

Enhancing Precision Weed Management with Federated Learning-Based GAN and Transfer Learning

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ABSTRACT- Precision weed management is critical to sustainable cotton production because overuse of herbicides can have detrimental environmental and health effects and increase production costs. The problem of weed recognition from field images is still difficult even with complex background, intra-class variation, class imbalance and limited number of images labeled for training. In this regard, this study proposes FedAgriGAN, a federated learning-based generative adversarial network to generate augmented cotton weed images and classify the images into the Cotton Weed ID15 dataset. The proposed framework uses one generator and three discriminators to collaboratively encode structural, textural and semantic features of field images, in order to generate a variety of realistic and diverse synthetic samples. The generated images are used to increase the size of the training set and to remove class imbalance. FedAgriGAN is compared with representative GAN models, such as InfoGAN, DCGAN, ViTGAN, and WGAN, both in terms of image qualities and classification performance. Experimental results show that FedAgriGAN outperforms the other models with an average FID score of 287.45. Moreover, the Vision Transformer (ViT) classifier achieves 98.57% testing accuracy, 97.81% testing precision, 97.33% testing recall, and 97.57% testing F1-score using the enhanced dataset. The improvements observed are statistically significant ($p < 0.01$) proving the efficiency of the proposed framework for precision weed management applications.

Keywords: Triple Discriminator Generative Network, Deep Neural Networks, Image Augmentation, Artificial Image Synthesis, GAN-Based Weed Image Synthesis.

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1. INTRODUCTION

Cotton is one such fibre crop that has significant economic importance in agriculture. It is called “white gold” in India due to its role in the area of cultivation, agricultural income and textile industry [1]. Weed removal is required for sustainable cotton production because the weed plants are competing for nutrients, moisture, sunlight and space with the cotton plants [3]. Manual methods or herbicide are the main approaches to controlling weeds. These traditional methods for eliminating weeds are often expensive, time consuming and impractical in big or odd shaped fields. Excessive herbicide use also has environmental and biological effects and this requires automated or site-specific weed removal systems. Computer vision-based weed detection using artificial intelligence, convolutional neural networks and Internet-of-Things (IoT) for agricultural monitoring systems have therefore been

investigated in recent research [2, 4, 5]. In practical agricultural environments, deep learning-based weed recognition systems have not performed as well as in experimental settings, although they have shown promising results in experimental environments. There is considerable visual complexity due to variation in illumination, overlap of vegetation, background clutter, variation in plant growth stages and seasonal variation. Besides, agricultural data is often unequally distributed, with a small number of samples for some weed species. This imbalance can cause the learning algorithms to focus on the majority classes and make it harder to get the less common weed categories correct. Therefore, creating a reliable weed-recognition system in the context of limited amounts of data and imbalanced classes is still a difficult task in precision agriculture.

A novel model is designed with DCGAN and CGAN models with an enhanced generator [17]. In this model the low-quality images are produced by the generator making the discriminator's job difficult and inefficient [18]. The GAN-based deep learning method proposed in [19] uses synthetically generated images to train and test the model leaving the model in doubt for real time images dataset. GRG-ViT method was proposed in [20] which was developed by combining Vision Transformer (ViT), Generative AI (GenAI), and Explainable AI (XAI). The proposed model was not evaluated on images from real time farms making the output of the model doubtful in real time scenarios.

Deep learning architectures are usually quite efficient, but require a large amount of properly labelled data to be effective. Datasets like these are difficult to acquire in agriculture as they would be influenced by changes in illumination, occlusion, background clutter, growth stages and seasonality. Labelling, too, requires highly specialized expertise and a considerable amount of work. These challenges are the motivation for developing effective augmentation strategies for agricultural image analysis [6]. Scientists have addressed this issue of insufficient training data by employing data augmentation, transfer learning and generative adversarial networks. Traditional augmentation includes image manipulation methods, including rotation, scaling, flipping and color manipulation [8,9]. The idea of generative adversarial networks (GANs) is to learn the visual distribution of real images and create new images [7, 10]. On the other hand, the augmentation techniques based on traditional GANs are subject to two main drawbacks. The first is that most are built based on the premise of a centralised training system, which may not be applicable when the agricultural data is spread out over various farms, research institutes, or agricultural businesses. The second limitation is that a single discriminator GAN might not be able to provide enough supervisory signals in the case of complex field backgrounds and visually similar classes. It might not be able to capture both global scene structure and fine-grained texture patterns along with class-specific semantic properties in complex field imagery. Thus, the samples produced may not be representative of agricultural field variations and complexities. In addition to data scarcity, modern agricultural image repositories are often geographically distributed across farms, agricultural enterprises, research institutions, and precision-farming platforms. In many situations, image sharing may be restricted due to ownership policies, privacy concerns, storage limitations, or communication constraints. As a result, constructing a centralized repository for training data-intensive deep learning models is not always feasible. These challenges motivate the need for privacy-preserving learning frameworks

that enable collaborative model development without requiring direct exchange of raw agricultural images.

