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ORIGINAL ARTICLE

Image-based rice leaf disease detection using CNN and generative adversarial network

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Abstract

Rice is a major crop and staple food for more than half of the world's population and plays a vital role in ensuring food security as well as the global economy pests and diseases pose a threat to the production of rice and have a substantial impact on the yield and quality of the crop. In recent times, deep learning methods have gained prominence in predicting rice leaf diseases. Despite the increasing use of these methods, there are notable limitations in existing approaches. These include a scarcity of extensive and diverse collections of leaf disease images, lower accuracy rates, higher time complexity, and challenges in real-time leaf disease detection. To address the limitations, we explicitly investigate various data augmentation approaches using different generative adversarial networks (GANs) for rice leaf disease detection. Along with the GAN model, advanced CNN-based classifiers have been applied to classify the images with improving data augmentation. Our approach involves employing various GANs to generate high-quality synthetic images. This strategy aims to tackle the challenges posed by limited and imbalanced datasets in the identification of leaf diseases. The key benefit of incorporating GANs in leaf disease detection lies in their ability to create synthetic images, effectively augmenting the dataset's size, enhancing diversity, and reducing the risk of overfitting. For dataset augmentation, we used three distinct GAN architectures—namely simple GAN, CycleGAN, and DCGAN. Our experiments demonstrated that models utilizing the GAN-augmented dataset generally outperformed those relying on the non-augmented dataset. Notably, the CycleGAN architecture exhibited the most favorable outcomes, with the MobileNet model achieving an accuracy of 98.54%. These findings underscore the significant potential of GAN models in improving the performance of detection models for rice leaf diseases, suggesting their promising role in the future research within this domain.

Keywords Leaf disease · GAN · Deep learning · Classifier · Data augmentation

1 Introduction

Over half of the world's population relies on rice as a source of food, making it one of the most significant crops in the world. According to the Food and Agriculture Organization (FAO) of the United Nations, rice is the most extensively consumed grain in the world and the staple food for more than 3.5 billion people (FAO, 2023) [1]. Aside from its importance in human nutrition, rice is also important in many countries' economies and cultures. Rice diseases can have a considerable impact on rice productivity and quality, as rice is a staple food for a huge section of the world's population. According to a study done in Vietnam, rice diseases like rice blast and sheath blight can cut yields by as much as 70% [2]. Diseases can also lower the quality of rice by lowering its nutritional content and flavor, in addition to reducing yield. In order to preserve rice output and quality and eventually ensure food security for the expanding population, efficient disease management measures are required.

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The use of deep learning techniques to identify diseases in rice leaves has grown in popularity [3, 4]. Compared to manual detection techniques, it can save a great deal of time and work. Furthermore, deep learning algorithms can process enormous amounts of data and spot patterns that the human eye might miss. Facilitating early identification and focused treatment can also contribute to a decrease in the demand for pesticides and other dangerous chemicals. The detection of illnesses in rice leaves using deep learning techniques has yielded encouraging results, and it has the potential to increase the precision and effectiveness of disease detection in rice crops.

Unbalanced datasets are a major issue in deep learning, particularly in the identification of rice leaf disease. Due to the lack of images of diseased rice leaves, the dataset is not always balanced in terms of the number of samples for each type of disease. As a result, the machine learning models have a higher probability of correctly classifying the majority class while having a higher chance of misclassifying the minority class which results in poor detection accuracy. Therefore, approaches for balancing the dataset, such as data augmentation or resampling, are required to increase the effectiveness of machine learning models in detecting all types of rice leaf diseases.

Generative adversarial networks (GANs) have been utilized to overcome the problem of unbalanced datasets in rice leaf disease detection. Using variations that can assist in balancing the dataset, GANs can produce artificial images that resemble the ones in the original dataset. The dataset can be balanced, and the results for the detection of rice leaf diseases can be more precise by producing additional images of diseased rice leaves. As they offer a wider and more diverse dataset for training the models, GANs have been found to be effective in enhancing the performance of detection models for diseases of rice leaves.

Currently, only limited work has been done on using GAN for rice leaf disease detection. Researchers are exploring the use of GAN to solve the problem of unbalanced datasets in this field. The use of GAN in rice leaf disease detection is a promising area of research that can potentially improve the accuracy and reliability of detection models. However, more research is needed in this field to fully explore the potential of GAN in improving the detection of rice leaf diseases. Through an assessment of the literature, we identified a number of gaps and research limitations on the use of the GAN models. Higher accuracy still eludes detection technique developments, highlighting the necessity for more research into GANs' capacity to improve and elevate the dependability of rice leaf disease detection models. To fully realize the potential of GANs and fill up the gaps in this developing field, more study is essential.

In this paper, we have explored various kinds of generative adversarial networks (GANs) in rice leaf disease detection which holds significant promise for addressing critical challenges in the field. Furthermore, we present a comparative study of classification results obtained from various GAN-augmented datasets and the original datasets in rice leaf disease detection. Our study showed that the use of GAN-augmented datasets improves the performance of classification models for rice leaf disease detection, and CycleGAN outperformed the other GAN models in most cases. These findings demonstrate the potential of GAN models as a data augmentation technique for improving the performance of classification models in rice leaf disease detection and can serve as a promising future research area.

The novelty of this paper is as follows:

1. We conducted a comprehensive empirical experiment to compare GAN-based data augmentation with other augmentation techniques in the context of rice leaf disease classification. The paper presents the classification results obtained from a dataset augmented using GANs and compares them with the results from the original dataset for the detection of rice leaf diseases. In contrast to recent studies [5], our research introduces three distinct GAN models. Additionally, we evaluate the performance of these GAN-augmented datasets using seven different classification models, namely Densenet21, Densenet169, VGG16, ResNet50, ResNet50V2, Xception, and MobileNetV2.
2. We performed data augmentation and enhanced data labels through the utilization of various GAN models. The research suggests the optimal GAN model among three distinct architectures—GAN, DCGAN, and CycleGAN—as effective data augmentation techniques for detecting rice leaf diseases. Subsequently, the augmented dataset is subjected to classification using the best-performing deep learning models, specifically MobileNet, within the realm of CNN-based approaches for rice leaf disease classification.
3. Design an interactive and user-friendly online web-based deep learning application to classify realistic single images to predict rice leaf diseases.

The structure of the paper follows a standard format. Section 2 provides an extensive literature review of the current state-of-the-art techniques for detecting rice leaf diseases. In Section 3, the authors describe the methodology employed in this study, which includes the use of GANs for data augmentation and various deep learning models for classification. Section 4 reports the experimental results obtained from comparing the performance of the GAN-augmented dataset with the original dataset using different deep learning models. Finally, the paper concludes with a discussion of the findings and the potential for future research in this field.

2 Literature review

The use of machine learning and deep learning models in rice leaf disease detection has become popular in recent years [3, 6]. The authors [7] have offered a thorough solution to the issue by concentrating on three important leaf diseases which include leaf smut, bacterial leaf blight, and brown spot. The dataset was efficiently preprocessed, and the results were produced by the use of several algorithms including K-nearest neighbor (KNN), J48 (decision tree), Naive Bayes, and logistic regression. After tenfold cross-validation, the decision tree method produced the maximum accuracy of 97%. Along with accuracy, the four algorithms are tested for other performance metrics like true-positive rate (TPR), false-positive rate (FPR), precision value (positive predictive value), recall value (sensitivity), F-measure, and AUC (area under ROC).

The study by Matin et al. [8] focuses on the detection of rice leaf diseases using the AlexNet approach. The authors explicitly targeted bacterial blight, brown spot, and leaf smut, intending to outperform previous research in terms of accuracy. They successfully used image augmentation to handle the limited dataset size, resulting in a remarkable disease diagnosis accuracy of more than 99%. A significant disadvantage of the article could be the absence of rigorous investigation of the proposed technique's generalizability to a broader spectrum of rice leaf diseases. The study carried out by Vasantha et al. [9] offers a thorough assessment of machine learning techniques for rice leaf disease identification. The study identifies the ideal solution after a thorough analysis of several approaches and performance indicators, with the CNN model using a high-level fusion strategy attaining a perfect accuracy of 1.0, closely followed by the AlexNet Neural Network with 0.99 accuracy. In addition, the deep feature-based SVM algorithm outperforms previous approaches in terms of accuracy and F1-score. The lack of research into the scalability and application of the suggested strategies to a bigger and more varied dataset of rice leaf images could be a possible weakness of the work. Pothen and Pai's [10] delivers a comprehensive investigation on rice leaf disease identification utilizing image processing techniques and machine learning algorithms. The dataset is made up of 120 images, with 40 samples representing each of the main disorders. The research investigates the use of LBP and HOG feature descriptors, as well as SVM classifiers and alternative kernels, to increase accuracy. The SVM model with the polynomial kernel and HOG descriptors outperforms the other techniques. The very modest dataset size, however, may limit the applicability of the suggested methodology to a more extensive and diverse collection of images of rice leaf disease. Ramesh and Vydeki [11] present a method for identifying blast illness in rice plants using machine learning techniques. The method entails taking images of rice crops, preprocessing, feature extraction, and classification using an artificial neural network (ANN). For segmentation, the study employs a high-resolution camera and image processing techniques such as HSV conversion and K-means clustering. The results reveal excellent accuracy during the training phase; however, a shortcoming of the paper is the significantly lower accuracy reached during the testing phase for both infected and uninfected images, indicating the need for additional refining and validation of the suggested approach. The approach of using convolutional neural networks (CNNs) and vision transformers (ViTs) has shown promising results in various crops such as maize, wheat, and mango. Ramadan et al. [12] compared ViTs and CNN-based classifiers for maize leaf disease detection, highlighting the superior accuracy of the ViT-B/16 model using the SGD optimizer.

