ADVANCING PLANT DISEASE DETECTION: A COMPARATIVE ANALYSIS OF DEEP LEARNING AND HYBRID MACHINE LEARNING MODELS

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Abstract Detecting plant diseases is essential for precision agriculture, as it enhances crop production and ensures the security of the food supply. We adopted two methods for this research: a method based on deep learning, through Convolutional Neural Networks (CNN), and a hybrid model using classical machine learning. The dataset comprised images of plant leaves from Kirtan village in Hisar, Haryana, which were annotated by plant pathologists. The CNN model, which autonomously extracts hierarchical spatial features, achieved an accuracy of 97.57%, making it ideal for large datasets. Conversely, the Hybrid model utilizing handcrafted GLCM and LBP features and SVM classifiers achieved 91.73% accuracy while providing interpretability and computational efficiency in resource limited setups. The performance of the models was measured in terms of accuracy, precision, recall and F1-score. Applications range from on-line monitoring with drones to diagnostic equipment for the farmer.

Keywords: plant disease detection, hybrid model, machine learning, deep learning, GLCM, LBP, CNNs, SVMs, feature extraction, data augmentation, classification models, evaluation metrics, precision agriculture.

1. Introduction

Detecting plant diseases is essential in contemporary agriculture, with considerable implications for global food security, crop management, and environmental sustainability. Early and accurate recognition of plant diseases empowers farmers with the means to make respective treatments. Traditional detection methods reliant on manual inspection and expert knowledge are characterized by high labor intensity, significant time consumption, and susceptibility to human error.

Recent developments in machine learning and computer vision have helped to develop automated systems to diagnose plant diseases. Early methodologies utilized classical machine learning techniques that incorporated hand-crafted features, including the Grey-Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP), in conjunction with classifiers such as Support Vector Machines (SVM). These models exhibit interpretability and demonstrate strong performance on small datasets; however, they are constrained by their reliance on manual feature engineering and exhibit limited scalability.

The advent of deep learning, in particular Convolutional Neural Networks (CNNs), has transformed the area with the ability to learn features directly from the image data.

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This leads to enhanced accuracy and scalability. CNNs require significant computational resources and extensive labeled datasets, rendering them less appropriate for low-resource agricultural settings.

This research compares between CNN and hybrid-based machine learning models for plant disease classification, which fills the gap between these two approaches in plant disease detection. We measure the performance of each model on a locally acquired and annotated dataset by applying accuracy, precision, recall, and F1-score, and assessing their respective applicability in on-site agricultural practices. The results are intended to aid in the design of practical and scalable disease detection solutions in precision agriculture. To contextualize these contributions, the following literature review examines prior studies on machine learning and deep learning approaches, highlighting their strengths, limitations, and areas where this research advances the field.

The remaining parts of this paper are as follows. After the literature review in Section 2, the proposed methodology for plant disease detection will be presented in Section 3. The results of classifications will be shown in Section 4. The comparison between the CNN and the hybrid-based machine learning models will be made in Section 5. Finally, the paper will be concluded in Section 6.

2. Literature Review

Machine learning-based (ML) techniques for plant disease classification have been explored in several studies. Iniyan et al. [8] used Support Vector Machines (SVM) and Artificial Neural Networks (ANN) for detecting plant diseases, showing the benefits of classical ML algorithms. Similarly, Saleem et al. [14] notably found that ML models lagged behind the deep learning-based classifiers in this regard, since it was a comparative analysis. Dixit et al. [5] presented an ML-based model for wheat crop disease detection, resulting in more efficient monitoring of agriculture.

One promising solution for plant disease detection is deep tissue learning. Bakr et al. [1] used transfer learning with DenseNet to classify tomato diseases and concluded with a high accuracy in tomato disease classification. Balafas et al. [2] presented a detailed comparison between ML and DL models; it was shown to achieve better results in CNN when applied to tasks in detecting plant diseases. Khalid and Karan [11] discussed the effectiveness of deep learning and proposed an end-to-end automatic disease classification model. Sharma and Guleria [16] explored and compared numerous deep learning models for image classification, indicating that CNNs performed remarkably well with regard to generalization across datasets. Yu [20] conducted a review of deep learning methods used for image-based classification tasks and confirmed their effectiveness.

