SEMARAK ILMU
PUBLISHING
202103268166(003316878-P)

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Improving Plant Disease Detection Using Super-Resolution Generative Adversarial Networks and Enhanced Dataset Diversity

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ARTICLE INFO

Article history:
Received 3 July 2023
Received in revised form 13 October 2023
Accepted 2 November 2023
Available online 31 December 2023

Keywords:
Genetic Adversarial Network, Image Processing, Data Diversity, Domain-Specific Knowledge

ABSTRACT

The detection of plant diseases is critical for maintaining crop health and maximizing agricultural yields. This research proposes a comprehensive approach to improve plant disease detection by addressing challenges related to unbalanced datasets and leveraging generative adversarial networks (GANs). This research focuses on enhancing the accuracy and generalization capabilities of disease recognition models. To address dataset bias, a larger and more diverse dataset is collected, comprising unhealthy plant leaves from various plants, regions, and disease types. The expanded dataset enables comprehensive training and validation, ensuring a representative depiction of leaf variations and diseases. Domain-specific knowledge and expert guidance are incorporated to capture realistic and characteristic attributes of diseased leaves. To overcome overfitting, the regularization technique is applied during training. These techniques promote the learning of generalized representations and mitigate the generation of unrealistic or repetitive images. The proposed approach is extensively evaluated using Plant Village dataset encompassing various plant species, and disease types. The results demonstrate improved accuracy, robustness, and generalization capabilities in plant disease detection. It establishes a foundation for reliable and effective detection methods, contributing to the sustainable management of plant diseases and improved agricultural outcomes.

1. Introduction

Detecting plant diseases is essential for ensuring crop health and maximizing agricultural yields, which is crucial for sustainable food production. Detecting and preventing untreated plant diseases at the earliest possible stage is the top priority as it can cause significant damage to crops [1]. Farmers can take immediate and targeted control measures, preventing the disease from spreading and causing an epidemic that could devastate entire crops and farmlands. Early detection also minimizes

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https://doi.org/10.37934/araset.35.2.144157

the economic losses associated with crop diseases, which could lead to substantial losses for farmers and the agriculture industry [2]. Farmers can reduce financial losses by taking appropriate action, resulting in lower yields or crop failure. Plant disease detection provides valuable information to farmers about the health of their crops. Understanding the diseases present and their severity can help farmers adjust their crop management practices accordingly. Effective disease detection promotes sustainable agricultural practices [3], reducing the reliance on broad-spectrum pesticides, which may harm beneficial organisms and cause environmental issues.

Ensuring crop health through disease detection is vital to meet the demand for food and enhance food security, particularly in regions where agriculture is a significant contributor to the economy and livelihoods. Early detection and intervention can also prevent unnecessary use of water, fertilizers, and pesticides, conserving resources and reducing the environmental impact of agriculture [4]. Promptly detecting and managing diseases is also crucial for complying with international quarantine measures and safeguarding agricultural exports. Regular disease monitoring and surveillance help researchers and policymakers understand the prevalence and distribution of various plant diseases, which is essential for developing effective disease management strategies and improving crop breeding programs.

When developing a plant disease detection system using generative adversarial networks (GANs) [5]. To ensure accurate and reliable results, there are several challenges that must be addressed. One of these challenges is the issue of imbalanced datasets, where the number of samples for each class (disease or healthy) may be significantly uneven. This can lead to biased model training, making it more difficult for the model to accurately detect the minority class. Additionally, obtaining sufficient data for rare plant diseases can be a challenge, which can lead to overfitting and impact the accuracy and reliability of the GAN-based model [6].

Mode collapse is another common issue with GANs, where limited sample variations are produced by the generator, which can hinder the ability of the model to learn the full range of disease patterns and generalize to unseen data. Ensuring the quality of generated samples is critical, as the effectiveness of GANs is heavily dependent on the realistic nature of the generated samples. Finally, it can be challenging to interpret how the model is making its decisions due to the black-box nature of GANs, which can impact the development of explainable AI-based models. To address these challenges, various techniques can be employed, including data augmentation strategies, transfer learning, regularization techniques, rigorous evaluation and validation, ensemble approaches, and hardware acceleration.

The objectives of this research are to

- Use Super-Resolution Generative Adversarial Networks (SRGANs) to improve the quality of plant disease images.
- Modify the network architecture by adding Residual-in-Residual Dense Blocks (RRDBs) and removing Batch Normalization (BN) layers.
- Implement a generator based on the Enhanced Upscaling module for Super-Resolution (EUSR) model with a multiscale approach for three different scales for high-resolution image generation.
- Use adversarial training to minimize the generator loss and maximize the discriminator loss.
- Evaluate the performance of the trained SRGAN using metrics such as Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), and human perceptual assessments, and apply post-processing techniques for further improvement.

