Marine Bird Classification

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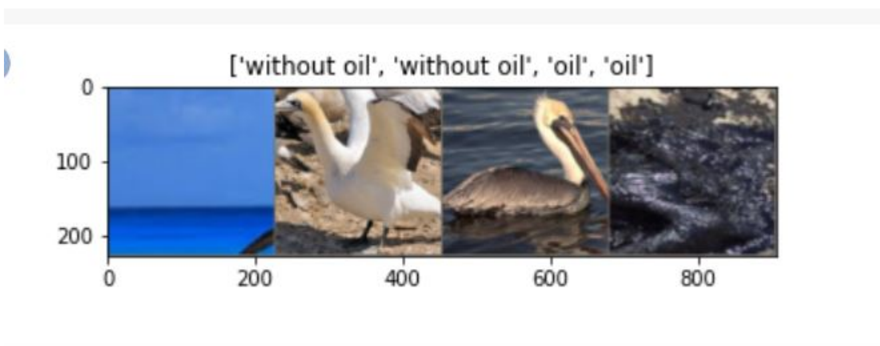
Abstract

In this report we introduced how to identify a marine bird(without oil) from a set of marine birds covered with oil from oil spill.

1 Introduction

First, we downloaded 100 images of two categories which are the birds with oil and without oil in marine areas.We used 80/20 split and our goal is to identify the birds covered with oil or without oil correctly. This figure shows the example for two categories.



2 Procedure

We made a simple classifier to make classification using pytorch.Model is based on cross-entropy loss and stochastic gradient decent algorithm used to find out the points which have minimum loss.After that resnet18 weights used as the weight of our classifier.After running several epochs,accuracy values for training and validation have recorded to check the performance of the model.

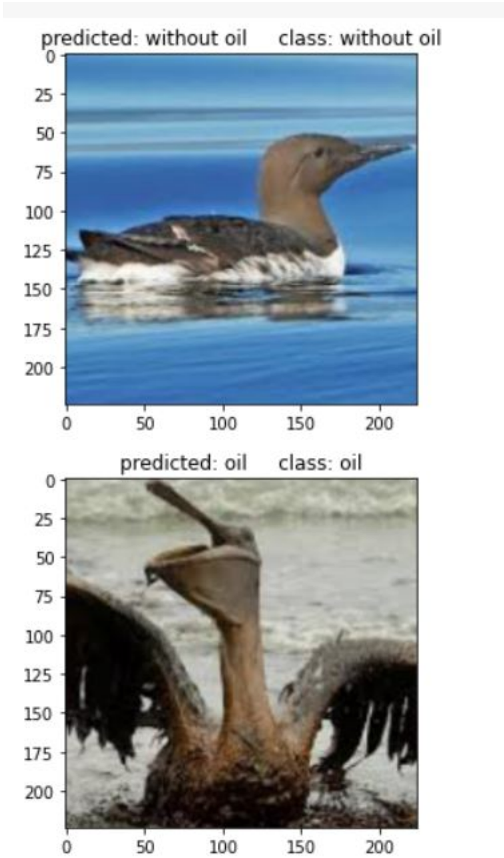
```
def train_model(model, num_epochs=25):

    model = model.to(device)
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)
```

```
    scheduler = lr_scheduler.StepLR(optimizer, step_size=7, gamma=0.1)

    for epoch in range(num_epochs):

        print('Epoch: ',epoch+1,'/',num_epochs)

        ###Train
        model.train()
        running_corrects = 0
        for inputs, labels in Bar(dataloaders['train']):
            inputs = inputs.to(device)
            labels = labels.to(device)

            optimizer.zero_grad()

            outputs = model(inputs)

            preds = torch.max(outputs, 1)[1]
            running_corrects += torch.sum(preds == labels.data)

            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

print("Train ", 'Acc: {:.2f}'.format(running_corrects.
double()/dataset_sizes['train']))

        scheduler.step()

        ###Val
        model.eval()
        running_corrects = 0
        for inputs, labels in Bar(dataloaders['valid']):
            inputs = inputs.to(device)
            labels = labels.to(device)

            outputs = model(inputs)
            preds = torch.max(outputs, 1)[1]
            running_corrects += torch.sum(preds == labels.data)

print("Valid ", 'Acc: {:.2f}'.format(running_corrects.double()/
dataset_sizes['valid']))
print("#######################")
    return model
```

3 Prediction using Resnet18

Finally we check the testing image with their actual and predicted class.The code is as follows.

