A Comprehensive Analysis of Machine Learning and Deep Learning Approaches in Detecting Plant Disease Diagnosis

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Abstract

Plant diseases create major problems for agricultural production which threatens food security throughout the world [1], [11]. Current disease identification methods based on human interference face challenges because they consume time while depending on human decision and lack the ability to handle large number of samples. Detection of plant diseases through analysis of image has become possible because of recent machine learning (ML) & deep learning (DL) advancements which use convolutional neural networks (CNNs) for automated and correct disease identification [1], [4], [6]. The process of effective crop management needs identification as well as assessment of severity of disease and correct treatment protocols. The research provides an extensive evaluation of ML and DL methods which detect plant diseases and measure their severity and suggest appropriate treatments. The paper presents a general description of detection pipelines to establish the current state of detection methods while avoiding technical explanations of their operation. The review conducts a comparative analysis of previous research to determine vital knowledge deficits which stem from insufficient connections between disease identification and severity assessment and treatment guidance. The research demonstrates that agricultural decision-making requires deployable plant disease management systems which should operate as a single unified system.

Keywords: Generative AI, CNN, Deep Learning

1. Introduction

Agriculture plays the critical role of maintaining economic stability and providing food security. Plant diseases that result from fungal, bacterial, and viral pathogens cause major annual yield reductions throughout the world [1], [11], but this impacts the developing nations severely. The current disease detection methods depend on expert visual examination, which proves to be time taking and produces incorrect results and also cannot handle the needs of extensive agricultural farming systems.

Researchers used digital imaging devices and agricultural datasets to develop artificial intelligence (AI) methods that precisely perform automated plant disease analysis [4], [6]. Plant image analysis through machine learning & deep learning models allows doctors to find diseases at their beginning stages, which enables them to provide appropriate medical care. The technique of CNN has proven to be the most effective approach for image based disease classification [4], [9], [6].

The detection of diseases has become more accurate through research but farmers need to know both the extent of disease damage and which control methods will work best for their crops. Severity determines how much intense the disease has impacted,

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whereas treatment determines the cure of the disease. Research studies conduct individual investigations to study each of these elements. The review assesses current studies about plant disease detection techniques and disease severity evaluation and treatment recommendation systems to identify essential elements that require development for building complete plant disease management systems.

2. Machine Learning Approaches for Plant Disease Detection

Old detection systems for detecting plant disease use classical machine learning methods alongside traditional image processing techniques for their operations. The systems operate through a sequential process which starts with image preprocessing, followed by feature extraction, and ends with classification.

The preprocessing stage requires three fundamental operations, which include noise reduction , background segmentation and color normalization. The methods of feature extraction aim to identify visual characteristics which describe diseased areas through color descriptors and texture features including GLCM ,LBP and shape-based attributes [6], [11]. The classification process of these features occurs through Support Vector Machines ,k-Nearest Neighbors and Decision Trees [6] & shallow Artificial Neural Networks.

The methods achieve acceptable results when operating under controlled conditions, yet their dependence on handcrafted features makes them less reliable. The system produces various results based on how well the lighting conditions match the background elements and the specific symptoms which need to be identified. The current system limitations stop these systems from developing new functions because they cannot use their learned knowledge in real-world applications which drives researchers to adopt deep learning methods.

3. Deep Learning Approaches and CNN Architectures

3.1. CNN-Based Disease Detection

The dominant approach for plant disease detection now uses deep learning methods [12] which include CNN based architectures. This network learns to detect hierarchical features from unprocessed images which eliminate the need to design features manually. The system develops improved resistance to environmental changes and complex disease patterns.

In agricultural disease classification architectures like VGG, ResNet, Inception, DenseNet and EfficientNet [4], [6], [15] have been thoroughly tested [13]. The use of pretrained models along with transfer learning methods produces better results while shortening training time because there are not enough labeled agricultural datasets available. As per recent studies CNN-based models perform better than traditional machine learning methods in terms of accuracy and generalization [6], [4], [5].

3.2. Lightweight and Emerging Architectures

Recent research studies concentrate on creating lightweight CNNs and optimized architectures which deliver high accuracy through minimal computational resources for real-time and mobile applications [14], [17]. Research has investigated hybrid CNN transformer models which use attention-based mechanisms to obtain global contextual information [7] . These methods demonstrate potential but their application in full disease management systems has not reached a significant level of integration. Below Figure 1 shows pipeline for detecting diseases in plants.

