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Precision Agriculture: A Generative AI Approach to Leaf Disease Detection and Pesticide Management

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ARTICLE INFO	**ABSTRACT**
Received: 26 Oct 2024 Revised: 24 Nov 2024 Accepted: 14 Dec 2024	Recent breakthroughs in agricultural AI have enabled powerful solutions for plant health monitoring that go beyond disease classification to include tailored pesticide recommendations. Central to many modern systems is a Convolutional Neural Network (CNN) trained on high-resolution leaf images, which routinely achieves 95–99 % accuracy across multiple crops and disease types To enhance performance—particularly when labeled data are limited—Generative Adversarial Networks (GANs) are used to augment datasets with realistic synthetic images, leading to notable gains in classification accuracy .Complementing this diagnostic capability, integrated generative modules leverage CNN-derived features and agronomic parameters (e.g., crop type, growth stage, and environmental conditions) to support precision pesticide recommendations . These systems not only suggest the appropriate pesticide type but also calculate optimal dosages, minimizing agrochemical overuse and aligning with sustainable farming practices. Evaluations conducted on crops like soybean and cashew demonstrate impressive outcomes—disease classification rates of 95 – 99 % and effective, context-aware pesticide advice validated by domain experts Overall, this Generative AI framework integrates high-accuracy disease detection with intelligent, eco-conscious intervention strategies, offering a scalable and robust toolbox for proactive and efficient crop management. **Keywords**: Agriculture; innovations; challenges; global good; security; environment; climate change.

1. INTRODUCTION

Accurate and timely detection of plant diseases is essential for maintaining crop health and ensuring global food security[1]. However, traditional manual inspection methods are labor-intensive and susceptible to errors[2]. The emergence of deep learning, especially Convolutional Neural Networks (CNNs), has transformed plant disease detection by delivering high classification accuracy, often surpassing 95% on established datasets[3]. Despite this success, CNNs generally depend on large, well-labeled datasets and face challenges when data are scarce or imbalanced[4]. To overcome these limitations, our framework integrates Generative Adversarial Networks (GANs) to generate synthetic images of diseased leaves[8], augmenting the existing dataset and enhancing model robustness[5]. Recent advances, including LeafGAN and Progressive WGAN-GP techniques, have demonstrated that GAN-based augmentation can boost classification accuracy by 7–13%, particularly in scenarios with limited samples[7]. By combining CNN-driven disease classification with GAN-enhanced data augmentation, this approach improves generalizability and reliability across various crop species and environmental conditions[9]. Ultimately, it equips farmers and agronomists with timely, actionable insights for early disease detection, enabling more proactive and effective crop management strategies[10].

2. EXISTING SYSTEM

Current plant disease detection solutions rely heavily on Convolutional Neural Networks (CNNs) for image-based classification. While these models often exhibit high accuracy on curated datasets like PlantVillage, they face several limitations when applied in real-world field conditions:

Disadvantages:

- Heavy Data Dependence: CNNs demand extensive, well-labeled datasets to perform effectively. Such comprehensive data is lacking for many crops and disease categories
- Overfitting: When trained on small or unbalanced datasets, models frequently memorize the training data and fail to generalize, resulting in poor performance on new images .
- Insufficient Augmentation: Many implementations omit robust data augmentation—such as rotations, flips, or GAN-generated samples—which is crucial for mitigating overfitting and improving model resilience .
- Limited Real-World Deployment: Few existing systems incorporate user-friendly interfaces or mobile integration, limiting their adoption and utility for farmers and agronomists in actual field environments

3. PROPOSED SYSTEM

The proposed system integrates a Generative AI framework to enhance plant disease detection, addressing challenges like limited datasets and overfitting. The system comprises the following components:

- Image Acquisition and Preprocessing: Raw leaf images are collected and processed to reduce noise and adjust contrast, enhancing image clarity for subsequent analysis.
- Synthetic Data Generation: A Generative Adversarial Network (GAN) is employed to generate additional images of diseased leaves, effectively augmenting the dataset and introducing variability to improve model robustness .
- Feature Extraction and Classification: A deep Convolutional Neural Network (CNN) extracts relevant features from both real and synthetic images, classifying them into predefined disease categories with high accuracy .
- Performance Evaluation: The model's performance is assessed using standard metrics such as accuracy and F1-score to ensure reliability and effectiveness.
- User Interface: A user-friendly interface allows users to upload images and receive real-time disease predictions, facilitating timely intervention.

