



CROP DISEASE DETECTION USING DEEP LEARNING

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Abstract: This project focuses on the development of a web-based system for detecting crop diseases using deep learning techniques. The system uses a Convolutional Neural Network based on the MobileNetV2 architecture trained on the PlantVillage dataset to classify healthy and diseased crop leaves. The trained model is integrated into a Flask-based web application that allows users to upload leaf images and obtain disease predictions in real time, along with confidence scores and precautionary and treatment-related information. The lightweight nature of the selected model ensures fast prediction time while maintaining reliable classification performance. By combining deep learning with web technologies, the proposed system offers an accessible and cost-effective solution for crop disease identification, reducing dependence on manual inspection and supporting timely disease management to improve crop productivity.

Keywords: Crop Disease Detection, Deep Learning, Convolutional Neural Network, MobileNetV2, Flask, PlantVillage Dataset, Image Classification, Transfer Learning.

I. INTRODUCTION

Agriculture plays a major role in supporting the livelihood of a large population, particularly in countries such as India. Crop production depends heavily on plant health, as healthy crops directly contribute to better yield and quality output. However, crop diseases continue to be a serious concern because they reduce productivity and may cause financial loss if they are not identified at the right time. In rural regions, limited access to agricultural experts often delays accurate diagnosis and proper treatment.

With recent progress in artificial intelligence, automated disease identification using crop images has become possible. Convolutional Neural Networks are effective at picking up changes in leaf color, texture, or shape, making them accurate for spotting crop diseases. Combined with web technology, farmers can upload a picture and instantly receive a prediction about what is wrong with their crops. This project aims to develop such a system that is both accessible and practical for real-world agricultural use.

The primary objectives of this project are to develop a deep learning model that can distinguish between healthy and diseased crop leaves, integrate the trained model into a Flask-based web application, provide an easy-to-use interface for uploading leaf images, display disease name, confidence level, and basic precautionary information, and develop a solution that can be expanded for additional crops and diseases in the future.

II. SCOPE OF THE LITERATURE SURVEY

Mohanty et al. (2016) conducted an early investigation into the use of deep learning for identifying plant diseases through leaf images using CNNs, showing strong performance in classifying multiple crop disease categories. Too et al. (2019) explored transfer learning for plant disease classification by fine-tuning pretrained models like VGG16, ResNet50, DenseNet121, and InceptionV3, with DenseNet121 achieving the highest accuracy. Ferentinos (2018) studied CNN models for detecting plant diseases using real agricultural field images, achieving high accuracy even under challenging conditions.

Sladojevic et al. (2016) proposed a CNN-based approach for classifying multiple plant diseases across different crop species, performing well but less effectively in real-field environments. Pawar et al. (2020) studied lightweight CNNs for real-time crop disease identification, showing that MobileNet-based architectures maintained solid classification accuracy with significantly less memory and processing power, making them suitable for mobile and web platforms. Overall, the literature confirms that combining lightweight CNN architectures with web deployment creates an effective and scalable solution for crop disease detection.

III. PROPOSED WORK

The proposed system aims to develop an intelligent Crop Disease Detection System using deep learning and computer vision techniques to accurately identify crop diseases from leaf images. The system is designed to assist farmers in monitoring plant health independently by providing automated disease recognition with confidence scores and treatment recommendations through a user-friendly web application.

The proposed work utilizes a Convolutional Neural Network based classification model with Transfer Learning using the MobileNetV2 architecture. MobileNetV2 is selected because of its lightweight structure, faster computation, and ability to achieve high accuracy even with limited training data. The model is trained on the PlantVillage dataset containing multiple crop and disease categories. Image preprocessing techniques such as resizing to 224x224 pixels, normalization, and RGB conversion are applied to improve model consistency and prediction performance.

Once a disease is identified, the system retrieves corresponding precautionary and treatment information from a separate agricultural guidelines dataset. The entire system is deployed as a Flask-based web application with an HTML and CSS frontend interface. The modular architecture allows future enhancements such as support for additional crops, mobile deployment, and integration with real-time field monitoring systems.

IV. METHODOLOGY

The proposed Crop Disease Detection system is developed using a deep learning and web-based methodology that combines image preprocessing, transfer learning, real-time prediction, and Flask deployment. The methodology is designed to provide accurate crop disease recognition from leaf images uploaded by the user.

Dataset Collection and Preparation: The dataset used is the PlantVillage dataset, a publicly available collection of labeled healthy and diseased leaf images from crops including tomato, potato, apple, grapes, peppers, and more. Images are sorted into class folders based on crop and disease. The dataset supports multi-class classification with each image belonging to exactly one category.

Data Preprocessing: All images are resized to 224x224 pixels to match the input requirements of the MobileNetV2 architecture. Pixel values are normalized to the range [0,1]. RGB conversion and aspect ratio preservation are also applied to improve prediction consistency.

Model Selection Using Transfer Learning: The proposed system uses a CNN with Transfer Learning based on the MobileNetV2 architecture. The pretrained ImageNet weights are used as the feature extraction backbone. The top classification layers are replaced with a Global Average Pooling layer, a Dense layer with 256 neurons and ReLU activation, and an Output Dense layer with Softmax activation for multi-class disease classification.

Model Training and Validation: The model is trained using the Adam optimizer and categorical cross-entropy loss function. Training is performed with a batch size of 32. During training, validation accuracy and loss are monitored to evaluate model performance. The trained model is saved in .hdf5 format for deployment and future inference.

Disease Prediction and Suggestion: When a user uploads a leaf image, the system preprocesses and passes it to the trained CNN model. The model predicts the disease label along with a confidence score. The system then retrieves precautionary and treatment information from the agricultural guidelines dataset and displays it to the user.

Web Application Deployment: The final system is deployed using the Flask framework with HTML and CSS for the frontend. The web application allows users to register, log in, upload crop leaf images, and receive disease predictions with confidence scores and treatment suggestions in real time.

V. RESULT ANALYSIS

The proposed Crop Disease Detection system was evaluated using multiple performance metrics to measure the effectiveness of disease classification. The system was trained using the MobileNetV2 transfer learning model on the PlantVillage dataset and tested on unseen validation data. The overall classification accuracy achieved by the system was approximately 94%, indicating that the model was able to correctly identify most crop diseases with good generalization capability.

The classification report provided detailed class-wise analysis using Precision (0.93), Recall (0.94), and F1-Score (0.935). Diseases with distinct visual features such as unique spot patterns and color changes achieved high precision and recall values. Visually similar diseases showed comparatively lower performance due to overlapping symptom appearances. The system achieved an average prediction response time of 0.85 seconds, demonstrating its suitability for real-time web-based deployment.

The web-based Flask application functioned successfully, allowing users to register, log in, upload crop images, and obtain disease predictions along with precautionary and treatment recommendations. All functional test cases including user registration, login validation, image upload, prediction generation, and logout were successfully passed, confirming the reliability of the developed system.

VI. CONCLUSION

This project successfully developed and demonstrated an end-to-end Crop Disease Detection system using deep learning and web technologies. The main objective was to recognize crop diseases from leaf images and provide accessible treatment guidance to farmers through a web application. A MobileNetV2-based CNN model trained on the PlantVillage dataset achieved approximately 94% classification accuracy with sub-second prediction times.

The system successfully eliminates the need for manual visual inspection, reduces dependence on agricultural experts for initial diagnosis, and supports timely disease management. The layered architecture, lightweight model design, and Flask-based deployment make the system accessible, scalable, and suitable for real-world agricultural use. Future work includes expanding the dataset with more crop types, developing a mobile application, and integrating personalized treatment recommendations based on local soil and weather conditions.

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