the potato plants before harvest. These problems are mostly caused by the late identification of diseases in potato plants and errors in disease diagnosis.



Fig. 1. Input Image of Potato Leaf Disease Classification.

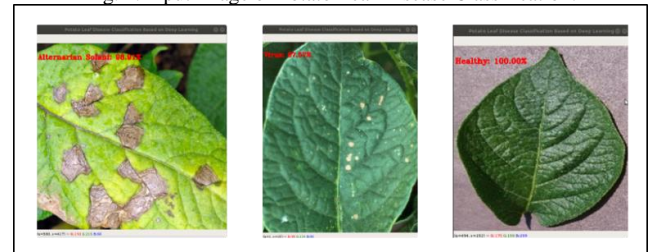


Fig. 2. Output Image of Potato Leaf Disease Classification.

The identification of diseases in potato plants quickly and accurately is highly essential to reduce the impact of diseases on plants. Manual monitoring activities carried out by farmers become difficult and impractical because it takes a long time and in-depth knowledge. Identification of plants diseases types that are slow will trigger the spread of diseases in plants uncontrollably. Besides, farmers generally identify diseases in plants in a way that is approximately and assumptions that allow inaccurate identification results because the symptoms on the leaves appear to have similarities that are difficult to describe at a glance. Farmers use the results of personal identification without expert advice in the field of plant diseases as a reference in the prevention of plants infected with the disease. As a result, preventive measures taken by farmers may be ineffective and can damage crops due to inadequate knowledge and misinterpretation of disease intensity, excessive dosage, or lack of dosage [4]. This problem is the foundation of the proposed research to facilitate farmers in identifying and classifying diseases in potato plants that are fast and accurate.

The proposed research methodology focuses on the classification and identification of healthy and disease-infected leaf conditions using the Deep Learning approach as in Fig. 2. The architecture used in this study is VGG16 and VGG19, which is a Convolutional Neural Network architecture model of the VGGNet Group. Both architectures have five layers of convolution and have a difference in the number of layers. In accordance with the names of the two, VGG16 has 16 layers and VGG19 has 19 layers. The architectural layer allows us to study effective features for classifying diseases through leaves.

II. RELATED WORK

Research in the field of disease classification in plants has been carried out even with various methods. However, it is considered still lacking [5] and become one area of research that continues to be developed because the subject in this field varies significantly. Thirty-seven papers in agriculture were published in the 2015-2017 period. More precisely, 15 papers were published in 2017, 15 in 2016, and 7 in 2016. This fact shows how new and modern this technique is in the agricultural domain [6].

In order to learn an effective features representation, a deep learning-based method can be devised. Deep learning [7] has shown very good performance in many visual perception tasks, such as text detection [8], [9], victims detection, [10], [11], target tracking [12], [13], object detection [14], [15], [16]. A deeper network can boost accuracy. Interestingly, the work [10] has been proven theoretically and empirically that the last layers of the deep network can capture more semantics information or abstraction; thus, it is more robust to variation of pose, colour, scale, and deformable object, that is it could be suitable to classify the leaf diseases robustly.

Prajwala *et al.* [4] This paper uses the LeNet architectural model, Convolutional Neural Network model architecture to detect and identify tomato leaf diseases that are commonly found in tomato additions; Septoria Leaf Spot and Yellow Leaf Curl. The dataset was obtained by researchers from one of the Open Access image databases, PlantVillage. The level of accuracy resulting from the methodology proposed for this paper is 94% -95%.

Experimental results on a developed model by Srdjan Sladojevic *et al.* [17] with a new approach to recognize diseases in five types of plants and 13 different kinds of diseases using the convolutional neural network (CNN) method. From this study, an average accuracy of 96.3% was obtained. Using the same method but with a different architecture, Erika Fujita *et al.* [18] made a disease diagnosis system in cucumber plants using the Convolutional Neural Network method by adopting the AlexNet architecture and obtaining an average accuracy of 82.3%.

A total of 2000 images of corn leaf were obtained by Raja P *et al.* [19] from the open-access image database, PlantVillage. The dataset is used as an object classification of 3 types of diseases in maize leaves using a bag of features with the Multiclass SVM (Support Vector Machine) method. On this occasion, the researchers also evaluated the accuracy of the method compared to the histogram method and feature-based grey level co-occurrence. The results obtained show that the SVM (Support Vector Machine) Multiclass method is entirely accurate. Pranjali B. Padol and Prof. Anjali A. Yadav [20] uses segmentation with K-mean clustering to found the disease region, and then the colour and texture of the image are extracted. While for classification, they use the SVM (Support Vector Machine) Classifier method and get an accuracy of 88.89%.

