Enhancing Rice Disease Detection with K-Means Segmentation and Comparison of EfficientNetB0, ResNet50, and Xception

Fajar Sarasati
Department of Digital Business
Universitas Nusa Mandiri
Jakarta, Indonesia
fajar.fss@nusamandiri.ac.id

Candra Agustina
Dept of Accounting Information System
Universitas Bina Sarana Informatika
Jakarta, Indonesia
candra.caa@bsi.ac.id

Widi Astuti
Department of Digital Business
Universitas Nusa Mandiri
Jakarta, Indonesia
widiastuti.wtu@nusamandiri.ac.id

Tri Wahyudi
Dept of Information System
Universitas Bina Sarana Informatika
Jakarta, Indonesia
tri.twi@bsi.ac.id

Eva Argarini Pratama
Dept of Information System
Universitas Bina Sarana Informatika
Jakarta, Indonesia
eva.eap@bsi.ac.id

Abstract*—Rice cultivation in Indonesia faces persistent threats from various diseases, posing significant challenges to food security and agricultural sustainability. This study addresses the crucial issue of disease identification in rice plants through advanced image classification techniques. Leveraging the EfficientNetB0 method and K-Means segmentation, we propose an optimized approach to classify five common rice diseases: Blast, Brown Spot, Hawar, Kresek, and Narrow Brown Spot. We collected a dataset comprising 1,275 images of diseased rice leaves acquired from rice fields across three provinces in Indonesia. Following manual classification and preprocessing, we applied K-Means segmentation to distinguish disease-affected areas. Subsequently, the EfficientNetB0 architecture was employed for disease classification. Our methodology achieved an accuracy rate of 89.06% on a test dataset of 128 images, with precision, recall, and F1- scores of 0.85, 0.81, and 0.83 for Blast; 0.86, 0.75, and 0.80 for Brown Spot; 0.96, 0.96, and 0.96 for Hawar; 0.86, 1.00, and 0.93 for Kresek; and 0.92, 0.86, and 0.89 for Narrow Brown Spot, respectively. Comparison with existing architectures revealed the superiority of EfficientNetB0 in terms of accuracy and loss. Additionally, evaluation metrics validate the robustness of our classification model. Our study contributes to the development of diagnostic systems for rice diseases, offering a valuable tool for farmers to identify and manage crop diseases effectively.

Keywords*— *Image classification, K-Mean segmentation, Agricultural sustainability, Convolutional Neural Network (CNN), EfficientNetB0 architecture, Precision agriculture, Crop disease management

I. INTRODUCTION

Rice plays an important role in Indonesia as a staple food and is the main food source for most of the population. As a vital agricultural crop, rice not only contributes significantly to the country's economy, but also plays an important role in meeting the food needs of the Indonesian people [1]. Rice cultivation is prevalent across a diverse range of landscapes, from fertile rice fields to mountainous regions, illustrating its ability to thrive in various ecological conditions. Given its significant role in the Indonesian diet, the prosperity and productivity of rice crops have a direct and substantial influence on the nation's food security and overall welfare [2]. Consequently, the cultivation of rice, technological advancements, and agricultural policies are closely monitored and developed to ensure a stable and sustainable supply of this essential grain, highlighting the crucial relationship between rice production and the daily lives of Indonesians [3].

Nonetheless, the projected rice harvest in Indonesia is often impeded by a multitude of plant diseases, such as blast, brown spot, narrow brown spot, crackle, and bacterial leaf blight [4]. Collectively, these diseases pose a major challenge to the agricultural sector, leading to reduced crop quality and quantity. Blast disease, caused by the fungus Pyricularia oryzae, manifests in small brown lesions on the leaves, thereby affecting overall crop health and productivity [5]. Brown spot, a prevalent ailment, is distinguished by the presence of dark brown, circular spots that may merge, resulting in significant harm to the leaves [6]. Narrow brown spot, caused by the fungus Cercospora janseana, further adds to the challenge by causing long, narrow lesions on leaves [7]. In addition, bacterial leaf blight or crackle caused by Xanthomonas oryzae, and blight characterized by dark streaks on the leaves caused by Xanthomonas oryzae pv. oryzae, add to the threat to rice plants [8].