To achieve higher classification accuracy, hybrid and attention-based models were explored. Shao et al. [15] developed a hybrid ViT-CNN model by combining Vision Transformers (ViT) and CNN to achieve fine-grained classification. Kalim et al. [10]

developed a hybrid CNN-RF model that combines the initial feature extraction and machine learning classifiers for the detection of diseases in citrus leaves. Bera et al. [3] introduced an attention-based deep network, where n features selection is optimized for plant disease classification. Gao et al. [7] propose a two-branch channel attention-based model, which improved the crop disease identification accuracy.

Comparative analyses of different classification models have been performed in some studies. Wang et al. [19] conducted a systematic comparison between conventional ML and DL methods in the context of image classification, thus further confirming the superiority of deep learning. Lorente et al. [12] referenced several classical and modern deep learning methods for classification of plant diseases. Deep learning methods for image classification have been extensively reviewed, with Wu et al. [13] providing a detailed summary of key advancements in CNN, ViT, and Hybrid models.

However, despite all this progress, there are still problems when it comes to real-world use. Shoaib et al. [17] provided an overview of recent advances in deep learning-based approaches for plant disease detection and underscored the need for better model generalization and larger datasets. To enhance the robustness of the model, data augmentation techniques are essential, as highlighted by Furqan et al. [6]. Kabir et al. [9] explored differences in Gray-Level Co-occurrence Matrix (GLCMs) and advised GLCM optimization to enhance feature extraction for deep learning models. Chen et al. [4] addressed the problems of real-world occlusions and illuminations while showing robustness via detection techniques. A survey on smart agriculture applications by combining ML and DL techniques for crop disease prediction was provided by Subbarayudu and Kubendiran [18].

A review of the literature (Table 1) shows a clear trajectory of moving from traditional machine learning approaches to recently used deep learning-based methods for detecting plant diseases. Although CNN is a popular architecture, hybrid and attention-based models have led to greater accuracy. Future research should focus on overcoming dataset limitations, improving model interpretability, and deploying AI-driven solutions in real-world agricultural situations should gain more attention.

Tab. 1. Comparative analysis of different studies.

Reference	**Methodology used**	**Limitations**
Iniyan et al. [8]	SVM, ANN for plant disease detection.	Limited dataset, potential overfitting
Saleem et al. [14]	Comparison of ML vs DL models	DL models require high computational power
Dixit et al. [5]	Machine Learning for wheat crop disease	ML models lack scalability for large datasets

to be continued in the next page

Tab. 1. Comparative analysis of different studies (continued).

Reference	**Methodology used**	**Limitations**
Bakr et al. [1]	DenseNet with Transfer Learning.	Transfer learning effectiveness depends on pre-trained model
Balafas et al. [2]	Comparison of ML and DL models	ML models underperform compared to DL
Khalid & Karan [11]	Deep Learning-based model for classification	End-to-end DL model needs large labeled datasets
Sharma & Guleria [16]	Comparison of CNN-based image classification models	CNNs require large amounts of training data
Yu [20]	Evaluation of deep learning architectures	Performance varies across architectures
Shao et al. [15]	Hybrid ViT-CNN for fine-grained classification	Hybrid model complexity may hinder real-time deployment
Kalim et al. [10]	Hybrid CNN-RF model for citrus leaf disease	CNN-RF may struggle with unseen datasets
Bera et al. [3]	Attention-based deep learning network	Attention-based models increase inference time
Gao et al. [7]	Dual-branch channel attention model	Attention mechanism increases computational cost
Wang et al. [19]	Comparative analysis of ML and DL approaches	Deep learning models need extensive training
Lorente et al. [12]	Comparison of classical and deep learning techniques	Classic methods less accurate than DL
Wu et al. [13]	Comprehensive review of DL for image classification	Review lacks implementation details
Shoaib et al. [17]	Review of advanced deep learning models	Advanced DL models require extensive resources
Furqan et al. [6]	Deep learning for plant disease classification	Limited generalization on diverse plant datasets
Kabir et al. [9]	GLCM feature extraction analysis	GLCM feature extraction is computationally expensive
Chen et al. [4]	Handling occlusion and illumination in fruit detection	Occlusion handling reduces detection speed
Subbarayudu & Kubendiran [18]	Survey on ML, DL techniques for smart agriculture	Survey lacks experimental validation

