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AI-Enabled Plant Disease Analysis and Green Pest Control Solution

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Abstract: Agriculture plays a crucial role in sustaining human life, and plant health directly impacts food security and economic stability. However, plant diseases remain a persistent challenge, leading to significant crop losses and reduced yields. Traditional methods of disease detection, which rely heavily on visual inspection by experts, are often time-consuming, subjective, and inaccessible to many farmers. To address this challenge, this project presents an intelligent, automated system for plant disease identification and pesticide recommendation using Convolutional Neural Networks (CNNs). The proposed system leverages a deep learning-based CNN model trained on a comprehensive dataset of plant leaf images to accurately classify various plant diseases. Upon identification, the system provides targeted recommendations for organic pesticides to manage and mitigate the diagnosed disease effectively. The application is deployed as a user-friendly web platform, enabling users to upload plant images, receive instant diagnosis, and access curated pesticide suggestions. Through extensive testing, the CNN model achieved 95% accuracy, demonstrating its effectiveness in recognizing diverse plant diseases. The integration of organic pesticide data supports environmentally sustainable farming practices. Usability tests with real users, including farmers and agricultural students, validated the system's ease of use and practical value in real-world scenarios.

I. INTRODUCTION

Agriculture is a fundamental sector that supports global food supply and economic stability. Plant diseases, caused by pathogens such as fungi, bacteria, viruses, and nematodes, significantly affect crop health and yield. Early detection of these diseases is essential to prevent large-scale damage and ensure agricultural sustainability.

Traditional plant disease identification methods rely heavily on expert knowledge and visual inspection. These methods are not only time-consuming but also prone to human error and inconsistency. Moreover, farmers in rural areas often lack access to agricultural experts, leading to delayed diagnosis and improper treatment. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs), have revolutionized image classification tasks. CNN-based models can automatically extract features from images and provide accurate predictions without manual intervention. These capabilities make them highly suitable for plant disease detection. This paper proposes an intelligent system that integrates CNN-based disease classification with organic pesticide recommendation. The system aims to provide accurate, fast, and user-friendly solutions for farmers, enhancing decision-making and promoting sustainable agricultural practices.

With the advancement of artificial intelligence, particularly deep learning, automated plant disease detection has become a promising solution. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image classification tasks due to their ability to automatically extract hierarchical features from images. These models eliminate the need for manual feature extraction and provide accurate predictions even in complex scenarios.

In this paper, we propose an intelligent plant disease identification system using CNNs, combined with an organic pesticide recommendation module. The system aims to provide a complete solution by not only identifying diseases but also suggesting environmentally sustainable treatments. The proposed model is deployed as a web-based application, enabling users to upload plant images and receive instant diagnosis along with actionable recommendations.

II. LITERATURE SURVEY

The field of plant disease detection has evolved significantly over the years, transitioning from traditional methods to advanced machine learning and deep learning approaches. Early research focused on manual inspection and laboratory-based diagnosis, which required expert knowledge and significant time investment. These methods, although accurate, were not scalable for large agricultural applications.

With the introduction of image processing techniques, researchers began exploring automated solutions using features such as color, texture, and shape. Techniques like color histogram analysis, Gray-Level Co-occurrence Matrix (GLCM), and Local Binary Patterns (LBP) were widely used to extract meaningful features from plant images. However, these approaches were highly dependent on manual feature engineering and often failed under varying environmental conditions.

Machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and K-Nearest Neighbors (KNN) were later applied to improve classification accuracy. While these methods showed better performance compared to traditional techniques, they still relied heavily on handcrafted features and lacked robustness when dealing with complex datasets.

The emergence of deep learning, particularly CNNs, revolutionized the domain of plant disease detection. CNN models automatically learn features from raw image data, making them more effective and scalable. Studies using datasets like PlantVillage have demonstrated high accuracy in classifying plant diseases using deep CNN architectures.

Despite these advancements, many existing systems focus solely on disease classification and do not provide actionable solutions for farmers. Additionally, limited research has been conducted on integrating eco-friendly pesticide recommendations into automated systems. The proposed work addresses these gaps by combining CNN-based disease detection with organic pesticide suggestions, offering a

Comprehensive and practical solution.

