Recent Advances in Deep Learning CNN Models for Plant Disease Detection

14

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Abstract

Machine learning and deep learning techniques are being used frequently in recent days for plant disease detection. The deep CNN models have been used in different fields and have gained immense result. With the growing population in the world, the importance of plant protection that produces food is also tremendously increasing. Various recent works have applied deep CNN models in the agricultural field and contributed a lot to specially w.r.t. various disease detection. It not only gives high prediction accuracies but also improves the other parameters, i.e., sensitivity, specificity, and F1 score of the model, which signifies better model for plant disease detection. Here, a survey of papers has been presented showing the use of different pre-trained CNN models in the field of plant disease detection. The summarized findings clearly indicate that CNN models are enriched with techniques that give promising performance with better precision and accuracy.

Keywords

Deep learning · AlexNet · ResNet · CNN model · Plant disease

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14.1 Introduction

Every farmer should go through smart farming in order to increase productivity, face the adverse environment, and more importantly ensure food security (Gebbers and Adamchuk 2010). Due to the hike in global population (Kitzes et al. 2008), food production should also increase in the same proportion to meet the balance. There are various reasons behind plant diseases; it can be caused by viruses, bacteria, fungi, pest, or other agents. The symptom of disease can be found in root, stem, leaf, and fruit (Riley et al. 2002). The crop yield decreases due to plant diseases resulting in food crisis. The aim must be not only to produce high-quality nutritious food but also to maintain the farming ecosystem (Carvalho 2006). For these, there is the requirement to understand the complex agricultural ecosystem. This can be achieved by continuously measuring various complex phenomena. Disease detection is getting more challenging with the introduction of various crop varieties. The method of disease detection is very tedious and costly, so there is the requirement of evolvement of new techniques (Sharma et al. 2020). With the introduction of computer vision, new techniques are getting evolved for the quick and accurate detection of plant diseases with visible symptoms. Difficulties of identifying different features of diseases have been reduced with the introduction of deep learning models. Various studies in recent years have proved the capabilities of deep learning models in the identification of diseases (Kurniawati et al. 2009; Mohanty et al. 2016; Wang et al. 2017). The main challenge with different models is the huge difference between the training and the testing accuracies. This in technical terms is known as the model overfitting or the model underfitting. Different methodologies like simplifying or enhancing the complexities of deep models have been followed to overcome the challenges. Also, the volume of data set significantly impacts the achievement of better accuracy. Convolutional neural network (CNN) has been used in deep models for feature extraction by identifying the patterns. But it needs huge data set known as training and testing set containing images (Lee et al. 2015).

This chapter presents the survey on various deep CNN models like AlexNet, VGGNet, and ResNet used for plant disease detection with their output and accuracy. It contains seven sections. It highlights the knowledge about various plant diseases and describes about different CNN models in detail. It also focuses on various data sets available, highlights the deep models used in various papers, and makes comparison in terms of various parameters. At last, a brief summarization of results, further research scope, and conclusion is made.

14.2 Various Plant Diseases

Plant diseases can be biotic or abiotic. Biotic diseases are caused by the living organisms, and abiotic diseases are due to bad environmental effect. The latter is less dangerous and can be avoided (Sankaran et al. 2010). But biotic diseases are much dangerous and cause severe damage to food production. There are three major players.

14.2.1 Caused by Fungus

More than 80% of plant diseases are caused by fungus. Wide varieties of vegetables are affected by fungus. Due to the damage of cell by fungal infection, the plant stress increases. The source of infection can be contaminated soil, water, animals, etc. They enter through natural stomatal opening or through wounds caused by harvesting, insects, animals, etc. Table 14.1 shows fungal diseases with the crops they affect and conducive factors that help them to grow.

14.2.2 Caused by Bacteria

There are approximately 200 types of bacteria that cause plant diseases. With conducive environment, bacteria get active and harm the plant because they multiply themselves in favorable conditions like high humidity, poor soil health, and irregular watering. Bacteria of different strains harm different types of vegetable crops. Some bacterial diseases with their conducive environment and the plants they affect with the symptom are given in Table 14.2.

