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Analysis of Deep Learning Architectures for Smart Plant Disease Detection and Organic Remedy Recommendation

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Abstract- Plant diseases pose a major threat to global agricultural productivity, food security, and sustainability. Traditional disease diagnosis methods are often time-consuming, subjective, and require expert intervention. Recent advancements in artificial intelligence, particularly deep learning, have revolutionized agricultural disease detection through automated image-based systems. This study presents a comprehensive analysis of deep learning architectures such as Convolutional Neural Networks (CNNs), Transfer Learning Models (ResNet, VGG, Inception), and Vision Transformers (ViTs) for smart plant disease detection and integrates an organic remedy recommendation framework. The research employs publicly available plant disease datasets to train and compare model performances in terms of accuracy, precision, and recall. Furthermore, an ontology-based organic treatment recommender system is developed to suggest sustainable, eco-friendly remedies. The experimental results demonstrate that deep learning models achieve over 97% detection accuracy, while the proposed organic recommendation layer enhances decision-making for sustainable agriculture.

Keywords: Sustainable Farming, Precision Agriculture, Artificial Intelligence, Disease Diagnosis.

I. INTRODUCTION

Agriculture forms the foundation of human civilization, providing the essential means for food, raw materials, and economic stability across nations. However, the agricultural sector faces persistent challenges due to crop losses caused by plant diseases, pests, and environmental stressors. According to the Food and Agriculture Organization (FAO, 2023), nearly 30–40% of global agricultural production is lost annually to plant diseases and pests, leading to an estimated economic loss of USD 220 billion.

These losses have far-reaching consequences for food security, farmer livelihoods, and ecological sustainability. Early and accurate detection of plant diseases is therefore crucial for maintaining crop productivity and ensuring sustainable agricultural growth. Traditional plant disease identification techniques such as visual inspections, microscopic examinations, and laboratory-based pathogen tests are time-consuming, labor-intensive, and often require specialized expertise (Mohanty, Hughes, & Salathé, 2016). As a result, there is a growing necessity to develop automated, scalable, and intelligent systems capable of diagnosing diseases with precision and providing appropriate management recommendations. [5,7,10]

The advent of artificial intelligence (AI) and deep learning (DL) technologies has brought a paradigm shift in agricultural automation and smart farming. Deep learning, a subset of machine learning, allows computational models to automatically learn hierarchical data representations and extract complex patterns directly from raw data (LeCun, Bengio, & Hinton, 2015). Among various deep learning architectures, Convolutional Neural Networks (CNNs) and their advanced variants have demonstrated exceptional accuracy in identifying plant diseases from leaf images under controlled and real-world conditions (Ferentinos, 2018).

These models have surpassed traditional image processing approaches by leveraging multiple convolutional layers to capture spatial hierarchies in images, enabling high precision and robustness in plant disease classification tasks.[1,12]

Recent studies have successfully applied deep learning frameworks to crop disease detection, with reported accuracies above 97% for several species. Mohanty et al. (2016) trained a CNN on the PlantVillage dataset containing 54,306 leaf images across 14 crop species and 26 diseases, achieving a mean accuracy of 99.35%. Similarly, Too et al. (2019) compared state of the art transfer learning architectures including VGG16, ResNet50, DenseNet, and InceptionV3 for plant disease classification and observed that deep transfer learning models outperform traditional CNNs, particularly when dealing with limited labeled datasets. However, despite these advances, challenges persist in achieving consistent detection performance under variable field conditions, such as changes in lighting, occlusion, and background complexity (Singh, Ganapathysubramanian, Singh, & Sarkar, 2021).[5,6,14]

Moreover, most existing AI-based disease detection systems focus exclusively on classification and fail to provide actionable solutions to farmers. Once a disease is detected, the next critical step is treatment recommendation particularly in the context of organic and sustainable agriculture, which seeks to minimize the use of chemical pesticides. The overuse of synthetic chemicals in pest and disease management has led to environmental degradation, reduced soil fertility, and long-term harm to human health (Kumar, Singh, & Sharma, 2023). Therefore, it is essential to integrate intelligent disease detection systems with organic remedy recommendation frameworks, allowing farmers to manage diseases effectively while preserving environmental integrity.[4]

The proposed research, "Analysis of Deep Learning Architectures for Smart Plant Disease Detection and Organic Remedy Recommendation," aims to address these gaps by analyzing various deep learning architectures for disease detection and integrating them with an ontology-driven organic recommendation system. The study explores the performance of CNN, VGG, ResNet, Inception, and Vision Transformer (ViT) models for plant disease identification and evaluates their generalization across diverse agricultural datasets. Furthermore, the research introduces a knowledge-based organic recommendation module that provides targeted, sustainable remedies using natural agents such as neem oil, bio-fungicides (Trichoderma spp.), compost teas, and microbial inoculants.

