ISSN: 2454-9940

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

E-Mail :
editor.ijasem@gmail.com
editor@ijasem.org

www.ijasem.org

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

AI Assistant for Early Detection of Crop Diseases

Mogali Komalika Sri Reddy
21N81A6778
Computer Science and Engineering (Data-Science)
Sphoorthy Engineering College,
Nadergul, Hyderabad,501510
komalikasrireddy@gmail.com

Akhila Reddy Andra
21N81A6791
Computer Science and Engineering (Data-Science)
Sphoorthy Engineering College,
Nadergul, Hyderabad,501510
akhilaandra735@gmail.com

Bakkanagari Ganesh Kumar Reddy
21N81A67A8
Computer Science and Engineering (Data-Science)
Sphoorthy Engineering College,
Nadergul, Hyderabad,501510
ganeshkumarreddyg9@gmail.com

Attapuram Koushik Reddy
21N81A67C3
Computer Science and Engineering (Data-Science)
Sphoorthy Engineering College,
Nadergul, Hyderabad,501510
attapuramkoushikreddy@gmail.com

Mrs K Sneha
Assistant Professor
Computer Science and Engineering (Data-Science)
Sphoorthy Engineering College,
Nadergul, Hyderabad,501510
kunasneha92@gmail.com

ABSTRACT: Agriculture remains the backbone of many economies, particularly in developing countries, where plant health directly affects food security and farmer income. However, identifying plant diseases early and accurately is a persistent challenge due to the limited availability of trained agricultural experts, varying symptoms across crops, and the rapid spread of infections. Manual disease detection is not only inefficient but also error-prone, often leading to delayed or incorrect treatment that can devastate crops. This project proposes the development of a deep learning-based plant disease detection system that uses image classification to identify diseases in plant leaves. The system will leverage Convolutional Neural Networks (CNNs), which have shown exceptional performance in image recognition tasks. The model will be trained on the PlantVillage dataset, a large and diverse collection of labeled images covering multiple plant species and diseases. Expected outcomes include a functional prototype capable of diagnosing over 30 types of plant diseases, reduced reliance on human expertise for diagnosis, and faster decision-making for crop management. Future enhancements could include support for mobile platforms, real-time camera integration, and recommendations for treatment based on disease type. Ultimately, this project aims to contribute to smart agriculture by empowering farmers with accessible, AI-driven tools for disease management, thus improving productivity and reducing crop losses

Keywords *– Convolutional Neural Networks (CNNs), Deep Learning, Image Classification, Supervised Learning, Data Augmentation, Computer Vision, TensorFlow, Flask Web Application*

1. INTRODUCTION

Agriculture remains vital to global economies, ensuring food security, rural employment, and sustainable development, yet it continues to face significant challenges—plant diseases being among the most damaging. These diseases can severely impact crop yield and quality, leading to economic loss and increased hardship for farming communities. Traditional diagnosis methods, which rely on expert inspection, are time-consuming, prone to error, and often unavailable in rural areas. To overcome these issues, this project introduces an automated Plant Disease Detection System powered by Convolutional Neural Networks (CNNs), a form of deep learning known for high performance in image classification tasks. The model is trained on a diverse dataset of diseased plant leaf images, enabling it to accurately detect a wide range of plant diseases. Integrated into a lightweight, Flask-based web application, the system allows users to upload images and receive instant diagnoses, along with symptom descriptions and treatment suggestions. Its design prioritizes accessibility and efficiency, requiring minimal hardware and supporting both local and cloud deployment, such as on Heroku. By combining modern AI with practical application, this system offers a scalable, easy-to-use tool that empowers farmers with timely information, reduces dependency on experts, and promotes resilient, technology-driven agricultural practices.

