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Plant Disease Detection using Deep Transfer Learning

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ABSTRACT

Our long-standing tradition is in agriculture. Low output prices, problems with the irrigation system, and pest infestations are just a few of the concerns that farmers have. Plant infections have become more prevalent over the past few decades and have become a big issue for farmers. The detection and treatment of plant diseases are crucial for preventing output losses. The method that can be used to identify plant diseases is deep learning. Statistical machine learning techniques called "deep learning" use neural network design to evaluate feature hierarchies. It has become a focus of research in the field of agricultural plant protection, particularly in the identification and range assessment of pests. The datasets were gathered from the Plant Village collection, which includes pictures of both healthy and diseased plant leaves along with the labels that go with them. Convolutional Neural Networks is a deep learning system that can be used to diagnose diseases using leaf picture inputs (CNN). Various phases of picture analysis are performed until the required patterns are found. The proposed model will be trained and tested on the data using the Mobile Net, Inception V3, and VGG 16 architectures of CNN. Farmers will use the design that produces good accuracy to prevent yield losses and for disease detection.

Keywords: Plant disease detection, Deep learning, Image classification, Convolutional Neural Networks, MobileNet, VGG-16.

1. Introduction

All of the earth's living things are directly reliant on plants. Everyone must make sure that suitable precautions and methodical techniques are taken to identify and study the illnesses that affect plants because they are so important to everyone. The primary food source for all living things, including humans, is plants. Crop yields are reduced as a result of natural disasters, attacks by worms, pests, and insects, and the failure to detect plant diseases in their early stages. Early disease detection and analysis can result in better crop results, which benefits farmers and the agricultural industry. Early disease detection and analysis can result in better crop results, which benefits farmers and the agricultural industry. Since early disease identification requires more time manually, Deep Transfer Learning is used in the implementation of plant disease detection. In order to ensure sustainable growth in the agricultural sector, it is important to promptly ensure the detection of plant diseases and their early treatment. An technique to deep learning (and machine learning) called transfer learning involves moving knowledge from one model to another. By applying transfer learning, we can use all or a portion of a model that has already been trained for another task to address a specific problem. Both in the deep learning and machine learning fields, transfer learning can be employed in a variety of ways.

2. Literature Survey

In paper [1]. The author proposed a memory-efficient deep learning model that uses convolutional neural networks to categorise symptoms of plant diseases. The pepper dataset, which has 99,507 photos and 24 classes, and the plant village dataset, which has 38 crop disease pairs, were both employed by the author. Image preprocessing techniques used by the author included rotation, flipping, cropping, saturation, fluctuation, and lighting. The author employed step-by-step transfer learning to handle the issue of class imbalance in the dataset, preventing biassed training from occurring and producing effective results. CNN was employed by the authors to find the plant diseases. The models are created in CNN using a variety of architectures, including Inception V3, Resnet-50, and VGG-16. On the Pepper dataset, accuracy of 99% and 99.69% are from the plant village dataset

In paper [2]. To identify plant leaf diseases using leaf photos, the author suggested a novel 14-layered deep convolutional neural network (14-DCNN). A dataset of 147,500 photos of 58 different healthy and ill plant leaf classes as well as one class with no leaves was employed by the author. The author employed data augmentation techniques in this because by including certain augmented photographs in the training dataset, they can increase dataset size while decreasing overfitting. BIM, DGCNN, and NST are the augmentation techniques used. When compared to conventional transfer learning techniques, the suggested DCNN model performs more accurately in terms of classification.

In paper [3]. Convolutional neural networks, in particular, are becoming much more significant in recent years for the identification of plant diseases thanks to deep learning. The author's primary goal is to cut back on the number of parameters in order to slow down calculation. In this study, three datasets were employed, and each of them had a sizable amount of photos. The rice plant dataset, cassava plant dataset, and plant village dataset were used. Due to their reduced parameter requirements and ability to address the vanishing gradient problem, the author of this work presented a unique architecture built on ResNet and Inception. When normal convolution is converted to depth-wise and point-wise convolution, the author uses depth-wise separable convolution to produce superior results.