In their study, Rumy et al. [13] describe an Internet of Things (IoT)-based system for detecting rice leaf disease that employs edge intelligence and low-level artificial intelligence techniques. The study used a Raspberry Pi as the edge device, making the system both cost-effective and power-efficient. The methodology uses a variety of machine learning algorithms for image preprocessing, segmentation, feature extraction, model training, and classification. On the test dataset, the system achieves an excellent accuracy of 97.50% and exhibits quick leaf classification times. However, the relatively modest quantity of the training and testing datasets may limit the proposed system's generalizability to a larger and more diversified variety of rice leaf diseases and field circumstances. The study by Saha and Ahsan [14] proposes a potential rice leaf disease diagnosis method based on intensity moments and the random forest classifier. The technology detects diseases with an accuracy rate of 91.47%. The workflow is well-organized, comprising image acquisition, feature extraction utilizing intensity moments, and disease classification. However, one major shortcoming of the paper is the lack of a full examination or explanation of the system's efficacy in dealing with different forms of rice leaf diseases or its scalability to bigger datasets. Jiang et al. wheat [15] presents a novel technique for diagnosing rice and wheat leaf diseases using multitask transfer learning. The authors improve the VGG16 model using transfer learning and multitask learning procedures, reaching outstanding accuracies of 97.22% for rice leaf diseases and 98.75% for wheat leaf diseases.

The use of offline enhancement techniques to data improves recognition accuracy even more. Through comparative studies, the paper proves the feasibility of the proposed approach. However, one weakness of the article could be the absence of in-depth analysis or discussion on the model's resilience and generalizability to a broader range of diseases and environmental variables, which could be useful for real-world applications.

The paper by Sethy et al. [16] investigates the identification of four types of rice leaf diseases using deep feature plus SVM approach and transfer learning with 11 CNN models. The utilization of a large dataset consisting of 5932 on-field images adds realism to the study. The deep feature plus SVM strategy outperforms the transfer learning approach, with ResNet50 plus SVM achieving the highest F1-score of 0.9838. However, a limitation of the paper is the lack of discussion on the generalizability of the proposed method to different environmental conditions or variations in disease severity. Andrianto et al. [17] describe a deep learning-based rice plant disease detection system that incorporates a cloud-based machine learning application and a smartphone application. The technology detects several diseases in rice plants by taking leaf images and analyzing them in the cloud. The system's performance with the VGG16 architecture achieves good training accuracy but relatively poor test accuracy, highlighting the need for more diversified and higher-quality datasets. The report delves into the research approach used to create the smartphone application and underlines the system's potential for increasing rice plant disease control. A shortcoming of the work is the need for additional research to improve test accuracy and evaluate the system's performance in real-world settings. Archana and Sahayadhas [18] describe an automatic detection method for certain illnesses in rice leaves using image processing techniques. The work examines hybrid methodologies for image segmentation and classification algorithms, offering an efficient and fully automated detection method. The use of high-resolution images and brightness/color alteration techniques improves visual impact and information segmentation. The paper lacks a thorough analysis and comparison with other methods making it difficult to judge how well it performs in comparison to other strategies. Ghosal and Sarkar [19] offer a deep learning model for automated identification and classification of rice leaf diseases, reaching an outstanding accuracy of 92.46% utilizing transfer learning. The use of a huge dataset collected from fields and the Internet improves the model's robustness. One of the drawbacks of the paper is the lack of extensive study and comparison with other state-of-the-art models, which would provide more insights into the proposed model's performance and competitiveness with existing approaches. Further exploration of mango and wheat leaf disease detection using ViT, and CNN-based models enhanced classification accuracy through CycleGAN-augmented dataset [20, 21].

The researchers utilized Agile modeling and Extreme Programming to develop the prototype, which was tested by feeding images to the system to validate the accuracy of the trained model [22]. Krishnamoorthy and Parameswari [23] describe an efficient method for detecting rice leaf diseases using deep neural networks and transfer learning. The study shows that pretrained models with high accuracies between 87.08% and 95.41%, such as InceptionV3, ResNet50, and VGG16, are preferable. A drawback of the article is the lack of data on how well the suggested strategy performs on a bigger and more varied dataset, which would help to better appreciate its generalization potential.

GANs are being utilized in rice leaf disease detection to overcome the limitation of unbalanced datasets. Haruna et al. [5] propose an improved approach to detect rice leaf diseases by addressing the issue of unbalanced datasets through a GAN-based data augmentation pipeline. The study demonstrates the effectiveness of the SG2-ADA model in enhancing the performance of faster-RCNN and SSD models, achieving mean average precision (mAP) values of 0.93 and 0.91, respectively. The paper provides valuable insights for researchers and developers working with imbalanced datasets, offering a workflow that generates high-quality synthetic images. Also, this study offers a very accurate custom transfer learning-based architecture for classifying rice leaf diseases. Other transfer learning models like MobileNet, ResNet50, ResNet101, InceptionV3, and Xception are outperformed by the suggested RiceDenseNet model. The suggested model was evaluated on three datasets using the metrics accuracy, F1-score, precision, and recall. The analysis revealed that the suggested model surpassed earlier research, achieving 97.71% accuracy on the Leaf Diseases Dataset. The base dataset and the GAN-augmented dataset produced tenfold cross-validation results with an average accuracy of 98.38% and 98.79%, respectively [24]. Another study proposed using generative adversarial networks (GANs) to generate synthetic wheat leaf disease images from a limited dataset [25]. Moreover, the research on wheat leaf disease classification evaluated different augmentation strategies like SMOTE and CycleGAN, improving model performance with limited data [26]. The quantity of disease samples is balanced by GAN augmentation, which increases the model's precision. The results also suggest that GAN-based augmentation techniques hold promise, though their full potential warrants further exploration.

2.1 Research gap

The following is an overview of these issues:

1. A problem in detecting rice leaf disease is a lack of diversity and labeled training data. It is difficult to train reliable and effective models for disease detection without a large dataset.
2. Traditional data augmentation techniques may not properly capture the differences and the detailed evidence in rice leaf disease images. This limitation might hamper the effectiveness of disease detection models, as they may fail to generalize previously unknown data.
3. Despite advancements in rice leaf disease detection techniques, achieving higher accuracy remains a significant challenge.

3 Methodology

Classifying leaf diseases is a difficult process that can be handled in several ways. One method is to train a model using a dataset of labeled images of sick and healthy leaves using conventional machine learning methods, such as random forest or support vector machines. The effectiveness of this strategy can vary depending on the dataset's size and quality. Another recently used technique is to generate synthetic images of leaf diseases using generative adversarial networks (GANs) and then apply the classification. This can be accomplished by training a GAN on a dataset of healthy leaves and then utilizing the GAN's generator component to generate synthetic images of diseased leaves. This can be helpful for expanding the dataset's size and diversity, as well as for improving the classifier's performance. In this study, we intend to explore the latter. In Fig. 1, we demonstrate the overall workflow diagram.

We divided the whole methodology into two part:

- **Part 1: Method of Classification with Original Dataset** In this case, the method of classification with the original dataset does not incorporate any data augmentation techniques, which stands as a benchmark element of the classification process. This phase comprises three steps: (i) raw dataset, (ii) data processing, and (iii) classification.
- **Part 2: Method of Classification with Data Augmentation using GAN** Traditional data augmentation has been conducted in this part, which leads to two main phases here, (i) data augmentation using GAN, and (ii) classification. Initially, the dataset undergoes enhancement through the utilization of several GANs independently. Subsequently, the augmented dataset is employed for disease categorization using the CNN models described earlier.

3.1 Part 1: Method of classification with original dataset

(a) Raw Dataset

The dataset comprises four different types of diseases that affect rice leaves, including bacterial blight, brown spot, blast, and tungro. The complete collection includes 10025 images [27–29]. Table 1 displays the number of samples per disease.

