Dog vs Cat Classification using SVM

```
import matplotlib.pyplot as plt
import numpy as np
%matplotlib notebook
from sklearn import svm, metrics
from sklearn.utils import Bunch
from sklearn.model_selection import train_test_split
import time
from skimage.transform import resize
from skimage import io
import skimage
import cv2
from glob import glob
import pandas as pd
from tqdm import tqdm
from sklearn.metrics import ConfusionMatrixDisplay
```

Prepare

Load

```
def load_image_files(container_path, dimension=(64, 64)):
    image_dir = glob(f'{container_path}/*', recursive=True)
    categories = ['dog', 'cat']
    descr = "A image classification dataset"
    images = []
    flat_data = []
    target = []
    for image in tqdm(image_dir):
            img = skimage.io.imread(image)
            img_resized = resize(img, dimension, anti_aliasing=True,
mode='reflect')
            flat_data.append(img_resized.flatten())
            images.append(img_resized)
            if 'dog' in image:
                target.append(1)
            else:
                target.append(0)
    flat_data = np.array(flat_data)
    target = np.array(target)
    images = np.array(images)

    return Bunch(data=flat_data,
                 target=target,
```

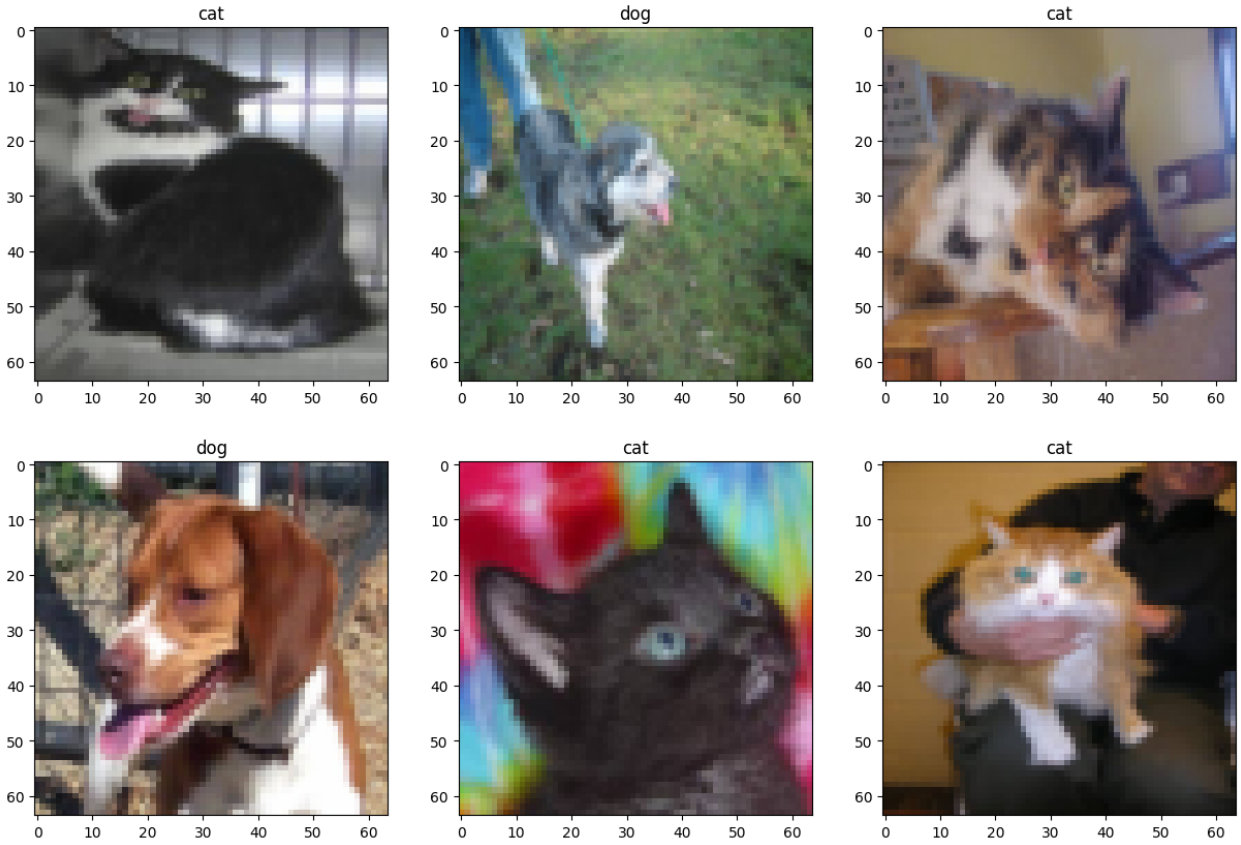
```
                  target_names=categories,
                  images=images,
                  DESCR=descr)

start_time = time.time()
image_dataset = load_image_files("train")
end_time = time.time()
print(f"Total time taken to load the dataset is {(end_time -
start_time):.5f} seconds")
```

```
100%|██████████| 25000/25000 [06:43<00:00, 61.99it/s]

Total time taken to load the dataset is 411.14143 seconds
```

