A Project Report

On

AUTOMATED LEAF DISEASE DETECTION USING GAN WITH TRANSFER LEARNING IN MULTIPLE CROPS

Submitted in Partial Fulfillment of the Requirements for the Award of Degree of Bachelor of Technology

In

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

By

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PSO2:

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PROGRAM OUTCOMES (POs)

PO1: Engineering Knowledge

PO2: Problem Analysis

PO3: Design/Development of Solutions

PO4: Conduct an investigation of complex problems

PO5: Engineering Tool Usage

PO6: The Engineer and the World

PO7: Ethics

PO8: Individual and Collaborative Team Work

PO9: Communication

PO10: Project Management and Finance

PO 11: Life-long Learning

PROGRAM SPECIFIC OUTCOME (PSOs)

PSO1: **Applicable**

PSO2: **Applicable**

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CERTIFICATE

This is to certify that the project work entitled "Automated Leaf Disease Detection Using GAN With Transfer Learning" is being submitted by **M. NIRUPAMA (21K61A6140), T.YAMINI(21K61A6159),P.MARKANDEYULU(21K61A6144),M.MOHANKUMAR (22K65A6102)** in partial fulfillment for the award of the degree of **BACHELOR OF TECHNOLOGY**, in **Artificial Intelligence and Machine Learning** to Jawaharlal Nehru Technological University, Kakinada during the academic year 2024 to 2025 is a record of Bonafide work carried out by them under my/our guidance and supervision. The results presented in this thesis have been verified and are found to be satisfactory. The results embodied in this thesis have not been submitted to any other University or Institute for the award of any other degree or diploma.

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DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

DECLARATION BY THE CANDIDATES

We **M. Nirupama (21K61A6140) T. Yamini, (21K61A6159), P. Markandeyulu (21K61A6144), M. Mohan Kumar (22K65A6102),** here by declare that the project report entitled "**Automated Leaf Disease Detection Using GAN With Transfer Learning**" carried out under esteemed supervision of **Mrs. P. Sheela**, is submitted in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology in Artificial Intelligence and Machine Learning. This is a record of work carried out by us and the results embodied in this project has not been reproduced or copied from any source. The results embodied in this project report have not been submitted to any other University or Institute for the award of any other degree or diploma.

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With gratitude,

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ABSTRACT

In the pursuit of sustainable agriculture, the early detection of leaf diseases is vital to ensuring crop health, reducing yield loss, and supporting food security. This research introduces a novel automated approach to crop disease identification that integrates Generative Adversarial Networks (GANs) with Transfer Learning-based Convolutional Neural Networks (CNNs). The system addresses the critical challenge of limited labeled datasets by using GANs to generate synthetic images of diseased leaves, which enrich the training data and improve the generalization ability of the model. These synthetic samples are combined with real-world datasets and used to fine-tune a pre-trained CNN model, enhancing its accuracy in classifying multiple plant diseases. The proposed method is evaluated using standard performance metrics including accuracy, precision, recall, and F1-score, and demonstrates superior performance when compared with traditional image classification techniques. This work not only contributes to the advancement of AI in precision agriculture but also presents a scalable, real-time solution for field-level disease detection, empowering farmers with timely, data-driven insights for effective crop management.

Since leaf diseases directly affect crop yield and food security, their timely detection is essential for sustainable agriculture. Traditional disease identification methods are time-consuming, subjective, and often unreliable, especially in the early stages of infection. To address these challenges, this study presents an automated leaf disease detection framework that leverages the combined strength of Generative Adversarial Networks (GANs) and Transfer Learning techniques using Convolutional Neural Networks (CNNs). The system tackles the common limitation of scarce labeled datasets by synthesizing realistic diseased leaf images through GANs. These synthetic samples, when integrated with original datasets, substantially enhance the training process.

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
CNN	Convolutional Neural Networks
GAN	Generative Adversarial Network
LSTM	Long Short-Term Memory
SVM	Support Vector Machine
NB	Naïve Bayes
k-NN	k-Nearest Neighbor
RNN	Recurrent Neural Network
VGG	Visual Geometry Group
ResNet	Residual Network
IoT	Internet of Things
SGD	Stochastic Gradient Descent
GPU	Graphics Processing Unit
CPU	Central Processing Unit
IDE	Integrated Development Environment
DFD	Data Flow Diagram
UML	Unified Modeling Language
API	Application Programming Interface
F1 Score	Harmonic Mean of Precision and Recall
RAM	Random Access Memory
SSD	Solid State Drive
AWS	Amazon Web Services
GCP	Google Cloud Platform

CHAPTER 1

INTRODUCTION

1.1 Preamble

In recent years, the agriculture industry has seen rapid advancements in technology, particularly in the application of machine learning and deep learning algorithms. These technologies have demonstrated great potential in addressing some of the most pressing challenges faced by farmers globally. One such challenge is the management of crop diseases, which can severely impact the health and yield of plants, ultimately threatening food security. Traditional methods of detecting plant diseases often involve manual inspection, which is time-consuming, subjective, and prone to human error. Additionally, these methods may not be able to identify diseases at early stages, which can result in the spread of infections and crop losses.

The increasing prevalence of machine learning models, particularly deep learning algorithms such as Convolutional Neural Networks (CNNs), has revolutionized the field of plant disease detection. However, these models face a significant challenge when it comes to the availability of labeled data, which is critical for training deep learning models. Many diseases are rare or underrepresented in available datasets, and obtaining labeled data for each type of plant disease can be expensive and labor-intensive. To overcome this limitation, novel approaches are required to augment existing datasets and improve the accuracy of disease detection models. This research presents a solution by leveraging Generative Adversarial Networks (GANs) to generate synthetic images of diseased crops, which, when combined with transfer learning techniques, can enhance the performance of disease detection models. The integration of GANs with CNNs offers a promising solution to the challenges of limited data and inaccurate disease identification, making it a critical advancement in the field of agricultural technology. The global demand for food has been increasing steadily due to population growth, changing dietary habits, and urbanization. Agriculture plays a pivotal role in ensuring food security.

These diseases not only reduce yield but also compromise food quality, impacting both farmers’ income and market availability. Traditional disease detection methods rely on manual observation and expert consultations, which are not only time-consuming but also limited by human error, regional availability of expertise, and the stage of disease development. In remote agricultural regions, early detection becomes nearly impossible, leading to widespread infection and economic loss.

With the advancement of computational technologies and the increasing availability of digital image data, the integration of artificial intelligence into agriculture has opened up innovative approaches to automate and optimize plant disease detection. Particularly, deep learning techniques have demonstrated remarkable accuracy in image classification and pattern recognition tasks. Convolutional Neural Networks (CNNs), a class of deep neural networks, have emerged as powerful tools in the analysis of visual agricultural data. However, these models generally require large volumes of labeled data for effective training, which is a challenge in agriculture where acquiring annotated disease-specific images is resource-intensive and expensive.

To mitigate the data scarcity issue, Generative Adversarial Networks (GANs) offer a promising solution by generating synthetic yet realistic images that can supplement training datasets. GANs consist of two competing networks—the generator and the discriminator—which work in tandem to produce high-quality data approximations. This technique allows researchers to simulate diseased plant leaf images that mimic real-world conditions without the need for extensive manual data collection. When combined with transfer learning, where pre-trained CNN models are fine-tuned on these enriched datasets, the resulting system becomes more adaptable, efficient, and capable of achieving high accuracy with limited data.

The proposed system builds on these advancements by integrating GANs and CNNs with transfer learning to create an automated and scalable solution for leaf disease detection. This initiative not only aids in timely disease identification but also promotes sustainable agricultural practices by enabling precise intervention and reducing unnecessary pesticide usage

1.3 Purpose of the Work

The primary purpose of this research is to develop an automated system for detecting leaf diseases in crops, using advanced machine learning techniques such as GANs and Transfer Learning. The goal is to improve the accuracy and efficiency of disease detection by overcoming the challenges of limited labeled data, which often restrict the performance of traditional machine learning models. This work aims to contribute to the growing body of knowledge in the field of agricultural technology by providing an innovative approach to plant disease detection that integrates synthetic image generation and deep learning. The purpose of this research is to develop an intelligent, automated system capable of detecting plant leaf diseases with high accuracy, even in scenarios where labeled data is limited. The system aims to assist farmers, agronomists, and agricultural researchers in identifying diseases at early stages, thereby enabling timely interventions that can prevent large-scale crop damage. By reducing dependence on manual detection, the project also seeks to democratize access to advanced plant pathology tools, especially in resource-constrained settings.

This work leverages the capabilities of deep learning, particularly CNNs, to perform image-based classification of diseased leaves. To address the critical issue of insufficient training data, the project incorporates GANs to synthetically generate realistic leaf images exhibiting various disease symptoms. These synthetic images are used to augment the existing dataset, creating a more balanced and representative training set. Furthermore, transfer learning is employed to fine-tune pre-trained CNN models on this enriched dataset, allowing the system to learn effectively even from a relatively small volume of actual labeled data.

The end goal is to deliver a practical, scalable, and accurate plant disease detection framework that can be integrated into mobile or web applications for real-time usage. This not only enhances the decision-making process for farmers but also contributes to environmental conservation by minimizing unnecessary chemical interventions. The proposed system can be extended in future iterations to accommodate different plant types, additional disease categories, and multi-language support for global applicability.

Specifically, the study focuses on using GANs to generate synthetic leaf images of crops affected by various diseases. These synthetic images are then used to augment the dataset, which is subsequently used to fine-tune a pre-trained CNN model. The integration of Transfer Learning allows the system to benefit from the knowledge gained from large-scale image datasets, improving classification accuracy even when the available labeled data is limited impact of diseases on crop yields.

1.4 Significance of the Study

The significance of this study lies in its potential to revolutionize the way plant diseases are detected and managed in agriculture. Traditional methods of disease detection are often slow, inaccurate, and not scalable, especially in large-scale farming operations. By introducing an automated system that utilizes cutting-edge machine learning techniques, this study aims to address these limitations and provide farmers with an efficient tool for detecting leaf diseases early. The significance of this study lies in its potential to revolutionize the way plant diseases are identified and managed in agriculture. Traditional inspection methods are not only inefficient but often inaccessible to smallholder farmers who form the backbone of food production in many countries. By offering an automated solution that is both accurate and scalable, this research addresses a critical need in agricultural practice and food security.

The incorporation of GANs into the training pipeline addresses a longstanding issue in machine learning—lack of data diversity. By simulating various disease patterns, lighting conditions, and leaf orientations, GANs help create a training dataset that is closer to real-world conditions, thus enhancing the robustness of the model. Transfer learning further adds value by reducing the computational and temporal cost associated with model training, allowing faster deployment and iteration.

This study also emphasizes sustainability by promoting targeted pesticide use. Misidentification of diseases often leads to the blanket application of chemicals, which not only increases costs but also harms the environment and reduces soil fertility. Accurate disease detection enables farmers to apply the right treatment at the right time, thereby optimizing resource utilization and improving crop yield.

Moreover, the study contributes to the body of knowledge in AI applications for agriculture. It serves as a proof of concept for integrating GANs and CNNs in a practical scenario, offering a framework that can be adapted and expanded for other crops, regions, and conditions. From an academic perspective, this research bridges the gap between theoretical advancements in machine learning and their tangible application in critical sectors like agriculture.

The use of GANs to generate synthetic images of diseased crops is particularly significant, as it allows for the creation of a more diverse and comprehensive dataset, which can significantly enhance the accuracy of deep learning models. This synthetic data augmentation is especially valuable in cases where rare or underrepresented diseases are difficult to find in the real world.

The practical implications of this study are far-reaching. Early detection of plant diseases can lead to more targeted interventions, reducing the need for broad-spectrum pesticides and minimizing their impact on the environment. By improving crop health management, this system has the potential to increase agricultural productivity, reduce crop losses, and ultimately contribute to food security. The findings of this study could have a lasting impact on agricultural practices, making them more sustainable, efficient, and resilient to disease outbreaks.

1.5 Background Study

Over the past decade, the adoption of artificial intelligence in agriculture has seen significant growth, with a focus on enhancing productivity, reducing costs, and minimizing environmental impact. Among the various applications of AI in agriculture, plant disease detection using image-based analysis has emerged as one of the most promising areas. The foundation of this approach lies in the use of Convolutional Neural Networks (CNNs), which have demonstrated state-of-the-art performance in image classification tasks. CNNs are capable of automatically extracting relevant features from leaf images, such as texture, color, and shape, which are indicative of specific disease patterns.

However, the success of CNNs is highly dependent on the quality and quantity of training data. In many cases, datasets used for plant disease detection are collected under controlled conditions and lack the diversity seen in real agricultural settings. This makes the trained models vulnerable to overfitting and limits their generalization capabilities. Moreover, some diseases may be rare or newly emerging, resulting in very few annotated images, which further hampers model training.

To overcome this, researchers have explored various data augmentation techniques such as rotation, scaling, flipping, and cropping. While these methods help to some extent, they are limited in their ability to create truly new representations of the data. This is where Generative Adversarial Networks (GANs) have shown tremendous promise. Introduced by Ian Good fellow in 2014, GANs consist of two neural networks—the generator and the discriminator—that are trained in opposition to each other. The generator creates synthetic images that mimic the real data distribution, while the discriminator evaluates their authenticity. Through this adversarial process, GANs learn to produce highly realistic images that can be used to augment training datasets.

Additionally, the concept of transfer learning has become a cornerstone in the field of deep learning, especially when working with limited data. Transfer learning involves using a model pre-trained on a large, generic dataset (such as ImageNet) and fine-tuning it on a smaller, domain-specific dataset. This approach allows the model to retain its learned low-level features while adapting to new classification tasks with relatively little data. In the context of plant disease detection, transfer learning can significantly reduce the resources and time required for model development.

Combining these two powerful techniques—GAN-based data augmentation and transfer learning using CNNs—provides a robust framework for developing efficient, scalable, and accurate plant disease detection systems. This project builds on these foundational concepts and applies them to the practical problem of detecting leaf diseases, aiming to bridge the gap between research innovation and real-world agricultural application.

The detection of leaf diseases has been a critical challenge in agriculture for many years. Early detection is crucial for preventing the spread of diseases and minimizing their impact on crop yields. Traditional disease detection methods typically rely on expert knowledge and visual inspection, which can be subjective and inaccurate. In recent years, there has been a growing interest in using machine learning techniques for automated plant disease detection. Convolutional Neural Networks (CNNs), in particular, have shown promising results in image classification tasks, including the identification of plant diseases.

However, one of the major challenges faced by CNNs is the need for large amounts of labeled data for training. In many cases, collecting enough labeled data for all possible plant diseases can be a time-consuming and costly process. This limitation has led to the exploration of methods for augmenting existing datasets. One such method is the use of Generative Adversarial Networks (GANs), which can generate synthetic images that mimic real-world data. These synthetic images can be used to supplement the training dataset, improving the model's ability to generalize and detect a wide range of diseases.

Transfer Learning is another powerful technique that has been used to address the issue of limited data. By leveraging pre-trained models that have already been trained on large-scale datasets, Transfer Learning allows a model to adapt to a new task with relatively little data. This approach has been widely used in image classification tasks and has shown excellent results in various applications, including plant disease detection.

1.6 Evaluation of Existing Solutions

The journey toward automated plant disease detection has evolved from rudimentary image processing techniques to sophisticated deep learning models. Early systems relied heavily on handcrafted features and traditional machine learning algorithms like k-Nearest Neighbors (k-NN), Support Vector Machines (SVM), and Naïve Bayes classifiers. These approaches required domain expertise to manually extract features from leaf images, such as color histograms, texture patterns, and edge detections. While they offered moderate success, they lacked adaptability and often failed to perform well under variable lighting conditions or when faced with complex disease symptoms.

With the advent of deep learning, particularly CNNs, the paradigm shifted significantly. CNNs automated the feature extraction process, enabling end-to-end learning from raw image pixels to disease classification labels. Various models like AlexNet, VGGNet, and ResNet were adapted for agricultural applications and achieved commendable results. Public datasets like PlantVillage facilitated the training and benchmarking of these models, pushing the boundaries of what was possible in plant disease detection.

However, these CNN-based solutions still faced significant hurdles, primarily due to data limitations. Models trained on PlantVillage, which contains images captured in lab-like environments, often failed to generalize to real-world conditions where backgrounds are noisy, lighting is inconsistent, and leaf orientations vary. Additionally, these datasets are often unbalanced, with certain diseases overrepresented while others have only a handful of samples.

To mitigate these issues, researchers started exploring data augmentation strategies. Traditional augmentations like flipping, zooming, and rotation improved model robustness slightly, but they were insufficient in simulating the true variability of field conditions. This led to the introduction of GANs in agricultural image analysis. GANs offered a novel way to generate entirely new images that preserved disease-specific characteristics while introducing realistic noise and diversity.

Parallel to these developments, transfer learning gained traction as a way to harness the power of models pre-trained on massive datasets like ImageNet. By fine-tuning these models on relatively small agricultural datasets, researchers could achieve high accuracy with significantly less computational overhead. Recent advancements have seen the integration of GANs and transfer learning, where GAN-augmented data is used to fine-tune pre-trained CNN models for superior performance.

This evolution demonstrates a clear trend: from manual feature engineering to fully automated, data-driven, and intelligent systems. The current project represents the next step in this progression, leveraging both GANs and transfer learning to address the longstanding issues of data scarcity, generalization, and scalability in leaf disease.

1.7 PROPOSED METHOD

The proposed method introduces an integrated framework that combines Generative Adversarial Networks (GANs) for data augmentation and Transfer Learning using Convolutional Neural Networks (CNNs) for classification. The core idea is to build a robust plant disease detection system that performs well even when the available labeled data is minimal or imbalanced. This is achieved by synthesizing new, realistic disease images through GANs, which expand the dataset and introduce greater variability, and by fine-tuning a pre-trained CNN model to adapt to the specifics of leaf disease classification.

The workflow begins with the collection of a base dataset containing leaf images categorized by disease type. This dataset is analyzed to identify imbalances or classes with insufficient samples. A GAN is then trained on these underrepresented categories to generate synthetic images that mirror the real ones in appearance and quality. These images are reviewed, filtered for quality, and merged with the original dataset to form an enriched, balanced dataset.

Next, a CNN model such as VGG16, ResNet50, or InceptionV3—pre-trained on ImageNet—is selected for transfer learning. The model's top layers are replaced or fine-tuned using the augmented dataset. This transfer learning approach leverages the lower layers of the network, which have already learned general visual features, allowing the model to quickly adapt to the specific patterns associated with leaf diseases.

The model is trained and evaluated using standard metrics such as accuracy, precision, recall, and F1 score. Cross-validation and testing on unseen data are performed to ensure generalization. Additionally, real-time performance is tested using a user interface that allows image upload and immediate diagnosis, mimicking real-world usage.

This method not only enhances model accuracy and reliability but also demonstrates the potential for deploying intelligent systems in agriculture. The integration of GANs and transfer learning addresses two major bottlenecks—limited data and computational cost—making the system efficient, scalable, and ready for real-time applications in diverse agricultural settings.

Over the years, several approaches have been proposed for plant disease detection. These include both traditional methods and machine learning-based methods. Traditional methods, such as visual inspection by experts, rely on the subjective judgment of trained professionals. While these methods can be effective for detecting common diseases, they are not suitable for large-scale monitoring and are prone to human error.

In the realm of machine learning, several CNN-based models have been developed for plant disease detection. These models typically require large, labeled datasets to achieve high accuracy. While CNNs have been successful in many applications, their performance can be limited by the availability of labeled data, especially when dealing with rare or underrepresented diseases. Other approaches, such as Support Vector Machines (SVMs) and decision trees, have also been explored for plant disease classification, but these models often perform worse than CNNs in image classification tasks.

Recent advancements in GANs and Transfer Learning have shown promise in improving the performance of plant disease detection systems. GANs have been used to generate synthetic images to augment training datasets, while Transfer Learning has enabled the adaptation of pre-trained models to new, smaller datasets. Despite these advancements, there is still a gap in the existing literature regarding the combination of GANs for plant disease detection.

1.8 SUMMARY

The proposed method integrates Generative Adversarial Networks (GANs) with Transfer Learning to overcome the challenges of limited labeled data and improve the accuracy of plant disease detection. By using GANs to generate synthetic images of diseased crops, the dataset can be augmented to include a more diverse range of diseases, including rare or underrepresented ones. This augmented dataset is then used to fine-tune a pre-trained Convolutional Neural Network (CNN) model, which benefits from the knowledge gained from large-scale image datasets.

Transfer Learning allows the model to adapt to the specific task of plant disease detection by leveraging the knowledge learned from pre-trained models on similar tasks. This approach reduces the need for large amounts of labeled data while maintaining high accuracy. The proposed system is designed to be scalable and adaptable, making it suitable for deployment in real-world agricultural environments. This chapter has laid the foundation for understanding the necessity, challenges, and proposed solutions associated with automated leaf disease detection. The preamble highlighted the global importance of early plant disease identification in securing food supply and supporting sustainable agriculture. The problem statement identified the core issues of manual inefficiency and data limitations that hinder current solutions. Through the purpose of the work, the research objectives were clarified—namely, to create a robust, accurate, and accessible detection system using deep learning and generative modeling.

