Report_HW1

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Github: https://github.com/WhiteOuO/VRDL.git

Introduction:

In this experiment, I mainly used the ResNet50 model and the pretrained weights ResNet50_Weights.IMAGENET1K_V2.

The top-1 accuracy of IMAGENET1K_V2 is 4% higher than that of V1.

ResNet50_Weights.IMAGENET1K_V1:

These weights reproduce closely the results of the paper using a simple training recipe.

acc@1 (on ImageNet-1K)	76.13
acc@5 (on ImageNet-1K)	92.862
min_size	height=1, width=1
categories	tench, goldfish, great white shark, ... (997 omitted)
num_params	25557032
recipe	link
GFLOPS	4.09
File size	97.8 MB

ResNet50_Weights.IMAGENET1K_V2:

These weights improve upon the results of the original paper by using TorchVision's new training recipe. Also available as `ResNet50_Weights.DEFAULT`.

acc@1 (on ImageNet-1K)	80.858
acc@5 (on ImageNet-1K)	95.434
min_size	height=1, width=1
categories	tench, goldfish, great white shark, ... (997 omitted)
num_params	25557032
recipe	link
GFLOPS	4.09
File size	97.8 MB

I have chosen to use pretrained weights for image recognition, which will give me a good starting point, and then let the model gradually adapt to my dataset and learn. I plan to implement some data augmentation so that each image in my training set can be transformed through different image processing techniques to provide more comprehensive features for that class, such as horizontal flipping, slight changes in brightness and hue, and cropping the image.

In addition to image processing techniques, I also plan to use methods to exclude outliers from the training data. I believe this will help the model better learn the common features of the class from the normal data.
Furthermore, I will also apply a learning rate adjustment strategy to help my

model progress more effectively.

Method:

1. **Outlier Exclusion:**

   I used a model called Autoencoder, which is an unsupervised learning method commonly used for data compression or denoising. The model consists of two parts:

- **Encoder**: Converts input data (images) into smaller dimensions.
- **Decoder**: Reconstructs the input data from the smaller dimensions, aiming to make the reconstruction as close as possible to the original input.

```python
# train Autoencoder
autoencoder = build_autoencoder()
autoencoder.fit(train_images, train_images, epochs=30, batch_size=32, shuffle=True, validation_data=(val_images, val_images))

# reduild `train set` and eval the error
reconstructed_train = autoencoder.predict(train_images)
train_errors = np.mean((train_images - reconstructed_train) ** 2, axis=(1, 2, 3))

# rebuild `validation set` and eval the error
reconstructed_val = autoencoder.predict(val_images)
val_errors = np.mean((val_images - reconstructed_val) ** 2, axis=(1, 2, 3))
```

I first use the training data to train the Autoencoder. When it learns the features of the class, we ask it to reconstruct those data that have been reduced to lower dimensions.

