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Foliar symptom-based disease detection in black pepper using convolutional neural network

P. T. Sreethu[1*], Manju Mary Paul[2], Pratheesh P. Gopinath[2], I. L. Shahana[3] and N. S. Radhika[4]

Abstract

Black pepper is the most important and widely consumed spice in the world. Insects and diseases are the major concerns for black pepper production, among the many variables causing a decline in black pepper productivity. The major diseases that affect black pepper are foot rot (*Phytophthora capsica*) and anthracnose (*Colletotrichum gloeosporioides*). Early and precise diagnosis of diseases is crucial as it will enable the farmers to make timely interventions. In the current scenario, the application of image processing and deep learning techniques for the automatic detection of plant diseases emerges as a solution capable of promptly delivering interventions in time-sensitive scenarios, given its capacity to deliver performance approaching expert levels. Through this study, a deep learning-based approach has been developed to classify black pepper diseases based on leaf images. A model has been developed to detect the two major diseases of black pepper, i.e., anthracnose and foot rot diseases, using a Convolutional Neural Network (CNN) in Kerala, India. We have collected 2786 leaf images from different black pepper farms in Kerala, belonging to three classes of pepper diseases and one healthy leaf class in total. The classes of leaf diseases considered include an early and advanced stage of anthracnose, and Phytophthora foot rot. As the accuracy of the model increases with the number of images, different image augmentation techniques are performed on the originally captured images to generate a total of 18,234 images. The developed CNN model has been compared with eight other pre-trained state-of-the-art models, such as VGG16, VGG19, ResNet50, ResNet50V2, MobileNet V2, DenseNet121, InceptionV3, and Xception. The result shows that the developed CNN model attained a higher classification accuracy, precision, recall, and F1-score of 98.72%, 99.28%, 97.65%, and 98.66% respectively, on the unseen test dataset. A web application named "Black pepper Disease Identification App" for demonstrating the proposed model is developed. According to an overall performance assessment, deep learning is an effective technique for classifying black pepper diseases based on leaf images and identifying them in their early stages. Based on the overall performance, the newly developed model is found to be efficient in classifying the selected pepper diseases. The proposed model holds significant promise for enabling the timely identification of diseases with minimal human intervention. Its deployment benefits both researchers and farmers by facilitating prompt disease detection directly in the field.

Keywords Black pepper, Anthracnose, Foot rot, Healthy, Convolutional neural network, Early disease detection, Deep learning, Transfer learning

*Correspondence:
P. T. Sreethu
sreesreethu56@gmail.com
Full list of author information is available at the end of the article

Background

Black pepper (*Piper nigrum* L.), also known as the "king of spices" and "black gold", is one of the most important and widely consumed spices across the globe; it is cultivated in over 26 countries and produces about 561,500 tonnes of pepper annually (Krishnamoorthy and Parthasarathy 2010; Ravindran et al. 2012). Among the pepper-growing countries, India stands in the third position in terms of production (64,000 tonnes) with an area of 278,050 ha. Within India, Kerala holds the second position, contributing 32.6% of the national production with 21,000 tonnes (Spices Board 2023). Black pepper is valued for its distinctive flavour and pungency, and it is used in culinary applications and ayurvedic medicine to treat ailments like colds and fever. However, its yield can be significantly impacted by various diseases. Among the reported 17 diseases of black pepper (Anandaraj and Sarma 1995), phytophthora foot rot and anthracnose diseases are particularly prevalent in Indian pepper growing regions. Phytophthora foot rot is estimated to cause crop loss ranging from 25 to 30% in Kerala and affecting 44–48% of vines in Karnataka, India (Mammootty et al. 2008). Specifically, in the Kozhikode and Kannur districts of Kerala, annual losses have been reported to reach 1000 tonnes. Additionally, anthracnose disease poses a considerable threat to pepper spikes, causing damage ranging from 1.93 to 9.54%, with potential losses reaching as high as 67% under extreme circumstances (Devasahayam et al. 2008).

Early and accurate disease identification is crucial for effective management and controlling the spread of diseases (Sethy et al. 2020). The traditional approach relies on visual inspection by plant pathologists, experienced farmers, or agricultural specialists. However, this method requires specialized skills and demands more time, energy, resources, and physical energy to a large extent (Sankaran et al. 2010; Li et al. 2020). Also, visual inspection demands consistent monitoring by experts, which makes it an expensive affair to the farmers in remote locations (Lu et al. 2017; Ramcharan et al. 2017; Chen et al. 2020). Consequently, the development of a fast, automated, cost-effective, and accurate approach to plant disease detection is imperative.

The advent of Deep Learning (DL) has revolutionized the field of image analysis and computer vision (Hemanth and Estrela 2017; Chandel et al. 2021). Recently, DL, a class of Machine Learning techniques, has outperformed humans in tasks like image classification and can automatically identify optimal features for plant disease detection (Bock et al. 2020). Convolutional Neural Networks (CNNs), a DL technique, have become a prominent tool for automatic disease identification in crops utilizing digital images (Kamilaris and Prenafeta-Boldu 2018; Haque et al. 2022). In the current scenario, DL-based automated disease identification approaches are achieving expert-level performance during critical periods and outperforming conventional disease detection methodologies.