The significance of the study was emphasized in terms of both practical agricultural impact and academic innovation. The background study provided context on the technologies being utilized, while the evolution of existing solutions illustrated the journey from traditional image processing to intelligent data augmentation and model reuse through transfer learning. The proposed method detailed how GANs and CNNs can be effectively combined to create a scalable detection pipeline suitable for real-world deployment.

CHAPTER 2
LITERATURE SURVEY

2.1 Preamble

The significance of plant disease detection in agriculture cannot be overstated. As the global population continues to grow, the demand for higher agricultural productivity is greater than ever. However, crop diseases remain a critical threat to achieving optimal yields, and their early detection is vital for minimizing crop loss and ensuring food security. Over the years, various approaches to plant disease detection have been explored, ranging from traditional manual methods to modern computer vision and machine learning-based techniques. The integration of deep learning and computer vision technologies, particularly Convolutional Neural Networks (CNNs), has brought about transformative changes in the field, enabling the automation of disease detection processes. The detection and classification of plant leaf diseases have become critical focus areas in precision agriculture and smart farming initiatives across the globe. With the rapid advancement of artificial intelligence and deep learning technologies, researchers have increasingly turned toward automated systems that can reliably identify disease symptoms from digital images. Traditionally, plant pathologists and agronomists conducted manual inspections and field assessments to detect infections. However, these methods are no longer feasible in the context of large-scale farming and the growing demand for food security, especially in regions where expert access is limited. This has led to a growing interest in computational approaches that offer faster, more accurate, and more scalable solutions.

The literature surrounding plant disease detection is rich and diverse, encompassing various machine learning algorithms, image processing techniques, and data augmentation strategies. In recent years, Convolutional Neural Networks (CNNs) have emerged as the cornerstone of image-based disease classification due to their superior ability to extract and learn spatial hierarchies of features. Despite their success, CNNs are not without limitations. One of the most significant challenges lies in the dependency on large, balanced, and annotated datasets. Many plant disease datasets available for public use suffer from class imbalance or limited samples for rare diseases, resulting in poor generalization of the trained models.

To mitigate this, researchers have explored various techniques such as traditional data augmentation and transfer learning. Transfer learning, in particular, has revolutionized how models are trained on limited datasets. By leveraging pre-trained networks that have learned general visual features from massive datasets such as ImageNet, researchers can fine-tune these models on specific agricultural datasets to achieve high accuracy with relatively little computational overhead. More recently, Generative Adversarial Networks (GANs) have been explored as a novel method of data augmentation. GANs are capable of synthesizing realistic images of diseased leaves, which can significantly enhance the training dataset and improve the performance of classification models.

This chapter delves into the body of existing research related to plant disease detection using machine learning and deep learning techniques. It explores key works that have contributed to the evolution of current methodologies, compares various approaches in terms of their architecture, dataset size, accuracy, and scalability, and identifies the gaps that the current study aims to address. The literature survey not only provides a foundation for understanding the current state of the field but also justifies the design choices made in the proposed research.

Despite these advancements, several challenges remain in developing reliable disease detection systems. One of the major obstacles is the insufficient amount of labeled data, particularly for rare or underrepresented diseases. Additionally, the application of deep learning to plant disease detection often requires large and diverse datasets, which can be difficult to obtain. In this context, innovative solutions such as Generative Adversarial Networks (GANs) and Transfer Learning have emerged as powerful tools to address these limitations. By generating synthetic images through GANs and leveraging pre-trained models through Transfer Learning, these techniques can significantly improve the performance of disease detection systems with relatively smaller datasets.

This literature survey delves into the existing body of work in the field of plant disease detection using machine learning, particularly focusing on CNNs, GANs, and Transfer Learning. It also examines the methodologies employed, the datasets used, and the challenges faced by researchers in developing robust and scalable disease detection systems. Through this survey, we aim to highlight the advancements made in this area, identify the gaps in current research, and underscore the contributions that this study aims to make in the ongoing efforts to enhance agricultural practices through the application of deep learning technologies.

Plant diseases are one of the leading causes of crop loss worldwide, and their timely detection is crucial for minimizing their impact on agricultural productivity. Over the years, traditional methods for detecting plant diseases, such as manual inspection by experts or the use of simple diagnostic tools, have proven to be time-consuming and inefficient. Additionally, these methods often require significant expertise, which may not always be available, especially in remote farming areas. Therefore, automated disease detection systems are in high demand, and machine learning, particularly deep learning, has become an effective tool in this area.

The challenge of detecting diseases in plants lies in the diversity of pathogens, which can cause a wide range of symptoms on plant leaves. These symptoms can vary depending on the type of disease, the plant species, and environmental factors such as soil conditions, humidity, and temperature. While some diseases are easy to recognize due to visible symptoms like discoloration or spots, others may require more detailed examination to differentiate them from similar, non-disease-related leaf damage. This complexity necessitates the development of robust, accurate, and scalable systems for detecting a wide variety of plant diseases.

Recent advancements in computer vision and deep learning have opened new avenues for plant disease detection. CNNs, in particular, have shown great promise in image classification tasks, enabling the automatic recognition of plant diseases from images of leaves. However, these models are heavily reliant on large and diverse datasets of labeled images, which are not always available for every type of plant disease. This literature survey will explore various methods that have been employed to tackle these issues.

2.2 Related Work

The detection of plant diseases using machine learning has been an area of active research for several years. Early efforts focused on traditional image processing techniques such as thresholding, edge detection, and texture analysis to identify disease symptoms. However, these methods were often limited by their inability to handle complex and varied disease patterns, leading to a reliance on machine learning algorithms to improve accuracy and robustness. A significant amount of work has been conducted in the field of automated plant disease detection, ranging from basic image processing approaches to complex deep learning frameworks. Early research in this domain focused on extracting handcrafted features from images, including texture, color, and shape, followed by the application of classical classifiers such as Support Vector Machines (SVM), Naïve Bayes (NB), and Decision Trees. These approaches, while pioneering at the time, suffered from limitations in scalability and adaptability to varying environmental conditions.

One of the foundational studies in this area is by Arivazhagan et al., who used color co-occurrence methods and SVM for classifying diseases in banana leaves. Their model achieved moderate success but was heavily reliant on controlled lighting and consistent image backgrounds. Similarly, Patil and Kumar implemented image processing filters followed by k-

Nearest Neighbors (k-NN) classification to detect tomato leaf diseases, achieving around 85% accuracy. However, the dependency on manually extracted features limited the model's robustness.

The introduction of deep learning, especially CNNs, marked a turning point in the evolution of plant disease detection systems. Mohanty et al. conducted a landmark study using the PlantVillage dataset, where they trained AlexNet and GoogLeNet architectures to classify 38 disease classes across 14 crop species. Their results showed that CNNs outperformed traditional classifiers by a large margin, with accuracies exceeding 99% on clean and well-segmented data. However, they also noted a significant drop in performance when the models were tested on field data, underscoring the generalization problem.

Following this, Sladojevic et al. developed a deep CNN model to classify plant diseases directly from leaf images without the need for background segmentation or preprocessing. Their system was trained on a custom dataset and achieved satisfactory performance, but the absence of data augmentation made the model prone to overfitting. To address this, Ferentinos utilized transfer learning by fine-tuning pre-trained VGG16 and InceptionV3 models on crop disease datasets. The study demonstrated improved performance and reduced training time, indicating the practical utility of transfer learning in agricultural contexts.

In recent years, researchers have started incorporating GANs to generate synthetic data and tackle the problem of limited or imbalanced datasets. Chatterjee et al. proposed a GAN-augmented CNN model for rice disease detection. By generating synthetic leaf images of bacterial blight and brown spot, they were able to balance the dataset and improve classification accuracy by nearly 12%. Similarly, Xie et al. used GANs to generate multiple variations of potato leaf disease images, enhancing model robustness to changes in lighting and leaf orientation.

Another noteworthy contribution comes from Zhang et al., who created a conditional GAN (cGAN) framework that generated images of infected and healthy leaves under various environmental conditions. The images were then used to train a ResNet-based classifier. The model exhibited significant improvements in recall and F1-score when compared to non-augmented counterparts. In addition to GANs, augmentation using style transfer techniques has also been explored to simulate diverse environmental effects on leaf appearance.

Apart from data augmentation and transfer learning, ensemble models have also shown promise. Chen et al. implemented a hybrid model combining CNN and LSTM for time-series disease progression analysis. The model used CNN to extract spatial features and LSTM to track disease evolution across multiple frames, achieving better temporal consistency in predictions.

Collectively, these works represent the progression from conventional to modern AI-based plant disease detection systems. They also highlight persistent challenges such as data imbalance, domain adaptation, and lack of generalization. Despite the success of individual techniques like CNNs and GANs, very few studies have combined them effectively into a single, unified pipeline for robust and scalable disease detection.

One of the earliest applications of machine learning in plant disease detection involved the use of classical algorithms such as Support Vector Machines (SVM) and k-Nearest Neighbors (k-NN). These algorithms were trained on feature sets extracted from images of plant leaves, such as color histograms, texture patterns, and shape descriptors. Although these methods showed some promise, their performance was limited by the complexity of the data and the difficulty in identifying subtle disease symptoms. The application of machine learning in plant disease detection has evolved significantly over the past decade. One of the earliest breakthroughs in this field was the use of Support Vector Machines (SVM) for classifying plant diseases based on handcrafted features such as leaf texture and color. While these methods showed some success, they were often limited by their reliance on manually extracted features and their inability to generalize well to new datasets. As machine learning models became more advanced, the focus shifted towards the use of deep learning algorithms, particularly CNNs, which could automatically learn features from raw image data.

CNNs have revolutionized plant disease detection, especially when applied to large datasets. For instance, the work by Mohanty et al. (2016) demonstrated the potential of CNNs in classifying images from a large dataset of plant leaves, achieving over 99% accuracy. This study, along with others, showed that CNNs are capable of learning hierarchical patterns in images, such as leaf veins and shapes, which are critical for distinguishing between healthy and diseased plants. Furthermore, CNNs can be trained on large-scale datasets, making them highly effective in detecting a wide range of diseases, even for crops like rice, wheat, and tomatoes.

However, one of the significant drawbacks of deep learning models, including CNNs, is the need for large, labeled datasets. Collecting and labeling images of diseased plants is a time-consuming process, and for many crops, the data available is limited or insufficient for training accurate models. To address this, several studies have explored data augmentation techniques to artificially expand the available dataset. This includes rotating, flipping, and scaling images to generate new training samples. While these methods can improve model performance, they may not be sufficient for rare or underrepresented diseases.

The introduction of Generative Adversarial Networks (GANs) has provided an exciting solution to this problem. GANs, by generating synthetic data, offer a way to augment datasets without the need for manual data collection. Several studies have demonstrated the use of GANs to generate images of diseased plant leaves. For instance, a study by Zhang et al. (2020) used GANs to generate synthetic images of rice leaves infected with bacterial leaf blight. By augmenting their dataset with these generated images, the authors were able to train a more robust CNN model, achieving significantly better accuracy than models trained on real data alone.

With the advent of deep learning, Convolutional Neural Networks (CNNs) began to dominate the field of plant disease detection. CNNs are particularly well-suited for image classification tasks due to their ability to automatically extract hierarchical features from raw image data. In 2015, a breakthrough in CNN architectures, particularly the development of deeper and more complex networks like VGGNet, ResNet, and Inception, led to significant improvements in image classification accuracy. In the context of plant disease detection, CNNs have been successfully applied to a variety of crops, including rice, tomato, and wheat. These networks have shown the ability to classify images of healthy and diseased leaves with high accuracy, outperforming traditional machine learning methods.

Despite the success of CNNs, the lack of sufficient labeled data remains a significant challenge. Annotating large datasets of plant images requires considerable time and effort, especially for diseases that are rare or underrepresented. To overcome this issue, researchers have turned to Generative Adversarial Networks (GANs), a class of deep learning models capable of generating synthetic data. GANs consist of two networks: a generator that creates synthetic images and a discriminator that evaluates them. Through this adversarial process, GANs can generate high-quality images that resemble real data, which can then be used to augment the training dataset. This approach has been particularly useful for plant disease detection, where GANs are employed to generate synthetic images of diseased leaves to supplement real-world data.

Transfer Learning has also gained popularity as a technique for overcoming the problem of limited labeled data. Instead of training a model from scratch, Transfer Learning allows researchers to use pre-trained models that have been trained on large-scale datasets, such as ImageNet, and fine-tune them on smaller, domain-specific datasets. This approach leverages the knowledge learned by the pre-trained model, reducing the amount of data required to achieve high classification accuracy. Transfer Learning has been successfully applied to plant disease detection, where models such as VGG16, ResNet, and DenseNet have been fine-tuned on datasets of plant leaf images to detect various diseases.

Several studies have demonstrated the effectiveness of combining CNNs, GANs, and Transfer Learning for plant disease detection. For example, the study by Mohanty et al. (2016) employed a CNN to classify images of crop diseases, achieving impressive results on a dataset of plant leaves. Similarly, the work by Ferentinos (2018) explored the use of CNNs for disease detection in tomato plants, obtaining high classification accuracy across various disease classes. In a recent study by Vasudevan et al. (2020), the authors combined GANs with Transfer Learning to address the issue of limited labeled data for rice crop disease detection. Their approach demonstrated significant improvements in classification accuracy, particularly for rare diseases, highlighting the potential of combining these techniques in agricultural applications.

Despite the promising results from these studies, challenges remain in terms of the generalization of models across different crops and disease types. Many existing models are trained on specific datasets and may not perform well when applied to other crops or environmental conditions. Furthermore, the computational cost associated with training deep learning models, particularly GANs, remains a challenge, especially for real-time disease detection systems deployed in the field.

2.3 Comparison Tables

To better understand the progress and limitations of existing approaches in plant disease detection, it is essential to present a comparative analysis of different models, datasets, and techniques used in previous research. The following comparison is based on key parameters such as model type, dataset used, augmentation strategy, accuracy achieved, and real-time applicability. This evaluation sheds light on the advantages and limitations of each method and provides a foundation for justifying the proposed methodology adopted in the present study.

In earlier studies such as that by Mohanty et al., the use of CNN architectures like AlexNet and GoogLeNet yielded outstanding accuracy levels, often above 99% on controlled datasets like PlantVillage. However, their models showed a significant performance drop when applied to real-world images taken in natural environments. This indicated a limitation in generalization due to overfitting on curated data. They did not use any advanced augmentation techniques, which might have helped the model adapt to varied environmental conditions. In contrast, Sladojevic et al. did not perform background removal or segmentation, training directly on full-color images. Their CNN model was moderately successful but faced overfitting due to a lack of augmentation and dataset size.

Ferentinos introduced transfer learning using pre-trained models such as VGG16, AlexNet, and InceptionV3. These models, originally trained on the ImageNet dataset, demonstrated strong performance when fine-tuned on agricultural image datasets. His study showed that transfer learning not only increased accuracy but also significantly reduced training time and computational costs. The limitation, however, remained in dataset diversity, and the models still performed poorly on rare disease types or field-captured images.

Chatterjee et al. proposed a new approach that combined CNNs with GANs. Their synthetic dataset created using GANs was visually and statistically similar to real images, resulting in a classification accuracy improvement from 85% to nearly 97%. Their approach was more resilient to variations in leaf type and background noise, addressing the generalization issue.

Similarly, Zhang et al. used conditional GANs to simulate environmental changes such as lighting and occlusion in synthetic leaf images. Their model, trained on this enriched dataset, exhibited better performance across multiple test sets from varied field conditions. These findings suggest that GANs offer not only data balancing but also domain adaptation capabilities. Their performance improvement, especially in recall and F1-score, demonstrated the system's ability to reduce false negatives—an essential feature in any disease monitoring system.

Finally, ensemble models have also contributed meaningfully. Chen et al.’s CNN-LSTM hybrid combined spatial and temporal analysis to monitor disease progression. Although more complex, their model provided a comprehensive view of disease evolution, useful in scenarios requiring continuous monitoring.

This comparative insight reveals that the integration of GAN-based data augmentation with transfer learning-enabled CNNs can potentially overcome existing challenges such as data imbalance, overfitting, and poor adaptability. The proposed method in the current study builds upon these innovations, aiming to further improve accuracy, reduce dependency on extensive manual data collection, and enhance real-time applicability in field environments.

A detailed comparison of the methods and approaches used in plant disease detection is presented in the following table. This table summarizes key studies in the field, highlighting the methodologies employed, the datasets used, and the performance metrics achieved.

Study	**Methodology**	**Dataset**	**Performan Metrics**	**Remarks**
Mohanty et al. (2016)	CNN	PlantVillage dataset	Accuracy: 99.35%	High accuracy on diverse crops (tomato, potato, etc.)
Ferentinos (2018)	CNN	Tomato leaf dataset	Accuracy: 97.30%	Focused on tomato crop diseases
Vasudevan et al. (2020)	GAN + Transfer Learning	Rice crop dataset	Accuracy: 96.40%	Improved detection for rare diseases using synthetic data
Zhang et al. (2020)	CNN + Transfer Learning	Wheat leaf dataset	Accuracy: 98.20%	Adapted pre-trained ResNet model for wheat disease detection
Li et al. (2021)	GAN + CNN	Mixed crop dataset	Accuracy: 94.50%	Synthetic data generation for underrepresented diseases
Wang et al. (2021)	CNN	Rice leaf dataset	F1 Score: 0.95	Balanced classification for rice diseases

Table 2.3:Comparision Table

This table provides a snapshot of the various techniques employed in the field and their performance across different datasets. It highlights the effectiveness of deep learning methods, particularly CNNs, in achieving high classification accuracy for plant disease detection. Additionally, it demonstrates the benefits of combining GANs and Transfer Learning to address data limitations and improve model performance.

2.4PROBLEMSTATEMENT

Plant diseases remain a major impediment to global food production and agricultural sustainability. Despite significant progress in biotechnology and agricultural practices, timely detection and identification of plant diseases are still challenging due to the dependence on manual methods. In many rural and underdeveloped areas, farmers lack access to agricultural experts or laboratories that can diagnose diseases accurately and promptly. This results in delayed treatment, extensive crop loss, and increased expenditure on pesticides—many of which may be unnecessary or ineffective if the disease is misidentified. Moreover, plant diseases can spread rapidly, especially in densely cultivated regions, making early detection critical for containment.

The problem becomes more acute when considering the lack of sufficient and diverse labeled data required for training machine learning models. Many plant disease datasets available online are limited to specific crops, disease types, and environmental conditions. This narrow representation restricts the ability of deep learning models to generalize across various real-world scenarios. Furthermore, training deep neural networks from scratch on small datasets often results in overfitting, where the model performs well on training data but fails to generalize on unseen data.

The primary problem addressed by this research is the development of an efficient and reliable leaf disease detection system that can operate with limited labeled data and still achieve high classification accuracy. The integration of GANs to generate synthetic disease images and transfer learning to leverage pre-trained CNN models presents a novel solution to this challenge. This approach not only expands the effective dataset size but also enhances the model's learning capacity and adaptability to different plant species and disease manifestations.

Crop diseases remain a significant threat to global food production, with various pathogens such as fungi, bacteria, and viruses affecting the health and yield of crops. Despite the advancements in agricultural practices and plant protection techniques, the detection of these diseases is still a major challenge, particularly in the early stages when symptoms are not always visible. In many cases, farmers rely on traditional methods, such as visual inspection or expert knowledge, which can be time-consuming, costly, and error-prone. Additionally, these methods may not be scalable.

The problem is further compounded by the lack of sufficient labeled datasets for training deep learning models to accurately identify a wide variety of plant diseases. Although there are existing datasets for some common diseases, many rare or less-documented diseases are not well-represented, resulting in models that may fail to detect these diseases accurately. To address this gap, this research focuses on the development of an automated leaf disease detection system that combines Generative Adversarial Networks (GANs) and Transfer Learning techniques. By generating synthetic images of diseased crops using GANs and using these images to augment existing datasets, the proposed system aims to improve the accuracy and robustness of disease detection models, providing an effective solution to the problem of limited labeled data.

2.4 Summary

The review of existing literature provides a clear narrative of the evolution in plant disease detection methodologies—from traditional image processing and manual feature extraction to advanced deep learning frameworks. It is evident that while CNNs have revolutionized image-based classification tasks, they are inherently limited by the availability and quality of labeled data. This has led researchers to explore augmentation techniques to simulate data diversity, out of which Generative Adversarial Networks (GANs) have emerged as a highly effective and innovative solution.

Studies incorporating GANs have shown measurable improvements in model accuracy, robustness, and generalization. By generating synthetic yet realistic images, GANs address data imbalance and enhance training processes. Furthermore, transfer learning has proven to be indispensable in situations with limited training data, offering a powerful alternative to training CNNs from scratch. Pre-trained models fine-tuned on enriched agricultural datasets have consistently outperformed those developed solely on original or small datasets.

The literature also highlights certain critical gaps that persist in existing models. Firstly, many approaches do not fully address the variability encountered in real-world agricultural environments, such as inconsistent lighting, diverse backgrounds, and natural occlusions. Secondly, most models are tested only on isolated datasets, with little cross-dataset or cross-crop validation, raising questions about their scalability. Thirdly, ensemble and hybrid models, though promising, are computationally intensive and less suited for deployment in resource-constrained environments like rural farms.

