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Detection of Disease and Pest of Kenaf Plant using Convolutional Neural Network

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Abstract. Kenaf fiber is mainly used for forest wood substitute industrial products. Thus, the kenaf fiber can be promoted as the main composition of environmentally friendly goods. Unfortunately, there are several Kenaf gardens that have been stricken with the disease-causing a lack of yield. By utilizing advances in technology, it was felt to be able to help kenaf farmers quickly and accurately detect which pests or diseases attacked their crops. This paper will discuss the application of the machine learning method which is a Convolutional Neural Network (CNN) that can provide results for inputting leaf images into the results of temporary diagnoses. The data used are 838 image data for 4 classes. The average results prove that with CNN an accuracy value of 73% can be achieved for the detection of diseases and plant pests in Kenaf plants.

Keyword : data, kenaf, learning, neural

1. Introduction

Kenaf plants are fiber-producing plants from its bark. This fiber has many functions, including forest wood substitution industry products, secondary products and environmental management. Since 1978, kenaf fiber has been developed in the People's Sack Fiber Intesification Programs (ISKARA) known for the manufacture of gunny sacks. Research continues to develop so that kenaf fibers can be successfully processed with textile structural techniques: knitting, crochet, weaving and macrame techniques that produce early-level textile samples such as that done by Ciptadi [1], [2] and developed by Hapidh [3]. This is sufficient to provide added value and the latest innovations in textile products. Another advantages of Kenaf as an environmental management that has now become the center of global attention is the use of kenaf's fiber as a luxury car interior substitute for plastic materials so that it becomes an environmentally friendly luxury car [4]. These situations causes an increase in opportunities for exports of kenaf's fiber raw materials that refer to the agricultural sector. With a situation like this, it is not impossible if nothing problems in the agricultural sector itself. One of them is in some areas of the Kenaf's garden that are attacked by diseases and pests that can slow the growth of Kenaf plants or lead to the death of plants and cause crop failure to make a loss. To anticipate the fatality things like this, an information technology discovery is needed that can help farmers or kenaf's garden owners to diagnose diseases or pests that attack their plants.

In the development of information technology systems, this can be overcome by instilling knowledge in machines known as artificial intelligence. Artificial intelligence is a designation for learning methods carried out by machines by imitating how a basic system of the human brain works. The basic system of the human brain is called a neural network. Planting knowledge with neural networks has been widely applied by many people, one example is applied by Saragih who identifies Jatropha plant diseases using Fuzzy Neural Network [5] which is one of the artificial intelligence systems that can detect types of plant diseases based on their symptoms. Unfortunately the level of accuracy achieved is only about 30% and then optimization is done again so that the results are further improved by using Simulated Annealing [6]. So that research can increase the level of accuracy or in other words the results of detection of the type of the disease are accurate, so do deeper research in the Neural Network. Deeper learning systems on the Neural Network are known as deep learning. Deep learning is called "Deep" because the structure and number of neural networks in the algorithm can reach up to hundreds of layers [7]. Techniques and algorithms in Deep Learning can be used both for the needs of supervised learning, unsupervised learning and semi-directed learning in various applications such as image recognition, speech recognition, text classification, and so on. Many studies use deep learning to recognize objects. Deep learning also refers to the introduction of learning based on images [8]. One of them applied by [9] to detect types of bacteria and some other object recognition studies [10], [11], [12]. Deep learning is effective to train large scale data [10]. With deeper learning and strong computing factors, it will provide maximum results [7]. Related to some previous studies relating to deep learning, the research will be made a system with an introduction to the types of diseases and pests that attack the Kenaf plant so that the existence of this system can help farmers to avoid crop failures caused by diseases and pests attack. The type of deep learning that is applied is the Convolutional Neural Network (CNN) which is a development of Multi-Layer Perceptron (MLP) which is specifically designed to process two-dimensional data. Two-dimensional data object are images. Image is the result of the sampling process that has been processed from discrete images. The sampling process is a process of spatial digitization (x, y)[13]. CNN was first introduced by Yann LeCun, et al. with an architecture named LeNet-5, consisting of seven layers, i.e. four layers of feature extraction and three fully connected layers [14]. This network succeeded in recognizing handwritten numeric images in the Modified National Institute of Standards and Technology (MNIST) database containing 60,000 data and ten classes. The LeNet-5 learning process is carried out with 50,000 data and 10,000 data as test data. After that, the development of CNN continued, especially since 2010 the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) competition began to aim to identify 1,000 classes from 1.2 million learning data. Based on the latest CNN developments along with some previous research, the CNN method is expected to be able to provide solutions to the problem of Kenaf plant diseases detection based on images.