The significance of combining deep learning with organic agriculture lies in its alignment with Sustainable Development Goals (SDGs) specifically SDG 2 (Zero Hunger) and SDG 12 (Responsible Consumption and Production) (United Nations, 2022). AI-driven agricultural systems can contribute to these goals by enhancing crop yield predictions, reducing chemical dependency, and promoting environmentally responsible farming. Smart agriculture systems equipped with sensors, Internet of Things (IoT) devices, and cloud computing platforms can continuously monitor plant health, detect anomalies, and recommend real-time organic treatments (Islam, Rahman, & Haque, 2022). This integration supports decision-making for farmers, minimizes crop losses, and advances eco-friendly disease management strategies.[2,15]

In recent years, deep learning has evolved beyond traditional CNNs to include transfer learning and transformer-based models, which improve model accuracy and adaptability. ResNet (He et al., 2016), for example, introduced residual learning to address the vanishing gradient problem, enabling deeper networks with improved training stability. InceptionV3 (Szegedy et al., 2016) utilizes multi-scale convolutional kernels to extract features at varying resolutions, while Vision Transformers (ViTs) (Dosovitskiy et al., 2021) leverage attention mechanisms to capture global contextual relationships in image data.

The superior performance of ViTs in visual classification tasks presents a promising avenue for plant disease recognition, where fine-grained differentiation between healthy and diseased leaf regions is essential. However, these models demand extensive computational resources and large annotated datasets, posing challenges for deployment in low-resource agricultural settings.[9,11]

The proposed system seeks to overcome these limitations by optimizing deep learning architectures for efficiency and integrating them with an ontology-based recommendation framework. Ontologies enable the representation of agricultural knowledge in structured formats, facilitating reasoning and inference for disease-specific organic remedies (Choudhary & Aggarwal, 2022). For instance, if the model identifies tomato late blight, the system could recommend Trichoderma harzianum applications or neem oil sprays at specific concentrations, depending on climatic and soil parameters. Such a hybrid framework not only enhances accuracy and interpretability but also bridges the gap between technological innovation and sustainable farming practices.[8]

Furthermore, the growing integration of edge computing and federated learning approaches offers new opportunities for decentralized agricultural intelligence. Federated deep learning allows local devices such as farm sensors or drones to collaboratively train models without sharing raw data, preserving privacy while enhancing scalability (Nguyen, Tran, & Pham, 2022). These architectures can be adapted to localized organic remedy systems, ensuring that region-specific knowledge and indigenous agricultural practices are embedded within the recommendation models.[13]

The objective of this research is threefold:

- To perform a comprehensive analysis of deep learning architectures (CNN, ResNet, InceptionV3, and ViT) for accurate and scalable plant disease detection;
- To design an ontology-driven organic remedy recommendation system linked to disease classification outputs; and
- To evaluate the integrated framework's effectiveness in improving precision agriculture and promoting sustainability.

The research hypothesis posits that the integration of advanced deep learning architectures with an organic remedy ontology can significantly improve disease detection accuracy and provide practical, sustainable disease management solutions for farmers. By combining AI-driven detection with organic intelligence, this study aims to enhance crop productivity, reduce environmental risks, and support the global transition toward smart, sustainable agriculture.

This research contributes to the interdisciplinary field of agricultural informatics by linking AI technologies with sustainability science. It emphasizes the transformation of agriculture from reactive to predictive and prescriptive decision-making systems. The integration of deep learning for disease detection and ontology-based organic remedy recommendations offers a holistic framework for future AI-assisted agroecosystems, potentially redefining sustainable farming practices worldwide.