To overcome these shortcomings, this paper proposes a federated GAN framework, FedAgriGAN, which consists of one generator and three discriminators. The federated learning approach enables to train models collaboratively without sharing raw image data with clients [12, 13]. Three discriminators are related to the global structural consistency, local texture patterns, and semantic weed characteristics. The discriminators are used to deliver supervised signals to the generator to produce realistic and diverse synthetic weed images for downstream classification tasks. The results of the experimental evaluation show that the proposed FedAgriGAN system achieves better classification accuracy and image quality than the current augmentation techniques based on GANs. In particular, the framework has the smallest FID score and has shown to be significantly better in the weed classification of the Cotton Weed ID15 dataset using the Vision Transformer model. The overall framework aims to tackle the issues of distributed agricultural data management, class imbalance, and data scarcity in precision weed recognition. The rest of the paper is organized as follows. *Section 2* introduces the proposed approach, *section 3* describes the performance analysis and results, *section 4* concludes the paper.

2. PROPOSED METHOD

The overall workflow of the proposed approach is depicted in *Figure 1*. As shown, the methodology is structured into four key phases in which: initially, cotton weed samples are obtained from an existing dataset. In the second stage, various image processing techniques are applied to generate high-resolution synthetic images. To facilitate this, a novel GAN variant, FedAgriGAN, has been developed specifically for effective cotton weed augmentation. In the third stage, the quality and utility of the augmented dataset are assessed using cutting-edge models for transfer learning.

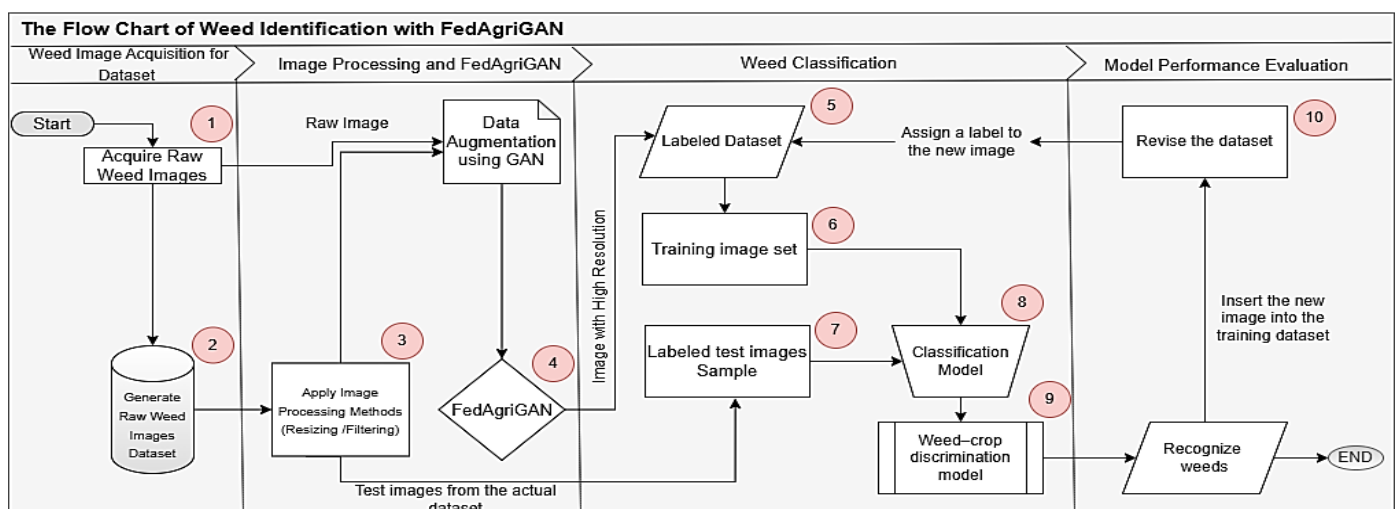


Figure 1. Architecture of the proposed cotton weed detection framework

Weeds exhibit a wide range of species and possess complex natural characteristics, including varying shapes, size diversity, irregular developmental trajectories, and erratic growth. During the early budding stage, most weed plants are small, display morphological variability, and show high germination density. These traits make accurate statistical analysis a significant challenge. To address this, the primary objective of the proposed FedAgriGAN framework is to synthesize high-definition images capturing precise lesion patterns in weeds while preserving intricate image details. The proposed architecture of the FedAgriGAN network, including the generator and the three discriminators (WD₁, WD₂, and WD₃),

is illustrated in figure 2. The proposed framework incorporates three discriminators to improve model stability and reduce the computational overhead typically associated with a single discriminator. The generator is trained to bypass the discriminators, facilitating more effective learning. It utilizes multiple upsampling layers to convert input noise Z into synthetic image data $P_z(z)$, producing images of size 128×128 in batches of 24. Each batch is divided into three equal subsets of 8 images, which are then fed to discriminators WD₁, WD₂, and WD₃, respectively. During this process, the generator undergoes backpropagation while all discriminators remain frozen.

