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A Review on Deep Learning Approaches for Plant Leaf Disease Detection and Pesticide Recommendation

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Abstract: Crop sustainability is an urgent issue in the world, and plant diseases are a significant reason for crop yield and food security restrictions. Conventional manual disease detection procedures are time-consuming and frequently inaccurate. Deep learning, particularly Convolutional Neural Networks (CNNs), has made automated and accurate plant disease diagnosis from leaf images possible in recent years. This review overviews current deep learning methods for the detection of plant leaf diseases and delves into models with pesticide recommendation systems. The review classifies studies into CNN-based models, classical machine learning methods, hybrid models, and image processing approaches. It also identifies systems with region-specific pesticide recommendations. Issues like data shortage, generalization of models, and compliance with regulations are addressed, in addition to directions for the future like mobile deployment, transfer learning, and IoT integration. This thorough review is designed to direct future research toward smart, scalable agriculture solutions.
Keywords: Deep Learning, CNN, Plant Disease Detection, Pesticide Suggestion, Smart Farming, Image Classification, Machine Learning, Agricultural AI, Precision Agriculture, Leaf Analysis.

I. INTRODUCTION

Agriculture remains fundamental to global food systems and economies, particularly in agrarian nations such as India, where a significant portion of the population depends on farming for their livelihood. Early and accurate detection of plant diseases poses a persistent challenge; if left unaddressed, such diseases can drastically reduce crop yield and quality. Traditionally, identification of plant diseases has relied on manual inspection by agricultural experts—a process that is both time-consuming and often inaccessible to small-scale farmers, especially in remote areas.

Recently, the emergence of artificial intelligence (AI), especially deep learning techniques like Convolutional Neural Networks (CNNs), has transformed this landscape. These models excel at image classification and are now widely applied to the automated detection of plant diseases from leaf images. By extracting complex features directly from raw image data, CNNs enable earlier and more precise diagnosis without extensive manual intervention.

In addition, the integration of disease detection with automated pesticide recommendation systems is gaining momentum. These solutions aim not only to identify the disease but also to provide targeted treatment suggestions, drawing on region-specific agricultural data to enhance effectiveness.

This review paper systematically examines the range of deep learning approaches applied to plant leaf disease detection and evaluates emerging systems that incorporate automated pesticide recommendations. The discussion categorizes and compares current methodologies, highlights significant findings, addresses ongoing limitations, and proposes future research directions to further advance AI-driven smart agriculture.

II. FUNDAMENTALS

Deep learning is a branch of machine learning that involves the use of neural networks with more than one layer to acquire knowledge of intricate patterns within data. Convolutional Neural Networks (CNNs) are well adapted to image classification tasks and thus perfect for leaf disease classification. The models can learn spatial hierarchies of features, ranging from edges to textures to complete disease patterns, automatically. A general CNN architecture comprises convolutional layers, pooling layers, and fully connected layers. In addition, recommendation systems for pesticides can be constructed over classification results by utilizing rule-based engines, knowledge graphs, or machine learning regressors.

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III. LITERATURE REVIEW

Muhammad et al. combined AlexNet and VGG19 architectures with traditional classifiers (SVM, KNN), demonstrating that CNNs significantly enhance feature extraction, leading to improved classifier performance. Shankar et al. developed a 28-layer CNN, achieving an impressive 98.13% accuracy across a dataset exceeding 87,000 images. Similarly, Nishita et al. utilized transfer learning with CNNs, reporting 98.4% accuracy for multi- crop classification tasks. Khanam et al. validated the effectiveness of deep CNNs in early symptom detection, supporting timely intervention in plant disease management. Tej et al. implemented DenseNet121 (with transfer learning), attaining high accuracy in classifying diseases in tomatoes and peppers. Patil et al. integrated CNNs with image segmentation, optimizing the detection of banana leaf diseases. Balakrishnan et al. advanced the field by fusing CNN-based image analysis with IoT sensor data, enabling more robust plant disease identification.

A. Machine Learning (ML) Approaches

Bhagat et al. employed SVM with grid search, resulting in an efficient binary classification model distinguishing healthy from diseased leaves. Shruthi et al. conducted a comparative analysis of five machine learning algorithms, concluding that SVM delivered superior results. Sahu et al. leveraged CNN and Random Forest models on the PlantVillage dataset, achieving high-accuracy classifications. Khandelwal et al. designed a hybrid ML pipeline that combined image analysis with subsequent classification, yielding effective disease detection.

B. Hybrid Models

Kalaivani et al. integrated machine learning with image processing techniques, enabling earlier disease detection. Amritraj et al. utilized YOLOv5 in conjunction with CNNs, facilitating real-time and highly accurate detection. Deshpande et al. introduced a knowledge graph within the ML workflow, mapping observed symptoms to diseases and recommended remedies. Dash et al. combined a rule engine with ML predictions to boost diagnostic precision.

