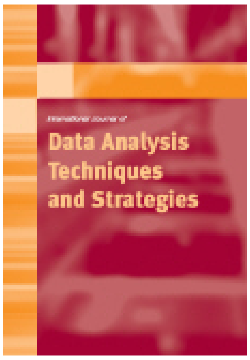

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Improving the accuracy of real field pomegranate fruit diseases detection and visualisation using convolution neural networks and grad-CAM

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Abstract: Pomegranate (*Punica granatum* L) is one of the vital cash fruit crops of arid and semiarid regions in India. The occurrence of pests and diseases affects the development and quality of fruits. Our objective is to develop an automated pomegranate disease detection system on an actual field image dataset using convolution neural networks. The collected images are classified into six categories namely healthy, bacterial blight, anthracnose, fruit spot, fusarium wilt, and fruit borer. In this paper, we have measured the performance of CNN-based architectures VGG16, VGG19, InceptionV3, Resnet50, and Xception with hyperparameter tuning. The experimental results show that Resnet50 is a suitable model for our dataset with a disease detection accuracy of 98.55%. To deal with DL 'black box' problem, the gradient-weighted class activation mapping (Grad-CAM) model is integrated with ResNet50 to highlight the important regions on the fruits to locate accurate diseases and recommend appropriate disease treatment to farmers.

Keywords: convolution neural network; CNN; pomegranate; disease detection; black box; agriculture; gradient-weighted class activation mapping; grad-CAM; deep learning.

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1 Introduction

Nowadays, a lot of research is being done in the agriculture field, and the Indian government also provides a lot of opportunities to improve research and development in the agriculture field. Agriculture is a major revenue-producing sector in India and most people are dependent on agricultural resources. Abrupt changes in climatic conditions lead to occurrences of various known and unknown pests and diseases that affect the development and quality of fruits in horticulture areas. Pomegranate (*Punica granatum L.*) is one of the commercial fruit and the entire pomegranate tree has huge financial importance (Melgarejo-Sánchez et al., 2021). India is one of the biggest producers of pomegranates in the world. At present, Maharashtra is the leading state with thousands of hector areas under pomegranate cultivation followed by Karnataka, Gujrat, and Andhra Pradesh. According to the National Horticulture Board (NHB), Maharashtra cultivates pomegranates in 90,000 ha areas with a yearly production of 9.45 lakh Mt tones. Maharashtra contributes 78% of India's total area and 84% of its total production (Yadav et al., 2020). Different pomegranate varieties are available in India and mostly Ganesh, and Bhagwa varieties are cultivated in Maharashtra for export purposes (Melgarejo-Sánchez et al., 2021).

India is the only country in the world where pomegranate is cultivated throughout the year thanks to its unique geographical location and environmental conditions. There is a high demand for pomegranate fruits from November to February for export with a high price in other countries. According to the Indian Council of Agricultural Research (ICAR) Vision-2050, it's projected that by the year 2025, production is predicted to extend by ten times and export by seven times. Therefore, there is a requirement for sustainable efforts in pomegranate research and development to achieve these objectives. Though pomegranate export earns a substantial foreign exchange for India, less research work has been carried out on pomegranate fruit disease detection and prediction to boost the standard of fruits (Tewari and Avinashilingam, 2020). Environmental factors are the main sources of real farm fruit losses. Several diseases and pests are the major threats to the pomegranate industry and create fear among the farmers. Due to heavy losses, many farmers have uprooted the orchards. Every year, because of a sudden change in weather pomegranate fruits affected by various known and unknown diseases result in losses of about Rs 10,000 crore in production and about Rs 2,000 crore in export. The timely and accurate analysis of plant diseases plays a key role in avoiding the loss of production and quality.

Recently, deep learning (DL) techniques successfully entered in Agriculture domain to resolve agriculture classification and prediction problems. Automatic real-field fruit disease detection and classification is difficult due to the presence of complex backgrounds and disease symptoms are not well-defined. Automatic feature extraction is the main ability of DL models which makes them more effective in the agriculture domain. Technological advancements and automation in agriculture are incredibly important to assist farmers. Drone technology (UAV) is widely used for surveillance, military, mining, construction industries, etc. Recently, an agriculture drone (UAV) successfully entered various agriculture areas to optimise agriculture processes, crop plantation, monitor crop growth, and improve the quality and quantity of crop production.

The contents of this paper are organised as follows: Section 2 presents a literature review that describes existing methods of fruits diseases detection, classification, and visualisation. Section 3 presents materials and methods which describe detailed research methodology. Section 4 presents experimental findings, results, and a discussion of system deployment. Section 5 provides a conclusion by highlighting the most suitable CNN-based model for our collected dataset.

2 Literature review

This section briefly explains work associated with the application of convolution neural networks (CNNs) for fruits diseases detection, classification, and visualisation using the gradient-weighted class activation mapping (grad-CAM) model.