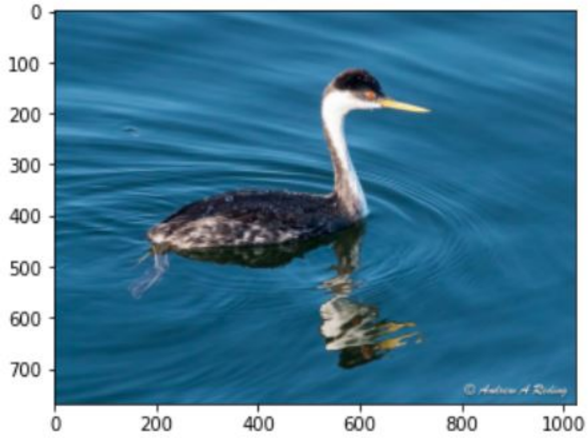
```
model = train_model(model, num_epochs=3)#train the model

def visualize_model(model, num_images=16):
    model.eval()
    index = 0
    for i, (inputs, labels) in enumerate(dataloaders['valid']):
        inputs = inputs.to(device)
        labels = labels.to(device)

        outputs = model(inputs)

        preds = torch.max(outputs, 1)[1]

for j in range(inputs.size()[0]):
index += 1
title1 = 'predicted: ' +dataset_labels[int(class_names[preds[j]])-1] + '
class: ' + dataset_labels[int(class_names[labels[j]])-1]
imshow(inputs.cpu().data[j],title1)

if index == num_images:
return
```



3.1 Prediction for new image

```
image = io.imread('https://images-na.ssl-images-
amazon.com/images/I/51dZp-%2B4W9L._AC_.jpg')
plt.imshow(image);
img = apply_transforms(image).
clone().detach().requires_grad_(True).to(device)
outputs = model(img)
preds = torch.max(outputs, 1)[1]
print('predicted: ' + dataset_labels[int(class_names[preds])-1])
```

```
image = io.imread('https://www.eopugetsound.org/sites/default/files/topical_article/images/10298390
plt.imshow(image);
```



```
img = apply_transforms(image).clone().detach().requires_grad_(True).to(device)
```

```
outputs = model(img)
preds = torch.max(outputs, 1)[1]
```

```
print('predicted: ' + dataset_labels[preds])
```

```
predicted: without oil
```

Finally we calculate the precision,recall and F1 score for each category and calculated the classification accuracy using our confusion matrix.

3.2 Classification Report

- True positive (TP) The number of correctly identified samples.
- True negative (TN) The number of correctly identified negative samples
- False positive (FP) The number of wrongly identified samples, i.e., a commonly called a "false alarm".
- False negative (FN) The number of wrongly identified negative samples.

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3.2.1 Precision

Precision (PREC) This metric is also frequently called the positive predictive value, and shows the ratio of samples that are correctly identified as positive.

- Precision for Without oil bird = 1.0
- Precision for With oil bird = 1.0

3.2.2 Recall

Recall (REC) This metric is also frequently called sensitivity, probability of detection and true positive rate, and it is the ratio of samples that are correctly identified as positive among all existing positive samples.

- Recall for Without oil bird = 1.0
- Recall for With oil bird = 1.0

3.2.3 F1 Score

F1 score (F1) A measure of a test's accuracy by calculating the harmonic mean of the precision and recall.

- F1 score Without oil bird = 1.0
- F1 scorer With oil bird = 1.0

3.2.4 Accuracy

Accuracy (ACC) The percentage of correctly identified true and false samples.

- Classification-Accuracy = 1.0