Plant Disease Detection Using CNN and GAN

Dr.D.Deepika
Assistant Professor, Department of Emerging Technologies, Mahatma Gandhi Institute of Technology, Hyderabad, Telangana – 500 075

G.Rithika
Student, Department of Emerging Technologies (CSE-Data Science), Mahatma Gandhi Institute of Technology, Hyderabad, Telangana – 500 075
deshmukhdeepika@gmail.com

How to Cite this Article:

G.Rithika, (2026). Plant Disease Detection Using CNN and GAN. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(6). https://doi.org/10.55041/ijcope.v2i6.296

https://doi.org/ 10.55041/ijcope.v2i6.296

ABSTRACT

Agriculture is a critical sector for global food security, but plant diseases and nutrient deficiencies remain major challenges that reduce crop yield and economic returns for farmers. Traditional diagnosis methods depend on manual observation and expert intervention, which are often time-consuming, subjective, and inaccessible in remote regions. This paper presents an intelligent crop health analysis system that automates the detection of plant diseases and nutrient deficiencies using a hybrid deep learning framework. The proposed approach integrates Convolutional Neural Networks (CNNs) for feature extraction and classification with Generative Adversarial Networks (GANs) for synthetic image generation and dataset augmentation. The CNN model learns discriminative features such as color variations, texture patterns, and lesion characteristics from leaf images, while the GAN enhances dataset diversity by generating realistic samples, thereby addressing class imbalance and limited training data. The system is trained on a dataset containing more than 55,000 leaf images across 32 classes and is deployed through a Flask-based web application. It supports two operational modes: Basic Mode for disease identification and Advanced Mode for comprehensive crop health assessment through the integration of CNN-based predictions and rule-based nutrient analysis. Experimental results demonstrate improved classification performance, robustness, and scalability under real-world conditions. Additionally, the multilingual user interface enhances accessibility for farmers from diverse linguistic backgrounds. The proposed system provides an effective and practical solution for early crop health monitoring, enabling timely intervention, reducing dependency on agricultural experts, and contributing to increased agricultural productivity and sustainable farming practices.

Keywords— Plant Disease Detection, Nutrient Deficiency Analysis, Deep Learning, Convolutional Neural Network (CNN), Generative Adversarial Network (GAN), Crop Health Monitoring, Image Classification, Precision Agriculture.

1. INTRODUCTION

Plant health plays a vital role in agricultural productivity and food security. However, plant diseases and nutrient deficiencies continue to pose significant challenges to farmers, leading to reduced crop yield and economic losses. Traditional methods for diagnosing these issues rely heavily on expert knowledge and laboratory testing, which are often time-consuming, expensive, and inaccessible to small-scale farmers. With the increasing integration of technology in agriculture, there is a growing need for intelligent systems that can enable real-time decision-making and early detection of crop-related problems. This project introduces *Plant disease dectection*, a machine learning-based web application designed to predict plant diseases and nutrient deficiencies using leaf images and soil nutrient data. The system leverages a hybrid deep learning approach that combines **Convolutional Neural Networks (CNN)** and **Generative Adversarial Networks (GAN)**. The CNN model is trained on a dataset of over 55,000 images across 32 classes and is capable of learning complex visual patterns such as color variations, texture, and lesion structures associated with plant diseases and deficiencies.To enhance the performance and robustness of the model, GAN is incorporated for data augmentation by generating realistic synthetic leaf images. This helps address challenges such as limited dataset size, class imbalance, and variations in real-world conditions like lighting, noise, and background complexity. As a result, the system becomes more reliable and capable of generalizing across diverse agricultural environments.A user-friendly web interface, developed using Flask, allows users to upload leaf images and receive instant predictions along with treatment recommendations. The application operates in two modes: **Basic Mode**, which performs disease detection using image classification, and **Advanced Mode**, which integrates rule-based logic to analyze additional soil nutrient inputs and evaluate interactions between diseases and nutrient deficiencies. This modular design ensures scalability and supports future enhancements such as mobile integration, multilingual support, and cloud-based deployment. Through this initiative, the project bridges the gap between advanced artificial intelligence techniques and real-world agricultural challenges. It empowers farmers and researchers with a practical, cost-effective, and accessible tool for improving crop diagnosis accuracy and response time, while also providing valuable experience in applied machine learning, computer vision, and intelligent system design.