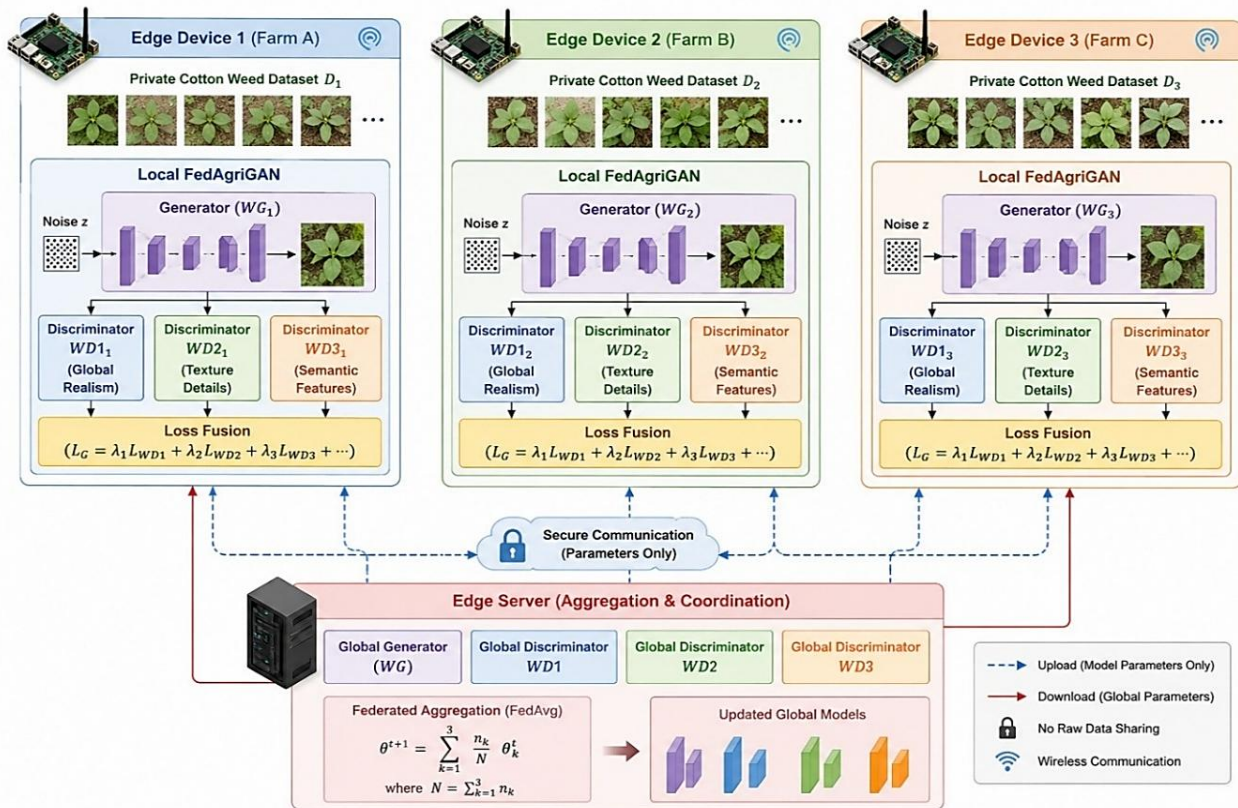


Figure 2. An illustration of the Discriminators of FedAgriGAN

The discriminator network is heavily trained using both captured images as well as artificial samples produced by the generator. During backpropagation of the generator, each discriminator receives an independent batch comprising real and generated images. The discriminators compute loss values for both categories of data. Subsequently, the auxiliary and adversarial losses corresponding to the real and synthetic samples from all three discriminators are averaged independently, and the resulting combined loss is utilized to update and fine-tune the discriminator networks. The training procedure is iteratively performed for a thousand epochs to achieve the final model. The developed FedAgriGAN model is trained on a dataset containing 9,700 images spanning nine cotton-weed classes, namely Carpetweeds, Eclipta, Morningglory, Nutsedge, Palmer Amaranth, Purslane, Sicklepod, Spotted Spurge, and Waterhemp.

Algorithm 1. Pseudo code: FedAgriGAN

Input: Cotton-Weed ID15 images

Output: Classification Results

Set N_{epochs} as the total training epochs

for epoch = 1 to N_{epochs} **do**

for batch = 1 to T **do**

Sample random noise vector $z \sim P_{fake}(X)$

Sample real images $x \sim P(x)$ from dataset of size (128, 128, 3) to train generator G

Generate batch of 24 synthetic images: $F = G(z)$

Randomly split F into three equal halves: F_1 , F_2 , and F_3

Obtain discriminator predictions: $P1F, C1F = D1(F_1)$, $P2F, CF_2 = D2(F_2)$ and $P3F, CF_3 = D3(F_3)$

calculate generator adversarial losses L_{advG1} , L_{advG2} , and L_{advG3}

Fine-tune generator G using combined adversarial loss
*Select real batch $R_i \in D(I)$; split as $R1 = Ri[0 : 7]$, $R2 = Ri[8 : 15]$,
and $R3 = Ri[16 : 23]$*
*Compute discriminator adversarial losses: $L_{advD} 1$, $L_{advD} 2$, and
 $L_{advD} 3$*
*Compute discriminator auxiliary losses: $L_{auxD} 1$, $L_{auxD} 2$, and
 $L_{auxD} 3$*
*Compute total discriminator loss: $L_{totalD} = (L_{advD} 1 + L_{auxD} 2$
 $+ L_{auxD} 3)/3$*
Optimize $D1$, $D2$, and $D3$ using L_{totalD}
end for
end for
Save trained generator model $G1$, $G2$
Train ESRGAN for image resolution enhancement
Obtain final generator model $G3$ after ESRGAN training
*Generate low-resolution images $ILR = G1(z)$, and $G2(z)$ from random
noise z*
Generate high-resolution images $IHR = G3(ILR)$
Perform classification on both the original and augmented datasets

