



RESEARCH ARTICLE

Hybrid convolutional neural network–random forest framework for automated detection of bell pepper leaf diseases using image analysis

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Abstract

Diseases that affect plants considerably lower the production of crops and pose a significant threat to global food security, particularly in high-value crops like bell pepper (*Capsicum annuum* L.). The timely and sensitive identification of the disease is essential in reducing losses related to yield and paving the way to sustainable management of crops. Although automated plant disease diagnosis has been improved by artificial intelligence (AI)-driven image analysis, single-model methods are not always robust or generalisable. The study proposes a hybrid convolutional neural network-random forest (CNN-RF) framework for the early detection of bell pepper leaf diseases. Deep visual features of leaf images were extracted and subsequently used with a pretrained ResNet50 model and then used to classify the images with the help of a RF ensemble algorithm. Experiments were conducted on a publicly available PlantVillage bell pepper dataset comprising 495 leaf images (199 bacterial spot and 296 healthy samples). The classification accuracy of the proposed hybrid model was 97.98 % with high class-wise precision, recall and F1-scores. Receiver operating characteristic (ROC) analysis produced an area under the curve (AUC) of 0.98, indicating excellent discriminative performance. The dataset was evaluated using a stratified 80 : 20 train-test split. The results show that deep feature extraction combined with an ensemble learning method can improve classification accuracy and offer a scalable solution to assist in precision agriculture and timely disease control. However, the framework was evaluated only on the PlantVillage dataset and has not yet been validated under real-field agricultural conditions. The framework demonstrates potential for extension to multi-disease classification tasks, although further validation on field-acquired datasets is required.

Keywords: bell pepper; convolutional neural networks; ensemble learning; hybrid models; plant disease detection; precision agriculture

Introduction

Plant diseases present a constant menace to worldwide agricultural productivity, resulting in massive yield losses and economic harm. Plant pathogens are believed to cause 20–40 % of the annual loss in crop yield globally and significant adverse impacts are experienced in developing territories where there is limited access to professional diagnosis (1, 2). The outbreak of plant diseases caused by climate change, enhanced agricultural activities and changes in the resistance of pathogens further intensify outbreak occurrences and severity.

Bell pepper (*Capsicum annuum* L.) is an economically important horticultural crop worldwide. Bacterial spot diseases pose serious challenges to the health of the leaves, photosynthetic ability and the general plants, causing low yield and value in the market. Early detection of disease symptoms is hence critical for disease management and the elimination of unnecessary pesticide use (3, 4).

The old method of diagnosing plant diseases is based on visual examination by the specialist or through laboratory methods and this is usually time-consuming, subjective and in large-scale

monitoring, is not practical. Artificial intelligence (AI) and computer vision have made it possible in recent years to detect disease based on the analysis of leaf images obtained through smartphones, drones and field sensors. Classical machine learning methods, such as the support vector machines and the random forests (RFs), can be promising, especially when handcrafted features are used, though their effectiveness is heavily reliant on feature engineering (5–7).

Deep learning and especially convolutional neural networks (CNNs) have proved to be more effective as they learn hierarchical representations automatically from raw images. Convolutional neural networks-based models often require large datasets and can be overfitted or only have low interpretability, even though successful. To overcome these shortcomings, hybrid AI methods, which combine deep feature extraction with ensemble-based classification, have been introduced as an effective alternative (8–10).

Even though the research has paid a lot of attention to main crops like tomato and potato, relatively little research has been conducted on the detection of bell pepper disease with the use of hybrid AI frameworks. This paper fills this gap by creating and testing

a CNN-ensemble hybrid model to classify bell pepper leaf disease based on robustness, understandability and real-world usefulness (11, 12).

Recent studies have demonstrated the effectiveness of hybrid deep learning and machine learning approaches for plant disease classification. Hybrid CNN-RF frameworks, support vector machine and particle swarm optimization (PSO) have shown promising performance for multi-crop disease classification (9). Convolutional neural networks -RF frameworks have also been applied for tomato disease detection (10), while CNN-based feature extraction combined with handcrafted descriptors and RF classification has been used for coriander disease identification (13). Transfer-learning-based approaches have also shown promising results, including ResNet- and ConvNet-based frameworks for multi-crop disease prediction (14), DenseNet-based disease classification (15) and comparative evaluations of CNN, ResNet and EfficientNet architectures (16). These studies confirm the effectiveness of deep learning and hybrid AI methods for plant disease diagnosis.

