

PREDICTION OF PLANT DISEASES USING DEEP LEARNING TECHNIQUES

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Abstract

Plant diseases are an important thing regarding the growth and yield of plants. Plant disease can be easily identified by image processing using deep learning methods. Plants are imperative assets that are available on the earth. They play an important job in the improvement of the general public and they have incredible importance in ecological insurance, clinical drug, rural turn of events, and food-related applications. A significant starting point for any plant-related work is the distinguishing proof of plant aggregate that alludes to the physiological and biochemical attributes of plants, including their shading, shape, surface, etc., which are controlled by the two qualities and the climate. The horticultural creation rate assumes an essential part in the financial advancement of a country. Be that as it may, plant infections are the main hindrance to the creation and nature of food. The recognizable proof of plant infections at a beginning phase is critical for worldwide well being and prosperity. The conventional determination process includes visual appraisal of a single plant through location visits. In any case, assessment of crop illness through manual.

methods gives less accurate values. To handle such issues, there is an interest to configuration computerized approaches prepared to do productively recognizing and sorting various plant illnesses. Due to low precision data in the pictures, the exact ID and order of plant illnesses is a time consuming task.

Keywords: Image Processing, Deep Learning, Convolutional Neural Network (CNN).

I. INTRODUCTION

Plants contribute much to our economy. Hence diseases affected to plants may lead to serious threats to our Agricultural sector. Identifying each and every crop disease from every single plant is not at all possible in the case of large farms. So some methods must be developed to identify crop diseases in a wide range. Detecting plant disease in the earlier stage will help the farmers to protect their crops from danger. Asian countries are very much dependent on Agriculture. Early detection of diseases is important to prevent Agricultural losses.

Detection of illness from the picture of plants will help a lot for the Agricultural industry. Image processing of plants is used to detect diseases in leaves and stems. Various studies have already been devised to identify the disease in plants[1]. The development of Deep Learning techniques

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made it simpler to identify plant illnesses. Machine learning's deep learning subfield makes use of multi-layered neural networks. In essence, it is an area of AI that closely imitates the functioning of the human brain. Different Deep Learning algorithms, like CNN, have already demonstrated their effectiveness in detecting plant diseases.

In our work, a review of six different works on plant disease detection using deep learning methods.

The article is categorized into four parts. Section 1 gives the introduction. Section 2 describes the models selected, the methodology employed and an analysis of each model. Section 3 gives a summary of the entire study and section 4 gives the conclusion.

II. DESCRIPTION OF MODELS

The topographies and descriptions of the different models that were studied are covered in this section. All of these models predict the likelihood of diseases in plant leaves and stems using various deep-learning methods. Their use of architecture and the data set for the research are different.

2.1 Konstantinos P. Ferentino, "Deep learning models for plant disease detection and diagnosis". CNN models were employed in this study for identifying diseases in plants. This algorithm had a success rate of 99.53%. This model uses the five fundamental architectures AlexNet, LalexNetOWTBn, GoogLeNet, Overfeat, and VGG. The dataset used was an open database called plant village. There were 58 distinct classes in this database. Each class is described as a

combination of a disease and a plant. The set of data used for training and the set of data used for testing. From this dataset, 80% was used as a training set, and 20% was used as a test set. Among the five different models, a high success rate was achieved by VGG and AlexNetOWTBn architectures.

Convolutional neural network using VGG, with a rate of performance of 99.53%, was the most effective model. This method has proven that Convolutional Neural networks provide a better solution to identify plant diseases. The performance results of various methods are shown in Table 1.

The Model used	Rate of success
Alex Net Model	99.06
AlexNetOWTBn Model	99.44
Google Net Model	97.27
Overfeat Model	98.96
VGG Model	99.53

Table 1: The success rate of different models of Konstantinos P. Ferentinos

2.2 Sharada P. Mohanty¹, David P. Hughes, and Marcel Salathé, "Using Deep Learning for Image-Based Plant Disease Detection".