Table 14.1 Various fungal diseases (Dean et al. 2012)

Fungal disease	Factors conducive to spread	Crops affected	Symptoms
White rust	Within 3–4 h (6–24 °C)	Brassicas	White blisters and swellings on the leaves
Downy mildews	High humidity and leaf wetness	Onion, peas, and spinach	Yellow spot on leaves turns brown later
Powdery mildews	Moderate temperature (20–25 °C)	Potato, tomato, cabbage, and peas	Small white patches on the underside of leaves
Clubroot	Warm weather and acidic soil	Brassicas	Plant becomes yellow with clubroots
Pythium species	Cold and wet soil	Brassicas and cucurbits	Seedlings are affected and will die
Sclerotinia rots	Moist and warm condition	Beans, beets, carrots, and potatoes	Yellowish growth surrounds the disease area
Botrytis rots	Cool and wet weather	Cucumber, brassicas, and tomato	Sunken spot appears on leaves
Anthracnose	Wet and cool atmosphere	Tomato, potato, and capsicum	Yellowish growth surrounds the disease area
Tuber disease		Potato and sweet potato	Infection in potato tuber
Black root rot	Cool and moisture soil	Beans and cucurbits	Blackening of root

Table 14.2 Various bacterial diseases (Mansfield et al. 2012)

Bacterial disease	Factors conducive to spread	Crops affected	Symptoms
Black rot	Wet and warm condition	Brassicas	V-shaped yellow leaves
Bacterial canker	High humidity	Capsicum and tomato	Yellow leaves and tissue discolor
Bacterial leaf	Wind and overirrigation	Capsicum, tomato, and cucurbits	Black outer leaves and stems get greasy spot
Bacterial blight	Windy and wet condition	Peas	Dark brown leaves
Bacterial brown spot	Cool and windy condition	Beans	Reddish-brown leaves

Table 14.3 Various viral diseases (Scholthof et al. 2011)

Viral disease	Type of virus	Crop affected	Symptoms
Tobacco mosaic virus	Single-stranded RNA virus	*N. tabacum*	Mosaic patches on tobacco
Tomato spotted wilt virus	RNA virus	Tomato plant	Necrotic or chlorotic rings on leaves
Tomate yellow leaf curl virus	Single-stranded DNA	Tomato plant	Yellow leaf tomato
Cucumber mosaic virus	RNA virus	Cucumber plant	Light or dark green mosaic pattern
Potato virus	Single-stranded RNA	Potato plant	Brown and black line pattern
Cauliflower mosaic virus	DNA virus	Cauliflower	Mosaic marbling effect on leaf

14.2.3 Caused by Virus

Plant diseases caused by viruses are the rarest. If any plant gets affected, then the solution is to remove all infected ones, as it cannot be stopped by chemical treatment. Table 14.3 gives some of the plant diseases caused by viruses.

14.3 Different Deep CNN Models

Deep CNN models are the group of neural network models which have taken part in different computer vision competitions and have shown outstanding performances. They are giving exciting results in some of the applications like segmentation, classification, object detection, and natural language processing. For the automatic feature extraction in a deep model, we need huge data set because deep model is a complex model with huge parameters to set, so if the data set size is small, then there might be the chance of overfitting. Layer by layer, the feature extraction and weight optimization are given in Eq. (14.1):

$$X^1 - > W^1 - > X^2 - > \ldots\ldots - > X^{l-} - > W^{l-1} - > X^l - > W^l - > \tag{14.1}$$

X^1 is the input layer and W^1 is the weight vector associated with the neurons. The output layer is X^l, which gives the resultant feature matric. With each training, the error generated leads to the upgradation of the weight by backpropagating. A loss function known as least square error is given below in Eq. (14.2):

$$\text{Loss} = \frac{1}{2}\left\|t - x^l\right\|^2 \tag{14.2}$$

The loss is needed in the neural network for the learning or the upgradation of the parameter. Weight upgradation takes place by the following different ways like stochastic gradient descent (SGD). SGD is a way of optimization given in Eq. (14.3):

$$w^i < -w^i - \eta \frac{\partial \text{loss}}{\partial w^i} \tag{14.3}$$

η is the learning rate.

Convolution means the inter-twinning of two functions as given in Eq. (14.4), where $f(x, y)$ and $h(m, n)$ represent the image and kernel, respectively:

$$(x, y) = \sum_{m=\frac{-M}{2}}^{\frac{M}{2}} \sum_{n=\frac{-N}{2}}^{\frac{N}{2}} h(m, n) f(x - m, y - n) \tag{14.4}$$

Then activation function is acted upon to add nonlinearity. Here, the deep CNN models that we will focus on will be the model that participated in ImageNet challenges like AlexNet, VGGNet, and ResNet.