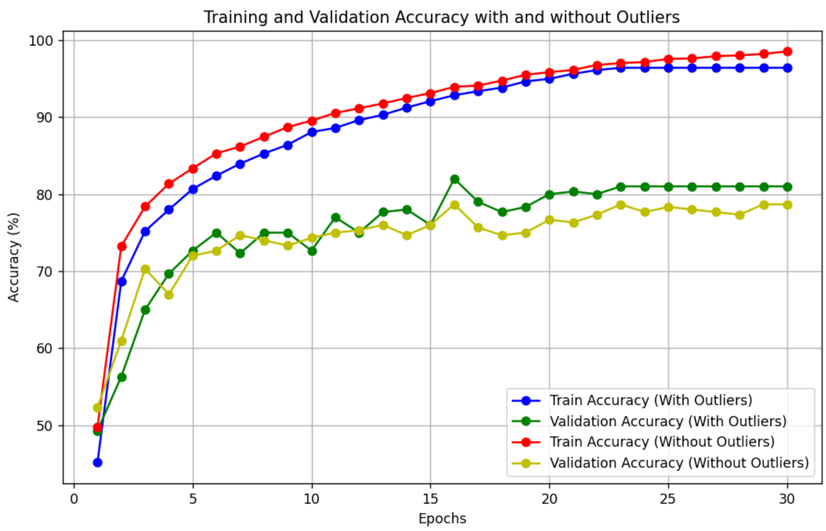
If the reconstruction result differs significantly from the original image, we can reasonably suspect that the features of that image are not similar to the common features of the class. We can then infer that it is an outlier.(If the reconstruction error is above the threshold, I will classify the image as an outlier.)

```python
# Set initial Outlier threshold
threshold = np.percentile(train_errors, 95)
print(f"Class {class_name} initial Outlier detection threshold: {threshold:.5f}")

# Check the maximum error of the `validation set`
max_val_error = np.max(val_errors)
print(f"Class {class_name} `validation set` maximum error: {max_val_error:.5f}")

# If the maximum error in the `validation set` exceeds the threshold, relax the threshold
if max_val_error > threshold:
    print(f"Class {class_name} `validation set` error exceeds the threshold, adjusting the threshold...")
    threshold = max_val_error * 1.1  # Relax by 10%
    print(f"Class {class_name} updated Outlier threshold: {threshold:.5f}")

# **Filter Outliers in the `train set` and delete them**
num_deleted = 0
for i, error in enumerate(train_errors):
    if error > threshold:  # Outlier if error exceeds the threshold
        os.remove(train_image_paths[i])  # **Directly delete the image**
        num_deleted += 1
        print(f"Class {class_name} deleted `train set` Outlier: {train_image_paths[i]}")
```

This threshold is typically set to the 95th percentile of the training errors for all images. Additionally, to avoid the validation data being misclassified as outliers, I will also compress and reconstruct the validation data and calculate the error. If the error is smaller than the threshold, we will not consider the validation data as an outlier. If the error is greater than the threshold, the threshold will be updated to 1.1 times the error from the validation data.

This method ensures that the validation data is not misclassified as an outlier and helps to eliminate anomalous images whose features deviate too much from the common features of other images in the same class.

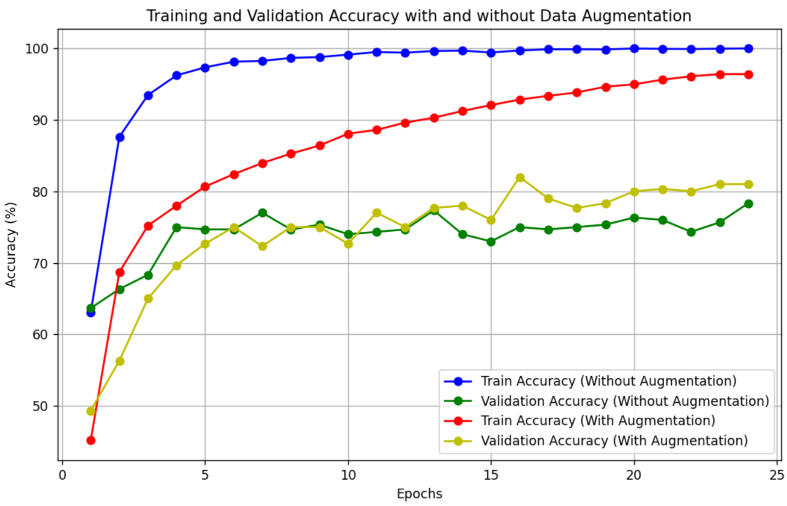
Here are the training results using this method and directly using the original, unmodified dataset. It can be seen that with outlier exclusion, the training stopped early at epoch 23 (early stopping), showing faster training and better results.



- With outliers, the training stopped early at epoch 23. At epoch 16, the validation accuracy reached a maximum of 82.00%.
- Without outliers, the validation accuracy reached a maximum of 79.67% at epoch 23. The training continued until epoch 30 before early stopping occurred.

