Plant Disease Classification using CNN and DenseNet, a Comparative Study

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Abstract - *This study focuses on the classification of different types of plant diseases using deep learning algorithms like DenseNet, CNN. Identifying the Plant disease is one of the major hurdles in the field of agriculture faced by farmers all around the world. In this study, classification is carried based on the properties of the leaf, like the color, shape, etc for segregating the diseases into different varieties like Healthy, Bacterial spot, Leaf Mould. We utilized New Village dataset for training the model and for evaluating the output. Essentially comparing the two popular Deep Learning Algorithms i.e., Convolutional Neural Network (CNN) and DenseNet calculating the proportion by which each algorithm classifies the disease type. Finally, the disease classification was based on these 38 different types of classes with an accuracy of about 95% in DenseNet.*

1. INTRODUCTION

In today's technologically advanced world, everything is becoming automated with the intervention of various advancements in their respective fields. These advancements not only focused on manufacturing processes but also on supporting tasks [6]. For instance, in the last ten years, more and more AI robots have been introduced and it started to replace the human labor in the workspace in big time, as these robots are far cheaper to build and they don't require the expenses like hiring, training and paying the associated person, more and more companies are moving towards automation. In the field of agriculture, for instance, the advancements in various domains made this a successful venture than ever before. Numerous advancements like fertilizers, pesticides have made the harvesting time to an all-time low. After the advent of tractors and motor pumps, time and labour work has been reduced drastically. However, food security remains threatened by a number of factors including climate change and other environmental factors [5]. Inculcating Deep Learning algorithms into Agriculture has gained traction over the last 2 decades. With algorithms becoming much more sophisticated compared to the past, Bright minds all over the world are finding ways to implement these algorithms into every possible domain. Agriculture is one area where machine learning engineers are always interested to apply their specialization.

The present conventional techniques in humans by visual inspection make it impossible to categorize plant diseases. Advances in computer vision models offer fast, normalized, and accurate answers to these problems. So, utilizing machine learning and deep learning algorithms for plant disease classification can be a major support for those involved in agriculture. The image classification of plant disease is an arduous process as it contains a variety of challenges like the presence of an extensive range of visual characteristics, the possibility of multiple simultaneous disorders in a single plant [2].

2. LITERATURE SURVEY

The paper focuses on studying the characteristics of Convolutional Neural Networks in classifying plant disease images with image augmentation, resizing, and the major types of background removal process (positive, negative, and mixed) and comparing the results with the deep learning model trained with original images through transfer learning. The results observed with and without background have a significant change in the accuracy because the CNN is also using background information to perform the classification, which should not happen but it is an unavoidable consequence if the training dataset is very small [1].

This paper [9] explains the new ways to classify the diseases in leaves using Convolutional Neural Network (CNN) and built a model with GoogleNet. They made two models by varying the depth of the network. To reduce the number of parameters they used the VGGNet model which was developed by Oxford University. By factorizing the convolutional filter, they could reduce the number of parameters which helped them to create a model with the deep network using several small layers.

There are many deep learning models exclusively built for image detection, segmentation, classification like ResNet, GoogleNet, SegNet since the inception of AlexNet in 2012. These deep learning models with varying number of layers, parameters, and accuracy were initially implemented for the detection of tomato leaf diseases. In spite of the evolution of deep learning models and their increasing accuracy, the paper signifies that the adaptation of these models over time in the detection of plant diseases, since the severity of plant diseases changes with time [10].

It also discusses that the images captured and tested with the model should be classified correctly since the

PlantVillage dataset contains images of simple/plain background. The classification accuracy should be good in a real-time environment regardless of background or illumination.

3. NEURAL NETWORKS

The concept of Deep Learning has evolved with the advent of neural networks. The Neural network is inspired by the neurons in the human brain. Artificial Neural networks can be defined as the interconnection of complex neurons that can compute a set of values as inputs through an objective function and thereby produce the desired output.

