Comparative Analysis of Convolutional Neural Networks and Traditional Machine Learning Algorithms for Multi-Crop Plant Disease Detection

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Abstract

Diseases in Plant are among the leading causes of reduced productivity in Agriculture across the world, terrifying global level food security and economic stability. Preliminary and exact disease identification is important for effective crop control and yield optimization. This study shows a complete comparative analysis of Convolutional Neural Networks (CNNs) and traditional machine learning (ML) algorithms, Support Vector Machine (SVM), Random Forest (RF), K Nearest Neighbour (KNN), and Decision Tree (DT) for multi crop plant disease detection. Using multi crop data set gained from Plant Village collection and enhanced with additional field samples, models were Analyzed on factors such as Accuracy, Precision, Recall, F1 Score, AUC ROC, and computational efficiency. The CNN architecture works with six convolutional layers, batch normalization, dropout regularization, and activation for multi class classification. Experimental results demonstrated that CNN achieved an accuracy of 98.12%, outperforming SVM (91.45%), RF (93.30%), KNN (89.67%), and DT (87.90%). Visualization through Grad CAM heatmaps further validated CNN's interpretability by highlighting disease infected regions on leaves. This approach provides effective and scalable solution for real time agricultural monitoring, laying groundwork for integration with IoT based precision farming systems.

Keywords

Plant Disease Detection, Deep Learning, Convolutional Neural Network (CNN), Machine Learning, Agriculture, Image Classification, Precision Farming

1. Introduction

Agriculture forms backbone of most markets, contributing continuously to food security and employment. However, crop disease remains one of major risk to sustainable agricultural productivity. According to Food and Agriculture Organization (FAO), nearly 30% to 40% of global crop deliever is lost yearly due to plant diseases and bugs. Traditional disease identification methods depend heavily on manual examination by agricultural experts, which is subjective, inefficient and time consuming especially in large scale farming operations.

Recent progress in artificial intelligence (AI) and computer vision have transformed plant disease detection. Machine Learning (ML) algorithms such as Support Vector Machines (SVM), Random Forests (RF), Decision Trees (DT), and K Nearest Neighbours (KNN) have been widely applied for classification tasks in plant study of diseases. While these models can handle structured data, they often struggle with difficult and high dimensional image traits.

Convolutional Neural Networks (CNNs), subset of deep learning, offer a powerful substitute by automatically learning hierarchical dimensional features from raw images. CNN based systems have gained superior results in image classification tasks across multiple fields, including agriculture. Studies such as Ahad et al., 2023 and Demilie, 2024 showed that CNN models surpass traditional identifier by significant margins in multi crop datasets.

This paper targets to perform a detailed comparable analysis between CNN and conventional ML algorithms for plant disease detection using various multi crop dataset. The objective is to analyze how CNN's feature extraction capabilities and end to end learning exceed traditional methods in both accuracy and generalization.

2. Literature Review

In recent years, rise of deep learning has modified computer vision based agricultural systems. Researchers have investigated several architectures for plant disease classification, varying from classical ML methods to advanced CNN based solutions. This section talks about related studies focusing on algorithmic performance, dataset complexity, and growth from handmade to deep feature retrieval.

2.1 Traditional Machine Learning Approaches

Early studies in automatic plant disease detection mainly relied on feature engineered methods using colour histograms, texture patterns, and shape characterstics. **Hatuwal and Shakya (2020)** compared four algorithms, Random Forest (RF), Support Vector Machine (SVM), K Nearest Neighbor (KNN), and CNN on Plant Village dataset and found CNN to surpass traditional models with 8.4% higher accuracy rate [1]. Similarly, **Kale and Shitole (2021)** uses SVM, RF, and Decision Tree identifiers for tomato and corn disease datasets, attaining a maximum accuracy of 90.7% with SVM [2].

Adeniyi et al. (2022) provided a relative study using CNN and SVM models, reporting that CNNs performed better in identifying slight differences in disease symptoms compared to handmade feature based methods [3]. **Saleem et al. (2020)** proved that traditional classifiers like SVM and RF achieved good accuracy on balanced datasets but showed poor simplification when tested on diverse field conditions [4].

