Crop disease recognition and diagnosis using ResNet

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Abstract. Crop disease is a serious problem in the agricultural sector. To prevent crop disease we have to detect the disease at an early stage. Various technologies are emerging these days to determine specific diseases in crops. Deep Learning is one of the best approaches to detect crop disease. This research paper includes a deep learning framework to classify between healthy and diseased crops. For image recognition, ResNet was built using Keras applications. It is a deep residual learning approach that was used, as its framework is easy for training networks. Our used dataset consists of 87,354 images of 14 different sets of crops including both healthy and diseased images. The model architecture that was trained gives us an accuracy of 99.53% in finding the diseased crop images successfully. The high success rate of this model makes it very useful and most effective in real life applications. The further expansion of this idea “Crop disease diagnosis using deep learning” will help to contribute towards the operation in real cultivation conditions.

Keywords: Crop disease, ResNet, Keras, Deep Learning, PyTorch.

1 Introduction

Crop disease is the biggest economic threat to farming. Pests and pathogens are responsible for crop diseases, which further leads to a fall in the growth rate of plants. This results in the reduction of the genetic potential of plants which disturbs the growth cycle. In tropical countries, the loss in flora is huge and thus results in an unbalance in biodiversity. Most of the time the precautions taken to reduce the area of damaged crops are not sufficient, as plant pathogen populations are variable in time, space and genotype.

As per the study made by the Food and Agriculture Organization of the United Nations (FAO), there has been a loss of around **35-40%** in crop production globally and this percentage is increasing every year. Generally, bacterias or pathogens which cause crop disease do not affect humans. But a study reported that few pathogens like the *Pepper mild mottlevirus* affect the human immune system.

The first step towards an active solution to this loss in plants is to find out the plant disease or pests in the initial stage. Technically various methods are possible and are being used these days to detect the disease in its early phase. Random forest, KNN, Random tree, Naive Bayes, and Regression are some of the famous methods that give good results in this case. The highest accuracy for detecting plant disease can be achieved by using deep learning algorithms.

In this paper, we are going to use **ResNet** which is one of the successful processes towards computer vision. We will also be using PyTorch as it is one of the most optimized libraries used for deep learning applications. The main aim is to build a convenient model which can distinguish between healthy and diseased crops with the most accuracy.

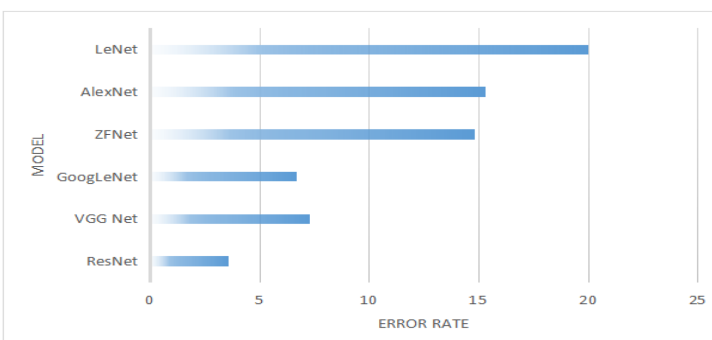


Fig.1. Comparison of ResNet with other models

Figure 1 shows the error rates of different models. ResNet has the lowest error rate amongst all i.e **3.5%**. With such an error rate the model gives the most accurate results.

2 Literature Survey

Muhammad Hammad Saleem in his paper "Plant Disease Detection and Classification by Deep Learning" [1] approached a method using Deep Learning which had a great potential in terms of accuracy. He used deep learning with several visualization techniques to find out the plant disease with the best accuracy. It gives us a proper approach using DL to visualize each part of plant disease.

According to the paper "Plant Disease Detection Using Image Processing" [2] by Sachin D. Khirade, first, we need to observe those patterns seen on the plant. But to manually do this is a very hectic task and thus image processing comes into play. He developed his model using four different techniques as discussed in the paper.

Mr. P V Vinod in his paper "Plant Disease Detection Using Machine Learning" [3] made an approach using the Random Forest technique to detect between healthy and diseased plants. He used a different method for a feature extraction known as the HOG technique.

Konstantinos Ferentinos in his paper "Deep learning models for plant disease detection and diagnosis" [4] discussed a CNN approach to detect plant disease. The success rate of his model was around 99% and easily usable.

In this paper "Wheat disease detection using image processing'', [5] Gaikwad introduced a new software solution that can classify between healthy and diseased leaves. For classification, he used a neural network classifier.

According to the paper " Using deep learning for image-based plant disease detection" [6] by Mohanty, he trained a deep convolutional network which was used to identify 14 crop species. The model that he made was found to be working extensively well in detecting plant disease through unique software in smartphones.