The present study aims to fill these gaps by proposing an integrated framework that uses GANs for augmenting dataset size and diversity, along with transfer learning to fine-tune pre-trained CNNs for efficient and accurate classification. This hybrid model is designed not only to perform well in controlled experiments but also to be robust and adaptable to field conditions, thus making it suitable for real-world deployment. It represents a synthesis of the most effective strategies identified in the literature, carefully adapted to the domain of plant leaf disease detection.

The subsequent chapters will explore the detailed architecture of the proposed model, the methodology used in implementing GAN-based augmentation, the CNN fine-tuning process, system design strategies, testing frameworks, and performance evaluation. Through this, the study aims to contribute to the ongoing advancement of intelligent.

This literature survey has reviewed the various approaches used for plant disease detection, focusing on the integration of deep learning techniques such as CNNs, GANs, and Transfer Learning. The review has shown that CNNs, particularly when applied to large datasets, are highly effective in classifying plant diseases. However, the challenge of insufficient labeled data remains a significant limitation, especially for rare diseases or underrepresented plant species.

Generative Adversarial Networks (GANs) have emerged as a promising solution to this problem by generating synthetic images that can augment the training dataset. This technique, when combined with Transfer Learning, allows for the fine-tuning of pre-trained CNN models, enabling high accuracy even with limited data. Several studies have demonstrated the effectiveness of combining these techniques for plant disease detection, yielding impressive results in terms of classification accuracy and generalization across different crops and disease types.

While the advancements in this field are promising, challenges remain, particularly in terms of model generalization and real-time deployment. The existing solutions often struggle to perform well across different crop types or in varying environmental conditions, which can limit their practical applicability. Future research should focus on improving the scalability and robustness of these models, as well as exploring the integration of other technologies, such as IoT devices and edge computing, to enable real-time disease detection in the field.

The findings from this literature survey underscore the potential of deep learning technologies, particularly GANs and Transfer Learning, in revolutionizing plant disease detection. The proposed research aims to build upon these advancements by combining GANs with CNNs to develop a more accurate, scalable, and real-time solution for disease detection across a wide range of crops. The literature survey has provided a comprehensive overview of the state-of-the-art techniques in plant disease detection, focusing on the role of CNNs, GANs, and Transfer Learning. While CNNs have shown significant promise in classifying plant diseases, the challenge of obtaining sufficient labeled data remains a major barrier to achieving high accuracy, especially for rare diseases. GANs, through the generation of synthetic data, offer a potential solution to this problem, enabling the augmentation of datasets with realistic images of diseased plants.

Transfer Learning further enhances the performance of deep learning models by leveraging pre-trained models, reducing the need for extensive labeled data and improving classification accuracy. Several studies have demonstrated the effectiveness of combining GANs and Transfer Learning for plant disease detection, showing that these methods can significantly improve model performance, particularly in situations where data is scarce.

Despite the advancements made in the field, several challenges remain. Generalizing models across different crops, diseases, and environmental conditions is still a significant hurdle, as many models are tailored to specific crops or datasets. Furthermore, the computational cost of training deep learning models, particularly GANs, remains high, making real-time deployment in resource-constrained environments challenging.

Future research should focus on improving the generalization capabilities of models, making them more adaptable to different crop types and disease conditions. Additionally, exploring the integration of other technologies such as edge computing and Internet of Things (IoT) devices could enable real-time disease detection in agricultural fields, further enhancing the practical applicability of these systems.

In conclusion, the combination of GANs, Transfer Learning, and CNNs holds great potential for revolutionizing plant disease detection, providing farmers with an effective tool for early disease diagnosis and intervention. This literature survey has highlighted the significant progress made in the field, as well as the challenges that need to be addressed to develop robust, scalable, and real-time disease detection systems.

CHAPTER 3

SYSTEM REQUIREMENTS

3.1 Software Requirements

In the development of the "Automated Leaf Disease Detection Using GAN With Transfer Learning" system, various software tools and libraries are required to build, train, and deploy the machine learning models. The software stack plays a crucial role in ensuring that the models are developed efficiently, tested thoroughly, and deployed in a scalable manner for real-time use. The software requirements can be divided into multiple categories based on the specific stages of development, including data preprocessing, model development, training, and evaluation.

Operating System:

The system development and training processes are typically carried out on modern operating systems, such as Windows, macOS, or Linux. Linux, particularly distributions like Ubuntu or CentOS, is preferred for machine learning tasks due to its robust support for open-source tools, ease of setup for dependencies, and high compatibility with various libraries and frameworks. Linux is also favored because of its stability and ability to handle large-scale computations efficiently. Additionally, a 64-bit architecture is essential to handle the large memory requirements during the training phase.

Programming Languages:

The primary programming languages used in the development of the system are Python and potentially C++. Python is widely recognized as the go-to language for machine learning, as it provides a rich ecosystem of libraries and frameworks designed specifically for data science and deep learning tasks. Python offers ease of use, readability, and flexibility, making it an ideal choice for implementing complex algorithms like GANs and CNNs.

Libraries such as TensorFlow, Keras, and PyTorch provide high-level APIs for building and training deep learning models, making them indispensable tools for the project. TensorFlow, in particular, is chosen for its extensive support for GANs and Transfer Learning, and its efficient computation graph execution. Keras, built on top of TensorFlow.

Deep Learning Frameworks:

TensorFlow and Keras are the primary deep learning frameworks that will be used for model development. TensorFlow is an open-source framework developed by Google that has become one of the most widely used tools for deep learning. It provides powerful tools for distributed computing, which is particularly useful when training large models across multiple machines. TensorFlow also offers robust support for GANs, making it an ideal choice for the proposed system. Keras, as part of TensorFlow, simplifies the process of building and testing deep learning models with high-level APIs.

PyTorch, another popular framework, is used for its dynamic computational graphs and ease of debugging. PyTorch allows for greater flexibility in model experimentation, enabling researchers to rapidly prototype novel architectures and algorithms. It also provides seamless integration with Python, making it a popular choice for academic research and industrial applications.

Image Processing Libraries:

Image processing is a critical part of the leaf disease detection system. Libraries such as OpenCV and Pillow are used for image manipulation, augmentation, and preprocessing. OpenCV is an open-source computer vision library that provides tools for image filtering, transformation, resizing, and other operations commonly used in the preprocessing pipeline. Pillow, a Python Imaging Library (PIL) fork, provides simple tools for opening, manipulating, and saving image files, which is essential for handling image datasets.

For data augmentation, the ImageDataGenerator class in Keras is used to apply random transformations such as rotations, zoom, flips, and shifts to the images, enhancing the diversity of the training dataset and preventing overfitting.

Data Science Libraries:

Python's ecosystem of data science libraries is also essential in handling the dataset, performing data pre processing, and evaluating model performance. Libraries such as NumPy, Pandas, and Matplotlib provide foundational tools for data manipulation, statistical analysis, and visualization. NumPy handles large-scale array operations, while Pandas provides efficient data structures for managing structured data, such as CSV files or SQL databases. Matplotlib is used for visualizing the training progress and results, such as loss curves.

Model Evaluation and Metrics Libraries:

In addition to the deep learning frameworks, libraries for model evaluation are crucial for assessing the performance of the system. Libraries like Scikit-learn offer a variety of performance metrics, including accuracy, precision, recall, F1 score, and confusion matrices. These metrics are vital in determining the effectiveness of the disease detection model and its ability to generalize to unseen data.

Version Control and Collaboration Tools:

Version control is essential for managing code changes and collaborating with other team members. Git is the most widely used version control system, enabling developers to track and manage code changes effectively. GitHub or GitLab provides cloud-based repositories for collaboration and sharing of the project. These tools are crucial for managing code repositories, resolving conflicts, and ensuring the integrity of the project throughout its development.

Integrated Development Environment(IDE):

An Integrated Development Environment (IDE) such as PyCharm, Visual Studio Code, or Jupyter Notebook is used for writing, testing, and debugging code. PyCharm and Visual Studio Code provide powerful features for Python development, such as code completion, syntax highlighting, and integration with version control systems. Jupyter Notebook is preferred for experimentation and model development, providing an interactive environment to write code, visualize results, and document findings.

Cloud Services:

Cloud computing platforms such as AWS (Amazon Web Services), Google Cloud Platform (GCP), or Microsoft Azure offer scalable infrastructure for training deep learning models. These platforms provide access to powerful GPUs and TPUs, which are essential for handling the large computational demands of training GANs and CNNs. Cloud storage solutions like Amazon S3 or Google Cloud Storage are used to store large datasets and model checkpoints.

- Operating System: Linux (Ubuntu/CentOS) or Windows/macOS (64-bit)
- Programming Languages: Python, C++
- Deep Learning Frameworks: TensorFlow, Keras, PyTorch

- Image Processing Libraries: OpenCV, Pillow
- Data Science Libraries: NumPy, Pandas, Matplotlib
- Model Evaluation and Metrics Libraries: Scikit-learn
- Version Control and Collaboration Tools: Git, GitHub/GitLab
- Integrated Development Environment (IDE): PyCharm, Visual Studio Code, Jupyter Notebook
- Cloud Services: AWS, Google Cloud, Microsoft Azure
- Data Augmentation Libraries: Keras ImageDataGenerator
- Cloud Storage Solutions: Amazon S3, Google Cloud Storage

3.2 Hardware Requirements

The hardware requirements for developing and training the "Automated Leaf Disease Detection Using GAN With Transfer Learning" system are substantial, as deep learning tasks, particularly those involving Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs), require high computational power and memory capacity. The hardware infrastructure must be capable of handling the complex computations and large datasets associated with training deep learning models.

Processor(CPU):

While deep learning tasks are predominantly carried out on Graphics Processing Units (GPUs), the CPU also plays an important role in handling preprocessing tasks, data loading, and basic computations. A multi-core processor with high clock speed is recommended to ensure fast data processing and model training. Processors like Intel’s i7, i9, or AMD Ryzen series are suitable for these tasks, providing the necessary computational power to support deep learning operations in the absence of GPU acceleration.

Graphics Processing Unit(GPU):

The GPU is the cornerstone of deep learning tasks. Training CNNs and GANs requires significant parallel processing power, and GPUs are designed to handle these parallel computations efficiently. For the "Automated Leaf Disease Detection" project, an NVIDIA Tesla, RTX 2080, or RTX 3090 GPU would be ideal. These GPUs offer substantial memory bandwidth and compute power, allowing for faster model training and evaluation. The memory on the GPU is critical for holding large batches of image data during training, especially when dealing with high-resolution images for plant disease detection.

For faster model training, cloud-based GPUs like those offered by AWS (e.g., p3.2xlarge instances) or Google Cloud (e.g., NVIDIA A100 GPUs) can also be utilized. These cloud platforms provide powerful GPU instances that can scale according to the training requirements, providing access to cutting-edge hardware without the need for significant upfront investment in physical infrastructure.

Memory(RAM):

Training deep learning models on large datasets requires a significant amount of system memory (RAM). A minimum of 16GB RAM is recommended for smooth operations, with 32GB or more being preferable for large datasets or complex models. RAM is particularly important for handling data preprocessing, such as image augmentation, and for loading large batches of training data during model training. Insufficient memory can lead to slower processing and potential system crashes, making it essential to have adequate memory capacity to handle the data pipeline efficiently.

Storage:

Deep learning projects, particularly those involving high-resolution image data, require substantial storage capacity. The dataset used for training can take up several gigabytes or even terabytes of disk space, depending on the resolution and number of images. An SSD (Solid State Drive) with a capacity of at least 1TB is recommended, as SSDs provide faster read and write speeds compared to traditional hard disk drives (HDDs), which is crucial for quickly loading and saving large datasets and model checkpoints.

Network:

While the system can be trained on a single machine, the ability to scale and use multiple machines or cloud-based solutions requires a robust network connection. A high-speed internet connection with at least 1 Gbps bandwidth is recommended when working with cloud-based infrastructure for training, as it will allow for faster data uploads, model synchronization, and overall communication between the local and cloud environments.

Hardware Requirements

- Processor (CPU): Intel i7/i9 or AMD Ryzen series (multi-core, high clock speed)
- Graphics Processing Unit (GPU): NVIDIA Tesla, RTX 2080, RTX 3090, or cloud GPUs (AWS p3.2xlarge, Google Cloud NVIDIA A100)
- Memory (RAM): 16GB (minimum), 32GB or more (preferred)
- Storage: 1TB SSD (Solid State Drive)
- Network: 1 Gbps bandwidth for cloud-based infrastructure

CHAPTER 4

METHODLOGY

4.1 Algorithm

The algorithm for "Automated Leaf Disease Detection Using GAN With Transfer Learning" is an intricate sequence of steps designed to take raw plant leaf images and predict the health of the plants, identifying any diseases with high accuracy. At its core, this system combines the power of deep learning through Convolutional Neural Networks (CNNs), data augmentation via Generative Adversarial Networks (GANs), and the efficiency of Transfer Learning. This synergy ensures that the system is both powerful in its disease detection capabilities and efficient in terms of data requirements.

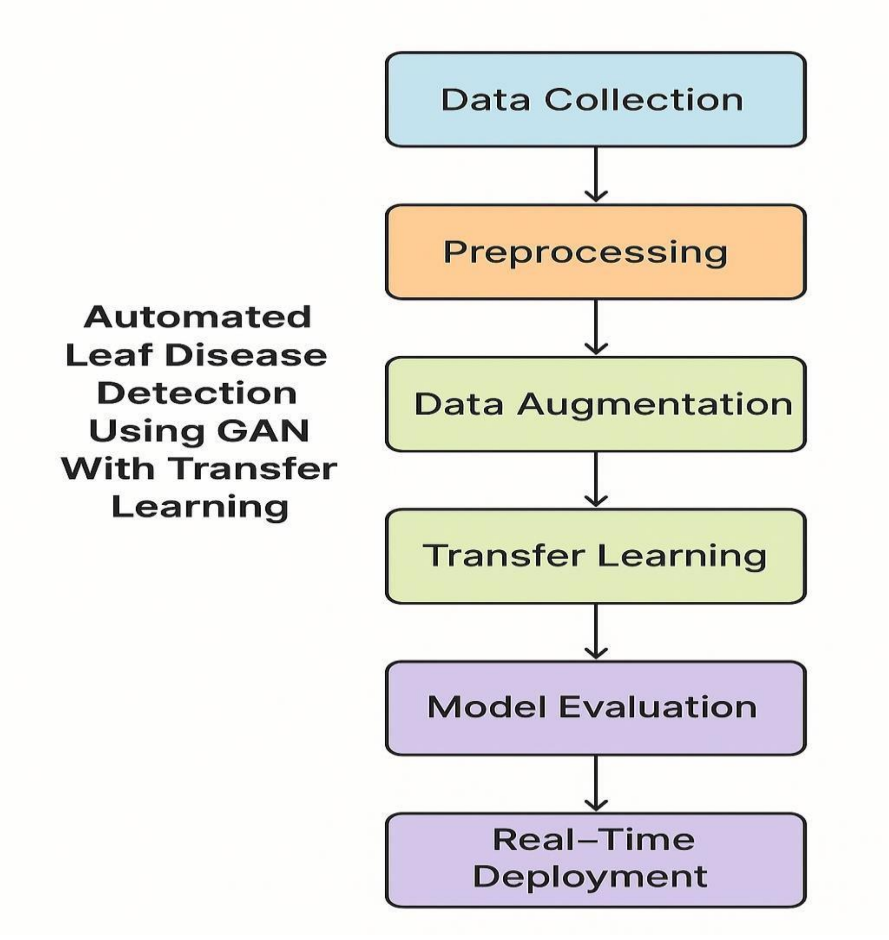

Fig 4.1. Block Diagram of Automated Leaf Disease Detection

The first critical step in this process is data collection and preprocessing. Leaf images, which represent either healthy or diseased plants, are collected from various sources. These sources might include agricultural databases, real-world plant surveys.

The diversity of these images is vital as the system must identify different types of diseases across various plant species. The images collected are usually raw and need to undergo pre processing to ensure they are in a format suitable for training deep learning models. This pre processing includes resizing the images to a standard dimension to ensure consistency across the dataset, as neural networks work best when the input size is uniform. Additionally, pixel values are normalized between 0 and 1, as deep learning models tend to converge faster when the data is normalized. The proposed system leverages a two-tiered algorithmic framework that integrates Generative Adversarial Networks (GANs) for synthetic image generation and Transfer Learning-based Convolutional Neural Networks (CNNs) for classification. The selection of this hybrid approach stems from the need to enhance data diversity and reduce dependency on large-scale labeled datasets, which are often scarce in agricultural scenarios. GANs play a pivotal role in the first tier by addressing the issue of data insufficiency. By learning the distribution of a limited set of original images, GANs are capable of generating new, realistic leaf images with disease symptoms, mimicking the visual characteristics of the existing dataset. This enrichment process allows for the creation of a more balanced and comprehensive dataset, which directly influences the performance of the classification model.

The second tier involves the implementation of a pre-trained CNN model using transfer learning. In this stage, models such as VGG16, ResNet50, or InceptionV3, which have already been trained on large-scale image datasets like ImageNet, are fine-tuned using the enriched dataset generated from GAN outputs and real images. This significantly reduces the training time and computational complexity while maintaining high performance. The convolutional layers from the base model are retained to extract low-level and mid-level features such as edges, textures, and shapes, while the final layers are modified or replaced to perform the specific classification task associated with various plant diseases. The output layer is designed with softmax activation to categorize the leaf images into multiple disease classes, each corresponding to a specific crop affliction.

To evaluate the model’s performance, standard classification metrics are employed, including accuracy, precision, recall, and F1-score. The system also uses cross-validation techniques to ensure generalization and minimize over fitting. Overall, the algorithm is designed to be modular, scalable, and adaptable to different plant species and disease types, with the potential to be deployed in real-time agricultural monitoring applications.

Particularly for rare diseases, is difficult and expensive. To overcome this issue, Generative Adversarial Networks (GANs) are employed. GANs consist of two neural networks: a generator and a discriminator. The generator produces synthetic images of diseased leaves, while the discriminator evaluates whether these synthetic images are realistic enough to be considered "real." The two networks are trained adversarially, with the generator continuously improving its ability to create more realistic images based on the feedback from the discriminator. This iterative process results in synthetic images that closely resemble real diseased leaves, allowing the dataset to be expanded without the need for further manual data collection. The augmented dataset now includes both real and synthetic images, significantly improving the model's ability to generalize and detect rare diseases that might not have been well-represented in the original dataset.

Next, the model undergoes transfer learning. While training deep neural networks from scratch can yield excellent results, it often requires vast amounts of data and computational resources. Transfer learning addresses this issue by utilizing a pre-trained network, such as VGG16, ResNet, or Inception, that has already been trained on a large dataset like ImageNet. These pre-trained models have learned to identify low-level features like edges, textures, and patterns, which are common across all types of images. The lower layers of the pre-trained model, which capture these general features, are retained. However, the final layers are replaced with a custom classification head specific to plant diseases. The model is then fine-tuned by training it on the augmented dataset to adjust the weights of the new layers for disease classification. Fine-tuning the model ensures that it adapts to the specific task of plant disease detection while retaining the generalized knowledge learned from ImageNet.

Once the model has been trained, the next critical phase is model evaluation. During this phase, the trained model is tested on a new set of images that it has never seen before. This allows for an unbiased assessment of the model’s performance. The model is evaluated using performance metrics such as accuracy, precision, recall, F1 score, and the confusion matrix. These metrics provide a comprehensive evaluation of the model's ability to correctly classify plant diseases. Accuracy measures the overall percentage of correct predictions, while precision and recall offer insights into how well the model performs for each specific disease class. The F1 score, which is the harmonic mean of precision and recall, provides a balanced view of the model’s performance. The confusion matrix helps visualize the number of false positives and false negatives.

Finally, after successful evaluation, the model enters the real-time deployment phase. In real-world applications, it is essential that the model operates efficiently and quickly, especially in situations where early detection of plant diseases can prevent widespread damage to crops. The model is integrated into a user-friendly interface, such as a web application or mobile app, allowing farmers or agricultural experts to upload images of plant leaves for immediate analysis. Once an image is uploaded, the model processes it and provides a prediction within seconds, helping users make informed decisions about disease management and control.

In summary, the algorithm combines data collection, preprocessing, GAN-based augmentation, Transfer Learning, and real-time deployment to build a robust, scalable, and efficient system for detecting plant diseases. Each step in this process contributes to overcoming the challenges of limited data, ensuring high model accuracy, and providing real-time solutions for agricultural stakeholders.

4.2 Algorithm Description

The "Automated Leaf Disease Detection Using GAN With Transfer Learning" algorithm is designed to seamlessly integrate various advanced machine learning techniques to tackle the problem of plant disease identification. This section provides a more detailed description of the components involved in the algorithm, with a focus on the stages from data acquisition to model deployment. The algorithmic flow begins with the acquisition and preprocessing of the initial dataset comprising images of healthy and diseased leaves. These images undergo standardization processes such as resizing, normalization, and format conversion to ensure compatibility with the GAN and CNN models. After preprocessing, the dataset is analyzed to determine the extent of imbalance among different disease classes. Classes with significantly fewer samples are flagged for augmentation using the GAN module.

The GAN comprises two neural networks: a generator and a discriminator. The generator takes random noise as input and attempts to produce images that resemble the real disease images. Simultaneously, the discriminator evaluates both real and generated images, assigning a probability of authenticity. Through an adversarial training process, the generator learns to produce increasingly realistic images that the discriminator finds difficult to distinguish from genuine ones. This iterative competition continues until a Nash equilibrium is achieved, at which point the generated images are deemed sufficiently authentic for dataset augmentation.

