Plant Disease Detection using ResNet

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Abstract:

Deep learning and computer vision have recently emerged as useful methods for the phenotyping of sick plant tissue. The majority of prior research focused on illness categorization based on images. In conventional agricultural procedures, the diagnosis of illnesses affecting rice plants is performed by professionals in a manner that is very subjective, while laboratory testing takes a significant amount of time. As a direct result of this, there is a decrease in agricultural productivity, which results in economic loss for farmers. In order to find a solution to this problem, there is a pressing need to create methods that are quick and accurate in identifying and categorizing illnesses that affect rice plants. In the field of agriculture, the development of image-based automated systems for the categorization of rice plant diseases has become an intriguing and expanding study subject. When it comes to classifying rice plant diseases, color is one of the most crucial factors. Within the scope of this investigation, an image-based method is provided for classifying rice plant diseases based on color characteristics. Deep convolutional neural systems consume recently realized astonishing results in a number of applications, one of which is the classification of tomato plants that have been affected with many illnesses. Deep convolutional neural networks with a variety of residual networks underpin our work. In conclusion, this research study has conducted disease classification based on tomato leaves by employing a pre-trained deep CNN in conjunction with the residual network. The result that ResNet-50 produced demonstrates a remarkable result with an accuracy of 96.35%

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Agriculture stays the most important and vital source of generating national revenue since it is dependent on the quality and quantity of items, particularly crops and plants, produced by a country. The majority of the people who rely on agriculture as their primary source of income are located in India, as shown by a study compiled by the community of the Ministry of Agriculture and Farmers Welfare (MAFW). Losses in agricultural output caused by natural causes including pests, weeds, and illnesses account for 15–25 percent of the total[1].

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***Abstract*—Deep learning and computer vision have recently emerged as useful methods for the phenotyping of sick plant tissue. The majority of prior research focused on illness categorization based on images. In conventional agricultural procedures, the diagnosis of illnesses affecting rice plants is performed by professionals in a manner that is very subjective, while laboratory testing takes a significant amount of time. As a direct result of this, there is a decrease in agricultural productivity, which results in economic loss for farmers. In order to find a solution to this problem, there is a pressing need to create methods that are quick and accurate in identifying and categorizing illnesses that affect rice plants. In the field of agriculture, the development of image-based automated systems for the categorization of rice plant diseases has become an intriguing and expanding study subject. When it comes to classifying rice plant diseases, color is one of the most crucial factors. Within the scope of this investigation, we provided an image-based method for classifying rice plant diseases only based on color characteristics.Deep convolutional neural systemsconsume recently realized astonishing results in a number of applications, one of which is the classification of tomato plants that have been affected with many illnesses. Deep convolutional neural networks with a variety of residual networks underpin our work. In conclusion, we have conducted disease classification on tomato leaves by employing a pre-trained deep CNN in conjunction with the residual network. The result that ResNet-50 produced demonstrates a remarkable result with a level of accuracy of 96.35%**

Keywords—Classification,Resnet-50,CNN,Agriculture.

I. Introduction

Agriculture stays the most important and vital source of generating national revenue since it is dependent on the quality and quantity of items, particularly crops and plants, produced by a country. The majority of the people who rely on agriculture as their primary source of income are located in India, as shown by a study compiled by the community of the Ministry of Agriculture and Farmers Welfare (MAFW). Losses in agricultural output caused by natural causes including pests, weeds, and illnesses account for 15–25 percent of the total[1].

In today's world, controlling diseases and pests is an essential stage in the process of minimising crop losses. The Mediterranean fruit fly (MFF), also known as both the Mediterranean citrus fruit fly, is one of the least destructive pests that may infest agricultural products including citrus fruits. It is also one of the most common. This pest has stayed able to quickly expand over the globe because to its fast reproduction rate, tolerance to mixedclimaticalsituations, absence of natural adversaries, and the availability of more than 350 varieties of hosts (fruits and root vegetable) aimed at it.

