INTENSIF, Vol.9 No.1 February 2025
ISSN: 2580-409X (Print) / 2549-6824 (Online)
DOI: https://doi.org/10.29407/intensif.v9i1.23834

Optimizing Rice Plant Disease Classification Using Data Augmentation with GANs on Convolutional Neural Networks

Received:
21 November 2024
Accepted:
26 January 2025
Published:
23 February 2025

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Abstract—Background: Rice disease classification using CNN models faces challenges due to limited data, particularly in minority classes, and inconsistent image quality, which affect model performance. Data augmentation techniques can potentially enhance classification accuracy by improving data diversity and quality. **Objective:** This study evaluates the effectiveness of data augmentation techniques, specifically classical augmentation and Deep Convolutional Generative Adversarial Networks (DCGAN), in improving CNN performance for rice disease classification. **Methods:** A quantitative study was conducted using four CNN training scenarios: no augmentation, classical augmentation, DCGAN augmentation, and a combination of both. Model accuracy was analyzed to determine the impact of each augmentation technique. **Results:** The baseline CNN model achieved an accuracy of 91.88%. Classical augmentation improved accuracy by 2.56%, while DCGAN augmentation led to a 5.44% increase. The combination of classical augmentation and DCGAN yielded the highest accuracy of 98.13%. **Conclusion:** Data augmentation significantly enhances CNN performance in rice disease classification, with the combined approach of classical augmentation and DCGAN proving to be the most effective. These findings highlight the importance of augmentation techniques in addressing data limitations and improving classification accuracy. Future research should explore additional augmentation strategies and test the model across different datasets to further validate its effectiveness.

Keywords—CNN; DCGAN; Image Quality Enhancement; Imbalanced Datasets; Synthetic Data

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ISSN: 2580-409X (Print) / 2549-6824 (Online)
DOI: https://doi.org/10.29407/intensif.v9i1.23834

I. INTRODUCTION

Indonesia, as an agricultural country, has an agricultural sector that is the main pillar of the economy. According to the Central Statistics Agency (BPS), this sector contributed around 13.7% to Gross Domestic Product (GDP) in 2021 [1]. The agricultural sector provides a living for most Indonesians, particularly those residing in rural areas, and contributes to the country's food security. However, although the agricultural sector has great potential, various challenges still hinder the optimization of its productivity, one of which is the threat of plant diseases [2]. Plant diseases pose a significant risk to agricultural productivity as they can result in a variety of damages, including fruit wilting, death, or deformity [3]. The impact is a decrease in the quality and quantity of the harvest, as well as major economic losses for farmers [4].

Indonesia's tropical climate, characterized by extreme weather fluctuations and the prevalence of diverse pathogens, exacerbates plant vulnerability to diseases [5]. Improper or late handling can cause major economic losses and disrupt agricultural production [6]. Plant disease identification necessitates a thorough comprehension of the symptoms that manifest so that appropriate treatment solutions can be applied [7]. However, there are several challenges in this process. Classifying plant diseases, especially in leaves, is difficult due to the complex pattern variations and high levels of similarity between disease classes [8]. In addition, not all farmers have adequate knowledge about the various types of plant diseases and how to handle them [9]. Conventional methods such as manual inspection are often time-consuming and inefficient [10]. Therefore, an automated system based on artificial intelligence technology is needed for faster and more accurate identification and handling of plant diseases [11].

Research on plant disease identification has been widely conducted, but development opportunities in this field are still wide open. A study by [12], emphasized that although technology has developed in detecting plant diseases, further and integrated approaches are still needed to improve identification accuracy and provide more effective solutions for farmers. CNN (Convolutional Neural Network) has proven efficient in handling image data, recognizing complex patterns, identifying and categorizing a variety of plant [13]. A CNN-based system achieved 95.1% accuracy in detecting rice leaf diseases by extracting detailed visual features [14]. Other researchers have also shown very good results using CNN [15]. However, for this artificial intelligence system to function effectively, adequate and quality data is needed [16].

CNN-based models are extensively used in various areas of plant disease identification. The quality of the dataset plays a crucial role in enhancing model generalization and preventing overfitting [17]. In the agricultural sector, data collection is often challenging, due to varying field conditions, unpredictable weather, and limited resources to conduct thorough documentation [18].

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Researchers have also observed that an imbalance in the number of examples between classes in a dataset can negatively impact model performance [19]. In the context of disease detection, this imbalance can cause models to fail to detect actual disease cases or even misclassify examples from minority classes [20]. To resolve this matter, data augmentation techniques have been implemented to produce new data that preserves the same information as the original data [21]. However, traditional augmentation techniques are often not effective enough in improving model generalization. Therefore, more sophisticated augmentation techniques are needed to improve model performance under more realistic conditions [22].

