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DeepLeafGuard: A CNN-Enabled Monitoring System for Accurate Plant Leaves Disease Detection

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Abstract

For food security and sustainable agriculture to coexist, early and accurate identification of plant diseases is essential. This study offers a real-time monitoring system that uses deep learning algorithms to accurately identify plant illness in leaves. A complete dataset of 19,953 photos spanning four plant kinds (potato, tomato, pepper bell and rice) and 21 disease classes are obtained by combining Rice Leaf disease dataset and PlantVillage Dataset. To detect plant diseases, a specialized Convolutional Neural Network (CNN) model has been created. For that model, an accuracy around 99% has been achieved. Three distinct CNN models (VGG16, VGG19, and InceptionV3) have been used to the split dataset in order to identify particular plant diseases and compare which model performed better for subsequent deployment. A web application has been developed based on the best-performing models, allowing users to insert or capture images of plant leaves, detect diseases, and receive treatment suggestions with high confidence levels.

Keywords: Convolutional Neural Network, Plant Disease Detection, Computer Vision, Performance Evaluation, Practical Implementation

1. Introduction

Plant diseases that damage leaves, stems, roots, and fruits reduce crop quality and quantity, which exacerbates worldwide food insecurity and deprivation [1]. Crop diseases cause an estimated 16% of the world's annual yield loss, which is the main cause of both food shortages and rising production costs [2]. The Food and Agriculture Organization Report (FAO) projects that by 2050, there will be about 9.1 billion people on the planet. Approximately 70% of the expansion in food production is needed to provide a stable food supply [3]. Factors categorized as illnesses and disorders have an impact on plants and the products they produce. Moisture, temperature, precipitation, and nutrient shortages are examples of abiotic variables that can lead to disease. Biotic factors include diseases caused by bacteria, fungi, or algae [4]. The subjective nature of visual inspections by farmers often results in inconsistent and unreliable diagnoses, leading to misidentification of diseases or missed early symptoms. Because manual checks take a lot of time and labor, large-scale farms cannot use them, and illnesses might spread unchecked. Traditional methods also struggle with scalability, increasing the risk of widespread outbreaks in vast agricultural regions. Late or missed diagnoses can cause significant economic losses due to reduced yields and higher production costs. Ineffective disease management threatens food security as the global population grows, while over-reliance on chemical treatments from misdiagnosis poses environmental and health risks.

2. Literature Review

In recent years, the widespread adoption of Convolutional Neural Network (CNN) models has become a hallmark in tackling image classification challenges. Zhou et al. [5] engineered a K-Means clustering algorithm and Faster R-CNN Fusion protocol to the problem of rice disease detection. Such approach first presented by Sharma et al. [6] elaborate by image pre-processing follow by k-means clustering, segmentation and four classifiers; nevertheless, there are research space to evaluate the individual performance of each component and an effective aggregation for better leaf disease detection. Sardogan et al. proposed model consisted of a CNN based on the LVQ algorithm to detect and classify tomato leaf diseases [7]. Ozguven et al. [8] updated the Faster R-CNN algorithm and retrained CNN architecture parameters to detect sugar beet leaf spot disease. Another advanced rice disease identification model was developed by Lu et al. [9] who used 500 natural images from rice experimental fields to identify and recognize rice diseases through a deep convolutional neural network (CNN) with image preprocessing. Kawasaki et al. [10] proposed a new model for viral plant disease detection with improved accuracy using 4-fold cross-validation based on CNN techniques, an original image pre-processing technique and 800

