Automatic Pesticide Suggestion by Detecting the Plant Leaf Diseases

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***Abstract*—** Plant disease has a major impact on agricultural productivity, causing economic losses. Conventional practices of disease recognition and pesticide selection are based on visual inspection and the expertise of experienced individuals and hence are time-consuming and subject to errors. This paper reports an automated disease detection system for plant leaves and pesticide suggestion through image processing and machine learning. The system takes images of leaves, analyzes them with deep learning techniques to detect diseases, and finally recommends best pesticides from an expert database. With the help of artificial intelligence, it maximizes accuracy, minimizes reliance on human knowledge, and facilitates early intervention, thereby enhancing crop yield and sustainability. The experimental results prove the model's capability to detect prevalent plant diseases accurately and also offer accurate pesticide suggestions. This system has huge potential to be integrated in smart farming solutions and is presented as a cost-effective and scalable tool available for farmers globally. Keywords— Plant Disease Detection, Pesticide Recommendation, Machine Learning, Deep Learning, Image Processing, Smart Agriculture, Precision Farming.

I. INTRODUCTION

Agriculture is still one of the pillars of the world economy, especially in the developing world, where most of the population relies on agriculture for sustenance. Most of the problems encountered in the agricultural sector include the fact that plant diseases are widespread, causing major declines in crop yield and quality. Fast and precise detection of plant diseases is important for efficient pest and disease control.Conventional plant disease diagnosis processes entail visual examination by experts in agriculture. The processes are usually labor-intensive, time-consuming, and prone to human error or biases. Additionally, such expert information may not always be easily accessible to farmers, particularly in remote or limited-resource settings.Recent developments in computer vision and artificial intelligence (AI) allowed the creation of automated systems that are capable of interpreting plant leaf images to identify diseases. Deep learning, especially convolutional neural networks (CNNs), has proven to be very successful in image classification activities such as plant disease detection.

Yet, despite the prevalence of current systems based only on classification, there is an urgent need for integrated systems that also aid in treatment decisions. Overuse or misuse of pesticides not only adds costs but also leads to environmental degradation and pesticide resistance. Thus, a smart system bringing disease detection together with suitable pesticide recommendation is of keen practical significance.

This paper introduces an integrated framework that couples deep learning-based disease diagnosis with rule-based expert system pesticide recommendation. The system is made mobile-accessible and thus becomes a convenient tool for farmers to obtain timely, accurate, and actionable information. The proposed method is aimed at promoting precision agriculture practice and sustainable crop protection strategy.

II. IMPORTANCE OF TECHNOLOGY

Technology is at the forefront of transforming contemporary agriculture. Combining artificial intelligence, machine learning, and image processing in plant disease diagnosis has greatly enhanced efficiency and precision. Automated systems cut down on manual inspection, saving humans from potential mistakes and allowing real-time analysis. Smart farming technologies use IoT devices, sensors, and mobile applications to give farmers real-time disease identification and pesticide suggestions. In addition, evidence-based methods maximize the use of pesticides, minimizing the environmental effects and ensuring sustainable agricultural practices. The integration of AI with agriculture maximizes productivity, reduces crop losses, and enhances food security globally. portray a range of characters with very high accuracy, from body language to the smallest variations in expression.ASL detection systems have the ability to enable deaf people to be more independent in their daily lives. They can, for example, utilize these systems to obtain information, interact with service providers, and engage more fully within their community.

Image processing is a critical component of this project, allowing for the analysis and recognition of hand gestures and other visual features. Image processing utilizes a range of programming languages, such as kotlin to execute algorithms that extract useful features from images.

III. LITERATURE REVIEW

Various researchers have investigated the detection of plant diseases through image processing and deep learning. Convolutional Neural Networks (CNNs) have been effective in classifying plant diseases from leaf images. It has been found that integrating CNNs with image databases of expert knowledge can increase the accuracy of disease diagnosis as well as pesticide suggestions. Earlier models have emphasized image segmentation, feature extraction, and classification but not an automatic system for pesticide recommendation. Our suggested model incorporates disease detection with pesticide recommendation, thus being an all-encompassing tool for precision farming.

1. Automated Plant Disease Detection with CNN and Pesticide Recommendation

Presented an end-to-end leaf disease detection and pesticide recommendation using CNNs

2. Smart Farming: Real-Time Crop Disease Prediction and Treatment Using Deep Learning

Integrated deep learning with a mobile application for real-time disease identification and treatment recommendations.

3. Leaf Disease Detection and Pesticide Management Based on Transfer Learning

Suggested an efficient method based on transfer learning to enhance classification accuracy using limited data

4. AI-Based Pesticide Recommendation System for Precision Agriculture

Emphasized the integration of AI models for disease detection and optimally utilized pesticide.