Despite these advances, limited attention has been given to transfer-learning-based hybrid frameworks specifically designed for bell pepper bacterial spot detection. In addition, several existing studies rely on handcrafted feature engineering, additional optimisation algorithms, or computationally intensive end-to-end training. These limitations motivate the development of the proposed ResNet50-RF framework. Table 1 presents a comparison between the proposed framework and representative plant disease detection studies reported in the literature.

The present study contributes to the literature by developing a transfer-learning-based ResNet50-RF framework for bell pepper bacterial spot detection. The proposed approach utilises pretrained deep feature representations without relying on handcrafted feature engineering and integrates ensemble-based classification to improve robustness and generalisation. In addition, RF feature importance analysis is incorporated to enhance model interpretability and provide insight into the relative contribution of extracted deep features. The framework further demonstrates competitive classification performance, achieving 97.98% accuracy and an area under the curve (AUC) of 0.98, while maintaining computational efficiency and scalability. These characteristics indicate its potential applicability in precision agriculture

applications, subject to further validation using real-field datasets.

Materials and Methods

Dataset description

The experiment was performed on a publicly available subset of the PlantVillage dataset, namely bell pepper (*C. annuum*), which is widely used as a benchmark dataset for image-based plant disease detection studies. The PlantVillage dataset contains high-quality red-green-blue (RGB) colour images of crop leaves captured under controlled laboratory conditions with uniform backgrounds and consistent illumination. In this study, the bell pepper subset comprising healthy leaves and bacterial spot-infected leaves was utilised to develop and evaluate the proposed classification framework (17–19).

In this test, only the images of bell pepper leaves were used to focus specifically on a crop that is relatively under-researched in the AI-based plant pathology research. The dataset consisted of two classes: pepper (bell) - bacterial spot and pepper (bell) - healthy. Bacterial spot is a widespread leaf disease that appears in the form of necrotic spots and chlorotic spots on the leaves, reducing photosynthesis and crop yield. Normal leaf samples are evenly green in colour without any sign of disease (20, 21).

All images are named and arranged in a directory scheme based on classes, thereby facilitating supervised learning. The data is diverse in terms of leaf texture, intensity of colour and the level of disease, which facilitates the strong assessment of the model generalisation conditions, which are controlled (22, 23). The PlantVillage bell pepper subset contained a total of 495 images, comprising 199 bacterial spot-infected leaves and 296 healthy leaves. The dataset was obtained from the publicly available repository in its curated form. No additional duplicate-image removal procedure was performed and no images were excluded from the dataset. The original class distribution was retained during model development. Images were visually inspected during preprocessing to ensure suitability for training and evaluation. The dataset was subsequently partitioned using stratified sampling, with 80 % of the images allocated for training and 20 % reserved for independent testing. The composition of the PlantVillage bell pepper dataset used in this study is summarised in Table 2. The

Table 1. Comparison of recent plant disease detection studies and the proposed framework

Method	Crop	Accuracy (%)	References
CNN+RF+PSO	Multi-crop	95.0	(9)
CNN+RF	Tomato	97.03	(10)
CNN+RF + handcrafted features	Coriander	98.0	(13)
ResNet + ConvNet	Multi-crop	98.2	(14)
DenseNet	Plant village	99.76	(15)
EfficientNet	Potato and mango	97.8	(16)
ResNet50 + RF	Bell pepper	97.98	Proposed study

CNN: convolutional neural network; RF: random forest; PSO: particle swarm optimization; ResNet: residual network; ConvNet: convolutional neural network; DenseNet: densely connected convolutional network; EfficientNet: efficient neural network.

Table 2. Summary of the bell pepper subset of the PlantVillage dataset used in this study

Crop species	Class label	Description	Number of images
Bell pepper	Bacterial spot	Leaves infected with bacterial spot disease	199
Bell pepper	Healthy	Disease-free leaf samples	296
Total	—	Binary classification dataset	495

Table 3. Dataset partitioning used in the study

Dataset subset	Number of images
Training set	396
Validation set	Not used
Test set	99
Total	495

resulting dataset partitioning is presented in Table 3, while Fig. 1 shows representative sample images of the two classes.

The images of representative bell pepper (*C. annuum*) leaves in the PlantVillage database were utilised in this study (Fig. 1). The upper row contains leaf samples with bacterial spot disease, which have necrotic lesions and some chlorotic areas, whereas the lower row contains normal leaf samples with evenly distributed green colour. The images show the visual variability with which the proposed hybrid CNN-RF model is trained and evaluated.

