Bulletin of Electrical Engineering and Informatics
Vol. 14, No. 2, April 2025, pp. 1099~1107
ISSN: 2302-9285, DOI: 10.11591/eei.v14i2.8498

Shallot disease classification system based on deep learning

Lita Lidyawati, Arsyad Ramadhan Darlis, Sofa Jauharotul Munawaroh
Department of Electrical Engineering, Faculty of Industrial Technology, Institut Teknologi Nasional, Bandung, Indonesia

Article Info

Article history:

Received Mar 25, 2024
Revised Oct 28, 2024
Accepted Nov 19, 2024

Keywords:

Convolutional neural network
Deep learning
Jetson Nano
ResNet-18
Shallot disease

ABSTRACT

Shallot is one of the important horticultural commodities for society and has high economic value. The problem with shallot cultivation is disease attacks on plants, one of which is Fusarium wilt. With the condition that the shallot commodity at the farmer level has a high failure rate, it is hoped that this research can assist farmers in providing information about shallot plants that have diseased plant characteristics using deep learning system convolutional neural network (CNN) method by utilizing leaf images on shallot plants. This research was conducted using the ResNet-18 architecture, with a total of 400 data in the dataset divided into 2 categories, namely healthy and diseased Fusarium wilt. The device used to carry out the classification process in this research is a Jetson Nano 2 GB. The ratio used to form a model from the dataset is 80-20 (80% training data and 20% validation data). The accuracy results for the classification of shallot plant diseases using real-time leaf images during the day have an average accuracy value of 68% on healthy plants and 62% on Fusarium wilt plants, while at night it has an average accuracy value of 53% on healthy plants and 47% on Fusarium wilt plants.

Corresponding Author:

Arsyad Ramadhan Darlis
Department of Electrical Engineering, Faculty of Industrial Technology, Institut Teknologi Nasional
Bandung, Indonesia
Email: arsyad@itenas.ac.id

1. INTRODUCTION

Shallots are a horticultural commodity that has economic value and play an important role in the daily lives of the Indonesian people. According to the results of the National Socioeconomic Survey (SUSENAS) in September 2021, the average consumer of shallots in Indonesia can reach 790.63 thousand tons [1]. In shallot cultivation, there are issues with harvest failures, mostly caused by pest and disease infestations [2]. One of the diseases that disrupt the growth of shallots is Fusarium wilt, caused by the fungus *Fusarium oxysporium* [3]. Shallots are one of the types of bulbs commonly used as a cooking spice. In shallot plants, the bulbs can be eaten raw, used as a cooking spice, for medicinal purposes, the skin of the bulb can be used as a dye, and the leaves can be used as an ingredient in vegetable dishes.

The leaves of healthy shallot plants can be used to distinguish them from those affected by Fusarium wilt. The official website of agricultural science (agrotechnology) Indonesia provides information that shows that healthy shallot plants have distinctive leaf characteristics. Healthy shallot plants exhibit lush, green leaves that vary from light green to dark green. The leaves are cylindrical and elongated, resembling pipes. They range in length from 45 to 70 cm, tapering to a pointed tip [4].

According to the official website of the Agricultural Extension and Human Resources Development Agency (BPPSDMP), shallot plants displaying symptoms of Fusarium wilt disease exhibit the following characteristics: the plants appear wilted, the color of the leaves turns yellow and curls, plant growth is stunted, the leaves droop towards the surface, and the leaves become wrinkled or twisted. The affected plants may appear smaller than healthy plants of the same age due to this disease [5]. Fusarium wilt disease in shallot plants is typically noticeable after the plants are around 20 days old [6].

The advancements in information technology and computers have enabled the identification of diseases using cutting-edge technology, including artificial intelligence which constitutes a strategic innovation pathway to strengthen ecological plant health management amidst climate change, globalization, and agricultural intensification pressures [7]. Artificial intelligence has evolved into two subfields, namely machine learning and deep learning [8]. Numerous studies have been conducted using deep learning systems to classify plant diseases, such as the research conducted by Amar *et al.* [9], which utilized the convolutional neural network (CNN) method with the LeNet architecture using color images and grayscale segmentation for plant disease classification based on leaf images. Rachburee and Punlumjeak [10] experimented with the VGG16 architecture, ResNet152V2, and MobileNetV2 to specify Lotus species base on transfer learning. In addition, Gogoi *et al.* [11] investigated the classification of rice diseases using the CNN method. An object classification using the CNN method has shown to be more precise and effective, especially when dealing with images.