In this paper [], they used smartphone-assisted disease diagnosis using Convolutional Neural Networks. The Plant Village (Hughes and Salathe, 2015) dataset was used in this study. 14 crop types

with 26 diseases have been captured in 54,306 pictures. A grayscale variant of the Plant Village dataset had been used for testing. All extra background material was eliminated after segmenting the leaves. The technique was based on a set of masks. The examination of the color, light, and completeness of various sections of the images produces the masks

They used a train-test group where 20% sample of the dataset was tested and for training, 80% of the dataset was used. Another collection where training was done with 40% of the dataset and 60% of the dataset. The third one includes 50% of the entire dataset for testing and 50% for training, 40% of the entire collection for testing and 60% for training, and 80% of the whole dataset is used for training, and 20% is used for testing. Calculations were made for each experiment's average recall, average F1 score, and average accuracy for the whole training period. The average F1 value for each of the various experimental configurations was used to compare the outcomes.

.The functional architecture of the model is shown in Table 2

Deep learning architecture used	AlexNet, GoogLeNet.
The mechanism used for training	Training from Scratch, Transfer Learning.
Type of Dataset	Grayscale, Color, and Leaf Segmented
Distribution of training and testing set:	80% train, 20%test,60%test,40%test,50%test,40%test.60%test, 20%test, 80%train, 20%test

Table 2 Architectural Parameters of the Model

Compared to existing traditional methods, this model has demonstrated 99.35 % accuracy using CNN.

2.3 Junde Chena ,Jinxiu Chena , Defu Zhanga, * Yuandong Sunb , Y.A. Nanekkarana,”.Using deep transfer learning for image-based plant disease identification”.

Deep transfer learning was incorporated into this algorithm to identify plant diseases based on images. The maize dataset of plant village was taken as the dataset. They have taken several images of rice and maize crop leaf images from Fujian Subtropical Botany Institute, Xiamen, China. First, using Photoshop tools, the photos of the sick leaves are evenly turned into RGB models, and then the image sizes are altered to 224 and 224 pixels

On images of the affected leaves, various image processing methods were employed including sharpening, resizing, filtering, and grey transformation... The dataset was enlarged using the methods such as random rotation, flipping and translation. The suggested method (VGGNet) was then trained using the sample images as input. The usage of transfer learning has been made. It enables them to initialise the weights using a trained network on large data sets. VGGNet is the transfer learning method used.

The pre-trained module is the first of the two sections of the newly formed networks. This module becomes the basic feature extractor.

Extended layers is the second which is used to extract high-dimensional features. Here, two consecutive 3x3 convolution layers are used in lieu of the single 5x5 convolution layer in a consecutive convolution architecture. This method reduced the number of parameters and also it maintained the range of perceptive fields.

They conducted experiments using the public plant village dataset and their own image dataset. On the public dataset, the proposed system had an accuracy score of 91.83%. The average accuracy level received for collected rice disease images was 92.00%.

2.4 Abhinav Sagar, Dheeba J Vellore Institute of Technology, Vellore, Tamil Nadu, India,” On Using Transfer Learning For Plant Disease Detection”.

This paper is a study on plant diseases using deep neural networks. They have used the public dataset, Plant Village. VGG16, ResNet50, InceptionV3, InceptionResNet, and DenseNet169 are five different pre-trained models that have been compared. This method yields the best outcomes on the ResNet50 test set that employed skip connections with a residual layer. To expand the information, they employed strategies like brightness shift, flipping, zooming, and shearing. To avoid misclassification, they had used the metrics true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). By dividing the total number of correctly predicted positive observations by the total

number of successfully anticipated positive observations, they calculated the precision. The accuracy is determined by dividing the proportion of correctly predicted positive observations by the total number of real class observations. For the purpose of determining the F1 score, Precision and Recall are weighted averaged. As a next step, the confusion matrix for all the pairs with and without sickness was plotted. This helped to analyse the misclassifications.

The concept of transfer learning is used in this method for classification. In this technique, the Python-based Keras deep learning library was used to implement the picture augmentation technique. Three sets of the data are created: a train set, a validation set, and a test set. An accuracy percentage of 98.2% is received with residual network architecture in this model. This version executed with an accuracy of 98. The results of the various models and results are shown in Table 3

Pre-trained model used	Result
ResNet50	0.982
Precision	0.94
F1	0.94

Table 3: Results of various models in Abhinav Sagar.