Assume k is the number of clients, each of which keeps its own local image and trains a local replica of the generator and discriminator networks. After that, only model parameters are disseminated to the central server, which integrates client updates using Federated Averaging, as discussed in equation 2.

$$w_{(t+1)} = \sum_{k=1}^k \frac{n_k}{N} w_k^{(t)} \quad (2)$$

where n_k is the training sample, $w_k^{(t)}$ is the model's parameters obtained from iteration t by client k , and $\sum_{k=1}^k \frac{n_k}{N}$ is the entire sample across all clients. The integrated global parameters are then sent back to all clients, starting the subsequent training round. This procedure permits joint model learning without centralizing raw agricultural images.

2.3. Loss Function

To enrich the pictorial fidelity of synthetic images yielded from the Cotton Weed dataset, the proposed approach utilises a hybrid loss function that integrates auxiliary and adversarial components.

2.3.1. Adversarial Loss: FedAgriGAN

It encourages the generator to produce images that closely mimic real samples from the captured image set. In the FedAgriGAN architecture, the generator and discriminators are trained alternately using an adversarial loss. The discriminators collectively aim to distinguish between authentic and synthetic images. Each discriminator is optimised using binary cross-entropy during backpropagation. The final loss for the generator is computed by aggregating the adversarial signals received from discriminators. The adversarial objective is defined in equation (3).

$$L_{adv} = E_{x \sim p_{data(x)}} [\log \log D(x)] + E_{z \sim p_z(z)} (1 - D(G(z))) \quad (3)$$

where $p_{z(z)}$ is the latent noise distribution, $p_{data(x)}$ signifies the distribution of real weed images $G(\cdot)$, and $D(\cdot)$ denotes the generator and discriminator network simultaneously.

2.3.2. Auxiliary Loss: FedAgriGAN

Due to the high variety of weed types, the adversarial loss alone shows poor efficacy on the complex cotton weed image dataset. Therefore, an auxiliary loss function is also included to improve the model's capability to predict the accurate label for each image. The auxiliary loss, indicated as L_{aux} , illustrates the log-likelihood of the actual class and is formulated as shown in equation (4).

$$L_{aux} = E_{x, c \sim p_{data}} [-\log \log P(x)] + E_{z, c \sim p_z} [-\log \log P(G(z))] \quad (4)$$

where $P(C=c|\cdot)$ is the predicted class probability and C is the actual weed class label.

In the proposed FedAgriGAN framework, the discriminators leverage adversarial and auxiliary loss functions to stabilize the training procedure and improve the network's overall performance. The final composite loss is represented in equation (5).

$$L_{FedAgriGAN-D} = \lambda_1 L_{adv} + \lambda_2 L_{aux} \quad (5)$$

where λ_1 and λ_2 are weighting coefficients that balance the contributions of adversarial learning and class-aware supervision. This formulation enables the generator to simultaneously enhance image authenticity and maintain discriminative weed aspects during federated training.

3. PERFORMANCE ANALYSIS AND RESULTS

The efficacy of the developed FedAgriGAN is evaluated through a twofold validation process. First, its ability to generate augmented images is assessed using the FID score [14], which measures the statistical similarity between the captured images and the synthesized images. A smaller value of FID score indicates that the synthetic image is more realistic and closely resembles the real data distribution. Second, the evaluation is conducted using five metrics: recall, F1-score, testing accuracy, precision, and training accuracy.

3.1. Experimental Configuration and Assessment Metrics

All experiments were conducted on an Ubuntu 24.04.3 LTS (64-bit) server equipped with an Intel Xeon E5-2686 operating at 2.30 GHz across 18 cores. Computation was accelerated using GPU: GeForce RTX 3060 Ti 12GB GDDR6X. The GPU has a maximum core frequency of 1,490 MHz and delivers a single-precision performance of 10 TFLOPS. The developed FedAgriGAN was simulated using the PyTorch library.

Training is performed for 1,000 epochs with a fixed learning rate of 0.002, and the developed FedAgriGAN model is saved automatically during the course of iterations. Adam is employed

because of its effectiveness in dealing with non-stationary objectives and sparse gradient updates. Further, the dropout rate of 0.5 is applied between layers to reduce overfitting and prevent memorization. Experimental Outcomes and Discussion The efficacy of the developed FedAgriGAN has been tested against cotton-weedID15 [15] benchmark dataset. A total of 4469 RGB images belonging to nine different classes, namely: Sicklepod, Morningglory, Eclipta, SpottedSpurge, Purslane, Waterhemp, Carpetweeds, Nutsedge and PalmerAmaranth have been used for training the developed model. The developed FedAgriGAN has been trained using captured images, images generated using basic augmentation methods and synthetic images. The basic augmentation includes the images generated using translation, flip, zoom, and rotation. Whereas the synthetic images were generated using the developed FedAgriGAN method. Count of captured/original and general augmented and FedAgriGAN augmented images is presented in *table 1*.

