MSC. Data Science

UNSUPERVISED REPRESENTATION LEARNING WITH DEEP CONVOLUTIONAL GENERATIVE ADVERSARIAL NETWORKS FOR PRECISION AGRICULTURE

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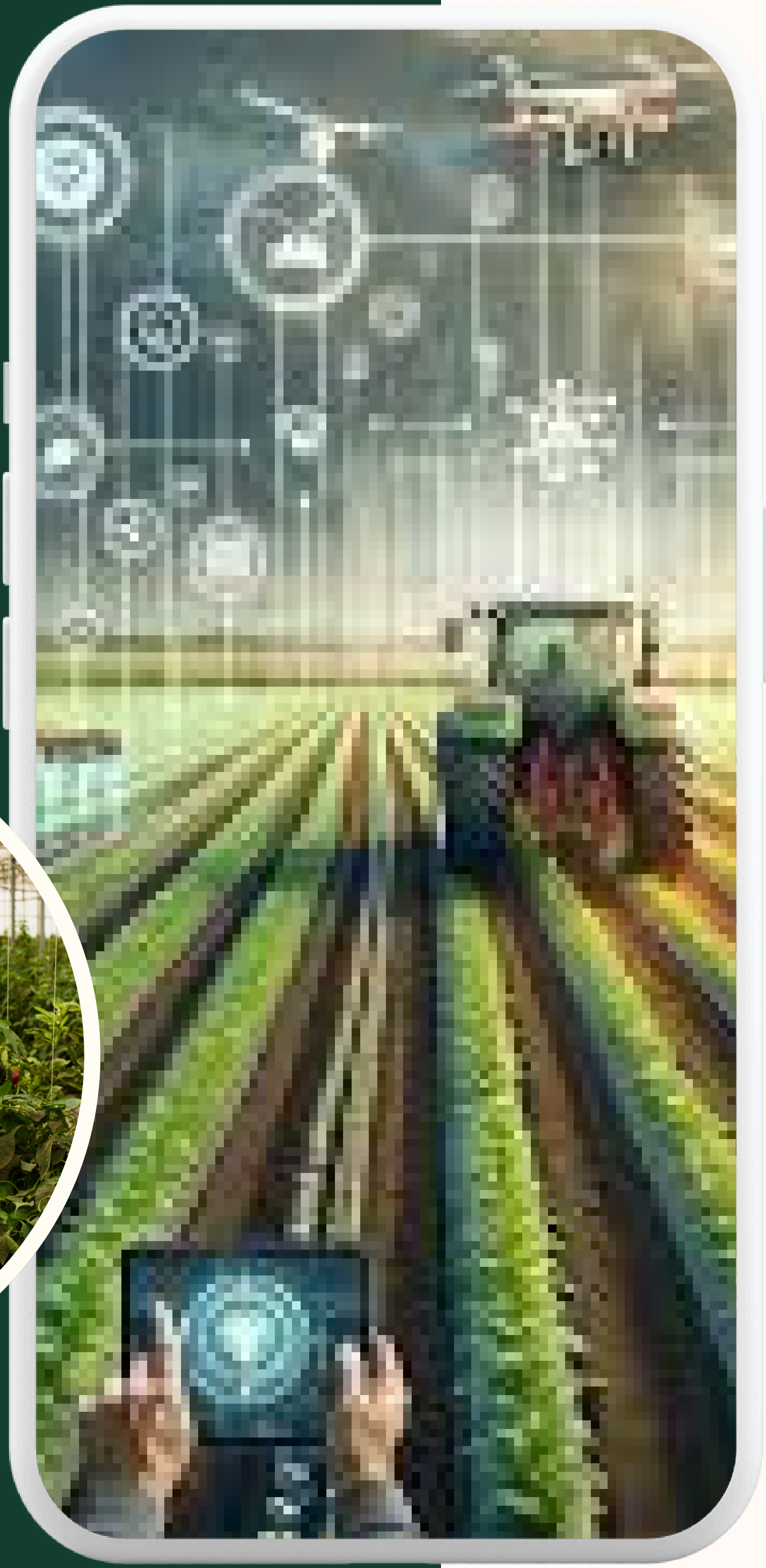
Precision Agriculture



- Modern farming method utilizing technologies like IoT, AI, and ML.
- Enhances crop productivity, optimizes resources, and reduces environmental impact.

Impact of Weeds on Crop Health and Yield

- **Nutrient Competition:**
  - Weeds compete with crops for essential nutrients in the soil.
  - Leads to nutrient deficiency in crops, impacting growth and development.

- **Water Competition:**
  - Weeds absorb significant amounts of water, reducing the availability for crops.

Related Work

(Hasan et al.'s 2021)

- Focus on in-depth analysis of Deep Learning methods for weed classification and detection in agricultural photos.
- Examine Deep Learning techniques in agriculture with a focus on weed identification, and discuss difficulties in differentiating weeds from crops that share characteristics.
- Categorizes literature into four areas and highlights CNNs for image analysis and LSTMs for handling sequential data.
- Deep Learning models perform better than conventional Machine Learning techniques, particularly when handling big datasets and automatic feature learning.
- The lack of real-world data and practical challenges suggests including case studies to create a connection between theory and practice.

Hasan, A. S. M. M., Sohel, F., Diepeveen, D., Laga, H., & Jones, M. G. K. (2021). A survey of deep learning techniques for weed detection from images. ArXiv Preprint, arXiv:2103.01415. Available at: https://arxiv.org/abs/2103.01415 [Accessed 05 July. 2024].

Related Work

(Pai, Kamath, and Balachandra 2024)

- The main objective is to conduct an extensive evaluation of deep learning techniques for weed identification in agricultural environments, with particular focus on the changes in detection and localization.
- Analyze existing Deep Learning-based weed detection methods, highlighting advances in precision and effectiveness for crop weed localization, identification, and classification.
- An in-depth review of CNN architectures, including Deep Convolutional Neural Networks and Regional Convolutional Neural Networks, and how they can be integrated with modern technology like drones and UAVs to improve weed control.
- Models are assessed based on their ability to distinguish between crops and weeds, considering image quality, color, and additional non-imaging detectors.
- Despite positive results in controlled environments, challenges remain for practical deployment due to factors like climate change and species differentiation. The paper lacks discussion on scalability, field implementation, computational requirements, and the environmental and financial impacts of these technologies.

Pai, D. G., Kamath, R., & Balachandra, M. (2024). Deep Learning Techniques for Weed Detection in Agricultural Environments: A Comprehensive Review.
Available at: https://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=10570187[Accessed 07 July. 2024].