Bacterial blight is caused by the bacterium Xanthomonas oryzae, which results in leaf necrosis and water-soaked lesions. Blast is caused by the fungus Magnaporthe oryzae and results in circular, gray-white lesions on leaves. Brown spot is caused by the fungus Rhizoctonia solani and results in circular, reddish brown, or grayish-white lesions on leaves. Tungro is caused by a combination of two viruses, Rice tungro bacilliform virus and Rice tungro spherical virus, and results in yellowing and wilting of leaves. Figure 2 shows four types of affected leaves used in the dataset.

(b) Data Preprocessing

Data preprocessing is a crucial step in the process of detecting leaf diseases using CNN models. The primary goal of data preprocessing is to prepare the data for the model in a way that allows the model to learn effectively and generalize well to new data. Some of the key steps involved in data preprocessing for leaf disease detection include:

1. *Resizing the images:* The images need to be resized to a consistent size to ensure that the model can process them effectively.
2. *Normalization:* The images should be normalized to have a mean of zero and a standard deviation of one. This helps to reduce the impact of lighting conditions and other variations in the images.
3. *Splitting the data:* The data should be split into training, validation, and testing sets. This will allow the model to be trained and evaluated effectively.

It is important to note that data preprocessing is an iterative process, it can be improved over time by experimenting with different techniques and fine-tuning the parameters. It is also important to consider the specific characteristics of the dataset and the problem when preprocessing the data.

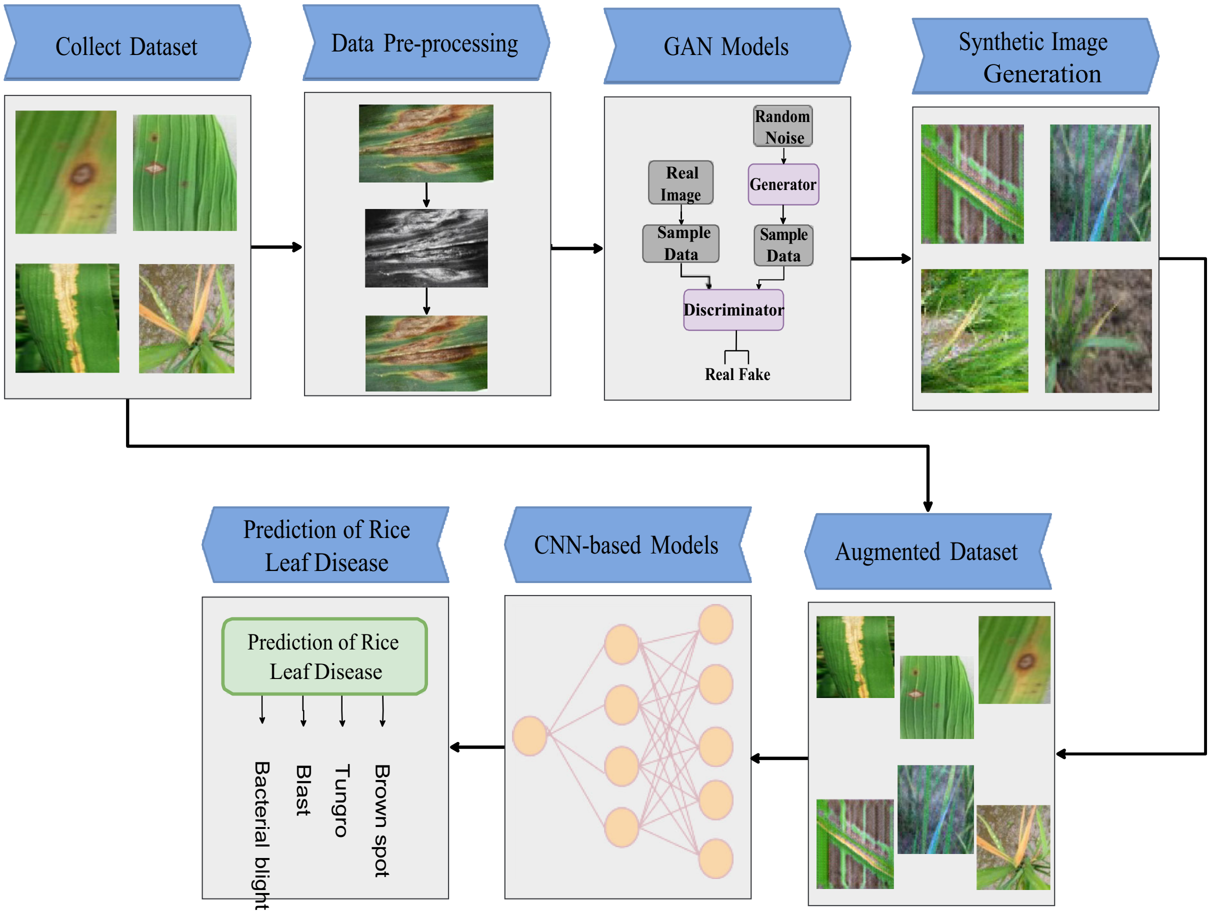


Fig. 1 Overall workflow of the study

Table 1 The state of the dataset

Disease	Number of samples
Bacterial blight	1584
Blast	3924
Brown spot	3209
Tungro	1308

(c) Classification

The process of detecting rice leaf diseases using CNN models involves several steps, including data collection, preprocessing, model training, evaluation, and deployment. The first step is to collect a large dataset of images of rice leaves, both healthy and diseased. The next step is to preprocess the data, which includes resizing the images to a consistent size, normalizing the images, and converting the images into feature vectors that can be used as input to the model. The next step is to train a CNN model on the preprocessed data, this step typically involves defining the model architecture, selecting the optimizer and loss function, and training the model using a training set and validating it using a validation set. After training the model, it is evaluated using a testing set, this step will allow us to evaluate the model's performance in terms of accuracy, precision, recall, F1-score, etc. Once the model has been trained and evaluated, it can be deployed in a real-world scenario, where it can be used to classify new images of rice leaves into healthy or diseased. In order to improve the model's performance, it can be fine-tuned by adjusting the architecture and/or the parameters.

The steps are as follows listed in Algorithm 1.

The hyperparameters used in the process are shown in Table 2.

3.2 Method of classification with data augmentation using GAN

The process is divided into two steps when GAN is used as the data augmentation technique. The dataset is first

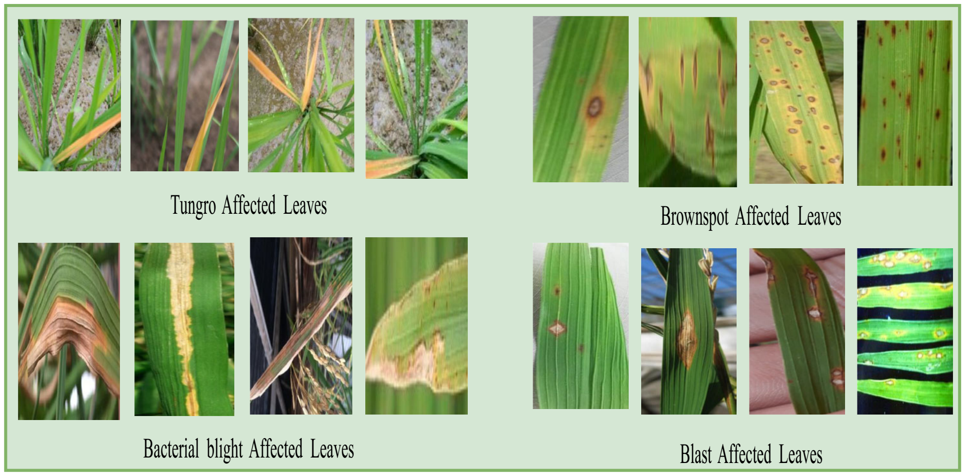


Fig. 2 Samples of leaves affected by rice leaf diseases

Table 2 Hyperparameters of classifiers

Learning rate	Epochs	Batch SIZE	Optimizer	Loss function
0.0001	50	64	SGD	Categorical cross-entropy

enhanced using several GANs individually, and the augmented dataset is then utilized to categorize diseases using the previously described CNN models.

(a) Data Augmentation using GAN

Generative adversarial network (GAN)-based data augmentation is a technique that uses GANs to artificially generate new data samples. This technique can be used to increase the size of the training dataset and to improve the performance of the model by increasing the diversity of the training data. The basic idea behind GAN-based data augmentation is to use a GAN to generate new data samples that are similar to the original training data. The GAN is trained on the original training data, and it learns to generate new samples that are similar in appearance and characteristics to the original data. Once the GAN is trained, it can be used to generate new data samples that can be added to the training dataset. This increases the size of the training dataset and improves the model's ability to generalize to new data. GAN-based data augmentation can be applied to a wide range of applications, including image classification, object detection, and semantic segmentation. It is also considered a powerful tool that can be used to overcome the problem of limited data availability. The GAN model training is depicted in Algorithm 2. Several GAN architectures were utilized here, but the basic procedures were nearly identical.