This invasive species has a life cycle that ranges from 21 to 30 days in length and could be segmented into four clearly defined phases. The first stage involves the womanlyhover biting into the fruit and placing her seedconfidential of it. The next three stages involve the hatching of the eggs into larvae, which feed on the fruit and cause it to gradually rot as a result of the grubs creating tunnels in the fruit that allow fungi and bacteria to enter the fruit. 3) The larva emerges from the capsule to pupate and then falls to the ground below; 4) The grub completes the developmentpoint in the earth and then emerges after the ground; mating begins after five days[2].

The categorization of plant diseases has been approached using a wide variety of traditional machine learning (ML) methods. In a similar manner, state-of-the-art imaging methods such as hyperspectral and multispectral imaging have also been used for the purpose of identifying plant and leaf diseasesHowever, as a direct result of the advent of deep learning (DL), a number of cutting-edge architectures, including as AlexNet, Visual Geometry Group (VGG), DenseNet, Inception-v4, and ResNet, have shown impressive results for said diagnosis of crop diseases [3].

There have only been a handful of studies done to further enhance the study of plant disease categorization by using a variety of different training methods. In, the presentation of dual well-known DL representations (AlexNet and GoogLeNet) that stayed learned through transfer learning and score methodologies was compared. Both models were trained from scratch. Fine-tuning was used in Reference's implementation of the ResNet, VGG, and Inception-v4 models. DenseNet was also included in this implementation. These methods were used.A further study analysed the differences between the

The remaining parts of this work are structured as described below. In Section 2, go over some fundamental information such as the idea of deep learning, the basis, the framework, the history of model development, model assessment criteria, the datasets on plant leaves disease, and the techniques for data augmentation, etc. In Section 3, we take a look at the scientific work that has been done so far towards the use of deep learning in crop leaf disease identification from a variety of perspectives. The diagnosis

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of plant diseases using just a tiny data sample is the topic of discussion in Section 4. In Section 5, we will go through a few applications of hyper-spectral imaging that may be used in the diagnosis of plant diseases.

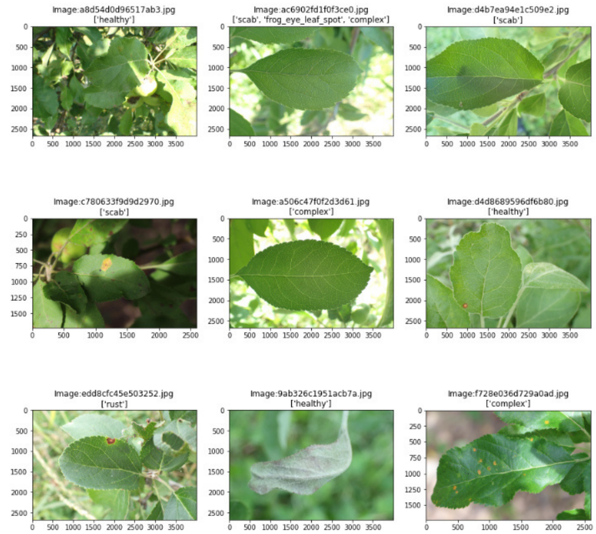

Fig. 1. Different plant leaf diseases

II. RELATED WORK

built an integrated model using an enhanced version of VGG16 and the ResNet-50 network. In order to make improvements to the CNN design, the VGG16 filledassociated layer was dropped, and then it was linked with the following full composed layer in order to minimise the amount of complicated processing required. The input picture size layer of ResNet-50 has been modified to reflect the latest changes. The BAU-agro dataset was used to train this specific Improved CNN architecture model, which was then used to identify agro-crop leaf diseases.

In direction to cutting the specific characteristics of the wheat illnesssigns, the first 7x7 convolutional layer of the ResNet50 network was improved by switching to two 3x3 convolutions, and the softmax layer was replaced with a sigmoid activation function. And obtained an accuracy of 96% using the enhanced ResNet50 network to diagnose the initial three wheat illnesses (septoria, tan spot, and rust), on the balanced dataset[4].