Stacked neural networks commonly known as Deep learning consist of a network of several layers, called nodes. A node is a place where the actual mathematical computations take place. These nodes combine the input from the data with their respective coefficients or weights, which can either amplify or dampen the input signal. These input weights are then summed and are passed to the nodes activation function to determine whether the signal should progress if so to what extent it should through the network to acquire the final output, i.e., classification.

Each independent node is considered as its own regression model, composed of input data, weights, a bias, and an output.

$$\text{output} = f(x) = \begin{cases} 1 \text{ if } \sum w_1 x_1 + b \geq 0 \\ 0 \text{ if } \sum w_1 x_1 + b < 0 \end{cases}$$

Broad classification of neural networks:

- Convolutional Neural Networks (CNN)
- Recurrent Neural Networks (RNN)

Convolutional neural networks (CNNs) are usually utilized for image recognition, pattern recognition, and computer vision. These networks use principles from linear algebra, particularly matrix multiplication, to identify patterns within an image.

Recurrent neural networks (RNNs) are discerned by their feedback loops. These learning algorithms are primarily leveraged when using time-series data to make predictions about future outcomes, such as sales forecasting or stock market predictions.

3.1 Convolutional Neural Networks (CNN)

The Convolutional Neural Network abbreviated as CNN is one of the many Deep Learning algorithms available in the market. It takes in an image, assigns the weights or biases, and classifies them apart from one other. The objectives of using CNN are to classify images, cluster those images by similarities, and then perform object recognition. There are four layers constituting CNN.

First, is the convolutional layer which is the core of the whole algorithm and does the bulk of work required. Data or imaged is convolved using filters or kernels. Filters are small units that we apply across the data through a sliding window.

The second layer is known as the Activation layer, here we apply the rectifier function i.e., ReLU (Rectified Linear Unit) to improve non-linearity in the CNN working.

Third, is Pooling Layer, which is helpful to down sample features in the image. It is used in every layer. There are few hyperparameters for this layer.

- Dimension of spatial extent
- Stride

3.2 DenseNet 201

Many researchers ignore the fact that CNN requires the input images to be in a particular manner for the algorithm to be efficient in its working. It required these input images in high quality with a white background to be effective. Even though few studies used images close to reality, they miss out on unforeseen consequences.

To overcome this disparity DenseNet 201 was employed to minimize error and maximize the performance. DenseNet is proposed as one of the best performers in image classification of popular datasets such as CIFAR-10, ImageNet, etc. DenseNet uses a simple pattern for connecting layers to each other directly in a feed-forward pattern, that is each layer consists of several additional inputs from previous layers and transmits its own feature maps to subsequent layers.

4. DATASET ANALYSIS

In order to perform classification, we used the New Plant village Dataset which is a hugely popular dataset available, we download it from Kaggle which is a crowd-sourced and open-source platform used by data scientists all over the world where they get trained, challenged to solve numerous problems. The New PlantVillage dataset consists of 54306 images of plant leaves distributed over 38 different species and types of disease [3]. The images are then split in the ratio as train and test sets. We then resized every image into 256 X 256 pixels to perform model predictions on these images.

5. PROPOSED METHOD

Plants are susceptible to various diseases. By using deep learning algorithms, we are not only detecting but also classifying the type of disease a plant leaf is affected with. Deep learning is an active research field in image classification and computer vision. Convolutional Neural Networks(CNN) consists of an input and an output layer, as well as multiple hidden layers. These hidden layers normally consist of convolutional layers, pooling layers, fully connected layers, and in some cases Softmax layer [7]. We used a famous dataset known as New PlantVillage which consists of 38 disease classes of various plants leaves [8]. Since Neural networks are capable of classification of images, we used them to train our deep learning model which not only detects but also is so efficient. CNN is the most popular neural network model for image classification, as it is not a pre-trained model we trained the model with 6 layers deep. Using ImageDataGenerator we expand the size of the dataset by augmenting the images through various parameters for the transformation of the image.