The consequences of these diseases extend beyond mere visual symptoms, significantly compromising the health and productivity of rice plants as a whole. Effective management strategies, including the development and adoption of disease-resistant varieties, integrated pest management practices, and farmer education programs, are crucial for mitigating these challenges and ensuring the resilience of the rice farming industry in Indonesia [9].

The adoption of environmentally friendly agricultural technology is one of the alternatives that is increasingly being practiced by farmers. Sustainable agriculture aims to increase and maintain high productivity by considering organic fertilizer use, minimizing dependence on anorganic fertilizers, improving soil biota, ecological-based pest management, and plant diversification. The application of environmentally friendly rice farming, in addition to being able to obtain high-yielding rice, is also healthier and more sustainable [10].

Plant disease classification can be instrumental in mitigating the threat of crop failure due to diseases affecting plants. The following categories of rice leaves were studied: Brown Spot, Hawar, Leaf Brown, and Healthy Leaves. The research involved Literature Study, Data Collection, Data Preprocessing, and Data Analysis. The research findings were derived from training, testing, and validation data [11]. The process of classifying the rice leaf disease involves the use of histograms, which are plots depicting the healthy leaf image components. This process is repeated for testing the leaves, and the results are compared and saved. Moreover, the system conducts feature extraction to examine the morphological changes in the rice plant leaves affected by the disease based on their texture [12].

Other research to answer the challenge of rice disease prediction focuses on automatic detection methods for image segmentation and automatic detection methods to identify certain diseases [13]. The K-Means method based on centroid feeding is used to segment parts of the disease. combined with the SVM method for classification of several classes [14]. Other research explores the CaffeNet deep learning method to classify 13 types of rice pests and diseases. However, in comparison with other deep learning methods on the same dataset, the classification results are still lacking [15]. Based on the problem described, the author proposes the use of the Convolutional Neural Network (CNN) method for classifying rice diseases using the EfficientNetB0 architecture in this research report [16]. Previously, the author conducted segmentation to separate foreground objects or front leaves from background leaves on rice leaves. This is to improve the accuracy of classification. CNN is chosen as an effort to follow technological advancements, and it is hoped that classification of rice diseases using this method can help farmers in early detection of rice diseases as a pest control effort to prevent crop failures.

II. METHODOLOGY

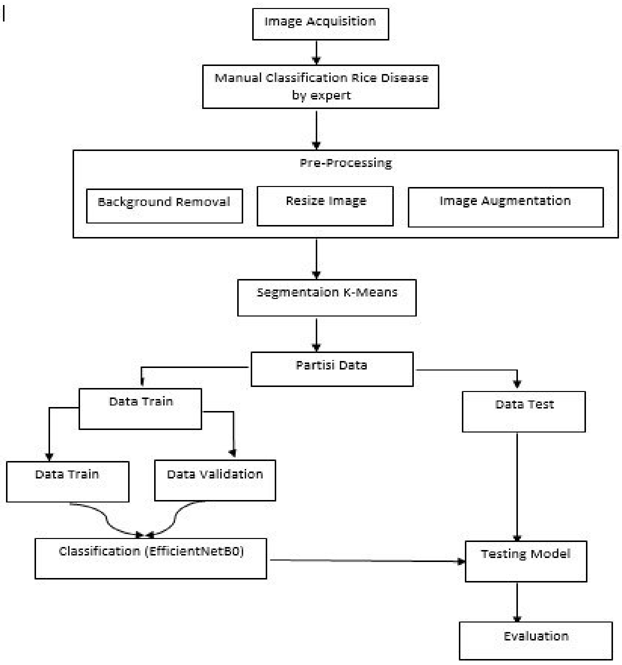


Fig. 1. Methodology

In conducting this research, the author designed a plan that outlined the procedures or steps taken during the course of the study. The stages of the research conducted by the author included the following based on Figure 1. The author proposes the following research method with an explanation: the testing on the rice leaves is performed in a computerized manner. Here are the detailed steps:

A. *Image Acquisition*

The image acquisition for this study was conducted in a systematic and controlled manner to ensure the quality and consistency of the data. The following steps outline the procedure: Sample Collection: The images were collected directly from rice fields located in three provinces in Indonesia: Klaten Regency in Central Java, Gunung Kidul Regency in Yogyakarta Special Region (DIY), and Sukabumi Regency in West Java. A total of 1,275 images of diseased rice leaves were captured, representing a comprehensive dataset covering five common rice diseases: Blast, Brown Spot, Hawar, Kresek, and Narrow Brown Spot.

Camera and Settings: The images were captured using a Samsung A10 smartphone camera. This choice was made to ensure practicality and ease of use in the field. The camera was set to capture images at a resolution suitable for detailed analysis. While the exact resolution is not specified in the current version of the paper, ensuring high resolution is crucial for accurate segmentation and classification.

Camera Angle and Positioning: The images were taken at a consistent angle and distance to minimize variability. The camera was positioned perpendicular to the leaf surface to capture the entire leaf area clearly. Each leaf was isolated from the background as much as possible to ensure that the images focused solely on the leaf and its disease symptoms.

Lighting Conditions: Natural lighting conditions were used whenever possible to maintain consistency with real-world scenarios. In cases where natural lighting was insufficient, additional light sources were used to ensure that the images were well-lit, and the disease symptoms were clearly visible.

Preprocessing: After capturing the images, preprocessing steps were applied to enhance the quality and usability of the data. This included background removal, image resizing, and data augmentation techniques such as rotation, flipping, and scaling to increase the diversity of the dataset and improve the robustness of the classification model.

Dataset Division: The dataset of 1,275 images was divided into training, testing, and validation sets. The exact ratio of the division was not mentioned in the paper but should typically follow a standard practice such as 70% for training, 20% for testing, and 10% for validation to ensure a balanced and effective model training and evaluation process. The chosen dataset split percentages are based on standard practices in machine learning to ensure a balanced and effective model training and evaluation process. A 70-20-10 split ratio is commonly used to provide a sufficient amount of data for training while reserving adequate samples for testing and validation [17]. However, in this study, a slightly different ratio was used where the testing set constitutes 10% of the total dataset. This decision was made due to the relatively small size of the dataset (1,275 images). By allocating 10% of the data for testing (128 images), we ensured that the training set remains large enough to train the model effectively, while the testing set is still sufficient to evaluate the model's performance reliably. The validation set was kept at 10% to fine-tune the model and avoid overfitting.

B. *Manual Classification*

The manual classification process pertains to the task of labelling a dataset. In this instance, the author collaborated with nine agricultural experts to complete the task. Each expert was provided with a questionnaire that contained 194 questions, along with an accompanying photo of a rice leaf. The experts were instructed to classify each image based on the type of disease present. To ensure the accuracy of the labels, the labelled images were cross-referenced with the book "Pests and Diseases of Rice Plants" from the Center for Agricultural Technology Study of the Riau Islands. Furthermore, the author personally verified the classification results with some of the experts to guarantee the reliability of the labels.

TABLE I. SAMPLE OF CLASSIFICATION RESULTS BY EXPERT

Classification Results	Image Sample	Information
Blast		Disease
Brown Spot		Disease
Blight		Disease
Bacterial Leaf Blight		Disease
Narrow Brown Spot		Disease
Necrosis		Pest
Chanaphalocrosis Medinalis		Pest

The labelled dataset that resulted from this manual classification process was subsequently utilized for training and testing the CNN model. The labels served as a benchmark for the supervised learning algorithm, allowing it to learn and accurately predict the disease classes.