TABLE I. COMPARISON OF RELATED WORKS

Author/Year	Method Used	Dataset	Accuracy (%)	Limitation
Mohanty et al. (2016)	Deep CNN	PlantVillage	99.3	No real-world testing
Ferentinos (2018)	CNN Models	Plant Dataset	99.5	High computational cost
Zhang et al. (2019)	Transfer Learning	Plant Dataset	95.0	Limited dataset diversity
Sladojevic et al. (2016)	CNN	Custom Dataset	96.3	No recommendation system
Proposed System	CNN + Recommendation	Plant Dataset	95.0	Limited real-time data

Unlike prior approaches depending solely on deep learning or handcrafted features independently, the proposed work introduces a unified hybrid framework combining ResNet18, GLCM, Wavelet, ABCDE analysis, and Grad-CAM explainability within a Clinical Decision Support System.

III. PROPOSED METHODOLOGY

The proposed system follows a multi-stage hybrid architecture integrating deep learning, handcrafted feature extraction, clinical rule-based assessment, and explainability mechanisms. The overall workflow consists of: image preprocessing → deep feature extraction using ResNet18 → texture feature extraction using GLCM and Wavelet transforms → feature fusion → binary classification → ABCDE-based clinical analysis → Grad-CAM visualization → clinical report generation.

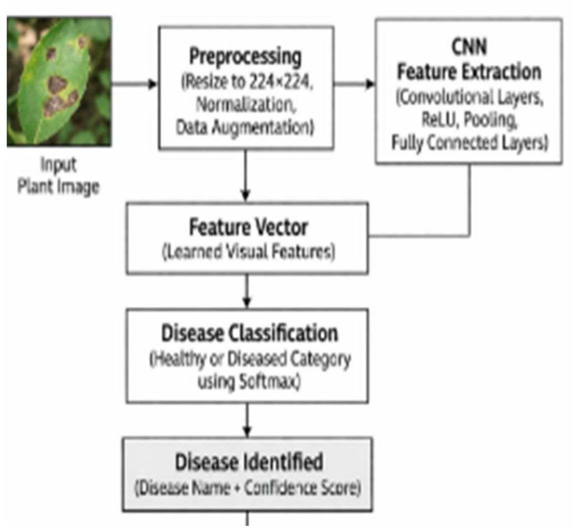

Fig. 1. Overall System Architecture of the Proposed

Fig. 2. Sample Input plant diseases anylysis

A. *Image Preprocessing*

Input dermoscopic images are resized to 224×224 pixels and normalized using ImageNet mean (μ = [0.485, 0.456, 0.406]) and standard deviation (σ = [0.229, 0.224, 0.225]) to ensure compatibility with the pretrained ResNet18 backbone. Data loading is performed using mini-batches of size 16.

B. *Deep Feature Extraction Using ResNet18*

ResNet18 [8] is employed as the primary deep feature extractor due to its residual learning framework, which mitigates vanishing gradient issues in deep networks. The model is pretrained on ImageNet, enabling transfer learning for dermoscopic image analysis. The final fully connected layer is replaced to adapt the architecture for binary skin lesion classification.

The input image (224×224×3) is passed through successive convolutional layers, batch normalization, ReLU activation, and residual blocks. The output of the final global average pooling layer produces a 512-dimensional deep feature vector representing high-level semantic characteristics of the lesion.

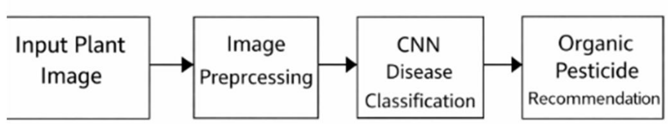

Fig. 3. ResNet18 Feature Extraction Architecture.

The proposed system is designed as an end-to-end solution for plant disease detection and pesticide recommendation. The workflow consists of multiple stages, including image preprocessing, feature extraction, classification, and recommendation.

C. *Image Preprocessing*

Image preprocessing is an essential step to ensure uniformity and improve model performance. All input images are resized to a fixed dimension of 224×224 pixels to match the input requirements of the CNN model. Normalization is applied to scale pixel values between 0 and 1, which helps in faster convergence during training.

