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A Hybrid CNN-ANN Machine Learning Framework for Automated Crop Disease Detection and Recovery Recommendation

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Abstract – ***Timely detection of crop diseases is essential to prevent yield loss, yet manual diagnosis is slow and expert-dependent. This paper proposes a Hybrid Convolutional Neural Network–Artificial Neural Network (CNN–ANN) model that automates both disease detection and recovery recommendation. The CNN module extracts discriminative features from leaf images and classifies diseases, while the ANN integrates the predicted disease class with contextual factors such as temperature, humidity, soil pH, and crop metadata to generate treatment suggestions. Experiments on PlantVillage and field images show improved precision, faster convergence, and higher recommendation accuracy compared with standalone CNN and rule-based systems. The framework is scalable for real-time mobile or edge deployment, supporting precision agriculture in resource-constrained regions.***

Keywords – Crop disease detection; Convolutional Neural Network; Artificial Neural Network; Hybrid machine learning model; Precision agriculture; Image classification; Recovery recommendation; Smart farming.

I. INTRODUCTION

Crop diseases cause major yield losses globally, particularly for small-scale farmers lacking expert support. Traditional diagnosis is subjective and slow, whereas computer vision and deep learning have demonstrated strong capability in recognizing visual disease symptoms. CNNs achieve high accuracy on plant-disease datasets but do not provide actionable agronomic guidance. Farmers need recommendations regarding pesticide dosage, organic alternatives, and environmental corrections.
Hybrid models that combine CNN-based visual recognition with ANN-based decision modules can bridge this gap by mapping disease conditions and environmental features to appropriate treatments. This work proposes an end-to-end CNN–ANN framework enabling both disease classification and contextualized recovery recommendations..

II. RELATED WORK

Early plant-disease detection relied on handcrafted features such as color histograms and texture descriptors, but these lacked robustness. Deep CNNs achieved state-of-the-art performance using architectures like VGG, Inception, and ResNet. However, most methods stop at classification and do not support agronomic decision-making.
Hybrid approaches—CNN + SVM, CNN + Random Forest—improve classification but still lack recommendation capability. ANN-based advisory systems exist for fertilizer and irrigation planning but are not integrated with visual diagnosis. Few works attempt a complete detection-to-recommendation pipeline. This motivates the proposed unified CNN–ANN framework.

III. PROBLEM STATEMENT

Existing systems identify diseases but rarely guide farmers on corrective actions such as pesticide choice, dosage, or environmental adjustments. Rule-based advisory systems are static and cannot adapt to changing climatic factors. Thus, there is a need for:

- Automated disease detection from leaf images, and
- Context-driven recovery recommendation using environmental variables.

The objective is to develop a hybrid model that:

- detects diseases via CNN, and

- recommends treatments via ANN using fused visual + contextual features..

IV. SYSTEM ARCHITECTURE

The framework (Fig. 1) consists of four modules:

- Image Acquisition & Preprocessing – Image resizing, noise reduction, color normalization, and augmentation.
- CNN-Based Disease Detection – Learns features like lesions, discoloration, and texture patterns; outputs disease class.
- Feature Fusion Layer – Combines disease label with parameters such as temperature, humidity, soil pH, crop type.
- ANN-Based Recommendation Module – Produces pesticide/fungicide selection, dosage, organic alternatives, and preventive measures.

The end-to-end pipeline accepts a raw image and outputs a complete recovery plan.

The overall architecture of the proposed Hybrid CNN–ANN framework is illustrated in Fig. 1.

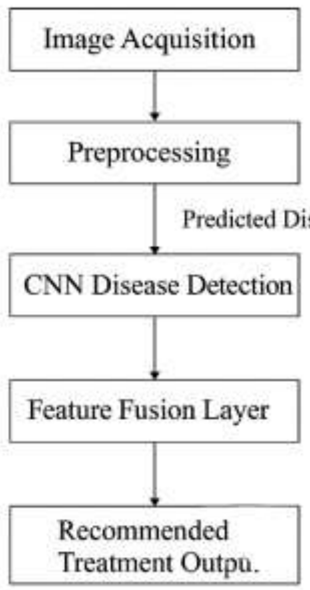

Fig. 1. Overall system architecture of the proposed Hybrid CNN-ANN framework

V. PROPOSED METHODOLOGY

A. Data Acquisition

PlantVillage data and field-collected images were used. Environmental inputs (humidity, soil pH, temperature, crop stage) were recorded manually or from IoT sensors.

