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DETECTION OF LEAF SPOT DISEASE IN OIL PALM SEEDLINGS USING CONVOLUTIONAL NEURAL NETWORK METHOD

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Abstract: This research aims to develop a method for detecting leaf spot disease in oil palm seedlings using Convolutional Neural Network (CNN). Leaf spot disease in oil palm seedlings can hinder growth and production. CNN has proven effective in image processing and classification, particularly in plant disease detection. In this study, we utilized a dataset of images containing oil palm seedling leaves infected with leaf spot disease and healthy leaves. We performed data processing, built a CNN model, and conducted hyperparameter tuning. The test results demonstrate that the developed CNN model achieves high accuracy in recognizing and distinguishing between oil palm seedling leaves infected with leaf spot disease and healthy ones. This research contributes to the development of plant disease detection technology that can support economic growth in the oil palm plantation sector.

Keywords: Convolutional Neural Network, image processing, leaf spot disease detection, oil palm seedlings.

Abstrak: Penelitian ini bertujuan untuk mengembangkan metode deteksi penyakit bercak pada bibit kelapa sawit menggunakan Convolutional Neural Network (CNN). Bibit kelapa sawit yang terinfeksi penyakit bercak dapat menghambat pertumbuhan dan produksi kelapa sawit. Metode CNN telah terbukti efektif dalam pengolahan citra dan klasifikasi, khususnya dalam deteksi penyakit pada tanaman. Dalam penelitian ini, kami menggunakan dataset citra daun bibit kelapa sawit yang terinfeksi penyakit bercak dan yang normal. Kami melakukan processing data, membangun model CNN, dan melakukan tuning hyperparameter. Hasil pengujian menunjukkan bahwa model CNN yang dikembangkan memiliki akurasi yang tinggi dalam mengenali dan membedakan citra daun bibit kelapa sawit yang terinfeksi penyakit bercak dan yang normal. Penelitian ini memberikan kontribusi dalam pengembangan teknologi deteksi penyakit tanaman yang dapat mendukung pertumbuhan ekonomi di sektor perkebunan kelapa sawit.

Kata kunci: bibit kelapa sawit, Convolutional Neural Network, deteksi penyakit bercak, pengolahan citra.

INTRODUCTION

Indonesia is a country rich in plantations, plantations play an important role in Indonesia's economic growth. Currently, palm oil has become one of the main commodities in Indonesian agriculture that plays an important role in generating foreign exchange revenue. The palm oil industry sector has a growing market share, reaching an increase of 9.23% in 2017. In addition, the industry is also the largest contributor to foreign exchange earnings from the non-oil and gas sector, reaching around 34.33% in the same year. According to data from the Directorate General of Plantations of the Ministry of Agriculture, the area of oil palm plantations in Indonesia has expanded to reach 8.9 million hectares[1].

Oil palm plantation development relies heavily on nursery activities[2]. Seedling growth is a key factor that can affect the success of oil palm production in the field[2]. In nursery activities, it is important to pay attention to the presence of diseases that can attack seedlings[3]. Therefore, it is important to study the incidence of disease in plants in order to effectively control the disease, ensure oil palm seed production runs smoothly, free from disease, and optimal growth. One of the most common diseases on oil palm seedlings is leaf spot disease[4]. Leaf spot disease caused by Curvularia sp. in oil palm nurseries can reach 38%[5]. The disease infects newly developed leaves or young leaves that have opened. Leaf spot disease is caused by pathogenic fungi of the genus Curvularia sp., also known as Curvularia leaf blight. It can be spread through the soil, dispersed by wind, rainwater, and possibly transmitted by insects[6].

Current technological advances can help oil palm farmers in determining spot disease in oil palm, by utilising artificial intelligence methods, namely the Convolutional Neural Network (CNN) method. Convolutional Neural Network (CNN) is one of the deep learning algorithms which is a development of Multilayer Perceptron (MLP) designed to process data in two-dimensional form, such as images or sounds[7]. Currently, the use of Convolutional Neural Network (CNN) method in image classification is popular. The main advantage of this method is its ability to classify images with high accuracy, as it can cope with image transformations such as rotation and translation, and reduce the number of parameters required[8]. The CNN method also allows the process of training the model before testing, so there is no need to retrain the model when testing is performed[9]. However, despite its advantages, the CNN method also has disadvantages. If used with a large enough dataset, the training process will take longer, and the risk of overfitting may arise, resulting in less accurate predictions[10]. To overcome this problem, it is necessary to improve the learning efficiency of the CNN model. There are several approaches to improve learning efficiency in CNN models such as model initialisation, data augmentation, the use of dropouts, batch normalisation[11].

