Image Classification of Plant Pathology 2021

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Content

1. Introduction

Apples are one of the most important temperate fruit crops in the world. They contain a lot of vitamin C. It can improve the body's immunity, as well as reduce blood pressure, if people eat it regularly. As a result, apples have become a daily staple for many people. This not only provides huge benefits for consumers, but also for growers. However, foliar (leaf) diseases pose a major threat to the overall productivity and quality of apple orchards. This has the potential to cause huge losses for growers.

The U.S. apple industry, annually worth $15 billion, experiences millions of dollars in annual losses due to various biotic and abiotic stresses, ongoing stress management, and multi-year impacts from the loss of fruit-bearing trees. Over the growing season, apple orchards are under constant threat from a large number of insects, as well as fungal, bacterial, and viral pathogens, particularly in the northeastern United States. Depending on the incidence and severity of infection by diseases and insects, impacts range from unappealing cosmetic appearance, low marketability, and poor quality of fruit, to decreased yield or complete loss of fruit or trees, causing huge economic losses. Early pest and disease detection are critical for appropriate and timely deployment of disease and pest management programs.

Currently, disease and pest detection in commercial apple orchards relies on manual scouting by crop consultants and service providers. Unfortunately, very few experienced scouts are available, forcing them to cover many large orchards within a narrow time frame. Scouts require a great deal of expertise and training before they can be efficient and accurate in diagnosing an orchard. Generally, they are first trained using images of disease symptoms and insect damage, but due to the presence of a great number of variables in an actual orchard, they need considerable time to familiarize themselves with the many symptom classes caused by either the age and type of infected tissues or the stage of the disease or pest cycle, as well as by changing weather, geographical variances, and cultural differences. Many symptoms of diseases, pests, and abiotic stresses in an apple orchard are distinct enough to differentiate based on visual symptoms alone. However, several disease symptoms look similar enough to each other that it is difficult to accurately determine their cause. At the same time, visual symptoms of a single disease or particular insect can vary greatly between apple varieties, due to differences in leaf color, morphology, and physiology. In addition to the time spent in the orchard, a scout spends a significant amount of time on each client, entering the scouting report, interpreting results, and providing recommendations for action. Overall, human scouting is usually time consuming, expensive, and in some cases, prone to errors.

In recent years, digital imaging and machine learning have shown great potential to speed up plant disease diagnosis. In this report, we use deep learning to train models to categorize apple plant pathology categories. Transfer learning method is selected here. We apply pre-trained model approach to use parts of the pre-trained model. The models include VGG model and ResNet model in this research. These two models are developed by a challenging image classification task, ImageNet 1000-class photograph classification competition. These models can take days or weeks to train on modern hardware. They can be downloaded and incorporated directly into new models that expect image data as input. In order to improve the performance of models, some approaches are applied, such as deleting duplicates, encoding, transforming, image augmentation and so on.

We are going to break everything into logical steps that allow us to ensure the cleanest, most realistic data for our model to make accurate predictions from:

1. Load Data and Packages in Kaggle
2. Preprocessing of Dataset
    2.1. Analyzing
    2.2. Removing Duplicates
    2.3. Data Expansion
3. Modeling and Categorizing
    3.1. VGG16 Model
    3.2. ResNet50 Model
    3.3. Ensemble Model

2. Description of Dataset

2.1 Overview of the dataset

We obtained data from Plant Pathology 2021-FGVC8 challenge competition in Kaggle. Plant Pathology 2020-FGVC7 challenge competition had a pilot dataset of 3,651 RGB images of foliar disease of apples. For Plant Pathology 2021-FGVC8, dataset has significantly increased the number of foliar disease images and added additional disease categories. The dataset contains approximately 23,000 high-quality RGB images of apple foliar diseases, including a large expert-annotated disease dataset. This dataset reflects real field scenarios by representing non-homogeneous backgrounds of leaf images taken at different maturity stages and at different times of day under different focal camera settings.

The train.csv file contains two columns, image and labels. Image indicates the image ID and labels represents the target classes, a space delimited list of all diseases found in the image.

The original train.csv file contains 18632 images. The detailed number of each disease is listed in Table 1.