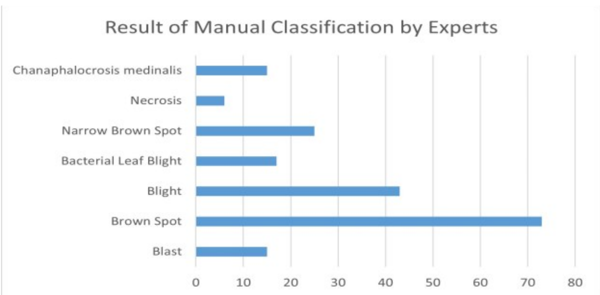


Fig. 2. Results of Manual Classification by Experts

Figure 2 illustrates the distribution of the original images collected and manually classified according to the type of rice disease. This chart shows the number of images for each dis- ease category before any data augmentation was performed. A collection of classification results data which includes images for diseases and pests is listed in Table 1.

C. *Preprocessing*

In this preprocessing stage, the author removes the back- ground image, resizes the image, and performs data augmentation on the image of paddy plants to increase the dataset.

D. *Segmentation*

The clustering process initiated by the author involved categorizing images based on three color segments: green, brown, and black. However, it is crucial to consider that diseased leaves can exhibit a range of colors, such as yellowish and reddish hues. To address this, the segmentation process was extended to include additional color ranges: Green, representing healthy parts of the leaf; Brown, representing severely affected parts; Black, representing the background to isolate the leaf from its surroundings; Yellow, representing early-stage disease or nutrient deficiency; and Red, representing advanced stages of certain diseases. Incorporating these additional color ranges into the K-Means segmentation enabled the model to accurately segment and analyze leaves with yellowish and reddish segments, as demonstrated in Table 1. This enhancement significantly improves the accuracy and reliability of the disease classification process by providing a more detailed and accurate representation of the affected leaf areas.

E. *Split Data*

In this stage, the author properly divided the dataset into training, testing, and validation sets to ensure a balanced and effective training and evaluation process. The dataset, consist- ing of 1,275 images, was divided as follows: Training Set, approximately 892 images, constituting 70% of the dataset, were used for training the model. The purpose of this set is to teach the model to recognize and classify the different types of rice diseases. Testing Set, approximately 255 images, representing 20% of the dataset, were used for testing the model. This set serves to evaluate the model's performance and ensure that it generalizes well to new, unseen data. Validation Set, approximately 128 images, making up 10% of the dataset, were used for validation during the training process. The purpose of this set is to fine-tune the model's hyperparameters and prevent overfitting. This division of the dataset adheres to the standard practices in machine learning, ensuring that the model is trained, validated, and tested on separate subsets of data, thus providing a robust evaluation of its performance.

F. *Classification*

At the stage of classifying paddy diseases, the author uses the CNN method to classify paddy diseases based on manual categorization of paddy disease categories. At this stage, the author uses the EfficientNetB0 architecture. At the classification stage, the author performs modeling and initialization to build the architecture model that will be used to classify paddy diseases.

G. Evaluation

At this stage, the author performs an evaluation of the model that has been built, and here the author produces test results in terms of loss and accuracy.

III. PROPOSED METHOD

The method proposed by the author in this research is to utilize one of the CNN architectures, namely EfficientNetB0, based on several experiments conducted by the author using the same dataset. EfficientNetB0 architecture has a high level of accuracy compared to other architectures, which is sup- ported by previous research that shows that EfficientNet is better than ResNet, Xception, Inception, and others. In this research, the author designed a method for classifying paddy diseases as shown in the following diagram.

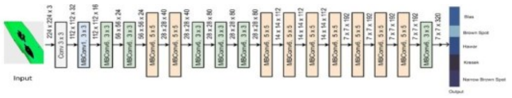


Fig. 3. Design of Proposed Methods

The image above depicts the method designed by the author. The input architecture is EfficientNetB0, which has a resolution of 224x224x3 (RGB). The EfficientNetB0 architecture comprises one convolutional layer, followed by mobile bottleneck convolutional (MBConv), which consists of 16 layers. Each layer of MBConv contains various different operations. The final layer produces an output in the form of a classification of 5 paddy diseases. In carrying out this research the author used several tools or frameworks listed in Table 2.