Using the ResNet50 architecture as a foundation, we designed a system that is skilled of recognizing and assessing the level of pressure that is generated by biological agents on coffee leaf tissue. When it came to the categorization of biological stress on coffee leaves, the arrangementrequired an exactness of 95.24%, while it had an accuracy of 86.51% when estimating the intensity of the stress[5].

Our engineers came up with a framework for the video detection of plant diseases and insect pests that was based on deep learning and had a distinctive backbone. This architecture was proposed. This design has the potential to produce a more realistic representation of the quality of video detection in experiments. Tests revealed that the custom backend system was preferable than the VGG16, ResNet50, and ResNet101 backbone methods, as well as YOLOv3, but when came to the recognition of unstructured video footage pertaining to riceRice sheath blight and rice stem borer indicators were readily recognised by the custom-built DCNN backbone, which had remarkable detection sensitivity. This was possible due to the backbone's outstanding detection limit. Furthermore, the frequency of identification was thirty pictures per second[6].

We established a cataloguingstructure for the severity of agricultural illnesses and insect vermin, as well as suggested an enhanced version of the ResNet50 model (CDCNNv2) and integrated it with deep transfer learning. In addition to real-time and totally automated identification of agricultural pests and diseases, the scheme also incorporates a variety of backup services such as advice for anticipation and management as well as treatment recommendations[7].

TABLE I. RECENT WORKS OF PRE TRAINED MODELS

Reference	*Model*	*Dataset*	*Data enhancement*	*Metric*
[8]	VGG, Inception v3	Self-acquired	Rotate, Flip	Average accuracy
[9]	VGG 16 , Inception v3, GooLENEt	Plant Village IPM Bing	Mirroring and arbitrary cropping of the image	Rate of Detection and Accuracy of Classification
[10]	Mask RCNN	Self-acquired	Chunking + traditional	Average accuracy
[11]	ResNet 152, nception v3, Mobile Net	Self-acquired	In order to cut and grayscale, random rotation is used.	The time required to accurately analyses each picture, on average
[12]	VGG 16	Self-acquired plant village	Rotate, Flip	Average accuracy

Can use an exact copy of the PlantVillage dataset, two variants of the MobileNet model have been recommended, and their performances were compared with that of the classic MobileNet model, as well as against that of the AlexNet and VGG technologiesThe findings of a piece of research that offered a feedforward form of DL infrastructure to diagnose diseases in apple leaves were more effective when compared to AlexNet, GoogLeNet, VGG-16, Inception-v3, and other versions of ResNet configurations. This research was conducted to diagnose diseases in immature fruits.

On the other hand, none of the prior research have shown that state-of-the-art DL optimizers may enhance the categorization of plant diseases. Using the lens of comparative research on the plants

III. METHODOLOGY

This section will begin by presenting the overall architecture of the proposed method for this study. Following that, it will present the specific details of the proposed network model. Finally, it will present agriculture the specific details of the ideas and principles that underlie the proposed loss function. Figure 2 illustrates the basic structure of the suggested research methodology for this investigation.

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A. Transfer Learning Algorithm

In order to boost the speed at which the network converges, the authors of this research make use of a transfer learning system that is based on ResNet. Specifically, they move the thin structure of the neural network for the unlabeled data to the cnn architecture for the source task.This had been implemented in order to alleviate the issue of the long training period that the convolutional neural network model demanded from its users.