By leveraging technological advancements to enhance the quality of shallot production through the classification of shallot plants afflicted with diseases requiring special attention. Deep learning is utilized to classify the condition of shallot plants using leaf images. Farmers can improve the plant's condition by intervening early and yielding high-quality shallot bulbs. Given the high failure rate of shallot commodities at the farmer level, this research aims to assist farmers by providing information on shallot plants exhibiting disease symptoms using the CNN method with the ResNet-18 architecture, utilizing Jetson Nano 2 GB for the classification process based on leaf shape and color to determine the condition of shallot plants.

2. METHOD

In this research, hardware system design was carried out using Jetson Nano 2 GB, a webcam camera, and a computer as shown in Figure 1. Based on the block diagram in Figure 1, to perform disease classification on shallot plants, a dataset containing leaf images of shallot plants is required, with samples consisting of images of healthy leaves and images of leaves with Fusarium wilt disease. The devices used for disease classification on shallot plants are shown in Figure 1. Jetson Nano serves as a small computer that will execute programs and systems for conducting real-time classification testing of 2 categories of input data. Jetson Nano 2 GB is one of NVIDIA's products, a leading technology company renowned for their graphics processing units (GPU). It is the latest iteration of the Jetson Nano, specifically designed for heavy-duty computing tasks such as image processing and artificial intelligence especially deep learning on smaller, energy-efficient devices [12].

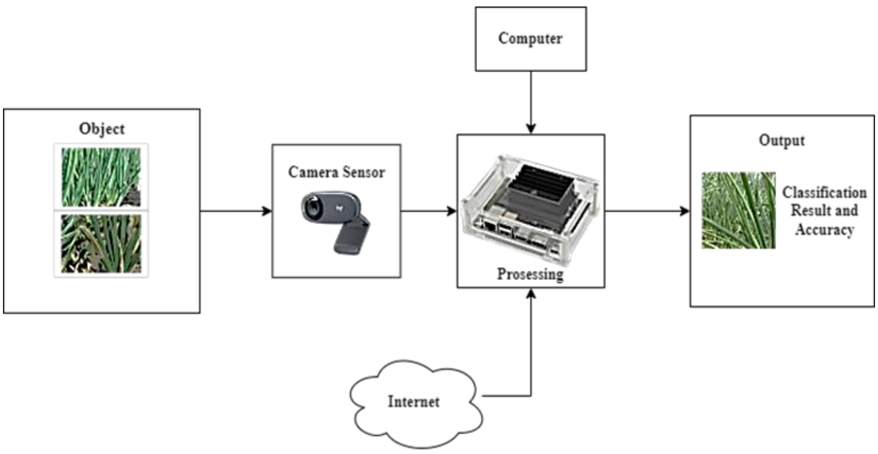


Figure 1. Hardware system block diagram

Deep learning is a subset of machine learning, essentially resembling a neural network with three or more layers. Neural networks attempt to simulate the workings of the human brain [13]. While a single-layer neural network can still make predictions or estimations, the addition of extra layers helps optimize and enhance accuracy. The CNN is considered one of the foundational neural network models among several deep learning models [14], [15].

The CNN is one of the deep neural network types commonly employed in image recognition and processing. The CNN algorithm consists of neurons designed to operate similarly to the visual cortex in the frontal lobe of the human and animal brain [16]. The visual cortex is responsible for processing visual stimuli. In the development of CNN, there are several architecture models, and one of them is the residual neural network (ResNet) architecture.

The ResNet architecture emerged as the top performer in the ImageNet large scale visual recognition challenge (ILSVRC) and common objects in context (COCO) competitions in 2015 on ImageNet [17]. In this regard, ResNet demonstrated that this neural network architecture could be more easily optimized and achieve high accuracy, reaching 80.62% [18]. ResNet is a CNN architecture designed for image processing and classification tasks. Within ResNet, a critical component known as the residual block exists. Skip connections play a crucial role in preventing training saturation and mitigating high errors. In this research, ResNet-18 was employed, which consists of 18 layers, including 17 convolutional layers and 1 fully connected layer [19].

