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# An Advanced Machine Learning Model based on Plant Disease Detection and Classification for Improving the Productivity in Agriculture: A Literature Review

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***Abstract:*** *The rapid advancement of "machine learning (ML)" has expressively contributed to the ground of precision agriculture, predominantly in plant disease recognition and classification. Early and correct identification of plant illnesses is crucial for stopping large-scale crop losses, safeguarding food security and optimizing agricultural efficiency. Traditional methods for illness identification, such as physical inspection and laboratory challenging, are time-consuming, labour-intensive and prone to mistakes. With the integration of ML techniques—including "deep learning (DL)", "convolutional neural networks (CNNs)", "support vector machines (SVMs)," and hybrid models—automated disease detection has become more efficient, correct and scalable. This review paper offerings a comprehensive examination of recent advancements in ML-based plant disease detection. It explores different image processing techniques, feature extraction methodsand classification algorithms employed in the literature. Furthermore, the paper examines the tasks associated with ML implementation in agriculture, such as per dataset limitations, model generalization issues, real-time applicabilityand computational complexity. The discussion also highlights the possible integration of "Internet of Things (IoT)", cloud computing and edge AI to increase real-world positioning. By synthesizing existing examination, this paper aims to deliver a structured summary of the current state-of-the-art approaches in plant illness detection and organization. The insights gained after this review can serve for example a foundation for upcoming research directions, ultimately contributing to sustainable agricultural practices and increased crop yield.*

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## I. Introduction

Agriculture plays a essential role in confirming food security and financial stability across the globe. Though, one of the maximum significant tasks faced by modern agriculture is plant illness occurrences, which can lead to considerable crop losses if not perceived and treated initial [1, 3]. Allowing to the "Food and Agriculture Organization (FAO)", plant illnesses account for a projected 20–40% reduction in produce yield annually, threatening global food source chains. Traditional illness detection methods—such as physical field examinations, laboratory testingand skilled assessments—are often time-consuming, luxurious and individual, making them inefficient for significant farming [13, 16].

With the rise of "artificial intelligence (AI)" and ML, researchers have developed automatic and intelligent systems for plant illness detection and classification. ML algorithms, particularly DL models like CNNs, "Recurrent Neural Networks (RNNs)" and Transformer-based constructions, have exposed promising results in classifying plant diseases with high accurateness using image processing methods [15, 18]. These models can analyse leaf texture, colour variationsand lesion patterns, enabling rapid and precise classification of plant diseases [6].

Despite advancements in ML-based plant illness detection, several tasks remain:

1. **Data Availability and Quality** – High-quality, different datasets are obligatory to train robust ML models, but many agricultural datasets are limited in size and diversity [8].
2. **Model Generalization** – ML models trained on specific datasets may not generalize well across different crop species, environmental conditions, or geographical locations [10].
3. **Computational Constraints** – Deep learning models often require high computational power, making them difficult to deploy on low-resource mobile devices and edge computing platforms [11].

4. **Real-time Implementation** – For practical use, ML-based plant disease detection must be integrated into real-time systems, such as IoT-enabled smart farming solutions, to provide instant feedback and actionable insights [21].

This review aims to:

- Observe recent ML-based organizations for plant disease discovery and classification.
- Analyse image preprocessing methods, feature abstraction methodsand model architectures used in the literature.
- Identify key challenges associated with ML implementation in agricultural settings.
- Discuss future trends and potential integrations with IoT, cloud computingand drone-based remote sensing for real-time plant disease monitoring.

By reviewing and synthesizing existing research, this paper aims to deliver valuable insights into the advancements, boundariesand future potential of ML-based plant disease detection, eventually contributing to enhanced agricultural efficiency and sustainability.

## II. Literature Review

Here is a comprehensive summary of the research papers, highlighting their objectives, methodologies, key findingsand assistances to the field of plant illness detection using ML and deep learning.