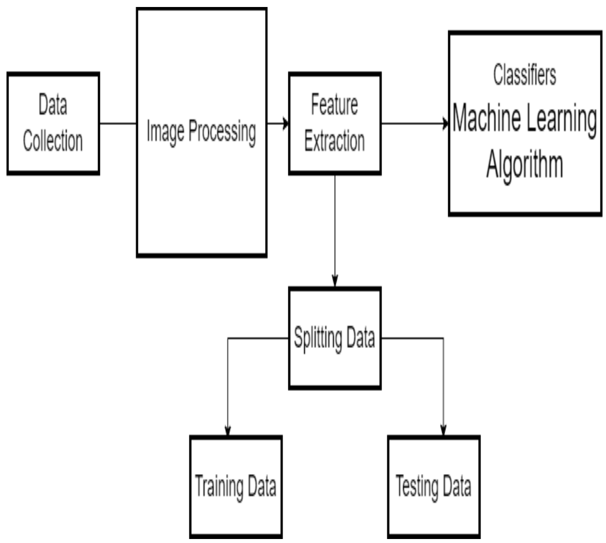

Fig. 2. Proposed Architecture model

In recent years, the renaissance in Deep Learning has led to the development of deeper neural networks. State-of-the-art neural networks have expanded from having just a few layers (like VGG16) to having over one hundred layers. A very deep system's ability to express extremely complicated functions is its key advantage. Additionally, it can learn features at many different levels of abstraction, such as edges in the case of an image (at the lower layers) and extremely complicated features (at the deeper layers). The infamous vanishing gradient is one of the matters that ResNets report. This is unpaid to the detail that when the network is excessively deep, the gradients used to compute the loss function simply drop to zero after a number of chain rule submissions. As a result, there is no learning taking place because the masses'standards are not everefficient.

Resnet rectifies the layers such that they are shown as residual learning functions with reference layer entries. Previously, it had been learning uncited functions and providing the residual learning model.

There are certain shortcut links available in "ResNet" that are designed to bypass one or more of the restrictions listed below. These shortcut connections carry out an identity mapping, and the outputs of those connections are appended at the point where stacked layers terminate. Nevertheless, these short-cut connections do not include any new characteristics and do not make the process more complicated.

IV. RESULTS AND DISCUSSION

The majority of the DL outlines described in the works perform well in terms of detection on the datasets they were designed for, but perform poorly when applied to other datasets, indicating that the model lacks robustness.

Better resilience DL models are therefore required to accommodate the various illness datasets. The PlantVillage dataset was used in the majority of the studies in order to analyse and assess the effectiveness of the DL models. Even though this collection contains a large number of photos of various plant species with their illnesses, the photographs were all shot in a laboratory setting. As a result, it is anticipated that a comprehensive dataset of plant diseases would be established under natural settings.

This is a difficult process with varying degrees of accuracy that takes a lot of time. As a result, we suggested in this work an apple leaf disease diagnosis approach that was low-cost, stable, and had a high level of accuracy. Using the MobileNet model allows us to accomplish this goal. To begin, as compared to a standard deep learning model, this particular model has a LOW COST. This is due to the fact that it is readily deployable on mobile devices.

Second, with the assistance of our algorithm, anybody may complete the inspection of apple leaf diseases in a SUSTAINABLE manner, eliminating the need for qualified professionals. Thirdly, the accuracy of MobileNet is quite comparable to that of other sophisticated deep learning models already in existence. In conclusion, a number of studies aimed at identifying apple leaf diseases have been carried out in order to illustrate how successful our suggested technique is.

ResNet152 and InceptionV3 are two well-known CNN models[13] , and we have evaluated how well they perform in terms of accuracy and efficiency. Apple disease statistics, covering classifications such as rust leaf and Alternaria leaf blotch, were gathered here by agricultural specialists in Shaanxi Province, China.

Since 2012, [14] CNNs that are utilised in the ImageNet dataset have gotten increasingly complicated, which has led to an improvement in accuracy; nevertheless, many models are inefficient when it comes to the amount of computing load they need. The results of the experiments shown that in comparison with the VGG16, ResNet50, and ResNet101 backbone systems [15].

The deep convolutional neural network model that has been created is trained to recognise the four most frequent illnesses that affect apple leaf. The results of the experiments reveal, when the hold-out test set is used, that the suggested illness detection strategy based on the convolutional neural network is successful.

According to the findings of this study, the proposed deep learning model [16] offers an improved method of disease control for apple leaf diseases, boasting both a high level of accuracy and a rapid rate of convergence. Additionally, the proposed image generation technique offers an improved method of disease detection.

