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Plant Disease Detection using Deep Learning

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Abstract: Farming is critical to the nation's economy and progress. Precision Farming (PA), on the other hand, is still in its development when it comes to technology-driven growth. Various plant diseases have caused pain to untold millions of people around the world over the years, with an estimated annual yield loss of 14% globally. Computerized disease segmentation and diagnosis from based on leaf photos has the potential to be more effective than the current method. Image capture, pre-processing, and segmentation are followed by augmentation, feature extraction, and classification using models for automatic plant disease diagnosis. This project employs VGG-16, ResNet-50, AlexNet, DenseNet-169, and InceptionV3 Deep Learning models to identify plant illnesses from photos in the Plant Village Dataset and reliably classify them into two classes. The results of the experiment revealed that the ResNet-50 has achieved highest accuracy of 97.80 % as compare to other applied deep learning models for disease classification.
Keywords: VGG16, ResNet50, Inception V3, CNN, GoogleNet, AlexNet

I. INTRODUCTION

In today's world, crop production is just no limited to food supplies. Plants have developed into a significant source of nutrition and play a major role in resolving a variety of environmental issues, including global climate change. There are some plant pests that have the ability to have disastrous conservative, economic, and environmental implications. Moreover, detecting symptoms of diseases in the crop is crucial for harvesting plan. Ordinary crop studies are often challenging to do when big areas are being developed. Agriculture has a significant role in India's economy. As a result, plant disease identification has become increasingly crucial in the agricultural industry. Using an automated disease detection system to detect plant ailments as soon as they occur is beneficial [2]. Micro aspergillus for example, is amongst the most devastating diseases that affects cherry trees in the United States. Due to the restricted development, the damaged tree will die in a few years [3]. A technology that can recognize the disease in its earliest stages could be beneficial in this scenario. Irrigation, on the other hand, is critical to the production of high yields. Irrigation can help you achieve better yields [4].

Currently, the only viable way for diagnosing and recognizing illness in plants is through human observation. In order to execute proper inspection, a team of agricultural scientists must conduct observation by human eyes at regular intervals. It can be very costly and time-consuming to manage large farms. In certain nations, the scarcity of agricultural experts might be a problem. In these cases, equipment that can detect illness automatically can be useful. It is a simpler and less expensive method of identifying diseases by comparing characteristics of healthy and sick plant leaves. Artificial intelligence (AI) will be integrated to agriculture using this technique, and it will be utilised for farming machine guiding and computerized fertilization. In both the medical and agricultural fields, image processing and machine learning are efficient methods for detecting disease. [5] Using an automatic disease detection and watering system, on the other hand, will surely help to address the aforementioned problems. Variable colour strains, curled leaves, and dangerous illness are all typical problems seen in the same kind of plants. The location and kind of infection are determined via image processing.

Image segmentation is the process of separating or breaking a digital impression into several discrete segments. There are now two picture segmentation algorithms available: Basic image segmentation and advanced colour image segmentation are two types of image segmentation. Typically, such elements are linked to items that humans can easily recognize and distinguish as distinct entities. Because computers are unable to correctly distinguish objects, a range of ways for dividing images into distinct components has been developed. [6] Many ways for segmenting photographs have already been devised due to machines' inability to effectively identify things. The image segmentation approach makes use of a number of attributes that are identified while the image is processed. These elements include colour data, picture boundaries, and a region of photographs. With the help of a genetic algorithm, colour images are segmented. The CNN algorithm was used to segment the images in our suggested model.

A range of factors influence decision-making in judicial procedures. Furthermore, depending on the type of case, these features can change dramatically. [7] There is no way to isolate and include all of the components in any forecasting system. As a result, when making forecasts, the most important attributes are taken into account.

Self-contained soft computing is a term used to describe a type of computing that is not connected to CNN is employed in the suggested methodology for detecting and classifying fungal diseases on plant leaves. The approach assigns optimal weight to a traditional neural network using the xavier assignment function and the relu activation function (CNN). The author proposes a feed forward neural network with five standard layers, a pool layer, and two fully connected layers after that. The rectified linear activation function (relu) produces output if the input is positive; it produces zero if the input is negative.