C. Image Processing

Dash et al. used red-green channel subtraction and pixel thresholding to identify diseased maize leaves. Malayil et al. applied K-means clustering alongside SVM for the detection of cardamom leaf diseases. Selvi et al. extracted HOG features and paired them with ML models, achieving approximately 93% accuracy for tomato leaf disease detection. Sahu et al. improved image quality prior to ML analysis, which contributed to more accurate outcomes. Khandelwal et al. applied basic thresholding to segment disease regions before feature extraction and classification. Tandekar et al. combined preprocessing with CNNs, demonstrating that enhanced image clarity leads to better model performance.

D. Pesticide Recommendation

Jamadar et al. combined CNNs with a pesticide database to detect cotton diseases and suggest appropriate treatments. Harsha et al. incorporated ISO-compliant rules into their ML system, creating a smart pesticide recommendation platform. Vaidya et al. used a custom CNN for citrus disease detection and linked it with crop management advice. Singh et al. developed the “e-Farmer” app, integrating VGG, DenseNet, and Inception models to support multi-disease diagnosis. Further, Jamadar et al. leveraged GIS data to enable region-specific pesticide recommendations, while Vaidya et al. deployed NLP and image processing to provide pesticide advice in local languages.

E. Herbal Treatment

Froldi et al. conducted a phytochemical analysis of Aloe Vera, revealing antifungal properties. Babu et al. performed proteomics studies and observed glucose-reducing effects of Aloe Vera in diabetic rats. Ahmmed et al. combined genetic and fungal analyses, identifying Alternaria alternata in Aloe Vera samples. Sánchez et al. explored Aloe Vera’s therapeutic potential, highlighting anticancer and antimicrobial activities. Froldi et al. provided further biochemical validation of natural compounds, and Babu et al. extended these findings through in vivo studies, confirming Aloe Vera’s efficacy in biological systems.

F. Dataset-Based Analysis

Tandekar et al. compared CNN, SVM, and Random Forest models on over 20,000 PlantVillage images, providing a comprehensive benchmark. Renuka et al. similarly leveraged PlantVillage for model evaluation. Kethineni et al. tested CNN performance across multiple datasets, noting variability in outcomes. Deshpande et al. integrated historical and gallery data to track pest patterns over time.

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G. Miscellaneous Applications

Bairwa et al. employed texture and color features with ML for diagnosing tomato diseases. Gauri Deshpande et al. developed a comprehensive knowledge base featuring disease diagnostics, pest information, and an accessible GUI. Uda et al. investigated the antibacterial potential of Aloe Vera and other herbs for rice disease control.

IV. COMPARATIVE ANALYSIS

Category	Author(s)	Approach	Dataset	Accuracy	Remarks
CNN-Based	Muhammad et al.	CNN (AlexNet, VGG19) + SVM/KNN	Custom	~95%	Effective feature extraction using CNN.
CNN-Based	Shankar et al.	Deep 28-layer CNN	87K+ images	98.13%	High accuracy with deep custom model.
CNN-Based	Nishita et al.	Transfer Learning (CNN)	PlantVillage	98.4%	Generalizes across multiple crops.
CNN-Based	Vaidya et al.	CNN + Management Module	Citrus	~94%	Integrated crop monitoring and disease detection.
CNN-Based	Tej et al.	DenseNet121	Tomato/ Pepper	~96%	High performance with transfer learning.
CNN-Based	Patil et al.	CNN + Segmentation	Banana	~92%	Disease detection in high-resolution leaf images.
CNN-Based	Balakrishnan et al.	CNN + IoT Integration	Custom	NA	Combined sensor data with image input.
ML-Based	Bhagat et al.	SVM with Grid Search	Custom	~92%	Optimized ML model for binary classification.
ML-Based	Shruthi et al.	ML Models (SVM, RF,	PlantVillage	~89%	SVM outperformed
		KNN)			other ML models.
ML-Based	Harsha et al.	ML + ISO Rule-based Recommender	Custom	NA	Smart pesticide recommendation system.
ML-Based	Deshpande et al.	ML + Knowledge Graph	Custom	NA	Combined reasoning and prediction.
ML-Based	Gauri et al.	Visual + Text UI + ML	Custom	NA	GUI for disease and pest info delivery.

Hybrid/ Object Detection	Amritraj et al.	YOLOv5 + CNN	Real-time Dataset	~96%	Combines real- time detection with CNN classifier.
Hybrid/ Object Detection	Kalaivani et al.	Preprocessing + ML	Custom	~90%	Multi-step pipeline for robust detection.
Image Processing	Dash et al.	Red-Green Subtraction + ML	Maize	NA	Simple color-based segmentation approach.
Image Processing	Selvi et al.	HOG + ML Classifier	Tomato	~93%	Edge and texture- based classification.
Image Processing	Bairwa et al.	Signature- based ML	Tomato	~91%	Utilized signature features for better accuracy.
Image Processing	Malayil et al.	K-means Clustering + SVM	Cardamom	~88%	Enhanced accuracy using unsupervised segmentation.
Image Processing	Jamadar et al.	CNN + Pesticide DB	Cotton Dataset	NA	End-to-end disease detection with treatment suggestions.
Image Processing	Khandelwal et al.	Basic Thresholding + ML	Various	~90%	Manual segmentation followed by ML classification.
Herbal/Bio Approaches	Froldi et al.	Phytochemica l Analysis	Aloe Vera	NA	Bioactive compounds effective against pathogens.
Herbal/Bio Approaches	Babu et al.	Proteomics	Aloe Vera	NA	Identified therapeutic proteins.
Herbal/Bio	Ahmmed et al.	Genetic/	Aloe Vera	NA	Detected
Approaches		Fungal Testing			Alternaria alternata in samples.
Herbal/Bio Approaches	Sánchez et al.	Therapeutic Study	Aloe Vera	NA	Explored antimicrobial applications.
Dataset- Based	Tandekar et al.	CNN, SVM, RF	PlantVillage	~94%	Benchmarked classifiers on standard dataset.