While the results were promising, we looked for alternatives and found DenseNet201 which is a pre-trained model which consists of 201 layers compared to 6 in CNN, and by a process known as Transfer Learning, we re-trained the Densenet201 model by augmenting images, resized them to 256X256 size. The results were much more promising. Our main objective was to compare the performance of both models and find out which one was more accurate and efficient.

For the implementation of these models, the background of the images is considered to evaluate the performance of the model for better accuracy. The selected datasets consist of plain background which is not realistic in practical application [4].

6. PERFORMANCE ANALYSIS

6.1 Convolutional Neural Network (CNN)

The matrix shown below gives the interactive heatmap of the confusion matrix between predictions and test images. The matrix illustrates the first four classes out of 38 classes, to make the values legible. The confusion matrix is used to make the summary of the prediction in a graphical way. It compares actual test images with predictions made by the model after training and running the test images through CNN. Rows represent the predicted class, while columns represent the actual test values. From the table it is evident that model predictions are almost accurate, which is indicated by the intensity of the Green color, i.e., the more intense the color more accurate is the prediction. The intensity level can be viewed on the right side.

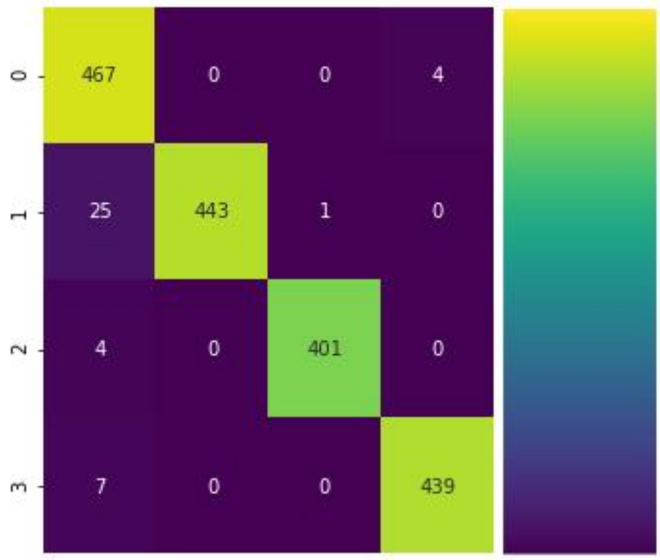
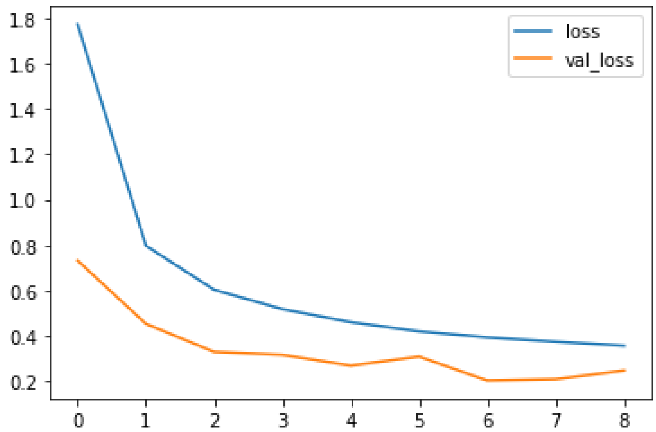


Chart -1: CNN confusion matrix

The graph illustrates the plot between Loss and Validation Loss of CNN model training. We used 10 epochs and patience as 2. While in the beginning, the Loss is very high around 1.8, validation loss is below 0.8, during training, after each epoch, both loss and validation loss comes down. During the 4th epoch, there was a slight increase in Val loss but it comes down again in the next epoch, the training still continued as we specified patience as 2. After the 6th epoch the Val loss begins to rise, model initiates early stopping.