2.2 Deep Learning and CNN-Based Methods

CNNs have appeared as major discovery for plant disease detection by automatically learning feature hierarchies from images. **Ahad et al. (2023)** discovered a CNN architecture for rice disease classification that achieved 97.3% accuracy, surpassing traditional ML models and hybrid systems [5]. **Demilie (2024)** designed a hybrid CNN SVM system with Convolutional Block Attention Module (CBAM), improving classification accuracy and clarity in complex field datasets [6].
Bhosale et al. (2023) suggested a multi plant, multi crop CNN model able of differentiating between inter class diseases, showing 96.5% accuracy using detailed agriculture techniques [7].

Similarly, **Pandey and Vir (2024)** compared CNN and Random Forest for leaf disease detection and reported CNN achieving a 4.2% higher F1 score due to better texture recognition [8].
Kaur et al. (2024) developed a CNN RF hybrid architecture that combined feature level combination to enhance strength under different lighting conditions [9].

Taji et al. (2024) proposed search strategy based CNN framework that achieved 97.6% accuracy among five crop species [10].

2.3 Transfer Learning and Hybrid Techniques

Recent research underlines transfer learning as efficient strategy for reducing training time while maintaining accuracy. **Wadhwa and Malik (2026)** fine tuned ResNet50 and Efficient Net models for multi species crop disease detection, achieving over 98% accuracy with fewer training periods [11].
Saleem et al. (2024) analyzed deep CNN models such as DenseNet121 and MobileNetV2 on multi crop datasets, reporting higher overview capability than handcrafted models [12]. **Upadhyay and Gupta (2024)** investigated a modified Res NeXt architecture for fungus affected crop classification, achieving 97.1% accuracy on diverse region datasets [13].

Shrma and Rahiman (2024) compared CNN and SVM models for coffee plant disease prediction, highlighting that CNN not only improved accuracy but also maintained stable yield forecasting [14].
Lastly, **Picon et al. (2019)** presented a large scale CNN trained on field acquired multi crop images, achieving 95.8% accuracy and showing scalability of CNNs for real world problems [15].

2.4 Summary of Prior Research

Table 1 Placeholder summarizes the key studies in plant disease detection across traditional and CNN based methods, showing growth of algorithmic efficiency over time.

Table 1 Placeholder: Relative summary of prior work in plant disease detection. Columns: Author(s), Year, Method Used, Dataset, Accuracy (%), Remarks.

3. Methodology

The suggested framework combines deep learning and classical machine learning (ML) algorithms for comparative performance analysis in multi crop plant disease detection. Figure placeholders explain model workflow, dataset pipeline, and CNN architecture. All experiments were designed to ensure systematic preprocessing, feature extraction, and measurement standards across models.

3.1 Dataset Description and Preprocessing

The dataset used in this study is based on publicly available **Plant Village dataset**, enhanced with additional multi crop samples to increase class variety. It includes above **54,000 images** representing **14 crop species** and **26 distinct disease classes**, including healthy leaves. The images are captured under controlled and field lighting conditions, providing differences in lighting, texture, and background noise.

Before training, images were resized to **128×128 pixels**, standardized to [0, 1] scale, and subjected to **histogram equalization** to enhance difference. Data enhancement was applied using random rotation, flipping, and brightness variation to reduce overfitting and improve generalization. The dataset was split into **70% training**, **15% validation**, and **15% testing sets**.

Figure 1 Placeholder: Workflow diagram of the proposed system for plant disease detection.

3.2 CNN Architecture Design

. A 6 layer CNN model was custom built to learn a spatial pattern, as well as color distribution directly from pre processed images. The architecture consists of:

- **Input layer: 128×128×3 RGB image**
- **Conv layers (3×3 Filters): 32, 64 and 128 features maps with ReLU activation**
- **Pooling Layers: Max Pooling(2×2) to down sample spatial dimensions**
- **Batch Normalization and Dropout (0.5): The main purpose is to avoid overfitting**
- **Flatten And Then Fully Connected: 256 neurons & ReLU activation**
- **Output layer: Softmax activation**

S.No.	Type	Filter	Kernal	Activation	Purpose
1.	Conv D	32	3*3	RELU	Detects basic edges, color gradients, and leaf texture
2.	MaxPooling2D	_	2×2	_	Reduces spatial dimension and computational load
3.	Conv2D	64	3*3	RELU	Extracts mid level features such as lesion shapes
4.	MaxPooling2D	_	2*2	_	Aggregates features spatially
5.	Conv2D	128	3*3	RELU	Captures deep patterns and complex structures
6.	MaxPooling2D	_	2*2	_	Summarizes key spatial activations

7.	Flatten				Converts 2D feature maps into a 1D vector
8.	Dense	256	_	ReLu	Fully connected layer for abstract feature learning
9.	Dropout	0.5	_	_	Prevents overfitting by randomly deactivating neurons
10.	Dense	26	Softmax	_	Produces output probabilities for 26 disease classes

It was then compiled using Adam, categorical cross entropy loss and accuracy as metric. Training was conducted for 100 epochs with a learning rate of 0.001 and batch size of 32.