14.3.1 AlexNet

AlexNet is a deep network model proposed by the group of members named A. Krizhevsky, G. Hinton, and I. Sutskever. It has bagged the first position of the ImageNet challenge in 2012. ImageNet is a database consisting of around 1.1 million images with 1000 classes. AlexNet has set up a strong base for the future of the CNN models. The top 5% error rate of AlexNet using the ImageNet database for classification was around 25% (Krizhevsky et al. 2012). Figure 14.1 gives the architecture of AlexNet, which contains five convolutional and three fully connected layers. The use of ReLU activation function here adds nonlinearity. Around 60 million parameters have been updated during the training through ImageNet data set. Convolution in deep network is the inter-twinning of image and the filter to generate

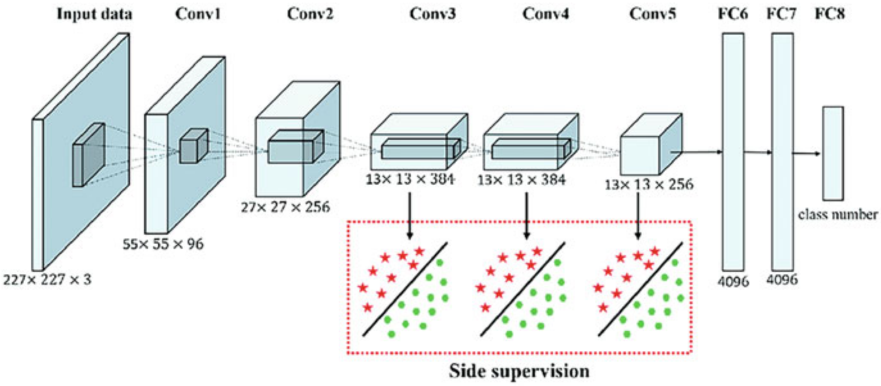

Fig. 14.1 AlexNet architecture (Krizhevsky et al. 2012)

Table 14.4 Detailed components of AlexNet architecture (Krizhevsky et al. 2012)

Layer	Input	Kernel	Output
Conv2D/4	227 × 227 × 3	11 × 11 × 64/4	55×55 × 64
Pool/2	55 × 55 × 64	3 × 3/2	27 × 27 × 64
Conv2D	27 × 27 × 64	5 × 5 × 192	27 × 27 × 192
Pool/2	27 × 27 × 192	3 × 3/2	13 × 13 × 192
Conv2D	13 × 13 × 192	3 × 3 × 384	13 × 13 × 384
Conv2D	13 × 13 × 384	3 × 3 × 384	13 × 13 × 384
Conv2D	13 × 13 × 384	3 × 3 × 256	13 × 13 × 256
Pool/2	13 × 13 × 256	3 × 3/2	6 × 6 × 256
FC1	6 × 6 × 256	5 × 5 × 4096	1 × 1 × 4096
FC2	1 × 1 × 4096	1 × 1 × 4096	1 × 1 × 4096
FC3	1 × 1 × 4096	1 × 1 × 1000	1 × 1 × 1000

a feature map. After one or many convolutions, the pooling layer has been used to extract the max or average feature using a window (Table 14.4).

Here, FC represents fully connected layer, pooling is done max value, and Conv2D represents 2D convolution. The drawback associated with AlexNet was the depth, which may lead to overfitting. This drawback has been challenged by Krizhevsky et al. (2012), by adapting the concept of Hughes et al. (2015), where they introduced the idea of neuron dropout. Neuron dropout is a technique for regularization. Also, the introduction of ReLU solves the problem of vanishing gradient. Here, the large-size filters like 11 × 11 and 5 × 5 have been used to restrict the length of deep model.

14.3.2 VGGNet

A research group of the University of Oxford has developed the deep network named Visual Geometry Group (VGG). It is also known as VGG-16 because it consists of 16 convolution layers. It has bagged the first runner-up position at ImageNet challenge 2014. It has been trained with ImageNet data set with 4 GPUs for 3 weeks. It is the most commonly used pre-training for classification. In VGGNet, around 138 million parameters have been trained. The architecture is explained below (Figs. 14.2 and 14.3).

Here, it has been considered that the reduced filter size can enhance the network performance. Here, instead of 11 $\times$ 11 and 5 $\times$ 5, 3 $\times$ 3 has been used. Also, it reduces the computational complexity. In VGG, padding has been done for maintaining spatial resolution. But here it is required to update approximately 138 million parameters, so it is computationally expensive.