2. LITERATURE REVIEW

Recent advancements in deep learning have significantly improved plant disease detection systems. Abbas et al. (2021) proposed a GAN-based data augmentation approach to enhance tomato disease detection under varying real-world lighting conditions. Dhaka et al. (2021) presented a comprehensive survey of deep learning techniques used in plant disease detection. Selvaraj et al. (2020) demonstrated the effectiveness of deep learning for cassava disease detection using real-world field images. Similarly, Zhang et al. (2020) utilized DCGAN for generating synthetic images to improve plant disease classification. Further studies focused on improving classification accuracy using CNN-based approaches. Rahman et al. (2020) developed a hybrid CNN model for rice disease detection, while Khandelwal et al. (2020) applied GAN-based augmentation for potato leaf disease detection. Hasan et al. (2020) evaluated different CNN architectures to identify the most effective models for plant disease detection. Singh et al. (2020) employed deep residual networks to handle complex environmental conditions, and Too et al. (2019) conducted a comparative study of deep learning models for plant disease classification. In addition, several researchers explored the use of GANs to enhance dataset quality and model performance. Pires et al. (2019) and Arsenovic et al. (2019) demonstrated the effectiveness of GAN-generated synthetic data in improving disease recognition accuracy. Ferentinos (2018) developed deep learning models achieving high accuracy in plant disease detection, while Rangarajan et al. (2018) focused on paddy crop disease classification using CNN. Barbedo (2018) analyzed factors affecting deep learning performance in real-world conditions. Earlier works by Fuentes et al. (2017), Amara et al. (2017), Lu et al. (2017), and Islam et al. (2017) applied deep learning techniques for various crop diseases. Mohanty et al. (2016) provided one of the earliest benchmarks for image-based plant disease detection using deep learning, and Goodfellow et al. (2014) introduced Generative Adversarial Networks (GANs), which have since become a key technique for data augmentation in this domain.

3. PROPOSED METHODOLOGY

This project presents an intelligent approach to improving agricultural practices by predicting plant diseases and nutrient deficiencies using deep learning techniques. The methodology integrates data preprocessing, **GAN-based data augmentation**, CNN-based image classification, model training, and deployment into a user-friendly web interface. By automating the analysis of leaf images through a hybrid **CNN–GAN model**, *Plant disease dectection* improves diagnostic accuracy, reduces manual effort, and provides real-time recommendations through an interactive application.

The proposed methodology focuses on building a robust system that can handle real-world challenges such as limited datasets, class imbalance, and environmental variations like lighting and noise. GAN is incorporated to generate realistic synthetic images, which enhances dataset diversity and improves the generalization ability of the CNN model.

The key steps involved in this methodology include:

Data Acquisition: Collecting a large dataset of crop leaf images representing various diseases and nutrient deficiencies.

Image Preprocessing: Resizing, normalization, and noise removal to ensure consistent input quality for the model.

Data Augmentation (GAN): Using **Generative Adversarial Networks (GAN)** to generate synthetic leaf images, addressing class imbalance and improving robustness under different conditions.

CNN Model Training: Training a custom **Convolutional Neural Network (CNN)** to extract features and classify plant diseases and deficiencies accurately.

Model Validation and Evaluation: Evaluating performance using metrics such as accuracy, precision, recall, and F1-score to select the best model.

Frontend Development: Designing a user-friendly interface using HTML, CSS, and JavaScript for easy interaction.

Backend Integration: Integrating the trained CNN model and GAN-enhanced dataset with a Flask-based backend to provide real-time predictions and treatment suggestions.