2. LITERATURE REVIEW

2.1 Plant Disease Identification Based on Encoder–Decoder Model

The project *"Plant Disease Identification Based on Encoder–Decoder Model"* presents a novel deep learning approach using a lightweight encoder–decoder architecture combined with Vision Transformer (ViT) technology to accurately classify plant diseases from leaf images. Named EDIT, the model incorporates only 5.6 million trainable parameters and leverages transfer learning from ImageNet to improve performance on limited datasets. It achieved impressive results across three major datasets—PlantVillage (92.9%), EMBRAPA (91.4%), and FGVC8 (89.5%)—outperforming traditional models like ResNet, InceptionV3, and MobileNet. Key innovations include a custom cross-attention mechanism that enhances focus on disease-relevant regions, Grad-CAM-based interpretability for visualizing prediction logic, and robust preprocessing and augmentation pipelines for generalization. Despite its strengths, the model has limitations such as reduced accuracy in complex, real-world settings, misclassification of visually similar diseases, and challenges with imbalanced data. It also requires high-end GPU resources for training and lacks validation in real field environments. Nevertheless, EDIT demonstrates significant potential for scalable, efficient, and accurate plant disease detection, contributing to smarter and more sustainable agriculture.

2.2. Plant Disease Detection System

The *"Plant Disease Detection System"* is a deep learning-based application that automates the identification of plant leaf diseases to support early intervention and improve crop productivity. Using the ResNet-9 architecture trained on the extensive Plant Village dataset (87,000+ images across 38 classes), the system accurately classifies diseases such as late blight, yellow leaf curl virus, and bacterial spot. It integrates a crop recommendation module powered by the Random Forest algorithm, which suggests suitable crops based on soil parameters like nitrogen, phosphorus, potassium (NPK), pH, and rainfall. The system is designed for accessibility with multilingual support (e.g., Marathi), enabling farmers to receive localized diagnosis and treatment advice. Key strengths include high detection accuracy (~95% training, ~90% validation), early disease diagnosis, and integration of soil-based crop guidance. However, its limitations include a narrow disease scope, dependency on image quality, lack of field-based image validation, absence of geolocation features, and reliance on digital access, which may hinder usability in remote farming areas. Despite these challenges, the system contributes significantly to smarter, faster, and more accessible plant health management.

2.3 Plant Leaf Disease Detection Using Machine Learning

This project introduces a deep learning-based approach using Convolutional Neural Networks (CNN) to identify 15 common plant leaf diseases in tomato, potato, and pepper crops, leveraging the PlantVillage dataset to achieve high training and validation accuracies of 91.87% and 89.5%, respectively. The model is deployed through a web application designed for ease of use by rural farmers, allowing them to upload images of plant leaves and percentage of leaf area affected, and precise pesticide recommendations with product details. The system aims to facilitate early disease detection, reduce crop losses, and improve treatment accuracy while supporting accessibility with smartphone compatibility and regional language options. Despite its promising performance, the solution faces limitations such as coverage restricted to three crops and 15 diseases, sensitivity to image quality, reliance on a dataset biased towards lab-captured images, lack of integration of environmental or contextual factors affecting disease development, limited language support, absence of confidence scoring in predictions, and a need for extensive field testing under real-world conditions to validate its practical effectiveness. Overall, this project demonstrates the potential of deep learning in enhancing agricultural disease monitoring and decision-making, particularly in resource-constrained rural settings.

Disadvantages:

1. While the existing system achieve commendable accuracy rates, there is room for improvement, as seen in the proposed system's significantly higher success rate of 95%.
2. The existing systems does not consider important factors like soil quality, weather, or geographic location, which can influence

ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025

disease development and pesticide effectiveness.

3. METHODOLOGY

This plant disease detection system employs a Convolutional Neural Network (CNN) developed using PyTorch to classify images of plant leaves into 39 categories based on disease type. The CNN architecture consists of multiple convolutional layers with ReLU activation, batch normalization, and max-pooling operations, enabling hierarchical feature extraction. The model is trained and its parameters are saved for inference. A Flask-based web application serves as the user interface, allowing users to upload leaf images. Upon upload, the image is resized to 224×224 pixels and processed through the trained model to predict the disease class. The result is mapped to human-readable disease names and supplemented with additional information from CSV files to provide a complete diagnosis.