II. LITERATURE REVIEW

Several infections cause distortion in the leaves rather than causing the plant to change colour. Further down, the identification of disease based on leaf shape is detailed.

Mamta Gahlot et al. [8] With minimum resources, uses five different CNN models to classify tomato leaf diseases into ten different classifications. The models are AlexNet, VGG16, GoogleNet, ResNet-101, and DenseNet-121 and Of the five models, this is the tiniest, DenseNet-121, has the greatest precision (99.694%) as well as the finest size (113.28MB). Plant Villages pictures were utilised in the recommended system, which totaled 14529. Data Generator was used to reduce memory use because loading 14529 photographs with 256 256 sizes was difficult.

Xin Li et al.[9] A model was created using a dataset of apple grey-spot disease, black star disease, and cedar rust disease, as well as healthy leaves, to examine the identification and classification of apple leaf disorders. Picture segmentation was done with SVM classifiers, and image classification was done with ResNet and VGG convolutional neural network models. When comparing the two models, the results indicate that ResNet-18 has a greater prediction performance of 98.5% because it has less layers of ResNet.

Muhammad Sufyan Arshad et al. [10] ResNet50 outperforms VGG16 and MCNN, which were both created from the ground up and trained from scratch, with ResNet50 achieving the highest performance of 98.7% for plant disease detection. ResNet50 and Transfer Learning were used to identify illnesses in potatoes, tomatoes, and maize. From the Plant Village dataset, the software can identify 16 different plant diseases. The project's scope can be expanded by using the training model on a larger number of classes.

.Singh A. et al [11] created a new disease detection system that distinguishes between damaged and healthy wheat plants using a feature extraction strategy The system was trained using a deep convolutional neural network (DCNN) and a transfer learning approach. The CIMMTY dataset is used to evaluate multiple CNN models, including VGG16, VGG19, AlexNet, ResNet-34, ResNet-101, ResNet-50, and ResNet-18, with the RESNET-101 model having the greatest accuracy of 98%.

Kirti et al. [12] The proposed approach for diagnosing Black Measles Disease in Grape Plants was developed using the Grape Plant information from the Plant Village Database. A total of 1807 pictures are included in the dataset (healthy and diseased). The suggested model computes the results utilising the ResNet 50 Deep Neural Network structure, Transfer Learning, and Fine Tuning, and achieves an efficiency of over 97 percent, outperforming earlier feature extraction techniques.

Philomina Simon1[13] et al Recommended employ Convolution Neural Network (CNN) features to extract features and a Support Vector Machine as a classifier in a texture classification technique. We used cross entropy as the loss function to study the efficiency of CNN features obtained from various pre-trained networks, including DenseNet201 and ResNet50, and classification to investigate the efficiency of CNN features taken from multiple pre-trained networks. A prominent discriminative classifier for classification is the support vector machine. The model's performance is evaluated using grey and colour texture datasets including KTH-TIPS and CURET, as well as floral datasets. Across a number of datasets, the results demonstrate good to remarkable accuracy of about 85% to 95%. The suggested technique's computation time is cut in half.

Mohit Agarwala, at al.[14] The Plant Village dataset was used to create a CNN-based algorithm for identifying sickness in tomato plants. Three convolution and max pooling layers, each with a different number of filters, are included in the proposed CNN-based design. There are nine disease categories in the collection, as well as a healthy image category. Because the photographs in the class were uneven, data augmentation techniques were used to equalise them. The model's average testing accuracy is 91.2 percent, according to experiments. The suggested model uses only 1.5 MB of storage space, compared to roughly 100 MB for pre-trained algorithms, demonstrating its superiority to pre-trained algorithms.