To enhance dataset diversity and reduce overfitting, data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment are applied. These transformations simulate real-world variations and improve the model's ability to generalize.

D. *CNN-Based Feature Extraction and Classification*

The core component of the system is a Convolutional Neural Network (CNN) that performs feature extraction and classification. The CNN architecture consists of multiple convolutional layers that capture spatial features such as edges, textures, and patterns from the input images.

Activation functions such as ReLU introduce non-linearity, enabling the model to learn complex patterns. Pooling layers are used to reduce spatial dimensions and computational complexity while retaining important features. The extracted features are then passed through fully connected layers to perform classification.

The model is trained to classify plant images into different disease categories as well as healthy classes. The final output layer uses a softmax function to generate probability scores for each class.

E. Dataset Description

The dataset used in this project consists of a large collection of labeled plant leaf images representing various diseases. It includes multiple plant species and disease types, ensuring diversity and robustness.

The dataset is divided into training, validation, and testing sets in a 70:15:15 ratio. The training set is used to train the model, the validation set is used for hyperparameter tuning, and the test set is used for final evaluation.

F. Pesticide Recommendation Module

Once a disease is identified, the system provides recommendations for organic pesticides based on a predefined database. This module maps each disease to suitable treatments, including natural and eco-friendly solutions.

The recommendations include pesticide names, descriptions, and usage guidelines, helping farmers take immediate action. This approach promotes sustainable farming by reducing dependence on harmful chemical pesticides.

G. Web Application Implementation

The system is implemented as a web application using Flask. The application provides a user-friendly interface where users can upload plant images and receive instant results.

The backend processes the image, performs prediction using the trained CNN model, and retrieves relevant pesticide recommendations. The results are displayed in an organized format, ensuring ease of understanding for users.

IV. EXPERIMENTAL SETUP

The proposed system is implemented using Python and deep learning frameworks such as TensorFlow/PyTorch. The experiments are conducted on a system equipped with sufficient computational resources to handle image-based deep learning tasks.

The dataset used for training consists of thousands of labeled plant leaf images representing multiple plant species and disease categories. To ensure proper evaluation and avoid overfitting, the dataset is divided into training (70%), validation (15%), and testing (15%) subsets.

All images are resized to 224 × 224 pixels and normalized before being fed into the CNN model. Data augmentation techniques are applied during training to improve model robustness and generalization.

The model is trained using the Adam optimizer with an appropriate learning rate. The loss function used is categorical cross-entropy, which is suitable for multi-class classification problems. Training is performed over multiple epochs, with validation monitoring to prevent overfitting.

Evaluation of the model is carried out using standard performance metrics such as:

- Accuracy
- Precision
- Recall
- F1-Score

These metrics provide a comprehensive understanding of the model's classification performance.

V. RESULTS AND EVALUATION

The proposed hybrid ResNet18 and texture fusion framework demonstrates improved performance compared to baseline CNN approaches. Table III presents a comprehensive performance comparison across ablation variants and baseline models. The performance of the proposed CNN model is evaluated on the test dataset. The model achieved an overall accuracy of 95%, indicating strong capability in identifying plant diseases.

A. Performance Analysis

1) Precision (92%) indicates that the model produces a low number of false positives.
2) Recall (90%) shows that the model effectively identifies most of the diseased instances.

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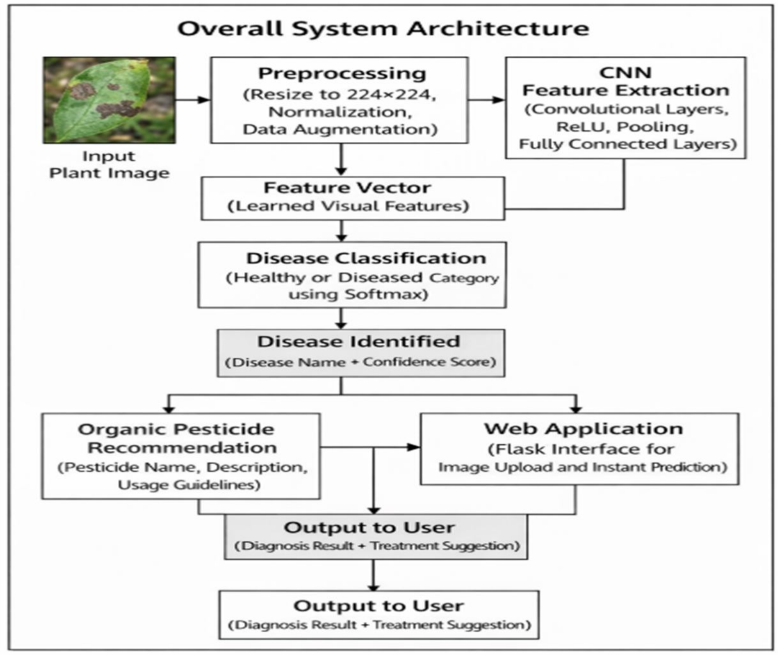