Explore and preprocess

Visualize

```
# load 5 images and plot them, make fige size bigger 3*2 and print dog
if label is 1, else print cat
%matplotlib inline
fig, ax=plt.subplots(2,3, figsize=(15,10))
for i in range(6):
    ax[i//3, i%3].imshow(image_dataset.images[i])
    if image_dataset.target[i]==1:
        ax[i//3, i%3].set_title('dog')
    else:
        ax[i//3, i%3].set_title('cat')
```



Split

```
X_train, X_test, y_train, y_test = train_test_split(
    image_dataset.data, image_dataset.target,
test_size=0.2,random_state=42)

%time
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
CPU times: user 3 µs, sys: 0 ns, total: 3 µs
Wall time: 7.15 µs

((20000, 12288), (5000, 12288), (20000,), (5000,))
```

Train

```
model=svm.SVC()

start_time = time.time()
model.fit(X_train, y_train)
end_time = time.time()
```

```
print(f"Total time taken to train the model is {(end_time -
start_time):.5f} seconds")
```

```
[LibSVM]..............*....*
optimization finished, #iter = 18232
obj = -11709.329475, rho = 0.851154
nSV = 16499, nBSV = 12745
Total nSV = 16499
Total time taken to train the model is 3881.43218 seconds
```

```
start_time = time.time()
model.score(X_test, y_test)
end_time = time.time()
print(f"Total time taken to test the model is {(end_time -
start_time):.5f} seconds")
```