Vasumathi and Kamarasan (2021) proposed a combined CNN LSTM DL model to correctly detect pomegranate disease and classify fruits into healthy and infected classes with an accuracy of 98.17%. Maeda-Gutiérrez et al. (2020) implemented a tomato leaves disease classification system using transfer learning models namely AlexNet, GoogLeNet, Inception V3, ResNet18, and ResNet 50 with different performance metrics. Out of these models, Google Net performed better with 99.72% classification accuracy. Arivazhagan and Ligi (2018) proposed CNN-based architectures to identify and classify five different diseases in mango with an accuracy of 96.67%. Liu et al. (2020a) proposed a novel deep improved convolution neural network (DICNN) to identify six common diseases in grape leaves with 97.22% accuracy. Al Haque et al. (2019) implemented three different CNN-based architectures to detect Guava diseases and recommended disease treatment with an accuracy of 95.61%. Tian et al. (2019) developed an anthracnose disease detection model for the apple using a DL approach of CycleGAN and YOLOV3-Densenet with an accuracy of 95.57%. Selvaraj et al. (2019) proposed six different transfer learning models on 18 different classes and images collected from different parts of the banana plant. Their study showed that ResNet50 and InceptionV2 models performed better than MobileNetV1. Militante and Gerardo (2019) proposed an adaptive deep-learning model to detect sugarcane diseases. Five pre-trained models were used in this study namely StridedNet, AlexNet, LeNet, VGGNet, and GoogleNet. The VGGNet model achieves the highest accuracy of 95% among these trained models. Liu et al. (2020b) introduced a novel approach based on improved convolutional neural networks for kiwi fruit leaf disease detection with an accuracy of 98.54%. Ahmad et al. (2020) proposed an effective CNN-based disease detection system in plum under real field environment with an accuracy of 92%. Xiao et al. (2020) developed a model for strawberry disease recognition based on deep CNN. Toda and Okura (2019) introduced various visualisation methods using CNN on publicly available plant village datasets to detect leaf diseases. Yebasse et al. (2021) proposed three visualisation methods grad-CAM, Grad-CAM++, and score-CAM to visualise and locate coffee diseases and classify healthy and unhealthy coffee plant leaves. Khamparia and Pandey (2020) proposed a novel technique for the detection of chronic kidney disease. They combined principal component analysis (PCA) data reduction technique with a support vector machine (SVM) for disease detection. Meti and Sangam (2019) implemented a neural network approach to improve the performance of fault detection and analysis. Enhancement is performed in ANN by considering cascade feed-forward propagation. Chauhan and Kaur (2017) proposed an integrated technique of machine learning and statistical techniques for feature selection from large-scale databases.

Table 1 Disease incidence on pomegranate (%)

Period	*State/district/ Taluka/villages*	*No. of orchids*	*Cropping season*	*Variety*	*Type of soil*	*Age of plant (yrs.)*	*Type of irrigation*	*Types of disease*	*% disease incidence*
Oct. 2020–March 2021	Maharashtra/ Nashik/ Sinnar/ Pathare	3 (1,221)	Hast Bahar	Bhagwa	Loamy, alkaline, well drained (Poyta)	*4*	*Drip*	Bacterial blight	14
								Anthracnose	10.56
								Fruit spot	3.68
								Blight Blora	2.45
								Fusarium Wilt	0.81
				Total (%)					*31.5*
Aug. 2021–Sept. 2021	Maharashtra/ Nashik/ Sinnar/ Pathare	2 (250)	Ambia Bahar	Ganesh	Loamy, alkaline, well drained (Poyta)	*1*	*Drip*	Bacterial blight	21.2
								Anthracnose	19
								Fruit spot	5.20
								Blight Blora	5.60
								Fusarium Wilt	9.20
				Total (%)					*60.2*

For our study and experimentation, we have used a real field dataset and five different CNN-based transfer learning models (Zhuang et al., 2021). We have also published a detailed literature review about plant and fruit disease detection and prediction with gap identifications (Nirgude and Rathi, 2020).

The key contributions of this research paper are:

- An actual farm survey and agriculture domain expert's survey from agriculture universities were conducted to take suggestions and identify research gaps for finalising research objectives and problem statements (Nirgude and Rathi, 2020).
- Designed and developed a data collection framework using a Raspberry pi camera that is mounted on an agriculture drone to collect real field stage-wise disease development fruits and leaf images.
- Research work emphasises improving pomegranate disease detection and prediction accuracy in the real field environment.
- Most of the researchers used publicly available datasets (source: PlantVillage) for pomegranate disease diagnosis but for our experimentation, we collected two different seasons' stagewise disease development real field fruits and leaves image datasets (Location: Pathare/Nashik/Maharashtra).
- Most of the researchers considered one or two pomegranate diseases but in this research work, the most prominent five different diseases (bacterial blight, anthracnose, fruit spot, Wilt, and fruit borer) are considered for study and analysis.
- Popular transfer learning models (VGG16, VGG19, Inception V3, Xception, and Resnet50) have been used for improving disease detection accuracy and investigated the most suitable model for our collected dataset.
- A gradient-based visualisation technique – grad-CAM (Selvaraju et al., 2019) has been integrated with Resnet50 to deal with CNN 'black box' problem and disease visualisation. Additionally, recommendations for pomegranate disease treatment to farmers.

3 Materials and methods

The proposed research methodology of automatic pomegranate fruit disease detection and classification using CNNs and disease visualisation using the grad-CAM model is presented in Figure 1. The proposed architecture is divided into three different stages: stage-1: real field data collection and pre-processing, stage 2: pomegranate disease detection, stage 3: disease visualisation.

3.1 Stage 1 (A) – real field data collection

The dataset contains real field images of pomegranate fruits and leaves. Stagewise fruit diseases development images are captured through a Raspberry pi camera at an interval of 25 days for a total of 180 days (cropping season: Hast Bahar, Duration: Oct 2020–March 2021 and Ambia Bahar, Duration: Aug. 2021–Oct. 2021). Data collection was done by visiting several pomegranate orchards situated in Nashik district, Maharashtra. The farmers in the Nashik district mostly cultivate Bhagava and Ganesh varieties (Melgarejo-Sánchez et al., 2021). Initially, we collected 5,000 real field images but many are blurry and less than the required size, so all such images are discarded and finally, 1,221 good-quality images are selected for experimentation. The most occurring diseases on pomegranates are studied and classified into six different classes. Figure 2 shows real field sample images of major diseases (bacterial blight (Telya), anthracnose, fruit spot (rot), Fusarium Wilt, blight borer/fruit borer). Table 1 shows disease incidence on collected images of pomegranate (value in %) and equation (1) is used to compute disease incidence. Statistical analysis shows that farmers are advised to cultivate pomegranates in Hasta Bahar season. This practice helps to prevent bacterial blight problems but is recommended for those areas where enough water supplies are available. Ambia Bahar gives a good yield but is more affected by various diseases.

