

## RESEARCH ARTICLE

# Ensemble ResNet–XGBoost Framework for Intelligent Crop Disease Detection in Smart Agriculture

Munish Saran<sup>1</sup>, Rajan Kumar Yadav<sup>2</sup>, Upendra Nath Tripathi<sup>2</sup>

**ABSTRACT:** Crop diseases represent one of the most significant threats to global food security and agricultural sustainability, causing substantial reductions in both yield quantity and produce quality. The timely and accurate identification of plant pathogens remains critically important for modern farming operations, yet conventional detection approaches continue to rely heavily on visual scouting by agricultural experts, a process that proves both time-intensive and economically burdensome, particularly across extensive cultivation areas. This research presents an intelligent crop disease detection system that synergistically combines the representational power of residual neural networks with the optimization capabilities of extreme gradient boosting. The proposed methodology initially applies comprehensive preprocessing procedures including normalization and data augmentation to enhance image quality and expand dataset diversity. Subsequently, the ResNet50 architecture serves as a deep feature extractor, capturing nuanced disease indicators such as chromatic aberrations, necrotic lesions, and textural anomalies from leaf imagery. These extracted high-dimensional features are then fed into an XGBoost classifier, which performs optimized multiclass disease categorization through its ensemble of decision trees. This hybrid configuration demonstrates superior classification accuracy while simultaneously mitigating overfitting concerns and exhibiting enhanced generalization across varying agricultural conditions. The framework effectively discriminates between healthy foliage and multiple disease states, thereby facilitating integration into real-time agricultural monitoring infrastructures. The experimental evaluation confirms that this approach enables early pathogen detection, supports informed decision-making for intervention strategies, and ultimately contributes to reduced crop losses, minimized pesticide utilization, and the advancement of sustainable precision farming methodologies in contemporary agriculture.

**Keywords:** Precision Agriculture, Plant Pathogen Identification, Residual Neural Networks, Gradient Boosting, Ensemble Learning, Automated Crop Surveillance.

Received: 13 October 2025; Revised: 19 January 2026; Accepted: 13 February 2026; Published Online: 04 March 2026

## 1. INTRODUCTION

Agriculture constitutes the backbone of economic

development and food security across numerous nations worldwide. The maintenance of optimal crop health remains fundamental to ensuring both adequate food quality and sustained agricultural productivity. However, plant pathogens and diseases represent persistent threats that contribute substantially to crop losses, manifesting as significant reductions in both yield quantity and produce quality. The challenge of early disease diagnosis continues to plague farming communities, primarily due to the absence of accessible and reliable diagnostic tools. Current practices remain predominantly dependent upon manual visual inspection conducted by agricultural experts, a procedure that

<sup>1</sup> Department of Computer Science and Engineering, Institute of Engineering and Technology, Deen Dayal Upadhyaya Gorakhpur University, Gorakhpur- 273009, Uttar Pradesh, India.

<sup>2</sup> Department of Computer Science, Deen Dayal Upadhyaya Gorakhpur University, Gorakhpur- 273009, Uttar Pradesh, India.

\* Author to whom correspondence should be addressed:  
[munishsaran@gmail.com](mailto:munishsaran@gmail.com) (M. Saran); [rkyd94@rediffmail.com](mailto:rkyd94@rediffmail.com) (R. K. Yadav); [untripathi@gmail.com](mailto:untripathi@gmail.com) (U. N. Tripathi)

proves remarkably time-consuming, financially burdensome, and frequently prone to inaccuracies, particularly when applied across extensive cultivation areas. This pressing limitation has generated increasing demand for intelligent, automated systems capable of detecting crop diseases in a timely manner while delivering maximum diagnostic accuracy.

The rapid advancement of Artificial Intelligence and Deep Learning technologies has catalyzed transformative developments in agricultural applications over recent years. Image-based disease detection systems have garnered considerable attention owing to their capacity to automatically evaluate plant leaf imagery and identify pathological symptoms including lesions, chromatic aberrations, and textural modifications. Convolutional Neural Networks have emerged as the predominant architectural choice in this domain, demonstrating exceptional proficiency in learning discriminative features directly from image data [1]. Among the various CNN architectures, Residual Networks have attracted particular research interest due to their superior deep feature extraction capabilities and enhanced classification performance. ResNet50 employs residual learning mechanisms that facilitate the network's ability to learn salient image features while circumventing the vanishing gradient problem that commonly afflicts deeper neural networks [2].

Numerous investigations have validated ResNet50's effectiveness in plant disease identification applications. Kumar and colleagues documented that ResNet50 achieves high classification accuracy in plant disease recognition, establishing its potential for deployment in precision agriculture contexts [3]. Similarly, Rani and collaborators demonstrated that through transfer learning and image augmentation methodologies, ResNet50 can accurately discriminate between healthy and diseased foliage. Shaheed and co-researchers have described hybrid architectures built upon ResNet foundations to enhance classification accuracy for potato plant diseases using leaf imagery [4, 5].