Junde Chena et al.[15] Research involving the use of a pre-trained model derived from big datasets and then translated to a specific goal based on our own data, as well as the use of deep convolutional neural networks to detect plant leaf diseases using transfer learning. VGGNet pre-trained on ImageNet was used in the suggested model, and the Inception module was used for additional categorization. Instead of starting from the beginning and arbitrarily initialising the weights, ImageNet used pre-trained networks on a large labelled dataset to do so. The proposed method achieves a validation accuracy of no less than 91.83 percent on the publicly accessible dataset, which is a major improvement over previous state-of-the-art methods.

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V.V Srinidhi [16] suggested scheme improved the apple leaf disease dataset by applying data augmentation and picture annotation techniques such as Canny Edge Detection, Blurring, and Flipping to correctly classify them under four classes applying Deep CNN architecture such as EfficientNet and DenseNet. The classifications are "healthy," "scab," "rust," and "many diseases," and the models have efficiency of 99.8% and 99.75%, respectively, overcoming known convolutional neural network weaknesses.
T. Vijaykanth Reddy and Dr. K Shashi Rekha[17] Prepare a new model called CIDCNN-TL and compare it to current models like AlexNet, GoogleNet, VGG-16, and ResNet-20 on the Apple Leaf Dastaset. Their proposed model has a 97.62% accuracy, which is better than the other existing models. The suggested model requires 33.45 minutes of training time and 2.84GB of memory.

III.METHODOLOGY

Figure 1 depicts the suggested system design. The suggested method makes use of the Plant Village dataset, which comprises records of plant disease symptoms. The VGG16, Inception16, GoogleNet, AlexNet, and ResNet architectures are applied to the dataset to provide an efficient approach.

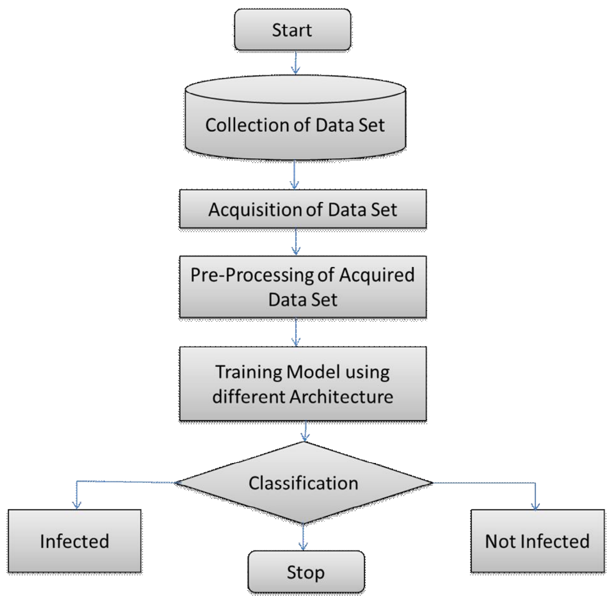

figure 1. Represents the suggested Proposed System flow chart, which demonstrates how the acquired dataset is preprocessed before being used for feature extraction and disease diagnosis of plant leaves.

A. Data Collection

The publically accessible PlantVillage dataset [8] is used in this study. There are approximately 54000 annotated photos in the PlantVillage collection. These photos are made up of 14 different cropping. There are 14529 tomato leaf photos in the dataset, divided into 10 different classifications. There are nine diseased tomato leaf classes and one healthy tomato leaf class among these nine. The image is 256 x 256 pixels in size. The database is partitioned into 80:20, this indicates 80% of the photos are used for training and 20% are used for testing. The photos in the collection are in JPEG format and are in the RGB colour space.

TABLE I. Relative Description of Complete Dataset

Class	Plant Name	Disease Name	Cause Virus Name	Type of disease	No. Of Images
C1	Apple	Healthy	-	-	1645
C2	Apple	Apple Scab	Venturia inaequalis	Fungus	630
C3	Apple	Black rot	Botryosphaeria obtuse	Fungus	621
C4	Apple	Cedar apple rust	Gymnosporangium	Fungus	275