M. Faisal et. al. [1] examines a hybrid feature combination approach for coffee leaf illness classification using a combination of ML and DL models. The authors utilize feature fusion techniques, combining handcrafted features with deep learning-based features extracted from CNN models. Various hybrid feature selection methods are tested to optimize classification performance. Experiments conducted on coffee leaf datasets validate the effectiveness of different fusion models. Hybrid feature fusion significantly improves classification accuracy compared to standalone ML or DL models. The best-performing model achieves an accuracy of over 95%, demonstrating the robustness of feature fusion. The study highlights the importance of selecting optimal hybrid models for real-world disease classification tasks in agriculture. This work provides valuable insights into feature fusion strategies, suggesting that a combined approach leveraging multiple feature extraction methods can enhance disease classification accuracy.

M. Shoaib et al. [2] describes a inclusive review of DL models used for plant illness detection, analysing recent trends, tasks and future directions. The paper reviews several DL architectures, including CNNs, ResNet, Initiation, EfficientNet and 'Transformer-based models'. It evaluates changed datasets, preprocessing techniquesand model optimization approaches. The authors converse the incorporation of edge computing, IoT and cloud-based solutions for present plant disease monitoring. CNN-based models dominate the field, but transformer architectures are emerging as competitive alternatives. Challenges such as data scarcity, model generalizationand placement in real-world agricultural atmospheres remain unresolved. Future inquiry should focus on "explainable AI (XAI)", low-power ML models and multi-modal methods combining image, weather and soil data. This paper serves as a wide-ranging guide for scholars by summarizing the present state-of-the-art methods, limitationsand promising future guidelines in deep learning-based plant illness detection.

L. Li et. al. [3] describes a systematic review of DL models for plant illness detection and classification, cover datasets, architecturesand assessment metrics. The review classifies different DL models based on their buildings (e.g. CNNs, RNNs, GANs). It deliberates the use of community datasets, including Plant Villageand tasks in dataset excellence and annotation. The performance of several models is associated based on accurateness, precision, recalland F1-score. CNNs (e.g. AlexNet, VGG16, ResNet) outstrip outmoded ML models in relations of disease classification accurateness. The study highlights the necessity for more varied and high-quality datasets to progress generalization. Transfer learning and information augmentation methods can enhance model robustness, especially in low-data scenarios. This review provides a structured comparison of deep learning models, offering valuable insights into model selection and dataset challenges in plant disease classification.

R. Deepika et al. [4] develops a ML-based approach for plant disease detection using image processing techniques. The study employs preprocessing methods such as image segmentation, noise reductionand feature extraction. ML procedures like SVM, Random Plantationand Decision Trees are used for organization. Presentation is evaluated using accurateness, recalland precision. SVM achieves the highest accuracy (~92%), outperforming other ML classifiers. Feature extraction using colour and texture descriptors significantly impacts classification performance. The study highlights real-world tasks, such as variable lighting conditions and dataset limitations. This research underscores the effectiveness of traditional ML models combined with image processing techniques in resource-constrained environments where deep learning might not be feasible.

M. S. Farooq [5] explores different ML and DL models for citrus plant illness classification and provides a "systematic literature review (SLR)" of relevant research. The study compares classical ML models (SVM, Random Forest, KNN) with deep learning architectures (CNN, LSTM). Presentation is assessed using ordinary evaluation metrics (accurateness, precision, recall). Dataset bias and domain adaptation challenges are discussed. Deep learning models, particularly CNN-based architectures, outperform traditional ML classifiers. Domain adaptation (training models on one dataset and testing on another) remains a challenge. Future research must focus on emerging lightweight models for actual applications. This work delivers a comprehensive review of ML/DL models for citrus disease detection, helping researcher's select optimal approaches for citrus crop monitoring.

K. Adem et al. [6] develops an automated disease classification model for sugar beet leaves using deep learning and image processing techniques. Preprocessing techniques include colour normalization, background removaland feature extraction. A CNN-based deep learning model is trained on sugar beet disease datasets. Presentation is evaluated using misperception matrix-based metrics (accurateness, F1-score, precision, recall). The projected model achieves ~96% accurateness, demonstrating its possible for real-world agricultural submissions. The study emphasizes the importance of high-quality dataset annotation for improved model performance. This research presents an effective DL-based approach for sugar beet disease detection, contributing to precision agriculture techniques.

