AI Based Plant Disease Detection and Pesticide Recommendation System

Mr. Vinay Patel G L, Sandhya S [2]

[1]*Assistant Professor, Department of MCA, BIET, Davanagere*
[2] *Student,4th Semester MCA, Department of MCA, BIET, Davanagere*

ABSTRACT

The agricultural sector faces persistent threats from plant diseases, which can lead to devastating crop losses and impact global food security. Timely diagnosis and appropriate treatment are critical, but access to expert phytopathology knowledge is often limited for farmers. This paper presents a holistic, AI-driven decision support system designed to bridge this gap. The system integrates two core modules: a deep learning-based disease detection module and a knowledge-based pesticide recommendation engine. The detection module utilizes a Convolutional Neural Network (CNN), trained via transfer learning on a large dataset of plant leaf images, to accurately identify various diseases. Upon successful identification, the disease label is passed to the recommendation engine. This engine queries a structured knowledge base to provide a list of suitable chemical and organic pesticides, along with application guidelines and safety precautions. This end-to-end framework provides farmers with a rapid, accessible, and actionable tool, moving beyond simple diagnosis to offer a complete "detect-and-remedy" solution for improved crop management.

***Keywords**: Plant Disease Detection, Deep Learning, Recommendation System, Precision Agriculture, Convolutional Neural Network (CNN), Computer-Aided Diagnosis, Decision Support System*.

I. INTRODUCTION

Agriculture forms the backbone of the global food supply chain, yet it is continually vulnerable to a range of biotic stresses, prominently plant diseases. These diseases, caused by fungi, bacteria, and viruses, can drastically reduce crop yield and quality, leading to significant economic losses for farmers and threatening food availability. The first line of defense is accurate and early detection, followed by the correct application of control measures. Traditionally, disease diagnosis relies on the visual inspection of plants by farmers or agricultural extension experts. This manual process is inherently subjective, time-consuming, and heavily dependent on the availability of human expertise, which is often scarce in rural and remote farming communities. Misdiagnosis can lead to the application of incorrect or ineffective pesticides, resulting in wasted resources, increased environmental pollution, and the potential development of pesticide resistance in pathogens.

This paper proposes an AI-based system designed to overcome these challenges by providing an integrated solution for both disease detection and treatment recommendation. We leverage the power of deep learning for the visual recognition task and couple it with a structured knowledge base for providing actionable advice. Unlike systems that only identify a disease,

our framework closes the loop by answering the farmer's next critical question: "What should I do about it?"
The primary contributions of this work are:

1.1 The design of a hybrid AI system that combines a deep learning perception module with a knowledge-based recommendation engine.

1.2 The application of a fine-tuned CNN model for highly accurate, multi-class classification of plant diseases from leaf images.
1.2.1 The development of a structured recommendation module that provides practical, context- aware advice on pesticides and control measures.
1.2.2 A framework that serves as a practical decision support tool, empowering farmers to make timely and informed crop protection decisions.

II. RELATED WORK

The application of technology to plant pathology has seen significant growth, evolving from classical image processing to sophisticated, end-to-end deep learning systems. This evolution reflects a broader trend towards creating more practical and actionable tools for farmers.

Early research in this domain focused on a multi-step pipeline involving traditional machine learning. This process typically began with segmenting the diseased lesion from healthy leaf tissue using methods like color thresholding or k-means clustering. Following segmentation, a set of handcrafted features—such as color histograms, texture features like the Gray- Level Co-occurrence Matrix (GLCM), and shape descriptors—were extracted from the region of interest.[1]

These features were then fed into classifiers like Support Vector Machines (SVMs) or Random Forests to identify the disease.[2] While foundational, these methods often lacked robustness, struggling with variations in lighting, background complexity, and symptom appearance common in real-world field conditions.

