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An Intelligent Deep Learning-Based Smart Agro-Cure System for Plant Disease Detection and Pesticide Recommendation Using Convolutional Neural Networks

Ms. Rebaka Theresa Joe¹, Salagrama Manaswini², Voggu Thanuja Devi³, Gudala Sai Phanindra⁴, Kandula Venkata Naveen Chowdary⁵, Chinnam Manoj Varma⁶

¹Assistant Professor, Department of Computer Science and Engineering (AI), Pragati Engineering College, ADB Road, Surampalem, Near Kakinada, East Godavari District, Andhra Pradesh, India-533437

^{2,3,4,5,6}B.Tech Students, Department of Computer Science and Engineering(AI), Pragati Engineering College, ADB Road, Surampalem, Near Kakinada, East Godavari District, Andhra Pradesh, India-533437

Abstract: *The agricultural sector faces significant challenges due to plant diseases, which lead to reduced crop productivity and economic losses. Traditional disease identification methods rely on manual inspection, which is time-consuming, error-prone, and requires expert knowledge. This paper proposes a Smart Agro-Cure system that leverages deep learning techniques, specifically Convolutional Neural Networks (CNNs), to automatically detect plant diseases from leaf images and recommend appropriate pesticides. The system allows users to upload plant leaf images, which are processed using image preprocessing techniques such as resizing, normalization, and noise reduction. The processed images are then analysed by a trained CNN model to classify plant diseases with high accuracy. Based on the predicted disease, the system retrieves relevant information and pesticide recommendations from a structured database. The results are displayed through an intuitive user interface, enabling farmers to take timely action. The proposed system ensures fast diagnosis, improved accuracy, and sustainable pesticide usage. Experimental results demonstrate that the model achieves over 90% accuracy in disease classification, making it suitable for real-world agricultural applications. The system supports scalability and can be extended with IoT integration and real-time monitoring for smart farming.*

Keywords: *Plant Disease Detection, CNN, Smart Agriculture, Deep Learning, Image Processing, Pesticide Recommendation, Computer Vision.*

I. INTRODUCTION

Agriculture plays a crucial role in the global economy, but crop productivity is significantly affected by plant diseases. Early detection and proper treatment are essential to prevent large-scale losses. Traditional disease detection methods rely on human expertise, which is often unavailable in rural areas and prone to errors.

With advancements in artificial intelligence and deep learning, automated systems can analyze plant images and detect diseases with high accuracy. The proposed Smart Agro-Cure system utilizes CNN-based image classification to identify plant diseases and recommend suitable pesticides. This system bridges the gap between modern AI technologies and traditional farming practices, enabling farmers to make informed decisions.

A. Problem Statement

Plant disease detection is a critical challenge in agriculture due to the lack of accessible and accurate diagnostic tools. Manual identification is time-consuming and often inaccurate due to similar visual symptoms among diseases. Farmers may also lack access to expert guidance, leading to improper pesticide usage. Additionally, excessive use of pesticides causes environmental damage and health risks. Therefore, there is a need for an intelligent system that can automatically detect plant diseases and provide accurate treatment recommendations

B. Motivation

The motivation behind this research is to develop an AI-driven solution that assists farmers in diagnosing plant diseases quickly and accurately. The system aims to reduce dependency on experts, promote sustainable pesticide usage, and improve crop productivity. By integrating deep learning and computer vision, the project enables efficient disease detection and supports modern agricultural practices

C. Key objectives of this research include

The key objectives of this research are to design and develop an intelligent plant disease detection system using deep learning techniques; to implement efficient image preprocessing and feature extraction methods for accurate classification; to build a CNN-based model capable of identifying multiple plant diseases; to integrate a database-driven pesticide recommendation system for appropriate treatment; and to develop a user-friendly interface that enables farmers to easily upload images and receive real-time results, thereby improving agricultural productivity and promoting sustainable farming practices.

II. LITERATURE SURVEY

Recent advancements in deep learning and computer vision have enabled automated plant disease detection systems using image classification techniques. Traditional methods relied on manual inspection and rule-based systems, which lacked accuracy and scalability. Modern approaches use CNN models to analyze leaf images and identify disease patterns with high precision. Additionally, research focuses on integrating AI systems with agricultural practices to improve productivity and sustainability.

