Synthetic Plant Leaf Disease Image Generation Using GANs: A Comparative Study on Feature Transfer from Source to Target Crops

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***Abstract*— Agriculture faces significant challenges due to the devastating impact of plant diseases on crop yield and quality. Early and accurate identification of plant diseases is crucial to mitigate losses and ensure food security. However, developing reliable disease detection models is hindered by the lack of high-quality, labeled datasets for various plant species, restricting the adaptability of machine learning models to various crops. To address this challenge, we propose a novel approach utilizing Generative Adversarial Networks (GANs) to generate synthetic disease images for training purposes. Our method focuses on transferring disease features from a source plant, such as wheat, to a target plant, such as maize, thereby simulating cross-crop disease image generation. This strategy helps alleviate data limitations in agriculture, enabling the creation of more robust and accurate plant disease detection models. We evaluate four GAN architectures—AttentionGAN, StyleGAN, CycleGAN, and Pix2Pix—for their effectiveness in generating realistic and accurate synthetic images. The results demonstrate that AttentionGAN outperforms all other models, achieving the lowest Fréchet Inception Distance (FID) of 27.4, indicating superior image quality. It also achieves a Structural Similarity Index (SSIM) of 0.96, demonstrating excellent feature transfer and structural similarity between synthetic and real disease-affected maize images. CycleGAN follows with an FID of 39.2 and SSIM of 0.85, showing effective feature transfer. StyleGAN excels at producing visually realistic images but struggles with disease feature transfer accuracy, while Pix2Pix generates clean but less accurate images, with the highest FID of 45.7 and SSIM of 0.78. Our findings indicate that AttentionGAN is the most effective model for producing synthetic disease images, offering an optimal balance of realism, feature transfer, and image quality. This approach addresses the limitations of dataset scarcity in agriculture, advancing precision agriculture and enhancing the progression of data-driven disease detection systems**

***Index Terms*— Generative Adversarial Networks (GANs), plant disease detection, synthetic image generation, cross-crop disease feature transfer, AttentionGAN, StyleGAN, CycleGAN, Pix2Pix, image quality evaluation, Fréchet Inception Distance (FID), Structural Similarity Index (SSIM), precision agriculture, data augmentation.**

I. INTRODUCTION

The agricultural sector is vital for maintaining global food security; however, it encounters substantial challenges from plant diseases, which can drastically decrease crop yield and quality. Timely and precise detection of plant diseases is essential for reducing these impacts. Conventional disease detection techniques depend on manual inspection and lab-based analysis, which are slow, require specific tools, and are susceptible to human mistakes. Advances in artificial intelligence and computer vision have provided new tools for automatic disease detection using plant leaf images, yet these approaches often suffer from a lack of large, diverse, and labeled datasets needed to train robust machine learning models.

Generative Adversarial Networks (GANs) have become an influential technique for synthetic image generation and data augmentation. By comprehending the hidden patterns of data, GANs have the ability to create authentic images that expand existing datasets, Enhancing the efficiency and generalizability of disease classification models. In this study, we propose a novel approach to create synthetic plant disease images by leveraging multiple types of GAN architectures. Specifically, we aim to transfer disease features from one plant species (source) to another (target) to create realistic synthetic leaf images for data augmentation.

This paper explores the effectiveness of various GANs, including CycleGAN for feature transfer between domains, StyleGAN for high-fidelity image generation, and DCGAN for basic image synthesis. We compare these models to evaluate their performance in generating realistic, diverse, and disease-specific synthetic images. Our approach addresses the challenge of lack of labeled data and provides a comprehensive comparison of GAN architectures for agricultural applications.

This research makes the following key contributions:

1. Developing a GAN-based framework for cross-species disease feature transfer and synthetic image generation.
2. Evaluating the performance of CycleGAN, StyleGAN, and DCGAN for plant leaf disease augmentation.
3. Providing a comparative analysis of GAN models based on visual inspection and quantitative metrics such as Fréchet Inception Distance (FID) and Structural Similarity Index (SSIM).