3.2.1. Performance Discussion of Developed FedAgriGAN

In this study, FID [16] is utilised to assess the performance of the FedAgriGAN approach. To compute the FID score, *equation (6)* is used, where $|\mu_r - \mu_g|$ denotes the feature-wise mean difference between the actual and generated images.

$$FID = \|\mu_r - \mu_g\|_2^2 + Tr(C_a + C_{a^*} - 2(C_a C_{a^*})^{\frac{1}{2}}) \quad (5)$$

The performance of the developed FedAgriGAN is validated with 4 other existing conventional GAN models: VITGAN, WacGAN, GrapeGAN and DCGAN. The class-wise performance of the various GAN based models in terms of FID score has been presented in *table 2*. As shown in the *table 2*, the developed FedAgriGAN has Surpassed other GAN-based models compared, with FID score of 281.86. Further, it can also be visualized that VIT-GAN has achieved the second highest accuracy with an FID score of 298.91. The class-wise images generated using FedAgriGAN and other considered methods have been depicted in *figure 3*. FedAgriGAN was able to get a higher FID score since the fed learning approach was able to learn a wide range of data distributions without sharing the raw data. Furthermore, the GAN network helped in preserving the

textures and colors of the diseases by retaining the fine visual characteristics, which made the synthetic images resemble actual data and give a low FID score. It can be concluded from the image outputs that the developed model is generating superior images of the cotton weed dataset as compared to other considered methods. Furthermore, the performance of the developed discriminators WD_1 , WD_2 , and WD_3 is also compared against 4 other conventional GAN models namely VITGAN, WacGAN, GrapeGAN and DCGAN. The experimental findings of the proposed and considered methods are presented in *table 3*. It is clearly visualized from the presented results that FedAgriGAN has achieved better performance on evaluation over other methods in terms of discriminant accuracy.

3.2.2. Classification Performance Analysis

In this section, the classification accuracy of the developed FedAgriGAN has been analyzed. The performance is tested on three combinations of datasets formed by the original and augmented datasets. As shown in *table 4*, three combinations of datasets have been considered for evaluation. The images of augmented dataset are obtained by applying basic transformation methods such as rotation, flipping, zooming, and translation.

Whereas the third set contains the images generated using the proposed FedAgriGAN method. As shown in *table 5* the classification efficiency of the developed FedAgriGAN has been tested in terms of five metrics. For performing the experiments, 80% of the images were used for the training, whereas testing was performed on the rest 20%.

The experimental findings of the developed and the compared methods are presented in *table 5*, *6* and *7*. Thus, it is concluded from the experimental results that all the considered methods have performed better on FedAgriGAN-generated images, showing a significant improvement over the original and basic augmented dataset. Therefore, it can be concluded from the experimental findings that the developed FedAgriGAN can serve as an alternative for generating quality images to mitigate the class imbalance problem.

Table 1. Comparison of image counts in original and augmented dataset

Weed Type	Original Dataset	General Augmented Dataset	FedAgriGAN Augmented Dataset
Sicklepod	243	484	1100
Morningglory	1125	387	1400
Eclipta	253	513	1100
SpottedSpurge	513	237	1100
Purslane	237	450	1100
Waterhemp	450	455	1100
Carpetweeds	769	769	1300
Nutsedge	277	277	1100
PalmerAmaranth	687	687	1250

Table 2. Fréchet Inception Distance (FID) metrics for various GAN variants on Cotton Weed ID 15

Dataset Model Name	Purslane	Sicklepod	Water hemp	Eclipta	Spotted Spurge	Morning Glory	Palmer Amaranth	Carpet Weed	Nutsedge	Average FID
VIT-GAN	298.29	299.23	291.63	307.61	301.52	308.33	311.66	299.91	302.44	303.05
WacGAN	380.51	372.27	376.32	385.85	380.47	384.10	371.05	376.83	369.17	377.39
GrapeGAN	326.33	325.05	318.67	329.87	323.79	331.77	324.68	320.53	308.43	323.22
DC-GAN	421.17	412.83	414.31	427.77	422.15	423.67	419.73	413.40	409.33	418.21
FedAgriGAN	293.12	288.98	285.61	295.32	289.56	290.43	285.87	281.86	275.48	287.45