DL techniques have demonstrated effectiveness in identifying diseases across a range of crops, including citrus (Barman et al. 2020), apple (Liu et al. 2017; Wang et al. 2017; Luo et al. 2021), potato (Oppenheim et al. 2019; Verma et al. 2020), rice (Lu et al. 2017; Shrivastava et al. 2019; Sharma et al. 2020), tomato (Ashqar and Abu-Naser 2019; Tm et al. 2018; Agarwal et al. 2020; Kaushik et al. 2020; Kibriya et al. 2021; Islam et al. 2022), soybean (Wallelign et al. 2018), banana (Amara et al. 2017), maize (Mishra et al. 2020; Prashanthi and Srinivas 2020; Haque et al 2022), peach (Bedi and Gole 2021), cassava (Abayomi-Alli et al. 2021), sunflower (Sirohi and Malik 2021), guava (Mostafa et al. 2021), vine (Kerkech et al. 2020), coffee (Kumar et al. 2020), and multiple leaf diseases (Mohanty et al. 2016; Sladojevic et al. 2016; Ferentinos 2018; Yadav et al. 2018; Francis and Deisy 2019; Pallagani et al. 2019; Madhulatha and Ramadevi 2020; Ahmed and Reddy 2021; Chowdhury et al. 2021; Tiwari et al. 2021; Pandian et al. 2022). Additionally, a few deep-learning models have been specifically developed for disease classification in black pepper crops (Khew et al. 2021; Chen et al. 2023; Kini et al. 2024).

While CNNs have demonstrated promise in this area, further exploration is necessary to optimize their performance for specific crops and disease classifications. This study aims to investigate the application of a CNN model for classifying black pepper leaf diseases. The developed CNN model is designed to differentiate between healthy leaves and leaves infected with two prevalent diseases: phytophthora foot rot and anthracnose. Our proposed model achieves noteworthy outcomes during the classification of black pepper diseases. Also, a comparative analysis demonstrates that our model outperforms pre-trained state-of-the-art CNN models. The following are the major contributions of the study: initially, a novel image dataset encompassing four classes of black pepper leaves was constructed. Images were captured from various pepper fields in Kerala, India, ensuring diverse real-field conditions. Second, we developed a CNN model by optimizing the hyperparameters by iteratively tuning while monitoring the model's performance. Compared to other pre-trained models, the customized model achieved a significant performance in classifying images of black pepper even with diverse and complex backgrounds.

Results

Proposed model

The first convolutional layer employs 32 filters with a 3×3 kernel and ReLU activation function, designed to process 128×128 pixel RGB images. Subsequent convolutional layers progressively increase the number of filters (64, 128, 512) to capture increasingly complex features. Following each convolutional layer, a max-pooling layer with a 2×2 window downsamples the feature maps. A flattening layer transforms the output from the convolutional layers into a one-dimensional vector. This vector is then fed into two fully connected layers with 512 and 64 neurons, respectively, both utilizing ReLU activation. To prevent overfitting, L2 kernel regularization with a strength of 0.001 is applied in these dense layers. The final dense layer uses softmax activation to classify the input into one of the four classes (Additional file 1: Figure S1). The model is compiled with a categorical cross-entropy loss function and the Adam optimizer with a learning rate of 0.001. Training is conducted for 50 epochs with a batch size of 64. The total number of trainable parameters in the model is 10,154,372 (Table 1).

Assessment of the model's performance with different combinations of dropout and kernel regularizer

To optimize the model's performance, we experimented with different combinations of L2 Kernel regularization strength and dropout rate in the final output layer, while keeping all other parameters constant (four convolutional-max pooling blocks, two fully connected layers with 512 and 64 neurons, and an output layer). As shown in Fig. 1, when the dropout rate was fixed at 0.1, models with a lower L2 regularization strength (0.001) achieved higher test accuracy compared to those with a higher strength (0.01). This suggests that a weaker L2 regularization might help prevent overfitting, leading to better model generalization. Interestingly, the model with only L2 regularization (strength of 0.001) achieved the highest test accuracy, indicating its strong ability to perform well on unseen data. The performance of the model without L2 regularization and dropout was comparable to the best-performing model.

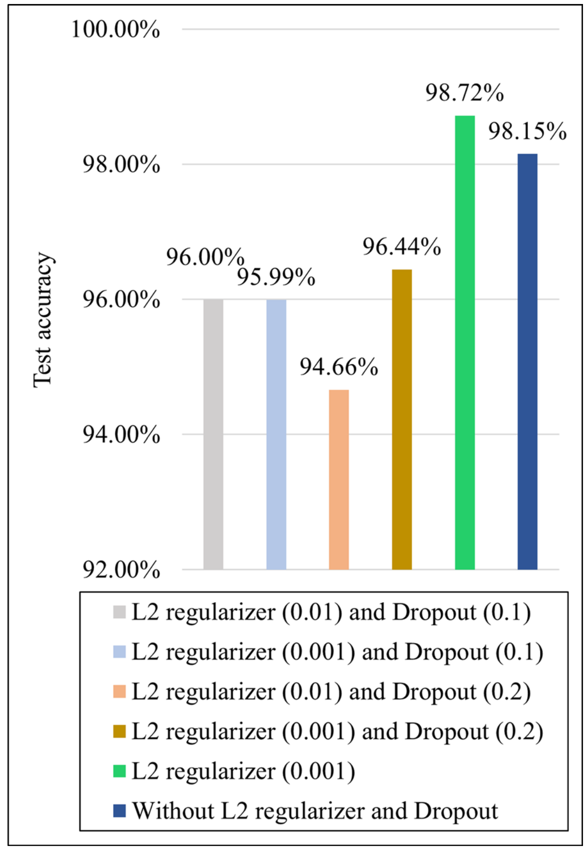

Fig. 1 Test accuracies of different combinations of Dropout and L2 Kernel Regularizer

Table 1 Model parameters of the proposed CNN model

Layer type	Output shape	Parameter[a]
conv2d (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_2 (Conv2D)	(None, 28, 28, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 128)	0
conv2d_3 (Conv2D)	(None, 12, 12, 512)	590,336
max_pooling2d_3 (MaxPooling2D)	(None, 6, 6, 512)	0
flatten (Flatten)	(None, 18,432)	0
dense (Dense)	(None,512)	9,437,696
dense_1 (Dense)	(None, 64)	590,336
dense_2 (Dense)	(None, 4)	32,832

[a] parameter refers to the weights and biases associated with the neurons in the network