Data collection is carried out to fulfill the system's needs or dataset, where the collected data consists of leaf images of shallot plants in two conditions: healthy and affected by Fusarium wilt disease. Leaf images are captured using a smartphone camera. JPG format with a 1:1 aspect ratio. A dataset is a collection of data required as a unit by a computer [20]. This data collection contains a diverse set of data that can be utilized in algorithmic training to identify predictive patterns in the entire dataset. In this research, the dataset object of interest is shallot leaf images. The dataset utilizes leaf images that are divided into two types of condition: healthy and affected by Fusarium wilt disease, with each image sample having 200 images. As a result, there are a total of 400 image samples in the dataset. Clear and distinct object images in terms of color and shape are required for the training process, which is why the dataset image capture was conducted during daylight hours. The data split ratio for this research was 80-20, with 80% being used for training and 20% for validation. Furthermore, the 80-20 ratio also aligns with the Pareto principle, which states that in various situations, approximately 80% of the results are caused by about 20% of the causes, or it can be said that 20% of the dataset represents 80% of the dataset [21].

2.1. Training

Training data in a CNN is a collection of data used to train the CNN model to recognize specific patterns or features within the input data and perform classification with high accuracy [22]. This training data plays a crucial role in the development of CNN models because the model will 'learn' from this data to make predictions or classifications on previously unseen data. The model is evaluated using validation data after training to assess its performance on unseen data. This helps identify whether the model is overfitting or not [23]. The model design employed in this research utilizes the CNN model with the ResNet-18 architecture. Figure 2 represents the flowchart in the model design.

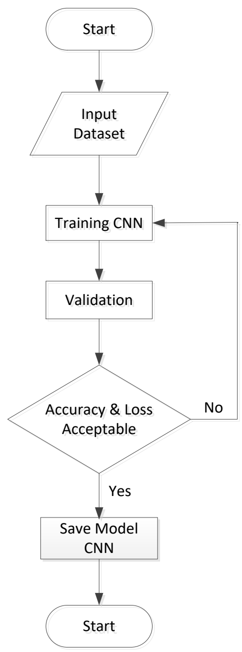


Figure 2. Training process

2.2. Testing

Testing in a CNN is a crucial stage in model development, where the trained model is assessed and evaluated in classifying or making predictions on unseen data [24]. The purpose of testing is to measure how well the CNN model can generalize from the training data to new data. Figure 3 represents the flowchart of the testing process conducted. Accuracy in research data refers to the degree of correctness or precision with which data represents the real-world phenomena or measurements being studied. It is a fundamental concept in research and data analysis because the accuracy of data can significantly impact the validity and reliability of research findings and conclusions [25].

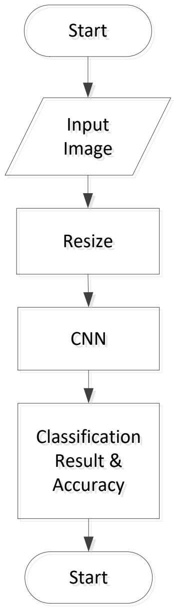


Figure 3. Testing process

3. RESULTS AND DISCUSSION

3.1. Dataset

The dataset used consists of a total of 400 leaf images. In Figure 4(a), it represents the dataset for the healthy category, and in Figure 4(b), it represents the dataset for the Fusarium wilt disease category. Each category consists of 200 leaf images. A Logitech C270 camera was used to capture this image, which was then preprocessed to have 400×400 pixels dimensions. The amount of dataset needed for conducting research using CNN varies depending on several factors, including the type of problem to be solved, the complexity of the CNN model, and the number of classes or categories to be identified. In Table 1, it represents the dataset that will be used for training.

(a) (b)

Figure 4. Dataset for categories with conditions: (a) healthy and (b) Fusarium wilt

Table 1. Dataset description

Shallot plant dataset	
Number of datasets	400
Image size	400×400 px
Categories	1. Healthy 2. Fusarium wilt
Image capture time	Daytime

3.2. Training

In the training data process, we used the ResNet-18 architecture, which consists of 17 convolutional layers, 2 pooling layers, and 1 fully connected layer. Table 2 displays the parameters utilized during the training process. In the context of training a neural network model, an epoch refers to one complete pass through the entire training dataset. During each epoch, the entire training dataset is used to update the weights and parameters of the model [26]. The number of epochs is one of the parameters that can be configured in the neural network training process and is crucial for controlling how long or how many training iterations will be performed.