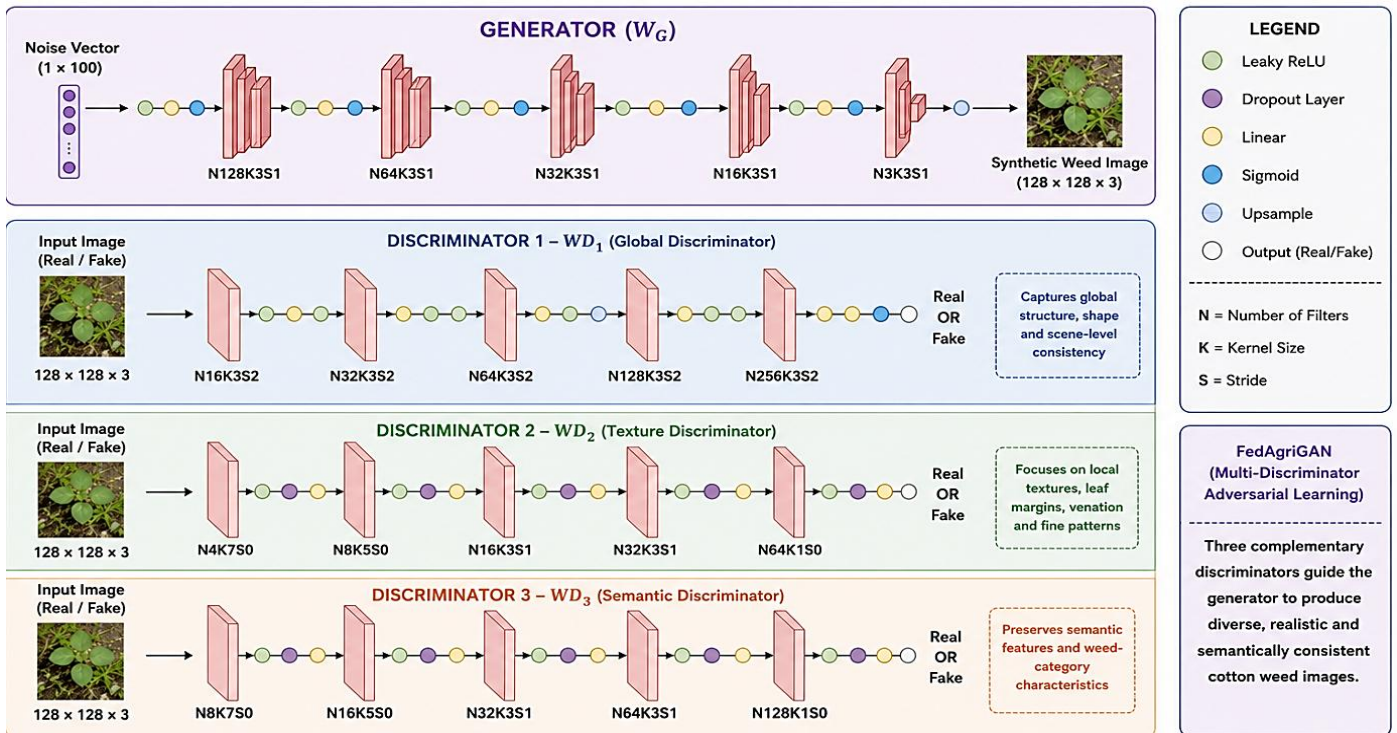


Figure 3. Visual samples produced by multiple GAN architectures on the Cotton Weed dataset

Table 3. Performance in Terms of Accuracy of Discriminator on GANs

Different GANs	Discriminator Accuracy
VitGAN	93.81 ± 1.77
WacGAN	97.44 ± 1.47
GrapeGAN	94.13 ± 0.67
DCGAN	96.29 ± 1.43
FedAgri-GAN	98.63 ± 0.24

Table 4. Different training and testing samples

Sample for Training	Sample Count	Training Count	Testing Count
Original Dataset	4467	3858	609
Original + General Augmented Dataset	5470	4724	746
Original + FedAgriGAN Augmented Dataset	9700	8377	1323

Table 5. Model Performance on the Original Dataset

Considered Models	Training Accuracy	Testing Accuracy	Precision	Recall	F1 Score
EfficientNet	94.73 ± 0.53	89.67 ± 0.73	84.22 ± 0.27	85.57 ± 0.63	84.89 ± 0.54
MobileNetV2	96.19 ± 0.22	92.21 ± 0.65	93.02 ± 0.19	94.09 ± 0.43	93.73 ± 0.33
AlexNet	99.93 ± 0.63	84.61 ± 0.83	82.57 ± 0.42	81.43 ± 0.13	81.97 ± 0.32
Resnet50	93.17 ± 0.63	91.97 ± 0.83	92.07 ± 0.67	91.28 ± 0.03	91.68 ± 0.61

ViT	98.68 ± 0.53	95.67 ± 0.83	95.13 ± 0.26	93.70 ± 0.83	94.46 ± 0.91
VGG16	98.93 ± 0.73	87.27 ± 0.29	84.13 ± 0.93	85.09 ± 0.53	84.57 ± 0.74
NASNeT	97.34 ± 0.2	91.59 ± 0.54	92.62 ± 0.23	92.13 ± 0.65	92.37 ± 0.42