cucumber images. Jiang et al. [11] proposed the INAR-SSD model and applied it to the Caffe structure of GoogLeNet Inception structure with Rainbow concatenation on the GPU platform to identify disease in apple leaves in real time using the Apple leaf disease dataset. Islam et al. [12] suggested a segment-based, multi-SVM-based model for detecting potato illnesses. Iqbal, M. A. et al. [13] performed image segmentation on 450 pictures of healthy and damaged potato leaves from the free Plant dataset. Mangla et al. [14] proposed a method for detecting and diagnosing rice leaf disease using image pre-processing and segmentation techniques combined with SVM classifiers. Rizqi et al. [15] introduced a methodology leveraging deep learning, employing VGG16 and VGG19 CNN architectures to classify four distinct diseases in potato plants based on leaf conditions. Andrew et al. [16] utilized diverse transfer learning models to forecast distinct plant diseases, employing data augmentation techniques to expand image samples through minor adjustments in image orientation. Azath et al. [17] devised a smart diagnostic system for identifying diseases in cotton plant leaves through the utilization of a CNN. The collection of cotton leaf samples originated from diverse Arab regions, with the dataset categorized into three distinct infected classes and one healthy class of images. Md. Manowarul Islam et al. [18] tested CNN, VGG-16, VGG-19, and ResNet-50 models on a PlantVillage 10,000 picture dataset to detect crop illnesses, with accuracy rates of 98.60%, 92.39%, 96.15%, and 98.98%, respectively. The study found that ResNet-50 surpasses the other models with an accuracy of 98.98%. Omkar Kulkarni [19] proposes a deep learning model built on a public dataset of healthy and damaged crop leaves. The program accurately classifies leaf images as unhealthy based on defect patterns, with the goal of improving disease identification and management in agricultural practices. Murk Chohan et al. [20] introduced a deep learning-based model, the Plant Disease Detector, focused on identifying plant diseases using leaf images. They utilized augmentation techniques to expand their dataset, employed CNN with multiple convolution and pooling layers, and achieved a testing accuracy of 98.3% on the PlantVillage dataset.

3. Methodology

The plant leaf damage detection procedure is flowcharted in Fig. 1., with each step from dataset selection to model evaluation shown. After achieving a satisfactory model, it is saved and transferred to TensorFlow Serving, which acts as a local server to run the model on a local machine. This server facilitates real-time predictions by hosting the model and making it accessible for inference. The FastAPI service is utilized to enable seamless and effective communication between the web interface and the machine learning model in order to incorporate the model into an online application.

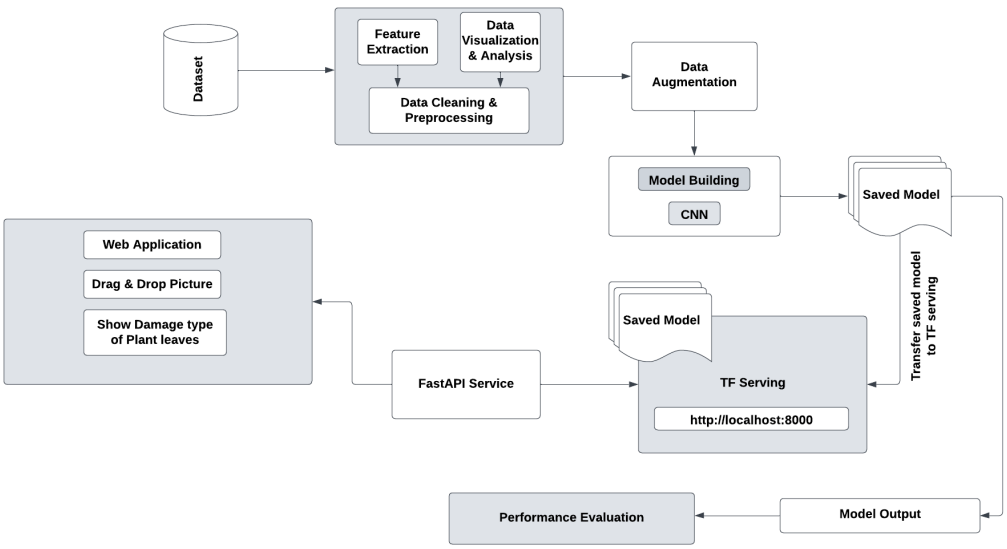


Fig. 1. Deep Learning-based flowchart and framework for plant leaf disease detection

Dataset Collection and Annotation

A total of 19,953 photos from four different plant species are included in the dataset utilized in this study, which mixes images from the PlantVillage collection with a rice leaf disease dataset. This hybrid dataset ensures thorough coverage of scenarios seen in agriculture with 21 separate classes, each reflecting a particular plant disease or healthy condition. The model's capacity to identify and distinguish between distinct illness manifestations was improved through precise annotation, which was done using the VGG Image Annotator to name several disease areas inside each image.

