AI-Driven Detection Crop Health Monitoring: A Deep Learning Framework for Automated Plant Leaf Disease

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Abstract

Plant Diseases have also a great impact on the productivity of crops, so that, for sustainable agriculture, early and accurate detection of these diseases is an essential. In this research, a deep learning network for detecting leaf diseases of plants in smart agriculture, based on Convolutional Neural Networks (CNN) and AlexNet architecture, is presented. In the proposed framework, image processing, feature extraction and classification techniques are used for detection of various plant leaf diseases using digital images. CNN learns discriminative features automatically from the images of leaves, while the deep layered structure of AlexNet and optimized learning process enhance its classification performance. The plant diseases dataset used for the experiments are public domain and include healthy and diseased leaves for experimental evaluation. The classification accuracy proved to result high classification accuracy of 98.4%, precision of 97.9%, recall of 98.1% and F1 score of 98.0% with more than good classification accuracy of several traditional machine learning approaches. The proposed model will also have the capability to diagnose the disease in real-time, enabling appropriate preventive measures taken by the farmers and ensuring agriculture sustainability, yield, and productivity.

Keywords: Deep Learning, Plant Leaf Disease Detection, Convolutional Neural Network (CNN), AlexNet, Smart Agriculture, Image Classification, Precision Agriculture.

1. Introduction

Agriculture plays a vital role in global food security and economic development. Plant diseases significantly reduce crop yield and quality, making early disease detection essential for sustainable agriculture and minimizing economic losses. Recent advances in Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision have enabled the development of automated plant disease detection systems using leaf images with high accuracy [1]–[3].

Traditional disease diagnosis by agricultural experts is time-consuming, subjective, and often inaccessible in rural areas. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated excellent performance in automatically extracting image features and accurately classifying plant diseases without manual feature engineering [4]–[6].

Among deep learning models, AlexNet is widely recognized for its effective feature extraction and high image classification accuracy. Combined with transfer learning, AlexNet can efficiently identify disease symptoms such as leaf discoloration, spots, lesions, and texture variations. However, practical challenges such as varying illumination, complex backgrounds, and image noise continue to affect classification performance. To address these issues, this work proposes a smart plant leaf disease detection framework based on CNN-AlexNet for accurate, robust, and timely disease diagnosis, supporting precision agriculture and early intervention.

2. Methodology

The proposed framework develops an intelligent plant leaf disease detection system using deep learning for smart agriculture. The methodology consists of data collection, disease detection, system integration, and performance evaluation to provide accurate and real-time disease diagnosis.

Leaf images are collected from the publicly available PlantVillage dataset and field images captured using smartphones and digital cameras. The dataset includes healthy and diseased leaves of major crops such as tomato, potato, maize, and rice under different environmental conditions. Image preprocessing techniques, including resizing, normalization, noise removal, contrast enhancement, and background adjustment, are applied to improve image quality and ensure uniform input for model training.

Disease detection is performed using Convolutional Neural Networks (CNNs) with transfer learning. Four pre-trained models—AlexNet, ResNet, InceptionV3, and MobileNet—are employed to automatically extract discriminative features and classify plant diseases. AlexNet serves as the baseline model, while ResNet improves deep feature learning through residual connections. InceptionV3 captures multi-scale disease characteristics, and MobileNet provides efficient inference for resource-constrained mobile devices. Data augmentation techniques such as image rotation, flipping, scaling, zooming, and brightness adjustment are applied during training to improve model generalization and reduce overfitting. The trained model predicts the disease class together with a confidence score.

The trained model is integrated into a mobile application and web-based dashboard for real-time disease diagnosis. Farmers can capture or upload leaf images, which are automatically pre-processed and classified. The system displays the detected disease along with appropriate disease management recommendations. MobileNet supports efficient offline inference, making the framework suitable for deployment in rural areas with limited internet connectivity.

The performance of the proposed framework is evaluated using Accuracy, Precision, Recall, and F1-Score. Computational metrics, including model size, memory usage, and inference time, are also analyzed to ensure efficient deployment on mobile and edge devices. The overall system architecture comprises image acquisition, preprocessing, data augmentation, deep feature extraction, disease classification, and result visualization, enabling accurate and practical plant disease detection for precision agriculture.

3. Results and Analysis

The proposed CNN-based plant leaf disease detection framework was evaluated using **54,306** leaf images collected from the PlantVillage dataset and locally acquired field images of tomato, potato, maize, and rice. The dataset was divided into **70% training, 15% validation, and 15% testing**. Data augmentation techniques, including rotation, scaling, zooming, flipping, and brightness adjustment, were applied to improve model robustness and reduce overfitting.