Algorithm 1 Training a CNN model for leaf disease classification

1: Load the data (images of leaves with and without diseases). Let the dataset be denoted by D.
2: Split the data into training and testing sets. Let the training dataset be denoted by D_{train} and the testing dataset be denoted by D_{test}.
3: Preprocess the data (resize, normalize, etc.). Let the preprocessed training dataset be denoted by $D_{train\ pre}$ and the preprocessed testing dataset be denoted by D_{test_pre}.
4: Train the CNN model on the training data. Let the CNN model be denoted by M . Train the model using the preprocessed training dataset D_{train_pre}. Update the weights of the model using the gradient of the loss function with respect to the model's parameters.
5: Test the CNN model on the testing data. Evaluate the performance of the model (accuracy, loss, precision, recall, etc.) on the preprocessed testing dataset $D_{test\ pre}$.
6: Use the trained model to predict the class of new images of leaves. Given a new image of a leaf, preprocess the image and feed it into the trained model M to obtain the predicted class of the leaf.
7: If the performance is not satisfactory, fine-tune the model by adjusting the architecture and/or the parameters. Repeat steps 4-6 with the updated model until the desired performance is achieved. Let the updated model be denoted by M'.

Using GANs for rice leaf disease detection can be a robust approach as it can be used to artificially increase the size of the training dataset, improve the diversity of the data, and overcome the problem of limited data availability. But, to get the best results, it is important to choose the right type of GAN architecture and to fine-tune it to the specific characteristics of the rice leaf images and the disease symptoms.

(b) Expanding Dataset using GANs

The model can improve its ability to identify and categorize several disease kinds, including bacterial blight, blast, brown spot, and tungro, by expanding the dataset with a variety of images. In comparison to employing conventional data augmentation techniques, the employment of GANs in data augmentation can produce more accurate findings in the

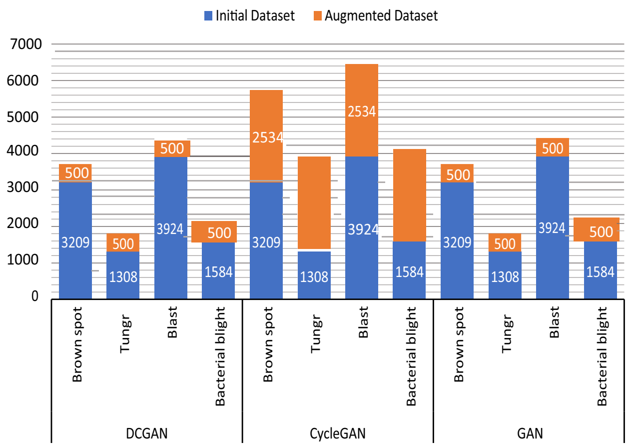


Fig. 3 Dataset after augmentation

identification of rice leaf disease. Using GAN and DCGAN, the number of images for each disease class has been raised by 500, for a total of 2000 extra images that have been added to the initial dataset, whereas CycleGAN has produced a total of 10136 more images, 2534 images for each disease class. Later on, this dataset will be used in the categorization process. The augmented state of the dataset is shown in Fig. 3.

Algorithm 2 Generative Adversarial Network (GAN) Training

```
Initialize the generator network G and discriminator network D with random weights.
Define the loss functions for the generator and discriminator. Let the loss function for the generator be denoted by L_G and the loss function for the discriminator be denoted by L_D.
Load the training data. Let the training dataset be denoted by D_train.
while Desired performance or a fixed number of iterations is not reached do
  for each iteration t do
    Generate fake data samples using the generator. Let the generated samples be denoted by G(z), where z is a random noise vector.
    Combine the fake data with real data. Let the combined data be denoted by D_t = x_i, y_i where x_i is a real sample from D_train and y_i is the corresponding label (1 for real, 0 for fake).
    Train the discriminator on the combined data D_t. Update the weights of the discriminator network D using the gradient of L_D with respect to D's parameters.
    Generate fake data samples using the generator. Let the generated samples be denoted by G(z).
    Train the generator using the fake data samples. Update the weights of the generator network G using the gradient of L_G with respect to G's parameters.
    Calculate the loss for both the generator and discriminator. Let the loss for the generator be denoted by L_G(z) and the loss for the discriminator be denoted by L_D(D_t).
  end for
end while
Save the trained generator and discriminator models for future use.
```

The discriminator and generator models in a GAN have several parameters that affect their performance and the overall outcome of the GAN. For the discriminator model, some of the important parameters include the depth of the model, the number of neurons and layers, the activation function used, the optimizer and its hyperparameters, and the batch normalization used. These parameters determine the ability of the discriminator model to identify fake and real samples and the speed and accuracy of the discriminator's training.

For the generator model, important parameters also include the depth of the model, the number of neurons and layers, the activation function used, the optimizer and its hyperparameters, the type of noise input, and the use of upsampling and concatenation layers. These parameters determine the ability of the generator model to generate realistic fake samples that can fool the discriminator and the speed and accuracy of the generator's training. Tuning these parameters can greatly impact the outcome and performance of the GAN, and the process of finding the optimal set of parameters can be a challenge. However, proper tuning can lead to better performance and higher accuracy in the classification of rice leaf diseases.

GAN The generative adversarial network (GAN) generates images with dimensions (64, 64, 3). A generator neural network and a discriminator neural network make up a GAN. The discriminator receives actual images and phony images as input and returns a probability indicating whether the input is real or fake. The generator creates fake images using the input of random noise. The discriminator's loss, which is reduced, and the generator's loss, which is maximized, are calculated using the binary cross-entropy loss function.

The (64, 64, 3) image is produced by the generator network, which consists of four completely linked layers with an increasing number of units. ReLU is the activation function employed by the generator. The discriminator network likewise has four fully connected layers, but it has fewer units in each layer. A sigmoid layer is then used to output a probability in the discriminator network. The discriminator's activation function, leaky ReLU, aids in avoiding the "dying ReLU" issue. The Adam optimizer is used to train the GAN, and its learning rate is set at 0.0001. The optimizer is used to modify the weights of the generator and discriminator.

DCGAN Deep convolutional generative adversarial network (DCGAN), a form of generative adversarial network (GAN), uses convolutional neural networks (CNNs) for both the generator and the discriminator. The generator outputs images that are comparable to the training data after receiving input from random noise. The discriminator, on the other hand, analyzes images and determines whether they are authentic or phony.

The generator model generates images with $64 \times 64 \times 3$ resolution. The resolution of the output image is steadily increased by each of the generator model's four transposed convolutional layers. The first layer produces an 8 × 8 × 512-shaped tensor from an input 100-dimensional random noise vector. This tensor is first flattened to 8 × 8 × 512, and then it is routed through three further transposed convolutional layers, progressively increasing the resolution of the output image to 64 × 64 × 3. The [−1,1] range is created by translating the pixel values in the final layer using the Tanh activation function. Batch normalization and LeakyReLU activation are used after every transposed convolutional layer. Binary cross-entropy calculates the discrepancy between each binary classification's true label and predicted probability, and serves as the loss function in DCGAN.

CycleGAN Image-to-image translation is performed using the CycleGAN generative model. Without requiring paired samples, it learns a mapping between two image domains. In order to help in the diagnosis and treatment of plant illnesses, we use CycleGAN in this research to create synthetic images of damaged plant leaves from healthy plant leaves.

Two generating networks and two discriminator networks make up the CycleGAN architecture. While the discriminator networks try to tell the difference between real and fake images, the generator networks learn how to translate images from one domain to another.

The overall CycleGAN training procedure is specified by the composite model function. Each generator network in the composite model is optimized using four loss functions. Using mean square error (MSE), the adversarial loss calculates the variance between the discriminator's output on fake and real images. Using mean absolute error (MAE), the identity loss quantifies the variation between the output of the generator on an input image and the original image. The forward cycle loss calculates the difference between the output of the first generator when given an input image and the output of the second generator when given the output of the first generator. With the generators switched, the backward cycle loss measures the same difference.

Using an Adam optimizer with a learning rate of 0.0002 and a beta value of 0.5, the composite model is created. The four losses listed above are combined into one loss function, with weights given to each loss to equalize their contributions.

The final image size is (128, 128, 3). In order to convert healthy to diseased rice leaf disease, the CycleGAN was trained in our work utilizing images of healthy rice leaf disease in one domain and diseased rice leaf disease in another domain.

Binary cross-entropy loss function for DCGAN and GAN is computed as the Eq. (1):

$$Mn_G Mx_D(D,G) = E_{x-p} d\log[D(x)] + E_{Z-P} z(z)\log(1-D(G(z))) \tag{1}$$

where Z describes the number of random vectors in P_Z, E expresses expectations, x represents the distribution of the real data, x represents a sample image, and P_Z represents randomly distributed noise.