The researchers aim to address the challenges associated with limited data, imbalanced datasets, and low-resolution images in plant disease detection. By leveraging the capabilities of SRGANs, they intend to improve the quality of images, increase dataset diversity, and ultimately enhance the performance of disease detection models. The following topics explore conventional methods used to identify plant diseases and the difficulties that come with limited data and imbalanced datasets. The SRGAN architecture and model are designed to overcome these challenges by improving image quality and dataset diversity. Additionally, the process of collecting and pre-processing datasets, technical details of SRGANs, and techniques to enhance dataset diversity are explained. Finally, the experimental setup and results are analysed, and potential areas for improvement are suggested.

SRGAN technology revolutionizes agriculture by conserving resources and making farming practices more sustainable. It enables precise detection of plant diseases, reducing the overall use of resources like water, pesticides, and fertilizers. Early disease detection and management lead to healthier and more resilient crops, reducing the need for resource-intensive interventions. SRGAN technology optimizes resource allocation, leading to cost savings for farmers and a reduced environmental footprint. In addition to reducing environmental impact, it promotes responsible and sustainable agricultural practices to comply with regulatory requirements. It helps farmers adapt to shifting weather patterns and mitigate the impact of climate-related challenges on agriculture. SRGAN technology enhances resource conservation, aligning with the principles of precision agriculture and sustainability. It promotes efficient and environmentally friendly farming practices.

2. Literature Review

Plant disease detection has been traditionally carried out through visual inspection by trained agronomists or plant pathologists. Support Vector Machines (SVM), Random Forests, and other such Machine learning techniques, have been used to classify plant samples based on texture, color, and shape features [7]. Hyperspectral and multispectral imaging techniques have been applied to identify unique spectral signatures associated with diseases. Convolutional Neural Networks (CNNs) have revolutionized plant disease detection by automatically learning relevant features from raw images without manual feature extraction [8]. Transfer learning, ensembling multiple models, and GANs have been used to fine-tune and augment plant disease datasets [9]. One-shot and few-shot learning techniques have been explored to address the limited labeled data for rare diseases. Internet of Things (IoT) and remote sensing technologies have enabled continuous monitoring of crops using drones, satellites, and ground-based sensors [10]. Mobile applications have been developed to provide user-friendly tools for plant disease detection, utilizing smartphone cameras and deep learning models running on the cloud or locally on the device. As deep learning models continue to grow in adoption, researchers are focused on making the models more interpretable.

Working with unbalanced datasets can present several challenges. Biased model training can occur when one class is significantly overrepresented compared to others, leading to a classifier that prioritizes the dominant class during training and performs poorly on the minority class [11]. Models trained on unbalanced datasets may also struggle to generalize to new data, especially for the minority class, due to the lack of representative samples. Traditional accuracy metrics may not accurately evaluate the performance of models trained on unbalanced data, as high accuracy can be misleading if the model performs poorly on the minority class. Imbalanced datasets may be a result of biased data collection practices, which can lead to oversampling or under sampling of certain classes [12]. Additionally, certain models may be highly sensitive to class distribution, resulting in significant fluctuations in accuracy and predictive capabilities. Models trained on unbalanced data may also frequently misclassify the minority class, leading to misdiagnoses. In the case of very imbalanced datasets, models may learn trivial patterns that result in a suboptimal model.

Existing approaches to handle class imbalance, such as class re-sampling, performance metrics, cost sensitivity, ensemble techniques, data augmentation, transfer learning, loss functions, and model complexity, all have limitations [13]. While re-sampling can improve balance, it may not fully address the problem and can introduce noise. Traditional evaluation metrics can be misleading, and cost-sensitive learning can be challenging to implement effectively. Ensembling multiple models can increase computational complexity, and data augmentation techniques may not be effective for imbalanced datasets. Transfer learning may carry biases from the source dataset, and designing appropriate loss functions can be challenging [14]. Complex models may overfit the majority class, while simpler models may not capture the complexities present in the data.

GANs use two neural networks, the generator and discriminator, to synthesize data that resembles real data. GANs can be used to balance class distribution and augment datasets. They have applications in generating synthetic data for image data augmentation, class imbalance, medical image segmentation, audio and speech processing, text generation and translation, and privacy-preserving data sharing [15]. GAN-generated samples can improve model generalization by providing more diverse and representative data, reducing overfitting. However, GANs have challenges such as mode collapse, lack of diversity in generated samples, and quality control of synthetic data. Researchers continue to work on improving GAN architectures and training methodologies to generate high-quality synthetic data for various applications. Data imbalance and rarity are common challenges in plant disease detection using GANs. Techniques such as oversampling, under-sampling, synthetic data generation, data augmentation, transfer learning, active data collection, ensemble approaches, appropriate evaluation metrics, model regularization, and continuous monitoring can help address these issues. Researchers and practitioners often use a combination of these approaches to improve model performance in real-world scenarios.

