International Journal of Electrical, Electronics and Computer Engineering **14**(1&2): 79-82(2025)
ISSN No. (Online): 2277-2626

A Comprehensive Literature Review on Plant Leaf Disease Prediction using CNN

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(Received: 08 March 2025, Accepted: 14 April 2025)
(Published by Research Trend, Website: www.researchtrend.net)

ABSTRACT: A robust AI-driven system has been developed for the early detection and prediction of fungal diseases in various plants, addressing a key challenge in precision agriculture. High-resolution leaf images are analyzed using Convolutional Neural Networks (CNNs) to identify disease symptoms with high accuracy. Two leading CNN architectures, ResNet and AlexNet, were tested on a diverse dataset covering multiple climates and disease types, with AlexNet achieving a 94.72% accuracy. The results highlight the system's potential to provide farmers with timely insights, enabling rapid intervention to minimize crop losses. By facilitating proactive disease detection, this tool contributes to sustainable agriculture and a more resilient food supply chain.

Keywords: Artificial Intelligence, Plant Disease Detection, Deep Learning, Convolutional Neural Networks, Agricultural Innovation.

INTRODUCTION

Extensive research has explored the integration of artificial intelligence (AI) and machine learning in plant disease detection across various crops, emphasizing their potential to revolutionize precision agriculture. A comprehensive review was conducted on machine learning techniques for disease detection and classification, highlighting the significance of dataset quality, model robustness, and real-time applicability. Computer vision algorithms have been effectively utilized to analyze leaf images for automatic disease identification, demonstrating their potential to provide real-time insights that empower farmers by enabling early intervention and preventing disease spread. Further advancements in image processing and deep learning have led to the development of automated disease recognition systems that integrate machine learning algorithms, facilitating precise disease control and optimizing resource utilization in agricultural research and precision farming. Artificial neural networks have been trained on diverse datasets to classify multiple disease types with high accuracy, reinforcing their relevance in developing targeted disease management strategies (Upadhya & Kumar 2022). Convolutional Neural Networks (CNNs), in particular, have proven to be highly effective in plant image analysis, aiding in disease prediction and prevention while supporting innovation in agri-tech startups focused on sustainable farming solution. The importance of high-quality and diverse datasets has also been underscored, as well-curated datasets enhance CNN model accuracy and generalization across different plant species and environmental conditions (Garg & Singh (2023). These advancements contribute significantly to large-scale crop protection initiatives, assisting government programs in safeguarding agricultural yields. This body of research forms the foundation of the Plant Disease Prediction System developed in this g study, leveraging CNN architectures such as ResNet and AlexNet to improve detection accuracy and ensure a more resilient food supply chain.

RELATED WORK

In recent years, the application of Convolutional Neural Networks (CNNs) in plant disease detection has garnered significant attention. Several studies have explored various CNN architectures and methodologies to enhance the accuracy and efficiency of disease identification in plants.

Deep learning models to assess plant disease detection, achieving an accuracy of 99.53% in identifying diseases in 25 different plant species (Ferentinos, 2018). A CNN-based approach for plant leaf disease detection, achieving high accuracy in identifying multiple diseases across various plant species (Militante *et al*., 2019).

A CNN-based approach for leaf disease detection, achieving an accuracy of 92.23% in classifying various plant diseases, underscoring the potential of machine learning in agricultural innovation (Guo, 2016).

A created a bacterial blight detection method for pomegranate plants in 2019 utilizing variable, correlation, entropy, and edges (Sharath and collegues 2019). CNN models to identify and diagnose plant diseases from leaf images, achieving a disease-classification accuracy rate of up to 99.56%, outperforming traditional handcrafted-feature-based methods (Picon *et al.,* 2019). Explored deep-learning approaches for plant identification and disease classification from leaf images. They proposed a new model named Generalized Stacking Multi-output CNN

(GSMo-CNN), achieving state-of-the-art performance on benchmark datasets (Yao *et al*., 2021). A multi-plant disease diagnosis method using CNNs, focusing on a multi-label classification approach to identify both the plant and the type of disease simultaneously. Their model was tested on leaf images of six plants, including tomato, potato, rice, corn, grape, and apple, demonstrating the effectiveness of architectures like Exception and DenseNet in multi-label plant disease classification tasks (Kabir *et al*., 2021).