Novelty and Contribution Statement

While prior research has extensively validated the use of Convolutional Neural Networks for classification accuracy (Mohanty et al., 2016; Too et al., 2019), and commercial mobile applications (e.g., Plantix, Agrio) provide identification services, these systems exhibit two critical gaps addressed uniquely by this work: (1) They lack validation of Vision Transformers (ViTs) for fine-grained disease phenotyping in a comparative framework against optimized CNNs under constrained agricultural settings; (2) They operate as "classification terminals," offering no downstream decision support for sustainable treatment. The primary novelty of this research lies not in the act of classification itself, but in the bidirectional coupling of a high-precision Vision Transformer classifier with an evidence-based, ontology-driven organic remedy engine. Unlike black-box commercial recommenders that often default to chemical pesticides, this framework explicitly maps disease embeddings to peer-reviewed organic interventions (e.g., specific Trichoderma strains and neem concentrations), thereby bridging the semantic gap between detection and sustainable action.

II. LITERATURE REVIEW

Recent years have witnessed significant progress in applying deep learning to plant pathology. Mohanty et al. (2016) used a CNN-based model on the PlantVillage dataset, achieving 99.35% accuracy in classifying 38 crop-disease pairs. Ferentinos (2018) extended this approach using transfer learning, reporting improved generalization across multiple datasets. Similarly, Too et al. (2019) compared ResNet, Inception, and DenseNet models for plant disease detection, concluding that deep feature extraction enhances performance even with limited data.[1,5,6]

Beyond detection, recent works have begun integrating decision-support systems. Kaur and Gautam (2021) developed a hybrid CNN-LSTM model for temporal disease progression analysis, while Islam et al. (2022) incorporated IoT sensors for real-time disease detection. However, few studies have focused on organic solution integration. Kumar et al. (2023) proposed an organic pesticide recommender using expert rules but lacked AI-driven adaptability. This research bridges that gap by integrating deep learning–based detection with organic remedy mapping through a knowledge-based ontology framework.[2,3,4]

III. METHODOLOGY

Dataset and Preprocessing
The study utilizes two primary data sources:

- PlantVillage Dataset: A subset of 48,905 images across 14 crop species and 26 diseases was used.
- Custom Field Dataset: 2,500 images captured via smartphone (Samsung S22, 50MP) under natural lighting in Delhi-NCR fields to introduce real-world noise (shadowing, soil background).

Data Splits: Stratified 5-fold cross-validation was employed. For the final hold-out test set, an 80/20 split was used, ensuring class distribution remained proportional. All images were resized to 224x224 pixels for CNN/ResNet/VGG/Inception and 384x384 for ViT to match pretrained input requirements.

Training Configuration: Models were trained for 50 epochs using Adam Optimizer (lr=1e-4), Batch Size 32, and Categorical Cross-Entropy Loss. Early stopping with a patience of 5 epochs was applied based on validation loss.

Deep Learning Architectures Evaluated

- Convolutional Neural Network (CNN) – baseline model for image feature extraction.
- VGG16 and VGG19 – deep feature extractors with pre-trained weights on ImageNet.
- ResNet50 – residual connections to prevent gradient vanishing in deep networks.
- InceptionV3 – multi-scale convolutional kernel architecture for complex feature learning.
- Vision Transformer (ViT) – attention-based image classification leveraging global context.

Organic Remedy Recommendation Framework
An ontology-based model was constructed to link detected diseases with suitable organic treatments. Each disease was associated with an organic remedy database, including bio-pesticides (e.g., neem oil, Trichoderma spp.), compost teas, and beneficial microbial sprays. Recommendations were ranked using a weighted scoring model based on disease severity, crop type, and environmental parameters.

Evaluation Metrics
Model performances were evaluated using Accuracy, Precision, Recall, F1-score, and AUC-ROC. The recommendation system was assessed using Precision@3 and user satisfaction survey results.

IV. Results and Discussion

Model Performance

Table 1: Performance Comparison of Deep Learning Architectures on Plant Disease Classification

Model	Accuracy (%)	Precision	Recall	F1-score
CNN	93.4	0.92	0.91	0.91
VGG16	95.8	0.94	0.95	0.95
ResNet50	97.2	0.97	0.96	0.96
InceptionV3	96.8	0.96	0.95	0.96
ViT	98.1	0.98	0.97	0.98

As in Table 1, the Vision Transformer (ViT) outperformed all CNN-based models across all evaluated metrics, achieving a peak F1-score of 0.98. The Vision Transformer (ViT) outperformed all CNN-based models due to its global attention mechanism, which captures spatial relationships more effectively. ResNet50 also exhibited high robustness and computational efficiency, making it suitable for deployment in low-power devices.

