IARJSET

ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology

ISO 3297:2007 Certified ⁜ Impact Factor 7.105 ⁜ Vol. 9, Issue 6, June 2022

DOI: 10.17148/IARJSET.2022.9637

Plant Disease Detection Using Pre-trained Models

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Abstract: In India the major percentage, around 70% of the population relies on agriculture. In order to produce a healthy yield, the identification of the plant diseases is important. The diseases that affect plants cannot be manually observed by the farmers. It's a troublesome and a very time-consuming process for them to detect the plant diseases manually. Hence, image processing and machine learning models can be used to detect the plant diseases at an early stage. Plant disease detection majorly relies on the image classification concept of machine learning. The benefit of using transfer learning is the model being used has a pre-build knowledge on which the model starts from different patterns. These patterns been learnt while training on a different dataset used for a different problem which is similar to the problem being solved using the same model. Automatic recognition and classification of various diseases of a specific crop are necessary for accurate identification. This study mainly concentrates on the transfer learning phenomenon based on four different pre-trained models such as VGG-16, ResNet-34, ResNet-50, and ResNet-50 v2 and then compared the four models based on various standard evaluation metrics such as accuracy, recall and precision. The dataset considered for the study includes the various diseased and healthy leaves of different plants and crops such as Apple, Corn, Pepper, Potato, and Tomato, etc.

The goal is to study and recognize the best and most efficient method that can be used to detect the diseases in the crops. Various methodologies with their corresponding accuracies along with a detailed comparison, discussion of the features, input parameters and experimental setup will be discussed. The comparative study of the pre-trained models in terms of their performance will be carried out.

Keywords: Deep learning, Transfer learning, Pre-trained models, Image classification

I. INTRODUCTION

Plant diseases lower crop quality and hence productivity, plant diseases have always been a major problem in agriculture. Plant diseases can cause anything from slight symptoms to severe crop damage across large planted regions, which has a significant negative impact on the agricultural economy particularly in underdeveloped nations that rely primarily on a single crop or a small number of crops.

Various techniques for disease diagnosis have been developed in order to minimise significant losses. The exact identification of causative agents is made possible by techniques developed in molecular biology and immunology. These techniques, however, are not available to many farmers and are expensive and resource-intensive to use[5]. The majority of farms in the world are small and run by families in poor nations, according to the Food and Agriculture Organization of the United Nations[2]. A large portion of the world's population receives food from these households. Despite this, access to markets and services is restricted, and poverty and food insecurity are frequent. For the reasons outlined above, extensive study has been done to develop approaches that will be sufficient in accuracy and available to the majority of farmers.

Modern technology is used in precision agriculture to enhance the decision-making process. Modern digital technologies have made it possible to collect enormous amounts of data in real-time and employ a variety of machine learning (ML) algorithms to get the best possible judgments[11]. This has reduced expenses. The decision-support systems that assist in converting vast volumes of data into helpful recommendations are one area where there is still room for progress in this field.

Proposed methodology

Deep learning (DL) has recently made some important advancements in the field of image recognition and classification. The advantages of both ResNet and VGG architectures are combined using a new model called Res VGG, which was built by fusing two separate DL models, such as ResNet and VGG16. This methodology has been used to identify and classify the signs of plant diseases.

In our proposed model, there are a total of 12 layers: 2 fully connected layers, 1 softmax layer, and 9 convolutional

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layers. The effectiveness of this proposed model has been evaluated and validated using the Plant Village dataset. The experimental research shows that the proposed model can identify illnesses better than existing models, allowing for the effective prevention of these diseases and the resolution of the food security problem.