CycleGAN's mean absolute error (MAE) is calculated as follows:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|Y_i - \hat{Y}_i| \tag{2}$$

CycleGAN's mean square error (MSE) is calculated as follows:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \hat{Y}_i|^2 \tag{3}$$

where Y_i indicates the observed values and $\hat{Y}_i$ indicates the predicted value.

Figure 4 display the GAN, DCGAN, and CycleGAN-generated images of the four diseases.

(c) Classification

The classification phase is the same as in Phase 1. However, instead of using the original dataset in this case, the augmented dataset is used to categorize the diseases. The basic pseudocode for using various GANs to detect rice leaf disease using CNN models are listed in Algorithm 3. Figure 5 illustrates the overall procedure for detecting rice leaf disease using GAN-based data augmentation.

Algorithm 3 Hybrid Model for Rice Leaf Disease Detection with GANs and CNN based pre-trained models

```
Prepare the dataset of rice leaf images, including images of healthy leaves
  and images of leaves with different diseases. Let the dataset be denoted by D.
Split the dataset D into training, validation, and test sets. Let the training
  set be denoted by D_train, the validation set be denoted by D_val, and the
  test set be denoted by D_test.
Define the GAN architecture to be used. Let the set of GANs be denoted
  by G = GAN, DCGAN, CycleGAN.
Initialize the generator and the discriminator networks of the GANs. Let
  the generator network of GAN i be denoted by G_i and the discriminator
  network be denoted by D_i, for i ∈ 1, 2, 3.
for each GAN G_i in G do
  Train G_i using D_train, using the corresponding loss function L_i of GAN
   i.
    Use the trained G_i to generate new images of rice leaves with different
    diseases. Let the generated images be denoted by G(D_train, G_i).
    Use G(D_train, G_i) to train CNN models for leaf disease detection. Let the
    set of CNN models be denoted by C.
    for each CNN model C_j in C do
      Fine-tune C_j using D_val.
      Test C_j using D_test and evaluate its performance.
    end for
end for
Compare the performance of different GANs and choose the best one for
  the rice leaf disease detection task based on the evaluation results.
```

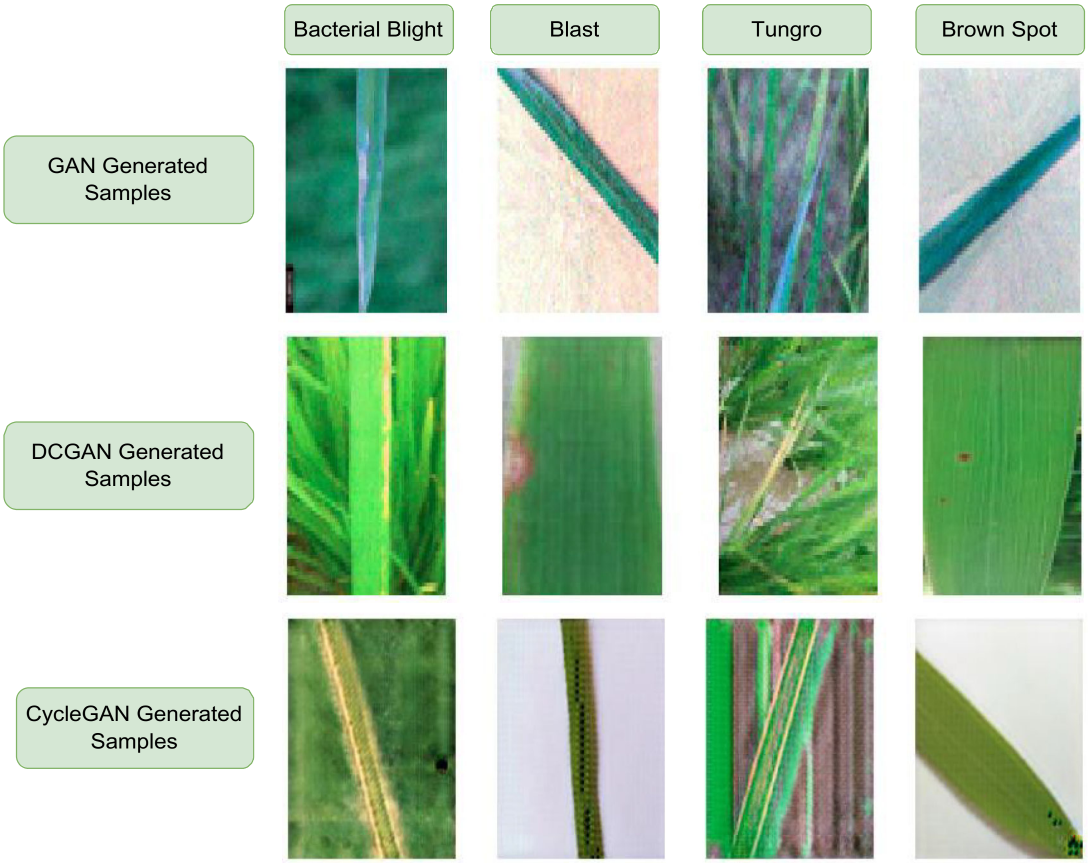
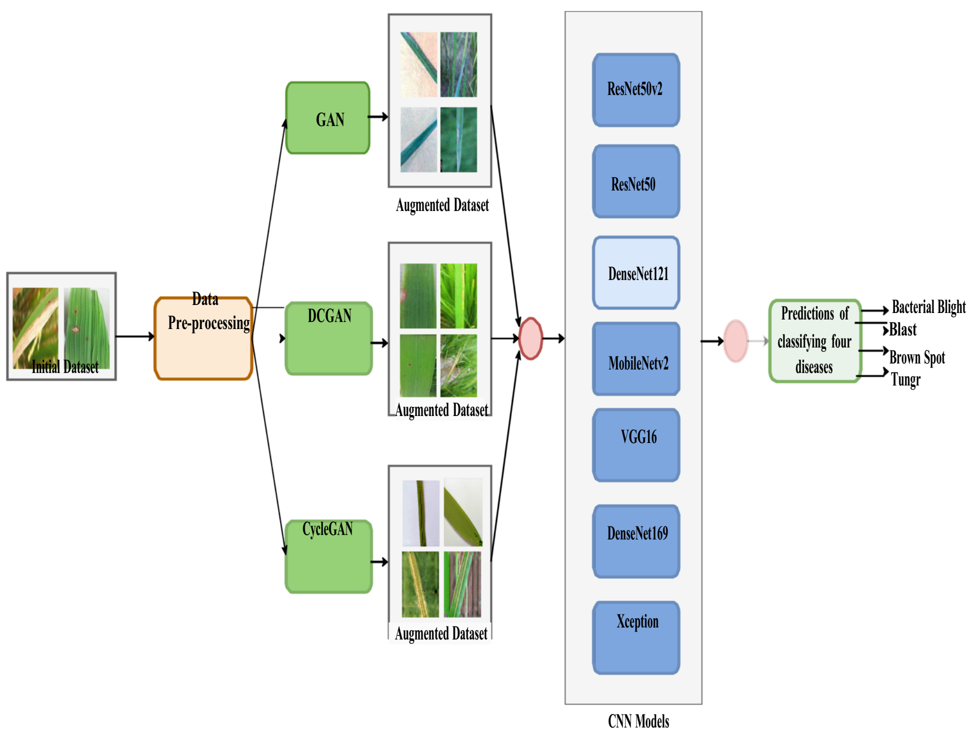


Fig. 4 GAN, DCGAN, and CycleGAN-generated samples

Fig. 5 Main flowchart for the classification of diseases using GANs



3.3 Evaluation metrics

The accuracy of a model refers to how well it predicts or classifies the data compared to the actual ground truth. It is one of the most common metrics used to evaluate the performance of a machine learning model. The accuracy of a model is calculated by dividing the number of correct predictions by the total number of predictions made. Higher accuracy indicates that the model makes fewer incorrect predictions, which is a good sign of its performance. However, it is important to note that accuracy alone does not provide a complete image of a model's performance, and other metrics such as precision, recall, F1-score, etc., should also be considered to have a more comprehensive understanding. In this paper, only accuracy is considered to evaluate the models. The calculation of metrics used in our method are given in Eqs. (4)–(9).

$$\textbf{Accuracy} = (\text{Correct Predictions})/(\text{Total Predictions}) \tag{4}$$

$$\textbf{Precision} = (\text{TP})/(\text{TP} + \text{FP}) \tag{5}$$

$$\textbf{Recall/Sensitivity} = (\text{TP})/(\text{TP} + \text{FN}) \tag{6}$$

$$\textbf{Specificity} = (\text{TN})/(\text{TN} + \text{FP}) \tag{7}$$

$$\text{F1} = 2* \frac{(\text{Precession} \cdot \text{Recall})}{\text{Precession} + \text{Recall}} \tag{8}$$

$$\textbf{Loss}(\mathbf{y}) = y_i \log(y_i) + (1 - y_i) + \log(1 - y_i) \tag{9}$$

where true positives (TPs) are the instances that are correctly predicted as positive by the model, true negatives (TNs) are the instances that are correctly predicted as negative by the model, and total predictions are the sum of true positives, false positives (FP), false negatives (FN), and true negatives. FP is the instances that are incorrectly predicted as positive by the model, while FN is the instances that are incorrectly predicted as negative by the model.

