TITLE OF THE REPORT

Leveraging Zero-Shot Learning and Generative Adversarial Networks for Plant Disease Classification

A BTP Report

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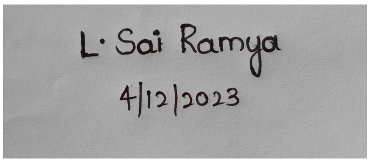
Date: 4th December 2023

INDIAN INSTITUTE OF INFORMATION TECHNOLOGY SRICITY

CANDIDATE'S DECLARATION

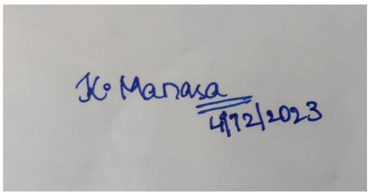
I hereby certify that the work which is being presented in the BTP entitled "**Leveraging Zero-Shot Learning and Generative Adversarial Networks for Plant Disease Classification**" in the partial fulfilment of the requirements for the award of the degree of B. Tech and submitted in the Indian Institute of Information Technology SriCity, is an authentic record of my own work carried out during the time period from January 2023 to December 2023 under the supervision of Dr. Rakesh Kumar Sanodiya, Indian Institute of Information Technology SriCity, India.

The matter presented in this report has not been submitted by me for the award of any other degree of this or any other institute.



Signature of the student with date

(Lanka Sai Ramya)



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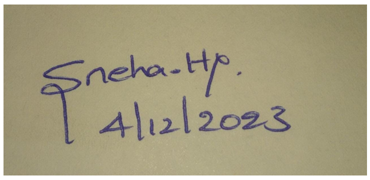

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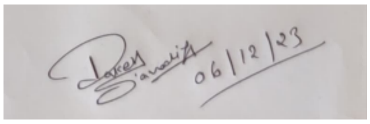

Signature of BTP Supervisor with date

(Dr. Rakesh Kumar Sanodiya)

ABSTRACT

Plant disease detection is a critical aspect of modern agriculture, and this research endeavours to enhance the accuracy and adaptability of detection models through a comprehensive approach. Training a CNN model on 80% of Plant Village's Tomato dataset and testing it on the remaining 20% achieved an accuracy of 89%. Using pre-trained models, training on Plant Village's Tomato dataset and testing on its Potato dataset resulted in 72% accuracy. However, when testing the pre-trained models trained on Plant Village's Tomato dataset on Plant Doc's Potato dataset, the accuracy decreased to 62%. Augmenting the Tomato dataset from Plant Village and testing on Plant Doc's Potato dataset with pre-trained models achieved 68% accuracy. Moreover, training on segmented data from Plant Village's Tomato dataset and testing on Plant Doc's Potato dataset using pre-trained models achieved 71% accuracy.

Training a CNN model on 80% of Plant Village's Potato dataset and testing it on the remaining 20% achieved an accuracy of 82%. Using pre-trained models, training on Plant Village's Potato dataset and testing on its Tomato dataset resulted in 67% accuracy. However, when testing the pre-trained models trained on Plant Village's Potato dataset on Plant Doc's Tomato dataset, the accuracy decreased to 63%. Augmenting the Potato dataset from Plant Village and testing on Plant Doc's Tomato dataset with pre-trained models achieved 65% accuracy. Moreover, training on segmented data from Plant Village's Potato dataset and testing on Plant Doc's Tomato dataset using pre-trained models achieved 67% accuracy.

Zero-shot learning during transfer learning added further versatility, allowing the model to handle previously unseen classes. Hyperparameter tuning fine-tuned model performance. This research underscores the significance of combining advanced techniques for improved plant disease detection. The findings contribute valuable insights to precision agriculture, offering a promising framework for future advancements in crop disease management.