Assessment of the model's performance using different batch size

To determine the optimal batch size for training, we experimented with four configurations: 8, 16, 32, and 64 images per batch. As illustrated in Fig. 2a, increasing the batch size from 8 to 64 generally led to improved test accuracy. A smaller batch size of 8 resulted in a slightly lower test accuracy (92.32%) compared to larger batch sizes. The model with a batch size of 64 achieved the highest test accuracy of 98.72%. Interestingly, Fig. 2b demonstrates a clear trend of decreasing training time with increasing batch size. A larger batch size (64) resulted in a significantly shorter training time (10.888 min)

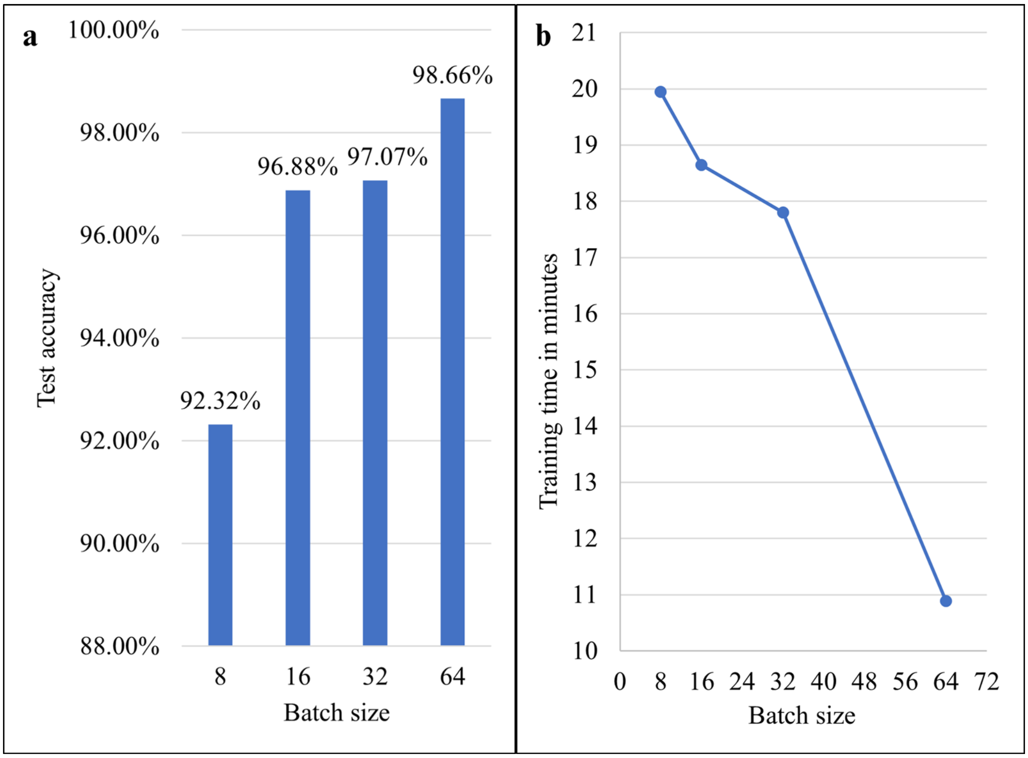

Fig. 2 Effect of batch size in training a CNN model. **a** The column shows the test accuracies obtained with different batch sizes., **b** In the line graph, the y-axis indicates the training time required for training the model for 50 epochs for different batch sizes in the x-axis

compared to a smaller batch size of 8 (19.945 min) for 50 epochs. These observations suggest that increasing the batch size facilitates enhanced parallelization during the training process. Consequently, larger batch sizes (e.g., 64) demonstrably achieve both superior test accuracy and reduced training times. However, it is crucial to consider the limitations of available computational resources when selecting an optimal batch size.

Assessment of the model's performance with batch size 64 and different learning rates of Adam optimizer

A performance analysis of the model with different learning rates for Adam optimizer and their corresponding test accuracy has been presented in Fig. 3a, and it can be observed that the choice of learning rate is crucial for the training process. Experimenting with a range of learning rates (0.1–0.00001) revealed that excessively high rates (0.1 and 0.01) resulted in low test accuracies (23.75% and 24.91%, respectively). Conversely, an overly low rate (0.00001) also led to decreased accuracy (93.77%). The optimal learning rate was identified as 0.001, achieving high test accuracy comparable to 0.0001 and enabling faster convergence during training (Fig. 3b, c).

A CNN model was developed by combining the parameters, and it has shown promising results. Further, the proposed CNN was evaluated with the help of the confusion matrix and ROC curve which are presented in Fig. 4a, b. The normalized confusion matrix (Fig. 4a), presented in terms of percentage, demonstrates exceptional classification accuracy across all classes (healthy: 100%, foot rot: 97.42%, advanced anthracnose: 97.82%, initial anthracnose: 99.33%). The model achieved an outstanding average test accuracy of 98.72% with a low-test loss of 0.1060. Precision, recall, and F1-score further confirm the model's effectiveness, with average values of 99.28%, 97.65%, and 98.66% respectively (Fig. 4c). These exceptional results demonstrate the model's robust capability for accurate disease classification in black pepper leaves.