Data preprocessing

All images of bell pepper leaves were subjected to a normal preprocessing pipeline before model training and feature extraction so that the model can produce the same results across all images (24). Given that the original images in the PlantVillage data have varying spatial resolution, the images were resized to 224×224 pixels, the size of the input dimension of the pretrained CNN that will be used in the current research (25).

The ImageNet mean and standard deviation were used to normalise pixel intensity values, which made it possible to transfer learning by matching the distribution of the input data with that of the pretrained CNN (26). This normative procedure allows the occurrence of quick convergence in feature extraction and helps minimise the effect of the illumination difference between images (13).

No aggressive data augmentation techniques were applied, as they could introduce artificial bias and alter the original characteristics of the dataset. Such a selection would make the extracted features be that of real disease-related visual features and not those artificially introduced (27). Preprocessing procedures were

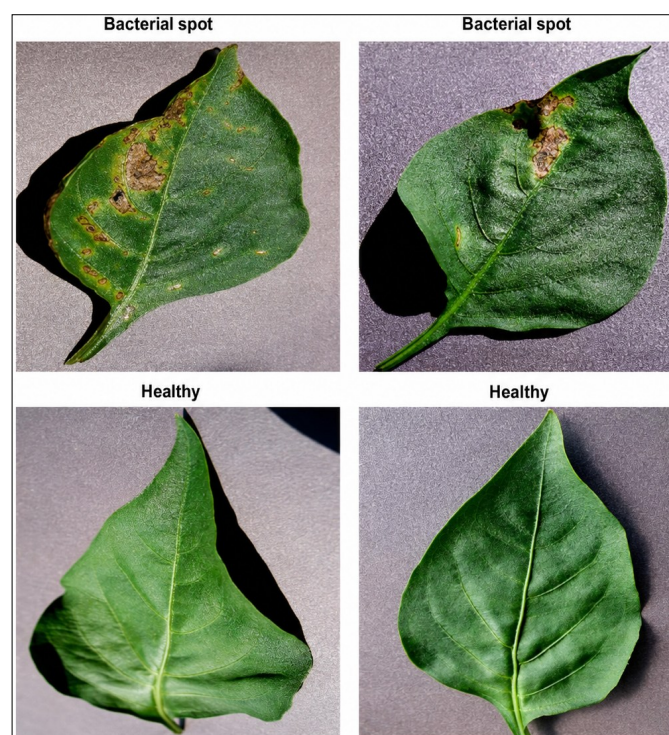


Fig. 1. Representative sample images of healthy and bacterial spot-infected bell pepper leaves from the PlantVillage dataset.

used equally in both healthy and disease categories to have equal representation and reproducibility.

After the preprocessing stage, the data were ready to be learned using supervised learning by transforming images into tensors that can be used in extracting deep features. The extracted deep features were then taken as the input to the CNN feature extractor and at that point, the obtained deep feature vectors were provided as input to the ensemble classifier, which was subsequently trained and tested (28).

Convolutional neural networks-based feature extraction

For deep feature extraction, a pretrained ResNet50 CNN was used, which was chosen due to its effectiveness in visual recognition and is commonly used in the research on the detection of plant diseases. ResNet50 uses residual learning, consisting of skip connections, which makes deep architecture training easier by eliminating the issue of vanishing gradients and enhancing the capacity of features (29,30).

In this experiment, the ResNet50 model that was trained on the ImageNet dataset served as a fixed feature extractor (29). The last layer of the fully connected classification was eliminated and the network produced deep feature vectors of 2048 dimensions, which described high-level spatial and textural features of bell pepper leaf images. Such characteristics code disease symptom complex visual patterns, including the shape of the lesion, colour distribution and irregularities in the texture.

Several benefits come with using a pretrained CNN, such as lower computational cost and generalisation when dealing with small datasets. With the use of the large-scale natural image collections that it has learned, the model can produce meaningful representations without the need to undergo a large amount of task-specific retraining (8). The CNN weights were held constant during feature extraction to avoid overfitting as well as to guarantee a similar generation of features in every sample.

The classifier was the ensemble-based classifier, which was input with the extracted deep feature vectors in the next subsection. This feature learning and classification disaggregation allows customised combinations of machine learning models, yet with the representational power of deep convolutional networks.

Overview of the proposed hybrid CNN-RF framework for bell pepper leaf disease classification (Fig. 2). Leaf images are first processed using a pretrained ResNet50 model to extract deep feature representations. The extracted features are subsequently provided to a RF classifier, which distinguishes between healthy leaves and leaves affected by bacterial spot disease.