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C5	Blueberry	Healthy	-	-	1502
C6	Cherry	Healthy	-	-	854
C7	Cherry	Powdery mildew	Podosphaera clandestine	Biotrophic Fungus	1052
C8	Corn	Healthy	-	-	1162
C9	Corn	Cercospora leaf spot	Cercosporazeaemaydis	Fungal	513
C10	Corn	Common rust	Pucinia sorghi	Fungus	1192
C11	Corn	Northern Leaf Blight	Exserohilum turcicum	Foliar	985
C12	Grape	Healthy	-	-	423
C13	Grape	Black rot	Guignardia bidwellii	Fungus	1180
C14	Grape	Esca (BlackMeasles)	Phaeomoniella chlamydospora	Fungus	1383
C15	Grape	Leaf blight (Isariopsis)	Pseudocercospora	Fungus	1076
C16	Orange	Healthy	-	-	5507
C17	Peach	Healthy	-	-	360
C18	Peach	Bacterial spot	Xanthomonascampestris pv. Pruni	Bacterial	2297
C19	Pepper/bell	Healthy	-	-	1478
C20	Pepper/bell	Bacterial spot	Xanthomonas campestris pv.	Bacterial	997
C21	Potato	Healthy	-	-	152
C22	Potato	Early blight	Alternaria solani	Fungal	1000
C23	Potato	Late blight	Phytophthora infestans	Fungal	1000
C24	Raspberry	Healthy	-	-	371
C25	Soyabean	Healthy	-	-	5090
C26	Squash	Powdery mildew	Podosphaera xanthii	Fungal	1835
C27	Strawberry	Healthy	-	-	456
C28	Strawberry	Leaf scorch	Diplocarpon earliana	Fungal	1109
C29	Tomato	Healthy	-	-	1591
C30	Tomato	Bacterial spot	Xanthomonas perforans	Bacterial	2127
C31	Tomato	Early blight	Alternaria sp.	Fungal	1000
C32	Tomato	Late blight	Phytophthora infestans	Fungal	1909
C33	Tomato	Leaf Mold	Lycopersicon	Fungal	952

C34	Tomato	Septoria leaf spot	Septoria lycopersici	Fungal	1771
C35	Tomato	Spider mites	Tetranychus spp.	Pest	1676
C36	Tomato	Target spot	Corynespora cassiicola	Fungal	1404
C37	Tomato	Tomato mosaic virus	Tomato mosaic	Viral	373
C38	Tomato	Tomato yellow leaf	Begomovirus	Viral	5357

The likelihood of a plant disease developing is influenced by a number of factors, including the symptoms. The process of segmenting the sick area is the most challenging. The colour, size, and shape of an illness might vary to the next one. The dataset's reference has also been adopted by one of the other paper[15] [18]. Figure 2 is from the study [19][20] and depicts the collecting of data on a variety of plant leaf diseases. As indicated below, there are 38 plant disease classes and one backdrop photo class in the collection:

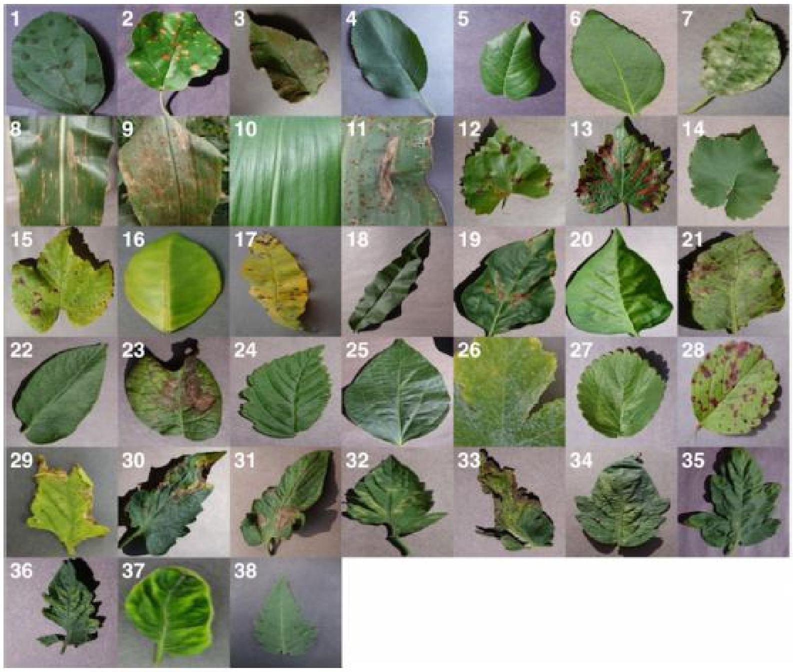

Fig 2. Represents the acquired Plant Pest Class Database from [19], [20]. The dataset mentioned above is a subset of the PlantVillage dataset.

B. Data Collection

Image processing is used in the plant disease detection domain. The infection diagnosis method includes stages such as image acquisition, pre-processing, image segmentation, feature extraction, and classification.

In three different ways, the Plant Village database is used in all of our investigations. The proposed study begins with the Plant Village dataset in its original colour, then does all of the experiments on a gray-scaled version of the PlantVillage dataset, and lastly runs all of the experiments on a PlantVillage dataset with segmented leaves. As a result, all of the extra background data has been removed, which may result in some inherent bias in the dataset due to the Plant Village dataset's regularised data gathering process. Segmentation was automated using software that has been adjusted to fit our dataset. The proposed study has decided on a strategy based on a series of masks created by analysing the colour, brightness, and saturation components of different parts of images in various colour spaces (Lab and HSB). Researchers were able to successfully erase colour casts that were particularly evident in specific subgroups of the dataset during one of the procedure rounds, removing yet another possible bias. As mentioned in [15][18], the Dataset has been processed in a variety of ways. [20] was used to create Figure 3 in this paper.

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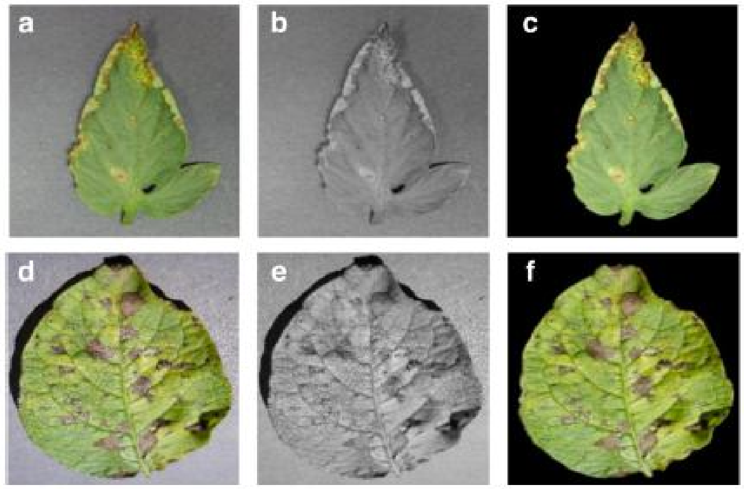

Fig 3. Represents about Preprocessed and Segmented data From [18].

Although some visualisation techniques were employed without modification, others needed to be adjusted to target a specific layer that caught all of the attributes and generated useful outcomes. Moreover, by examining the produced attention maps, some layers that were not participating to inference were identified and eliminated from the system, lowering the number of parameters by 75% without impacting accuracy of classification.

C. Training DataSet

Training and testing data have been isolated first from database inside this approach. The data in the paper presents a design has been segmented into 8:2 ratio of learning to evaluating the model.

