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To Classify The Detection of Plant Diseases With Organic Solution Using Deep Learning-Based Approach

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Abstract- The increasing prevalence of plant diseases poses a significant threat to agricultural productivity, food security, and sustainable crop production. Conventional disease management practices frequently rely on synthetic pesticides, whose excessive use can adversely affect soil health, water quality, biodiversity, and human health. Organic treatment solutions provide a more environmentally sustainable alternative; however, their integration with automated plant disease detection and post-treatment monitoring remains relatively underexplored. This study proposes an image-based deep-learning framework for plant disease classification and organic treatment assessment using leaf images. A comprehensive dataset comprising healthy and diseased leaf images was developed using publicly available datasets and field-collected samples, with additional organically treated samples incorporated to represent post-treatment conditions. The proposed framework employs transfer learning with an EfficientNet-B4 based architecture enhanced with attention mechanisms and feature-level integration of color, texture, and shape characteristics. The model was trained and evaluated using accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrix analysis. Experimental results demonstrate that the proposed framework achieved a reported overall accuracy of 96.72%, with precision, recall, F1-score, and ROC-AUC values of 0.963, 0.968, 0.965, and 0.982 respectively. Comparative evaluation demonstrated that the proposed framework outperformed SVM, ResNet50, and conventional EfficientNet-B4 baseline models. The proposed system further provides disease-specific organic treatment recommendations through a knowledge-based decision module. The framework has potential for integration into mobile and edge-based agricultural applications, enabling rapid disease diagnosis, post-treatment monitoring, and environmentally responsible crop management.

Keywords: Plant Disease Detection, Deep Learning, EfficientNet B4, Transfer Learning, Organic Treatment, Computer Vision, Sustainable Agriculture, Precision Agriculture.

I. INTRODUCTION

Agriculture remains the backbone of global food security, economic stability, and rural livelihoods, yet it faces persistent and evolving threats from plant diseases. According to the Food and Agriculture Organization (FAO), plant pathogens are responsible for the loss of up to 40% of global crop yields annually, resulting in billions of dollars in economic losses and severe impacts on farmers' incomes. These losses are particularly devastating in developing regions, where subsistence agriculture is prevalent and access to effective plant protection technologies is limited. Consequently, early and accurate detection of plant diseases is critical to ensuring stable crop production, reducing economic losses, and safeguarding food availability for a growing global population.

Traditionally, farmers have relied on visual inspection to identify plant diseases, a process that is inherently subjective, time-consuming, and prone to errors, especially in the early stages of infection when visual

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symptoms may be subtle or resemble nutrient deficiencies or abiotic stress. To address these limitations, the use of chemical pesticides has become widespread. While chemical control measures are often effective in mitigating disease outbreaks, their excessive and indiscriminate use has raised serious concerns about environmental sustainability, soil health, water contamination, pesticide resistance, and long-term human health impacts.

In recent years, there has been growing interest in organic plant protection solutions, such as neem-based biopesticides, garlic-chili sprays, and microbial formulations, that offer eco-friendly alternatives to synthetic chemicals. These treatments not only reduce the environmental footprint of agricultural practices but also align with global trends toward sustainable and organic farming. However, while such organic solutions can be highly effective against a range of plant diseases, monitoring their real-world impact and adoption at scale remains a challenge. Most farmers rely on personal observation to judge the effectiveness of a treatment, which is inherently subjective and varies depending on the observer's expertise.

This challenge presents an opportunity for automation and artificial intelligence (AI) to play a transformative role. Advances in computer vision and deep learning have made it possible to detect and classify plant diseases from leaf images with high accuracy, enabling rapid and scalable monitoring. Convolutional Neural Networks (CNNs), in particular, have proven exceptionally effective at extracting complex spatial features from images, outperforming traditional machine learning techniques that rely on handcrafted features. Pre-trained models such as VGGNet, ResNet, DenseNet, and Inception architectures, when fine-tuned for agricultural datasets, have demonstrated strong performance on plant disease detection tasks.

However, while the application of deep learning to plant disease detection is well documented, there is a significant gap in research that incorporates the detection of organically treated leaves alongside untreated healthy and diseased samples. The visual characteristics of a leaf after organic treatment can differ from both healthy and untreated diseased states due to partial symptom suppression, discoloration, or leaf texture changes. Accurately identifying these treatment states could provide farmers and agricultural extension services with valuable insights into the effectiveness of organic disease control measures in real time.

The present study addresses this gap by developing a deep learning-based classification framework that not only detects and categorizes plant diseases but also distinguishes organically treated leaves from untreated samples. The framework employs an EfficientNet-B4 architecture, selected for its favorable balance between classification accuracy and computational efficiency, fine-tuned on an expanded version of the PlantVillage dataset enriched with custom-acquired images of organically treated leaves from controlled greenhouse experiments.

The proposed framework serves two complementary purposes.

- It provides accurate identification of healthy and diseased plant leaves, enabling timely intervention and reducing potential crop losses.
- It supports post-treatment monitoring by incorporating organically treated leaf samples into the classification framework, allowing the system to distinguish treatment-related visual conditions and providing an objective mechanism for monitoring changes following organic treatment.

In addition to technical performance metrics such as accuracy, precision, recall, F1-score, and ROC-AUC, this study evaluates the practical applicability of the proposed framework in agricultural decision-making. The framework can potentially be deployed through a mobile or edge-computing application, allowing farmers to capture leaf images using smartphones and obtain rapid disease classification alongside corresponding organic treatment recommendations.
By combining deep learning-based disease detection with sustainable disease-management practices, the proposed framework contributes to the broader objectives of precision agriculture and environmentally responsible crop production. The research is particularly relevant to Sustainable Development Goal 2 (Zero Hunger) and Sustainable Development Goal 12 (Responsible Consumption and Production).

Overall, this study aims to bridge the gap between automated plant disease diagnosis and sustainable treatment management by integrating deep learning, image analysis, and organic treatment recommendations into a unified decision-support framework.

II. LITERATURE REVIEW

The field of automated plant disease detection has seen significant advancement in recent years, largely driven by the adoption of deep learning methods. This literature review surveys key contributions from 2022 onward, focusing on innovations in model architectures, mobile deployment, multi-crop systems, augmentation strategies, and explainability, as well as attempts to integrate holistic diagnosis tasks such as treatment evaluation. surveillance and the timely reporting of suspicious transactions to the Financial Intelligence Unit (FIU).

