DEVELOPMENT OF A RESNET50 MODEL FOR PLANT DISEASE DETECTION

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Abstract—The project addresses the critical issue of low crop yield caused by plant diseases in the field of food production. Historically reliant on agriculture, the identification of plant diseases has become paramount to ensure optimal crop yield. This research project focuses on the development of a robust ResNet50 model to detect plant diseases. The dataset is chosen from Kaggle. Utilizing deep learning tools such as Tensorflow, Sklearn and Python, the project follows a systematic approach. It begins with Data pre-processing, where images undergo necessary transformations for effective model training. Data Augmentation is used to ensure every class in the dataset has a minimum of 1000 images. The core of the project involves training of a ResNet50 model. The ultimate objective of the project is to contribute to increased crop production by enabling the early detection of plant diseases. The research aims to demonstrate the effectiveness of ResNet50 in plant disease detection, providing valuable insights for the agricultural sector and fostering sustainable food production practices.

1 Introduction

Plant disease detection is a critical aspect of crop and plant management, with the timely identification of diseases playing a pivotal role in preventing their spread, minimizing crop losses, and ensuring food security. In the realm of plant pathology, various methods and technologies are employed for disease detection, ranging from traditional visual inspection to cutting-edge techniques such as image processing, machine learning, and sensor-based systems. This project uses the ResNet50 model to identify plant diseases. Before training the model, the data undergoes many preprocessing steps like transformation, data augmentation etc. Data Augmentation is performed to ensure every class has a minimum of 1000 images. Then the data is split into training, validation and testing data. The Resnet50 model is trained on train and validation data. The test data is used to evaluate the trained model. Confusion matrix, classification report are used to compare the results.

2 Related Work

Many have worked on this dataset. Most of them have proposed a model which works only on a single plant, mostly on Potato. This project is proposed to work on all the classes of the dataset. In a study, a CNN-based Potato Disease Classification Model was proposed. The focus of this study was on a curated dataset specifically narrowed down to encompass only three distinct classes of potato diseases. This strategic reduction in the dataset aimed to streamline the classification process and enhance the model's efficacy in accurately identifying and categorizing Potato plants. Every image is resized to 256*256*3. Then the dataset was partitioned into training, validation and testing data after shuffling the dataset. The proposed CNN model is then trained on training and validation data. In another study, a InceptionV3 based model was proposed. The project focused on Transfer Learning. Every image is transformed to 224*224*3. The data is split into training, validation and test data. The project used a pre-trained InceptionV3 model where all the layers were frozen and then few layers were added. The model produced good results.

3 Data Description

The performance of the model largely depends on the quality and characteristics of the dataset. For this project, the dataset is sourced from Kaggle. It comprises 20,638 images across three different plants: Potato, Pepper, and Tomato. These images are categorized into 15 distinct classes, representing various health conditions of the plants. The classes are as follows:

- Pepper bell Bacterial spot
- Pepper bell healthy
- Potato Early blight
- Potato Late blight
- Potato healthy
- Tomato Bacterial spot
- Tomato Early blight
- Tomato Late blight
- Tomato Leaf Mold
- Tomato Septoria leaf spot
- Tomato Spider mites Two-spotted spider mite
- Tomato Target Spot
- Tomato Yellow Leaf Curl Virus
- Tomato mosaic virus
- Tomato healthy

This diverse and comprehensive dataset provides a robust foundation for training and evaluating the ResNet50 model in the task of plant disease detection.

Every image in the dataset is resized to (180*180**3). The Fig. 1 displays the class distribution in the dataset.

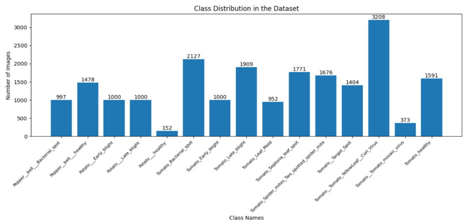

Fig. 1. Class Distribution in the Original Data

The data distribution shows that there is a data inconsistency. To avoid the data inconsistency, data augmentation is used. Data Augmentation is performed, such that every class has a minimum of 1000 images. The Fig. 2 shows the class distribution of the augmented data.

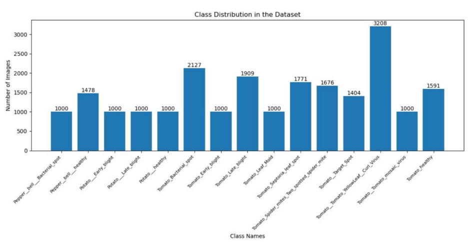

Fig. 2. Class Distribution in the Augumented Data

Then the data is split into training, validation and testing data in the ratio 0.8:0.1:0.1 respectively. The splitting can be done by using splitfolders methods which facilitates the division of a dataset into evenly-sized classes based on their respective classes. This strategic approach proves to be particularly beneficial for training ResNet models efficiently. By ensuring that all classes are present in the training dataset, the model is equipped with a comprehensive and diverse set of examples, enhancing its capacity to learn and generalize effectively across various categories. This systematic splitting process contributes to the optimization of ResNet model training, ultimately leading to improved performance and robust classification outcomes. The class distribution of training(Fig. 3), validation(Fig. 4) and testing data(Fig. 5) are shown respectively.

