Plant Disease Prediction Using Convolutional Neural Network

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Abstract – Plant diseases are a serious threat to agricultural production and food security around the world. Early and precise diagnosis of plant diseases is key to the success of preventing and controlling crop loss. In this research, we present a deep learning model using CNN to automatically identify different plant diseases from the leaf images. CNN's work well in learning hierarchical spatial features, and represent a great fit for image-based classification. The model is trained and validated using a large dataset of labeled images of healthy and diseased plant leaves. The proposed system preprocesses the input images, extracts appropriate features and categories the features into its corresponding disease properties. The model is not only accurate and robust but also superior to the conventional machine learning methods. This platform also provides a scalable and cost-effective option for real-time disease diagnosis, allowing farmers and other agricultural professionals to act promptly. The use of these AI based tools in agriculture can boost the crop yield, reduce reliance on the interference of experts, and achieve sustainability in farming.

Keywords - Deep Learning, Plant Disease Prediction, CNN, Image-based diagnosis

I. INTRODUCTION

Agriculture continues to be one of the main pillars of the world economy, supplying food and raw materials to prop up the economy and create employment for most people. Nonetheless, plant diseases seriously sabotage crop yields, causing immense economic losses and impairing food security. Conventional disease diagnostic measures heavily rely on manual scouting and observation, which are time consuming, subjective and are inadequate for poor farmers. In recent years, with the development of artificial intelligence (especially deep learning), there are more prospect for plant disease detection to be done automatically. Among different deep learning models, Convolutional Neural Networks (CNN's) have achieved outstanding performance to image recognition tasks, as they can automatically extract and learn spatial hierarchies of features from raw images. Applying CNN's to detect and categorize plant diseases can be an efficient, scalable and accurate approach. This study proposes a CNN model for the detection and classification of plant diseases based on leaf images. The goal is to aid high throughput early diagnosis and intervention to prevent or manage crop loss and support agricultural production. The discovery, development and deployment of AI-based tools within agriculture has the potential to revolutionise the way that farming has been approached and the way that sustainable crop management is achieved.

II. LITERATURE REVIEW

Table 01: Literature Survey

Sr. No.	Author(s) & Year	Key Findings / Contributions	Accuracy
1	Yong Wang et al., 2024	Proposed attention-based and multi-scale fusion for tomato leaf disease detection.	98.7%
2	Huimin Lu et al., 2023	Applied Vision Transformers to classify tomato leaf diseases.	97.6%
3	Vinoda et al., 2022	Classified cotton leaf diseases using VGG16 and dimensionality reduction.	92.3%
4	Ahmed M.R., 2021	Used CNN with transfer learning for cotton disease recognition.	90.6%
5	Iftikhar Ahmad et al., 2020	Optimized CNNs for tomato disease detection.	98.8%

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III. METHODOLOGY

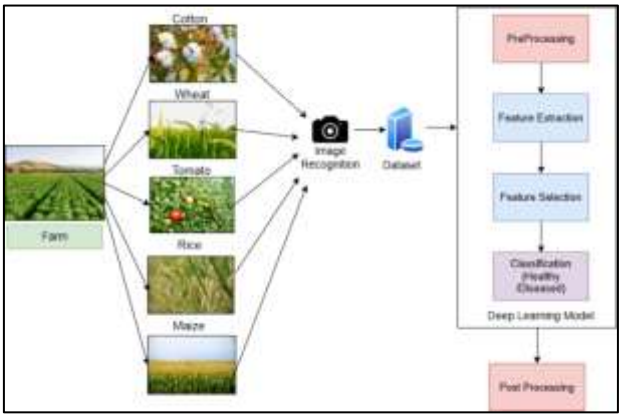

Fig. 1- System Architecture for disease prediction

The architecture describes an image-based deep learning pipeline for automated plant disease detection on crops such as cotton, wheat, tomato, rice and maize. Pictures are taken in-field through an image recognition system to form a structured database. The first step is preprocessing where the images are resized, normalized, and cleaned to achieve consistency and quality. At the heart of the system, a Convolutional Neural Network (CNN) operates on the images across multiple layers. Wounds in HPs are detected using filters in the convolutional layers to find local features, such as spots, textures, and color variations associated with disease. These are then succeeded by ReLU which introduces non linearity to model complex patterns, and pooling layers that performs downsampling operation to decrease computational overhead and keep the useful information. The features are then forwarded through dense layers which summarizes the data and makes the decision, whether the plant is healthy or unhealthy. By a process of classification, post-processing makes sense out of the results according to some interpretation that is manageable for users. This end-to-end pipeline provides the capability to detect plant diseases accurately, at scale and in a cost-effective manner, across various types of crops.