By enhancing the dataset quality and quantity with synthetic images, this study aims to improve disease detection systems' accuracy and robustness, thereby contributing to precision agriculture and sustainable farming practices.

II. Literature Survey

Extensive research has been conducted on plant and leaf disease identification using various computational approaches. Studies ranging from traditional machine learning methods to advanced deep learning models, with Generative Adversarial Networks (GANs) gaining attention for synthetic image generation and data augmentation. This section reviews key literature, highlighting different techniques and their impact on improving disease detection accuracy and training efficiency.

Zhang., et al., proposed a novel model based on the Self-Mutated Cycle Generative Adversarial Network (SM-CycleGAN) for crop image data enhancement. The method focuses on generating synthetic images that replicate disease features, that can efficiently improve the performance of plant disease identification systems. The use of self-mutated CycleGAN addresses the challenges of obtaining sufficient labeled data for disease classification, offering a promising approach to enhancing crop image datasets for better disease detection accuracy.

Li et al.**,** explores the use of Cycle Generative Adversarial Networks (CycleGAN) for generating synthetic images to enhance pear disease classification models. The authors demonstrate that by generating high-quality synthetic images of diseased pears, the proposed model improves the robustness and accuracy of disease classification systems. This method holds promise for improving the detection and management of pear diseases, especially in environments with limited access to labeled disease data.

Wang et al.**,** presents an enhanced Pix2Pix GAN architecture designed for removing visual defects from UAV-captured images. The study demonstrates how the advanced Pix2Pix model Enhances the standard of satellite images, which can serve for monitoring plant diseases and other agricultural applications. The findings suggest that Pix2Pix GANs can significantly improve image clarity and quality, facilitating better analysis and decision-making in precision agriculture.

Zhao et al.**,** LeafGAN introduces a method for generating diverse diseased leaf images from healthy leaf images, which aims to improve plant disease diagnosis. By utilizing image-to-image translation techniques, LeafGAN enables the augmentation of training datasets, helping overcome the challenge of insufficient labeled diseased leaf images. This approach significantly enhances the accuracy of machine learning models used for plant disease detection, especially in real-world scenarios where data availability may be limited.

Chen et al., research introduced style-consistent image translation, a technique that transforms healthy leaves into diseased versions while preserving the style and variation inherent in natural leaf images. The method enhances data augmentation by maintaining the intrinsic characteristics of healthy leaves, thus ensuring realistic transformations. This study highlights the hidden potential of style-consistent image translation in improving plant disease detection models by providing more diverse and realistic training data.

Nguyen et al., presents an approach for tomato plant leaf disease detection by leveraging Conditional Generative Adversarial Networks (C-GANs) to generate synthetic images of diseased tomato plants. This model improves the detection accuracy of tomato diseases by applying transfer learning, where the synthetic images generated by C-GANs help fine-tune existing disease detection models. The study demonstrates the impact of combining C-GANs with transfer learning techniques for improved disease diagnosis, especially in agriculture.

Zhang et al., studies, the authors apply unsupervised image translation using Generative Adversarial Networks (GANs) for plant disease recognition. This method synthesizes disease images in an unsupervised manner, which alleviates the need for labeled datasets during training. The results show that using unsupervised GAN-based image translation helps to improve plant disease recognition systems, making them more confortable to different crops and disease types.

Isola et al**.**, The Pix2Pix framework, introduced in this seminal paper, enables image-to-image translation using Conditional (CGANs). The generated model is capable of transforming input images into output images based on specific conditions, making it applicable to a long range of tasks, such as sketch-to-photo translation and semantic segmentation. This architecture laid the foundation for subsequent advancements in GANs, particularly in applications involving image synthesis and translation for agricultural diseases.