14.4 ResNet

ResNet model was developed by Kaiming et al. (2015). It was the winner of ImageNet challenge 2015. It has introduced the skip connection concept. It has solved the problem of vanishing gradient. A total of 152 layers are there in ResNet. It reduced the top 5% error to 3.57%. The performance has enhanced much in object detection because of the residual network concept (Fig. 14.4).

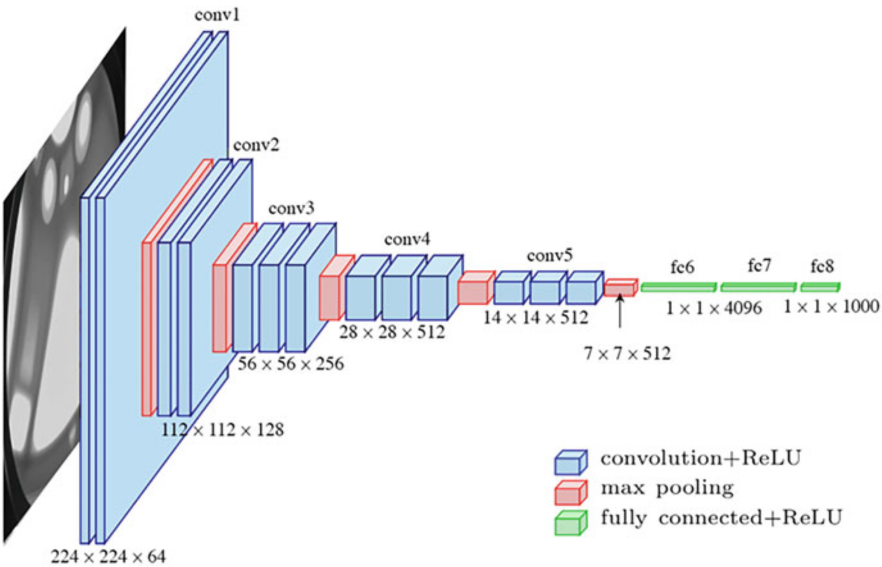

Fig. 14.2 VGGNet architecture (Simonyan and Zisserman 2014)

Layer (type)	Output shape	Param #
input_1 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_poo1 (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
flatten (Flatten)	(None, 25088)	0
fc1 (Dense)	(None, 4096)	102764544
fc2 (Dense)	(None, 4096)	16781312
predictions (Dense)	(None, 1000)	4097000

Fig. 14.3 VGGNet layer details

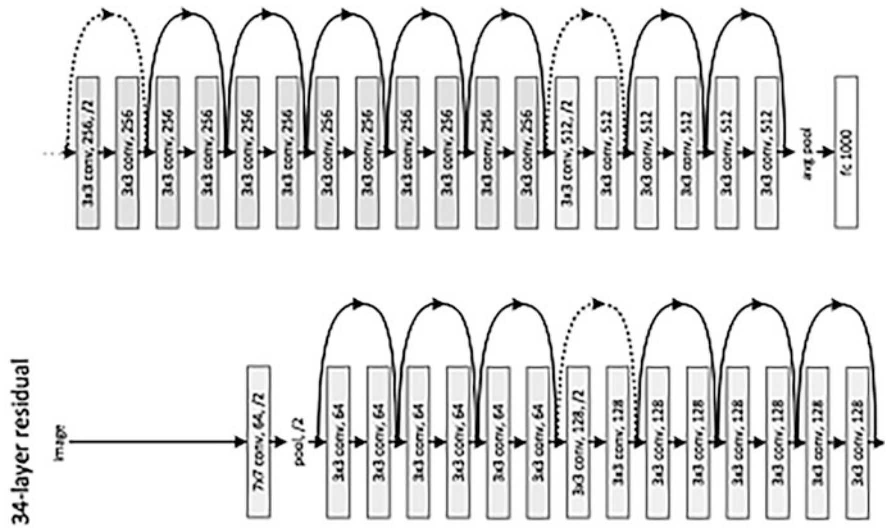

Fig. 14.4 ResNet50 architecture (Kaiming et al. 2015)

It has introduced the idea of residual network in deep CNN. The depth of ResNet is around 10–20 times than VGG and AlexNet. ResNet shows good performance over image localization and recognition. Different ResNet models are ResNet50 or 101 or 152 depending on their depth.