Deployment: Hosting the application locally or on cloud platforms to ensure accessibility and scalability.

This end-to-end methodology provides a fast, reliable, and scalable solution for early plant disease detection and nutrient analysis. By combining CNN for classification and GAN for data enhancement, the system ensures improved performance in real-world agricultural environments and supports farmers in making timely and informed decisions.

DEVELOPMENT PROCESS

The system was built following a structured and iterative development lifecycle comprising five key stages:

1. *Requirements Gathering*

Initial discussions with agricultural domain knowledge and project objectives were conducted to identify key functionalities, including:

Detection of plant diseases and nutrient deficiencies from leaf images, Real-time prediction through a web interface, Providing treatment recommendations and user-friendly outputs.

This stage also focused on defining system requirements such as accuracy, usability, scalability, and accessibility for farmers.

2. *System Design*

A modular architecture was designed to integrate deep learning models with a web-based application. Key components include:
Image preprocessing and augmentation module, GAN module for synthetic image generation, CNN model for classification,
Flask-based backend and interactive frontend interface.

The design ensures scalability and easy integration of future enhancements.

3. *Implementation*

The development phase of Plant disease detection was carried out in Python and included the following key components:

Model Training: A hybrid deep learning model combining **Convolutional Neural Network (CNN)** and **Generative Adversarial Network (GAN)** was implemented. The CNN was trained on preprocessed leaf image datasets to accurately classify plant diseases and nutrient deficiencies, while the GAN was used to generate synthetic images to improve dataset diversity and model robustness.

Data Handling: Scripts were developed to clean and preprocess raw image data, including resizing, normalization, and noise removal. **GAN-based augmentation** was applied to address class imbalance, and the dataset was organized into training, validation, and test sets.
Frontend Development: A user-friendly web interface was created using HTML, CSS, and JavaScript, allowing users to upload leaf images and receive real-time predictions, confidence scores, and treatment recommendations.
Backend Integration: A Flask-based backend was developed to integrate the trained CNN model with the web interface, enabling seamless processing of user inputs and real- time prediction outputs.