Most banks nevertheless still rely on rule-based systems (RBS) that apply static if-then thresholds to individual accounts. Such systems are reported to generate false-positive alert rates as high as 95% [4, 5], leaving investigators to spend much of their time clearing benign alerts and exposing them to alert fatigue. Because they inspect one account or network at a time, they also struggle to detect the non-linear, cross-channel loops that characterise layering [6]. In Zimbabwe's multi-currency economy, continuous inflation and exchange-rate movements between local transactional tokens and United States dollar (USD) balances make fixed value thresholds obsolete almost immediately, a phenomenon referred to in this paper as model decay. Launderers exploit these weaknesses by splitting funds into small amounts ("smurfing") and routing them through high-velocity interbank platforms such as ZIPIT and mobile money wallets [7].

Predictive Data Analytics (PDA), which combines machine learning, behavioural profiling and graph-based network analytics, offers a way to replace fixed thresholds with dynamic behavioural baselines. The local bank integrated the Vneuron AML platform in November 2025, yet empirical evidence on how effectively PDA performs in Zimbabwean commercial banks remains limited. Existing studies concentrate largely on algorithmic accuracy [8, 9], whereas the operational and regulatory outcomes that matter to compliance teams and the FIU, namely alert quality, investigation efficiency and the quality of reporting, are seldom examined. This paper addresses that gap.

1. Aim, objectives and hypotheses

The aim was to evaluate the effectiveness of PDA in improving AML transaction monitoring, reducing false positives and strengthening regulatory compliance at the local bank. Five objectives guided the study: (1) to assess the limitations of the bank's traditional rule-based monitoring; (2) to examine how PDA improves the detection of suspicious layering patterns; (3) to evaluate the role of anomaly detection and network analytics in identifying hidden transaction relationships; (4) to assess whether PDA reduces false positives and improves investigation efficiency; and (5) to determine how PDA outputs support FIU regulatory reporting.

Three alternative hypotheses were tested. H1: PDA significantly improves the detection of suspicious layering patterns. H2: Anomaly detection and network analytics significantly enhance the identification of hidden transaction relationships and cross-channel routing paths. H3: PDA significantly reduces false-positive alerts and improves investigation efficiency

2. Advancements in CNN and Hybrid Architectures

Researchers continue to exploit convolutional neural networks for disease classification. Kini et al. (2024) demonstrated an ensemble transfer-learning approach on black pepper leaf diseases, achieving F1 scores up to 0.98 using models such as ResNet-18, Inception-V3, GoogleNet, and SqueezeNet [1]. Sreethu et al. (2025) applied CNNs to black pepper foliar disease detection, achieving high accuracy after augmenting the dataset and addressing specific conditions such as anthracnose and foot rot [2].

Beyond standard CNNs, transformer-based models tailored for resource-constrained environments are emerging. Tonmoy et al. (2025) introduced MobilePlantViT, a lightweight hybrid Vision Transformer achieving test accuracies from 80% to over 99% across diverse plant disease datasets, with only 0.69 million parameters, making it well suited to mobile deployment [3].

2. Multi Crop and Dual Stream Architectures

To address scalability across different crops, Khandagale et al. (2025) proposed FourCropNet, a CNN-based system with attention mechanisms and residual blocks, achieving up to 99.7% accuracy for grapes and 99.5% for corn, outperforming MobileNet, VGG-16, and EfficientNet [4]. In a parallel direction, Song & Yang (2025) developed DS_FusionNet, a dual-stream fusion network enhanced with bidirectional knowledge distillation. Without extensive additional data, it achieved accuracies above 90% on datasets such as PlantDisease and CIFAR-10, demonstrating robustness to occlusion and illumination challenges [5].

3. Data Augmentation and Transfer Learning

Data scarcity remains a key bottleneck. Aminuddin et al. (2022) used geometric augmentation to enhance a small dataset of chili leaves, boosting model accuracy to around 97% with CNN and ResNet-18 [6]. Related work on Bayesian-enhanced residual networks further improved classification, achieving 98.9% accuracy on PlantVillage subsets without overfitting [6].

4. Explainability and Interpretability

Thakur et al. (2022) proposed PlantXViT, integrating Vision Transformers with CNNs and improving explainability via Grad-CAM and LIME. The hybrid model achieved accuracies exceeding 98% on datasets for apple, maize, and rice while remaining lightweight (0.8 million parameters) [7].

5. Nutrient Deficiency and Multi Task Detection

A 2022 study published in Agronomy examined deep learning for leaf disease detection that also handled nutrient deficiency classification. CNN, ANN, MobileNetV2, and VGG-16 models achieved validation accuracies of 96–97%, underlining deep learning's utility across multiple diagnostic tasks, reinforced with ROC and confusion matrix analyses [8]. Separately, Choudhury et al. (2024) explored root disease detection using hyperspectral imaging and advanced image processing techniques, highlighting the potential of combining spectral and visual data for early detection [9].

6. Comprehensive Surveys and Review Articles

A recent review examined challenges and feature engineering techniques for machine learning and deep learning in plant disease detection, with particular attention to texture analysis via Haralick features, Gabor filters, and FFTs [10]. Another review summarized deep learning methods for chili disease detection, in which SECNN models achieved 99.12% accuracy with augmentation, outperforming both traditional deep learning and machine learning classifiers such as SVM and Random Forest [11].

Table 1. Summary of Recent Contributions in Plant Disease Detection (2022–2025)

Year	Study / Model	Key Highlights
2022	Aminuddin et al.	Geometric augmentation → ~97% accuracy (CNN, ResNet-18) Frontiers
2022	Agronomy et al.	Multi-task detection (disease + nutrient) → 96–97% val. accuracy MDPI
2022	Thakur et al.(PlantXViT)	Hybrid ViT CNN with explainability → >98%, 0.8M params arXiv
2023	Smart Agri Techreview	Texture feature engineering techniques overview ScienceDirect
2024	Kini et al.	Transfer-learning ensemble → high F1 up to 0.98 AZoAi
2024	Frontiers review	SECNN achieves 99.12% with augmentation on chili dataset Frontiers
2024	Sreethu et al.	CNN on black pepper foliar diseases, high accuracy BioMed Central
2024	Choudhury et al.	Hyperspectral root disease detection advanced methods SAGE Journals
2025	MobilePlantViT	Lightweight ViT model, 0.69M params, 80–99% accuracy arXiv
2025	FourCropNet	Multi-crop CNN with attention → up to 99.7% accuracy arXiv
2025	DS_FusionNet	Dual-stream fusion with knowledge distillation→>90% accuracy arXiv
2025	Reddy et al.	ResNet CNN detection on chili plants for automated monitoring ResearchGate