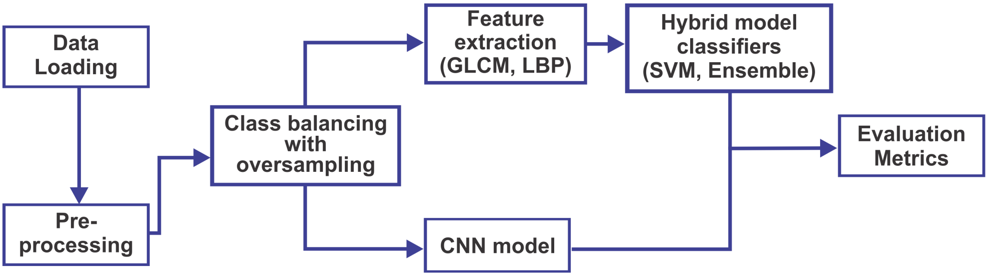

Fig. 1. Proposed system model demonstrating the CNN model pathway and the Hybrid model pathway.

3. Methodology

The methodology for plant disease detection (Figure 1) highlights two separate approaches: a CNN-based model and a hybrid traditional machine learning model. The process begins with data loading, where the dataset is prepared and structured for analysis, followed by preprocessing, which includes resizing, normalization, and augmentation to ensure consistency and diversity in the data.

To address class imbalances, class balancing with oversampling was employed to ensure the equal representation of all classes in the dataset. The workflow then branched into two distinct pathways.

CNN Model Pathway: The balanced dataset was directly input into a CNN model, which automatically extracted hierarchical spatial features and performed end-to-end classification.

Hybrid model pathway: The balanced dataset undergoes feature extraction using GLCM and LBP to capture texture-based information. These features are then used to train traditional classifiers such as SVMs and ensemble models.

The two pipelines meet at the evaluation phase where they are evaluated independently using performance metrics like accuracy, precision, recall, and F-1 score. This approach allowed a comparison of the two approaches and highlighted the advantages and application cases of both the scenarios.

3.1. Data collection and preprocessing

The dataset images were obtained directly from agricultural fields in the nearby village of Kirtan, Hisar, Haryana (India). The acquired images mimic the field environment and are therefore practical. An expert plant pathologist labelled multiple images of a

Class	Shuffled sample 1	Shuffled sample 2
Healthy		
Diseased		

Fig. 2. Randomly shuffled samples from the dataset.

particular plant disease to create high-quality annotated data suitable for the effective training and evaluation of models.

3.2. Data loading

The dataset, which contained labeled images of plant leaves, was organized into structured directories. Using TensorFlow, the data were loaded and automatically split into training, validation, and testing sets. This ensured a clean separation for model training and performance evaluation.

Representative samples from the dataset (Figure 2) illustrate various plant leaf conditions utilized for training and evaluation purposes. This encompasses healthy and diseased leaves across various classifications. Healthy leaf samples demonstrate uniform

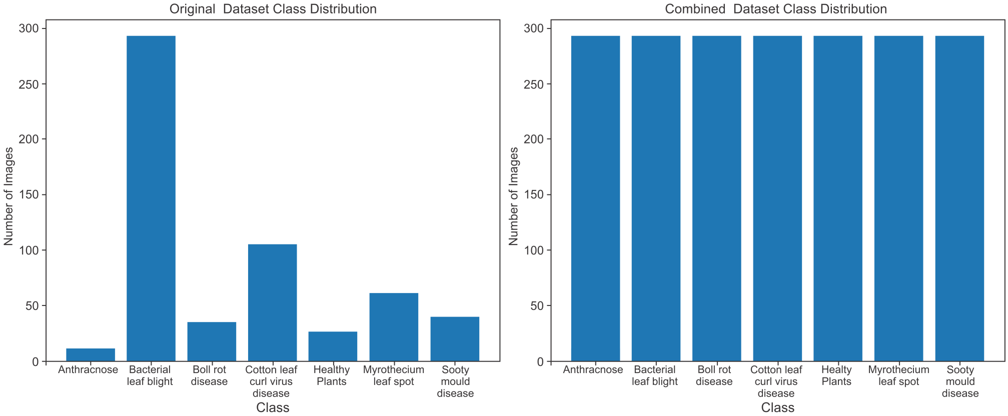

Fig. 3. Exploratory Data Analysis of the data spread before and after oversampling.

color and texture, while diseased samples show distinct symptoms, including spots, discoloration, or fungal patches. The images were obtained under natural field conditions, ensuring that the dataset accurately reflects real-world agricultural environments.

