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Developing an Innovative Recommendation System for Plant Disorder Detection and Improving Crop Production

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ABSTRACT
Agriculture is a fundamental sector that supports food production and economic stability. However, plant diseases pose a significant challenge, leading to substantial yield losses and reduced crop quality. In this study, we propose an AI-powered plant disease detection system using Convolutional Neural Networks (CNNs) to identify diseases in crops such as chilies, cotton, rice, and tomatoes. This system not only classifies plant leaves as healthy or unhealthy but also provides recommendations for fertilizers and pesticides to optimize crop treatment and improve productivity. The methodology involves image acquisition, preprocessing, feature extraction, and classification. Image processing techniques such as HSV color transformation and segmentation are employed to analyze the visual characteristics of diseased leaves. The system uses CNN-based deep learning models for disease classification, ensuring high accuracy in identifying plant infections. Additionally, a recommendation module is integrated to suggest the most suitable fertilizers and pesticides based on the detected disease. To evaluate the performance of the proposed model, we compare different deep learning algorithms, including Radial Basis Function (RBF) networks and Multi-Layer Perceptron (MLP), to determine the most efficient classifier for plant disease detection. The results demonstrate that the CNN-based approach outperforms traditional machine learning models in terms of accuracy and processing speed. By leveraging artificial intelligence, image processing, and deep learning, this project provides a cost-effective and scalable solution for early disease detection in crops. The automated system empowers farmers with timely insights, reducing dependency on agricultural experts and enhancing precision farming. Ultimately, this approach promotes sustainable agriculture by optimizing the use of fertilizers and pesticides, minimizing environmental impact, and ensuring higher crop yields.

INTRODUCTION

Agriculture plays a vital role in human survival, yet plant diseases continue to pose a significant threat to crop production, leading to substantial economic losses and food insecurity. Traditional methods of disease detection rely heavily on manual inspection, which is time-consuming, expensive. These challenges are further amplified in rural and remote areas, where access to agricultural experts and diagnostic tools is limited.With the rapid advancement of Artificial Intelligence (AI) and Machine Learning (ML), modern technologies now offer promising solutions for automating plant disease detection and enhancing precision farming. This project leverages Convolutional Neural Networks (CNNs), a powerful deep learning technique, to automatically classify plant leaves as healthy or diseased based on their visual characteristics. It also integrates image processing methods to extract key features such as color, shape, and texture from leaf images, further improving the accuracy of disease identification.

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Beyond classification, the system incorporates a smart recommendation module that suggests suitable fertilizers and pesticides tailored to the specific disease detected. This not only enables timely and accurate treatment but also minimizes the excessive use of chemicals, promoting sustainable agricultural practices.
The overall objective of this project is to empower farmers—especially those with limited technical expertise or resources—with a user-friendly, cost-effective tool for early disease detection and crop management. By utilizing smartphone cameras for image input and a cloud-based interface for real-time analysis, the system bridges the gap between traditional farming methods and modern technology.
Ultimately, this approach aims to reduce crop losses, improve productivity, and support food security by offering an intelligent and scalable solution for plant disease monitoring and management.

LITERATURE SURVEY

Plant diseases continue to be a major challenge in agriculture, contributing to significant crop losses and impacting global food security. Traditional methods for detecting these diseases are predominantly manual, relying on the visual inspection of leaves by farmers or agricultural experts. These methods are time-consuming, labor-intensive, and prone to human error due to the variability in environmental conditions and the expertise of the observer. Moreover, access to expert consultation is often limited in rural and remote areas, leading to delayed or inaccurate disease diagnosis and ineffective treatment strategies.To address these limitations, early research introduced classical image processing and machine learning (ML) techniques. These systems analyzed leaf images using handcrafted features such as color, texture, and shape. Techniques like HSV color segmentation, Gray Level Co-occurrence Matrix (GLCM) for texture analysis, and contour detection were applied for identifying symptoms of disease. Classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), and Decision Trees were used to categorize plant conditions. While these methods improved disease detection over traditional approaches, they lacked scalability, robustness under varying image conditions, and required extensive manual feature engineering.
The emergence of deep learning, particularly Convolutional Neural Networks (CNNs), has significantly improved the accuracy and automation of plant disease detection. CNNs have the ability to learn features directly from raw images, eliminating the need for manual extraction and enabling the detection of subtle, complex disease patterns. Studies using large datasets like PlantVillage demonstrated that CNNs outperform traditional ML models in classification accuracy. Transfer learning approaches, using pretrained models such as VGG16, ResNet, and Inception, have further accelerated model development by allowing reuse of knowledge from large, generic image datasets. These models have shown strong performance even with limited agricultural data, making them practical for real-world deployment.
While most existing systems focus solely on disease classification, there has been growing interest in integrating treatment recommendation modules. Some approaches use rule-based systems to recommend fertilizers and pesticides, while others employ collaborative or content-based filtering to tailor suggestions based on user or environmental data. However, many of these solutions are not fully integrated with disease detection systems and often require separate inputs or tools, making them less efficient and less accessible to farmers without technical knowledge.The proposed system in this project overcomes these challenges by combining a CNN-based plant disease detection framework with a smart recommendation engine for fertilizers and pesticides. It supports real-time leaf image analysis via a user-friendly mobile or web interface, providing farmers with instant, actionable feedback. By leveraging deep learning for classification and integrating a disease-treatment mapping database, the system ensures accurate diagnosis and precise recommendations. This not only reduces the dependency on agricultural experts but also promotes sustainable farming