7. Research Gap

Despite considerable progress in deep learning-based plant disease detection, several important research gaps remain. First, most existing studies concentrate primarily on classifying healthy and diseased leaves, while comparatively limited attention has been given to

the visual characterization of leaves following organic treatment. Organic treatments such as neem-based formulations, garlic-chili preparations, and other botanical products may alter leaf pigmentation, surface texture, lesion appearance, and disease severity; these treatment-related changes need to be represented during model development to improve the applicability of Second, many benchmark datasets, particularly PlantVillage, consist predominantly of laboratory or controlled-environment images with relatively uniform backgrounds and illumination. Such datasets may not adequately represent real agricultural environments characterized by variations in illumination, background complexity, leaf orientation, disease severity, and environmental conditions. Consequently, models trained exclusively on benchmark datasets may generalize poorly when deployed under field conditions. Third, existing studies generally emphasize classification accuracy while providing limited integration between disease diagnosis and sustainable treatment recommendations. A practical agricultural decision-support system should not only identify a disease but should also assist users in selecting appropriate and environmentally responsible management strategies. Fourth, the interpretability of deep learning predictions remains an important consideration. Farmers and agricultural professionals may be reluctant to rely on automated predictions without an indication of the visual regions responsible for a classification decision. Explainable AI techniques such as Grad-CAM and saliency-based visualization can therefore improve transparency and user confidence.

Finally, there is limited research integrating deep learning-based plant disease classification, organic treatment monitoring, and treatment recommendation into a single framework. The present study addresses these gaps by developing a deep learning-based classification system incorporating healthy, diseased, and organically treated leaf images, while additionally providing disease-specific organic treatment recommendations through a knowledge-based module. Addressing these gaps requires building organically aware deep learning models, incorporating diverse real-field image datasets, enhancing interpretability, and linking detection outputs with organic treatment recommendations to achieve sustainable agricultural impact.

III. RESEARCH METHODOLOGY

This study presents an image-based deep-learning framework for plant disease detection and organic treatment assessment using leaf images. The proposed methodology consists of seven major stages: dataset acquisition and preparation, image preprocessing, feature analysis, deep learning model development, model training and optimization, organic treatment recommendation, and deployment. The overall workflow is designed to provide automated disease classification while supporting sustainable disease-management decisions.

1. Dataset Acquisition and Preparation

The dataset was constructed from publicly available plant disease image repositories, including PlantVillage and the Kaggle Plant Pathology Challenge, supplemented with field-collected leaf images from organic farms across three regions of India. Additional images representing organically treated plants were incorporated to improve the representation of post-treatment conditions. The combined dataset covered nine crop species and fifteen disease classes, including early blight, late blight, powdery mildew, bacterial leaf spot, and rust, together with a healthy-leaf category. Table 2 summarizes the dataset composition by crop.

The dataset contains images captured under different lighting conditions, backgrounds, leaf orientations, and disease progression stages. Particular attention was given to maintaining a suitable representation of healthy, diseased, and organically treated samples.

Before model training, duplicate and severely corrupted images were removed. All images were resized to 224 × 224 pixels to provide a standardized input format, and pixel values were normalized using mean–std scaling consistent with the preprocessing procedure associated with the EfficientNet architecture. Background masking via Otsu's thresholding was applied to isolate leaf regions where required. Data augmentation was performed using random rotation (±15°), horizontal and vertical flipping, random zooming (±20%), cropping, and controlled contrast

variation. These transformations were applied only to the training data to prevent information leakage between training and evaluation sets.The final dataset was divided into training, validation, and testing subsets using a 70:15:15 ratio. The test dataset was kept completely independent and was used only for final performance evaluation.

2. Image Preprocessing

Image preprocessing was performed to improve image consistency and reduce variations unrelated to disease characteristics. The preprocessing pipeline included image resizing, pixel normalization, background enhancement, and data augmentation.Background masking and contrast enhancement were applied where required to improve the visibility of leaf regions, and augmentation techniques were used to simulate variations that may occur during field-level image acquisition.

3. Feature Analysis

Although the proposed deep learning model automatically learns discriminative features from images, conventional image descriptors were also analyzed to understand disease-related visual characteristics, including color, texture, and shape. Color characteristics were analyzed using hue, saturation, and intensity distributions. Texture characteristics were investigated using Gray-Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP) descriptors. Shape-related characteristics included leaf area, contour properties, edge characteristics, and circularity. This exploratory analysis informed layer design in the network, ensuring that early layers remain sensitive to edge and texturefeatures while deeper layer scapture more complex disease patterns, and provided additional insight into the visual characteristics associated with disease development and treatment-related changes.

4. Proposed Model Architecture and Algorithm

Deep learning approach to classify plant diseases and recommend organic treatments. The primary classification architecture used in the analysis is EfficientNet-B4 with transfer learning. EfficientNet-B4 is adopted as the backbone for the feature extraction process because it provides an optimal blend of the accuracy and efficiency.

The proposed architecture utilizes Squeeze-and-Excitation attention mechanisms to emphasize the important visual patterns indicative of a disease. The model leverages learned features of the plant leaf to learn the characteristics of the disease while emphasizing the informative patterns related to each particular case. In addition to automatic feature extraction and utilization, the approach uses colour, texture, shape, and circularity characteristics of the leaf as features for training the model. Colour features are represented via hue, saturation, and intensity distribution, texture properties are captured using Gray-Level Co-occurrence Matrix and Local Binary Pattern, while shape features include the area, contour, edges, and circularity.

For evaluation and comparison purposes, the proposed EfficientNet-B4 is compared against Support Vector Machine, ResNet50, and standard EfficientNet-B4 model. Comparison is achieved by calculating the accuracy, precision, recall, F1-score, and ROC-AUC, alongside the confusion matrix analysis. The model predicts the probability of occurrence of each of the classes, which are then

leveraged to make a final prediction of plant disease. Based on the disease predicted, the model recommends organic treatments to address the disease.

The proposed model was implemented using Python and TensorFlow/Keras. Transfer learning was employed to initialize the EfficientNet-B4 backbone using pretrained weights. During the initial training stage, the pretrained feature-extraction layers were partially frozen to preserve general visual representations; selected upper layers were subsequently fine-tuned using the study dataset to adapt the learned representations to plant disease characteristics. The model was trained using the Adam optimizer and a categorical cross-entropy loss function, with a batch size of 32, for a maximum of 50 epochs with early stopping (patience of 10 epochs) based on validation loss. A learning-rate scheduler reduced the learning

rate when validation loss plateaued. Table 3 summarizes the training configuration.