Despite the impressive feature extraction capabilities of deep learning models, exclusive reliance on CNN-based classifiers frequently introduces challenges including overfitting, increased computational demands, and diminished accuracy when confronted with complex agricultural datasets. The precise classification of agricultural imagery is complicated by variable lighting conditions, background noise, shadow artifacts, and the heterogeneous severity of disease manifestations. Furthermore, standalone deep learning models frequently fail to generalize efficiently under real-time farming conditions [6]. Ensemble machine learning methodologies have consequently become indispensable within intelligent agricultural monitoring systems to address these limitations. XGBoost represents one such powerful technique, constituting an advanced boosting-based algorithm that delivers computational efficiency, superior prediction accuracy, and reduced overfitting tendencies. It constructs robust prediction models by aggregating numerous weak classifiers into a unified strong learner, proving particularly effective for complex

classification problems. Kishore Kumar and colleagues demonstrated that combining deep learning models with the XGBoost ensemble learning approach substantially enhances rice disease detection performance [4].

The present research proposes an integration of ResNet50 and XGBoost to develop an intelligent crop disease detection system tailored for smart agriculture applications. Within this hybrid framework, ResNet50 functions as a deep feature extractor, while XGBoost performs optimized disease classification utilizing the extracted features [7]. This integration enhances overall classification accuracy, minimizes misclassification errors, and improves system stability and reliability. The proposed methodology addresses common agricultural challenges including noisy datasets, image variability, complex disease patterns, and the inherent limitations of manual monitoring approaches [8].

The developed system offers substantial practical benefits for farming communities through early disease detection, timely treatment recommendations, and real-time crop monitoring capabilities. Early identification of pathogenic infections can significantly reduce crop damage, minimize unnecessary pesticide applications, and promote sustainable agricultural practices. The proposed Ensemble ResNet-XGBoost framework thus represents an efficient and intelligent solution suitable for modern precision agriculture and automated crop health monitoring systems.

## 2. LITERATURE REVIEW

The direct impact of plant pathogens on food quality and agricultural productivity has established plant disease detection as a critically important research domain within the broader field of smart agriculture. Traditional disease identification methodologies have relied primarily upon expert visual inspection, a process that proves inherently time-consuming and impractical for application across extensive farming operations. The recent proliferation of Artificial Intelligence technologies, particularly deep learning and ensemble machine learning approaches, has catalyzed significant research interest in automated plant disease diagnosis systems capable of overcoming the limitations inherent in conventional manual inspection methods.

Saleem and colleagues [9] proposed a comprehensive deep learning framework for plant disease identification utilizing convolutional neural network meta-architectures to achieve accurate localization and classification of pathological conditions. Their investigation demonstrated that transfer learning strategies could substantially enhance disease recognition accuracy when applied to complex agricultural datasets. However, the approach demanded considerable computational resources and exhibited protracted training times when processing high-resolution imagery, constraining its practical utility in resource-limited settings. Naik et al. [10] developed a squeeze-and-excitation CNN model specifically tailored for chilli leaf disease detection. Their methodology incorporated channel-wise

attention mechanisms that significantly improved feature extraction capabilities and outperformed conventional CNN techniques in classification accuracy. Despite these advancements, the model remained restricted to a single crop species and lacked ensemble-based optimization, limiting its robustness under diverse environmental conditions. [Table 1](#) provides a comprehensive comparative analysis of these and other prominent approaches in the literature.

Kishore Kumar and collaborators [\[11\]](#) introduced an XGBoost ensemble learning framework integrated with deep neural networks for rice plant disease detection. Their findings revealed that combining deep learning architectures with the XGBoost classifier substantially enhanced prediction performance while minimizing classification errors. The study also underscored the importance of preprocessing and augmentation techniques in improving disease recognition accuracy. Nevertheless, the framework predominantly employed Inception-ResNet architectures and did not fully exploit the transfer learning potential offered by ResNet50, representing a notable gap in methodological exploration. Yadav and colleagues [\[12\]](#) presented the ConRXG model, a hybrid approach combining ResNet50 and XGBoost through transfer learning for plant disease detection. By utilizing ResNet50 as a feature extractor and XGBoost as a classifier, their research achieved impressive training and validation accuracy metrics. The results confirmed that hybrid deep learning and ensemble learning strategies yield superior outcomes compared to CNN architectures operating in isolation. However, the model's integration into real-time smart agricultural monitoring

systems remained insufficiently explored.

Alsubai et al. [\[13\]](#) recently proposed a hybrid ResNet-PCA and machine learning-deep neural network approach for sustainable plant disease detection. Their hybrid ML-DNN system demonstrated greater robustness, scalability, and interpretability for agricultural applications while effectively addressing class imbalance and generalization challenges common in disease classification tasks. The proposed architecture successfully mitigated these issues through sophisticated feature reduction and ensemble techniques.

