Journal of Information Systems and Informatics
Vol. 6, No. 3, September 2024 e-ISSN: 2656-4882 p-ISSN: 2656-5935
DOI: 10.51519/journalisi.v6i3.865 Published By DRPM-UBD

Comparing CNN Models for Rice Disease Detection: ResNet50, VGG16, and MobileNetV3-Small

Muhammad Taufik Roseno[1*], Serly Oktarina[2], Yuwinti Nearti[3], Hadi Syaputra[4], Nirmala Jayanti[5]

[1,2,4]Faculty of Computer Science, Universitas Sumatera Selatan, Palembang, Indonesia
[3,5] Faculty of Agribusiness, Universitas Sumatera Selatan, Palembang, Indonesia
Email: [1]mtroseno@uss.ac.id, [2]serlyoktarina@uss.ac.id, [3]yuwintinearti@uss.ac.id, [4]hadisyaputra@uss.ac.id, [5]nirmala.jayanti@uss.ac.id

Abstract

The Oryza sativa (rice) plant is an important staple food source, especially in the Asian region. Rice production is often disrupted by diseases such as Brown Spot, Leaf Scald, Rice Blast, Rice Tungro, and Sheath Blight, which can reduce yield and crop quality. This research aims to classify rice plant diseases using a deep learning approach with Convolutional Neural Networks (CNN) architecture, namely ResNet50, VGG16, and MobileNetV3-Small. The dataset used is Rice Leaf Disease Classification which consists of 1305 images with five disease labels. The data is divided into training, validation, and testing sets with proportions of 70%, 15%, and 15%. The results showed that the MobileNetV3-Small model provided the best accuracy on the test data of 79%, while VGG16 achieved the validation accuracy of 78.84%. Based on these results, MobileNetV3-Small is considered the most superior model for rice disease classification. This research shows the great potential of applying deep learning in automatic rice disease detection.

Keywords: Rice, Plant Disease, CNN, ResNet50, VGG16, MobileNetV3-Small, Deep Learning

1. INTRODUCTION

Oryza sativa (rice) is a vital staple food crop globally, particularly in Asia, where nearly 92% of the world's rice is both produced and consumed [1]. Rice serves as the primary source of carbohydrates for a significant portion of the global population, including Indonesia, where it is a fundamental component of daily meals [2], [3], [4]. However, despite its importance, rice cultivation faces critical challenges, particularly from diseases that reduce crop yields and degrade rice quality [5]. Diseases such as Brown Spot, Leaf Scald, Rice Blast, Rice Tungro, and Sheath Blight pose serious threats to rice production [6], [7], [8], leading to significant economic losses affecting farmers, traders, communities, and the broader economy [9].

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

The rise of information and computing technology, particularly in the area of deep learning, has created new opportunities for addressing the problem of rice plant diseases [10]. Deep learning, a branch of machine learning, uses artificial neural networks to analyze large amounts of data and has shown significant success in applications such as image recognition and object detection [11]. Specifically, by analyzing images of infected rice plants, deep learning models can be trained to detect visual patterns associated with specific diseases. This approach holds promise in helping farmers and agricultural experts identify diseases more quickly and accurately, allowing for timely intervention.

One of the most effective deep learning methods for image classification is Convolutional Neural Networks (CNNs), which have been widely used for identifying diseases based on visual symptoms in plants [12], [13], [14]. These models can classify diseases by analyzing symptoms present on leaves, stems, and other parts of the plant. Several CNN architectures, including ResNet50, VGG16, and MobileNetV3-Small, have been developed and applied to rice disease classification. Recent research has demonstrated the ability of these models to achieve high levels of accuracy in detecting and classifying rice plant diseases, which could significantly improve agricultural outcomes.

Despite the promising results from CNN-based models, there remains a notable research gap. Current studies have focused primarily on individual models without comprehensive comparisons between different architectures, particularly regarding their performance on varying dataset sizes. Further research is needed to evaluate and compare the effectiveness of different CNN architectures in classifying rice diseases. Addressing this gap is crucial for improving the accuracy and efficiency of these models, which could lead to better disease management strategies in rice farming.