Parameter	Selected Value
Input image size	224 × 224 × 3
Batch size	32
Initial learning rate	0.001
Optimizer	Adam
Maximum epochs	50
Dropout rate	0.4
Loss function	Categorical Cross-Entropy
Data split	70:15:15
Early stopping patience	10 epochs

The best-performing model was selected according to validation performance and subsequently evaluated on the independent test dataset.

6. Organic Treatment Recommendation Module

A knowledge-based recommendation module was integrated into the proposed framework to connect the predicted disease class with suitable organic or biologically based disease-management options. The recommendation database was developed using information obtained from established agricultural guidelines, published literature, and crop-specific disease-management recommendations.

The module operates as a rule-based lookup system: once the model predicts a disease class, the corresponding management options are retrieved from the knowledge base. Recommendations may include botanical extracts, biocontrol agents, cultural practices, and other permitted organic disease-management approaches.

Representative examples include a neem oil spray (3%) applied every 7 days for powdery mildew in grapes, copper oxychloride (organic-certified, 3 g/L) for late blight in potatoes, and sulfur dusting (25 kg/ha) for rust in wheat. The exact concentration, application interval, formulation, and permitted use should be determined according to crop-specific agricultural guidelines, product labels, and applicable organic certification requirements.The recommendation module is therefore intended as a decision-support component rather than a substitute for professional agricultural advice; disease diagnosis and treatment recommendation are treated as separate components so that the model prediction does not automatically imply treatment efficacy.

IV. DATASETACQUISITION AND PREPROCESSING

To create our own dataset, we selected various open-source image repositories including PlantVillage, Kaggle Plant Pathology Challenge and the images collected from organic farms of three locations of India. Our dataset included nine different crop species and fifteen different categories of diseases (such as early blight, late blight, powdery mildew, bacterial leaf spot, rust), including one class named “healthy leaves.”

Table 1: Dataset DistributionTable 1

Crop	No. of Classes	Total Images	Healthy Samples	Diseased Samples
Tomato	5	3,200	700	2,500
Potato	3	2,150	600	1,550
Apple	3	2,500	800	1,700
Maize	2	1,800	500	1,300
Grape	2	1,500	400	1,100

These images were captured under various illumination conditions, backgrounds and disease stages; hence, normalizing and augmenting the data was essential for generalization in the model.

These were the preprocessing steps:

- Resizing all images to 224x224 pixels for the compatibility of deep learning model.
- Color Normalization using mean-std scaling to mitigate lighting variations.
- Background Masking using Otsu’s Thresholding to separate leaf from background.

- Data augmentation by performing random rotations (±15°), flips (horizontal & vertical), zoom (±20%) and adjustment of contrasts to mimic different field environments.
- The data was divided in 70:15:15 ratio in training, validation and test sets respectively to prevent any data leakage.

1. Feature Extraction

While algorithms using deep learning can automatically identify features, traditional leaf image features were first investigated for patterns associated with specific diseases. These features are:

- Color features: Saturation, Hue histograms
- Texture Features: Gray Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP).
- Shape characteristics are circularity, leaf area, and edge sharpness.

This initial study was designed to help design the layers of the convolutional neural network (CNN) model, where the early layers detect edges and improve the performance.

3. Model Architecture Design

In this case, an enhanced form of EfficientNet-B4 is employed as the deep learning model.

Other modifications in the architecture comprise:

- The input layer processes images that measure 224x224x3 and capture different colors (RGB).
- Convolution layer implements a depthwise type of separable convolution that means fewer parameters in use.
- The mechanism of attention involves SE block that provides means for detecting disease areas in images under analysis.

- 4. The dropout layer has a value of 0.4 for the purpose of combating overfitting.
- 5. The last layer is fully connected, comprising 512 neurons. The output layer counts 16 nodes with Softmax activation function.

3. Model Training and Optimization

Model training was conducted using TensorFlow 2.14 and utilized an NVIDIA RTX 4090 GPU. The crucial hyperparameters were optimized through the use of Bayesian optimization. The optimized hyperparameters are given below:

Table 2: Optimized Hyperparameters

Parameter	Range Tested	Optimal Value
Learning rate	1e-5 – 1e-2	3e-4
Batch size	16–64	32
Optimizer	Adam, RMSprop, SGD	Adam
Epochs	20–80	50
Dropout rate	0.2–0.5	0.4

The categorical cross-entropy loss was minimized and early stopping was invoked when the validation loss was stalled for 10 successive epochs. Learning rate reduction because of plateau also helped improve convergence.

5. Organic Solution Recommendation Module

Beyond classification, the system involves the knowledge-based correlation of disease labels with appropriate organic treatments. This uses the FAO agricultural guidelines and the practices of organic farming in India.

Some examples are:

- Powdery mildew (grapes) → 3% Neem oil spray need to be on weekly basis
- Late blight (potatoes) → Copper oxychloride (organic-certified) 3g/L
- Rust (wheat) → 25kg/ha of Sulfur dusting

This function operates like a database table and works on receiving disease class from prediction.

6. Evaluation Metrics

Performance metrics included the following:

- ACC (accuracy): Overall ratio of correctly predicted samples.
- P, R, and F1: Used to manage class imbalance issue.
- ROC (Receiver Operating Characteristic) curve and AUC (Area Under the Curve): For binary and multiclass classification capability.
- 4. Confusion matrix: Used for misclassification identification.

7. Deployment Strategy

The trained model was converted to TensorFlow Lite format for mobile integration, and a progressive web application (PWA) was developed to allow farmers to:

- 1. Capture a leaf photograph via smartphone
- 2. Receive an instant disease classification,
- 3. View the recommended organic treatment plan.

The application was field-tested with 40 farmers across Bihar, Haryana, and

Maharashtra, achieving 92% user satisfaction in preliminary surveys.

8. Ethical Considerations and Data Privacy

- Informed consent was obtained for field-collected images.
- Data was anonymized before model training.
- The organic treatment recommendations comply with Indian agricultural regulations and organic certification standards.

The methodology integrates robust image preprocessing, efficient model architecture, rigorous optimization, and practical treatment recommendations. Unlike conventional approaches that stop at classification, our system closes the loop by guiding farmers toward environmentally sustainable disease management practices.

V. EXPERIMENTAL SETUP

The experimental setup for this study was carefully designed to ensure reproducibility, computational efficiency, and robust evaluation of the proposed deep learning-based approach for classifying plant diseases and identifying suitable organic solutions. This section details the hardware specifications, software environment, dataset preparation, training configuration, and evaluation metrics employed during the experimental phase.

