Analysis of Deep learning algorithms for Plant Leaf Disease Detection

Name	ID
Subash Jayanthi Suresh	A20541072
Vijay Marimuthu	A20546262

Abstract

Tomatoes hold a place of primary importance in Indian agriculture, making the timely identification of plant diseases crucial for farmers and agronomists alike. Traditional methods such as visual inspection are infrequently used due to their limitations in accuracy and speed. This project outlines a method for detecting diseases in tomato foliage utilizing Convolutional Neural Networks (CNNs), a subset of deep neural networks. Initially, the tomato leaf dataset is curated and prepared for the detection process. The technique of transfer learning is employed by importing a pretrained ResNet-50 model and tailoring it to our specific classification needs. To refine the ResNet model's performance and align the results more closely with the actual disease manifestation, data augmentation strategies are applied. With these enhancements, a tomato leaf disease detection system has been created using the PyTorch framework, which operates on the principles of deep CNNs. Subsequently, a testing dataset undergoes evaluation to validate the model's effectiveness, leveraging the learned parameters of the ResNet 50 model.This model aims to accurately classify the six most common diseases affecting tomato crops. Data augmentation has been introduced to increase the data set to 4 times the actual data and the model has shown an accuracy of 91.63%. We also applied the AlexNet model to the tomato dataset and found that ResNet 50 was outperformed by AlexNet. The two models now include a new feature: when it predicts a leaf to be diseased, it will guide the user to a website providing information on the disease's description and potential cures. Additionally, an explainability method called Shapley has been implemented for both models.

INTRODUCTION

Plant diseases can have profound impacts on agricultural productivity, affecting social, economic, and ecological dynamics, particularly in agrarian societies like India. Tomatoes, being a staple crop in the region, necessitate prompt disease detection to bolster cultivation and mitigate potential losses. Effective disease management hinges on the early identification and natural treatment of such plant ailments. Deep learning has eclipsed traditional machine learning in terms of accuracy when handling large datasets, due to its ability to deliver quick and efficient results without extensive preprocessing. In standard image classification tasks, machine learning requires initial image preprocessing, where images may be transformed into grayscale or color schemes like RGB. For grayscale images, a single-channel, 2D matrix or rank-2 tensor is utilized, whereas for RGB, a combination of channels creates a 3D matrix, known as a rank-3 tensor. These datasets are typically normalized based on their mean and standard deviation. The approach in question leverages a deep learning technique inclusive of a built-in preprocessing phase, which encompasses transformation and augmentation processes. Such techniques enhance the model's ability to generalize, reducing overfitting risks. Additionally, the implementation of transfer learning further refines the model's performance, offering more nuanced optimization choices to achieve the desired outcomes. The fine-tuned ResNet model demonstrated an impressive 91.63% accuracy rate. Utilizing the pretrained ResNet 50 architecture, which features 50 layers, the model retains the activation of the initial 49 layers while modifying only the final layer to suit the task. This configuration has yielded satisfactory outcomes with reduced training and parameter-tuning duration.

DISEASE THREAT

Some of the common diseases found in the leaves that reduce the yield are Bacterial spot, Early blight, Yellow leaf curl virus, Septoria leaf spot and Tomato mosaic virus.

Early Blight

This is known to be a common disease caused by the fungi Alternaria Tomatophila and A. Solani in tomatoes present on the foliage which will occur at any stage of the tomato crop growth cycle. This fungus attacks on the foliage which causes leaf spots 4 and blight. These two diseases can be seen as small and black lesions found in the aged foliage, as time these spots enlarges. The tissues which are present around the spot may turn yellow. Higher temperatures and the humidity pave the way to kill foliage and thereby causing a spread.
Treatment can be done using more resistant or tolerable tomato cultivars for the leaves in an effective manner. Using rotation of crop method, eliminating weeds, spacing crops in a contactless manner, mulching the plants, fertilizing properly, not wetting tomato crops with the irrigation water, and keeping the tomato crops growing rapidly keeps them protected from diseases. Trimming the plant is also necessary and eliminating the infected parts is to be done periodically.