D. Applied Model

In picture categorization challenges, deep neural networks have had a lot of success. This research explains how neural networks can be used to recognise plant diseases in the context of image categorization. This system made use of the Plant Village dataset, which includes 38 disease categories and is freely available. As a result, the problem at hand is a multi-class classification problem that must be solved. Three unique designs, including VGG16, ResNet50, AlexNet, GoogleNet, and InceptionV3, are studied as the backbones for our research. The following is an explanation of the predefined architecture:

1) *VGG16:* Simonyan and Zisserman[14] In 2015, for the ILSVRC-2014 competition, I designed the VGG net CNN model. The term "max pooling" refers to a procedure for reducing the volumetric size (down- sampling). There are two fully connected tiers having 4096 nodes each, as well as a softmax classifier. The VGG16 architecture was granted to the Visual Geometry Group. VGG-16 is made up of 13 convolution layers and three completely connected layers and it is known for its modesty. It, like AlexNet, makes use of the ReLU function. The VGG16 is a layered AlexNet design that adds more convolution layers to the model. Small - sized filters, such as 2 x 2 and 3 × 3, are used in the models. It has a combination of 138 M parameters [8].
2) *Inception V3:* In the GoogLeNet architecture [14], Szegedy was the first to offer the "Inception" concept. The GoogLeNet design's successive incarnations are referred to as Inception V3. In this structure, Remaining connections are matched with the Inception notion. Their aim was to make the Inception network training program precede more quickly. With less parameters, it's a 42-layer deep learning network. To minimise the number of parameters, factorising convolutions is utilised. The parameters of this approach are reduced from 5 5 = 25 to 3 3+3 3 = 18. The number of parameters is decreased by 28% as a result. With fewer parameters, the model will be less overfit and thus more accurate. This model came in second place in the ILSVRC-2015.
3) *ResNet:* The ResNet model,Identity shortcut connections were introduced in ResNet-101 [21], which means skipping one or more layers as needed. Kaiming He et al suggested a new design that some connections are skipped and gave the knowledge of high batch normalisation, which they called ResNet. The skip connection aids in the reduction of the vanishing gradient issue. The residual units are convolution, pooling, and layering. While ResNet is roughly 8 times deeper than the VGG net, which contains 33 filters, the design is equivalent. This is because global average pooling is used instead of fully-connected layers.

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The fundamental downside of this network is that, due to the enormous number of parameters, evaluating it is fairly costly. Therefore, by eliminating the very first layer that is fully connected (It is in charge of the vast majority of parameters), the set of parameters can be lowered to some amount without harming performance [22].

4) *AlexNet:* AlexNet [8] was initially developed in 2012 during the ImageNet image classification competition by Krizhevsky et al. It has a total of eight layers, five of which are convolutional and three of which are fully linked. Rectified Linear Unit was utilised for first time on this design. In the AlexNet model, convolution layers are separated by ReLU, maxpooling, and normalising layers.
5) *GoogleNet:* The GoogLeNet [8] architecture is based on conception. The ILSVRC 2014 competition was won by GoogleNet. In GoogleNet, the overall number of parameters was about 68 lakh. The layout of GoogLeNet is similar to inception, which means network in network [and it uses a parallel combination of 11 convolutional layers, 3 convolutional layers, and 5 convolutional layers long with 3 max-pooling layer, with the 11 convolutional layer being used before the 3 and 5 convolutional layers. It aids in shrinking GoogLeNet's spatial dimension and limiting its size. GoogleNet employs 1 x 1 convolution, which aids in size reduction. The accuracy of the GoogLeNet is increased by using global average pooling.

IV. RESULT

On the processed data of the Plant Village dataset, we discovered that utilising the VGG-16 model led in a test accuracy of 97.32 percent, 97.2 percent with the ResNet 50 model, 96.1 percent with inception V3, 97.69 percent with GoogleNet, and 91.19 percent with AlexNet. We were able to achieve the best results by using the VGG-16 system model.

TABLE II. Obtain Accuracy of Test Score

	Test Accuracy			
	Inception V3	ResNet-50	DenseNet-169	AlexNet
Obtain Accuracy	97.18%	97.80%	97.41%	94.70%

A. 10 Fold Cross Validation Analysis

To test how well our algorithms behaved on updated data that had not been used for the training period, we employed the 10-fold cross validation procedure. The average validation data score of the implemented methods is shown in Table III. We got the best result in 10-fold cross validation with the VGG-16 model, which was 96%.