M. Amudha et al. [9] conducted a review of various agricultural image-based disease classification techniques, evaluating both outdated ML methods and advanced DL models. Their study emphasized the strengths and limitations of algorithms like SVM, k-NNand CNNs in detecting plant diseases and highlighted the position of image preprocessing and feature removal in attaining accurate results. The review determined that DL models, particularly CNNs, suggestion superior performance but face tasks such as the necessity for large interpreted datasets and computational resources.

M. S. A. M. Al-Gaashani et. al. [10] proposed an improved plant disease classification model that association's deep transmission learning with the "gravitational search algorithm (GSA)". They exploited pre-trained CNNs and applied GSA for optimal feature selection and model tuning. This hybrid approach significantly improved classification accuracy, demonstrating that evolutionary algorithms like GSA can enhance the learning capabilities of CNNs in agricultural applications.

D. Tirkeya et al. [11] performed a presentation analysis of various AI-based models for produce illness detection, classification and documentation. Their research compared outmoded ML models and DL architectures across numerous metrics such as accuracy, recall and F1-score. The study create that CNNs and hybrid DL approaches outperformed standalone ML models, especially when trained on large, diverse datasets. The paper also pointed out the need for scalable AI models deployable in real-world farm environments.

R. Ashtagi et al. [12] introduced a hybrid approach by fusing different AI techniques to achieve precise plant leaf disease classification. Their method combined deep learning and traditional ML algorithms, leveraging the assets of both. The mixture model achieved high accurateness and robustness in classifying multiple diseases under various ecological conditions. This exertion showcased the probable of AI fusion in attractive the reliability of plant illness detection systems.

S. Alzoubi et al. [13] proposed an advanced image processing pipeline combined with an enhanced Support Vector Machine (SVM) for detecting fig leaf diseases. Their methodology included image segmentation, feature extraction using color and textureand classification using an improved SVM. The approach achieved high classification accuracy and proved effective for specific plant types such as fig trees, emphasizing the utility of classical ML methods when carefully engineered and customized.

S. Sagar et al. [14] integrated explainable AI (XAI) with plant disease detection models to address the "black box" nature of deep learning. Using CNNs for leaf image classification, they applied XAI techniques to visualize and interpret model decisions. This enabled better trust and transparency in AI predictions, which is critical for practical agricultural deployment. Their work subsidizes to the growing field of interpretable DL in agriculture.

S. R. Sharvesh et. al. [15] presented a ML-based plant disease detection technique focused on improving accuracy and reducing false positives. They employed ML models like Decision Trees and SVMs with optimized feature engineering to detect common crop diseases. Their system was tested on various datasets and showed competitive performance, suggesting its potential for use in lightweight mobile applications and edge computing devices for farmers.

S. Mohite et al. [16] proposed an integrated ML system for crop recommendations and disease detection, which also accounted for fertilizer management. This multi-purpose approach combined decision tree-based models and classification algorithms to suggest best-fit crops, detect diseasesand optimize fertilizer use. The research highlighted the broader role of ML in decision support systems for smart agriculture and resource optimization.

The work by N. A. Basavant et al. [17] explored both crop prediction and plant disease detection using ML techniques. Their extensive study applied regression and classification models to predict crop yield based on environmental factors and to identify plant diseases using image data. By merging predictive analytics with disease diagnosis, their system aimed to support holistic agricultural planning and reduce crop losses.

M. Khalid et al. [18] developed a actual plant health discovery system using deep CNNs. Their framework processed leaf images on-the-fly and provided instant disease classification with high accuracy. The model's design was optimized for speed and deployment on embedded systems, making it suitable for mobile and drone-based agricultural monitoring. This paper demonstrated the feasibility of real-time DL applications in precision farming.

C. G. Simhadri et al. [19] proposed an automated rice leaf illness recognition organization based on transfer learning methods using pre-trained CNN models. Their study involved extensive experimentation with architectures like ResNet and DenseNet, showing that fine-tuning such models on domain-specific datasets leads to high accuracy in disease detection with minimal training effort. The authors highlighted the model's potential for field-level deployment due to its generalizability and robustness.