Analysis of the model in comparison with different pre-trained model

The proposed CNN model achieved exceptional performance in classifying black pepper leaf diseases, surpassing the capabilities of pre-trained models on all evaluated metrics (precision, recall, F1-score, and accuracy). As shown in Table 2, pre-trained models (trained with a standard 80:10:10 data split for 50 epochs) exhibited varying degrees of performance. Among the models, ResNet50 performed least in terms of all the performance metrics (65.13% test accuracy); DenseNet121 achieved

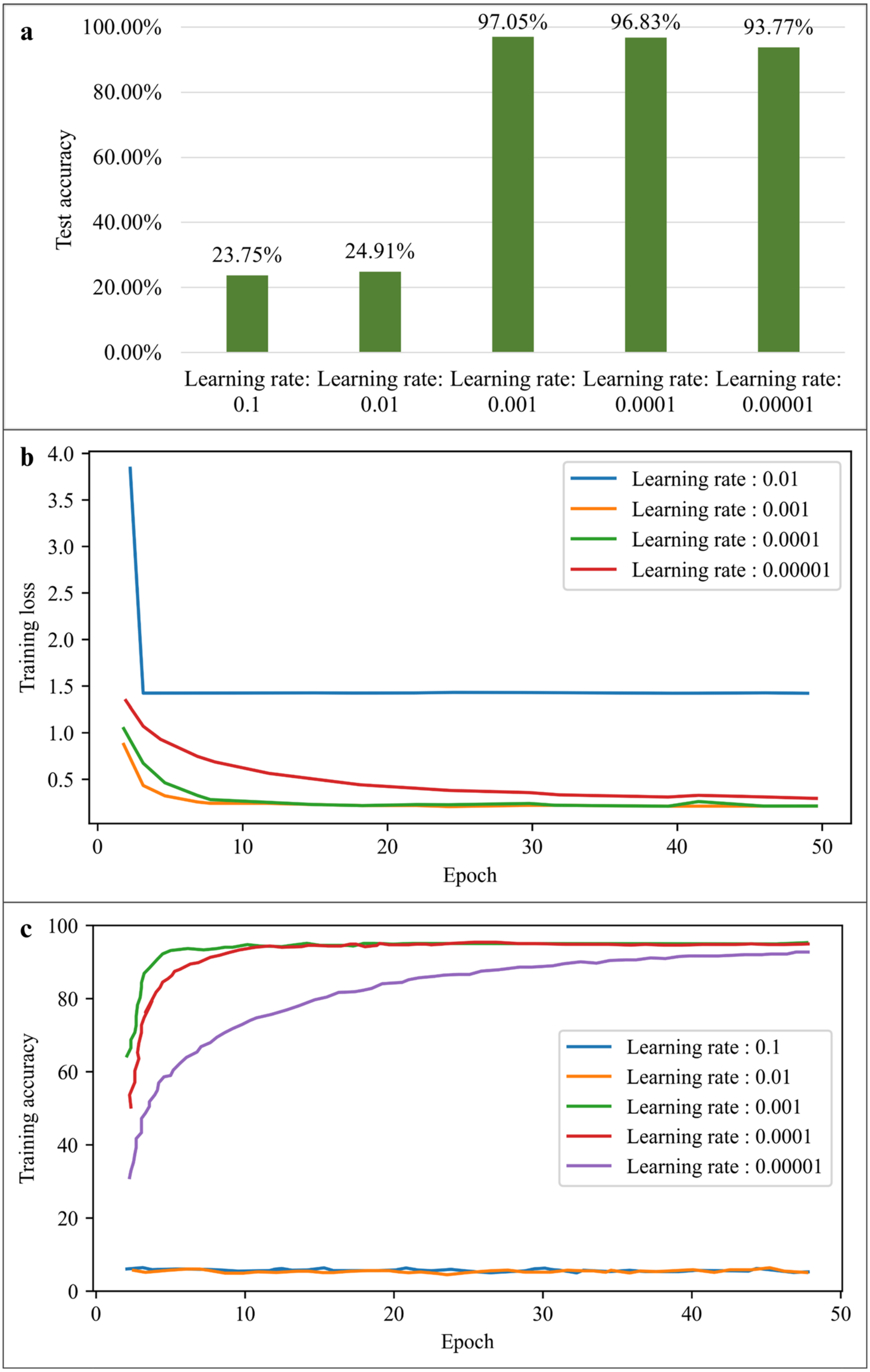

Fig. 3 Effect of different learning rates in training a model. **a** The overall accuracy of the model with different learning rates. **b** Training loss graph with different learning rate configurations. **c** Training accuracy graph of the model with different learning rate configurations