Jobin Francis *et al.* [21] was adopting the Backpropagation Neural Network method to classify disease types in pepper plants and GLCM (Gray Level Co-occurrence) for feature extraction step. Types of pepper plant diseases that can be

detected are Berry Spot Disease, a kind of fungal infection found in pepper and Rapid Disease, a kind of disease caused by mineral deficiencies such as nitrogen, magnesium, and potassium. Eftekhari Hossain *et al.* [22] used the same method for the classification of diseases such as Alternaria Alternata, Anthracnose, Bacterial Rot, Leaf Spot, and Plant Leaf Cancer. The performance of the KNN disease detection system in this paper is 96.76% accuracy.

Aakanksha Rastogi *et al.* [23] conducted a study using artificial neural networks and fuzzy logic methods to detect diseases in plants based on leaf conditions. This study focuses on identifying and classifying diseases in maple and hydrangea leaves. The condition of leaves of plants affected by the disease is divided into two categories, namely leaf spot, and scorch leaf. Leaf spots are where the disease on the leaves is at specific points of the leaf, while scorched leaves are where the disease on the leaves spreads evenly on the leaves.

III. PROPOSED METHODOLOGY

As shown in Fig. 3. The proposed methodology in this paper includes the following four main steps: data acquisition, data pre-processing, data augmentation, and image classification.

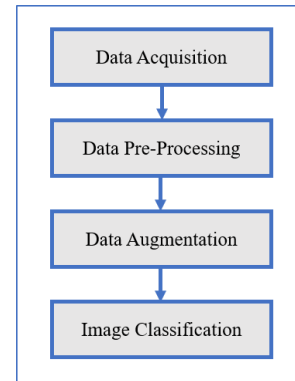


Fig. 3. Diagram Block Proposed Methodology.

A. Data Acquisition

Different image resolutions and sizes were obtained from several sources, including those collected by authors from a potato plantation in Malang, Indonesia, PlantVillage [24] an open-access image database, and Google images. Obtained a dataset of about 5,100 images and divided into class five: diseases caused by Alternaria Solani as in Fig. 4. healthy as in Fig. 5. Phytophthora Infestans as in Fig. 6. Viruses as in Fig. 7. and Insects as in Fig. 8.



Fig. 4. Alternaria Solani. Symptoms in this disease are leaves with brown, non-glossy dead spots, concentric rings in a target-board pattern.



Fig. 5. Healthy.



Fig. 6. Insect. The symptom of an attack from insects is visible holes in the leaves.



Fig. 7. Virus. There are several types of viruses that attack potato leaves but the symptoms are limited by leaves that have necrotic spots.



Fig. 8. *Phytophthora infestans*. Symptoms of this disease are leaves with irregular, dark brown to black spots on leaves.

B. Data Pre-Processing

Pre-processing data aims to improve the quality of data to realize an accurate training model output. The first step is to minimize the noise in the image, and if there is excessive noise in the image, then it will not be used. Acquired images have a variety of sizes, and images are resized to 800x600 pixels to standardize the input of images in datasets

C. Data Augmentation

Deep Learning (deep network) requires much data when compared to the shallow network of machine learning. The lack of training data and the balance of the amount of data in each class are common problems in Machine Learning [25]. The method used to overcome this problem is data augmentation. Data augmentation is a technique of manipulating data without losing the essence of the data. Data augmentation needs to be applied in this study because 5100 datasets are still inadequate to get optimal performance. Number of augmented data that we generate is 9000 images. Many methods are used in data augmentation, ranging from simple image transformation methods such as turning, rotating, enlarging, and cropping images to the histogram-based method. In this study, only simple transformation methods such as rotating and cropping were applied.