Related Work

(Kerdegari et al. 2023)

- This paper focus on a semi-supervised GAN framework for classifying multispectral images in precision farming, specifically for weed growth detection using UAVs with multispectral cameras.
- The semi-supervised GAN consists of two main components:
    - **Generator Network:** Generates realistic synthetic images from random noise to mimic the distribution of actual multispectral data.
    - **Discriminator Network**: A modified DCNN that performs multi-class classification (crop, weed, background) and distinguishes between real and synthetic images.
- The approach was tested using multispectral images (Red and NIR channels) with varying percentages (30%, 40%, and 50%) of labeled data, achieving an F1 score of approximately 0.85 with 50% labeled data.
- Although the semi-supervised GAN produces encouraging results, there are limits to how many datasets and scenarios it can be applied to. To improve stability and application, future research could examine more multispectral bands and assess how well the model performs in various agricultural contexts.

**Kerdegari, H., Razaak, M., Argyriou, V., & Remagnino, P. (2023). Semi-supervised GAN for Classification of Multispectral Imagery Acquired by UAVs. Precision Agriculture.
Available at: https://arxiv.org/pdf/1905.10920[Accessed 12 July. 2024].**

Problem Statement

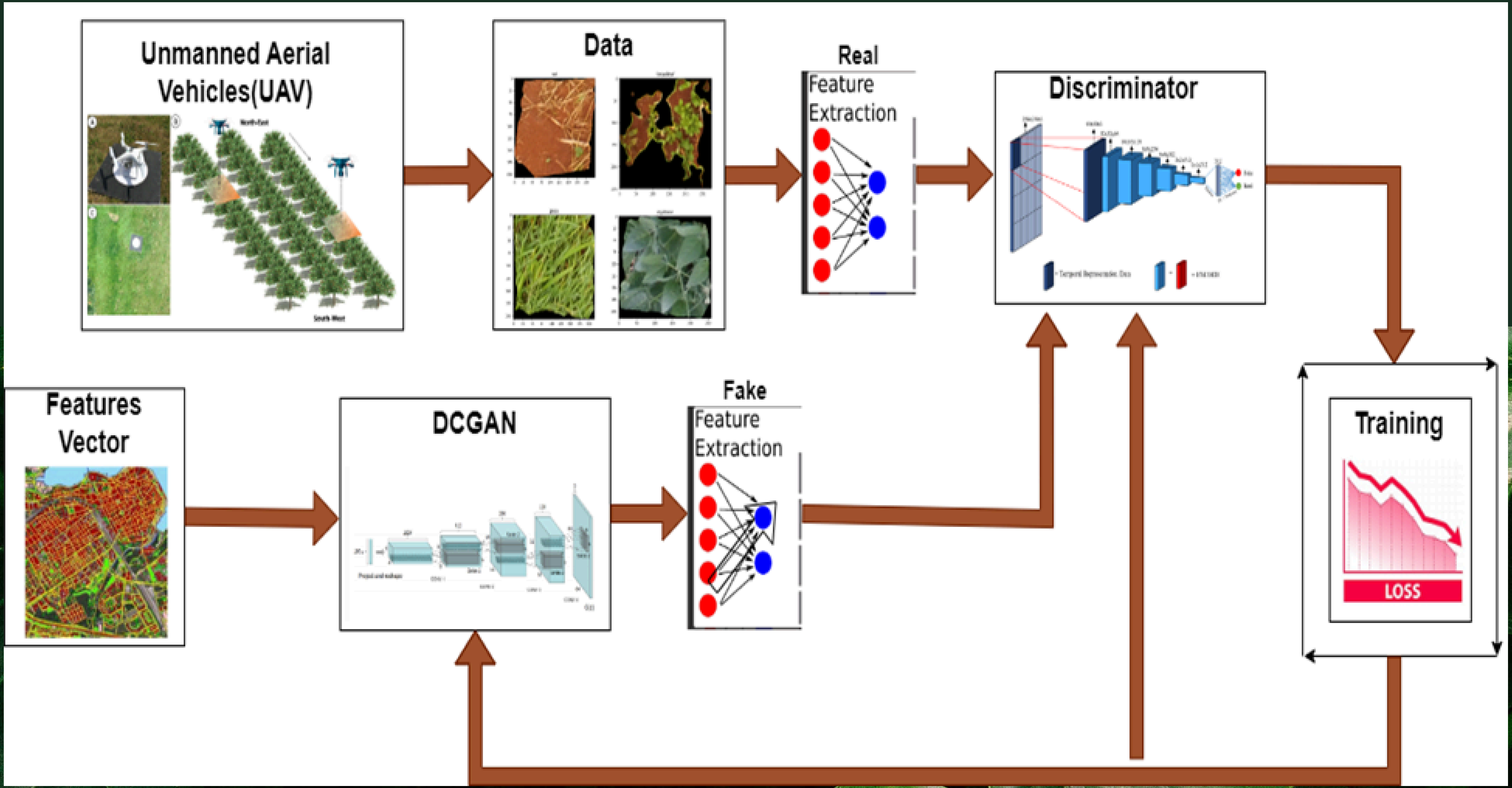
- By competing with crops for essential resources like nutrients, water, and sunlight, weeds lower crop production.
- Manual weed control is expensive, time-consuming, and often ineffective.
- Machine learning models struggle with limited data and class imbalance, leading to reduced accuracy.
- High false-positive rates in weed detection increase herbicide use, negatively affecting the environment.
- An accurate, automated weed detection system is needed to overcome data limitations and class imbalance, improving detection for both common and rare weed species.

RESEARCH QUESTIONS

1. How effectively can DCGANs generate synthetic UAV imagery that closely resembles real-world UAV-captured images in terms of visual and statistical similarity?