Ensemble classification using random forest

After the extraction of deep features, the feature vectors obtained were then categorised using a RF ensemble classifier. Random forest is a widely utilised ensemble learning model that is trained to create numerous decision trees and combine their predictions through majority voting to improve classification performance and reduce overfitting (31).

Random forest has been chosen in this study because it has the qualities to model non-linear, complex decision boundaries, as well as being resistant to noise and feature correlations that are inherent in high-dimensional deep feature representations (32). Random forest, as compared to the single decision tree models, offers a better generalisation performance due to the added

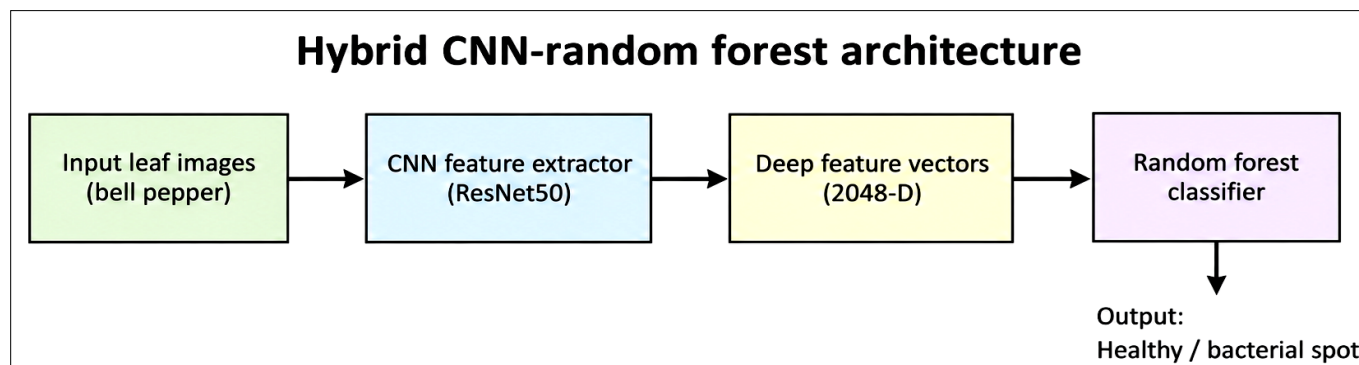


Fig. 2. Architecture of the proposed hybrid convolutional neural network–random forest (CNN-RF) framework. Bell pepper leaf images are processed using a pretrained ResNet50 model for deep feature extraction, and the resulting 2048-dimensional feature vectors are classified using a random forest classifier to distinguish between healthy leaves and bacterial spot-infected leaves.

randomness in feature selection and sampling of data used in constructing a tree.

In this application, the deep feature vectors extracted by the CNN were 2048-dimensions and the CNN was used to train the RF classifier. Stratified sampling was used to divide the dataset into training and testing subsets while preserving the original class distribution. Approximately 80 % of the images (396 samples) were allocated for training and 20 % (99 samples) were reserved for testing. No separate validation subset was employed in the present study, and model performance was evaluated using the independent test set (28, 32). The RF classifier was configured with 300 decision trees to ensure stable performance while maintaining reasonable computational cost. The dataset partitioning used in this study is summarised in Table 3.

Implementation details

The proposed framework was implemented in Python using PyTorch for deep feature extraction and Scikit-learn for classification. A pretrained ResNet50 model was employed as a fixed feature extractor to generate 2048-dimensional feature vectors from resized 224×224 pixel images. The RF classifier was configured with 300 decision trees ($n_estimators = 300$) and a random seed of 42. Since ResNet50 was used exclusively for feature extraction, no optimiser selection, learning-rate scheduling, epoch-based training, or fine-tuning was performed. Experiments were conducted using Google Colab with NVIDIA Tesla T4 GPU acceleration and a standard personal computer environment.

Random forest classifier gives both the class probabilities and discrete class predictions, which allows the ability to evaluate its performance using multiple metrics. This classification step, which is based on the ensemble approach, can supplement the CNN feature extractor since it offers interpretable and reliable decision-making, thereby strengthening the holistic resilience of the proposed hybrid framework.

Model evaluation metrics

The effectiveness of the suggested hybrid CNN-RF framework was measured with the help of a set of standard and widely used measures of classification because it is necessary to guarantee a comprehensive and trustworthy assessment of the model's effectiveness (31, 32). These measures were chosen to measure overall predictive power, as well as discrimination between bacterial spot-infected and healthy samples of bell pepper leaf on a class basis.