This research aims to address the gap by conducting a comparative analysis of three CNN architectures—ResNet50, VGG16, and MobileNetV3-Small—in classifying rice plant diseases. By comparing the accuracy of these models and evaluating their performance, the study seeks to determine how effectively each architecture can classify images of rice diseases. The findings are expected to contribute to the development of more accurate and efficient deep learning models, which can play a pivotal role in improving rice disease detection and enhancing agricultural productivity.

2. MATERIAL AND METHODS

In the research there are several stages that will be carried out, namely, collecting datasets, pre-processing, splitting data into training and test data, performing classification, finding accuracy and analyzing differences in accuracy. In the

p-ISSN: 2656-5935 http://journal-isi.org/index.php/isi e-ISSN: 2656-4882

research conducted, there are several steps to get the desired results as shown in Figure 1.

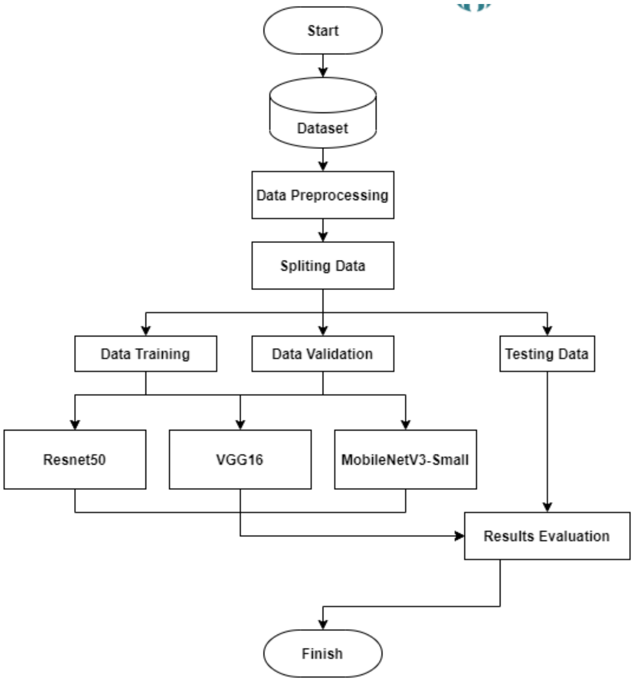


Figure 1. Research Flow

2.1. Datasets

Dataset of Rice Leaf Disease Classification for Bangladeshi Local Rice [15] which has 5 rice plant disease labels namely, Brown Spot, Leaf Scaled, Rice Blast, Rice Tungro, and Sheath Blight. The image dimensions are 1952 x 4160 with a total of 1305 image data subjects in the dataset. Some examples of the data are shown in Figure 2.

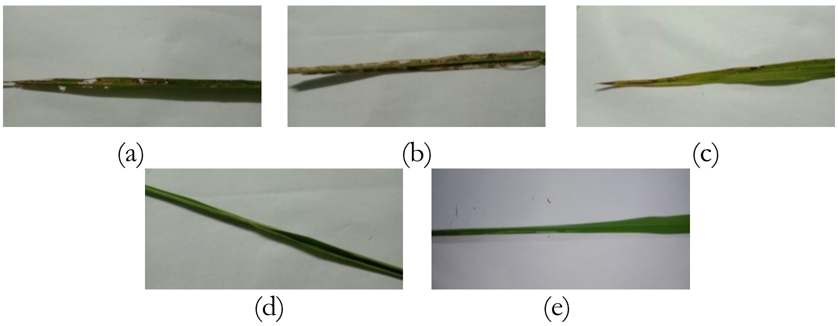


Figure 2. Rice Plant Diseases: (a) Brown Spot, (b) Leaf Scaled, (c) Rice Blast, (d) Rice Tungro, (e) Shath Blight

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

Based on the number of images for each class, Brown Spot consists of 90 images, Leaf Scaled has 143 images, Rice Blast contains 198 images, Rice Tungro includes 119 images, and Leaf Blight has 219 images.

2.2. Data Spliting

Furthermore, the data split process is carried out, in this study the data is divided into 3, namely training data, validation data and test data with a ratio of 70% training data, 15% validation data and 15% test data.