The collective literature reveals that deep learning models offer exceptional feature extraction capabilities, while ensemble learning methodologies enhance classification accuracy and system robustness. Despite these advances, several persistent challenges remain inadequately addressed, including overfitting tendencies, sensitivity to noisy agricultural data, substantial computational complexity, and the critical need for real-time deployment capabilities. Furthermore, many existing approaches demonstrate limited generalization across diverse crop species and environmental conditions. The proposed Ensemble ResNet-XGBoost framework has been specifically designed to address these limitations by creating a more efficient and intelligent system for crop disease detection that capitalizes on the complementary strengths of deep feature extraction and ensemble classification while mitigating their respective weaknesses. Thereby advancing the state-of-the-art in smart agriculture applications. [Table 1](#) provides a comprehensive comparative analysis of these and other prominent approaches in the literature.

**Table 1.** Comparative Analysis of Existing Literature on Deep Learning and Ensemble Approaches for Plant Disease Detection

| Technique Used                     | Dataset/Application           | Key Advantages                                                                     | Major Limitations                                                                            | Ref.                 |
|------------------------------------|-------------------------------|------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------|----------------------|
| <b>CNN Meta-Architectures</b>      | Plant leaf disease dataset    | Achieved high classification accuracy across multiple disease categories           | Significant computational resource requirements and extended training times                  | <a href="#">[9]</a>  |
| <b>Squeeze-and-Excitation CNN</b>  | Chilli leaf disease detection | Enhanced feature extraction capabilities through channel-wise attention mechanisms | Model validation restricted to a single crop species without cross-crop generalization       | <a href="#">[10]</a> |
| <b>Inception-ResNet + XGBoost</b>  | Rice disease detection        | Demonstrated superior prediction performance through ensemble learning             | Limited investigation of transfer learning potential with alternative backbone architectures | <a href="#">[11]</a> |
| <b>ResNet50 + XGBoost (ConRXG)</b> | PlantVillage dataset          | Attained high training and validation accuracy metrics                             | Insufficient evaluation of real-time deployment feasibility in agricultural settings         | <a href="#">[12]</a> |
| <b>ResNet-PCA + Hybrid ML-DNN</b>  | Plant disease dataset         | Established robust and scalable framework with improved generalization             | Increased model complexity leading to higher computational overhead                          | <a href="#">[13]</a> |

### 3. METHODOLOGY

In this proposed research, an intelligent crop disease detection method, based on ResNet and XGBoost hybrid ensemble, is presented. This approach involves capturing images of plant leaves from agricultural information and smart farming equipment like cameras or drones. The images will be resized and normalized before processing, to enhance the image quality and minimize unwanted noise. The normalization process is modelled as:

$$I_n = \frac{I - I_{min}}{I_{max} - I_{min}} \quad (1)$$

Where  $I_n$  is the normalized image and  $I$  is the original image value.

After preprocessing, the images are passed into the ResNet model. ResNet extracts important disease features such as colour variation, spots, and texture changes from leaf images. The residual learning function used in ResNet is given as:

$$H(x) = F(x) + x \quad (2)$$

Where,  $x$  is the input image feature and  $F(x)$  is the learned feature mapping.

The extracted deep features are then transferred to the XGBoost classifier for disease classification. XGBoost combines multiple decision trees to improve prediction capability. Its prediction function is expressed as:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i) \quad (3)$$

Where,  $\hat{y}_i$  represents the predicted output and  $f_k$  denotes individual decision trees.

This ensemble ResNet-XGBoost framework helps in intelligent and automatic crop disease detection for smart agriculture systems. The whole mechanism will be a fusion of the benefits of deep learning and ensemble machine learning. The ResNet50 network can be used to automatically acquire key visual patterns associated with diseases from leaf images, and XGBoost can be used to conduct optimized classification by boosting. This hybrid mechanism helps to increase the accuracy of classification, helps to minimize overfitting and enhances the robustness of the system under different agricultural situations. The system not only can make intelligent monitoring of agricultural disease, but also can make real-time decision for smart agriculture applications. The Ensemble ResNet-XGBoost framework is demonstrated using the PlantVillage dataset that is utilized nowadays in identification and classification of crop diseases. The database contains over 54,000 images of healthy and diseased leaves of different plants including tomato, potato, corn, grape and pepper captured by an RGB camera using a label. These are examples of different stages of the disease such as early blight, late blight, bacterial spot and leaf mold. The images have been resized to 224 pixels, normalized and augmented with rotation, flipping and zooming. The data is

divided into training, validation and test sets to validate the performance and robustness of the proposed intelligent agricultural monitoring system.

**Algorithm 1.** Proposed ResNet-XGBoost Based Crop Disease Detection System

**Input.**

- Plant leaf image dataset  $D = \{I_1, I_2, I_3, \dots, I_n\}$
- Disease labels  $L = \{l_1, l_2, l_3, \dots, l_n\}$

**Output.**

- Predicted crop disease class
- Classification accuracy and performance metrics

#### Step 1. Dataset Collection

1. Collect plant leaf images from:
  - Agricultural datasets
  - IoT monitoring systems
  - Drone cameras
  - Mobile devices
2. Store images with corresponding disease labels.