2. Data augmentation
   - **Padding & Resize**: All images are padded to the same size square, ensuring that no aspect ratio distortion occurs when resizing the image.

- **RandomResizedCrop**: A random region of the image is cropped, allowing us to get a close-up, which is then scaled to 224x224, the size required by ResNet.
- **ColorJitter on Brightness, Contrast, Saturation, and Hue**: This mainly affects the RGB factors of the image. By slightly adjusting the brightness, contrast, and saturation, the model can accommodate a wider range of photographic conditions.
- **Random Rotation**: Since most of the objects in the images are plants and animals (rather than numbers or text), this technique can effectively provide variations of the features in the images from different shooting angles.
- **Random Horizontal Flip**: A 50% chance of flipping the image horizontally.



- The plot shows that training accuracy with data augmentation (red line) improves more slowly compared to the model without data augmentation (blue line). This indicates that data augmentation helps the model avoid overfitting and generalize better.
- On the other hand, the validation accuracy without data augmentation (green line) stagnates or fluctuates, showing that the model struggles to generalize well to unseen data.
- Overall, data augmentation improves the model's generalization ability, leading to better performance on the validation set.

Results:

- **Model**: seresnet152d.ra2_in1k

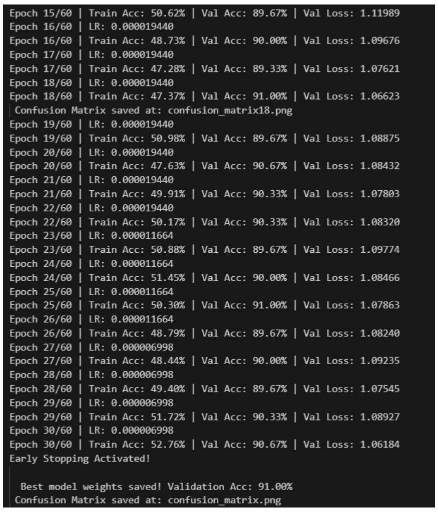
- https://huggingface.co/timm/seresnet152d.ra2_in1k

seresnextaa101d_32x8d.sw_in12k_ft_in1k	224	85.96	97.82	93.6	17.2	34.2
resnext101_32x32d.fb_wsl_ig1b_ft_in1k	224	85.11	97.44	468.5	87.3	91.1
resnetrs420.tf_in1k	416	85.0	97.12	191.9	108.4	213.8
ecaresnet269d.ra2_in1k	352	84.96	97.22	102.1	50.2	101.2
ecaresnet269d.ra2_in1k	320	84.73	97.18	102.1	41.5	83.7
resnetrs350.tf_in1k	384	84.71	96.99	164.0	77.6	154.7
seresnextaa101d_32x8d.ah_in1k	288	84.57	97.08	93.6	28.5	56.4
resnetrs200.tf_in1k	320	84.45	97.08	93.2	31.5	67.8
resnetrs270.tf_in1k	352	84.43	96.97	129.9	51.1	105.5
seresnext101d_32x8d.ah_in1k	288	84.36	96.92	93.6	27.6	53.0
seresnet152d.ra2_in1k	320	84.35	97.04	66.8	24.1	47.7
resnetrs350.tf_in1k	288	84.3	96.94	164.0	43.7	87.1
resnext101_32x8d.fb_swsl_ig1b_ft_in1k	224	84.28	97.17	88.8	16.5	31.2
resnetrs420.tf_in1k	320	84.24	96.86	191.9	64.2	126.6
seresnext101_32x8d.ah_in1k	288	84.19	96.87	93.6	27.2	51.6
resnext101_32x16d.fb_wsl_ig1b_ft_in1k	224	84.18	97.19	194.0	36.3	51.2