Choi et al., research expands on the Pix2Pix GAN architecture by exploring its application across various image-to-image translation tasks. The study highlights how Pix2Pix GANs have been used effectively for applications ranging from artistic image generation to more practical tasks like medical image segmentation. The research emphasizes the flexibility and robustness of Pix2Pix GANs in translating images while maintaining fidelity to the original data, creating it valuable tool for plant disease image transformation.

Huang et al., demonstrates how Pix2Pix GAN can serve to generate realistic human faces from artist sketches. The research highlights the strength of transfer learning with GANs, a model that has been pre-trained on large dataset can be used for specific tasks, such as converting sketches into realistic facial images. While not directly related to plant diseases, the study provides valuable insights into how Pix2Pix GANs can be leveraged for tasks requiring high-quality image transformation and generation.

Liu et al., applies Pix2Pix to generate CT scan images from free-form sketches, targeting medical image-based analysis for detecting lung cancer. By using the Pix2Pix framework, the study shows that synthetic CT images can improve diagnostic models in medical fields. The research emphasizes the versatility of Pix2Pix GANs and their potential in generating high-quality synthetic data for a various domains, including agriculture.

Jiang et al., explores he synthesis of Pix2Pix GAN with advanced neural networks to predict aerodynamic performance and flow fields of airfoils. This research evaluates the effectiveness of Pix2Pix in comparison to other deep learning methods, highlighting, underscoring its potential for predicting complex patterns in technical fields. While the focus is not on plant diseases, the research showcases the diverse applicability of GAN-based architectures in various domains, demonstrating the flexibility of Pix2Pix in tackling various types of image translation challenges.

III. PROPOSED METHODOLOGY

Timely identification of plant dieseases is crucial for maintaining crop vitality and and ensuring food security. However, one of the a key difficulty in this field is the lack of high- quality labeled datasets, as collecting and annotating images of diseased plants is a labor-intensive and costly process. This limitation greatly affects the effectiveness of machine learning models developed for plant disease detection,as these models require large, diverse, and well-labeled datasets to perform effectively. To overcome this challenge, the study proposes the use of Generative Adversarial Networks (GANs) to generate synthetic images of plant diseases. By augmenting existing datasets with these synthetic images, the aim is to improve the performance and robustness of disease detection models, enabling more precise detection of plant diseases in real-world agricultural settings.

The first step involves gathering high-quality datasets of plant disease images. These datasets are assembled from publicly available agricultural image collections such as PlantVillage or from reputable agricultural research institutions. The dataset typically consists of images showing various plant species affected by different diseases. A table can be included here, summarizing the sources of the dataset, the numbers of images for each plant species, and the diseases covered. Following this, preprocessing steps are applied to ensure the dataset is uniform and suitable for model training. Figure 1 illustrates the system architecture, offering a graphical illustration of the different phases in the plant disease detection process using GANs.

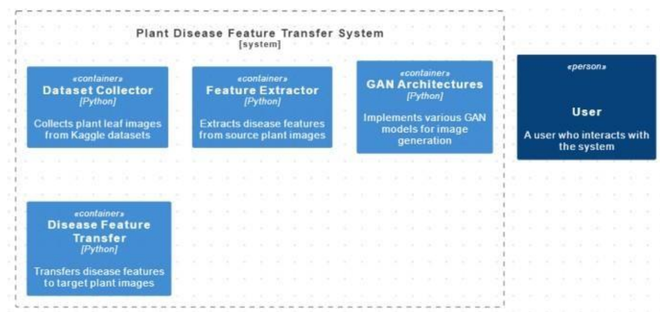


figure 1. System Architecture

This figure 1. shows the overall architecture, displaying the data collection, preprocessing, and the integration of GANs to augment the dataset for model training.