Table 6. Model Performance on Traditionally Augmented data-set

Classification Models	Training Accuracy	Testing Accuracy	Precision	Recall	F1 Score
EfficientNet	94.77 ± 0.57	88.93 ± 0.21	83.39 ± 0.57	81.63 ± 0.31	82.55 ± 0.67
MobileNetV2	96.87 ± 0.78	92.24 ± 0.33	93.22 ± 0.23	93.27 ± 0.74	93.24 ± 0.38
AlexNet	99.93 ± 0.62	84.62 ± 0.74	83.21 ± 0.95	82.13 ± 0.52	82.62 ± 0.53
Resnet50	93.21 ± 0.63	91.97 ± 0.83	92.07 ± 0.94	91.27 ± 0.47	91.67 ± 0.83
ViT	99.37 ± 0.29	95.95 ± 0.81	94.52 ± 0.41	96.31 ± 0.26	95.37 ± 0.94
VGG16	98.98 ± 0.73	88.03 ± 0.78	84.73 ± 0.53	84.17 ± 0.84	84.43 ± 0.75
NASNeT	97.50 ± 1.23	91.82 ± 0.89	92.98 ± 0.23	93.05 ± 0.63	93.01 ± 0.23

Table 7. Model Performance on FedAgriGAN Augmented dataset

Classification Models	Training Accuracy	Testing Accuracy	Precision	Recall	F1 Score
EfficientNet	95.39 ± 0.62	89.97 ± 0.24	85.75 ± 0.23	86.12 ± 0.26	85.94 ± 0.93
MobileNetV2	98.77 ± 0.25	96.12 ± 0.81	94.81 ± 0.22	94.18 ± 0.43	94.47 ± 0.21
AlexNet	99.98 ± 0.71	88.33 ± 0.24	83.23 ± 0.82	83.79 ± 0.18	83.47 ± 0.12
Resnet50	95.54 ± 0.72	92.98 ± 0.23	93.76 ± 0.12	93.21 ± 0.24	93.49 ± 0.53
ViT	99.67 ± 0.63	98.57 ± 0.85	97.81 ± 0.82	97.33 ± 0.33	97.57 ± 0.93
VGG16	99.44 ± 0.63	88.92 ± 0.63	84.67 ± 0.25	84.77 ± 0.84	84.73 ± 0.62
NASNeT	98.73 ± 0.23	93.50 ± 0.54	93.58 ± 0.87	93.32 ± 0.65	93.44 ± 0.65

Table 8. Ablation Study of FedAgriGAN for Cotton Weed Classification

Configuration	Training Accuracy (%)	Testing Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
Original Dataset (No Augmentation)	94.52 ± 1.08	91.42 ± 1.12	89.76 ± 1.31	88.64 ± 1.28	88.11 ± 1.14
Traditional Augmentation (Flip, Rotation, Scaling)	96.87 ± 0.94	94.36 ± 0.97	93.08 ± 1.02	92.57 ± 0.94	92.11 ± 0.88
FedAgriGAN (1 Generator + 1 Discriminator)	98.24 ± 0.81	96.83 ± 0.86	95.44 ± 0.94	94.78 ± 0.91	94.31 ± 0.72
FedAgriGAN (1 Generator + 2 Discriminators)	99.11 ± 0.72	98.41 ± 0.75	97.11 ± 0.88	96.54 ± 0.84	96.02 ± 0.58
Proposed FedAgriGAN (1 Generator+ Discriminators)	99.91 ± 0.29	99.67 ± 0.63	98.57 ± 0.85	97.81 ± 0.82	97.33 ± 0.33

Table 9. Significance analysis of ViT-based classification

Comparison	Mean Accuracy (%)	Improvement (%)	p-value	Significance
Original Dataset vs. Traditional Augmentation	95.67 vs. 95.95	+0.28	< 0.05	Significant
Original Dataset vs. FedAgriGAN Augmentation	95.67 vs. 98.57	+2.90	< 0.01	Highly Significant
Traditional Augmentation vs. FedAgriGAN Augmentation	95.95 vs. 98.57	+2.62	< 0.01	Highly Significant

3.2.3. Ablation Study

Ablation study demonstrates the significance of each element in the designed FedAgriGAN architecture. The experimental results are shown in *table 8*. As seen from the analysis carried out on the initial dataset, there is continuous improvement in classification accuracy when using conventional augmentation and GANs to generate data. In addition, the more discriminators there are, the higher the quality and variability of the generated

data, which improves the learning ability of the system. The whole system that includes one generator and three discriminators yields the highest accuracy of 99.67 ± 0.63% for cotton weeds classification.

3.2.4. Statistical Significance Analysis

To verify that the observed performance improvements obtained using the proposed FedAgriGAN augmentation are not attributable to random variation, a statistical significance analysis was conducted. Since all experiments were repeated multiple times with different random initializations, the resulting testing accuracies were subjected to a paired Student's t-test at a significance level of 0.05. The analysis compared the classification performance achieved using the original dataset, the traditionally augmented dataset, and the FedAgriGAN-augmented dataset. The results in *table 8* show that the performance gains from FedAgriGAN augmentation are statistically significant compared with both the original and the traditionally augmented datasets. It can be observed that the ViT classifier, which attained the best test accuracy, exhibited substantial improvements after combining FedAgriGAN-generated samples. The *p*-values were invariably below 0.05, suggesting that the proposed approach meaningfully contributes to classifier performance rather than being attributable to random changes.