D. Image Classification

Deep learning (DL), similarly known as deep neural learning or deep neural network, is part of machine learning (ML) in artificial intelligence (AI). The term "deep" means that Deep Learning has more layers than Machine Learning. Deep learning methods have improved the state-of-the-art in

image classification, speech recognition, visual object recognition, object detection, and many other domains [7]. In Deep Learning, Convolutional Neural Network is one of the popular classes. Some studies use the convolutional neural network method to detect diseases in plants based on leaf conditions [4] [17] [18]. Convolutional Neural Networks generally consist of one or more convolutional layers that are grouped by function. Often the subsampling layer is followed by one or more layers that are fully connected as a standard neural network. Each feature layer receives input from a feature set located in a small area on the previous layer. LeNet was the beginning of the CNN architecture model and has now evolved into modern CNN architectural models such as AlexNet, VGG network, GoogLeNet, residual networks (ResNet), densely connected networks (DenseNet) [26].

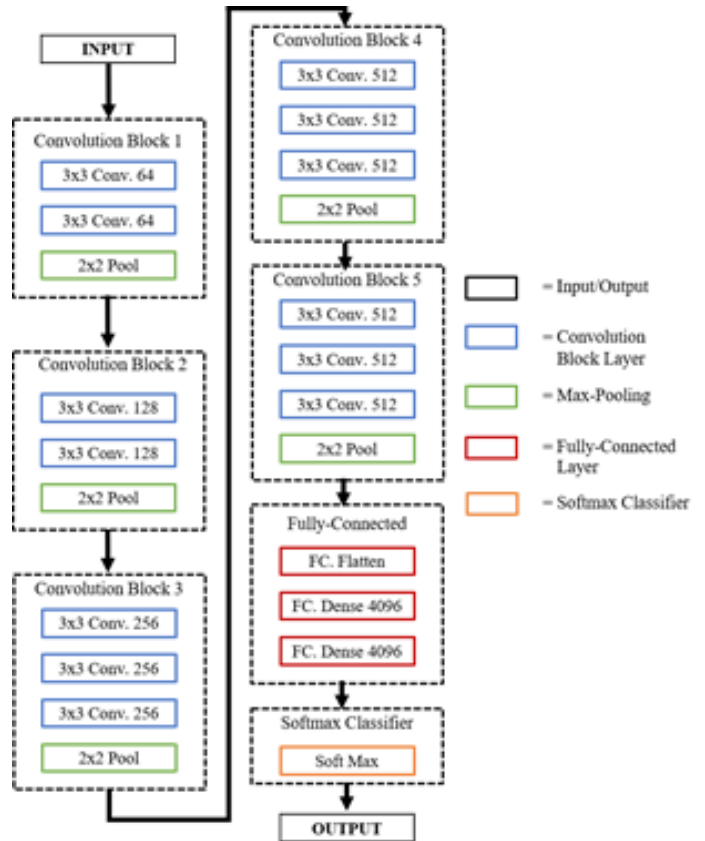


Fig. 9. VGG16 Architectural Model.

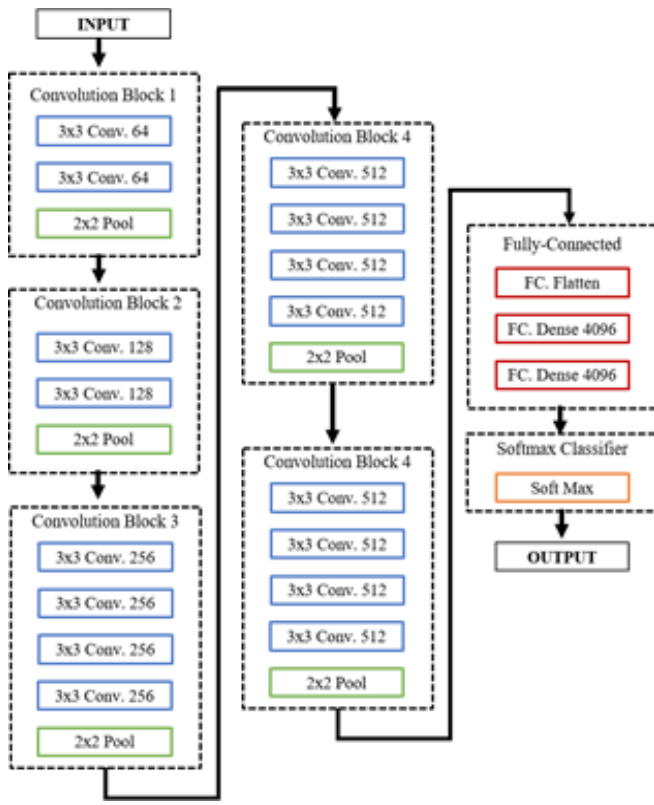


Fig. 10. VGG19 Architectural Model.