Table 2. Training process parameters

Epoch	Batch size	Learning rate
5	2	0.001

Batch size is one of the crucial parameters in training a neural network model. It refers to the number of data samples used to compute gradients and update the model's weights in each iteration during training [27]. Properly configuring the batch size can impact training speed, memory usage, and model convergence.

Learning rate is a factor that determines how much a neural network model will adjust its weights during training [28]. A low learning rate can result in training being slow and taking a long time to achieve good results. If the learning rate is too high, the model may not converge or experience divergence, which leads to an increase in training errors.

3.2. Testing result

In the testing process, the CNN method is used, with the result being the accuracy value from the testing to assess the extent of the classification recognition performed by Jetson Nano. In executing the testing process, real-time image capture is conducted using a camera sensor directed towards the shallot plant, as shown in Figure 5. To classify shallot plants, as shown in Figure 5, it is necessary to capture images of leaves from the plant. Object classification prediction results with accurate values can be found on the right side. The testing is carried out in real-time at two different times: in daytime and at night in an open space. Different times at different distances between the camera sensor and the object, such as 5 cm and 10 cm, are used for testing. Testing is carried out in the daytime using natural sunlight, and in the nighttime, it is carried out with additional light from a flashlight.

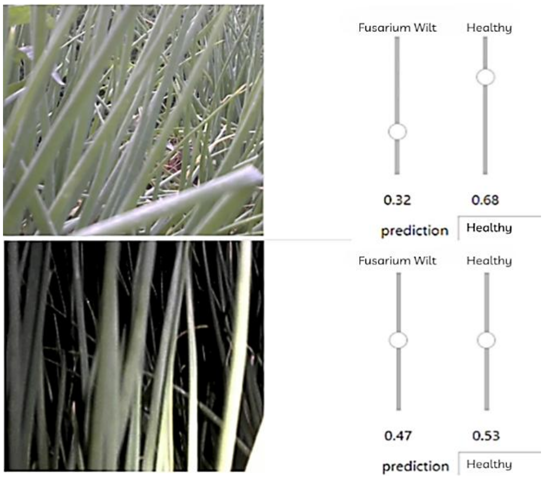
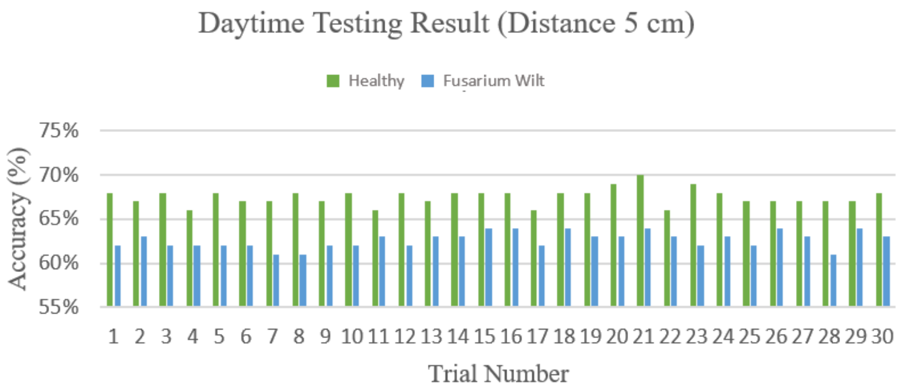