TABLE III. 10 Fold Cross Validation Accuracy of Test Score

	Validation Score			
	Inception V3	ResNet-50	DenseNet-169	AlexNet
10 fold cross validated Accuracy	95.93%	97.20%	96.11%	93.58%

B. Confusion Matrix Analysis

An N x N matrices is used to evaluate the reliability of a classification model, where N represents the size of specific groups. The total number of training in the proposed model is two. The matrix compares actual goal values to the deep learning model's predictions. This allows us to see how well our classification model is functioning and the types of errors it makes. This matrix compares how the model classified the various fault groups with how they were actually classified. [23] This is encapsulated in the following four pieces of data:

True Positive (TP): Non-nutritional Leaf Accurately identified as Non-nutritional
False Positive (FP): Nutritional Leaf improperly identified as Non-nutritional
True Negative (TN): Nutritional Leaf Accurately Identified as Nutritional
False Negative (FN): Non-nutritional Leaf improperly identified as Nutritional

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TABLE IV. Score on the Comparison Parameter

Model	Precision	Recall	F1 Score
ResNet-50	0.92	0.93	0.91
AlexNet	0.91	0.92	0.92
DenseNet-169	0.91	0.93	0.93
Inception V3	0.93	0.93	0.92

V. CONCLUSION

Plants, like all living things, are susceptible to infection and are impacted by it in terms of leaf, fruit, flower, and other plant parts growth. These infections might be fatal in some cases. As an outcome, the suggested method detects fungal infection on a plant using a typical neural network based on a leaf image. As a conclusion, we've used a variety of CNN-based algorithms to detect and identify plant-leaf illnesses, and they beat other methods in terms of detection, classification, processing efficiency, and cost. The classify-cation result on the ResNet-50 model has the maximum accuracy of 97.80 percent. In the future, we plan to investigate different deep learning techniques with architecture modification to provide novel contribution in this research domain.