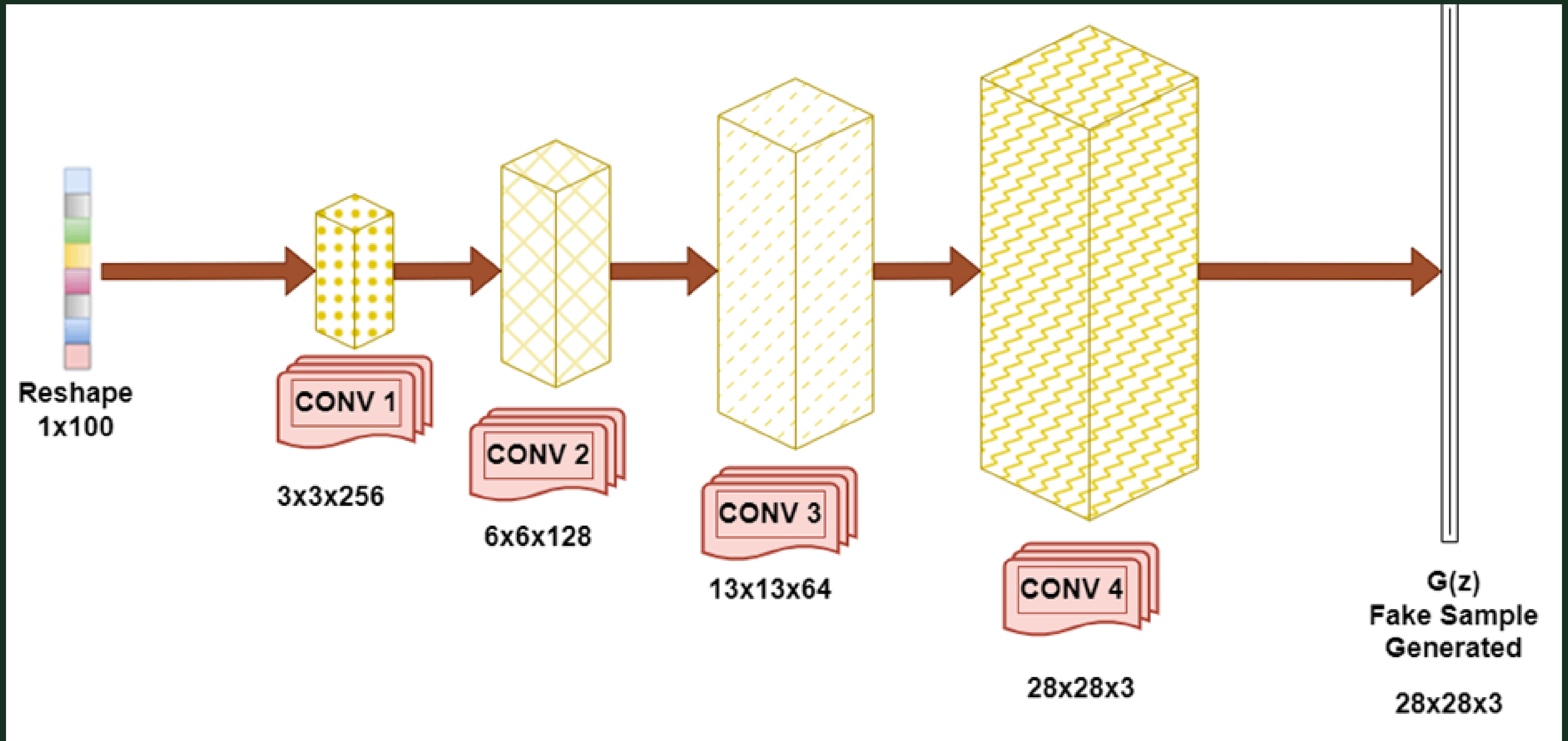
2. Can the inclusion of DCGAN-augmented synthetic UAV imagery improve the classification accuracy of CNN models for weed identification in Precision Agriculture?

PROPOSED SOLUTION



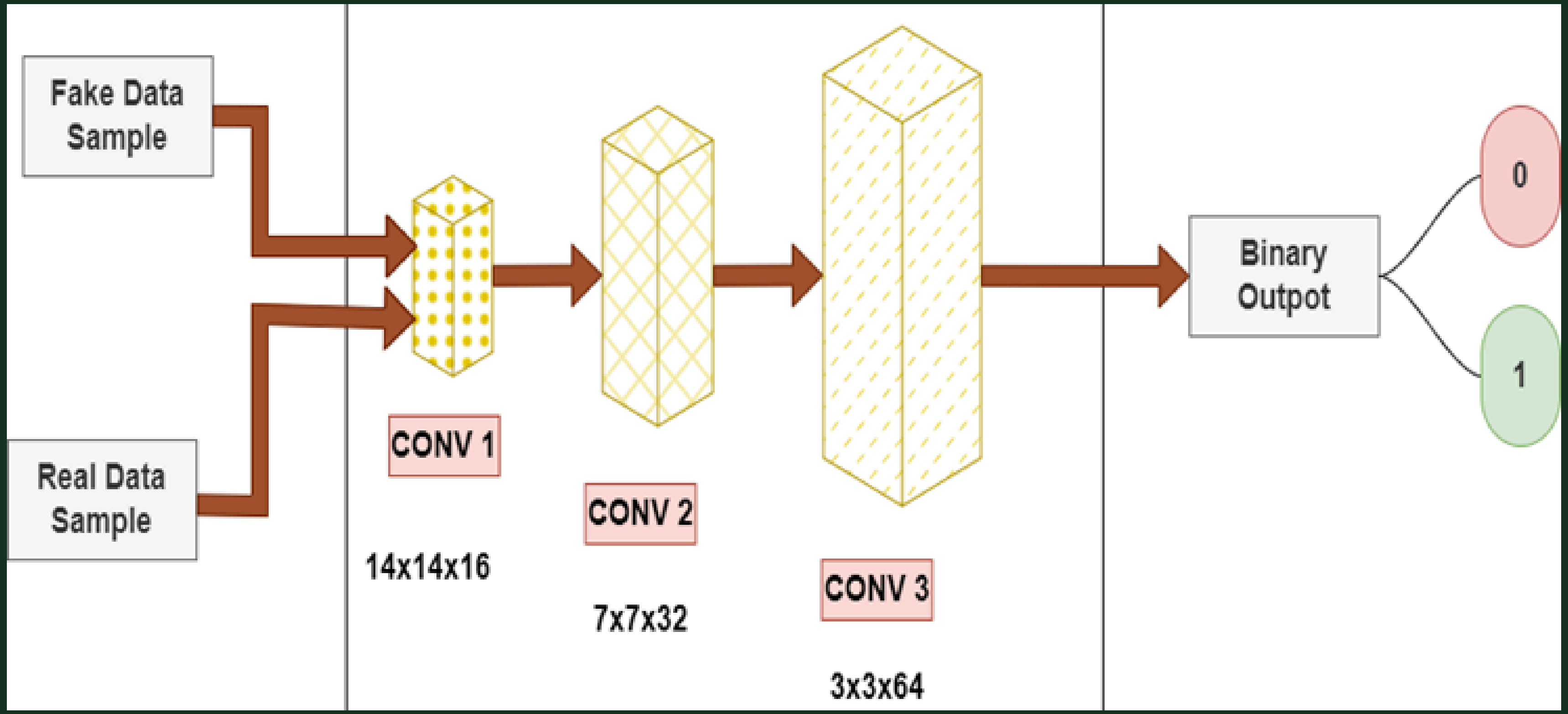
DCGAN DESIGN

GENERATOR



The figure shows how a generator network in a DCGAN is constructed and how a random noise vector is converted into a synthetic image.

DISCRIMINATOR



The architecture of a discriminator network, which is used in a DCGAN, is shown in the diagram. The goal is to use extracted features to classify input data samples as real or fake.

