FAKULTAS ILMU KOMPUTER
UPN VETERAN JAKARTA

PROCEEDINGS

4th INTERNATIONAL CONFERENCE

ICIMCIS

INFORMATICS, MULTIMEDIA, CYBER, AND INFORMATION SYSTEM

Technical Co-Sponsored by IEEE INDONESIA SECTION

ICIMCIS PROCEEDINGS 2022

2022

2022 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS) | 978-1-6654-7327-9/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICIMCIS56303.2022.10017840

2022 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS) | 978-1-6654-7327-9/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICIMCIS56303.2022.10017595

2022 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS)

Organizing Committee
International Advisory Committee

Dr. Ing Wahyudi Hasbi, S.Si, M.Kom. - IEEE IS Chair
Prof. Dr. Ir. Gamantyo Hendrantoro, Ph.D. - IEEE IS Vice-Chair
Ir. Linawati, M.Eng.Sc., Ph.D. - IEEE IS Secretary
Dr. Karlisa Priandana, M.Eng - IEEE IS Vice Secretary
Dr. Kemas Muslim Lhaksmana - IEEE IS Treasurer
Dr. Prima Dewi Purnamasari, S.T., M.Sc - IEEE IS Vice Treasurer
Dr. Anter Venus, MA, Comm – Rector Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Dr. R. Dudy Heryadi, M.Si – Vice Rector for Academic Affairs Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Dr. Ec. Prasetyo Hadi, SE., MM., CFMP – Vice Rector for General and Financial Affairs Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Dr. dr. Ria Maria Theresa, Sp.KJ., MH. – Vice Rector for Student Affairs and Cooperation Universitas Pembangunan Nasional Veteran Jakarta, Indonesia

Steering Committee

Prof. Teddy Mantoro – Universitas Sampoerna, Indonesia
Prof. Achmad Nizar Hidayanto - Universitas Indonesia, Indonesia
Prof. Dr. Achmad Benny Mutiara Q.N. – Universitas Gunadarma, Indonesia
Prof. Dra. Sri Hartati, M.Sc., Ph.D – Universitas Gajah Mada, Indonesia
Prof. Dr.Ir. Agus Buono, M.Si, M.Kom – IPB University, Indonesia
Prof. Dr. Ir. Siti Nurmaini, MT – Universitas Sriwijaya, Indonesia
Dr. Djuniadi, MT – Universitas Negeri Semarang, Indonesia
Dr. Ermatita, M.Kom – Universitas Sriwijaya, Indonesia
Dr. Didit Widiyanto – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Dr. Tjahjanto – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Dr. Widya Cholil, S.Kom., M.IT – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Dr. Bambang Saras – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Dr. Deris Setiawan - Universitas Sriwijaya, Indonesia

General Chair

Dr. Widya Cholil, S.Kom., M.IT – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia

General Co-Chairs

M. Octaviano Pratama, S.Kom, M.Kom. – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia

Secretarial

Kraugusteeliana, M.Kom., MM – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Diyah Retnowati, S.Kom – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Saimin, S.Kom – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia

Event, Publicity, Website & Documentation Division

Ati Zaidiah, S.Kom., MTI – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Andhika Octa Indarso, MMSI – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Astrianto Afandi, Amd.Kom – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Didit Suryahartono, S.Kom – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Mochammad Fariz Setyawan, S.Kom – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia

Proceeding Division

Erly Krisnanik, S.Kom, MM – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Artika Arista, S.Kom., MMSI – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Ika Nurlaili Isnainiyah, S.Kom, M.Sc – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Helena Nurramdhani Irmanda, S.Pd., M.Kom. – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Muhammad Adrezo, S.Kom, M.Sc – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Ria Astriratma, S.Kom, M.Cs - Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Neny Rosmawarni, M.Kom - Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Muhammad Panji Muslim, S.Pd., M.Kom. - Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Mustofa Galih Pradana, M.Kom - Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Triando Damiri Burlian, S.Kom, M.S.Eng, M.Sc. – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Novi Trisman Hadi, S.Pd., M.Kom. - Universitas Pembangunan Nasional Veteran Jakarta, Indonesia