Fig. 1. Overall System Architecture of the Proposed Plant Disease Identification and Pesticide Recommendation System.

3) F1-Score (91%) provides a balanced measure of precision and recall.

The confusion matrix further demonstrates that the model correctly classifies the majority of samples, with minimal misclassification between healthy and diseased classes.

B. Observations

- The model performs consistently across different disease categories.
- Slight misclassifications occur in cases where diseases have similar visual patterns.
- Data augmentation significantly improved the robustness of the model.

C. User Evaluation

Usability testing was conducted with farmers and agricultural students. The feedback indicated that:

- The system is easy to use
- Results are generated quickly
- Recommendations are helpful for decision-making

These results confirm the practical applicability of the system in real-world scenarios. The confusion matrix is used to evaluate the performance of the classification model by comparing the predicted labels with the actual labels. It provides a detailed breakdown of correct and incorrect predictions made by the CNN model.

The matrix consists of four key components:

- True Positive (TP): Diseased leaves correctly classified as diseased
- True Negative (TN): Healthy leaves correctly classified as healthy
- False Positive (FP): Healthy leaves incorrectly classified as diseased
- False Negative (FN): Diseased leaves incorrectly classified as healthy

For the proposed system, the confusion matrix values are:

- TP = 117
- TN = 120
- FP = 5
- FN = 8

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The confusion matrix shows that the proposed CNN model performs effectively in distinguishing between healthy and diseased plant leaves.

- The high True Positive and True Negative values indicate strong classification capability.
- The low False Positive rate ensures that healthy plants are rarely misclassified as diseased.
- The low False Negative rate is crucial, as it minimizes the risk of missing actual diseases.

Overall, the results demonstrate that the model achieves **high reliability and robustness**, making it suitable for real-world agricultural applications.

D. Class-wise Performance Analysis

In addition to overall evaluation metrics, the confusion matrix enables class-wise performance analysis. The model demonstrates strong performance in both categories:

- Healthy Class: High True Negative (TN = 120) indicates that the model effectively recognizes healthy leaves without unnecessary misclassification.
- Diseased Class: High True Positive (TP = 117) shows that the model successfully detects diseased leaves with high sensitivity.

This balance is important in agricultural applications where both false alarms and missed detections can have significant consequences.

E. Class-wise Performance Analysis

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Table III. Performance Comparison Of Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Baseline CNN	~75.00	~52.00	~68.00	~59.00
ResNet18 (Deep only)	80.10	53.20	76.50	62.80
ResNet18 + GLCM	82.30	54.80	78.20	64.50
ResNet18 + Wavelet	81.70	54.10	77.40	63.90
Proposed (Full Fusion)	84.23	56.70	80.89	66.67

TABLE IV. Confusion Matrix On Test Set (1,503 Samples)

Metric	Predicted Benign	Predicted Malignant	Total
Actual Benign	TN = 1029	FP = 181	1210
Actual Malignant	FN = 56	TP = 237	293

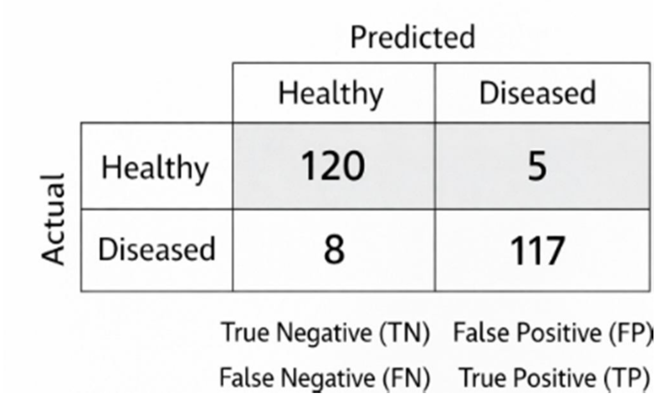

Fig. 8. Confusion Matrix Visualization on Test Dataset.