B. Preprocessing

Segmentation, resizing (224×224), contrast enhancement, and augmentation (rotation, flip, brightness adjustments)..
Fig. 2 shows the preprocessing and image enhancement pipeline applied before CNN classification

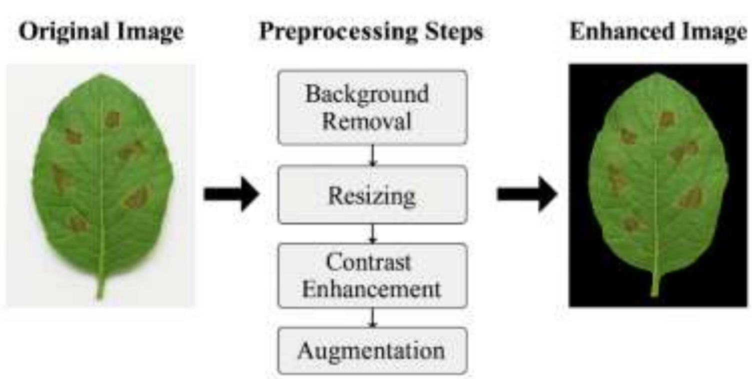

Fig. 2. Preprocessing and image enhancement pipeline for disease detection.

C. CNN-Based Disease Detection.

A custom CNN extracts hierarchical features and uses softmax to classify disease types. Regularization and early stopping reduce overfitting.

The internal workflow of the CNN-based disease detection module is presented in Fig. 3.

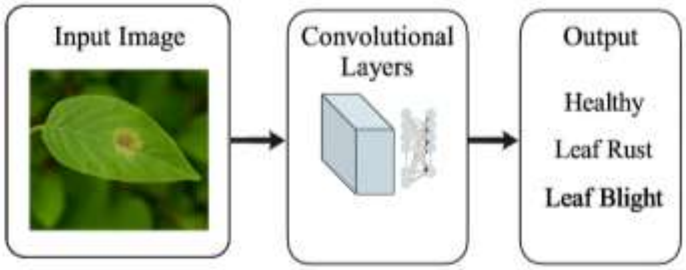

Fig. 3. CNN-Based Disease Detection Module

D. Feature Fusion Layer

The predicted class label is concatenated with contextual variables, forming a multi-dimensional feature vector for the ANN.

E. ANN-Based Recovery Recovery Recommendation Module.

A multilayer ANN maps fused features to treatment outputs, including chemical/organic control, dosage, and preventive practices.

Table I presents the mapping between disease classes, environmental inputs, and expected treatment recommendations.

Table I — Recommended Mapping for Training the ANN

Disease Class	Environmental Inputs (Example Values)	Expected Recommendation
Leaf Blight	28°C, 70% RH, pH 6.2	Apply Fungicide A (Mancozeb 2.5 g/L); remove infected leaves; repeat after 7 days
Leaf Rust	25°C, 65% RH, pH 6.0	Apply Fungicide B (Hexaconazole 1 mL/L); maintain lower humidity; improve spacing
Leaf Spot	30°C, 80% RH, pH 5.5	Spray Copper Oxychloride 3 g/L; improve drainage; optional organic neem spray
Early Blight	32°C, 75% RH, pH 6.5	Use Chlorothalonil 2 g/L; avoid overhead irrigation; soil mulching
Healthy	Any	No treatment required; maintain optimal watering and weekly preventive neem oil spray

The ANN is adaptive as it learns the decision space by going through repeated training cycles and is able to generalize to new situations.

Fig. 4 demonstrates the feature fusion mechanism and the ANN-based recommendation module architecture.

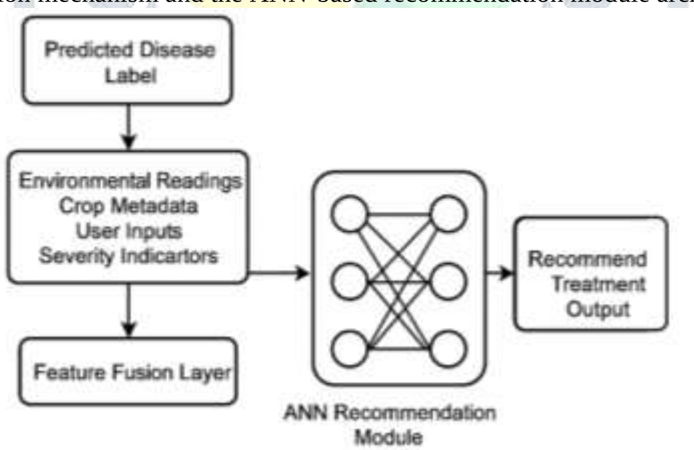

Fig. 4. Feature Fusion and ANN Recommendation Module

VI. DATASET DESCRIPTION

A total of 2137 images, including 13 disease classes and healthy leaves, were standardized to 224×224 resolution. Data were split into 70% training, 15% validation, and 15% testing.