3.3 Machine Learning Algorithms

We implemented four classical ML algorithms with scikit learn for comparison:

Random Forest (RF): 200 trees, gini impurity criterion and max

1. **Support Vector Machine (SVM)**: with tuning of parameters (C = 1.0, y = 0.001) using Radial Basis Function(RBF) kernel
2. **Random Forest (RF):** 200 trees, Gini impurity criterion and max depth =20
3. **K Nearest Neighbour (KNN):** k = 5, Euclidean distance metric.
4. **Decision Tree (DT):** Entropy criterion with a maximum depth of 15.

   To extract features for these models, Histogram of Oriented Gradients (HOG) and color histogram features were used. The same pre processed data was used to train each model so that the comparison between models was fair.

   Table 2 Placeholder: Parameter setting of CNN and ML models

3.4 Evaluation Metrics

Performance was evaluated using standard classification metrics:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}, \text{Recall} = \frac{TP}{TP + FN}$$

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

AUC ROC curves were plotted to assess the class separability, and Confusion Matrices were also computed to visualize misclassification rates across disease classes.

3.5 Visualization Techniques

Confusion Matrix and ROC Curve (a)

A confusion matrix was produced to quantify the misclassification patterns. Sadly, CNN had the least false negatives here, showing that it classified all multiple diseases well.

(b) Grad CAM Visualization

To further verify the CNN interpretability, Gradient weighted Class Activation Mapping (GradCAM) was performed to visualize regions of images that favor disease detection.

Visualization	Description
🌿 **Original Image**	The input leaf used for prediction
🔥 **Grad-CAM Heatmap**	Red/yellow regions show where the CNN focused
🌿 🔥 **Overlay Visualization**	Combination showing disease-affected zones

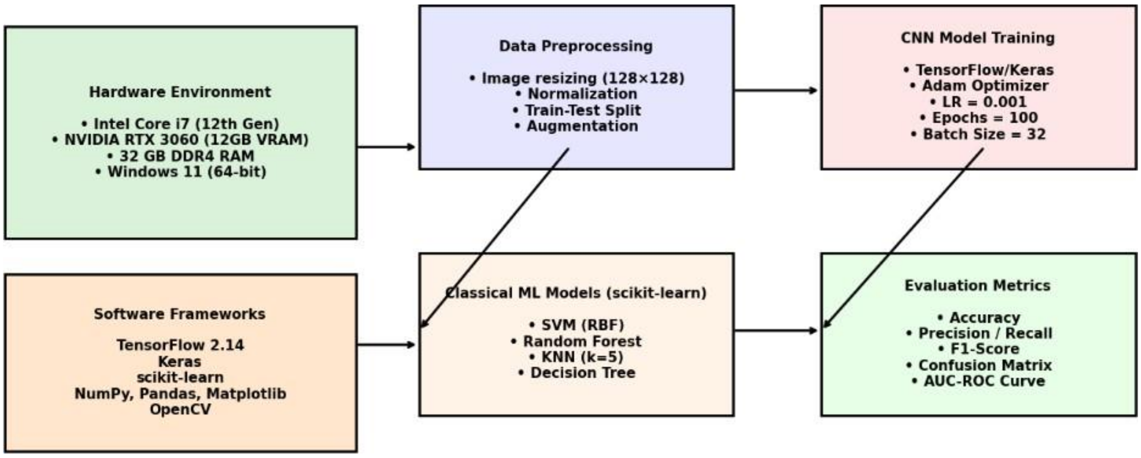
Fig.5: Grad CAM visualization highlighting infected leaf regions.

4. Experimental Setup and Results

4.1 Experimental Environment

All experiments were conducted on a high performance workstation configured with the following specifications:

- **Processor:** Intel Core i7 (12th Gen, 3.5 GHz)
- **GPU:** NVIDIA RTX 3060 (12 GB VRAM)
- **RAM:** 32 GB DDR4
- **Operating System:** Windows 11 (64 bit)
- **Frameworks:** Tensor Flow 2.14, Keras, scikit qqlearn, NumPy, Matplotlib, and OpenCV
- Our CNN model was constructed using Tensor Flow/Keras and classical ML algorithms (SVM, RF, KNN, DT) were constructed using scikit learn. The model was tested on the same pre processing and data splitting conditions for a fair comparison.