S.No	Citation	Research Focus	Methodology	Key Findings
1	Mohanty et al., 2016	Plant disease classification	Deep CNN (AlexNet, GoogleNet)	Achieved 99% accuracy on PlantVillage dataset
2	Ferentinos, 2018	Multi-crop disease detection	Deep CNN models	High accuracy across multiple plant species
3	Too et al., 2019	CNN architecture comparison	VGG16, ResNet, DenseNet	DenseNet achieved highest accuracy
4	Brahimi et al., 2017	Plant disease recognition	CNN with feature extraction	Effective classification of tomato diseases
5	Sladojevic et al., 2016	Disease detection via images	CNN-based classification	Automated disease recognition system developed
6	Picon et al., 2019	Crop disease identification	Deep learning + image segmentation	Improved disease localization accuracy
7	Zhang et al., 2020	Real-time disease detection	CNN + MobileNet	Lightweight model for real-time usage
8	Kaur et al., 2021	Smart agriculture systems	CNN + IoT integration	Improved monitoring and early detection
9	Liu et al., 2020	Leaf disease classification	Deep CNN + augmentation	Enhanced performance under varied conditions
10	Chen et al., 2021	Disease detection optimization	Transfer learning (ResNet)	Reduced training time with high accuracy

III. BACKGROUND WORK

The development of intelligent plant disease detection systems has gained significant attention with the advancement of artificial intelligence and computer vision techniques. Traditional methods relied heavily on manual observation and expert knowledge, which are often time-consuming, inconsistent, and not scalable for large agricultural fields. The integration of deep learning models has enabled automated and accurate identification of plant diseases using digital images.

A. *Image-Based Disease Detection*

Image-based disease detection is a widely used approach in modern agriculture, where plant leaf images are analyzed to identify disease symptoms. These symptoms typically include discoloration, spots, texture changes, and abnormal patterns. Earlier methods relied on handcrafted features such as colour histograms and texture descriptors. However, these approaches lacked generalization capability and failed under varying environmental conditions. Deep learning techniques overcome these limitations by automatically extracting relevant features from images.

B. *Convolutional Neural Networks (CNNs)*

Convolutional Neural Networks (CNNs) are powerful deep learning models specifically designed for image classification tasks. CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers, which work together to extract hierarchical features from images. In plant disease detection, CNNs learn complex patterns such as leaf texture, colour variations, and shape distortions. Their ability to generalize across datasets makes them highly effective for agricultural applications.

C. *Image Preprocessing Techniques*

Preprocessing plays a crucial role in improving model performance by enhancing image quality and reducing noise. Common preprocessing techniques include resizing images to a fixed dimension, normalization of pixel values, and noise removal using filters. These steps ensure uniform input to the CNN model and improve classification accuracy. Proper preprocessing also reduces computational complexity and speeds up training and inference.

D. *Dataset and Feature Representation*

The system uses labelled datasets containing images of healthy and diseased plant leaves. Each image is associated with a specific disease category. The CNN model automatically extracts features such as edges, textures, and colour patterns during training. These features are used to distinguish between different diseases. Data augmentation techniques such as rotation, flipping, and scaling are applied to improve model robustness.

E. *Smart Agriculture and AI Integration*

The integration of AI in agriculture has led to the development of smart farming solutions that enhance productivity and sustainability. AI-based disease detection systems help farmers make informed decisions by providing accurate and timely information. These systems reduce dependency on manual inspection and minimize the misuse of pesticides. The proposed Smart Agro-Cure system aligns with modern agricultural practices by combining deep learning and automation.

IV. PROPOSED MODEL

The proposed Smart Agro-Cure system is an intelligent framework designed to detect plant diseases and recommend suitable treatments using deep learning techniques. The system integrates image preprocessing, CNN-based classification, and database-driven recommendations to provide accurate and real-time results. It is designed to be user-friendly, scalable, and efficient for practical agricultural applications.

A. *Image Acquisition*

The image acquisition module allows users to capture or upload plant leaf images through a graphical interface. It supports various image formats and ensures proper handling of input data. This module acts as the entry point of the system and plays a crucial role in determining overall accuracy. High-resolution images improve detection performance by providing clearer visual features.