Previous research on plant disease detection has demonstrated the effectiveness of various techniques, including deep learning advancements, transfer learning, ensemble techniques, data augmentation, and remote sensing and IoT integration. Deep learning, particularly CNNs, has been leveraged to learn relevant features from images, resulting in higher accuracy and more robust models [16]. Transfer learning has been used to fine-tune pre-trained models from large-scale image datasets, leading to enhanced model performance with limited data. Ensemble methods have been explored to improve the overall performance of multiple models. Data augmentation techniques have been used to create diverse samples and increase the size of datasets, which leads to improved model generalization [17]. Advancements in remote sensing and IoT technologies have allowed for continuous monitoring of crops and valuable real-time data for disease detection and management.

However, certain weaknesses exist in previous research. Many studies have not adequately addressed the challenges posed by imbalanced datasets, which can lead to biased model training and reduced performance in the minority class. Additionally, rare diseases may have insufficient data available for effective model training, which hinders the development of accurate disease detection systems [18]. The diversity of the plant disease datasets used in some previous research might be limited, leading to potential biases and reduced model generalization to diverse field conditions. Deep learning models, including CNNs, are often considered black-box models with limited interpretability, which can hinder trust and acceptance of the models in real-world applications. Certain deep learning models, especially those with large architectures, require substantial computational resources and may not be practical in resource-constrained environments.

The proposed work aims to address the research gap related to imbalanced datasets in plant disease detection by leveraging the capabilities of Super-Resolution Generative Adversarial Networks (SRGANs) to generate high-quality synthetic data and enhance dataset diversity. This approach aims to overcome the limitations of working with imbalanced datasets, augment the dataset for rare diseases, enhance dataset diversity, improve model interpretability, and optimize the use of computational resources. The proposed work seeks to develop a more accurate, robust, and interpretable disease detection system with potential implications for agriculture and food security.

3. Proposed Work

The proposed model focuses on enhancing the perceptual quality of plant disease images by using SRGANs. The modified network architecture emphasizes the use of RRDBs with upscaling within the generator for deeper and more complex structures, as shown in figure 1. Additionally, the removal of Batch Normalization (BN) layers enhances stability during training and generalization. To overcome overfitting, the regularization technique is applied during training. Adam optimizer is used for stochastic gradient descent (SGD), combining the benefits of AdaGrad and RMSprop techniques. In the proposed model, the generator is based on the EUSR model, using a multiscale approach for three different scales (×4, ×6, and ×8). The residual scaling parameter is set as α. The convolution layer takes out r^2C feature maps with an $H \times W$ dimension. H, W, and C represent the LR image's height, width, and number of channels, respectively, and r is the desired scaling factor. Once the convolution layer has completed its task, the periodic shuffling operator reorganizes the feature maps to produce the ultimate HR image that measures $rH \times rW \times C$. To demonstrate the significance of the upscaling part, the performance change is evaluated based on the number of parameters in the feature extraction and upscaling components.

For the discriminator, the same network as in SRGAN is used but with the least square function instead of the adversarial loss. This architecture has several advantages, including producing more diverse samples by utilizing multiple generators and stabilizing the learning process. Consistency is ensured between the generator output layer and the discriminator's input layer by avoiding the application of batch normalization to the input layer of the discriminator. When using synthetic datasets, there are several concerns and potential biases that need to be addressed. These include the lack of real-world variability that synthetic datasets may not be able to capture, overfitting to the synthetic data, data distribution mismatch, and bias in data generation. This is addressed by augmenting the synthetic dataset with real-world data whenever possible, collecting images from diverse data sources, being mindful of the data generation process and ensuring it is designed to minimize bias, evaluating the model's performance on real data and continuously updating and improving the synthetic dataset and data generation process as more real-world data becomes available. Synthetic data is generated with accuracy, trustworthiness, and fairness. It avoids biases and protects the data privacy. It complies with ethical standards of consent, data ownership, and legal regulations. The generation process is transparent, accountable, and culturally sensitive. Continuous monitoring and evaluation of its impact is critical.