Generator Algorithm

```
hidden_dim, and noise dimension z_dim.
Generator Function: make_gen_block(self, input_channels, output_channels, kernel_size=3,
stride=2, final_layer=False)
    If final_layer is False:
        Return nn.Sequential(nn stands for Neural Network) with:
            nn.ConvTranspose2d(input_channels, output_channels,
            kernel_size=kernel_size, stride=stride)
            nn.BatchNorm2d with output_channels
            nn.ReLU activation.
    Else:
        Return nn.Sequential with:
            nn.ConvTranspose2d(input_channels, output_channels, kernel_size, stride)
            nn.Tanh activation.
Define unsqueeze_noise Function // Random noise tensors are produced.
    Input: noise
    Output: Reshaped noise tensor with dimensions (n_samples, z_dim, 1, 1).
Define forward Function // The reshaped noise is passed through the generator network to
produce images.
    Input: noise
    Output: Generated images.
```

Discriminator Algorithm

*Define the **DISC class inheriting from nn.Module(nn stands for Neural Network).***

1 *Initialize the class with parameters **im_chan** (number of channels in the images) and **hidden_dim** (inner dimension).*

2 *Call the parent class **(nn.Module)** constructor using super(DISC, self).__init__().*

3 *Create the sequential model **self.disc** which consists of multiple **DISC** blocks. Each block is created using the **make_disc_block** method.*

4 *Create **DISC** Function (**make_disc_block** method)*

5 *Define the **make_disc_block** method with parameters: **input_channels, output_channels, kernel_size, stride, padding, and final_layer.***

6 *Check if the block is the final layer using the **final_layer** flag.*

7 *If **not** the final layer:*

8 *Create a **sequential block** with **nn.Conv2d, nn.BatchNorm2d, and nn.LeakyReLU layers.***

9 *If **it is** the final layer:*

10 *Create a sequential block with only the **nn.Conv2d** layer.*

11 *Create Forward Function (**forward** method)*

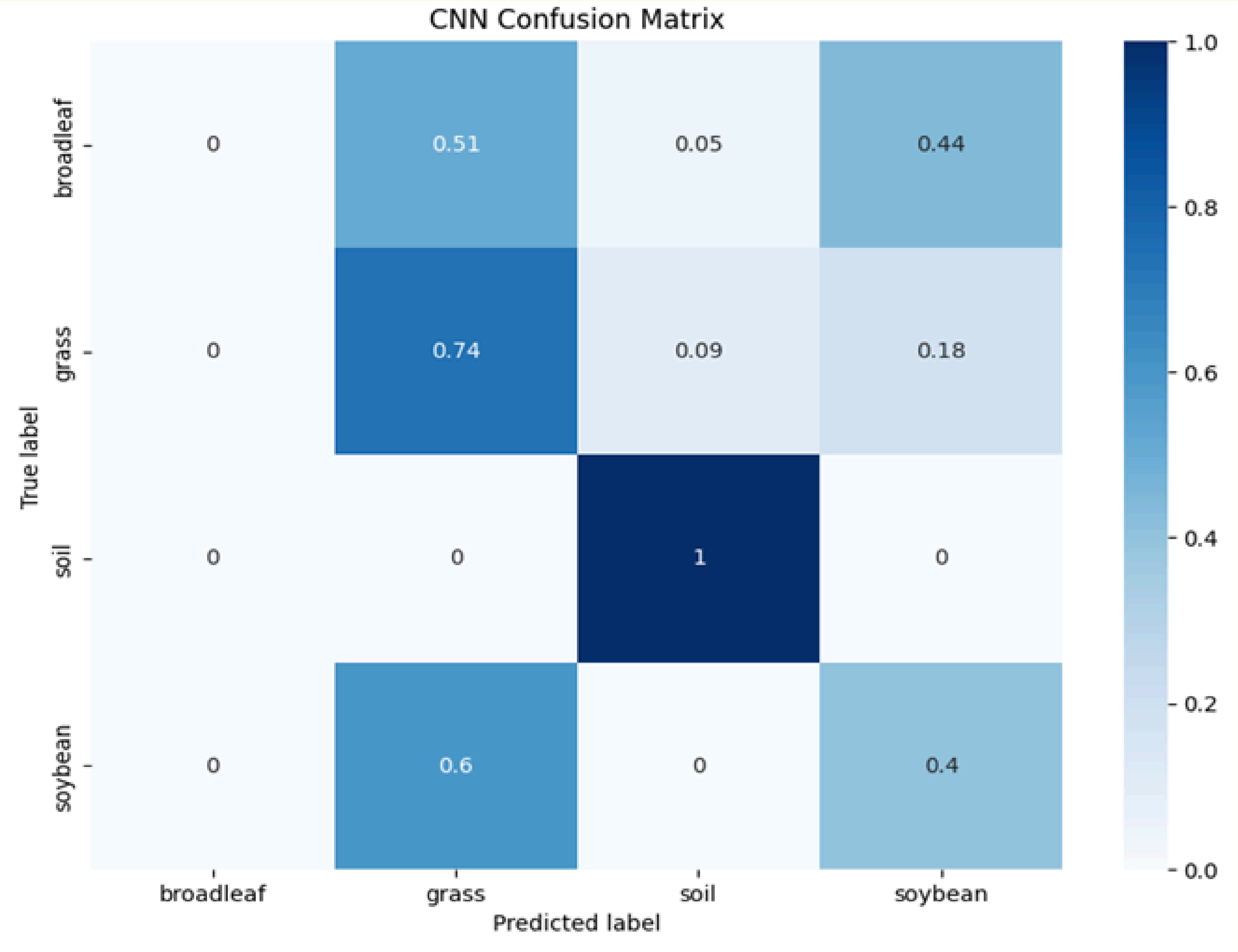
12 *Define the **forward** method with a parameter **image**.*

13 *Pass the input image through the sequential model **self.disc** to get the DISC's prediction (**disc_pred**).*