6.2 DenseNet201

The matrix shown below gives the interactive heatmap of the confusion matrix between predictions and test images. The matrix illustrates the first four classes out of 38 classes, to make the values legible. The confusion matrix is used to make the summary of the prediction in a graphical way. It compares actual test images with predictions made by the model after training and running the test images through the DenseNet 201. Rows represent the predicted class, while columns represent the actual test values. From the table it is evident that model predictions are almost accurate, which is indicated by the intensity of the Green color, i.e., the more intense the color more accurate is the prediction. The intensity level can be viewed on the right side.

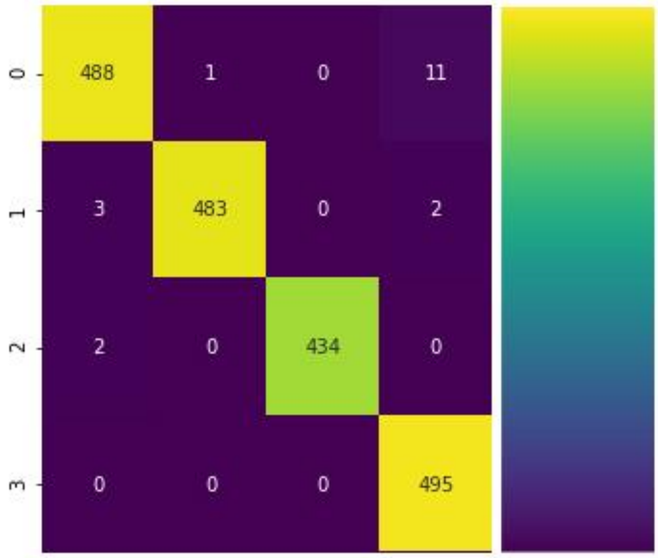
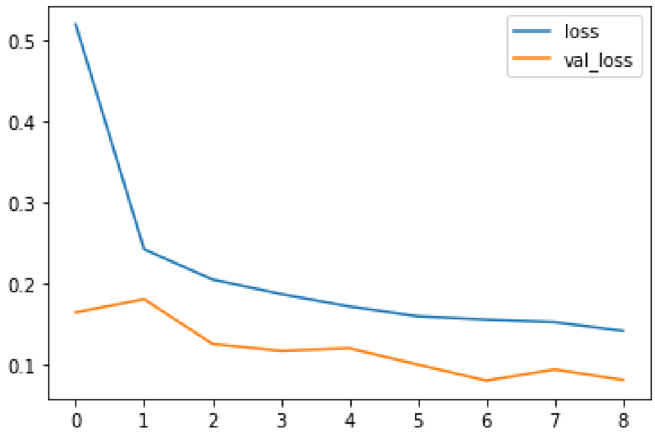


Fig -1: DenseNet201 confusion matrix

The graph illustrates the plot between Loss and Validation Loss of DenseNet model training. We used 10 epochs and patience as 2. While in the beginning, the Loss is very high around 1.8, validation loss is below 0.8, during training, after each epoch, both loss and validation loss comes down. During the 4th epoch, there was a slight increase in Val loss but it comes down again in the next epoch, the training still continued as we specified patience as 2. After the 6th epoch the validation loss begins to rise, model initiates early stopping.



7. CONCLUSIONS

In this paper, we have done an investigation using deep learning concepts such as convolutional neural networks and transfer learning and studied the impact on how deep learning models can help in plant pathology. The study was carried by using the popular New Plant Village dataset and two different types of convolutional neural networks, one is basic CNN built from scratch and another is a pre-trained model called Densenet201. It is evident that Densenet201 performs better in classifying different types of plant diseases in most of the scenarios than a basic CNN. In the training of both networks, image augmentation techniques were implemented to improve the classification accuracy to make it adaptive in different scenarios.

The shortcoming of our model is dealing with the background of the image to be predicted since images with constant or white backgrounds are predicted accurately than images with complex backgrounds. Our goal is to make image augmentation work better in eliminating the negative effects of having complex backgrounds in test images and to develop a mobile application that can help users predict plant diseases from any place.

8. REFERENCES

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