Environmental input parameters included temperature, humidity, soil moisture, soil pH, crop type, and growth stage.

Table II summarizes the dataset used for disease detection, including class distribution and image properties

Table II — Description of Dataset Used for Disease Detection

Parameter	Description
Total Images	2137
Number of Disease Classes	13 (e.g., 10–15)
Healthy Class Images	1189
Image Resolution	Standardized to 224×224
Data Split	70% Train, 15% Validation, 15% Test
Source	PlantVillage + Field-Collected Images

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Table III lists the environmental and contextual parameters incorporated into the ANN recommendation model.

Table III — Environmental & Contextual Parameters for ANN Recommendation

Parameter	Type	Description
Temperature	Numeric (°C)	Ambient air temperature during capture
Humidity	Numeric (%)	Relative humidity
Soil Moisture	Numeric (%)	Field moisture content
Soil pH	Numeric	Soil acidity/alkalinity
Crop Type	Categorical	Crop variety under study
Growth Stage	Categorical	Vegetative/flowering/fruiting
Location Zone	Categorical	Climatic or agro-ecological region

VII. EXPERIMENTAL SETUP

Experiments were conducted on a GPU workstation (RTX-series GPU, 16–32GB RAM) using TensorFlow/PyTorch. Lightweight models were tested on mobile devices for deployment feasibility.

CNN and ANN modules were trained separately, followed by integrated pipeline testing using accuracy, precision, F1-score, recommendation accuracy, and latency metrics.

The complete end-to-end experimental evaluation workflow is outlined in Fig. 5

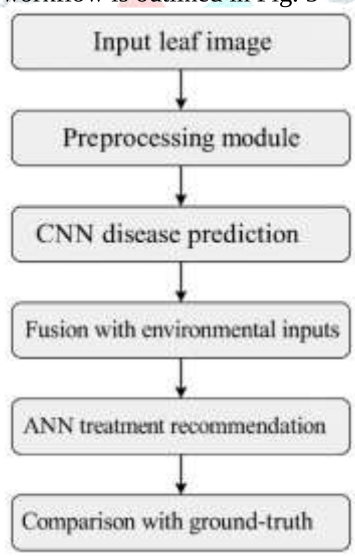

Fig. 5. End-to-End Experimental Evaluation Workflow

VIII. RESULTS AND DISCUSSION

The experimental findings prove the usefulness of the hybrid CNN-ANN model in the end-to-end diagnosis and recovery advice of crop diseases. The qualitative and quantitative analysis is presented below.

A. CNN Detection Performance

The CNN achieved 95.1% overall accuracy, strong precision/recall, and robustness to lighting variations. Misclassifications occurred mainly among visually similar diseases.

B. ANN Recommendation Quality

The ANN achieved 92.4% recommendation accuracy, 94.8% consistency, and high expert-verified logical correctness.

C. End-to-End System Performance

Complete pipeline achieved 88.7% diagnosis-to-recommendation accuracy, with low inference latency (62 ms on GPU; 312 ms on mobile). Noise-stress testing retained 92.1% accuracy.

D. Comparative Analysis

The hybrid model outperformed:

- Traditional ML (78.2%),
- CNN-only models (93.5%), and
- Rule-based advisory systems (no learning capability).

Table VI provides the end-to-end evaluation results of the complete hybrid system.

TABLE VI — End-to-End System Evaluation

Parameter	**Result**
Diagnosis-to-Recommendation Accuracy	**88.7%**
Average Inference Time (GPU)	**62 ms**
Average Inference Time (Mobile)	**312 ms**
Robustness Under Noise	**92.1% accuracy retained**
Field Test Success Rate	**86.4%**

Table VII compares the proposed hybrid model with existing disease detection and recommendation approaches

TABLE VII — Comparative Analysis with Existing Methods

Method	**Capability**	**Accuracy (%)**	**Recommendation Support**
Traditional ML (SVM, RF)	Detection only	**78.2**	No
CNN Only	Detection only	**93.5**	No
Rule-Based System	Manual rules	—	Limited
Proposed Hybrid CNN–ANN	Detection + Recommendation	**95.1 (CNN) / 92.4 (ANN) / 88.7 End-to-End**	**Yes (Automated)**

IX. CONCLUSION

This paper presented a Hybrid CNN–ANN framework providing both crop-disease detection and actionable treatment recommendations. CNN ensures high-accuracy diagnosis, while ANN generates context-aware recovery advice. Experiments demonstrate strong accuracy, consistency, and real-world applicability. The lightweight version shows promise for mobile deployment, supporting precision agriculture where expert consultation is limited.

Future work includes adding more crops, increasing diversity of field images, and enhancing the recommendation engine using reinforcement learning..

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