3.2.1. Image resizing and normalisation

All images were resized to 224×224 pixels to ensure the image size was compatible with the deep learning architectures. The pixel values were normalized between 0 and 1.

$$I_{\text{norm}}(x,y) = \frac{I(x,y)}{255}\,. \tag{1}$$

3.2.2. Class balancing with oversampling

In order to rectify the imbalance in classes, oversampling techniques were used. Figure 3 shows how oversampling affects the distribution of the dataset, showing better balance among plant disease classes. This guarantees equal contributions from each class during training, which is essential for avoiding biased predictions and enhancing model generalization in practical situations.

3.2.3. Dataset augmentation

Training used to be performed on data with augmented examples for improved generalization. The augmentation techniques included the following:
- rotation (±20 degrees),
- horizontal and vertical flipping,
- scaling (±10%).

This process artificially increases the dataset diversity, reduces overfitting, and improves the robustness to real-world variations.

3.3. Hybrid model

The Hybrid model combines traditional feature extraction techniques with machine-learning classifiers.

3.3.1. Feature extraction

Grey-level co-occurrence matrix (GLCM): Textural features, such as contrast, energy, homogeneity, and correlation, were derived. The formulas for contrast and energy are as follows:

$$\begin{aligned} \text{Contrast} &= \sum_{k,l} Z(k,l) \cdot (k-l)^2 \,, && (2) \\ \text{Energy} &= \sum_{k,l} Z(k,l)^2 \,. && (3) \end{aligned}$$

Local Binary Patterns (LBP): Local texture patterns were encoded as binary values by comparing each pixel with its neighbors:

$$\text{LBP}(k_a, l_a) = \sum_{c=0}^{c-1} 2^c \cdot S(I_c - I_k) \,. \tag{4}$$

The GLCM was chosen for its robust capability in characterizing texture by summarizing the spatial relationships of pixel intensities, which is vital for differentiating plant diseases. We employed Local Binary Patterns (LBP), which are robust against illumination variations with sufficient precision, to analyze plant images collected in a natural field environment. Both methods were selected for their previous successes in similar agricultural studies.

3.3.2. Classifier models

Traditional classifiers

The features were then used to train classical classifiers like support vector machines or gradient boosting classifiers.

SVM with RBF kernel

We adopt the SVM model with RBF kernel, in which the kernel function is given as:

$$K(k,m) = \exp\left(-\gamma \|k-m\|^2\right) \,, \tag{5}$$

where γ is a parameter that balances the contribution of a single training example.

Ensemble classifiers

Stacking Multiple classifier outputs like SVM with RBF kernel, K-nearest Neighbors (KNN), Random Forest (RF) and Gradient Boosting (GB) were combined to form a stacked ensemble. The output of ensemble classifier can be expressed as:

$$\hat{y}_{\text{final}} = \sum_{i=1}^{n} w_i \cdot \hat{y}_i \,, \tag{6}$$

where $\hat{y}_i$ is the predicted output from the i-th classifier, and w_i are the corresponding weights of each classifier.

3.4. CNN-based deep learning model

The CNN model was developed as a standalone solution for plant disease classification.

3.4.1. Convolutional layers

These layers extracted spatial features from the images using filters. The feature maps produced represent patterns such as edges and textures. The convolution operation is defined as:

$$f(m,n) = (I * K)(m,n) = \sum_{i,j} I(m+i, n+j) \cdot K(i,j) \,, \tag{7}$$

where K denotes the convolutional kernel.

3.4.2. Pooling layers

By contrast, max-pooling stacked down the spatial dimension of feature maps by rejecting unimportant features.

$$P(m,n) = \max \{ f(o,q) \}_{(o,q) \in \text{window}} \,. \tag{8}$$

3.4.3. Dropout Layers

These layers randomly deactivate neurons during training to prevent overfitting.

3.4.4. Fully connected layers

The last fully connected layers transform the retrieved characteristics to the class probability with the softmax function. where the softmax is given by:

$$\hat{y}_i = \frac{\exp(z_i)}{\sum_j \exp(z_j)} \,, \tag{9}$$

where z_i represents the input to the i-th output unit.

