

ISSN: 2582-7219



International Journal of Multidisciplinary Research in Science, Engineering and Technology

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.206

Volume 8, Issue 5, May 2025

ISSN: 2582-7219 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|



International Journal of Multidisciplinary Research in Science, Engineering and Technology (IJMRSET) (A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

Herbal Leaf Healthy and Pathogen Detection using Deep Learning

S Alangaram¹, Ramya P², Nathiya R³, Meharin Fathima U⁴

Assistant Professor, Department of Information Technology, Jaya Engineering College, Anna University,

Chennai, India¹

UG Student, Department of Information Technology, Jaya Engineering College, Anna University, Chennai, India²⁻⁴

ABSTRACT: The early detection and classification of plant diseases play a crucial role in sustaining agricultural productivity and minimizing economic losses. Traditional disease identification methods are often labor-intensive, time-consuming, and inaccurate. This project proposes an advanced automated system for identifying and categorizing herbal plant diseases using Convolutional Neural Networks (CNNs). The system integrates multi-layered feature extraction and transfer learning techniques to enhance accuracy and efficiency. Preprocessing steps, including data normalization and augmentation, improve the robustness of the model, ensuring better generalization across diverse datasets. By leveraging pre-trained deep learning models, the system expedites training while achieving high precision in disease detection. Real-time disease identification enables early intervention, significantly reducing crop losses and promoting sustainable farming practices. This technology-driven approach offers a scalable and efficient solution for plant health monitoring, revolutionizing agricultural disease management.

KEYWORDS: Herbal Plant Disease, Deep Learning, CNNs, Transfer Learning, Image Processing, Disease Classification, Sustainable Agriculture.

I. INTRODUCTION

Agriculture plays a crucial role in ensuring food security and supporting the economy. Herbal plants, commonly used in traditional medicine, are often susceptible to a variety of pathogens that can severely affect their growth and medicinal value. Timely identification of plant diseases is necessary to implement appropriate treatment measures and reduce losses. However, traditional methods of disease identification rely heavily on visual inspection by agricultural experts, which is both labor-intensive and subjective. Recent advancements in artificial intelligence and deep learning have paved the way for automated disease detection systems. Among various deep learning models, Convolutional Neural Networks (CNNs) have shown remarkable success in image classification tasks due to their ability to automatically learn and extract features from raw image data. In this study, we present a CNN-based herbal plant disease detection system that classifies leaf images into healthy and infected categories. The system leverages the strengths of LeNet and AlexNet CNN models, and it is implemented with a user-friendly interface for real-time predictions. Through this research, we aim to support farmers and researchers with a reliable and intelligent plant disease detection tool.

II. SYSTEM MODEL AND ASSUMPTIONS

The system architecture designed for herbal leaf disease detection includes multiple stages beginning from data collection to classification and deployment. Initially, images of herbal leaves are collected from open-source repositories such as Kaggle, which include various disease classes and healthy samples. Each image is subjected to preprocessing steps such as resizing, normalization, and augmentation to standardize input dimensions and enrich dataset diversity. This improves the generalization capability of the model across different environmental conditions. The CNN models are implemented using Python and trained using the TensorFlow/Keras deep learning framework. During the training process, the dataset is divided into training, validation, and testing subsets. LeNet and AlexNet are used as the primary CNN architectures for comparison. Each model undergoes training on the processed images, and performance is evaluated based on classification accuracy, precision, recall, and F1-score. The trained model is then integrated with a web application built using Django, which allows users to upload leaf images and receive disease predictions in real-time. A SQLite3 database is used to log predictions and user feedback for future retraining. The



model assumes that users will provide clear leaf images under proper lighting conditions, and it is capable of handling variations in image backgrounds and orientations.

III. DISEASE CLASSIFICATION USING CNN

The core of the system lies in its disease classification ability using CNN architectures. LeNet, one of the earliest CNN models, consists of two convolutional layers followed by pooling layers, fully connected layers, and a softmax output. It is lightweight and suitable for small datasets, offering reasonable performance with faster training times. AlexNet, on the other hand, is a deeper and more complex architecture that includes five convolutional layers, three fully connected layers, ReLU activation functions, and dropout regularization. AlexNet is designed to handle large datasets and has proven its effectiveness in high-resolution image classification. Both models are trained using the categorical cross-entropy loss function and optimized using the Adam optimizer. Training is conducted over multiple epochs with minibatch gradient descent, and the models are evaluated on a separate validation set. The classification results indicate that AlexNet outperforms LeNet in terms of accuracy and robustness, making it more suitable for deployment in real-world environments. The trained models are saved and used for prediction in the web interface, enabling users to classify new images instantly.