4. System Architecture

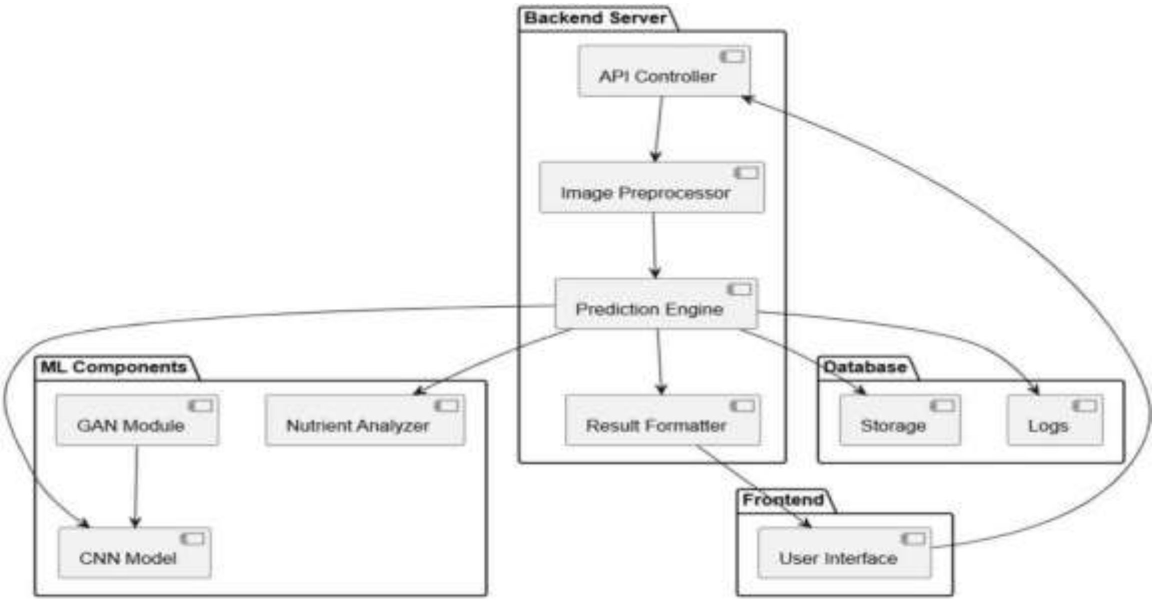

Figure 1 : System Architecture Diagram

Figure 1 describes a modular and scalable design, emphasizing clean separation of concerns.

Layers:

Client-Side Layer

Frontend Interface: Developed using HTML, CSS, and JavaScript for real-time image upload and interaction. Visualization Panel: Displays predictions, confidence scores, and treatment recommendations in a user-friendly format.

Application Layer

Flask Backend: Handles user requests, processes inputs, and connects frontend with deep learning models. Session Handling: Manages user interactions and request flow within the application.

Machine Learning Layer

CNN Model: Performs disease and nutrient deficiency classification from leaf images.

GAN Module: Generates synthetic images during training to improve dataset diversity and model robustness. Model Handler: Converts input images into model-compatible format and processes prediction outputs.

Data Layer

Dataset Storage: Stores original and GAN-generated leaf image datasets.

Logs & Results: Maintains prediction history, user inputs, and system logs for analysis and improvement.

Deployment & Monitoring Layer

Deployment: Hosted on local server or cloud platforms such as AWS or Azure. Version Control: GitHub used for code management and updates.

Monitoring : System performance and model accuracy are tracked using logs and evaluation metrics.

5. RESULTS AND DISCUSSION

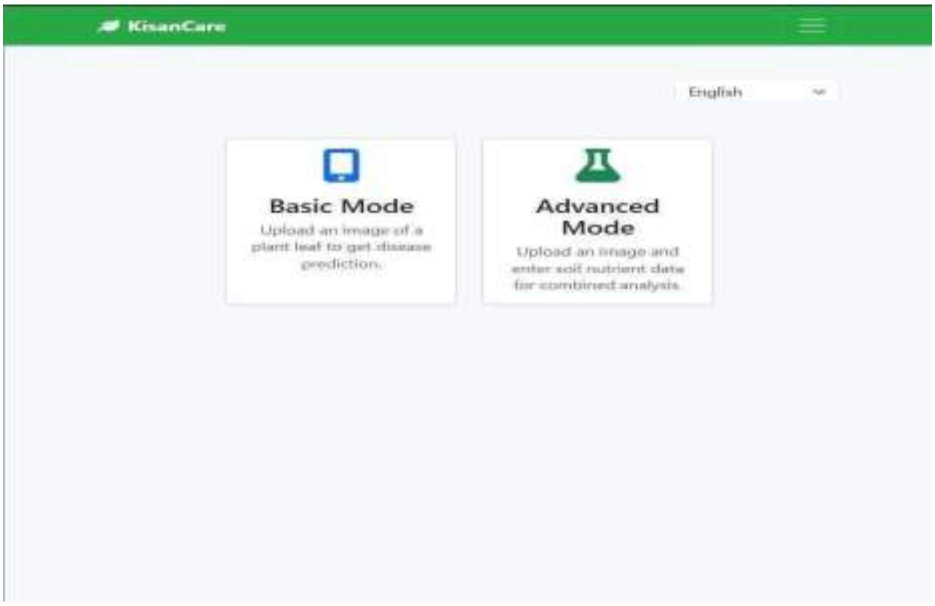

Figure 2 : Homepage of Plant disease detection – AI-Powered Plant Health Diagnosis

Figure 2 describes The homepage allows users to upload plant leaf images and optionally enter nutrient data. It provides Basic and Advanced modes for disease detection with treatment suggestions.