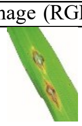
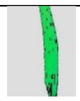
TABLE II. TOOLS AND FRAMEWORK VERSION PURPOSE

Tool/Framework	Version	Purpose
Python	3.8.5	Programming Language
Open CV	4.5.1	Image Processing
Tensorflow	2.4	Framework
Keras	2.4.3	Deep learning API
scikit-learn	0.24	Machine Learning Library
pandas	2.2.2	Machine Learning Library
numpy	2.0	Machine Learning Library
matplotlib	3.9.1	Machine Learning Library
seabron	0.11.1	Library visualization

IV. RESULT AND DISCUSSION

In this section, the author discusses several classification processes for rice diseases, starting with the division of data into training, testing, and validation sets. Previously, the author conducted image segmentation of rice diseases by dividing them into three segments, as shown in Table 3.

TABLE III. SAMPLE OF SEGMENTATION RESULT

Image (RGB)	Segmentation Result (K-Means)
	
	

Based on Table 3 above, the impact resulting from this segmentation is that spots on rice leaves which indicate disease are increasingly visible, including leaves with narrow spots such as narrow brown spot disease. Although in reality there are some images that cannot be segmented properly because the spots are spread almost throughout the leaf so that the segmentation results are leaky. Then at this stage the author evaluates the model that has been built. The evaluation here produces the results of loss testing and accuracy testing. At this evaluation stage the author carries out an evaluation with the aim of testing the accuracy of the model built. Through this stage, the comparison between the classification results carried out by the model and the actual classification results can be seen. At this stage the author visualizes it in the form of a confusion matrix as in Figure 4. Where the confusion matrix is displayed in the form of a matrix table which describes the performance of the classification model on a series of test data whose true values are known. The author uses an evaluation model based on accuracy values in graphic form as in Figure 4.

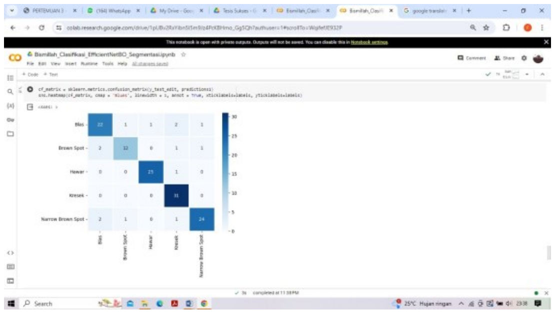


Fig. 4. Confusion Matrix

TABLE IV. CLASSIFICATION REPORT

Class	Precision	Recall	F1-Score
Blas	0.85	0.81	0.83
Brown Spot	0.86	0.75	0.80
Hawar	0.96	0.96	0.96
Kresek	0.86	1.00	0.93
Narrow Brown Spot	0.92	0.86	0.89

According to Table 4 above, the author reports the model's performance evaluation in the form of precision, recall, and f1-score. Based on the information in the table, the precision value produced indicates that the model's accuracy in distinguishing between data on paddy diseases and the model's predictions shows a high level of accuracy, above 90%. Furthermore, for the recall value, it appears that the model's success in finding information or predicting true positives (TP) compared to the total true positives (TP) is quite good. The model's success in predicting the Brown Spot class is still relatively weak compared to when the model predicts other classes. However, this model has proven to be successful in predicting true data, with an accuracy of up to 96% in the Hawar class. The next performance report is the f1-score value, where based on the table, the f1-score value is quite good, with a score above 90%, indicating that the classification method used has good precision and recall.

In this section, the author discusses several classification processes for rice diseases, starting with the division of data into training, testing, and validation sets.

The performance of the model was primarily evaluated using the testing set to ensure that the results are representative of the model's ability to generalize to new data. Figure 4 illustrates the confusion matrix generated from the test data, showcasing the accuracy of the model in predicting each class of rice disease. The confusion matrix is a comprehensive evaluation tool that offers a detailed overview of a model's performance on test data. The rows in the matrix represent the actual classes, while the columns represent the predicted classes. The cells in the matrix illustrate the number of correct and incorrect predictions made by the model. Additionally, the diagonal cells indicate the number of correct predictions for each class. Based on the accuracy demonstrated in the confusion matrix: The first class, Blas, attains an accuracy of 85%. The second class, Brown Spot, exhibits the lowest accuracy among the classes, which is 86%. The third class, Hawar, achieves an accuracy level of 96%. The fourth class, Kresek, achieves an accuracy level of 86%.The last class, Narrow Brown Spot, obtains an accuracy of 92%. The test data results indicate that the model demonstrates proficient performance across various classes of rice diseases, showcasing its dependability and efficacy.