2. Kenaf Plants

The Kenaf plant has the scientific name Hibiscus cannabinus L. Its an annual plant that only grows in the dry season. Kenaf began to be known in Indonesia since 1904 and began to develop commercially in 1978. Kenaf plants are known by different names in each country. The leaves of the Kenaf plant are located on the main stems and branches and are intermittent. Kenaf leaves vary in color according to the subspecies. Leaves in the Kenaf plants consist of three forms, namely single leaf (unlobed), partially lobed and deeply lobed. The palmately lobed leaf has 5 sections and 7 sections with jagged at the edge of leaves [15]. Abnormal physiological processes that are caused by interference with pathogens or weather that does not support plant growth normally causes disease in plants [16].

2.1 Leaf Blight

Most of these diseases can be found in times of high humidity and rainfall. Symptoms of this disease can be seen through the leaves and bark of the plant. Leaves infected with this disease are dirty green, then become reddish or brownie and black spots which are a fungus pycnidia and the fingers of the leaves will shrink. The Leaf Blight disease is shown in figure 1.


Figure 1. Leaf Blight Disease on Kenaf Leaf

2.2 Sundapteryx Bigutulla

Amrasca (Sundapteryx) bigutulla is a pest that attacks kenaf plants. This pest can suck 19% of the fiber in plants. These pests lay their eggs on the leaf bone or leaf stalk. This pest attacks by sucking plant cell fluids. The initial symptom of the plant is that the edges of the leaves turn yellowish and then turn reddish and curved. The color of the leaves will extend to the entire surface until the leaves become dry and then fall out. The leaf affected by the pest Amrasca (Sundapteryx) bigutulla shown in figure 2.

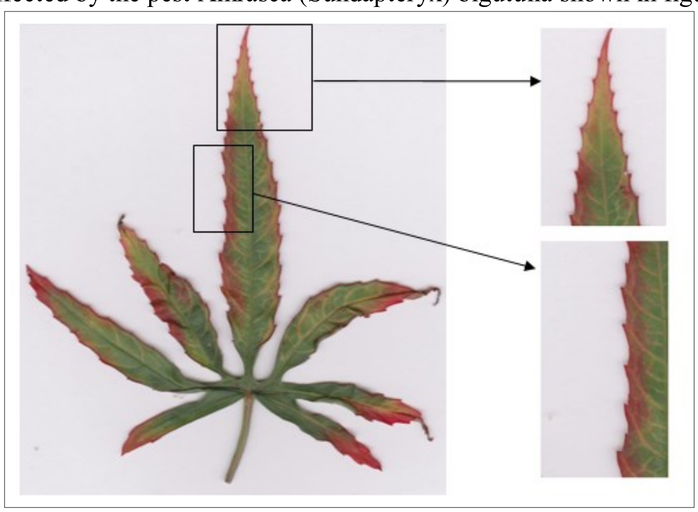
Figure 2. Sundapteryx Bigutulla on Kenaf Leaf

2.3 Tungau

Tungau (Tetranychus urticae) or mite is a polyphagous pest that attacks approximately 1100 plant species. Damage to the leaves of the kenaf plant is also caused by mites. Symptoms detected on Kenaf leaves are the appearance of reddish spots that spread on the surface of the leaf. These pests absorb liquid plant cells so that if ignored, the red spots will spread throughout the surface of the leaf, then the leaves fall out and the plant will die. The leaf affected by the pest Tungau shown in figure 3.

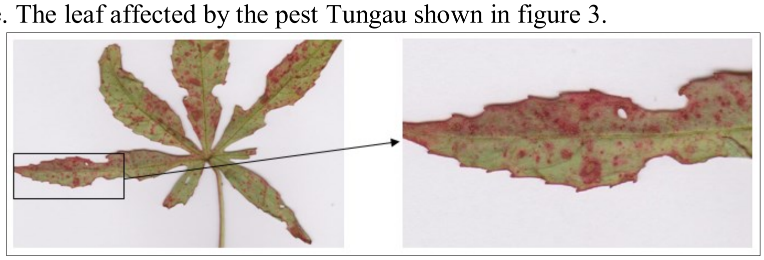
Figure 3. Tungau affected in Kenaf Leaf

3 Methodology

This research was conducted to detect diseases from Kenaf plant diseases using deep learning methods from the Neural Network, namely Convolutional Neural Network.