Generative Adversarial Network (GAN) offers an innovative solution to the problem of data imbalance by generating realistic synthetic data. The generator is tasked with generating new images that are similar to the original data, while the discriminator is tasked with distinguishing between the original and synthetic images [23]s. Several researchers have shown that GAN is effective in addressing data imbalance by generating new digital data that is similar to the original data, thereby improving model performance [24], [25]. Innovations in GAN technology continues to bring great progress. Recent researches [26], shows that GAN is capable of generating realistic images that support detection models with better results.

GANs have been effectively used to improve the accuracy of CNNs in plant disease detection and classification with promising results. For example, in tomato plants, GANs were employed for data augmentation, enriching the variation in the training data, and successfully improving disease classification accuracy to 93.7% [27]. The combination of GAN and CNN has also shown improved performance in detecting diseases across various plant species, with an accuracy of 92.5% achieved through diverse data augmentation techniques [28]. CycleGAN, for instance, was used in cassava plant disease classification, increasing CNN accuracy to 89.8% [29]. Different GAN variants have been explored with varying success. For example, Wasserstein GAN with gradient penalty (WGAN-GP) improved plant disease classification accuracy by 24.4% compared to classical augmentation techniques [30]. Other approaches, such as DuelGAN, used by [31] were able to improve the stability of generated samples and mitigate the mode collapse problem, making them more efficient and effective in generating realistic images. However, methods such as CycleGAN proposed by [32] for augmenting plant disease samples have difficulty in generalizing to different plant species and require intensive parameter tuning.

Furthermore, [33] introduced a novel model for plant disease identification based on leaf image classification, which combined DCGAN and a Multi-Layer Perceptron (MLP) classifier trained with a pseudoinverse autoencoder algorithm. This approach proved effective in addressing dataset imbalance and improving training efficiency. have successfully generated new images for training CNN, with an accuracy of 91.4% in detecting plant leaf diseases. Recent studies have

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further explored the integration of DCGAN with CNNs in plant disease classification. For instance, a study by [34] evaluated the use of GANs, including DCGAN, to generate synthetic images and augment the dataset for rice leaf disease classification using CNN. This approach demonstrated a significant improvement in classification accuracy. Similarly, [35] utilized the CNN InceptionNet architecture alongside transfer learning for coffee plant disease detection and classification, incorporating DCGAN for dataset enhancement. This composite model outperformed the standard CNN model, showing better results.

Based on this background, DCGAN is used in this study due to its ability to generate realistic synthetic data, enriching datasets and expanding the feature space. This study aims to develop a deep learning model that integrates CNN and DCGAN for the classification of rice leaf diseases. The proposed approach leverages CNN architecture, which is enhanced by integrating DCGAN to address the challenges posed by limited training data. DCGAN is recognized for its ability to generate realistic synthetic data, enriching datasets and expanding the feature space, thereby improving model training efficiency and generalization capabilities. This integration is expected to strengthen the CNN's capacity to recognize complex patterns in plant disease symptoms, leading to higher classification accuracy. In addition, this solution is also expected to be the first step in developing a more integrated smart farming system (Smart Tani). The implementation of this system can help farmers identify plant diseases more quickly and accurately, which is very important for faster decision making in disease management. Thus, the results of this study are expected to increase efficiency in agricultural management, reduce losses due to plant diseases, and improve food security and farmer welfare in Indonesia.

II. RESEARCH METHOD

Each step of the research is explained in stages, starting from data collection and preprocessing to the implementation of DCGAN to generate synthetic images and training CNN models to evaluation. To further clarify the research flow, it can be seen in Fig 1.