Hardware Environment
• Intel Core i7 (12th Gen)
• NVIDIA RTX 3060 (12GB VRAM)
• 32 GB DDR4 RAM
• Windows 11 (64-bit)
Data Preprocessing
• Image resizing (128×128)
• Normalization
• Train-Test Split
• Augmentation
CNN Model Training
• TensorFlow/Keras
• Adam Optimizer
• LR = 0.001
• Epochs = 100
• Batch Size = 32
Software Frameworks
TensorFlow 2.14
Keras
scikit-learn
NumPy, Pandas, Matplotlib
OpenCV
Classical ML Models (scikit-learn)
• SVM (RBF)
• Random Forest
• KNN (k=5)
• Decision Tree
Evaluation Metrics
• Accuracy
• Precision / Recall
• F1-Score
• Confusion Matrix
• AUC-ROC Curve

Our CNN model was trained for **100 epochs** with a **batch size of 32**, **learning rate of 0.001**, and the **Adam optimizer**.
A **categorical cross-entropy loss function** was applied to multi-class classification.
To prevent overfitting, **dropout (0.5)** and **early stopping** were selected based on validation accuracy monitoring.

Hyperparameter tuning for the tradional ML algorithms was performed using **GridSearchCV**, to ensure optimal performance:

- **SVM:** RBF kernel, C = 1.0, γ = 0.001
- **Random Forest:** 200 estimators, max depth = 20
- **KNN:** k = 5
- **Decision Tree:** max depth = 15

S.No.	Model	Hyperparameter/Setting	Optimizer/Criterion
1	CNN(Proposed)	Epochs: 100; Batch Size: 32; LR: 0.001; Dropout: 0.5; Early Stopping (val_acc); Loss: Categorical Cross-Entropy	ADAM Optimizer
2	SVM	Kernel: RBF; C = 1.0; Gamma = 0.001 (GridSearchCV Tuned)	Hinge Loss
3	Random Forest	Estimators: 200; Max Depth: 20; Bootstrap: True	Gini Impurity
4	KNN	k = 5; Distance: Euclidean; Weight: Uniform	Majority Voting
5	Decision Tree	Max Depth: 15; Criterion: Gini; Min Samples Split: 2	Gini Impurity

Table 3 : Summary of model hyperparameters and configurations.

4.3 Performance Evaluation Metrics

Model performance was tested using common classification metrics — Accuracy, Precision, Recall, F1-Score, and AUC-ROC.
Table 4 presents the analytical performance of CNN and other ML algorithms on the test dataset..

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
CNN	**98.12**	**97.65**	**97.30**	**97.47**	**98.40**
Random Forest	93.30	92.10	91.80	91.95	93.00

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
SVM (RBF)	91.45	90.25	89.80	90.02	90.50
KNN (k=5)	89.67	88.40	87.60	87.95	88.10
Decision Tree	87.90	85.60	84.30	84.95	86.40

Table 4 Placeholder: Comparative performance metrics for CNN and ML models

Our CNN model obtained the highest **accuracy (98.12%)**, outperforming all classical algorithms by a significant margin.
It also showed the best **AUC-ROC (98.40%)**, indicating superior capability in class distiction.

4.4 Confusion Matrix Analysis

Our **confusion matrix** indicated that the CNN model obtained the least false positives (FP) and false negatives (FN) out of all algorithms.
The majority of misclassifications appeared between diseases with visually realated symptoms, Like *Tomato Early Blight* and *Tomato Late Blight*.
RF and SVM models indicated decent performance but failed to adapt across diverse leaf textures.