The overall classification accuracy was taken as a key measure of model performance that was the percentage of

accurately classified samples in the test set. Precision, recall and F1-score of individual classes were calculated to give a broader understanding of class-specific behaviour. Precision is the fraction of correctly predicted samples in all the samples that are attributed to a single class, whereas recall measures the ability of the model to identify all the pertinent instances of a single class. The F1-score, which is the harmonic average of the precision and recall, is a more balanced measure of evaluation, especially when data does not have equal class distributions.

A confusion matrix was created to display the classification results and study the data on true positives, true negatives, false positives and false negatives. This study is particularly useful in agricultural disease detection, where false negatives (missed cases of disease) can have an important practical impact on crop management.

In addition to threshold-dependent metrics, receiver operating characteristic (ROC) analysis was performed to evaluate the discriminative capability of the proposed model across different classification thresholds. The area under the ROC curve (AUC) was used as a threshold-independent performance measure, where higher AUC values indicate better class separability and overall classification performance. Collectively, these evaluation metrics provide a comprehensive assessment of the effectiveness, reliability, and robustness of the proposed hybrid CNN-RF framework.

Reproducibility statement

To help guarantee reproducibility, the experiments were all run on publicly available data and standard open-source libraries. The data structure, data pre-processing procedures, model architecture and testing protocol are described in sufficient detail to enable reproduction of the reported findings. The implementation was developed using Python, PyTorch and Scikit-learn. Experimental execution was performed using Google Colab with NVIDIA Tesla T4 GPU acceleration. Implementation details and experimental configurations can be made available upon reasonable request.

Results

The CNN-RF hybrid model demonstrated high efficacy in classifying the bell pepper dataset. This model achieved an overall accuracy of 97.98 %, indicating that it reliably distinguishes between bacterial spot-infected and healthy leaf samples. Precision, recall and F1-score are detailed class-wise performance metrics as shown in Table 4.

Class-wise analysis showed that both classes achieved precision and recall values above 0.96, indicating balanced

Table 4. Classification performance metrics of the proposed hybrid convolutional neural network-random forest model

Class	Precision (%)	Recall	F1-score
Pepper (bell)–Bacterial spot	0.98	0.96	0.97
Pepper (bell)–Healthy	0.98	0.99	0.98
Macro average	0.98	0.98	0.98
Weighted average	0.98	0.98	0.98
Overall accuracy	97.98	—	—

predictive performance despite the slight class imbalance present in the dataset. The bacterial spot class had a recall of 0.96, which means that the diseased leaves were identified effectively, which is especially crucial when detecting the disease early in agriculture.

The distribution of errors was also studied by a confusion matrix (Fig. 3). The model had a false negative rate of 7 and a false

positive rate of 3, which depicts a low rate of misclassification. The false negative count was low and this indicates most of the diseased samples were properly identified and in practical implementation of this system, the chances of unidentified disease transmission are lower.

The ROC analysis was done to evaluate threshold-independent discriminative performance. Fig. 4, which showed the ROC curve, revealed a value of 0.98 AUC, which proved that excellent separability between bacterial spot-infected and healthy leaf samples was achieved over the extensive detector range of decision thresholds.

An integrated overview of measurement indicators is presented in Table 5 that displays the general durability and stability of the suggested framework. Besides, the feature importance analysis generated by the RF classifier (Fig. 5) helps to visualise the relative contribution of the most influential deep feature