Data Cleaning

Data cleaning is the process of picking and manipulating pertinent information from a dataset while simultaneously looking for patterns and insights. This is done through feature extraction and analysis. This procedure improves the quality of the dataset for additional analysis. Three essential methods include encoding categorical variables, correcting outliers, and handling missing values.

Data Preprocessing

Prior to using machine learning models, photos should be resized to a consistent size, such as 256 by 256 pixels, and their pixel values should be normalized to fall between 0 and 1. As normalization accelerates convergence and improves training stability, resizing guarantees consistency throughout the dataset, increasing the effectiveness of model training. These procedures work together to create models that are more reliable and accurate.

Data augmentation and Splitting

To increase dataset size and boost model robustness in plant leaf damage detection, augmentation techniques such random rotation, flipping, zooming, cropping, brightness adjustment, and adding noise are crucial. By adding variability, simulating various scenarios, and improving the model's generalization capacity, these techniques improve detection accuracy and dependability. The dataset is divided into three parts: training, testing, and validation. Specifically, 80% of the data is allocated for training purposes, 10% for testing, and the remaining 10% for validation.

CNN Logic and Model Building

The CNN (Convolutional Neural Network) implemented for leaf classification and disease detection is designed to analyze image features systematically and accurately. It begins with convolutional layers, which scan the input images to identify critical features such as edges, textures, and shapes. ReLU activation functions are applied after each convolution to introduce non-linearity, ensuring the network can capture complex patterns in the data. Pooling layers, such as max pooling, follow the convolutional layers to down sample feature maps. This step reduces the spatial dimensions of the data while retaining the most important features, lowering the computational complexity and enhancing model efficiency. The output of the pooling layers is flattened into a one-dimensional array and passed through fully connected (dense) layers for high-level learning and decision-making. The final classification is handled by a SoftMax layer, which assigns probabilities to each class and determines the most likely leaf type or disease. To improve model generalization and robustness, techniques such as data augmentation (rotations, flips, and scaling) are used to diversify the training data, and dropout layers are added to prevent overfitting. For this research study, different CNN algorithms have been used for various plant leaves disease detection like VGG16, VGG19, Custom CNN, InceptionV3. Each model's unique architecture and combination aim to enhance accuracy and performance across different types of plant leaves and diseases.

Converting Model into TensorFlow Serving

Converting a model to TensorFlow Serving involves several key steps. After training, the model is saved in the Keras format, preserving its architecture and weights. TensorFlow Serving, a high-performance serving system, is then installed, preferably using Docker for simplified deployment. The saved model is organized into a versioned directory structure, allowing easy updates and rollbacks. The model directory is mapped and the serving of different model versions for testing and continuous delivery is made possible when the TensorFlow Serving container is finally started.

Development Phase

Following model conversion, a solid backend API service is built to identify plant diseases. Postman was used to thoroughly test the backend API. Python API development framework FastAPI is a contemporary web framework that was used to carefully create the backend API service. React is a popular JavaScript framework that is renowned for its scalability and efficiency. It was utilized to construct the frontend of the online application. Users can interact with the application by dragging and dropping leaf images thanks to the smooth integration of the backend API with the React frontend. After that, the program examines the photos to find any illnesses that may be present and offers appropriate treatment plans.

4. Experimental Results

An extensive dataset of 2,152 photos of potato plant leaves was carefully selected to classify potato plant illnesses. Three separate classes—potato early blight, potato healthy, and potato late blight—are used to arrange this dataset. The dataset includes, specifically, 1,000 photographs of early blight-affected potato leaves, 152 images of healthy potato leaves, and an additional 1,000 images showing indications of late blight.