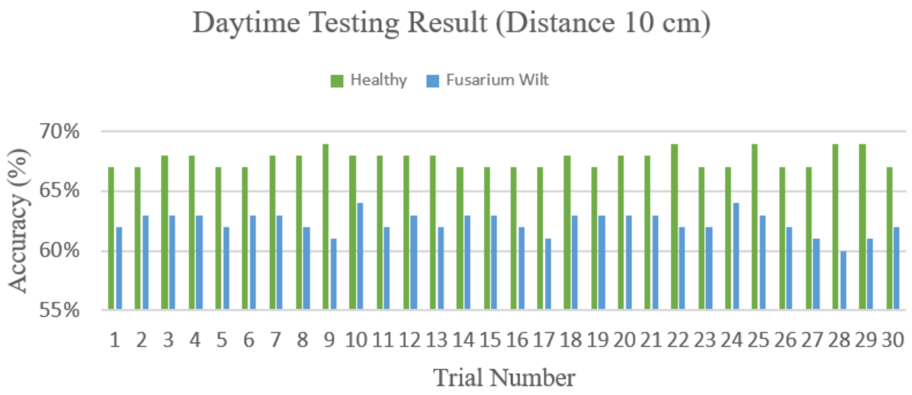
Figure 5. Testing results

3.2.1. Daytime testing results

During the daytime for the classification of healthy and Fusarium wilt shallot plants, 30 trials were carried out at distances of 5 cm and 10 cm. The testing results during the daytime at a distance of 5 cm can be seen in Figures 6(a) and (b). The accuracy of shallot plant condition classification at a 5 cm distance under healthy conditions has the highest accuracy value of 70% and the lowest value of 66%, with an average of 68%. For 30 data points under the condition of Fusarium wilt disease, the highest accuracy is 64%, the lowest is 62%, with an average of 62%. The results from a 10 cm distance under healthy conditions have the highest accuracy value of 69% and the lowest value of 67%, with an average of 68%. For 30 data points under the condition of Fusarium wilt disease, the highest accuracy is 64%, the lowest is 60%, with an average of 62%.



(a)

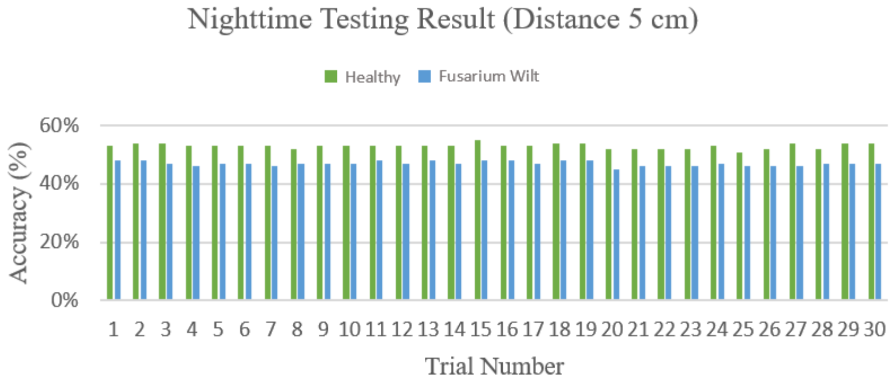


(b)

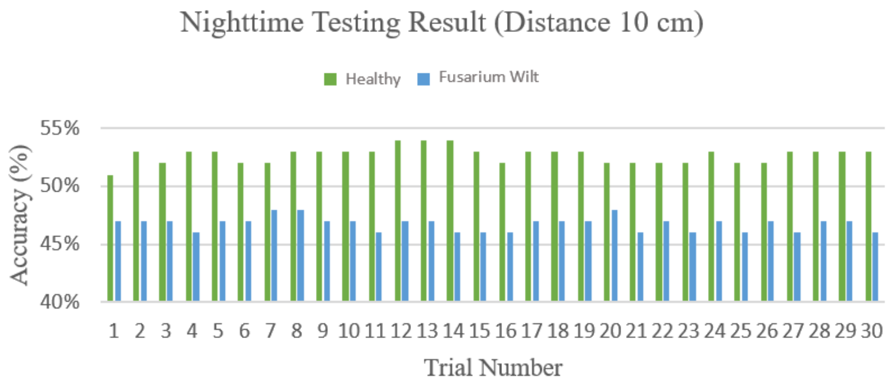
Figure 6. Comparison of daytime testing results at: (a) 5 cm and (b) 10 cm distance

3.2.2. Nighttime testing results

During the testing process conducted at night for the classification of shallot plants into healthy and Fusarium wilt categories, a total of 30 experiments were conducted at distances of 5 cm and 10 cm. The results of the nighttime testing can be seen in Figures 7(a) and (b). The results from a 5 cm distance under healthy conditions have the highest accuracy value of 55% and the lowest value of 51%, with an average of 53%. For 30 data points under the condition of Fusarium wilt disease, the highest accuracy is 48%, the lowest is 45%, with an average of 46%. And the results from a 10 cm distance under healthy conditions have the highest accuracy value of 54% and the lowest value of 51%, with an average of 53%. For 30 data points under the condition of Fusarium wilt disease, the highest accuracy is 48%, the lowest is 46%, with an average of 47%.