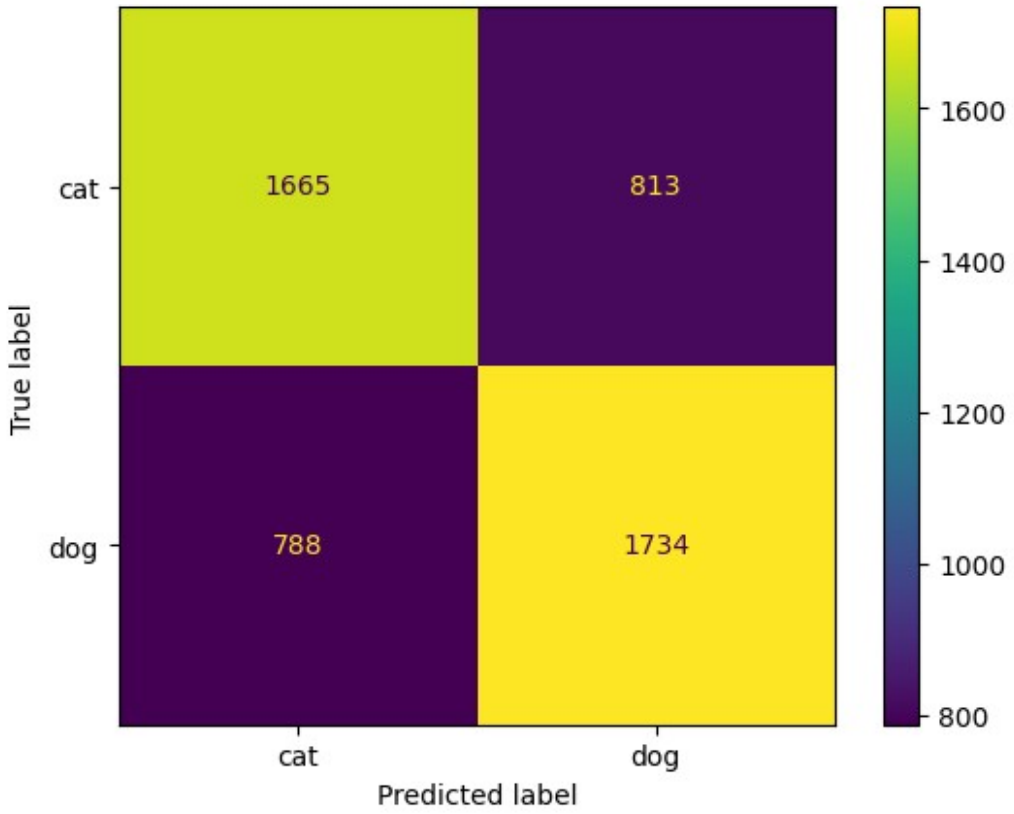
```
Total time taken to test the model is 2175.20540 seconds
```

```
# print classification report
start_time = time.time()
y_pred = model.predict(X_test)
print(metrics.classification_report(y_test, y_pred))
end_time = time.time()
print(f"Total time taken to print the classification report is
{(end_time - start_time):.5f} seconds")
```

```
              precision    recall  f1-score   support

           0       0.68      0.67      0.68      2478
           1       0.68      0.69      0.68      2522

    accuracy                           0.68      5000
   macro avg       0.68      0.68      0.68      5000
weighted avg       0.68      0.68      0.68      5000
```

```
Total time taken to print the classification report is 2211.34103
seconds
```

```
# print confusion matrix
cm = metrics.confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=['cat', 'dog'])

disp.plot()
plt.show()
```

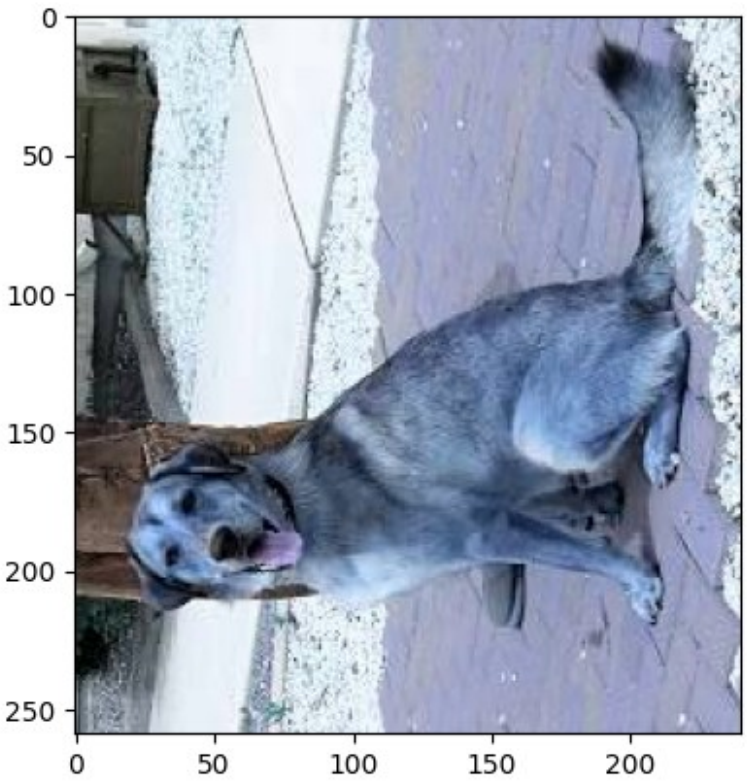



```
# load test images
test_images = glob(f'test1/*', recursive=True)

test_images[0]
```

```
'test1/1997.jpg'
```

```
# rotate one image then predict
image = cv2.imread(test_images[3])
image = cv2.rotate(image, cv2.ROTATE_90_COUNTERCLOCKWISE)

# predict the rotated image and print the result the and teh image
%matplotlib inline
img = resize(image, (64, 64))
# predict the image and print dog if label is 1, else print cat
pred=model.predict(img.flatten().reshape(1,-1))
if pred==1:
    print('dog')
else:
    print('cat')
plt.imshow(image);
```

```
cat
```