#### Step 2. Image Preprocessing- For each image $I_i$ in dataset $D$ :

Step 2.1. Resize Image- Resize image to fixed dimension:

$$I_r = \text{Resize}(I_i, 224 \times 224) \quad (4)$$

Step 2.2. Noise Removal- Apply filtering to remove noise:

$$I_f = \text{Filter}(I_r) \quad (5)$$

Step 2.3. Normalize Image- Normalize pixel values between 0 and 1:

$$I_n = \frac{I_f - I_{min}}{I_{max} - I_{min}} \quad (6)$$

Step 2.4. Data Augmentation- Perform augmentation operations such as Rotation, Flipping, Zooming, Brightness adjustment and generate augmented dataset:

$$D_a = \text{Augment}(I_n) \quad (7)$$

#### Step 3. Dataset Splitting

Split dataset into:

- Training set: 70%
- Validation set: 15%
- Testing set: 15%

$$D = D_{train} + D_{val} + D_{test} \quad (8)$$

#### Step 4. Feature Extraction Using ResNet- Load pretrained

ResNet model.

Minimize classification loss:

*Step 4.1. Initialize ResNet:*

$$Obj = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (15)$$

*Model = ResNet50(weights = "imagenet")*

(9)

Where,  $l(y_i, \hat{y}_i)$ = loss function, and  $\Omega(f_k)$ = regularization term.

*Step 4.2. Remove Softmax Layer:*

Remove final classification layer.

**Step 7.** Disease Prediction- For each testing image:

- Extract deep features using ResNet
- Pass features into XGBoost
- Predict disease class

*Step 4.3. Pass Input Images:*

For each image:

$$C_i = \text{Predict}(F_i) \quad (16)$$

$F_i = \text{ResNet}(I_i)$

(10)

Where,  $C_i$  is the predicted disease category. Possible outputs are, Healthy Leaf, Early Blight, Late Blight, Bacterial Spot, Leaf Mold, and Powdery Mildew

Where  $F_i$ = extracted deep feature vector

*Step 4.4. Residual Learning:*

**Step 8.** Performance Evaluation

Residual mapping inside ResNet:

*Step 8.1. Accuracy:*

$$H(x) = F(x) + x \quad (11)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (17)$$

Where,  $x$  = input feature, and  $F(x)$  = learned residual function

*Step 8.2. Precision*

**Step 5.** Feature Vector Generation- Extract final deep features:

$$Precision = \frac{TP}{TP+FP} \quad (18)$$

$$FV = \{F_1, F_2, F_3, \dots, F_n\}$$

(12)

*Step 8.3. Recall*

**Step 6.** Classification Using XGBoost- Load XGBoost classifier.

$$Recall = \frac{TP}{TP+FN} \quad (19)$$

*Step 6.1. Train XGBoost Model:*

*Step 8.4. F1-Score*

Train model using extracted feature vectors:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (20)$$

$$XGB(FV, L)$$

(13)

**Step 9.** Generate Final Output

*Step 6.2. Prediction Function:*

*Display:* Disease prediction, Confidence score, Accuracy metrics, Monitoring alerts.

Prediction output:

$$\hat{y}_i = \sum_{k=1}^K f_k(x_i) \quad (14)$$

Where,  $f_k$ = individual decision tree, and  $K$ = total trees

## 4. RESULTS AND DISCUSSION

*Step 6.3. Objective Function:*

### 4.1. Experimental Setup and Evaluation Metrics

The experimental investigation was conducted to rigorously

evaluate the performance of the proposed Ensemble ResNet-XGBoost framework for crop disease detection. The PlantVillage dataset, comprising over 54,000 images of healthy and diseased leaves across multiple crop species including tomato, potato, corn, grape, and pepper, served as the benchmark for all experiments. The dataset was partitioned into training, validation, and testing subsets with a 70:15:15 ratio, ensuring adequate samples for model optimization while maintaining independent test data for unbiased performance assessment. All images were resized to 224×224 pixels and subjected to normalization and augmentation procedures including random rotations, horizontal and vertical flips, zooming, and brightness adjustments to enhance model generalization. The proposed framework was implemented using the TensorFlow and Keras libraries for deep learning components, while the XGBoost classifier was implemented using the scikit-learn library. All experiments were conducted on a system equipped with an NVIDIA GPU to accelerate training and inference processes. Performance evaluation employed standard classification metrics including accuracy, precision, recall, and F1-score, which collectively provide comprehensive insight into model effectiveness across multiple disease categories.