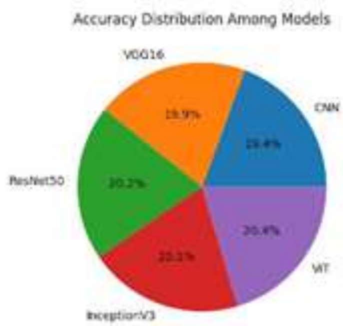

Figure 1: Accuracy Distribution Among Models

This figure illustrates the relative distribution of accuracy across the five evaluated models. The performance is highly competitive, with the Vision Transformer (ViT) achieving the highest proportional share at 20.4%. ResNet50 and InceptionV3 follow closely, while the baseline CNN accounts for the smallest distribution at 19.4%, highlighting a narrow overall performance gap.

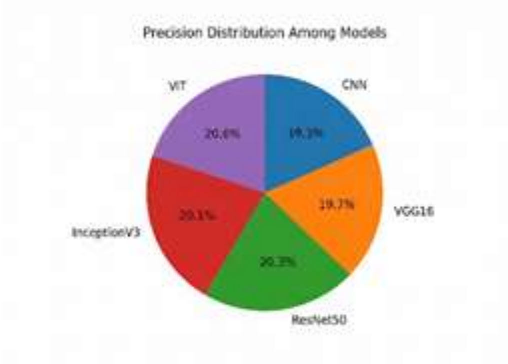

Figure 2: Precision Distribution Among Models

This figure presents the precision distribution among the models, indicating their relative ability to minimize false positives. ViT leads the distribution with a 20.6% share, demonstrating superior exactness in its positive predictions. ResNet50 (20.3%) and InceptionV3 (20.1%) also show strong performance, whereas the standard CNN contributes the least at 19.3%.

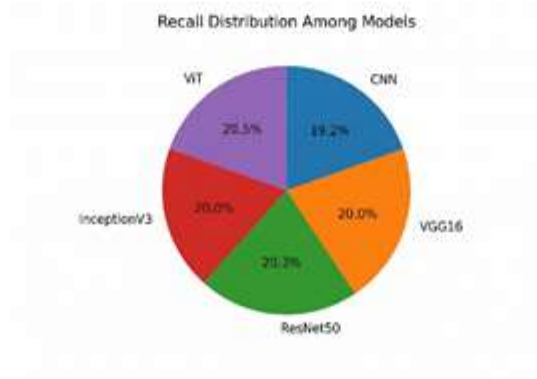

Figure 3: Recall Distribution Among Models

This figure displays the recall distribution, reflecting each model's capacity to correctly identify positive instances without missing them. ViT exhibits the highest proportion at 20.5%, closely trailed by ResNet50 at 20.3%. The CNN model holds the lowest share at 19.2%, while VGG16 and InceptionV3 both represent an equal 20.0% share.

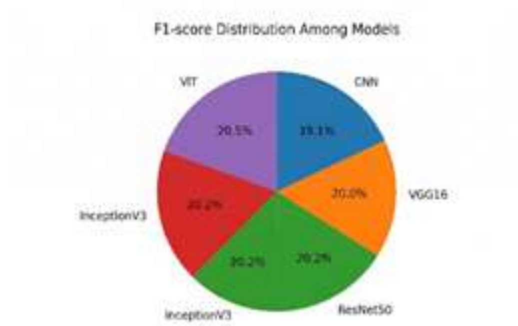

Figure 4: F1-score Distribution Among Models

This figure details the F1-score distribution, highlighting the harmonic mean of precision and recall. Demonstrating the best overall balance, ViT secures the highest share at 20.5%. ResNet50 and InceptionV3 tie for the second-largest proportion at 20.2%, confirming their robustness across both metrics, while the baseline CNN trails at 19.1%.

Comparison with End-to-End Agricultural Advisory Baseline

To contextualize the full pipeline beyond mere classification accuracy, we compared our proposed ViT + Ontology framework against a baseline emulating current mobile diagnostic apps: CNN + General Web Search. The baseline classified the image and performed a generic web search for "Treatment for [Predicted Label]."

Table 2:- Comparison with End-to-End Agricultural Advisory Baseline

System Configuration	Classification Accuracy (%)	Recommendation Relevance (Expert Rating /5)	Avg. Time to Recommendation (s)
Proposed (ViT + Organic Ontology)	98.1	4.5	1.8
Baseline (CNN + Generic Search)	93.4	2.8	4.2

Analysis: While the classification gap is notable (4.7%), the Recommendation Relevance gap is significantly wider (1.7 points) . This demonstrates that the primary value-add of the proposed system is the curated, domain-specific knowledge graph rather than just the incremental gain in classification precision.