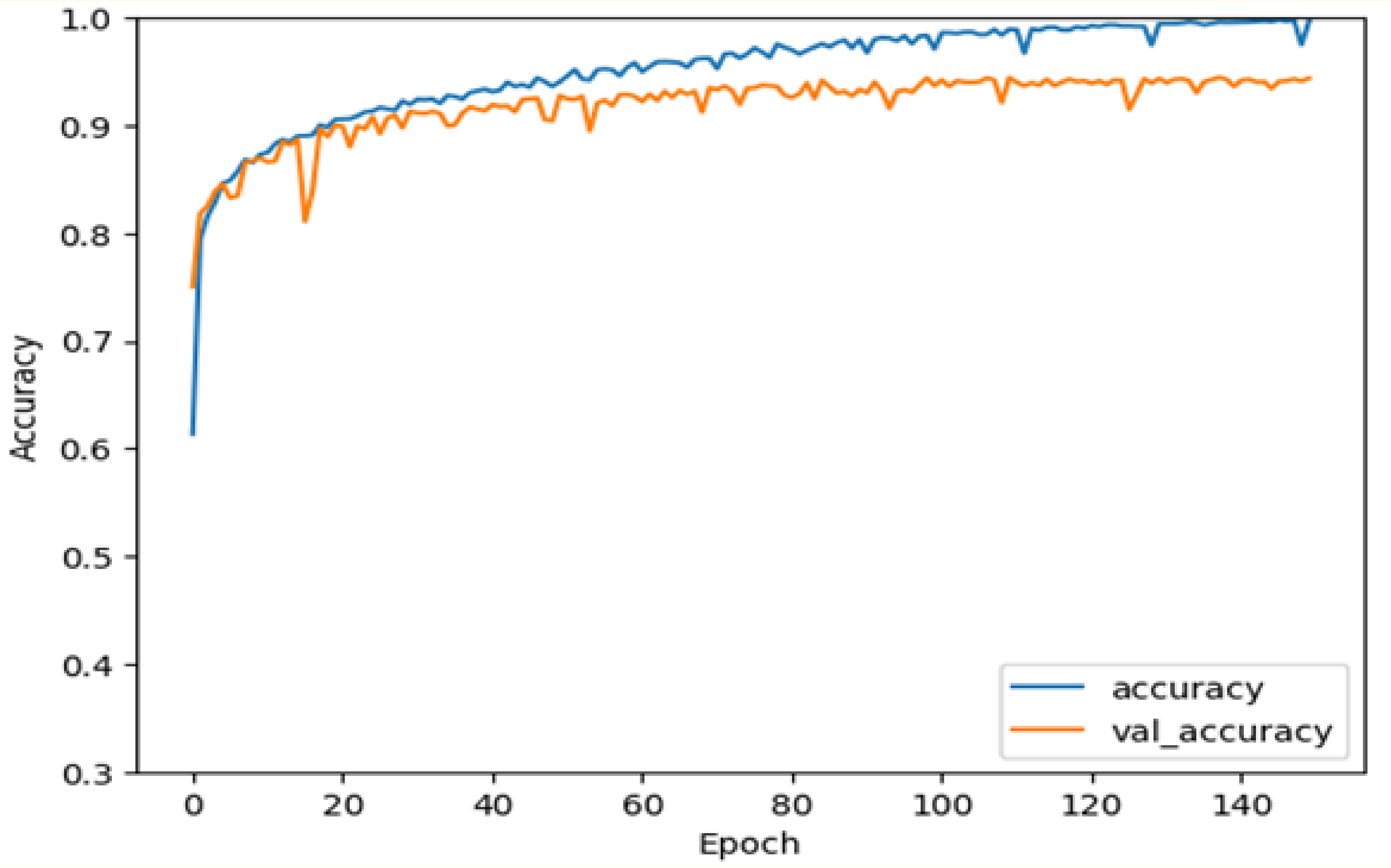
14 *Reshape **disc_pred** using a view to ensure it is a **1-dimensional tensor** per input image.*