$$Disease\ Incidence(\%) = \frac{No.\ of\ infected\ fruits}{Total\ no.\ of\ fruits\ sample} \tag{1}$$

Figure 1 Stepwise proposed research methodology of automated pomegranate disease detection and visualisation (see online version for colours)

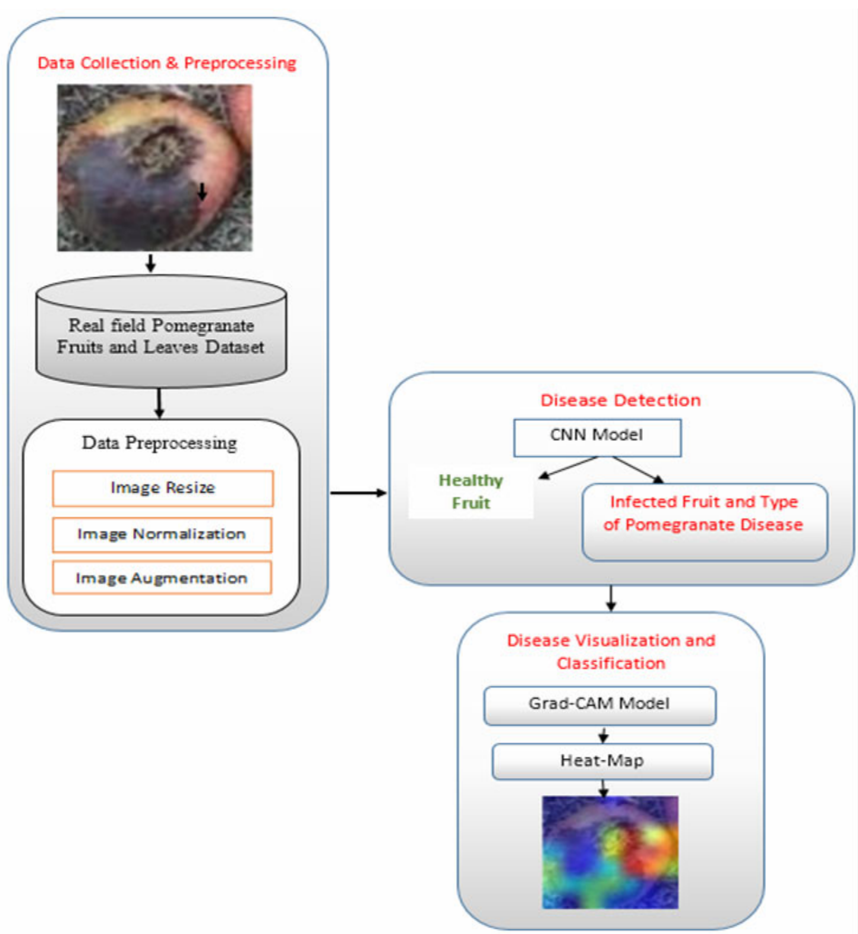
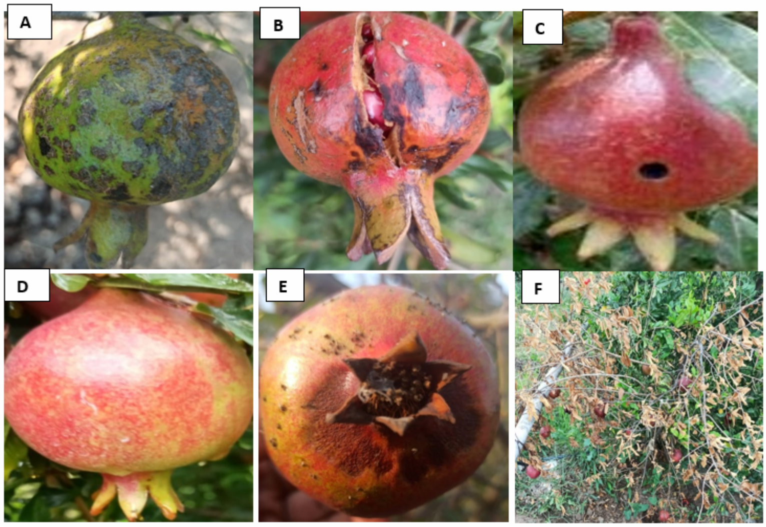


Figure 2 Sample real field pomegranate images of six different classes: variety Bhagwa and cropping season: Hast Bahar, (a) class 0: anthracnose, (b) class 1: bacterial blight, (c) class 2: blight borer, (d) class 3: healthy fruit, (e) class 4: rot, (f) class 5: Fusarium Wilt (see online version for colours)



3.2 Stage 1 (B) – data pre-processing

Data pre-processing has been performed by resizing the input images (224 × 224 × 3) to match the size of the input layer of the CNN-based architecture. Secondly, images are normalised (batch normalisation) to support the faster model training and to better generalise on unknown data (Taylor and Nitschke, 2018). We have used a supervised deep-learning method where a disease label is associated with each input image. Therefore, Data annotation has been performed which is time-consuming and needs domain expert suggestions. Though DL models work extremely well on image detection and classification sometimes models get overfitted. Therefore, data augmentation is performed to increase the dataset and its diverseness. Data augmentation also helps to solve unbalanced data and makes the model more robust. Data augmentation has been performed by horizontal and vertical rotation, scaling, random cropping, zooming, changing brightness, removal of background, and adding noise. To perform the experiments, our dataset has been divided into a 60% training set, a 20% validation set, and a 20% testing set. The experiments are performed on a virtual machine with Intel Xeon(R) CPU, 2.30GHz, 12GB RAM, and NVIDIA Tesla T4 16 GB GPU. First, we analysed the performance of CNN models on default parameters, then we performed hyperparameter tuning and selected the best parameters to improve the model's performance. Further model performances were tested on the test dataset.

