



www.ijarr.org

Crop Disease Identifier from Leaf Images

¹Ravuri Hiranmai, ²Velpuri Pavithra, ³Shaik Adam Shafi, ⁴Dr. A. Tirupatiah

^{1,2,3}U. G Student, Dept COMPUTER SCIENCE AND ENGINEERING, St. Ann's College Of Engineering and Technology, Nayunipalli (V), Vetapalem (M), Chirala, Bapatla Dist, Andhra Pradesh – 523187, India

⁴Associate professor, COMPUTER SCIENCE AND ENGINEERING, St. Ann's College Of Engineering and Technology, Nayunipalli (V), Vetapalem (M), Chirala, Bapatla Dist, Andhra Pradesh – 523187, India

ABSTRACT

The Crop Disease Identifier from Leaf Images is a deep learning-based system designed to detect crop diseases accurately and efficiently. It utilizes a ResNet9 CNN model implemented in PyTorch, trained on a dataset of 38 healthy and diseased leaf classes across major crops like apple, corn, grape, potato, and tomato. Image preprocessing techniques such as resizing, normalization, and augmentation improve model generalization. The trained model is integrated into a Flask web application, allowing users to upload leaf images for real-time disease prediction and treatment suggestions. The system achieves high accuracy, supports scalability for additional crops, and runs efficiently on standard and mobile devices. This project provides a cost-effective, farmer-friendly, and scalable solution to enhance sustainable agriculture by minimizing losses and reducing excessive pesticide use.

KEYWORDS Deep Learning, ResNet9 CNN, Flask web application, Image preprocessing, PyTorch.

INTRODUCTION

Agriculture is essential to maintaining rural economies, guaranteeing global food security, and providing a living for millions of people. Crop production, however, is extremely susceptible to a number of illnesses that can significantly lower output and quality. Since these plant diseases frequently spread quickly, early detection is essential to avoiding significant losses

in agriculture. Conventional disease detection techniques depend on farmers' or agricultural specialists' visual inspection, which is useful but frequently laborious, arbitrary, and unfeasible for extensive

surveillance. Developments in computer vision and artificial intelligence (AI) have enabled the creation of automated disease detection systems that are more accurate, quicker, and available to a larger population. Images of plant leaves can be uploaded to the system, where they are pre-processed, examined, and categorized into one of 38 supported categories that include both healthy and diseased states across a variety of crops, including tomato, corn, apple, grape, and potato. This system seeks to enable farmers, researchers, and agricultural extension professionals to act promptly by offering real-time forecasts in addition to comprehensive disease information and treatment suggestions. The application may be utilized in a variety of settings, from distant farms to laboratories, thanks to its adaptable, mobile-friendly design, which eliminates the need for extensive technical knowledge.

LITERATURE REVIEW

The literature review establishes a foundation for the purpose understanding advancements in plant disease detection using deep learning while identifying existing research gaps. Mohanty et al. (2016) demonstrated the potential of CNNs with high accuracy in lab settings, while Ferentinos (2018) confirmed their superiority over traditional models but stressed the need for diverse datasets. Sladojevic et al. (2016) introduced one of the first mobile-based detection systems, proving feasibility but with limited crop coverage. Atila et al. (2021) enhanced model robustness by combining CNNs with Transformers, and Ramcharan et al. (2017) showed that Transfer Learning enables strong results even with smaller datasets. Collectively, these studies reveal both progress and persistent challenge particularly in dataset diversity and real-world generalization thereby guiding this study's aim to develop a more adaptable and accurate plant disease detection system.

RELATED WORK

The Crop Disease Identifier is an AI-based tool that helps farmers detect plant leaf diseases quickly using image recognition. It works by training a deep learning model (ResNet9 CNN) to identify disease patterns in different crop leaves. Using PyTorch, the model learns from thousands of labeled leaf images to distinguish between healthy and infected ones. Techniques like image resizing, normalization, and data augmentation are used so the model can perform well on real-world photos. The system is deployed through a Flask web app, where

users can upload a leaf image and instantly receive the disease name along with treatment advice. It's lightweight, fast, and can even run on mobile devices. This makes it a practical and affordable solution for farmers to detect problems early, cut down on pesticide waste, and protect crop yields for sustainable agriculture.