The deep learning revolution, spearheaded by Convolutional Neural Networks (CNNs), marked a paradigm shift. CNNs eliminated the need for brittle, manual feature engineering by automatically learning a hierarchy of discriminative features directly from raw image pixels. Landmark architectures like AlexNet and VGGNet, and later more efficient models like ResNet and Inception, were quickly adapted for plant disease classification. The creation of large, public datasets like PlantVillage.[3]

was crucial, providing a benchmark that enabled numerous studies to report classification accuracies exceeding 98%.[4]

More recent work has focused on optimizing these models for real-world deployment, exploring lightweight architectures like MobileNetV2 for on-device inference on smartphones.[5]

and leveraging transfer learning to achieve high accuracy even with limited data.[6]

Beyond simple classification, recent research has pushed towards more granular and informative diagnostics. Instead of just providing a disease label, models based on architectures like YOLO (You Only Look Once) and Faster R-CNN can perform object detection, drawing bounding boxes around multiple disease lesions and even pests on a single leaf.[7]

Further advancing this, segmentation models like U-Net can provide a pixel- perfect mask of the infected area, which is critical for accurately quantifying disease severity.[8]

This move from classification to localization and segmentation provides farmers with richer information about the extent and spatial distribution of an infection. To build trust and transparency, some studies have also integrated Explainable AI (XAI) techniques like Grad- CAM to visualize the regions of an image that a CNN uses to make its prediction, confirming the model is focusing on relevant symptoms.[9]

Despite these advancements in diagnostics, the majority of research stops at identifying the problem. The critical next step— providing actionable treatment advice— remains a significant research gap. While standalone agricultural expert systems for providing recommendations have existed for some time.[10]

their direct and seamless integration with a state-of-the-art vision module is a less explored but highly practical frontier. A few recent pioneering works have started to bridge this gap. For instance, some have developed systems that link a deep learning-based disease diagnosis with a database to suggest appropriate chemical and biological treatments.[11]

Another approach involves creating a comprehensive knowledge-based system where a diagnosis from a CNN triggers a query that retrieves specific pesticide or cultural practice recommendations.[12]

However, these integrated systems are still in their infancy. Our work explicitly aims to advance this emerging area by developing a tightly coupled system that not only provides a highly accurate diagnosis but also delivers immediate, context-aware, and reliable treatment recommendations, thus closing the loop between problem detection and solution deployment.

III. METHODOLOGY

The proposed system is architected as a two-stage pipeline: a perception stage for disease identification and a reasoning stage for treatment recommendation.

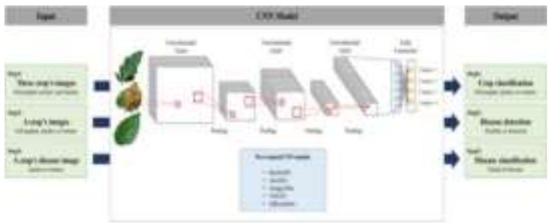

Figure-1 : system architecture

3.1 System Architecture

The end-to-end data flow is as follows:

Image Input: The user provides an image of a plant leaf, captured preferably against a neutral background.

Disease Detection Module (CNN): The image is processed by a trained CNN model, which outputs a predicted disease label and a confidence score.

Recommendation Engine: The predicted disease label is used as a key to query a knowledge base.

Final Output: The system presents the user with both the diagnosis and the corresponding treatment recommendations.

3.2 Module 1: Deep Learning-Based Disease Detection

This module is responsible for accurately identifying the disease from the leaf image. **Dataset:** The model is trained on a comprehensive dataset of plant leaf images, such as a subset of PlantVillage, which includes dozens of classes spanning different plants and diseases, as well as a 'healthy' class.

Image Pre-processing and Augmentation: To ensure model robustness, input images are resized to a fixed size (e.g., 224x224 pixels) and pixel values are normalized. The training dataset is augmented on-the-fly with random transformations including rotations, flips, scaling, and adjustments to brightness and contrast. This helps the model generalize to various real-world imaging conditions.