Import pytorch assets

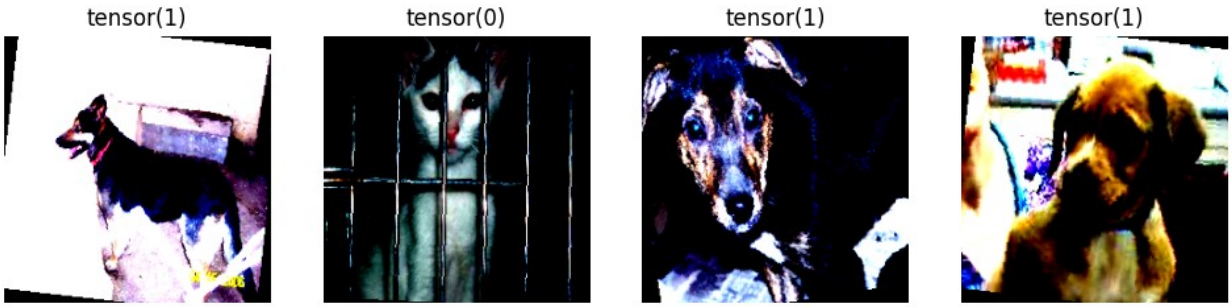
```
import torch
import torchvision
import torchvision.transforms as transforms
import torch.nn as nn
import torch.nn.functional as F
from torch.utils.data import Dataset, DataLoader
from torchvision import datasets, transforms, models
from torch.optim import lr_scheduler
import torch.optim as optim
from torch.autograd import Variable
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
import os
import time
import copy
from PIL import Image

# Read the train data,
train_dir = 'train'
```

```
test_dir = 'test1'
images=glob(os.path.join(train_dir,'*.jpg'))

# Define transforms for the training data and testing data
train_transforms = transforms.Compose([transforms.Resize((224,224)),

transforms.RandomHorizontalFlip(),
                                       transforms.RandomRotation(10),
                                       transforms.ToTensor(),
                                       transforms.Normalize([0.485,
0.456, 0.406],
                                                            [0.229,
0.224, 0.225])])
test_transforms = transforms.Compose([transforms.Resize((224,224)),
                                      transforms.ToTensor(),
                                      transforms.Normalize([0.485,
0.456, 0.406],
                                                           [0.229,
0.224, 0.225])])

class CustomDataset(Dataset):
    def __init__(self, file_list, transform=None):
        self.file_list = file_list
        self.transform = transform

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

    def __getitem__(self, idx):
        image = Image.open(self.file_list[idx]).convert('RGB')

        if self.transform:
            image = self.transform(image)

        label = os.path.splitext(self.file_list[idx])[0].split('.')
[0].split('/')[-1]
        if label == 'dog':
            label = 1
        elif label == 'cat':
            label = 0

        return image, label

start_time = time.time()
train_files, val_files = train_test_split(images, test_size=0.2,
random_state=42)
train_dataset = CustomDataset( train_files,
transform=train_transforms)
val_dataset = CustomDataset( val_files, transform=test_transforms)
batch_size = 32
train_dataloader = DataLoader(train_dataset, batch_size=batch_size,
```

```
shuffle=True)
val_dataloader = DataLoader(val_dataset, batch_size=batch_size,
shuffle=False)
end_time = time.time()
print(f"Total time taken to load the dataset is {(end_time -
start_time):.5f} seconds")
```

```
Total time taken to load the dataset is 0.01133 seconds
```

```
# load sample images
dataiter = next(iter(train_dataloader))

# show images
%matplotlib inline
fig, axes = plt.subplots(figsize=(12, 12), ncols=4)
for i in range(4):
    ax = axes[i]
    ax.imshow(dataiter[0][i].permute(1, 2, 0))
    ax.axis('off')
    ax.set_title(dataiter[1][i])
```




```
# load pretrained model
model = models.vgg16(pretrained=True)
```

```
/opt/conda/lib/python3.10/site-packages/torchvision/models/
_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated
since 0.13 and may be removed in the future, please use 'weights'
instead.
  warnings.warn(