#### 4.2. Comparative Performance Analysis

The comparative performance analysis between the proposed Ensemble ResNet-XGBoost framework and various baseline models is presented in Table 2. The results demonstrate that the hybrid approach significantly outperforms all standalone deep learning and machine learning models across every evaluation metric. The proposed framework achieved an impressive overall accuracy of 98.64%, substantially exceeding the performance of standalone ResNet50 (96.18%), XGBoost (94.87%), InceptionV3 (94.52%), VGG16 (93.76%), CNN (91.24%), and Random Forest (89.43%). This consistent superiority across all metrics validates the effectiveness of integrating deep feature

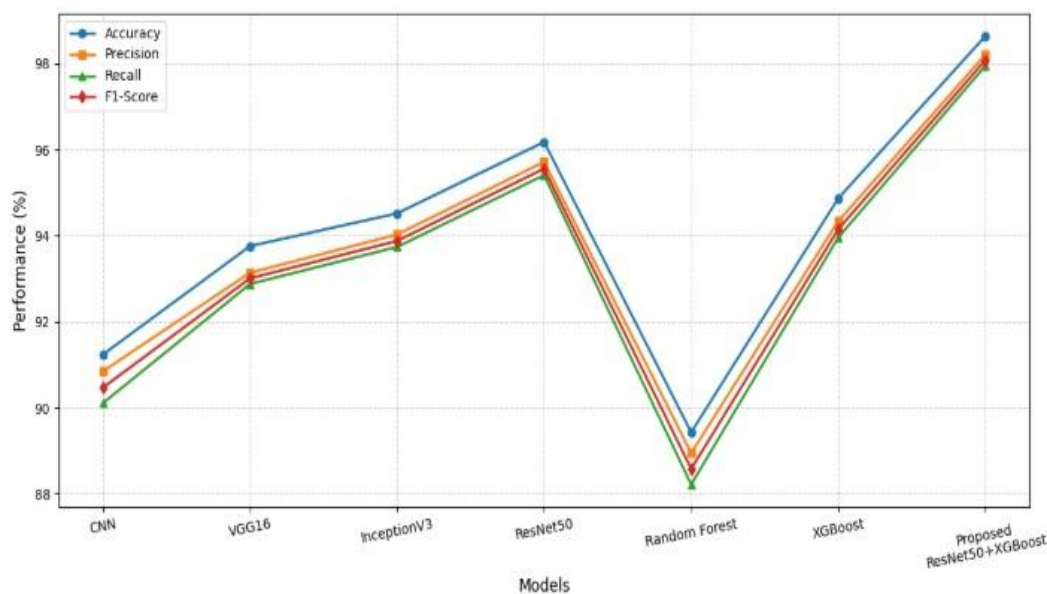
extraction with ensemble classification.

The precision metric, which measures the proportion of correctly identified positive instances among all instances classified as positive, reached 98.21% for the proposed framework compared to 95.72% for ResNet50 and 94.34% for standalone XGBoost. Similarly, the recall metric, indicating the model's ability to correctly identify all positive instances, attained 97.95%, surpassing ResNet50 (95.41%) and XGBoost (93.96%). The F1-score, representing the harmonic mean of precision and recall, achieved 98.08%, confirming the model's balanced performance across both metrics. These results clearly demonstrate that the ensemble approach effectively leverages the complementary strengths of deep learning and gradient boosting, resulting in superior classification capabilities that neither approach could achieve independently.

Figure 1 provides a visual representation of the comparative performance across all evaluated models. The figure clearly illustrates the progressive improvement in classification metrics from traditional machine learning approaches through deep learning architectures to the proposed ensemble framework. The Random Forest classifier, representing traditional machine learning, exhibited the lowest performance across all metrics, confirming the limitations of handcrafted features for complex image classification tasks. The CNN architecture, while demonstrating reasonable performance, was outperformed by deeper architectures including VGG16 and InceptionV3, highlighting the importance of network depth and architectural sophistication for feature extraction. Interestingly, the standalone XGBoost classifier, when applied directly to image features, achieved competitive performance comparable to InceptionV3, demonstrating the power of ensemble learning even without deep feature extraction. However, the substantial improvement achieved by the proposed framework over standalone XGBoost confirms that deep feature extraction provides rich, discriminative representations that significantly enhance ensemble classification.