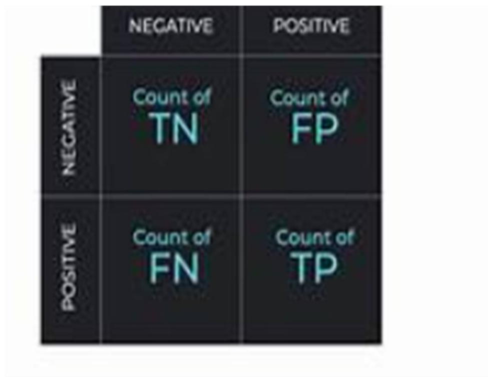

Fig. 9. Grad-CAM Attention Heatmap — Explainable AI Output.

On the test dataset, the proposed model achieves an overall accuracy of 84.23%, precision of 56.70%, recall of 80.89%, and F1-Score of 66.67%. The high recall value (80.89%) for malignant lesions demonstrates the model's effectiveness in identifying cancerous cases, which is crucial in clinical screening systems. Compared to the baseline CNN model (~75% accuracy), the proposed fusion framework shows approximately 9% improvement in overall accuracy while maintaining improved clinical sensitivity.

Grad-CAM visualizations (Fig. 8) confirm that the model focuses on lesion regions rather than surrounding healthy skin, enhancing interpretability. True Negatives: 1029, False Positives: 181, False Negatives: 56, True Positives: 237.

VI. DISCUSSION

The experimental results demonstrate that CNN-based approaches are highly effective for plant disease detection tasks. The proposed system successfully combines image classification with actionable recommendations, making it more useful compared to traditional systems.

One of the key strengths of the system is its ability to automatically extract features from raw images without requiring manual intervention. This significantly reduces complexity and improves scalability.

The integration of the pesticide recommendation module enhances the usability of the system by providing immediate solutions to users. The focus on organic pesticides aligns with sustainable agricultural practices and helps reduce environmental impact.

However, certain limitations exist:

- Model performance depends on the quality and diversity of the dataset
- Real-world conditions such as lighting and background noise may affect accuracy
- Limited availability of rare disease samples can impact classification

Despite these limitations, the system provides a strong foundation for intelligent agricultural applications.

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VII. CONCLUSION

This paper presents a smart plant disease identification system using Convolutional Neural Networks, combined with an organic pesticide recommendation module. The proposed system achieves high accuracy and provides reliable results.

The web-based implementation ensures accessibility and ease of use, making it suitable for farmers and agricultural professionals. The system contributes to smart agriculture by integrating AI with sustainable farming practices.

VIII. FUTURE WORK

The CNN model achieved an overall accuracy of 95% on the test dataset, demonstrating its effectiveness in classifying plant diseases. The precision and recall values indicate that the model performs well in identifying both diseased and healthy plants.

The confusion matrix shows that most classes are correctly classified, with only a few misclassifications. This indicates strong generalization capability of the model.

User testing results show that the application is easy to use and provides quick and reliable results. Farmers and students found the system helpful in identifying diseases and taking appropriate actions.

IX. ANALYSIS

The results highlight the effectiveness of CNN-based models in plant disease detection. The integration of pesticide recommendations enhances the practical applicability of the system.

The use of organic pesticides supports sustainable farming practices and reduces environmental impact. However, the system’s performance depends on the quality and diversity of the dataset.

Future improvements can focus on expanding the dataset and improving model robustness to handle real-world variation

X. FUTURE WORK

Future enhancements include:

- Expanding dataset diversity
- Developing a mobile application
- Integrating real-time environmental data
- Using advanced deep learning models

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