/opt/conda/lib/python3.10/site-packages/torchvision/models/_utils.py:2
23: UserWarning: Arguments other than a weight enum or `None` for
'weights' are deprecated since 0.13 and may be removed in the future.
The current behavior is equivalent to passing
`weights=VGG16_Weights.IMAGENET1K_V1`. You can also use
`weights=VGG16_Weights.DEFAULT` to get the most up-to-date weights.
  warnings.warn(msg)
Downloading: "https://download.pytorch.org/models/vgg16-397923af.pth"
to /root/.cache/torch/hub/checkpoints/vgg16-397923af.pth
100%|██████████| 528M/528M [00:01<00:00, 297MB/s]
```

```
# freeze all model parameters
for param in model.parameters():
    param.requires_grad = False

# change the last layer
model.classifier[6] = nn.Linear(4096, 2)

# check if cuda is available
device = torch.device("cuda:0" if torch.cuda.is_available() else
"cpu")
# move model to GPU if cuda is available
model = model.to(device)

# define loss function
criterion = nn.CrossEntropyLoss()
# define optimizer
optimizer = optim.SGD(model.parameters(), lr=0.001, momentum=0.9)
# define learning rate scheduler
exp_lr_scheduler = lr_scheduler.StepLR(optimizer, step_size=7,
gamma=0.1)

# train the model
num_epochs = 10
for epoch in range(num_epochs):
    exp_lr_scheduler.step()
    train_loss = 0.0
    train_acc = 0.0
    val_loss = 0.0
    val_acc = 0.0
    model.train()
    # use tqdm to show progress bar
    for i, (inputs, labels) in tqdm(enumerate(train_dataloader),
total=len(train_dataloader)):
        inputs = inputs.to(device)
        labels = labels.to(device)
        optimizer.zero_grad()
        outputs = model(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        train_loss += loss.item() * inputs.size(0)
        ret, predictions = torch.max(outputs.data, 1)
        correct_counts =
predictions.eq(labels.data.view_as(predictions))
        acc = torch.mean(correct_counts.type(torch.FloatTensor))
        train_acc += acc.item() * inputs.size(0)
        # print training loss and accuracy of each epoch
    train_loss = train_loss / len(train_dataloader.dataset)
```

```
    train_acc = train_acc / len(train_dataloader.dataset)
    print('Epoch: {} \tTraining Loss: {:.6f} \tTraining Accuracy:
{:.6f}'.format(
        epoch + 1, train_loss, train_acc))
    model.eval()
    # use tqdm to show progress bar
    for i, (inputs, labels) in tqdm(enumerate(val_dataloader),
total=len(val_dataloader)):
        inputs = inputs.to(device)
        labels = labels.to(device)
        optimizer.zero_grad()
        outputs = model(inputs)
        loss = criterion(outputs, labels)
        val_loss += loss.item() * inputs.size(0)
        ret, predictions = torch.max(outputs.data, 1)
        correct_counts =
predictions.eq(labels.data.view_as(predictions))
        acc = torch.mean(correct_counts.type(torch.FloatTensor))
        val_acc += acc.item() * inputs.size(0)
        # print validation loss and accuracy of each epoch
    val_loss = val_loss / len(val_dataloader.dataset)
    val_acc = val_acc / len(val_dataloader.dataset)
    print('Epoch: {} \tValidation Loss: {:.6f} \tValidation Accuracy:
{:.6f}'.format(
        epoch + 1, val_loss, val_acc))
```