In the paper "Plant leaf disease detection and classification based on CNN with LVQ algorithm", [7] by Melike Sardogan wrote an approach using the Learning Vector Quantization algorithm.

According to the paper “Study of digital image processing techniques for leaf disease detection and classification”, [8] by Vinay Kumar, he discussed a comprehensive approach to detect plant disease on the basis of state of art techniques.
In the paper “Plant leaf disease detection and classification using image processing” [9], Yin Min Oo proposed a methodology in which he analyzed leaf disease with digital image processing techniques.
The paper “Automated leaf disease detection in different crop species through image features analysis and One-Class Classifiers”, [10] by D.Moshou, introduced a one-class classifier for the feature extraction. His model achieved a success rate of 95 percent.
According to the paper “Leaf disease detection: feature extraction with K-means clustering and classification with ANN”, [11] by kumari C U, she used a neural network classifier to identify the plant disease. Her model got an average accuracy of 92.5 %.
In the paper “Automated image capturing system for deep learning-based tomato plant leaf disease detection and recognition”, [12] Rober G, represented a system using CNN to identify three multiple diseases. He trained a unique model F-RCNN which gave an accuracy of around 95.75%.

3 Dataset

The dataset that is used is created with offline augmentation. The dataset used in the research consists of rgb images of healthy and diseased leaves both, which counts to 87,000 approx. Those rgb images were further divided into 38 different sets. The total dataset has a training and validation ratio of 80/20. The dataset consists of 14 unique variety plant leaf images both healthy and diseased.

4 System Overview

From **figure 2** (below) it can be observed that data collection is the first step. As said earlier, the data of crop images were stored using offline augmentation. The next step is data preparation in which datasets were loaded using torch libraries. After successfully preparing the data, the model was built. The model that was built for recognition was ResNet using Keras. The next step was to train the model, in this we used a rate scheduler that changed the rate of learning after every batch of training.

And then the model was ready to test and predict. Now let's see the major steps in brief.

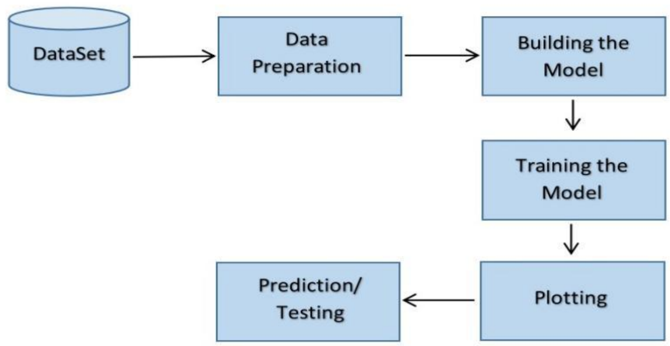


Fig.2. Structure of the system

4.1 Data Preparation

In the data preparation part, one of the optimized libraries of deep learning that is **PyTorch** was used [14-17]. There are other deep learning frameworks but Pytorch is more optimized and more flexible as it provides a high-level feature to define a tensor class in order to store and work on a large dataset of multidimensional arrays. Pytorch is a library used for Deep learning applications. As it uses GPUs and CPUs it has a rich set of powerful APIs to extend its libraries.

4.2 Building the model

ResNet (Residual Network) is one of the most powerful and an easy-to-use model which is quite popular in computer vision tasks. **ResNet** was used to build the model architecture to detect crop disease. The major importance of Resnet is that it allows training extremely deep neural networks with **150+ layers** successfully and prevents vanishing gradient problems. Its main goal is to build a deeper neural network as it provides multiple layers which gradually reduces the error percentage when compared with neural networks with plain layers. ResNet is quite more suitable to use as it has an error rate of only 3.57%. ResNet is capable of detecting important features in an image and thus external image processing techniques are not required. As Resnet gives the feature of reducing the number of parameters without losing the actual quality of the model, the model becomes more understandable. The mechanism of ResNet is different from other neural networks as every layer of ResNet passes into the next layer and to the further layers directly. This feature of ResNet makes it better and more popular to use as it avoids overfitting conditions.