Financial

Rudhy Ho Purabaya, SE., MMSI – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Yami - Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Suryadi, Amd.Kom - Universitas Pembangunan Nasional Veteran Jakarta, Indonesia

Administration & Logistic

Musenah, S.Pd, M.Kes – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Zaenudin – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia
Abdul Rahman – Universitas Pembangunan Nasional Veteran Jakarta, Indonesia

2022 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS) took place November 16th – 17th, 2022 in virtual, Indonesia.

ISBN: 978-1-6654-7327-9 (ART) / 978-1-6654-7326-2 (USB)

2022 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS) | 978-1-6654-7327-9/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICIMCIS56303.2022.10017457

2022 International Conference on Informatics, Multimedia, Cyber and Information System (ICIMCIS) | 978-1-6654-7327-9/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICIMCIS56303.2022.10017593

Table of Content

Comparison ADAM-optimizer and SGDM for Classification Images of Rice Leaf Disease

1st Pujo Hari Saputro
Engineering Faculty
Sam Ratulangi University
Manado, Indonesia
pujoharisaputro@unsrat.ac.id

2nd Dhina Puspasari Wijaya
Computer Engineering Faculty
Alma Ata University
Yogyakarta, Indonesia
dhina.puspa@almaata.ac.id

3rd Musthofa Galih Pradana
Computer Faculty
UPN Veteran
Jakarta, Indonesia
musthofagalihpradana@upnvj.ac.id

4th Dyah Listianing Tyas
Science technology and Teacher Faculty
Trinita University
Manado, Indonesia
dyahlistianingtyas@gmail.com

5th Wahyuni Fithratul Zalmi
Engineering Faculty
Sam Ratulangi University
Manado, Indonesia
wahyuni.fithratul.czalmi@unsrat.ac.id

***Abstract*— One of the most important sectors related to the food security of a country is the agricultural sector. Considering rice plants are currently the largest commodity, the amount of rice production becomes the biggest concern. One of the factors influencing the fertility of rice is the rice plants diseases. The innovation are conducted to overcome this problem by collaborating with various sectors, one of them is computer science, especially computer vision. Deep learning methodology is a branch of computer vision and convolutional neural network (CNN). It is often used since it can compress features automatically and more efficiently. Hence, it can produce the accurate classification. Alexnet is an architecture or model on CNN for images classification. This study compared two optimizers, namely the Adam and SGDM optimizer. The result study obtained the best validation accuracy of types classification of rice leaf is the Adam optimizer as 10 epochs and a learning rate of 0.0001 as 95.33 %. The Adam optimizer generate a preferable validation accuracy than SGDM optimizer in a training dataset by the slightly epochs. However, a large number of epochs SGDM are better in training epochs.**

***Keywords*— CNN, rice plant, Adam, SGDM**

I. Introduction

Deep learning is branch of machine learning to set computer in accompanying humans work as the computer learn training process [1]. In pattern recognition, deep learning is one of important topic that effectively can solve a problem in identification of disease particularly vegetable pathology. Deep learning usually is conducting for complex features selection and accompanying in the larger dataset. This technique is useful to improve performance or accuracy on machine learning in order toward selecting features. The most popular deep learning method is the Convolutional Neural Network (CNN) for image processing [2], [3], [4]. CNN can handle image dataset and these techniques are belongs to deep learning type since its depth in the network. The advantage of CNN can shorten features automatically and efficiently so that the classification results are accurate [5], [6].

The agricultural sector is one of the most crucial sectors related to the food security of a country [7]. Considering rice plants are the largest commodity today, then total production of rice is the biggest concern [8]. The rice plants disease is one of the affecting factors of rice fertility. Improper or inaccurate treatment effects failure cropping resulting in decreased rice production as well as reduced farmers' income. The rice plants disease symptoms are difficult to distinguish especially advanced symptoms [9].