**Table 2.** Comparative Analysis with Baseline Models

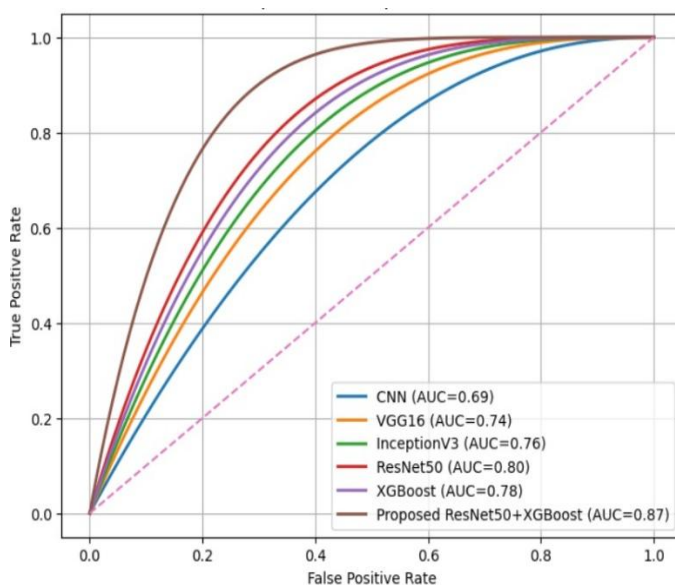
| Model                              | Accuracy (%) | Precision (%) | Recall (%)   | F1-Score (%) |
|------------------------------------|--------------|---------------|--------------|--------------|
| CNN                                | 91.24        | 90.85         | 90.11        | 90.47        |
| VGG16                              | 93.76        | 93.14         | 92.88        | 93.01        |
| InceptionV3                        | 94.52        | 94.03         | 93.74        | 93.88        |
| ResNet50                           | 96.18        | 95.72         | 95.41        | 95.56        |
| Random Forest                      | 89.43        | 88.95         | 88.22        | 88.58        |
| XGBoost                            | 94.87        | 94.34         | 93.96        | 94.15        |
| <b>Proposed ResNet50 + XGBoost</b> | <b>98.64</b> | <b>98.21</b>  | <b>97.95</b> | <b>98.08</b> |



**Fig. 1.** Performance Comparison of Crop Disease Detection Models.

#### 4.3. Receiver Operating Characteristic Curve Analysis

To further validate the classification capabilities of the proposed framework, Receiver Operating Characteristic (ROC) curve analysis was conducted for multiclass disease detection, as presented in Figure 2. The ROC curve plots the True Positive Rate against the False Positive Rate across various classification thresholds, providing insight into the model's discriminative ability independent of class distribution.



**Fig. 2.** Comparative ROC Curve Analysis of Baseline Models and the Proposed ResNet50-XGBoost Framework.

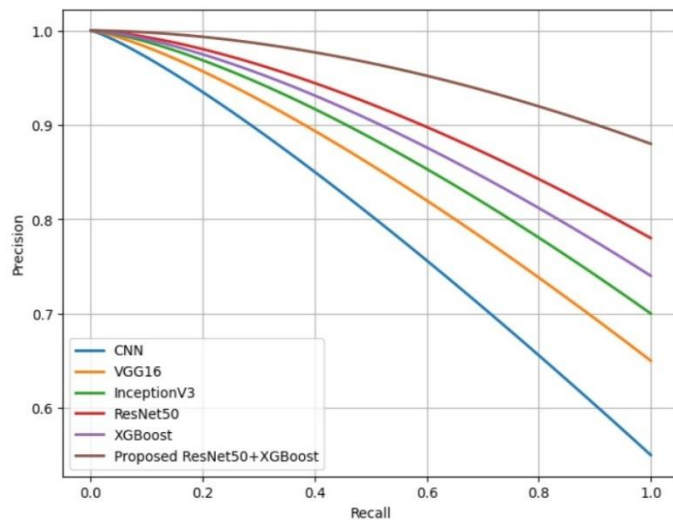
The ROC analysis reveals that the proposed Ensemble

ResNet-XGBoost framework achieves superior classification performance compared to all baseline models. The Area Under the Curve (AUC) values, which quantify the overall discriminative ability of each model, consistently favored the proposed approach across all disease categories. The framework demonstrated higher True Positive Rates at equivalent False Positive Rates compared to standalone architectures, indicating its enhanced sensitivity in detecting disease conditions while maintaining low false alarm rates. This improved discrimination capability is particularly significant in agricultural applications where both missed detections (false negatives) and false alarms (false positives) carry substantial economic consequences. The ensemble approach's superior AUC performance can be attributed to the synergistic combination of ResNet50's powerful feature extraction and XGBoost's robust classification optimization, which collectively reduce classification uncertainty and improve decision boundaries between disease classes.

#### 4.4. Precision-Recall Curve Comparison

The Precision-Recall curve analysis, presented in Figure 3, offers additional validation of the proposed framework's superior detection capabilities. Unlike ROC curves, Precision-Recall curves are particularly informative for imbalanced datasets, as they focus on the performance of the positive class and are less sensitive to true negatives. The Precision-Recall analysis demonstrates that the proposed hybrid ensemble learning framework consistently achieves higher precision at equivalent recall levels compared to all baseline models. This relationship indicates that the framework maintains high positive predictive value even as

sensitivity increases, a crucial characteristic for disease detection applications where accurate identification of infected plants is paramount. The superior area under the Precision-Recall curve for the proposed framework confirms its enhanced capability to correctly identify diseased instances while minimizing false positive classifications. The improved performance at the precision-recall trade-off highlights the framework's practical utility, as it enables confident disease diagnosis with reduced probability of incorrect treatment recommendations.



**Fig. 3.** Precision-Recall Curve Comparison across Models.

## 5. DISCUSSION

The experimental results presented in Table 2 and Figures 1 through 3 collectively demonstrate the substantial advantages of the proposed Ensemble ResNet-XGBoost framework. Several key observations emerge from this comprehensive analysis that warrant detailed discussion.