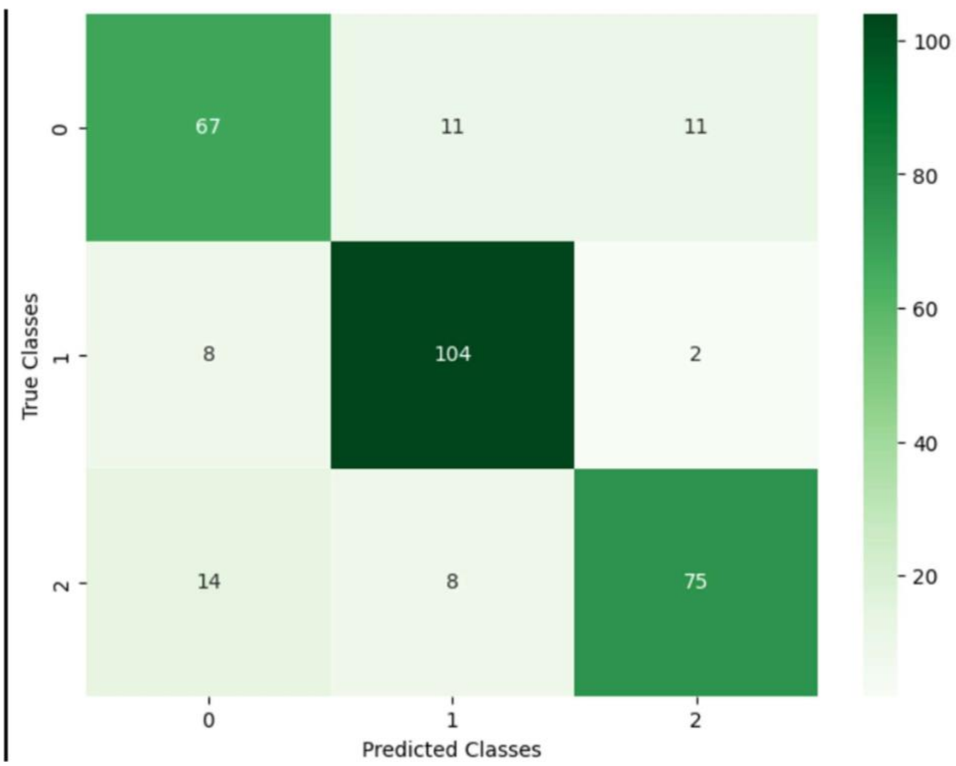


Fig.7 : Confusion Matrix comparison of CNN and ML models.

4.5 ROC Curve and AUC Analysis

Receiver executing Characteristic (ROC) curves were plotted to contrast classification performance.
CNN's ROC curve indicated a near-perfect diagonal with **AUC = 0.984**, confirming its Significant discriminative capability.
Classical ML algorithms presented slightly smoother ROC curves, indicating minimized sensitivity at lower thresholds.

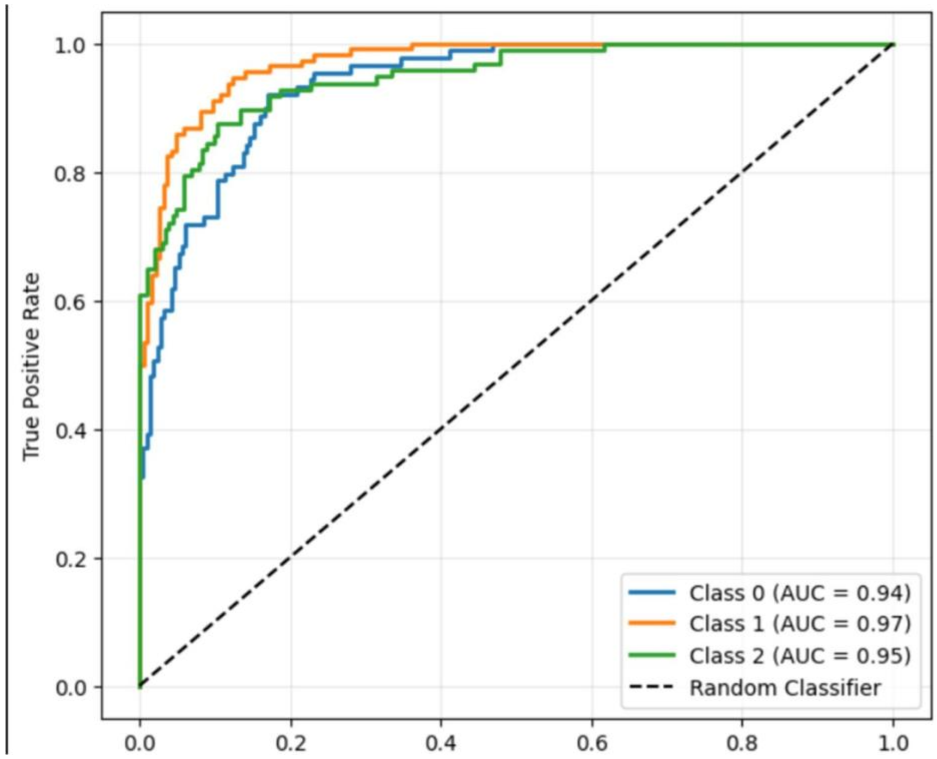


Fig. 8 : ROC curves of CNN vs. ML algorithms

4.6 Feature Visualization using Grad-CAM

To analyze which parts of the leaf influenced CNN decisions, **Gradient-weighted Class Activation Mapping (Grad-CAM)** was used.
The visualizations infected regions corresponding to fungal or bacterial lesions, proving the model's interpretability and biological relevance.