Table 3 The result obtained by CNN models without augmentation

CNN model	Accuracy (%)	Loss
DenseNet121	94.86	0.1444
MobileNetV2	96.26	0.1149
VGG16	89.78	0.2638
DenseNet169	96.06	0.1209
ResNet50	67.58	0.8113
ResNet50V2	**97.51**	**0.0880**
Xception	96.96	0.1110

The table showcases the results obtained by CNN models without any data augmentation, highlighting their baseline performance and providing a benchmark for comparison. This is crucial as it establishes the effectiveness of CNNs in the absence of different data augmentation techniques.

4 Result analysis

4.1 Method of classification with original dataset

Table 3 displays the accuracy and loss results for the identification of rice leaf disease from several CNN models. ResNet50 has the lowest accuracy of these models, at 67.58%, showing that it has difficulty correctly classifying samples of rice leaf disease on its own. In contrast, ResNet50V2 gets the best accuracy (97.51%), closely followed by Xception (96.96%). In terms of loss, VGG16 has the greatest loss value of 0.2638, indicating that it has trouble minimizing errors during training followed by MobileNetV2 comes in second with a loss of 0.1149, and ResNet50V2 has the lowest loss value of 0.0880.

4.2 Classification using augmented dataset

The classification result of rice leaf diseases using GANs can vary depending on the type of GAN used and the quality of the dataset. Simple GANs can produce basic results, while more advanced GANs such as DCGAN and CycleGAN can produce more refined results. The results can be further improved by using a combination of GANs and CNN models, where the GAN generates the augmented dataset and the CNN model classifies the diseases. Table 4 displays the results using the augmented dataset with several CNN Models. Table displays the accuracy results obtained by various GAN models, including GAN, DCGAN, and CycleGAN, when combined with various classifiers.Resnet50 shows the lowest accuracy of the three GAN models, with the CycleGAN model having the best accuracy at 73.35%. MobileNetV2 paired with CycleGAN has the highest accuracy of all models, with 98.54% accuracy. With all three GAN models, DenseNet121, DenseNet169, and Xception exhibit great accuracy ranging from 95.38% to 97.37%. However, VGG16 performs better

Table 4 The accuracy (%) obtained by GANs

CNN model	GAN (%)	DCGAN (%)	CycleGAN (%)
DenseNet121	95.38	**95.63**	95.54
DenseNet169	96.13	**97.63**	97.32
VGG16	89.02	88.65	**94.20**
ResNet50	61.87	65.90	**73.35**
ResNet50V2	97.30	**98.21**	95.17
Xception	96.34	97.05	**97.37**
MobileNetV2	96.80	96.96	**98.54**

The table details the accuracy percentages achieved by different Generative Adversarial Networks (GANs), including GAN, DCGAN, and CycleGAN, illustrating their capability to improve performance through different data augmentation methods

Table 5 The loss obtained by GANs

CNN model	GAN	DCGAN	CycleGAN
DenseNet121	0.1124	0.1208	**0.1049**
DenseNet169	0.1285	0.0913	**0.0819**
VGG16	0.2750	0.2582	**0.1593**
ResNet50	0.9687	0.8245	**0.6062**
ResNet50V2	0.1023	**0.0799**	0.2018
Xception	0.1089	0.0970	**0.0718**
MobileNetV2	0.1039	0.0760	**0.0480**

The table presents the loss metrics obtained by different GANs, offering insight into the model's learning efficiency and stability

with CycleGAN, obtaining an accuracy of 94.20%, but has significantly lower accuracy with GAN and DCGAN. Table 5 displays the loss values obtained by various GAN models, including GAN, DCGAN, and CycleGAN, when combined with various classifiers. Resnet50 has the biggest loss for all three GANs, indicating lower performance in terms of capturing the underlying patterns and characteristics from the rice leaf images. In contrast, CycleGAN consistently has the lowest loss with various classifiers, indicating its ability in generating synthetic images that closely resemble genuine rice leaf samples. The outcome shows that all of the CNN models perform better and achieve the best accuracy when using the CycleGAN-produced dataset. CycleGAN works better compared to GAN and DCGAN because of its ability to perform image-to-image translation. The main idea behind CycleGAN is to use two generative models, one for the source image and the other for the target image. The two models work together to ensure that the generated image is realistic and resembles the target image. This is achieved by using cycle consistency loss, which helps in maintaining the structural information of the source image. This is crucial for accurately classifying rice leaf diseases because it guarantees that the data provided are biologically relevant and usable. In comparison to employing only CNN models, the GAN augmentation and cycle consistency combination improve the accuracy of rice leaf disease detection. On the other hand, GAN and DCGAN can generate images, but the quality of the images generated is not as good as that of CycleGAN. Therefore, in the case of image-to-image translation, CycleGAN proves to be more efficient and effective compared to GAN and DCGAN. When we compare this result to the output of the CNN models without the GAN augmentation, we can observe the difference. Figure 6 plots the result obtained by the use of CNN models with different types of datasets. The accuracy graph analyzes the performance of several datasets in conjunction with various CNN architectures for rice leaf disease diagnosis, including DenseNet121, MobileNetV2, VGG16, DenseNet169, ResNet50, ResNet50V2, and Xception. The datasets used for comparison include GAN-generated dataset, CycleGAN-generated dataset, DCGAN-generated dataset, and a dataset with no augmentation. The results show that the combination of the CycleGAN-produced dataset and MobileNetV2 achieves the maximum accuracy, approaching 100%. This shows that the data provided by the CycleGAN augmentation technique improves the discriminative capacity of MobileNetV2, resulting in accurate rice leaf disease identification. Contrarily, ResNet50 performs poorly across all dataset types, with the GAN-generated dataset showing the worst accuracy. This comparison shows how important dataset augmentation and CNN architecture selection are for the precision of rice leaf disease diagnosis. It implies that employing CycleGAN augmentation with MobileNetV2 architecture can considerably enhance accuracy, however, using ResNet50 for this work should be done with caution. The loss graph in Figure 7 examines the performance of several datasets in conjunction with various CNN architectures for rice leaf disease detection, including

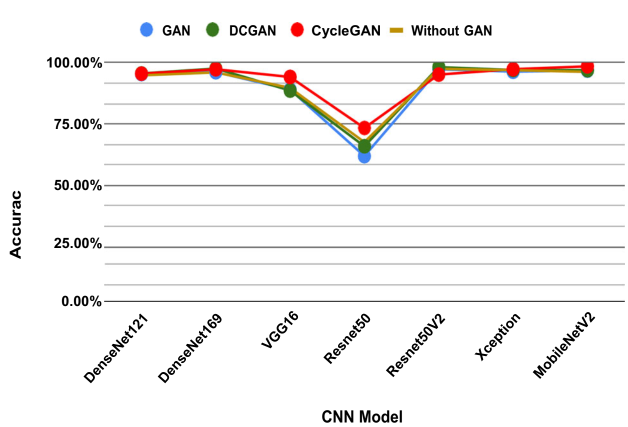


Fig. 6 Comparison of accuracy among with and without the use of GAN

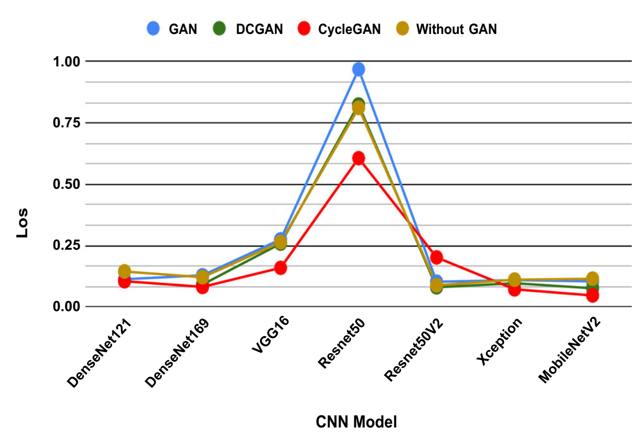


Fig. 7 Comparison of loss among with and without the use of GAN

Table 6 Comparison with other papers

Author	Augmentation method	Classifier	Dataset name	Number of classes of diseases	Accuracy (%)
Haruna etal. [5]	StyleGAN2	Proposed RiceDenseNet	Mendeley Data	Total-5932 Bacterial blight-1584 Tungro-1308 Brown Spot-1440 Rice Blast-1600	86.66
Kathiresan et al. [24]	StyleGAN2-ADA	Faster-RCNN	Rice leaf diseases	Total-120 Bacterial leaf blight-40 Brown spot-40 Leaf smut-40	91.83
Zhang et al. [30]	WGAN-GP, Real-ESRGAN	ResNet18	The rice leaf dataset	Total-2,538 Brown Spot-846 Leaf Blast-846 Bacterial blight-846	91.65
Ramadan et al. [31]	SRGAN	DenseNet169, MobileNetV2	Mendeley Data	Total-5,932 Bacterial blight-1584 Tungro-1308 Brown Spot-1440 Rice Blast-1600	94.30
Our paper	GAN	ResNet50V2	Mendeley and Kaggle Data	Total-10,025 Bacterial Blight-1584 Blast-3924 Brown Spot-3209 Tungro-1308	97.30
Our paper	DCGAN	ResNet50V2	Mendeley and Kaggle Data	Total-10,025 Bacterial Blight-1584 Blast-3924 Brown Spot-3209 Tungro-1308	98.21
Our paper	CycleGAN	MobileNetV2	Mendeley and Kaggle Data	Total-10,025 Bacterial Blight-1584 Blast-3924 Brown Spot-3209 Tungro-1308	**98.54**