1. Hardware Configuration

To efficiently train computationally intensive deep learning models, a high-performance workstation was employed. The hardware configuration is as follows:

- GPU: NVIDIA GeForce RTX 3090 (24 GB GDDR6X VRAM) –

selected for its high parallel processing capabilities and ability to handle large-scale image datasets efficiently. The CUDA cores and Tensor cores significantly accelerate training and inference.

- CPU: Intel Core i9-12900K Processor chosen for its high clock speed and multi-core performance, ensuring rapid preprocessing, data augmentation, and I/O handling without bottlenecks.
- RAM: 32 GB DDR5 sufficient to manage large datasets and parallel training tasks without causing memory overflow.
- Storage: 2 TB NVMe SSD to allow high-speed data loading and model checkpoint saving, reducing I/O delays during training.
- Operating System: Ubuntu 22.04 LTS selected for its stability, compatibility with deep learning frameworks, and efficient GPU driver management.

This configuration allowed for training deep convolutional neural networks with large batch sizes, thereby improving convergence speed and enabling extensive hyperparameter tuning.

2. Software Environment

- The software stack was chosen for its reliability, community support, and compatibility with state-of-the-art deep learning workflows:
- **Programming Language**: Python 3.10 widely used in the machine learning community for its extensive libraries and clean syntax.
- **Deep Learning Frameworks:** o TensorFlow 2.12 for model building, training, and deployment, leveraging
- GPU acceleration through CUDA.
- Keras API for high level model design and rapid prototyping of deep architectures.

Image Processing and Data Handling:

- o OpenCV 4.7 for preprocessing operations including resizing,
- normalization, contrast
- enhancement, and augmentation.
- NumPy for efficient numerical computations, especially during dataset preparation.
- Supporting Tools: Pandas for tabular data handling, Matplotlib and Seaborn for visualization of results, and Scikit-learn for evaluation metrics and confusion matrix generation.
- CUDA Toolkit 11.8 and cuDNN 8.6 – to enable GPU acceleration for TensorFlow operations.
- The software environment was containerized using Docker to ensure reproducibility and portability across different systems.

3. Dataset Preparation

The dataset consisted of high-resolution images of plant leaves with various disease symptoms, as well as healthy samples. Each image underwent preprocessing to standardize input dimensions (224×224 pixels) and normalize pixel values between 0 and 1. Augmentation techniques such as rotation (±25°), horizontal/vertical flipping, Gaussian noise injection, and random cropping were applied to enhance generalization and mitigate overfitting.

Data was split into:

- Training Set: 70% of the dataset, used for model fitting.
- Validation Set: 15% for hyperparameter tuning.
- Test Set: 15% for final performance evaluation.

5. Model Training Configuration

The deep learning architecture employed was a modified Convolutional Neural Network (CNN) optimized for feature extraction from plant leaf images. Transfer learning using pre-trained weights (from EfficientNet-B3) was also tested for performance improvement.

Key training settings included:

- Batch Size: 32
- Learning Rate: Initially set to 0.001, reduced using a scheduler on plateau.
- Optimizer: Adam, chosen for its adaptive learning capabilities.
- Epochs: 50, with early stopping based on validation loss.
- Loss Function: Categorical CrossEntropy, suitable for multiclass classification.

Model checkpoints and logs were maintained for reproducibility.

6. Evaluation Metrics

To comprehensively assess the classification performance, multiple metrics were used:

- Accuracy: Measures the proportion of correctly classified samples across all classes.
- Precision: Evaluates the proportion of true positive predictions against all positive predictions, important for minimizing false positives.
- Recall (Sensitivity): Calculates the proportion of actual positives correctly identified, crucial in disease detection scenarios where missing a diseased sample could have severe consequences.
- F1 score: The harmonic mean of precision and recall, providing a balanced metric for imbalanced datasets.
- ROC AUC (Receiver Operating Characteristic Area Under the Curve): Evaluates the model's ability to discriminate between classes over varying thresholds, ensuring robustness against bias in class distribution.

The combination of these metrics provided a holistic view of model performance, enabling informed comparisons with existing approaches.

7. Experimental Reproducibility and Documentation

To ensure transparency and reproducibility, all hyperparameters, dataset splits, and preprocessing scripts were documented. The training environment was logged, and model weights were stored for future benchmarking.

This well-structured experimental setup ensured that the developed system could be reliably evaluated and compared against existing solutions, forming a solid

foundation for advancing deep learning in plant disease classification with an organic solution integration perspective.

VI. RESULTS AND DISCUSSION

The proposed deep learning framework was evaluated using an independent test dataset containing healthy and diseased plant leaf images, together with organically treated samples where applicable. The evaluation focused on the model's ability to distinguish disease categories and treatment-related conditions. Quantitative performance was assessed using accuracy, precision, recall, F1-score, and ROC-AUC, while confusion matrices and ablation experiments were used to investigate class-specific performance and the contribution of individual feature categories.

1. Quantitative Performance Evaluation

The proposed framework achieved an overall classification accuracy of 96.72% on the independent test dataset. The corresponding precision, recall, F1 score, and ROC AUC values were 0.963, 0.968, 0.965, and 0.982, respectively.

The precision value of 0.963 indicates that the model generated relatively few false-positive predictions. The recall value of 0.968 demonstrates that the model successfully identified a high proportion of diseased samples. The F1 score of 0.965 indicates a balanced relationship between precision and recall. The ROC AUC value of 0.982 further demonstrates strong discriminatory capability across the evaluated classes.

These results indicate that the proposed EfficientNet B4 based framework can effectively learn disease-related visual characteristics from plant leaf images while maintaining strong generalization on previously unseen test samples.

2. Quantitative Performance Evaluation

The model's performance was evaluated using Accuracy, Precision, Recall, F1 score, and ROC AUC. The results indicate that the proposed framework achieved an overall accuracy of 96.72%, outperforming existing approaches by a margin of 3–5% depending on the baseline considered.

- Precision (0.963) reflects the model's ability to minimize false positives, meaning the system rarely misclassified healthy leaves as diseased.
- Recall (0.968) demonstrates its effectiveness in detecting actual diseased instances, indicating low false-negative rates.
- F1-score (0.965) shows a balanced performance between precision and recall, which is essential in
- agricultural disease monitoring where both false alarms and missed detections can have significant economic impacts.
- ROC AUC (0.982) confirms the model's excellent discrimination capability between diseased and healthy classes across different classification thresholds.

The confusion matrix revealed that the model performed consistently across different disease categories, with the lowest misclassification rate observed in early-stage disease samples.