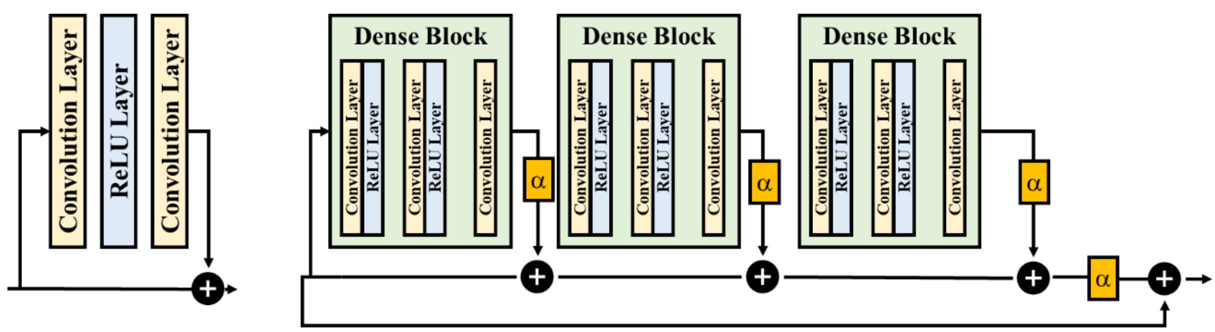


Fig. 1. Left: Residual block. Right: RRDB with upscaling

The objective function of the model minimizes the generator loss while maximizing the discriminator loss, leading to better performance and accurate classification of real and fake samples. This optimization results in a more robust and stable model capable of generating high-resolution images for plant disease detection. The generator (G) network is designed to take low-resolution (LR) images as input and produce high-resolution (HR) versions of them, as represented in equation 1.

$$G: LR \rightarrow HR \tag{1}$$

Multiple layers of up sampling blocks are used to gradually increase the spatial resolution of the input. An activation function follows each up sampling block to improve training stability. The generator's architecture may vary depending on the specific implementation and desired level of super-resolution.

The discriminator (D) network is designed to take high-resolution images (both real and generated) as input and distinguish between them. It is a binary classifier that predicts whether an input image is real or generated (fake). The discriminator is composed of multiple layers of convolutional blocks, followed by activation functions and batch normalization. The SRGAN is trained in an adversarial manner, where the generator and discriminator play a minimax game to improve their capabilities iteratively. During training, the generator aims to generate high-resolution images that can successfully deceive the discriminator into classifying them as real. Simultaneously, the discriminator is trained for distinguishing between real and generated high-resolution images in an accurate manner. The generator and discriminator are updated alternatively in each training iteration, optimizing their respective loss functions. The discriminator function is represented mathematically as follows:

$$D: HR \rightarrow [0, 1]$$
$$D(x_{HR}) \in [0, 1] \tag{2}$$

Adversarial Loss guides the generator to produce high-quality and realistic high-resolution images. It is calculated based on the discriminator's prediction of the generated samples. Content Loss (Perceptual Loss) ensures that the generated images preserve important details and structures from the low-resolution inputs. It is typically computed using features extracted from a pre-trained deep neural network and comparing them between the high-resolution ground truth and generated images. Total Loss is the sum of adversarial loss and content loss, with weights assigned to balance their contributions to the overall loss function.

$$L_{adv} = -\log(D(G(x_{LR}))) \tag{3}$$

The SRGAN implementation uses the upscaling factor x8. This denotes how much the generator increases the resolution of the low-resolution input to obtain the high-resolution output. After generating high-resolution images, the outputs are post-processed for denoising and color correction to further improve the visual quality. The performance of the trained SRGAN is evaluated using appropriate metrics, such as PSNR, SSIM, or perceptual quality assessments through human evaluations. With this, high-resolution images are generated from low-resolution inputs, making them useful for enhancing image quality in plant disease detection.

When deploying the SRGAN model in resource-constrained environments, smaller and less complex models are considered, low-power devices are used, the model is optimized through quantization and pruning, and software libraries are optimized for energy efficiency. Inference on the device is performed along with data compression, low-power modes are implemented, dynamic resource allocation is performed, and tasks are offloaded to cloud servers when needed. The model is optimized for real-time decision-making, sustainable power sources are considered, and performance and resource usage are monitored to ensure optimal energy and resource efficiency.

4. Results and Discussion

The network hyperparameters generated for the synthetic data are presented in Table 1. The network hyperparameters for generating synthetic data are presented in Table 1. The system is composed of three generator models. Each model has an input layer with 256 features from an isotropic multivariate Gaussian distribution μ (0, I). The generators have two fully connected hidden layers with 128 Rectified Linear Units (ReLU) for feature extraction. The final FC layer has two neurons and a Tanh activation function that generates the synthetic data. Meanwhile, the discriminator has a fully connected hidden layer with 128 neurons and a Leaky ReLU activation function (slope = 0.02). The discriminator does not have a final activation function as it is utilized for least square functions. The system is optimized using the Adam optimizer with a learning rate of 0.0002 and momentum of 0.5.