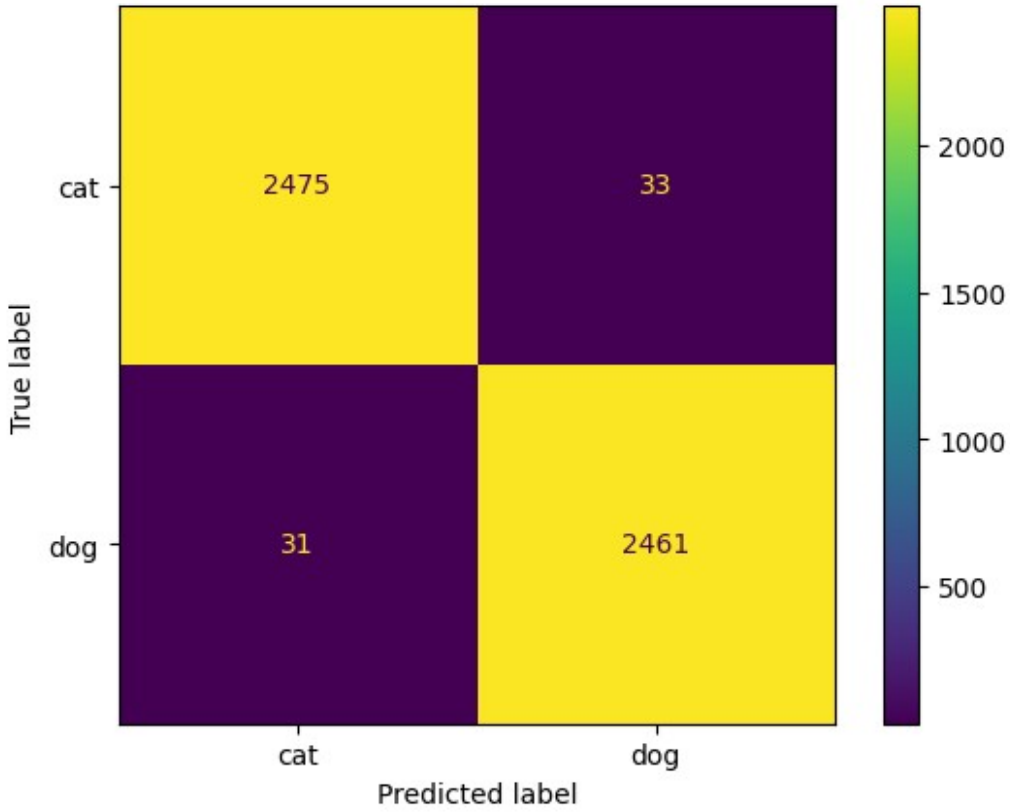
```
100%|██████████| 625/625 [02:06<00:00,  4.93it/s]

Epoch: 1   Training Loss: 0.038661    Training Accuracy: 0.986150

100%|██████████| 157/157 [00:29<00:00,  5.28it/s]

Epoch: 1   Validation Loss: 0.030556  Validation Accuracy: 0.987200

100%|██████████| 625/625 [02:06<00:00,  4.94it/s]

Epoch: 2   Training Loss: 0.039623    Training Accuracy: 0.984850

100%|██████████| 157/157 [00:29<00:00,  5.27it/s]

Epoch: 2   Validation Loss: 0.030623  Validation Accuracy: 0.987400

100%|██████████| 625/625 [02:06<00:00,  4.94it/s]

Epoch: 3   Training Loss: 0.039750    Training Accuracy: 0.985300

100%|██████████| 157/157 [00:29<00:00,  5.31it/s]

Epoch: 3   Validation Loss: 0.030808  Validation Accuracy: 0.987200

100%|██████████| 625/625 [02:06<00:00,  4.96it/s]
```

```
Epoch: 4   Training Loss: 0.042036    Training Accuracy: 0.984200
100%|██████████| 157/157 [00:29<00:00,  5.32it/s]
Epoch: 4   Validation Loss: 0.030835  Validation Accuracy: 0.987000
100%|██████████| 625/625 [02:06<00:00,  4.95it/s]
Epoch: 5   Training Loss: 0.038423    Training Accuracy: 0.986700
100%|██████████| 157/157 [00:29<00:00,  5.34it/s]
Epoch: 5   Validation Loss: 0.030845  Validation Accuracy: 0.987200
100%|██████████| 625/625 [02:07<00:00,  4.92it/s]
Epoch: 6   Training Loss: 0.038059    Training Accuracy: 0.985650
100%|██████████| 157/157 [00:29<00:00,  5.27it/s]
Epoch: 6   Validation Loss: 0.030847  Validation Accuracy: 0.987200
100%|██████████| 625/625 [02:06<00:00,  4.94it/s]
Epoch: 7   Training Loss: 0.038785    Training Accuracy: 0.984750
100%|██████████| 157/157 [00:29<00:00,  5.29it/s]
Epoch: 7   Validation Loss: 0.030834  Validation Accuracy: 0.987200
