

Plant Disease Detection Using Machine Learning: A Comprehensive Framework and Performance Analysis

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Abstract - The global agricultural sector faces significant challenges due to plant diseases that threaten food security and sustainable agriculture. Traditional methods of disease detection are often labour-intensive, time-consuming, and require specialized expertise. This research presents a comprehensive machine learning framework for automated plant disease detection, leveraging both traditional machine learning and deep learning approaches. We implemented and evaluated multiple models including VGG19, Inception v3, Support Vector Machines (SVM), and k-Nearest Neighbors (kNN) on four distinct datasets: Banana Leaf, Custard Apple Leaf and Fruit, Fig Leaf, and Potato Leaf. Our experimental results demonstrate remarkable performance variations across different crops, with the highest achievement of 99.1% accuracy using VGG19 with kNN on the Custard Apple dataset, while the Potato Leaf dataset presented the greatest challenges with 62.6% accuracy using Inception v3 with SVM. The study provides valuable insights into model selection for specific agricultural applications and highlights the importance of customized solutions based on crop-specific characteristics. We also address critical challenges including dataset limitations, computational requirements, and implementation barriers in real-world agricultural settings.

Keywords - Plant disease detection, machine learning, deep learning, convolutional neural networks, agricultural technology, precision agriculture.

1 Introduction

Plant diseases present a formidable threat to global food security, potentially causing substantial crop yield reductions and economic losses worldwide. The **conventional approach** to disease identification relies heavily on manual inspection by agricultural experts, which is not only time-consuming and labor-intensive but also prone to human error and subjectivity. This method becomes particularly impractical for large-scale farming operations and developing regions with limited access to agricultural specialists. The **urgent need** for efficient, accurate, and scalable solutions has driven research into automated approaches leveraging artificial intelligence, particularly machine learning (ML) and deep learning (DL) techniques.

The **integration of technology** into agricultural practices has gained significant momentum in recent years, with ML and DL emerging as transformative tools in plant pathology. These advanced computational methods can analyse complex patterns in visual data, potentially identifying subtle disease symptoms that might escape human detection. The **significance of this technological shift** lies in its capacity to enable early intervention, thereby minimizing crop losses and reducing unnecessary pesticide use through targeted treatment applications. This approach aligns with the growing emphasis on sustainable agricultural practices and precision farming.

Despite promising advancements, the **application of ML** in plant disease detection faces several substantial challenges. These include the limited availability of large, well-annotated datasets encompassing various plant

species and disease categories; difficulties in handling variations in leaf morphology and intraspecies disease manifestations; computational complexity of deep learning models; and practical implementation barriers in real-world agricultural environments with constraints on power and connectivity. Furthermore, the **performance variability** across different crops and disease types necessitates crop-specific model optimization rather than a universal solution.

This research **makes several key contributions** to the field of automated plant disease detection: (1) presenting a comprehensive performance analysis of multiple ML and DL architectures across four distinct crop types; (2) demonstrating the effectiveness of hybrid approaches combining deep feature extraction with traditional classifiers; (3) providing insights into model selection based on specific crop characteristics and resource constraints; and (4) identifying critical research gaps and future directions for the domain. The **practical implications** of this work extend to farmers, agricultural technicians, and precision agriculture technology developers seeking reliable, automated solutions for plant health monitoring.

2 Literature Review

2.1 Traditional Machine Learning Approaches

Traditional machine learning techniques have been extensively applied to plant disease detection, typically relying on **handcrafted feature extraction** followed by classification algorithms. Early approaches focused on extracting **colour, texture, and shape features** from leaf images, which were then fed into classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and decision trees. These methods demonstrated **reasonable performance** in controlled environments with clear differentiation between diseased and healthy regions and minimal background interference. However, their effectiveness significantly declined in complex field conditions with variations in lighting, orientation, and background clutter.