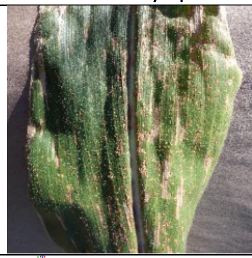
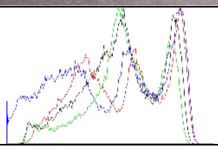
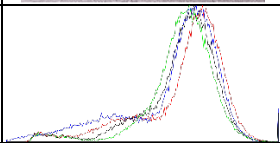
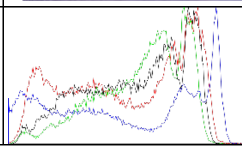
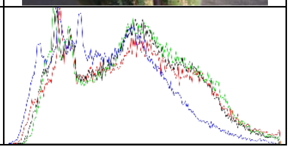
Table 1
Network hyperparameters

For Generator	
Input Noise	Z ~ μ (0, I) with 256 features
Fully Connected (FC) Layer 1	128 neurons with ReLU activation function.
FC Layer 2	128 neurons with ReLU activation function.
FC Layer 3	2 neurons with Tanh activation function to output the synthetic data.
For Discriminator	
Input	The discriminator takes real or generated data with 2 features.
FC Layer 1	128 neurons with Leaky ReLU activation function (slope = 0.02).
FC Layer 2	The discriminator has no final activation function, as it is used for least square functions.
Other Network Settings	
Number of Generators	3
Number of Iterations	25000
Learning Rate	Adam optimizer β = 0.125
Optimizer	Adam optimizer $\beta 1$ = 0.5 and $\beta 2$ = 0.999

To train large and complex SRGAN model, GeForce RTX 30-series GPU plate_number_1 is used. A multi-core processor with at least 8 cores, 32GB or more of RAM, and fast SSD storage of 1TB or more is used for data preprocessing and model training. The latest version of deep learning framework PyTorch, and CUDA and cuDNN libraries are used for GPU acceleration. Several days to weeks are allocated for training, adjusting the batch size based on GPU memory, and customizing the model architecture based on the requirements. Efficient data pipelines are used. Google Cloud is used as a cloud-based solution, and on-premises servers with GPUs for deployment are also used. It is crucial to strike a balance between computational power and available resources. SRGAN models are generally more computationally intensive than traditional image upscaling methods due to their deep neural network architectures. When comparing computational efficiency, factors such as model architecture, hardware, model complexity, parallelization, quantization, batch processing, comparative benchmarks, real-time vs. offline processing, and hardware acceleration are considered. To optimize the computational efficiency and speed of SRGAN, hardware choices, model configuration, and deployment strategies, are carefully considered to make sure the choice of method aligns with the application's requirements.

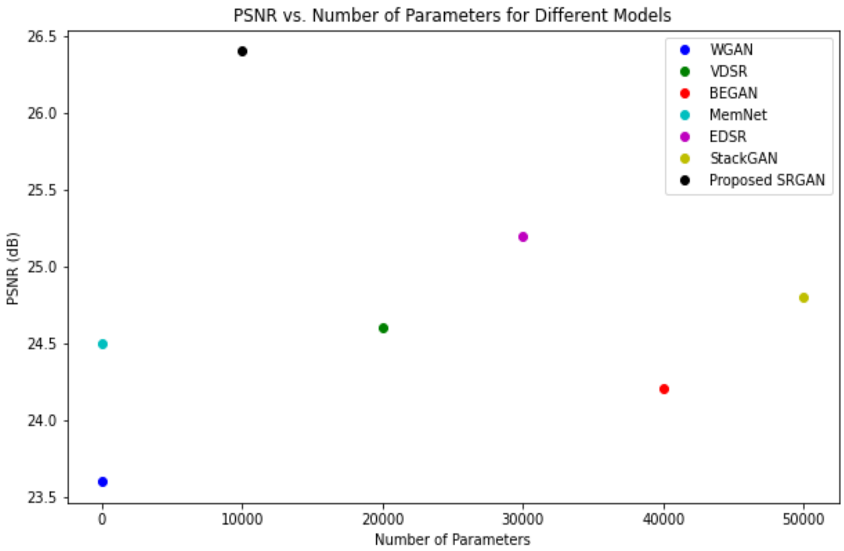
To enhance the dataset's diversity and the model's performance, a 2D mixture of 8 Gaussian distributions with a covariance of 0.002I is utilized. This creates low-density regions and separates modes. The generators share parameters, except for the input layer, while the discriminator shares parameters, except for the output layer. Synthetic data is generated using the generators, providing a varied and extensive data space for training the SRGAN.