14.5 Various Materials Available Related to Plant Diseases

For different plant diseases, different image data are available. To train and test the huge deep CNN model, a large volume of data is needed. Also, different pre-trained models like AlexNet, VGGNet, and ResNet can be used via transfer learning to utilize the optimized weight. Hughes et al. (2015) have described very few number of data sets. It contains 58 classes with corresponding diseases and also some healthy plants (Table 14.5).

Sibiya and Sumbwanyambe (2019), presented in Table 14.3, have captured the possible maize plant diseases using their smart phone. Here, they have considered images for the diseases like leaf blight, leaf spot, leaf rust, and normal plant with 100 images each. They have used these data for the classification of different diseases and achieved an average of 92.85% accuracy. Zhang et al. (2018) used data set for different tomato disease detection using some predefined neural network like ResNet, GoogleNet, and AlexNet. Here, they have considered the diseases like early blight, Corynespora leaf spot, late blight, leaf mold, Septoria leaf spot, spider mite, virus diseases, and yellow leaf. The data set is divided into 80:20 as training and testing data. Then, the training data again undergoes augmentation process to generate large data set by doing horizontal, vertical, and diagonal flipping and

Table 14.5 Data set details

Author	Data set	Plant	Classes of disease	No. of images/ class
Sibiya and Sumbwanyambe (2019)	PlantVillage	Maize	Leaf blight, leaf spot, rust, normal images	100 each
Zhang et al. (2018)	PlantVillage	Tomato	Early blight	405
			Corynespora	547
			Late blight	726
			Leaf mold	480
			Septoria leaf	734
			Spider mite	720
			Virus disease	481
			Yellow leaf	814
			Normal leaf	643
Amara et al. (2017)	PlantVillage	Banana	Black sigatoka	240
			Black speckle	1817
			Normal	1643
Ferentinos (2018)	PlantVillage in-field image	Apple	Apple scab	630
			Apple rust	276
			Black rot	712
		Cabbage	Black rot	64
		Cassava	Brown leaf spot	43
		Celery	Early blight	1204
		Cherry	Powdery mildew	1052
		Corn	Cercospora leaf spot	1457
			Common rust	1614
		Cucumber	Downy mildew	1318
		Gourd	Downy mildew	114
		Grape	Black rot	1180
			Black measles	1384
			Leaf blight	1074
		Orange	Huanglongbing	5507
		Peach	Bacterial spot	2297
		Pepper	Bacterial spot	997
		Potato	Late blight	1000
			Early blight	3167
		Pumpkin	Cucumber mosaic	2387
		Soybean	Downey mildew	851
			Frogeye leaf spot	2023
		Strawberry	Leaf scorch	3396
Türkoğlu and Hanbay (2019)	Real-field data set	Walnut	Walnut leaf mite	69

(continued)

Table 14.5 (continued)

Author	Data set	Plant	Classes of disease	No. of images/ class
		Apricot	Apricot monilia laxa	85
		Rice	Xanthomonas	143
			Arboricola	
Lu et al. (2017)	Real-field data	Rice	Rice brown spot	500

contrast changing. The best accuracy of 96.8% is achieved with ResNet50. Amara et al. (2017) used the data set for different diseases in banana like black sigatoka and black speckle. The images are of different sizes, poses, orientation, and illuminations. Ferentinos (2018) has used the open database with 87,848 images, including 58 classes. Among those, 70,300 and 17,548 are used as training and testing images, respectively. It got an accuracy of 99.53% with VGGNet. Türkoğlu and Hanbay (2019)) have obtained images for different plant diseases as described in Table 14.3 using Nikon camera. Each color (RGB) image is with a resolution of 4000×6000. It is observed that AlexNet with SVM classifier achieved an accuracy of 95.5% over the combination of classifiers like Extreme Learning Machine (ELM) and K-nearest neighbor (KNN) with deep models like AlexNet, VGG16, and VGG19. Lu et al. (2017) have used the data set for rice diseases of ten kinds and achieved an accuracy of 95.48% with a deep model with stochastic pooling in comparison to mean and max pooling.