Countries with rice as their staple food are innovating to overcome that disease aggressively. It was conducted in order to stabilize the readiness of the basic commodities. The innovation can be conducted by collaborating in various sectors, for example computer science. The collaboration between agricultural sector and computer science related to the pattern recognition using a computer vision system. This system can identify rice plants diseases, so that the farmers can treat these diseases easily [10].

The use of machine learning in deep learning is usually for complex features selection cases and conducting in large dataset. This is useful to improve selecting features performance quickly. The popular deep learning method is the convolutional neural network (CNN) because it is often used. CNN can shorten features automatically and efficiently so that the classification results are accurate [5], One of the CNN architectures or models is ALexnet. This study used the Alexnet architecture by Adam and SGDM optimizer to find the highest validation accuracy on rice lead disease dataset.

II. State of the Art

A. Rice Plants

Rice plants are a food crop in grass clumping appearance from two continents, Asia and tropical as well as subtropical West Africa. Rice plants are grown since 3,000 BC in Zhejiang, China [11]. Most of half population in the world, especially from developing countries including Indonesia eats rice as the staple food to meet their daily food [12].

Rice plants have spiritual, cultural, economic and political values toward the Indonesian people as they can meet the population needs [13]. Rice plants as the staple food can meet 56-80% of the people calories in Indonesia [14]. Division : *Spermatophyta,* Sub division : *Angiospermae,* Class : *Monocotyledoneae,* Ordo : *Poales,* Family : *Graminae,* Genus : *Oryza Linn,* Species : *Oryza sativa L.*

B. Digital Image

Image is a 2-dimensional picture. In Mathematics concept, image is a continuous function of 2-dimensional light intensity [15]. The bit is the smallest unit of digital image and it represents in binary numeral systems. Its value can be 0 or 1. A set of the 8-bit is a data unit called byte and its value can range from 0 to 255. A set of bytes with specific structure is called the 8-bit digital image in software. Pixel (picture elements) is a dot that refers to the smallest element in images. The numeric number (1 byte) of pixel represents the digital number (DN). The DN can be displayed in gray, ranging from

978-1-6654-7327-9/22/$31.00 ©2022 IEEE

white and black (gray scale), related to the detected energy level. The correct pixels composition will create an image.

C. Convolutional Neural Network (CNN)

One of the neural network types in image data is usually CNN. Convolutional neural network (CNN) belongs to deep learning type since its depth network. The deep learning is branch of machine learning to set computer in conducting humans work as the computer learn training process [1], [16], [17].

The main components in CNN are Convolution Layer, Pooling Layer, Fully Connected Layer, and Dropout.

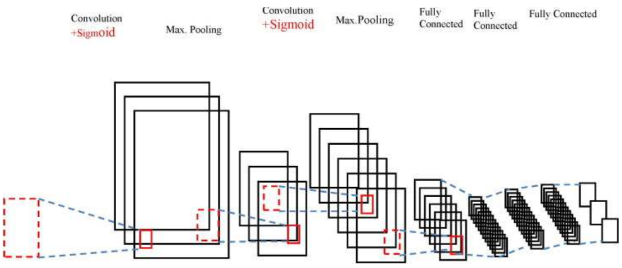


Fig. 1. Basic Architecture of CNN [18]. [1].

1) Convolution Layer

Convolution layer is a main layer in CNN method. The convolution layer itself is produced a new image which shows the input image features. Each image applies a convolution layers filter in the process. The layer consists of neurons which are arranged as a filter with the width and height (pixels). As an example, the first layer of extraction layer feature is convolutional layer of size 6x6x3 where the width is 6 pixels, the height is 6 pixels, and the weight is 3 based on the figure channel. These three filters will be switch to entire parts of image.