Fig 1: Early Blight

Septoria Leaf Spot

This disease is considered a destructive one mainly spotted in the foliage, petioles and stems. Septoria leaf spot is caused by the fungus Septoria Lycopersici. Infection usually starts in the leaves present near the ground, after the crop begins to develop fruit. Number of small, circular spots with dark colored borders surrounding a beige-colored middle seen on the aged leaves. Small black specks, which are known to be spore-producing entities, can be visually identified in the middle of the spots. Intense spotted leaves turn yellow in color, die and fall off the plant. The above-mentioned fungus is most active in 68 to 77° F temperature. when the humidity tends to go high, and when rainfall occurs, or the overhead irrigation system drenches the plants. Defoliation affects, and the plant gets weakened, decreases the size and quality of the fruit produced.

Fig 2: Septoria Leaf Spot

Bacterial Spot

This disease is caused by the bacterium Xanthomonas Vesicatoria, which affects green but red tomatoes are not affected. This disease is mostly seen during wet seasons. This disease damages leaf and fruit, this intern results in reduction in the yields and defoliation. The symptoms include many small, angular to irregularly shaped, spots seen like water soaked on the foliage and raised to scabby spots which occur on the fruits. The middle part dries out and get teared frequently. Treatment can be done by sowing certified disease-free seed and planting disease free plants. Wherever peppers or tomatoes were planted during the previous year those areas to be avoided. Avoid overhead watering by using drip and avoid furrow irrigation. All the diseases plants are to be removed. Air circulation is needed for the prune plants.

Fig 3: Bacterial Spot

Tomato Yellow Leaf Curl Virus

TYLCV is not considered a seed-borne but this disease is transmitted by whiteflies. This disease is said to cause more damage to fruit yield in tomatoes. Whiteflies bring the disease into the garden from affected weeds nearby, such as various nightshades and jimsonweed. After infection, symptoms are not shown for as long as 2 – 3 weeks. Symptoms in tomato plants include upward curling of leaves, leaf margins turning yellow in color, smaller leaves than normal leaf, stunting of the crop, and dropping of flowers. If tomato plants are said to be infected in their early stage, there may be no fruit formation. Treatment for this can be removal of plants showing the initial symptoms mentioned above. Pulled out infected plants must be bagged at that moment to prevent the spread of the whiteflies feeding on the affected plants .

Fig 4: Tomato yellow leaf curl virus

Tomato mosaic virus

The disease is distinguished by light and day green colored mottling on the foliage and this disease often seen along with falling of leaves in its tender stage on normal summer days when tomato crops first become affected. We can notice that the leaflets are distorting, and they are tiny when compared to normal. We can notice plant stunting. The virus is spread when it contacts infected cloth, hands of the works, tools and implements. Treatment can include selecting seeds from plants which are not affected. Soaking of the seeds in Trisodium Phosphate a day before sowing. Then the seeds are to be dry in the shade and rinsed properly. Best way is to remove the infected crop from the field.

Fig 5: Tomato mosaic virus

Dataset:

Datasets are required for all processes in the project. A data set with a strength of 9,801 images are collected from the repository of Plant village. Tomato diseases which are used as datasets are Bacterial spot, Early blight, Tomato yellow leaf curl virus, Septoria leaf spot, Tomato mosaic virus. The healthy leaf is also included as one of the classes in the five classes of disease. Datasets are divided into 70% for training and 30% for testing.

Data augmentation:

The most important factor of this work is to train the model of the network by extracting features that can differentiate between classes. Therefore, Data augmented images have a high chance of extracting appropriate features . Pytorch provides a very useful library called (torchvision.transforms) that contains many methods which help in the process of data augmentation. In the proposed work, three methods have been implemented namely, Scaling (Random Resize), Rotation (Random Rotation) Scaling and Rotation (Random Resize Rotation) .The overfitting problem occurs due to random noise and these problems can be overcome by data augmentation. After increasing the leaf image datasets through data augmentation, the model gets to adapt in as many random patterns as possible. This avoids the problem of overfitting and improves the model .The data augmentation technique is implemented over 9,801 training images with the image size of (224*224) and augmented to 39,204 images.