The architectural model used in this study to detect potato leaf disease is VGGNet. This architecture is the development of the AlexNet architecture model by changing the kernel size to smaller, several filters measuring 3X3 one by one. Stacked small kernels are considered more efficient and cheaper compared to large kernels. In VGGNet, the input as in Fig. 1. Passed through 5 convolutional layer blocks where each block consists of an increase in the number of 3x3 filters. The ReLU activation layer is applied in each block to recognize non-linearity so that the model can more easily adapt to various data. Dropout management techniques are used with a fixed probability of 0.25 to reduce overfitting conditions. Max-pooling layer separates blocks. Three fully connected (FC) layers follow five convolutional layer blocks. The softmax layer is the last layer to produce class probabilities. VGGNet evaluates very deep convolution networks in up to 19 layers. In this study, the authors used the two most popular types of VGGNet. VGG16 architecture shown in Fig. 9. contained 16 layers while VGG19 architecture shown in Fig. 10. contained 19 layers. The difference between the VGG16 architectures and VGG19 architecture is in the number of layers, as shown in Fig. 7. and Fig. 8.

IV. EXPERIMENT RESULT

A. Training Process

The dataset learning experiment was carried out using the Neural Network Convolutional method using the VGGNet family architecture model, specifically VGG19, which has 19 layers and VGG16, which has 16 layers. The epoch specified in this study was 250 epochs with 64 batch size and a learning rate is 0.01 to improve the performance of the model. The learning process means that the algorithm with

the proposed method seeks to come across values in the image dataset to be able to recognize new images. Each step of the epoch must be the same as the value of the image being trained. The results of the epochs will be recorded to determine the value of loss and accuracy. Loss is an indication of a bad value on the model, the value of the loss obtained must be close to zero or equal to zero and accuracy value is a parameter of the success level of the system in classifying objects.

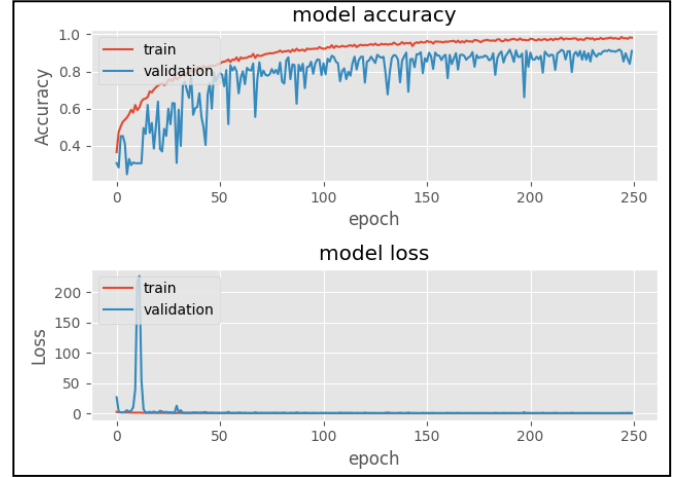


Fig. 11. The Plot of Accuracy and Loss using VGG19.

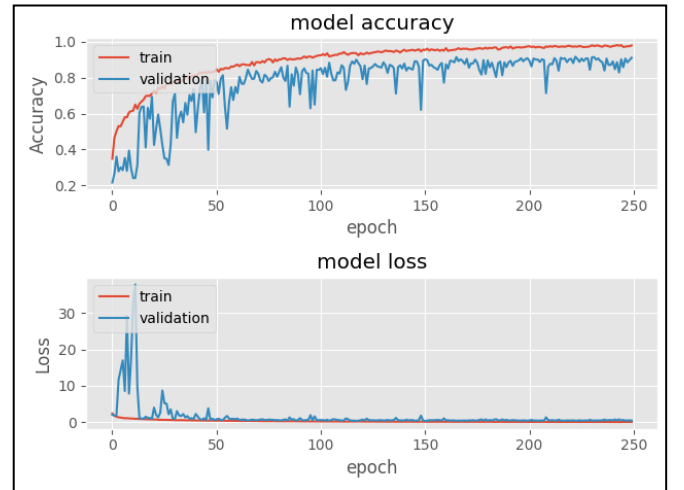


Fig. 12. The Plot of Accuracy and Loss using VGG16.