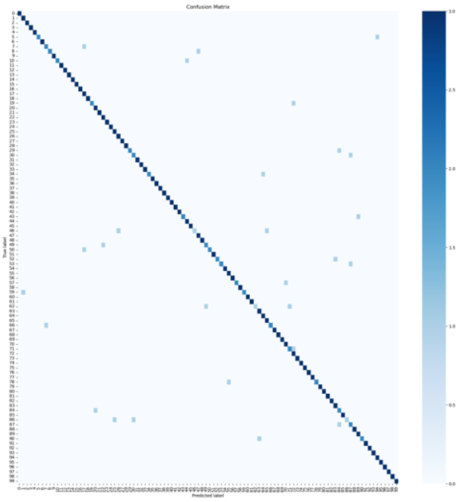
- **Learning Rate**:
  - Initial learning rate: 0.00015
  - Learning rate decay:

```
# Manually adjust the learning rate if no improvement
if(early_stop_counter%2==0 and early_stop_counter!=0):
    optimizer.param_groups[0]['lr'] = optimizer.param_groups[0]['lr'] * 0.8
```

  - Training strategy:
    - Early stopping: patience = 10 (Terminate the training if the validation accuracy does not improve for 10 consecutive times)
    - Reduce the learning rate by a factor of 0.8 if there is no improvement in validation accuracy for two consecutive epochs.
- **Outlier Elimination**: Applied
- **Data Augmentation**: All techniques above applied.
- **Mix up applied.**



```
Epoch 15/60 | Train Acc: 50.62% | Val Acc: 89.67% | Val Loss: 1.11989
Epoch 16/60 | LR: 0.000019440
Epoch 16/60 | Train Acc: 48.73% | Val Acc: 90.00% | Val Loss: 1.09676
Epoch 17/60 | LR: 0.000019440
Epoch 17/60 | Train Acc: 47.28% | Val Acc: 89.33% | Val Loss: 1.07621
Epoch 18/60 | LR: 0.000019440
Epoch 18/60 | Train Acc: 47.37% | Val Acc: 91.00% | Val Loss: 1.06623
 Confusion Matrix saved at: confusion_matrix18.png
Epoch 19/60 | LR: 0.000019440
Epoch 19/60 | Train Acc: 50.98% | Val Acc: 89.67% | Val Loss: 1.08875
Epoch 20/60 | LR: 0.000019440
Epoch 20/60 | Train Acc: 47.63% | Val Acc: 90.67% | Val Loss: 1.08432
Epoch 21/60 | LR: 0.000019440
Epoch 21/60 | Train Acc: 49.91% | Val Acc: 90.33% | Val Loss: 1.07803
Epoch 22/60 | LR: 0.000019440
Epoch 22/60 | Train Acc: 50.17% | Val Acc: 90.33% | Val Loss: 1.08320
Epoch 23/60 | LR: 0.000011664
Epoch 23/60 | Train Acc: 50.88% | Val Acc: 89.67% | Val Loss: 1.09774
Epoch 24/60 | LR: 0.000011664
Epoch 24/60 | Train Acc: 51.45% | Val Acc: 90.00% | Val Loss: 1.08466
Epoch 25/60 | LR: 0.000011664
Epoch 25/60 | Train Acc: 50.30% | Val Acc: 91.00% | Val Loss: 1.07863
Epoch 26/60 | LR: 0.000011664
Epoch 26/60 | Train Acc: 48.79% | Val Acc: 89.67% | Val Loss: 1.08240
Epoch 27/60 | LR: 0.000006998
Epoch 27/60 | Train Acc: 48.44% | Val Acc: 90.00% | Val Loss: 1.09235
Epoch 28/60 | LR: 0.000006998
Epoch 28/60 | Train Acc: 49.40% | Val Acc: 89.67% | Val Loss: 1.07545
Epoch 29/60 | LR: 0.000006998
Epoch 29/60 | Train Acc: 51.72% | Val Acc: 90.33% | Val Loss: 1.08927
Epoch 30/60 | LR: 0.000006998
Epoch 30/60 | Train Acc: 52.76% | Val Acc: 90.67% | Val Loss: 1.06184
Early Stopping Activated!

  Best model weights saved! Validation Acc: 91.00%
 Confusion Matrix saved at: confusion_matrix.png
```



Test: public:0.933

I finally used a very strong model, and traditional data augmentation methods struggled to prevent overfitting. Therefore, I added mixup, which helps prevent the train loss from dropping too quickly, giving the val loss more time to decrease.