Tabel 1. Spliting Data

Class	Spliting		
	Train (70%)	**Validation (15%)**	**Test (15%)**
Brown Spot	62	13	15
Leaf Scaled	100	21	22
Rice Blast	138	29	31
Rice Tungro	83	17	19
Shath Blight	153	32	34

For the Brown Spot class, the dataset consists of 62 training data, 13 validation data, and 15 testing data. The Leaf Scaled class has 100 training data, 21 validation data, and 22 testing data. The Rice Blast class consists of 138 training data, 29 validation data, and 31 testing data. The Rice Tungro class has 83 training data, 17 validation data, and 19 testing data. Finally, the Shath Blight class consists of 153 training data, 32 validation data, and 34 testing data. Overall, this dataset has a total of 769 data points.

2.3. Pre-Processing

The purpose of the pre-processing stage is to ensure that all images have a consistent format and size so they can be effectively used in the training, validation, and testing processes of the model. Each image is resized to 224 x 224 pixels, which is the standard input size expected by the model. This is done to ensure that all images have uniform dimensions, as most image classification models require consistent input sizes for efficient data processing. Next, data transformation is performed to prepare the images in a format that can be interpreted by the model. Different transformations are applied for the three datasets: train (training), val (validation), and test (testing). Additionally, each image is converted from standard formats like JPG or PNG into a tensor, a numerical format used by deep learning models such as PyTorch. This transformation to tensors allows the images to be processed as numerical data that can be computed by the model during further operations.

Journal of Information Systems and Informatics
Vol. 6, No. 3, September 2024

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

2.4. Model Design

CNN, which stands for Convolutional Neural Network, is a type of artificial neural network commonly used for image recognition and processing. CNN is often used to recognize objects or detect certain features in an image (Arrofiqoh et al, 2018). The development of CNN architecture will adopt transfer learning from three popular architectures, namely Resnet50, VGG16, and MobileNetV3-Small. in each model. A summary of the model is shown in Figure 3.

3. RESULTS AND DISCUSSION

3.1 Experimental Results

In this research, the classification process is carried out using 769 images that have been divided into training data, validation data, and testing data. The next step is to run the training process on the rice disease image into the fit model. In Figures 3, 4, and 5 can observe the results of the fit model generator for each of the best architectures, where from epoch 10, 50 and epoch 100, there is an increasing trend in accuracy values for both training and testing data.

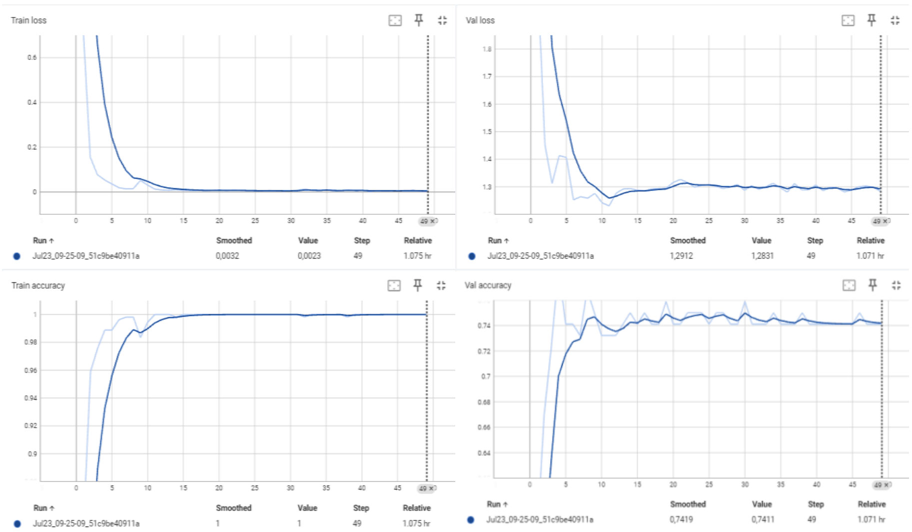


Figure 3. - Graph of Training and Validation Data loss and Accuracy Values from the ResNet50 Architecture