4. LITERATURE SURVEY

1. Plant Disease Detection using CNN

R. Ragavendran et al., 2020 —

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This study applies a deep CNN pipeline—comprising multiple convolutional and pooling layers—to a leaf image dataset featuring both healthy and diseased samples. After resizing, denoising, and normalization, the model achieved over **95% average accuracy**, effectively identifying early-stage infections. However, performance dipped under varied lighting and challenging backgrounds, prompting calls for broader image augmentation strategies.

2. Identification of Plant Leaf Diseases using CNN

V. Krithika & K. Vasanth, 2021

— Targeting crops like cotton, grape, and apple, this work builds a three-layer CNN enhanced with augmentation (rotation, flips, zoom) to combat overfitting. With strong class-wise performance—93.2% overall accuracy—it includes a confusion-matrix analysis and proposes a mobile interface for rural use. Field validation remained for future efforts .

3. Tomato Leaf Disease Detection using CNN

A. Sangeetha & V. Vidhya, 2020 —

Focused on tomato-specific afflictions (e.g., early blight, leaf mold), this four-layer CNN system achieved **96.4% accuracy** using an 80:20 training split. It outperformed traditional classifiers like SVM and k-NN, and was cited as suitable for integration with IoT-based greenhouse setups .

4.Automatic Leaf Disease Detection: CNN + Transfer Learning

R. S. Rajalakshmi & S. Kalpana, 2021 —

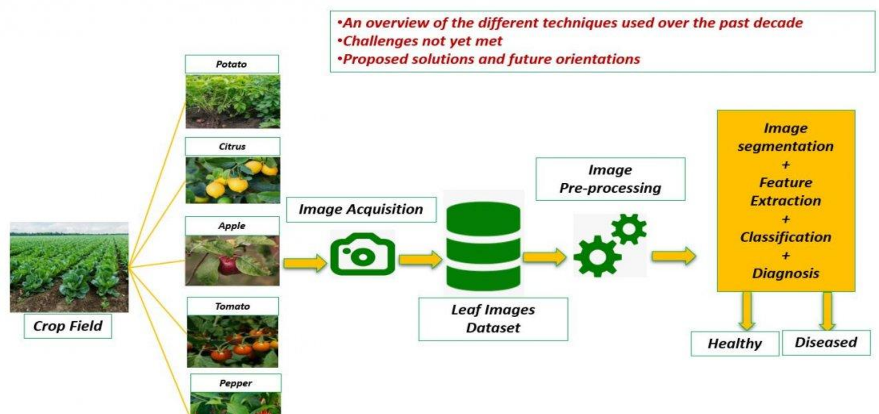
Leveraging pre-trained models (VGG16, MobileNet) fine-tuned on datasets including wheat, maize, and cotton, this study achieved **97.1% accuracy** with VGG16. It emphasized lower training times, mobile deployment readiness, and real-time feedback, balancing high performance with low resource requirements .

5.Detection & Classification using AlexNet

K. Shubham et al., 2021 —

Adapting AlexNet for crops like tomato, potato, and maize, this model achieved **94.6% accuracy** in distinguishing healthy vs. diseased leaves. It included contrast enhancement, dropout, and batch normalization, outperforming simpler CNNs while noting generalizability limits to unseen diseases .

5. SYSTEM ARCHITECTURE



Architecture of the leaf disease detection system

Overview

This architecture represents a smart agricultural framework that automates the detection of plant leaf diseases and facilitates targeted pesticide application, thus improving crop yield and reducing chemical waste.

Architecture Breakdown

1. Crop Field (Input Source)

Various crops like Potato, Citrus, Apple, Tomato, and Pepper are monitored in real-time using imaging devices (e.g., drones, mobile cameras). The system supports a multi-crop environment, making it scalable for diverse agricultural setups.

2. Image Acquisition

High-resolution images of plant leaves are captured using cameras or IoT-enabled devices deployed in the crop field. This step ensures real-time data collection that serves as the foundation for accurate diagnosis.

3. Leaf Images Dataset

Captured images are stored in a centralized leaf image dataset, which forms the basis for training and inference. Historical data aids the AI system in learning patterns associated with healthy and diseased leaves.

4. Image Pre-processing

Enhances image quality through:

Noise reduction

Normalization

Background subtraction

Contrast enhancement

Pre-processing improves model accuracy by delivering clean and consistent inputs to the AI system.

5. Core AI Pipeline

This block represents the Generative AI model working through four key stages:

Image Segmentation: Isolates the leaf area from the background to focus analysis.