2.5 Muammer TÜRKOĞLU1, Davut HANBAY2, “Plant disease and pest detection using deep learning-based features”.

A deep CNN model is created in this study [for the diagnosis of pests and diseases in plants. They had imported a dataset from Turkey that contained photos of actual plant diseases and pests. They initially used this dataset to extract features using deep learning architectures. ResNet50, ResNet101, InceptionV3, InceptionResNetV2, AlexNet, VGG16, and VGG19 are some examples of ResNet networks. SVM, ELM, and KNN classify the features that can be extracted from them. Afterward, utilising transfer learning, it was adjusted.

The Alexnet, VGG16, and VGG19 models' respective deep features from the three layers are used to calculate performances throughout the classification phase. The deep features of the top layer are then chosen by contrasting the results of the different layers. AlexNet's fc6, fc7, and fc8 layers, as well as VGG16 and VGG19's deep features, were tested using models built using SVM, ELM, and KNN techniques. For the fc6 layer, this model offers the best accuracy results

Classifier Methods	AlexNet Model	VGG16 Model	VGG19 Model
SVM	95.5%	95%	94%
ELM	80.6%	90.2%	94.74%
KNN	90.3%	94.7%	95.1%

Table 4: Best results of various classifier methods.

Next, they extracted deep features using the fully connected layer using models of CNN like

ResNet50, ResNet101, InceptionV3, ResNetResNetV2, and SqueezeNet models. From each of the layers from these models, deep characteristics are taken out. Then the performance is calculated using various classifiers like KNN,ELM and SVM.

CNN MODELS	SVM	ELM	KNN
GoogleNet	95.22	94.18	89.16
ResNet50	97.86	97.65	90.48
ResNet101	96.74	97.45	91.20
InceptionV3	94.96	94.54	88.65
InceptionResNet V2	94.76	95.20	88.80
SqueezeNet	95.62	95.10	87.02

Table 5: Results of different CNN models.

This study compares the effectiveness of deep feature extraction and transfer learning for spotting plant illnesses and pests. For transfer learning and deep feature extraction, they used nine features of deep neural networks. The results of the deep feature extraction has shown better results than transfer learning methods. An accuracy percentage of 97.86% has been obtained from ResNet50 and SVM classifier. 2.6 Yan Guo, Jin Zhang, Chengxin Yin,Xiaonan Hu, Yu Zou, Zhipeng Xue, and Wei Wang,” Plant Disease Identification Based on Deep Learning Algorithm in Smart Farming”.

This model [8,9] offers a mathematical model for

detecting plant diseases using deep learning techniques in smart farming. Dataset was obtained from the Sichuan Province's Key Laboratory of Agricultural Information Engineering.

A complex environment's leaves are originally identified using the region proposal network (RPN). Based on the RPN results that comprised the characteristic of symptoms, the pictures were segmented using the Chan-Vese (CV) method[10]. The results of segmentation are provided to the transfer learning model as input. When compared to conventional approaches, this method has an accuracy rate of 83.57%.

The steps involved in this method is shown in the following Figure 1

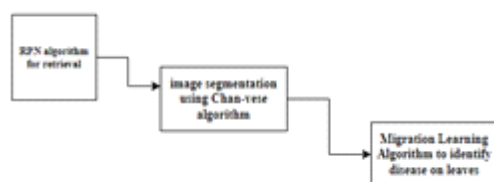


Fig 1: Steps in Deep Learning Algorithm in Smart Farming

Finding the infected leaves is the first stage, and the leaf dataset is trained using the RPN algorithm. Second step is the segmentation of diseased leaves using Chan-Vese algorithm. The identification of leaf disease species is done in the third stage, and a transfer learning model is used to identify plant diseases. An accuracy of 83.75% is obtained from this method. In this study, a model based on the RPN, CV, and TL algorithms was proposed.

III. Results and Discussion

The six papers on plant disease prediction using various deep learning algorithms were evaluated in the article. Different models use different deep learning models, training data sets, and metrics to assess these models. In this work, we compare the performance of each of these models using the accuracy %. Here, we've discussed how accurate each model was based on the relevant studies.