The table compares our findings with those from other studies, emphasizing the relevance and competitive nature of our results within the existing body of literature

DenseNet121, MobileNetV2, VGG16, DenseNet169, ResNet50, ResNet50V2, and Xception. The results demonstrate that ResNet50 consistently has the largest loss across all dataset types, showing that it struggles to reliably categorize rice leaf disease samples. MobileNetV2, on the other hand, consistently gets the lowest loss, showing that it performs the best among the examined CNN designs across all types of datasets.

4.3 Comparative result analysis with various GAN method

Table 6 includes information on the authors, augmentation methods, classifiers utilized, datasets, number of classes, and accuracy percentages attained in detecting rice leaf diseases using various GAN-based approaches. StyleGAN2 was proposed in the paper by Yunusa Haruna and Mesmin J. Mbyamm Kiki, together with the RiceDenseNet classifier, to detect diseases in the rice leaf dataset. The collection included 5,932 samples from four disease classes: bacterial blight, tungro, brown spot, and rice blast. The accuracy of the suggested approach was 86.66%. Gugan Kathiresan, Anirudh M, Nagharjun M, and Karthik R used the Rice Leaf Diseases dataset with StyleGAN2-ADA and Faster-RCNN. The dataset included 120 samples from three disease classes: bacterial leaf blight, brown spot, and leaf smut. The method had a 91.83% accuracy rate. Zhao Zhang, Quan Gao, and Lirong Liu used WGAN-GP and

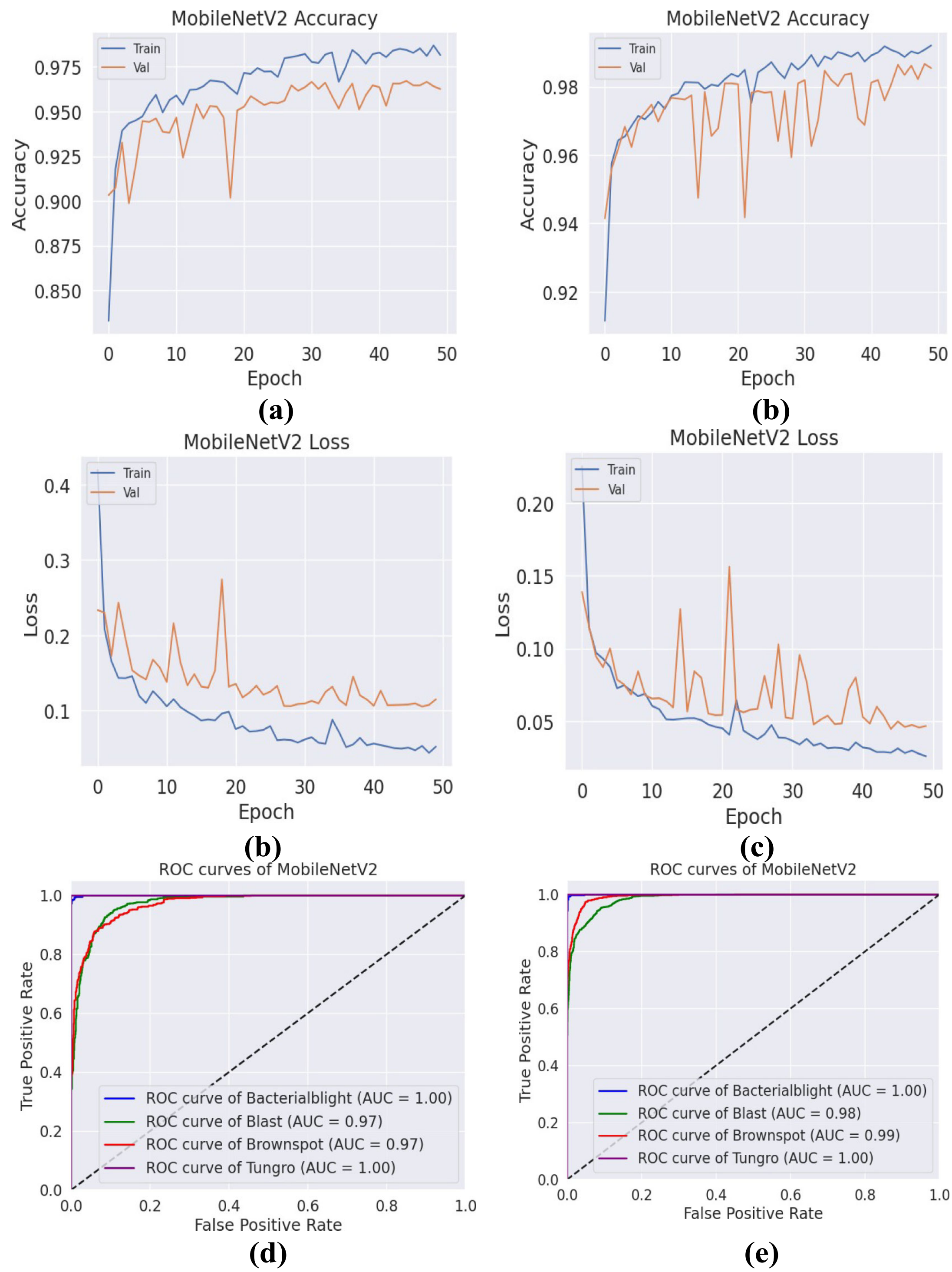
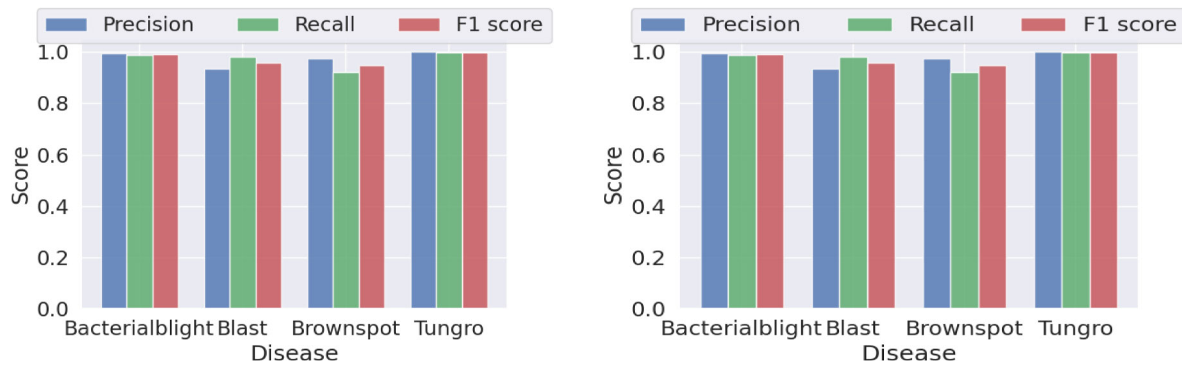


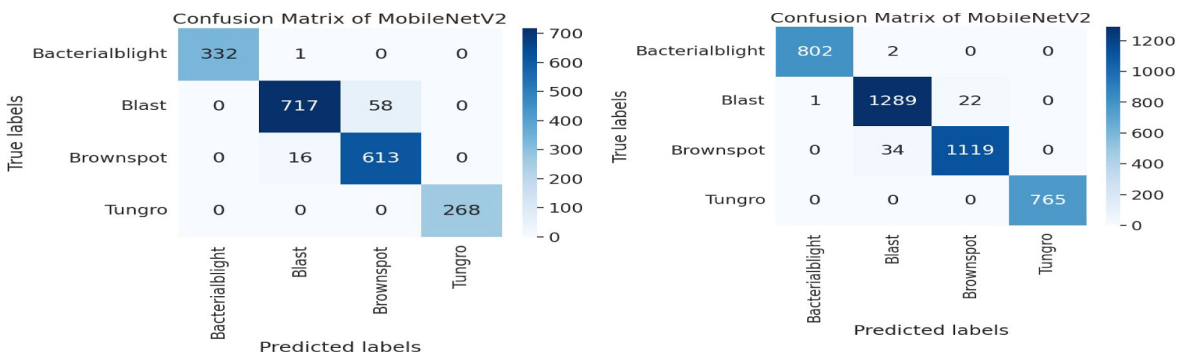
Fig. 8 Accuracy, loss, and ROC function result for MobileNet without GAN and with CycleGAN