15 *Return the reshaped tensor **disc_pred.***

Results Without Augmentation

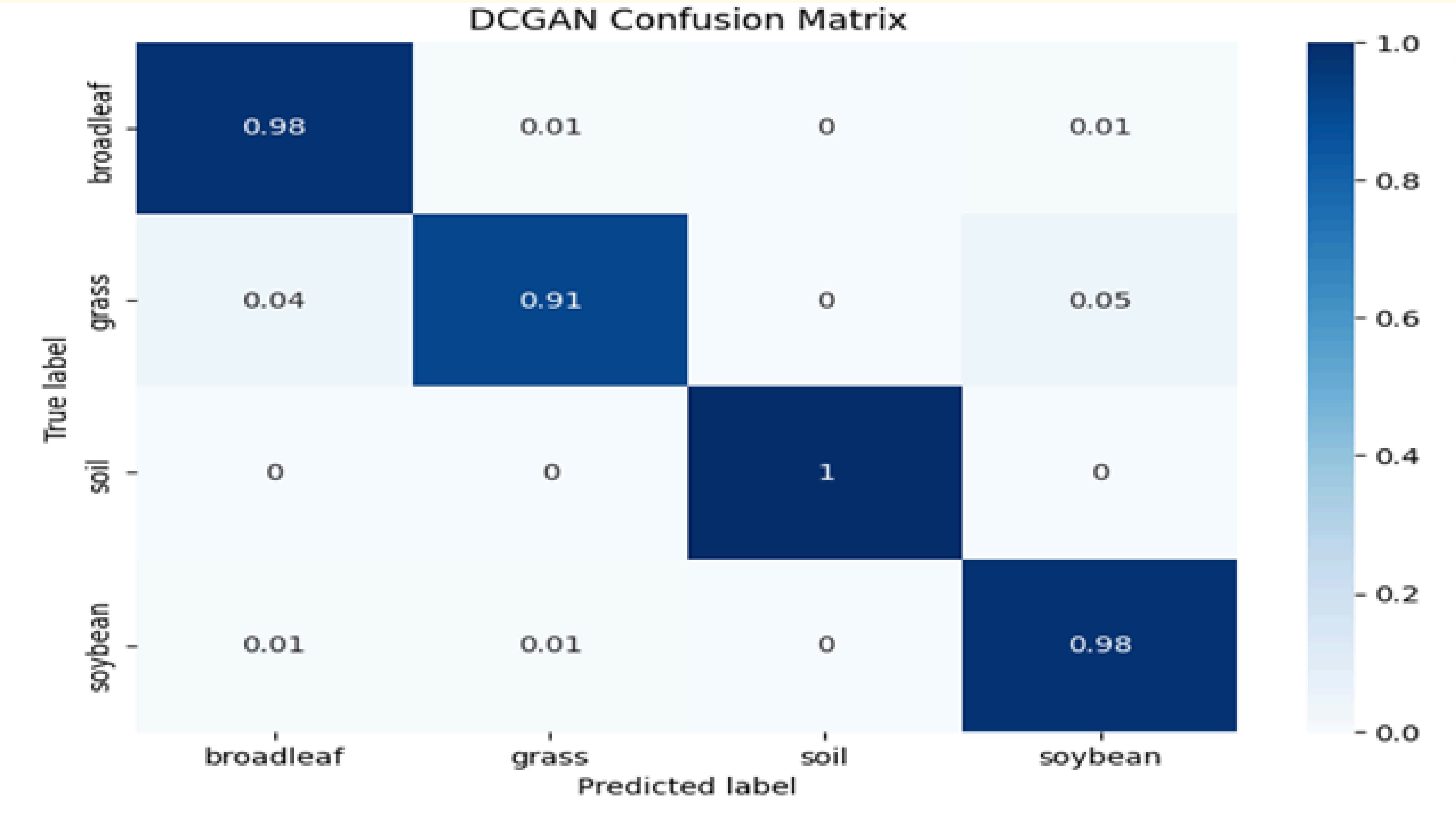


CNN Confusion Matrix

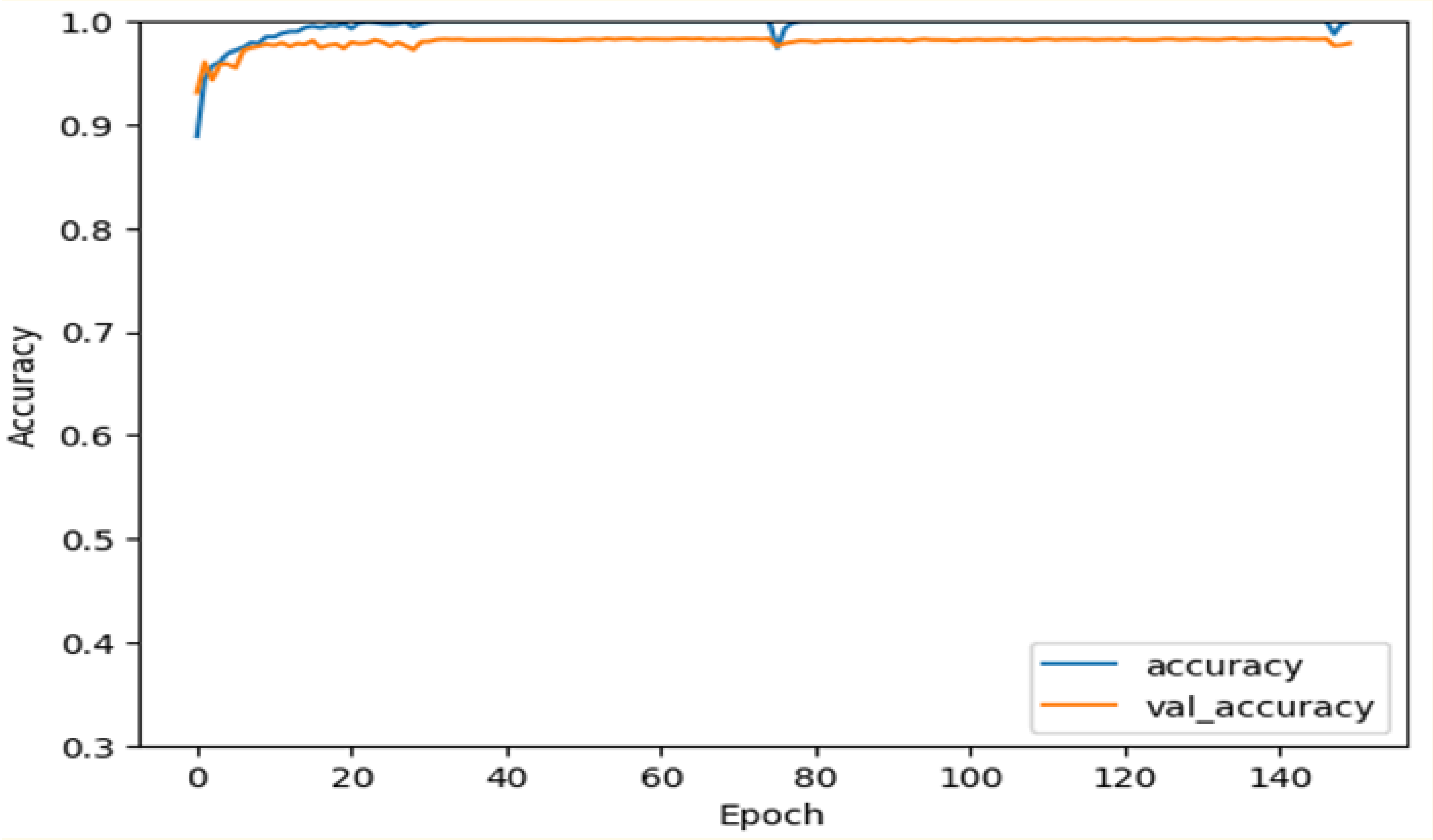


CNN Accuracy Score

Results With DCGAN Augmentation

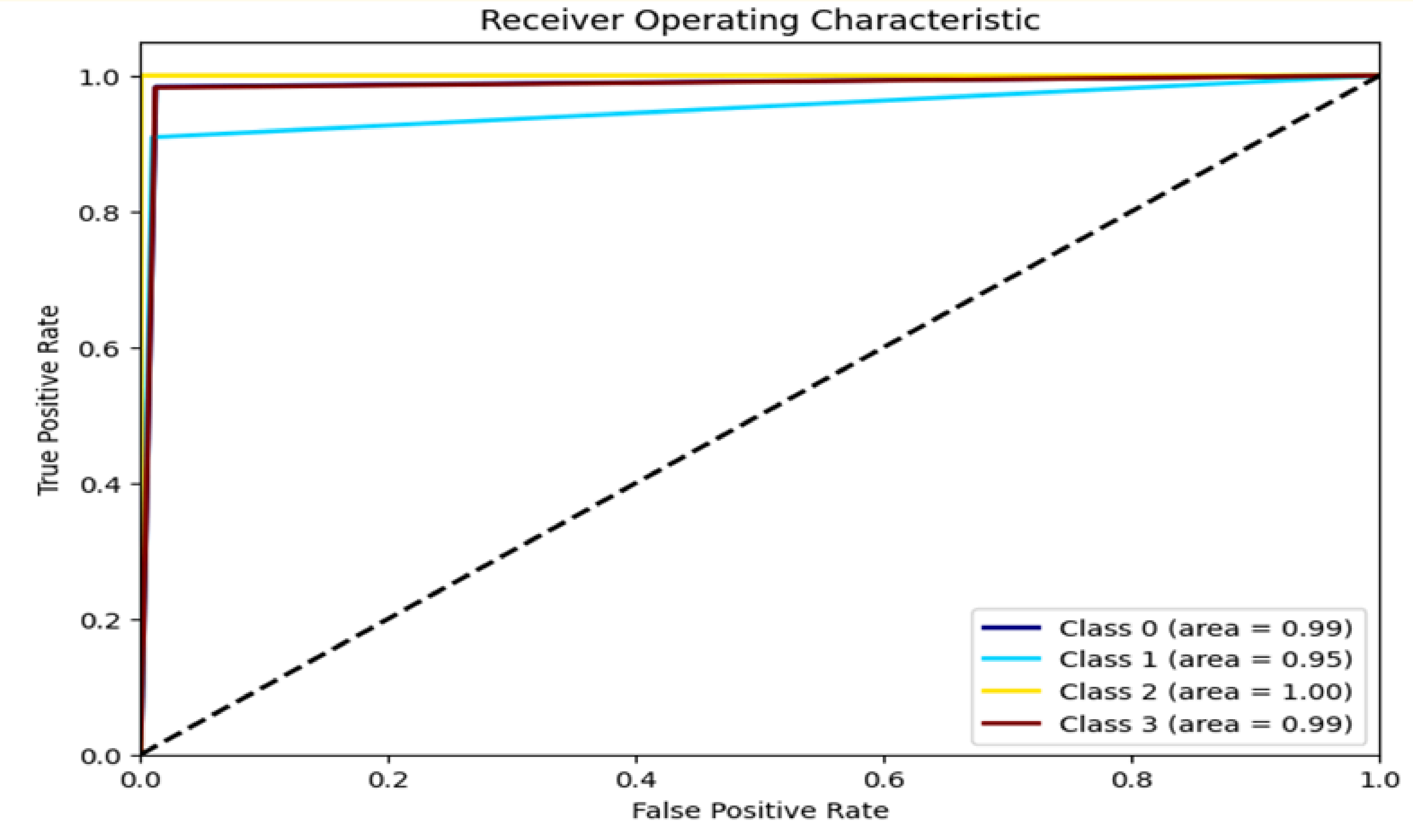


DCGAN Confusion Matrix

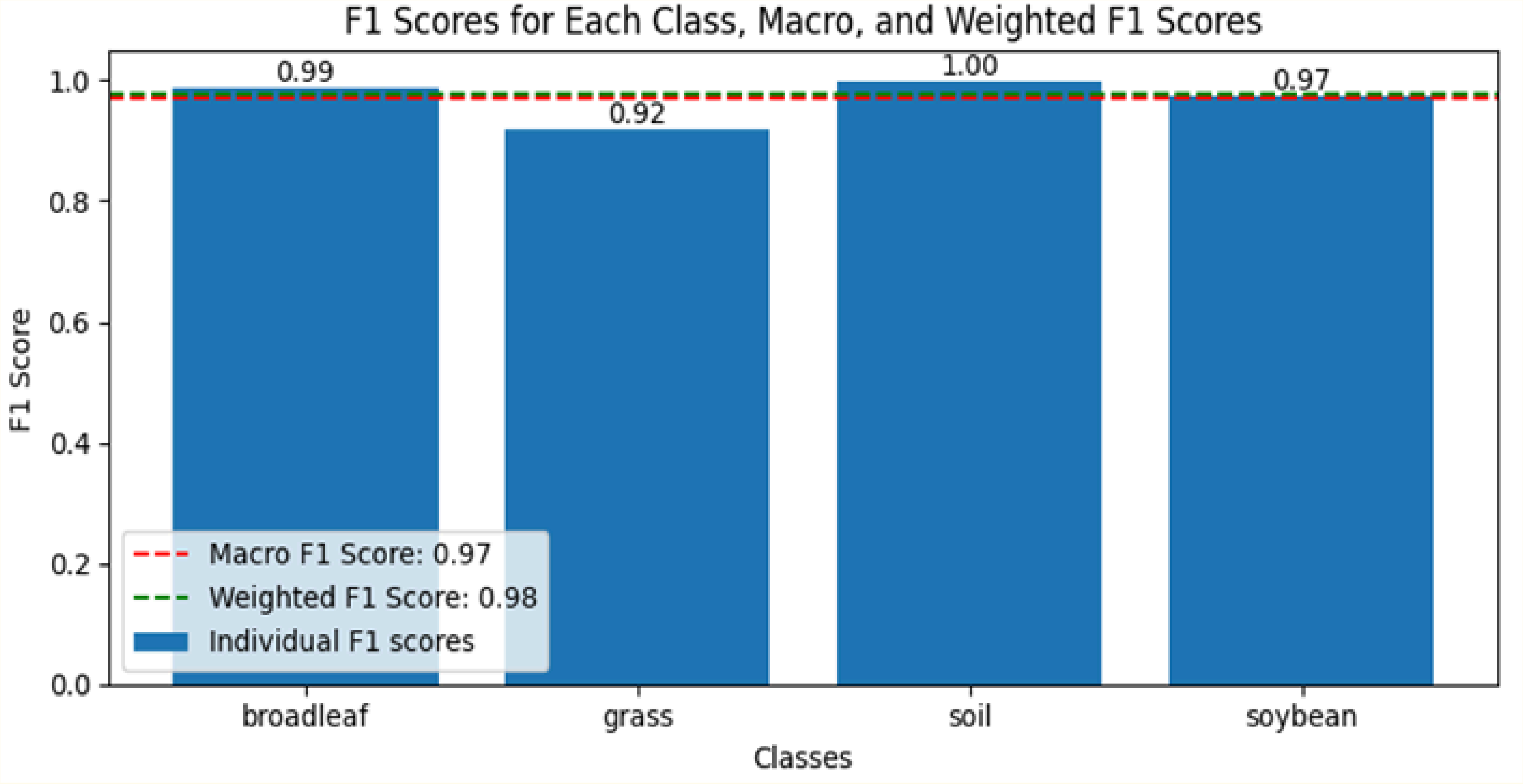


CNN Result with DCGAN

Results With DCGAN Augmentation

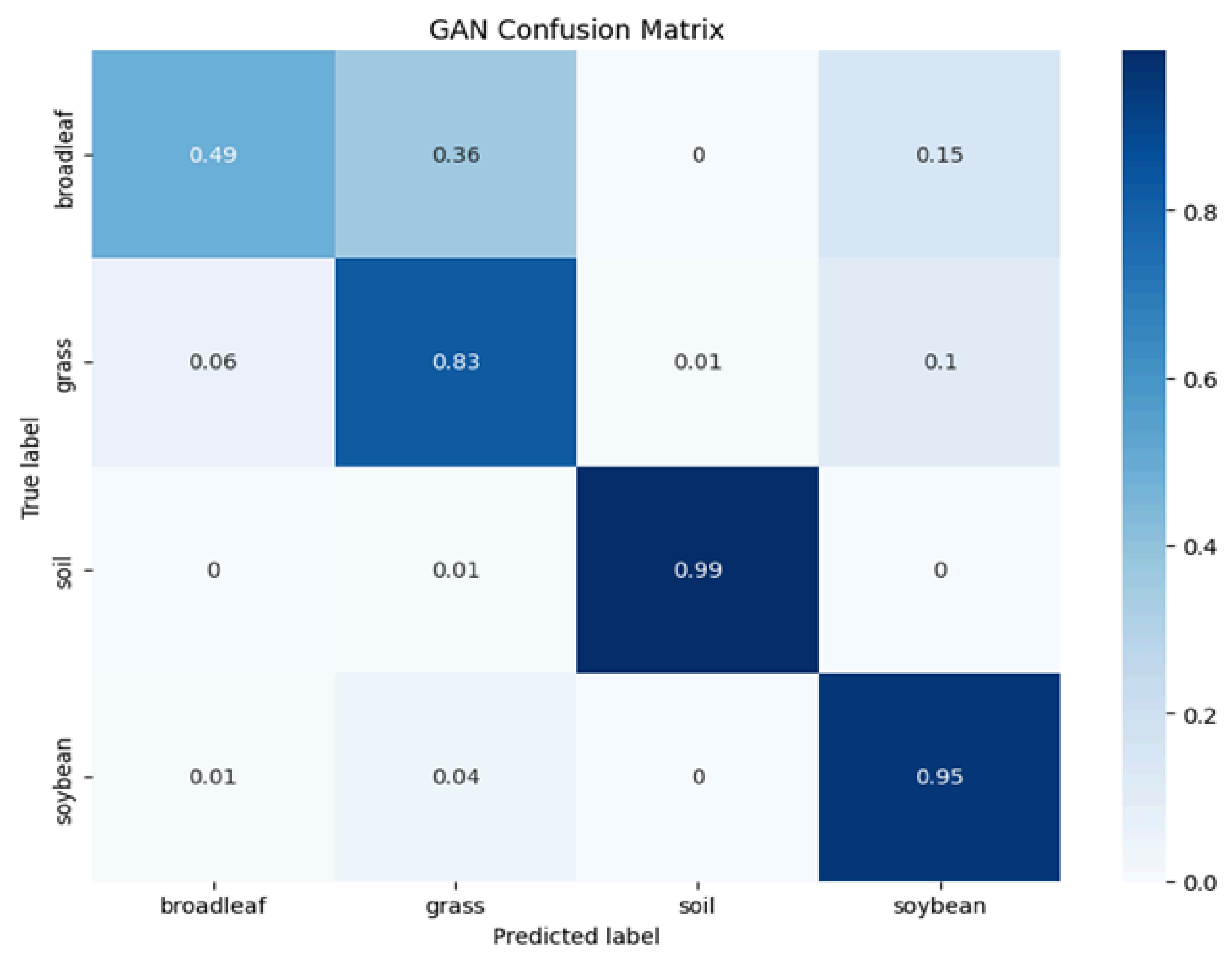


AUC ROC Curves

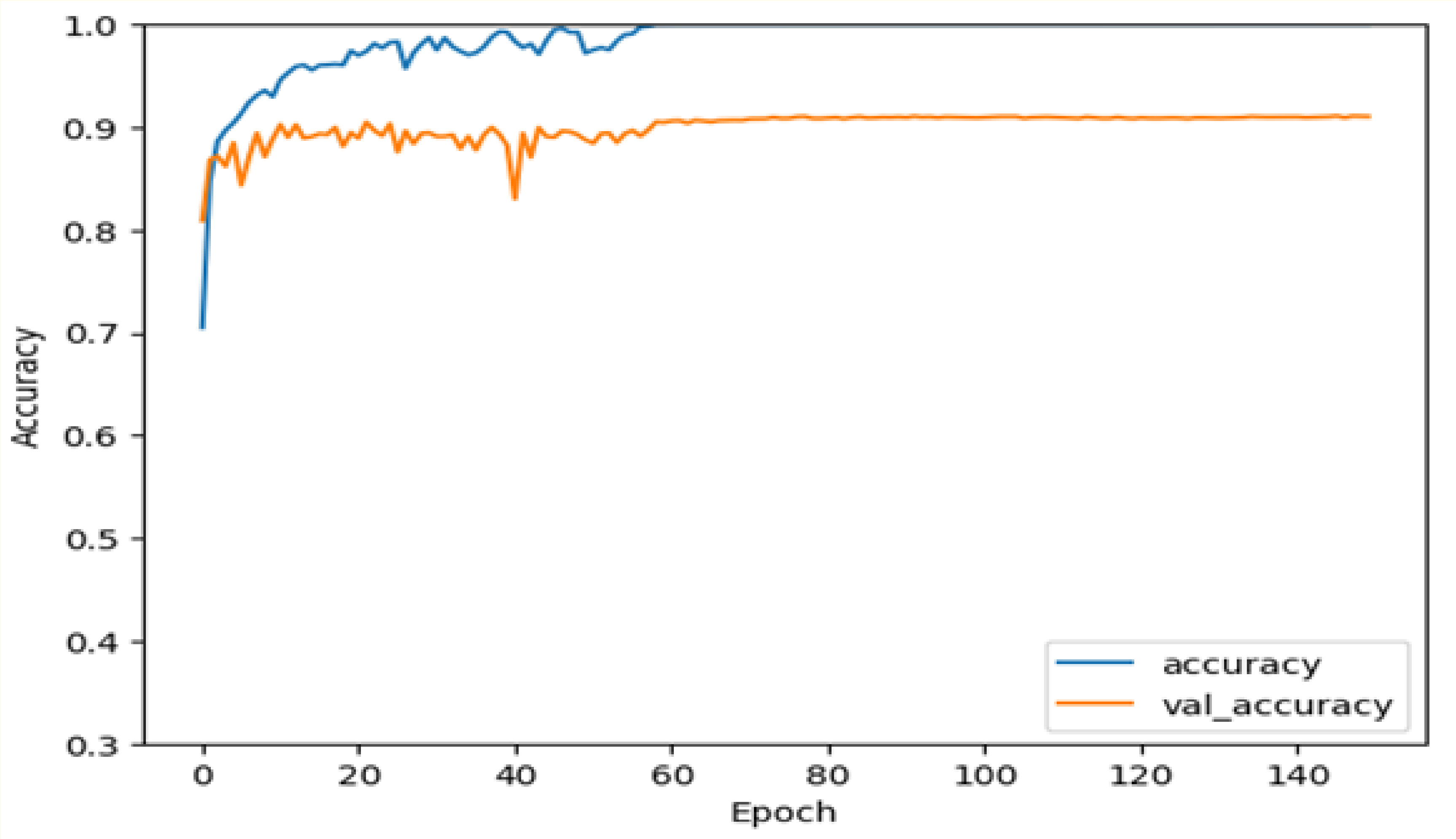


F1 Score

Results With GAN Augmentation



GAN with CNN Confusion Matrix



GAN with CNN Accuracy Score

Conclusion

- To improve CNN's performance in weed identification within precision agriculture, this thesis investigated the use of DCGAN for data augmentation. It addressed issues such as class imbalance and a lack of training data.