3.3 Stage 2 –pomegranate disease detection using CNN-based architectures

We have designed and developed an automatic fruit disease detection system using CNNs (Zeiler and Fergus, 2013). We have used transfer learning models. Transfer learning is a process of reusing a pre-trained model on a new problem. There is a total of 15 CNN-based architectures that are trained on the ImageNet dataset consist 1,000 classes and 1.2 million images. ImageNet large scale visual recognition challenge (ILSVRC) competition is held every year to evaluate the performance of algorithms for object detection and image classification (Russakovsky et al., 2015). In the proposed approach, we have considered five popular CNN-based architectures namely VGG16, VGG19, InceptionV3, Resnet50, and Xception. In the further section, these models have been explained with novelty. The VGG architecture with 16 layers (VGG16) and 19 layers (VGG19) are the variants of the visual geometry group (VGG). Its simpler but deeper architecture consists of 138 M trainable parameters and requires more storage space (Simonyan and Zisserman, 2015). In our experimentation, both VGG16 and VGG19 Models have been overfitted and needed more training time and space. Therefore, VGG architecture is not suitable for our dataset. The inception model is also called 'network in-network' architecture where the inception module is the key innovation (Szegedy et al., 2016). Adding inception modules with different filter sizes reduces computational time and improves detection accuracy. Architecture grows width-wise instead of depth-wise with 23 M parameters. In our experimentation, the InceptionV3 model has given better accuracy than the VGG architecture. The Xception model is an adaptation from Inception V3, where the inception modules are replaced with depth-wise separable convolutions (Chollet, 2017). The Xception model also supports 23 M of parameters but gives better accuracy than Inception V3. Experimental result shows that Xception performs slightly better than Inception V3 on our domain dataset. Residual network is added to the ResNet model to solve the vanishing and exploding gradient problem. Additionally, a bottleneck layer has been added for dimensionality reduction (He et al., 2015). ResNet50, skip connection with the help of identity block is used to provide the value of the input to the output layer. ResNet 50 gives the best disease detection accuracy on our dataset. Therefore, we have integrated the grad-CAM model with ResNet50 for disease localisation and visualisation.

3.4 Stage 3 – pomegranate disease visualisation using grad-CAM model

DL has the potential to improve detection and prediction accuracy, but it is suffered from the black box problem. It hides detailed representations from users. A lot of effort is being taken to make the DL model more understandable and explanatory. Selvaraju et al. (2019) have introduced a grad-CAM based colour visualisation approach. Grad-CAM generates a heatmap that highlights the important regions of the fruit image based on the gradients. As shown in Figure 3, the Input image (fruit borer disease) feeds to CNN (ResNet50) model to detect the disease, and the grad-CAM model is applied to the last convolution layer of ResNet50 for disease visualisation.

3.4.1 Grad-CAM works in three different steps as follows

Step 1 Compute the gradient of y^c (i.e., the output for class c before the SoftMax) w.r.t the feature map activations A^k of a convolution layer, i.e.

$$\frac{\partial y^c}{\partial A^k} \tag{2}$$

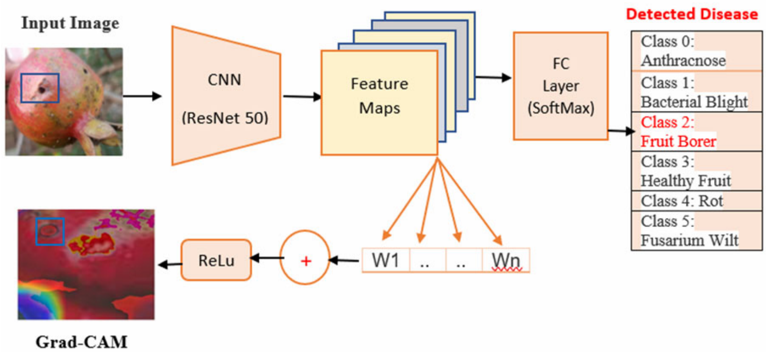
Step 2 Calculate alphas by averaging gradients.

$$\alpha_k^c = \frac{1}{2}\sum_i \sum_j \frac{\partial y^c}{\partial A^k} \tag{3}$$

Step 3 Compute grad-CAM heatmap (class discriminative localisation map).

$$L_{Grad\text{-}CAM}^c = \mathrm{Re}\,Lu\left(\sum_k \alpha_k^c A^k\right) \tag{4}$$

Figure 3 Block diagram of pomegranate disease visualisation using a gradient-based technique: grad-CAM (see online version for colours)



4 Results and discussion

The performance of the CNN architectures depends on various criteria, such as architecture, the number of trainable parameters, the selection of hyperparameters, training time, and freezing/unfreezing layers. This section shows our findings and the experimental results.

4.1 Performance evaluation of CNN based architectures

To evaluate the performance of the DL model, we have calculated the precision, recall, F-measure, Cohen's Kappa, and Accuracy using the confusion matrix (Liu et al., 2014). The confusion matrix is a multiway classification table (six classes). Accuracy is the ratio of correctly predicted samples to the whole number of samples. Precision is a fraction of correct positive detected samples. The recall is correctly classified samples. F-score is a harmonic mean of the model's precision and recall. CNN models are trained using a Python library called Keras with the tensor flow DL framework. The network was optimised using Adam optimiser with a learning rate of 0.001. A batch of 128 images with a size of 224 × 224 × 3 was supplied to the networks and the number of epochs is 20. Table 2 and Figure 4 show the comparative performance of five CNN-based architectures namely VGG16, VGG19, ResNet50, InceptionV3, and Xception. VGG architecture has gained better training and validation accuracy, but test accuracy is low which indicates the model is overfitted for the given dataset. Whereas InceptionV3, Xception, and Resnet50 models have achieved better training, validation, and testing accuracy with minimum error rate. Table 3 shows categorical loss values obtained using CNN models.