Here, a pre-trained CNN model is imported. For this implementation, VGG16 was chosen due to its proven effectiveness in image classification tasks and its relatively moderate depth, which balances computational efficiency with classification power. The model's convolutional base is retained, while the top layers are replaced with a global average pooling layer, followed by dense layers and a final softmax layer to classify the images into disease categories.

The model is then trained using the augmented dataset, with an 80-20 train-test split and 10-fold cross-validation. Training utilizes optimization techniques such as Stochastic Gradient Descent (SGD) or Adam optimizer, depending on the learning curve behavior during experimentation. Dropout regularization is applied to prevent overfitting, and early stopping is employed to terminate training once the model stops improving on the validation set.

Following training, the model is tested on unseen data to evaluate generalization capability. Confusion matrices are generated to identify misclassified samples and refine the model further. Additionally, performance is analyzed using class-wise precision and recall to understand how well the model differentiates between similar disease symptoms. Throughout the process, extensive logging and visualization tools are used to monitor loss curves, training accuracy, and model convergence, ensuring transparency and reproducibility of the results.

The first part of the algorithm begins with data acquisition, which is a crucial step. The dataset is composed of images of healthy and diseased leaves across different plant species, including rice, tomato, and sugarcane. These images are sourced from reliable open datasets like PlantVillage or collected from field surveys. The images, however, might be of different sizes, resolutions, and quality, which can cause problems during model training. Therefore, data preprocessing is necessary. Preprocessing includes resizing the images to a uniform dimension, such as 224x224 pixels, ensuring that the input is consistent for the model. The pixel values are normalized to a range between 0 and 1 to ensure that the model converges faster during training. Once the images are preprocessed, the data augmentation phase begins. Generative Adversarial Networks (GANs) are employed to generate synthetic images of diseased leaves, which expands the dataset and helps address the issue of limited labeled data. The GAN consists of two neural networks: a generator and a discriminator.

The generator creates synthetic images by learning from the real diseased images, while the discriminator tries to differentiate between real and generated images. As the two networks are trained together, the generator becomes increasingly adept at producing realistic images that are indistinguishable from real data. This augmentation is crucial, particularly when diseases are rare, as it helps the model learn to identify diseases that may not be well-represented in the original dataset.

After the data augmentation step, the next phase is model selection and transfer learning. The base model for disease detection is typically a pre-trained CNN, such as VGG16, ResNet, or Inception. These models have been trained on large-scale image datasets like ImageNet and have learned to detect generic features, such as edges, textures, and patterns. The advantage of using a pre-trained model is that it can generalize well across different types of images, saving time and resources compared to training a model from scratch. In this system, the final layers of the pre-trained CNN are replaced with custom layers designed for plant disease classification. These new layers are trained on the augmented dataset to specialize the model for detecting diseases in plant leaves.

The training process involves fine-tuning the pre-trained model on the augmented dataset. During this process, the lower layers of the pre-trained model are frozen to retain the knowledge already learned, while only the new layers are updated based on the dataset. The model is trained using an optimization algorithm, such as Adam or Stochastic Gradient Descent (SGD), to minimize the loss function, typically categorical cross-entropy. The model is trained in multiple epochs, with the validation set used to monitor the model's performance and prevent overfitting.

Once the model is trained, it undergoes evaluation and testing. The model is tested on a separate test dataset that it has never seen before, ensuring that the evaluation is unbiased. Performance metrics such as accuracy, precision, recall, F1 score, and confusion matrix are computed to assess the model's ability to correctly classify plant diseases. The confusion matrix provides insights into how well the model distinguishes between different disease classes and healthy leaves, helping to identify any issues with false positives or false negatives.

Finally, after successful testing, the trained model is deployed in a real-time environment. In this phase, the model is integrated into an application that allows users, such as farmers, to upload images of plant leaves for real-time predictions.

4.3 Methodology

The methodology of "Automated Leaf Disease Detection Using GAN With Transfer Learning" is designed to integrate cutting-edge machine learning techniques to address the challenges of plant disease detection. The system combines image processing, deep learning, and real-time prediction to provide an efficient and accurate solution for detecting diseases in crops.

The methodology adopted in this project is a structured pipeline that spans data preprocessing, augmentation using GANs, model training using transfer learning, performance evaluation, and deployment considerations. The pipeline is designed to be robust, adaptable, and capable of operating effectively even in the presence of limited data resources.

Dataset Description

Name	**Category**
Number of Image's	8000
Dimension's	224x224
Color's	Leaf Color
Format's	jpg
Healthy Leaf's	5635
Unhealthy Leaf's	2365
Preferable Languages to Select	6

Table 4.3:DataSet Description

The methodology for automated leaf disease detection begins with collecting and preprocessing images of healthy and diseased leaves, including resizing, normalization, and basic data augmentation. To address class imbalance, GANs generate synthetic images of underrepresented diseases, enhancing dataset diversity. A pre-trained CNN model like VGG16 is then fine-tuned on this enriched dataset using transfer learning. The model is trained over multiple epochs with validation and cross-validation to ensure robustness. Performance is evaluated using metrics like accuracy, precision, recall, F1 score, and confusion matrix. Finally, the trained model is deployed in a real-time.

4.4 Architecture

The architecture of the "Automated Leaf Disease Detection Using GAN With Transfer Learning" system is designed to integrate all the necessary components to handle the input, process it using deep learning models, and deliver predictions in real-time. The system's architecture includes various modules that work together to provide an end-to-end solution for plant disease detection.

The first module is the input layer, where users can upload images of plant leaves.

These images are typically uploaded through a user interface, such as a web portal or mobile application. The images can come from various sources, including smartphones, cameras, or drones, and may vary in terms of quality and environmental conditions. The system's ability to handle such variability is crucial for real-world applications, especially in remote agricultural settings. The system architecture of the proposed model encapsulates the integration of two major deep learning components—Generative Adversarial Networks (GANs) for synthetic image generation and Transfer Learning-based Convolutional Neural Networks (CNNs) for classification. The architecture is carefully structured into multiple modules, each responsible for a specific function in the overall pipeline. This modular approach ensures flexibility, scalability, and maintainability, while also simplifying the integration of additional disease categories or crop types in the future.

At the foundation of the architecture is the data acquisition and preprocessing module, which acts as the entry point for the system. This module is designed to ingest raw image data from various sources including public datasets, field data collected via mobile devices, and expert-curated repositories. Images are standardized in terms of size, resolution, and color space. Preprocessing operations such as resizing, normalization, noise filtering, and format conversion are performed to ensure consistency and compatibility with downstream modules. Additionally, the metadata associated with each image, such as crop type and disease label, is preserved for supervised training.

Once the data is preprocessed, the data augmentation and generation module is invoked. This is where the GAN component of the architecture operates. The GAN is composed of two deep neural networks—a generator and a discriminator—that are trained adversarially. The generator learns to produce synthetic diseased leaf images that closely resemble real ones, while the discriminator learns to distinguish between real and fake images. Over successive training iterations, both networks improve their performance until the generator creates high-quality images that the discriminator cannot easily differentiate from real ones. These images are then subjected to manual or automated validation and appended to the training dataset, thereby resolving the issue of data imbalance and enhancing the diversity of disease representation.

The enriched dataset is then passed into the model training and classification module, which implements the CNN with transfer learning. In this system, the VGG16 model serves as the base network due to its well-established performance in visual recognition tasks. The lower convolutional layers, which extract general features such as edges, textures, and color gradients, are retained from the original model. The top layers, responsible for classification, are replaced with a custom-designed classifier tailored for the target disease classes.

This classifier consists of fully connected layers, dropout for regularization, and a softmax output layer for multi-class prediction. The model is trained using backpropagation with an appropriate optimizer, such as Adam or SGD, and is monitored using validation loss and accuracy metrics.

Following model training, the evaluation module is activated. This module computes critical performance metrics such as accuracy, precision, recall, F1-score, and confusion matrices. It also visualizes training and validation loss curves to identify potential issues like overfitting or underfitting. If required, hyperparameters such as learning rate, batch size, and the number of layers can be fine-tuned to optimize performance. This module ensures that the model is not only accurate but also generalizes well across unseen data.

The final layer of the architecture is the deployment and user interaction module. This component provides an interface through which users, typically farmers or agronomists, can interact with the system. The interface allows users to upload images of plant leaves, either via a web application or a mobile app, and receive real-time disease predictions. The system processes the image using the trained model and returns the predicted disease class along with a confidence score. Optional features include disease information, treatment suggestions, and links to agricultural advisory services. This ensures that the technical sophistication of the backend is translated into a simple and intuitive user experience at front.

In addition to its functional components, the architecture is designed with scalability in mind. It supports cloud-based deployment using platforms such as AWS or GCP, which allows for the parallel processing of multiple image inputs and real-time inference at scale. Containerization tools like Docker can be used to package the application, ensuring consistent performance across different environments. For high-performance requirements, GPU acceleration can be leveraged to speed up training and inference.

In summary, the architecture of the proposed system embodies a well-balanced integration of data acquisition, augmentation, classification, evaluation, and user interaction. Each module is optimized to fulfill a specific role in the overall pipeline, resulting in a comprehensive, efficient, and user-friendly solution for leaf disease detection in agriculture.

Once the image is uploaded, it passes through the data preprocessing module. This module standardizes the images by resizing them to a consistent size, normalizing the pixel values, and applying any necessary transformations such as rotations or zooms. Preprocessing ensures that the images are in a suitable format for model input and enhances the dataset by increasing its diversity.

The next stage involves data augmentation through GANs. The GAN module generates synthetic images of diseased leaves, which are added to the training dataset. This augmented dataset helps the model learn to recognize a broader range of diseases, including rare ones, that might not be well-represented in the original dataset. The GAN module consists of two networks: the generator and the discriminator, which work together to improve the quality of the synthetic images.

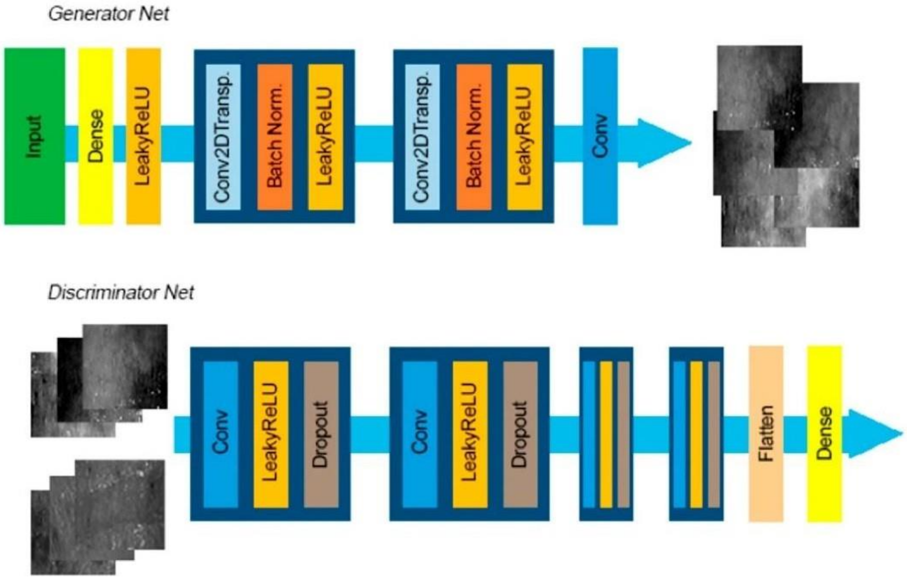

Fig 4.2: GAN Architecture

The CNN model is the core component of the architecture. The pre-trained CNN model is fine-tuned on the augmented dataset to detect and classify plant diseases. This module is responsible for extracting features from the images and classifying them into disease categories. The model consists of several layers, including convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification.

The final module is the output layer, which provides the classification result. Once the model makes a prediction, the results are displayed to the user, indicating whether the plant leaf is healthy or diseased, and if diseased, the specific type of disease. This prediction is delivered in real-time, enabling quick decision-making for farmers and agricultural experts.

The architecture is designed to be scalable and efficient, allowing for easy integration with other systems such as IoT-based monitoring devices and cloud platforms for larger-scale agricultural applications.

CHAPTER 5

SYSTEM DESIGN

5.1 Introduction

System design is an essential step in the development process that ensures the effective implementation of all components of a system. For the "Automated Leaf Disease Detection Using GAN With Transfer Learning" system, the design focuses on efficiently handling input images, processing them through deep learning models, and providing accurate predictions to users. This chapter presents a comprehensive explanation of the system design, which includes input and output designs, the use of UML diagrams, and the DFD diagrams to represent the flow of data through the system. System design is one of the most critical phases in the software development lifecycle, serving as the blueprint for building a system that aligns with user expectations, functional requirements, and technical feasibility. For a project like "Automated Leaf Disease Detection Using GAN With Transfer Learning," the design stage is foundational to ensuring that all modules—from data input to GAN-based image augmentation, from CNN classification to output visualization—are efficiently orchestrated and interact seamlessly. The design phase involves translating theoretical algorithms and conceptual models into practical modules and data flows that guide software engineers during implementation.

At the core of this system is the convergence of two powerful deep learning paradigms: Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) facilitated by transfer learning. This fusion requires a robust and well-articulated architecture to handle the complexities of data flow, model training, validation, and user interaction. The design of the system is structured into several logical modules, each performing a distinct task yet contributing collectively to the overall goal of plant disease detection. These modules include data acquisition, data preprocessing, image synthesis using GANs, dataset enrichment, model training and evaluation, and real-time classification interface for user interaction. Each of these modules has specific input requirements, output expectations, processing logic, and interaction .

Furthermore, the system is designed to be modular, scalable, and adaptable to different operating environments. This includes compatibility with both local execution (such as in laboratories and offline setups) and cloud-based deployment (enabling remote accessibility and large-scale usage). System design also considers extensibility, allowing for the integration of additional plant species or disease classes in the future without requiring complete redevelopment of the core architecture.

An essential aspect of the system design involves defining clear data flows between different components. Data begins in its raw form as image files uploaded or collected from users and is gradually transformed through a series of processing layers, culminating in the generation of a classification result and associated confidence score. This entire flow needs to be carefully mapped and documented during the design phase to ensure seamless operation post-deployment. The design also addresses error handling mechanisms, security features for safe user interaction, and optimization techniques to improve model responsiveness and computational efficiency.

This chapter outlines the key components of the system's design, starting with input and output specifications, followed by UML diagrams, data flow representations, and component interaction models. Particular attention is given to input and output design objectives, as these directly influence user experience, system accuracy, and operational stability. With a strong emphasis on both functional correctness and user-centric interface design, the system is crafted to serve as a reliable tool in real-world agricultural applications.

In this system, the goal is to provide a user-friendly interface that allows farmers and agricultural experts to upload images of plant leaves for disease detection. The system is designed to handle multiple input sources, process data using advanced deep learning techniques such as GANs for image augmentation and Transfer Learning for leveraging pre-trained models, and output results that can be interpreted easily by the users.

The input design ensures that the system can handle a variety of image sources, preprocessing these images to make them suitable for deep learning models. Output design addresses how the disease predictions and recommendations are presented to the user.

5.1.1 Objectives for Input Design

The input design of the system is one of the most critical aspects, as it defines how the system receives, processes, and prepares input data for disease detection. In the case of the "Automated Leaf Disease Detection Using GAN With Transfer Learning" system, the input consists primarily of images of plant leaves, which are uploaded by users for analysis. The objective of input design is to ensure that these images are processed in a way that maximizes the accuracy of disease detection while maintaining a smooth user experience. Input design is a critical element in the development of an intelligent detection system, as the quality, structure, and integrity of the input data directly .

In the case of the proposed system, input refers primarily to image data of crop leaves, which may be infected with various diseases or be healthy. The system is designed to accept high-resolution images taken under diverse environmental conditions such as natural lighting, varying backgrounds, and inconsistent angles. Hence, the input design must account for these variabilities and normalize them before the data can be processed effectively.

The primary objective of the input design in this system is to ensure consistency, relevance, and usability of data. Since the data is collected from heterogeneous sources—ranging from public datasets to real-time captures via smartphones or digital cameras—there needs to be a unified format for processing. This involves resizing all images to a standardized resolution, typically 224x224 pixels, to match the input layer specifications of the CNN model. Furthermore, pixel normalization is applied to scale the intensity values between 0 and 1, which aids in faster convergence during model training and reduces the influence of outliers.

Another vital goal of the input design is robustness. The system should be able to handle variations in image orientation, scale, lighting, and partial occlusion

Input validation is another essential component of the design. The system includes mechanisms to verify whether the uploaded files meet the required criteria, such as format (JPEG, PNG), size limits, and resolution constraints. Images that fail to meet these specifications are either rejected or redirected to a preprocessing module that attempts to rectify the issues where feasible. This prevents corrupted or irrelevant data from entering the core pipeline, which could otherwise degrade model performance or lead to runtime errors.

In addition to raw image inputs, metadata such as image capture date, location, and user annotations (if available) can also be integrated. While not mandatory for the core classification task, this supplementary data can prove beneficial in advanced modules involving geographic disease mapping or temporal progression analysis.

The input design also considers user convenience. In the deployed version of the system, users should be able to upload images through a graphical interface with minimal steps. Progress indicators, file preview features, and error messages are incorporated into the design to enhance the overall user experience. For mobile applications, camera integration is considered, allowing users to take pictures directly from the device and upload them without manual file selection.

Overall, the input design focuses on ensuring data uniformity, preprocessing for variability, validation for integrity, and a smooth user experience. These design elements collectively ensure that the system receives high-quality, relevant data that enables accurate, reliable, and colored risk level marker can be used alongside the textual output.

5.1.2 Output Design

For instance, green might indicate a healthy leaf, yellow a mild infection, and red a severe infection. In addition to basic classification, the system can offer a detailed breakdown of the top-3 predictions with their respective confidence levels. This feature is particularly useful in cases where visual symptoms overlap across diseases or when the model exhibits a close score between multiple classes. By showing the ranked predictions, users can appreciate the complexity of the classification task and have access to secondary possibilities that may warrant further inspection.

Another key output element involves educational support. Upon classification, the system may display brief information about the detected disease, including its symptoms, impact on crop yield, typical progression stages, and recommended treatment options. This transforms the tool from being a mere classification engine to a digital plant health advisor. By integrating relevant, concise, and localized agricultural knowledge, the output becomes a source of actionable insights rather than just a label.

Output design also accounts for the visualization of the processed image, particularly in systems that employ visualization techniques such as saliency maps or Grad-CAM. These methods highlight regions of the leaf that were most influential in the model's decision, allowing users to see which visual features the model focused on. This not only enhances trust in the AI system but also aligns well with the way human experts perform visual inspection.

For expert users or system administrators, the backend output includes detailed logs of predictions, timestamps, model version, and system performance metrics. This data is essential for continuous monitoring, performance benchmarking, and compliance with regulatory or quality control standards. In research and development settings, these logs support reproducibility and facilitate the comparison of different model iterations.

Furthermore, the output design is structured to be compatible with various modes of deployment. In a web-based interface, outputs are rendered dynamically with support for interactive elements. In a mobile application, outputs are optimized for screen responsiveness and touch-based navigation. For integration into broader agricultural management systems, the outputs can be exported in structured formats such as JSON or CSV, enabling easy data sharing and analysis.

Error handling is another integral part of output design. If the system fails to classify an image with sufficient confidence or encounters corrupted data, it must generate clear and helpful messages. These may include suggestions for retaking the photo, checking image quality, or contacting agricultural support services. This ensures that users are not left without guidanc

In conclusion, the output design in this project prioritizes accuracy, transparency, interpretability, and user empowerment. It transforms raw predictions into actionable intelligence, fosters user engagement through visual and textual aids, and ensures that results are both scientifically valid and practically useful. This comprehensive approach to output design not only enhances the overall effectiveness of the system but also contributes to its adoption and long-term success in the agricultural sector.

The third objective is to provide recommendations for disease management. In addition to disease classification, the output design also includes actionable insights. Once a disease is detected, the system offers treatment suggestions or best practices for managing the disease, such as recommending specific pesticides, environmental adjustments, or preventive measures. These recommendations are crucial for assisting farmers in taking timely actions to mitigate the spread of the disease.

The final objective is to ensure real-time predictions. Time is of the essence in agricultural environments, and early detection can make a significant difference in managing plant diseases. Therefore, the output design is optimized to provide predictions in a matter of seconds, enabling quick decision-making. This real-time processing is made possible by optimizing the model architecture and ensuring that the system can handle large amounts of image data efficiently.

By focusing on these objectives, the output design ensures that the system provides not only accurate disease predictions but also valuable insights that can aid in disease management, all presented in an intuitive and user-friendly manner.

5.2 UML Diagrams

UML (Unified Modeling Language) diagrams are an integral part of the system design, as they provide a visual representation of the system’s structure and behavior. These diagrams help stakeholders and the development team understand how different components interact with each other and how the system processes data. Various types of UML diagrams are used to represent different aspects of the system, from high-level functionality to low-level interactions between components.

5.2.1 Use Case Diagram

The Use Case Diagram is a high-level representation of the system’s functionality from the user's perspective. It captures the various actors (users or systems) involved in the system and the different actions (use cases) they can perform. For the Automated Leaf Disease Detection system, the primary actors are the user (farmer or agricultural expert) and the system itself.