The results of the Loss values are presented in both plots using VGG19 in Fig. 11. and VGG16 in Fig. 12. getting values close to zero. VGG16 had more oscillation values in the early epoch. The accuracy value presented in both architectures related to training with all datasets containing original images after the 250th epoch reaches 91%.

Data augmentation is added in this study to enrich variations of the potato leaf dataset used with the same architecture. In this part, using the VGG16 architecture with a dataset that developed from collected datasets before, augmentation gives a graph of loss and accuracy result that different, shown in Fig.13. The accuracy obtained by adding augmentation data is about 93%.

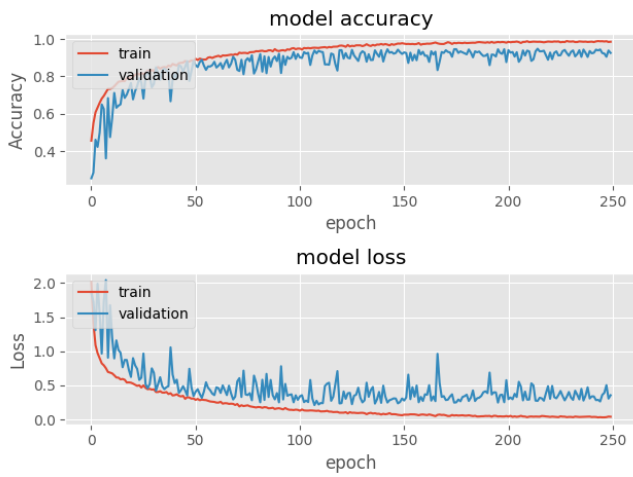


Fig. 13. The Plot of Loss and Accuracy using Data Augmentation.

The results of the system that has been done will be validated to measure the performance of a classification system that provides performance information from the resulting model. Some terms represent the results of the classification process, including True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN). Based on TP, TN, FP, and FN values. Then the accuracy, precision, F1 score and recall value can be obtained. The validation performed through all the validation datasets and the result of precision and recall.

B. Testing Process

After conducting the training process on the collected datasets, we retrieve the new data outside the training datasets to be tested with each model; VGG16, VGG16 with data augmentation and VGG19.

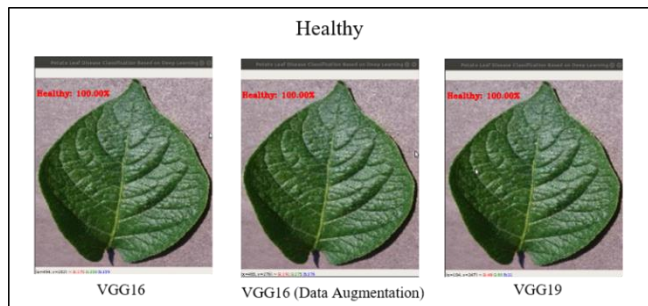


Fig. 14. Result of Healthy Leaf Testing.

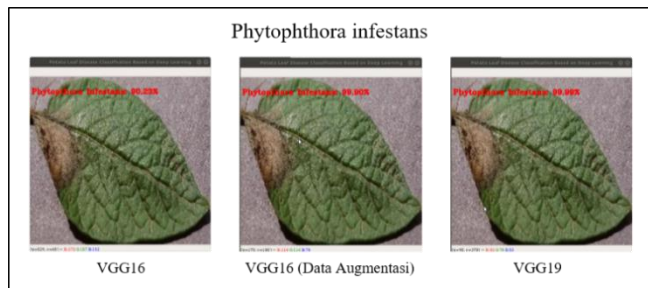


Fig. 15. Result of Phytophthora Infestans Testing.

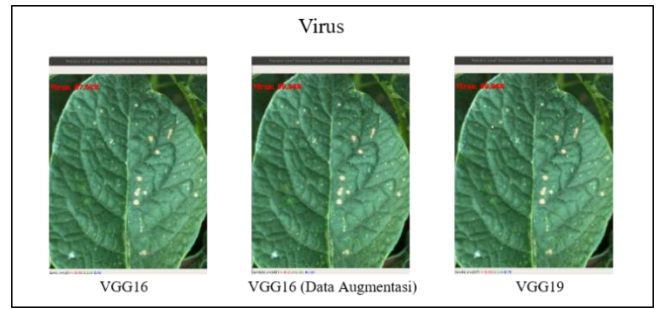


Fig. 16. Result of Virus Testing.