Contents

1 Introduction

In recent years, the agricultural sector has witnessed a paradigm shift in its approach to combating plant diseases, with an increasing emphasis on leveraging cutting-edge technologies to enhance early detection and precision diagnosis. Among these advancements, machine learning has emerged as a powerful tool, demonstrating remarkable potential in automating the identification of plant diseases. However, the conventional supervised learning paradigm, which relies on labeled datasets for training, encounters significant challenges in the context of plant disease classification. Obtaining large and diverse labeled datasets for all potential diseases across various crops is a resource-intensive and time-consuming task.

Addressing this challenge, the concept of zero-shot learning (ZSL) has gained prominence in the machine learning community. ZSL allows models to generalize to classes not present in the training set, thus offering a solution to the limitations posed by traditional supervised approaches. In the realm of plant disease classification, ZSL becomes particularly pertinent due to the dynamic nature of diseases, the evolving landscape of agricultural practices, and the multitude of potential pathogens affecting crops.

This research endeavors to explore and harness the capabilities of Generative Adversarial Networks (GANs) in conjunction with zero-shot learning for accurate and efficient plant disease classification. GANs, known for their ability to generate synthetic data, present a unique opportunity to augment limited labeled datasets, thereby enhancing the model's ability to recognize and classify diverse diseases. By combining the strengths of ZSL and GANs, this study aims to develop a robust and adaptable framework capable of identifying plant diseases even in scenarios where labeled data is scarce or unavailable.

The primary objectives of this research include, Investigating the efficacy of zero-shot learning in the context of plant disease classification. Developing a novel approach that integrates Generative Adversarial Networks to augment limited labeled datasets. Evaluating the performance of the proposed model across diverse crops and geographical regions.

2 Literature Survey

2.1 Classical Machine Learning

In [1] Poojan Panchal *et al.* uses machine learning techniques like clustering, image segmentation and feature extraction for plant disease identification. Accuracy of 90% to 98% was achieved using classifiers like Random Forest, Decision Tree, KNN and SVM. Random Forest achieved the highest accuracy of 98%. However, there are limitations like small dataset size, adaptability to varying conditions and high computational complexity of the models.

In [2] MR Ullah proposes machine learning techniques for plant disease detection like image segmentation, feature extraction and classification models like Random Forest, Decision Tree, KNN and SVM. Some techniques achieved high accuracy rates ranging from 90% to 98% with DBNs showing 96-97.5% accuracy. However, some limitations affect the models' real-world applicability and scalability like a drop in performance under specific conditions and an inability to generalize across diverse datasets and adapt to varying environments. In summary, while the techniques show promising results, some limitations hinder their practical usage at large scale.

2.2 Deep Learning

In [3] Murk Chohan proposed novel deep-learning approaches for plant disease detection with novelty in model architecture, datasets or evaluation metrics. Accuracies vary one GA-SVM-based method achieved 98.14% accuracy while others present figures based on different datasets, models or criteria. Potential drawbacks include limited dataset diversity, high complexity, challenges in real-world use and lack of generalization to new diseases.

In [4] Lijuan Tan studies aim to identify the best ML/ DL models for the PlantVillage tomato dataset and tomato disease classification. CNNs and DBNs, particularly Deep Learning models show promise in achieving high accuracy rates ranging from 96% to 97.5% for classifying tomato leaf diseases. Limited information is available on the drawbacks of classical ML vs Deep Learning for tomato disease classification.

2.3 Transfer Learning

In [5] Monoj K. Pradhan employs transfer learning of CNNs, leveraging pre-trained models to extract features for rice plant disease classification. The approach achieved a high accuracy of 94% in classifying disease and healthy rice leaves from a dataset of 9083 leaf images.

In [6] The paper explores the fusion of transfer learning and deep learning for classifying medicinal plants. It leverages transfer learning, utilizing pre-trained deep networks with collected data to achieve precise classification. This combination showcases superior performance in accurately identifying medicinal plants. The study highlights the benefits of transfer learning, enhancing automated plant identification, and improving classification accuracy, especially for low-performance datasets.