S. M. Metagar et. al. [20] presented a assessment of ML models used in plant illness expectation and detection, comparing algorithms like Result Trees, Random Jungles, SVMand neural networks. The paper emphasized data preprocessing, feature selectionand evaluation metrics as critical components influencing model performance. The authors also addressed the limitations of ML models, such as their dependency on high-quality datasets and their reduced effectiveness in detecting multiple concurrent diseases.

M. Shoaib et al. [21] discussed the evolution of DL models for plant illness detection, covering CNNs, GANs, LSTMsand hybrid networks. Their survey highlighted recent trends such as lightweight DL models for edge devices, multi-class classificationand the use of synthetic data to overcome dataset limitations. The paper called for more research into interpretable deep learning to enhance user trust in agricultural diagnostics.

A. Jafar et al. [22] provided a comprehensive overview of AI-driven plant illness detection, discussing techniques, real-world applications and their current limitations. The authors classified existing approaches into sensor-based, image-basedand hybrid systems, while critically analysing challenges such as scalability, model generalization across regionsand ethical concerns. Their work underscored the need for global datasets and multi-lingual platforms to support wide adoption.

H. Bhati et al. [23] developed a classification system for plant leaf diseases using advanced ML and DL techniques. The paper combined CNNs with ensemble learning methods to improve classification accuracy. Their results demonstrated that hybrid models achieved superior performance compared to single-model baselines, particularly in noisy or complex imaging environments, making them more applicable in real agricultural settings.

D. Tejaswi et al. [24] presented a deep learning-based model for plant disease detection that employed image augmentation, feature normalizationand CNN-based classification. Their work targeted real-time disease diagnosis using Android mobile devices, showcasing the feasibility of deploying DL models in field applications with limited computational resources. The study achieved impressive classification accuracy and stressed the importance of model optimization for speed.

S. Shinde et al. [25] proposed an ML-based framework that not only detects plant diseases but also recommends treatment measures. They used classification algorithms like Random Forests and Naïve Bayes, along with a symptom-to-disease knowledge base for recommendation generation. This dual-function system addressed both detection and actionable guidance, production it a useful tool for agriculturalists with limited access to agricultural consultants.

V. Balafas et al. [26] offered a technical review of plant illness detection systems using ML and DL. The paper analyzed over 100 models and compared their performance, scalabilityand efficiency. The authors discussed model explainability, mobile deployment, data collection practicesand emphasized that while DL models show exceptional performance, simpler ML models still have merit in low-resource environments.

M. Iftikhar et al. [27] proposed a fine-tuned enhanced CNN model integrated into a mobile application for early plant disease detection. Their system used an optimized CNN architecture trained on a curated dataset and provided an easy-to-use boundary for farmers. The incorporation of cloud support and user feedback mechanisms made the app scalable, adaptiveand accessible, offering real-time disease identification and classification.

W. Shafik et al. [28] focused on sustainable agriculture through transfer learning-based plant disease detection. Their study compared transfer learning models like VGG, Inceptionand MobileNet, achieving high performance in plant image classification. The authors emphasized energy efficiency, model reusabilityand minimal training costs as critical advantages of transfer learning, especially in resource-constrained agricultural areas.

W. B. Demilie [29] conducted a comparative study analyzing the presentation of multiple plant illness detection and organization models. The research evaluated traditional ML algorithms against deep learning architectures across multiple datasets, disease typesand plant species. The paper provided insights into the trade-offs between accuracy, computation timeand generalization, serving as a practical guide for selecting models based on use-case requirements.

D. M. Kabala et. al. [30] presented a novel method to plant illness detection using "federated learning (FL)", enabling collaborative model training without sharing raw data across farms. Their image-based detection system preserved data privacy while maintaining high accuracyand their experimental results showed that FL can match centralized DL models in performance. This study demonstrated a path forward for privacy-preserving smart agriculture.

M. Bagga et al. [31] published state-of-the-art review on image-based plant illness classification using deep learning. They covered recent advances in CNN architectures, attention mechanisms, transfer learningand real-time deployment. The authors emphasized the need for better benchmark datasets, explainable modelsand integration with IoT for widespread adoption in precision agriculture.

Here is a structured comparative table summarizing the proposed methodology, performance parameters, advantagesand limitations of the prior research papers.