Table 2 Performance evaluation of CNN models using accuracy metrics

CNN-based architectures	*Training accuracy (%)*	*Validation accuracy (%)*	*Testing accuracy (%)*
VGG16	100	92.79	70.74
VGG19	99.67	93.69	64.18
ResNet50	*100*	*93.7*	*98.55*
InceptionV3	99.8	93.24	97.21
Xception	99.89	94.14	98.33

Figure 4 Comparison of the training, validation and testing accuracy obtained using CNN models (see online version for colours)

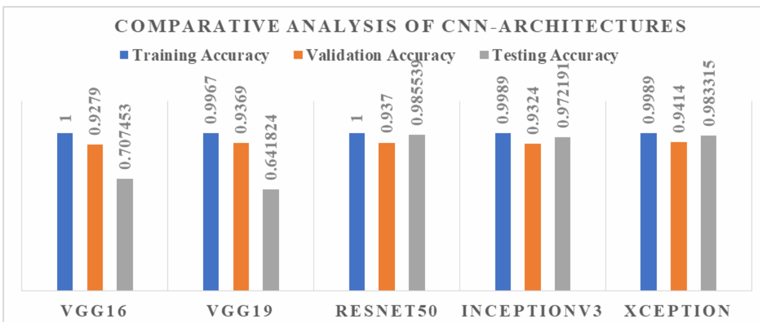


Table 3 Performance evaluation of CNN models using multiclass cross-entropy loss

CNN architecture	*Training loss*	*Validation loss*	*Testing loss*
VGG16	0.0335	0.2114	0.292547
VGG19	0.0828	0.2236	0.358176
ResNet50	*6.2781E-06*	*0.602*	*0.014461*
InceptionV3	0.0068	0.4257	0.027809
Xception	0.0062	0.2876	0.016685

The experimental result illustrates that Resnet50 outperformed therefore it is the perfect model for the collected dataset with 98.55% test accuracy and test loss is 0.014461. We have also computed precision, Recall, F-score for better understanding and analysing the result. Cohen's Kappa (K) metric is used to evaluate the performance of the classification models. The K value in the range 0.8–1.0 indicates an almost perfect classification model. The confusion matrix and classification report of Resnet50 is shown in Table 4. Radar (spider chart of ResNet50 is depicting that train and test accuracy is much better than validation accuracy. Precision, recall, and F-score values are comparable. Multiclass cross-entropy train and test loss values are closer to 0 suggest a good fit model. Whereas Kappa value indicates Resnet50 is the best classification model for the collected image dataset.

Figure 5 Graph depicting the comparison of the training, validation, and test loss obtained using CNN models (see online version for colours)