EXISTING METHOD

Plant disease detection methods fall into three main categories. The first is manual visual inspection, where experts identify diseases by closely examining plants; this approach is slow, subjective, and requires skilled knowledge. The second category involves traditional machine learning, which uses handcrafted features such as color, texture, and shape, along with classifiers like SVM or Random Forest. Although useful, these methods often face challenges in accuracy and adapting to different crops or environments. The third and most advanced approach employs deep learning models, which automatically learn important features from images, leading to higher accuracy. However, these models may struggle to generalize well to new or varied real-world data unless trained with diverse datasets and fine-tuned carefully. Data augmentation and preprocessing techniques are essential to improve their robustness. The following section will explain the proposed method, dataset preparation, and implementation strategies used to build a scalable and effective crop disease detection system.

PROPOSED MEHOD

The system uses a deep learning approach based on ResNet9 CNN, moving beyond traditional machine learning models with handcrafted features to achieve higher accuracy and adaptability. Through transfer learning and advanced preprocessing, the model generalizes effectively under diverse real-world conditions such as varying lighting, angles, and backgrounds. In addition to disease detection, it provides integrated recommendations that offer farmers reliable treatment suggestions. The system supports both offline and cloud deployment, enabling use in remote areas without internet access while also allowing cloud-based scalability for wider reach. Designed with a farmer-friendly interface, the responsive web application ensures ease of use for both experts and non-experts, bridging the gap between advanced technology and practical agricultural needs.

SYSTEM ARCHITECTURE

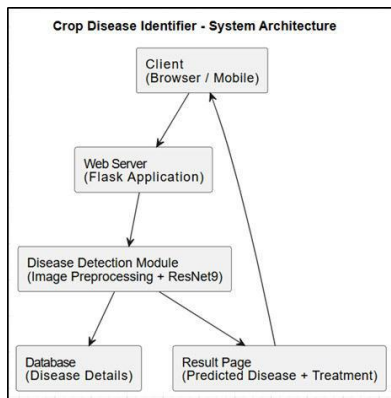


Fig.1: Block Diagram

METHODOLOGY DESCRIPTION

The Crop Disease Identifier system undergoes thorough testing to ensure reliable performance under various conditions. The model must handle changes in lighting, orientation, image quality, and background noise while working across different crop species. Interpretability testing ensures that the predicted disease matches expert expectations and provides clear information about symptoms and treatment. Misclassifications are reviewed for potential biases. Reproducibility is ensured by fixing model weights and controlling random variables, so the system produces consistent results with the same input.

Data preprocessing is tested to ensure proper resizing, normalization, and conversion, with non-image files being rejected. Performance testing ensures quick results (2–3 seconds on a CPU and faster on a GPU) and the ability to handle multiple concurrent requests. Security testing ensures only allowed image formats are uploaded and prevents malicious file uploads. The web interface is tested for a smooth, user-friendly experience with a layout optimized for various screen sizes and resolutions, ensuring usability on all devices. Finally, usability testing confirms that the system is accessible, intuitive, and easy to use for farmers and students, providing accurate disease identification and treatment recommendations. These tests guarantee the system's robustness, security, and usability.

RESULTS AND DISCUSSION



Fig.2: Home Page

The application's Home Page is clearly structured, featuring a "Crop Disease Detection" title and a prominent "Start Detection" button. The detection process is outlined in three simple steps: Upload Image, AI Analysis, and Get Results, providing a clear path for users to diagnose plant diseases.