A disease recognition model supported by leaf image classification using CNNs, effectively detecting plant diseases and emphasizing the importance of image processing in disease identification (Shelar *et al*., 2022). Research has been conducted on hybrid models, such as combinig CNNs with Long Short-Term Memory (LSTM) networks. This aim to leverage the spatial features extraction capabilities of CNNs and the tempory dependency modelling of LSTMs (Gopinath *et al*., 2023). Introduced a novel CNN-based model for the detection of tomato and corn leaf diseases. Their approach involved training CNNs with architectures like Inception-V3, DenseNet-121, ResNet-101-V2, and Xception on a newly created plant disease image dataset, achieving a validation accuracy of 95.08% for tomato and 92.21% for corn using the Xception model (Yasin and Fatima 2023). An advanced technique for tomato leaf disease detection and classification, utilizing insights from the latest pretrained CNN models. They introduced a sophisticated approach within the domain of tensor subspace learning, known as Higher-Order Whitened Singular Value Decomposition (HOWSVD), achieving accuracy scores of up to 98.36% on the Plant Village dataset (Ouamane *et al*., 2023).

ANFIS Fuzzy convolutional neural network model for leaf disease detection- "This research is focusing on the use of ANFIS Fuzzy convolutional neural network (CNN) integration with local binary pattern (LBP) features (Frontiers, 2024). These studies collectively highlight the advancements in applying CNNs for plant disease detection, demonstrating the potential for improved accuracy and efficiency in agricultural diagnostics.

Table 1: Comparative study of existing techniques.

Authors	Techniques Used	Objective	Performance Metrics	Dataset	Simulation Outcomes
Upadhya & Kumar (2022)	Otsu's thresholding	Develop a Robust Detection System, Noise Removal for Improved Accuracy, Enhance Precision Agriculture	Accuracy, Precision, Recall, and F1-Score	4000 rice leaf sample	99.7% accuracy
Alalakh *et al.* (2022)	hybrid approach: CNN, Convolutional Block Attention Module, Support Vector Machine (SVM)	Improve Disease Detection Accuracy, Enhance Feature Learning, Lightweight Model for Real-World Deployment	Accuracy, Precision, Recall, and F1-Score	Ranging from 100 to 1000 of samples	97.2% accuracy
Paulos &Woldeyohannis (2023)	Training from Scratch, Transfer Learning (TL) MobileNet, ResNet50	Improve Disease Detection, Leverage Augmented Datasets, Evaluate Deep Learning Models,Optimize Accuracy	Training-fromscratch, Transfer Learning: MobileNet, ResNet50	mixture dataset	Training-fromscratch: 98.5% accuracy. Transfer LearningMobileNet: 97.01% accuracyResNet50:
Garg & Singh (2023)	triplet and crossTntropy loss with MobileNetV2	Enhancing Feature Representation, Leveraging Lightweight Architectures, Improving Classification Accuracy	MobileNetV2 architecture was employed for feature extraction, with the aggregated loss function (combining triplet loss and crossentropy loss) used for optimization.	Plantdoc Dataset Size: 2,598 samples	Accuracy improvements of: 1.49% on split-1 16.25% on split-2 2.9% on split-3 2.1% on split-4 (PlantVillage dataset).
Frontiers (2024)	Fuzzy Logic (ANFIS), Deep learning	Develop the ANFIS Fuzzy convolutional neural network	Accuracy, Precision, Recall, F1-Score, Confusion matrix	Ranging from 100 to 10000 of samples	98% accuracy

RESEARCH GAP

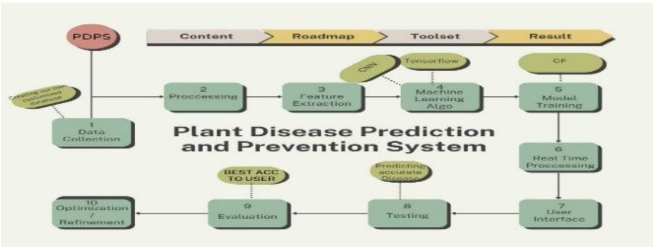
Research Gap Identified. This literature review presents comprehensive Studies in the field of plant disease recognition and detection systems. This broad literature Review serves as a roadmap to uncover the Limitations of current approaches and leads to the improvement of well-defined research Problems. After such a broad review, it was found that in the past decades, deep learning based CNN algorithms have been highlighted as one of the significant methods being researched. In agriculture domains. Despite the fact that various deep learning algorithms have been applied and developed for apple leaf disease Diagnosis and detection, this is still a fertile area of research and should result in improvements For better diagnosis of apple leaf diseases. From This literature review, we found that there is a Lack of reliable publicly available apple leaf Disease datasets. In addition, they did not consider an important type of pest named spider, which affects the whole apple surface leaf. Therefore, it is necessary to improve and Construct a new dataset that includes various Plant organs and leaf diseases. As a result, Constructing a reliable apple leaf disease type and healthy dataset is essential.