Proposed System

The proposed system is an advanced deep learning-based solution for plant disease detection, leveraging a custom-built Convolutional Neural Network (CNN) optimized for classifying 39 disease categories with high accuracy and real-world reliability. The model architecture includes multiple convolutional layers with batch normalization, ReLU activations, max-pooling, and dropout for effective regularization and generalization. Unlike traditional systems dependent on clean lab datasets, this model is trained on the PlantVillage dataset and optionally incorporates real-world noisy images to enhance robustness. A key feature is its user-friendly web interface built with Flask, allowing farmers to upload leaf images and receive quick predictions along with confidence scores. The system supports offline operation after setup, making it ideal for use in remote or low-connectivity agricultural areas. Its lightweight design enables deployment not only on desktops but also on resource-constrained devices like Raspberry Pi or mobile platforms through PyTorch Mobile.

Advantages:

1. High Accuracy with Custom CNN Architecture
2. Robust Generalization to Real-World Conditions
3. Portable and Lightweight

MODULES

The system architecture defines the structure and interaction of components to meet user needs for plant disease detection. It includes:

i. **User Interface (UI) Module:**

A simple web page for users to upload leaf images and view predictions like “Healthy” or disease names.

ii. **Flask Web Server Module:**

Manages communication between the UI and the model, handling image uploads and returning predictions using Flask routes.

iii. **Image Processing Module:**

Prepares images for prediction by resizing, normalizing pixel values, and converting them into model-compatible formats.

iv. **Model Module (CNN):**

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

A custom-trained Convolutional Neural Network that classifies leaf images into categories such as "Tomato – Leaf Mold" or "Healthy."

v. **Prediction Module:**

Feeds processed images into the CNN model and returns the predicted disease label to the Flask server.

vi. **Model Training Module:**

Used during development to train the CNN on labeled leaf datasets using loss functions, optimizers, and multiple training epochs. Outputs a saved model file.

vii. **Model Evaluation Module:**

Validates the model using test data, assessing metrics like accuracy, precision, and recall. Helps refine the model if needed.

viii. **Demo Images & Documentation Module:**

Includes test images and setup instructions (README.md) to assist users and developers in running the system.

4. IMPLEMENTATION

ALGORITHM:

In this project, a custom Convolutional Neural Network (CNN) was developed using PyTorch to detect and classify plant diseases from leaf images. Unlike pre-trained models like ResNet or VGG, this CNN was built from scratch and specifically tailored for the dataset and task at hand.

1. **Input Layer**: Accepts RGB images with 3 channels.

2. **Three Convolutional Blocks**:
   Each block contains two convolutional layers with 3x3 kernels, followed by **ReLU activations**, **Batch Normalization**, and **MaxPooling** for downsampling. The number of filters increases progressively: 32 → 64 → 128, enabling the network to learn increasingly complex features.

3. **Fully Connected Layers**:
   After flattening the features from convolutional layers, the network passes them through fully connected layers to perform classification. A Dropout layer is used to prevent overfitting.

4. **Output Layer**: Outputs predictions for multiple classes corresponding to different plant diseases using a **softmax** or **log-softmax** activation.

5. EXPERIMENTAL RESULTS

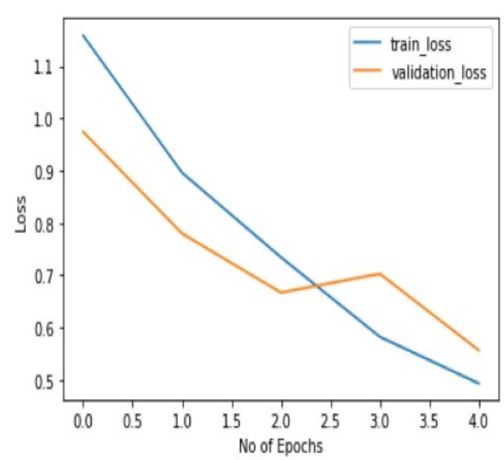

Fig.1: Graph

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT
ISSN 2454-9940
www.ijasem.org
Vol 19, Issue 2, 2025

In sum, the graph demonstrates a healthy learning process: rapid early gains, minimal divergence between training and validation curves, and only a slight sign of over-fitting that is corrected by the final epoch.