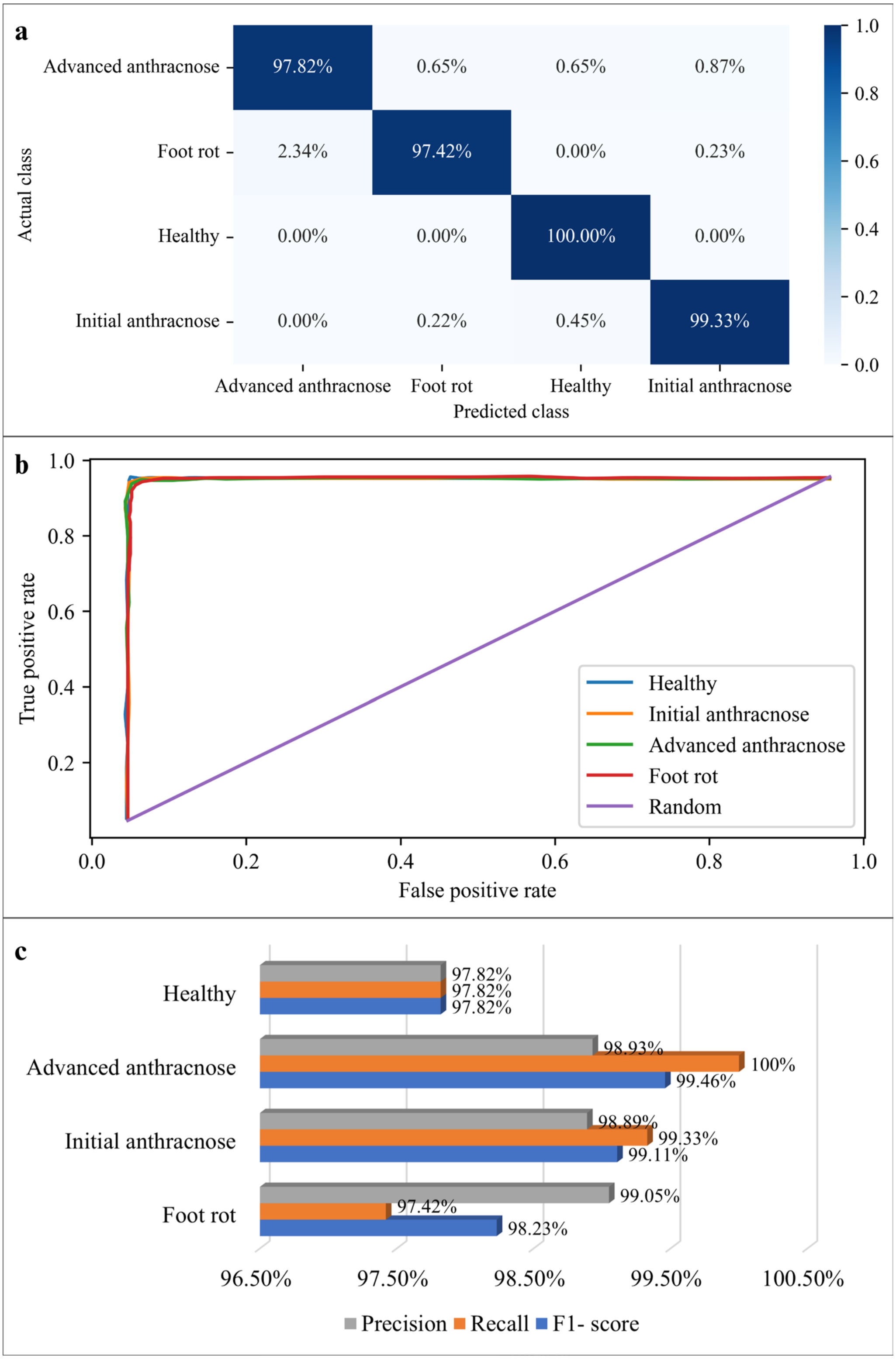

Fig. 4 **a** The detailed breakdown of model having confusion matrix with true labels and predicted labels, **b** ROC curve of the proposed CNN model, and **c** F1 score, recall, and Precision of all the four classes

Table 2 Comparative analysis of the performance of pre-trained models and proposed models' precision, recall, F1 score, and accuracy

Sl No	Models	Precision	Recall	F1 score	Accuracy
1	VGG16	92.64%	92.55%	92.54%	92.55%
2	ResNet50	65.52%	65.13%	64.9%	65.13%
3	VGG19	91.38%	91.16%	91.1%	91.16%
4	MobileNet V2	96.07%	96.05%	96.05%	96.05%
5	DenseNet121	96.71%	96.72%	96.71%	96.72%
6	InceptionV3	91.44%	91.32%	91.29%	91.32%
7	Xception	92.01%	91.94%	91.86%	91.94%
8	ResNet50V2	93.31%	93.16%	93.19%	93.16%
9	Proposed model	99.28%	97.65%	98.66%	98.72%

the best performance among pre-trained models, with recall, precision, F1-score, and average accuracy of 96.72%, 96.71%, 96.71%, and 96.72%, respectively. While analyzing the total number of weights and biases that can be learned or adjusted during the training process (trainable parameters) of pre-trained models, VGG16 and VGG 19 required significantly less trainable parameters compared to other complex models (Additional file 1: Figure S2). However, our proposed model demonstrates exceptional performance, significantly outperforming all other compared pre-trained models, by achieving an outstanding average test accuracy of 98.72% (Table 2). This superior performance suggests that a customized CNN model, specifically trained on a dataset of black pepper leaf diseases, can capture and extract features more effectively compared to other pre-trained models. Thus, it emerges as a scientifically sound and dependable solution for classification tasks within this specialized domain.

Web application for black pepper disease identification

A web application titled "Black pepper Disease identification App" has been developed specifically for pepper farmers and extension personnels by utilizing the deployed CNN model. This platform enables users to upload images of black pepper leaves, which are then categorized into distinct classes: initial anthracnose, advanced anthracnose, foot rot, and healthy. A table showcasing the class name along with their respective class probabilities is presented while selecting the predict class option. This feature facilitates an understanding of the model's accuracy in predicting each class. The user interface of the web application has been provided in Fig. 5. The application can be accessed at the following link: https://agstatkau.shinyapps.io/pepper_disease_app/.

Discussion

Through this study, DL technique, CNN has been applied for the classification and identification of black pepper leaf images, differentiating diseases such as foot rot, anthracnose, and healthy leaves. As DL represents the expansion of Traditional ML, it introduces additional depth to the models. This work aims to enhance the accuracy and efficiency of disease diagnosis of black pepper plants, contributing to the field of agricultural image analysis.

The CNN model used in this study is a DL architecture made up of a series of layers with different functional responsibilities, such as convolution, pooling, flattening, and fully connected layers. Although there are a number of CNN architectures as well as pre-trained models available, through this study, the best CNN algorithm for the identification of two major diseases of black pepper has been developed. The hyperparameters influencing