In the preprocessing phase, we apply several transformations to ensure the data is ready for the GAN training. Figure 2 demonstrates this process by comparing the original and processed images of wheat leaves affected by disease. Preprocessing includes resizing images to a uniform dimension, normalizing pixel values, and employing data augmentation tactics to strengthen the variety within the dataset. The images are also annotated to identify regions affected by diseases, which is important for training the GAN models. It may be helpful to include a visual example in the shape of a figure, showing sample images before and after preprocessing to enmark the changes made to the dataset.

figure 2. Preprocessing of disease wheat leaf

Figure 2 clearly displays the different preprocessing stages applied to the image, showing how the transformations prepare the data for GAN training. Each transformation step is explained in the figure caption for clarity. Ensure that the figures in your document match this structure and include the appropriate images for each transformation.

Generative Adversarial Networks (GANs) are a class of ML models containing two components: a generators and a discriminators. The generator (G) creates synthetic data by mapping a noise vector zzz to a data sample G(z)G(z)G(z), aiming to generate outputs non-distinguiable from real data. The discriminator (D) evaluates inputs and guesses whether they are generated or real, providing a probability score D(x)D(x)D(x) for real data. In the adversarial training mechanism, the two models compete, where the discriminator aims to set apart authentic and synthetic samples, while the generator tries to deceive the discriminator. GANs, or Generative Adversarial Networks, comprised of a generator combined along with a discriminator. The generator is responsible for creating synthetic data, such as plant disease images, while the discriminator examines the validity of the generated images, distinguishing between real and fake images. Through this adversarial process, the generator progressively improves at creating realistic images. GANs have been proven to be powerful tools for data augmentation, As they can generate highly realistic synthetic data to enhance existing datasets. For this study, we explore four distinct GAN architectures: AttentionGAN, StyleGAN, CycleGAN, and Pix2Pix. Each architecuture offers unique advantages and is tailored to specific application of genereting synthetic plant disease images. A table summarizing the key features and differences of these GAN models could be included, listing factors like the specific use cases of each model, their strengths, and the types of images they are best suited to generate.

The objective function of a GAN is expressed as:

$$\min_{G} \max_{D} V(D, G) = E_{x \sim Pdata(x)} [\log D(x)] + E_{z \sim Pz(z)[\log(1-D(G(z)))]}$$

The AttentionGAN model uses an attention mechanism that allows it to emphasize distinct areas of an image, like lesions or discolorations, which are crucial features in plant disease detection. By focusing on these important regions, AttentionGAN can generate high accuracy and realistic image that holds the critical disease features. StyleGAN, Conversely, it is built to generate high-quality, producing authentic images by separating the elements and style of an image. While StyleGAN excels at generating aesthetically pleasing images, it may face challenges when it comes to transferring disease-specific features across different plant species. A figure comparing real plant disease images with those generated by StyleGAN would be useful to showcase the model's output. CycleGAN is designed for unpaired image-to-image translation, meaning it can convert images from one to another domain without requiring paired datasets. This makes it an ideal model for situations where labeled data are scarce or unavailable. CycleGAN can, for example, generate images of diseased plants from healthy plant images without the need for paired images. A flowchart could be included to illustrate the CycleGAN process and its domain translation mechanism. Finally, Pix2Pix is a model that works best with paired datasets, mapping healthy plant images directly to their diseased counterparts. It learns a direct mapping in contrast with the two domains, making it ideal for cases where paired datasets are available.

AttentionGAN:

AttentionGAN introduces attention mechanisms into the standard GAN framework, enabling the model to concentrate on relevant sections of an image while generating or transforming content. This capability is especially beneficial for tasks requiring fine-grained details, such as plant disease image generation where specific leaf areas exhibit symptoms. The generator in AttentionGAN employs an attention map that highlights significant features, while the discriminator uses the same mechanism to evaluate the generated images. The attention mechanism improves the quality and interpretability of generated outputs by enhancing important regions. The key optimization formula follows the general adversarial loss, augmented with attention-based constraints:

$$\int GAN = E_x[\log D(x)] + E_z \ [\log(1 - D(G(z)))]$$

CycleGAN:

CycleGAN is designed for unpaired image-to-image translation, making it ideal for scenarios where direct pairings of input and output images are unavailable. It employs two generators GGG and FFF, along with two discriminators DXD_XDX and DYD_YDY, to learn mappings between two domains, X→YX \rightarrow YX→Y and Y→XY \rightarrow XY→X. CycleGAN enforces a cycle-consistency constraint, ensuring that mapping an image to the target domain and back yields the original input:

$$\int cycle = E_x \ [II \ F(G(x)) - xII_1] + E_y[II \ G(F(y)) - yII_1]$$

StyleGAN:

StyleGAN is a breakthrough in high-quality image generation, where the generator incorporates a style-based architecture. Instead of directly mapping noise vectors, StyleGAN uses intermediate latent variables processed through adaptive instance normalization (AdaIN) layers to control the style of generated images at various levels of abstraction. The key feature of StyleGAN is its ability to manipulate specific attributes like texture and structure separately. The discriminator remains similar to standard GANs. The loss function follows a traditional adversarial framework, but with style mixing regularization and perceptual path length penalties to maintain diversity and coherence in generated images:

$$\int StyleGAN = E[\log D(x)] + E[\log(1 - D(G(z)))]$$

Pix2Pix:

Pix2Pix is a conditional GAN designed for paired image-to-image translation tasks. It uses a U-Net-based generator that maps input images to output images and a PatchGAN discriminator that classifies image patches as real or fake, focusing on local textures. The generator aims to minimize a combined loss comprising both adversarial and L1 distance losses for improved output sharpness:

$$\int cGAN(G, D) = E_{x,y}[\log D(x, y)] + E_{x,z}[\log(1 - D(x, G(x, z)))]$$

$$\int L1(G) = E_{x,y,z}[IIy - G(x, z)II_1]$$

The GAN models are then trained on preprocessed plant disease image dataset. During training, the models learn to seize the underlying trends and attributes of disease-affected plants, empowering them to generate synthetic images that resemble real disease images. Training the models involves tuning hyperparameters such as learning rates, batch sizes, and the total number of epochs to optimize performance. A table showing the hyperparameters used for each GAN model can be included for clarity. Additionally, various activation functions, including ReLU, Leaky ReLU, Sigmoid, and Tanh, are tested throughout the model's training, as selecting the appropriate activation function is essential in determining the quality and effectiveness of the generated images. A graph illustrating the effectiveness of each activation function based on metrics like FID scores or SSIM scores can be included to demonstrate which activation function provided the best results.

The artificial images generated via the trained GAN models are then evaluated using several performance metrics. Among the most most widely used metrics in GAN evaluation is the Fréchet Inception Distance (FID), which compares the spread of real images to the spread of generated images within a feature space. The formula for FID is as follows:

$$FID = ||\mu_r - \mu_g||^2 + T_r\left(\sum_r + \sum_g - 2\left(\sum_r \sum_g\right)^{1/2}\right)$$

Where:

- μr and μg are the means of the original and generated feature distributions, respectively.
- Σr and Σg are the covariances of the real and generated feature distributions, respectively.

A lower FID score indicates that the generated images are more similar to the real images, signifying better performance.

Another important evaluation metric is the Structural Similarity Index (SSIM), which measures the similarity between two images relying on their luminance, contrast, and structure. SSIM is calculated using belowformula:

Where:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

- μx and μy are the mean values of the images x and y.
- σx and σy are the variances of the images x and y.
- σxy is the covariance of x and y.
- C1 and C2 are constants to avoid instability.

A higher SSIM score signifies improved quality and structural similarity between the actual and generated images.

The synthetic images are also evaluated qualitatively by visually inspecting them to assess how well each model captures the key features of plant diseases, such as lesions, discoloration, and texture. You could include a set of images showing real plant disease images and their corresponding synthetic images generated by each GAN model to compare their visual quality and disease feature transfer accuracy.