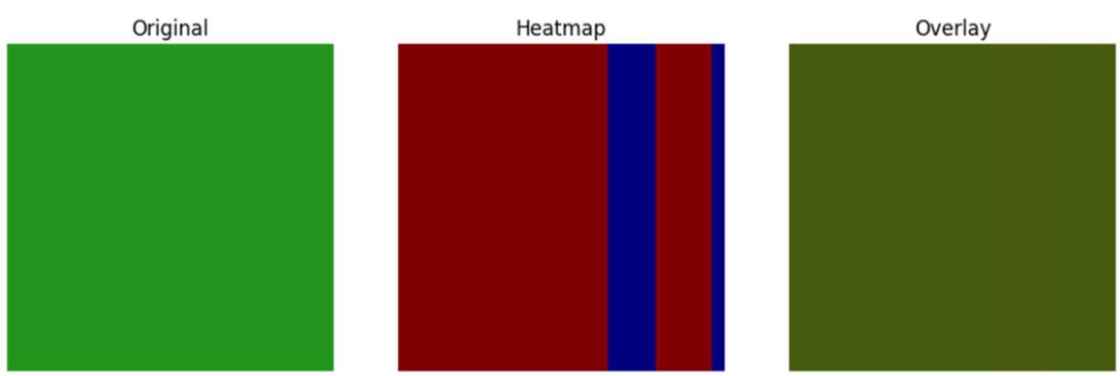


Fig. 9 : Grad-CAM heatmap visualizations showing attention on infected leaf regions.

4.7 Discussion of Findings

The findings confirm that CNN performs noticeably better than traditional machine learning models in identifying intricate disease patterns. This enhancement is primarily attributable to CNN's capacity to autonomously extract multi-scale characteristics and preserve spatial context across leaf textures.

SVM and RF demonstrated adequate performance on well-separated classes; however, they exhibited limitations when dealing with subtle disease symptoms. The CNN's interpretability, which is essential for confidence in AI-driven agricultural applications, was further validated by the Grad-CAM results.