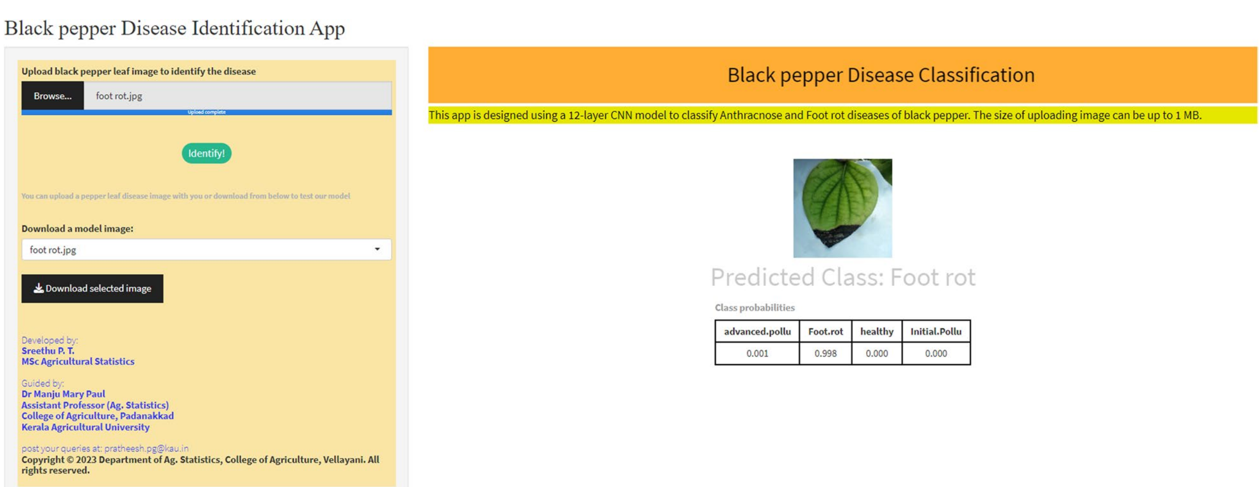

Fig. 5 The user interface of developed black pepper disease identification App

the image-based CNN model were optimized to develop a resilient CNN-based model capable of accurately and precisely classifying foliar images into various black pepper diseases.

The original dataset, comprising 2786 images, has been augmented to generate a dataset comprising 18,234 images by employing various image augmentation techniques. These include rotation, flipping, skewing, brightness adjustment, and a combination of the aforementioned techniques. The model was trained using the augmented black pepper image datasets.

During the CNN model development, a configuration featuring four blocks of convolution and a max-pooling layer showed a higher test accuracy. Interestingly, a model with a smaller strength of kernel regularizer (0.001) and no dropout rates performed efficiently compared to all the combinations of dropouts and L2 regularizers. Optimal training parameters were identified with a batch size of 64, with the Adam optimizer having a learning rate of 0.001. This configuration achieved higher accuracies across all the sets with minimal training time (10.888 min). The comprehensive CNN model, incorporating these parameters, achieved a training accuracy of 99.98%, validation accuracy of 99.88%, and test accuracy of 98.72%.

Further, the developed CNN model has been compared with several state-of-the-art pre-trained models such as VGG16, VGG19, ResNet50, ResNet50V2, MobileNet V2, DenseNet121, InceptionV3, and Xception, in the task of classifying images of black pepper leaves. Each model was initially pre-trained with ImageNet weights and evaluated using a dataset of black pepper leaf images, comprising training, validation, and testing subsets. To ensure a fair and objective comparison across the different architectures, all models were trained with consistent hyperparameters: a batch size of 64, the Adam optimizer with learning rate = 0.001, and 50 epochs. Performance metrics such as accuracy, precision, recall, and F1 score were obtained from the confusion metrices. All CNN models obtained excellent accuracy during the training phase. These results affirm the practicality of CNNs for the classification of black pepper leaf images. Out of the 8 CNN architectures employed, namely, VGG16, VGG19, ResNet50, ResNet50V2, MobileNet V2, DenseNet121, InceptionV3, and Xception in this study, DenseNet121 showed the highest overall accuracy equal to 96.71% on the test dataset. In our study, both of the ResNet50 architectures showed lower accuracy, precision, recall, and F1 scores compared to other models. Notably, DenseNet121 displayed remarkable precision equal to 96.71% and recall equal to 96.72%, which was the highest among considered CNN architectures. Swaminathan et al. (2021) achieved similar observations on an automated detection technique using CNN models on 35,779 images from the Plant Village dataset to classify 29 different diseases across seven plants. They found that DenseNet121 achieved an average accuracy of 94.96%. Rohith and Kumar (2020), in their study on remote sensing signature classification of agriculture detection using deep CNN, found that DenseNet121 architecture outperformed ResNet50, VGG16, VGG19, and other models, alike to our findings. Similarly, the observation made by Gehlot and Saini (2020) on disease detection with the help of CNN in tomato leaves is similar to our result. They noted that DenseNet121 shows a higher accuracy compared to VGG16 and other models.

While comparing the present study with the already existing research works in this direction, it can be found that Khew et al. (2021) constructed a customized CNN and compared it with VGG16 and InceptionV3 to identify two diseases such as red rust and sooty mold and six nutritional disorders of black pepper, using a dataset of 947 leaf images. A classification sensitivity rate of 0.98 was obtained for the customized model, surpassing the other two models. Similarly, Kini et al. (2024) employed a CNN to classify various leaf diseases, including anthracnose, slow wilt, early stage of phytophthora, phytophthora, and yellowing as well as healthy leaves. The CNN model, pre-trained on the ImageNet dataset, was tested on 1800 distinct in-field images of all classes and achieved an average accuracy of 99.1–99.5% across the InceptionV3, GoogleNet, SqueezeNet, and ResNet18 models. In a study similar to the present one, Chen et al. (2023) employed CNN to classify the black pepper images based on symptoms or malnutrition indicated on leaves using a dataset of 1043 image samples. Their study compared a customized CNN model with EfficientNet-B0, MobileNet-v2, ResNet-V2-50, and DenseNet121 as pre-trained models, reporting classification accuracy rates of 85.0%, 88.0%, 88.0%, 86.0%, and 85.0%, respectively, on the test set. Hence, from this experiment, it can be shown that the developed model has shown better or comparable overall accuracy than the above-mentioned findings.

In the future, the proposed model can be extended to more disease identification of black pepper such as slow decline, mottle virus disease, etc. A comprehensive disease identification system could be implemented to address the variation in symptoms observed among different black pepper varieties, which is attributed to host–pathogen interactions.