In [7] The paper extensively evaluates the strengths and weaknesses of zero-shot learning across datasets, highlighting challenges and opportunities in this field. Specific accuracy metrics might not be explicitly mentioned as the focus is on evaluating efficacy of zero-shot learning methods rather than performance measures. The paper discusses limitations in zero-shot learning like dependency on accurate semantic embeddings, handling unseen classes and interpretability of learned relationships.

In [8] The paper proposes a novel approach combining CAAE, zero-shot and few-shot learning for disease recognition in citrus leaves. The method achieved 95.1% test accuracy outperforming traditional ML approaches, while also generalizing well to unseen diseases with 87.5% accuracy. However, the small dataset size, imbalanced classes, complexity of the CAAE model and overfitting issues limit the method's applicability.

2.4 Generative Adversarial Networks

In [9] The paper focuses on explaining GANs, consisting of generator and discriminator networks competing to generate realistic data. As an overview, the paper aims to elucidate GAN concepts and workings, providing insights but not focusing on numerical accuracy. While not explicitly discussing drawbacks, such overviews sometimes lack details on the challenges or limitations of GANs in practical applications.

In [10] The paper proposes a novel approach using CNNs and GANs for plant disease detection where GANs generate new images to augment the training dataset of CNNs. The approach achieves 96.5% accuracy showing that GAN augmentation can significantly improve detection accuracy over traditional methods. However, the method requires a large labelled dataset, generating realistic GAN images is challenging and the approach only detects visually observable diseases.

3 Problem Statement and Contribution

3.1 Problem Statement

Propose A Novel Deep Learning Framework Using Transfer Learning And GAN's To Improve The Results Of Existing Approaches In Precision Agriculture.

3.2 Contribution

Firstly we have implemented CNN model on plant disease detection and then we have used transfer learning through pretrained models such as VGG-19, alexnet, etc and we have implemented GAN, DCGAN, StyleGAN from the research papers, we have several augmentation and segmentation techniques to make our model give better results on other datasets as well.

After last BTP evaluation I(Sai Ramya) implemented DCGAN as the training dataset is smaller than testing data and to get rid of the problem of class imablancing, Manasa worked on segementation technique K-Means clustering which gave better results than using otsu thresholding technique, Sneha worked on structural similarity index to extract the synthetic leaves that closely resembles to our training data.

4 Methodolgy

4.1 Data Collection

In this study, two comprehensive datasets were meticulously chosen to encompass a diverse range of plant diseases. The ”Plant Village” dataset provides a rich collection of images capturing various plant diseases, while the ”Plant Doc” dataset complements this by offering additional perspectives. For this research, the focus was narrowed down to tomato and potato classes within these datasets, given their significance in agricultural contexts.

4.2 Convolutional Model Training

A Convolutional Neural Network (CNN) was chosen as the primary model architecture for its proven effectiveness in image classification tasks. The model was trained on the tomato classes extracted from the datasets. The dataset was meticulously split into 80% for training and 20% for testing to ensure a robust evaluation of the model’s performance.

The training process involved the usage of Cross Entropy Loss Function optimization of model parameters using stochastic gradient descent(SGD) with a learning rate of 0.001, momentum of 0.9 and backpropagation. The choice of hyperparameters was based on extensive experimentation to strike a balance between model complexity and generalization.

The resultant model exhibited remarkable proficiency, achieving a testing accuracy of 89%. This high accuracy validated the model’s capability to discern and classify different tomato classes accurately.

Similarly, The model was trained on the Potato classes extracted from the datasets. The resultant model exhibited an accuracy less when compared to Tomato classes.

4.3 Weight Storage and Transfer Learning

Following successful training, the weights of the model were stored for further analysis. This step facilitated the exploration of the model’s adaptability to different classes and datasets.