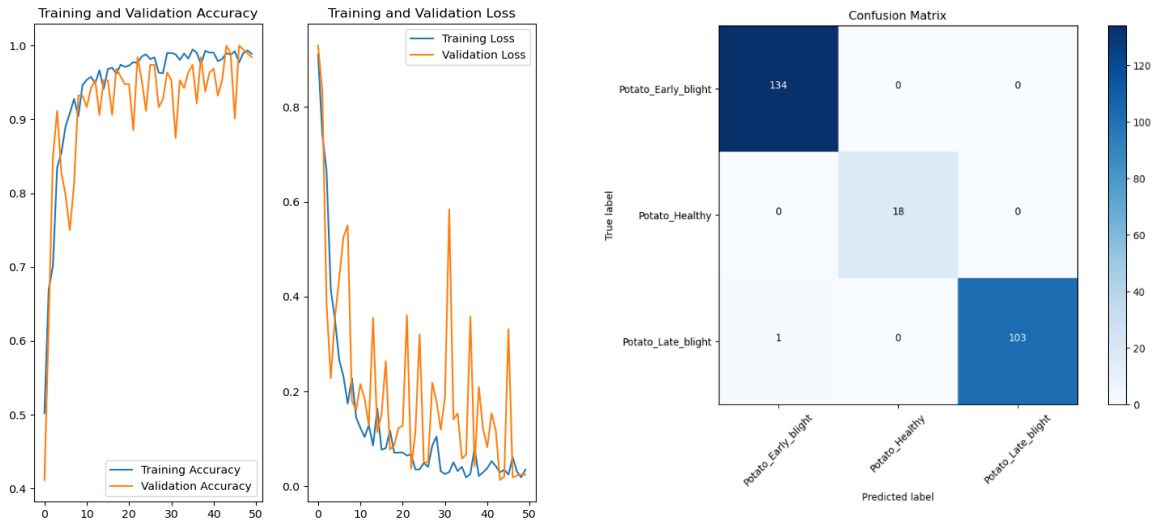


Fig. 2. Best Model's Confidence Matrix of Potato Plant Leaves; Training and Validation Accuracy vs. Epochs; Training and Validation Loss vs. Epochs

Fig. 2. indicates the confusion matrix, accuracy vs epochs, loss vs epochs for potato plant disease. Table 1 represents the comparison of accuracy, precision, recall and f1 score for various CNN models based on potato. Similarly, accuracy vs epochs, loss vs epochs, and confusion matrix for tomato plants, pepper bell plants and rice plants have been obtained in this research study.

Table 1. Performance Evaluation for Potato Plants on Various CNN Models

CNN Models	Accuracy	Precision	Recall	F1-score
Custom CNN	100%	0.9967	0.9967	1.0000
VGG16	97%	0.95	0.9633	0.9533
VGG19	97%	0.9467	0.9467	0.9467
InceptionV3	97%	0.98	0.93	0.9533

A dataset of 13,226 images of tomato plant leaves was used to classify 10 distinct diseases. It includes 2,127 images of bacterial spot, 1,000 early blight, 1,592 healthy leaves, 1,909 late blights, 952 leaf mold, 373 of mosaic virus, 1,771 of septoria leaf spot, 1,676 of spider mites, 1,404 of target spot, and 422 of yellow leaf curl virus.

Table 2. Performance Evaluation for Tomato Plants on Various CNN Models

CNN Models	Accuracy	Precision	Recall	F1-score
Custom CNN	98%	0.9820	0.9750	0.9790
VGG16	98%	0.9800	0.9810	0.9800
VGG19	97%	0.9750	0.9710	0.9720
InceptionV3	98%	0.9780	0.9770	0.9800

Table 2 offers a comparative analysis of various convolutional neural network (CNN) models by presenting their accuracy, precision, recall, and F1 scores for the classification of tomato plant diseases.