ResNet18 with the Real-ESRGAN Leaf Dataset. A total of 2,538 samples from three disease classes: brown spot, leaf blast, and bacterial blight—were included in the collection. The method had a 91.65% accuracy rate. Taha Ramadan et al. employed SRGAN as the data augmentation method and DenseNet169 and MobileNetV2 as classifiers on a dataset of 5,932 images. Their method identified bacterial blight, tungro, brown spot, and rice blast with an accuracy of 94.30%. In our paper, we utilized GAN (GAN, DCGAN, and CycleGAN) along with several classifiers. The dataset comprised a total of 10,025 samples from Mendeley and Kaggle data sources. The dataset consisted of four classes



(a) Bar chart result of mobileNetV2 without GAN (b) Bar chart result of MobileNetv2 with CycleGAN

Fig. 9 Bar chart result for MobielNetV2 without GAN and with CycleGAN



(a) Confusion matrix of mobileNetV2 Without GAN (b) Confusion matrix of MobileNetv2 with CycleGAN

Fig. 10 Confusion matrix outcome for MobielNetV2 without GAN and with CycleGAN

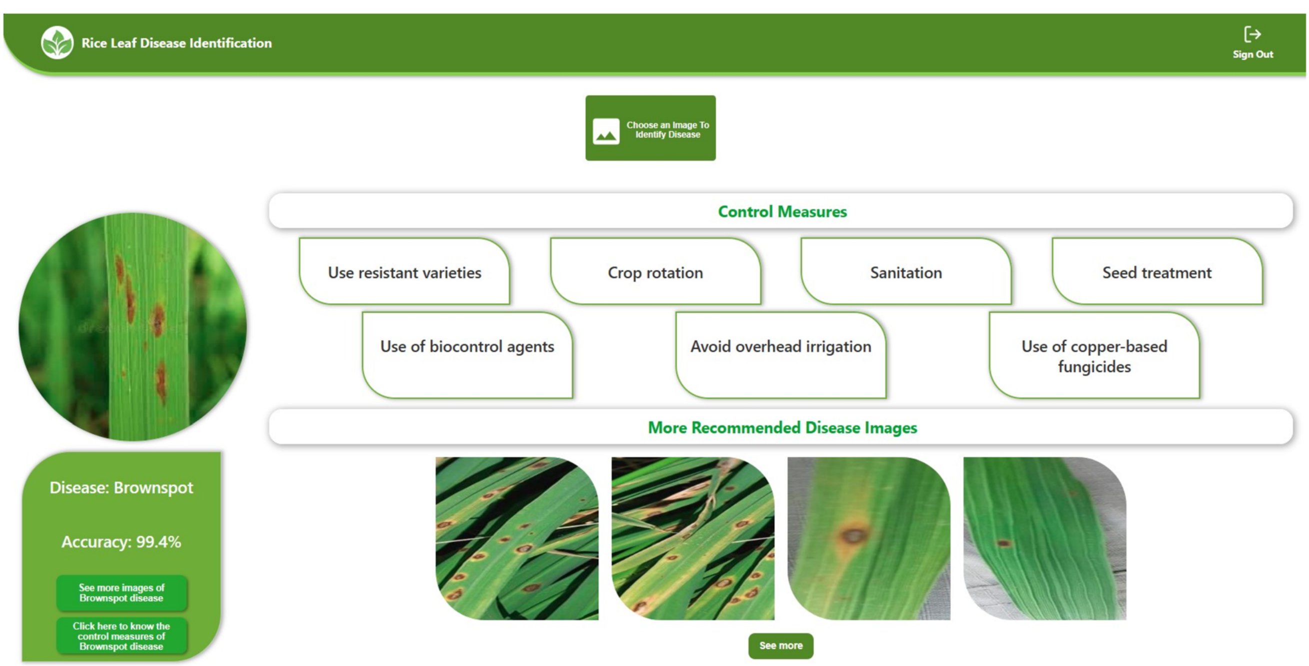


Fig. 11 Web application of rice leaf disease classification using CycleGAN with MobileNetV2 model

of diseases, including bacterial blight, blast, brown spot, and tungro. The proposed methods achieved high accuracies, with the DCGAN and CycleGAN models combined with the MobileNetV2 classifier achieving the highest accuracy of 98.54%.

4.4 Best classifier recommendation based on the best GAN-based augmentation

The study describes a novel approach for using GANs to increase the accuracy of rice leaf disease identification. To generate realistic images of rice leaf diseases, the dataset was enhanced with several GAN models, and the data label was improved. The study compared the classification results of the GAN-augmented dataset and the original dataset to evaluate the performance of the GAN models. The performance of the GAN-augmented dataset was essentially better than without any augmentation. CycleGAN, DCGAN, and simple GAN were the three generative adversarial network (GAN) models that we compared in this study. Our findings show that CycleGAN performs better at producing realistic and high-quality images than both DCGAN and simple GAN. CycleGAN's capacity to do image-to-image translation without paired training data is its key advantage over the other two models. This is accomplished by employing cycle consistency loss, which requires that the reconstructed image be identical to the original image after passing through the generator and discriminator twice. This makes the model more adaptable and simple to use for various image translation applications by enabling it to learn the mapping between two different image domains in an unsupervised manner. The use of batch normalization, which reduces internal covariant shifts and enhances the stability and convergence of the network, allows DCGAN to perform better than simple GAN by normalizing the output of each layer to have a zero mean and unit variance. Our findings underline how crucial it is to choose the best GAN model for a task depending on a variety of variables, such as the availability of paired training data, the difficulty of the image translation task, and the desired level of image quality. CycleGAN offers a potent solution for unsupervised image-to-image translation in cases when paired training data are either not available or difficult to obtain. The study used the expanded dataset and CNN-based deep learning models to precisely classify the disease affecting rice leaves. In addition, a user-friendly and interactive web-based deep learning application has been developed that can categorize a single realistic image of rice leaf diseases. The results of the study can help the agricultural sector by offering a quick and affordable way to identify diseases that affect rice leaves. Based on the comparative result as shown in Table 6 and our deeply demonstrated result as shown in Fig. 8 (showing accuracy, loss, and ROC result of CycleGAN with MobileNetV3 for both raw and augmented data), Fig. 9 (showing Bar chart result of CycleGAN with MobileNetV3 for both raw and augmented data), and Fig. 10 (confusion matrix result of CycleGAN with MobileNetV3 for both raw and augmented data) highly recommend that our CycleGAN with MobileNeV2 give more precise results. Our findings reveal that the CycleGAN-based MobileNetV2 model excels in predicting rice leaf diseases, outperforming alternative approaches. This assertion is substantiated by thorough analysis and compelling results, affirming the model's preeminence in the field.

4.5 Machine Learning-based real-time application of rice leaf disease prediction

The web application provides a platform for the precise and quick diagnosis of rice leaf diseases, assisting farmers, researchers, and crop security specialists. The inclusion of CycleGAN enables the creation of synthetic images, increasing the dataset and improving the CNN model's capacity to accurately generalize and identify various rice leaf diseases. The implementation of the website shows the potential of forefront deep learning approaches in tackling the issues presented by sparsely labeled data, paving the way for more efficient and long-lasting disease management strategies in the agriculture sector. Figure 11 demonstrates the rice leaf disease classification using real-world rice leaf disease images.

5 Challenges

The main drawback of this approach is the incompatibility with multiple datasets, wherein one classifier trained on a particular dataset does not give accurate results on other datasets, which limits its application for real-time detection. That is why the research was done to see which plant or fruit dataset works better on which combination of GAN and classifier. Finding a particular dataset was also a challenge, as there was an insufficient amount of images available of the diseased leaf. Also, creating a particular database is another huge task.

6 Future work

In the future, this research could be expanded by adding more datasets on various plants and fruits to identify leaf disease. Also, it is expected that many advanced GAN methods will be invented soon, which can give better results. This is also true for pretrained classifiers. It would be ideal if one particular GAN could be invented, which will give the best possible result for all possible datasets. For GAN to be properly trained and to produce accurate detection results, a large training dataset is required. Future studies can also focus on refining the technical aspects of the current GAN model in order to achieve higher levels of output accuracy while using a smaller number of training datasets. Eventually, it will make great strides, expanding into the realm of disease detection in other agricultural crops.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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