Journal of Information Systems and Informatics
Vol. 6, No. 3, September 2024
p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

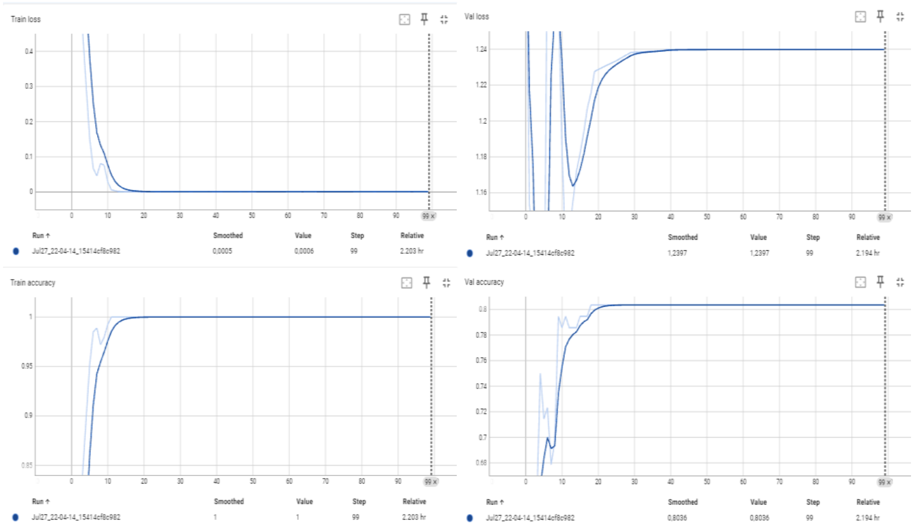


Figure 4. Graph of Training and Validation Data loss and Accuracy Values from the VGG16 Architecture

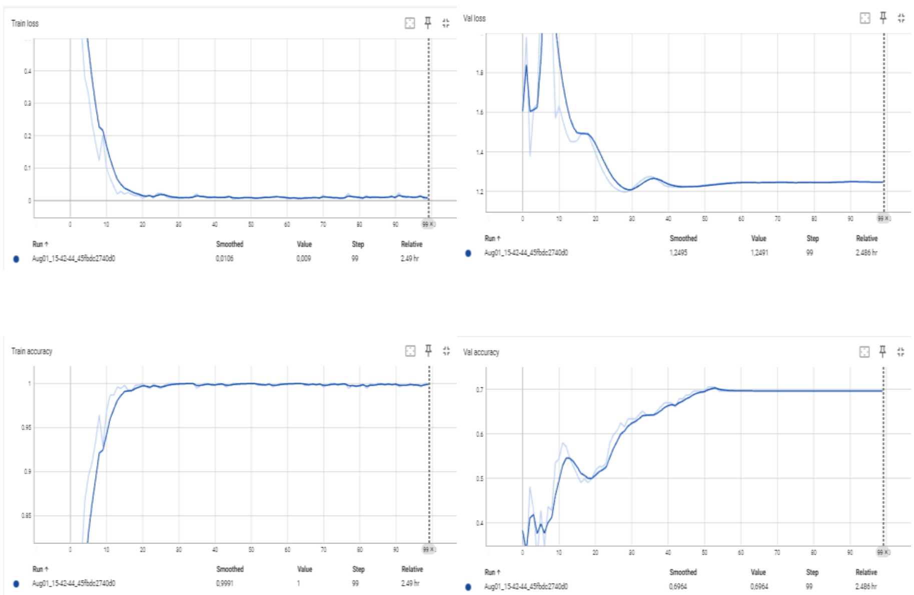


Figure 5. - Graph of Training and Validation Data loss and Accuracy Values from the MobileNetV3-Small Architecture