Every movement will be operating on dot between the input and the filter value then it generates an output called an activation map or feature map [19].

2) Pooling Layer

Pooling layer represents a function layer for Feature Maps as an input even processing it to various proximate statistical operations pixel. In the CNN model, the pooling layers are usually inserted behind several convolution layers regularly. This layer can reduce the output volume on Feature Maps progressively. Therefore, this layer can decrease the parameters and the network calculations as well as control over fitting. The important thing of constructing the CNN model is selecting the multiple types of pooling layers in order to be worthwhile for model performance. In essence, the pooling layer contains a filter with the specific size and stride and it will be move across the feature map area. Commonly, the pooling layers use Max Pooling and Average Pooling. Its aim to decrease the feature map (down sampling) dimensions, thereby speeding up th computation and reducing parameters reform and overcoming over-fitting [20].

3) Fully Connected Layer

Fully connected layer has a good level of accuracy [18], [21], the feature map result from feature extraction is still on a multidimensional array, therefore it should be flatten or reshape into a vector for the fully-connected layer input. The fully-connected layer contains the activity neurons from the previous layer to the next layer as an artificial neural network. Every activity from the previous layer needs to be converted into one-dimensional data before linked to all neurons in the Fully-Connected layer. The Fully-Connected Layer is usually applied in the Multi-layer Perceptron method and intended to process the data so that it can be classified. The difference between the Fully-Connected layer and the regular convolutional layer is the neurons in the convolutional layer linked to the certain input area. Meanwhile, the Fully Connected layer has neurons linked to all parts. However, both layers still operate dot products, so their functions are same.

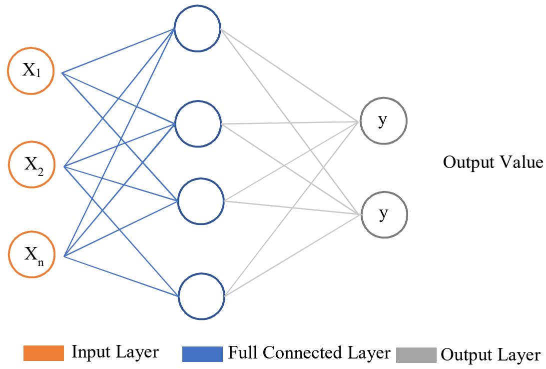


Fig. 2. The Fully Connected Layer

4) Dropout

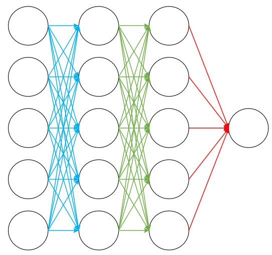


Fig. 3. The ordinary neural network

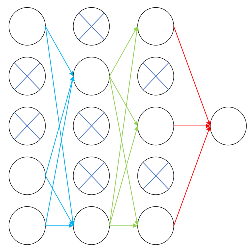


Fig. 4. The Neural Network Subjected Dropout Technique

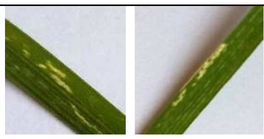
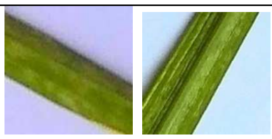
Dropout is a neural network regularization technique where several neurons will be randomly selected and do not used in training. These neurons are discarded randomly. It means that the contribution of the discarded neurons will be temporarily stopped by the network and the new weight is also not applied to the neurons at the back propagation. Dropout is a process to prevent over fitting and advance the learning process. Dropout refers to remove either hidden neurons or visible layers on the network. Omit a neuron means omit neuron temporarily from the existing network.