Table 1. Counts of Each Disease

Disease	**Counts**
scab	4826
healthy	4624
frog_eye_leaf_spot	3181
rust	1860
complex	1602
powdery_mildew	1184
scab frog_eye_leaf_spot	686
scab frog_eye_leaf_spot complex	200
frog_eye_leaf_spot complex	165
rust frog_eye_leaf_spot	120
rust complex	97
powdery_mildew complex	87

It is clearer to see the number and proportion of different categories in a pie chart. The dataset has series imbalance problem. Disease like scrab and health plant contain almost half of all images, while diseases like powdery_mildew contains only 6.35% and some other categories containing more than one disease even account for less than 1%. So, we will try some methods to deal with it.

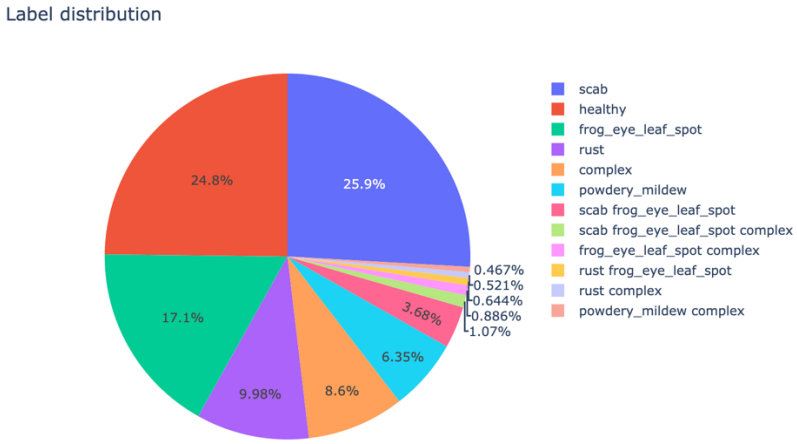


Figure 1. Pie Chart of Categories

2.2 Exploratory Data Analysis

2.2.1 Duplicates Values

Duplicates are always harmful for training process: differently labeled duplicates produce noise in the dataset, while equally labeled duplicates lead to data leakage. Duplicate data will affect the statistical results and mislead decision makers. In the dataset, there are more than 50 duplicates.

In this report, we used the result of a notebook in Kaggle to solve duplicates (https://www.kaggle.com/nickuzmenkov/pp2021-duplicates-revealing/output). In his notebook, firstly he saved downscaled images to boost performance because of long time taken by computing hash over original images of very high quality. Then, he used hash to find duplicated images and save them into a csv file. We use this csv file directly to get a dataset without duplicates.

2.2.2 Encoder

In this report, we take different targets as different labels instead of using multi-labels. That is label ‘complex’ as one category, label ‘frog_eye_leaf_spot’ as one category, and label ‘frog_eye_leaf_spot complex’ as one category. So, there are total of 12 categories in the dataset, including ‘complex’, ‘frog_eye_leaf_spot’, ‘frog_eye_leaf_spot complex’,

'healthy', 'powdery_mildew', 'powdery_mildew complex', 'rust', 'rust complex', 'rust frog_eye_leaf_spot', 'scab', 'scab frog_eye_leaf_spot', 'scab frog_eye_leaf_spot complex'. Thus, the labels are encoded into 0 to 11 depending on different categories.

Figure 2 gives the example of the 12 categories image:

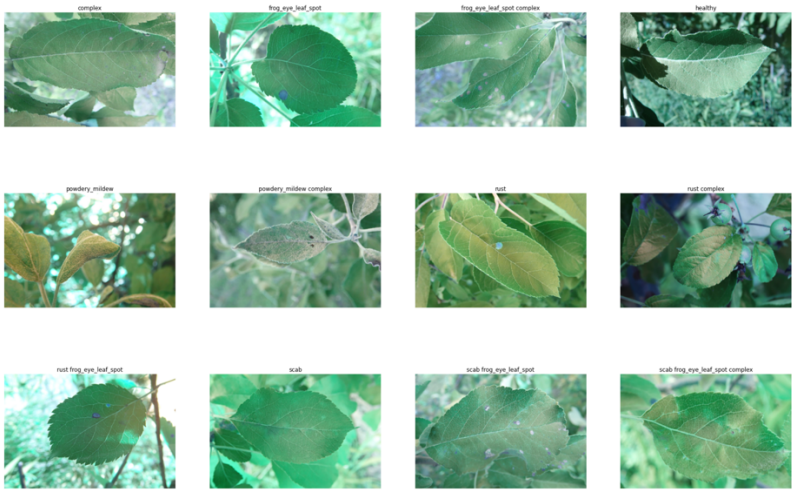


Figure 2. Examples of 12 Categories' Images

2.3 Data Expansion

Since our data set is imbalance and to solve this imbalance problem, the most straight forward consideration we think is using data expansion method.