Several studies have been conducted related to disease detection in plants using deep learning. Research conducted by Simanjuntak A in 2022 with the title Classification of Palm Leaf Disease Using Artificial Neural Network Method with Local Binary Pattern Features[12]. The objective of the study was to recognise whether the palm leaves were affected by disease or not through a programme. An accurate approach is required to achieve a high level of accuracy. The researcher used the Artificial Neural Network (ANN) classification method along with the Local Binary Pattern (LBP) extraction method. The first step taken on the image was to convert it to grayscale, and then proceed with the extraction using the LBP method. The results were analysed through a JST with the application of 17 training functions resulting in 5 neurons. The results show an average accuracy of about 81%, a precision accuracy of about 95%, and a recovery rate of about 94%. On using 10 neurons, the accuracy increased to an average of 95%, with a precision of about 97%, and a recovery rate of about 96%. When using 20 neurons, the average accuracy reached 97%, with a precision and recovery rate of about 97% and 96% respectively[12].

Referring to previous research [12], There are similarities in the focus of the discussion, namely disease detection in oil palm leaves. However, the significant difference lies in the method implemented and the emphasis on one type of palm leaf disease. The method applied in this research is Convolutional Neural Network (CNN). The dataset used consists of images of oil palm seedling leaves that have spot disease and healthy oil palm seedling leaves. This dataset is obtained by direct collection. The final result expected from this research is to achieve the highest accuracy, precision, and recall values.

METHOD

The method used is the Convolutional Neural Network (CNN) method. The flow diagram of the research methodology can be seen in Image 1.

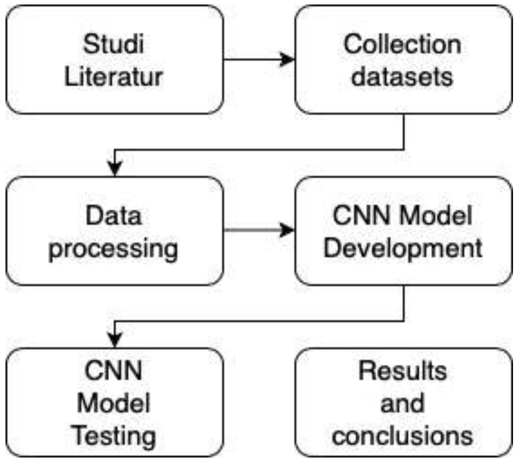

Image 1. Flow of Research Methodology

The first stage of conducting a literature study, in general, a literature study is a method for overcoming problems by investigating references to previously existing writings. The literature study in this research involves searching for journals that are relevant to the research topic to be carried out. The next stage is data collection, Data collection is a phase in the research process where researchers use certain scientific methods and techniques to collect data in a structured manner for analysis purposes. In this study, the dataset was collected directly from PPKS Marihat, Sei Kumango Village, Tambusai, Rokan Hulu Regency, Riau Province. At the data processing stage, the dataset will be divided into two, namely training data and validation data. After the data is divided into two, normalise and resize the dataset. Continue with the construction of the CNN model, the structure used involves convolution layers, maximum fusion, dropout, and output layers, with the aim of producing a model that is effective in recognising features on image datasets. This research will end by presenting the

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results and conclusions obtained.

Dataset

The dataset used in this study consists of leaves of oil palm seedlings affected by spot disease and leaves of oil palm seedlings that are normal or not affected by disease. Dataset collection was carried out directly from PPKS Marihat, Sei Kumango Village, Tambusai, Rokan Hulu Regency, Riau Province, for palm leaves affected by spot disease using a Canon camera and for normal palm leaves using an Oppo Smartphone camera.

(a)

(b)

Image 2. (a) Normal leaves of oil palm seedlings (b) Spotted leaves of oil palm seedlings

As can be seen in Image 2, there is a sample dataset of normal palm seedling leaves and a dataset of palm seedling leaves affected by spot disease. The total dataset consists of 600 palm seedling leaves, with 300 seedlings infected with spot disease and 300 healthy palm seedling leaves. The dataset will be divided into two parts, 70% for training data and 30% for validation data.