14.6 Related Work

14.6.1 Application

Jadhav et al. (2020) have used AlexNet for the classification of disease plant and normal soybean plant. Three types of soybean plant diseases have been classified here named as bacterial blight, brown spot, and frogeye spot. The final fully connected layer of AlexNet has been changed with a layer of four neurons. Using 649 images as training and 80 images as testing, the model has achieved 98.75% accuracy in 20 epochs. Zhang et al. (2018) have used fine-tunned ResNet50 by unfreezing the last three layers to classify the tomato diseases. The eight categories of tomato diseases like early blight, yellow leaf, virus disease, spotted spider, leaf mold, late blight, leaf spot, Corynespora, and one healthy leaf have been classified with 97.19% accuracy. Here, ResNet50 has been fine-tuned with last three layers and trained and tested with 4440 and 1110 images, respectively. Brahimi et al. (2017) have used a large data set containing around 14,828 images. The visualization method has been used here to analyze the model. Using AlexNet, they have achieved 99% accuracy than the classification models like SVM or Random Forest. Liu et al. (2018) have used AlexNet for the four-class classification of apple diseases where the deep model is used not only for the retrieval of feature but also to learn layered features. The deep model achieved 91.19% accuracy. Durmuş et al. (2017) have used the AlexNet and SqueezeNet for the classification of diseases in tomato plants. PlantVillage data set has been used here with 80:20 as training and testing data. By keeping the batch size of 20 and using stochastic gradient descent optimizer, AlexNet has achieved 97.22% accuracy. Hu et al. (2020) proposed a deep network with IoT technology for multiple crop disease recognition. Here, they found that ResNet gives good result in comparison with others. The proposed system is the combination of video cameras and deep networks. The system achieved an average accuracy of 93.96% over VGGNet and AlexNet. Saleem et al. (2020) have made a comparative analysis of classification of 26 classes using various pre-trained deep networks available, but with ResNet, they achieved 95.66% accuracy. Srivastava et al. (2020) came up with a technique for sugarcane disease detection. Here, they have used different pre-trained models like VGG-16, VGG-19, and Inception V3 model in combination with different classifiers like SVM, KNN, and naive Bayes and found that VGG-16 with SVM classifier gives AUC as 90.2%. Models named VGGNet and ResNet have been used by Aversano et al. (2020) with around 1600 images to classify them into 10 classes. VGGNet gives an accuracy of 97% with a good precision. Qiu et al. (2021) have used the VGGNet as a feature extractor and linear discriminant technique for classification using 10 classes, where 9 are leaf with diseases and 1 is healthy leaf. By using augmentation, 5000 images are generated out of 1000 images where each class gets balanced with 500 images each. After tenfold cross-validation, the model got an accuracy of 97.08% with average precision and recall of 94.83% and 83.75%, respectively. Jiang et al. (2020) have done the identification of plant diseases by using ResNet. Here, they have frozen the layers to use the weights of ResNet optimized by training with ImageNet data set.

14.6.2 Comparison Accuracies with Training Samples

Figure 14.5 shows accuracies of different deep models like AlexNet, VGGNet, and ResNet w.r.t. a number of training samples as per Table 14.6. It is seen that AlexNet with less number of training sample is showing better performance over others. But as we know, with less number of training samples, there is the possibility of overfitting. Then, also with more number of training samples, AlexNet shows good performance in comparison with others.

Figure 14.6 shows the amount of training samples used for different deep models like AlexNet, VGGNet, and ResNet to show more or less same accuracy as per Table 14.6. So, for different cases, different pre-trained deep CNN models are chosen. It can be done by transfer learning or fine-tuning. In transfer learning, they can be directly used as feature extractor, and in fine-tuning, we can go for changing some of the layers or some hyperparameters.

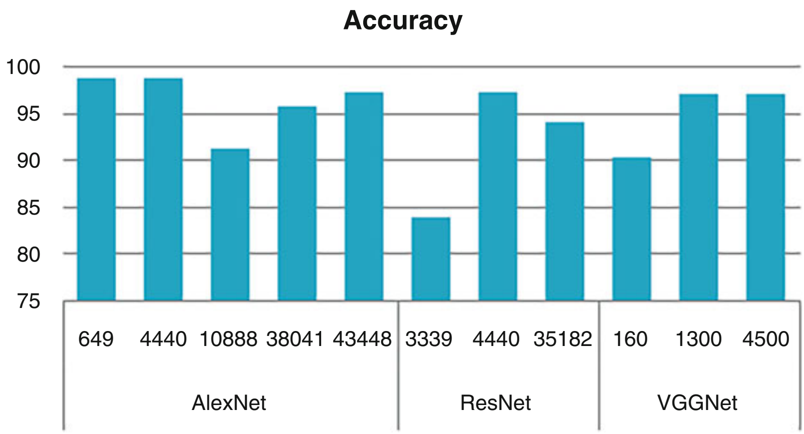

Fig. 14.5 Accuracies of different deep models w.r.t. training samples

14.7 Conclusion

In different types of computer vision-related analyses, CNN has always shown its supremacy. Various experiments have been done to improve the performance of CNN. The main parameters to build a better CNN model involve activation function, loss function, regularization, optimization, learning rate, etc. Here, we came across different CNN models like AlexNet, VGGNet, and ResNet with their architectural design, parameters, accuracies, etc. Various papers that include these models have been discussed with their advantages and challenges.