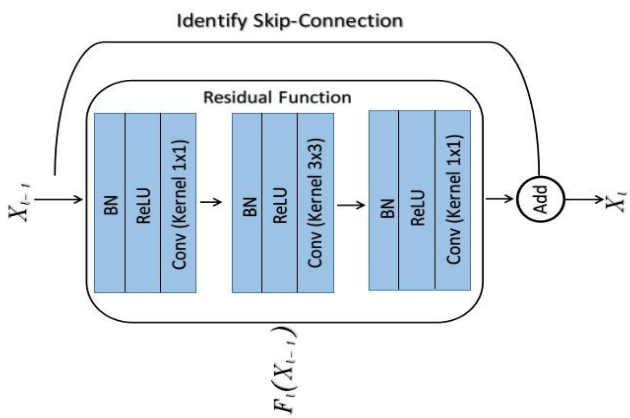


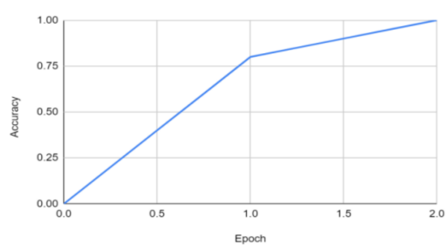
Fig.3. Residual Block

4.3 Training the model

Now that the model has been built, it's time to execute the model. The model was trained and fitted using the evaluate function (for the validation phase) and **fit_one_cycle** function for the entire training process. For training the model, a **learning rate scheduler** was used, which changes the rate of learning the model after every batch of training. The one strategy that was used for varying the learning rate is the **"One cycle learning rate policy"**. This strategy is very efficient as it starts varying with a low learning rate and then increases batch by batch to a higher rate with epochs around 30 percent and then again gradually decreases to a very low value of epoch. In order to prevent the weights from becoming too large, an additional term was used i.e **loss function**, this is a regularization technique known as **Weight Decay**. Gradient Clipping helps to limit the values of gradients to a small range which prevents undesirable changes in parameters. The training occurred in a total of 20 epochs and each epoch was split into diff batches.

5 Results and Explanation

The last step is results, where we consider our model ready for practical applications. After completion, the model is capable of drawing its own conclusion on the basis of its datasets and training. This step is important because this gives us the end result of the whole model. The imported dataset contained crop images of a lot of varieties, making the dataset huge. The ResNet model executed well in unit time as the decision-making process is faster.



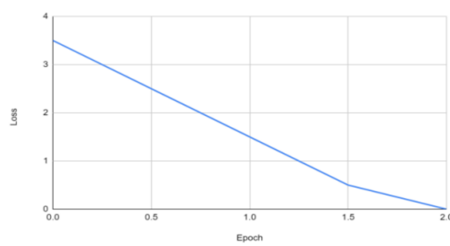


Fig.4. Validation Accuracy**Fig.5.** Validation Loss

Figure 4 shows the validation accuracy i.e how the model is able to classify the set of pictures given in the validation dataset. And the validation loss as shown in **figure 5**, shows how well the model fits in the data. As per the research, the validation accuracy found in the first epoch was **0.8319** and the validation accuracy in the last epoch was increased to **0.9953**. After the first epoch, the value of validation loss was found to be **0.5865** and till the last epoch, it decreased to **0.0269**. This shows how the ResNet model overcomes overfitting conditions.

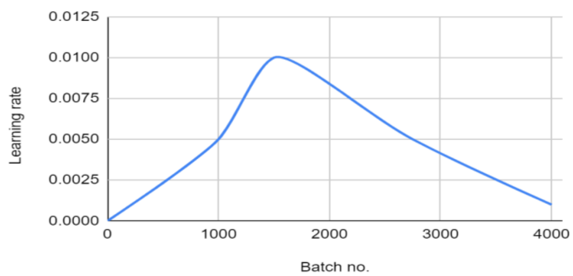


Fig.6. Learning Rate Vs Batch no.

Figure 6, shows the learning rate of the model i.e hyper-parameter that controls the weight of the ResNet. From the research, as there were more epochs, the learning rate found was very quick.

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Epoch [0], last_lr: 0.00812, train_loss: 0.7466, val_loss: 0.5865, val_acc: 0.8319
Epoch [1], last_lr: 0.00000, train_loss: 0.1248, val_loss: 0.0269, val_acc: 0.9953
CPU times: user 11min 16s, sys: 7min 13s, total: 18min 30s
Wall time: 19min 53s
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The accuracy of the ResNet model was found to be **99.53%** which is the best till now. As earlier said, ResNet properly handles the vanishing gradient problem which gives such an accurate result.

6 Conclusion

The paper deals with 14 unique images of plant leaves which is in a total of 87 thousand approx. PyTorch was used due to its flexibility and computational power. Pytorch provides us with the easiest and best way to print model summaries. For the detection of plants, disease authors have used one of the best models known as residual neural network (ResNet) which gives us the highest accuracy that is **99.53** percent. ResNet gives us the lowest error rate 3.5% when compared with other models like AlexNet, GoogLeNet, etc. The higher accuracy was achieved because ResNet's are different in their approach to the forward propagation step. Each ResNet block sends the error to the following block which acts on the mechanism of self-correction.

As it is observed, from the result and explanation of the accuracy versus a number of epoch graphs it can be concluded that after each epoch the accuracy of the system is increasing drastically. Thus it can be concluded that the model can accurately predict crop disease at an early stage and prevent it from spreading further.

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