Here, we use a package called albumentaions to achieve this goal. Albumentations is a Python library for fast and flexible image augmentations. Albumentations efficiently implements a rich variety of image transform operations that are optimized for performance, and does so while providing a concise, yet powerful image augmentation interface for different computer vision tasks, including object classification, segmentation, and detection. In this package, there are mainly two different image transformation: the pixel_level transform and the spatial_level transform.

Pixel-level transforms will change just an input image and will leave any additional targets such as masks, bounding boxes, and keypoints unchanged. Usually, PLT will add noise to the original image. Spatial-level transforms will simultaneously change both an input image as well as additional targets such as masks, bounding boxes, and keypoints. Usually, SLT will not add noise to the original image.

To solve this imbalance problem, we build two different expanded datasets based on different strategies: the first one, we combine the pixel_level transform and the

spatial_level transform together to generate our new image and the second one we only use spatial_level transform.

The reason we build two expanded datasets is for the first dataset, we applied many different pixel_level transform, which may be good for preventing overfitting, but it may cause too much noises added to original image as well. To eliminate this possibility, we adjust the porpotion of pixel_level transform we use in our second expanded dataset and apply both expanded dataset to our model to check which is better.

Finally, after data expansion, we expand the amount of our image data from 14000 to 44000 and 39000, separately.

3. Model and Algorithm

3.1 VGG Model

VGG is the brainchild of the Visual Geometry Group in Oxford. This network is the related work in ILSVRC 2014, the main work is to prove that increasing the depth of the network can affect the final performance of the network to a certain extent. VGG has two structures, namely VGG16 and VGG19. There is no essential difference between the two, only the network depth is different.

One improvement over AlexNet is that VGG16 uses several 3x3 convolution cores in a row instead of the larger convolution cores in AlexNet (11x11, 7x7, 5x5). Using a stacked small convolution kernel is better than using a large convolution kernel, because multiple nonlinear layers can increase the depth of the network to ensure learning more complex patterns at a lower cost (fewer parameters).

In short, in VGG, 3 3 by 3 convolution kernels are used to replace 7 by 7 convolution kernels, and 2 3 by 3 convolution kernels are used to replace 5 by 5 convolution kernels. The main purpose of this is to improve the depth of the network and the effect of the neural network to some extent under the condition of ensuring the same perceptual field.

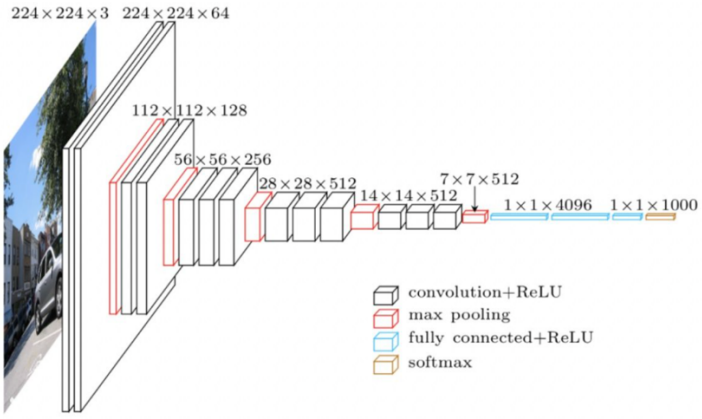


Figure 3. Structure of VGG16 Model

Figure 3 shows the simple structure of VGG16 model. The model can be simply divided into five stages, each layer is composed of two convolutional cores pooled, and is finally connected by three layers for classification.

As the Figure 3 and Table 2 show, processing of VGG16 is: firstly, input the picture of 224x224x3, and make two convolution and ReLU function through 64 3x3 convolution cores, and the size of the convolution becomes 224x224x64. Then, max pooling is carried out, and the pooling unit size is 2x2 (the effect is to halve the image size), and the pooled

size is changed to 112x112x64. Then, double convolution and ReLU function through 128 3x3 convolution kernels, and the size becomes 112x112x128. After this, 2x2 max pooling is conducted, and the size is changed to 56x56x128. Then, make three convolution and ReLU function through 256 3x3 convolution kernel, and the size becomes 56x56x256, followed by 2x2 max pooling, and the size is changed to 28x28x256. Then, through 512 3x3 convolution kernels for three times and ReLU function, the size becomes 28x28x512. And conduct 2x2 max pooling and change the size to 14x14x512. After that, through 512 3x3 convolution kernels for three times and ReLU function, the size becomes 14x14x512. Conduct 2x2 max pooling and change the size to 7x7x512. Finally, full connection with layer 2 1x1x4096 and layer 1 1x1x1000 and RELU function and output 1000 forecast results through Softmax.