Architecture Diagram

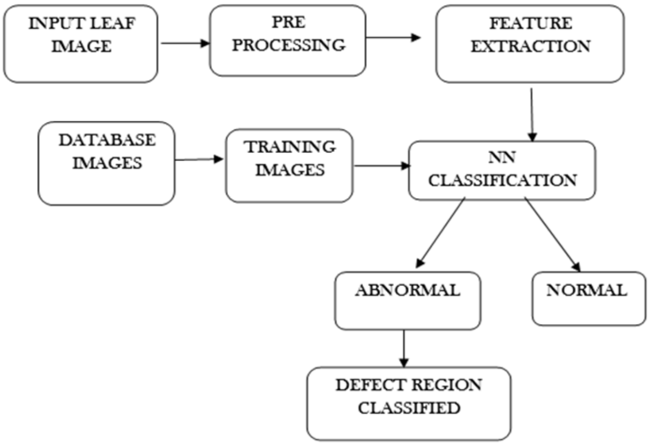

Fig. 1: Architecture Diagram

II LITERATURE SURVEY

The paper[1] explains the deep learning-based models and transfer learning-based models can be used for classifying images of diseased plant leaves into 38 categories of plant disease based on its defect on a Plant Village dataset. It has been observed that DenseNet achieves the best result on the test data with an accuracy of 99 percent.
The paper[2] uses machine learning and deep learning methods like CNN architecture based on transfer learning are been explored by training them on the available Plant Village dataset and these experiments help us understand the various parameters that contribute to the performance of the model.
The paper[3] proposes the primary objective of this research is to present a pre-trained ImageNet network architecture that is well suited for dealing with plant-based data, even when sample sizes collected are limited. Different convolutional neural network-based architectures such as InceptionV3, MobileNetV2, Xception, VGG16, and VGG19 to classify plant leaf images are used and compared. Deep neural networks can be used for plant disease recognition in the context of image classification.
In the paper[6], the publicly available Plant Village dataset which has 38 classes of diseases is the most used dataset for plant disease classification is used. There are various pre-trained models that can be used for plant disease classification, and they can be experimented with the Plant Village Dataset available.
In the paper[7], Pre-trained deep learning ensemble models with transfer learning can also be used for plant disease detection. It reports comparative evaluation results of the three deep learning ensemble models with an SVM-based model.
In the paper[8], The implemented models used for transfer learning were trained with an open dataset consisting of 14 different plant species, and 38 different categorical disease classes and healthy plant leaves.

In the paper[11], A classification system for the severity of agricultural illnesses and insect pests was built using an enhanced ResNet50 model (CDCNNv2) in conjunction with deep transfer learning.
In the paper[15], The PARNet model was created by fusing the attention mechanism with the residual structure, and the WEB application was finished. The platform's 96.84 percent average accuracy for five tomato leaf diseases is impressive. It was 2.25 percent higher than alternative models by 11.58 percent (VGG16, ResNet50, and SENet).

II. COMPARISION PARAMETERS

Different parameters were considered while studying about the performance of various pre-trained models used in plant disease detection. Some of the parameters are listed below:

- Pooling layers : ResNet50 uses a global average pooling layer, while VGG 16 uses several max pooling layers
- Edges and Target Object: ResNet50 is more sensitive to edges and target objects than other neural networks.

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- Speed and Complexity: ResNet 50 is faster in terms of training time while VGG 16 is slower and more complex
- Vanishing Gradient Problem : In VGG 16, this value is continuously multiplied by each local gradient, resulting in a very small gradient value, however in ResNet 50, the local gradient is set to 1.

III. CONCLUSION

The PlantVillage dataset was utilised in the majority of studies (as stated in the preceding sections) to assess the efficacy and performance of the corresponding DL models/architectures. This dataset has a simple/plain background despite having several photos of various plant types with their illnesses. However, the actual environment needs to be taken into account for a realistic scenario.

This comparative study described transfer learning methods for identifying plant diseases. In addition, a variety of visualisation methods and mappings were compiled to identify disease symptoms. The study mainly concentrated on the transfer learning phenomenon based on three different pre-trained models such as VGG-16, ResNet-50, and ResNet-50 v2, and then compared the three models based on transfer learning models based on various standard evaluation metrics. VGG-16-based transfer learning model achieved an accuracy of 98.74%, ResNet-50-based transfer learning model achieved an accuracy of 98.84%, and ResNet-50 v2-based transfer learning model achieved an accuracy of 98.21%.

REFERENCES

[1] Bincy Chellapandi; M. Vijayalakshmi; Shalu Chopra, ”Comparison of Pre-Trained Models Using Transfer Learning for Detecting Plant Disease”, 2021 International Conference on Computing, Communication, and Intelligent Systems (ICCCIS)

[2] Marko Arsenovic,Mirjana Karanovic,Srdjan Sladojevic,Andras Anderla, "Solving Current Limitations of Deep Learning Based Approaches for Plant Disease Detection”, Symmetry 2019, 11(7), 939.

[3] Krishnaswamy Rangarajan, A., Purushothaman, R, "Disease Classification in Eggplant Using Pre-trained VGG16 and MSVM", Sci Rep 10, 2322 (2020).