As can be seen from Figures 3 and 4, both accuracy and loss occurred throughout the training period, and the rationale for this is inversely proportional to the total number of epochs. The rate of performance improvement is seen in Figure 5. Table I presents a number of different pre-trained models together with the outcomes of an accuracy debate pertaining to an image.

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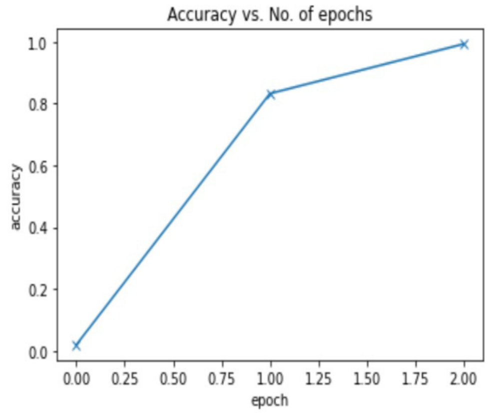

Fig. 3. Accuracy plot

In this section, we offer our implementation in which we explain the operation of "RESNET50" for the aim of detecting and categorising plant illnesses on the leaves. This section is included since it is relevant to the discussion.

We used distinct training and testing packages for each and every methodology. On the test set, each and every detail is presented. For all of our deep learning models, the programming language Python 3.7 and the OpenCV computer vision library were indispensable tools. We utilised the ResNet-50 models to train and evaluate both the original picture as well as the image after image segmentation and extraction so that we could make the model more reliable.

Following a series of experiments, we have determined that 10 iterations of training will result in an accuracy of 94.8 percent for our trained model.

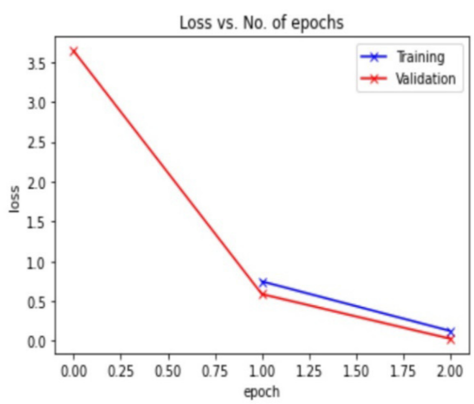

Fig. 4. Loss plot

Then, by using the "Data Augmentation" approach on our own data set in order to increase the accuracy of the model without diminishing the learning efficiency, we are also able to get an accuracy of 97.2%.

Finally, the entire detection performance reaches good accuracy after being implemented using the "ResNet" architecture. The suggested system that we have demonstrates its dependability and speed with an accuracy that is adequate at 98.96%. When compared to the GoogleNet methodology, this indicates an improvement of 1.3%, and when compared to the AlexNet network, this is a 9.5% improvement.

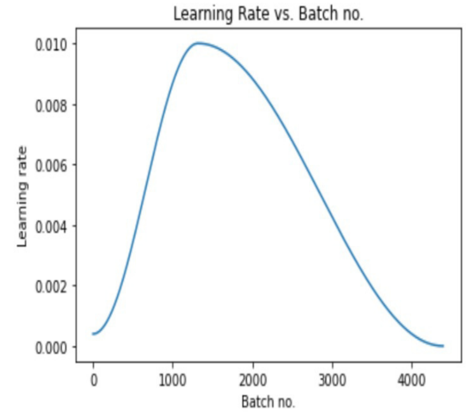

Fig. 5. Learning Rate of Model

V. CONCLUSION

The objective of this investigation is not only to determine whether or not there are sick leaves or healthy leaves present, but also to identify a confidence score that indicates the possibility that there is a proper (true positive) class inside a bounding box.The approach that is utilised in this study to detect and categorise leaf diseases is based on image processing and artificial intelligence learning.In order to achieve effective classification of the apple leaf characteristics, the grey interdependence matrix was used as the feature training. Due to the fact that there were not an excessive amount of dark and bright areas, the segmentation effect was rather excellent, which resulted in a high classification accuracy.

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