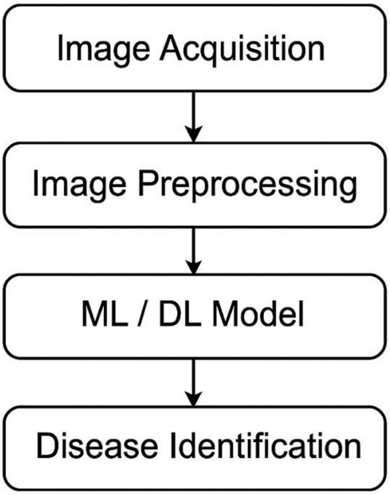


Fig. 1. Generic Plant Disease Detection

4. Comparative Study of Methods

4.1. Notation

- **True Positive (TP):** Cases where a diseased leaf is accurately identified as diseased.
- **True Negative (TN):** Cases where a healthy leaf is correctly recognized as healthy.
- **False Positive (FP):** Instances in which a healthy leaf is wrongly classified as diseased.
- **False Negative (FN):** Instances where a diseased leaf is mistakenly classified as healthy.

4.2. Evaluation Metrics

- **Accuracy**

Accuracy is calculated by dividing the sum of true positives & true negatives by the total number of samples, which includes true positives, true negatives, false positives, and false negatives. Accuracy shows how often the model makes the correct predictions overall.

- **Precision**

Precision = TP /(TP + FP)

indicates the fraction of plants that were diseased among all those predicted by the model to be diseased.

- **Recall (Sensitivity)**

Recall = TP / (TP + FN)

Recall measures the ability of the model to correctly detect diseased leaves out of all diseased samples.

- **F1 Score**

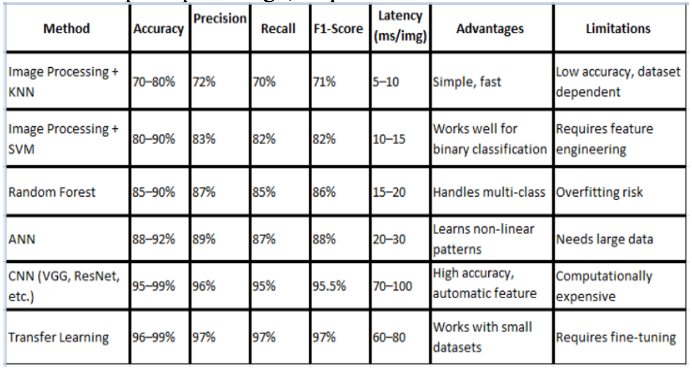
F1 = 2 * TP / (2 * TP + FP + FN)

Balances precision and recall, used for imbalanced datasets.

- **Latency**

Latency = t_end - t_start

Measures inference speed per image, important for real-time use.



Method	Accuracy	Precision	Recall	F1-Score	Latency (ms/img)	Advantages	Limitations
Image Processing + KNN	70–80%	72%	70%	71%	5–10	Simple, fast	Low accuracy, dataset dependent
Image Processing + SVM	80–90%	83%	82%	82%	10–15	Works well for binary classification	Requires feature engineering
Random Forest	85–90%	87%	85%	86%	15–20	Handles multi-class	Overfitting risk
ANN	88–92%	89%	87%	88%	20–30	Learns non-linear patterns	Needs large data
CNN (VGG, ResNet, etc.)	95–99%	96%	95%	95.5%	70–100	High accuracy, automatic feature	Computationally expensive
Transfer Learning	96–99%	97%	97%	97%	60–80	Works with small datasets	Requires fine-tuning

Fig. 2. Comparative analysis

From the comparison table (Fig. 2.) above, it is observed that classical machine learning methods (KNN, SVM, Random Forest) provide reasonable accuracy but are limited in handling large, complex, and real-world datasets. Artificial Neural Networks (ANNs) generate better results but they need large amount of training data. Convolutional Neural Networks (CNNs) & Transfer Learning models perform better than traditional methods, achieving accuracies over 95%. The systems require good processing power along with large amount of data. Fig. 3., Fig. 4., Fig. 5. Shows the accuracy, Precision, recall and F1 Analysis, and Latency for different methods.