Preprocessing

Preprocessing is a stage or step in data analysis that aims to improve the data and prepare it to be processed by an algorithm or model. By preprocessing, data can be transformed into a form that is more suitable for further analysis, such as removing empty data, changing the data format, or normalising the data scale, so as to produce cleaner data that is ready to be used in the data labelling and modelling process [13]. After the data is divided, the next step is to preprocess the dataset with normalisation using the Rescale 1/255 function. This normalisation rescales the image so that the pixel values are in the range of 0 to 1. In addition, the size of the target image to be used in the training process is 600 x 400 pixels.

Convolutional Neural Network

Convolutional Neural Network (CNN) is a type of Deep Learning algorithm that was created specifically to recognise and process images or image input. This algorithm has the capability to extract important information or learnable weights from various aspects or objects in the image, and is also able to separate and identify each object separately[14]. The feature extraction process in the CNN model is executed automatically through a convolution process, which consists of a convolution layer and a pooling layer[15].

CNN Model Development

The next stage is the construction

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of the CNN Model, the Convolutional Neural Network structure used in this study can be seen in Table 1.

Table 1. CNN structure

Layer (type)	Output Shape	Param #
InputLayer	400,600,3	0
Convolutional_12	400,600,16	448
Max Pooling_12	200,300,16	0
Convolutional_13	200,300,32	4640
Max Pooling_13	100,150,32	0
Convolutional_14	100,15,64	18496
Max Pooling_14	50,75,64	0
Flatten	240000	0
Dense	128	30720128
Dropout	240000	0
Dense	1	129

Pooling layers are used to reduce the dimensions of feature maps, especially for width and height, while maintaining depth. Max pooling is a type of pooling that produces maximum values within the region of the image covered by the filter. Max pooling is more suitable for extracting dominant features, and is therefore considered better in some cases. In the process of building the model, there are several stages consisting of convolution blocks and max pool layer. To avoid overfitting which can lead to poor predictions on the dataset, the Dropout layer technique is used. Dropout is a technique in CNN that helps overcome the dependency problem between neurons[16]. Next, the 'Flatten' layer is processed, which aims to convert the input into a single vector without parameters, so that it will not affect the batch size in the dataset training process.

Hyperparameter Tuning

Hyperparameter tuning is a crucial aspect in the world of machine learning to achieve maximum accuracy. The process of determining the optimal configuration in hyperparameter tuning involves repeated iterations with various combinations of different configurations.

Table 2. Hyperparameters

	Parameter
Batch Size	5
Dropout	0.1
Optimizer	Adam
Learning Rate	0.0001

Using Batch Size 5 and Learning Rate 0.0001 can get optimal results[17]. The aim is to select one configuration that can provide the highest accuracy. By repeating and varying the configuration, it is expected that the model can be optimally adjusted so that it can provide accurate predictions on new data. Through the hyperparameter tuning process, the model can be optimised and able to produce better performance than using the default configuration[18].

RESULTS AND DISCUSSION

In this study, the Convolutional Neural Network (CNN) method is used to detect spot disease in oil palm seedlings. The dataset used consists of 600 images of oil palm seedling leaves, with 420 images used as training data and 180 images as validation data. The next process is preprocessing the training data and validation data, which involves

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Resize, Data normalisation, and Encoder label transformation. After preprocessing is complete, the next step is to build a CNN model for spot disease detection on the leaves of oil palm seedlings using the Python programming language. The CNN model architecture is built using a sequential model and Adam as an optimiser. After the CNN model is built, testing is carried out by applying the model that has been made. Furthermore, the calculation of Accuracy, Recall, Precision, and F1-Score values is carried out.

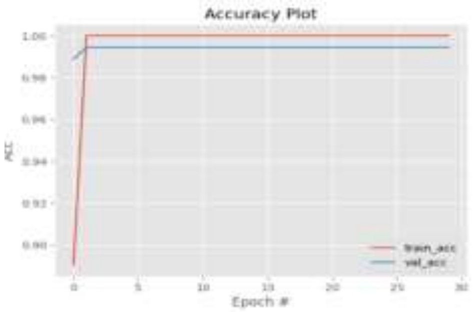

Image 3. Accuracy Plot

The accuracy result graph of training and validation shows the x-axis represents the number of epochs in training the model from 0 to 30, while the y-axis represents the accuracy level from 0.75 to 1.00. The graph in Image 3 shows excellent performance. It can be seen that the training accuracy increases rapidly as the number of epochs increases, while the validation accuracy also increases.