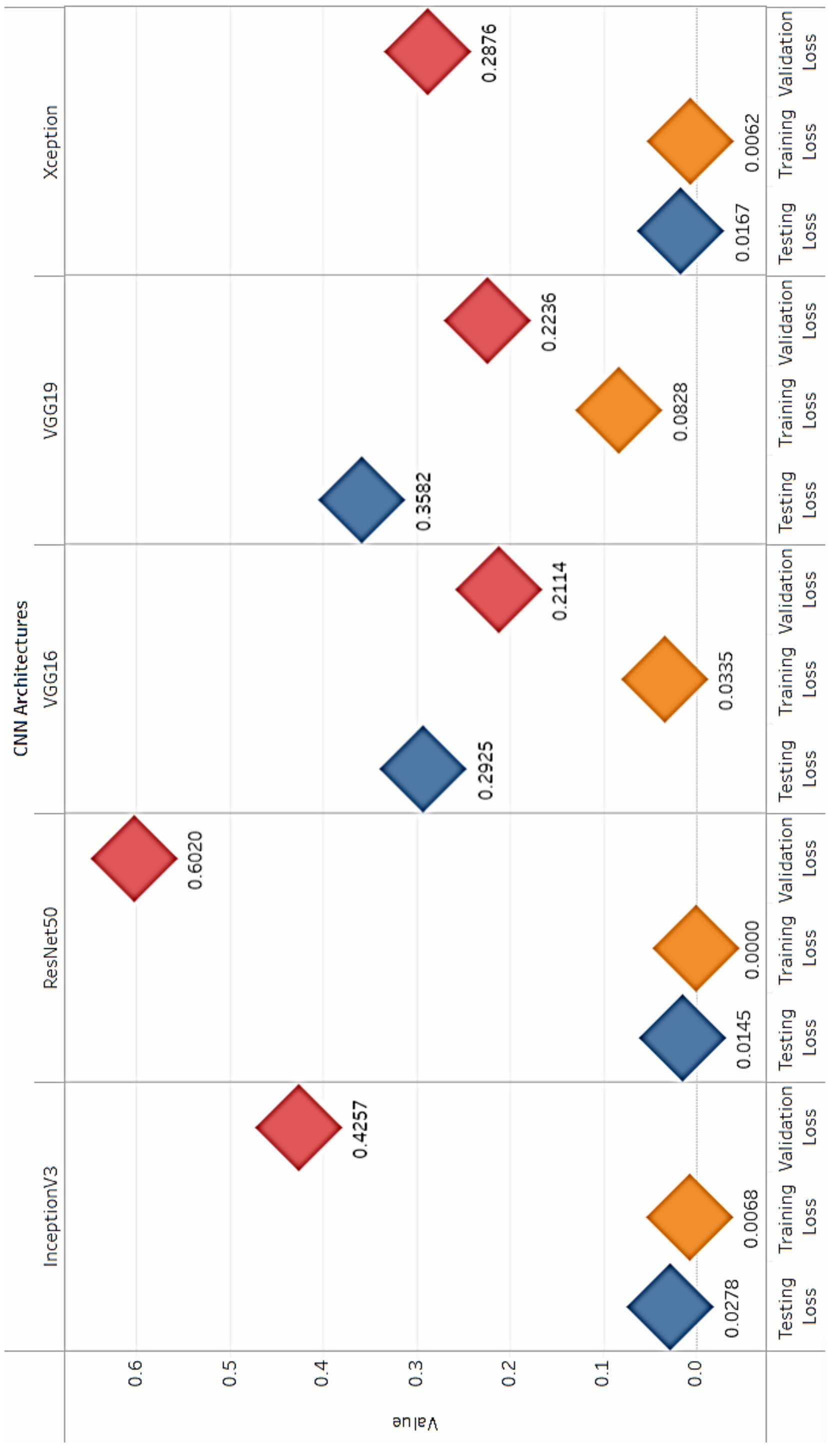


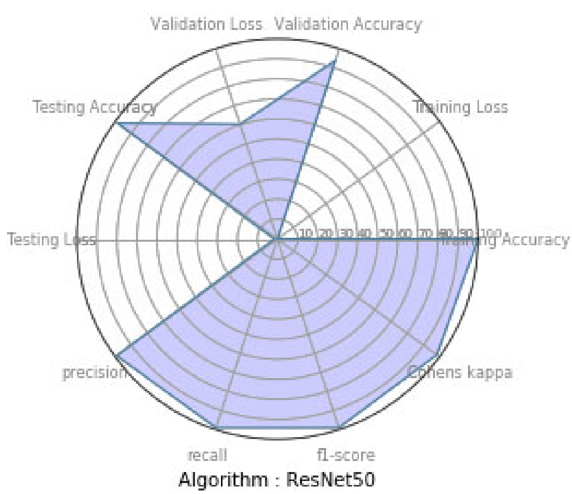
Table 4 Confusion matrix and classification report of Resnet50, (a) confusion matrix, (b) classification report of ResNet 50, (c) radar (spider) chart showing the performance of ResNet50 (see online version for colours)

0	1	2	3	4	5
[[146	3	0	0	0	0]
[4	146	0	0	0	0]
[0	1	149	0	0	0]
[2	1	0	147	0	0]
[0	2	0	0	148	0]
[0	0	0	0	0	150]]

(a)

	Precision	*Recall*	*f1-score*	*Support*
Class 0 (Anthracnose)	0.96	0.98	0.97	149
Class 1 (Bacterial Blight)	0.95	0.97	0.96	150
Class 2 (Blight Borer)	1.00	0.99	1.00	150
Class 3 (Healthy)	1.00	0.98	0.99	150
Class 4 (Rot)	1.00	0.99	0.99	150
Class 5 (Fusarium Wilt)	1.00	1.00	1.00	150
Accuracy			0.99	899
Macro avg. 0.99	0.99	0.99	899	
Weighted avg.	0.99	0.99	0.99	899
Cohens kappa: 0.982647				

(b)



(c)

Table 5 gives a summary of the DL model's performance. A high F-score value indicates the classifier is robust and correctly detected and classified the fruit diseases. The low F-score value of the VGG model shows that it is not precise and robust. Therefore, the VGG model is not suitable for our collected dataset. Whereas ResNet50, InceptionV3, and Xception models give high F-score values mean models are good classifiers and suitable for the collected dataset.

Table 5 Overall classification report of CNN based architectures

CNN-based architecture	Precision	Recall	F1-score	Cohen's Kappa
VGG16	0.85	0.71	0.73	0.648908
VGG19	0.79	0.64	0.66	0.570192
ResNet50	*0.99*	*0.99*	*0.99*	*0.982647*
InceptionV3	0.97	0.97	0.97	0.96663
Xception	0.98	0.98	0.98	0.979978

4.2 Hyperparameters tuning

The performance of CNN is dependent on various parameters such as learning rate, batch size, number of epochs, optimiser, etc. We considered a batch size of 128 so each time 128 sample images are in a single batch. Epoch means the number of times a full dataset is transmitted forward and backward through the CNN. All five models have been trained for 20 epochs. Adam optimiser is used to reduce the loss. Learning rate is a parameter that controls how often need to adjust the weights of the CNN model with respect to the gradient loss. Batch sizes indicate the number of training samples present in a single batch. InceptionV3 required less training time than other DL models. The list of DL model training hyperparameters is shown in Table 6.

Table 6 Hyperparameter tuning and training time for the DL models

CNN-based architecture	*Optimiser*	*Learning rate*	*Training images (before augmentation)*	*Testing images (before augmentation)*	*Epoch*	*Training time (in sec.)*
VGG16	Adam	0.001	899	222	20	6,794.88
VGG19	Adam	0.001	899	222	20	14,648.75
ResNet50	Adam	0.001	899	222	20	3,635.6
InceptionV3	Adam	0.001	899	222	20	2,315.45
Xception	Adam	0.001	899	222	20	3,574.13

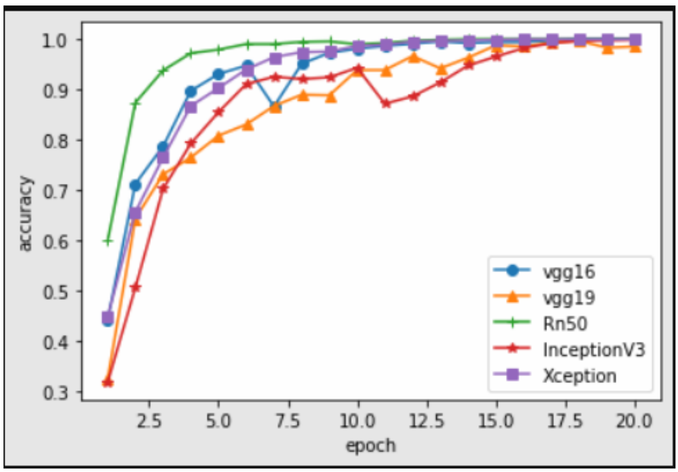
4.3 Accuracy and loss learning curves (LCs) of CNN models

LC indicates how the model improves over time and determines when to stop training. It also tests whether the model is overfitted or under fitted and according to this adjusts the hyperparameters. The gap between training and test accuracy is a clear indication of overfitting. A large gap indicates the model is overfitted. Experimentation proves, VGG16 and VGG19 are overfitted models for our dataset, and Resnet50, InceptionV3, Xception best-fitted models for the collected dataset. Figure 6 represents training and validation LCs of accuracy and loss function.