[4] Nisar Ahmad; Samayveer Singh,"Comparative Study of Disease Detection in Plants using Machine Learning and Deep Learning.”, 2021 2nd International Conference on Secure Cyber Computing and Communications (ICSCCC).

[5] Sk Mahmudul Hassan and Arnab Kumar Maji,"Plant Disease Identification Using a Novel Convolutional Neural Network" , 2021 IEEE Fifth Ecuador Technical Chapters Meeting (ETCM), 2021, pp. 1-6.

[6] N Rohan Sai, T Sudarshan Rao, G. L. Aruna Kumari,"Comparative Study on Reliability of Transfer Learning to Classify Plant-Based Diseases", International Journal of Engineering and Advanced Technology (IJEAT) ISSN: 2249-8958 (Online), Volume-10 Issue-6, August 2021.

[7] Abhinav Sagar,Dheeba Jacob,"On Using Transfer Learning For Plant Disease Detection", 2021 11th International Conference on Advanced Computer Information Technologies (ACIT), 2021.

[8] Bipasa Bose; Jyotsna Priya; Sonam Welekar; Zeyu Gao ,"Hemp Disease Detection and Classification Using Machine Learning and Deep Learning", 2020 IEEE Intl Conf on Parallel & Distributed Processing with Applications, Big Data & Cloud Computing, Sustainable Computing & Communications, Social Computing & Networking.

[9] Sk Mahmudul Hassan , Arnab Kumar Maji , Michał Jasi, Zbigniew Leonowicz and Elzbieta Jasi "Identification of Plant-Leaf Diseases Using CNN and Transfer-Learning Approach", Electronics 2021, 10, 1388. https://doi.org/10.3390/electronics10121388.

[10] Waleed Albattah, Marriam Nawaz, Ali Javed, Momina Masood & Saleh Albahli, "A novel deep learning method for detection and classification of plant diseases”, Complex & Intelligent Systems volume 8, pages507–524 (2022).

[11] P. Dwivedi, S. Kumar, S. Vijh and Y. Chaturvedi, "Study of Machine Learning Techniques for Plant Disease Recognition in Agriculture," 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence), Noida, India, 2021.

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DOI: 10.17148/IARJSET.2022.9637

[12] L. Li, S. Zhang and B. Wang, "Plant Disease Detection and Classification by Deep Learning—A Review," in IEEE Access, vol. 9, 2021.

[13] F.-Q. Jiang, C. Li, D.-W. Yu, M. Sun, and E.-B. Zhang, ‘‘Design and experiment of tobacco leaf grade recognition system based on caffe,’’ J. Chin. Agricult. Mech., vol. 40, no. 1, pp. 126–131, Jan. 2019.

[14] M.-M. Zhou, ‘‘Apple foliage diseases recognition in Android system with transfer learning-based,’’ M.S. thesis, Dept. Inf. Eng., Northwest A&F Univ., Yangling, China, 2019.

[15] Y. Liu, Q. Feng, and S.-Z. Wang, ‘‘Plant disease identification method based on lightweight CNN and mobile application,’’ Trans. Chin. Soc. Agricult. Eng., vol. 35, no. 17, pp. 194–204, Jun. 2019.

[16] J. G. M. Esgario, R. A. Krohling, and J. A. Ventura, ‘‘Deep learning for classification and severity estimation of coffee leaf biotic stress,’’ Comput. Electron. Agricult., vol. 169, Feb. 2020, Art. no. 105162.

[17]. Y. Xiong, L. Liang, L. Wang, J. She, and M. Wu, ‘‘Identification of cash crop diseases using automatic image segmentation algorithm and deep learning with expanded dataset,’’ Comput. Electron. Agricult., vol. 177, Oct. 2020.

[18] M. M. Ozguven and K. Adem, ‘‘Automatic detection and classification of leaf spot disease in sugar beet using deep learning algorithms,’’ Phys. A, Stat. Mech. Appl., vol. 535, Dec. 2019

[19] B. Wang and D. Wang, ‘‘Plant leaves classification: A few-shot learning method based on Siamese network,’’ IEEE Access, vol. 7, pp. 151754–151763, 2019

[20] D. Das and C. S. G. Lee, ‘‘A two-stage approach to few-shot learning for image recognition,’’ IEEE Trans. Image Process., vol. 29, no. 5,Dec. 2020.

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