Analysis of Potential Overfitting

One of the essential aspects of assessing a machine learning model is to evaluate its potential for overfitting. Overfitting occurs when a model learns the training data too well, capturing noise and details that do not generalize to new, unseen data, resulting in high accuracy on the training set but lower accuracy on the test set. To determine the likelihood of overfitting in our experiment, we compared the accuracy and loss values between the training and testing datasets. The tables below provide a summary of these performance metrics.

TABLE V. COMPARISON OF RESEARCH RESULT

Model	Accuracy (Training)	Accuracy (Testing)	Loss (Training)	Loss (Testing)
ResNet50	74%	74%	62%	62%
XCeption	88%	88%	42%	42%
EfficientNetB0	89%	89%	33%	33%

As evidenced by Table 5, the accuracy and loss values for The results indicate that the model demonstrates minimal over- fitting, as evidenced by the close similarity between the training and testing accuracy and loss metrics for EfficientNetB0. This suggests that the model has the ability to generalize effectively to new data. The data presented in Table 4 indicates that the precision, recall, and F1-score values are consistently high across all classes, which underscores the model's robustness. For in- stance, the high recall value for the Kresek class demonstrates that the model successfully identifies most of the true positive cases, which is crucial in preventing overfitting.

The outcomes from the test data corroborate that the model performs well across a variety of rice disease classes, showcasing its effectiveness and dependability. The minimal disparity between the training and testing performance metrics suggests that the EfficientNetB0 model does not suffer from overfitting and maintains its capacity for generalization.

In summary, the assessment of the training and testing results, in conjunction with the evaluation metrics, suggests that the EfficientNetB0 model utilized in this study is sturdy and does not exhibit significant overfitting. This ensures that the model can be effectively employed for practical applications in diagnosing rice diseases.

V. CONCLUSION

In this research, we effectively tackled the issue of crop failure in rice plants by employing modern diagnostic techniques. By utilizing the EfficientNetB0 architecture in conjunction with the K-Means segmentation method, we analysed and classified 1,275 images of five different types of rice diseases. The achieved accuracy rate of 89.06% from 128 test images demonstrates the effectiveness of our approach in diagnosing rice diseases. The classification results show that ”Kresek” was the most prevalent disease, with 31 images identified, followed by ”Blas” with 22 images, ”Hawar” with 25 images, ”Narrow Brown Spot” with 24 images, and ”Brown Spot” with 12 images. Furthermore, our findings indicate that the use of the K-Means segmentation method significantly enhanced the classification accuracy in the EfficientNetB0 architecture. This study makes a substantial contribution to the development of diagnostic systems for rice plant diseases, which can assist farmers in identifying and managing diseases more efficiently.

During the course of this research, we encountered several challenges, including data imbalance, variable image quality, and the time-consuming task of manual labelling. To address these, we implemented data augmentation, utilized weighted loss functions, and ensured consistent image capturing conditions. Moving forward, expanding the dataset, developing auto- mated image collection systems, and exploring advanced seg- mentation methods can further improve model performance. Furthermore, creating mobile applications for real-time disease detection and conducting field trials can enhance practical usability and reliability. Taking these steps will build upon the foundation of our study to develop more effective and scalable solutions for rice disease detection and management.

REFERENCES

[1] H. P. Saliem, E. Suryani, R. N. Suhaeti, M. Ariani, *et al.*, “The dynamics of indonesian consumption patterns of rice and rice-based food eaten away from home,” *Analisis Kebijakan Pertanian*, vol. 17, no. 2, pp. 95– 110, 2019.