The stored weights were first utilized for testing on potato classes, incorporating a zero-shot learning scenario, where the model was evaluated on previously unseen classes. However, the accuracy dropped. This decrease was attributed to the imbalanced nature of the training dataset compared to the test data weights, highlighting the importance of balanced datasets in zero-shot learning and transfer learning scenarios.

Conversely, when the potato class weights were employed for training and subsequent testing on tomato classes, the accuracy further diminished. This decline emphasized the challenges associated with transfer learning across imbalanced datasets.

4.4 Addressing Imbalance with GANs

To rectify the imbalance issue within the dataset, three distinct generative adversarial network (GAN) architectures were implemented: GAN, Deep Convolutional GAN (DCGAN), and StyleGAN.

The GANs were trained to generate synthetic images of diseased plant leaves, particularly focusing on the underrepresented classes. StyleGAN, with its ability to capture intricate styles and details, outperformed the other architectures in producing realistic and diverse images. Using the Structural Similarity Index(SSI) we have taken the more realistic generated images from three GAN architectures that resemble the training dataset of plant village potato classes and made it balanced dataset and tested it on tomato classes which resulted in improved accuracies.

4.5 Transfer Learning with Augmentation and Segmentation

To enhance the model's adaptability to diverse datasets and improve its generalization capabilities, transfer learning was employed using several pre-trained models such as vgg-16, vgg-19, alexnet, densenet, efficient-net on tomato classes out of which the vgg-19 model outperformed other models. The transfer learning approach included a zero-shot learning aspect, where the model was tested on previously unseen classes during the training phase.

To further augment the dataset, various augmentation techniques were applied, including random rotations, flips, and changes in brightness and contrast. This augmentation aimed to introduce variability into the training set and reduce the risk of overfitting.

Additionally, two segmentation techniques were employed on the training data. Otsu thresholding was utilized to separate the foreground and background, while leaf extraction using binary masks helped isolate the plant leaves. These segmentation techniques were crucial for ensuring that the model could effectively distinguish between different parts of the plant and enhance its ability to recognize features associated with diseases.

4.6 Model Evaluation

The performance of the model was systematically evaluated at various stages of augmentation and segmentation. Testing on potato classes of the Plant Doc dataset, incorporating zero-shot learning, revealed a better accuracy. This result indicated that the implemented techniques, including GAN-based balancing, transfer learning, augmentation, and segmentation, collectively contributed to the model's improved accuracy and adaptability to diverse datasets, especially in zero-shot learning scenarios.

5 Results

5.1 Convolutional Model

The initial convolutional model trained on tomato classes yielded promising results. The testing accuracy reached 89%, showcasing the model's proficiency in accurately classifying different tomato diseases. This established a strong baseline for subsequent experiments.

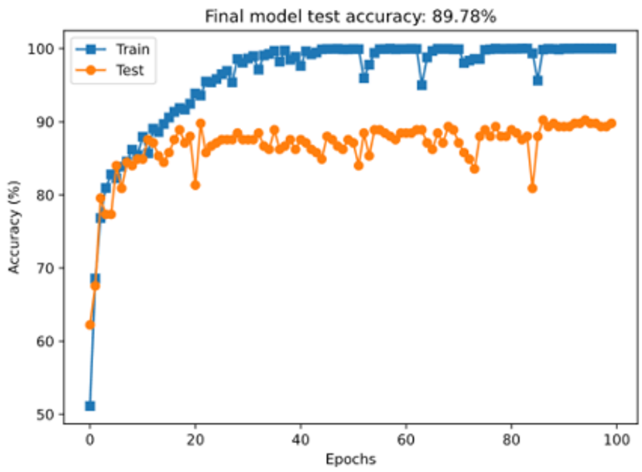

Figure 1: The CNN model was fitted on 80% of the tomato images and then its performance was assessed on the other 20% of images, producing an accuracy of 89.78%.