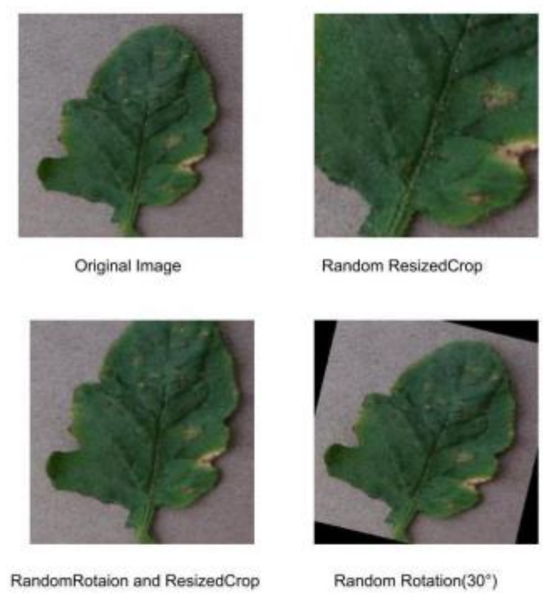


Fig 6: Leaf images after data augmentation for Bacterial Spot

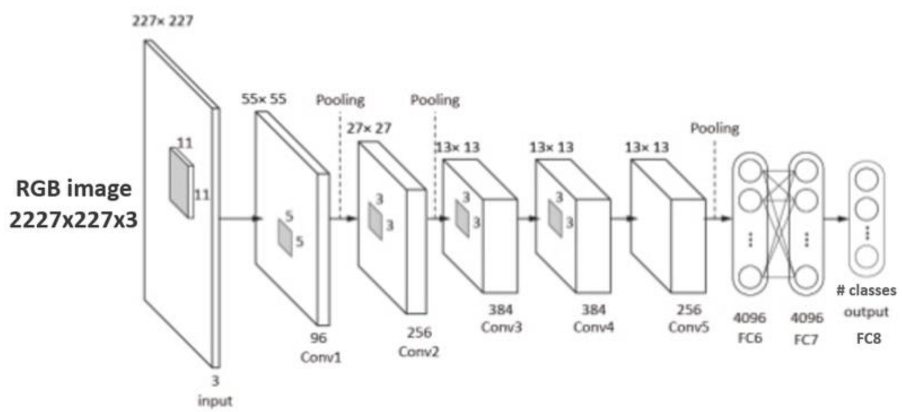
WHY WE CHOSE RESNET AND ALEXNET?

We wanted the following requirements to be satisfied by our models for our implementation,

- Transfer Learning: We wanted a model that was pretrained and has the capabilities to be fine tuned for our needs so that we could reduce the training time and improve performance.
- Deep Architecture: We wanted a deep architecture so that our models can extract more features accurately and ResNET was one of the popular choices for that with 50 layers that allows it to learn complex features from images.
- Accuracy: We wanted a model that is accurate for the given use case and ResNet was a popular choice for this.

The above reasons were behind our selection of ResNet and ALEXNET. While the results in the upcoming slides show that ALEXNET outperforms RESNET, both are equally good and based on the dataset and complexity the results might be different.