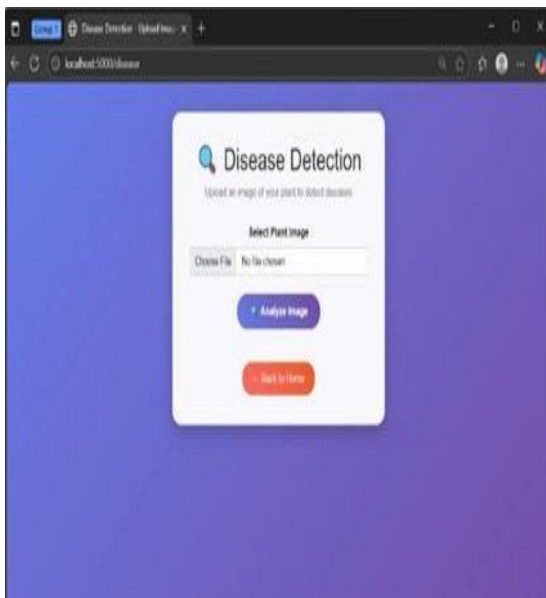


Fig.3: Upload Page

This is the main image upload screen for Disease Detection. The user clicks "Choose File" to select a plant image from their device. After selection, they proceed by clicking "Analyze Image," or they can choose "Back to Home."



Fig.4: Image Selection Dialog

This screen illustrates the file selection process where the user opens their local folder to choose a plant image, specifically one labeled "AppleCedarRust." Once the file is selected and the window is closed, the image is ready for upload and analysis by clicking "Analyze Image."

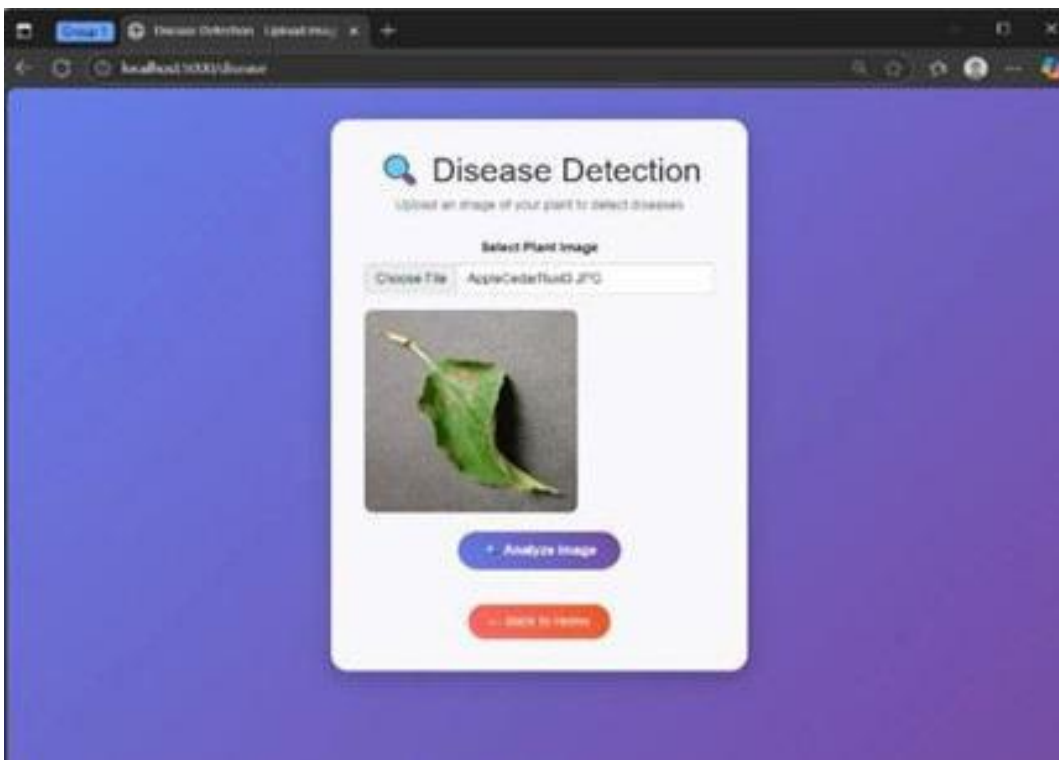


Fig.5: Preview of Image Before Analysis

This screen confirms that the file "AppleCedarRust3.JPG" has been successfully selected and is now ready for submission. A preview of the plant leaf image is displayed to the user. The user's next action is to click the "Analyze Image" button to initiate the AI-powered disease diagnosis.