Prediction Interface: This interface allows users to upload a leaf image and instantly receive predictions such as the disease/nutrient deficiency affecting the crop. It also provides the top-3 prediction confidences

along with precise treatment recommendations.

Figure 3: Predicted Output – Disease Detection and Treatment Suggestions

Figure 3 describes The predicted output displays the identified plant disease along with confidence level and recommended treatment measures. It helps users take timely action for effective crop management.

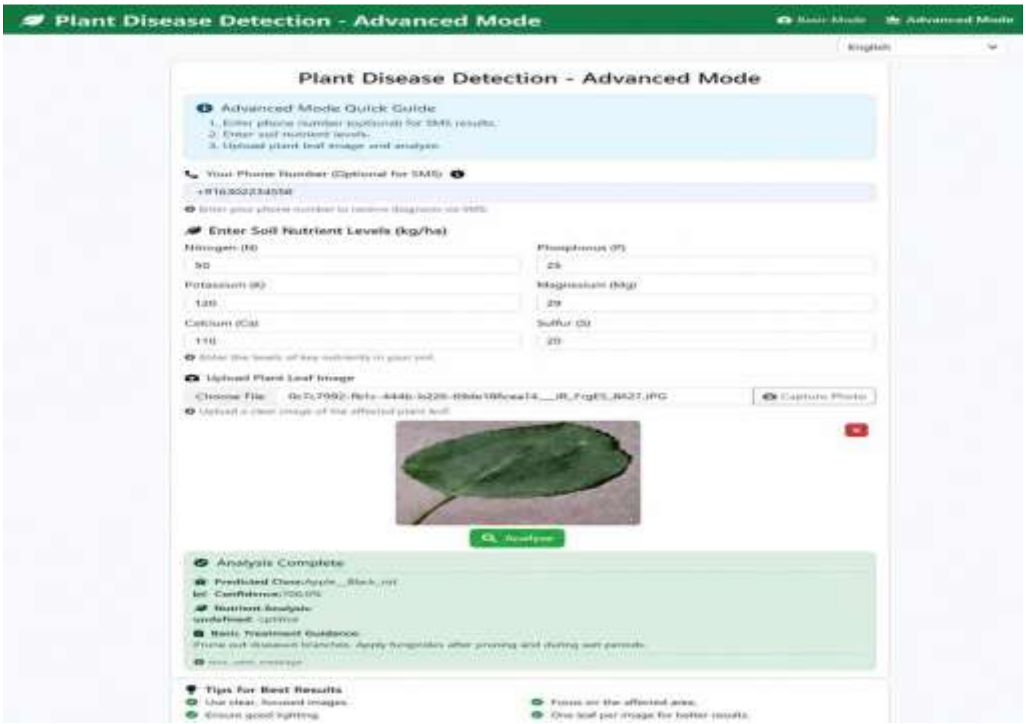

Figure 4: Predicted Output – Integrated Disease and Nutrient Deficiency Analysis

Figure 4 describes The output shows both the detected plant disease and nutrient deficiency based on image and input data. It provides combined insights and recommendations for better crop health management.

6. CONCLUSION AND FUTURE SCOPE

CONCLUSION

The *Plant Disease Detection using CNN and GAN* project demonstrates a practical and intelligent approach to diagnosing plant diseases and nutrient deficiencies using deep learning techniques. By allowing users to upload a single leaf image, the system provides real-time analysis and treatment recommendations without the need for expert intervention or laboratory testing.

The implementation of a hybrid model combining **Convolutional Neural Networks (CNN)** and **Generative Adversarial Networks (GAN)** ensures reliable and robust performance. The CNN model enables accurate classification across a wide range of crops and conditions, while GAN enhances the dataset by generating synthetic images, improving model generalization and handling real-world variability. Additionally, the rule-based logic in Advanced Mode adds another layer of agronomic insight by analyzing nutrient interactions.

The multilingual and user-friendly interface makes the system highly accessible to farmers and agricultural professionals. Overall, the proposed system offers a scalable, efficient, and impactful solution for precision agriculture, bridging the gap between advanced AI techniques and real-world farming challenges, and supporting better decision-making for improved crop productivity.