REFERENCES

[1] T. Talegaonkar , I. Parkar, M. Shaikh, D. Rai and S. Malik , 'Automatic Recognition of Leaf Diseases Tejaswini', Angew. Chemie Int. Ed. 6(11), 951–952., no. February, 2020,vol. 8, no. 2, Available:www.ijarset.com.
[2] V. SBhong, 'Study and Analysis of Cotton Leaf Disease Detection Using Image Processing', Int. J. Adv. Res. Sci. Eng. Technol., vol. 3, no. 2, pp. 1447–1454, 2016.
[3] V. Singh and A. K. Misra, 'Detection of plant leaf diseases using image segmentation and soft computing techniques', Inf. Process. Agric., vol. 4, no. 1, pp. 41–49, 2017, doi: 10.1016/j.inpa.2016.10.005.
[4] N. Tijare and S. Badnerkar, 'Image Recognition Based Crop Disease Identification System: a Survey', Int. J. Comput. Sci. Mob. Comput., vol. 3, no. 4, pp. 868–873, 2014.
[5] V. K. V and K. S. Vani, 'Agricultural Robot : Leaf Disease Detection and Monitoring the Field Condition Using Machine Learning and Image Processing', Int. J. Comput. Intell. Res., vol. 14, no. 7, pp. 551–561, 2018.
[6] G. K. Sandhu and R. Kaur, 'Plant Disease Detection Techniques: A Review', 2019 Int. Conf. Autom. Comput. Technol. Manag. ICACTM 2019, pp. 34–38, 2019, doi: 10.1109/ICACTM.2019.8776827.
[7] A. Jenifa, R. Ramalakshmi, and V. Ramachandran, 'Classification of Cotton Leaf Disease Using Multi-Support Vector Machine', IEEE Int. Conf. Intell. Tech. Control. Optim. Signal Process. INCOS 2019, pp. 1–4, 2019, doi: 10.1109/INCOS45849.2019.8951356.
[8] M. Gehlot and M. L. Saini, 'Analysis of Different CNN Architectures for Tomato Leaf Disease Classification', 2020 5th IEEE Int. Conf. Recent Adv. Innov. Eng. ICRAIE 2020 - Proceeding, vol. 2020, 2020, doi: 10.1109/ICRAIE51050.2020.9358279.
[9] X. Li and L. Rai, 'Apple Leaf Disease Identification and Classification using ResNet Models', ICEICT 2020 - IEEE 3rd Int. Conf. Electron. Inf. Commun. Technol., pp. 738–742, 2020, doi: 10.1109/ICEICT51264.2020.9334214.
[10] M. S. Arshad, U. A. Rehman, and M. M. Fraz, 'Plant Disease Identification Using Transfer Learning', 2021 Int. Conf. Digit. Futur. Transform. Technol. ICoDT2 2021, pp. 1–5, 2021, doi: 10.1109/ICoDT252288.2021.9441512.
[11] A. Singh and M. Arora, 'Wheat Crop', no. Icosec, pp. 121–125, 2020.
[12] K. Kirti, N. Rajpal, and J. Yadav, 'Black measles disease identification in grape plant (vitis vinifera) using deep learning', Proc. - IEEE 2021 Int. Conf. Comput. Commun. Intell. Syst. ICCCIS 2021, pp. 97–101, 2021, doi: 10.1109/ICCCIS51004.2021.9397205.
[13] P. Simon and V. Uma, 'Deep Learning based Feature Extraction for Texture Classification', Procedia Comput. Sci., vol. 171, no. 2019, pp. 1680–1687, 2020, doi: 10.1016/j.procs.2020.04.180.
[14] M. Agarwal, A. Singh, S. Arjaria, A. Sinha, and S. Gupta, 'ToLeD: Tomato Leaf Disease Detection using Convolution Neural Network', Procedia Comput. Sci., vol. 167, no. 2019, pp. 293–301, 2020, doi: 10.1016/j.procs.2020.03.225.
[15] J. Chen, J. Chen, D. Zhang, Y. Sun, and Y. A. Nanehkaran, 'Using deep transfer learning for image-based plant disease identification', Comput. Electron. Agric., vol. 173, no. November 2019, p. 105393, 2020, doi: 10.1016/j.compag.2020.105393.
[16] V. V. Srinidhi, A. Sahay, and K. Deeba, 'Plant Pathology Disease Detection in Apple Leaves Using Deep Convolutional Neural Networks : Apple Leaves Disease Detection using EfficientNet and DenseNet', Proc. - 5th Int. Conf. Comput. Methodol. Commun. ICCMC 2021, no. Iccmc, pp. 1119–1127, 2021, doi: 10.1109/ICCMC51019.2021.9418268.
[17] T. V. Reddy, '(DLDPF) with Transfer Learning for Automatic Leaf Disease Detection', no. Iccmc, pp. 1408–1415, 2021.
[18] A.K Maji and Z. Leonowicz, 'Identification of Plant-Leaf Diseases Using CNN and Transfer Learning Approach', 2021.
[19] A. Sagar and J. Dheeba, 'On using transfer learning for plant disease detection', bioRxiv, 2020, doi: 10.1101/2020.05.22.110957.
[20] S. P. Mohanty, D. P. Hughes, and M. Salathé, 'Using deep learning for image-based plant disease detection', Front. Plant Sci., vol. 7, no. September, pp. 1–10, 2016, doi: 10.3389/fpls.2016.01419.
[21] E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, 'A comparative study of fine-tuning deep learning models for plant disease identification', Comput. Electron. Agric., vol. 161, no. October 2017, pp. 272–279, 2019, doi: 10.1016/j.compag.2018.03.032.
[22] N. Aloysius and M. Geetha, 'A review on deep convolutional neural networks', Proc. 2017 IEEE Int. Conf. Commun. Signal Process. ICCSP 2017, vol. 2018-January, pp. 588–592, 2018, doi: 10.1109/ICCSP.2017.8286426.
[23] F. J. Ariza-López, J. Rodríguez-Avi, and M. V. Alba-Fernández, 'Complete control of an observed confusion matrix', Int. Geosci. Remote Sens. Symp., vol. 2018-July, pp. 1222–1225, 2018, doi: 10.1109/IGARSS.2018.8517540.