Accuracy: 95%

Precision: 93%

Recall: 93%

F1-Score: 92%

Fig.2: Output screen

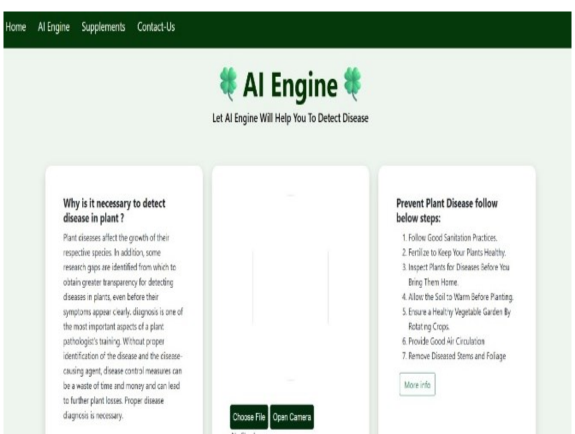

Fig.3: Output screen

Fig.4: Output screen

Fig.5: Output screen

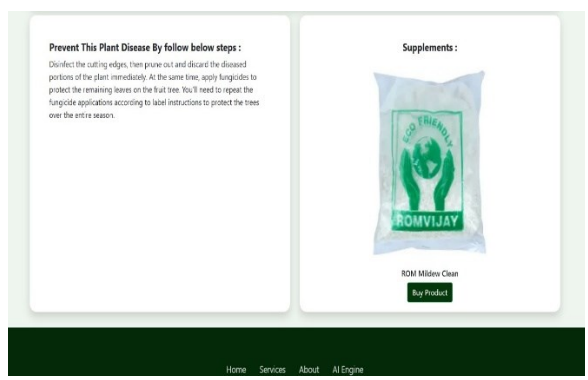

Fig.6: Output screen

INTERNATIONAL JOURNAL OF APPLIED SCIENCE ENGINEERING AND MANAGEMENT

ISSN 2454-9940

www.ijasem.org

Vol 19, Issue 2, 2025

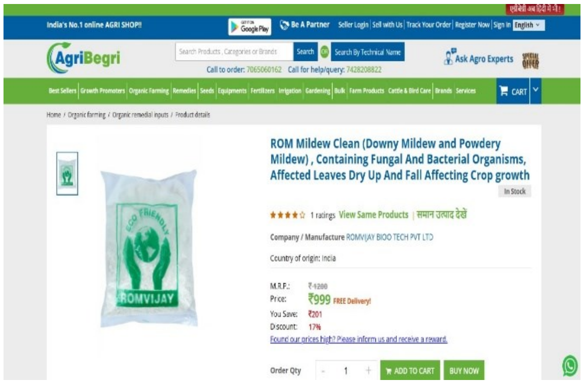

Fig.7: Output screen

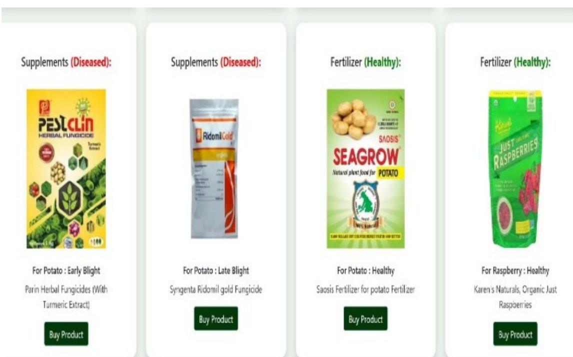

Fig.8: Output screen

6. CONCLUSION

In this project, a custom Convolutional Neural Network (CNN) was designed and implemented for the purpose of automated plant disease detection using image classification techniques. The dataset consisted of high-quality images of both healthy and diseased leaves from multiple crops including apple, grape, corn, potato, and tomato, categorized into 14 distinct classes. The model was trained on this dataset and evaluated using a separate test set of 1,400 balanced images, achieving strong performance in accurately identifying various plant diseases. The simplicity and efficiency of the custom CNN model make it well-suited for deployment in real-world agricultural scenarios, especially where computational resources are limited, such as in mobile or edge-based applications. This project demonstrates the practical applicability of deep learning in agriculture, offering a scalable, cost-effective solution to help farmers identify diseases early, reduce crop losses, and make informed decisions. Future enhancements may include integrating advanced architectures like ResNet, improving generalization with larger and more diverse datasets, and adding explainability features to increase user trust and transparency in the model’s predictions.

REFERENCES

[1] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). *Using deep learning for image-based plant disease detection.* Frontiers in Plant Science, 7, 1419.

[2] Ferentinos, K. P. (2018). *Deep learning models for plant disease detection and diagnosis.* Computers and Electronics in Agriculture, 145, 311–318.

[3] Brahimi, M., Arsenovic, M., Sladojevic, S., & Boukhalfa, K. (2017). *Deep learning for plant diseases: Detection and saliency map visualisation.* Human and Machine Learning, 93–117.