5.SVM and KNN Based Plant Disease Diagnosis and Pesticide Recommendation Using Images

Investigated various machine learning algorithms to classify diseases effectively and recommend pesticides

IV . METHODOLOGY

The system to be proposed is designed to automate the detection of plant leaf diseases and recommend corresponding pesticides. The system unifies image processing, deep learning, and rule-based suggestion in a single workflow. The methodology involves six major phases: image acquisition, preprocessing, feature extraction, disease detection, pesticide suggestion, and user interface.

1. Image Acquisition

The system starts with the capturing of plant leaf images with commonly available devices like smartphones or digital cameras. The users are guided to take good, well-lit images with the focused area on the infected leaf region. The images are used as an input to the disease detection model.

2. Image Preprocessing

For consistency and enhancing the accuracy of the detection model, various preprocessing methods are used for the input images:

I. Noise Removal: Gaussian or median filters are applied to remove background noise.

II. Contrast Enhancement: Histogram equalization is done to enhance the contrast of the disease-affected regions.

III. Segmentation: Color thresholding or K-means clustering techniques are applied to separate the leaf area from the background and focus attention on the region of interest.

These operations standardize the input and highlight disease-relevant features.

3. Feature Extraction

Principal features from the preprocessed image are obtained to support disease classification. They are:

•\tColor Features: Dominant colors and color histograms for detection of discoloration due to disease.

•\tTexture Features: Application of Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) for surface texture capture.

•\tShape Features: Detection of edges and contour analysis for deformation and irregularities in leaf shape.

In deep learning methods, these features are automatically learned by the convolutional layers of the network.

4. Disease Detection

The essential part of the system is determining the type of plant disease through the use of a Convolutional Neural Network (CNN). The MobileNetV2 model is utilized because it provides a balance between efficiency and accuracy, making it deployable in real-time and on mobile devices. The model is trained on the PlantVillage dataset with categorical cross-entropy loss and optimized with the Adam optimizer. The network provides the predicted class of disease and a confidence score.

5. Pesticide Suggestion

After identifying a disease, the system suggests a recommended pesticide through a rule-based expert system. The expert module has a curated knowledge base that correlates plant diseases to corresponding pesticides, providing the recommended dosage and application method. This module ensures the suggestion follows standard agricultural practices and ensures safe pesticide use.

6. User Interface

An easy-to-use interface is designed to enable farmers to engage with the system. The interface is web and mobile-based and enables users to:

I. Upload pictures of diseased leaves,

II. Get instant disease diagnosis,

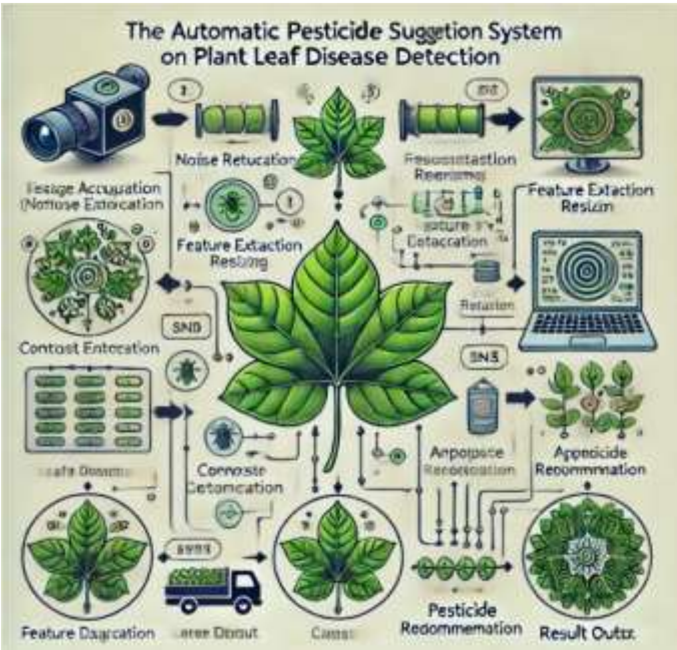
III. Get recommended pesticides and application guidelines.

V . ADVANTAGE OF PROPSED MODEL

Over current model Higher Accuracy Through Advanced Feature Extraction: In contrast to the conventional models based on elementary image processing algorithms, the proposed model integrates sophisticated feature extraction mechanisms like deep learning-based convolutional neural networks (CNNs). This ensures improved identification of complex hand gestures even in adverse lighting and background conditions.