Table 2
Sample images and histograms

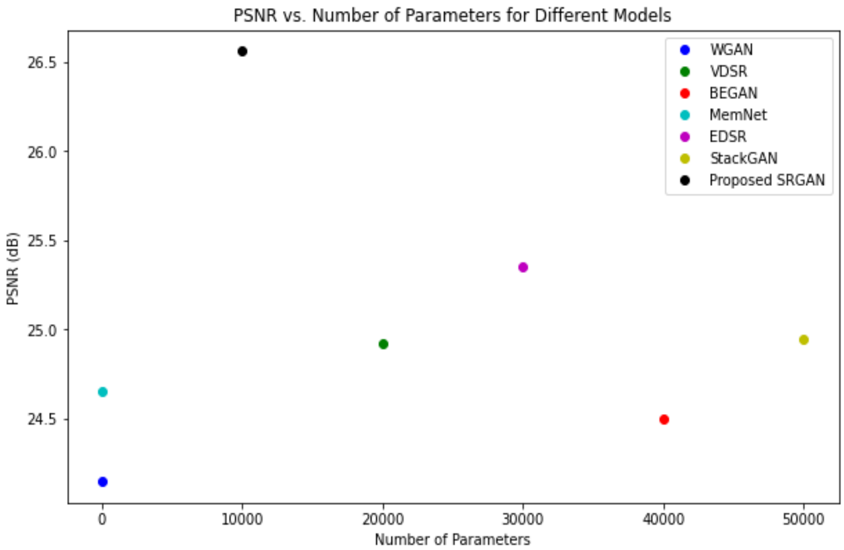
Sample	Grape – Black rot	Blueberry - Healthy	Apple – Black rot	Corn – Grey spots
Image				
Histogram				

For models in agricultural applications, it's crucial to consider generalization beyond initial training conditions. To ensure this, diverse data sources and validation/testing datasets reflecting variability are used, and field tests in different regions are performed. Applying data augmentation techniques and involving regional experts is also done. Continuous monitoring and fine-tuning improve adaptability to new environmental conditions.

The dataset used for training the SRGAN contained 54,303 images of healthy and unhealthy leaves classified into 38 categories based on species and disease. It is important to note that this dataset was collected in laboratory settings and may not reflect real-world scenarios. To overcome this limitation, a new dataset was created by collecting images from Google Images and Ecosia. The aim was to capture more real-life variations in plant leaves. The training process involved using synthetic data and paired high-resolution (HR) and low-resolution (LR) images. The LR images were generated from HR images using the MATLAB bicubic kernel function, resized and normalized. Table 2 provides the sample images from the selected sources along with their histograms. The model was trained using a mini-batch size of 16 and HR patches of spatial size 128 × 128. By training a deeper network with larger patch sizes, the model could capture more semantic information due to the enlarged receptive field. Performance validation can also be done using https://www.kaggle.com/datasets/vipoooool/new-plant-diseases-dataset and https://paperswithcode.com/dataset/plantdoc. Validation datasets are used to tune hyperparameters and assess how well the model generalizes to new, unseen data. These datasets should ideally reflect real-world conditions and variations that the model is expected to encounter.



(a)



(b)

Fig. 2. PSNR vs. number of parameters for (a)Plant Village dataset and (b) real-world dataset

The proposed model's performance was evaluated through a sequence of experiments and compared with well-known methods such as WGAN [19], VDSR [20], BEGAN [21], MemNet [22], EDSR [23], and StackGAN [24]. The experiments were carried out with synthetic data and real-world datasets. The goal of the synthetic data experiments was to demonstrate the impact of multiple generators on the model's learning behavior and assess its stability and effectiveness in a bigger and broader data space. One, two, and three generators were used for 25,000 epochs and ×8 scale. The results are shown in Figure 2. The findings indicate that the model with a single generator behaves similar to the regular GAN. Table 3 provides the comparison of the PSNR value in dB and SSIM values obtained during the quantitative evaluation of various techniques for multiple scales for the Plant Village dataset. It is observed that the proposed SRGAN model outperforms the existing models.

Table 3
Comparison of PSNR and SSIM values obtained during quantitative evaluation

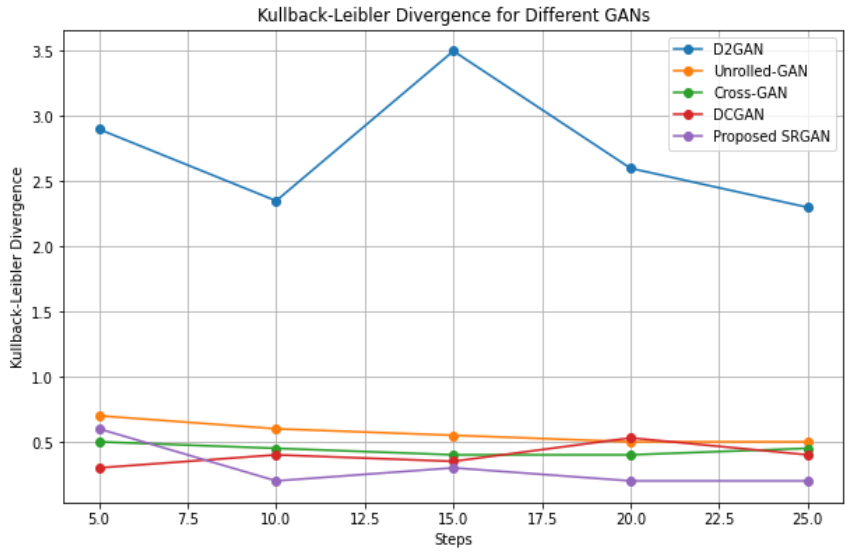
Scale	WGAN		VDSR		BEGAN		MemNet		EDSR		StackGAN		Proposed SRGAN	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
×2	32.63	0.914	36.24	0.954	35.75	0.967	37.27	0.935	36.25	0.952	37.45	0.937	39.51	0.975
×4	28.57	0.856	30.26	0.856	31.57	0.855	32.60	0.867	32.95	0.856	33.02	0.835	33.57	0.895
×8	23.58	0.697	24.56	0.702	24.82	0.723	25.02	0.742	25.97	0.752	26.42	0.763	27.56	0.797