For the classification of pepper bell plant diseases, a well-prepared dataset was utilized, consisting of a total of 2,475 images of pepper bell plant leaves, encompassing 2 classes. Specifically, the dataset includes 997 images of pepper bell leaves afflicted by bacterial spot and 1,478 images of healthy pepper bell leaves. Table 3 represents the comparison of accuracy, precision, recall and f1 score for various CNN models based on pepper bell plants.

Table 3. Performance Evaluation for Pepper Bell Plants on Various CNN Models

CNN Models	Accuracy	Precision	Recall	F1-score
Custom CNN	100%	1.0000	1.0000	1.0000
VGG16	98%	0.9750	0.9700	0.9700
VGG19	95%	0.9600	0.9450	0.9500
InceptionV3	99%	0.9850	0.9900	0.9850

For the classification of rice leaf diseases, a meticulously curated dataset comprising 2,100 images of rice leaves was utilized, featuring 6 distinct classes. Specifically, this dataset includes 350 images each of rice leaves affected by bacterial leaf blight, brown spot, healthy leaves, leaf blast, leaf scald, and narrow brown spot. Table 4 represents the comparison of accuracy, precision, recall and f1 score for various CNN models based on rice plants.

Table 4. Performance Evaluation for Rice Plants on Various CNN Models

CNN Models	Accuracy	Precision	Recall	F1-score
Custom CNN	90%	0.9117	0.9033	0.9050
VGG16	91%	0.9200	0.9100	0.9083
VGG19	95%	0.9533	0.9433	0.9433
InceptionV3	91%	0.9150	0.9067	0.9100

5. Web Application Development

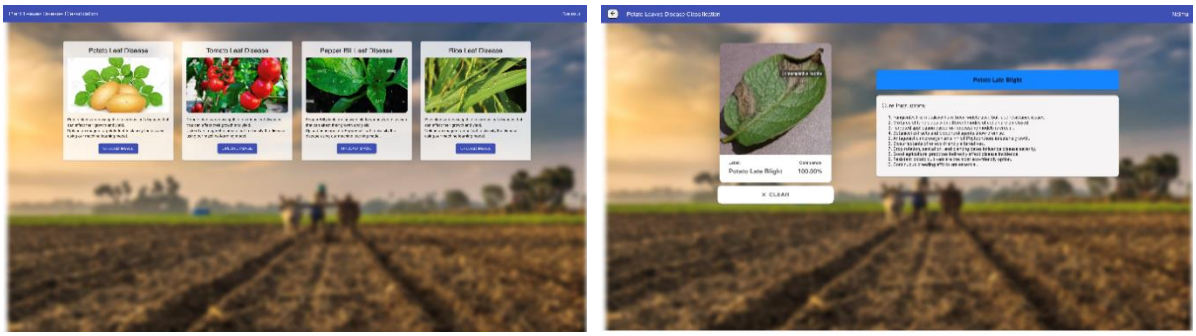


Fig. 3. Home Page and Individual plant's Image Upload Page of Web Application

A web application using the React framework has been developed for its robust frontend capabilities. The user-friendly interface features drag-and-drop functionality for easy image uploads. Upon uploading, the application connects with our backend to detect and identify plant leaf diseases. The homepage, shown in Fig. 3., allows users to select from eight plant categories and upload images for disease detection. The application then displays the disease name, confidence level, and provides detailed treatment instructions, aiding rapid identification and management of plant diseases.

6. Conclusion

After implementing four CNN models and comparison with them, it has been decided that custom CNN model gives the best result for detecting diseases on pepper-bell plant leaves and potato plant leaves. Inception V3 gives the best performance for detecting tomato plant leaves disease. VGG19 gives the best performance for detecting rice plant leaves disease. After taking these models, API has been built which gives highest confidence level.
Future work will expand the dataset to include more plant species and diseases, improving the system's versatility and accuracy. Integrating advanced augmentation techniques and exploring GANs for synthetic data generation will address data limitations. Additionally, extending the system to support real-time video analysis could enhance continuous crop monitoring and disease management.

Acknowledgement

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