100%|██████████| 625/625 [02:07<00:00,  4.92it/s]
Epoch: 8   Training Loss: 0.040387    Training Accuracy: 0.984850
100%|██████████| 157/157 [00:29<00:00,  5.30it/s]
Epoch: 8   Validation Loss: 0.030801  Validation Accuracy: 0.987200
100%|██████████| 625/625 [02:06<00:00,  4.92it/s]
Epoch: 9   Training Loss: 0.042287    Training Accuracy: 0.984650
100%|██████████| 157/157 [00:29<00:00,  5.30it/s]
Epoch: 9   Validation Loss: 0.030817  Validation Accuracy: 0.987200
100%|██████████| 625/625 [02:07<00:00,  4.91it/s]
Epoch: 10  Training Loss: 0.041499    Training Accuracy: 0.984750
100%|██████████| 157/157 [00:29<00:00,  5.31it/s]
Epoch: 10  Validation Loss: 0.030820  Validation Accuracy: 0.987200
```

```
y_pred = []
y_true = []
model.eval()
for i, (inputs, labels) in tqdm(enumerate(val_dataloader),
total=len(val_dataloader)):
    inputs = inputs.to(device)
    labels = labels.to(device)
    outputs = model(inputs)
    _, preds = torch.max(outputs, 1)
    y_pred.extend(preds.cpu().numpy())
    y_true.extend(labels.cpu().numpy())
```

```
100%|██████████| 157/157 [00:29<00:00,  5.23it/s]
```

```
cm = confusion_matrix(y_true, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm,
display_labels=['cat', 'dog'])

disp.plot()
plt.show()
```



We have come to conclusion, using skimge is slower than PIL, you can see that it takes about 40 minutes to train SVM and get accurcy about 68%. In contrast, when I used pre-trained model it takes only about 20 minutes to get 98% on validation set.

so in my opinion: 1- Using skimage is not a good idea 2- Using SVM on image data is a waste of time 3- CNN is better suited for unstructured data like image