3. Comparative Analysis with Existing Models

We benchmarked the proposed model against ResNet50, EfficientNetB4, and a traditional SVM-based feature classifier using the same dataset. The results are summarized in Table 5:

Model	Accuracy (%)	Precision	Recall	F1-score	ROC-AUC
SVM (GLCM + Color)	88.94	0.884	0.879	0.881	0.902
ResNet50	93.51	0.933	0.932	0.932	0.954
EfficientNetB4	94.26	0.941	0.936	0.938	0.961
Proposed Framework	96.72	0.963	0.968	0.965	0.982

This table highlights that while deep CNN models such as ResNet50 and EfficientNetB4 perform well, our fusion based approach integrating structural and histogram features further enhances classification accuracy. The improvement can be attributed to:

1. Complementary feature utilization: Structural parameters like circularity capture shape deformation patterns, while histogram-based texture and color parameters capture disease-specific pigmentation and spread patterns.

2.Feature-level fusion: Early fusion ensures that the combined feature space retains inter-parameter relationships, which are often lost in purely deep learning pipelines.

4. Impact of Feature Categories

Ablation studies were conducted to evaluate the contribution of each feature category:

- Color features only yielded an accuracy of 92.13%, indicating that while color provides useful information, it is insufficient for high accuracy due to variations in lighting conditions and leaf pigmentation.
- Texture features only achieved 93.08%, suggesting that texture is more robust than color under illumination changes but may fail when disease symptoms do not manifest as surface irregularities.
- Circularity and shape-based features alone achieved 90.82%, showing that geometry is valuable but less discriminative in isolation.
- Full feature combination achieved the highest performance (96.72%), proving the effectiveness of multimodal feature integration.

5. Training and Convergence Behaviour

Training curves for accuracy and loss (Figure 4) indicate that:

- The model converged within 40 epochs, suggesting computational efficiency.
- Validation accuracy closely tracked training accuracy, with minimal overfitting, thanks to dropout layers and data augmentation.
- Early stopping was employed to prevent unnecessary computation and ensure generalization.

The training loss steadily decreased from 0.29 to 0.03, while validation loss reduced from 0.31 to 0.04, indicating stable optimization and good generalization across unseen test samples.

6. Confusion Matrix Insights

The confusion matrix (Figure 5) shows that:

- Early-stage infections had slightly higher misclassification compared to mid- and late-stage infections, likely due to their subtle symptoms.
- The most frequent confusion occurred between "nutrient deficiency" and "early-stage fungal infection" due to similar yellowish color patterns.
- Despite these challenges, the model maintained above 95% recall for all classes, ensuring minimal missed detections.

7. ROC Curve and Threshold Sensitivity

The ROC curves (Figure 6) for all classes indicate:

- AUC values above 0.97 for every class, confirming robustness across different decision thresholds.
- A relatively stable performance for early-stage disease detection, which often suffers in other models.

By adjusting classification thresholds, the model can be optimized for either high recall (disease monitoring) or high precision (laboratory confirmation) depending on application needs.

7. Practical Implications in Agriculture

The proposed model's high accuracy and robustness make it suitable for real-time agricultural applications:

- On-field mobile diagnostics – Farmers can use smartphone-based leaf scans to detect diseases early.
- Automated greenhouse monitoring – Integrated into camera systems for 24/7 crop surveillance.
- Precision agriculture decision-making – Reducing unnecessary pesticide use by providing accurate, targeted disease treatment guidance.

Importantly, the computational cost is optimized to allow deployment on mid-tier GPUs and even edge devices with moderate processing power.

8. Limitations and Observations

While the results are promising, certain limitations were observed:

- **Lighting sensitivity** – Extreme variations in sunlight/shade can slightly affect color-based feature reliability.

- **Disease similarity** – Morphologically similar diseases remain challenging to differentiate without additional multispectral imaging.
- **Dataset diversity** – Although diverse, expanding to multiple geographic regions and crop varieties could further improve generalization.

Overall, the integration of color, texture, and shape descriptors, coupled with deep learning classifiers, resulted in significant accuracy gains over single-feature or CNN-only methods. The combination not only improved numerical performance but also enhanced interpretability, as each feature category provides a tangible, explainable disease characteristic:

- Color → pigment degradation / necrosis
- Texture → lesion spread / surface roughness
- Circularity → shape distortion due to tissue death

Such interpretability is crucial in agricultural contexts, where trust in automated systems is vital for adoption.

9. Linkage of Results and Discussion with Research Objectives and Hypotheses

The results and discussion presented in this study are directly aligned with the research objectives and the underlying research hypotheses. The first research objective focused on exploring suitable CNN architectures for efficient plant disease classification. This objective was achieved through the implementation of an EfficientNet-B4-based transfer learning architecture. The proposed framework achieved an overall accuracy of 96.72%, with precision, recall, F1-score, and ROC-AUC values of 0.963, 0.968, 0.965, and 0.982, respectively, demonstrating the effectiveness of the selected deep learning architecture for plant disease classification. Paper 02 Final (1)

The second research objective aimed to classify plant diseases through the extraction of disease-related features using suitable CNN architectures. The experimental results showed that the proposed framework successfully learned discriminative visual characteristics from plant leaf images. Comparative analysis further demonstrated that the proposed framework outperformed SVM, ResNet50, and conventional EfficientNet-B4 models, thereby supporting the effectiveness of the proposed deep learning-based feature extraction and classification approach. Paper 02 Final (1)

The third research objective focused on evaluating color, texture, and circularity-related characteristics associated with disease spread. The ablation analysis showed that color features achieved 92.13% accuracy, texture features achieved 93.08%, and circularity and shape-based features achieved 90.82%. The combined

feature framework achieved the highest accuracy of 96.72%, indicating that the integration of multiple visual feature categories improves disease classification performance. These findings support the hypothesis that combined color, texture, and shape-related features provide more effective discrimination than individual feature categories. Paper 02 Final (1)

The fourth research objective was to classify plant diseases and integrate suitable organic solutions using a deep learning-based approach. This objective was addressed through the knowledge-based organic treatment recommendation module, which links the predicted disease class with suitable organic or biologically based disease-management options. Thus, the proposed framework extends beyond disease identification and provides practical decision support for sustainable plant disease management. Paper 02 Final (1)

Overall, the obtained results are consistent with the stated research objectives and provide support for the corresponding research hypotheses. The findings demonstrate that the proposed deep learning framework can effectively classify plant diseases, that the integration of complementary visual features improves classification performance, and that automated disease detection can be successfully linked with organic treatment recommendations.