IV. WEB DEPLOYMENT AND SECURITY

The system is deployed as a web application to allow easy access for users such as farmers, researchers, and agricultural consultants. The frontend of the application is built using HTML, CSS, and JavaScript, providing a responsive and user-friendly interface for image upload and result display. The backend is developed using the Django framework in Python, which handles user requests, manages the model inference pipeline, and stores results. Upon uploading a leaf image, the backend processes the image, passes it through the trained CNN model, and returns the predicted class along with a confidence score. The application maintains a SQLite3 database to store user interaction history, image metadata, and feedback for model improvement. To ensure data security and privacy, all user data is encrypted, and secure protocols are followed for image storage and access. Access to the system is controlled through user authentication, and feedback mechanisms are implemented to allow users to confirm or correct predictions, thereby enabling continuous model learning. The application is optimized to deliver real-time predictions with minimal latency, and it can be extended to support multiple plant species and disease categories.

V. RESULT AND DISCUSSION

The system was tested using a dataset comprising images of six different herbal plants, each having healthy and diseased categories. After preprocessing and augmentation, the dataset was used to train and evaluate both LeNet and AlexNet models. The evaluation metrics showed that AlexNet achieved a classification accuracy of 98.6 percent, while LeNet achieved 81.1 percent. In terms of precision, recall, and F1-score, AlexNet consistently performed better, indicating its superior ability to handle complex image features and variations. Training and validation loss graphs demonstrated a smooth convergence pattern for both models, with AlexNet showing faster and more stable learning. A confusion matrix analysis revealed that the models made very few misclassifications, with AlexNet correctly identifying most disease types even in challenging conditions. Real-time testing on the deployed web application showed an average response time of under two seconds, and user feedback confirmed high satisfaction with prediction accuracy. These results validate the effectiveness of the proposed system and highlight its potential for real-world application in agricultural environments.



Fig A1.1: Home Page of the Herbal Leaf Health Detection Website

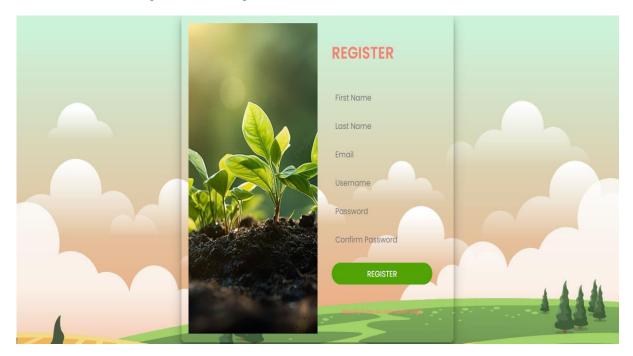


Fig A1.2: User Registration Page with Input Fields for Creating a New Account.

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 | www.ijmrset.com | Impact Factor: 8.206| ESTD Year: 2018|

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Fig A1.3: Login Page Allowing Existing Users to Access the Herbal Leaf Detection System.