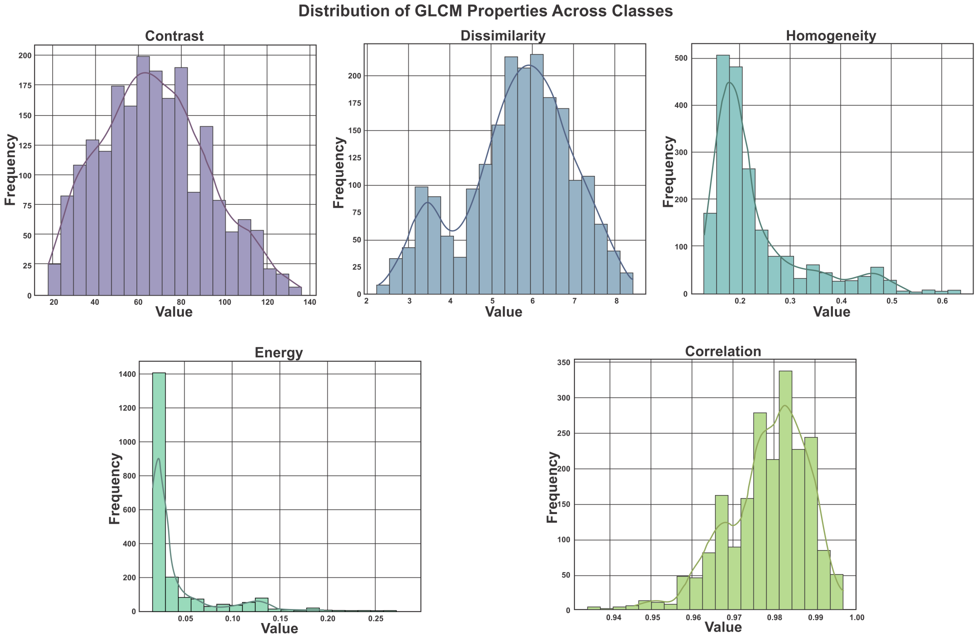

Fig. 4. Distribution of GLCM properties across classes.

3.4.5. Training process

The model was trained with Adam optimizer and categorical cross-entropy loss. We used the following loss function:

$$L = -\sum_i y_i \log(\hat{y}_i)\,. \tag{10}$$

We use early stopping to stop training as soon as the validation performance did not improve by more than a threshold used to control resource usage.

The algorithms applied in the Hybrid and the CNN models are shown as Algorithm 1, page 67, and Algorithm 2, page 68, respectively.

4. Results

Visualizations in Figure 4 illustrate the distribution of various GLCM properties—contrast, dissimilarity, homogeneity, energy, and correlation—across different classes within the dataset.

Algorithm 1 Plant disease detection using the Hybrid model

```
Input: Dataset of plant images $D$ resized to $224 \times 224$ pixels.
Output: Class predictions for test images.
Data Loading and Preprocessing:
Load dataset $D$ and split into $D_{\text{train}}$, $D_{\text{val}}$, and $D_{\text{test}}$.
Normalize the pixel values and apply Gaussian blurring for noise reduction.
Feature Extraction:
Compute GLCM features: contrast, energy, homogeneity, correlation.
Compute LBP features:
    $\text{LBP}(k_a, l_a) = \sum_{c=0}^{c-1} 2^c \cdot S(I_c - I_k)\,.$
Model Construction:
Train individual classifiers on the extracted features.
SVM with RBF kernel:
    $K(k, m) = \exp\left(-\gamma \|k - m\|^2\right)\,.$
Train Random Forest and Gradient Boosting classifiers.
Ensemble Model:
Combine predictions from classifiers using stacking:
    $\hat{y}_{\text{final}} = \sum_{i=1}^{n} w_i \cdot \hat{y}_i\,.$
Model Evaluation:
Evaluate the ensemble model on $D_{\text{test}}$.
Compute evaluation metrics: accuracy, precision, recall, and F1-score.
Class Prediction:
For an input test image, predict the disease class using the ensemble model.
```

1. **Contrast and Dissimilarity** exhibited a roughly symmetrical distribution, indicating that the texture variation in pixel intensity across classes follows a predictable pattern, which aids in distinguishing fine-grained details among diseases.
2. **Homogeneity** showed a skewed distribution toward lower values, suggesting that most images have less uniform textures, which are characteristic of diseased plant surfaces.
3. **Energy** has a highly skewed distribution, where most images exhibit low energy