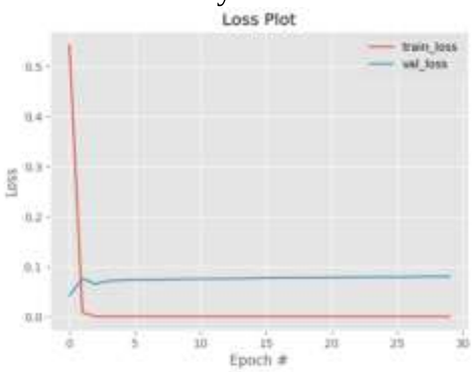

Image 4. Loss Plot

The graph of loss results from training and validation displays the x-axis representing the number of epochs in training the model from 0 to 30, and the y-axis representing the loss rate from 0.5 to 0.0. The graph in Image 4 shows excellent results. It can be seen that the loss in training decreases as the number of epochs increases, and the loss in validation also decreases consistently. This indicates that the model is working well and getting closer to the expected results as the training process progresses.

	precision	recall	f1-score	support
0	0.99	1.00	0.99	90
1	1.00	0.99	0.99	90
accuracy			0.99	180
macro avg	0.99	0.99	0.99	180
weighted avg	0.99	0.99	0.99	180

Image 5. Classification Report

The test results show the accuracy value of the CNN model that has been built with 30 epochs of 0.99, recall of 1.00, precision of 0.99, and f1-score of 0.99. The accuracy value that is close to 1 indicates that the performance of this model is very good in image matching or spot disease detection on oil palm seedlings. The higher the accuracy value, the more accurate the model is in predicting and classifying images between the leaves of oil palm seedlings affected by spotting and normal leaves. The high recall, precision, and f1-score values also indicate that the model can properly identify and distinguish between the disease class and the normal class. This shows that the CNN model built is very effective and reliable in detecting spot disease in oil palm seedlings.

CONCLUSIONS

This study successfully implemented a Convolutional Neural Network (CNN) to detect leaf spot disease on oil palm seedlings. By utilising a dataset of infected and healthy leaf images, the CNN model can recognise and distinguish between the two with a high level of accuracy. The model building process involves literature study, dataset collection, data preprocessing, and CNN architecture building. Test results showed excellent model performance, with accuracy reaching 99%, recall 100%, precision 99%, and f1-score 99%. The positive implications of this research include contributions to the development of plant disease detection technology, especially in oil palm seedlings, which can support economic growth in the plantation sector.

REFRENCES

[1] N. Haryanti, A. Marsono, and M. A. Sona, “Strategi Implementasi Pengembangan Perkebunan Kelapa Sawit Di Era Industri 4.0,” *Jurnal Dinamika Ekonomi Syariah*, vol. 8, no. 1, 2021, doi: 10.53429/jdes.v8i1.146.

[2] R. N. Rosa and S. Zaman, “Pengelolaan Pembibitan Tanaman Kelapa Sawit (Elais guineensis Jacq.) Di Kebun Bangun Bandar, Sumatera Utara,” *Buletin Agrohorti*, vol. 5, no. 3, 2017, doi: 10.29244/agrob.v5i3.16470.

[3] Y. Defitri, “Intensitas dan Persentase Serangan Beberapa Penyakit Utama Pada Tanaman Sawit (Elaeis guineensis Jacq.) di Desa Tebing Tinggi Kecamatan Mara Sebo Ulu Kabupaten Batanghari,” *Jurnal Ilmiah Universitas Batanghari Jambi*, vol. 21, no. 3, 2021, doi: 10.33087/jiubj.v21i3.1761.

[4] P. Andini, A. Agustinur, and N. C. Ritonga, “Kajian Insidensi Penyakit Bercak Daun pada Pembibitan Kelapa Sawit di Main Nursery PT. Socfindo Kebun Seunagan,” *Biofarm : Jurnal Ilmiah Pertanian*, vol. 18, no. 2, 2022, doi: 10.31941/biofarm.v18i2.2275.

[5] A. Susanto and A. Prasetyo, “Respons Curvularia lunata Penyebab Penyakit Bercak Daun Kelapa Sawit terhadap Berbagai Fungisida,” *Jurnal Fitopatologi Indonesia*, vol. 9, no. 6, pp. 165–172, Dec. 2013, doi: 10.14692/jfi.9.6.165.