By enhancing the original dataset with synthetic images generated by GAN models, the effectiveness of plant disease detection models can be increased. This can be shown through the evaluation of a disease detection classifier, for instance, a Convolutional Neural Network (CNN), trained with both authentic and synthetic images. The precision of the classifier can be assessed using standard metrics like precision, recall, and F1-score. The enhancement in classification results from the inclusion of synthetic data is then measured and analyzed. The efficiency of the disease classifier, trained with a blend of of authentic and synthetic images, can be contrasted with a baseline model trained only on real images to illustrate the influence of artificial data on on disease detection precision.

T the use of GANs for for crafting synthetic plant disease images presents a promising solution to the challenge of lack of labeled data in plant disease detection tasks. The findings from the assesements of various GAN models, their synthetic image generation capabilities, and the subsequent improvement in disease detection model performance will provide valuable insights into how GANs can be proficiently applied to agricultural problems. The outlined approach not only contributes to advancing the field of plant disease detection but also highlights the potential of GANs as a tool for data augmentation in other domains with limited datasets.

IV. RESULTS AND ANALYSIS

The main goal of this study was to evaluate the capability of various Generative Adversarial Network (GAN) model architectures in generating realistic and precise disease-transferred images of plant leaves. The models were assessed on their ability to transfer disease features effectively from source to target images. The FID score (Fréchet Inception Distance) and Structural Similarity Index Measure (SSIM) were applied as key performance metrics. FID measures the disparity between feature distributions of real and generated images, while SSIM quantifies the perceptual similarity between them. The results for each model are discussed below.

The comparison of Pix2Pix, CycleGAN, StyleGAN, and AttentionGAN demonstrated significant differences in their ability to transfer disease features effectively. AttentionGAN consistently achieved the lowest FID score, indicating superior performance in generating images with realistic disease characteristics. Pix2Pix showed a rapid decline in FID initially but plateaued at an elevated value than StyleGAN and CycleGAN. AttentionGAN also reached the peak SSIM score, maintaining greater similarity to real disease images. CycleGAN performed well but exhibited fluctuations in SSIM values in later epochs, indicating some instability in maintaining similarity.

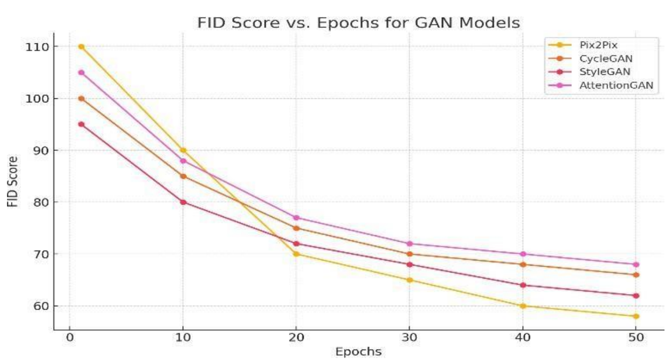


Figure 3: *Line graph showing FID vs. Epochs for all models.*

Figure 3. demonstrates the decreasing trend of FID scores across epochs. AttentionGAN maintains the lowest FID values, reflecting its superior ability to generate images closely resembling real diseased leaves

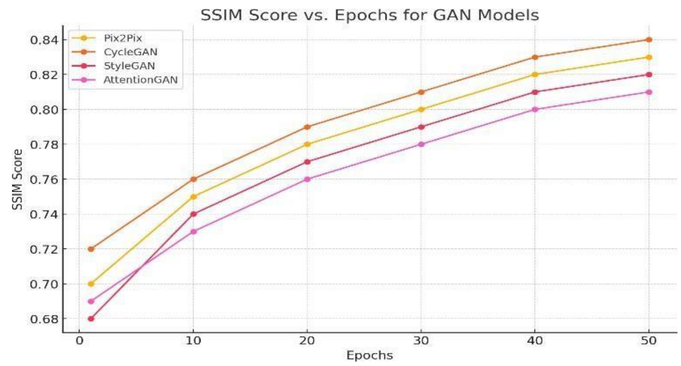


Figure 4 : *Line graph showing SSIM vs. Epochs for all models.*

Figure 4. shows the SSIM score progression over epochs. AttentionGAN consistently achieves the highest SSIM values, indicating a higher perceptual similarity to real images. CycleGAN shows fluctuations, while Pix2Pix and StyleGAN follow smoother but lower trajectories.