Table 2. Architecture of VGG Model

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

3.2 ResNet Model

The proposal of Deep Residual Network (ResNet) was a milestone in the history of CNN images.

From experience, the depth of the network is crucial to the performance of the model. When the number of network layers is increased, the network can carry out more complex feature pattern extraction, so better results can be obtained theoretically when the model is deeper.

The experiment found that the depth network presented a degradation problem: with the increase of the depth of the network, the network accuracy appeared saturation, or even decreased. The problem is clearly not caused by overfitting, because not only does the test error become higher as the network deepens, so does its training error. This can be seen from Figure 4.

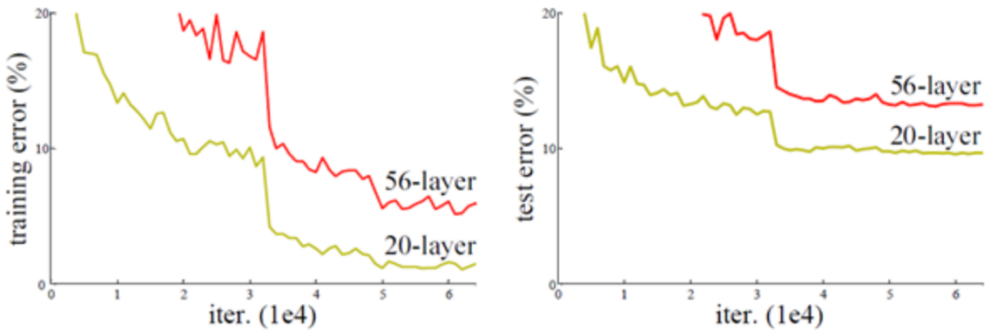


Figure 4. Degradation Problem

When the number of layers of the traditional neural network increases from 20 to 56, both the training error and the test error of the network increase significantly, that is to say, the performance of the network degenerates significantly with the increase of the depth. ResNet was created to solve this degradation problem.

Residual learning is proposed to solve the degradation problem. For a stacking layer structure, when the input is x, the feature learned is noted as $H(x)$. Now we hope that it can learn residual $F(x) = H(x) - x$, so that the original learning feature is actually $F(x) + x$. The reason for this is that it is easier to learn residuals than to learn the original features directly. When the residual is 0, the stack layer only does the identity mapping, and at least the network performance will not decrease. In fact, the residual will not be 0, which also makes the stack layer learn new features on the basis of input features, so as to have better performance. The structure of residual learning is shown in Figure 5. This is a kind of "short" in an electric circuit, so it's a shortcut connection.

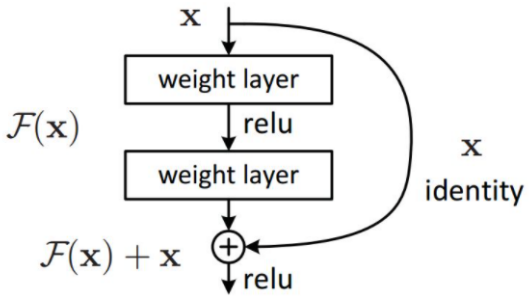


Figure 5. The Basic Unit of Residual Study

In this report, we use ResNet50 model. Table 3 shows the architecture of it. There are five big convolutional layers. The first layer consists of a convolution layer with 64 7 by 7 filters and 2 stride and a subsampling layer of max pooling. Then, there are four big convolutional layers. They consist of 9 layers, 12 layers, 18 layers and 9 layers respectively. Finally, there is a fully connected layer.

Table 3. Architecture of ResNet

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
		3×3 max pool, stride 2				
conv2_x	56×56	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

3.3 Ensemble Learning

In the supervised learning algorithm of machine learning, our goal is to learn a stable model with better performance in all aspects, but the actual situation is often not so ideal, sometimes we can only get multiple preferred models (weakly supervised model, better performance in some aspects). Ensemble learning is to combine several weak supervised models here in order to obtain a better and more comprehensive strong supervised model. The underlying idea of ensemble learning is that even if one weak classifier gets the wrong prediction, other weak classifiers can correct the error back. It contains Bagging, Boosting and Stacking.