(a)



(b)

Figure 7. Comparison of nighttime testing results at: (a) 5 cm and (b) 10 cm distance

Figure 8 shows a graph comparing the classification testing results with accuracy values during the day and night at distances of 5 cm and 10 cm. The graph indicates that the accuracy values tend to decrease for both categories between day and night. Nighttime testing has significantly lower accuracy compared to daytime testing. When it comes to distance data collection, there is minimal variation, and it can be concluded that classification of shallot plant diseases can still be performed effectively within the range of 5 cm to 10 cm. The prediction results of shallot plant classification in determining the correct categories of healthy and Fusarium wilt disease conditions using leaf images as the examined objects can be seen in Table 3.

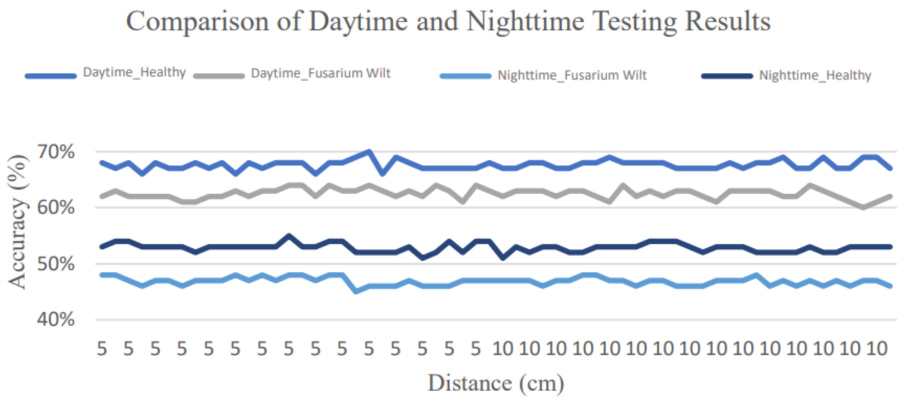


Figure 8. Comparison of daytime and nighttime testing results

Table 3. The results of shallot plant disease classification testing

Times	Categories	Distance	Accuracy (%)		
			Max (%)	Min (%)	Average (%)
Daytime	Healthy	5	70	66	68
		10	69	67	68
	Fusarium wilt	5	64	62	62
		10	64	60	62
Nighttime	Healthy	5	55	51	53
		10	54	51	53
	Fusarium wilt	5	48	45	47
		10	48	46	47

4. CONCLUSION

Deep learning system with a Jetson Nano 2 GB device in this research successfully classified diseases in shallot plants with an accuracy rate of up to 70%. Based on the testing time, there is a comparison of accuracy results. During the daytime, the accuracy results have an average value of 68% for healthy plants and 62% for Fusarium wilted plants. Meanwhile, during the nighttime, the accuracy results have an average value of 53% for healthy plants and 47% for Fusarium wilted plants. The testing result with 5 cm and 10 cm distance did not have an impact on the accuracy of disease classification in shallot. The average accuracy for testing at both 5 cm and 10 cm distances is 68% for the healthy category and 62% for the Fusarium wilted category. At nighttime, in dark conditions with the assistance of a flashlight, only the object itself receives illumination, while the background remains dark. Therefore, during the testing process, errors may occur because the system struggles to learn the object captured by the camera sensor. One avenue for future work is to conduct the study to better method in monitoring the plants such as using drone as a mobile system. This would allow for a more comprehensive understanding of how the system impact to the farmer.

ACKNOWLEDGEMENTS

This work was supported by Acceleration of Doctoral Study Grant from Institut Teknologi Nasional Bandung in number letter contract 414/F.003/LPPM/Itenas/VII/2023.

REFERENCES

[1] Susanawati, Masyhuri, Jamhari, and D. H. Darwanto, "Factors influencing income of shallot farming in Java Indonesia using UOP profit function model," *4th International Conference on Food and Agriculture Resources (FANRes 2018)*, 2018, vol. 172, pp. 68-74, doi: 10.2991/fanres-18.2018.14.