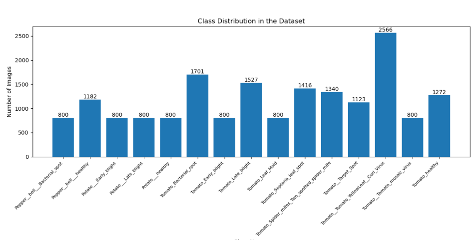

Fig. 3. Training

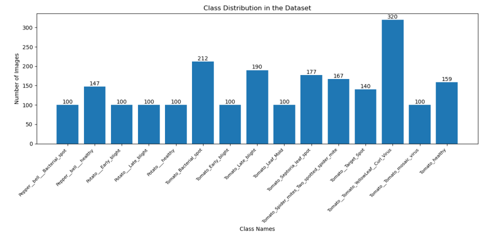

Fig. 4. Validation

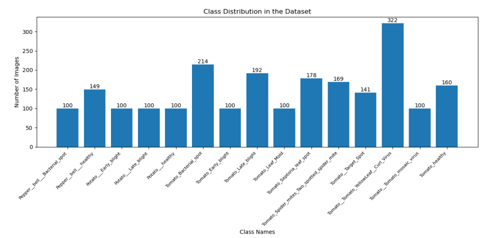

Fig. 5. Testing

4 Methods

The project capitalized on ResNet50, a model which is known for its deep architecture and remarkable accuracy in image recognition tasks. It is originally trained on the expansive ImageNet dataset, this model brings a wealth of knowledge from a diverse array of images, setting a solid foundation for the task.

Recognizing the unique demands of the project, the project adapted the input shape of the model to (180, 180, 3). This alteration ensures that the specific image data fits perfectly into the model. Tailoring the model further, it maintained 15 output classes, aligning precisely with the specialized classification requirements.

In this approach, the model strategically frozen the weights of the pre-trained layers. This choice is to simplify the training process by concentrating solely on the layers that require fine-tuning for the particular goal, while simultaneously it will not effect the significant learning the model has already attained.

To ensure that the model not only learns but also adapts to the specific dataset, it integrated a Flatten layer. This layer transforms the pooled feature maps into a single vector, paving the way for more dense layers. Then introduced a dense layer with 512 neurons, utilizing 'relu' activation for non-linear transformation. This is crucial for learning complex patterns in the data. Finally, a dense layer with 15 neurons and 'softmax' activation, enabling it to perform multi-class classification.

The result of these modifications is a robust, fine-tuned model that leverages the best of ResNet50 and adapts it to the unique image classification needs. This model is not just a technological achievement; it's a tool ideally suited for high-accuracy image classification tasks where specialized categories are the focus.

The adaptability and strength of the customized ResNet50 model open doors to new possibilities in image classification, especially in scenarios that demand a high level of precision and specialization.

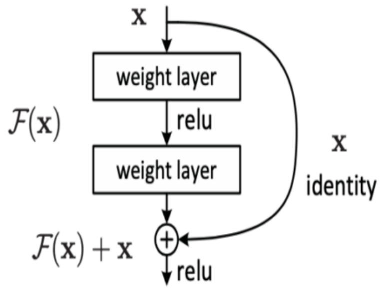

Fig. 6. ResNet Architecture

ResNet-50 has an architecture of 50-layer. ResNet uses a bottleneck design for the building block. A bottleneck residual block uses 1×1 convolutions, known as a "bottle-neck", which reduces the number of parameters and matrix multiplications. This enables much faster training of each layer. It uses a stack of three layers rather than two layers.

While ResNet-50 gained fame in image classification, it has found success in diverse applications. Its architectural principles are applicable to tasks such as object detection, image segmentation, and even non-image domains like natural language processing.

5 Experiments

Initially the model is trained without Data Augmentation. Then the training and validation accuracies are shown in the Fig.7.

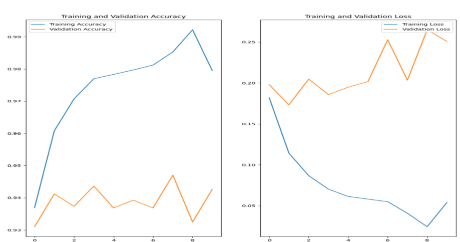

Fig. 7. Accuracy Graph

The test accuracy without Data Augmentation is 94.17. The confusion matrix without Data Augmentation is shown in Fig.8.