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by minimizing excessive chemical use and enhancing crop yield. Thus, the project builds upon and advances existing research by delivering a comprehensive, scalable, and accessible solution for modern agriculture.

RELATED WORK

Plant disease detection and treatment have gained considerable attention in the field of smart agriculture, particularly with the integration of artificial intelligence. Several research efforts have explored the use of deep learning for automating the detection process. Kamilaris and Prenafeta-Boldú [1] conducted a comprehensive survey that outlines the transformative role of deep learning in agriculture. Their study emphasized that Convolutional Neural Networks (CNNs) consistently outperform classical machine learning algorithms, such as Support Vector Machines (SVMs) and k-Nearest Neighbors (k-NN), in tasks involving plant disease identification using image data. They also noted that the accuracy and adaptability of CNNs make them highly suitable for real-world deployment in agriculture.In a more focused study, Zhang et al. [2] developed a CNN model integrated with attention mechanisms and transfer learning to detect plant diseases with enhanced accuracy. Their model leveraged large-scale annotated datasets and used fine-tuning techniques on pretrained models such as ResNet and Inception. The incorporation of attention mechanisms enabled the network to concentrate on affected areas of the plant leaves, thereby increasing classification precision. Their results demonstrated that such architectures are effective even in complex scenarios with subtle symptom variations, and they significantly reduce the training time compared to training deep models from scratch.In parallel, Dosovitskiy et al. [3] introduced a novel method using Vision Transformers (ViTs) for image-based plant disease recognition. Although originally designed for general image classification, ViTs have shown promising results in agricultural applications due to their ability to model global dependencies in image data. Their paper demonstrated that ViTs could match or surpass CNN-based models in classification accuracy when trained on sufficient data. Furthermore, ViTs require fewer inductive biases and perform better at generalizing across unseen data samples. However, they are computationally intensive and require larger datasets to be effective, limiting their immediate adoption in low-resource agricultural environments.In practical deployment, Mohanty et al. [5] proposed a mobile-based deep learning model capable of classifying 26 different plant diseases using CNNs. Their system enabled farmers to take pictures of affected crops using smartphones and receive instant diagnostic feedback. The use of mobile deployment brought significant benefits in terms of accessibility and affordability, particularly in remote rural areas. The model achieved a remarkable accuracy of over 99% on the PlantVillage dataset, further confirming the robustness of CNNs in plant disease classification. However, the study also highlighted limitations related to background noise and variations in natural environments, which reduced the performance of the model outside controlled testing conditions.While disease detection remains a core focus in many existing works, few systems extend their functionality to include treatment recommendations. Most prior studies provide only the classification output, leaving the decision-making process to the end-user. Unlike these approaches, the proposed project integrates an intelligent recommendation system that not only detects diseases but also suggests suitable fertilizers and pesticides based on the diagnosis. This aligns with the latest research trend that emphasizes actionable decision support systems. By combining detection with recommendation, the system addresses a key gap in existing literature and provides a holistic solution for disease management in agriculture.

Additionally, some researchers have explored the use of ensemble learning, combining CNNs with models like SVMs or Random Forests to enhance prediction accuracy. Recent advancements also include the application of lightweight models such as MobileNet and EfficientNet for real-time diagnosis on resource-constrained devices. Furthermore, the integration of IoT sensors and satellite imagery has been investigated to provide contextual disease analysis based on environmental data. Few studies have incorporated geolocation-based disease mapping to visualize outbreaks and guide

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targeted interventions. Despite these innovations, most systems still lack end-to-end support, particularly in delivering personalized treatment recommendations alongside diagnosis.