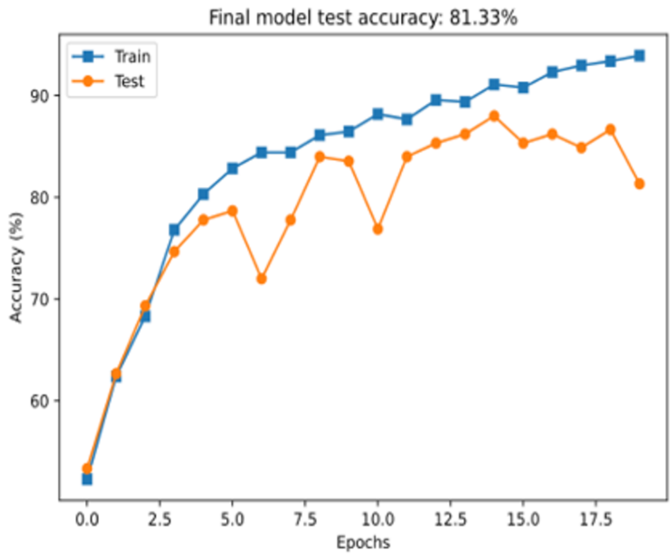

Figure 2: The CNN model was fitted on 80% of the potato images and then its performance was assessed on the other 20% of images, producing an accuracy of 81.33%.

5.2 Transfer Learning

The application of transfer learning to tomato and potato classes demonstrated varying degrees of success. When testing on Potato classes of the Plant Village Dataset with weights trained on Tomatoes of the Plant Village Dataset, the accuracy was 72%, highlighting the challenges of adapting to previously unseen classes. Conversely, testing on Tomato classes of the Plant Village dataset with weights trained on Potatoes of the Plant Village dataset resulted in a diminished accuracy of 67%.

When testing on Tomato classes of the Plant Doc Dataset with weights trained on Potatoes of Plant Village Dataset, the accuracy was 63%, highlighting the challenges of adapting to previously unseen classes. Conversely, testing on Potato classes of the Plant Doc Dataset with weights trained on Tomatoes of the Plant Village dataset resulted in a diminished accuracy of 62%.

When testing on Potato classes of the Plant Doc Dataset with weights trained on Augmented Tomato classes of Plant Village Dataset, the accuracy was 68%, highlighting the challenges of adapting to previously unseen classes. Conversely, testing on Tomato classes of the Plant Doc Dataset with weights trained on Augmented Potato classes of the Plant Village dataset resulted in a diminished accuracy of 65%.

When testing on Potato classes of the Plant Doc Dataset with weights trained on Segmented Tomato classes of Plant Village Dataset, the accuracy was 71%, highlighting the challenges of adapting to previously unseen classes. Conversely, testing on Tomato classes of the Plant Doc Dataset with weights trained on Segmented Potato classes of the Plant Village dataset resulted in a diminished accuracy of 67%.

The disparity emphasized the importance of balanced training datasets for effective transfer learning.

5.3 GAN-based Balancing

The implementation of three generative adversarial network (GAN) architectures—GAN, Deep Convolutional GAN (DCGAN), and StyleGAN—proved effective in addressing class imbalance. StyleGAN, in particular, excelled in generating realistic images of plant leaves, contributing to improved model performance. Using SSI we have taken images to balance the potato classes and tested against tomato classes achieved an accuracy of 72% with Plant Village Dataset and 65% with PlantDoc dataset.