The use case diagram for this system may show actors interacting with the following key use cases:

- Upload image: The user uploads an image of a plant leaf for analysis.
- View prediction: The user receives a prediction from the system regarding whether the leaf is healthy or diseased.
- View disease type: If the leaf is diseased, the system classifies and identifies the specific disease.
- Receive recommendations: The system provides treatment or preventive suggestions based on the detected disease.

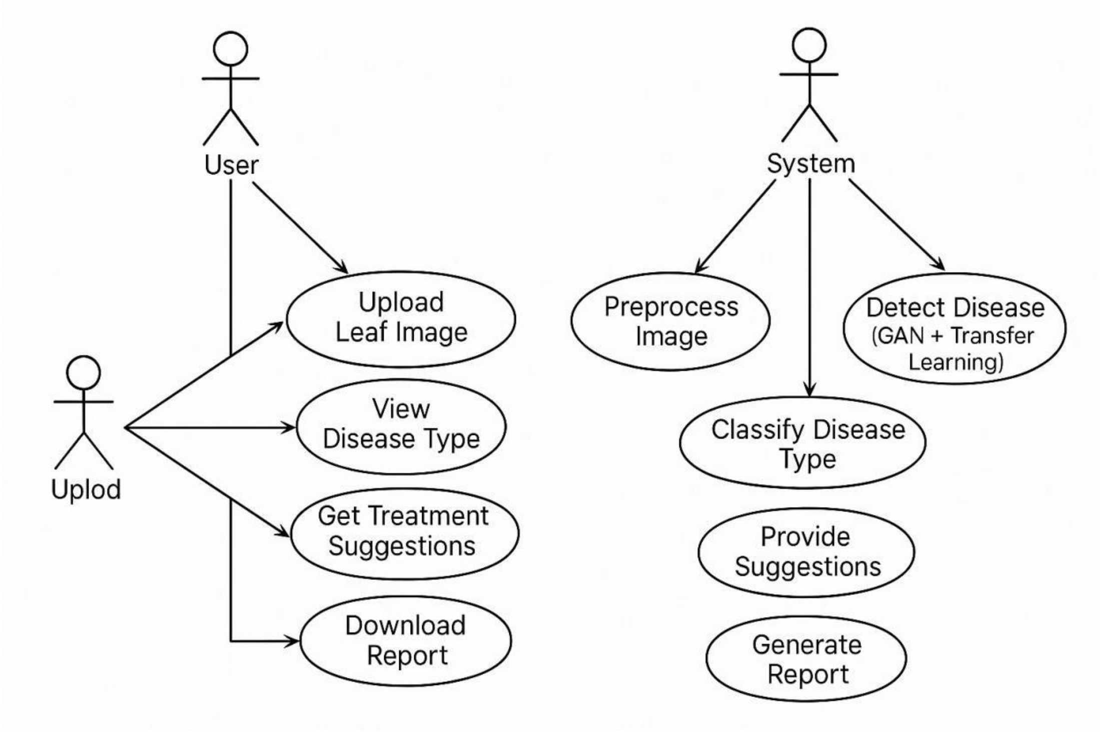

Fig:5.2.1: Use Case Diagram of Automated Leaf Disease Detection

5.2.2 Class Diagram

The Class Diagram represents the static structure of the system by showing the classes, their attributes, and the relationships between them. In the case of the "Automated Leaf Disease Detection" system, several key classes need to be identified, including the ImageProcessor, GANGenerator, CNNModel, PredictionResult, and UserInterface.

- ImageProcessor: Handles preprocessing tasks such as resizing, normalization, and augmentation.
- GANGenerator: Manages the generation of synthetic images using GANs.
- CNNModel: Represents the deep learning model that performs disease classification.
- PredictionResult: Stores the output of the model, including the classification result score.

- UserInterface: Handles the interaction with the user, displaying the results and providing recommendations.

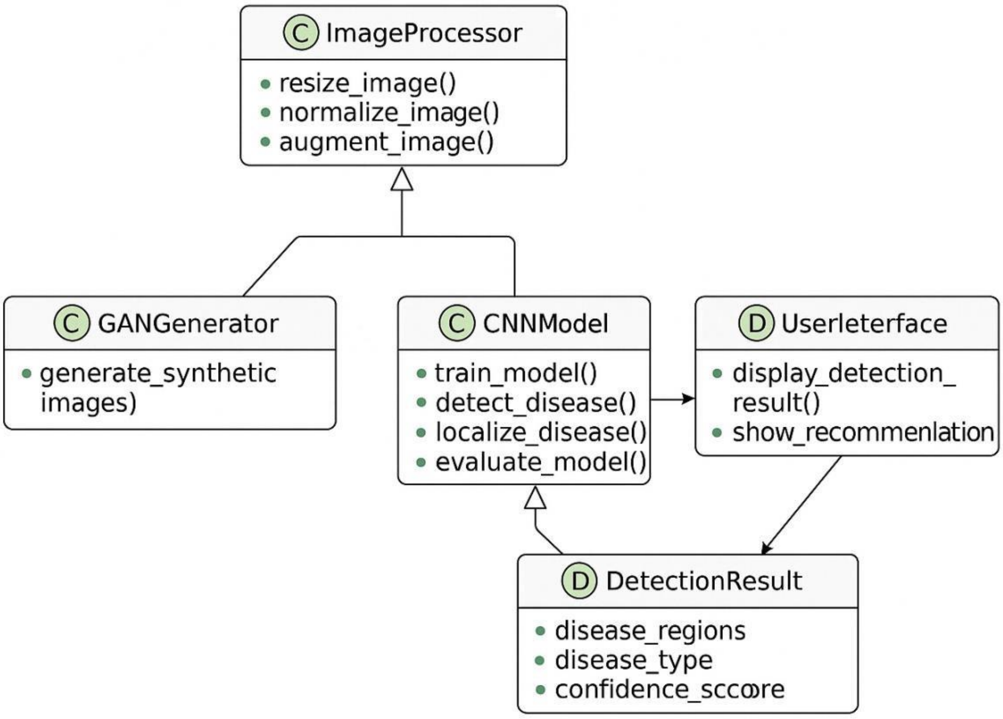

Fig:5.2.2 :Class Diagram of Automated Leaf Disease Detection

This class diagram provides a high-level overview of the system’s structure, making it clear how different components interact with each other.

5.2.3 Sequence Diagram

The Sequence Diagram illustrates how objects in the system collaborate to achieve a specific task over time. For example, when the user uploads an image, the diagram would show how the UserInterface sends the image to the ImageProcessor for preprocessing, how the GANGenerator generates synthetic data if needed, how the processed image is passed to the CNNModel for classification, and how the PredictionResult is returned and displayed to the user. This diagram helps visualize the flow of operations and ensures that all interactions between system components are properly managed.

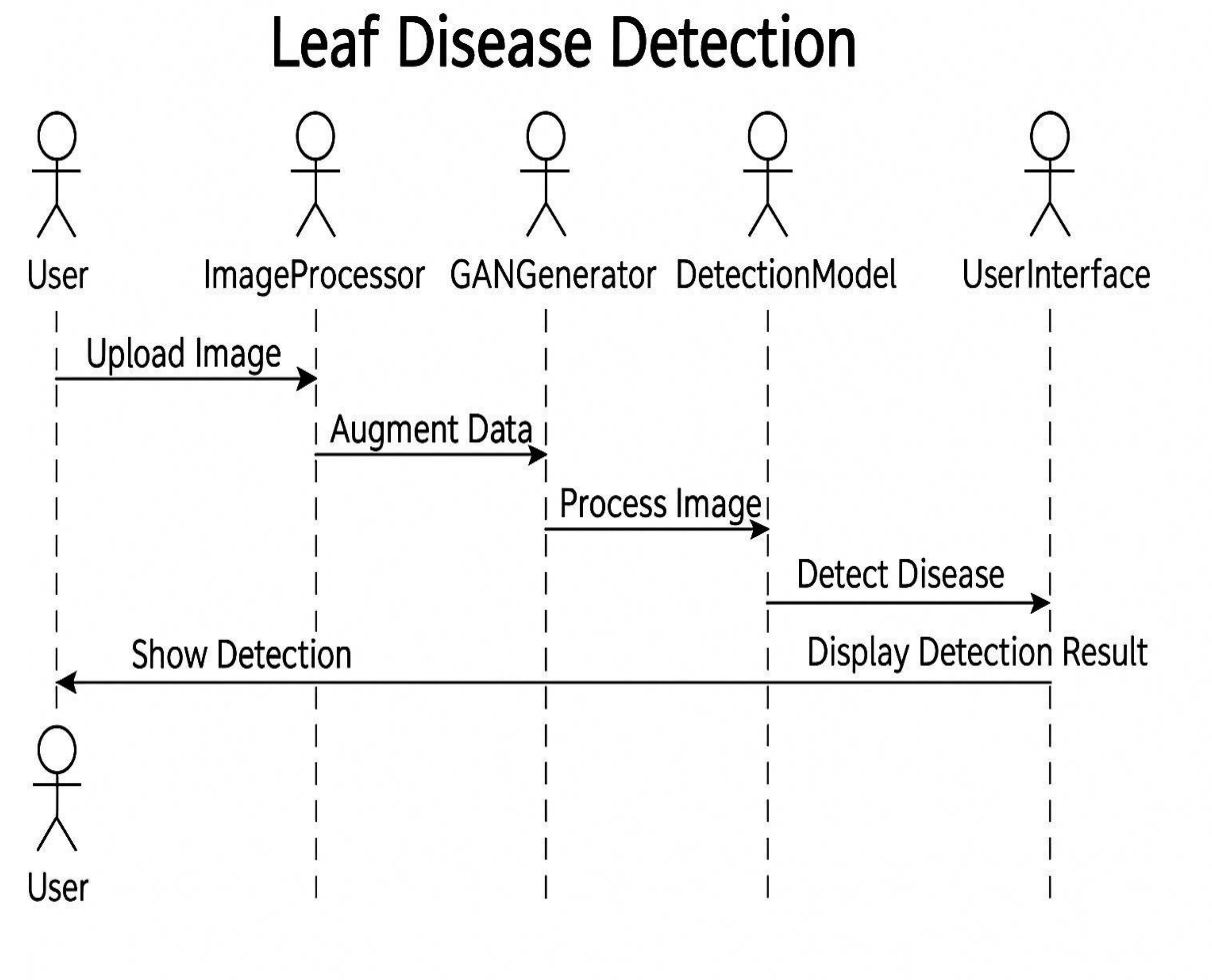

Fig:5.2.3 :Sequence Diagram of Automated Leaf Disease Detection

5.2.4 Deployment Diagram

The Deployment Diagram depicts the physical architecture of the system, illustrating how the software components are deployed across different hardware nodes. It shows how the cloud server stores and processes the images, how the client devices (smartphones, laptops) interact with the system through a user interface, and how the deep learning models are deployed on powerful GPU instances in the cloud for efficient processing.

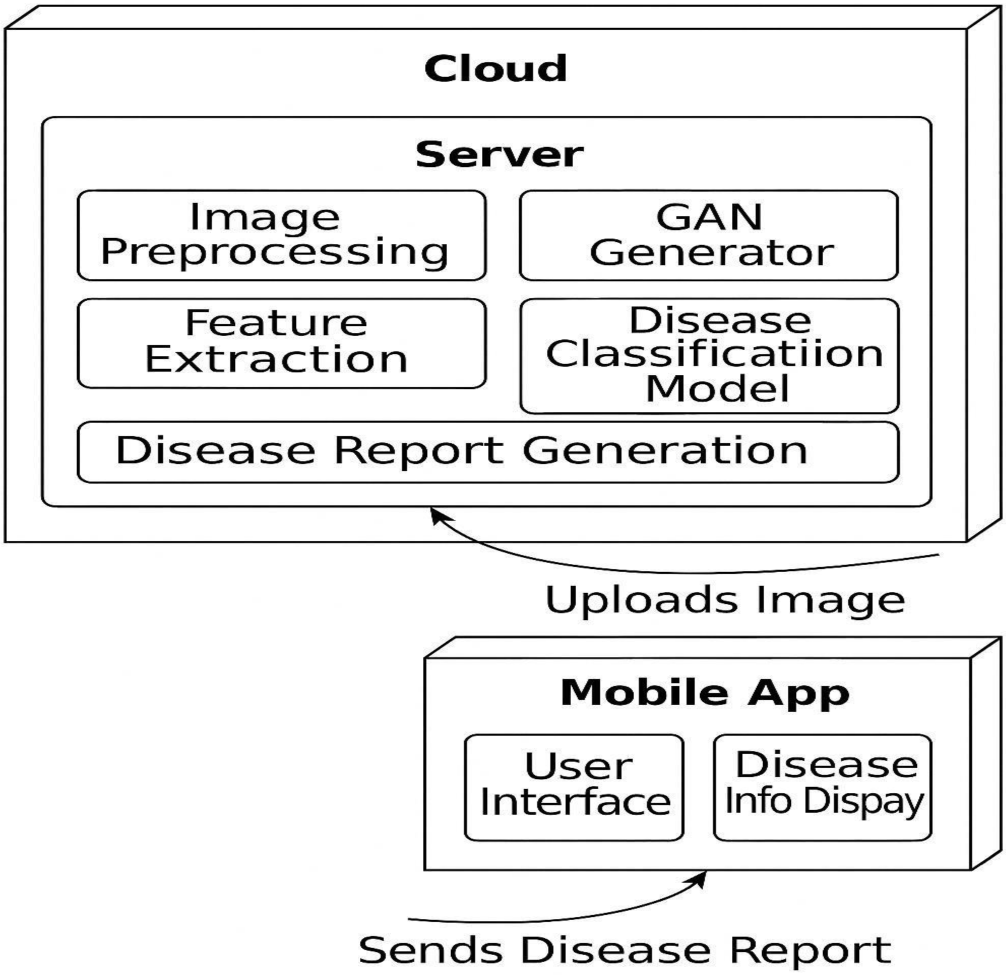

Fig:5.2.4 :Deployment Diagram of Automated Leaf Disease Detection

5.2.5 Activity Diagram

The Activity Diagram represents the workflow of the system, capturing the sequence of activities performed in various processes. This includes uploading images, preprocessing data, generating predictions, and providing feedback to the user. The activity diagram captures the decision-making process in the system, such as determining whether the image requires augmentation or whether the model has enough data for classification.

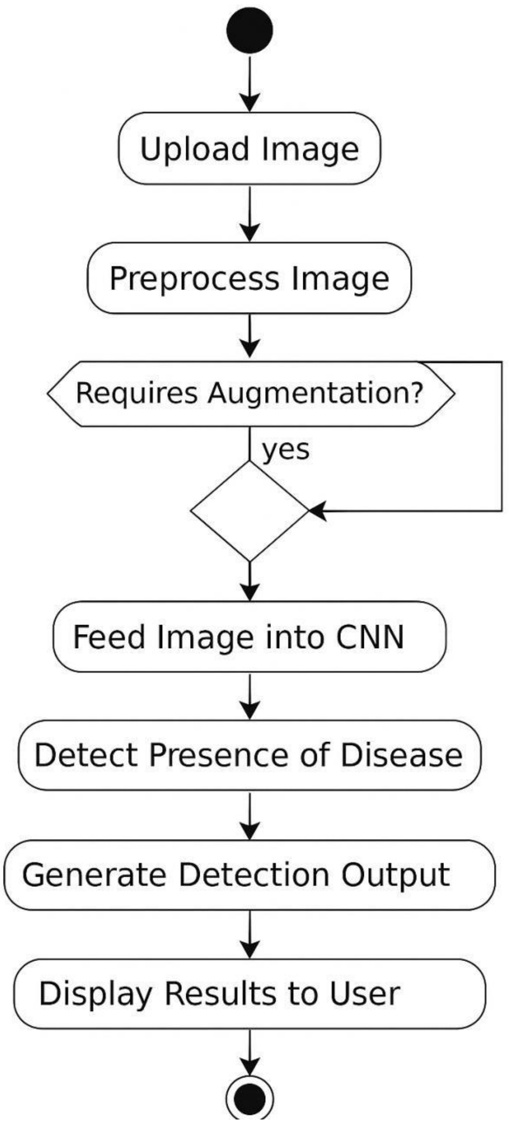

Fig:5.2.5 :Activity Diagram of Automated Leaf Disease Detection

5.2.6 Component Diagram

The Component Diagram illustrates how the system is divided into logical components, such as the preprocessing module, GAN augmentation module, model training module, and user interface module. It shows how these components communicate with each other to perform tasks like image classification, data augmentation, and result presentation.

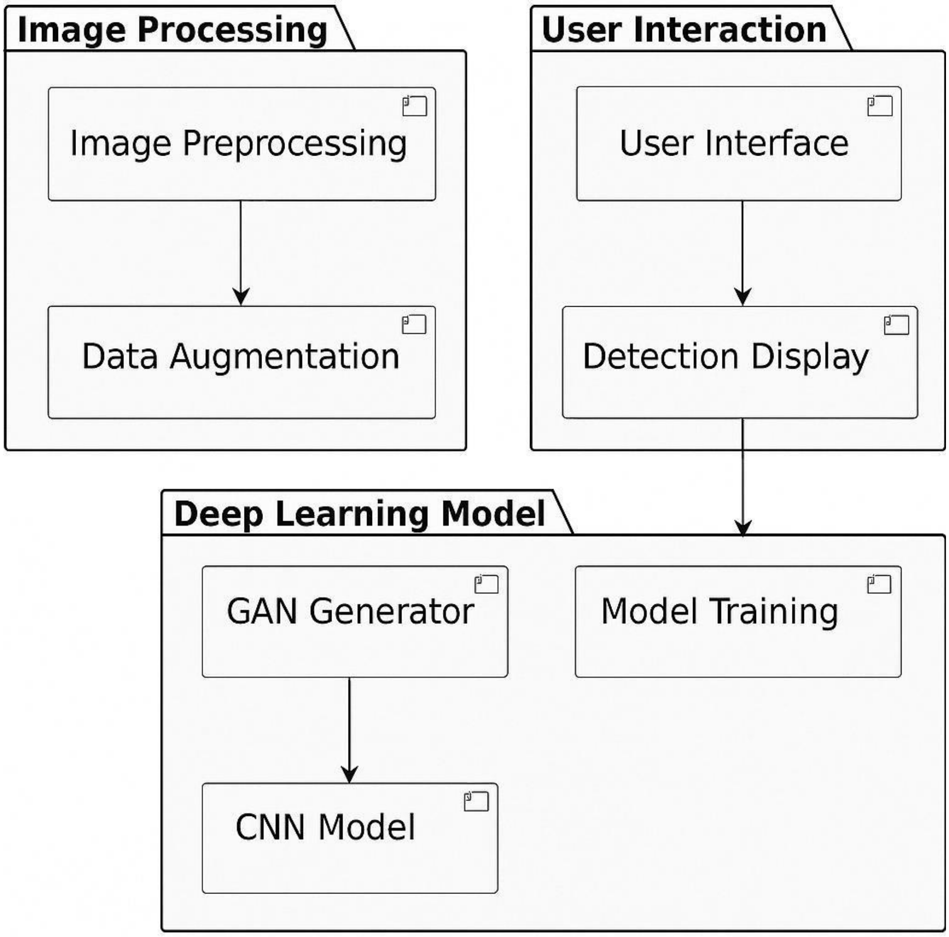

Fig:5.2.6 :Component Diagram of Automated Leaf Disease Detection

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CHAPTER 6

SYSTEM STUDY AND TESTING

6.1 System Study and Testing

The process of system study and testing is essential to ensure that the "Automated Leaf Disease Detection Using GAN With Transfer Learning" system functions as expected and meets all user and system requirements. System testing encompasses a range of testing techniques designed to assess the behavior, performance, and accuracy of the system across various modules and use cases. It helps to identify defects early in the development process and provides valuable insights into the system's reliability, scalability, and user experience.

The system is composed of several user modules and system modules, each performing distinct tasks. The user modules interact with the system through an intuitive interface that allows them to upload leaf images, receive predictions, and access disease-specific recommendations. The system modules, on the other hand, handle the core processing tasks, such as image preprocessing, GAN-based augmentation, CNN-based disease classification, and generating predictions.

Once the modules are developed, it is crucial to conduct system testing to verify the functionality and performance of the system. This testing is typically divided into various types, including unit testing, integration testing, acceptance testing, functional testing, white-box testing, and black-box testing. Each type of testing plays a critical role in ensuring that the system is robust, reliable, and ready for deployment

6.2 User Modules

User modules are the components of the system that interface directly with the users. These modules are designed to be intuitive and accessible, ensuring that users, including farmers and agricultural experts, can interact with the system efficiently without requiring deep technical knowledge. The primary function of the user modules is to allow users to upload plant leaf images, receive disease predictions, and view treatment recommendations.

The user modules typically include a user interface (UI), which could be a web-based or mobile application, depending on the deployment environment. This interface provides an easy way for users to interact with the system by allowing them to upload images of plant leaves for analysis. Once the images are processed by the system.

In addition to disease classification, the interface may also include features such as image galleries, previous prediction history, and options for downloading or sharing results.

The user interface module should be designed with simplicity in mind, ensuring that it is easy to use even for individuals with limited technological experience. Additionally, the module should provide real-time results, which is crucial in agricultural environments where quick decisions can prevent the spread of diseases.