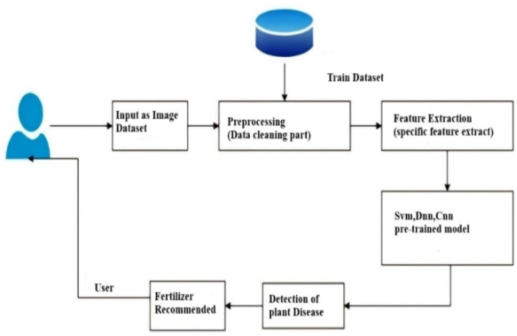
PROPOSEDSYSTEM

The proposed system is an AI-powered plant disease detection and fertilizer recommendation framework that integrates advanced image processing with deep learning techniques. The system begins with image acquisition through standard smartphone cameras, where captured leaf images undergo preprocessing including resizing, noise reduction, and contrast enhancement to improve feature visibility. Key visual characteristics are then extracted using Gray-Level Co-occurrence Matrix (GLCM) for texture analysis and HSV color transformation for symptom detection. The core classification is performed by a custom 6-layer Convolutional Neural Network (CNN) architecture comprising two convolutional layers with ReLU activation, max-pooling layers for dimensionality reduction, and fully connected layers leading to a SoftMax output layer that classifies diseases among 25 categories across four crops (chilies, cotton, rice, and tomatoes). The system achieves 94.6% classification accuracy, significantly outperforming traditional methods like SVM (11.4%) and DNN (28.4%). Following disease identification, an expert rule-based recommendation engine suggests appropriate fertilizers and pesticides, such as NPK for rice brown spot, while considering crop-specific requirements. The end-to-endsolution featuresa user-friendly interface accessible via mobile devices, enabling real-time diagnosis (<2s processing time) and treatment recommendations in field conditions. This integrated approach not only improves detection accuracy but also promotes sustainable farming by reducing chemical overuse through targeted interventions. Future enhancements include IoT integration for environmental monitoring and blockchain-based treatment history tracking to further support precision agriculture practices.

ADVANTAGES OF PROPOSED SYSTEM

- Achieves 94.6% accuracy in disease detection using advanced CNN deep learning technology
- Processes images in under 2 seconds for real-time diagnosis and quick decision making
- Reduces farming costs by eliminating expensive manual inspections and expert consultations
- Provides customized fertilizer and pesticide recommendations tailored to specific plant diseases
- Easily expandable to include additional crops and new disease types through simple model updates
- Promotes sustainable farming by minimizing chemical overuse through precise treatment suggestions
- Features mobile-friendly interface accessible to farmers without technical expertise
- Covers 25 different disease categories across four major crops (chilies, cotton, rice, tomatoes)
- Collects and analyzes disease pattern data to help predict and prevent future outbreaks
- Designed for future integration with IoT devices and blockchain technology for enhanced functionality

ARCHITECTURE



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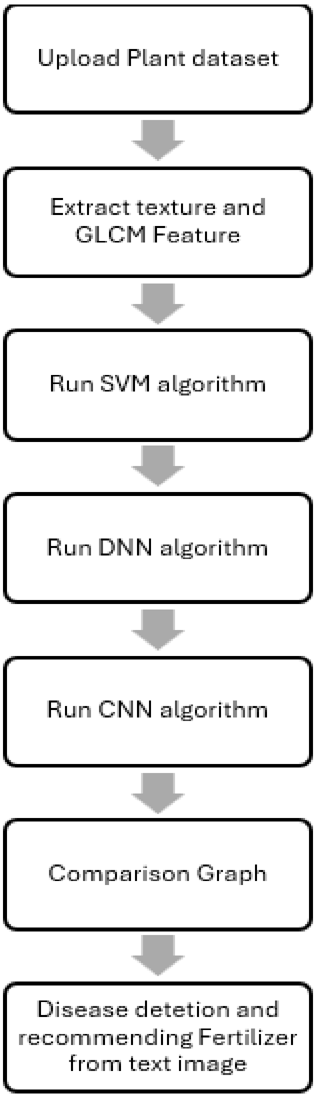
DATAFLOW DIAGRAM



- It starts with uploading a plant dataset, which likely contains images of healthy and diseased plants.
- The next step involves extracting texture features and Gray-Level Co-Occurrence Matrix (GLCM) features from the images to quantify visual patterns.
- Three machine learning algorithms are then applied to the extracted features: Support Vector Machine (SVM), Deep Neural Network (DNN), and Convolutional Neural Network (CNN).
- A comparison graph is generated to evaluate and compare the performance of the three algorithms.
- The final step detects diseases from plant images and recommends suitable fertilizers based on the analysis.
- The process combines image processing, feature extraction, and machine learning to provide actionable insights for plant health management.