In recent years, the structural modifications have been experimented to study the efficiency of deep models. Different pre-trained CNN models have also proved their capabilities. Their architectures come with different modules and make the entire phase clear to understand. We have shown the architecture of three pre-trained models named AlexNet, VGGNet, and ResNet with the data they get trained and accuracies. Our takeaway from here is that type of convolution, pooling, skip connection, connectivity of layers, and kernel size have improved the performances of different deep CNN models. We believe that it will help the researchers in future to carry out their research in the field of plant disease detection for sustainable agriculture.

Table 14.6 Classification of crop diseases with deep network

Author	Data	No. of classes	Models used	Trainable parameter	Train	Test	Accuracy (%)	Epoch	Precision (%)	Recall	Leaf image
Jadhav et al. (2020)	Soybean	4	AlexNet	0	649	80	98.75	20	98.75	100	
Brahimi et al. (2017)	Tomato	9	AlexNet	0	4440	1110	98.66	4992	98	97.85	
Liu et al. (2018)	Apple	4	AlexNet (SGD)	56,884,612	10,888	2801	91.19	20	97.81	99.67	
Durmuş et al. (2017)	Tomato	10	AlexNet (SGD)	0	43,448	10,861	97.22	–	–	–	
Saleem et al. (2020)	P.Village	26	AlexNet	60 M	38,041	5430	95.66	54	95.63	95.70	
Srivastava et al. (2020)	Sugarcane	6	VGGNet	0	160	80	90.2	–	–	–	
Aversano et al. (2020)	Tomato	10	VGGNet	0	1300	300	97	30	–	–	
Qiu et al. (2021)	Rice	10	VGGNet	0	4500	500	97.08	–	94.83	96.88	
Hu et al. (2020)	P.Village	10	ResNet	0	35,182	4540	93.96	–	82.79	82.33	

Jiang et al. (2020)	P.Village	4	ResNet	0	3339	835	83.75	4000	–	–	
Zhang et al. (2018)	Tomato	9	ResNet50	4092	4440	1110	97.19	4992	–	–	

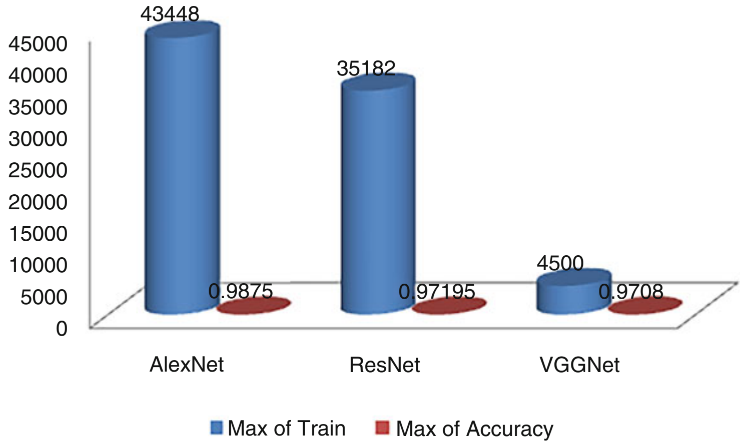

Fig. 14.6 Models showing max accuracy with max training samples

References

Amara J, Bouaziz B, Algergawy A (2017) A deep learning-based approach for banana leaf diseases classification. Datenbanksysteme für Business, Technologie und Web (BTW 2017)-Workshopband

Aversano L, Bernardi ML, Cimitile M et al (2020) Tomato diseases classification based on VGG and transfer learning. In: 2020 IEEE international workshop on metrology for agriculture and forestry (MetroAgriFor). IEEE, pp. 129–133

Brahimi M, Boukhalfa K, Moussaoui A (2017) Deep learning for tomato diseases: classification and symptoms visualization. Appl Artif Intel 31(4):299–315

Carvalho FP (2006) Agriculture, pesticides, food security and food safety. Environ Sci Pol 9(7–8): 685–692

Dean R, Van Kan JA, Pretorius ZA et al (2012) The top 10 fungal pathogens in molecular plant pathology. Mol Plant Pathol 13(4):414–430