B. *Image Preprocessing*

The preprocessing module enhances image quality by applying techniques such as resizing, normalization, and noise reduction. These operations standardize the input data and ensure compatibility with the CNN model. Preprocessing helps in removing irrelevant information and highlighting important features, thereby improving classification accuracy and system efficiency.

C. *Disease Detection (CNN Model)*

The CNN-based detection module analyzes the processed images to identify plant diseases. It extracts hierarchical features automatically and classifies images into predefined categories. The model is trained using labeled datasets and achieves high accuracy in identifying various diseases. This module forms the core of the system and ensures reliable predictions.

D. Database Interaction

The database module stores information about plant diseases, symptoms, and recommended treatments. Once a disease is detected, the system retrieves relevant data from the database. This ensures accurate and consistent output. The use of structured datasets enables efficient data management and retrieval.

E. Recommendation System

The recommendation module provides appropriate pesticide suggestions and preventive measures based on the detected disease. It helps farmers take timely action and reduces excessive pesticide usage. This module promotes sustainable farming practices and improves crop health.

F. User Interface

The user interface module displays results in a clear and interactive format. It shows the detected disease, treatment recommendations, and preventive measures. The interface is designed to be simple and accessible, enabling farmers to easily use the system without technical expertise.

G. Parallel Processing

The system supports efficient processing by handling multiple operations such as preprocessing, classification, and data retrieval simultaneously. This reduces processing time and ensures real-time performance. Parallel execution improves system responsiveness and scalability.

H. Integration

All modules are seamlessly integrated to ensure smooth data flow from input to output. The system maintains consistency and accuracy throughout the process. Integration enables efficient communication between modules and enhances overall system performance.

I. Workflow

The system workflow begins with image upload, followed by preprocessing to enhance image quality. The CNN model then analyzes the image and classifies the disease. The system retrieves relevant information from the database and generates pesticide recommendations. Finally, the results are displayed through the user interface.

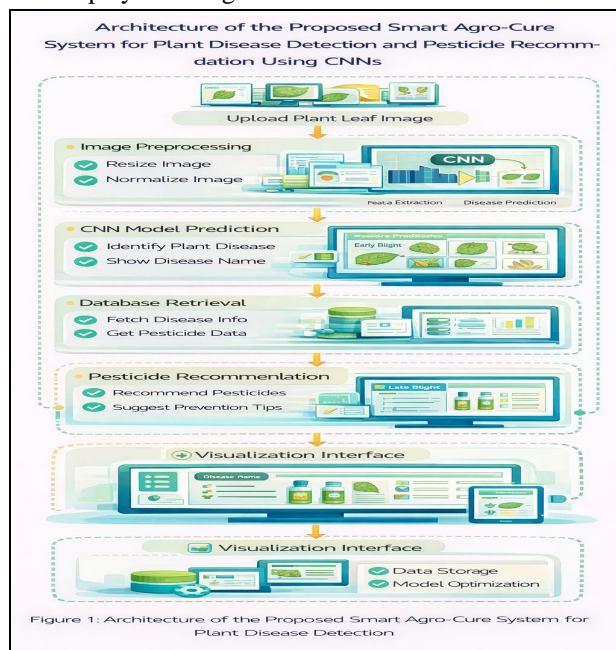


Figure 1: Architecture of the Proposed Smart Agro-Cure System for Plant Disease Detection and Pesticide Recommendation Using CNNs

Figure 1 illustrates the overall architecture of the proposed Smart Agro-Cure system, which is designed to detect plant diseases from leaf images and provide suitable pesticide recommendations. The process begins with the image upload stage, where the user submits a plant leaf image through the application interface. This uploaded image serves as the primary input for disease analysis. In the image preprocessing module, the system performs essential operations such as resizing and normalization to standardize the image before it is passed to the deep learning model. These preprocessing steps improve image quality, reduce inconsistencies, and ensure compatibility with the CNN architecture. By preparing the input image in a structured manner, the system enhances the accuracy and reliability of disease classification.

V. IMPLEMENTATION RESULTS

The proposed system is implemented using Python along with deep learning libraries such as TensorFlow and Keras. OpenCV is used for image processing, and Flask is used to develop the web-based interface. The system is capable of processing images in real time and providing quick predictions.