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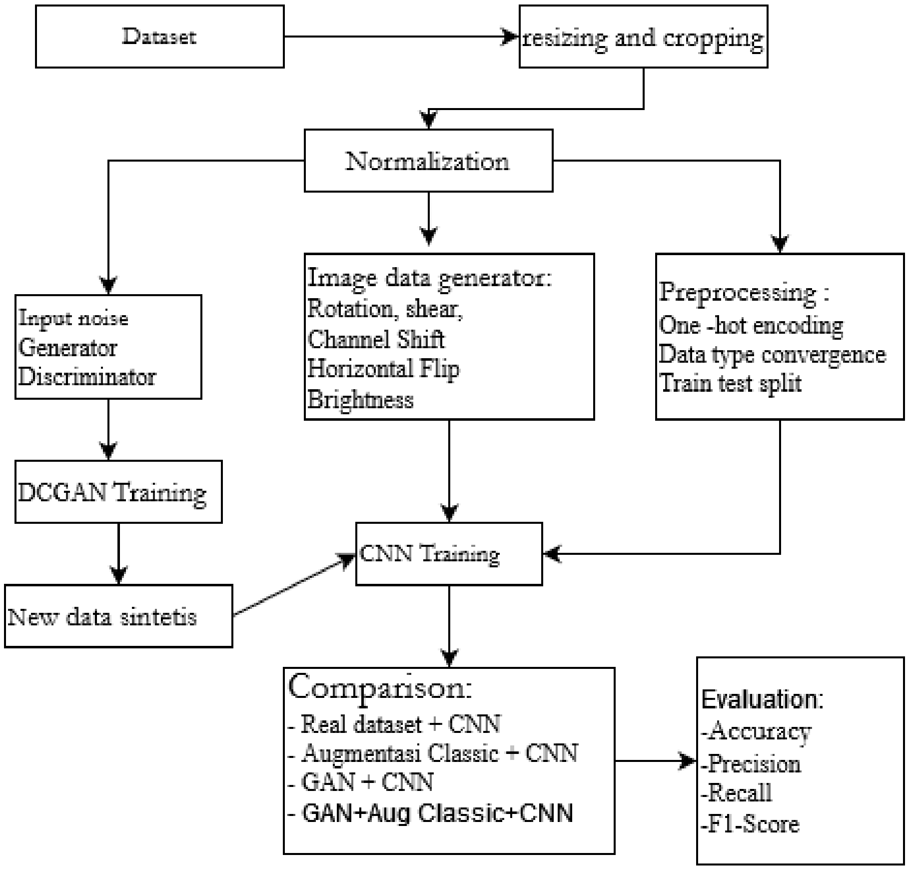

Fig 1. Research Flow

This study employs an experimental design with four scenarios to evaluate the impact of data augmentation on rice plant disease classification using the CNN MobileNet V2 model: Scenario 1: CNN trains and tests on the original dataset without augmentation. Scenario 2: Classical augmentation techniques are applied using *Image Data Generator* (IDG) to increase the variation of the dataset. Scenario 3: DCGAN is used to generate more varied synthetic images to increase the training data volume. Scenario 4: A combination of classical augmentation and DCGAN are used together to train CNN. The model's performance is evaluated using accuracy, precision, recall, and F1-score to determine the most effective augmentation method.

Researchers collected a dataset of rice leaf images obtained from public data sources on Kaggle. The labeling of the dataset has been confirmed by the Pest and Disease Observation Laboratory (LPHP) divided into 7 classification classes. Each class in the classification of plant diseases reflects a variation in typical visual symptoms, depending on the type of disease. For example, Brown Spot caused by fungi, is characterized by brown spots on the leaves. Meanwhile, Bacterial Blight is a bacterial disease that can cause rice leaves to die, with the characteristic of water spots appearing on the leaves [28] . These diseases are types that very often attack rice plants in Indonesia. Details of the dataset can be seen in table 1. This table also explains the division of the amount of data for training and testing on each dataset.

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Table 1. Dataset Plant of Disease

Class	Name of Disease	Initial Data
0	Blast_Disease	80
1	Bacterial_Blight_Disease	80
2	Brown_Spot_Disease	154
3	Healthy_Rice_Leaf	347
4	Leaf_Scald_Deases	233
5	Narrow_Brown_Spot	196
6	Tungro_Virus	79
Total		1169
Train data		935
Test data		234

Fig 2 shows a collection of rice leaf photos used as a dataset. Each image represents different conditions of leaves infected with the disease. These images were used as initial input in training CNN and GAN models before any augmentation or manipulation.

Fig 2. Rice Plant Disease Dataset

The preprocessing in this study aims to ensure consistency in data size, scale, and distribution to fit the format required by the CNN and GAN models. The preprocessing steps include: (1) Resizing images to 128x128 pixels. (2) Splitting the dataset into 80% for training and 20% for testing using train_test_split, with stratify to maintain class balance. (3) Converting X_train and X_test to float32 data type for compatibility with the CNN model input format. (4) Normalizing the pixel values to the range [-1, 1] to prevent overfitting and improve training speed. (5) Applying One-Hot Encoding to convert y_train and y_test labels into binary vectors using to_categorical.