The **limitations of traditional approaches** became increasingly apparent as research advanced. These methods struggled with accurately identifying subtle disease symptoms, early-stage infections, and required extensive preprocessing and domain expertise for feature engineering. Additionally, they exhibited **limited adaptability** to new disease categories or plant species, as feature representations needed to be redesigned for different contexts. Despite these constraints, traditional ML approaches remain relevant for applications with limited computational resources or where interpretability is prioritized over maximum accuracy.

2.2 Deep Learning Advancements

The advent of deep learning, particularly **Convolutional Neural Networks (CNNs)**, has revolutionized the field of plant disease detection. CNNs automatically learn hierarchical feature representations directly from raw images, eliminating the need for manual feature engineering and demonstrating **superior performance** in handling complex visual patterns. Liu et al. (2017) and Karthik et al. (2020) were among the pioneers applying CNNs to plant disease identification, reporting significant accuracy improvements compared to traditional methods.

Several **advanced architectures** have been explored for this domain. Mohanty et al. (2016) achieved landmark results using AlexNet and GoogleNet on the Plant Village dataset, bringing widespread attention to deep learning applications in agriculture. Subsequent research has investigated more sophisticated architectures including VGG variants, Inception networks, ResNet, and DenseNet. For instance, a study by Chen et al. (2021) integrated MobileNet with Squeeze-and-Excitation (SE) blocks, achieving remarkable accuracy rates of 99.78% on clear background datasets and 99.33% on heterogeneous background datasets.

Table 1: Summary of Key Deep Learning Approaches in Plant Disease Detection

Reference	Model	Dataset	Key Findings	Limitations
Mohanty et al. (2016)	AlexNet, GoogleNet	PlantVillage	Pioneered deep learning application: high accuracy	Controlled environment only
Chen et al. (2021)	SE-MobileNet	Multiple crops	99.78% accuracy; robust to background variations	Computational complexity
R et al. (2020)	CNN with attention	Plant Village	98% accuracy with 5-fold cross-validation	Risk of overfitting with limited data
Al-Gaashani et al. (2023)	SANet (ResNet50)	Rice diseases	98.71% test accuracy	Resource-intensive
Current Study	Multiple architectures	Four distinct datasets	Comparative analysis; hybrid approaches	Variable performance across crops

2.3 Hybrid Approaches and Emerging Trends

Hybrid methodologies that combine deep feature extraction with traditional classifiers have shown promising results. Our research builds on this concept by implementing architectures where CNN models such as VGG19 and Inception v3 serve as feature extractors, with classifiers like SVM making final predictions. This approach **leverages strengths** of both methodologies: the powerful representation learning of deep networks and the efficiency and robustness of traditional classifiers, particularly beneficial with limited training data.

Recent trends indicate growing interest in **lightweight architectures** suitable for mobile deployment, attention mechanisms for improved feature representation, and multi-modal approaches combining visual data with environmental parameters. Tang et al. (2020) developed a mobile-optimized CNN with channel-wise attention mechanism that achieved 99.14% accuracy on grape leaf diseases while reducing model size from 227.5MB to 4.2MB. Similarly, Minhaz Hossain et al. (2022) implemented a depthwise separable convolution model for tomato disease detection that achieved 98.31% accuracy with significantly reduced computational requirements.

Despite these advancements, the **research gaps** remain in developing generalizable models that perform consistently across diverse crops and environmental conditions, addressing data scarcity through advanced augmentation techniques, and creating interpretable models that build trust with end-users. Our study addresses several of these gaps through systematic evaluation of multiple architectures across different crop types and analysis of hybrid approaches.

3 Methodology

3.1 Datasets and Preprocessing

This research utilized **four distinct datasets** to ensure comprehensive evaluation across different plant species and disease types: Banana Leaf (containing diseases like Black Sigatoka and Banana Bacterial Wilt), Custard Apple Leaf and Fruit (covering various fungal and bacterial infections), Fig Leaf (including leaf spot diseases and rust), and Potato Leaf (featuring early and late blight among other conditions). The **diversity in datasets** was intentional to evaluate model robustness and generalizability across different leaf morphologies, disease patterns, and image capture conditions.