IV. DESIGN

Step 1: Data Acquisition

- Capture leaf images from different crops.
- Label each image according to its disease class.
- Suggested Kaggle Datasets for Different Plants:
  - Rice Dataset
  - Cotton Dataset
  - Tomato Dataset
  - Potato Dataset
  - Maize Dataset

Step 2: Data Preprocessing

- Resize images to a fixed dimension.
- Apply noise reduction.
- Normalize pixel values.

Step 3: Dataset Splitting

- Split the dataset into training, validation, and testing sets.

Step 4: Deep Learning Model Selection

- Choose a suitable model architecture.

Step 5: Model Training

- Compile the model with an appropriate loss function (e.g., categorical cross-entropy) and optimizer (e.g., Adam).
- Train the model using training data.
- Validate the model using validation data.

Step 6: Evaluation

- Evaluate the model on the test dataset.
- Measure performance using metrics like accuracy, precision, recall, F1-score, and confusion matrix.

Step 7: Prediction & Post-Processing

- Input new images into the trained model.
- Predict disease class.
- Display result and visualize heatmap.

Step 8: Deployment

- Deploy the trained model in a web/mobile app or integrate it with a smart farming system for real-time detection.

V. RESULT & DISCUSSION

Table 02: Classification Report

Class	Precision	Recall	F1 Score
Tomato_Bacterial_spot	0.89	0.98	0.93
Tomato_Early_blight	0.98	0.66	0.76

Tomato_Late_blight	0.83	0.65	0.74
Tomato_Leaf_Mold	0.94	0.89	0.91
Tomato_Septoria_leaf_spot	0.98	0.90	0.94
Tomato_Spider_mites	0.90	0.82	0.86
Tomato_Target_Spot	0.92	0.89	0.90
TomatoYellow_LeafCurlVirus	0.98	0.85	0.91
Tomato_mosaic_virus	0.91	0.99	0.96
Tomato_healthy	0.71	0.90	0.79
Cotton_Aphids	0.93	0.83	0.88
Cotton_Army_worm	0.74	0.83	0.78
Cotton_Bacterial_Blight	0.98	0.90	0.94
Cotton_Powdery_Mildew	0.96	0.96	0.96
Cotton_Target_spot	0.86	0.71	0.78
Cotton_healthy	0.80	0.96	0.87
Maize_Blight	0.95	0.89	0.92
Maize_Common_Rust	0.96	0.92	0.94
Maize_Healthy	0.95	0.96	0.96
Rice_Bacterial_blight	0.96	0.96	0.96
Rice_Blast	1.00	0.97	0.99
Rice_Brown_spot	0.96	0.96	0.96
Rice_healthy	1.00	0.97	0.99
Rice_Hispa	0.95	0.97	0.96
Rice_Bacterial_blight	0.75	0.98	0.86
Wheat_Brown_Rust	0.92	0.79	0.84
Wheat_Healthy	0.76	0.74	0.75
Wheat_Mildew	0.90	0.84	0.87
Wheat_Septoria	0.96	0.97	0.97
Wheat_Smut	0.75	0.86	0.80
Wheat_Yellow_Rust	0.74	0.86	0.79

The plant-disease detection model performed remarkably well with the training and testing accuracies of 98% and 90%, respectively, across multiple crops. There are several high-performing classes including Tomato_mosaic_virus, cotton_Powdery_Mildew, maize_healthy, and rice_Blast, with their F1-scores over 0.95. Proportionally low recall was recorded for rice_Hispa and Tomato_Early_blight diseases, suggesting the opportunity for enhancement in the detection of certain diseases. The performance of the model was consistent for tomato, cotton, maize, rice, wheat crops, which demonstrated its credibility and practicability in practical agriculture.

VI. CONCLUSION

In this study, we have successfully implemented a deep learning model to detect and differentiate plant diseases on leaves. We used Convolutional Neural Networks (CNNs) and our model was trained over a diverse dataset containing different plants species (e.g., tomato, cotton, rice, wheat and maize) affected by different crop diseases. The performances on the training and validation sets were high, indicating that our system was able to discriminate healthy plants from infected ones. The project in on enhancement of precision agriculture and it allows for early and accurate detection of plant diseases leading to crop loss, aiding the farmers in making early decisions. In conclusion, the proposed model is quite promising for real applications and can be incorporated into mobile or web applications to encourage sustainable farming practices..

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