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Data augmentation is a technique used to enrich the training dataset by creating variations from existing data without adding new data. This technique enhances the model's generalization ability and reduces the risk of overfitting. In this study, augmentation is performed using two approaches:

A. Classical Augmentation

During model training, Keras' IDG class performs real-time image augmentation. This technique aims to increase the diversity of a dataset without increasing its physical size. IDG generates images in batches during training, allowing the model to see more data variation in each epoch, even though the physical images do not increase [36]. We apply augmentation randomly and combinative, allowing each batch to incorporate distinct transformations for each image, thereby reducing overfitting and enhancing overall model performance. Various classical augmentation techniques with randomly set parameters, as presented in Table 2.

Table 2. The Parameter of Augmentation Technique

No	Data Augmentation Techniques
1	channel_shift_range =50, horizontal_flip = True, vertical_flip =True
2	horizontal_flip =True, vertical_flip =True, shear_range =0.2
3	channel_shift_range =50, horizontal_flip = True, vertical _flip =True, brightness_range = [0.2, 1.2]
4	channel_shift_range =50, horizontal_flip = True, vertical_flip =True, rotation_range =20
5	channel_shift_range =50, horizontal_flip = True, vertical_flip =True, brightness_range = [0.2, 1.2], zoom_range =[0.5, 1.0]

B. Build DCGAN Architecture

The process involves creating new images using the original data distribution, which enhances the dataset by adding more realistic variations. Alec Radford et al. introduced it in 2015. DCGAN has the unique ability to capture spatial structures in image data, allowing them to produce sharper and more realistic images than traditional GANs using fully connected neural networks. Fig3 illustrates the DCGAN architecture, which consists of two main networks: the generator and the discriminator. Both networks utilize convolutional layers and train using the binary cross-entropy loss function [37].

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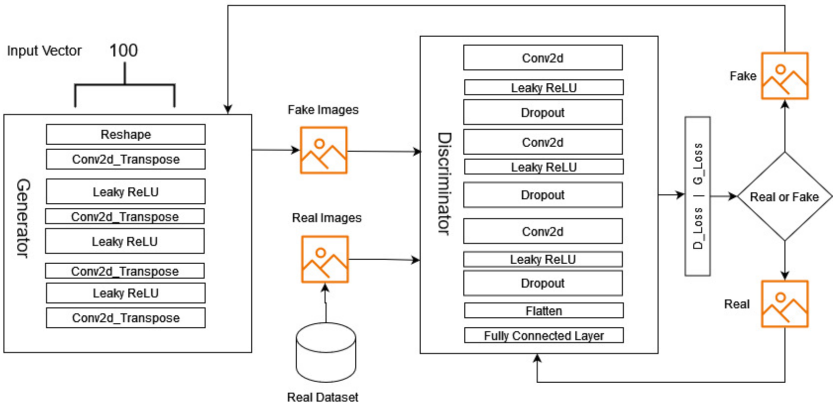

Fig3. DCGAN Architecture

The backpropagation method and Adam optimizer update the weights on both networks during training. We carry out this process iteratively for 20,000 epochs until the generator generates images so realistic that the discriminator struggles to distinguish between real and fake images. Once training is complete, we combine the synthetic images generated by GAN with the original dataset to train the CNN model.

C. CNN

The CNN architecture used in this project is MobileNetV2 transfer learning. This model was chosen because of its superior ability to extract features from images [38]. In addition, this model has also been compared with several other architectures, and the evaluation results show that this model is the most suitable for this work. By using MobileNetV2, complex visual features from plant disease images can be effectively extracted, helping the model achieve better performance in terms of accuracy and generalization.

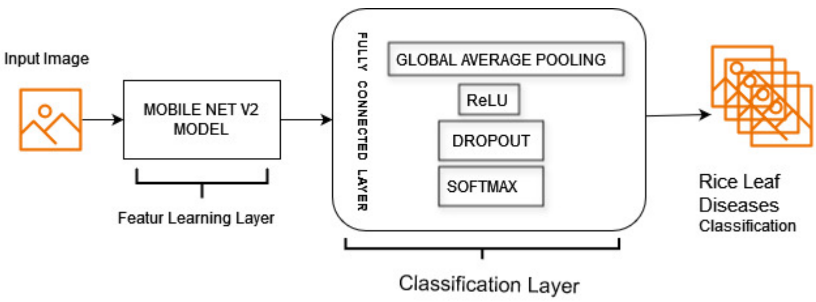

Fig 4. DCGAN Architecture

Fig 4 outlines the steps for building this architecture. First, MobileNetV2 is loaded without the last fully connected layer. The input image, sized 128x128x3, is processed to extract important features, followed by dimensionality reduction using the Global Average Pooling2D layer to minimize the risk of overfitting and enhance efficiency. Next, a Dense layer with 1024 neurons

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activated by ReLU is added to connect the features to the classification output. To further prevent overfitting, a Dropout layer with a rate of 0.4 is applied. The output layer consists of seven units with a SoftMax activation function for accurate predictions in multi-class classification. All pre-trained MobileNetV2 layers are frozen during training, allowing the model to leverage previously learned features without retraining entirely, resulting in an efficient model suitable for new datasets.