Algorithm 2 Plant disease detection using CNN-based deep learning

```
Input: Dataset of plant images $D$, resized to $224 \times 224$ pixels.
Output: Class predictions for test images.
Data Loading and Preprocessing:
Load the dataset $D$ and split it into training $D_{\text{train}}$, validation $D_{\text{val}}$, and test $D_{\text{test}}$ sets.
Normalize pixel values:
    $I_{\text{norm}}(x,y) = \frac{I(x,y)}{255}\,.$
Apply data augmentation (rotation, flipping, and scaling).
Model Construction:
Define the CNN architecture:
Convolutional layers for feature extraction:
    $f(x,y) = (I * K)(x,y)\,.$
Pooling layers for dimensionality reduction:
    $P(x,y) = \max\{f(i,j)\}_{(i,j)\in\text{window}}\,.$
Fully connected layers for classification.
Model Training:
Compile the model using categorical cross-entropy loss:
    $L = -\sum_i y_i \log(\hat{y}_i)\,.$
Use the Adam optimizer and train the model on $D_{\text{train}}$ with validation on $D_{\text{val}}$.
Model Evaluation:
Test the trained model on $D_{\text{test}}$.
Compute evaluation metrics: accuracy, precision, recall, and F1-score.
Class Prediction:
For an input test image, predict the disease class using the trained CNN.
```

values, reflecting lower uniformity or regularity in pixel patterns across most diseased samples.

4. **Correlation** demonstrates a bell-shaped curve, highlighting consistent relationships between neighboring pixel intensities, which can be leveraged to identify patterns specific to certain diseases.

Overall, these distributions emphasise the importance of GLCM features in capturing

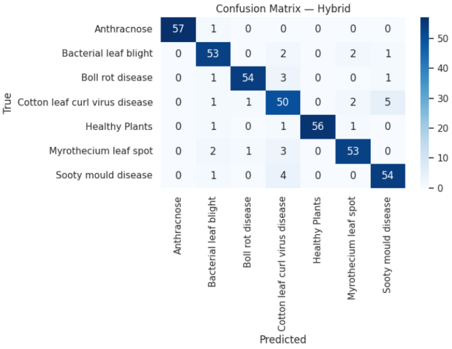

Fig. 5. Confusion matrix of Hybrid model.

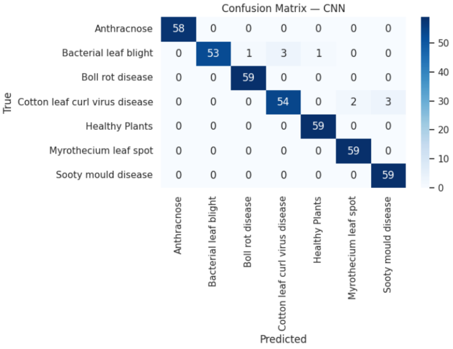

Fig. 6. Confusion matrix of CNN model.

critical textural details across various plant disease classes, making them essential inputs for traditional machine-learning classifiers.

The two confusion matrices provide a comparative evaluation of the Hybrid model (Figure 5) and the CNN model (Figure 6) for plant disease detection across multiple classes. The diagonal entries indicate the correct classifications, whereas the off-diagonal entries represent misclassifications.

1. The Hybrid model achieved strong accuracy across most classes (Figure 5). Anthracnose was classified almost perfectly (57/58 correct), while Boll Rot Disease (54/59) and Myrothecium Leaf Spot (53/59) also showed high reliability. Bacterial Leaf Blight had 53/58 correct, with minor confusion spread across Anthracnose, Myrothecium, and Cotton Leaf Curl Virus Disease. Healthy Plants were identified accurately in 56/59 cases, with a few errors toward Cotton Leaf Curl Virus Disease. The most challenging category was Cotton Leaf Curl Virus Disease, with 50/59 correct and misclassifications distributed into multiple related classes, including Sooty Mould Disease and Boll Rot Disease. Sooty Mould Disease itself was well distinguished (54/59), though again some overlap occurred with Cotton Leaf Curl Virus Disease. Overall, the Hybrid model performed robustly, though diseases with similar visual symptoms remained a source of confusion.