In paper [4]. For the purpose of recognising leaf vein patterns on various photos for illness diagnosis, a deep learning model based on CNN has been developed. The author used an available database with 87,848 images of healthy and diseased plant leaves for the training and testing of the CNN models. For training and testing reasons, the dataset has been divided in an 80:20 ratio by the author. 70300 training photos and 17548 training images. Five CNN fundamental architectures are employed in this paper to identify plant diseases. They are VGG, over feat, AlexNet, AlexNetOWTBn, and Google Net. The average error, success rate, number of epochs, and time consumed were the measures used by the author to compare all five of the basic models. After the assessment, It was found that VGG produced the best outcomes, with an accuracy of 99.53%.

In paper [5]. For the purpose of detecting leaf spots and subsequently identifying diseases, a convolutional neural network model for autonomous plant disease recognition was presented. The author used a dataset from a plant village that comprises a sizable number of photos with uniformly white backgrounds. Because a pre-trained Google Net architecture performs better, the author applied transfer learning to it. Divided into two major groups, the experiment was carried out by the author. The first group is concerned with classifying plant species, and the second group is concerned with identifying diseases. This model, which was developed with the idea of identifying several illnesses on a single leaf, generated successful outcomes. When compared to uncropped source photos, the accuracy was 12 percent greater.

Methodology:

Detecting plant diseases is one of the biggest problems in agriculture. Early disease detection and analysis can result in better crop results, which benefits farmers and the agricultural industry. Deep learning is used in the implementation of plant disease detection since it takes longer to manually identify diseases in their early stages. The author of this paper applied the transfer learning approach. Two primary algorithms, Mobile Net V3 and VGG-16, were employed in this paper. Pepper Data Set and Plant Village Dataset are the datasets that were used. In order to simplify the process of diagnosing and categorising crop diseases, a comprehensive strategy that incorporates a number of tried-and-true techniques is employed in this work. The figure below provides an overview of the suggested methodology.

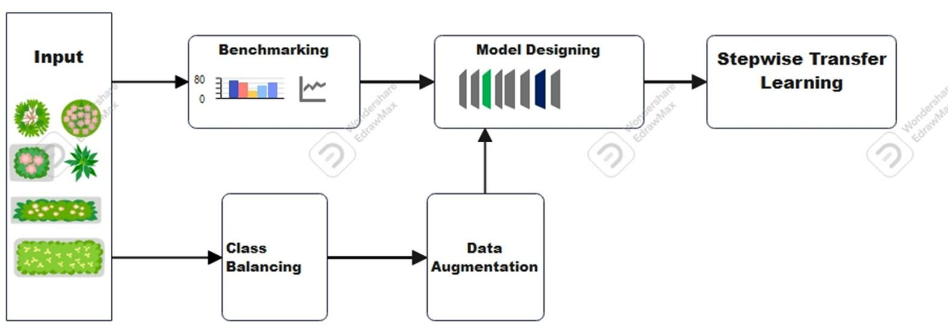

Fig: An overview of proposed methodology

3.1 Mobile Net

The CNN architecture model for Mobile Vision and Image Classification is called MobileNet. Because of this, it is an ideal fit for mobile devices, embedded systems, and PCs with limited computational efficiency or no GPU. They can be expanded upon for segmentation, embeddings, detection, and classification. Depth-wise separable convolutions are used by Mobile Net. When compared to a network with conventional convolutions of the same depth in the nets, it dramatically reduces the number of parameters. Other models exist as well, but MobileNet stands out since it requires relatively little processing resources to operate or use transfer learning

3.2 VGG-16

Visual Geometry Group is a 16-layer Transfer Learning architecture that goes by the name of VGG. It is an algorithm for object detection and classification. It is a well-liked technique for classifying images and is simple to employ with transfer learning. Thirteen convolutional layers, five Max Pooling layers, three Dense layers, and a total of 21 layers make up VGG16, but only sixteen of them are weight layers, also known as learnable parameters layers. The most distinctive feature of VGG16 is that it prioritised convolution layers of a 3x3 filter with stride 1 rather than a large number of hyper-parameters and consistently employed the same padding and maxpool layer of a 2x2 filter with stride 2. There are 64 filters in the Conv-1

Layer, 128 filters in Conv-2, 256 filters in Conv-3, and 512 filters in Conv-4 and Conv-5. A stack of convolutional layers is followed by three Fully-Connected (FC) layers