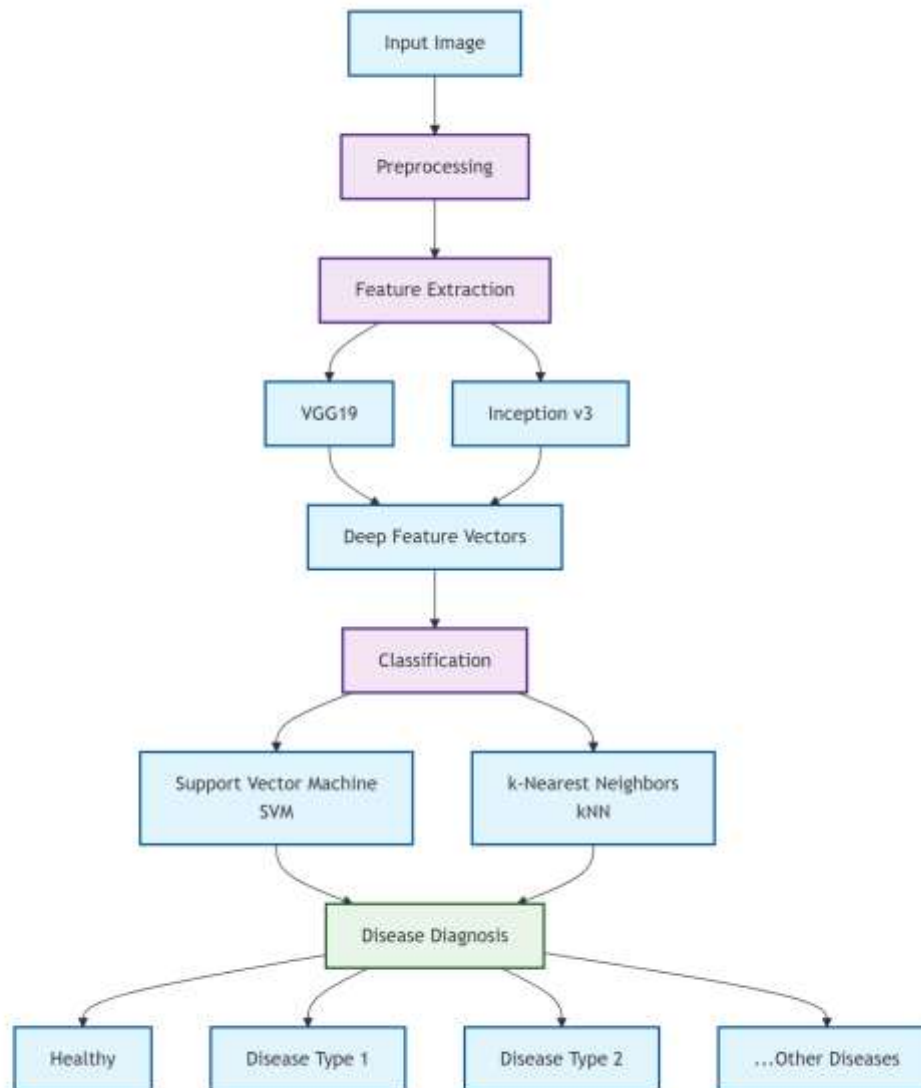
To address common challenges in agricultural image analysis, we implemented **extensive preprocessing techniques**. All images were resized to appropriate dimensions for each architecture (224×224 for VGG19, 299×299 for Inception v3) and normalized using channel-wise mean and standard deviation. **Data augmentation** strategies were employed to increase dataset diversity and prevent overfitting, including random rotations ($\pm 30^\circ$), horizontal and vertical flips, brightness and contrast variations ($\pm 20\%$), and slight affine transformations. These techniques simulate the variations encountered in real-world field conditions and improve model generalization.