3.1 Data

The data obtained is image data taken directly from 2 places, namely:

1. Kenaf plantations garden in Lamongan city, East Java.
2. Sweet and Fiber Research Institute, Malang Karangploso

The data taken is leaves image data. Data retrieval media are digital pocket cameras, cellphone cameras and scanners.

3.2 Pre Processing

The initial process in processing input data or preprocessing is wrapping and cropping. The wrapping process is a process that is carried out to check the edge of the image and then determine the maximum edge so that the process of cropping or cutting the image object remains intact manually.

3.3 Convolutional Neural Network

The CNN work system has similarities with MLP, the difference in neurons represented in the two-dimensional form on CNN and one-dimensional form in MLP. Many layers are used to translate object recognition identification. The number of layers forms a unity that forms an architecture. In 2015, zisserman and simonyan was proposed an architecture of Convolutional neural network called VGGNets [17]. Their paper focuses on the accuracy value that can be obtained in the use of convolutional neural network learning methods. The input will pass through the weight layer and the convolution layer in the VGGNet architecture after doing the preprocessing process. The VGGNet network architecture only uses 3x3 convolutional layers which are stacked with increasing depth and the volume size measure by maxpooling layer. In order to reduce excessive training time on deep learning, dropouts and normalization of overlapping batches are provided. So that no gradient is lost, it is necessary to provide an activation function, namely ReLU. This architecture is equipped with fully connected layers to connect between networks as well as software classifiers to provide classification decisions. Based on the excellence and simplicity that this architecture has to offer, then the architecture used in this study is VGGNet [17] with a little reduction into Smaller VGGNet. The designed layer consists of CONV → RELU → POOL, followed 2 sets CONV → RELU → CONV → RELU → POOL and set of FC → RELU → FC → SOFTMAX layers shown with table 1.

Table 1. Summary of Smaller VGG Net on Kenaf Plants Disease and Pest Detection

No	Layer Type	Input Size	Output Size	Filter Size / Stride
1	Input Image	96 × 96 × 3	96 × 96 × 3	
2	CONV	96 × 96 × 3	96 × 96 × 32	3 × 3; K=32
3	ACT FUNC	96 × 96 × 32	96 × 96 × 32	RELU
4	BATCH NORMALIZATION	96 × 96 × 32	96 × 96 × 32	
5	POOLING	96 × 96 × 32	32 × 32 × 32	3 × 3
6	DROPOUT	32 × 32 ×32	32 × 32 × 32	25%
7	CONV	32 × 32 × 32	32 × 32 × 64	3 × 3; K=64
8	ACT FUNC	32 × 32 × 64	32 × 32 × 64	RELU
9	BATCH NORMALIZATION	32 × 32 × 64	32 × 32 × 64	
10	CONV	32 × 32 × 64	32 × 32 × 64	
11	ACT FUNC	32 × 32 × 64	32 × 32 × 64	RELU
12	BATCH NORMALIZATION	32 × 32 × 64	32 × 32 × 64	
13	POOLING	32 × 32 × 64	16 × 16 × 64	2 × 2
14	DROPOUT	16 × 16 × 64	16 × 16 × 64	25%
15	CONV	16 × 16 × 64	16 × 16 × 128	3 × 3; K= 128
16	ACT FUNC	16 × 16 × 128	16 × 16 × 128	RELU
17	BATCH NORMALIZATION	16 × 16 × 128	16 × 16 × 128	
18	CONV	16 × 16 × 128	16 × 16 × 128	3 × 3

No	Layer Type	Input Size	Output Size	Filter Size / Stride
19	ACT FUNC	16 × 16 × 128	16 × 16 × 128	RELU
20	BATCH NORMALIZATION	16 × 16 × 128	16 × 16 × 128	
21	POOLING	16 × 16 × 128	8 × 8 × 128	2 × 2
22	DROPOUT	8 × 8 × 128	8 × 8 × 128	25 %
23	FLATTEN	8 × 8 × 128	8192	
24	FULLY CONNECTED	8192	1024	
25	ACT FUNC	1024	1024	
26	BATCH NORMALIZATION	1024	1024	
27	DROPOUT	1024	1024	50%
28	FULLY CONNECTED	1024	4	
29	SOFTMAX	4	4	

From Table 1, it is found how to utilize the layer dropout which is a neural network regularization technique in which some will be chosen randomly and not used during training data. These neurons are also disposed of at random. This means that the contribution of disposed of neurons will be temporarily stopped when the new weights are not applied to the neurons during backpropagation. As suggested by [17], an increase in the number of filters from 32 - 64 - 128, the deeper the network, the smaller the volume of spatial dimensions and the more parameters will be studied. The application of batch normalization and the dropout layer after the convolution layer and the activation function layer aims to reduce the overfitting of the classification. On the last layer, the fully connected neuron layer is reduced to 4, the same size as the target class of the image. Softmax classifier provides an opportunity for each prediction on the class label.