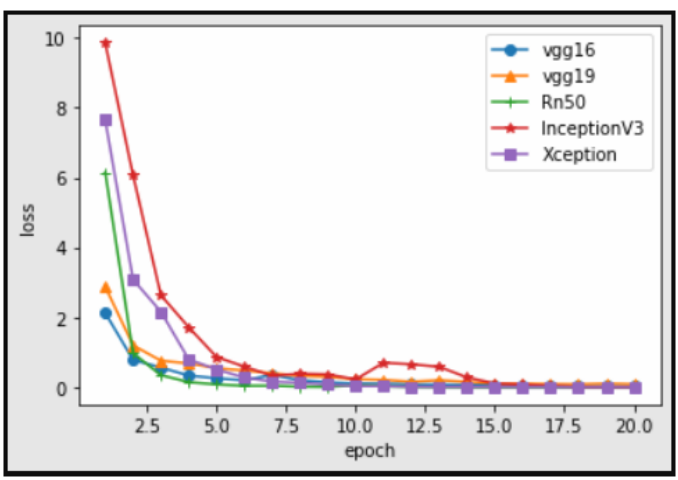
4.4 Comparison of proposed ResNet50 model with existing techniques

In Table 7, we have presented a comparative analysis of the proposed model with recent existing techniques. Comparative analysis shows that the proposed model performs better than existing techniques.

Figure 6 Graphs represent the LCs of VGG16, VGG19, ResNet50, InceptionV3, and Xception on LR: 0.001, epochs: 20, batch size: 128, (a) training accuracy curve, (b) training loss curve, (c) validation accuracy curve, (d) validation loss curve (see online version for colours)

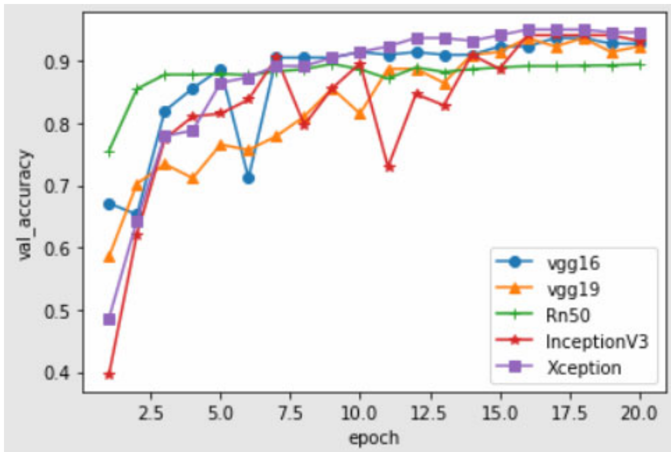


(a)

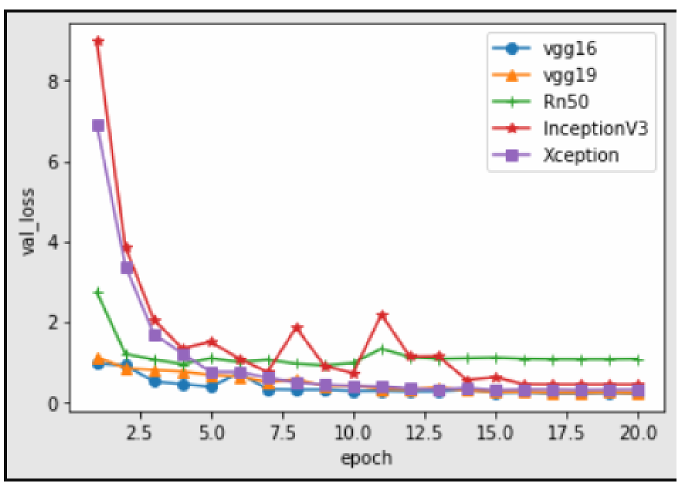


(b)

Figure 6 Graphs represent the LCs of VGG16, VGG19, ResNet50, InceptionV3, and Xception on LR: 0.001, epochs: 20, batch size: 128, (a) training accuracy curve, (b) training loss curve, (c) validation accuracy curve, (d) validation loss curve (continued) (see online version for colours)



(c)



(d)