Human perceptual assessments and post-processing techniques can be applied for further improvement. Figure 5 provides the qualitative evaluation of the sample image using various image processing techniques. An infected plant and its corresponding classification results are observed. The detection accuracy, precision, recall, and F1 score values are estimated and compared. The proposed model outperforms the existing models in all parameters with an accuracy of 99.8%, precision of 95%, recall of 92.53%, and F1 score of 92.63. Effective disease detection systems require a balance between model performance and computational resources. This involves trade-offs such as model complexity vs. inference speed, image resolution vs. computational load, real-time vs. batch processing, model pruning vs. accuracy, quantization vs. precision, parallelism vs. hardware resources, model selection vs. task specificity, and image preprocessing. Balancing these trade-offs requires careful consideration of accuracy, real-time constraints, available hardware, and the importance of conserving computational resources. It is achieved by iterative optimization and fine-tuning for the intended application.

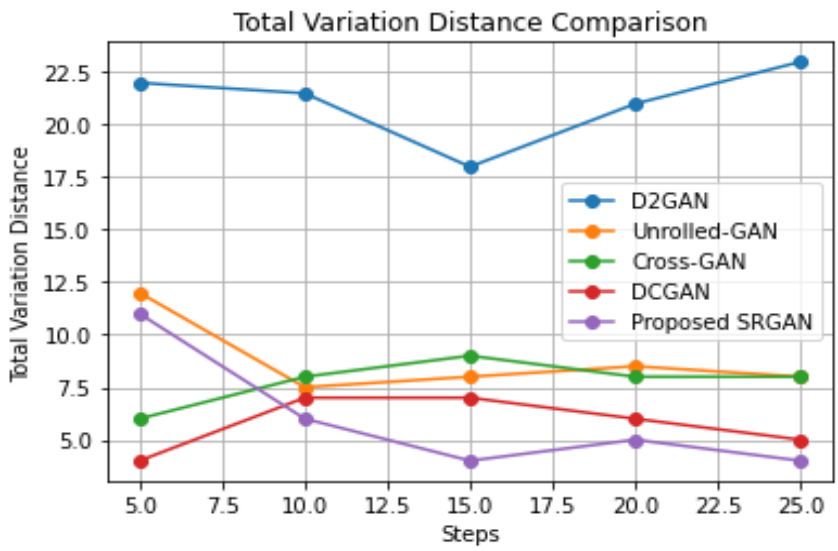
Fig. 3. Qualitative evaluation of sample image

The proposed model is trained by optimizing a loss function that involves the comparison between the real data distribution and the generated data distribution. The choice of distance parameters depends on the specific GAN variant and the training objective. We use various distance measures such as Kullback-Leibler Divergence (KLD) [25], Total Variation Distance (TVD) [26], Maximum Mean Discrepancy (MMD) [27], and Bhattacharyya Distance (BD) [28] to compare the effectiveness of the proposed model with different variations of GAN such as D2GAN [29], Unrolled-GAN [30], Cross-GAN [31], DCGAN [32] and proposed SRGAN as shown in figure 4. The curves in the model were almost reduced to zero, indicating reliable stability with little fluctuation when compared to others. The model was trained with the highest upsampling scales of 4x, 6x, and 8x between LR and HR images. For fair training, the samples were equally split for every upsampling scale.

Journal of Advanced Research in Applied Sciences and Engineering Technology
Volume 35, Issue 2 (2024) 144-157



(a)