[6] F. Afriliya and B. Al Fajar, “Keanekaragaman Jenis-Jenis Penyakit dan Cara Pengendaliannya di Pembibitan Kelapa Sawit (Elaeis Guinensis Jacq) PT. Perkebunan Nusantara I Langsa,” *Jurnal Biologi Samudra*, vol. 1, no. 1, 2019.

[7] S. Ilahiyah and A. Nilogiri, “Implementasi Deep Learning Pada Identifikasi Jenis Tumbuhan Berdasarkan Citra Daun Menggunakan Convolutional Neural Network,” *JUSTINDO (Jurnal Sistem dan Teknologi Informasi Indonesia)*, vol. 3, no. 2, 2018.

[8] L. A. Andika, H. Pratiwi, and S. S. Handajani, “KLASIFIKASI PENYAKIT PNEUMONIA MENGGUNAKAN METODE CONVOLUTIONAL NEURAL NETWORK DENGAN

OPTIMASI ADAPTIVE MOMENTUM," *Indonesian Journal of Statistics and Its Applications*, vol. 3, no. 3, 2019, doi: 10.29244/ijsa.v3i3.560.

[9] Y. Yohannes, S. Devella, and K. Arianto, "Deteksi Penyakit Malaria Menggunakan Convolutional Neural Network Berbasis Saliency," *JUITA: Jurnal Informatika*, vol. 8, no. 1, 2020, doi: 10.30595/juita.v8i1.6671.

[10] C. Garbin, X. Zhu, and O. Marques, "Dropout vs. batch normalization: an empirical study of their impact to deep learning," *Multimed Tools Appl*, vol. 79, no. 19–20, 2020, doi: 10.1007/s11042-019-08453-9.

[11] K. Sriporn, C. F. Tsai, C. E. Tsai, and P. Wang, "Analyzing malaria disease using effective deep learning approach," *Diagnostics*, vol. 10, no. 10, 2020, doi: 10.3390/diagnostics10100744.

[12] A. J. O. Simanjuntak and D. Udjulawa, "Klasifikasi Penyakit Daun Sawit Menggunakan Metode Jaringan Saraf Tiruan Dengan Fitur Local Binary Pattern," *Jurnal Algoritme*, vol. 3, no. 1, 2022, doi: 10.35957/algoritme.v3i1.3158.

[13] L. Mutawalli, M. T. A. Zaen, and W. Bagye, "KLASIFIKASI TEKS SOSIAL MEDIA TWITTER MENGGUNAKAN SUPPORT VECTOR MACHINE (Studi Kasus Penusukan Wiranto)," *Jurnal Informatika dan Rekayasa Elektronik*, vol. 2, no. 2, 2019, doi: 10.36595/jire.v2i2.117.

[14] S. Shubathra, P. C. D. Kalaivaani, and S. Santhoshkumar, "Clothing Image Recognition Based on Multiple Features Using Deep Neural Networks," in *Proceedings of the International Conference on Electronics and Sustainable Communication Systems, ICESC 2020*, 2020. doi: 10.1109/ICESC48915.2020.9155959.

[15] T. Bariyah, M. A. Rasyidi, and N. Ngatini, "Convolutional Neural Network untuk Metode Klasifikasi Multi-Label pada Motif Batik," *Techno.Com*, vol. 20, no. 1, 2021, doi: 10.33633/tc.v20i1.4224.

[16] F. K. Celsia and G. A. Sandag, "Implementation of Deep Learning on Number Recognition in Sign Language," *SISFOTENIKA*, vol. 11, no. 2, 2021, doi: 10.30700/jst.v11i2.1117.

[17] N. Rochmawati, H. B. Hidayati, Y. Yamasari, H. P. A. Tjahyaningtijas, W. Yustanti, and A. Prihanto, "Analisa Learning Rate dan Batch Size pada Klasifikasi Covid Menggunakan Deep Learning dengan Optimizer Adam," *Journal of Information Engineering and Educational Technology*, vol. 5, no. 2, 2021, doi: 10.26740/jieet.v5n2.p44-48.

[18] U. Misra *et al.*, "RubberBand: Cloud-based hyperparameter tuning," in *EuroSys 2021 - Proceedings of the 16th European Conference on Computer Systems*, 2021. doi: 10.1145/3447786.3456245.