CNN model evaluation is performed to assess the performance and effectiveness of the model after the training process. The first step is to monitor the accuracy and loss during training to help identify overfitting problems by comparing the model's performance on the training data and validation data. After training is complete, the model is tested using the test data (test set) with the model.evaluate() function, which produces accuracy and loss values on data not seen during training. Accuracy is used to assess how well the model predicts the correct class on the test data. In addition to accuracy, precision and recall are used to provide more detailed information about the model's performance. Precision shows how accurate the model's predictions are. While recall shows how many diseases were successfully detected. While F1-score, combining precision and recall, provides a more comprehensive metric in assessing model performance, especially when dealing with imbalanced datasets. For a deeper analysis, a confusion matrix is employed, presenting a comprehensive view of the classification results. This matrix illustrates the number of correct and incorrect predictions for each class, providing valuable insights into specific areas where the model performs well or needs improvement [39].

III. RESULT AND DISCUSSION

The initial dataset shown in Table 1 shows some data imbalance. For example, classes 0, 1, and 6 each have only about 80 images, while class 3 has 347 images. This imbalance can cause bias during model training, as the model is more likely to recognize classes with more data, thus ignoring minority classes with fewer images. This is evident by the evaluation results presented in Table 3, which encompass the F1-score metrics for each class, as well as precision, recall, and accuracy.

Table 3. Evaluation Results on Original Dataset

Label	Accuracy	Recall	Precision	F1-Score
Global	0.9188	0.9188	0.9164	0.9156
0	0.9354	0.9355	0.9062	0.9206
1	1.0	1.0	0.9792	0.9894
2	0.948	0.948	0.8604	0.9024
3	0.625	0.625	0.8333	0.7142
4	0.9375	0.9375	0.8823	0.9090
5	**0.9710**	**0.9710**	**0.9710**	**0.9710**
6	0.625	0.625	0.7692	0.6896

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Class 6 shows a drastic decline in performance, maybe due to the limited data. In deep learning, models require a large and diverse dataset to learn patterns effectively. The lack of data hinders the model's generalization, resulting in lower accuracy and F1-score. Class 1, despite having relatively fewer images, demonstrates almost perfect accuracy and F1-score. This is likely due to the visual characteristics of the pictures of this class being easier for the model to recognize. For instance, if the images in Class 1 have clear and consistent patterns or textures, the model can learn these patterns more effectively, even with a small dataset. The image quality, being more representative of the class, could also contribute to better model performance.

Class 3, despite having the largest amount of data, shows a lower performance than other classes. This could be attributed to poor image quality, such as low resolution, noise, or lack of variation that adequately represents the class characteristics. Even though the dataset is large, poor image quality limits the model's ability to identify pertinent patterns effectively. Bad image quality hinders the model's learning process, leading to lower accuracy.

These results emphasize that the amount of data and image quality play a crucial role in improving the model's performance. These test results are consistent with previous research [16] highlighting the significance of image quality in enhancing classification model performance. Therefore, improving image quality is as important as increasing the dataset size for optimal model performance.

A. Classic Augmentation Data Results

The evaluation compared the model's performance and generalization by examining Training Loss (train_loss) and Validation Loss (val_loss) values. This observation evaluates the model's learning ability, measures its effectiveness in classification, and assesses its performance on previously unseen validation data. By comparing these two metrics, researchers can detect potential overfitting, where the model is overly responsive to the training data.

Table 4. The Results of Augmentation Technique

No	F1-score	Train_acc	Val_acc	Train_Loss	Val_Loss
1	0.9442	0.9829	0.9444	0.0568	0.1611
2	0.9376	0.9818	0.9402	0.0702	0.1637
3	0.9298	0.9658	0.9316	0.1167	0.2064
4	0.8979	0.9348	0.9017	0.1838	0.2865
5	0.8724	0.9155	0.8846	0.3261	0.2447

Based on Table 4, the results of augmentation technique number 1 show that this technique is very effective in improving model performance. This can be seen from the small difference between *train_acc* and *val_acc,* as well as *train_loss* and *val_loss,* which shows that the model is capable of learning effectively without overfitting. This augmentation technique is considered optimal because it not only helps the model learn efficiently from the training data but also ensures

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strong generalization ability on validation data, which has never been seen before. The high F1-score value also confirms the balance between precision and recall in the model's prediction results.