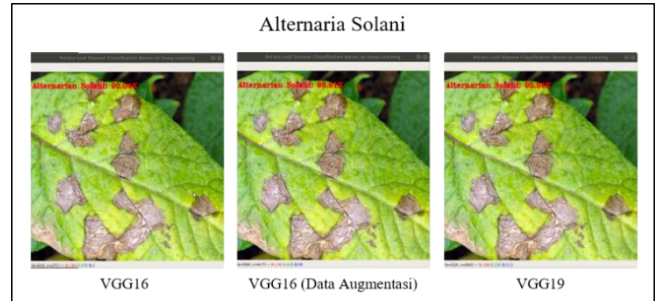


Fig. 17. Result of Alternaria Solani Testing.

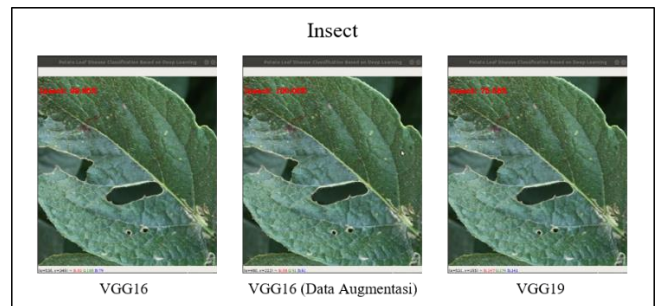


Fig. 18. Result of Insect Testing.

In this experiment, the effect of data augmentation was excellent. Most of the accuracy of the testing results with the VGG16 model using data augmentation is higher than testing using the VGG16 model without data augmentation. This is because data augmentation can multiply datasets with diverse variations without reducing the essence of the image. Besides, the difference in the accuracy of testing results from VGG16 and VGG19 is not significant. Whereas, in VGG19 layers, it has three more layers than VGG16 that make the training process using VGG19 spend more time than using VGG16. Some data shows that using VGG16 with data that is segmented produces better predictions.

It is imperative to note that when testing the model is the precision of the leaf image object, noise in the image will result in poor classification results. Minimization of noise in an image can be done by cutting off parts of the image other than the leaf object to be identified and making sure there is only one leaf in one frame.

V. CONCLUSION AND FUTURE WORK

The world demand for potatoes has increased significantly, mainly due to the world pandemic coronavirus. In this paper, we have presented the classification of leaf diseases from potato plants. VGGNetwork (VGG16 and VGG19) appears to be potential for studying effective features for image classification of leaf diseases. Added the

data augmentation process in the dataset would produce a more robust system. Experiments show that our proposed method can achieve an average accuracy of 91-93%. We believe this work can bring many benefits in agriculture-related to world food security.