Bagging is short for bootstrap aggregating. Bootstrap is also known as the self-help method. It is a sampling method with put back in order to get the distribution and confidence interval of statistics. In the Bagging method, the Bootstrap method is used to obtain N data sets by adopting the random return sampling from the overall data set, and a model is learned from each data set. The final prediction result is obtained by using the output of N models, specifically: For the classification problem, N models were used to predict the voting, and for the regression problem, N models were used to predict the average.

Boosting is a machine learning algorithm that can be used to reduce the bias in supervised learning. It is mainly to learn a series of weak classifiers and combine them into a strong classifier.

The Stacking method is to train one model to combine other models. First of all, we train several different models, and then train a model by using the output of each previously trained model as input to get a final output. In theory, Stacking can represent the two Ensemble approaches mentioned above, as long as we adopt the appropriate model combination strategy. But in practice, we usually use logistic regression as a combination strategy.

4. Experimental Setup

4.1 Create Data Pipeline

In this project, we mainly use pytorch to execute our model VGG16 and Resnet50. Before we configure our model, we need to create the data pipeline which is available to feed data to our model.

4.1.1 Transform Class Setup

Data does not always come in its final processed form that is required for training machine learning algorithms. Therefore, we use transforms to perform some manipulation of the data and make it suitable for training.

Here's the snippet of our transform class code:

```
class pl_transform():
    def __init__(self):
        self.plant_transform = {
            'train':transforms.Compose([
                transforms.RandomResizedCrop(
                    224, scale=(0.5, 1.0)),
#                 transforms.RandomHorizontalFlip(),
#                 transforms.RandomVerticalFlip(0.2)
                transforms.ToTensor(),
                transforms.Normalize(mean=[0.485, 0
```

We can add different transformation here, for example, VGG16 requires the input image size as 224 by 224 and normalize the image with mean = [0.485, 0.456, 0.406], std = [0.229, 0.224, 0.225]. what's more, we can use data augmentation techniques here, like the annotate snippet part shows, we can add random horizontal flip or random vertical flip and other transforms here to prevent overfitting.

4.1.2 Customized Dataset Class Setup

At the heart of PyTorch data loading utility is the 'torch.utils.data.DataLoader' class. It represents a Python iterable over a dataset and the most important argument of DataLoader constructor is dataset, which indicates a dataset object to load data from.

Since data loading order is entirely controlled by the user-defined iterable. We can easily define our own dataset shown below and this allows easier implementations of chunk-reading and dynamic batch size:

```
class mydataset(Dataset):
    def __init__(self , csv_file , img_dir , transforms=None, phase = 'train' ):
        self.targetfile = csv_file
        self.root = img_dir
        self.transforms = transforms
        self.phase = phase


    def __len__(self):
        return len(self.targetfile)

    def __getitem__(self, idx):
        img_path = os.path.join(self.root,self.targetfile.iloc[idx,0])
        image = Image.open(img_path)
        label = self.targetfile.iloc[idx,1]

        if self.transforms:
            image = self.transforms(image,self.phase)
        return image,label
```

As we can see, all we need to define is a __init__ function for initialization, __len__ function to return a customized length of dataset and __getitem__ function to retrieve the data.

After we defined our dataset, all we need to do is feed our dataset to a dataloader like this:

```
train_loader = DataLoader(train_dataset,
#                         sampler = wsampler,
                          batch_size = BATCH_SIZE,
                          shuffle = True,
                         )
```

At this point, we have completed all the data pipeline configuration.

4.2 Model Configuration

Since we don't need to build our own model, it's quite simple to load VGG16 and Resnet50 to our code like this:

```
def model_define():
    use_pretrained = True
    Mymodel = models.resnet18(pretrained=use_pretrained)
    Mymodel.fc = nn.Sequential(
#             nn.Linear(2048, 1024),
#             nn.ReLU(),
            nn.Dropout(0.5),
            nn.Linear(512, 12)
        )
```

As you can see, all we need to do is to change the last fully connected layers to make it match our expected output.