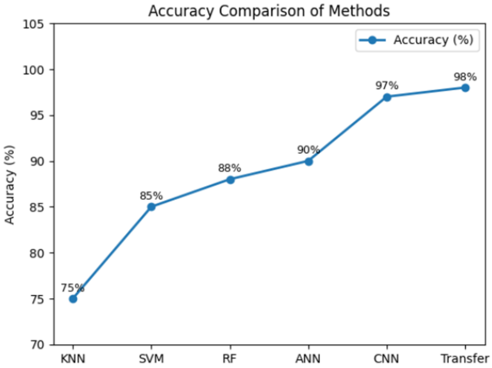


Fig. 3. Accuracy Comparison

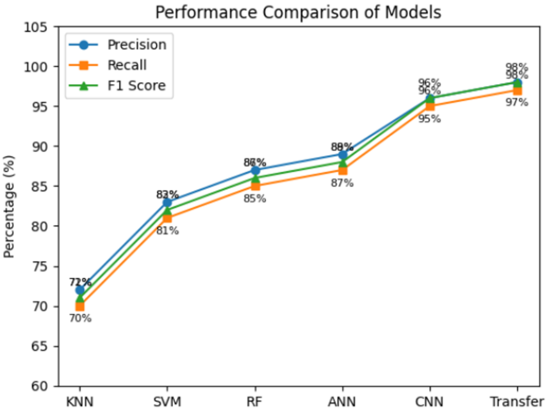


Fig. 4. Precision Recall and F1 Analysis

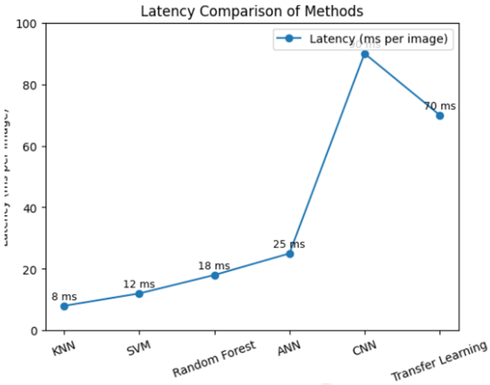


Fig. 5. Latency Comparison of Methods

5. Disease Severity Analysis

Analysis of disease severity helps doctors understand how severe the infection is which determines their choice of treatment methods. The process of disease classification identifies disease types, but severity estimation determines the extent of plant tissue damage.

Disease severity can be categorized into classification based and segmentation based methods [2] as depicted in Fig. 6. The classification based methods use discrete labels to identify disease severity which includes three categories of mild, moderate and severe [2]. Whereas segmentation based detects diseased areas before they calculate the ratio of infected area to the complete leaf structure [10].

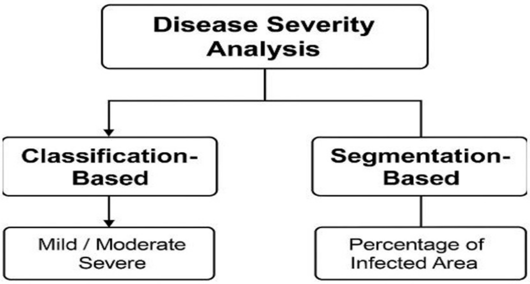


Fig. 6. Disease Severity Analysis Approaches

The current approaches to severity analysis encounter multiple problems that include different severity measurement standards and scarce datasets with severity information and different severity patterns between plant species and their development stages. The process of severity evaluation exists as an independent operation rather than integrated disease management systems [16].

6. Treatment Recommendation Systems

The main purpose of treatment recommendation systems is to offer specific recommendations which healthcare providers can use after they identify the disease.Existing systems use rule-based or knowledge-based mappings to link treatments or cure with disease labels [3], [8].

The systems prove their operational value, but they fail to consider the severity of diseases when they produce their suggestions. The treatment requirements for infections change substantially based on the severity of the infection which limits the ability of system to adapt. Development of treatment recommendation modules occurs separately from detection and severity analysis which leads to disconnected solution approaches.

7. Comparative Analysis of Existing Studies

Majority of research concentrate on individual component rather than integrated component for disease management. Fig. 7. is comparative analysis of it.

Research Focus	Detection	Severity	Treatment	Integration
Detection-centric studies	✓	✕ / Limited	✕	✕
Severity-focused studies	✓	✓	✕	✕
Treatment-oriented systems	✓	✕	✓	✕

Fig. 7. Analysis of Existing Studies

This comparison highlights below details:

- Detection centric studies mainly focus on identifying whether a problem exists but does not show how severe the issue is or how it can be treated.
- Severity focused studies further analyze how serious the detected problem is. Despite this improvement, they usually do not suggest treatment strategies.
- Treatment oriented systems emphasize providing solutions to the problem after it is detected, but donot show how severe the disease is and lack a unified framework that combines detection, severity, and treatment.