[2] Setyawati, E. S. Rahayu, H. Irianto, and J. Sutrisno, "Production and price risk analysis of shallot (allium stipitatum regel) cultivation among farm households in Berebes Districts, Indonesia," *Applied Ecology and Environmental Research*, vol. 21, no. 3, pp. 2625-2640, 2023: 10.15666/aeer/2103_26252640.

[3] Supyani, S. H. Poromarto, Supriyadi, R. Utaminingsih, and Hadiwiyono, "Health of shallot bulbs planted with mycorrhizal applications and several types of mulch in moler disease conducive land," *IOP Conference Series: Earth and Environmental Science, 4th International Conference on Food Science and Engineering (ICFSE)*, vol. 1200, 2022, doi: 10.1088/1755-1315/1200/1/012061.

[4] N. S. Idly, Susilawati, and Suwandi, "Characteristics of shallots (allium ascalonicum l) influenced by sulfur application in floating cultivation," *BIOVALENTIA: Biological Research Journal*, vol. 9, no. 2, pp. 84-90, Nov. 2023, doi: 10.24233/biov.9.2.2023.401.

[5] L. Herlina, B. Istiaji, and S. Wiyono, "the causal agent of Fusarium disease infested shallots in Java Islands of Indonesia," *International Conference on Agribusiness and Rural Development (IConARD 2020)*, 2021, vol. 232, doi: 10.1051/e3sconf/202123203003.

[6] Cennawati, E. Syam'un, and F. Haring, "Evaluation of beneficial fungus on production, pest, and disease incidence in shallot," *International Journal of Life Science and Agriculture Research,* vol. 2, pp. 63–70, May 2023, doi: 10.55677/ijlsar/V02I05Y2023-04.

[7] V. E. González-Rodríguez, I. Izquierdo-Bueno, J. M. Cantoral, M. Carbú, and C. Garrido, "Artificial intelligence: a promising tool for application in phytopathology," *Horticulturae*, vol. 10, no. 3, p. 197, 2024, doi: 10.3390/horticulturae10030197.

[8] I. Cholissodin, Sutrisno, A. A. Soebroto, U. Hasanah, and Y. I. Febiola, *AI, Machine Learning & Deep Learning*, Malang: FILKOM Universitas Brawijaya, 2020.

[9] J. Amar, B. Bouaziz, and A. Algergawy, "A deep learning-based approach for banana leaf diseases classification," *Lecture Notes in Informatics (LNI), Gesellschaft für Informatik*, 2017, pp. 79-88.

[10] N. Rachburee and W. Punlumjeak, "Lotus species classification using transfer learning based on VGG16, ResNet152V2, and MobileNetV2," *IAES International Journal of Artificial Intelligence (IJ-AI)*, vol. 11, no. 4, pp. 1344-1352, 2022, doi: 10.11591/ijai.v11.i4.pp1344-1352.

[11] M. Gogoi, V. Kumar, S. A. Begum, N. Sharma, and S. Kant, "Classification and detection of rice diseases using a 3-stage CNN architecture with transfer learning approach," *Agriculture*, vol. 13, no. 8, 1505, 2023, doi: 10.3390/agriculture13081505.

[12] M. L. Bukhori and E. E. Prasetiyo, "Jetson Nano- based mask detection system with tensorflow deep learning framerowk," *Jurnal Nasional Teknik Elektro dan Teknologi Informasi*, vol. 12, no. 1, pp. 15–20, 2023, doi: 10.22146/jnteti.v12i1.5472.

[13] I. Goodfellow, Y. Bengio, and A. Courville, *Deep learning,* Cambridge: MIT Press, 2016.