[2] M. Yamin, S. R. Andelia, S. Andini, M. F. Tafarini, and I. Alamsyah, “The response of rice planting area to rice availability in south sumatra, indonesia,” *Business Review and Case Studies*, vol. 4, no. 1, pp. 90–90, 2023.

[3] D. Dorairaj and N. T. Govender, “Rice and paddy industry in malaysia: Governance and policies, research trends, technology adoption and resilience,” *Frontiers in Sustainable Food Systems*, vol. 7, p. 1093605, 2023.

[4] S. Sofian, J. Nurdiana, *et al.*, “Diversity of diseases of rice (oryza sativa) in kutai kartanegara, indonesia,” *Asian Journal of Agriculture*, vol. 3, no. 2, 2019.

[5] A. E. Asibi, Q. Chai, and J. A. Coulter, “Rice blast: A disease with implications for global food security,” *Agronomy*, vol. 9, no. 8, p. 451, 2019.

[6] A. D. Bergdahl and A. Hill, "Diseases of trees in the great plains," Gen. Tech. Rep. RMRS-GTR-335. Fort Collins, CO: US Department of Agriculture, Forest Service, Rocky Mountain Research Station. 229 p., vol. 335, 2016.

[7] T. Priyadarshani, W. Wickramasinghe, and W. Egodawatta, "Effect of nutrient management and weeds on incidence of fungal diseases in rice," *Journal of Tropical Crop Science*, vol. 10, no. 2, 2023.

[8] T. Ahmad, M. Haider, T. Randhir, R. Randhir, and S. Ahmad, "Spatial analysis of factors influencing bacterial leaf blight in rice production," *Brazilian Journal of Biology*, vol. 83, p. e264249, 2023.

[9] F. Adhzima, Y. Arkeman, I. Hermadi, *et al.*, "The clustering rice plant diseases using fuzzy c-means and genetic algorithm," *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 6, no. 2, pp. 240–245, 2022.

[10] A. A. Santoso, E. Yulianingsih, M. Fikra, and J. Jumari, "Serangan hama penyakit pada teknologi budidaya padi ramah lingkungan," in *Prosiding Seminar Nasional Perlindungan Tanaman*, pp. 35–41, 2022.

[11] F. H. Hawari, F. Fadillah, M. R. Alviandi, and T. Arifin, "Klasifikasi penyakit tanaman padi menggunakan algoritma cnn (convolutional neu- ral network)," *Jurnal Responsif: Riset Sains Dan Informatika*, vol. 4, no. 2, pp. 184–189, 2022.

[12] A. Jinan and B. H. Hayadi, "Klasifikasi penyakit tanaman padi mengu- nakan metode convolutional neural network melalui citra daun (mul- tilayer perceptron)," *Journal of Computer and Engineering Science*, pp. 37–44, 2022.

[13] K. Archana and A. Sahayadhas, "Automatic rice leaf disease segmen- tation using image processing techniques," *Int. J. Eng. Technol*, vol. 7, no. 3.27, pp. 182–185, 2018.

[14] H. B. Prajapati, J. P. Shah, and V. K. Dabhi, "Detection and classification of rice plant diseases," *Intelligent Decision Technologies*, vol. 11, no. 3, pp. 357–373, 2017.

[15] A. A. Alfarisy, Q. Chen, and M. Guo, "Deep learning based classification for paddy pests & diseases recognition," in *Proceedings of 2018 international conference on mathematics and artificial intelligence*, pp. 21–25, 2018.

[16] A. Soni, P. K. Sethy, A. K. Dewangan, A. Nanthaamornphong, S. K. Behera, and B. Devi, "Enhancing oral squamous cell carcinoma detec- tion: a novel approach using improved efficientnet architecture," *BMC Oral Health*, vol. 24, no. 1, p. 601, 2024.

[17] M. Dhanaraju, P. Chenniappan, K. Ramalingam, S. Pazhanivelan, and R. Kaliaperumal, "Smart farming: Internet of things (iot)-based sustainable agriculture," *Agriculture*, vol. 12, no. 10, p. 1745, 2022.