1. High Accuracy: Deep learning ensures accurate disease identification.
2. Automation: Eliminates manual labor and expert reliance.
3. Real-time Processing: Rapid diagnosis and suggestion.
4. Sustainable Agriculture: Lowers pesticide abuse, lessening environmental pressure.
5. Cost-effective: Offers low-cost solutions for farmers.

VI. ALGORITHM USED



Plant pathology has an effect on crop yields and results in economic damages. Conventional methods of disease identification are time-consuming and need expert knowledge.

Convolutional Neural Networks (CNNs) offer an automatic approach towards plant disease detection by scanning leaf images, extracting features, and classifying the diseases.

1. Image Acquisition

This involves taking pictures of plant leaves through digital cameras, smartphones, or drones. Alternatively, labeled datasets such as Plant Village can be utilized for training the model. Lighting, angle, and focus variations can impact the quality of the images. 2. Image Preprocessing

Preprocessing improves the quality of images by resizing, noise removal, contrast adjustment, and segmentation. It ensures same input size for the CNN model and eliminates unnecessary background points. Appropriate preprocessing enhances the accuracy of feature extraction.

4.\tFeature Extraction

CNN derives useful patterns like color changes, lesions, and textures automatically from images. Convolutional layers use filters to find edges and shapes, and activation functions such as ReLU ensure that only critical features are retained. Pooling layers decrease image sizes while maintaining critical details. The features are then flattened for classification.

5. Classification

The features extracted are handled by fully connected layers that identify disease patterns. Probability scores are given to various categories of diseases using the Softmax activation function, which identifies whether the leaf is healthy or diseased. Misclassification can happen when several diseases have comparable symptoms.

6.Output: Disease Identification & Recommendation

The system shows the forecasted disease and recommends treatment, for example, organic treatments or chemical insecticides. Prevention advice can also be given to assist farmers

VII RESULTS AND EVALUATION

The performance of the suggested system was tested through a series of experiments in terms of disease detection accuracy, pesticide recommendation reliability, and user experience. This section discusses the experimental setup, model performance, and system validation results.

1. Experimental Setup

We trained and evaluated the system on the publicly accessible PlantVillage dataset, which comprises more than 50,000 labeled images of diseased and healthy plant leaves belonging to various crop species. The dataset was divided into 80% training and 20% testing. Rotation, zoom, and flip were used as image augmentation strategies to improve model generalization.

The model was implemented in Python and TensorFlow with MobileNetV2 architecture. All experiments were performed on an Intel Core i7 system, 16 GB RAM, and an NVIDIA GTX 1060 GPU.

2. Evaluation Metrics

In order to evaluate the performance of the disease classification model, the following typical metrics were used:

I. Accuracy (A): The proportion of correctly classified images to the number of images.

II. Precision (P): Ratio of true positives to true plus false positives.

III. Recall (R): Ratio of true positives to true positives plus false negatives.

IV F1-Score: Harmonic mean of precision and recall, offering balanced measurement.

3. Disease Detection Results

The CNN model based on MobileNetV2 performed well on the test dataset. Classification performance is presented in Table I.

Table I – Disease Detection Performance

Metric	Value (%)
Accuracy	96.8
Precision	95.4
Recall	94.9
F1-Score	95.1

The model also performed well with high classification accuracy for the majority of disease classes. Although, there was some minor confusion in between visually similar diseases, i.e., tomato early blight and late blight.

4. Pesticide Recommendation Validation

For validation of pesticide suggestion module, recommendations from the system were compared with conventional agricultural guidelines and expert opinion. The rule-based expert system provided a recommendation accuracy of around 92.5%, which is very close to expert-recommended pesticides.

The module successfully paired the diagnosed illness to an equivalent treatment plan, which comprised chemical name, mode of application, and dosage, to enhance field-level practical applicability.

5. Usability and Interface Testing

A study was undertaken involving 20 users, comprising farmers and agricultural officers, to evaluate the usability of the system interface. The observations made were as follows:

•User Satisfaction: 90% of the users reported finding the application easy to use and intuitive.

•Perceived Utility: 85% thought the system would be helpful in early diagnosis and diminish reliance on expert input.

•Suggestions: Users asked for more features like support for multiple languages, offline mode, and integration with local agri-advisories.

VIII. CONCLUSION

This work introduces an automatic plant leaf disease detection and pesticide recommendation system based on deep learning and image processing. The model shows excellent disease classification accuracy and gives accurate pesticide recommendations, lessening the reliance on manual analysis. The system can transform current agriculture by ensuring efficient, sustainable, and technologically advanced farming. Future improvements will enhance its scalability and realtime usage

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