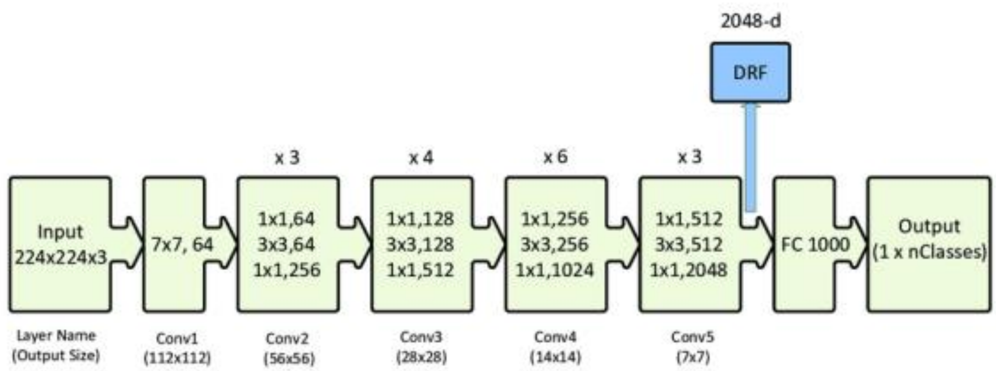
AlexNET MODEL ARCHITECTURE



The image illustrates the architecture of AlexNet, a groundbreaking deep learning model that significantly advanced the field of computer vision. Starting with an input of a 227x227 pixel RGB image, the model applies a series of convolutional layers, each followed by max pooling. The first convolutional layer filters the image with 96 different kernels, producing feature maps which are then downsampled through pooling. This process is repeated through several convolutional layers, each extracting more complex features.

After the final pooling layer, the data is flattened and passed through three fully connected layers, with the first two having 4096 neurons each. The final layer, FC8, outputs the predictions for the number of classes the model is trained to identify. Key features of AlexNet include the use of ReLU activation functions for faster convergence and dropout in the fully connected layers to combat overfitting. This structure allowed AlexNet to achieve remarkable accuracy on the ImageNet challenge and set the standard for many CNNs that followed.

RESNET-50 MODEL ARCHITECTURE



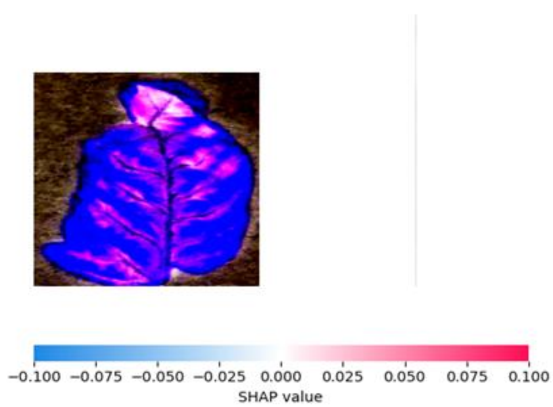
The image depicts a simplified representation of a ResNet (Residual Network) architecture, specifically designed to handle very deep networks. Starting with an input of a 224x224 pixel RGB image, the network employs a series of convolutional blocks. Each block has multiple convolutional layers with small filters (3x3), and the number of filters increases with the depth of the network, beginning with 64 and doubling in each subsequent block.
One of the defining features of ResNet is the use of shortcut connections that bypass one or more layers. These connections perform identity mapping, and their outputs are added to the outputs of the stacked layers, effectively allowing the network to learn residual functions with reference to the layer inputs. This alleviates the vanishing gradient problem and enables the training of very deep networks.
In this particular ResNet configuration, the convolutions are followed by a global average pooling layer, which reduces the spatial dimensions to 1x1, preserving the depth (number of filters). The final output is processed by a fully connected layer (FC) that translates the deep features into class scores for classification tasks.
The image also shows a block labeled "DRF," which is not standard in typical ResNet descriptions and might refer to a domain-specific feature or a custom modification to the standard architecture. Normally, the output of the last ResNet block would connect directly to the final fully connected layer for classification. The model's ability to train effectively even with a large number of layers is what made ResNet a milestone in deep learning for computer vision.

Shapley Explainability Method

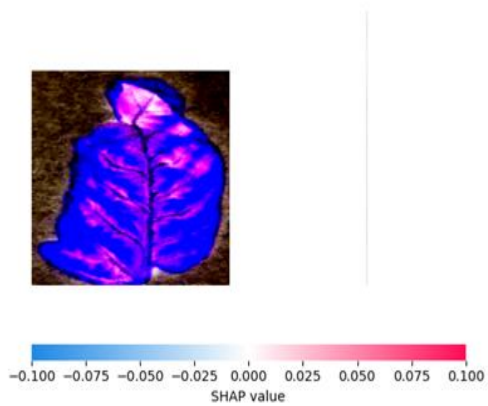
***Note**: We implemented this to show how different models handle their features and this method helps us visualize the results in a good way. This is additional work done to improve our solution. In case we wanted to implement a full solution unlike a comparison we could use this to visualize our findings.*

The Shapley value is a concept from cooperative game theory that has been adapted for use in explainable artificial intelligence (XAI), particularly in methods known as Shapley Additive Explanations (SHAP). It provides a principled approach to attribute the prediction of a machine learning model to its input features.

