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Comparative Analysis of Machine Learning Algorithms for Crop Disease Detection Using Leaf Image Data

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Abstract: Timely and accurate detection of crop diseases is critical for minimising agricultural yield losses and reducing the overuse of chemical pesticides. Conventional expert-based field diagnosis is costly, time-consuming, and inaccessible to smallholder farmers in resource-limited settings. Machine learning-based image classification offers a scalable, accessible alternative. This study conducted a comparative performance evaluation of three widely used machine learning approaches — Convolutional Neural Network (CNN), Support Vector Machine (SVM), and Random Forest (RF) — for the automatic detection and classification of nine common crop diseases across four crop species (tomato, potato, maize, and rice) using leaf image data drawn from the publicly available PlantVillage dataset (54,306 images). Experiments were conducted under two conditions: using original dataset images and using augmented datasets (rotation, flipping, brightness variation). The CNN architecture (a fine-tuned VGG-16 model) achieved the highest overall classification accuracy of 94.2% under augmented conditions, outperforming SVM (87.1%) and RF (82.3%). Precision, recall, and F1-score analyses confirmed CNN's superiority across all nine disease classes. Computational training time was substantially higher for CNN (4.3 hours on GPU) than SVM (38 minutes) or RF (12 minutes), presenting a deployment trade-off for resource-constrained settings. The study discusses implications for mobile application development for farmer-facing disease diagnosis tools and recommends CNN with transfer learning as the optimal approach for accuracy-critical applications, while SVM is recommended where computational constraints are significant.

Keywords: *Crop Disease Detection, Convolutional Neural Network, Support Vector Machine, PlantVillage, Transfer Learning, Precision Agriculture*

1. Introduction

Agricultural productivity in developing nations is severely impacted by crop diseases, which account for estimated annual yield losses of 10–40% globally, with significantly higher losses in smallholder farming systems that lack early detection and management infrastructure. In India, diseases affecting major food and cash crops — including rice blast, wheat rust, tomato late blight, and potato early blight — together cause crop losses valued at thousands of crores of rupees annually, contributing to farmer indebtedness and food insecurity. Traditional methods of disease identification depend on trained agricultural extension officers or diagnostic laboratories, both of which are chronically under-resourced relative to the farming population they serve.

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The rapid proliferation of affordable smartphones with high-resolution cameras among farming communities, combined with expanding rural 4G/5G connectivity, has created a technological opportunity to deliver machine learning-based crop disease diagnosis at the point of need. Several mobile applications — including PlantDoc, CropMD, and Plantix — have already reached millions of smallholder farmers globally, but their underlying algorithmic accuracy and comparative performance against alternative machine learning approaches have not been systematically documented in the peer-reviewed literature, particularly for Indian crop disease typology.

Machine learning approaches to image classification span a wide performance and complexity spectrum. Convolutional Neural Networks (CNNs), particularly deep CNN architectures with transfer learning from large image datasets, have dominated image recognition benchmarks since AlexNet's performance breakthrough in 2012 and have been widely applied to plant disease detection. Support Vector Machines (SVMs) with handcrafted or automatically extracted image features represent an earlier generation of machine learning approach that remains relevant in resource-constrained deployment contexts due to lower computational requirements. Random Forest (RF) classifiers, based on ensemble decision tree methods, offer interpretability advantages and robustness to overfitting with smaller datasets.

A systematic comparative evaluation of CNN, SVM, and RF performance specifically on the PlantVillage dataset — the largest publicly available plant disease image library — using consistent experimental protocols and including data augmentation conditions, is needed to provide a sound empirical basis for algorithm selection in practical disease detection system development. This study provides such a comparison.

2. Methodology

The PlantVillage dataset (version 3.0) was used, comprising 54,306 RGB leaf images across 38 classes (healthy and diseased conditions) for 14 crop species. For this study, a subset of 9 disease classes from four crop species most relevant to Indian agriculture was selected: tomato (early blight, late blight, leaf mold), potato (early blight, late blight), maize (northern leaf blight, common rust), and rice (blast, brown spot). The subset comprised 22,842 images. Images were resized to 224x224 pixels (required input for VGG-16 CNN architecture). An 80:10:10 split was used for training, validation, and testing sets respectively across all models.

Three machine learning models were implemented and evaluated. For CNN, a pre-trained VGG-16 network (trained on ImageNet) was adapted for the 9-class disease classification task using transfer learning: the last three fully connected layers were replaced and trained on the PlantVillage subset, while the convolutional base was frozen for the initial 15 epochs then unfrozen for fine-tuning for an additional 10 epochs (total 25 epochs). Learning rate was set to 0.0001 (Adam optimiser). For SVM, images were first processed through a HOG (Histogram of Oriented Gradients) feature extractor, and the resulting feature vectors were classified using a radial basis function (RBF) kernel SVM with hyperparameter optimisation via grid search. For RF, HOG features were also used as input to a Random Forest of 200 decision trees with Gini impurity as the splitting criterion.