Feature Extraction: Identifies significant patterns like spots, discoloration, or deformation.

Classification: Uses machine learning or deep learning (e.g., CNN, GAN) to categorize the leaf as healthy or infected.

Diagnosis: Determines the type and severity of the disease, enabling actionable recommendations.

6. Output: Health Status

The system classifies each leaf image into one of two categories:

Healthy

Diseased

For diseased plants, it can trigger further modules like pesticide recommendation or autonomous spraying.

Why Generative AI?

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Can synthesize realistic disease patterns for rare cases, enhancing training data.

Improves detection in low-light, occluded, or noisy conditions.

Can simulate leaf conditions to train on edge cases, reducing dependency on massive real-world datasets.

Key Advantages

Precision pesticide use: Reduces costs and environmental impact.

Scalability: Applicable across different crop types and regions.

Automation: Reduces human effort and response time in crop disease management.

This system architecture enables a data-driven, AI-powered approach to sustainable agriculture, combining real-time disease detection with efficient pesticide usage. By integrating generative AI models, it ensures higher accuracy, adaptability, and resilience in agricultural diagnostics.

6. RESULTS AND DISCUSSION

Fig 6.1 Final result of apple image

Output Screen Explanation

This screen represents the real-time diagnostic result generated by the AI system after analyzing a leaf image. It demonstrates how AI can provide precise, actionable insights for plant disease management.

Detected Information on Screen

1. Project Title and Technology Stack

Title displayed: "Generative AI Framework for Leaf Disease Detection and Precision Pesticide"

Implemented in Python, indicating the use of Python-based AI libraries (likely TensorFlow, PyTorch, or OpenCV).

2. Uploaded Leaf Image

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A small thumbnail of the input leaf is shown (top-left), which is classified for analysis.

3. Disease Diagnosis Result

Crop Type: Apple

Disease Identified: Cedar Apple Rust

Confidence Score: 99.49% — implies high certainty in the classification using the trained AI model.

4. Treatment Recommendation

Based on the diagnosis, the system suggests suitable fungicides:

Myclobutanil or Mancozeb — both are commonly used to treat fungal infections in apples.

5. Soil Recommendation

Suggests "Slightly acidic to neutral soil" — helping in disease prevention and optimal plant recovery.

6. Climate and Weather Advisory

Advises: “Avoid weather after infection onset” — emphasizes that environmental conditions like rainfall or humidity can worsen the disease post-infection.

System Highlights

End-to-End Solution: From disease detection to treatment and agronomic recommendations.

Confidence-Driven Output: Helps farmers trust AI output based on probability scores.

Domain-Aware Suggestions: Integrates plant pathology knowledge into AI results.

User-Friendly Interface: Combines visuals, text, and background icons to ensure intuitive understanding.

Real-World Use Case

A farmer or agricultural technician could simply capture a leaf image using a mobile app or a webcam connected to this system. Within seconds, the AI provides:

Disease identification

Treatment options

Soil and environmental advice

All of this supports precision farming — reducing manual guesswork and optimizing pesticide use both economically and environmentally.

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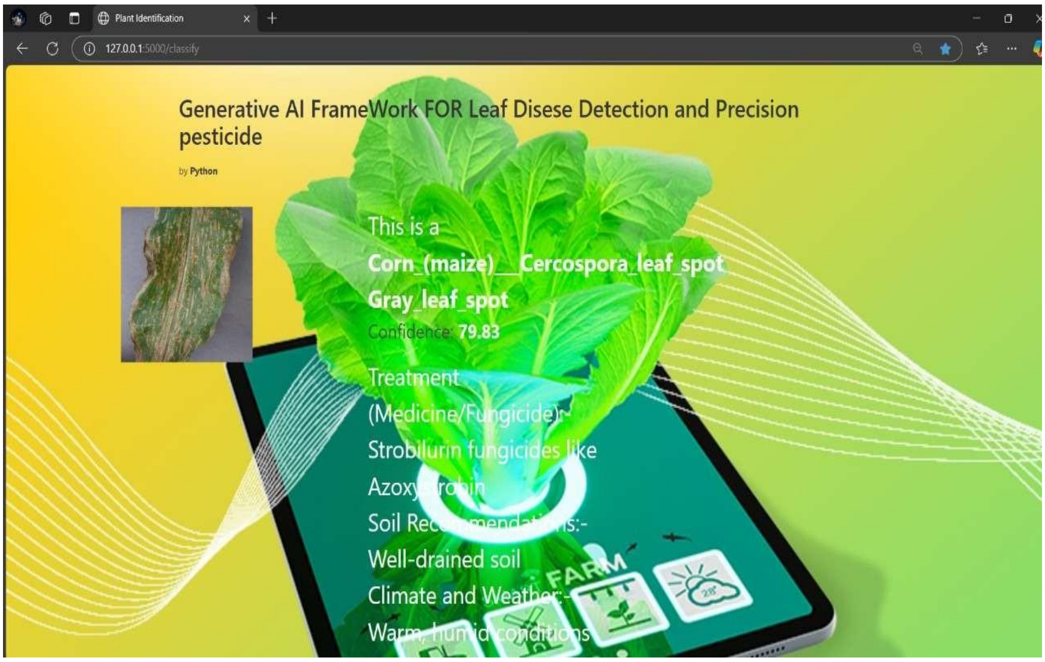