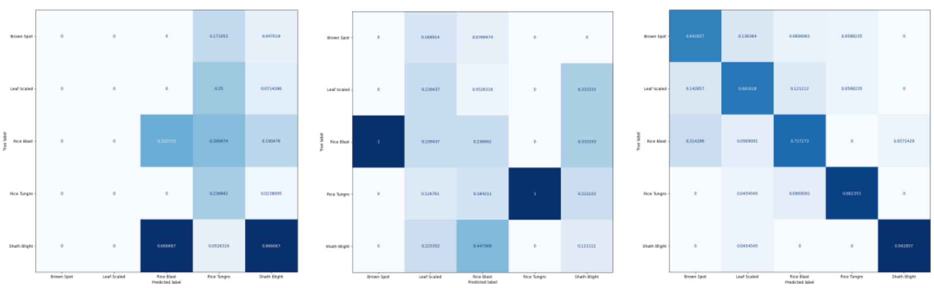
The best results for training, validation, and testing data for each model architecture from epoch 10, 50, and 100 with learning rates of 0.01, 0.001, and 0.0001 can be seen in Table 2.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

Table 2. Recapitulation of model results

Architecture	Epoch Acc	Learning Rate	Loss	Val Loss	Acc	Val Acc	Test Acc
Resnet50	50	0.0001	0.1197	1.3815	0.9818	0.7291	39%
VGG16	100	0.0001	0.0453	1.2253	0.9828	0.7884	23%
MobileNetV3-Small	100	0.001	0.0632	1.3455	0.9797	0.6328	79%

MobileNetV3-Small 100 0.001 0.0632 1.3455 0.9797 0.6328 79% Based on the model recapitulation results presented in Table 2, the selection of the best model is based on a number of key performance metrics, specifically Validation Accuracy (Val Acc) and Test Accuracy (Test Acc). The MobileNetV3-Small model recorded the highest Test Accuracy of 79% after training for 100 epochs with a learning rate of 0.001. This makes it a strong candidate if performance on test data is the main focus of the assessment. However, if the priority is more on the model's performance on validation data, then the VGG16 model, which achieved the highest Validation Accuracy of 78.84% in 100 epochs with a learning rate of 0.0001, can be considered as an alternative despite its relatively lower Test Accuracy of 23%. Meanwhile, the Resnet50 model shows a good balance of performance, with a Training Accuracy of 98.18% and a Validation Accuracy of 72.91%. However, its performance on test data was not as optimal as expected, with Test Accuracy only reaching 39%. Considering all these aspects, MobileNetV3-Small can be classified as the most superior model overall, especially if Test Accuracy is the main metric. On the other hand, VGG16 can be chosen if performance stability on validation data is preferred. Confusion matrix is used to measure the performance of model testing on data sets. The classification confusion matrix results for each architecture model in this study can be seen in Figure 6.



(a) (b) (c)

Figure 6. Confusion Matrix; (a) ResNet50, (b) VGG16, (c) MobileNetV3-Small

The Figure 6 shows three confusion matrices comparing the performance of ResNet50, VGG16, and MobileNetV3-Small models in rice disease classification. In figure (a) showing the performance of ResNet50, it can be seen that the model has significant misclassification especially in the Rice Blast and Rice Tungro classes, with misclassification rates of 33.3% and 23.68% respectively.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

ResNet50 also showed an error rate of 25% when trying to classify Leaf Scaled as Rice Blast. Meanwhile, the confusion matrix in figure (b) shows that VGG16 is better at predicting the Rice Blast class. However, there are still some misclassifications such as the Shath Blight class which was misclassified by 33.3% as Leaf Scaled and Rice Blast. Finally, in figure (c), MobileNetV3-Small showed the best performance among the three models with high accuracy in Brown Spot (64.29%), Rice Blast (72.73%), Rice Tungro (88.23%), and Shath Blight (94.29%) classes. However, MobileNetV3-Small still experienced minor misclassification in the Leaf Scaled class, where 14.29% of this class was misclassified as Rice Blast. Overall, MobileNetV3-Small showed better classification ability than the other two models based on the confusion matrix shown.