III. Research Methodology

The research material is rice leaf image affected by the disease. This leaf image was obtained on kaggle,com website. There are 4 types of rice leaf images, namely Brown Spot, Hispa, Leaf Blast, and Healthy (well). The research data was

1,000 images, where 250 images each type. In this study, 700 images as the training data and 300 images as the testing data. It means that there were 175 training images and 75 testing images of each type. The several rice plants diseases in this study as follows:

TABLE I. IMAGES SAMPLE

No.	Disease	Image Sample
1	Brown Spot	
2	Hispa	
3	Leaf Blast	
4	Healthy (Well)	

To design the CNN model for predicting Rice Leaf Disease, several phases were defined as shown in the Figure 5 below:

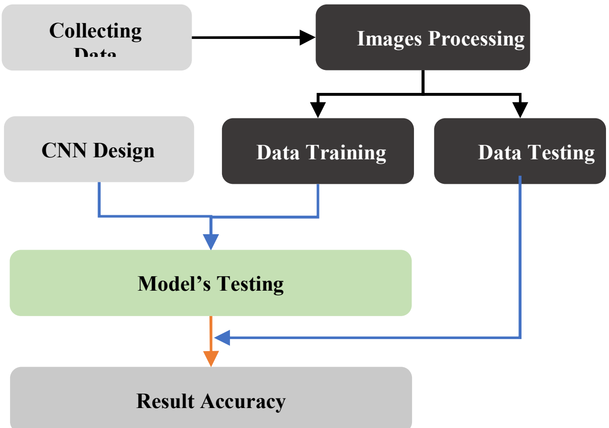


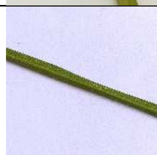
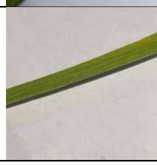
Fig. 5. Flowchart System Design

In the first stage, the researchers designed a CNN model to classify images. Then, the data was preparing the data by collecting each type of rice disease based on its type. After that, the researchers conducted the preprocessing process includes, cropping, and resizing. The next step divided the dataset into 2 parts for each type, namely the training dataset and the testing dataset. The classification was conducted randomly by the system. Furthermore, the researchers tested the CNN model using the training dataset. At this stage, many experiments conducted by varying the CNN model configuration to find the optimum validation.

IV. RESULT AND DISCUSSION

The first stage was the pre-processing stage. This stage was cropping and resizing. The reason of conducting cropping was making the CNN can process the images by focusing on the disease. In addition, the images will be resized to size 227 x 227 pixels. The cropping process should be accurate with the disease images so that it can be clear and well-studied by the CNN model. Meanwhile, resizing is conducting to align the images size before entering the CNN model. The following is an image sample before and cropping:

TABLE II. IMAGES CROPPING

No.	Type	Before Crop	After Crop
1	Brown Spot		
2	Hispa		
3	Leaf Blast		
4	Healthy		

The next stage was the training stage. In this research, the researchers conducted training data using the Alexnet architecture. Besides, the researchers also tried several optimizers, including the Adam optimizer and the Stochastic Gradient Descent with Momentum (SGDM) optimizer. The training process has different results and loss accuracy values, although results and loss generated by each optimizer are not significantly different. In this training process, several trainings were conducted using the two optimizers with different configurations of the epoch and learning rate.

A. The first training using Adam optimizer

Fig. 6. The Accuracy and Loss Chart of the First Training

The configuration of the first training can be seen as follows:

- Epoch : 10

- Activation function : relu
- Learning Rate : 0.0001

By using the configuration as above, the validation data accuracy is 95.33% where the training time of 16 minutes 9 seconds. The details will be shown in the following figure:

Figure 6. showed that the training process experiences consistency as 5 epochs to 10 epochs. The confusion matrix table from the first training is as follows:

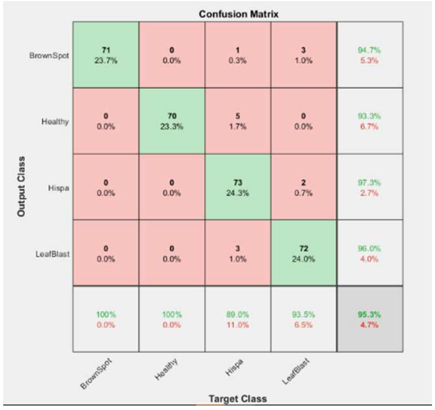


Fig. 7. The Confusin matrix of First Training

The confusion matrix figure 7 represents the classification results of 300 data testing / 75 data of each type. Based on the table above, it can be seen that the 75 testing data tested, none of them are classified as disease type (100%) correctly. The highest accuracy was hispa disease (97.3%), where only 2 images classified as Leaf Blast disease.