2. The CNN model demonstrated excellent performance (Figure 6), with near-perfect alignment between predicted and true labels. Anthracnose, Healthy Plants, and Myrothecium Leaf Spot were classified with 100% accuracy, while Boll Rot Disease and Sooty Mould Disease also achieved very high recognition rates (59/59 correct). Minor misclassifications appeared in Bacterial Leaf Blight (53/58 correct) and Cotton Leaf Curl Virus Disease (54/59 correct), though these errors were few and distributed

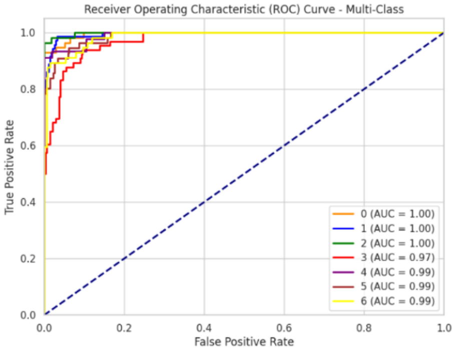

Fig. 7. ROC curves for the Hybrid model.

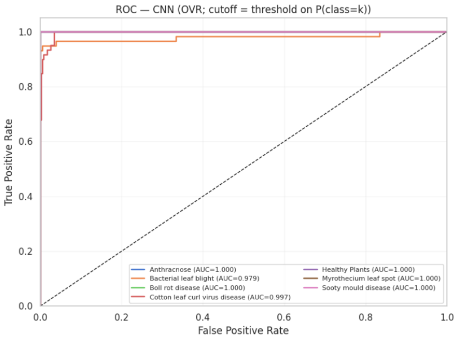

Fig. 8. ROC curves for the CNN model.

across related categories. Overall, the CNN model outperformed the Hybrid approach, achieving higher accuracy across all classes and showing stronger reliability in distinguishing visually similar diseases.

The ROC curves in Figures 7 and 8 illustrate the classification performance of the Hybrid and CNN models, respectively, across multiple plant disease categories. In both cases, the curves lie close to the top-left corner, indicating a very high true positive rate with minimal false positives. The Hybrid model (Figure 7) achieves near-perfect discrimination, with AUC values ranging from 0.97 to 1.00 across all seven classes, suggesting consistent reliability even in multi-class settings. Similarly, the CNN model (Figure 8) demonstrates excellent performance, with most classes such as Anthracnose, Healthy Plants, and Sooty mould disease achieving an AUC of 1.000, while a few, like Bacterial leaf blight (AUC = 0.979), are marginally lower but still highly accurate. Overall, both models show outstanding classification ability, though the Hybrid model provides more uniform performance across classes, whereas the CNN excels in certain categories with perfect separation.

The cutoff parameter used in the construction of the ROC curves was the decision threshold on the predicted probability $P(y = k \mid x)$, varied over the full interval $[0, 1]$.

In summary, the CNN model outperforms the Hybrid model by achieving near-perfect classification in most categories, highlighting its effectiveness in handling complex patterns and large datasets, whereas the Hybrid model exhibits moderate misclassifications, particularly in challenging classes like "Cotton Leaf Curl Virus Disease." Building on these findings, the next section provides a direct comparison of both models across key evaluation metrics, offering a deeper understanding of their relative strengths, weaknesses, and suitability for practical deployment.

The scores achieved by the two methods are compared in the Table 2.

Tab. 2. Scores of the Hybrid model and CNN model

Class	**Hybrid model**			**CNN**		
	precision	**recall**	**F1-score**	**precision**	**recall**	**F1-score**
Anthracnose	1.00	0.98	0.99	1.00	1.00	1.00
Bacterial leaf blight	0.89	0.91	0.90	1.00	0.91	0.95
Boll rot disease	0.96	0.92	0.94	0.98	1.00	0.99
Cotton leaf curl virus disease	0.79	0.85	0.82	0.95	0.92	0.93
Healthy Plants	1.00	0.95	0.97	0.98	1.00	0.99
Myrothecium leaf spot	0.91	0.90	0.91	0.97	1.00	0.98
Sooty mould disease	0.89	0.92	0.90	0.95	1.00	.98
Accuracy	0.9173			0.9757		
Macro Average	0.92	0.92	0.92	0.98	0.98	0.98
Weighted Average	0.92	0.92	0.92	0.98	0.98	0.98
Computational time [s]	27.14			64.66		

5. Comparison

The comparative performance of the Hybrid and CNN models (Figure 9) is shown on major evaluation measures: accuracy, precision, recall, and F1-score. CNN model performed consistently better than the Hybrid model with the accuracy of 97.57%, precision of 98%, recall 98%, F1-score 97%, which shows the excellent ability to deal with complex data and generalize appropriately. By contrast, our Hybrid model performed at 91.73% in all metrics. Despite slightly worse performance of the Hybrid model, it does qualify as a strong competitor in situations where computational efficiency and interpretability is crucial, especially when resources are limited. This comparison highlights that the CNN