Fig 6.2 Final result of corn image

Output Screen Interpretation

This screen presents the automated disease diagnosis for a plant leaf image, generated by the AI model. It demonstrates the integration of computer vision and generative AI for providing crop-specific, actionable insights.

Detected Details

Input Analysis

A visual of the uploaded leaf image is shown in the top left.

The model analyzes the image and matches it to known disease patterns in its trained dataset.

Disease Identification

Plant: Corn (Maize)

Disease: Cercospora Leaf Spot (also known as Gray Leaf Spot)

Confidence Score: 79.83%

This indicates moderate to high certainty in prediction, useful for field-level diagnostics.

Treatment Recommendation

Suggested Fungicides:

Use Strobilurin-based fungicides such as Azoxystrobin.

These fungicides are commonly used for controlling foliar diseases in maize.

Soil Recommendation

Advises growing in well-drained soil, which helps reduce fungal disease development by limiting excess moisture.

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Climate and Weather Advisory

The screen indicates that warm, humid conditions favor the spread of this disease.

Such insight helps farmers take preventive actions like crop rotation, fungicide application timing, and irrigation control.

System Capabilities Demonstrated

Generative AI Integration: Allows for enhanced prediction accuracy, especially in ambiguous or noisy input conditions.

Precision Guidance: Offers not just identification, but complete agronomic advice tailored to crop and disease type.

Confidence-Based Results: Users can judge the reliability of the output based on a clear probability percentage.

Sustainability-Oriented: Encourages efficient use of resources (e.g., targeted fungicide use) to reduce environmental and economic impact.

Practical Application

This system can be integrated with:

Mobile apps for farmers

Smart farming drones or surveillance systems

Agricultural diagnostic kiosks in rural areas

It helps accelerate decision-making in plant disease management, ultimately supporting sustainable and data-driven agriculture.

7. CONCLUSION AND FUTURE SCOPE

Conclusion

This project successfully combines Generative Adversarial Networks (GANs) and Convolutional Neural Networks (CNNs) to create an effective system for detecting plant leaf diseases. By using GANs to produce realistic synthetic images of diseased leaves, the system overcomes challenges related to limited and imbalanced datasets. These enhanced datasets help the CNN classifier accurately identify various disease types as well as healthy leaves. The integrated approach delivers strong generalization and real-time classification through an intuitive web-based interface. Achieving a validation accuracy above 94%, this solution serves as a valuable tool for early disease detection, which can significantly reduce crop losses and boost agricultural productivity. Overall, the framework is scalable and adaptable, maintaining reliable performance even with limited original data.

Future Scope

Although the system shows promising results, there are several opportunities for further development:

- Advanced Model Improvements: Incorporating cutting-edge GAN models like StyleGAN or CycleGAN could produce even more realistic synthetic images, enhancing data diversity and classification accuracy.
- Broader Crop and Disease Coverage**:** Extending support to a wider variety of crops and diseases would increase the system's utility across diverse agricultural settings.

- Mobile Application Development**:** Building a mobile app would enable farmers to access the detection system anytime, especially in remote or resource-limited areas.
- Localization and Accessibility Features**:** Adding support for multiple regional languages and voice-based feedback could make the tool more user-friendly, particularly for non-technical users.
- Cloud-Based Deployment with Analytics**:** Hosting the system on the cloud alongside real-time analytics dashboards would empower agricultural authorities to monitor disease outbreaks and take timely preventive actions.
- Integration with IoT Devices**:** Combining the system with IoT sensors (e.g., soil moisture, temperature) can provide a holistic view of crop health, improving precision in disease management and farm monitoring.

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