4.5 Pomegranate disease visualisation using grad-CAM model and system deployment

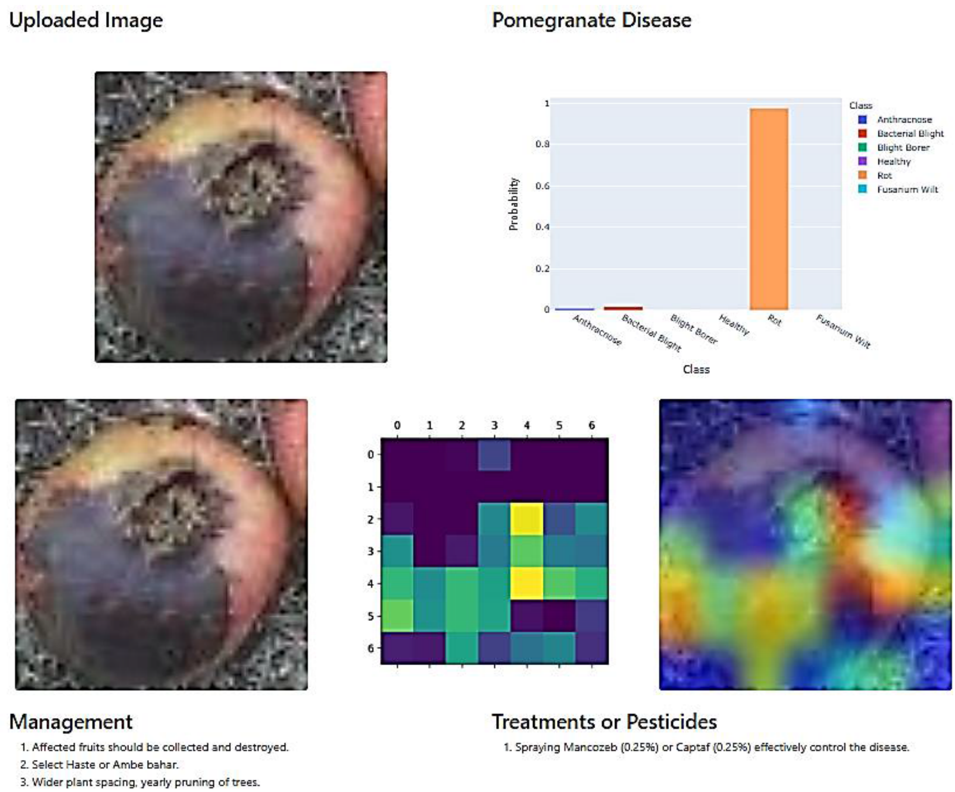
The proposed system for automatic pomegranate disease detection and visualisation is deployed using the flask web framework which can be accessed and operated on a computer system. The computing resources for model deployment are Dell laptop with Intel Core i7-7500U CPU, 2.70 GHz, 8 GB RAM. The working flow of the pomegranate disease detection and visualisation system is given below. Figure 7 shows sample bases correctly and incorrectly detected and classified diseases by system.

Step 1 Upload image of pomegranate fruit and disease detection using CNNs.

Step 2 Visualise diseases using the grad-CAM model.

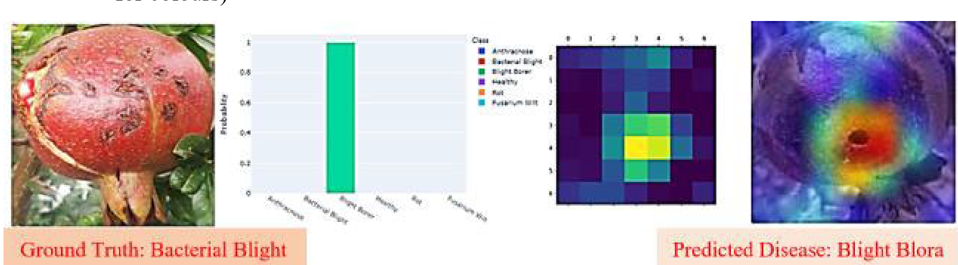
Step 3 Recommend cultural disease management and disease treatment/pesticides.

Figure 7 (a) Correctly detected disease and (b) Incorrectly detected (misclassified) disease by CNN model and disease visualisation using grad-CAM (see online version for colours)



(a)

Figure 7 (a) Correctly detected disease and (b) Incorrectly detected (misclassified) disease by CNN model and disease visualisation using grad-CAM (continued) (see online version for colours)



(b)

Table 7 Comparison of the proposed model with existing models

Ref.	*Name of the fruit/leaf*	*Size of dataset*	*Detected diseases*	*Classifiers*	*Accuracy (%)*
Arivazhagan and Ligi (2018)	Mango leaf	1,200	Anthracnose, Alternaria leaf spots, leaf gall, leaf Webber, leaf burn	Deep CNN (D-CNN) model	96.67
Liu et al. (2020a)	Grape leaf	4,023	Anthracnose, brown spot, mites, black rot, downy mildew, leaf blight	Dense inception convolutional neural network (DICNN)	97.22
Al Haque et al. (2019)	Guava leaf	10,000	Anthracnose, fruit rot, fruit canker	CNN	95.61
Militante and Gerardo (2019)	Sugarcane	14,725	Infected leaves	StridedNet, LeNet, VGGNet	95.40
Liu et al. (2020b)	Kiwifruit leaf	11,322	Brown spots, mosaic, anthracnose	Deep CNN	98.54
Xiao et al. (2020)	Strawberry fruit and leaf	1,306	Leaf blight, grey mould, powdery mildew	CNN	99.60
Proposed Model	Pomegranate fruits and leaf	1,221 (before data augmentation)	Bacterial blight (Telya), anthracnose, fruit spot, Fusarium Wilt, fruit borer	Proposed ResNet50	98.55

Experimental findings proved that ResNet50 is the best model for our collected dataset. Further, the grad-CAM model has integrated with ResNet50 to understand which features the model has considered for detecting diseases and to address the 'black box' problem. ResNet50 was able to give 98.55% disease detection accuracy and 1.45% misclassification was noted. Misclassification due to the presence of complex backgrounds and symptoms of diseases are not well defined. Further, this work can be extended for many more diseases of pomegranate and different varieties of fruits.

5 Conclusions

Automation in agriculture is incredibly important to assist farmers. In this paper, we proposed a DL approach for improving the detection and classification accuracy of the most prominent occurring diseases on pomegranate namely anthracnose, bacterial blight (Telya), blight borer, rot, Fusarium wilt. The proposed system provides a practical solution for accurately detecting and localisation of diseases on pomegranates. We have compared the performance of widely used transfer learning models VGG16, VGG19, ResNet 50, InceptionV3, and Xception using different statistical performance metrics. We have tried to investigate which is the most suitable model for the collected real-field dataset. Experimental results show that Inception V3, Xception, and Resnet50 are capable to detect the five different diseases with an accuracy of 97.21%, 98.33%, and 98.55% respectively. Performance analysis shows that Resnet50 gives the highest accuracy of all other models. Furthermore, we have integrated the grad-CAM model with ResNet50 to make the model more understandable and explainable. The grad-CAM model highlights the important regions on pomegranate that the ResNet50 model used to detect and classify the diseases. Additionally, recommended disease treatment and preventive measures to improve fruit quality and avoid losses.

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