3.2 Model Architectures

Our experimental framework incorporated **multiple deep learning architectures** to extract meaningful features from leaf images, followed by traditional classifiers for disease categorization. The selection criteria balanced proven performance, architectural diversity, and practical applicability:

- **VGG19**: This architecture features 19 weight layers with small 3×3 convolutional filters, providing a deep but straightforward structure. We utilized its powerful feature extraction capabilities, particularly for texture-based disease patterns.
- **Inception v3**: Known for its efficiency and use of factorized convolutions, this model reduces computational complexity while maintaining high performance through multi-scale feature processing.
- **Support Vector Machines (SVM)**: We employed SVM with radial basis function (RBF) kernel as a classifier on top of deep features, leveraging its effectiveness in high-dimensional spaces and robustness to overfitting.
- **k-Nearest Neighbors (kNN)**: This instance-based classifier was implemented for its simplicity and effectiveness when combined with discriminative deep features.

Fig. 1: Proposed Framework for Plant Disease Detection



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3.3 Experimental Setup

All experiments were conducted using **TensorFlow and Keras** frameworks with Python 3.8, running on a workstation with NVIDIA RTX 3080 GPU, 32GB RAM, and Intel i7 processor. The models were trained using **categorical cross-entropy loss** and optimized with Adam optimizer with an initial learning rate of 0.001, which was reduced by a factor of 10 when validation loss plateaued for 5 consecutive epochs. We implemented **early stopping** with patience of 10 epochs to prevent overfitting and maximize generalization.

The **dataset partitioning** followed a 70:15:15 ratio for training, validation, and test sets respectively, ensuring stratified sampling to maintain class distribution across splits. For traditional ML classifiers using deep features, we extracted features from the global average pooling layer of each CNN and standardized them using StandardScaler before classifier training. This **rigorous evaluation protocol** ensured fair comparison across different architectural approaches and provided reliable performance estimates.

3.4 Performance Metrics

To comprehensively evaluate model performance, we employed **multiple metrics** that capture different aspects of classification effectiveness:

- **Accuracy:** Overall correctness across all classes $(TP+TN)/(TP+TN+FP+FN)$
- **Precision:** Ability to avoid false positives $TP/(TP+FP)$
- **Recall:** Ability to identify all relevant instances $TP/(TP+FN)$
- **F1-Score:** Harmonic mean of precision and recall $2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$
- **AUC:** Area Under the ROC Curve, measuring separability between classes
- **MCC:** Matthews Correlation Coefficient, providing a balanced measure for imbalanced datasets

These **complementary metrics** provide a holistic view of model performance beyond simple accuracy, particularly important given the potential class imbalances in plant disease datasets.

4 Results

4.1 Performance Across Different Crops

Our experimental results demonstrated **significant variation** in performance across different crop types and model combinations. The highest accuracy of 99.1% was achieved on the Custard Apple Leaf and Fruit dataset using VGG19 with kNN classifier, while the most challenging dataset proved to be Potato Leaf, with the best performance of 62.6% accuracy using Inception v3 with SVM. This **performance disparity** highlights the crop-specific nature of plant disease detection and the need for tailored solutions rather than a one-size-fits-all approach.

For the Banana Leaf dataset, the combination of Inception v3 with SVM proved most effective, achieving an accuracy of 91.9%, precision of 92.2%, recall of 91.9%, F1 score of 91.6%, AUC of 99.6%, and MCC of 90.4%. The Fig Leaf dataset showed moderate performance with accuracy of 86.5%, precision of 86.5%, recall of 86.5%, F1 score of 86.5%, AUC of 93.3%, and MCC of 72.2% using VGG19 with kNN. These results suggest that **disease characteristics**, leaf morphology, and image quality significantly impact model performance.