8. Identified Research Gaps and Motivation

The following research gaps are identified on reviewing the literature.

- Disease detection, severity analysis, and treatment recommendation are often addressed independently.
- Severity information is rarely incorporated into treatment decision-making.
- End-to-end, deployable plant disease management systems are limited [18].
- Practical usability and real-world deployment considerations are insufficiently explored.

The above gaps motivate the development of integrated, severity assessment plant disease management system that provide good support to farmers and agricultural professionals.

9. Conclusion

The research provides an extensive evaluation of machine learning & deep learning methods which identify diseases of plants & measure their severity and suggest appropriate treatments. The performance of disease classification has improved through CNN-based models, yet these models do not effectively integrate severity assessment and treatment suggestion functions. The review used comparative analysis to find essential research gaps which need additional study for developing successful plant disease management systems. The agricultural sector will achieve better AI solution performance when scientists resolve existing knowledge deficits which block their understanding.

References

[1] J. Liu and X. Wang, “Plant diseases and pests detection based on deep learning: A review,” *Plant Methods*, vol. 17, no. 22, 2021.

[2] A. Tuncer, S. Dogan, and M. Ozyurt, “Plant disease severity estimation using deep learning,” *Neural Computing and Applications*, vol. 33, pp. 1–15, 2021.

[3] R. D. G. Garcia and R. L. dos Santos, “Decision support systems for plant disease management: A review,” *Computers and Electronics in Agriculture*, vol. 175, 2020.

[4] A. Fuentes, S. Yoon, S. Kim, and D. Park, “Deep learning-based plant disease detection in real-field conditions,” *Sensors*, vol. 21, no. 1, 2021.

[5] M. Wang, Y. Li, and Z. Wang, “Multi-task deep learning for plant disease classification and severity estimation,” *IEEE Access*, vol. 9, pp. 128–141, 2021.

[6] R. K. Gupta, A. Kumar, and S. Bansal, “Vision-based plant disease detection using deep learning: A comprehensive review,” *Artificial Intelligence in Agriculture*, vol. 6, pp. 1–15, 2022.

[7] A. Akbar, M. Z. Islam, and J. Kim, “Explainable AI for plant disease diagnosis using deep learning,” *Expert Systems with Applications*, vol. 213, 2023.

[8] S. Mishra, R. Sachan, and P. Singh, “An integrated decision-support system for plant disease detection and treatment recommendation,” *Computers and Electronics in Agriculture*, vol. 214, 2024.

[9] H. Saleem, J. Potgieter, and K. Arif, “Plant disease detection and classification by deep learning,” *Plants*, vol. 8, no. 11, 2019.

[10] N. Ferentinos and C. Kastritis, “Deep learning-based severity estimation for crop disease management,” *Agronomy*, vol. 11, no. 7, 2021.

[11] A. Kamilaris, A. Kartakoullis, and F. X. Prenafeta-Boldú, “A review on the practice of big data analysis in agriculture,” *Computers and Electronics in Agriculture*, vol. 143, 2020.

[12] S. Mohanty, D. P. Hughes, and M. Salathe,“Using deep learning for image-based plant disease detection,”*Frontiers in Plant Science*, vol. 7, 2016.

[13] Y. Lu, S. Yi, N. Zeng, Y. Liu, and Y. Zhang, “Identification of crop diseases using deep convolutional neural networks,” *Neurocomputing*, vol. 267, pp. 378–384, 2017.

[14] J. Chen, L. Zhang, and Q. Wang, “Lightweight CNN models for real-time plant disease detection,” *IEEE Access*, vol. 10, 2022.

[15] M. Hasan, M. Uddin, and M. Lee, “Transfer learning-based CNN for plant disease recognition,” *Applied Sciences*, vol. 10, no. 18, 2020.

[16] A. R. Singh and S. Verma, “Severity-aware plant disease diagnosis using deep learning,” *Journal of Intelligent & Fuzzy Systems*, vol. 41, 2021.

[17] P. Jiang et al., “Attention-based deep learning for plant disease detection,” *Computers and Electronics in Agriculture*, vol. 192, 2022.

[18] K. Li, Y. Zhang, and H. Liu, “End-to-end deep learning frameworks for smart agriculture applications,” *IEEE Internet of Things Journal*, vol. 11, no. 2, 2024.