[14] S. B. Imanulloh, A. R. Muslikh, and D. R. I. M. Setiadi, "Plant diseases classification based leaves image using convolutional

neural network," *Journal of Computing Theories and Applications*, vol. 1, no. 1, pp. 1–10, 2023, doi: 10.33633/jcta.v1i1.8877.
[15] H. T. Adityawan, O. Farroq, S. Santosa, H. M. M. Islam, M. K. Sarker, and D. R. I. M. Setiadi, "Butterflies recognition using enhanced transfer learning and data augmentation," *Journal of Computing Theories and Applications*, vol. 1, no. 2, pp. 115–128, 2023, doi: 10.33633/jcta.v1i2.9443.
[16] C. C. Aggarwal, *Neural networks and deep learning*, Switzerland: Springer Cham, 2019, doi: 10.1007/978-3-031-29642-0.
[17] A. R. Darlis *et al.*, "Autonomous human and animal classification using synthetic 2D tensor data based on dual-receiver mmwave radar system," *IEEE Access*, vol. 11, pp. 80284-80296, 2023, doi: 10.1109/ACCESS.2023.3299325.
[18] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," *The IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778, doi: 10.1109/CVPR.2016.90.
[19] F. Ramzan *et al.*, "A deep learning approach for automated diagnosis and multi-class classification of Alzheimer's disease stages using resting-state fMRI and residual neural networks," *Journal of Medical Systems*, pp. 37–44, 2020, doi: 10.1007/s10916-019-1475-2.
[20] L. Koesten, E. Simperl, T. Blount, E. Kacprzak, and J. Tennison, "Everything you always wanted to know about a dataset studies in data summarisation," *International Journal of Human-Computer Studies*, vol. 135, 2020, doi: 10.1016/j.ijhcs.2019.10.004.
[21] V. R. Joseph, "Optimal ratio for data splitting," *Wiley*, pp. 531–538, 2022, doi: 10.1002/sam.11583.
[22] M. M. Taye, "Theoretical understanding of convolutional neural network: concepts, architectures, applications, future directions," *Computation*, vol. 11, no. 3, pp. 52–75, 2019, doi: 10.3390/computation11030052.
[23] X. Ying, "An overview of overfitting and its solutions," *Journal of Physics: Conference Series*, vol. 1168, no. 2, pp. 1–5, 2019, doi: 10.1088/1742-6596/1168/2/022022.
[24] R. Yamashita, M. Nishio, R. K. G. Do, and K. Togashi, "Convolution neural network: an overview and application in radiology," *Insights into Imaging*, vol. 9, pp. 611–629, 2018, doi: 10.1007/s13244-018-0639-9.
[25] B. E. W. Jr. and M. E, Kite, *Principles of Research in Behavioral*, New York: Routledge, 2018.
[26] S. Afaq and S. Rao, "Significance of epoch on training neural network," *International Journal Of Scientific & Technology Research*, vol. 9, no. 6, pp. 485–488, 2020.
[27] I. Kandel and M. Castelli, "The effect of batch size on the generalizability of the convolutional neural networks on a histopathology dataset," *ICT Express*, vol. 6, no. 4, pp. 312–315, 2020, doi: 10.1016/j.icte.2020.04.010.
[28] C. Igiri, A. O. Uzoma, and A. Silas, "Effect of learning rate on artificial neural network in machine learning," *International Journal of Engineering Research (IJERT)*, vol. 4, no. 2, pp. 359-363, 2015.

BIOGRAPHIES OF AUTHORS

Lita Lidyawati was born in Yogyakarta (Indonesia), on March 9, 1977. She graduated from Institut Teknologi Nasional (ITENAS) Bandung, Department of Electrical Engineering (Indonesia), in 2000. She received a master's degree in electrical engineering from the Institut Teknologi Bandung (ITB) (Indonesia), in 2005. Her research interests concern: signals processing and visible light communications. She can be contacted at email: lita@itenas.ac.id.

Arsyad Ramadhan Darlis was born in Bandung (Indonesia), on May 1, 1987. He graduated from Institut Teknologi Nasional (ITENAS) Bandung, Department of Electrical Engineering (Indonesia), in 2009. He received a master's degree in electrical engineering from the Institut Teknologi Bandung (ITB) (Indonesia), in 2011. He obtained his Doctoral Program from Universitas Indonesia, Department of Electrical Engineering. His research interests concern in visible light communications, digital signal processing, and internet of things. He can be contacted at email: arsyad@itenas.ac.id.

Sofa Jauharotul Munawaroh was born in Bandung (Indonesia) on March 24, 2000. She graduated from Institut Teknologi Nasional (ITENAS) Bandung, Department of Electrical Engineering, in 2023. Her research interests concern: artificial intelligence. She can be contacted at email: sofajm15@gmail.com.