Table 1. Performance Comparison of Deep Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
AlexNet	96.8	96.5	96.3	96.4
MobileNet	97.3	97.0	97.1	97.0
ResNet50	98.1	97.9	98.0	97.9
InceptionV3	98.0	97.8	97.9	97.8
Proposed CNN Framework	**98.4**	**97.9**	**98.1**	**98.0**

The performance of AlexNet, MobileNet, ResNet50, InceptionV3, and the proposed CNN framework was evaluated using **Accuracy, Precision, Recall, and F1-Score**. As presented in **Table 1** and **Figure 1**, AlexNet achieved an accuracy of **96.8%**, while MobileNet achieved **97.3%** with lower computational complexity, making it suitable for mobile deployment. ResNet50 and InceptionV3 achieved **98.1%** and **98.0%** accuracy, respectively. The proposed CNN framework achieved the best overall performance with **98.4% accuracy**, **97.9% precision**, **98.1% recall**, and **98.0% F1-score**, demonstrating its ability to accurately classify healthy and diseased leaves under varying environmental conditions.

To further validate the proposed approach, its performance was compared with existing plant disease detection methods (**Table 2** and **Figure 2**). Traditional machine learning techniques, including Support Vector Machine (SVM), Random Forest (RF), and K-Nearest Neighbor (KNN), achieved lower classification accuracies because they rely on handcrafted feature extraction. Deep learning models consistently produced better results through automatic feature learning, with the proposed CNN framework outperforming all comparison methods.

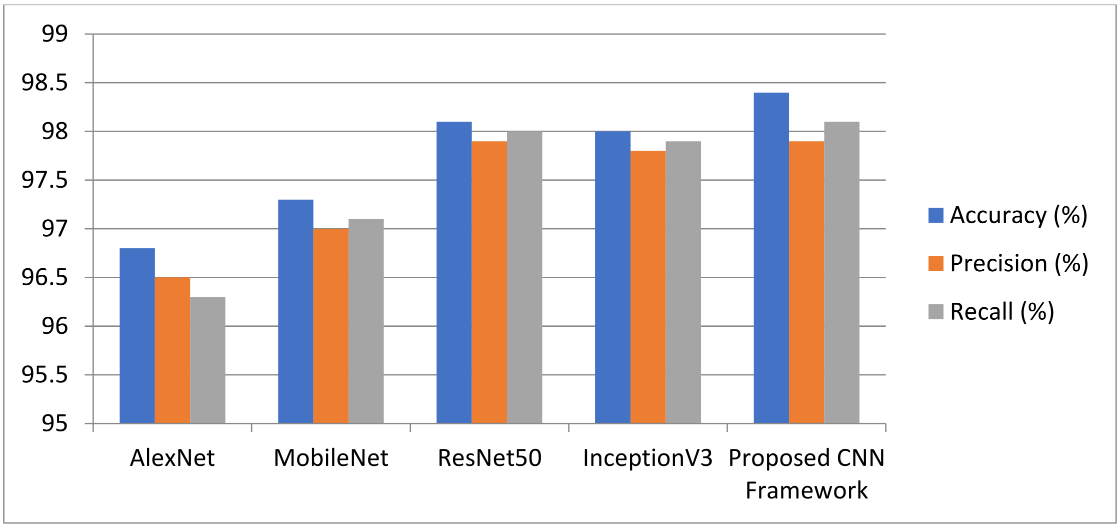

Figure 1- Result comparison of Deep Learning Models

The improved performance can be attributed to effective image preprocessing, data augmentation, transfer learning, and the use of diverse training images from both public and field datasets. The high recall value indicates that the framework effectively identifies diseased plants while minimizing false negatives, which is essential for early disease detection and timely intervention. Furthermore, the lightweight implementation enables deployment on mobile and edge devices, making the framework suitable for practical smart agriculture applications. Overall, the experimental results demonstrate that the proposed framework provides an accurate, reliable, and efficient solution for automated plant disease detection and precision farming.