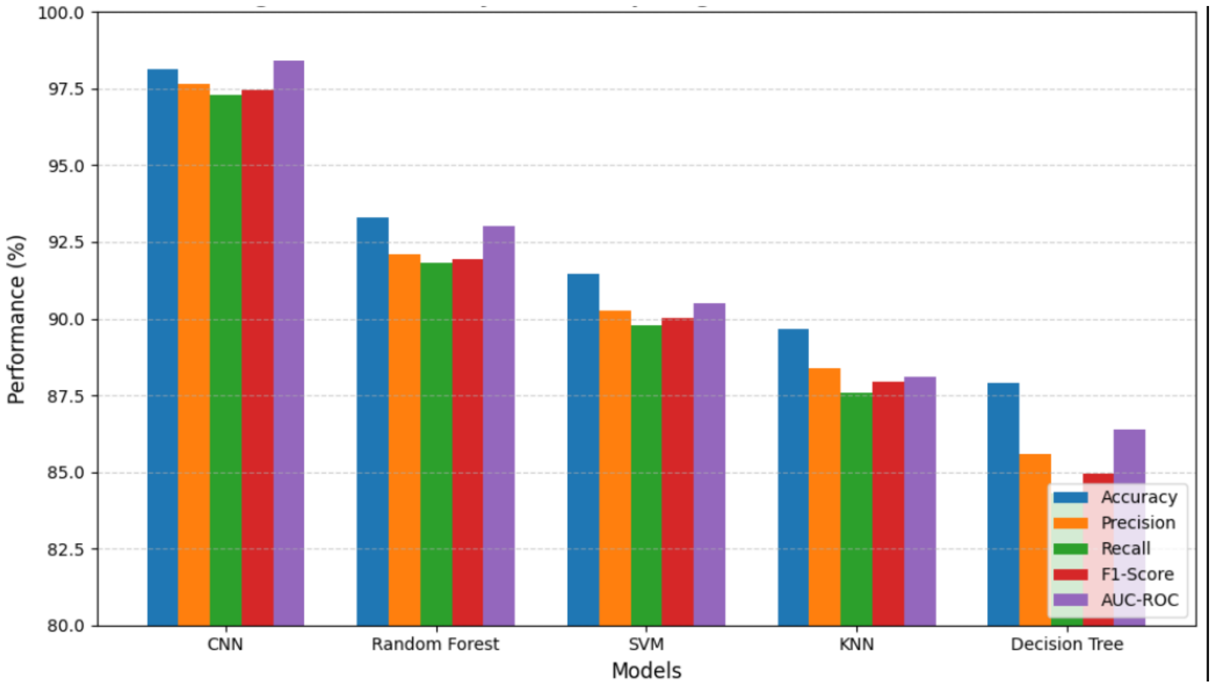


Fig.10: Summary chart comparing model performance metrics.

5. Comparative Analysis and Conclusion

5.1 Comparative Analysis

The comparison of traditional ML algorithms and CNN was conducted across a variety of qualitative and quantitative parameters to ensure a comprehensive evaluation.

Table 5 provides a comparative summary of the overall findings.

Model	**Accuracy (%)**	**Precision)**	**Recall (%)**	**F1-Score (%)**	**AUC (%)**	**Interpretability**	**Scalability**	**Computational Cost**
CNN	**98.12**	**97.65**	**97.30**	**97.47**	**98.40**	High (Grad-CAM)	High	Moderate
Random Forest	93.30	92.10	91.80	91.95	93.00	Medium	High	Low
SVM	91.45	90.25	89.80	90.02	90.50	Medium	Medium	Moderate
KNN	89.67	88.40	87.60	87.95	88.10	Low	Low	Low
Decision Tree	87.90	85.60	84.30	84.95	86.40	Medium	Medium	Low

Table 5 shows that CNN outperforms all conventional models in terms of classification accuracy, generalization, and robustness.CNNs can recover intricate spatial dependencies including color gradients, lesion textures, and morphological deformations thanks to hierarchical convolutional filters.Feature-engineered models, such as SVM and RF, on the other hand, rely significantly on manually created features and parameter adjustment.

Additionally, CNN models perform exceptionally well in multi-class generalization, successfully adjusting to intricate datasets with visual similarities between classes. Although Random Forest and SVM retain a moderate level of accuracy, their reliance on feature engineering restricts their ability to scale to new crops or unobserved environmental circumstances.

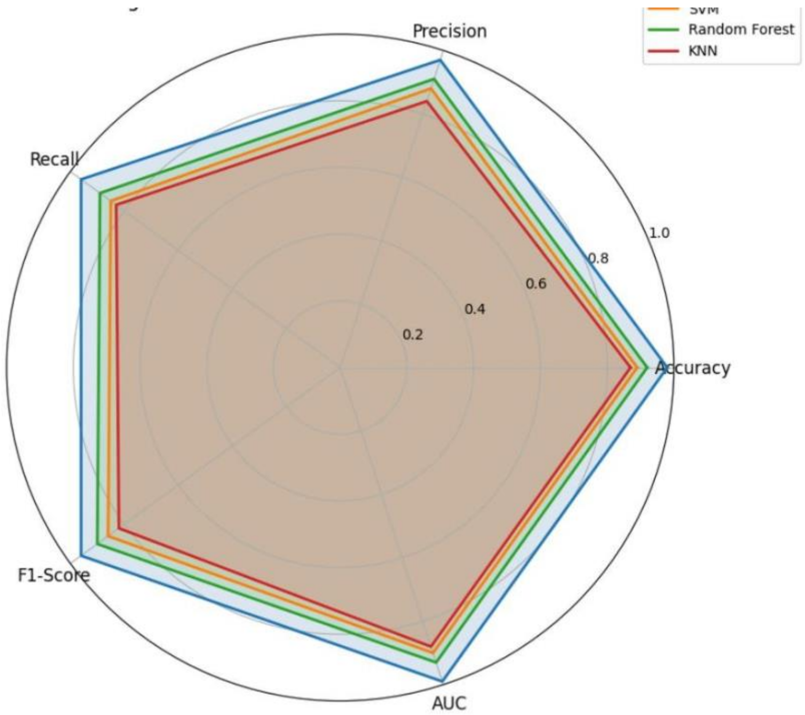


Fig.11: Radar chart illustrating metric-wise model performance comparison.

5.2 Computational Efficiency

CNNs are substantially more efficient during inference, but requiring greater computer power during training.