VII. CONCLUSION AND FUTURE WORK

1. Conclusion

This study presented a deep learning-based framework for automated plant disease classification with an integrated organic treatment recommendation component. The

proposed approach was developed to address the limitations of conventional visual disease diagnosis and to support sustainable agricultural disease-management practices.

An EfficientNet-B4 based transfer learning architecture was employed to learn discriminative visual representations from plant leaf images. The framework incorporated attention mechanisms alongside appropriate preprocessing and augmentation strategies to improve classification performance under variation in image characteristics. Experimental evaluation demonstrated a reported overall accuracy of 96.72%, with precision, recall, F1-score, and ROC-AUC values of 0.963, 0.968, 0.965, and 0.982 respectively.

Comparative experiments demonstrated that the proposed framework outperformed the evaluated SVM, ResNet50, and conventional EfficientNet-B4 baseline models, indicating that the proposed approach can provide reliable automated disease classification while reducing dependence on subjective visual inspection.
An additional contribution of the framework is the integration of a knowledge-based organic treatment recommendation module. Rather than relying exclusively on synthetic chemical control, the system provides information about potentially suitable organic and biologically based management options associated with the predicted disease class, connecting automated diagnosis with sustainable disease management.
The framework therefore provides a foundation for mobile and edge-based agricultural decision-support applications; recommendations should nonetheless be interpreted as decision-support information and validated against crop-specific agricultural guidelines and local regulatory requirements.One of the key contributions of this research lies in its ability not only to detect the presence of plant diseases but also to assess the post-treatment condition of leaves. By training the model with organically treated images, the system can identify subtle improvements in leaf texture, pigmentation, and morphology that indicate effective treatment outcomes, offering farmers and agricultural practitioners a means to monitor treatment efficacy in near real time and make informed decisions about follow-up actions.

The findings underscore the potential of deep learning to support sustainable crop management practices. Unlike chemical treatments, which may contribute to environmental degradation and long-term soil fertility loss, organic treatments align with eco-friendly agricultural goals while helping to maintain crop productivity. The proposed framework aligns with the United Nations Sustainable Development Goals, particularly Goal 2 (Zero Hunger) and Goal
12 (Responsible Consumption and Production), by offering a tool that supports environmentally sustainable farming without compromising disease-control efficiency.

From an application standpoint, the model's robustness to variation in lighting conditions and leaf orientation supports its suitability for real-world deployment, while the use of transfer learning substantially reduced training time relative to training from scratch, without sacrificing accuracy, making the approach computationally efficient for large-scale agricultural use.The research also highlights the value of integrating domain-specific knowledge, in this case plant pathology and organic farming practice, into AI model design. By embedding organically treated image data into the classification pipeline, the system moves beyond a binary healthy/diseased
framework toward a more nuanced, actionable decision-making tool.Overall, the results support the premise that deep learning models, when trained with enriched and diversified datasets, can bridge the gap between diagnosis and treatment evaluation in agriculture, serving as a valuable asset for precision farming.

2. Future Work

While the outcomes of this research are promising, several opportunities remain for further enhancement and broader applicability of the proposed framework.

Dataset Expansion Under Field Conditions.

Future research will focus on expanding the dataset with images collected under diverse field conditions, including variation in illumination, humidity, seasonal conditions, background complexity, leaf orientation, and disease severity. Increasing the number of crop species and geographic locations represented would further improve model generalization.

Integration of Hyperspectral Imaging.
The present framework relies primarily on RGB imagery. Future studies could incorporate hyperspectral or multispectral imaging to detect physiological and biochemical changes that occur before disease symptoms become visually apparent, potentially enabling earlier detection and reducing crop losses.

Mobile and Edge Deployment.
Future work will investigate optimized versions of the proposed model for deployment on smartphones and edge-computing devices. Model compression, quantization, pruning, and knowledge distillation could be explored to reduce computational requirements while maintaining acceptable classification performance, enabling in-field diagnosis without dependence on high-speed internet or cloud resources.

Integration with IoT and Precision Agriculture.
The proposed framework could be integrated with IoT-enabled agricultural monitoring systems, including environmental sensors, soil-monitoring devices, and automated crop-monitoring platforms, or connected with automated sprayers to support a closed-loop precision agriculture system in which diagnosis, treatment, and monitoring are more fully automated.

Explainable Artificial Intelligence.
Explainable AI techniques such as Grad-CAM, Integrated Gradients, and saliency mapping could be incorporated to identify the leaf regions responsible for model predictions, improving transparency and helping farmers and agricultural professionals understand and validate automated predictions.

Longitudinal Organic Treatment Monitoring.
Future studies should evaluate organically treated plants longitudinally, capturing images at multiple time intervals before and after treatment, to support models that estimate disease progression and treatment response rather than classifying individual images in isolation.

Sustainability and Socio-Economic Evaluation.
Future research should investigate the economic and environmental impact of deploying the proposed framework, including reductions in unnecessary pesticide application, treatment costs, crop yield outcomes, farmer adoption, and long-term soil health, to quantify the practical sustainability benefits of the system.

REFERENCES

1. X. Zhang, Y. Huang, and Z. Zhao, "Automated leaf disease detection and severity estimation using color features," Comput. Electron. Agric., vol. 178, pp. 105–112, 2020.
2. M. Khan, R. Ahmed, and S. Ali, "Texture-based classification of skin lesions using GLCM and SVM," Biomed. Signal Process. Control, vol. 62, p. 102120, 2020.
3. R. P. Singh, S. K. Sharma, and M. Kumar, "Deep learning based plant disease detection using ResNet architectures," Int. J. Comput. Appl., vol. 182, no. 34, pp. 1–7, 2021.
4. S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep neural networks based recognition of plant diseases by leaf image classification," Comput. Intell. Neurosci., vol. 2016, pp. 1–11, 2016.
5. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," Front. Plant Sci., vol. 7, p. 1419, 2016.
6. N. Brahimi, K. Boukhalfa, and A. Moussaoui, "Deep learning for tomato diseases: Classification and symptoms visualization," Appl. Artif. Intell., vol. 31, no. 4, pp. 299–315, 2017.
7. Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," Nature, vol. 521, pp. 436–444, 2015.
8. J. Liu et al., "Plant disease detection using convolutional neural networks," Biosyst. Eng., vol. 199, pp. 135–144, 2020.
9. H. Durmuş, E. O. Güneş, and M. Kırcı, "Disease detection on the leaves of the tomato plants by using deep learning," Proc. 6th Int. Conf. Agro-Geoinform., pp. 1–5, 2017.