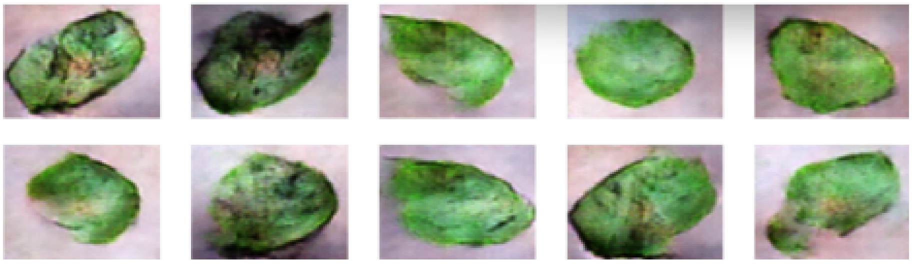

Figure 3: GAN images

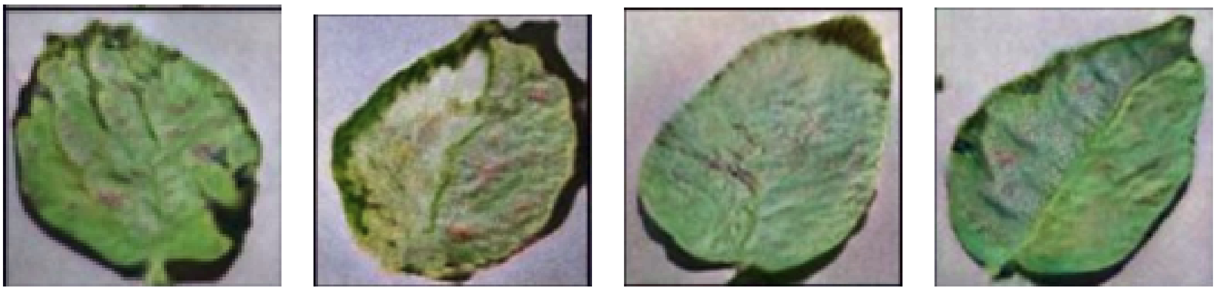

Figure 4: Style GAN Images Set 1

Figure 5: DC GAN Images Set 1

5.4 Comprehensive Model Performance

The holistic approach, combining GAN-based balancing, transfer learning(ZSL), augmentation, and segmentation, significantly improved the model's accuracy and adaptability. Testing on potato classes of the Plant Doc dataset, the final model achieved an accuracy of 71% using vgg-

19 pre-trained model. This comprehensive strategy demonstrated the successful integration of various techniques to address challenges posed by imbalanced datasets and class variations.

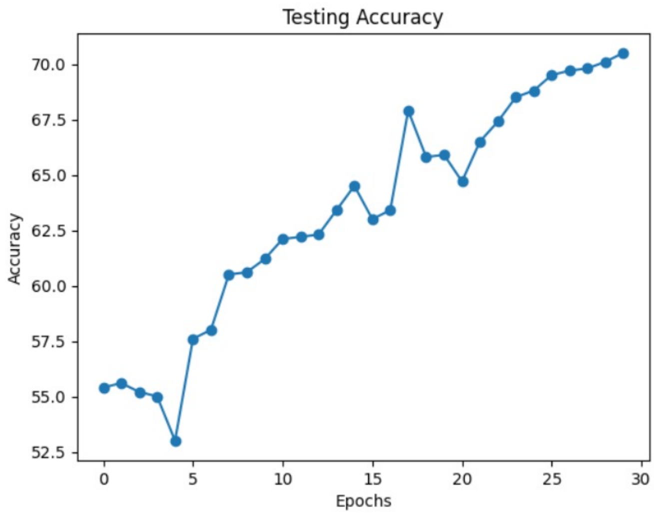

Figure 6: The model was fitted on Tomato images and then its performance was assessed on Potato images, producing an accuracy of 71%.