METHODOLOGY

1. Data Collection: A diverse dataset comprising high-resolution images of plant leaves affected by various diseases is compiled. Efforts are made to include multiple plant species and a wide range of disease variations. Each image is carefully labelled with the corresponding disease category to facilitate supervised learning.

2. Preprocessing: The dataset undergoes preprocessing to improve image quality and ensure consistency. Image sizes are standardized, brightness and contrast adjustments are applied, and noise is reduced. Techniques such as **histogram equalization** and **data augmentation** are employed to enhance model generalization. The dataset is then divided into training, validation, and testing subsets to ensure effective learning and

3. Model Architecture:



A deep Convolutional Neural Network (CNN) is designed to detect plant diseases by extracting meaningful patterns from leaf images. The architecture consists of several key components:

1. Convolutional Layers: Features such as edges, textures, and color variations are extracted using multiple filters (kernels). The ReLU activation function is applied to introduce non-linearity, enhancing the model's ability to learn complex patterns.

2. Pooling Layers: Max pooling is used to reduce the spatial dimensions of feature maps, retaining essential information while improving computational efficiency and reducing overfitting.

3. Batch Normalization and Dropout: Batch normalization stabilizes learning by normalizing activations, while dropout regularization prevents overfitting by randomly deactivating neurons during training.

4. Fully Connected Layers: Extracted features are passed through dense layers, where high-level reasoning is performed to classify the images into different disease categories.

5. Softmax Output Layer: A softmax function assigns by adopting this approach, the Plant Disease Prediction System provides an efficient and reliable solution for early disease detection. The insights generated assist farmers and agricultural professionals in diagnosing plant diseases accurately, contributing to improved crop health.

RESULT AND ANALYSIS

In an effort to enhance plant disease prediction, a detailed assessment was conducted on two deep convolutional neural network (CNN) models. Through a collaborative analysis of their performance and accuracy, the impact of architectural differences on disease classification across various crops was explored. Developed using the ResNet architecture, Model 1 was designed to leverage deep neural networks for effective disease identification. A diverse dataset containing high-resolution images of plant disease symptoms was utilized for extensive training. Despite its structural advantages, the model achieved an accuracy of 61.36% on the testing dataset, providing valuable insights into the challenges of training deep architectures for plant disease detection.

With a focus on improved feature extraction, Model 2 was built using the ALEXNet architecture. The same dataset was used, allowing for a direct comparison of performance. By leveraging its advanced design, ALEXNet demonstrated superior disease classification capabilities, achieving a remarkable accuracy of 94.72%. A significant disparity in performance was observed between the two models. While Model 1 showcased the capabilities of ResNet, Model 2 emerged as a more effective solution, reinforcing the critical role of architecture selection in plant disease prediction. These findings highlight the potential of advanced CNN models in transforming agricultural disease detection, paving the way for more efficient and accessible solutions.

This research is a collective step toward improving agricultural technology, providing farmers, researchers, and agritech innovators with deeper insights into precision disease management. By emphasizing the importance of architecture in disease prediction, this study contributes to the development of more accurate, scalable, and sustainable solutions, ultimately supporting global food security and sustainable farming practices.

CONCLUSION AND FUTURE WORK

This study introduced a Plant Disease Prediction System using Convolutional Neural Networks (CNNs) to detect plant leaf diseases with high accuracy. Through a comparative analysis of ResNet and AlexNet architectures, the system achieved 94.72% accuracy with AlexNet, demonstrating its effectiveness in disease identification. The proposed approach empowers farmers with early disease detection, enabling timely interventions to minimize crop losses and promote sustainable agricultural practices. This new approach will focus on Fine-tuning model parameters and using data Augmentation to address existing challenges. The Review highlights that current algorithm often Slow accuracy, emphasizing the importance of continuous improvement. By solving these Issues, a new CNN model could greatly enhance the early detection of apple leaf diseases and Assist farmers in managing their crops more Effectively. This gap in research motivates us to Create a deep learning model for detecting apple Leaf diseases. For future improvements, we aim to: Develop a treatment recommendation system to provide tailored advice on fertilizers and disease control measures. Expand the model's scope to cover a broader range of plant diseases beyond cultivation. Enhance real-time monitoring by integrating IoT-based sensors for continuous disease tracking. Optimize model efficiency for deployment in resource-constrained agricultural environments.

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