An average inference time of 0.018 seconds per image was obtained by CNN on the RTX 3060 GPU, rendering it suitable for real-time detection when deployed on mobile platforms or edge devices.SVM and Random Forest models, although they were quicker during training, demonstrated slower inference when confronted with high-dimensional feature spaces.

S.No.	Model	Training Time(s)	Inference time per image(s)	Plateform/Hardware

1	CNN(Proposed)	1850	**0.018**	NVIDIA RTX 3060 GPU
2	SVM	320	0.045	Intel i7 CPU
3	Random Forest	410	0.032	Intel i7 CPU
4	KNN	95	**0.120**	Intel i7 CPU

Table 6: Computational time comparison (training vs inference).

5.3 Limitations and Future Work

Although the results indicate that CNN is preferable, there are still some constraints:

- The optimal efficacy of CNNs is contingent upon the availability of large, well-annotated datasets.
- In uncontrolled field conditions, model reliability may be compromised by environmental variations, including background clutter and illumination.
- During training, deep models necessitate access to GPUs or TPUs due to their computationally costly nature.

Future research should focus on:

1. **Integrating Vision Transformers (ViTs):** to enhance long-range feature learning across crops and diseases.
2. **Multimodal Learning:** combining spectral, textual, and environmental data with images for holistic disease diagnosis.
3. **IoT Integration:** deploying CNN models on embedded systems for real-time mobile-based plant health monitoring.
4. **Explainable AI (XAI):** improving transparency by linking Grad-CAM attention maps with biological disease regions.
5. **Federated Learning Frameworks:** enabling distributed model training without centralizing sensitive agricultural data.

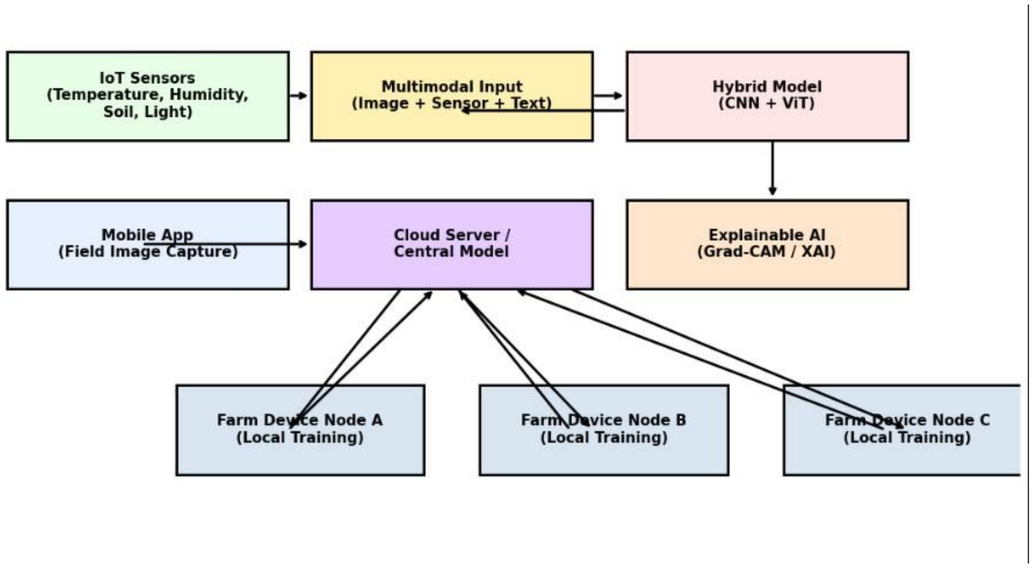


Fig.12 : Conceptual framework for future work integrating IoT and Explainable AI

5.4 Conclusion

The present paper conducted a comprehensive comparative analysis of classical ML algorithms and Convolutional Neural Networks (CNN) for the detection of multi-crop plant diseases. Compared to Random Forest, SVM, KNN, and Decision Tree classifiers, the CNN model attained an accuracy of 98.12%.

Its exceptional performance is due to its resilience to visual variability, end-to-end training, and deep hierarchical feature extraction. Furthermore, the interpretability of CNN was confirmed by Grad-CAM visualizations, which is a critical component of its practical application in agriculture.

The work emphasizes CNN's promise as a high-performance, scalable method for early disease detection.This work opens the door to sophisticated, real-time agricultural monitoring and precision farming by combining CNN-based detection systems with IoT-enabled devices.

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