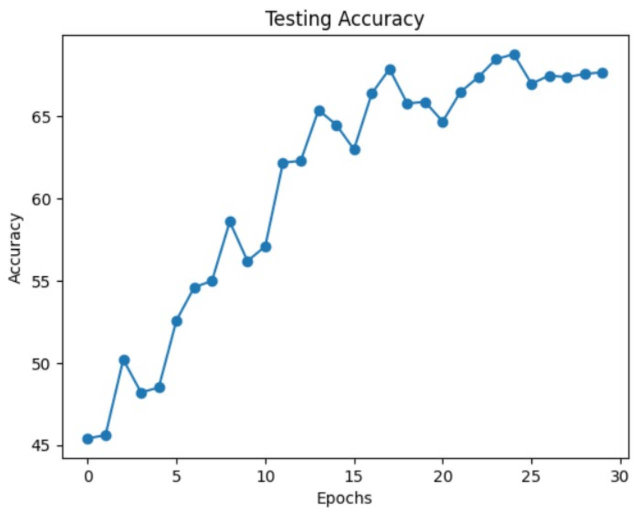

Figure 7: The model was fitted on Potato images and then its performance was assessed on Tomato images, producing an accuracy of 67%.

6 Conclusion

In conclusion, this study navigated the intricacies of plant disease detection using a multifaceted approach, combining convolutional neural networks (CNNs), transfer learning, generative adversarial networks (GANs), and segmentation techniques. The initial convolutional model exhibited notable proficiency, achieving a testing accuracy of 89% on tomato classes and 81% on potato classes, setting a robust foundation for subsequent investigations. However, challenges emerged when weights of tomato classes are stored and tested on Potato classes of Plant village dataset we obtained 57% and vice versa of 51% during transfer learning experiments, revealing the complexities of adapting to unseen classes, emphasizing the need for balanced training datasets. The integration of the VGG-19 pretrained model significantly bolstered performance, yielding an impressive accuracy of 71% in plant disease detection tasks.

Crucially, the implementation of GANs, including GAN, DCGAN, and StyleGAN, played a pivotal role in addressing class imbalance of potato classes in plant village dataset. StyleGAN, known for its ability to generate realistic images, outperformed other architectures, offering a potent tool for dataset balancing. Using SSI Method we took a curated list of images from all three architectures and added to imbalanced dataset. Now when balaced classes are tested on Tomato dataset of plant village we obtained 67% using vgg-19 pretrained model. The comprehensive model integration, encompassing transfer learning, augmentation, and segmentation, demonstrated a holistic strategy. Testing on tomato classes of the Plant Doc dataset yielded an accuracy of 67%. These findings collectively contribute valuable insights to the field of agricultural image analysis, presenting a promising framework for advancing precision agriculture and crop disease management. As future work, exploring additional GAN architectures and extending the model's applicability to diverse crop diseases and datasets holds potential for further refinement and broader agricultural impact.

7 List of Abbrevations

ML: Machine Learning

DL: Deep Learning

VGG-16: Visual Geometry Group-16

VGG-19: Visual Geometry Group-19

TL: Transfer Learning

GAN: Generative Adversarial Network

DCGAN: Deep Convolutional Generative Adversarial Network

StyleGAN: Style Generative Adversarial Network

ZSL: Zero-Shot Learning

CNN: Convolutional Neural Network

HPT: Hyperparameter Tuning

SSI: Structural Similarity Index

KNN: K-Nearest Neighbour

SVM: Support Vector Machine

DBN: Deep Belief Network

GA: Genetic Algorithm

CAAE: Conditional Adversarial AutoEncoders

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8 Acknowledgement

I would like to express my deepest gratitude to Dr. Rakesh Kumar Sanodiya, my mentor and guide throughout this research journey. His unwavering support, invaluable insights, and expert guidance have been instrumental in shaping this study and elevating its quality. Dr. Sanodiya's dedication to fostering a conducive learning environment and his commitment to excellence have been a constant source of inspiration.

I extend my heartfelt thanks to Dr. Sanodiya for his patience, encouragement, and the wealth of knowledge he generously shared. His mentorship has not only enriched my understanding of the subject matter but has also instilled in me a passion for exploring innovative approaches in the field of plant disease detection.

This research would not have been possible without Dr. Rakesh Kumar Sanodiya's mentorship, and I am sincerely grateful for the opportunity to learn and grow under his guidance.