On the other hand, augmentation with *shear_range* and *brightness_range* (augmentation number 2 and 3) gives a decreasing result compared to the first augmentation. Although there is a decrease in performance, *the F1-score*, *val_acc*, and *val_loss values* show that this augmentation is still able to maintain generalization performance quite well. The transformation resulting from this augmentation technique, although more complex, still maintains visual patterns that are relevant for plant disease classification, so it does not greatly affect the model's ability to recognize important patterns. In contrast, augmentation number 5 involving a combination of *brightness_range* and *zoom_range* shows a significant decrease in performance. The increase in *train_loss* and *val_loss,* as well as the decrease in accuracy, indicate the potential for overfitting.

The extreme variation of this technique seems to obscure the original patterns in the dataset. As a result, the model focuses more on irrelevant or overly variable features, making it difficult to apply the learned patterns when faced with validation data. This shows that excessive variation in augmentation can hinder the model's ability to recognize important patterns. This point emphasizes the importance of choosing a balanced augmentation technique. Augmentation that is too extreme or does not match the characteristics of the dataset can reduce the model's ability to learn and generalize and increase the risk of overfitting. Fig 5 shows a visual example of the results of classical augmentation applied to one of the classification classes. This visualization helps to understand how augmentation modifies the original data and enriches the diversity of the training data, which can ultimately improve the model's ability to better recognize plant disease patterns.

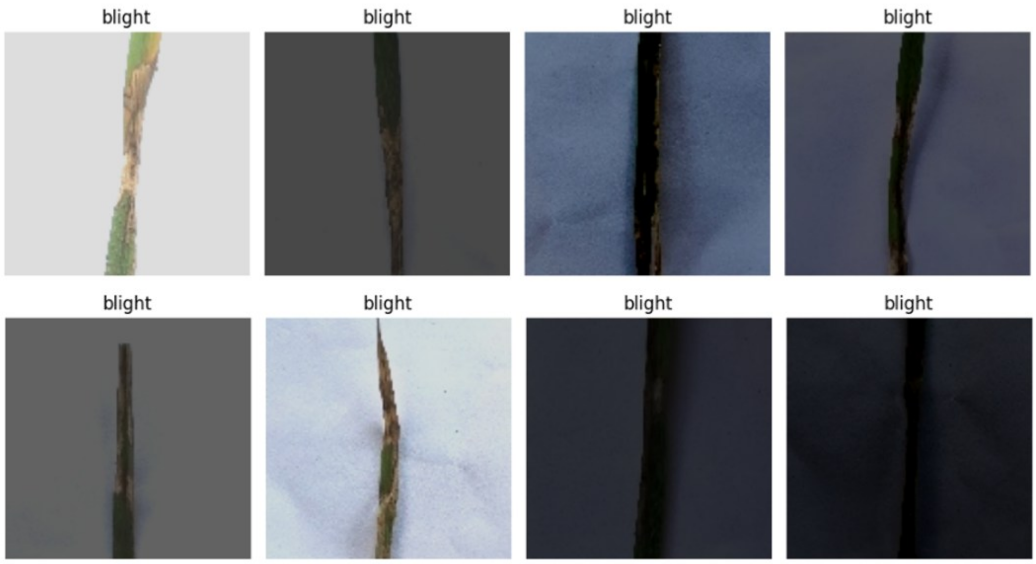

Fig 5. DCGAN Training Results

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B. DCGAN Training Results

Fig 6 shows the results of DCGAN training, where the generated synthetic images visually resemble the original dataset. Although some images still have shortcomings, such as blurring or imperfect artifacts, the results are good enough to enrich the dataset. These synthetic images are used as data augmentation, by adding as many as 100 images for each class, so that it can help improve the model's performance during training.

Fig 6. DCGAN Augmentation Result Dataset Image

This augmentation technique enhances the training dataset by introducing variations that mimic real-world conditions, which is particularly beneficial for training deep learning models like CNNs. The evaluation results of using DCGAN images can be seen in Table 5. This table shows the improvement in the performance of the CNN model.