- The CNN model performed inconsistently throughout classes without data augmentation, showing complete accuracy for soil but notable rates of misclassification for broadleaf and soybean.
- The CNN struggled particularly with differentiating between soybean and broadleaf due to their similar features, made worse by differences in class.
- The artificial images produced by DCGAN led to a noticeable increase in model accuracy, a decrease in overfitting, and an improvement in class representation, particularly for minority classes.
- The model trained with DCGAN augmentation achieved near-perfect accuracy on both training (1.00) and testing (0.98) sets, exceeded the non-augmented model.
- This research demonstrates the potential of GAN-based augmentation for addressing class imbalance and data limitations in precision agriculture. However, further research is needed to refine these methods and ensure they capture real-world data complexities without introducing new biases.

Future Works

- Some of the work is required for further studies as there are some drawbacks. More investigation is required on different GAN architectures and methodologies to optimize synthetic data generation for specific agricultural tasks.
- Explore combining GANs with other machine learning strategies, such as Transfer Learning or Active Learning , to further enhance model performance.
- Focus on the practical deployment of GAN-augmented models in real agricultural systems, addressing challenges like scalability, computational cost, and data collection.
- Create effective, lightweight GAN architectures that can be used on edge devices such as drones or tractors to enable their wide use in precision agriculture.
- To enhance the generalization, robustness, and accuracy of AI models in precision agriculture and ultimately encourage more efficient and sustainable farming methods, continue to enhance GAN-based data augmentation.


Thank You!