3.2 Discussion

The experimental results reveal important insights into the performance of three CNN architectures ResNet50, VGG16, and MobileNetV3-Small in classifying rice plant diseases. Based on the accuracy and loss metrics over multiple epochs, MobileNetV3-Small emerged as the most effective model when focusing on test data accuracy, achieving a Test Accuracy of 79%. This highlights its potential for real-world applications where the model's ability to generalize well to unseen data is critical. In contrast, the VGG16 model demonstrated the highest Validation Accuracy (78.84%), suggesting that it may offer better stability and consistency during training but struggled to maintain this performance on test data, as reflected in its low-Test Accuracy of 23%. ResNet50, while achieving high Training Accuracy, did not perform as well on test data, indicating possible overfitting.

The difference in performance between the models can be attributed to several factors, including their architectures and how well each model handles the complexity of the dataset. MobileNetV3-Small, being a more lightweight and efficient model, may have been better suited to the available dataset, enabling it to balance accuracy and computational efficiency. On the other hand, VGG16's deeper architecture, while powerful, may have struggled with the dataset's size or the learning rate, as evidenced by its strong performance during validation but poor generalization during testing. ResNet50's moderate performance across both validation and test data suggests that it could be more prone to overfitting, which is also evident from its substantial gap between Training Accuracy (98.18%) and Test Accuracy (39%).

The confusion matrix results further clarify each model's strengths and weaknesses in classifying specific rice disease classes. ResNet50 showed significant misclassification in the Rice Blast and Rice Tungro classes, which may

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

indicate that these classes are harder to distinguish with this architecture due to overlapping visual features. VGG16, while performing better in predicting the Rice Blast class, struggled with misclassifications in the Sheath Blight and Leaf Scald classes. This inconsistency suggests that VGG16 may not generalize as well across all disease categories, even though it performs well in individual instances. In contrast, MobileNetV3-Small demonstrated superior classification across most disease classes, with particularly strong performance in Brown Spot, Rice Blast, Rice Tungro, and Sheath Blight, which aligns with its high-Test Accuracy.

However, it is important to note that MobileNetV3-Small still experienced some misclassification in the Leaf Scald class, where a small percentage was incorrectly labeled as Rice Blast. This suggests that while the model outperformed the others, there is still room for improvement, particularly in handling more subtle distinctions between certain classes. The misclassifications could be further reduced through techniques like data augmentation or refining the model's architecture to better capture the unique characteristics of the more difficult-to-classify diseases.

The MobileNetV3-Small model shows the greatest potential for use in rice disease classification, particularly for applications that prioritize high accuracy on test data. Nevertheless, VGG16 may be preferred in cases where validation stability is crucial, despite its lower test performance. ResNet50, although not optimal for this specific dataset, may benefit from further tuning or the use of more diverse data to prevent overfitting. Future research could explore the application of larger or more complex datasets, as well as advanced techniques such as transfer learning or ensemble methods, to further improve classification performance.

4. CONCLUSION

This research has successfully implemented and compared three deep learning architectures, namely ResNet50, VGG16, and MobileNetV3-Small, for rice disease classification. From the analysis, MobileNetV3-Small showed the best performance with the highest testing accuracy of 79%, making it the best choice for rice disease detection. Although VGG16 showed the highest validation accuracy, its performance on the test data was lower than MobileNetV3-Small. The ResNet50 model showed balanced validation accuracy but was less optimal on the test data. Overall, this study proves that CNN architecture, especially MobileNetV3-Small, is effective in classifying rice diseases and has the potential to assist farmers in detecting diseases more quickly and accurately. Further research is recommended to use larger datasets and try other model architectures to improve classification performance.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

ACKNOLEDGEMENT

This research was funded by the Directorate General of Higher Education, Research, and Technology (DG Diktiristek) in 2024 under the BIMA 2024 Grant (Grant No. 104/E5/PG.02.00.PL/2024).