B. The second training using Adam optmizer

This second training used the same optimizer, but the epochs were increased with the assumption that the CNN model will process more so that the accuracy value is expected higher. The configuration was as follows:

- Epoch : 20
- Activation function : relu
- Learning Rate : 0.0001

Based on the configuration above, the validation data accuracy is 91.67% where a training time of 34 minutes 15 seconds. The details will be shown in the following figure:

Fig. 8. The accuracy and loss chart on the second training

Based on the Figure 8., the training process experiences consistency as 10 epochs to 20 epochs. The confusion matrix table was as follows:

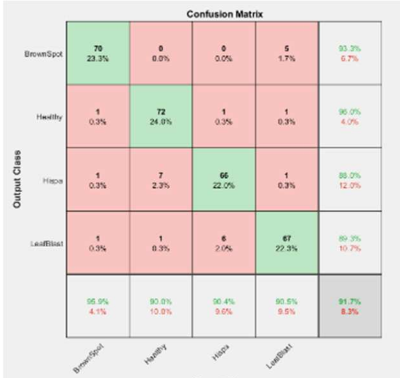


Fig. 9. The confusion matrix of the second training

Based on the Figure 9., there is no type of disease that as a whole (100%) is classified correctly according to its type from 75 testing data. The highest accuracy value was healthy leaf species, namely 96.00%, where only 3 images classified as Brown Spot, Hispa, and Leaf Blast.

C. The third training using the SGDM optimizer

This third training using the SGDM optimizer configuration can be seen as follows:

- Epoch : 10
- Activation function : relu
- Learning Rate : 0.0001

Based on the configuration, the validation data accuracy was 76.67% where a training time of 15 minutes 25 seconds. The details will be shown in the following figure:

Fig. 10. The accuracy and loss chart on the third training

The confusion matrix table from the third training was as follows:

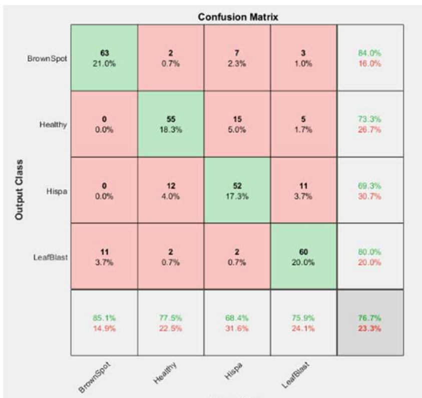


Fig. 11. The confusion matrix of the third training

Based on the figure 11, there is no type of disease that as a whole (100%) classified correctly according to its type from 75 testing data tested for each type. The highest accuracy value was the Brown Spot leaf type (84.00%) where 2 images classified as healthy, 7 images classified as Hispa, and 3 images classified as Leaf Blast.

D. The fourth training using the SGDM optimizer

This fourth training used the same optimizer as before, the epochs was increased with the assumption that the CNN model will learn more. The researchers expected that the accuracy value will be higher. The configuration was as follows:

- Epoch : 20
- Activation function : relu
- Learning Rate : 0.0001

Based on these data, the validation data accuracy was 91.00% where a training time of 28 minutes 51 seconds. The details will be shown in the following figure:

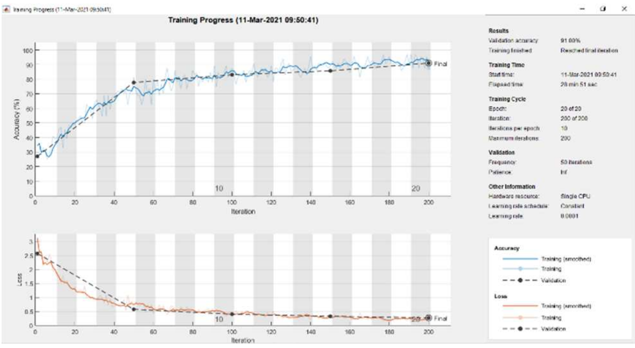


Fig. 12. The accuracy and loss chart if the fourth training

The confusion matrix table of the fourth training was as follows above fig. 13.

Based on the figure 13, there is no type of disease that as a whole (100%) is classified correctly according to its type from 75 testing data. The highest accuracy value was the Brown Spot leaf type (96.00%) where 1 leaf image classified as healthy leaf, and 2 leaf images classified as Leaf Blast.

Fig. 13. The confusion matrix of the fourth training

The several training results are presented in the following table 3. Based on the results table 3, the highest validation accuracy value was Adam optimizer as 10 epochs and the learning rate was 0.0001 of 95.33%. In addition, the Adam optimizer produced better validation accuracy values than the SGDM optimizer in a training dataset with small epochs. However, SGDM was better in the training time with high epochs.

TABLE III. THE CONCLUSION OF TRAINING RESULTS

No.	Epoch	Activation Function	Learning Rate	Optimization	Accuracy	Time Training
1	10	Relu	0.0001	Adam optimizer	95.33%	16 minutes 9 seconds
2	20	Relu	0.0001	Adam optimizer	91.67%	34 minutes 15 seconds
3	10	Relu	0.0001	SGDM optimizer	76.67%	15 minutes 25 seconds
4	20	Relu	0.0001	SGDM optimizer	91.00%	28 minutes 51 seconds

V. CONCLUSION

Based on the research results of the Adam and SGDM optimizer on the CNN model using an image of rice leaf disease, the Adam optimizer produced better validation accuracy than the SGDM optimizer in a training dataset with small epochs. However, SGDM is better in the training time with high epochs.

Furthermore, a comparison can be conducted between Adam and SGDM optimizer with other optimizers on the CNN model in classifying this rice leaf disease.

ACKNOWLEDGMENT

The authors would like to thank the anonymous reviewers for their valuable comments. This research is supported by Directorate of Research and Community Service, Sam Ratulangi University.

REFERENCES

[1] D. Deng, L., & Yu, "Deep Learning: Methods and Applications.," *Found. Trends® Signal Process.*, vol. 7, no. 3–4, pp. 197–387, 2014.

[2] S. and P. Bhatt , Sarangi , Shivhare, "Identification of diseases in corn leaves using convolutional neural networks and boosting.," *ICPRAM 2019 - Proc. 8th Int. Conf. Pattern Recognit. Appl. Methods*, vol. 1, 2019.

[3] C. Liang, jie, Zhang, Zhang, feng, "Rice Blast Disease Recognition Using a Deep Convolutional Neural Network," *Sci. Rep.*, vol. 9, no. 1, pp. 1–10, 2019.

[4] Z. Zhang, Qiao, Meng, Fan, "Identification of maize leaf diseases using improved deep convolutional neural networks," *IEEE Access*, vol. 6, pp. 30370–30377, 2018.

[5] W. Rahman, Arko, Ali, Iqbal Khan, Apon, Nowrin, "Identification and recognition of rice diseases and pests using convolutional neural networks.," *Biosyst. Eng.*, vol. 197, pp. 112–120, 2020.

[6] D. D. S. Ardiant Utomo, Edwin Farrel Juniawan, Vincent Lioe, "Local Features Based Deep Learning for Mammographic Image Classification: In Comparison to CNN Models," *Procedia Comput. Sci.*, vol. 179, pp. 169–176, 2021.