4 Experiments and Result

The implementation of the smaller VGG Net architecture to determine the performance of this study was done by calculating the accuracy value of the classification process. The composition for the use of training data and test data is 100%: 20% of the total amount of data. The results of this experiments will be seen from Epoch, Train Loss, Train Accuracy, Validation Loss and Validation accuracy in Table 2. One epoch is calculated when all the datasets we use have passed through all nodes on the neural network. There is no standard on how much epoch you have to run to produce an accurate value, so you have to do an epoch test. Training loss is the error on the training set of data. Validation loss is the error after running the validation set of data through the trained network. Train / valid is the ratio between the two.

Table 2. The accuracy value on the epoch is an approach to 400

No	**Epoch**	**Train Loss**	**Train Accuracy**	**Validation Loss**	**Validation Accuracy**	**Time**
1	396	0.1378	0.9543	0.8725	0.8	18s
2	397	0.1754	0.9421	1.8238	0.7111	18s
3	398	0.1395	0.9347	0.7878	0.8	19s
4	399	0.1426	0.9543	1.9904	0.6889	18s
5	400	0.1993	**0.9375**	3.5375	**0.4889**	17s

It can be seen in Table 2 that reached an accuracy rate of 93% so that further testing can proceed. The next test is to test the performance of the model that has been designed. The result classification of class images of disease types can be seen in table 3. Table 3 contains information about the model used to be able to classify images into 4 main classes which can then be applied to overcome problems with this Kenaf plant. Figure 4 shown the plot during training. Figure 5 shows the correct and wrong labels on disease detection systems using the smaller VGGnet application model architecture.

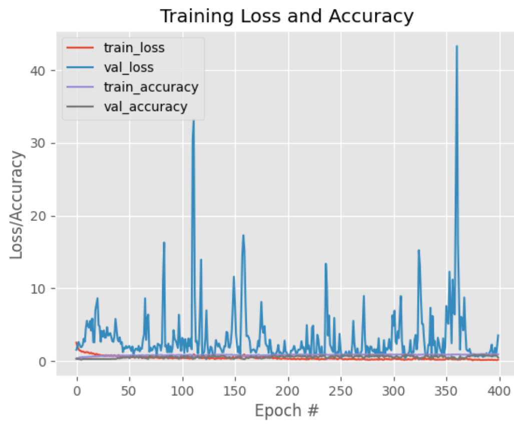

Figure 4. Training Loss and Accuracy

Table 3. Image Test Correct Data Classes

No	Class	Data	System
1	Hawar Daun (Leaf Blight)	40	30
2	Tungau	40	29
3	Sundapteryx Bigutulla	40	35
4	Sehat (Healthy)	40	28
	Total	**160**	**122**

Based on Table 3, the overall testing data amounted to 160 with 40 test images in each class. The accuracy value achieved in 4 classifications is 76.25% with Training set accuracy of 93.75% and validation accuracy is 48.89%, the average accuracy of the entire system is about 72.96%. In this study, the Convolutional Neural Network is sufficiently capable to be used to classify data that is labeled using the supervised learning method, in which the workings of supervised learning are that there are trained data and targeted variables. This can be seen from the results of the tests that have been carried out, that convolutional neural networks are quite capable in the field of image processing.

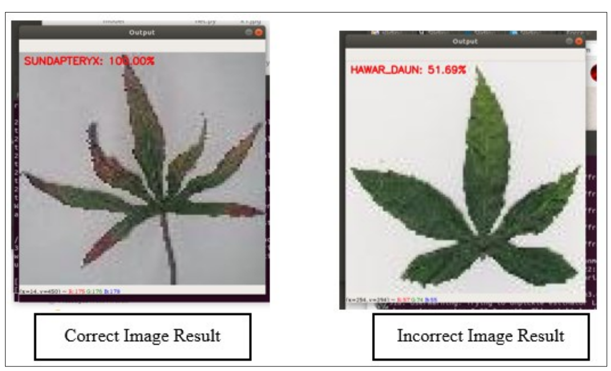

Figure 5. Result of an Image detection system

5 Conclusion

This study shows that the results of the detection of diseases and pest of kenaf plants can be done by the Convolutional neural network method with VGG architecture using data taken directly. The data used is very limited, the most data in one class classification is only 161 data while conducting deeper training can reach 1000 total data in each class. This system can reach an average accuracy point of 73% which means this result is good enough to be implemented. It can be done for further research by adding several layers that can reduce the parameters so that it increases the accuracy value or updates the latest data. Given that almost all kenaf plant farmers have used smartphones at this time, the existence of a decision system that is able to provide results according to field facts like this is very helpful for farmers to be able to detect faster and prevent harvest failure. So that in the future the research will be further refined.