Then, we use fine-tuning strategy to train our model. Fine-tuning means taking weights of a trained neural network and use it as initialization for a new model being trained on data from the same domain (often e.g. images). It is used to speed up the training or overcome small dataset size.

Here, for each of model, we will "freezing" some of the pre-trained weights (usually whole layers) and train and update only a part of the parameters of the network.

Take ResNet as example:

```
Parameters not to be learned :  layer4.0.bn1.bias
Parameters not to be learned :  layer4.0.conv2.weight
Parameters not to be learned :  layer4.0.bn2.weight
Parameters not to be learned :  layer4.0.bn2.bias
Parameters not to be learned :  layer4.0.downsample.0.weight
Parameters not to be learned :  layer4.0.downsample.1.weight
Parameters not to be learned :  layer4.0.downsample.1.bias
Store in params_to_update_1 : layer4.1.conv1.weight
Store in params_to_update_1 : layer4.1.bn1.weight
Store in params_to_update_1 : layer4.1.bn1.bias
Store in params_to_update_1 : layer4.1.conv2.weight
Store in params_to_update_1 : layer4.1.bn2.weight
Store in params_to_update_1 : layer4.1.bn2.bias
Store in params_to_update_1 : fc.1.weight
Store in params_to_update_1 : fc.1.bias
```

Figure 6. Information of ResNet50

From the printout information, it shows that from layers 1.0 to layers 4.0, all of the parameter will be freezed and in the training process, we will only update the parameters from layers 4.1 to the final fully connected layers.

After we finished our training processing, we will combine these two models' results and feed the results to an ensemble classifier and obtain our final prediction.

4.3 Metrics

Because our validation dataset is imbalance. So, accuracy is not an appropriate metrics to be used here. And because the competition uses mean f1-score. So, we will use f1-score as our metrics to judge the performance.

First, we introduce two concepts: Precision = True Positive / (True Positive + False Positive) and Recall = True Positive / (True Positive + False Negative). Recall is defined as the ratio of the total number of correctly classified positive examples divide to the total number of

positive examples. Precision can be calculated by dividing the total number of correctly classified positive examples by the total number of predicted positive examples.

F1 = 2 * (Precision * Recall) / (Precision + Recall). Now that the dataset is imbalanced, f1 score might be a better measure to use if we need to seek a balance between precision and recall.

4.4 Hyper-parameter

Here's the hyper-parameter we used:

```
SEED = 42
EPOCHS = 6
LR = 1e-5
MIN_LR = 1e-7
MODE = 'min'
FACTOR = 0.2
PATIENCE = 0
BATCH_SIZE = 128
TEST_SIZE = 0.2
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

For the epochs selection, we use early-stopping strategy, we can just plot the train loss curve and validation curve, then we can decide a suitable epochs number. Here's a snippet of our plot code:

```
fig = plt.figure(figsize=(7, 6))
plt.grid(True)
plt.plot(train_acc, color='r',marker='o', label='train/acc')
plt.plot(val_acc, color='b',marker='x',label='val/acc')
plt.ylabel('Accuracy')
plt.xlabel('Epochs')
plt.legend(loc='lower right')
plt.show()
```

In this model, we use ReduceLROnPlateau() function in torch.optim.lr_scheduler to determine training parameter, learning rate. When the evaluation index of the network is not improved, the network performance can be improved by reducing the learning rate of the network.

For the mini-batch size selection, in general, larger batch sizes result in faster progress in training, but don't always converge as fast. Smaller batch sizes train slower, but can converge faster. Therefore, we set our batch size as 32, 64, 128 and 256 and to check the performance.

The result shows in this dataset, 128 is a better choice.

4.5 Over-fitting

For the over-fitting problem, the mainly strategy is in transform part, we add many pixel_level transforms, include: Blur, ColorJitter, CLAHE, FancyPCA, RandomSunFlare, RandomFog and so on. By using this method, we can add noises manually to the original image, which is useful to prevent over-fitting.

The second strategy we use is increasing the rate of dropout layer in our model. As we know dropout layer is good for preventing over-fitting.

The third strategy, we decrease the model complexity, using Resnet18 as substitute.

5. Results

5.1 VGG16

Here's the VGG16 result:

```
val Loss: 1.2190 Acc: 0.5963
The f1 score is 0.6056423774343158
```

vgg_sub (version 6/6) Succeeded 0.640

a day ago by Yu Cao

From Notebook [vgg_sub]

As we can see, the local f1 score is 0.6056 and the leader board f1 score on Kaggle is 0.64. The LB score is better than Local, which is good news.

5.2 ResNet50

For the Resnet50 results, we plot the train_val accuracy, train_val loss and learning rate decay graphs and here are the results:

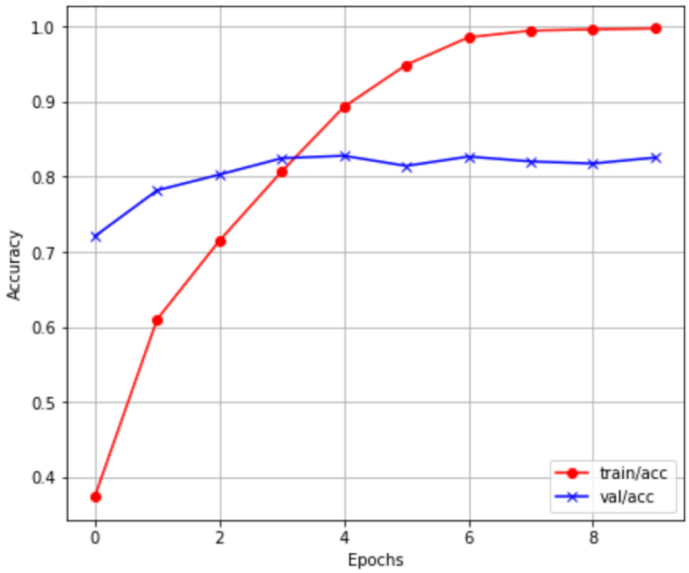


Figure 7. Accuracy of Train and Validation Datasets

Figure 7 shows the accuracy lines of train and validation datasets. We can see that the accuracy of both train and validation datasets increase as the epoch increase. And at about the fifth epoch, the accuracy of validation becomes stable and not increase obviously. The accuracy of validation dataset passes 0.8.

Figure 8 represents the loss lines of train and validation datasets. The loss of train and validation dataset decrease as the epoch increase. And the loss of validation dataset also become stable when it reaches the fifth epoch. It is less than 0.6.

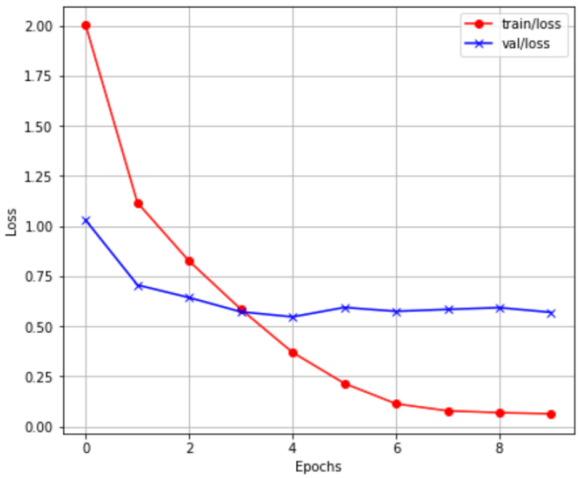


Figure 8. Loss of Train and Validation Datasets

The validation loss is 0.57, f1 score of it is 0.82, which performs well. And here is the best local result:

```
val Loss: 0.5716 Acc: 0.8248
The f1 score is 0.8215232721433382
Learning Rate is 1e-05
```

And here is the learning rate plot:

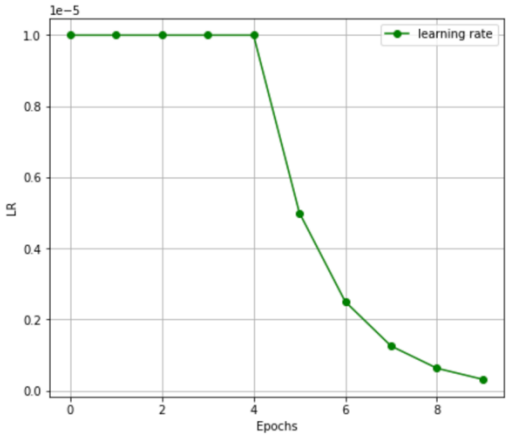
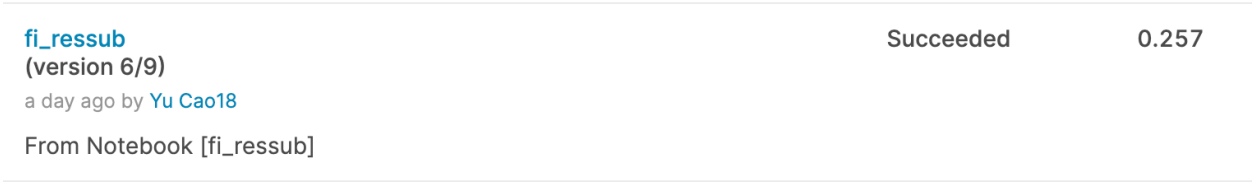


Figure 9. Learning Rate

Figure 9 shows the plot of learning rate. It decreases from the fourth epoch as epochs increase. So, the model might be overfitting since the fifth epoch. So, we submit the model with 5 epochs into Kaggle to train on test dataset. However, the score on the leader board is low:



The score is only 0.257. Then, we tried several methods to figure this problem. We applied the second expanded dataset to the model. Because the first one has a lot of transformation, which will generate many noises. This might be the reason why the result in test dataset is not very well. And in local, the loss of validation dataset is 1.1496 and f1 score is 0.649. The result on leaderboard is only 0.197, less than the first score. So, change the expanded dataset didn't solve this issue.

Then, we also take the depth of the model into consideration. If the model is too deep, the result might be not good. So, we tried ResNet18 model as a substitute to decrease the data complexity and the result is worse. The local validation dataset loss is 1.3389 and f1 score is 0.600. And the f1 score on the leaderboard is 0.119. So, the depth of the model might still not the reason why the model performs bad on test dataset. So, this is a direction that we can continue to study in the future.

5.3 Ensemble Result

In our schedule, we plan to use ensemble methods to combine the result of our single models and here's the result:

In our schedule, we plan to use ensemble methods to combine the result of our model and here's the result:

```
f1_score(pred,y_val,average='micro')
```

```
0.7190860215053764
```

On the local side, the f1 score is 0.71 and on leader board it is 0.603. The result is better than ResNet50 model, but is worse than VGG model. This might result from the performance of ResNet is not very well.

6. Summary and Conclusions

By conducting this study and writing the report, we have a comprehensive understanding of how to build a deep neural network, including how to define transform class, how to define dataset class and dataloader and how to use transfer learning using pytorch. what's more, this is the really interesting competition that we can handle some really good data. It gives us a lot.

In our final result, using single VGG16 obtains the best, but we certainly sure our model can be better if we can solve the problem of our resnet50 model and the potential problem we think are:

1, Too much noise

2, over-fitting

3, data distribution is different between train and test set

4, validation loss is smaller than train loss

In the future, except to solve the Resnet50's problem, we should also focus more on data preprocessing, like using suitable transformation to make the image easier to be recognized, adjust the image size more suitable and so on. What's more, we can solve this problem by treating this problem as a multilabel problem and using BCEloss() to deal with it. I think if we can combine more suitable models together, we can decrease the high variance of neural network and have a significant improvement.

7. References

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Appendix

GitHub Repo:

- ❏ Final-Project-Group2 (https://github.com/Yu-Cao2019/Final-Project-Group2)
  - ❏ Group-Proposal/
    - ❏ Group_Proposal.pdf
  - ❏ Final-Group-Project-Report/
    - ❏ Final_Group_Project_Report.pdf
  - ❏ Final-Group-Presentation/
    - ❏ Final_Group_Presentation.pdf
  - ❏ Code/
    - ❏ README.md
    - ❏ eda-plant-pathology-2021.ipynb
    - ❏ failed-ensemble.ipynb
    - ❏ model-conbination.ipynb
    - ❏ model-plant-pathology-2021.ipynb
    - ❏ new-eda.ipynb
    - ❏ resnet.ipynb
    - ❏ ressub.ipynb
    - ❏ val-aug.ipynb
    - ❏ vgg-v1.ipynb
  - ❏ Jinyi-Shang-Individual-Report /
    - ❏ Jinyi-Shang-final-project.pdf
    - ❏ Code/
      - ❏ RF.py
      - ❏ GBR.py
      - ❏ README.md
  - ❏ Yu-Cao-Individual-Report/
    - ❏ Yu-Cao-final-project.pdf
    - ❏ Code/
      - ❏ RandomizedSearchCV_Neural_Network.py
      - ❏ Neural Network.py
      - ❏ README.md
  - ❏ README.md