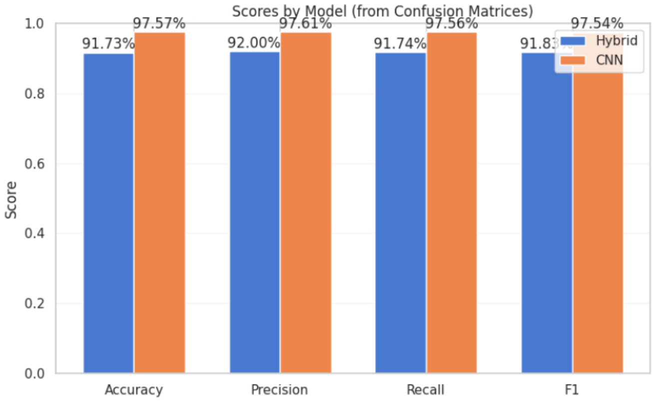

Fig. 9. Comparison charts of Hybrid and CNN models of the system pathway.

Tab. 3. Comparative analysis of Hybrid model and CNN model

Aspect	**CNN-based model**	**Hybrid model**
Accuracy	High, particularly on large and diverse datasets.	Moderate, depends on the quality of handcrafted features.
Scalability	Highly scalable to large datasets.	Limited scalability due to reliance on manual feature engineering.
Interpretability	Low, functions as a “black-box” model.	High, with explicit and interpretable features from GLCM and LBP.
Computational Efficiency	Computationally intensive; requires GPUs.	Efficient, suitable for environments with limited computational resources.
Generalization	Strong generalization on unseen data.	Moderate, struggles with variability in new datasets.
Suitability for Small Datasets	Limited; prone to overfitting without sufficient data.	High; performs well on small, structured datasets.
Ease of Implementation	Relatively straightforward with end-to-end learning.	Requires domain expertise for feature extraction.
Real-World Applications	Best for large-scale, automated systems.	Ideal for resource-constrained or interpretable decision-making scenarios.

model is well suited for large and diverse datasets, yet, the Hybrid model offers a powerful and interpretable alternative for simple or small scale applications. The comparison of the models in several aspects is shown in Table 3.

Our dataset suffers from potential bias as we have limited the dataset, based on a specific geographical location (Kirtan village, Hisar, India) and the diseases we select and can introduce a challenge to generalize the results to other types of diseases. Models primarily trained on local data might not generalize to other agricultural environments. In order to mitigate these biases and improve the robustness of the model, future studies should incorporate data from different regions and crop species.

6. Conclusion

Early diagnosis of plant disease is imperative for advanced Precision Agriculture and sustainable food production. In this paper, a comparison between a deep learning model using CNNs and a Hybrid model that integrates standard feature extraction methods and machine learning classifiers is conducted. Evaluation of both the models was performed using a custom dataset of plant leaf pictures collected locally with evaluation metrics with accuracy, precision, recall, and F1-score.

CNN model showed improved classification accuracy and scalability, so that it is fit for large-scale, unmanned agricultural applications. Unfortunately, it is computationally intensive and it is not applicable in a low-resource environment. They also demonstrated that the Hybrid (which was only slightly less accurate) was highly interpretable and computationally expedient. These features increase their real-world applicability (especially in pampered planet circumstance or when transparency of decision-making is critical). Finally, class imbalance was addressed by the use of data augmentation and oversampling methods to guarantee fair representation during training of the model. By visual and statistical analyses, we demonstrated the effectiveness of GLCM and LBP texture information for disease classification.

Notwithstanding these strengths, the study presents limitations. The dataset was collected solely from Kirtan village in Hisar, Haryana (India), potentially limiting the generalizability of the models to other agricultural contexts characterized by different environmental conditions and crop varieties. Future research should prioritize the curation of diverse datasets from various regions, the development of lightweight deep learning architectures suitable for on-field deployment, and the standardization of feature extraction techniques for Hybrid models.

In summary, both CNN and Hybrid models demonstrate considerable potential for facilitating intelligent, real-time detection of plant diseases. Their incorporation into agricultural systems, including drone surveillance and mobile diagnostic tools, provides farmers with actionable insights, enhances crop yield, and promotes sustainable farming practices globally.

Author's declarations

Conflict of interest

The authors have no conflict of interest to report.

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