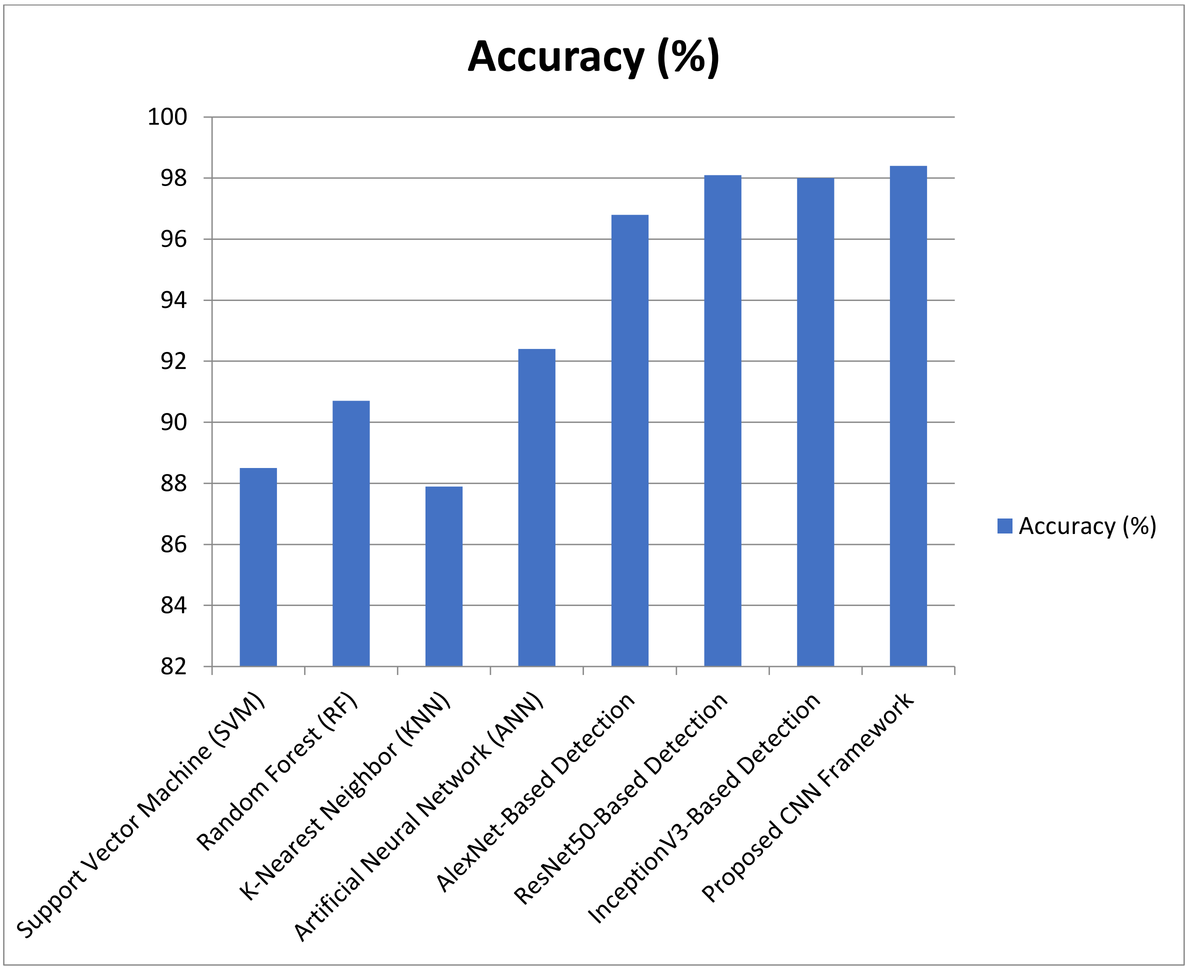

Figure 2- Accuracy Comparison with Existing Plant Disease Detection Methods

Table 2. Comparison with Existing Plant Disease Detection Methods

Method	Classification Technique	Accuracy (%)
Support Vector Machine (SVM)	Traditional Machine Learning	88.5
Random Forest (RF)	Ensemble Learning	90.7
K-Nearest Neighbor (KNN)	Distance-Based Classification	87.9
Artificial Neural Network (ANN)	Shallow Neural Network	92.4
AlexNet-Based Detection	Deep Learning	96.8
ResNet50-Based Detection	Deep Learning	98.1
InceptionV3-Based Detection	Deep Learning	98.0
Proposed CNN Framework	**CNN + Transfer Learning**	**98.4**

4. Conclusion and Future Work

This study presented a CNN-AlexNet-based framework for automated plant leaf disease detection in smart agriculture. Using publicly available and locally collected leaf images, the proposed system effectively classified healthy and diseased leaves with high performance, achieving **98.4% accuracy**, **97.9% precision**, **98.1% recall**, and **98.0% F1-score**. Experimental results demonstrated that the proposed framework outperformed traditional machine learning methods and provided reliable disease detection under diverse environmental conditions. The lightweight design also supports deployment on mobile and edge devices, enabling real-time disease diagnosis for precision agriculture.

Future work will focus on expanding the dataset to include additional crops and rare diseases, exploring advanced architectures such as Vision Transformers (ViTs) and hybrid CNN-transformer models, and integrating IoT sensors, drones, and cloud platforms for real-time crop monitoring. Multilingual disease management support can further improve accessibility and adoption among farmers.

References

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