[7] C. M. Gareth D. Borman, Walter S. de Boef, Flo Dirks, Yeray Saavedra Gonzalez, Abishkar Subedi, Marja H. Thijssen, Judith Jacobs, Ted Schrader, Salome Boyd, Hermine J. ten Hove, Edwin van der Maden, Irene Koomen, Sheila Assibey-Yeboah, "Putting food systems thinking into practice: Integrating agricultural sectors into a multi-level analytical framework," *Glob. Food Sec.*, vol. 33, 2022.

[8] S. R. Nomthandazo Precious Sibiya, Gloria Amo-Duodu, Emmanuel Kweinor Tetteh, "Model prediction of coagulation by magnetised rice starch for wastewater treatment using response surface methodology

(RSM) with artificial neural network (ANN)," *Sci. African*, vol. 17, 2022.

[9] A. Endang Anggiratih, Sri Siswanti, Saly Kurnia Octaviani, "Klasifikasi Penyakit Tanaman Padi Menggunakan Model Deep Learning Efficientnet B3 Dengan Transfer Learning," *J. Ilm. Sinus*, vol. 19, no. 1, 2021.

[10] N. A. Haris, "Kombinasi Ciri Bentuk dan Ciri Tekstur Untuk Identifikasi Penyakit Pada Tanaman Padi," *JATISI (Jurnal Tek. Inform. Dan Sist. Informasi)*, vol. 7, no. 2, pp. 237–250, 2020.

[11] P. dan H. Purnamawati, *Budidaya 8 jenis tanaman pangan unggul*. Depok: Penebar Swadaya, 2007.

[12] S. Rahmawati, "Status perkembangan perbaikan sifat genetik padi menggunakan transformasi argobacterium," *J. Agrobiogen*, vol. 2, no. 1, pp. 36 – 44, 2006.

[13] M. Z. H. Utama, *Budidaya Padi Lahan Marjinal Kiat Meningkatkan Produksi Padi*. Yogyakarta: ANDI Publisher, 2015.

[14] S. Renny Utami Somantri, "Penggunaan varietas unggul tahan hama dan penyakit mendukung peningkatan produksi padi nasional," *J. Litbang Pertan.*, vol. 35, no. 1, pp. 25–36, 2016.

[15] S. Sitorus, *Pengolahan Citra Digital*. Medan: USU Press, 2006.

[16] Y. Shakeel Ahmad, Muhammad Zubair Asghar, Fahad Mazaed Alotaibi, "A hybrid CNN + BILSTM deep learning-based DSS for efficient prediction of judicial case decisions," *Expert Syst. Appl.*, vol. 209, 2022.

[17] M. A. Sujan Ghimire, Ravinesh C. Deo, David Casillas-Pérez, Sancho Salcedo-Sanz, Ekta Sharma, "Deep learning CNN-LSTM-MLP hybrid fusion model for feature optimizations and daily solar radiation prediction," *Measurement*, vol. 202, 2022.

[18] L. C. M. Kotra Sankar Raja Sekhar, Tummala Ranga Babu, Goriparthi Prathibha, Kotra Vijay, "Dermoscopic image classification using CNN with Handcrafted features," *J. King Saud Univ. - Sci.*, vol. 33, no. 6, pp. 1–9, 2021.

[19] eiron O. and R. Nash, "An Introduction to Convolutional Neural Networks," *asXiv*, pp. 1–11, 2015.

[20] Z. T. Chen-Yu Lee, Patrick W. Gallagher, "Generalizing pooling functions in convolutional neural networks: Mixed, gated, and tree," *Artif. Intell. Stat. PMLR*, pp. 464–472, 2016.

[21] G. P. Qi Xua, Ming Zhanga, Zonghua Gub, "Overfitting remedy by sparsifying regularization on fully-connected layers of CNNs," *Neurocomputing*, vol. 328, pp. 69–44, 2019.