3.3 DCNN-14

Since DCNN needs more data for an effective training procedure, data augmentation techniques like BIM, DCGAN, and NST are utilised to create new images from the ones already present. Deep Convolution Neural Network (DCNN) 14 is referred called as such because it has 14 layers, including flatten, dropout, and 5 convolution layers, 5 max pooling layers, 2 dense layers, and 5 max layers. First convolution layer receives the input image, first max pool layer is added to minimise the dimension, first max pool layer's output is input to second convolution layer, and so on. In this procedure, the ReLu Activation Function is utilised. After the five convolution layers and the maximum pooling layer, the flatten layer is introduced. It transforms 3-D data into 1-D data. After the flatten layer, the first dense layer is added. This is followed by the dropout layer, which helps prevent overfitting, and the second dense layer, which is the final layer. The 14DCNN model received the photos of plant diseases as input. The name and disease are correctly predicted by the algorithm using the input photographs

4.Results and Discussion

This study compares different plant disease identification algorithms based on accuracy, recall, and precision metrics with a range of input photos. In this study, three distinct configurations were used to train the suggested model. First, there was no transfer of learning; the model was trained entirely from start. The model was then trained using straightforward transfer learning, and ultimately, stepwise transfer learning configuration. The comparison results demonstrate that VGG-16 with Transfer Learning, Mobile Net with Transfer Learning, and Mobile Net with Stepwise Transfer Learning all have lower accuracy, recall, and F1 scores than 14-DCNN. It displayed 99.96% accuracy without any Transfer Learning.

Table-1: Comparison among various methods

Model	Accuracy	Recall	F1-score
VGG-16 with TL	97.86 %	97.82%	97.82%
Mobile Net V3 with TL	98.50%	98.37%	97.12%
Mobile Net V3 with Stepwise TL	99.69%	99.40%	99.62%
14-DCNN	99.96%	99.79%	99.79%

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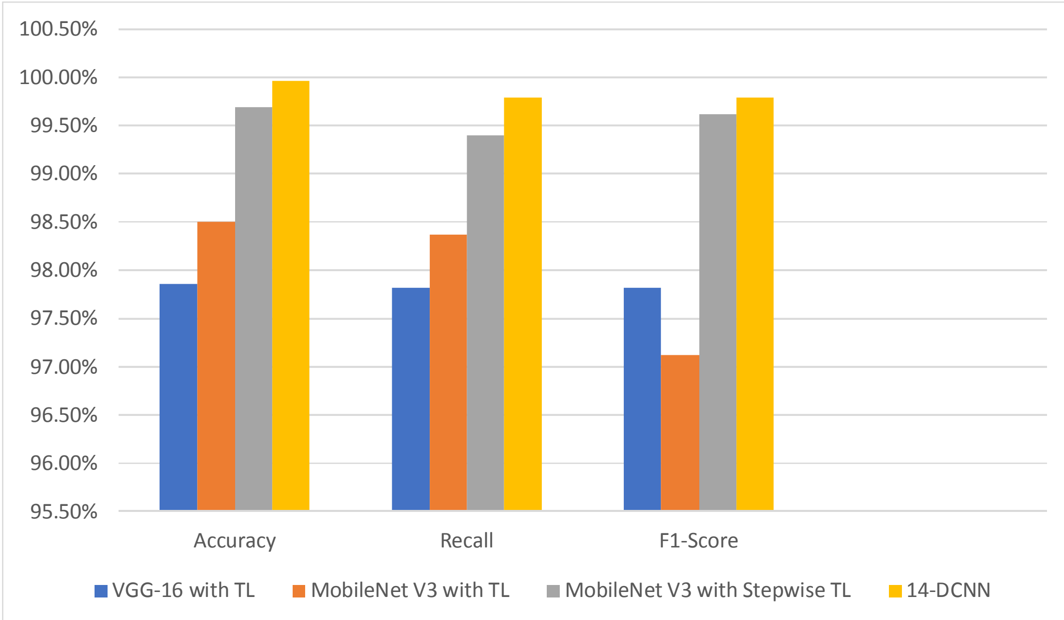

Fig: Graphical representation of various performance metrics

5.Conclusion

The agricultural sector has been a hotbed for research in plant disease detection. Farmers benefit from early plant disease detection. In this research, we proposed some models for plant disease detection because it takes time to detect plant diseases manually. Among all the aforementioned models, 14-DCNN, some were trained without the use of Transfer Learning, while others were trained using Stepwise Transfer Learning. It is ideally suited for plant disease detection since it uses a limited set of trainable parameters and a compact model, which lessens the complexity of the prediction process. It is trained without the use of transfer learning. The proposed 14-DCNN performs better than all previous models.

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