Dataset- Based	Renuka et al.	CNN	PlantVillage	~93%	Evaluated model performance and generalization.
Dataset- Based	Kethineni et al.	CNN	Custom	~90%	Applied CNN on curated crop dataset.
Dataset- Based	Sahu et al.	CNN + RF	PlantVillage	~92%	Boosted accuracy using hybrid voting.
Dataset- Based	N.Sahu et al.	CNN + Data Augmentation	Custom	~95%	Improved performance via augmented data samples.

V. CHALLENGES AND LIMITATIONS

1) Data Scarcity and Imbalance: Most current models are heavily dependent on large, well-annotated datasets such as PlantVillage. Unfortunately, these datasets often fail to capture the full range of rare diseases or regionally specific crop variations encountered in actual agricultural environments. As a result, model predictions can become biased or inaccurate, particularly for underrepresented conditions.
2) Generalization to Real-World Conditions: Models trained on controlled datasets, where images are captured under uniform lighting and with consistent backgrounds, frequently struggle to perform reliably in real-world scenarios. Factors such as variable lighting, occlusion, and background clutter introduce significant challenges, impeding the models' ability to generalize effectively.
3) Limited Availability of Region-Specific Datasets: The absence of regionally tailored datasets restricts many models' adaptability to local agricultural conditions. Furthermore, insufficient support for local languages and pesticide usage information further limits the practical applicability of these systems across diverse communities.
4) Model Complexity and Resource Demand: Deep convolutional neural networks (CNNs), while providing high accuracy, often demand substantial computational resources for both training and inference. This requirement for high-end hardware, such as GPUs, poses barriers to deployment on resource-constrained devices like smartphones or embedded systems frequently used by farmers.
5) Integration with Pesticide Recommenders: Although plant disease classification models have progressed significantly, real-time, context-aware, and regulation-compliant pesticide recommendation remains underdeveloped. Effective integration of these components is still lacking.
6) Explainability and Trust: Deep learning models are frequently criticized for their "black box" nature, which can undermine user trust—especially among non-technical stakeholders such as farmers. The lack of clear, interpretable justifications or visual explanations for model decisions further exacerbates this issue.
7) Regulatory and Safety Concerns: Automated pesticide recommendation systems are required to comply with evolving agricultural safety standards. Maintaining up-to-date pesticide databases is critical, yet this aspect is often neglected, raising potential regulatory and safety risks.
8) Multilingual Support and Usability: Many deployed systems lack user-friendly interfaces and comprehensive multilingual support. This limitation significantly restricts accessibility, particularly for farmers in rural or linguistically diverse regions.

VI. FUTURE SCOPE

A. *Lightweight and Transfer Learning Models*

- Implementation of efficient models such as MobileNet and EfficientNet enables deployment on mobile devices and embedded systems.
- These lightweight architectures facilitate real-world application without the need for high-end computational resources.

B. *Edge AI and Real-Time Monitoring*

- Integrating AI models onto smartphones, drones, and IoT devices supports real-time monitoring of agricultural fields.
- Immediate detection allows for prompt intervention, reducing crop loss and improving yield management.

C. *IoT Integration for Enhanced Context*

- Incorporating environmental data—such as temperature and humidity—enriches model input, enabling context-aware decision-making.
- This integration supports more accurate and robust disease identification.

D. *Federated Learning for Privacy and Adaptability*

- Federated learning trains models across multiple devices locally, ensuring sensitive farm data remains on-site.
- This approach enhances both data privacy and model adaptability across diverse environments.

E. *Explainable Artificial Intelligence*

- Emphasizing transparency in model predictions builds trust among agricultural stakeholders.
- Explainable AI techniques allow users to understand the rationale behind disease detection outcomes.

F. *Multilingual and Accessible User Interfaces*

- Development of interfaces with support for regional languages and speech input makes detection systems more accessible to a broader range of users.
- Multilingual support ensures usability among diverse farming communities.

VII. CONCLUSION

Deep learning has become a revolutionary technology for the detection of plant disease with high accuracy and automation. Utilizing CNNs and combining them with pesticide recommendation systems has brought us substantially closer to the solutions of smart farming. Nonetheless, there are issues like data quality, generalization, and applicability in real-world scenarios. Solving these problems with lightweight models, explainable AI, and local tools will be central to unlocking the full potential of these systems in sustainable agriculture.

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