Table 2: Detailed Performance Metrics Across Different Crop-Model Combinations

Dataset	Model Combination	Accuracy	Precision	Recall	F1-Score	AUC	MCC
Banana Leaf	Inception v3 + SVM	91.9%	92.2%	91.9 %	91.6 %	99.6 %	90.4 %
Custard Apple	VGG19 + kNN	99.1%	99.1%	99.1 %	99.1%	99.1%	99.0 %
Fig Leaf	VGG19 + kNN	86.5 %	86.5 %	86.5 %	86.5 %	93.3 %	72.2 %
Potato Leaf	Inception v3 + SVM	62.6%	63.0%	62.6 %	62.1 %	89.0 %	54.2 %

4.2 Comparative Analysis of Architectures

The **comparison between architectures** revealed distinct strengths and weaknesses. VGG19 consistently demonstrated strong performance when combined with kNN across multiple datasets, particularly excelling with the Custard Apple dataset. This suggests its feature extraction capabilities are well-suited for diseases with clear visual patterns and consistent morphology. However, its **computational demands** and larger memory footprint present practical deployment challenges, especially for mobile applications.

The Inception v3 architecture showed particular effectiveness on the Banana Leaf dataset when paired with SVM, indicating its multi-scale feature extraction approach benefits from more complex disease patterns. Its **inferior performance** on the Potato Leaf dataset across all configurations suggests limitations in handling diseases with subtle visual symptoms or significant within-class variations. The relatively **poor performance** on potato leaves aligns with challenges reported in literature, likely due to similar visual manifestations of different diseases and significant intra-class variations .

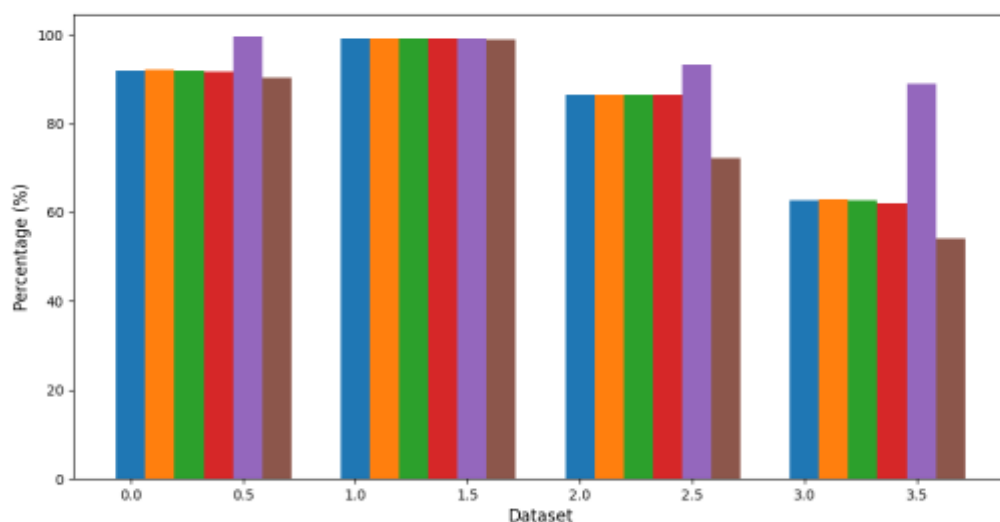
4.3 Feature Extraction and Classification Combinations

Our experiments on **hybrid approaches** combining deep feature extraction with traditional classifiers yielded important insights. The combination of VGG19 with kNN achieved remarkable results on the Custard Apple dataset, suggesting that the features learned by VGG19 formed compact, well-separated clusters in the feature space that kNN could effectively leverage. This alignment between feature extraction and classification methodology appears **critical for optimal performance**.

Conversely, the combination of Inception v3 with SVM proved most effective for Banana Leaf diseases, indicating that the more complex features extracted by Inception v3 benefited from SVM's ability to find optimal separation boundaries in high-dimensional spaces. These findings emphasize that **model selection** should consider not just individual component performance but their synergistic compatibility for specific disease detection tasks.