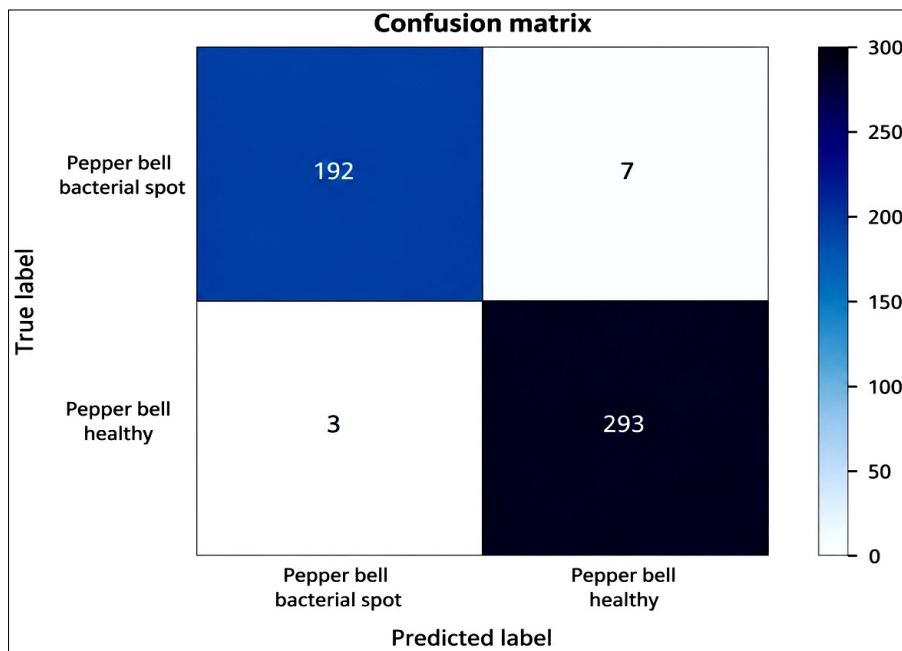


Fig. 3. Confusion matrix showing the classification performance of the proposed hybrid convolutional neural network-random forest (CNN-RF) model for bacterial spot and healthy bell pepper leaf samples.

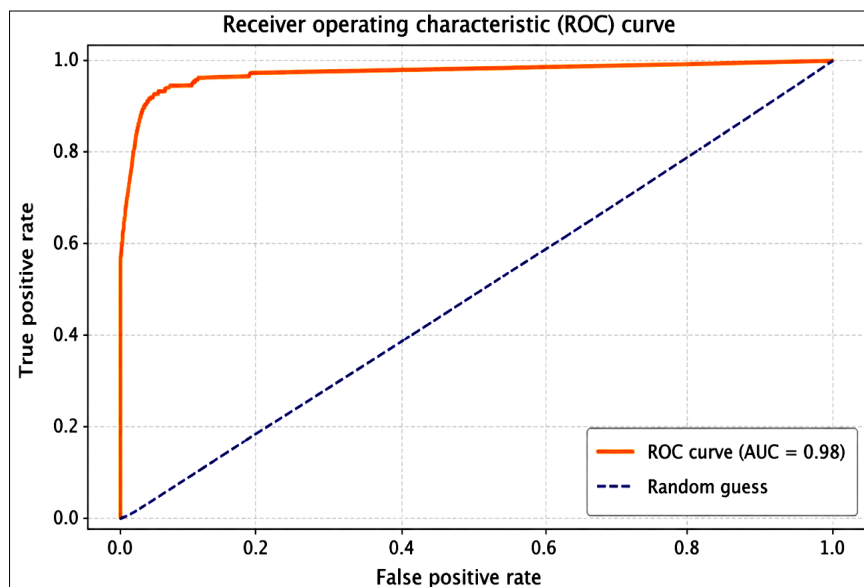


Fig. 4. Receiver operating characteristic (ROC) curve of the proposed hybrid convolutional neural network-random forest (CNN-RF) model. The curve illustrates the trade-off between true positive rate and false positive rate across different classification thresholds, achieving an area under the curve (AUC) value of 0.98, which indicates excellent discriminative performance.

Table 5. Summary of model evaluation metrics

Metric	Value (%)
Accuracy	97.98
Precision (average)	0.98
Recall (average)	0.98
F1-score (average)	0.98
AUC	0.98

AUC: area under the receiver operating characteristic curve.

representations. This discussion points out that a portion of CNN-extracted features is dominant and useful in disease classification, which is why the hybrid strategy of learning is effective.

Discussion

The mutual complementation between the deep feature learning approach and the ensemble-based classification approach is indicated by the superior performance of the proposed hybrid CNN-RF system in helping to identify plant diseases. The application of CNNs has proven to be able to perform well in plant disease recognition as it can learn hierarchical visual representations directly out of raw images (8, 29, 30). Nevertheless, single deep learning models can be vulnerable to overfitting or poor generalisation, especially when they are trained on rather small samples (6, 21). Enhancement of robustness using RF as an ensemble classifier involves combining several decision trees and is also attributed to minimising variance, thus boosting generalisation performance (31, 32). The given hybrid approach takes advantage of the representational power of CNNs and enjoys the stability of ensemble learning.

Furthermore, RF is less sensitive to overfitting on high-dimensional feature spaces and can effectively exploit the discriminative information contained in CNN-extracted representations, thereby contributing to the improved classification performance observed in this study.