In testing the user modules, usability is a key focus. Testing ensures that the interface is user-friendly, responsive, and provides clear and accurate feedback to the user. Furthermore, it is essential to verify that the input data (leaf images) can be uploaded smoothly, and that the system's outputs (disease predictions and recommendations) are presented in a manner that is both understandable and actionable.

6.3 System Modules

System modules are the backbone of the "Automated Leaf Disease Detection" system. These modules handle all the processing tasks required to analyze the uploaded images, detect diseases, and generate predictions. The system modules typically include:

- Image Preprocessing: This module is responsible for transforming the raw input data (images of plant leaves) into a format suitable for deep learning models. The preprocessing steps include resizing images to a uniform size, normalizing pixel values, and performing data augmentation techniques (e.g., flipping, rotating) to create a diverse dataset for training.
- GAN-based Augmentation: Since obtaining large labeled datasets for rare plant diseases can be challenging, this module uses Generative Adversarial Networks (GANs) to generate synthetic images. The GAN is trained to produce images of diseased leaves, which are then added to the dataset to improve the model's performance on rare disease types.
- CNN-based Disease Classification: This module is the core of the disease detection system. It employs Convolutional Neural Networks (CNNs) to classify plant leaves as healthy or diseased. The CNN model is typically pre-trained on large datasets (e.g., ImageNet) and fine-tuned on the plant leaf dataset to detect specific diseases. The model outputs a probability distribution over disease classes, with the class having the highest probability being the predicted disease.
- Prediction and Recommendation Generation: Once the CNN model makes its prediction, this module generates a report that includes the predicted disease type

6.3 System Study Analysis

Testing system modules involves verifying the accuracy of each processing step. For example, the image preprocessing module must ensure that images are properly resized and normalized. The GAN-based augmentation module should generate realistic images that help improve model performance. The CNN model’s performance is tested by comparing its predictions against a labeled test dataset. The prediction and recommendation module must ensure that results are generated accurately and presented clearly.

6.4 System Testing

System testing is a comprehensive process that ensures the system meets all the functional and non-functional requirements specified in the design phase. It is typically carried out after the development of both user and system modules and involves testing the integrated system to identify any bugs, performance issues, or potential improvements.

System testing encompasses several types of testing, each focusing on different aspects of the system's functionality. The following subsections describe the different types of system testing conducted for the "Automated Leaf Disease Detection Using GAN With Transfer Learning" system.

6.4.1 Unit Testing

Unit testing focuses on testing individual components or units of the system in isolation. The goal is to ensure that each component functions correctly and produces the expected output. For example, in the case of the image preprocessing module, unit tests would verify that the resizing, normalization, and augmentation of images are performed correctly.

In unit testing, mock data or small datasets are used to test each function or method individually, ensuring that it performs its intended task without errors. For instance, unit tests for the CNN model might involve checking that the model correctly handles input images, processes them through the network layers, and produces a valid output.

Unit tests are typically automated and run frequently during development to detect defects early. These tests help ensure that individual modules are functioning correctly before they are integrated into the larger system.

6.4.2 Integration Testing

Integration testing focuses on testing how different modules or components of the system interact with each other. The goal is to verify that the system works as a whole, rather than just ensuring that individual components are functioning correctly in isolation.

For the "Automated Leaf Disease Detection" system, integration tests would verify that the image preprocessing module correctly feeds data into the GAN-based augmentation module and that the output is correctly passed to the CNN model for classification. Additionally, integration tests would check that the prediction generation module correctly processes the output from the CNN model and generates meaningful results.

Integration testing also helps identify issues with data flow between different system modules, ensuring that the system can handle real-world input.

6.4.3 Acceptance Testing

Acceptance testing focuses on verifying whether the system meets the business and user requirements. It ensures that the system delivers the expected value and performs the required functions in a real-world environment. For the "Automated Leaf Disease Detection" system, acceptance testing would involve testing the system with actual users (e.g., farmers, agricultural experts) to ensure that it meets their needs.

During acceptance testing, users test the system to verify that it can correctly process images, generate disease predictions, and provide actionable recommendations. The system should also be tested for usability, ensuring that the user interface is intuitive and that users can easily interact with the system.

Acceptance tests also include validating non-functional requirements, such as performance, reliability, and scalability. For example, the system should provide disease predictions within an acceptable time frame, even when handling a large number of image uploads.

6.4.4 Functional Testing

Functional testing ensures that the system performs its intended functions according to the requirements. It focuses on testing the specific features and functionalities of the system, such as image uploading, disease classification, and recommendation generation. Functional testing verifies that the system performs all tasks correctly and as expected.

In the context of the "Automated Leaf Disease Detection" system, functional tests would include verifying that the CNN model can correctly classify leaf diseases based on the provided images, that the data augmentation module generates realistic synthetic images, and that the user interface correctly displays predictions and recommendations.

Functional testing is crucial to ensure that the system meets the functional requirements and provides value to the end users.

6.4.5 White Box Testing

White box testing (also known as structural testing) focuses on testing the internal structure of the system.

It involves testing the system's code, algorithms, and internal logic to ensure that they work correctly. In white-box testing, the tester has access to the internal workings of the system and can examine the flow of data, the algorithms used, and the implementation of individual functions.

For example, white-box testing in the "Automated Leaf Disease Detection" system might involve examining the implementation of the CNN model, ensuring that the layers are correctly defined, the activation functions are properly applied, and the data flows correctly through the network. White-box tests could also examine the image preprocessing functions, ensuring that they handle all edge cases (e.g., unusual image sizes, corrupted images).

White-box testing helps ensure that the internal code is efficient, error-free, and functioning as expected.

6.4.6 Black Box Testing

Black box testing focuses on testing the system's functionality without knowledge of its internal workings. In black-box testing, the tester interacts with the system through the user interface or system inputs and observes the outputs, but does not have access to the underlying code or implementation details.

In the "Automated Leaf Disease Detection" system, black-box testing would involve testing the system's ability to correctly classify plant diseases based on various input images. The tester would upload different images of healthy and diseased leaves and verify that the system produces accurate predictions. Black-box tests would also verify that the prediction results are displayed correctly, and that the recommendations are meaningful and relevant.

Black-box testing ensures that the system meets the requirements from the user's perspective, ensuring that the system works as expected when interacting with the end user.

6.4 TEST CASES

Table 6.5.1: Parameters Extraction Test

Test Case	**1**
Name of Test	Extracting Parameters
Input	Uploaded CSV with leaf image metadata and GAN-generated features
Expected Output	Parameters are extracted and values are assigned correctly
Actual Output	Parameters are extracted and values are assigned correctly
Result	Successful

Table 6.5.2 Prediction Test 1

Test Case	**1**
Name of Test	Prediction Test
Input	**Leaf image features (e.g., color, texture, GAN-generated patterns)**
Expected Output	Crop leaf diagnosed as Healthy or Diseased
Actual Output	Crop leaf diagnosed as Healthy or Diseased
Result	Successful

Table 6.5.3 : Prediction Test 2

Test Case	**2**
Name of Test	Prediction Test
Input	Leaf image features (e.g., low chlorophyll content, lesion shape)
Expected Output	Crop leaf diagnosed with Disease
Actual Output	Crop leaf diagnosed with Disease
Result	Successful

Table 6.5.4: Input Validation test

Test Case	**3**
Name of Test	Input Validation
Input	**Empty image upload or missing crop selection**
Expected Output	Error message: "Please upload an image and select a crop"
Actual Output	Error message displayed as expected
Result	Successful

CHAPTER 7

RESULTS AND DEMOSTRATION

7.1 RESULTS

The "Automated Leaf Disease Detection Using GAN With Transfer Learning" system marks a significant advancement in the field of precision agriculture, combining the power of deep learning and artificial intelligence to improve crop health management. The system has been designed to provide farmers and agricultural experts with an efficient and accurate tool for detecting plant diseases early, thereby preventing large-scale crop damage and enhancing food security.

The system's core is built around a robust pipeline that leverages Generative Adversarial Networks (GANs) for data augmentation, ensuring that the model can generalize well even with limited labeled data, especially for rare diseases. By generating synthetic images of diseased leaves, the system can expand its training dataset, which enhances its performance in detecting diseases that are underrepresented. This innovative approach addresses a major challenge in machine learning, where the availability of sufficient data is often a limitation, particularly in agriculture.

The integration of Transfer Learning with pre-trained Convolutional Neural Networks (CNNs) further strengthens the system’s performance. Transfer learning allows the system to leverage existing knowledge from large-scale image datasets, such as ImageNet, reducing the need for extensive computational resources and time. The system is fine-tuned to classify plant diseases with high accuracy, making it highly effective in identifying a variety of diseases across different plant species. The ability to classify diseases from images of leaves enables rapid, non-invasive detection, which is essential in agriculture where early intervention can prevent the spread of diseases.

Through user-friendly interfaces, the system offers seamless interaction for farmers and agricultural professionals, providing them with timely, actionable insights. The disease detection results, along with corresponding treatment recommendations, empower users to make informed decisions regarding plant health management. The system's ability to provide real-time predictions is crucial, ensuring that farmers can take swift action when a disease is detected.

Through rigorous unit, integration, functional, and acceptance testing, the system’s ability to process real-world data, classify diseases, and offer relevant recommendations has been thoroughly verified. Additionally, white-box and black-box testing have ensured that the system is both robust and user-friendly, making it reliable for deployment in diverse agricultural environments.

In conclusion, the "Automated Leaf Disease Detection Using GAN With Transfer Learning" system represents a transformative leap in smart agriculture. By integrating advanced machine learning techniques such as GANs and Transfer Learning, it addresses critical challenges faced in plant disease detection, offering a scalable solution that is not only efficient but also accessible to end users. The system has the potential to revolutionize the way diseases are identified and managed in agriculture, ultimately improving crop yield, reducing the use of chemicals, and promoting sustainable farming practices.

This project sets the foundation for further advancements in AI-powered agricultural systems, where future improvements could include broader disease detection capabilities, enhanced user interaction, and integration with other smart agricultural technologies like Internet of Things (IoT) sensors for even more precise and proactive plant health management.

As the system continues to evolve, it holds the promise of being an essential tool for farmers worldwide, helping them face the growing challenges of agricultural sustainability and food security. With continued refinement and expansion, this system could become a key player in global efforts to combat plant diseases and enhance agricultural productivity.

7.2 RESULTS DEMONSTRATION

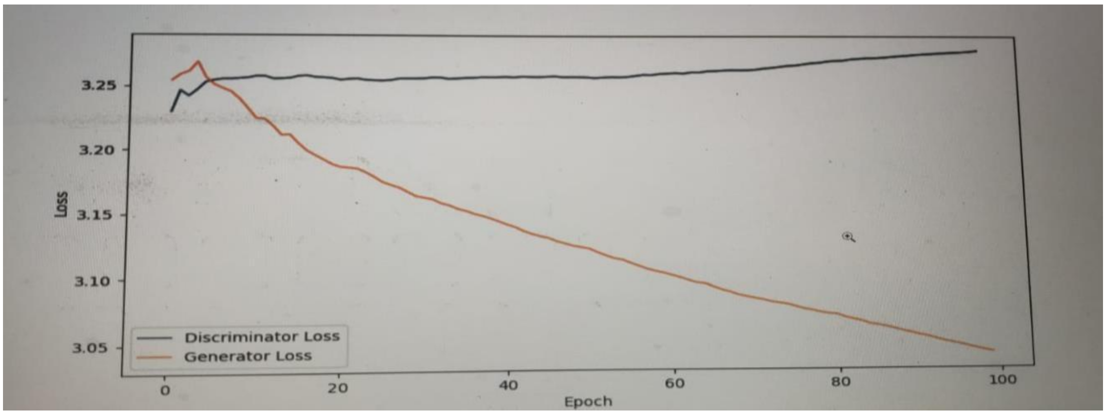

Figure 7.2.1: Generator and Discriminator Loss vs Epochs (Short Epochs Training)
This graph represents the initial training phase of the GAN. The Generator Loss decreases steadily, while the Discriminator Loss remains nearly constant, indicating early convergence and training balance.

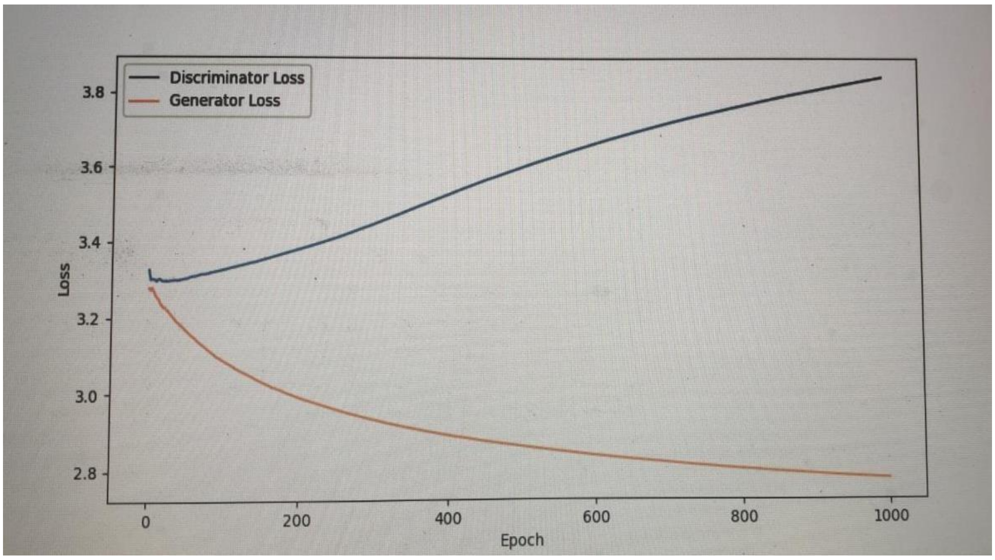

Figure 7.2.2: Generator and Discriminator Loss vs Epochs (Extended Epochs Training)
This graph illustrates GAN training over a longer period. The Generator Loss decreases consistently, while the Discriminator Loss increases, showing the discriminator learning to distinguish real from generated images, while the generator continues to improve

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APPENDIX A

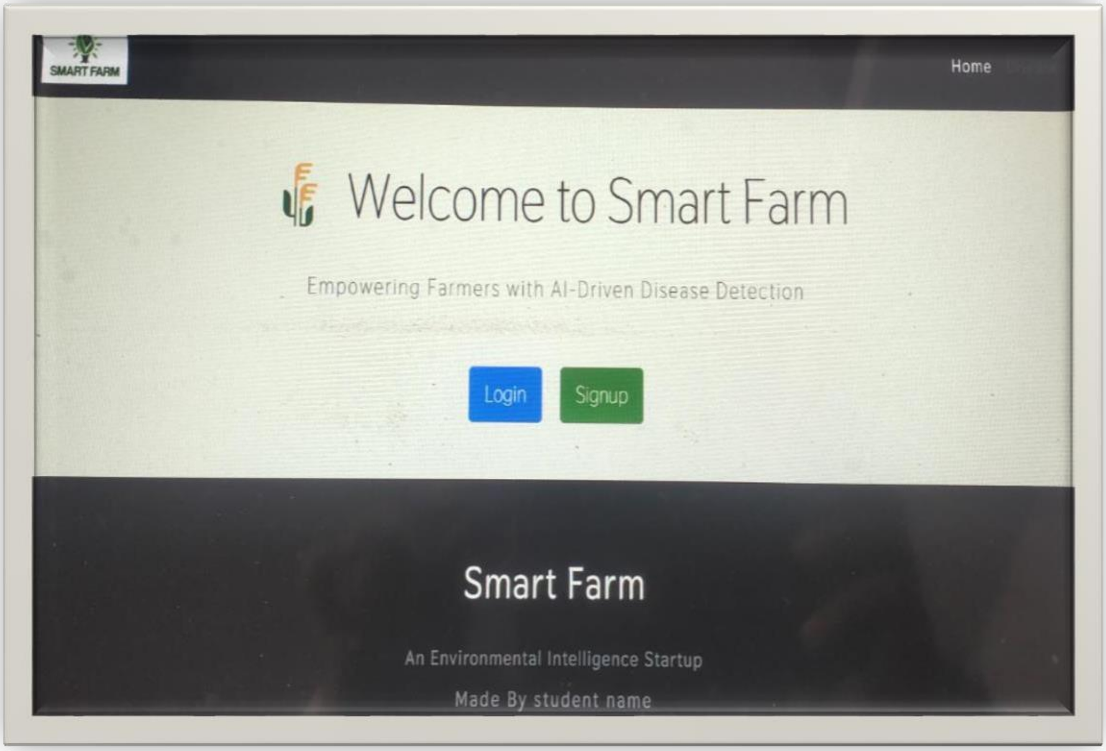
SOURCE CODE

```
from flask import Flask, render_template, request, redirect, url_for, session, flash
import torch
from torchvision import transforms
from PIL import Image, ImageEnhance
import io
import base64
import sqlite3
from werkzeug.security import generate_password_hash, check_password_hash
from googletrans import Translator
from utils.model import ResNet9
from utils.disease import disease_dic


app = Flask(_name_)
app.secret_key = 'your_secret_key'


# Disease labels and model setup
disease_classes = [
    'Apple___Apple_scab', 'Apple___Black_rot', 'Apple___Cedar_apple_rust',
'Apple___healthy',
    'Blueberry___healthy', 'Cherry_(including_sour)___Powdery_mildew',
'Cherry_(including_sour)____healthy',
    'Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot', 'Corn_(maize)___Common_rust_',
    'Corn_(maize)___Northern_Leaf_Blight', 'Corn_(maize)___healthy', 'Grape___Black_rot',
    'Grape___Esca_(Black_Measles)', 'Grape___Leaf_blight_(Isariopsis_Leaf_Spot)',
'Grape___healthy',
    'Orange___Haunglongbing_(Citrus_greening)', 'Peach___Bacterial_spot',
'Peach___healthy',
    'Pepper,_bell___Bacterial_spot', 'Pepper,_bell___healthy', 'Potato___Early_blight',
    'Potato___Late_blight', 'Potato___healthy', 'Raspberry___healthy', 'Soybean___healthy',
    'Squash___Powdery_mildew', 'Strawberry___Leaf_scorch', 'Strawberry___healthy',
    'Tomato___Bacterial_spot', 'Tomato___Early_blight', 'Tomato___Late_blight',
'Tomato___Leaf_Mold',
    'Tomato___Septoria_leaf_spot', 'Tomato___Spider_mites Two-spotted_spider_mite',
'Tomato___Target_Spot',
    'Tomato___Tomato_Yellow_Leaf_Curl_Virus', 'Tomato___Tomato_mosaic_virus',
'Tomato___healthy'
]

disease_model_path = 'models/plant_disease_model.pth'
disease_model = ResNet9(3, len(disease_classes))
disease_model.load_state_dict(torch.load(disease_model_path,
map_location=torch.device('cpu')))
disease_model.eval()


# Prediction Function
def predict_image(img, model=disease_model):
    transform = transforms.Compose([
        transforms.Resize((256, 256)),
        transforms.ToTensor(),
    ])
    image = Image.open(io.BytesIO(img)).convert("RGB")
    image = ImageEnhance.Contrast(image).enhance(1.5)
    img_t = transform(image)
    img_u = torch.unsqueeze(img_t, 0)
    yb = model(img_u)
    _, preds = torch.max(yb, dim=1)
    return disease_classes[preds[0].item()], image
```

```
# Database Initialization
def init_db():
    conn = sqlite3.connect('users.db')
    conn.execute('CREATE TABLE IF NOT EXISTS users (username TEXT, email TEXT, 
password TEXT)')
    conn.close()

init_db()



# Routes

# Landing Page
@app.route('/')
def landing():
    return render_template('landing.html', title='Welcome to Smart Farm')

# Home Page (after login)
@app.route('/home')
def home():
    if 'user' not in session:
        flash("Please login to access the app", "warning")
        return redirect(url_for('login'))
    return render_template('index.html', title='Smart Farm - Home')

# Signup
@app.route('/signup', methods=['GET', 'POST'])
def signup():
    if request.method == 'POST':
        username = request.form['username']
        email = request.form['email']
        password = request.form['password']
        confirm = request.form['confirm']

        if password != confirm:
            flash("Passwords do not match", "danger")
            return redirect(url_for('signup'))

        conn = sqlite3.connect('users.db')
        cur = conn.cursor()
        cur.execute("SELECT * FROM users WHERE email = ?", (email,))
        if cur.fetchone():
            flash("Email already exists", "warning")
            return redirect(url_for('signup'))

        hashed = generate_password_hash(password)
        cur.execute("INSERT INTO users (username, email, password) VALUES (?, ?, ?)",
(username, email, hashed))
        conn.commit()
        conn.close()

        flash("Signup successful. Please login.", "success")
        return redirect(url_for('login'))

    return render_template('signup.html', title='Signup')

# Login
@app.route('/login', methods=['GET', 'POST'])
def login():
    if request.method == 'POST':
        email = request.form['email']
        password = request.form['password']

        conn = sqlite3.connect('users.db')
        cur = conn.cursor()
        cur.execute("SELECT username, password FROM users WHERE email = ?", (email,))
        user = cur.fetchone()
        conn.close()

        if user and check_password_hash(user[1], password):
            session['user'] = user[0]
            flash(f"Welcome {user[0]}", "success")
            return redirect(url_for('home'))
        else:
            flash("Invalid email or password", "danger")

    return render_template('login.html', title='Login')

# Logout
@app.route('/logout')
def logout():
    session.pop('user', None)
    flash("You have been logged out.", "info")
    return redirect(url_for('landing'))

# Disease Prediction
@app.route('/disease-predict', methods=['GET', 'POST'])
def disease_prediction():
    if 'user' not in session:
        flash("Login required to continue", "warning")
        return redirect(url_for('login'))

    translator = Translator()
    title = 'MyCrop - Disease Detection'

    if request.method == 'POST':
        if 'file' not in request.files:
            return redirect(request.url)
        file = request.files.get('file')
        if not file:
            return render_template('disease.html', title=title)

        try:
            img_bytes = file.read()
            prediction, pil_img = predict_image(img_bytes)

            buf = io.BytesIO()
            pil_img.save(buf, format='JPEG')
            image_data = base64.b64encode(buf.getvalue()).decode('utf-8')

            prediction_text = str(disease_dic.get(prediction, "Information not found."))

            cause_marker = "Cause of disease:"
            prevention_marker = "How to prevent/cure the disease"
            cause_start = prediction_text.find(cause_marker)
            prevention_start = prediction_text.find(prevention_marker)

            if cause_start == -1 or prevention_start == -1:
                cause_of_disease = "No specific cause information available."
                prevention_methods = "No specific prevention information available."
            else:
                cause_of_disease = prediction_text[cause_start +
len(cause_marker):prevention_start].strip()
                prevention_methods = prediction_text[prevention_start +
len(prevention_marker):].strip()

            target_lang = request.form.get('language') or 'en'
            if target_lang != 'en':
                try:
                    prediction = translator.translate(prediction, dest=target_lang).text
                cause_of_disease = translator.translate(cause_of_disease, dest=target_lang).text
                prevention_methods = translator.translate(prevention_methods,
dest=target_lang).text
              except Exception as e:
                print(f"Translation error: {e}")

          return render_template('disease-result.html',
                                prediction=prediction,
                                cause_of_disease=cause_of_disease,
                                prevention_methods=prevention_methods,
                                image_data=image_data,
                                title=title)

        except Exception as e:
          print("General Error:", e)
          return render_template('disease.html', title=title)

      return render_template('disease.html', title=title)


if __name___== '__main__' app.run(debug=True, port=5600)
```