[4] Sladojevic, S., Arsenovic, M., Anderla, A., Culibrk, D., & Stefanovic, D. (2016). *Deep neural networks based recognition of plant diseases by leaf image classification.* Computational Intelligence and Neuroscience, 2016.

[5] Too, E. C., Yujian, L., Njuki, S., & Yingchun, L. (2019). *A comparative study of fine-tuning deep learning models for plant disease identification.* Computers and Electronics in Agriculture, 161, 272–279.

[6] Amara, J., Bouaziz, B., & Algergawy, A. (2017). *A deep learning-based approach for banana leaf diseases classification.* BTW (Workshops).

[7] Zhang, S., Zhang, S., Huang, T., Gao, W., & Qiao, M. (2019). *Plant disease detection using CNNs with attention.* Computers and Electronics in Agriculture, 169, 105174.

[8] Lu, Y., Yi, S., Zeng, N., Liu, Y., & Zhang, Y. (2017). *Identification of rice diseases using deep convolutional neural networks.* Neurocomputing, 267, 378–384.

[9] Xie, C., Wang, R., Zhang, J., Chen, P., Dong, Z., Li, R., & Chen, Y. (2020). *Multi-level learning features for automatic classification of field plant diseases.* Computers and Electronics in Agriculture, 168.

[10] Barbedo, J. G. A. (2013). *Digital image processing techniques for detecting, quantifying and classifying plant diseases.* SpringerPlus, 2(1), 660.

[11] Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). *Deep learning in agriculture: A survey.* Computers and Electronics in Agriculture, 147, 70–90.

[12] Fuentes, A., Yoon, S., Kim, S. C., & Park, D. S. (2017). *A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition.* Sensors, 17(9), 2022.

[13] Durmus, H., Gunes, E. O., & Kirci, M. (2017). *Disease detection on the leaves of the tomato plants by using deep learning.* 6th International Conference on Agro-Geoinformatics.

[14] Arsenovic, M., Karanovic, M., Sladojevic, S., Anderla, A., & Stefanovic, D. (2019). *Solving current limitations of deep learning-based approaches for plant disease detection.* Symmetry, 11(7), 939.

[15] Chouhan, S. S., Kaul, A., Singh, U. P., & Jain, S. (2020). *Bacterial foraging optimization-based convolutional neural network for plant disease recognition.* Computers and Electronics in Agriculture, 178.