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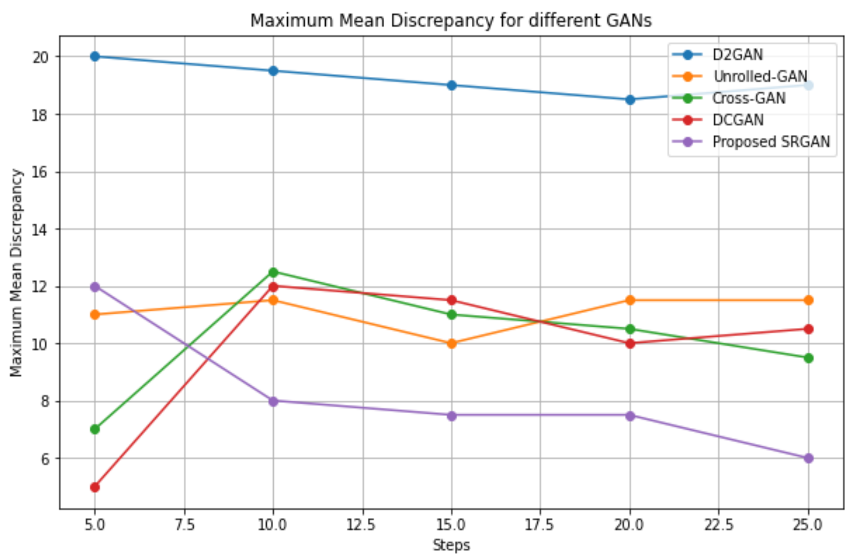
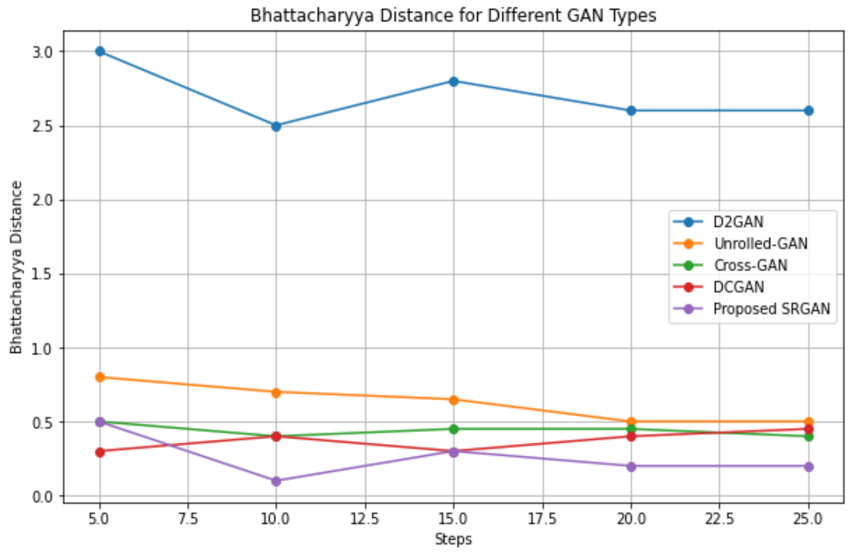


(c)



(d)

Fig. 4. Parameter comparison for various GAN types

Assessing the model's performance on unseen or out-of-sample data is crucial to determine its ability to generalize. In the proposed model, after training on a specific dataset, evaluation of the model performance is carried out on separate validation and test datasets. To evaluate a model's performance on different plant species and diseases not included in the training dataset, new data is collected and annotated using transfer learning techniques [33]. Further, the model is tested on real-world data, applied with cross-validation and benchmarking, and consulted with domain experts. It's important to rigorously evaluate the model's performance on these new and diverse data sources to ensure that it can generalize effectively to various plant diseases and species in real-world applications. This testing is a critical step before deploying the model for practical use in agriculture.

Climate change and weather conditions can have a significant impact on plant diseases. Considerations include the effects of climate change on disease dynamics, disease forecasting based on weather data, disease prevalence in varying weather conditions, data integration to enhance disease detection models, adaptability of detection models to different environments, and research collaboration. Considering the broader environmental context enhances the accuracy and relevance of disease detection models. To keep the plant disease detection model effective, new data is gathered and accurately annotated, the model is periodically re-trained, hyperparameters are fine-tuned, model performance is continuously evaluated, concept drift monitoring is implemented, a versioning system is maintained, model performance is validated, data augmentation is applied, collaboration is carried out with domain experts, an alert system is implemented, user feedback is obtained, ethical and legal concerns are addressed, compliance with regulations is ensured, external resources are tracked and continuous performance monitoring is ensured. This helps to maintain and update the model as new plant diseases emerge or as the dataset grows over time.

5. Conclusion and Future Scope

The combination of SRGANs and synthetic data generation is a promising approach for enhancing plant disease detection. The proposed model demonstrates superior performance over existing methods, both quantitatively and qualitatively. An accuracy of 99.8%, precision of 95%, recall of 92.53%, and F1 score of 92.63 is achieved, which is higher than the existing state-of-the-art models. By addressing the challenges of unbalanced datasets and limited data diversity, the proposed approach provides a valuable contribution to the field of plant disease detection and opens avenues for further research and application in real-world agricultural settings. Expanding the dataset and increasing data diversity can improve its effectiveness further. Refining the generative model and utilizing transfer learning can enhance its performance. Future research can be directed toward applications such as enhanced disease detection, precision agriculture, decision support systems, crop health monitoring, and global food security.

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