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Ref #	Reviewed Models	Architecture used	Dataset used	Accuracy rate
<u>2</u>	CNN	AlexNet, LalexNetOWTbn, GoogLeNet, Overfeat and VGG	PlantVillage	99.53%(VGG)
<u>3</u>	CNN	AlexNet, GoogLeNet.	Plant Village (Hughes and Salathe, 2015)	99.35%
<u>4</u>	Deep Transfer Learning	VGGNet	Plant Village	91.83%
<u>5</u>	Deep Neural Networks	VGG16, ResNet50, InceptionV3, InceptionResNet and DenseNet169	Plant Village	98.2%
<u>6</u>	Deep CNN	GoogleNet, ResNet50, ResNet101, InceptionV3, InceptionResNetV2, AlexNet, VGG16, and VGG19	Turkey	97.86(ResNet50)
<u>7</u>	Deep Learning	RPN algorithm, CV algorithm and TL algorithm.	Agricultural Information Engineering of Sichuan Province	83.57

IV. CONCLUSION

Plant disease causes a major loss in economy of agricultural industry worldwide. Automatic detection of plant diseases can very much contribute to the agricultural sector. Numerous studies are being conducted to identify, analyse, and forecast plant diseases thanks to the development of CNN and other deep learning techniques. In this study, we have reviewed six alternative deep learning models for the prediction of plant diseases. These models all made use of CNN, which was implemented using various architectural models. According to our investigation, the best prediction accuracy was found in CNN that used VGG, at 99.53% [2].

REFERENCES

1. <https://enterpriseproject.com/article/2019/7/deep-learning-explained-plain-english>
2. Konstantinos P. Ferentino, "Deep learning models for plant disease detection and diagnosis". *Computers and Electronics in Agriculture* Volume 145, February 2018, Pages 311-318
3. Sharada P. Mohanty¹, David P. Hughes, and Marcel Salathé, "Using Deep Learning for Image-Based Plant Disease Detection", *Front. Plant Sci.*, 22 September 2016 | <https://doi.org/10.3389/fpls.2016.01419>
4. Junde Chena, Jinxiu Chena, Defu Zhanga, *, Yuandong Sunb, Y.A. Nanekarana, "Using deep transfer learning for image-based plant disease identification" *Junde Chena, Jinxiu Chena, Defu Zhanga, *, Yuandong Sunb, Y.A. Nanekarana, Computers and Electronics in Agriculture*, Volume 173, June 2020, 105393
5. Abhinav Sagar, Dheebea J Vellore Institute of Technology, Vellore, Tamil Nadu, India, "On Using Transfer Learning For Plant Disease Detection", : <https://doi.org/10.1101/2020.05.22.110957>
6. Muammer Türkoğlu, Davut Hanbay, "Plant disease and pest detection using deep learning-based features", *Turkish Journal of Electrical Engineering & Computer Sciences* <http://journals.tubitak.gov.tr/elektrik/> doi:10.3906/elk-1809-181
7. Yan Guo,^{1,2} Jin Zhang,³ Chengxin Yin,⁴ Xiaonan Hu,¹ Yu Zou,¹ Zhipeng Xue,¹ and Wei Wang, "Plant Disease Identification Based on Deep Learning Algorithm in Smart Farming", *Hindawi Discrete Dynamics in Nature and Society* Volume 2020, Article ID 2479172, 11 pages <https://doi.org/10.1155/2020/2479172>
8. Xu, L., Ren, J. S., Liu, C., & Jia, J. (2014). "Deep convolutional neural network for image deconvolution". In *Advances in neural information processing systems* (pp. 1790-1798).

9. Fast and Accurate Detection and Classification of Plant Diseases H. Al-Hiary, S. Bani-Ahmad, M. Reyalat, M. Braik and Z. ALRahamneh
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10. Automatic and Reliable Leaf Disease Detection Using Deep Learning Techniques
Muhammad E. H. Chowdhury 1,* , Tawsifur Rahman 1 , Amith Khandakar 1 , Mohamed Arselene Ayari 2,* , Aftab Ullah Khan 3 , Muhammad Salman Khan 3,4, Nasser Al-Emadi 1 , Mamun Bin Ibne Reaz 5 , Mohammad Tariqul Islam 5 and Sawal Hamid Md Ali.