Table 5. Evaluation Results of using DCGAN

Label	Acc	Recall	Precision	F1-Score
Global	0.9732	0.9732	0.9737	0.9730
0	0.9803	0.9804	0.9434	0.9615
1	1.0	1.0	0.9889	0.9944
2	0.9831	0.9831	0.9831	0.9831
3	0.8889	0.8889	0.9412	0.9143
4	0.9167	0.9167	0.9429	0.9296
5	0.9722	0.9722	0.9722	0.9722
6	1.0	1.0	1.0	1.0

The evaluation results show a remarkable improvement in the performance of the CNN model. The recall value reaches a high value of 97.32%, indicating that the model rarely misses the correct sample. This means that the model can recognize 97.32% of the cases that belong to each class. In addition, the high precision reaches 97.37%, indicating that most predictions made by

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the model are accurate, with a very low error rate. The combination of high precision and recall produces an F1-score close to the maximum value, confirming that the overall performance of the model is very good in handling multi-class classification. The overall accuracy of the CNN model also reaches 97.32%, indicating that augmentation with synthetic images from DCGAN effectively enriches the dataset. This helps the model to learn more diverse and complex patterns, thereby improving the model's generalization ability on new data.

This improvement confirms that the use of DCGAN as a data augmentation method can provide significant contributions in improving model performance, especially on datasets that have limitations in the number and diversity of images. The results of this study are in line with previous research [24] [25] , which also shows that GAN-based augmentation can effectively improve the performance of classification models.

Based on Table 5, class 6 shows an excellent performance, with accuracy, precision, recall, and F1-score all being 1.0. This indicates that the model makes no mistakes in recognizing samples from this class. Every image from class 6 is successfully classified correctly, and every prediction made by the model in this class is very accurate. This excellent performance is the result of increasing the amount of data through GAN augmentation. GAN helps the model understand visual patterns in this class better. This improvement is very significant because before augmentation, class 6 was one of the classes with the most limited amount of data. The initial accuracy of this class was 62.5%, indicating that the model had difficulty in recognizing relevant patterns. After augmentation with DCGAN, the accuracy increased by 37.5%, reaching a perfect score. This improvement ensures that every image in this class is recognized consistently, both in the training data and the test data.

An outstanding improvement was also seen in class 3, which previously had problems related to image quality. Before augmentation, the model's performance on this class was low, reaching only 62.5%. However, augmentation with GANs successfully overcomes this challenge by generating synthetic images that increase the diversity and quality of the dataset. This allows the model to recognize patterns better. Although this class still shows lower results than the other classes, at 88.89%, the significant improvement after augmentation shows that GANs are a very effective tool in improving model performance, especially in classes that were previously difficult to recognize.

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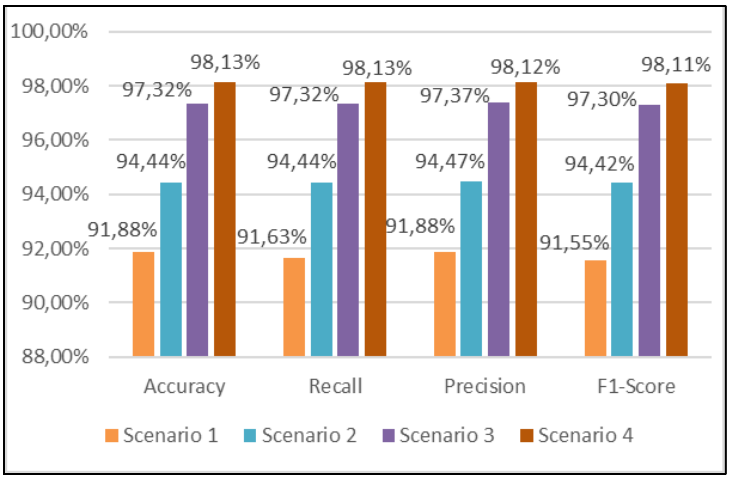

Fig 7. Comparison of CNN Performance on All Scenarios

The graph in Fig 7 provides a clear picture of the impact of different augmentation techniques on the performance of the CNN model. Each augmentation technique used shows a clear improvement in performance metrics such as accuracy, recall, precision, and F1-score. The first scenario shows the lowest performance. The model is trained using only the original dataset without any additional data variations, indicating the model's limitations in recognizing patterns from a limited dataset. The second scenario after applying classical augmentation, CNN performance improved. Accuracy increased by 2.56%, accompanied by similar improvements in other matrices. Classical augmentation helps introduce simple variations that improve the model's ability to recognize more diverse patterns, reduce the risk of overfitting and improve the model's generalization ability.