Conclusion

In this study, a Deep Convolutional Neural Network-based approach has been proposed to automatically identify the images of black pepper diseases along with healthy leaves. The dataset consisted of images of three disease classes (initial anthracnose, advanced anthracnose, and foot rot) as well as healthy leaves. To help the model become more broadly applicable to actual environmental scenarios, the collected dataset contains images with different backgrounds comprising actual field conditions. Addressing class imbalances, we augmented original images to 18,234 by employing rotation, flipping, skewing, and brightness enhancement methods. Our customized CNN architecture achieved high classification accuracy, precision, recall, and F1-score (98.72%, 99.28%, 97.65%, and 98.66%, respectively) on a separate test dataset. The model effectively extracted essential features from disease symptoms, demonstrating robust performance in predicting disease classes in data not included in the training set without conventional image preprocessing. To validate our model's viability, we conducted a comprehensive comparison with state-of-the-art models trained using transfer learning techniques. Results show that our proposed model outperformed other pre-trained models in classifying pathological features of diseases. This empirical analysis suggests that our CNN models may effectively learn both high-level and low-level features from the input images, leading to impressive results for the classification of the dataset under consideration.

Methods

Black pepper dataset preparation

In this study, we utilized a comprehensive dataset of 2786 digital photographs of black pepper leaves captured under field conditions. In addition to images with white and black backgrounds, our dataset also includes images captured under complex field conditions, featuring backgrounds with mud, plant parts, debris, and other environmental elements. By including a diverse dataset in our training, validation, and testing phases, we ensured that the model was exposed to a variety of conditions, enhancing its generalizability and practical applicability. The images of the black pepper leaves were collected from Pepper Research Station, Panniyur; Kannur, and other black pepper growing fields in Wayanad, Kasaragod, Kollam, Malappuram, and Thiruvananthapuram districts of Kerala, India. The dataset encompasses four classes: healthy leaves, leaves with initial and advanced stages of anthracnose, and leaves infected with foot rot for a more precise classification of diseases.

To capture images under varying real field conditions, photographs have been collected during both summer and rainy seasons following the procedures outlined by Haque et al. (2022). A diverse range of image-capturing devices has been utilized to increase dataset variability. These devices included a Nikon Z50 camera with a 16–50 mm lens and a 21.5 MP CMOS sensor, along with various smartphone cameras from Samsung (Galaxy A20s with 13 MP), Xiaomi (Redmi Note 9 Pro with 64 MP, Redmi 9 with 13 MP), Realme (9 Pro + with 50 MP), and Vivo (Y55s with 13 MP).With the help of plant pathologists, the gathered dataset of black pepper leaves, has been divided into four classes namely, "advanced anthracnose", "initial anthracnose", "foot rot", and "healthy" for this study. Sample photographs of each class are presented in Fig. 6 for visualization.

Data preparation

Image preprocessing is one of the important stages in an image classification model since the captured images may vary in illumination, noises, sizes, background etc. Therefore, applying preprocessing techniques such as resizing, rescaling, and augmentation is necessary to accelerate training procedures, which minimizes the computational cost, and improves classification accuracy (Pal and

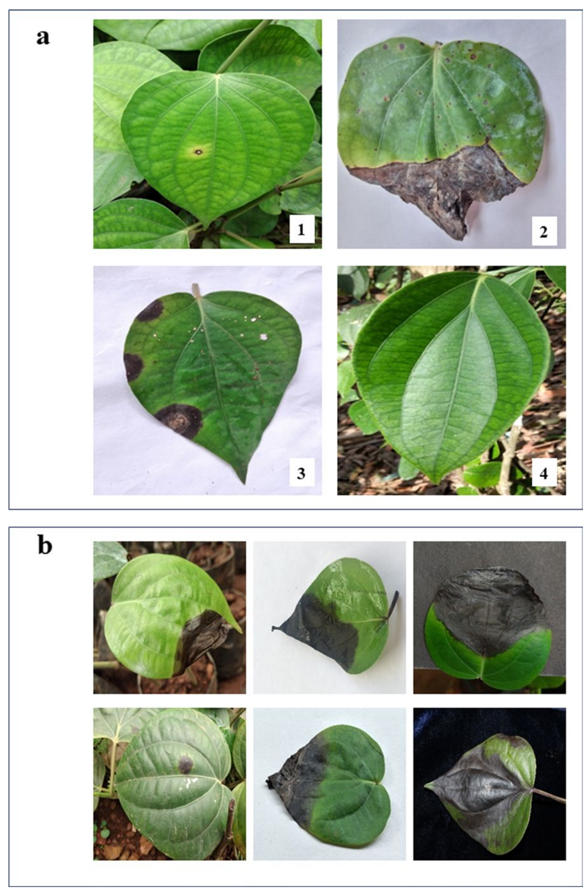

Fig. 6 Sample photographs of the black pepper dataset are presented in **a** (1) Initial anthracnose, (2) Advanced anthracnose, (3) Foot rot, and (4) Healthy. **b** The images represent foot rot disease with various backgrounds, including other plant parts, soil, white, and black backgrounds

Sudeep 2016). In this experiment, the actual images are resized to 128×128 pixels (resolution) and normalized into the range of 1 to 0 by dividing the pixel values by 255 to avoid the disturbance occurring due to the multiplication of small valued weights to large integer pixel values (Too et al. 2019).

The model's performance could be adversely affected by a varying number of images in each class. Artificial images are created to significantly increase the dataset's volume and variability in order to prevent the imbalance problem. In this research, the augmentation of image datasets involves distinct classes being subjected to various transformations, resulting in the generation of a total of 18,234 images. Augmentation techniques comprised image rotation, vertical flipping, horizontal flipping, horizontal-vertical flipping, brightness adjustment, skewing, and combinations of rotation and flipping. These transformations were implemented using OpenCV (Open Source Computer Vision) library. In Additional file 2: Table S1 presents the number of images in each class, including both original and augmented images generated through augmentation techniques.