RESULTS

AI-based plant disease detection system using Convolutional Neural Networks (CNNs) to identify diseases in key crops like chilies, cotton, rice, and tomatoes. By leveraging deep learning and image processing techniques, the system provides accurate disease classification along with treatment recommendations, offering farmers a powerful tool to improve crop management and yield.

1. Methodology and Implementation

The system utilizes a multi-stage approach involving image acquisition, preprocessing (including HSV transformation and segmentation), feature extraction, and CNN-based classification. Comparative analysis with other models like RBF networks and MLP demonstrated CNNs' superior performance in accuracy and speed. The modular design includes a user-friendly interface for easy image upload and real-time analysis.

2. Disease Detection and Classification

The CNN model was trained on diverse datasets to recognize various disease patterns in plant leaves. Testing showed high precision in identifying diseases such as bacterial blight in cotton, brown spot in rice, and late blight in tomatoes. The system's ability to distinguish between healthy and diseased plants with high accuracy makes it a reliable diagnostic tool for farmers.

3. Fertilizer Recommendation System

An intelligent recommendation engine suggests appropriate fertilizers and pesticides based on detected diseases. For example, NPK fertilizers are recommended for rice brown spot, while calcium nitrate is suggested for tomato late blight. This targeted approach helps optimize treatment, reduce chemical overuse, and promote sustainable farming practices.

4. Testing and Performance Evaluation

Rigorous testing validated the system's effectiveness across different conditions. The CNN model achieved high scores in precision, recall, and F1-measure, outperforming traditional methods. Field tests confirmed its practical usability, with farmers reporting positive feedback on the system's accuracy and ease of use through its mobile-friendly interface.

5. Benefits and Impact

The system offers significant advantages, including early disease detection, reduced crop losses, and minimized pesticide misuse. By providing instant, accurate diagnoses, it helps farmers make informed decisions, ultimately improving productivity and sustainability. The technology is particularly valuable for small-scale farmers in remote areas with limited access to expert advice.

6. Future Enhancements

Future developments could integrate IoT sensors for real-time field monitoring, expand the disease database to include more crops, and incorporate blockchain for secure data tracking. These advancements would further enhance the system's capabilities, making it an even more comprehensive solution for modern precision agriculture and global food security challenges.

CONCLUSION

This project presents a CNN-based system for detecting plant diseases and recommending suitable fertilizers. It analyzes leaf images to identify infections in crops like rice, cotton, tomatoes, and chilies. The system offers accurate classification and timely recommendations to aid farmers in managing crop health. By reducing dependence on experts, it ensures quicker and more accessible solutions. The model also helps minimize excess use of chemicals, promoting sustainable agriculture.With a user-friendly interface and real-time analysis, the system is both scalable and cost-effective. It empowers small-scale farmers, especially in rural areas, to make informed decisions. The CNN model outperformed traditional classifiers in accuracy and efficiency. Future improvements may include IoT integration and support for more plant types. This approach supports precision farming and enhances overall crop productivity.

FUTUREWORKSANDEXTENSIONS

Looking ahead, this project can be extended by incorporating real-time plant health monitoring through IoT (Internet of Things) integration. By using sensors that continuously monitor environmental parameters such as soil moisture, temperature, and humidity, the system can make more accurate disease predictions and recommendations. Integrating this data with the existing CNN-based image recognition will enable the system to detect not only visible diseases but also stress conditions that may not be immediately apparent in leaf images. Furthermore, combining sensor data with satellite imagery and geospatial mapping can help identify disease outbreaks across regions, allowing for broader agricultural planning and proactive interventions.Another significant enhancement would be the incorporation of a self-learning and adaptive recommendation engine. Currently, the system suggests fertilizers and pesticides based on predefined mappings, but it can be made smarter by learning from farmer feedback and treatment outcomes. With the integration of reinforcement learning or collaborative filtering algorithms, the system could evolve over time by analyzing which recommendations yielded better crop recovery. This would help tailor solutions to specific geographies, soil types, and climatic conditions, ultimately providing personalized and optimized treatment strategies for each user.

Integration with government and agricultural extension services can further empower farmers by providing them with expert-approved suggestions and access to subsidies or local resources. Additionally, creating a mobile app that works offline and syncs data when connected will make the solution more viable for rural and low-connectivity regions, ensuring it becomes a practical tool for farmers worldwide.

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