Additional Experiments:

1. Mix up

Ref: https://zhuanlan.zhihu.com/p/439205252

My score has been stagnating at a certain level, and no matter how I change the model, I cannot significantly improve the score. Therefore, I believe there are a few difficult-to-handle data points in the test set that the model cannot learn well in the training process. I suspect that some of the data points have features that are mixed between two categories, which makes it difficult for the model to confidently determine which category the image belongs to. As a result, I need to make changes to my training set to help the model better handle these situations.

The method I chose is mixup, which allows you to blend two training samples at a chosen ratio to create new data. By adding these mixed samples into the training process, the model can better handle samples that may fit multiple categories at once.

```
Epoch 14/60 | Train Acc: 93.96% | Val Acc: 83.33% | Val Loss: 1.31591
 Confusion Matrix saved at: confusion_matrix14.png
Epoch 15/60 | LR: 0.000090000
Epoch 15/60 | Train Acc: 94.69% | Val Acc: 80.67% | Val Loss: 1.45804
Epoch 16/60 | LR: 0.000090000
Epoch 16/60 | Train Acc: 94.87% | Val Acc: 80.33% | Val Loss: 1.41369
Epoch 17/60 | LR: 0.000054000
Epoch 17/60 | Train Acc: 95.74% | Val Acc: 84.00% | Val Loss: 1.35568
 Confusion Matrix saved at: confusion_matrix17.png
Epoch 18/60 | LR: 0.000054000
Epoch 18/60 | Train Acc: 95.83% | Val Acc: 82.00% | Val Loss: 1.30927
Epoch 19/60 | LR: 0.000054000
Epoch 19/60 | Train Acc: 96.47% | Val Acc: 84.33% | Val Loss: 1.29602
 Confusion Matrix saved at: confusion_matrix19.png
Epoch 20/60 | LR: 0.000054000
Epoch 20/60 | Train Acc: 96.43% | Val Acc: 83.67% | Val Loss: 1.33234
Epoch 21/60 | LR: 0.000054000
Epoch 21/60 | Train Acc: 96.51% | Val Acc: 85.33% | Val Loss: 1.28896
 Confusion Matrix saved at: confusion_matrix21.png
Epoch 22/60 | LR: 0.000054000
Epoch 22/60 | Train Acc: 96.93% | Val Acc: 83.00% | Val Loss: 1.32711
Epoch 23/60 | LR: 0.000054000
Epoch 23/60 | Train Acc: 96.62% | Val Acc: 85.00% | Val Loss: 1.28308
Epoch 24/60 | LR: 0.000032400
Epoch 24/60 | Train Acc: 97.08% | Val Acc: 84.33% | Val Loss: 1.29564
Epoch 25/60 | LR: 0.000032400
Epoch 25/60 | Train Acc: 97.54% | Val Acc: 85.33% | Val Loss: 1.29882
Epoch 26/60 | LR: 0.000019440
Epoch 26/60 | Train Acc: 97.62% | Val Acc: 85.67% | Val Loss: 1.26398
 Confusion Matrix saved at: confusion_matrix26.png
Epoch 27/60 | LR: 0.000019440
Epoch 27/60 | Train Acc: 97.88% | Val Acc: 86.00% | Val Loss: 1.27071
 Confusion Matrix saved at: confusion_matrix27.png
Epoch 28/60 | LR: 0.000019440
Epoch 28/60 | Train Acc: 97.87% | Val Acc: 83.33% | Val Loss: 1.28636