10. A. Ferentinos, "Deep learning models for plant disease detection and diagnosis," Comput. Electron. Agric., vol. 145, pp. 311–318, 2018.
11. K. P. Ferentinos, "Automatic plant disease diagnosis using deep learning," Neural Comput. Appl., vol. 31, no. 12, pp. 989–1002, 2019.
12. M. Iqbal, M. Hussain, and M. A. Khan, "Early detection of plant diseases from leaf images using deep learning," IEEE Access, vol. 9, pp. 10039–10054, 2021.
13. A. Kamilaris and F. Prenafeta-Boldú, "Deep learning in agriculture: A survey," Comput. Electron. Agric., vol. 147, pp. 70–90, 2018.
14. S. Barbedo, "Digital image processing techniques for detecting, quantifying and classifying plant diseases," SpringerPlus, vol. 2, p. 660, 2013.
15. S. Arsenovic et al., "Leaf disease detection using a convolutional neural network," J. Imag., vol. 4, no. 2, p. 41, 2018.
16. Y. Sun, P. Liu, and Z. Wang, "Deep learning for plant identification in natural environment," Comput. Electron. Agric., vol. 162, pp. 206–213, 2019.
17. M. Singh, D. Jain, and R. Singh, "An improved deep learning model for plant disease detection," Sustain. Comput. Inform. Syst., vol. 28, p. 100472, 2020.
18. S. P. Mohanty et al., "Image based plant disease detection using transfer learning," IEEE Access, vol. 7, pp. 110178–110193, 2019.
19. A. Das, D. Roy, and S. Chatterjee, "Plant leaf disease detection using deep learning and edge computing," Proc. IEEE Int. Conf. Commun. Electron. Syst., pp. 1–5, 2020.
20. A. Voulodimos, N. Doulamis, A. Doulamis, and E. Protopapadakis, "Deep learning for computer vision: A brief review," Comput. Intell. Neurosci., vol. 2018, p. 7068349, 2018.
21. P. Liu and Y. Li, "CNN-based plant disease recognition under complex field conditions," Comput. Electron. Agric., vol. 169, p. 105174, 2020.
22. J. Chen et al., "Plant disease recognition using convolutional neural networks," Sensors, vol. 20, p. 1485, 2020.
23. H. Saleem, M. Potgieter, and K. Arif, "Plant disease detection using deep learning and its significance in agriculture," J. Plant Pathol., vol. 103, pp. 319–331, 2021.
24. T. Li, X. Zhang, and H. Zhang, "Hyperspectral imaging for plant disease detection: A review," Remote Sens., vol. 12, p. 2995, 2020.
25. Y. Ge et al., "Recent advances in hyperspectral image processing for agriculture," Remote Sens., vol. 11, p. 2971, 2019.
26. S. Liu et al., "Mobile application for plant disease detection and treatment recommendation," IEEE Access, vol. 8, pp. 101451–101461, 2020.
27. H. Chen, W. Lin, and H. Wang, "Real-time plant disease detection using deep learning," Multimed. Tools Appl., vol. 79, no. 35–36, pp. 26455–26468, 2020.
28. D. S. Barman and M. Dutta, "Integrating mobile and cloud computing for smart farming," Proc. IEEE Int. Conf. Comput. Sustain. Global Dev., pp. 65–70, 2019.
29. V. Singh, S. Misra, and N. Singh, "Organic farming and its role in sustainable agriculture," Agric. Rev., vol. 40, no. 1, pp. 1–7, 2019.
30. R. Sharma and M. Kumar, "Organic treatment effects on plant health: A review," Int. J. Agron., vol. 2020, p. 4852756, 2020.
31. J. Patel and A. Mehta, "Effect of organic pesticides on disease suppression in crops," J. Org. Agric., vol. 8, pp. 135–144, 2018.
32. D. Singh et al., "Machine learning techniques for plant disease detection: Progress and prospects," IEEE Access, vol. 8, pp. 202370–202383, 2020.
33. A. N. Joshi and P. Mathur, "Comparison of deep learning architectures for crop disease detection," Procedia Comput. Sci., vol. 171, pp. 463–472, 2020.
34. N. L. Sharma and M. S. Arora, "Deep learning for plant health monitoring: Challenges and opportunities," AI Agric., vol. 4, pp. 60–68, 2020.
35. P. K. Dubey, A. Roy, and R. K. Sharma, "Organic agriculture and pest management strategies," Ecol. Eng., vol. 138, pp. 127–135, 2019.
36. H. P. Singh et al., "Sustainable crop management using AI and IoT technologies,"

Comput. Electron. Agric., vol. 170, p. 105246, 2020.
37. S. Liu et al., "Mobile application for plant disease detection and treatment recommendation," IEEE Access, vol. 8, pp. 101451–101461, 2020.
38. H. Chen, W. Lin, and H. Wang, "Real-time plant disease detection using deep learning," Multimed. Tools Appl., vol. 79, no. 35–36, pp. 26455–26468, 2020.
39. D. S. Barman and M. Dutta, "Integrating mobile and cloud computing for smart farming," Proc. IEEE Int. Conf. Comput. Sustain. Global Dev., pp. 65–70, 2019.
40. V. Singh, S. Misra, and N. Singh, "Organic farming and its role in sustainable agriculture," Agric. Rev., vol. 40, no. 1, pp. 1–7, 2019.
41. R. Sharma and M. Kumar, "Organic treatment effects on plant health: A review," Int. J. Agron., vol. 2020, p. 4852756, 2020.
42. J. Patel and A. Mehta, "Effect of organic pesticides on disease suppression in crops," J. Org. Agric., vol. 8, pp. 135–144, 2018.
43. D. Singh et al., "Machine learning techniques for plant disease detection: Progress and prospects," IEEE Access, vol. 8, pp. 202370–202383, 2020.
44. A. N. Joshi and P. Mathur, "Comparison of deep learning architectures for crop disease detection," Procedia Comput. Sci., vol. 171, pp. 463–472, 2020.
45. N. L. Sharma and M. S. Arora, "Deep learning for plant health monitoring: Challenges and opportunities," AI Agric., vol. 4, pp. 60–68, 2020.
46. P. K. Dubey, A. Roy, and R. K. Sharma, "Organic agriculture and pest management strategies," Ecol. Eng., vol. 138, pp. 127–135, 2019.
47. H. P. Singh et al., "Sustainable crop management using AI and IoT technologies," Comput. Electron. Agric., vol. 170, p. 105246, 2020.
48. L. Yang et al., "Transfer learning for plant disease recognition with limited data," IEEE Access, vol. 8, pp. 119690–119700, 2020.