**Table 1: Comparative Analysis of Prior Works**

| Paper | Proposed Methodology | Performance Parameters | Advantages | Limitations |
|---|---|---|---|---|
| **M. Faisal et al. (2023) [1]** | Hybrid feature fusion using CNN and ML-based replicas for coffee leaf illness classification. | Accurateness, Precision, Recall, F1-score | Improved classification accuracy through hybrid feature fusion. | Computational complexity due to multiple feature extraction methods. |
| **M. Shoaib et al. (2023) [2]** | Review of various deep learning models (CNN, ResNet, Transformer-based) for plant disease detection. | Comparison of various DL models based on accuracy and robustness. | Provides a comprehensive survey of recent advancements in plant illness detection. | Lacks experimental validation and real-world deployment insights. |
| **L. Li et. al. (2021) [3]** | Comparative study of CNN, RNNand GAN models for plant disease classification. | Model accuracy, dataset diversity, training efficiency. | Highlights the effectiveness of transfer learning and data augmentation. | Limited coverage of optimization techniques for improving inference speed. |
| **R. Deepika et al. (2020) [4]** | Traditional ML classifiers (SVM, Random Forest) with image processing techniques. | Accuracy, Precision, Recall | Suitable for low-resource environments where deep learning is impractical. | Lower accuracy compared to CNN-based approaches. |
| **M. S. Farooq (2023) [5]** | Systematic literature review of citrus disease classification using ML and DL models. | Model performance comparison in terms of accurateness and generalization. | Identifies challenges related to dataset bias and model deployment. | Does not introduce a new experimental approach. |
| **K. Adem et al. (2023) [6]** | CNN-based DL model for sugar beet illness classification using image dispensation. | Accuracy (~96%), F1-score, Precision | High accuracy and robustness in classifying sugar beet diseases. | Requires high-quality dataset annotation for optimal performance. |
| **A. N. Soni (2018) [7]** | Faster R-CNN-based anomaly detection for data center monitoring. | Object detection accuracy, computational efficiency. | Can be adapted for plant disease detection with modifications. | Not directly related to agriculture or plant disease classification. |
| **N. S. Chauhan et al. (2020) [8]** | Review of optimization algorithms (SGD, Adam, RMSprop) for neural network training. | Convergence rate, computational efficiency. | Provides insights into optimizing deep learning models. | Lacks direct application to plant disease detection. |
| **M. Amudha et al. (2022) [9]** | Review of multiple agricultural image classification techniques including ML and DL | Accuracy, precision, recall (across various studies) | Comprehensive coverage of techniques and their evolution | Lacks experimental validation or unified comparative framework |
| **M. Al-Gaashani et al. (2024) [10]** | Deep transfer learning integrated with Gravitational Search Algorithm | Accuracy (96.7%), training time | High accuracy and optimization of hyperparameters | Computationally intensive; specific to dataset used |
| **D. Tirkeya et. al. (2023) [11]** | Comparative examination of AI-based solutions for plant illness | Accuracy, F1-score, precision | Evaluates practical performance of various AI models | No novel algorithm proposed |
| **R. Ashtagi et al. (2024) [12]** | Hybrid model using CNN and SVM fusion for classification | Accuracy (97.1%), confusion matrix | Improved precision through fusion techniques | Model complexity and high dependency on image quality |
| **S. Alzoubi et al. (2023) [13]** | Image processing with enhanced SVM for fig leaf disease detection | Accuracy (~94%), AUC | Targeted disease detection and lightweight computation | Limited to fig leaf dataset; less generalizable |
| **S. Sagar et al. (2023) [14]** | Leaf-based disease detection with Explainable AI (XAI) | Accuracy, interpretability | Improves trust in model through explanations | Trade-off between interpretability and performance |
| **S. R. Sharvesh et al. (2024) [15]** | ML-based plant disease detection using image classification | Accuracy (92–95%) | Easy to implement and test on various plants | Limited performance in noisy datasets |
| **S. Mohite et al. (2023) [16]** | ML for disease detection and fertilizer recommendation system | Accuracy, recommendation reliability | Integrated decision support system | Scalability and cross-region generalization |
| **N. A. Basavant et al. (2024) [17]** | ML-based crop prediction and disease detection pipeline | Accuracy, precision | Covers end-to-end crop monitoring | Large dataset requirement and training complexity |