A. Home Page

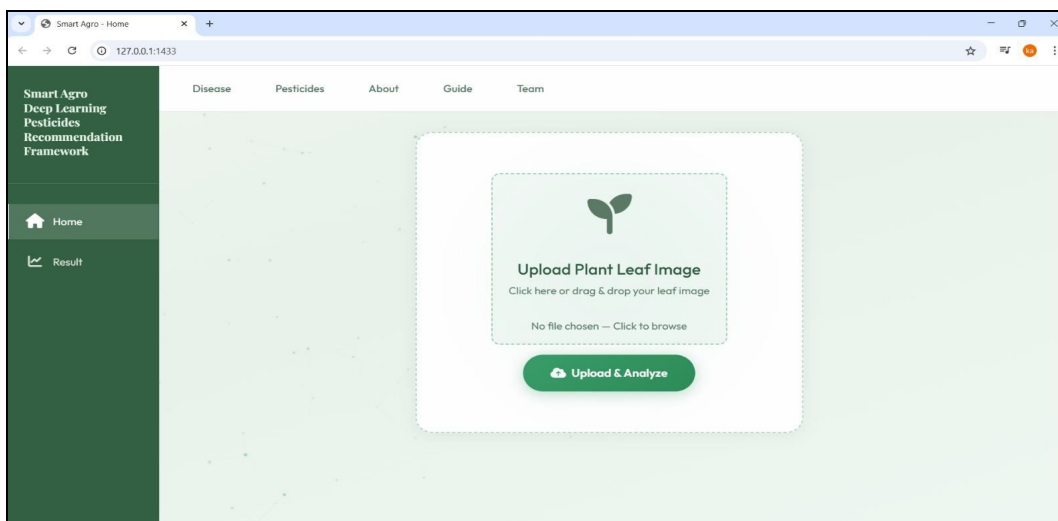


Figure 2: User Upload an Image

Figure 2 explains about the user is having option to upload plant leaf image and then try to analyze what is their in that plant.

B. Disease Prediction and Recommendation

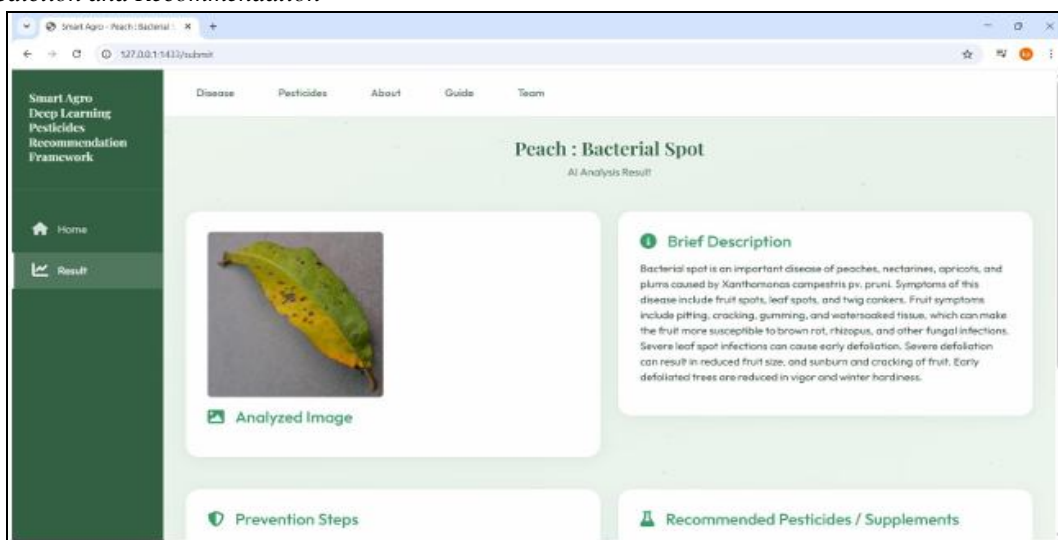


Figure 3. Disease Prediction and Recommendation Output Interface of the Smart Agro-Cure System

Figure 3 presents the output interface of the Smart Agro-Cure system, where the results of plant disease analysis are displayed after processing the uploaded leaf image. The interface shows the analyzed leaf image along with the predicted disease name, such as *Peach: Bacterial Spot*. It also provides a brief description of the disease, including its causes and symptoms, helping users understand the issue clearly.