Durmuş H, Güneş EO, Kırcı M (2017) Disease detection on the leaves of the tomato plants by using deep learning. In: 2017 6th international conference on agro-geoinformatics. IEEE, pp. 1–5

Ferentinos KP (2018) Deep learning models for plant disease detection and diagnosis. Comput Electron Agric 145:311–318

Gebbers R, Adamchuk VI (2010) Precision agriculture and food security. Science 327(5967): 828–831

Hu WJ, Fan J, Du YX et al (2020) MDFC–ResNet: an agricultural IoT system to accurately recognize crop diseases. IEEE Access 8:115287–115298

Hughes D, Salathé M et al (2015) An open access repository of images on plant health to enable the development of mobile disease diagnostics. arXiv preprint arXiv:151108060

Jadhav SB, Udupi VR, Patil SB (2020) Identification of plant diseases using convolutional neural networks. Int J Inform Technol 13(6):2461–2470

Jiang H, Xue ZP, Guo Y (2020) Research on plant leaf disease identification based on transfer learning algorithm. J Phys Conf Ser 1576:012023. IOP Publishing

Kaiming H, Xiangyu Z, Rea S (2015) Deep residual learning for image recognition. ResNet model. arXiv preprint arXiv:151203385

Kitzes J, Wackernagel M, Loh J et al (2008) Shrink and share: humanity's present and future ecological footprint. Philos Trans R Soc B 363(1491):467–475

Krizhevsky A, Sutskever I, Hinton GE (2012) Advances in neural information processing systems

Kurniawati NN, Abdullah SNHS, Abdullah S et al (2009) Investigation on image processing techniques for diagnosing paddy diseases. In: 2009 international conference of soft computing and pattern recognition. IEEE, pp. 272–277

Lee SH, Chan CS, Wilkin P, Remagnino P (2015) Deep-plant: plant identification with convolutional neural networks. In: 2015 IEEE international conference on image processing (ICIP). IEEE, pp. 452–456

Liu B, Zhang Y, He D et al (2018) Identification of apple leaf diseases based on deep convolutional neural networks. Symmetry 10(1):11

Lu Y, Yi S, Zeng N et al (2017) Identification of rice diseases using deep convolutional neural networks. Neurocomputing 267:378–384

Mansfield J, Genin S, Magori S et al (2012) Top 10 plant pathogenic bacteria in molecular plant pathology. Mol Plant Pathol 13(6):614–629

Mohanty SP, Hughes DP, Salathé M (2016) Using deep learning for image-based plant disease detection. Front Plant Sci 7:1419

Qiu J, Lu X, Wang X et al (2021) Research on rice disease identification model based on migration learning in VGG network. In: IOP conference series: earth and environmental science, vol 680. IOP Publishing, p. 012087

Riley MB, Williamson MR, Maloy O (2002) Plant disease diagnosis. Plant Health Instr:10

Saleem MH, Potgieter J, Arif KM (2020) Plant disease classification: a comparative evaluation of convolutional neural networks and deep learning optimizers. Plan Theory 9(10):1319

Sankaran S, Mishra A, Ehsani R et al (2010) A review of advanced techniques for detecting plant diseases. Comput Electron Agric 72(1):1–13

Scholthof KBG, Adkins S, Czosnek H et al (2011) Top 10 plant viruses in molecular plant pathology. Mol Plant Pathol 12(9):938–954

Sharma P, Berwal YPS, Ghai W (2020) Performance analysis of deep learning CNN models for disease detection in plants using image segmentation. Inf Process Agric 7(4):566–574

Sibiya M, Sumbwanyambe M (2019) A computational procedure for the recognition and classification of maize leaf diseases out of healthy leaves using convolutional neural networks. Agri Eng 1(1):119–131

Simonyan K, Zisserman A (2014) Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:14091556

Srivastava S, Kumar P, Mohd N et al (2020) A novel deep learning framework approach for sugarcane disease detection. SN Comput Sci 1(2):1–7

Türkoğlu M, Hanbay D (2019) Plant disease and pest detection using deep learning-based features. Turk J Elec Eng Comput Sci 27(3):1636–1651

Wang G, Sun Y, Wang J (2017) Automatic image-based plant disease severity estimation using deep learning. Comput Intel Neurosci 2017:1–8

Zhang K, Wu Q, Liu A et al (2018) Can deep learning identify tomato leaf disease? Adv Multimed 2018:1–10