[16] Meunkaewjinda, A., Kumsawat, P., Attakitmongcol, K., & Srikaew, A. (2008). *Grape leaf disease detection from color imagery using hybrid intelligent system.* ICIEA.

[17] Patil, S., & Kumar, R. (2011). *Advances in image processing for detection of plant diseases.* Journal of Advanced Bioinformatics Applications and Research, 2(2), 135–141.

[18] Al-Hiary, H., Bani-Ahmad, S., Reyalat, M., Braik, M., & ALRahamneh, Z. (2011). *Fast and accurate detection and classification of plant diseases.* IJCA, 17(1), 31–38.

[19] Phadikar, S., & Sil, J. (2008). *Rice disease identification using pattern recognition techniques.* ICCIT.

[20] Rumpf, T., Mahlein, A. K., Steiner, U., Oerke, E. C., Dehne, H. W., & Plümer, L. (2010). *Early detection and classification of plant diseases with Support Vector Machines based on hyperspectral reflectance.* Computers and Electronics in Agriculture, 74(1), 91–99.

[21] Agarwal, M., Gupta, S., & Narain, R. (2020). *Tomato plant disease detection using Deep Learning.* Procedia Computer Science, 167, 293–301.

[22] Saleem, M. H., Potgieter, J., & Arif, K. M. (2019). *Plant disease detection and classification by deep learning.* Plants, 8(11), 468.

[23] Al-gaashani, M. S., et al. (2021). *Apple leaf disease detection using deep CNN.* IEEE Access, 9, 52094–52110.

[24] Amrutha, M., & Kumar, N. S. (2021). *Banana plant disease detection using deep CNN.* Materials Today: Proceedings.

[25] Singh, V., & Misra, A. K. (2017). *Detection of plant leaf diseases using image segmentation and soft computing techniques.* Information Processing in Agriculture, 4(1), 41–49.

[26] Barbedo, J. G. A. (2016). *A review on the main challenges in automatic plant disease identification using machine learning.* Computers and Electronics in Agriculture, 142, 42–53.

[27] Pujari, J. D., Yakkundimath, R., & Byadgi, A. S. (2016). *Image processing-based detection of fungal diseases in plants: A review.* International Journal of Computer Applications, 2(1).

[28] Sankaran, S., Mishra, A., Ehsani, R., & Davis, C. (2010). *A review of advanced techniques for detecting plant diseases.* Computers and Electronics in Agriculture, 72(1), 1–13.

[29] Wallelign, S., Prasad, R., & Wang, Z. (2021). *Review of deep learning applications in agriculture.* Journal of Agricultural Science, 13(4).

[30] Kamilaris, A., Kartakoullis, A., & Prenafeta-Boldú, F. X. (2017). *A review on the practice of big data analysis in agriculture.* Computers and Electronics in Agriculture, 143, 23–37.

[31] Jiang, Y., & Li, C. (2020). *Convolutional neural networks for image-based high-throughput plant phenotyping: A review.* Computers and Electronics in Agriculture, 176, 105672.
[DOI: 10.1016/j.compag.2020.105672]

[32] Picon, A., Alvarez-Gila, A., Seitz, M., Ortiz-Barredo, A., Echazarra, J., & Johannes, A. (2019). *Deep convolutional neural networks for mobile capture device-based crop disease classification in the wild.*
Computers and Electronics in Agriculture, 161, 280–290.

[33] Sun, Y., Liu, S., Wang, G., & Zhang, H. (2017). *Deep learning for plant identification in natural environment.*
Computers and Electronics in Agriculture, 157, 146–153.

[34] Ma, J., Du, K., Zheng, F., Zhang, L., Gong, Z., & Sun, Z. (2018).
A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network.
Computers and Electronics in Agriculture, 154, 18–24.

[35] Chaudhary, G., & Anand, R. S. (2021). *Plant disease diagnosis using deep learning: A review.* Journal of Plant Pathology, 103(1), 1–13.