The third scenario shows a higher performance improvement, with an accuracy of 97.32%. The use of GANs allows the creation of realistic synthetic images but with wider variations. These results show that GAN-based augmentation is very effective in improving model performance, especially when the original data is limited. The model is more effective in recognizing complex and varied patterns. The F1-Score value shows that the model can detect disease classes with a very low error rate.

The last scenario gives the best result with an accuracy of 98.13%. The combination of classical augmentation and DCGAN provides a double benefit: classical augmentation introduces simple variations to the original data, while DCGAN enriches the dataset with new, more varied images. This combination allows the model to be more robust and improves generalization, making it more effective in handling patterns that have never been seen before.

C. Discussion

Overall, this comparison shows that the use of GANs, either alone or in combination with classical augmentation techniques, significantly improves the performance of CNNs. More

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advanced augmentation techniques allow the model to learn more diverse and complex patterns, which ultimately contributes to improved accuracy and better detection capabilities.

This study shows how important data augmentation is to improve the performance of CNN models in classifying rice plant diseases, especially when the dataset is limited or imbalanced. The use of DCGAN is very effective in creating quality synthetic data that helps the model improve. However, there are many obstacles in training DCGAN, such as requiring a lot of computing resources and complicated hyperparameter settings. So, making DCGAN may not always be practical when resources and time are limited. Although DCGAN can be the best solution for the problem of data shortage. In addition, data augmentation with DCGAN provides advantages in terms of creating new image variations that cannot be generated by classical augmentation. In the case of very small and difficult to obtain datasets, the use of GAN can improve model performance, as seen in the increase in accuracy in minority classes.

Classical augmentation methods, although simpler and faster to implement, have limitations in terms of the variety of data generated. Because they only modify existing data, they are unable to generate new visual patterns like GANs do. Therefore, classical augmentation is ideal for situations where the dataset is already relatively large and diverse enough to improve model performance without facing complex training challenges. but not effective enough when the dataset is very limited. One of the key findings of this study is that improving model performance depends not only on increasing the amount of data, especially on the minority class, but also on improving the overall image quality. Preprocessing and improving image quality, either through augmentation or other techniques, can help the model recognize clearer and more consistent patterns across classes. Therefore, combining classical augmentation and GANs proved to be an optimal approach, with classical augmentation adding variations to the original images and GANs enriching the dataset with new, realistic data.

IV. CONCLUSION

This study highlights the effectiveness of GANs, particularly DCGAN, in improving CNN performance for rice disease classification. GANs, either alone or combined with classical augmentation, enhance model accuracy by generating diverse and complex patterns. While classical augmentation is simpler and faster, it lacks the ability to create entirely new patterns, making it less effective for small or imbalanced datasets. In contrast, DCGAN-generated synthetic data significantly improve model performance, especially for minority classes.

Despite its advantages, DCGAN requires substantial computational resources and careful hyperparameter tuning, making implementation challenging. However, it provides a crucial benefit by generating realistic image variations that classical augmentation cannot achieve. This

ISSN: 2580-409X (Print) / 2549-6824 (Online)
DOI: https://doi.org/10.29407/intensif.v9i1.23834

makes DCGAN particularly valuable for small, hard-to-obtain datasets, where model performance heavily depends on data diversity.

A key finding is that improving model performance requires not only increasing data quantity but also enhancing image quality. Preprocessing and augmentation techniques help CNNs recognize clearer patterns across classes. The combination of classical augmentation and GANs proved to be the optimal approach, with classical methods introducing variations in existing images and GANs enriching the dataset with realistic synthetic data.

Author Contributions: *Tinuk Agustin*: Conceptualization, Methodology, Writing - Original Draft, Writing - Review & Editing, Supervision. *Indrawan Ady Saputro*: contributed to the conceptualization, methodology, and review for editing of the manuscript. *Mochammad Luthfi Rahmadi*: Software, Investigation, Data Curation.

All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by Direktorat Riset, Teknologi, dan Pengabdian kepada Masyarakat (DRTPM) research scheme for Penelitian Dosen Pemula (PDP).

Acknowledgments: We would like to thank Laboratorium Pengamatan Hama dan Penyakit Tanaman (LPHP) Solo for their expertise. We also extend our gratitude to the civitas of STMIK AMIKOM Surakarta for their assistance throughout this research.

Conflicts of Interest: The authors declare no conflict of interest.

Data Availability: You can contact the author’s email whenever you need an explanation for this research.

Informed Consent: There were no human subjects.

Animal Subjects: There were no animal subjects.

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