

Leaf Disease Detection and Planting Adviser Using Python

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Abstract: *Plant leaf diseases that lower yield and quality frequently pose a danger to crop productivity. Two commonly grown crops, potatoes and tomatoes, are especially susceptible to illnesses like Early Blight and Late Blight. Conventional illness detection techniques rely on manual observation, which is laborious, unreliable, and prone to human mistake. A Python-based automated framework for planting guidance support and the leaf disease detection is proposed in this study. The Convolutional Neural Networks (CNNs) are used by the system to accurately classify tomato and potato leaves as either healthy or unhealthy. A rule-based planting consultant module that offers crop suggestions based on soil pH, temperature, and humidity characteristics is also integrated. Utilize the plant village dataset to train and assess the suggested method, which showed encouraging real-time illness accuracy. With the goal of reducing losses, increasing productivity, and advancing precision agriculture, the model offers farmers a dependable decision-support tool by fusing automated diagnosis with practical planting suggestions.*

Keywords: *Plant leaf diseases*

I. INTRODUCTION

Global food security and economic growth are based on agriculture. Potatoes and tomatoes are two of the most extensively grown crops with substantial commercial and nutritional value. However, leaf diseases, especially the Early Blight and Late Blight, have an important effect on their production and can significantly lower both yield and quality. These infections spread quickly if they are not detected and treated in a timely manner, causing farmers to suffer significant financial losses. Conventional disease detection techniques depend on farmers or agricultural specialists manually inspecting leaves. In addition to being labor-intensive and time-consuming, this method is subjective and prone to human error, particularly in isolated locations with little access to experts. Delays in diagnosis hence frequently result in unsuitable therapies and decreased output. Automated and intelligent solutions are needed to help farmers manage crops and detect diseases in order to overcome these obstacles.

II. METHODOLOGY

- Gather soil data and photos of leaves.
- Preprocess photos by normalizing and resizing them.
- Mark leaves as either beneficial or detrimental.
- Sort the data into training and testing sets.
- Develop a CNN model to identify illnesses.
- Input soil info to suggest suitable crops.
- Test and assess the model.
- Enter soil data to recommend appropriate crops.
- Combine disease detection and planting adviser.
- Create a simple user interface.
- Install the system so that farmers can use it.



III. BACKGROUND & KEY MODEL FAMILIES

Although agriculture is essential to the provision of food, leaf diseases and improper planting conditions frequently reduce crop yield. Conventional techniques for detecting plant disease are labor-intensive, error-prone, and manual. Crop loss can be greatly decreased and productivity can be increased by early diagnosis of leaf diseases. Furthermore, farmers frequently find it is difficult to choose which crops to grow given the state of the soil and the surrounding environment. Modern methods that use deep learning, machine learning, and Python can automate the identification of leaf diseases and offer accurate planting recommendations in order to get beyond these challenges.

Convolutional Neural Networks (CNNs) are utilized in this system to automatically extract properties like color, shape, and texture from leaf photos in order to categorize them as ill or healthy. In order to suggest appropriate crops, machine learning algorithms such as Decision Trees or Random Forests examine soil pH, temperature, and humidity. The model's accuracy is improved by data pretreatment and augmentation methods such as image scaling, normalization, and soil data cleaning. Lastly, an integration module integrates crop selection and disease detection into a single user-friendly system, enabling farmers to enter soil data and upload leaf photos to get real-time advice.

IV. EVALUATION: METRICS AND METHODOLOGIES

Both numerical and qualitative methods utilize to evaluate the suggested system's performance. Metrics such as recall, accuracy, precisions, F1-score, and the confusion matrix used for assessments CNN model's performance for leaf disease identification on previously unknown leaf pictures. Precision and recall demonstrate how well the model detects sick leaves, whereas accuracy shows the proportion of correctly identified photos. To evaluate overall performance, the F1-score strikes a compromise between recall and precision. The system is assessed by the planting adviser based on user feedback, response time, and the proportion of accurate crop suggestions. Black-box testing involves supplying input data (leaf photos and soil data) without seeing the internal code and confirming the accuracy of the output. Overall, this assessment guarantees the accuracy and promptness of crop recommendations and the dependability of disease detection.