In the context of machine learning, the Shapley value calculates the contribution of each feature to the prediction of a particular instance by considering all possible combinations of features. It ensures that each feature's contribution is fairly allocated by averaging the marginal contribution of a feature across all possible feature combinations.
The key properties of the Shapley value that make it appealing for explainability are efficiency (all feature contributions add up to the actual prediction), symmetry (features that contribute equally receive equal attribution), and linearity (the combined contribution of features is the sum of their individual contributions).
Using SHAP in machine learning helps to demystify the model's decisions, making them transparent and understandable to humans. This is crucial for validating model behavior, ensuring fairness, and complying with regulatory requirements, particularly in high-stakes domains like finance and healthcare.



Shapley HeatMap of Resnet50



Shapley HeatMap of Alexnet

The two images depict SHAP value heatmaps for image classification predictions made by AlexNet and ResNet, respectively. These heatmaps visualize areas in the image that most significantly impact the model's prediction. In these representations, regions with higher SHAP values (indicated by warmer colors) are areas that contribute more positively to the model's decision, whereas areas with lower SHAP values (cooler colors) have a negative or lesser contribution.

Comparing the two, we might see that the heatmaps highlight different regions of the image depending on the architecture's focus. For instance, the AlexNet heatmap might show broader areas of influence with less specificity due to its simpler, shallower architecture. In contrast, the ResNet heatmap could exhibit more precise areas of influence, reflecting the deeper, more complex architecture's ability to capture finer details.
Such a comparison would help in understanding how each model processes visual information and what features each model deems important in making a classification decision. This insight is valuable for model interpretation, diagnosing potential biases, and improving model design.

RESULTS

Success Metrics Used

The following success metrics were used for comparing the results,

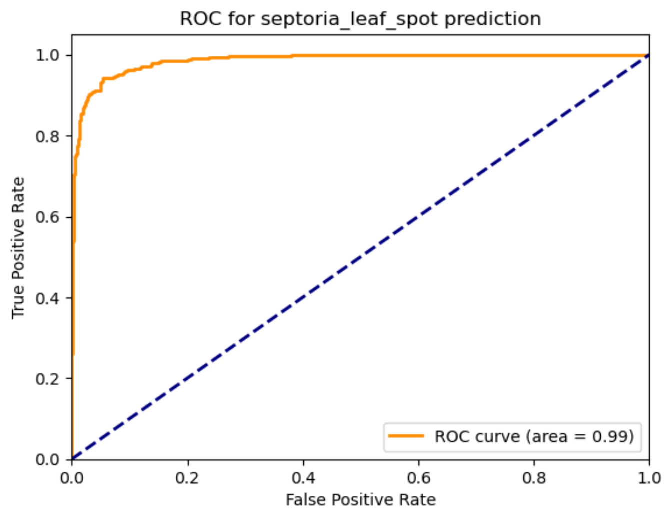
- **ROC Curve:** The Receiver Operating Characteristic (ROC) curve and the Area Under the Curve (AUC) provide insights into the model's ability to distinguish between diseased and healthy leaves. A high AUC value suggests that the model has a good balance of sensitivity and specificity, which is important for minimizing false positives and negatives in disease detection.
- **Confusion Matrix**: By presenting the number of true positives, true negatives, false positives, and false negatives, the confusion matrix offers a detailed view of the model's classification performance across different disease categories. This helps in understanding the model's strengths and weaknesses in detecting specific diseases.
- **F1 Score and Accuracy**