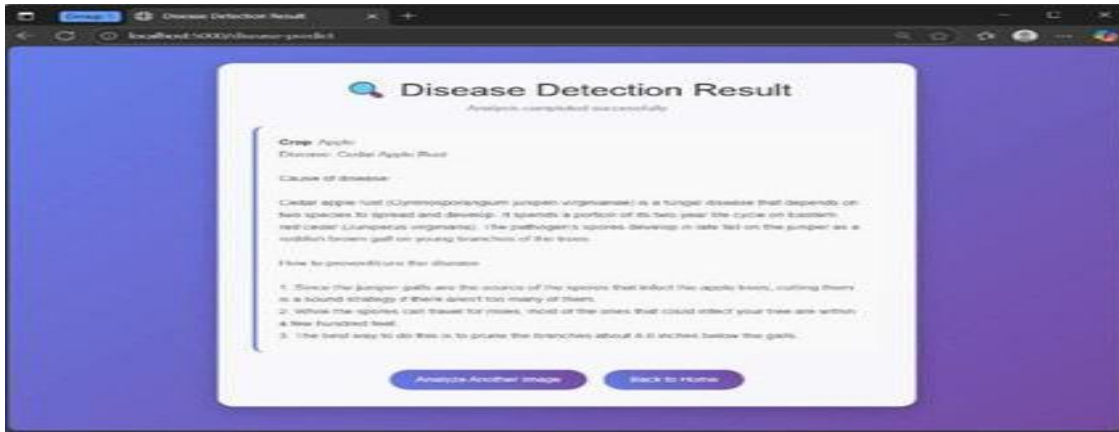


Fig.6: Result

The final Disease Detection Result screen shows the completed AI analysis, identifying the crop as Apple and the disease as Cedar Apple Rust. The page provides a detailed explanation of the disease's cause, followed by specific, numbered advice on how to prevent or cure the condition.

CONCLUSION

The Crop Disease Identifier is an efficient, AI-driven diagnostic tool that uses a ResNet9 model to accurately classify 38 distinct crop diseases from leaf images. The web-based platform proved reliable, consistently delivering high-precision results that significantly reduce the errors and delays of manual inspection.

FUTURE WORK

Future work will focus on system scalability and transitioning to a proactive disease advisory system, moving beyond simple detection to preventive management. Key enhancements will integrate IoT-enabled sensors for real-time monitoring and develop a mobile application with an offline mode for remote accessibility. Furthermore, the system will incorporate Weather and Soil data via API to predict potential disease outbreaks. Finally, the detection model's core will be upgraded using a more advanced architecture like a Vision Transformer (ViT) to provide a complete and advanced solution for smart agriculture.