The performance of the models was evaluated by calculating the accuracies of the model in each configuration. First, the whole dataset was divided into three partitions-training, validation, and testing sets of 80:10:10 were used for conducting a performance evaluation of the model. Splitting of the dataset was carried out by a Python script called 'splitfolders'. This Python script splits the dataset into 3 sets with different configurations. In this study, all the estimation and development procedures were performed using Python. The model was implemented on the Spyder environment by using Keras, a deep learning API for Python, built on top of TensorFlow, which is a Python-based, free, open-source machine learning platform. All the experiments were conducted on the NVIDIA GeForce RTX 3050 Ti Laptop GPU. The specifications of hardware configuration are provided in the Additional file 2: Table S2.

Methodology

Convolutional neural network

Convolutional Neural Networks (CNNs) are inspired by the workings of the brain and how neurons collaborate themselves for the recognition of patterns and analysis of input audio-visual information. They are supervised DL techniques that have revolutionized a wide range of image-based pattern recognition and computer vision applications (Francis and Deisy 2019). They perform automatic feature extraction and require less pre-processing of data than machine learning techniques, leading to improved performance and accuracy.

A CNN consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN are made up of convolutional layers, pooling layers, fully connected layers, and normalization layers mainly used for image processing and image recognition (LeCun et al. 2015; Yao et al. 2019; Subeesh et al. 2022). It uses two operations called 'convolution' and 'pooling' to reduce an image into its essential features, and it uses those features to understand and classify the image.

Transfer learning

Transfer learning in DL refers to using a pre-trained network for a new task. In the fields of computer vision and DL, transfer learning has become particularly popular since it can successfully train a network with minimal data and can achieve excellent precision. Through the use of prior information from one task, a machine can increase its generalization about another through transfer learning. The collected black pepper dataset has been trained on available pre-trained models using a transfer learning approach trained on the well-known 'ImageNet' dataset (Szegedy et al. 2016).

Performance metrics

In every experiment, the models were evaluated using a separate 10% unseen testing dataset following training and validation. Next, in order to determine the models' disease-wise classification performance, we built confusion matrices and ROC curves. A confusion matrix is a two-dimensional table with two dimensions, "Actual" and "Predicted," and its dimensions contain the results of the comparison between the predictions and the actual class labels. The four parameters of the confusion matrix including:

- True positive (TP): This is a case in which the image is predicted to be positive and true.
- True negative (TN): This is a case in which the image is predicted as negative, and it is true.
- False positive (FP): This is a case in which the image is predicted positive, and it is false (type I error).
- False negative (FN): This is a case in which the image is predicted negative, and it is false (Type II error).
- Classification Accuracy (CA): It is averaged among all the classes, and it measures the overall performance of the model.

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

- Precision: It measures the percentage of predicted positives that are actually positive. The fraction of true positives to the sum of TP and FP.

$$P = \frac{TP}{TP + FP}$$

- Recall: Measures the percent of actual positive that are predicted as positive. It is the fraction of TP from the total amount of TP and FN.

$$R = \frac{TP}{TP + FN}$$

- F1-score: Measures the robustness of the model. It is the harmonic mean of precision and recall.

$$F1 = \frac{2 * (TP * FP)}{TP + FP}$$

- Receiver Operating Characteristic (ROC) curve: It plots the True Positive Rate (TPR) and False Positive Rate (FPR) across varying thresholds.

$$\text{True positive rate} = \frac{TP}{TP + FN}$$

$$\text{False positive rate} = \frac{FP}{FP + TN}$$

Web application development

To develop a web application for disease detection, we utilized the Shiny package developed by the Rstudio company, written in the R programming language. This package supports the development of interactive web applications. The User Interface (UI) was designed using the 'fluidPage' function to create a flexible layout, and include various input elements, such as file upload buttons and sliders, for image data input. The server function was developed to manage the logic and computations, including the loading and preprocessing of images, the application of the developed pre-trained deep learning model for disease classification, and the generation of output results. The Shiny app effectively integrates the UI and server components, providing an interactive and user-friendly interface (Jia et al. 2022). The application was deployed on shinyapps.io, enabling users to detect diseases in their crops online by uploading images and receiving immediate diagnostic results.

Abbreviations

DL	Deep learning
ML	Machine learning
CNN	Convolutional neural network
TP	True positive
TN	True negative
FP	False positive
FN	False negative
ROC	Receiver operating characteristic
TPR	True positive rate
FPR	False positive rate
UI	User interface

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s42483-024-00305-1.

Additional file1: Figure S1. Example network architecture of the proposed model. Table 1 shows more details of the developed model. **Figure S2.** Comparative analysis of trainable parameters of pre-trained models.

Additional file2. Table S1. Dataset description after augmentation. **Table S2.** Hardware configuration.

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Author contributions

ST, MP, PG, SL, and RS conceived the study; ST conducted the experiments and implemented the models described; ST and MP analysed the results and wrote the manuscript; ST and SL collected, and RS contributed in classifying the image data; MP, SL, and PG provided the computational resources and facilities for data collection and conducting the experiments.

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Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Author details

[1]Agricultural Statistics, Department of Agricultural Statistics, College of Agriculture, Kerala Agricultural University, Vellayani, Thiruvananthapuram, Kerala 695522, India. [2]Department of Agricultural Statistics, College of Agriculture, Kerala Agricultural University, Vellayani, Thiruvananthapuram, Kerala 695522, India. [3]Department of Computer Science, College of Agriculture, Kerala Agricultural University, Padannakkad, Kasaragod, Kerala 671314, India. [4]Department of Plant Pathology, College of Agriculture, Kerala Agricultural University, Vellayani, Thiruvananthapuram, Kerala 695522, India.

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