REFERENCES

- [1] Statistics Indonesia, 2018 Inter-Census Agriculture Survey (SUTAS), Jakarta: Statistics Indonesia, 2018.
- [2] Ministry of Agriculture's Food Security Agency, 2017 Annual Report of the Ministry of Agriculture's Food Security Agency, Jakarta: Ministry of Agriculture's Food Security Agency, 2018.
- [3] K. . A. Beals, "Potatoes, Nutrition and Health," *American Journal of Potato Research*, no. 96, pp. 102-110, 2019.
- [4] P. TM, P. Alla, K. S. Ashirta, N. B. Chittaragi and S. G. Koolagudi, "Tomato Leaf Disease Detection using Convolutional Neural Network," *International Conference on Contemporary Computing (IC3)*, 2018.
- [5] S. Sladojevic, M. Arsenovic, A. Andras, D. Culibrk and D. Stefanovic, "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification," *Computational Intelligence and Neuroscience*, p. 11, 2016.
- [6] K. Andreas and F. X. Prenafeta-Boldú, "Deep Learning in Agriculture: A Survey," 2018.
- [7] Y. LeCun, Y. Bengio and G. Hinton, "Deep learning," *Nature*, vol. 521 no. 7553, p. 436, 2015.
- [8] A. Risnumawan, I. A. Sulistijono and J. Abawajy, "Text detection in low resolution scene images using convolutional neural network," in *International Conference on Soft Computing and Data Mining*, Bandung, 2016.
- [9] M. L. Afakh, A. Risnumawan, M. E. Anggraeni, M. N. Tamara and E. S. Ningrum, "Aksara jawa text detection in scene images using convolutional neural network," in *2017 International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC)*, 2017.
- [10] I. A. Sulistijono and A. Risnumawan, "From concrete to abstract: Multilayer neural networks for disaster victims detection," in *2016 International Electronics Symposium (IES)*, 2016.
- [11] I. A. Sulistijono, T. Imansyah, M. Muhajir, E. Sutoyo, M. K. Anwar, E. Satriyanto, A. Basuki and A. Risnumawan, "Implementation of Victims Detection Framework on Post Disaster Scenario," in *2018 International Electronics Symposium on Engineering Technology and Applications (IES-ETA)*, 2018.
- [12] M. K. Anwar, A. Risnumawan, A. Darmawan, M. N. Tamara and D. S. Purnomo, "Deep multilayer network for automatic targeting system of gun turret," in *2017 International Electronics Symposium on Engineering Technology and Applications (IES-ETA)*, 2017.
- [13] M. K. Anwar, M. Muhajir, E. Sutoyo, M. L. Afakh, A. Risnumawan, D. S. Purnomo, E. S. Ningrum, Z. Darojah, A. Darmawan and M. N. Tamara, "Deep Features Representation for Automatic Targeting System of Gun Turret," in *2018 International Electronics Symposium on Engineering Technology and Applications (IES-ETA)*, 2018.
- [14] H. Imaduddin, M. K. Anwar, M. I. Perdana, I. A. Sulistijono and A. Risnumawan, "Indonesian Vehicle License Plate Number Detection Using Deep Convolutional Neural Network," in *2018 International Electronics Symposium on Knowledge Creation and Intelligent Computing (IES-KCIC)*, 2018.
- [15] D. M. Dinama, Q. A'yun, A. D. Syahroni, I. A. Sulistijono and A. Risnumawan, "Human Detection and Tracking on Surveillance Video Footage Using Convolutional Neural Networks," in *2019 International Electronics Symposium (IES)*, 2019.
- [16] A. Risnumawan, M. I. Perdana, A. H. Hidayatulloh, A. K. Rizal, I. A. Sulistijono, A. Basuki and R. Febrianto, "Automatic Detection of Wrecked Airplanes from UAV Images," *International Journal of Engineering Technology (EMITTER)*, vol. Vol 7 no 2, pp. 570-585, 2019.
- [17] S. Sladojevic, M. Arsenovic, A. Andras, D. Culibrk and D. Stefanovic, "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification," *Computational Intelligence and Neuroscience*, 2016.
- [18] E. Fujita, Y. Kawasaki, H. Uga, S. Kagiwada and H. Iyatomi, "Basic investigation on a robust and practical plant diagnostic system," *2016 15th IEEE International Conference on Machine Learning and Applications*, pp. 989-992, 2016.
- [19] P. Raja, C. Szczepanski, K. V. Mukesh, R. Ashiwin and R. Anirudh, "Disease Classification in Maize Crop using Bag of Features and Multiclass Support Vector," *Second International Conference on Inventive Systems and Control*, pp. 1191-1196, 2018.
- [20] P. Padol and A. A. Yadav, "SVM Classifier Based Grape Leaf Disease Detection," *2016 Conference on Advances in Signal Processing (CASP)*, pp. 175-179, 2016.
- [21] J. Francis, A. S. Dhas D and A. B. K, "Identification of Leaf Disease in Pepper Plant Using Soft Computing Techniques," *Conference on Emerging Devices and Smart Systems (ICEDSS)*, 2016.
- [22] E. Hosaaain, M. F. Hossain and M. A. Rahaman, "A Color and Texture Based Approach for the Detection and Classification of Plant Leaf Disease Using KNN Classifier," *International Conference on Electrical, Computer and Communication Engineering (ECCE)*, 2019.
- [23] A. Rastogi, R. Arora and S. Sharma, "Leaf Disease Detection and Grading using Computer," *2nd International Conference on Signal Processing and Integrated Networks (SPIN)*, 2015.
- [24] S. P. Mohanty, D. Hughes and M. Salathe, "Using Deep Learning for Image-Based Plant," 2016.
- [25] A. Mikołajczyk and M. Grochowski, "Data augmentation for improving deep learning," *International Interdisciplinary PhD Workshop (IIPhDW)*, pp. 117-122, 2018.
- [26] A. Zhang, A. J. Smola, M. Li and Z. C. Lipton, *Dive into Deep Learning*, 2020.