V. APPLICATIONS (REPRESENTATIVE)

- Agriculture Support – Helps farmers identify leaf diseases early and take preventive measures.
- Crop Management – Provides advice on which crops to plant based on soil and environmental conditions.
- Yield Improvement – Reduces crop loss by detecting diseases early and recommending optimal planting strategies.
- Decision Support System – Acts as a digital assistant for farmers to make informed decisions.
- Educational Tool – Can be used to teach students about plant diseases and soil management.
- Mobile/Desktop Farming Apps – Can be integrated into apps for easy access by farmers.
- Sustainable Farming – Promotes better use of resources and healthier crops through timely interventions.

VI. KEY CHALLENGES & OPEN PROBLEMS

- Limited Dataset Availability – Collecting sufficient images of all types of leaf diseases is difficult.
- Variability in Leaf Images – Differences in lighting, angles, and background can affect model accuracy.
- Similar Disease Symptoms – Some diseases look very similar, making classification challenging.
- Soil & Environmental Data Collection – Accurate soil pH, temperature, and humidity data may not always be available.
- Generalization Across Crops – Extending the system to more crops beyond tomato and potato.
- Adaptation to Field Conditions – Improving model performance under varying real-world conditions.
- Early Disease Detection – Detecting disease at very early phases symptoms are barely visible.
- Resource Optimization – Reducing computational resources for deployment on mobile devices.
- Dynamic Crop Recommendations – Incorporating seasonal and market data for more precise planting advice.



VII. RECOMMENDATIONS & BEST PRACTICES

suggestions and best practices should be adhered to in order to guarantee the efficacy and dependability of the suggested Leaf Disease Detection and Planting Adviser system. The system should be updated frequently with new disease patterns and soil data, and the dataset should be enlarged to include additional leaf images for various crops and illnesses. To verify performance, field testing under actual farming settings is crucial, and farmers should receive training on how to take crisp leaf photos and provide precise soil data. The system will be easier to use if it is integrated into mobile applications, and a feedback system can assist forecasts get better over time. The Convolutional Neural Networks for accurate disease classification, validating soil input data to guarantee accurate crop suggestions, and appropriate data preprocessing, such as scaling, normalizing, and augmenting photos to improve model accuracy, are examples of best practices. To preserve efficiency, ease of maintenance, and long-term usability, a modular system design, ongoing performance monitoring, and thorough documentation are also advised.

VIII. CONCRETE EXPERIMENT IDEAS

Leaf Disease Classification

- Train a CNN model to classify tomato and potato leaves into healthy and diseased categories.
- Experiment with different architectures (e.g., LeNet, VGG16, ResNet) to compare accuracy.

Data Augmentation Effect

- Test the effect of image augmentation (rotation, flipping, zooming) on model performance.
- Comparison Regarding Machine Learning Models: Compare CNN with traditional machine learning algorithms (SVM, Random Forest) for leaf disease detection.

Early Disease Detection

- Evaluate the system's ability to detect disease in leaves at an early stage with subtle symptoms.

Planting Adviser Accuracy

- Input soil pH, temperature, and humidity data and check if recommended crops match actual suitability.

Integration Testing

- Combine leaf disease detection and planting adviser modules and test the system end-to-end with various inputs.

Performance Under Real Conditions

- Test the system with leaf images captured in different lighting, angles, and backgrounds to evaluate robustness.

Response Time Measurement

- Measure the time taken by the system to process an image and give planting recommendations.

User Feedback Evaluation

- Conduct a small survey with farmers to evaluate usability, clarity, and helpfulness of the recommendations.

Cross-Crop Extension

- Test the system with new crops beyond tomato and potato to study model generalization.

IX. CONCLUSION

The suggested Leaf Disease Detection and Planting Adviser system is an efficient way to assist contemporary agriculture. The technology gives farmers quick and accurate recommendations by merging a planting adviser that suggests crops based on soil and environmental data using a traditional neural network for accurate leaf disease classification. This strategy encourages sustainable farming methods, increases productivity, and lessens crop loss. Because of the system's user-friendly design, farmers can quickly submit leaf photos and enter soil data to get useful insights. Evaluation measures that show the system's dependability and efficiency include accuracy, precision, recall, and user feedback. This system has the potential to be a helpful tool in digital agriculture, filling the void between technology and real farming, with additional dataset extension, interaction with mobile applications, and ongoing upgrades.



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