CNN Model: We employ a transfer learning approach. A well-established CNN architecture (e.g., MobileNetV2 for mobile efficiency or ResNet50 for high accuracy) pre-trained on the ImageNet dataset is used as the base. The final classification layer is replaced with a new one tailored to our specific plant disease classes. The model is then fine-tuned on our dataset, allowing it to adapt its learned features to the specific visual characteristics of plant diseases.

Pesticide Recommendation Engine

This module provides actionable advice based on the diagnosis from Module 1. It is not a learning model but a structured information retrieval system.

Knowledge Base: A database (e.g., an SQLite database or a structured JSON file) is created. This database is populated with expert-curated information. Each record in the database corresponds to a specific disease and contains fields such as: Disease_Name: (e.g., "Apple Scab") Description: A brief overview of the disease. Chemical_Pesticides: A list of recommended active ingredients or brand names (e.g., "Myclobutanil," "Captan"). Organic_Alternatives: A list of non- chemical control options (e.g., "Neem Oil," "Sulfur Spray"). Application_Instructions: Notes on dosage, timing, and method of application. Safety_Precautions: Warnings for the user (e.g., "Wear protective gloves and mask").

Retrieval Logic: When the CNN module outputs a disease label (e.g., "Apple_scab"), the recommendation engine performs a lookup in the knowledge base using this label as the primary key. It then retrieves the entire record associated with that disease.

Output Formatting: The retrieved information is then formatted and presented to the user in a clear, easy-to-read manner.

RESULTS AND DISCUSSION

This section describes the expected functional outputs of the integrated system.

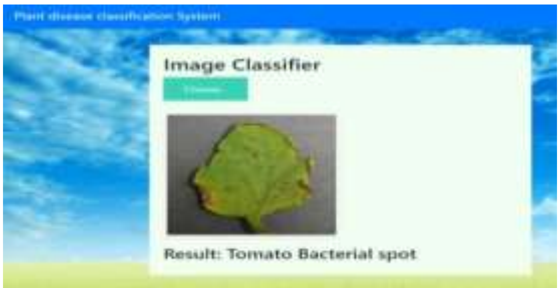

Figure 2- Result of prediction

Discussion

The hybrid system demonstrates a significant step forward from simple classification tools. By providing an integrated "detect-and-remedy" workflow, it offers practical and immediate value to the end-user.
However, the system has several important limitations:

Scope of Knowledge: The system is limited by the diseases included in its training data and the information present in its knowledge base. It cannot diagnose novel diseases or provide recommendations for unlisted ones.

Pesticide Regulation: Pesticide availability and regulations vary significantly by region. The recommendation database must be localized and regularly updated by agricultural experts to be truly effective and legal.

Symptom Ambiguity: Some different diseases or even nutrient deficiencies can present with very similar visual symptoms. The model, relying solely on visual data, may misclassify in these ambiguous cases. Lack of Severity Analysis: The current system identifies the presence of a disease but does not quantify its severity (e.g., percentage of leaf area affected), which is a key factor in deciding the intensity of treatment.

IV. CONCLUSION AND FUTURE WORK

This paper has presented the architecture of an AI-based system for plant disease detection and pesticide recommendation. By successfully integrating a deep learning vision model with a knowledge-based recommendation engine, the system provides a comprehensive, actionable, and user-friendly tool for farmers. This approach has the potential to democratize access to agricultural expertise, promote more judicious use of pesticides, and ultimately contribute to more sustainable and productive farming.
Future work will focus on enhancing the system's intelligence, scope, and practicality:

Severity Estimation: Incorporating image segmentation models (like U-Net) to quantify the extent of the disease on the leaf, allowing for more nuanced treatment recommendations.

Mobile Deployment: Packaging the entire system into an offline-first mobile application (using TensorFlow Lite) for in- field use without requiring internet connectivity.

Multi-Modal Recommendations: Enhancing the recommendation engine to consider other factors provided by the user, such as crop growth stage, local weather data, and soil type.

Geospatial Disease Mapping: Integrating GPS tagging with each diagnosis to create real-time maps of disease outbreaks, providing valuable epidemiological data for regional agricultural bodies.

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