The results of this work are aligned with recent studies that show that the hybrid and transfer learning models enhance the classification reliability when applied in plant pathology (22, 25, 27). Specifically, deep learning systems that are hybrid, that is, they integrate feature extraction with secondary classifiers, have

demonstrated enhanced interpretability and resilience on a variety of crop datasets (22). The proposed framework offers competitive accuracy compared to single-model CNN methods that have previously been used on bell pepper and other crops (11, 12), which still have structures that are simple to understand and computationally efficient.

The proposed framework demonstrates competitive performance compared with recent plant disease detection studies. Previous studies have reported classification accuracies ranging from 95.0–98.0 % using hybrid CNN-RF frameworks, PSO-based feature selection techniques and feature-rich machine learning models for plant disease classification (9, 10, 13). Transfer-learning-based approaches have also achieved strong classification performance using deep learning architectures such as residual network (ResNet), densely connected convolutional network (DenseNet), and efficient network (EfficientNet) for plant disease detection (14–16). Unlike these approaches, the proposed framework combines pretrained Resnet50-based deep feature extraction with RF classification for bell pepper bacterial spot detection without relying on handcrafted features or additional optimisation algorithms, while maintaining competitive classification accuracy and improved interpretability.

An additional advantage of the proposed framework is the incorporation of RF feature importance analysis, which provides insight into the relative contribution of CNN-extracted features during classification. Although the extracted deep features are represented as high-dimensional latent variables and cannot be directly mapped to specific biological symptoms, they are learned from visual patterns associated with disease manifestation. These patterns likely capture variations in lesion morphology, chlorotic and necrotic regions, colour distribution, texture irregularities and structural alterations present in infected leaves. The feature importance ranking shown in Fig. 5 demonstrates that a subset of deep features contributes more strongly to classification decisions, thereby improving the interpretability of the hybrid framework compared with purely end-to-end black-box models. Future studies may employ explainable AI techniques such as Grad-CAM, saliency maps, or activation visualisation methods to establish more direct

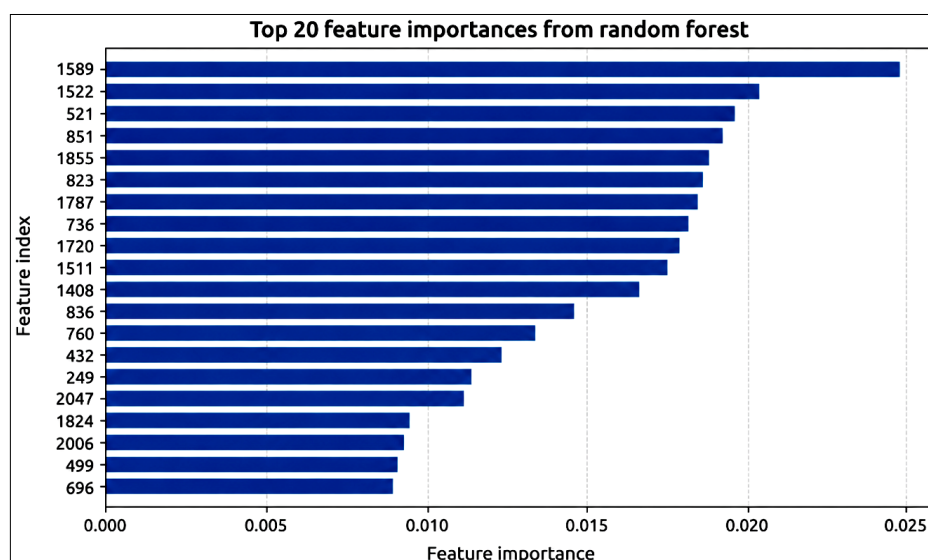


Fig. 5. Top 20 feature importances derived from the random forest classifier. The figure illustrates the relative contribution of the most influential deep features extracted by ResNet50 to the classification of healthy and bacterial spot-infected bell pepper leaves. Higher feature importance values indicate a greater contribution to the final classification decision.

relationships between learned features and specific biological disease symptoms.

Although the present study demonstrates competitive performance relative to recent literature, direct experimental comparisons with alternative baseline models, such as standalone CNN classifiers, support vector machines, handcrafted-feature-based RF models and other transfer-learning architectures, were not conducted within the scope of this work. Future research will perform comprehensive benchmarking across multiple classification frameworks using identical datasets and evaluation protocols to further quantify the relative advantages of the proposed hybrid approach.

This paper is part of a comparatively small amount of research dedicated to the detection of disease in bell pepper (*C. annuum*) specifically. Bell pepper is relatively underrepresented, even though significant crops like tomato and potato were primarily focused on in AI-based models of plant disease detection (12, 23). Capsicum disease detection surveys are recent, and they emphasise the necessity to develop stronger and scalable AI solutions dedicated to this crop (18, 23). The current work fills this gap and contributes to the existing evidence of the relevance of hybrid AI models to different horticultural plants.