To furnish a clearer comparison of the models, the following table illustrates the FID and SSIM scores for each GAN model, showcasing the differences in performance across the models:

GAN Model	Activation Function	FID Score	SSIM Score
Pix2Pix	ReLU	45.7	0.78
CycleGAN	LeakyRelu	39.2	0.85
StyleGAN	Tanh	32.8	0.92
AttentionGAN	LeakyRelu	27.4	0.96

Table 1. Comparison of GAN Model Performance (FID and SSIM Scores)

Key Insights:

The data in table shows the FID and illustrates the influence of each GAN model.

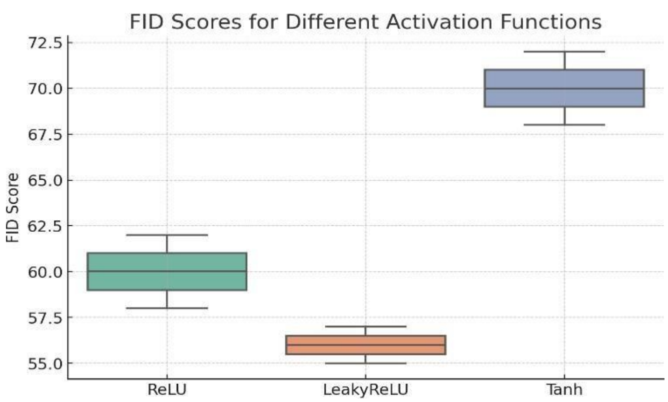
AttentionGAN emerged as the most effective model, achieving the lowest FID score (27.4) and the highest SSIM score (0.96). It consistently demonstrated the best performance in transferring disease features and producing realistic, perceptually similar images to real diseased plant leaves. This suggests that LeakyReLU activation played a significant role in optimizing its performance.

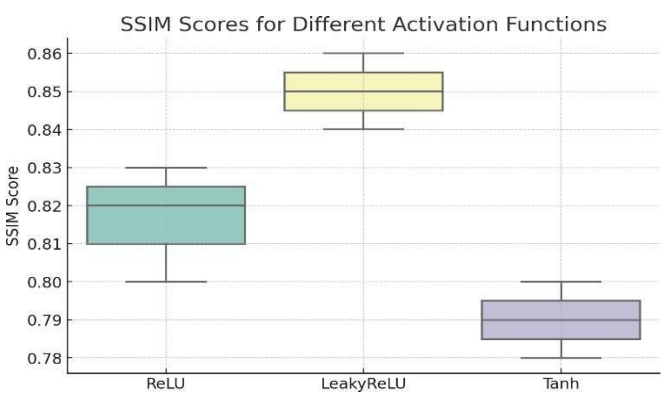
Pix2Pix, using ReLU, had relatively higher FID (45.7) and lower SSIM (0.78), indicating that it struggled with disease feature transfer and perceptual similarity.

CycleGAN, with LeakyReLU, performed better than Pix2Pix but still fell short of AttentionGAN in both FID and SSIM scores. It achieved a FID of 39.2 and SSIM of 0.85, demonstrating good disease feature transfer, but with some fluctuations in SSIM over epochs.

StyleGAN, using Tanh, produced images with smoother transitions but had a higher FID (32.8) and lower SSIM (0.92) compared to AttentionGAN. Although StyleGAN performed well in certain instances, it struggled with generalizing across different disease types, leading to some blurred or distorted outputs.

Activation functions were found to strongly affect the performance of the models. Models using LeakyReLU consistently outperformed those with ReLU and Tanh activation functions, achieving lower FID and higher SSIM scores. Tanh activation produced smoother transitions but occasionally introduced artifacts in the disease regions. Boxplots comparing the FID and SSIM scores across different activation functions showed that LeakyReLU provided more stable and superior performance with minimal variance, making it the most effective choice for this task.