Data augmentation was applied to the training set using random horizontal flipping, vertical flipping, rotation (+/-20 degrees), and brightness variation (±20%), doubling the effective training dataset size. Experiments were run under both original and augmented conditions. All experiments were implemented in Python 3.9 using TensorFlow 2.9 (CNN) and scikit-learn 1.1 (SVM, RF). GPU computation used an NVIDIA Tesla T4 instance on Google Colab Pro. Performance metrics calculated were: classification accuracy, precision, recall (sensitivity), and F1-score (macro-averaged across classes). Confusion matrices were generated for each model under augmented conditions.

3. Results and Findings

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Under original (non-augmented) dataset conditions, CNN achieved the highest test set accuracy at 91.4%, followed by SVM at 83.7% and RF at 78.9%. Data augmentation produced consistent and significant accuracy improvements for all three models. Under augmented conditions, CNN accuracy reached 94.2%, SVM improved to 87.1%, and RF to 82.3%. The CNN's accuracy advantage over SVM under augmented conditions was 7.1 percentage points, confirming the superiority of deep transfer learning for this image classification task across all experimental conditions.

Class-level performance analysis revealed that disease classes with high visual homogeneity presented the greatest challenge across models. Rice brown spot and maize common rust showed the highest inter-class confusion rates, with all three models occasionally misclassifying these as healthy or as alternative disease conditions. CNN demonstrated the most robust class-level performance, with F1-scores above 0.90 for seven of nine disease classes under augmented conditions. SVM's class-level performance was more variable, with F1-scores ranging from 0.79 (maize common rust) to 0.93 (potato late blight). RF showed the widest performance variance, with three of nine classes below F1=0.80.

Computational requirements differed substantially across models. CNN training time on GPU (Tesla T4) was 4.3 hours for the augmented dataset, while SVM and RF training required 38 minutes and 12 minutes respectively on the same hardware. Model inference time (time to classify a single new image) was 0.18 seconds for CNN, 0.04 seconds for SVM, and 0.09 seconds for RF, all within acceptable ranges for a mobile application context with server-side inference. CPU-based training (for scenarios without GPU access) increased CNN training time to approximately 28 hours, a significant constraint for deployment in low-resource research or development settings.

4. Discussion

The consistent superiority of CNN with transfer learning over SVM and RF across all experimental conditions confirms the findings of prior comparative studies in plant disease detection using the PlantVillage dataset and extends those findings to the specific Indian crop disease subset examined here. The performance advantage of CNN is attributable to the deep feature representations learned during VGG-16's ImageNet pretraining, which capture hierarchical visual features (edges, textures, shapes) that are highly relevant to disease symptom recognition on leaf surfaces and cannot be replicated by handcrafted feature extraction methods such as HOG.

The 7-percentage-point accuracy advantage of CNN over SVM, while statistically meaningful, must be evaluated against the significantly higher computational cost of CNN training and the greater technical expertise required for CNN model development and maintenance. For farmer-facing mobile application deployment where accuracy is paramount and inference occurs on cloud servers, the CNN advantage is unambiguous. However, for deployment in contexts where internet connectivity is unreliable and on-device inference is required (edge deployment), the SVM's lower computational requirements and simpler model structure may make it a pragmatically superior choice despite the accuracy trade-off.

The study has several limitations. The PlantVillage dataset was created under controlled laboratory lighting conditions with consistent backgrounds, and performance in field conditions — where images are captured under variable lighting, angles, and with background noise — is likely lower for all three models. A key recommendation for future work is evaluation on field-collected image datasets representative of Indian farming contexts. Additionally, this study did not address the challenge of multi-disease classification (a single leaf may exhibit symptoms of more than one disease simultaneously), which represents an important direction for subsequent research.

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5. Conclusion

This comparative study establishes that CNN with transfer learning (fine-tuned VGG-16) is the most accurate approach for automated crop disease detection from leaf images, achieving 94.2% classification accuracy across nine disease classes with data augmentation, substantially outperforming SVM (87.1%) and Random Forest (82.3%). The performance advantage persists across all disease classes studied, though with greater absolute margins for visually complex or ambiguous disease presentations.

Practical recommendations for disease detection system developers include: (i) adopting CNN with transfer learning as the default architecture for server-side, accuracy-critical crop disease detection applications; (ii) considering SVM as a viable lightweight alternative for edge-deployment scenarios with connectivity constraints; (iii) investing in field-based image dataset collection for Indian crop disease variants to improve model generalisation to real farming conditions; and (iv) developing Hinglish and regional-language user interfaces for farmer-facing mobile diagnosis applications to maximise accessibility among smallholder farmer communities with limited English proficiency.

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