References

1. F. Ciptadi, "Textile Product Design Made of Kenaf Fibre Grade-C," *Costume Cult. Assoc. 2014 Int. Text. Costume Cult. Congr. (CCA Ars Textrina*, 2014.
2. F. Ciptadi, K. Kahdar, and A. Sachari, "Quality Improvement of Raw Material of Natural Fibre Preparation using Pectinase Enzyme Case Study: The Harvest of Kenaf Fibre in Laren District, Lamongan Regency, East Java," *J. Chem. Mater. Res.*, vol. 6, no. 10, 2014.
3. A. B. Hapidh, "Eksplorasi Serat Kenaf sebagai Aplikasi Produk Fashion Aksesoris," Bandung, 17.04.1944, 2017.
4. Miyagawa and Tranggono, "Kebutuhan Serat Kenaf Sebagai Bahan Baku Industri PT TBINA," in *Seminar Nasional Serat Alam Serat Alam Inovasi Teknologi Serat Alam Mendukung Agroindustri yang Berkelanjutan*, 2015, pp. 54–59, [Online]. Available: http://pustaka.litbang.pertanian.go.id/publikasi/wr244026.pdf.
5. T. H. Saragih, D. M. N. Fajri, A. Hamdianah, W. F. Mahmudy, and Y. P. Anggodo, "Jatropha curcas disease identification using Fuzzy Neural Network," in *2017 International Conference on Sustainable Information Engineering and Technology (SIET)*, Nov. 2017, pp. 305–309, doi: 10.1109/SIET.2017.8304153.
6. D. M. N. Fajri, T. H. Saragih, A. Hamdianah, W. F. Mahmudy, and Y. P. Anggodo, "Optimized fuzzy neural network for Jatropha Curcas plant disease identification," in *2017 International Conference on Sustainable Information Engineering and Technology (SIET)*, Nov. 2017, pp. 297–304, doi: 10.1109/SIET.2017.8304152.
7. I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016.
8. Y. Lecun and K. Kavukcuoglu, "Convolutional Networks and Applications in Vision," in *Proceedings of 2010 IEEE International Symposium on Circuits and Systems*, 2010, pp. 253–256.
9. T. Treebupachatsakul and S. Poomrittigul, "Bacteria Classification using Image Processing and Deep learning," *2019 34th Int. Tech. Conf. Circuits/Systems, Comput. Commun.*, pp. 2–4, 2019.
10. Y. Bar, I. Diamant, L. Wolf, S. Lieberman, E. Konen, and H. Greenspan, "Chest Pathology Detection Using Deep Learning with Non-Medical Training," *2015 IEEE 12th Int. Symp. Biomed. Imaging*, pp. 294–297, 2015.
11. H. Jeelani, J. Martin, F. Vasquez, M. Salerno, and D. S. Weller, "Image Quality Affects Deep Learning Reconstruction of MRI," *2018 IEEE 15th Int. Symp. Biomed. Imaging (ISBI 2018)*, pp. 357–360, 2018.
12. D. Learning and F. C. Terrorism, "Font and Turkish Letter Recognition in Images with Deep Learning," *2018 Int. Congr. Big Data, Deep Learn. Fight. Cyber Terror.*, pp. 3–4, 2018.
13. M. Qamal, "Klasifikasi Usia Menggunakan Ciri Orde Dua," *TECHSI J. Penelit. Inform.*, vol. 5, no. 2, 2013.
14. Y. Lecun, L. Bottou, Y. Bengjo, and P. Haffnerr, "Gradient-Based Learning Applied to Document Recognition," *Proc. IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998.
15. U. S. Budi, "Biologi Tanaman Kenaf," in *Monograf Balittas: Kenaf (Hibiscus cannabinus L.)*, Balai Penelitian Tanaman Pemanis dan Serat, 2009, pp. 6–7.
16. T. Yulianti and Supriyono, "Penyakit Tanaman Kenaf dan Pengendaliannya," in *Monograf Balittas: Kenaf (Hibiscus cannabinus L.)*, 2009, p. 107.
17. K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large Scale Image Recognition," *3rd Int. Conf. Learn. Represent.*, pp. 1–14, 2015.