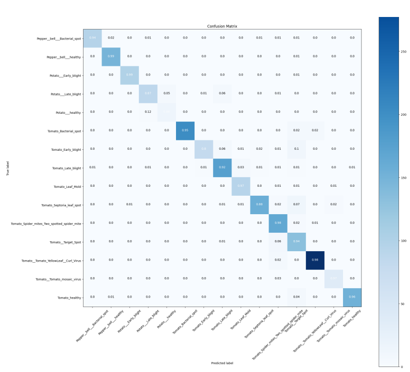

Fig. 8. Normalised Confusion Matrix without Data Augmentation

There are few classes with lesser precision. It is observed that the classes with lesser precision have less number of images in the dataset. Inorder to improve the performance of the model, Data Augmentation is used. The updated training and validation performance of the model are shown in Fig.9.

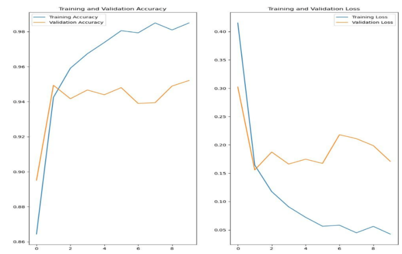

Fig. 9. Augmented Data Accuracy Graph

The model achieved an accuracy of 96 on the Augmented Test Data. The model gave an accuracy of 95.95 on Original Test Data. The confusion matrix of the model is shown in the Fig.10.

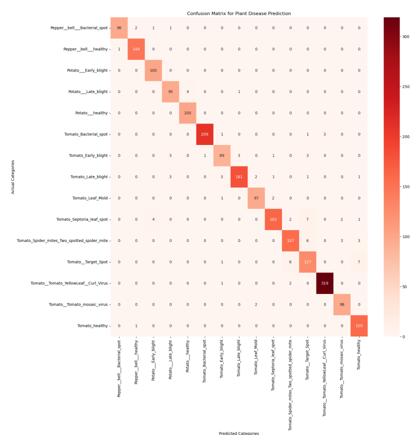

Fig. 10. Confusion Matrix

The Normalised Confusion Matrix of the model is shown in the Fig.11.

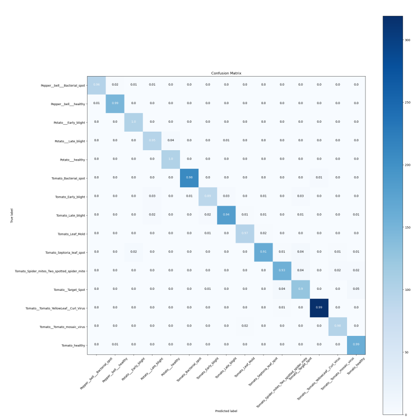

Fig. 11. Normalised Confusion Matrix with Data Augmentation

The classification report of the model is shown in the Fig.12. It shows that the precision is improved after Data Augmentation.

Classification Report

	precision	recall	f1-score	support
Pepper__bell___Bacterial_spot	0.99	0.96	0.97	100
Pepper__bell___healthy	0.98	0.99	0.99	149
Potato___Early_blight	0.95	1.00	0.98	100
Potato___Late_blight	0.93	0.95	0.94	100
Potato___healthy	0.96	1.00	0.98	100
Tomato_Bacterial_spot	1.00	0.98	0.99	214
Tomato_Early_blight	0.93	0.89	0.91	100
Tomato_Late_blight	0.98	0.94	0.96	192
Tomato_Leaf_Mold	0.96	0.97	0.97	100
Tomato_Septoria_leaf_spot	0.98	0.91	0.94	178
Tomato_Spider_mites_Two_spotted_spider_mite	0.94	0.93	0.93	169
Tomato__Target_Spot	0.88	0.90	0.89	141
Tomato__Tomato_YellowLeaf__Curl_Virus	0.99	0.99	0.99	322
Tomato__Tomato_mosaic_virus	0.95	0.98	0.97	100
Tomato_healthy	0.93	0.99	0.96	160
accuracy			0.96	2225
macro avg	0.96	0.96	0.96	2225
weighted avg	0.96	0.96	0.96	2225

Fig. 12. Classification Report

Some of the random images that the model predicted are shown in the Fig.13.

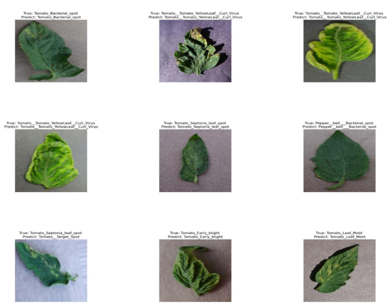

Fig. 13. Random Images Prediction

6 Conclusion

Initially CNN model is employed for the project. It generated training accuracies in the range of 60-80 percent and testing accuracy of 78 percent. Then ResNet50 model is used which yielded training accuracies in the range of 84-97 percent and testing accuracy of 94 percent. Later the ResNet50 model is trained on Augmented Data which produced the results of training accuracies in the range of 86-99 percent and testing accuracy of 96 percent. It is observed that the Resnet50 model performed way better than CNN model. Data Augmentation reduced Data Inconsistency, which even helped in better performance.

References

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