Epoch 29/60 | LR: 0.000019440
Epoch 29/60 | Train Acc: 98.02% | Val Acc: 84.33% | Val Loss: 1.28482
Epoch 30/60 | LR: 0.000011664
Epoch 30/60 | Train Acc: 97.98% | Val Acc: 84.67% | Val Loss: 1.27079
```

```
Epoch 22/60 | LR: 0.000032400
Epoch 22/60 | Train Acc: 48.33% | Val Acc: 88.00% | Val Loss: 1.14319
Epoch 23/60 | LR: 0.000032400
Epoch 23/60 | Train Acc: 51.26% | Val Acc: 88.67% | Val Loss: 1.13127
Epoch 24/60 | LR: 0.000019440
Epoch 24/60 | Train Acc: 51.88% | Val Acc: 89.00% | Val Loss: 1.10215
Epoch 25/60 | LR: 0.000019440
Epoch 25/60 | Train Acc: 49.79% | Val Acc: 90.00% | Val Loss: 1.11213
Epoch 26/60 | LR: 0.000011664
Epoch 26/60 | Train Acc: 50.12% | Val Acc: 91.67% | Val Loss: 1.09376
 Confusion Matrix saved at: confusion_matrix26.png
Epoch 27/60 | LR: 0.000011664
Epoch 27/60 | Train Acc: 48.44% | Val Acc: 90.33% | Val Loss: 1.11851
Epoch 28/60 | LR: 0.000011664
Epoch 28/60 | Train Acc: 45.46% | Val Acc: 90.67% | Val Loss: 1.09218
Epoch 29/60 | LR: 0.000006998
Epoch 29/60 | Train Acc: 48.03% | Val Acc: 90.67% | Val Loss: 1.09417
Epoch 30/60 | LR: 0.000006998
Epoch 30/60 | Train Acc: 49.34% | Val Acc: 90.67% | Val Loss: 1.08654
Epoch 31/60 | LR: 0.000004199
Epoch 31/60 | Train Acc: 48.40% | Val Acc: 91.33% | Val Loss: 1.08251
Epoch 32/60 | LR: 0.000004199
Epoch 32/60 | Train Acc: 51.74% | Val Acc: 91.33% | Val Loss: 1.09348
Epoch 33/60 | LR: 0.000002519
Epoch 33/60 | Train Acc: 47.62% | Val Acc: 90.00% | Val Loss: 1.10903
Epoch 34/60 | LR: 0.000002519
Epoch 34/60 | Train Acc: 47.72% | Val Acc: 91.00% | Val Loss: 1.08342
Epoch 35/60 | LR: 0.000001512
Epoch 35/60 | Train Acc: 48.29% | Val Acc: 91.00% | Val Loss: 1.09651
Epoch 36/60 | LR: 0.000001512
Epoch 36/60 | Train Acc: 51.73% | Val Acc: 91.00% | Val Loss: 1.08434
Epoch 37/60 | LR: 0.000000907
Epoch 37/60 | Train Acc: 48.60% | Val Acc: 91.33% | Val Loss: 1.08128
Epoch 38/60 | LR: 0.000000907
Epoch 38/60 | Train Acc: 51.49% | Val Acc: 90.67% | Val Loss: 1.08745
Early Stopping Activated!
```

Init LR:0.00015, Decay strategy: same,

Data augmentation: same

Drop out: 0.4

The left image shows the result without using mixup. The train accuracy quickly reaches near its peak, and the val loss decreases slowly.

In the right image, with mixup applied, the train accuracy stays below 50% for a long time, allowing the val accuracy to continue rising and eventually reach over 89%, a level not previously achieved. I believe this helped the model learn to handle ambiguous validation data. It is clear that mixup is very useful for dealing with tricky data, and when using a very strong model, it significantly enhances the model's growth potential, improving its overall generalization ability.