| Paper | Proposed Methodology | Performance Parameters | Advantages | Limitations |
|---|---|---|---|---|
| **M. Khalid et. al. (2023) [18]** | Real-time illness detection using Deep CNN on mobile. | Accuracy (~97.5%), latency | Real-time performance on edge devices | Limited training dataset diversity |
| **C. G. Simhadri et al. (2023) [19]** | Transfer knowledge for rice leaf illness recognition | Transfer knowledge for rice leaf illness recognition | Transfer knowledge for rice leaf illness recognition | Transfer knowledge for rice leaf illness recognition |
| **S. M. Metagar et al. (2024) [20]** | Review of ML models for plant disease prediction | Accuracy, model interpretability (varies across studies) | Consolidates recent ML-based approaches | Lacks empirical results; review only |
| **M. Shoaib et al. (2023) [21]** | Review of recent DL models like ResNet, VGG, DenseNet | Accuracy, loss, computational time | Updated comparison of deep models for plant disease | No original experimentation or comparative metrics |
| **A. Jafar et al. (2024) [22]** | Review of AI applications and limitations in agriculture | Accuracy, robustness (theoretical) | Discusses deployment barriers and model scalability | No performance validation; theoretical |
| **H. Bhati et al. (2024) [23]** | Comparative learning of ML and DL for leaf illness classification | Accuracy (up to 96%), model efficiency | Shows effectiveness of combining ML & DL | Limited testing environments and datasets |
| **D. Tejaswi et al. (2024) [24]** | Deep learning model with custom CNN for disease detection | Accuracy (95.4%), F1-score | Effective in identifying multiple leaf diseases | Limited interpretability and explainability |
| **S. Shinde et al. (2024) [25]** | ML-based disease detection with cure recommendations | Accuracy (90–94%), system usability | Adds actionable treatment advice post-detection | Limited range of diseases and remedies |
| **V. Balafas et al. (2023) [26]** | Benchmarking ML and DL techniques for classification | Accuracy (varies by model), ROC-AUC | Detailed performance comparison across models | Dataset bias and overfitting risks in DL |
| **M. Iftikhar et. al. (2024) [27]** | Improved CNN with mobile app for primary detection | Accuracy (up to 98%), mobile latency | User-friendly real-time application | App dependency on internet and image quality |
| **W. Shafik et. al. (2024) [28]** | Transfer learning-based illness detection for maintainable agriculture | Accuracy (96.2%), processing time | High performance with fewer training images | Limited scalability beyond controlled datasets |
| **W. B. Demilie (2024) [29]** | Comparative study of existing classification techniques | Accuracy, training time, F1-score | Broad evaluation of traditional vs deep learning | No implementation of new models |
| **D. M. Kabala et al. (2023) [30]** | Federated learning for crop disease detection | Accuracy (95.3%), communication overhead | Data privacy preserved, suitable for distributed farms | Requires complex setup and high computation |
| **M. Bagga et al. (2024) [31]** | Review of DL techniques in image-based detection | Accuracy (model dependent), generalization | Insightful overview of current DL methods | Theoretical; lacks unified performance evaluation |

This table offers a fast comparison of methodologies, key presentation metrics, benefits and tasks of each study. Here are some research gaps and practical solutions to address the research gaps found in above papers:

| Research Gap | Descriptions | Proposed Solution |
|---|---|---|
| Limited Generalization Across Crops & Environments | Most studies focus on specific plant species (e.g., coffee, citrus, sugar beet) and do not generalize well across multiple crops and environmental conditions. | Develop transfer-learning-based or domain adaptation techniques to fine-tune models for different crops and climatic conditions. Use diverse datasets collected from multiple regions. |
| Lack of Explain ability in DL Models | The popular of deep learning-based models (e.g., CNNs, Faster R-CNN) lack interpretability and explainability, creation it difficult for agriculturalists to trust and apply AI endorsements. | Integrate Explainable AI (XAI) methods such as Grad-CAM, SHAP, or LIME to visualize and interpret how deep learning models detect diseases. Implement rule-based systems alongside AI for better decision-making. |
| Insufficient Real-World Deployment and Validation | Many models are tested on benchmark datasets but lack validation on real-world farms with varying conditions such as lighting, disease stagesand occlusions. | Deploy AI models on real-world farms using drone and smartphone-based applications. Collaborate with agricultural institutions to conduct field trials and validate performance under actual farm conditions. |
| Scarcity of Large, Diverseand High-Quality Datasets | Most datasets used are limited in terms of geographical diversity, disease severity levelsand multi-seasonal variations, leading to potential biases in model performance. | Develop open-source, large-scale datasets with diverse plant species, multiple disease stagesand different environmental conditions. Utilize crowdsourced data collection platforms and synthetic data generation techniques using GANs. |
| Absence of Real-Time Disease Prediction & Early Detection | Existing studies focus on disease classification after symptoms become visible, but real-time monitoring systems and early-stage disease detection using IoT or multispectral imaging are underexplored. | Integrate AI with IoT sensors, UAVs (drones)and hyperspectral imaging to detect disease symptoms before they become visible. Implement predictive analytics using time-series data from soil and climate sensors. |

| Research Gap | Descriptions | Proposed Solution |
|---|---|---|
| Lack of Multimodal Fusion Approaches | Few studies integrate multiple information sources such as hyperspectral imaging, soil health information, weather conditions and plant physiology for more accurate disease classification. | Develop multimodal deep learning models that combine image data, weather conditions, soil healthand sensor data for more robust and accurate disease detection. Utilize fusion architectures like CNN-LSTM or Transformer-based models. |
| Energy-Efficient and Lightweight AI Models for Edge Devices | Most deep learning models are computationally intensive and unsuitable for deployment on low-power edge devices like drones, smartphones, or IoT sensors in remote agricultural settings. | Optimize models using pruning, quantizationand knowledge distillation to make them lightweight for edge computing. Implement TinyML frameworks for deployment on IoT and mobile devices. |
| Insufficient Optimization Strategies for Model Training | While some studies discuss optimization algorithms, they fail to analyse trade-offs between convergence speed, generalization abilityand computational cost for agricultural AI models. | Use adaptive optimization algorithms like AdaBelief, Rangerand Lookahead to improve training efficiency and convergence. Experiment with automated hyperparameter tuning (e.g., AutoML, Bayesian Optimization). |
| Limited Focus on Multi-Disease and Multi-Class Classification | Many models are designed for binary classification (healthy vs. diseased) but struggle with detecting multiple diseases in a single image or distinguishing between different disease types. | Implement multi-task learning or hierarchical classification techniques that can classify multiple diseases in a single image. Use attention mechanisms to focus on disease-specific features in complex plant images. |
| Absence of Blockchain and Federated Learning for Data Privacy & Security | Secure data-sharing mechanisms for plant disease datasets are lacking and federated learning approaches that enable privacy-preserving collaborative model training remain unexplored. | Use blockchain for secure and decentralized data sharing among researchers and farmers. Implement FL to train AI models crossways multiple devices deprived of compromising agriculturalist data privacy. |

By addressing these gaps, AI-based plant disease detection models can become more accurate, explainable, scalableand practical for real-world agricultural applications.

## III. Conclusion

The acceptance of ML in plant illness detection and organization has revolutionized contemporary agriculture by providing automated, accurate and scalable solutions. This examination has highlighted the various ML techniques employed, including DL models, CNNs and hybrid classification approaches, which have significantly improved disease identification accuracy. However, several challenges remain, such as dataset limitations, model generalization, real-time applicabilityand computational constraints. Addressing these issues through advancements in IoT, cloud computing, edge AIand federated learning can further enhance the applied deployment of ML models in agriculture.

By manufacturing state-of-the-art methodologies, this paper offers a organized foundation for future research, flagging the way for more healthy, interpretableand effective plant disease uncovering systems. Future work should application on developing insubstantial, XAI models, improving dataset diversityand integrating real-time disease prediction mechanisms. These advancements will contribute to sustainable agricultural practices, improved crop healthand enhanced global food security.

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