FUTURE SCOPE

Future enhancements to *Plant Disease Detection using CNN and GAN* could include:

- **Mobile App Deployment:** Developing a mobile application to enable offline usage in rural areas with limited internet connectivity.
- **Cloud-Based Hosting:** Deploying the system on cloud platforms such as AWS or Azure to support large-scale access and real-time remote inference.
- **Voice & Chatbot Integration:** Assisting farmers, especially those with low literacy levels, through voice-based interaction and AI-powered chatbots.
- **Expanded Dataset:** Incorporating additional crop types, regional disease variations, and real-time field images. Further use of **GAN** can enhance dataset diversity and improve model generalization.
- **Soil-Nutrient Integration:** Combining leaf image analysis with soil test data for more accurate and comprehensive nutrient diagnosis.
- **Automated Crop Logging:** Allowing users to maintain crop health records and receive seasonal alerts and recommendations.
- **IoT Integration:** Integrating environmental sensors (temperature, humidity, soil moisture) to build a complete smart farming ecosystem.

These advancements would transform the system from a basic diagnostic tool into a comprehensive digital farming assistant, promoting sustainable agriculture, improving crop yield, and empowering farmers with intelligent decision-making tools.

REFERENCES

[1] A. Abbas et al., "GAN-based data augmentation for tomato disease detection under
[2] varying real-world lighting conditions," 2021.
[3] V. S. Dhaka et al., "A survey of plant disease detection techniques using deep learning," 2021.
[4] M. G. Selvaraj et al., "AI-powered cassava disease detection using real-world images," Nature Communications, vol. 11, p. 293, 2020. doi: 10.1038/s41467-019-13967-0.
[5] S. Zhang et al., "Plant disease recognition based on deep learning and DCGAN, 2020.
[6] C. R. Rahman et al., "Identification of rice plant diseases using CNN-based models," 2020.
[7] I. Khandelwal et al., "Data augmentation using GAN for potato disease classification," 2020.
[8] M. Hasan et al., "Deep learning approaches for plant disease detection: A review," 2020.
[9] V. Singh et al., "Deep residual learning for plant disease classification," 2020.
[10] R. Pires et al., "GAN-based synthetic image generation for plant disease detection," 2019.
[11] M. Arsenovic et al., "Solving current limitations of deep learning-based plant disease detection using GAN," 2019.
[12] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Computers and Electronics in Agriculture, vol. 145, pp. 311–318, 2018. doi: 10.1016/j.compag.2018.01.009.
[13] A. K. Rangarajan et al., "A deep learning-based approach for classification of plant diseases," 2018.
[14] J. G. A. Barbedo, "Impact of dataset size and variety on the effectiveness of deep learning for plant disease classification," 2018. doi: 10.1016/j.compag.2018.03.013.
[15] A. Fuentes et al., "A robust deep-learning-based detector for real-time tomato plant diseases," Sensors, vol. 17, no. 9, p. 2022, 2017. doi: 10.3390/s17092022.
[16] J. Amara, B. Bouaziz, and A. Algergawy, "A deep learning-based approach for banana leaf disease classification," in Proc. BTW, 2017.

[17] J. Lu, J. Hu, G. Zhao, F. Mei, and C. Zhang, “An in-field automatic wheat disease diagnosis system,” Computers and Electronics in Agriculture, vol. 142, pp. 369–379, 2017. doi: 10.1016/j.compag.2017.09.012.

[18] M. Islam et al., “Detection of mango leaf diseases using image processing and deep learning,” 2017.

[19] S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using deep learning for image-based plant disease detection,” Frontiers in Plant Science, vol. 7, p. 1419, 2016. doi: 10.3389/fpls.2016.01419.

[20] I. Goodfellow et al., “Generative adversarial networks,” in Advances in Neural Information Processing System (NeurIPS), 2014.