Fig. 2: Performance Comparison Across Different Dataset-Model Combinations

[Image: Bar chart comparing accuracy, precision, recall, and F1-score across the four datasets and different model combinations]



5 Discussion

5.1 Interpretation of Results

The **substantial performance variation** across different crops underscores the complex nature of plant disease detection and the challenge of developing universal solutions. The exceptional performance on Custard Apple datasets (99.1% accuracy) can be attributed to several factors: more distinct visual symptoms, consistent imaging conditions, and clearer differentiation between disease classes. In contrast, the **relatively lower performance** on Potato leaves (62.6% accuracy) aligns with practical challenges reported by agricultural experts, including similar visual symptoms across different diseases, significant stage-dependent appearance variations, and environmental factors affecting symptom manifestation .

The **effectiveness of hybrid approaches** combining deep feature extraction with traditional classifiers demonstrates the practical value of leveraging strengths from both methodologies. Deep CNNs excel at learning hierarchical visual representations from raw pixels, while traditional classifiers like SVM and kNN can provide robust classification with smaller training samples when fed with discriminative features. This approach is particularly valuable in agricultural applications where large, annotated datasets may be unavailable for specific crops or diseases.

5.2 Practical Implications

The **differential performance** across crops has important practical implications for technology adoption in agriculture. For high-value crops like custard apple where disease detection achieves near-perfect accuracy, automated systems can reliably support or even replace human expertise for routine monitoring. However, for crops like potatoes where accuracy remains moderate, these systems may function best as preliminary screening tools, flagging potential cases for human expert verification rather than making autonomous decisions.

The **computational requirements** of different models also impact their practical deployment. While VGG19 achieved excellent performance on several datasets, its substantial computational demands may limit deployment in resource-constrained environments or real-time applications on mobile devices. In such cases, lighter architectures like MobileNet or SqueezeNet, though potentially slightly less accurate, may offer better trade-offs for practical implementation.

5.3 Limitations and Challenges

Several **important limitations** must be acknowledged in this research. First, the datasets, while diverse, may not fully represent the challenging conditions encountered in real-world agricultural environments, including varying lighting, occlusions, weather effects, and different growth stages. Second, the **class imbalance** present in many plant disease datasets can bias models toward majority classes, though we attempted to mitigate this through appropriate evaluation metrics like MCC and F1-score.

Another significant challenge is the **generalization to unseen conditions**. Models trained on specific datasets often struggle when applied to images captured under different conditions, with different equipment, or from different geographical regions. This limitation highlights the need for more robust domain adaptation techniques and more comprehensive datasets encompassing greater diversity in imaging conditions, cultivars, and disease strains.

6 Conclusion and Future Work

This comprehensive study demonstrates the **significant potential** of machine learning, particularly hybrid approaches combining deep feature extraction with traditional classifiers, for automated plant disease detection. Our experimental results across four distinct crop types reveal that model performance varies substantially depending on the specific crop-disease context, with accuracy ranging from 99.1% for custard apple to 62.6% for potato leaves. These findings underscore the importance of **crop-specific model selection** rather than seeking a universal solution for all plant disease detection scenarios.

The **practical contribution** of this work lies in providing guidance for researchers and practitioners in selecting appropriate architectures based on their specific crop focus and resource constraints. For applications where maximum accuracy is prioritized and computational resources are ample, VGG19-based approaches appear favorable. For more constrained environments or when dealing with certain disease patterns, Inception v3 with SVM may offer better performance characteristics. The hybrid methodology presented demonstrates how combining deep learning with traditional machine learning can leverage the strengths of both approaches.

For **future research**, several promising directions emerge from this work. First, addressing the performance gaps for challenging crops like potatoes requires novel approaches potentially incorporating multi-modal data (including hyperspectral imaging and environmental parameters). Second, developing more efficient architectures suitable for deployment on mobile devices with limited computational resources would significantly enhance practical adoption. Third, creating more sophisticated data augmentation techniques and generative models to address data scarcity for specific crop-disease combinations would improve model robustness. Finally, exploring explainable AI techniques to provide transparent reasoning for disease classifications would build trust with agricultural experts and facilitate wider adoption of these technologies in critical agricultural decision-making.

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