In the agricultural context, timely and accurate disease diagnosis is very important in minimising crop losses and promoting sustainable crop control (1, 2). Precision agriculture practices can be supported using AI-powered disease detection systems that can support timely intervention and manage the application of pesticides optimally (5, 23). Early detection, especially in bacterial illnesses, helps to reduce the spread of the disease and economic loss to a considerable degree (3, 4). The elevated AUC in this experiment also supports the discriminative consistency of the model under changing decision thresholds and is important in the real-world decision-support systems where sensitivity and specificity may be different.

From a practical perspective, the seven false negative predictions observed in this study represent disease leaves that may remain undetected and potentially contribute to disease progression if deployed in real agricultural settings. Conversely, the three false positive predictions may result in unnecessary inspection or treatment actions. However, the relatively small number of such misclassifications compared with the total number of samples suggests that the proposed framework maintains a high level of reliability for disease screening applications.

Despite the promising performance achieved by the proposed framework, several limitations should be acknowledged. The model was developed and evaluated exclusively using the PlantVillage dataset, which consists of images captured under controlled laboratory conditions with relatively uniform backgrounds, consistent illumination and minimal environmental variability. In contrast, real agricultural environments often contain complex backgrounds, varying lighting conditions, shadows, leaf occlusions, overlapping foliage and multiple disease symptoms occurring simultaneously. Such factors can significantly affect image quality and classification performance. Therefore, although the proposed framework achieved high accuracy on the benchmark dataset, its effectiveness under real-field conditions has not yet been validated. Future research should evaluate the proposed model using field-acquired datasets collected under diverse environmental

conditions to assess its robustness, generalisability and practical applicability in precision agriculture.

Another limitation of the present study is that model evaluation was based on a single stratified 80 : 20 train-test split. Although stratified sampling preserved class proportions and an independent test set was used for evaluation, performance estimates may still be influenced by the specific dataset partition selected. More robust validation strategies, such as k-fold cross-validation (CV), in which the dataset is partitioned into k subsets and each subset is used once as a validation set while the remaining subsets are used for training, or repeated random subsampling validation, could provide a more comprehensive assessment of model stability, robustness, and generalisation capability. Future work will investigate these evaluation protocols to strengthen the reliability of the proposed framework further. In addition, confidence intervals and formal statistical significance testing were not performed in the present study. Future investigations should incorporate these statistical analyses to provide a more comprehensive assessment of model uncertainty, robustness, and comparative performance.

In general, the findings show that hybrid AI models that involve the combination of deep feature extraction with ensemble-based classification schemes represent an optimal trade-off between accuracy, robustness, and scalability. These types of integrated systems have a high potential of being implemented in real-life agricultural monitoring settings, particularly in a field-acquired imagery and multi-disease situation.

Conclusion

This paper created a convolutional neural networks (CNN)-random forest (RF) model that would detect diseases on bell pepper leaves with high accuracy using images. The proposed model was able to produce high classification accuracy and great discriminative performance by integrating deep convolutional feature extraction and ensemble classification. These findings prove that the hybrid AI methods can be utilised to increase the robustness and reliability in the diagnosis of plant diseases. These systems demonstrate potential to support timely intervention, reduce yield losses and assist precision agriculture practices, although further validation under real-field conditions is required. Future research will focus on the multi-disease classification, field-acquired imagery and validation in the real agricultural environment. However, since the present study was validated only on the PlantVillage dataset and evaluated using a single stratified train-test split. Future work should focus on testing the framework using real-field images acquired under varying environmental conditions, employing more robust validation strategies, such as k-fold cross-validation (CV), and conducting comprehensive benchmarking against standalone CNN, support vector machine (SVM) and RF models, as well as alternative transfer-learning architectures, to further assess the robustness, generalisation capability, and practical deployment potential of the proposed framework.

Data availability statement

The data used in this research can be accessed freely on the Kaggle repository named PlantVillage (<https://www.kaggle.com/datasets/mohitsingh1804/PlantVillage>). The authors never produced any new

data. Images were visually inspected during preprocessing and no corrupted or unreadable samples were identified.

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Authors' contributions

GJG carried out the plant identification studies, participated in the sequence alignment and its design and coordination. SM participated in the sequence alignment, drafted the manuscript, designed the study and performed the software analysis. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare.

Ethical issues: None

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