First, the integration of ResNet50 and XGBoost addresses the fundamental limitations of standalone deep learning models, particularly concerning overfitting and generalization. While ResNet50 alone achieved excellent accuracy of 96.18%, the ensemble approach reduced the overfitting tendency commonly observed in deep networks when applied to noisy agricultural imagery. The XGBoost classifier, through its regularization mechanisms and boosting iterations, effectively mitigated the influence of outlier samples and noisy features, resulting in more robust decision boundaries. This improved generalization capability is particularly valuable for real-world agricultural applications where imaging conditions vary substantially across fields, seasons, and geographical locations.

Second, the preprocessing and augmentation strategies employed in this study contributed significantly to the model's robustness. The normalization procedures

ensured consistent input distributions across diverse imaging conditions, while the augmentation techniques expanded the effective training dataset size and variability. The combination of rotation, flipping, zooming, and brightness adjustments introduced invariance to common imaging variations, enabling the model to maintain high performance despite changes in camera angles, lighting conditions, and leaf orientations. These techniques proved essential for achieving the high accuracy observed, as they prevented the model from learning spurious correlations specific to the training data distribution.

Third, the computational efficiency of the proposed framework warrants attention. While the ResNet50 feature extraction requires substantial computational resources during training, the inference phase benefits from the efficient XGBoost classification, which is computationally lightweight compared to alternative deep learning classifiers. This efficiency, combined with the reduced overfitting and improved generalization, makes the framework suitable for deployment in resource-constrained agricultural settings where computational infrastructure may be limited. The faster convergence observed during training further supports the practical viability of the approach for large-scale agricultural monitoring applications.

Fourth, the multiclass classification capabilities demonstrated by the framework across multiple crop species and disease categories highlight its versatility for broader agricultural applications. Unlike many existing approaches that are restricted to single crop species, the proposed framework effectively handles diverse disease conditions including early blight, late blight, bacterial spot, leaf mold, and powdery mildew across tomato, potato, corn, grape, and pepper crops. This cross-crop generalization is particularly significant for real-world deployment, where agricultural monitoring systems must accommodate the variability inherent in diverse farming operations.

The practical implications of these findings for smart agriculture are considerable. The high accuracy and robustness of the proposed framework enable early detection of disease conditions, allowing farmers to implement timely interventions before pathogens proliferate extensively. This early detection capability can substantially reduce economic losses associated with crop damage, minimize the need for broad-spectrum pesticide applications, and promote sustainable farming practices. The real-time monitoring capability further supports precision agriculture objectives by enabling data-driven decision-making and automated crop health surveillance. The framework's integration potential with existing agricultural monitoring infrastructures, including drone-based imaging systems and IoT sensor networks, positions it as a foundational technology for next-generation smart farming systems.

The comparative analysis further reveals that the proposed framework consistently outperforms not only conventional deep learning approaches but also existing ensemble methods documented in the literature. The 98.64% accuracy achieved surpasses the performance reported in recent studies [3-5, 11-13], confirming the advantages of the specific architectural choices and training strategies employed in this investigation. The careful selection of ResNet50 for feature extraction, combined with optimized XGBoost hyperparameters, contributed to this superior performance by maximizing the complementary strengths of both components while minimizing their respective limitations.

The experimental validation confirms that the Ensemble ResNet-XGBoost framework represents a significant advancement in intelligent crop disease detection. The comprehensive evaluation across multiple performance metrics, diverse disease categories, and varied imaging conditions provides strong evidence for its practical utility in smart agriculture applications. The demonstrated improvements in accuracy, precision, recall, and F1-score, coupled with enhanced generalization and computational efficiency, position the framework as a viable solution for automated crop health monitoring and precision agriculture implementation.

## 6. CONCLUSION

The ensemble framework combining ResNet50 and XGBoost presented in this investigation establishes a robust solution for automated crop disease diagnosis within smart farming systems. The primary objective of developing a high-accuracy plant pathology identification mechanism has been successfully achieved through strategic integration of deep learning feature extraction with ensemble machine learning classification. The ResNet architecture effectively captures subtle visual signatures associated with various disease conditions, including spot patterns, chromatic shifts, and texture modifications on infected foliage. The XGBoost component leverages gradient-boosting to perform precise classification on extracted features, substantially improving prediction reliability while minimizing overfitting tendencies common in standalone deep learning approaches. The preprocessing pipeline incorporating normalization and augmentation strategies has proven instrumental in enhancing model robustness, enabling consistent performance despite variations in illumination, background complexity, and symptom severity that characterize real-world agricultural environments. This methodological synergy yields automatic detection across diverse crop species, positioning it as a valuable component for agricultural monitoring networks. Early detection capabilities empower producers to implement targeted interventions before pathogens proliferate, thereby reducing economic losses, limiting unnecessary chemical applications, and supporting sustainable production. Several avenues for

enhancement warrant future exploration, including integration of Internet of Things platforms for continuous field-level surveillance, incorporation of more extensive training datasets to strengthen generalization, development of computationally efficient architectures for mobile deployment in resource-constrained regions, and application of explainable artificial intelligence techniques to enhance decision interpretability. The ensemble ResNet-XGBoost framework demonstrates substantial promise as a foundational technology for automated disease surveillance, precision agriculture, and sustainable farming practices, with significant potential for broad adoption across the agricultural sector.