4. CONCLUSION

The proposed study presented a novel three-stage weed-recognition framework to solve weed classification tasks. In the proposed approach, the FedAgriGAN augmentation method is introduced to generate high-quality synthetic images, acquiring the lowest mean FID of 287.45 among other existing GANs. The experimental results demonstrated that the proposed augmentation approach attained improved classification performance across all models, with ViT attaining the best results: 98.57% accuracy and 97.57% F1-score. Additionally, the proposed framework also addresses class imbalance and limited labelled data issues which makes it a favourable solution for precision weed management and smart agricultural systems.

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Data Availability statement: The dataset used is openly available at, <https://www.kaggle.com/datasets/yuzhenlu/cottonweedid15>.

REFERENCES

- [1] I. Cotton, A. Profile (2010), The cotton corporation of india ltd. publication.
- [2] S. K. Behera, P. K. Sethy, S. K. Sahoo, S. Panigrahi, S. C. Rajpoot (2021), On-tree fruit monitoring system using iot and image analysis, *Concurrent Engineering* 29 (1) 6–15. doi:10. 1177/1063293X20988395.
- [3] E.-C. Oerke (2006), Crop losses to pests, *The Journal of Agricultural Science* 144 (1) 31–43.
- [4] C. Fern'andez-Quintanilla, J. Pe'na, D. And'ujar, J. Dorado, A. Ribeiro, F. L'opez-Granados (2018), Is the current state of the art of weed monitoring suitable for site-specific weed management in arable crops?, *Weed research* 58 (4), 259–272.

- [5] J. Su, D. Yi, M. Coombes, C. Liu, X. Zhai, K. McDonald-Maier, W.-H. Chen (2022), Spectral analysis and mapping of blackgrass weed by leveraging machine learning and uav multispectral imagery, *Computers and Electronics in Agriculture* 192, 106621.
- [6] J. G. Barbedo (2018), Factors influencing the use of deep learning for plant disease recognition, *Biosystems engineering* 172, 84–91.
- [7] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio (2014), Generative adversarial nets, *Advances in neural information processing systems* 27.
- [8] J. G. A. Barbedo (2019), Plant disease identification from individual lesions and spots using deep learning, *Biosystems Engineering* 180, 96–107.
- [9] L. Wang, L. Xiang, L. Tang, H. Jiang (2021), A convolutional neural network-based method for corn stand counting in the field, *Sensors* 21 (2), 507.
- [10] C. Huang, J. Wen, Y. Xu, Q. Jiang, J. Yang, Y. Wang, D. Zhang (2023), Self-supervised attentive generative adversarial networks for video anomaly detection, *IEEE Transactions on Neural Networks and Learning Systems*, 34(11):9389-9403. doi:10.1109/TNNLS.2022.3159538
- [11] L. Zhang, G. Zhou, C. Lu, A. Chen, Y. Wang, L. Li, W. Cai (2022), Mmdgan: A fusion data augmentation method for tomato-leaf disease identification, *Applied Soft Computing*, 108969.
- [12] J. Kone'cn'y, H. B. McMahan, F. X. Yu, P. Richt'arik, A. T. Suresh, D. Bacon (2016), Federated learning: Strategies for improving communication efficiency, *arXiv preprint arXiv:1610.05492*.
- [13] C. Fan, P. Liu (2020), Federated generative adversarial learning, *Chinese Conference on Pattern Recognition and Computer Vision (PRCV)*, Springer, 3–15
- [14] Yu, Yu & Zhang, Weibin & Deng, Yun. (2021), Frechet Inception Distance (FID) for Evaluating GANs.
- [15] D. Chen, Y. Lu, Z. Li, S. Young (2021), Performance evaluation of deep transfer learning on multiclass identification of common weed species in cotton production systems, *arXiv preprint arXiv:2110.04960*.
- [16] M. Heusel, H. Ramsauer, T. Unterthiner, B. Nessler, S. Hochreiter (2017), Gans trained by a two time-scale update rule converge to a local nash equilibrium, *Advances in neural information processing systems* 30.
- [17] I. H. Rather and S. Kumar (2024), "Generative adversarial network based synthetic data training model for lightweight convolutional neural networks," *Multimedia Tools Appl.*, 83 (2), 6249–6271.
- [18] Zahid Ur Rahman, Mohd Shahrimeh Mohd Asaari, Haidi Ibrahim, Intan Sorfina Zainal Abidin, Mohamad Khairi Ishak (2024), "Generative Adversarial Networks (GANs) for Image Augmentation in Farming: A Review," *IEEE Access*, 12, 179912 – 179943, doi: <https://doi.org/10.1109/access.2024.3505989>.
- [19] P. J and K. Dinakaran (2025), "Enhancing Groundnut Leaf Disease and Stress Detection Using GAN-Based Deep Learning Models," *International Conference on Computing and Communication Technologies (ICCTT)*, Chennai, India, 1-4, doi: 10.1109/ICCTT63501.2025.11019972.
- [20] S. A. M. F and B. R. K (2026), "Enhancing multiclass plant disease classification using GAN-boosted vision transformer with XAI insights," *Front. Plant Sci.* 16:1649399. doi: 10.3389/fpls.2025.1649399.



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