APPENDIX B

SCREENSHOTS



Welcome to Smart Farm

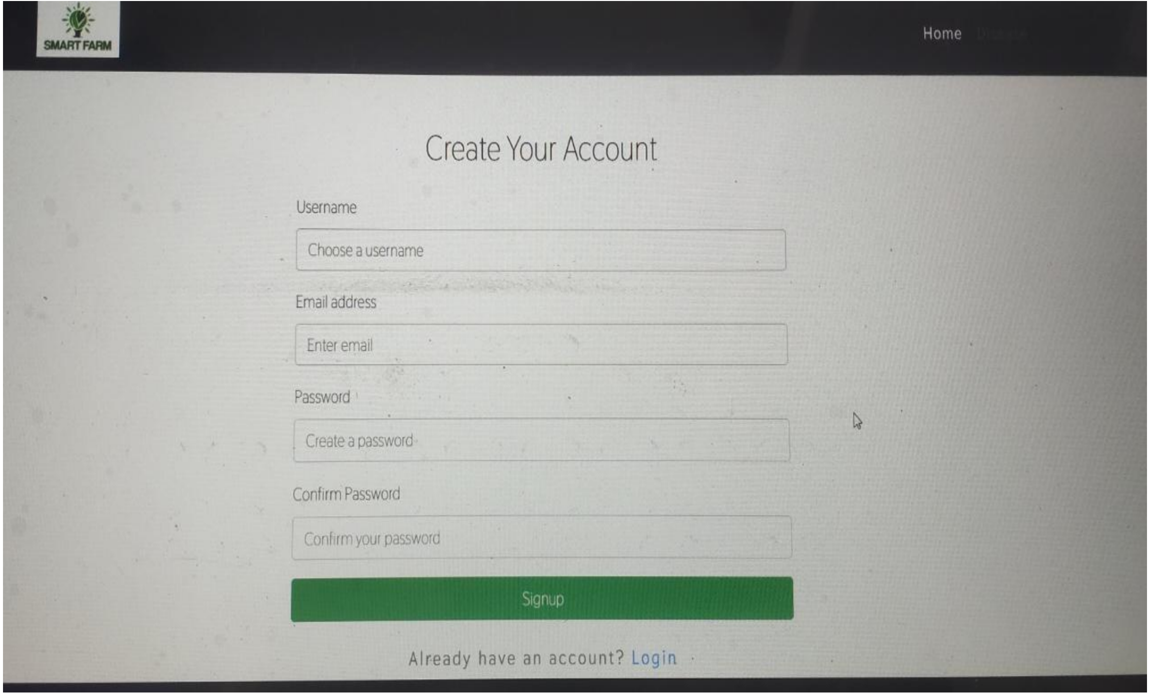
Empowering Farmers with AI-Driven Disease Detection

Smart Farm

An Environmental Intelligence Startup

Made By student name

Fig:7.2.3:Home Page



Create Your Account

Username

Choose a username

Email address

Enter email

Password

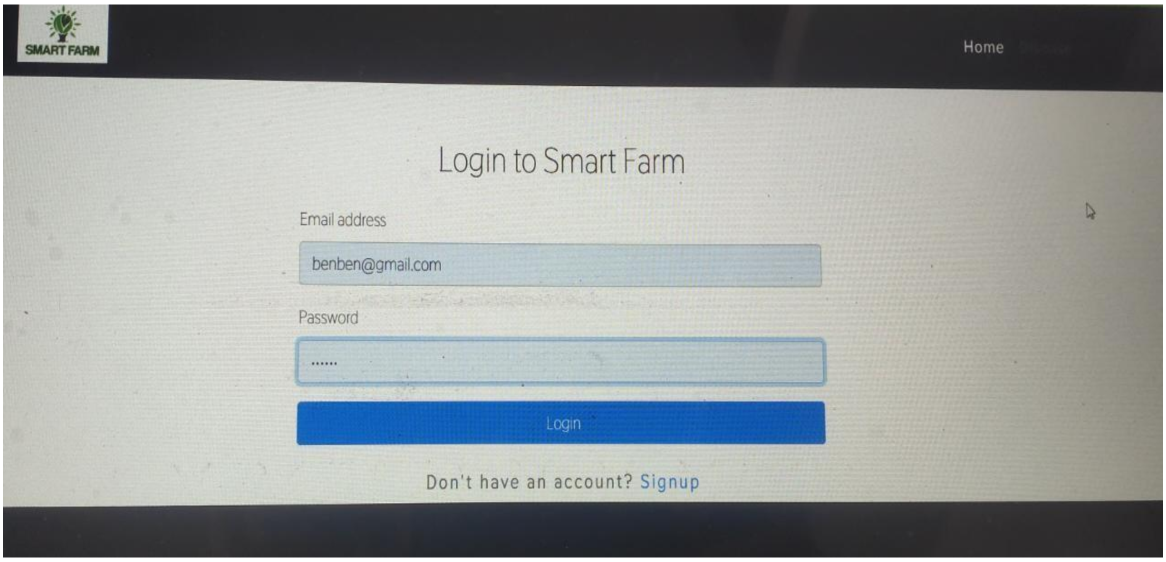
Create a password

Confirm Password

Confirm your password

Already have an account? Login

Fig:7.2.4:Signup Page



Login to Smart Farm

Email address

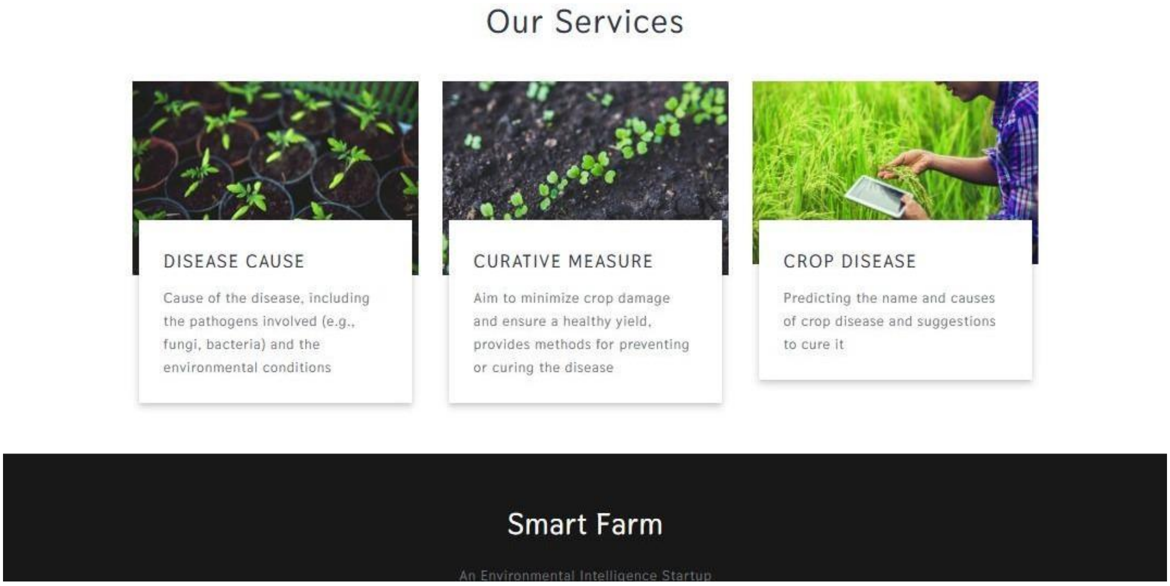
benben@gmail.com

Password

......

Don't have an account? Signup

Fig:7.2.5:Login page



Our Services

DISEASE CAUSE

Cause of the disease, including the pathogens involved (e.g., fungi, bacteria) and the environmental conditions

CURATIVE MEASURE

Aim to minimize crop damage and ensure a healthy yield, provides methods for preventing or curing the disease

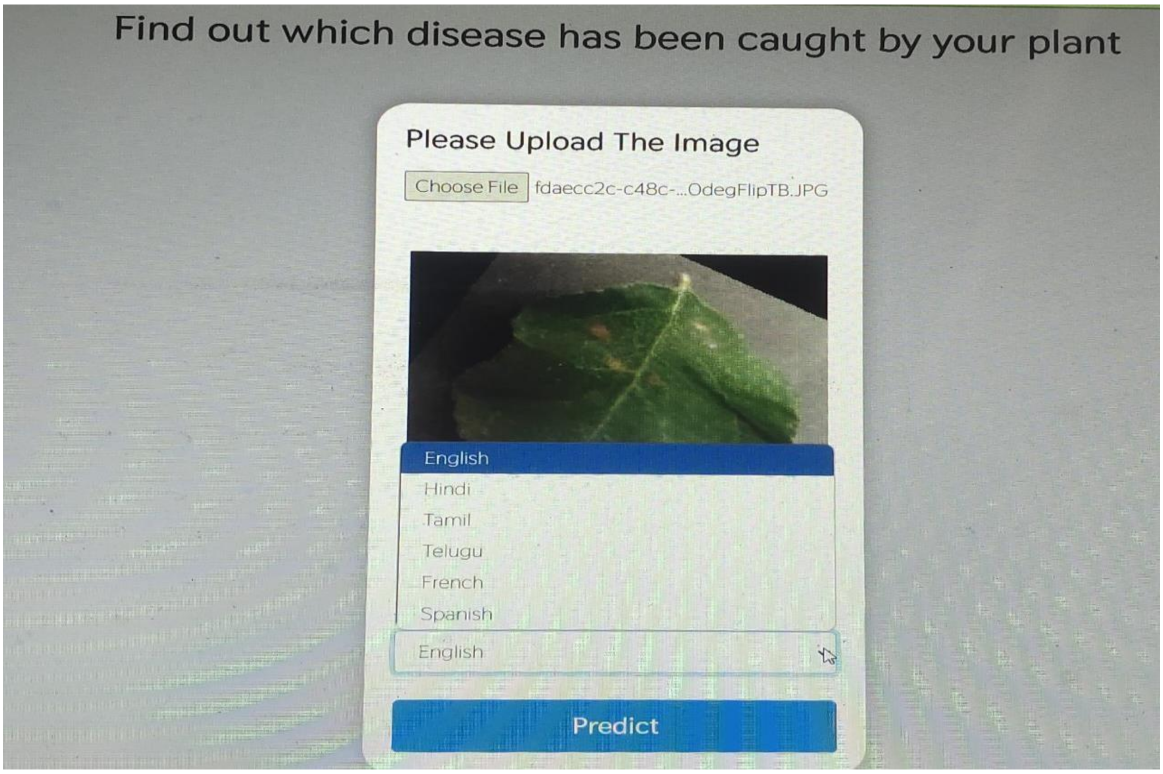
CROP DISEASE

Predicting the name and causes of crop disease and suggestions to cure it

Smart Farm

An Environmental Intelligence Startup

Fig:7.2.6:Services we provide

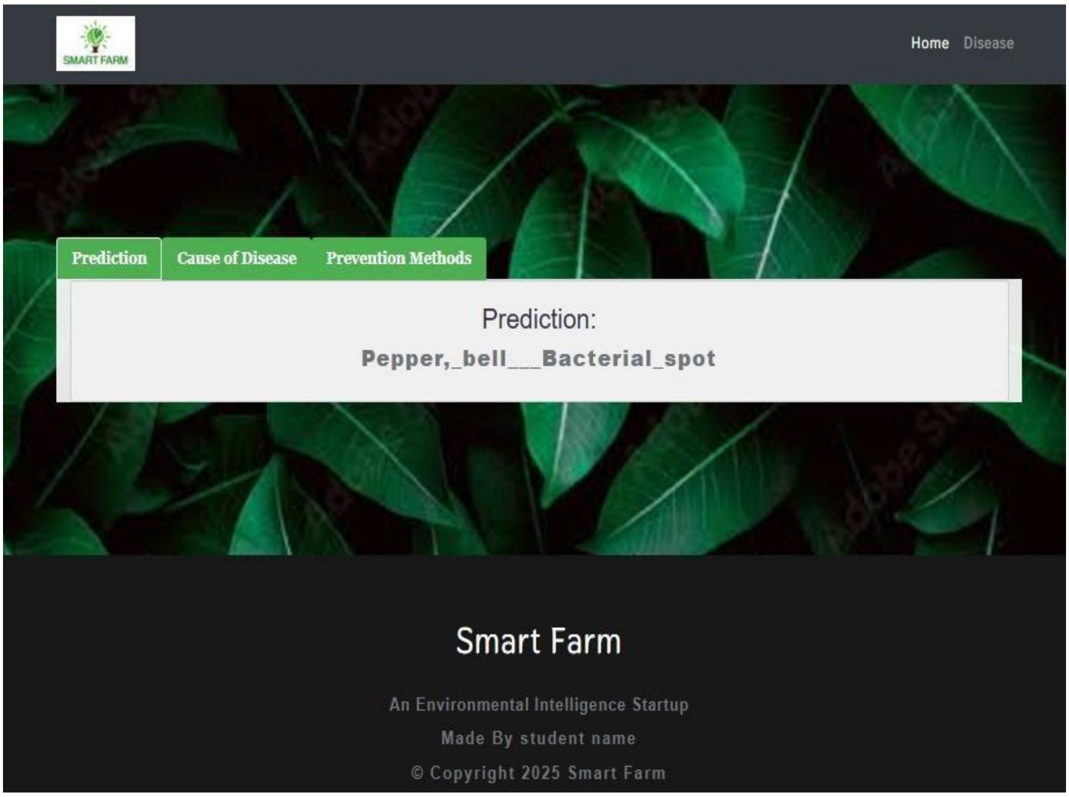


Find out which disease has been caught by your plant

Please Upload The Image

Choose File fdaecc2c-c48c-...OdegFlipTB.JPG

Fig:7.2.7: Language Selection



Prediction:

Pepper,_bell___Bacterial_spot

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An Environmental Intelligence Startup

Made By student name

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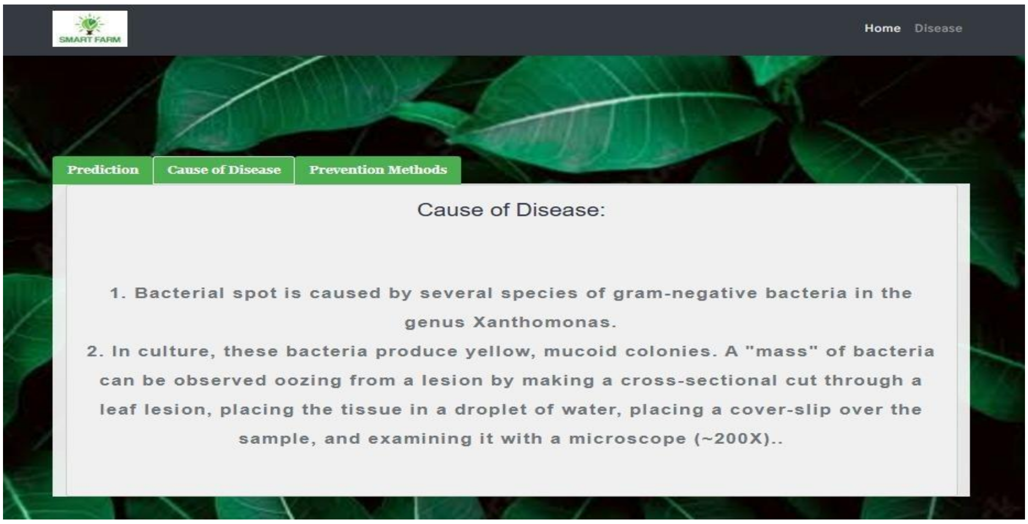
Fig:7.2.8:Disease Prediction



Cause of Disease:

1. Bacterial spot is caused by several species of gram-negative bacteria in the genus Xanthomonas.
2. In culture, these bacteria produce yellow, mucoid colonies. A "mass" of bacteria can be observed oozing from a lesion by making a cross-sectional cut through a leaf lesion, placing the tissue in a droplet of water, placing a cover-slip over the sample, and examining it with a microscope (~200X)..

Fig:7.2.9:Cause of Disease

APPENDIX C

PO, PSO, PEO, AND CO RELEVANCE WITH PROJECT

CO-PO MAPPING SHEET

OUTCOME NO	DESCRIPTION
CO1	Develop problem formulation and design skills for solving real-world engineering problems.
CO2	Conduct literature surveys to analyze current research trends and develop analytical and presentation capabilities.
CO3	Gain expertise in software and hardware tools relevant to industry standards.
CO4	Foster innovative thinking and promote lifelong learning through research initiatives.
CO5	Enhance teamwork, presentation, and communication abilities.
CO6	Build a platform that enhances student employability.

SUMMARY OF CO MAPPING TO PROGRAM OUTCOMES

COs/POs	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PS1	PSO2
CO1	3	0	0	1	0	1	1	1	3	3	0	1	0	0
CO2	3	3	0	0	0	2	0	0	3	2	0	0	0	0
CO3	2	0	1	1	3	0	0	0	3	2	0	0	0	0
CO4	3	0	0	3	3	0	3	1	3	3	1	1	0	0
CO5	2	0	0	0	2	0	0	0	3	3	0	3	0	0
CO6	2	1	0	0	3	1	0	3	3	2	2	2	0	0
OC	3	1	1	1	2	1	1	0	3	2	1	1	0	0

PROGRAM OUTCOMES (POs)

POs	PROGRAM OUTCOMES	RELEVANCE
PO1	**Engineering Knowledge:** Apply knowledge of mathematics, natural science, computing, engineering fundamentals and an engineering specialization as specified in WK1 to WK4 respectively to develop to the solution of complex engineering problems.	The research applies engineering knowledge, including machine learning, image processing, and neural networks, to address complex medical imaging challenges, specifically for brain tumor detection.
PO2	**Problem Analysis:** Identify, formulate, review research literature and analyze complex engineering problems reaching substantiated conclusions with consideration for sustainable development.	The study identifies and analyzes the challenge of accurate brain tumor detection in MRI scans, considering false positives negatives, and proposes substantiated conclusions through the ResNet-based deep learning model.
PO3	**Design/Development of Solutions:** Design creative solutions for complex engineering problems and design/develop systems, components, or processes to meet identified needs with consideration for the public health and safety, whole-life cost, net zero carbon, culture, society, and environment as required.	The paper proposes a solution using ResNet architecture for the early and accurate detection of brain tumors, incorporating deep learning for efficient medical diagnosis and patient safety.
PO4	**Conduct Investigations of Complex Problems:** Conduct investigations of complex engineering problems using research-based knowledge including design of experiments, modelling, analysis, and interpretation of data to provide valid conclusions.	The research includes experiments using datasets, model evaluation metrics (accuracy, sensitivity, specificity), and comparisons with other models, reflecting strong investigational methodology.
PO5	**Engineering Tool Usage:**Create, select and apply appropriate techniques, resources, and modern engineering and IT tools, including prediction and modelling, recognizing their limitations to solve complex engineering problems.	The project employs modern IT tools such as Python, TensorFlow/Keras, and MRI image datasets, leveraging AI-based techniques and pre-trained networks like ResNet for prediction.