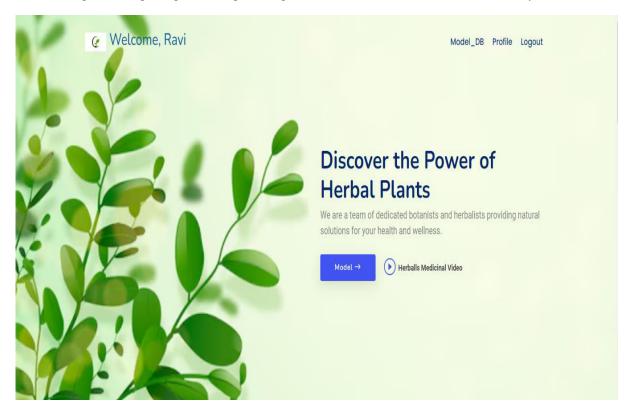


Fig. A1.4: User Dashboard - Herbal Plant Awareness

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Herbal Leaf Disease

Model Model_DB Profile Logout →

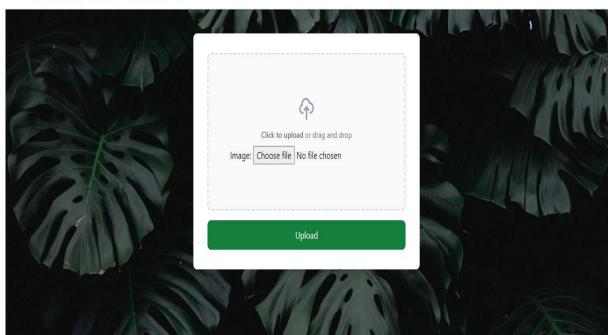
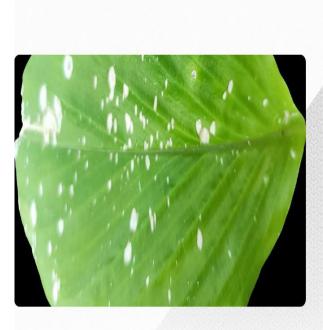


Fig. A1.5: Leaf Image Upload Interface for Disease Detection

Herbal Leaf Disease

Model Model_DB Profile Logout 🗗



CARDAMOM LEAF SPOT

FOUND THIS IMAGE IS CARDAMOM LEAF SPOT AFFECTED

PREVENTION

Ensure well-draining soil and proper spacing for good air circulation to reduce humidity. Water at the base of plants to avoid wetting the foliage. Apply preventive copper-based fungicides during favorable conditions.

PRECAUTION

Regularly inspect cardamom plants for early signs of leaf spot, including small dark lesions on leaves. Promptly remove and destroy infected leaves to prevent further spread. Practice crop rotation to disrupt the disease cycle.Additional Precaution: Use disease-resistant cardamom varieties and maintain a clean plantation by removing plant debris. Avoid overhead irrigation to minimize leaf wetness periods, and consider applying organic mulch to prevent soil splashing onto leaves.

CAUSES

Cardamom leaf spot is caused by the fungus Colletotrichum gloeosporioides, typically spread through water, wind, or contaminated tools. Dense foliage, high humidity, and prolonged leaf wetness create favorable conditions for infection, resulting in dark spots on cardamom leaves.

Fig. A1.6: Prediction Output - Cardamom Leaf Spot

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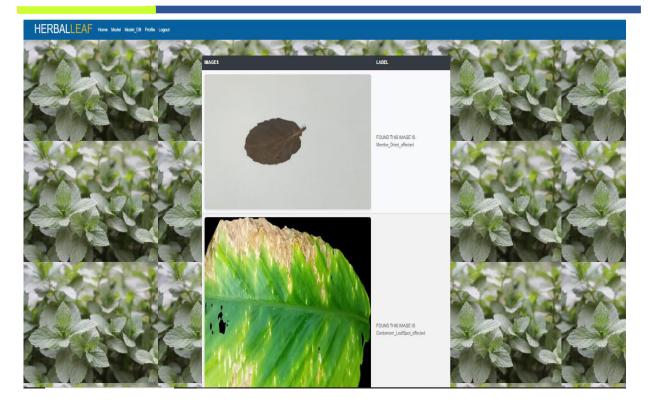


Fig. A1.7: Herbal Leaf Disease Model Database View

HERBALLEAF Home Model Model_DB Profil	e Logout
Username:	
ravi	
Email:	
ram123@gmail.com	
Change Password	
Change Avatar:	
Choose file No file chosen	
Bio:	
Fig A1.8.user profile for herbal leaf website	



VI. CONCLUSION

This paper presents a deep learning-based herbal leaf disease detection system using Convolutional Neural Network (CNN) architectures. The system is capable of accurately classifying various diseases in herbal plants by analyzing leaf images. Among the models implemented, AlexNet demonstrated superior performance with higher classification accuracy, precision, and F1-score when compared to LeNet. While LeNet offered faster training due to its simpler structure, it showed relatively lower accuracy and was less effective in capturing complex features from the input images. On the other hand, AlexNet, with its deeper layers and better feature extraction capabilities, achieved significantly higher accuracy, making it the preferred model for real-world deployment. The proposed system is integrated into a real-time web application, enabling users to upload leaf images and receive instant predictions. This empowers farmers and agricultural stakeholders to detect plant diseases at an early stage, take timely action, and reduce crop losses. Future improvements will focus on expanding the dataset to include more plant species and disease categories, integrating advanced models like EfficientNet, adding multilingual support, and implementing edge computing for offline access. The continuous feedback mechanism will ensure the system evolves with new data and maintains high reliability and adaptability.

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| Mobile No: +91-6381907438 | Whatsapp: +91-6381907438 | ijmrset@gmail.com |

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