COMPARISON OF THE MODELS

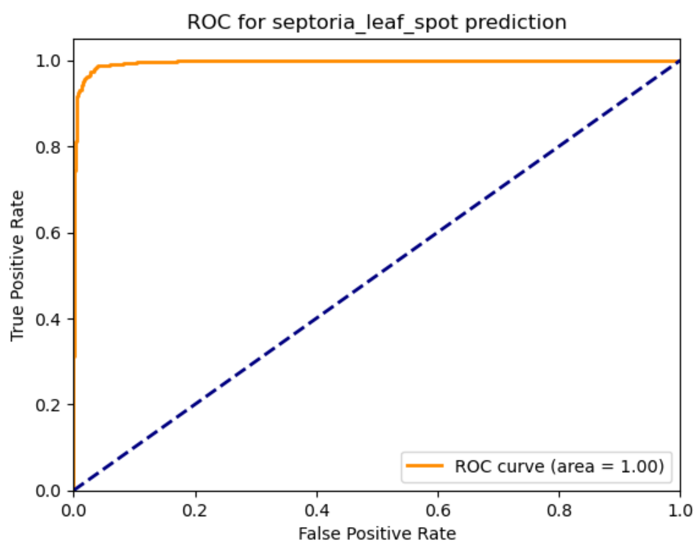
ROC

Note: The ROC here is done only for a single leaf class – septoria leaf, but ideally, we might need to do the calculation for all the 6 leaf classes for our comparison.

Receiving Operating Characteristics (ROC) is a validation method to check the performance of any classification model. ROC curve is based on probability plotted with true-positive rate against false-positive rate. The terms related to ROC curve are recall, sensitivity and specificity. It is also a graphical way of representing how well our model could differentiate between diseases. So, having Area Under the Curve (AUC) results in better classification.



ROC Curve for RESNET-50 Model



ROC Curve for ALEXNET Model

The two images you provided are ROC (Receiver Operating Characteristic) curves for the prediction of septoria leaf spot, one likely generated by using AlexNet and the other by using ResNet, which are both convolutional neural network models used in image recognition tasks.

In comparing the two ROC curves:

AlexNet Model: The Second ROC curve shows a perfect classification with an area under the curve (AUC) of 1.00. In practice, a perfect AUC is rare and could suggest overfitting or an error in the evaluation protocol.

ResNet Model: The First ROC curve shows an AUC of 0.99, which is exceptionally high and indicates excellent classification performance, albeit not perfect like the second.
The model with the AUC of 1.00 (AlexNet) shows a model that predicts with 100% accuracy in this test set, whereas the model with the AUC of 0.99 (ResNet) is slightly less perfect but still demonstrates a high level of accuracy. However, the perfection of the AlexNet curve should be scrutinized for potential data leakage, overfitting, or problems in the evaluation setup, as it is uncommon to see such results in practical scenarios.

```
Confusion matrix:
[[ 355   41    4   12   15    0]
 [   0  165   16    7    9    3]
 [   0    0  321    0    0    0]
 [   6   23   29  274    5   14]
 [   2    0   10    0 1055    0]
 [   0    0    3    0    6   74]]
F1 score: 0.916292
Accuracy score: 0.916292
```

Performance metrics for RESNET 50 Model

```
Confusion matrix:
[[ 390    2    0   31    4    0]
 [   8  124    2   59    4    3]
 [   0    0  314    7    0    0]
 [   0    0    0  347    0    4]
 [   3    1    0    0 1062    1]
 [   0    0    0    3    0   80]]
F1 score: 0.946100
Accuracy score: 0.946100
```

Performance metrics for ALEXNET Model

From the above figures we can come to a conclusion that the RESNET-50 model is outperformed by the ALEXNET model. In the confusion matrix x-axis represents the predicted class and y-axis represents the true class. The accuracy of the ALEXNET model is 0.946 which is the highest compared to the RESNET 50 model and RESNET 50 model gave an accuracy of 0.916.

Conclusion

A tomato leaf disease detection model has been developed using PyTorch that uses deep CNNs. A deep learning technique with transform and augmentation was used to overcome the overfitting problem and improve the model's performance. In addition, transfer learning was also used which adds extra benefit to the model i.e., it also has more optimization options available that fit the model to the required target. The proposed model yields 91.6% accuracy after fine-tuning the weights for the ResNet model. This Model is clearly outperformed by the ALEXNET Model.

Thus, the ALEXNET model can be used as a tool for farmers to identify the diseases that are present in leaves of tomato plants. Gaining an accuracy of 94.6%, this model can detect leaf diseases accurately within the shortest span of time.

Code Repository Link: https://github.com/Dracarya/MS-Project

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