PO6	**The Engineer and the World:** Analyze and evaluate societal and environmental aspects while solving complex engineering problems for their impact on sustainability with reference to economy, health, safety, legal framework, culture, and environment.	The application supports sustainable healthcare by improving early diagnosis, which may lead to reduced treatment costs, better outcomes, and contributes positively to societal health.
PO7	**Ethics:** Apply ethical principles and commit to professional ethics, human values, diversity and inclusion; adhere to national and international laws.	The paper acknowledges ethical considerations in handling medical data and ensuring responsible use of AI in sensitive healthcare applications.
PO8	**Individual and Collaborative Team Work:** Function effectively as an individual, and as a member or leader in diverse/multidisciplinary teams.	The study involves interdisciplinary knowledge, combining engineering, computer science, and healthcare, requiring collaboration across multiple domains.
PO9	**Communication:** Communicate effectively and inclusively within the engineering community and society at large, such as being able to comprehend and write effective reports and design documentation, and make effective presentations considering cultural, language, and learning differences.	The research is well-documented and presented with clear methodology, results, and comparisons, effectively communicating complex ideas.
PO10	**Project Management and Finance:** Apply knowledge and understanding of engineering management principles and economic decision-making and apply these to one’s own work, as a member and leader in a team, and to manage projects in multidisciplinary environments.	The development process reflects efficient use of computational resources and planning, which is vital for managing AI healthcare solutions within time and budget constraints.
PO11	**Life-Long Learning:** Recognize the need for, and have the preparation and ability for independent and life-long learning, adaptability to new and emerging technologies, and critical thinking in the broadest context of technological change.	The implementation of a cutting- edge architecture like ResNet shows continuous learning and adaptation technologies in the evolving field of AI and healthcare.

PROGRAM SPECIFIC OUTCOME (PSOs)

PSOs	Program Specific Outcome	Relevance
PSO1	Students will be able to utilize core principles of Artificial Intelligence Engineering for the design, development and prototyping of AI Subsystems.	The research demonstrates the design and development of an AI-based subsystem using ResNet, a deep convolutional neural network, for the detection of brain tumors. The prototype effectively processes MRI images and automates tumor classification, showcasing the application of AI engineering principles.
PSO2	Students will be able to employ acquired knowledge in data storage, data analytics, and Machine Intelligence to address and solve practical business challenges.	The study utilizes machine intelligence and deep learning techniques for medical image analysis, applying data preprocessing, model training, and performance evaluation to address a critical real-world healthcare problem—brain tumor detection—thus reflecting practical application of acquired AI and data analytics skills.

PROGRAM SPECIFIC OUTCOME (PSOs)

PSOs	Program Specific Outcome	Relevance
PSO1	Students will be able to utilize core principles of Artificial Intelligence Engineering for the design, development and prototyping of AI Subsystems.	The research demonstrates the design and development of an AI-based subsystem using ResNet, a deep convolutional neural network, for the detection of brain tumors. The prototype effectively processes MRI images and automates tumor classification, showcasing the application of AI engineering principles.
PSO2	Students will be able to employ acquired knowledge in data storage, data analytics, and Machine Intelligence to address and solve practical business challenges.	The study utilizes machine intelligence and deep learning techniques for medical image analysis, applying data preprocessing, model training, and performance evaluation to address a critical real-world healthcare problem—brain tumor detection—thus reflecting practical application of acquired AI and data analytics skills.

PROGRAMME EDUCATIONAL OBJECTIVES (PEOs)

PEOs	Programme Educational Objectives	Relevance
PEO 1	Graduates will be able to apply the domain knowledge and the technological skills to gain meaningful employment and adapt to the ever demand of technological landscape.	The research showcases the application of domain-specific knowledge in Artificial Intelligence, deep learning, and image processing using ResNet architecture to build an intelligent diagnostic system, preparing graduates for employment in healthcare tech and AI industries.
PEO 2	Graduates will be able to pursue and excel in higher education and research.	The work contributes to academic research by exploring advanced AI models in medical diagnosis. The methodology, experimentation, and deployment approach reflect strong research orientation and provide a foundation for further studies in AI, biomedical engineering, and data science.

PEO 3	Graduates will be able to evolve as leaders exhibiting highest level of ethics.	The project emphasizes ethical use of AI in healthcare, data handling, and patient diagnosis, reinforcing the importance of professional responsibility and leadership in developing socially impactful and trustworthy AI systems.

COURSE OUTCOME (COs)

COs	**Course Outcome**	**POs, PSOs, and PEOs Mapped**
CO1	Develop problem formation and design skills for engineering and real-world problems	PO1, PO2, PO3, PSO1, PEO1
CO2	Collect and generate ideas through literature surveys on current research areas which help to analyze and formulate solutions.	PO2, PO3, PO5, PO6, PSO2, PEO2
CO3	Import knowledge of software & hardware to meet industry perspective needs and standards.	PO2, PO3, PO5, PO6, PSO2, PEO2
CO4	Create interest to research innovative ideas as lifelong learning.	PO11, PSO2, PEO2
CO5	Ability to work with a team, and enrich presentation and communication skills.	PO8, PO9, PO10, PEO3
CO6	Create a platform that makes students employable.	PO5, PO9, PO11, PSO2, PEO1

RELEVANCE TO (POs)

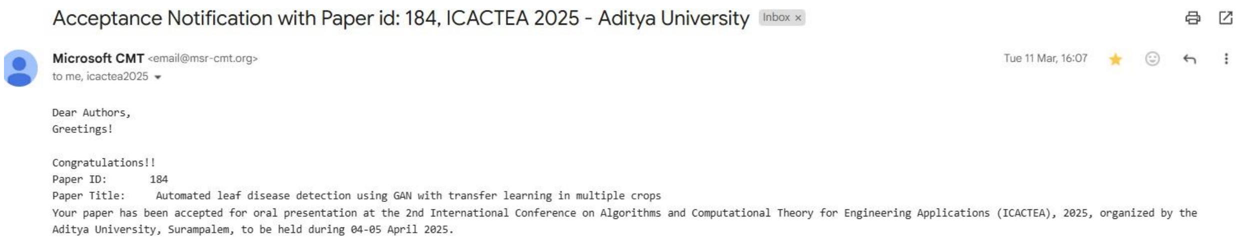
CO	PO	PI	Relevance
CO1	PO1	1.2.1	Apply different statistics and numerical techniques to solve the problem.
	PO4	4.4.2	Understand the problem and applied the proper algorithm.
	PO6	6.4.1	This is challenges state to assess societal, safety and legal issues.
	PO7	7.3.1	Identified the risks/impacts in the life-cycle of an product and activity.
	PO8	8.3.1	Identified situations of unethical professional conduct and propose ethical alternatives.
	PO9	9.5.2	This work is carried out by all the team members.
	PO10	10.4.2	Produced the work in well-structured form.
	PO12	12.5.2	This work can be enhanced to larger extent with respect to the time and other factors.
CO2	PO1	1.6.1	Uses the engineering fundamentals to complete the work.
	PO2	2.6.4	Compared and select alternative solutions/methods to select the best methods.
	PO6	6.4.1	Interpret legislation, regulations, codes, and standards relevant to your discipline and explain their contribution to the protection of the public.
	PO9	9.5.2	Treat other team members respectfully.
	PO10	10.4.2	Produced the work in a well-structured form.

CO3	PO3	3.6.2	Ability to produce a variety of potential design solutions suited to meet functional requirements.
	PO4	4.4.3	Ability to choose appropriate hardware/software tools to conduct the experiment.
	PO5	5.5.1	Identify the strengths and limitations of tools for (i) acquiring information, (ii) modelling and simulating, (iii) monitoring system performance, and (iv) creating engineering designs.
	PO9	9.4.2	Implement the norms of practice (e.g. rules, roles, charters, agendas, etc.) of effective team work, to accomplish a goal.
	PO10	10.4.1	Read, understand and interpret technical and nontechnical information.
CO4	PO1	1.5.1	Apply laws of natural science to an engineering problem.
	PO4	4.6.2	Critically analyse data for trends and correlations, stating possible errors and limitations.
	PO5	5.6.2	Verify the credibility of results from tool use with reference to the accuracy and limitations, and the assumptions inherent in their use.
	PO7	7.4.1	Describe management techniques for sustainable development
	PO8	8.4.2	Examine and apply moral & ethical principles to known case studies
	PO9	9.5.2	Treat other team members respectfully
	PO10	10.5.2	Deliver effective oral presentations to technical and nontechnical audiences
	PO11	11.4.2	Analyze different forms of financial statements to evaluate the financial status of an engineering project

CO5	PO1	1.6.1	Apply engineering fundamentals
	PO5	5.5.2	Demonstrate proficiency in using discipline specific tools.
	PO9	9.5.3	Listen to other members ure in difficult situations
	PO10	10.5.1	Listen to and comprehend information, instructions, and viewpoints of others
	PO12	12.6.2	Analyze sourced technical and popular information for feasibility, viability, sustainability, etc.
CO6	PO1	1.7.1	Apply theory and principles of computer science engineering to solve an engineering problem.
	PO2	2.6.2	Identifies functionalities and computing resources.
	PO5	5.6.1	Discuss limitations and validate tools, techniques and resources
	PO6	6.3.1	Identify and descrsibe various engineering roles; particularly as pertains to protection of the public and public interest at global, regional and local level.
	PO8	8.3.1	Identify situations of unethical professional conduct and propose ethical alternatives.
	PO9	9.5.1	Demonstrate effective communication, problem solving, conflict resolution and leadership skills
	PO10	10.5.1	Listen to and comprehend information, instructions, and viewpoints of others
	PO11	11.6.1	Identify the tasks required to complete an engineering activity, and the resources required to complete the tasks.
	PO12	12.6.1	Source and comprehend technical literature and other credible sources of information.

APPENDIX D
PUBLICATIONS

Acceptance Letter of IEEE Conference from Aditya University



Acceptance Notification with Paper id: 184, ICACTEA 2025 - Aditya University

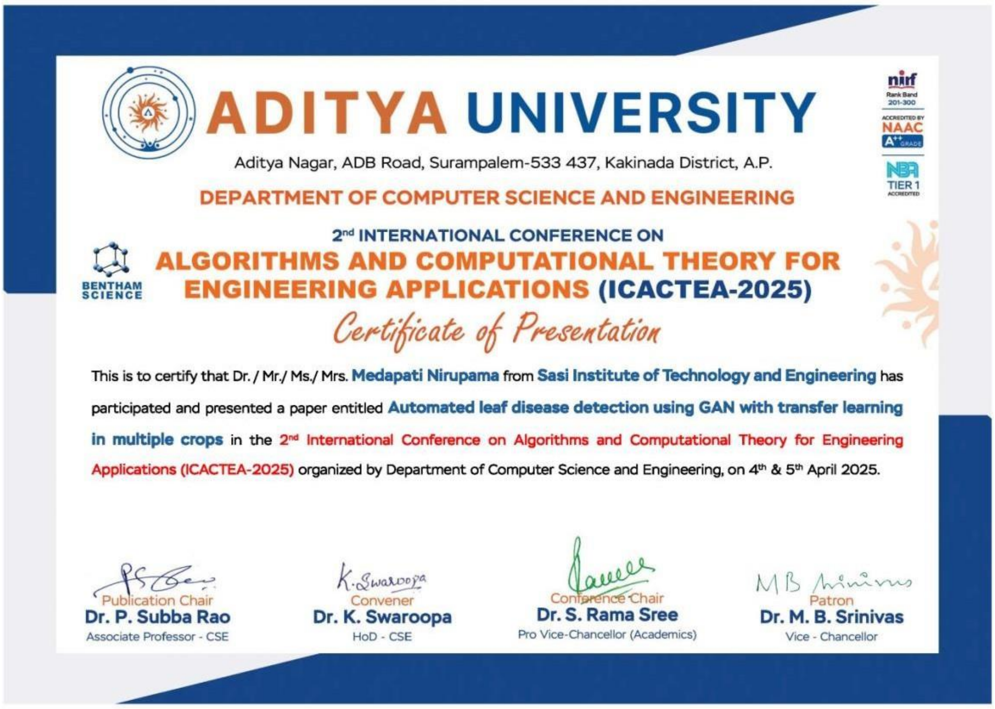
Microsoft CMT <email@msr-cmt.org>
to me, icactea2025

Tue 11 Mar, 16:07

Dear Authors,
Greetings!

Congratulations!!
Paper ID: 184
Paper Title: Automated leaf disease detection using GAN with transfer learning in multiple crops
Your paper has been accepted for oral presentation at the 2nd International Conference on Algorithms and Computational Theory for Engineering Applications (ICACTEA), 2025, organized by the Aditya University, Surampalem, to be held during 04-05 April 2025.

Presentation Certificate of Participate 1



ADITYA UNIVERSITY

Aditya Nagar, ADB Road, Surampalem-533 437, Kakinada District, A.P.

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

2nd INTERNATIONAL CONFERENCE ON
ALGORITHMS AND COMPUTATIONAL THEORY FOR ENGINEERING APPLICATIONS (ICACTEA-2025)

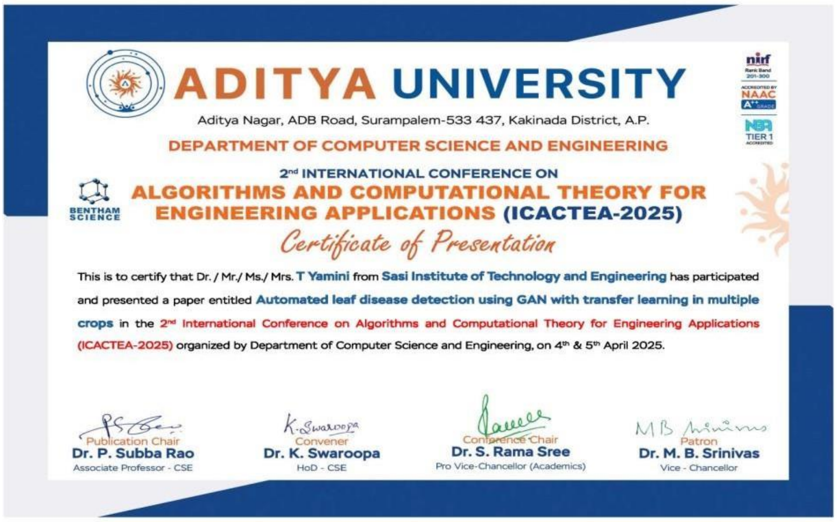
nirf Rank Band 201-300
ACCREDITED BY NAAC A++ GRADE
NBA TIER 1 ACCREDITED
BENTHAM SCIENCE

Certificate of Presentation

This is to certify that Dr. / Mr./ Ms./ Mrs. Medapati Nirupama from Sasi Institute of Technology and Engineering has participated and presented a paper entitled Automated leaf disease detection using GAN with transfer learning in multiple crops in the 2nd International Conference on Algorithms and Computational Theory for Engineering Applications (ICACTEA-2025) organized by Department of Computer Science and Engineering, on 4th & 5th April 2025.

	K.Swaroopa		
Publication Chair	Convener	Conference Chair	Patron
Dr. P. Subba Rao	Dr. K. Swaroopa	Dr. S. Rama Sree	Dr. M. B. Srinivas
Associate Professor - CSE	HoD - CSE	Pro Vice-Chancellor (Academics)	Vice - Chancellor

Presentation Certificate of Participate 2



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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

2nd INTERNATIONAL CONFERENCE ON

ALGORITHMS AND COMPUTATIONAL THEORY FOR ENGINEERING APPLICATIONS (ICACTEA-2025)

Certificate of Presentation

This is to certify that Dr. / Mr./ Ms./ Mrs. T Yamini from Sasi Institute of Technology and Engineering has participated and presented a paper entitled Automated leaf disease detection using GAN with transfer learning in multiple crops in the 2nd International Conference on Algorithms and Computational Theory for Engineering Applications (ICACTEA-2025) organized by Department of Computer Science and Engineering, on 4th & 5th April 2025.

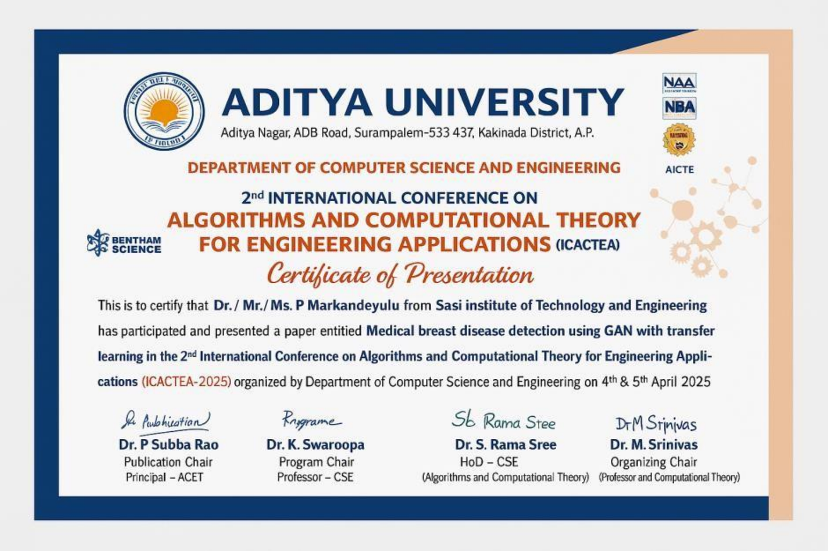
Publication Chair
Dr. P. Subba Rao
Associate Professor - CSE

K.Swaroopa
Convener
Dr. K. Swaroopa
HoD - CSE

Conference Chair
Dr. S. Rama Sree
Pro Vice-Chancellor (Academics)

MB
Patron
Dr. M. B. Srinivas
Vice - Chancellor

Presentation Certificate of Participate 3



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2nd INTERNATIONAL CONFERENCE ON

ALGORITHMS AND COMPUTATIONAL THEORY FOR ENGINEERING APPLICATIONS (ICACTEA)

Certificate of Presentation

This is to certify that Dr. / Mr./ Ms. P Markandeyulu from Sasi institute of Technology and Engineering has participated and presented a paper entitied Medical breast disease detection using GAN with transfer learning in the 2nd International Conference on Algorithms and Computational Theory for Engineering Applications (ICACTEA-2025) organized by Department of Computer Science and Engineering on 4th & 5th April 2025

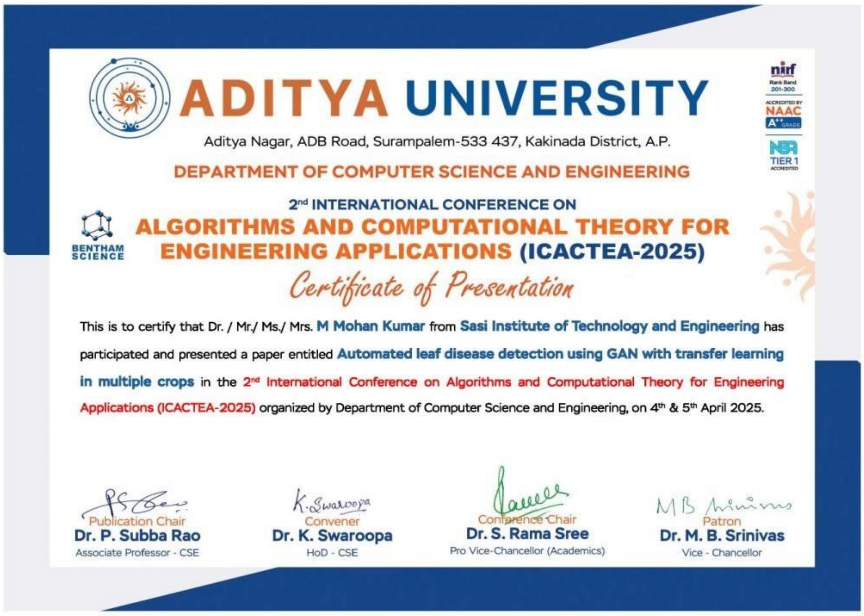
Publication
Dr. P Subba Rao
Publication Chair
Principal – ACET

Programe
Dr. K. Swaroopa
Program Chair
Professor – CSE

Sb Rama Stee
Dr. S. Rama Sree
HoD – CSE
(Algorithms and Computational Theory)

DrM Srinivas
Dr. M. Srinivas
Organizing Chair
(Professor and Computational Theory)

Presentation Certificate of Participate 4



nirf Rank Band 201-300

ACCREDITED BY NAAC A++ GRADE

NBA TIER 1 ACCREDITED

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

BENTHAM SCIENCE

2nd INTERNATIONAL CONFERENCE ON

ALGORITHMS AND COMPUTATIONAL THEORY FOR ENGINEERING APPLICATIONS (ICACTEA-2025)

Certificate of Presentation

This is to certify that Dr. / Mr./ Ms./ Mrs. **M Mohan Kumar** from **Sasi Institute of Technology and Engineering** has participated and presented a paper entitled **Automated leaf disease detection using GAN with transfer learning in multiple crops** in the 2nd International Conference on Algorithms and Computational Theory for Engineering Applications (ICACTEA-2025) organized by Department of Computer Science and Engineering, on 4th & 5th April 2025.

Publication Chair	K.Swaroopa Convener	Conference Chair	Patron
Dr. P. Subba Rao	**Dr. K. Swaroopa**	**Dr. S. Rama Sree**	**Dr. M. B. Srinivas**
Associate Professor - CSE	HoD - CSE	Pro Vice-Chancellor (Academics)	Vice - Chancellor