In addition, the system offers preventive measures and recommended pesticides or supplements to treat the detected disease effectively. The layout is designed to be user-friendly, ensuring that farmers and users can easily interpret the results and take appropriate action. This output interface plays a crucial role in delivering actionable insights and supporting informed agricultural decisions.

C. Results Page

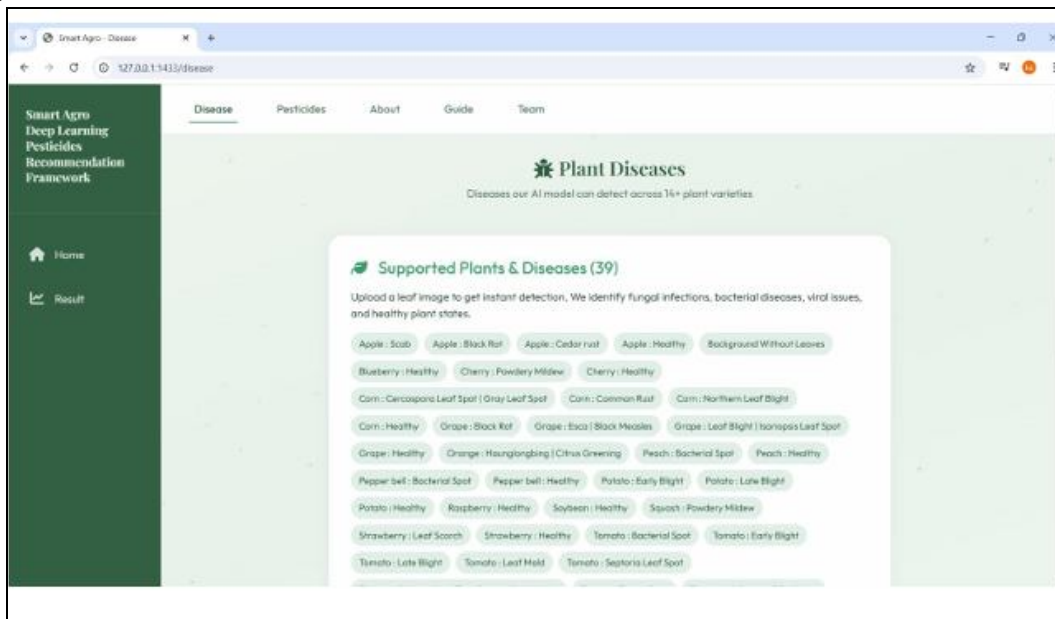


Figure 4: Supported Plant Diseases Interface of the Smart Agro-Cure System

Figure 4 illustrates the plant diseases information interface of the Smart Agro-Cure system, which displays the list of supported plants and their corresponding diseases. This page provides users with an overview of various plant categories and disease types that the system is capable of detecting, including fungal, bacterial, and viral infections, as well as healthy plant conditions.

The interface organizes the diseases in a structured and readable format, allowing users to easily browse through different plant varieties and their associated conditions. It also highlights the system's capability to handle multiple crops and disease classes, demonstrating its scalability and robustness. This section enhances user awareness and helps farmers understand the range of diseases that can be identified using the system.

VI. CONCLUSION

The proposed Smart Agro-Cure system presents an efficient and intelligent solution for automated plant disease detection and pesticide recommendation using deep learning techniques. By leveraging Convolutional Neural Networks (CNNs), the system is capable of accurately identifying plant diseases from leaf images and providing appropriate treatment suggestions in real time. This approach significantly reduces dependency on manual inspection and expert knowledge, making it highly beneficial for farmers, especially in rural and resource-limited areas. The integration of image preprocessing, CNN-based classification, and database-driven recommendation ensures high accuracy, fast response time, and reliable outputs. The user-friendly interface further enhances accessibility, allowing users to easily upload images and obtain actionable insights. The system not only improves disease diagnosis but also promotes sustainable agricultural practices by recommending targeted pesticide usage. Overall, the Smart Agro-Cure system contributes to the advancement of smart agriculture by combining artificial intelligence with practical farming needs. It offers a scalable, cost-effective, and robust solution for improving crop health and productivity. Future enhancements can focus on integrating IoT-based monitoring systems, expanding the dataset for broader disease coverage, and deploying the system as a mobile application to increase accessibility and real-time usability.



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