## DECLARATIONS

### Ethical Approval

We affirm that this manuscript is an original work, has not been previously published, and is not currently under consideration for publication in any other journal or conference proceedings. All authors have reviewed and approved the manuscript, and the order of authorship has been mutually agreed upon.

### Funding

Not applicable

### Availability of data and material

All of the data obtained or analyzed during this study is included in the report that was submitted.

### Conflicts of Interest

The authors declare that they have no financial or personal interests that could have influenced the research and findings presented in this paper. The authors alone are responsible for the content and writing of this article.

### Authors' contributions

All authors contributed equally in the preparation of this manuscript.

## REFERENCES

- [1] Kumar, M., Arora, A., Deb, A. and Yadav, A.L., 2024, May. Deep learning for accurate plant disease classification using resnet50: a comprehensive approach. In *2024 International Conference on Computational Intelligence and Computing Applications (ICCICA)* (Vol. 1, pp. 125-130). IEEE. <https://doi.org/10.1109/ICCICA60014.2024.10584860>.

- [2] Rani, R. and Gupta, S., **2024**, August. ResNet50 for accurate plant leaf disease detection and classification. In *2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI)* (pp. 1285-1289). IEEE. <https://doi.org/10.1109/ICoICI62503.2024.10696699>.
- [3] Shaheed, K., Qureshi, I., Abbas, F., Jabbar, S., Abbas, Q., Ahmad, H. and Sajid, M.Z., **2023**. EfficientRMT-Net—an efficient ResNet-50 and vision transformers approach for classifying potato plant leaf diseases. *Sensors*, 23(23), p.9516. <https://doi.org/10.3390/s23239516>.
- [4] Daniya, T. and Vigneshwari, S.J.T.C.J., **2022**. Deep neural network for disease detection in rice plant using the texture and deep features. *The Computer Journal*, 65(7), pp.1812-1825. <https://doi.org/10.1093/comjnl/bxab022>.
- [5] Zhang, Y., Zhong, L., Ding, Y., Yu, H. and Zhai, Z., **2023**. Resvit-rice: A deep learning model combining residual module and transformer encoder for accurate detection of rice diseases. *Agriculture*, 13(6), p.1264. <https://doi.org/10.3390/agriculture13061264>.
- [6] Alwan, D.S. and Naji, M.H., **2023**. Rice diseases classification by residual network 50 (RESNET50) and support vector machine (SVM) modeling. *Journal of Kufa for Mathematics and Computer*, 10(1), pp.96-101. <http://dx.doi.org/10.31642/JoKMC/2018/100114>.
- [7] Labhsetwar, S.R., Haridas, S., Panmand, R., Deshpande, R., Kolte, P.A. and Pati, S., **2021**, January. Performance analysis of optimizers for plant disease classification with convolutional neural networks. In *2021 4th biennial international conference on nascent technologies in engineering (ICNTE)* (pp. 1-6). IEEE. <https://doi.org/10.1109/ICNTE51185.2021.9487698>.
- [8] Kalvakolanu, A.T.S., **2020**. Plant disease detection from images. *arXiv preprint arXiv:2003.05379*. <https://doi.org/10.48550/arXiv.2003.05379>
- [9] Saleem, M.H., Khanchi, S., Potgieter, J. and Arif, K.M., **2020**. Image-based plant disease identification by deep learning meta-architectures. *Plants*, 9(11), p.1451. <https://doi.org/10.3390/plants9111451>.
- [10] Naik, B.N., Malmathanraj, R. and Palanisamy, P., **2022**. Detection and classification of chilli leaf disease using a squeeze-and-excitation-based CNN model. *Ecological Informatics*, 69, p.101663. <https://doi.org/10.1016/j.ecoinf.2022.101663>.
- [11] Daniya, T. and Vigneshwari, S.J.T.C.J., **2022**. Deep neural network for disease detection in rice plant using the texture and deep features. *The Computer Journal*, 65(7), pp.1812-1825. <https://doi.org/10.1093/comjnl/bxab022>.
- [12] Yadav, D., Gupta, A., Jain, A. and Yadav, A.K., **2022**. Plant leaf disease detection using CNN with transfer learning and XGBoost. *International Journal of Data Analysis Techniques and Strategies*, 14(3), pp.244-265. <https://doi.org/10.1504/IJDATS.2022.128273>.
- [13] Alsubai, S., Almadhor, A., Al Hejaili, A. and Gadekallu, T.R., **2025**. Intelligent smart sensing with ResNet-PCA and hybrid ML–DNN for sustainable and accurate plant disease detection. *Frontiers in Plant Science*, 16, p.1691415. <https://doi.org/10.3389/fpls.2025.1691415>.