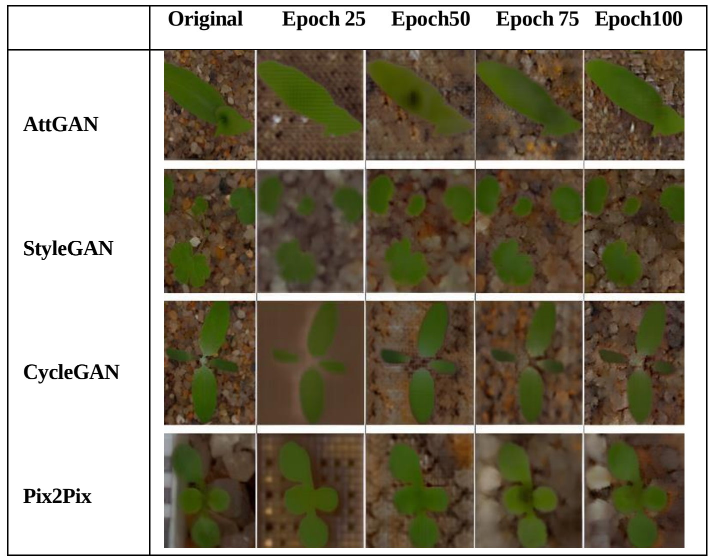




Figures: *Boxplots comparing FID and SSIM scores across activation functions.*

Qualitative analysis further confirmed the superiority of AttentionGAN. Visual comparisons of generated images alongside real diseased plant leaves demonstrated that AttentionGAN effectively captured intricate disease patterns, preserving vein structures and color variations with high fidelity. StyleGAN, while performing well in certain instances, struggled to generalize across multiple disease types, often producing blurred or distorted outputs.

Qualitative Visual Comparisons: Generated images from each model alongside real diseased leaves.



In conclusion, AttentionGAN emerged as the most robust model for realistic and accurate disease feature transfer in plant leaf images. It consistently outperformed the other models in terms of both FID and SSIM scores, and its qualitative outputs closely resembled real diseased plant leaves. These findings suggest that AttentionGAN holds strong potential for practical applications in automated plant disease diagnosis systems.

V. CONCLUSION

The research tackled the pressing challenge of limited labeled datasets in agriculture, which impedes the development of effective plant disease detection models that can generalize across various plant species. To overcome this challenge, we introduced an innovative method employing Generative Adversarial Networks (GANs) to transfer disease characteristics from a source plant to a target plant, facilitating the formation of synthetic disease-affected images intended for training applications. Through the implementation of four different GAN architectures— AttentionGAN, StyleGAN, CycleGAN, and Pix2Pix—we demonstrated the feasibility of cross-crop disease feature transfer, which enhances the training process for models intended to work across diverse plants.

Our analysis revealed that AttentionGAN significantly outperformed all other models, achieving the lowest Fréchet

Inception Distance (FID) of 27.4 and the highest Structural Similarity Index (SSIM) of 0.96. These results highlight AttentionGAN's superior ability to generate realistic, high-quality images and accurately transfer disease features, making it the best-suited model for this task. In comparison, CycleGAN, although effective, achieved an FID of 39.2 and SSIM of 0.85**,** while StyleGAN and Pix2Pix struggled with disease feature transfer, resulting in higher FIDs (32.8 and 45.**7**, respectively) and lower SSIM scores (0.92 and 0.78).

AttentionGAN's exceptional performance in both image realism and feature transfer accuracy positions it as the optimal choice for generating synthetic disease images for plant disease detection model training. This study marks a notable step forward in addressing the challenges posed by limited data in agricultural practices and enhances the effectiveness for disease diagnosis across various plant species. By giving a robust solution for training models with realistic, cross-crop disease images, our work played an important role in advancing precision agriculture and supporting the goal of ensuring food security.

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