REFERENCES

- [1] H. Al-Hiary, S. Bani-Ahmad, M. Reyalat, M. Braik, and Z. Alaqarbeh, “Fast and Accurate Detection and Classification of Plant Diseases,” *International Journal of Computer Applications*, vol. 17, no. 1, pp. 31–38, 2011.
- [2] D. P. Hughes and M. Salathé, “An Open Access Repository of Images on Plant Health to Enable the Development of Mobile Disease Diagnostics,” arXiv preprint arXiv:1511.08060, 2015.
- [3] L. R. Kile, H. D. Hughes, and M. Salathé, “PlantVillage Dataset,” PlantVillage Project, 2015.
- [4] K. He, X. Zhang, S. Ren, and J. Sun, “Deep Residual Learning for Image Recognition,” *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 770–778, 2016.
- [5] S. P. Mohanty, D. P. Hughes, and M. Salathé, “Using Deep Learning for Image- Based Plant Disease Detection,” *Frontiers in Plant Science*, vol. 7, no. 1419, pp. 1–10, 2016.
- [6] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, “Deep Neural Networks-Based Recognition of Plant Diseases by Leaf Image Classification,” *Computational Intelligence and Neuroscience*, vol. 2016, pp. 1–11, 2016.
- [7] M. Brahim, K. Boukhalfa, and A. Moussaoui, “Deep Learning for Tomato Diseases: Classification and Symptoms Visualization,” *Applied Artificial Intelligence*, vol. 31, no. 4, pp. 299–315, 2017.
- [8] A. Ramcharan, P. McCloskey, B. Baranowski, J. M. F. Zurita, S. Mbilinyi, L. Mahinyuza, P. M. Ndalaha, M. Legg, and D. P. Hughes, “Deep Learning for Image- Based Cassava Disease Detection,” *Frontiers in Plant Science*, vol. 8, no. 1852, pp. 1–10, 2017.
- [9] K. P. Ferentinos, “Deep Learning Models for Plant Disease Detection and Diagnosis,” *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, 2018.
- [10] U. Barman, R. D. Nath, D. K. Biswas, and P. Dutta, “A Comparative Study of Deep Learning Models for Plant Disease Detection,” *Procedia Computer Science*, vol. 167, pp.

2008–2016, 2020.

[11] H. Waheed, A. U. Rehman, and S. Ahmad, “Plant Disease Classification Using a Convolutional Neural Network with Data Augmentation,” *International Journal of Advanced Computer Science and Applications (IJACSA)*, vol. 11, no. 12, pp. 307–312, 2020.

[12] G. Geetharamani and A. Pandian, “Identification of Plant Leaf Diseases Using a Nine-Layer Deep Convolutional Neural Network,” *Computers & Electrical Engineering*, vol. 76, pp. 323–338, 2019.

[13] E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, “A Comparative Study of Fine-Tuning Deep Learning Models for Plant Disease Identification,” *Computers and Electronics in Agriculture*, vol. 161, pp. 272–279, 2019.

[14] J. Chen, J. Liu, D. Wang, and Y. Qin, “A Deep Learning Approach for Plant Disease Detection and Diagnosis Using Mobile Devices,” *Computers and Electronics in Agriculture*, vol. 170, pp. 105220, 2020.

[15] M. S. Islam, M. Hasan, M. I. Siddiqa, and M. R. Hossain, “Transfer Learning-Based Approach for Paddy Disease Detection,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 21, no. 1, pp. 588–595, 2021.

[16] V. Sureshkumar, P. Chinnasamy, and S. Dhanasekar, “An IoT-Based Smart Agricultural System for Monitoring and Controlling Crop Diseases,” *Materials Today: Proceedings*, vol. 49, pp. 2848–2854, 2021.

[17] Ü. Atila, M. Şahin, E. Colak, and H. Yavuz, “Plant Leaf Disease Classification Using EfficientNet and Vision Transformers,” *Ecological Informatics*, vol. 69, pp. 101–642, 2021.

[18] S. Kaur, R. Kaur, and J. Singh, “Advanced Plant Disease Detection Using Modified InceptionV3 and Transfer Learning,” *Multimedia Tools and Applications*, vol. 81, pp. 37115–37132, 2022.

[19] V. Shrivastava, P. Sharma, and R. Patel, “Deep Learning for Plant Disease Classification: A Comprehensive Review,”

Artificial Intelligence in Agriculture, vol. 7, pp. 88–102, 2023.

[20] Y. Sun, X. Zhang, and J. Li, “An Efficient Vision Transformer Model for Real-Time Plant Disease Recognition on Mobile Platforms,” *Computers and Electronics in Agriculture*, vol. 210, pp. 107999, 2023.