REFERENCES

[1] C. He, "Effects Of Furrow Irrigation On The Growth, Production, And Water Use Efficiency Of Direct Sowing Rice," *Sci. World J.*, Vol. 10, Pp. 1483–1497, 2010, Doi: 10.1100/Tsw.2010.146.
[2] D. A. Ramírez *Et Al.*, "Potato Zero-Tillage And Mulching Is Promising In Achieving Agronomic Gain In Asia," *Agronomy*, Vol. 12, No. 7, Art. No. 7, Jul. 2022, Doi: 10.3390/Agronomy12071494.
[3] A. M. Hafiz And G. M. Bhat, "A Survey On Instance Segmentation: State Of The Art," *Int. J. Multimed. Inf. Retr.*, Vol. 9, No. 3, Pp. 171–189, Sep. 2020, Doi: 10.1007/S13735-020-00195-X.
[4] A. Zainul, N. Hanani, D. Kustiono, S. Syafrial, And R. Asmara, "Forecasting The Basic Conditions Of Indonesia's Rice Economy 2019-2045," *Agric. Socio-Econ. J.*, Vol. 21, No. 2, Art. No. 2, Apr. 2021, Doi: 10.21776/Ub.Agrise.2021.021.2.4.
[5] L. Anthony, O. O. Alabi, E. S. Ebukiba, And V. Gamba, "Factors Influencing Output Of Rice Produced And Choice Of Marketing Outlets Among Smallholder Farming Households, Abuja, Nigeria," *Sarhad J. Agric.*, Vol. 37, No. 1, 2021, doi: 10.17582/Journal.Sja/2021/37.1.262.277.
[6] B. Chong, A. Wang, V. Borges, W. D. Byblow, P. Alan Barber, And C. Stinear, "Investigating The Structure-Function Relationship Of The Corticomotor System Early After Stroke Using Machine Learning," *Neuroimage Clin.*, Vol. 33, P. 102935, Jan. 2022, Doi: 10.1016/J.Nicl.2021.102935.
[7] D. Fan Fan, T. Roy, And K. Roy, "Classification and Detection Rice Leaf Diseases Using Information and Communication Technology (Ict) Tools," Vol. 7, No. 6, Jul. 2020.
[8] G. W. Wicaksono and Andreawan, "Resnet101 Model Performance Enhancement in Classifying Rice Diseases with Leaf Images," *J. Resti Rekayasa Sist. Dan Teknol. Inf.*, Vol. 7, No. 2, Pp. 345–352, Mar. 2023, Doi: 10.29207/Resti.V7i2.4575.
[9] A. Rahman, "Studi Kasus Gagal Panen Padi Dan Perekonomian Petani Kecamatan Wonomulyo Kabupaten Polewali Mandar Provinsi Sulawesi Barat," Vol. 2, 2022.
[10] Y. Lecun, Y. Bengio, And G. Hinton, "Deep Learning," *Nature*, Vol. 521, No. 7553, Pp. 436–444, May 2015, Doi: 10.1038/Nature14539.

p-ISSN: **2656-5935** http://journal-isi.org/index.php/isi e-ISSN: **2656-4882**

[11] N. Kühl, M. Schemmer, M. Goutier, And G. Satzger, "Artificial Intelligence And Machine Learning," *Electron. Mark.*, Vol. 32, No. 4, Pp. 2235–2244, Dec. 2022, Doi: 10.1007/S12525-022-00598-0.
[12] V. K. Shrivastava, M. K. Pradhan, S. Minz, And M. P. Thakur, "Rice Plant Disease Classification Using Transfer Learning Of Deep Convolution Neural Network," *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.*, Vol. Xlii-3-W6, Pp. 631–635, Jul. 2019, Doi: 10.5194/Isprs-Archives-Xlii-3-W6-631-2019.
[13] Md. M. Hasan *Et Al.*, "Enhancing Rice Crop Management: Disease Classification Using Convolutional Neural Networks And Mobile Application Integration," *Agriculture*, Vol. 13, No. 8, P. 1549, Aug. 2023, Doi: 10.3390/Agriculture13081549.
[14] A. R. Muslikh, D. R. I. M. Setiadi, And A. A. Ojugo, "Rice Disease Recognition Using Transfer Learning Xception Convolutional Neural Network," *J. Tek. Inform. Jutif*, Vol. 4, No. 6, Art. No. 6, Dec. 2023, Doi: 10.52436/1.Jutif.2023.4.6.1529.
[15] M. F. Hossain, "Dhan-Shomadhan: A Dataset of Rice Leaf Disease Classification for Bangladeshi Local Rice." Mendeley, Apr. 06, 2021. Doi: 10.17632/Znsxdctwtt.1.