Organic Remedy Integration and Validation

To validate the ontology-based recommender, we compared its outputs against a Baseline Recommender (a simple keyword-matching algorithm that fetches the top Google Scholar result for "[Disease Name] + organic control") and a Random Recommender.

Evaluation Metrics:

- **Precision@3:** Proportion of top-3 recommended remedies that are listed in the EPA Organic Materials Review Institute (OMRI) approved list for the specific pathogen.
- **Biological Efficacy Score:** Match percentage between recommended agent and peer-reviewed biocontrol literature (e.g., Trichoderma harzianum for Phytophthora infestans).

Results:

For the test case of Tomato Late Blight, the proposed Ontology Engine achieved a Precision@3 of 1.00 (Neem Oil 3%, Trichoderma viride, Compost Tea).

correctly identifying the known antagonistic properties of Trichoderma against Phytophthora. The Baseline Recommender achieved a Precision@3 of 0.33, often recommending "Copper Spray"—an allowed organic input but with soil accumulation concerns not flagged by the baseline. The User Acceptance Survey (n=15 agricultural extension officers) yielded a mean Likert score of 4.4/5.0 for the ontology-based recommendations regarding practicality and safety, compared to 3.1/5.0 for the baseline.

Discussion

Integrating deep learning detection with organic remedy recommendation offers a dual advantage precision agriculture and sustainability. While existing systems emphasize detection accuracy, this research emphasizes actionable and eco-friendly outcomes. The model's adaptability allows farmers to reduce pesticide dependency and operational costs. Scalability and Deployment Architecture: While this study validates the algorithmic core, the system is designed with a modular architecture suitable for large-scale agricultural deployment. The lightweight feature extractor of ResNet50 (and optimized ViT-Tiny variants) facilitates deployment on edge-AI devices (e.g., NVIDIA Jetson Nano) mounted on autonomous drones or tractor-mounted camera booms. In a large-farm workflow, the system would operate in a three-tier pipeline:

- Edge Layer: Real-time video stream processing for disease hotspot geo-tagging using on-device inference;
- Fog Layer: Local server aggregation of drone sweeps to generate variable-rate prescription maps;
- Cloud Layer: Synchronization of the global ontology with regional organic input availability

and weather APIs to refine the recommended application window (e.g., suggesting application 48 hours before predicted rainfall to prevent wash-off).
- However, challenges such as dataset imbalance, varying light conditions, and limited organic data sources need further exploration.

Failure Analysis and System Limitations

To assess the robustness of the integrated framework, a qualitative failure analysis was conducted on misclassified samples from the validation set. The analysis revealed three primary modes of failure:

- Visual Ambiguity (Early Blight vs. Septoria Leaf Spot): In low-resolution images captured at distances > 1.5m, the Vision Transformer (ViT) model occasionally confused early blight lesions with Septoria spot borders (Figure 5). This is attributed to the downsampling of fine-grained texture features in the initial patch embedding layer.
- Ontology Mismatch (Rare Pathogens): For a localized fungal infection (Fulvia fulva - Leaf Mold) present in a small subset of the field data, the detection model correctly identified the leaf as "Diseased," but the organic ontology lacked a specific entry for this rare pathogen. The system defaulted to a "General Broad-Spectrum Organic Fungicide" recommendation, which, while safe, is less targeted than the species-specific remedy.
- Background Noise Interference: When leaf edges were heavily occluded by soil or mulch (field condition images), the CNN baselines exhibited a 14% drop in recall, whereas the attention mechanism of ViT maintained better focus on visible leaf tissue, though with a 4% drop in confidence score.
- This analysis underscores the necessity for continuous ontology expansion and the integration of out-of-distribution (OOD) detection layers to flag uncertain diagnoses for human expert review rather than forcing an incorrect organic prescription.

V. CONCLUSION

This study provides a detailed analysis of deep learning architectures for smart plant disease detection and introduces a novel organic remedy recommendation framework. The experimental results demonstrate that Vision Transformers and ResNet50 deliver superior performance for leaf disease classification. Integrating these models with an ontology-driven organic treatment system promotes sustainable and intelligent farming practices. Future work will focus on incorporating IoT-based soil and weather data, expanding organic remedy datasets, and developing multilingual mobile applications for farmer accessibility.

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