Goal: Jailbreaking Deep Models

In this project, we develop different types of attacks and apply them to a portion of the ImageNet-1K dataset. The ImageNet-1K has 1000 different classes with several images for each class. An example class is guitar. By making many versions of the provided dataset and applying different attacking methods, the weaknesses of deep learning models are explored and understood.

This project does not have a Kaggle competition since it is the last project of the semester for the Deep Learning class at Tandon.

Task 1: Basics

The pretrained Resnet-34 model and provided ImageNet-1K dataset is loaded to the notebook. The data is processed. The model is evaluated with the original dataset.

Importing packages These packages are needed to start processing the data

In [156…

```
import os
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import torch
import torchvision
from torchvision import transforms
from torchvision import datasets
from datasets import load_dataset, Dataset, ClassLabel
import pickle
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
print(f"Using device: {device}")
```

```
Using device: cuda
```

Transformations were applied to the dataset to normalize the images. The dataset path also leads to my documents folder. The dataset and dataloader are created.

In [81]:

```
mean_norms = np.array([0.485, 0.456, 0.406])
std_norms = np.array([0.229, 0.224, 0.225])
plain_transforms = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize(mean=mean_norms,
    std=std_norms)
])
dataset_path = "C:\\Users\\nehag\\Documents\\TestDataSet\\TestDataSet"
dataset = torchvision.datasets.ImageFolder(root=dataset_path,
transform=plain_transforms)
dataloader = torch.utils.data.DataLoader(dataset, batch_size=32, shuffle=False, num
```

Essential step for processing the data. After examining the Json, I realized that the labels are from 401 to 500. They are identical to the indices already provded by the ImageFolder except they are a difference of 401. Therefore, I added 401 to each index to ensure easier classification with the model.

In [82]:
```
dataset.samples = [ (path, old_label + 401) for (path, old_label) in dataset.sample
dataset.targets = [ old_label + 401 for old_label in dataset.targets ]
```

Testing to see if the above operation worked for an example case.

In [83]:
```
img, label = dataset[0]
label
```

Out[83]: 401

How to extract the folder name where the image is located. Not needed.

In [84]:
```
class_name = dataset.classes[1]
class_name
```

Out[84]: 'n02676566'

Loading the model

In [157…
```
model = torchvision.models.resnet34(weights='IMAGENET1K_V1')
```

Created the evaluate_set function so that a model, dataset and its respective dataloader is fed as parameters. The top5 and top1 accuracies are calculated and printed. This function is handy since the top1 and top5 accuracies need to be found for many different attacks and when using a different model at the end of the program.

In [86]:
```
def evaluate_set(model, dataset, dataloader):
    model.eval() #switch model to evaluate mode
    model = model.to(device) #move model to gpu
    top1_correct = 0 # constant for counting correct predictions for top1
    total = 0 # total cases with correct and incorrect predictions
    top5_correct = 0 # constant for counting correct predictions for top5
    with torch.no_grad(): #turn off gradients since evaluating
        for images, labels in dataloader: #for each batch in data set (32)
            images = images.to(device) #move images to gpu
            labels = labels.to(device) #move labels to gpu

            outputs = model(images) #pass images through model
            top5 = torch.topk(outputs, k=5, dim=1) #compute top5 predictions
            top5_preds = top5.indices #specifically outline the labels

            top5_correct += sum([labels[i].item() in top5_preds[i] for i in range(l
            # if label matches a prediction for the top 5 return true = 1
            _, predicted = torch.max(outputs, 1) # find prediction for top1
            top1_correct += (predicted == labels).sum().item() # correct prediction
            total += labels.size(0) # add total amount of images each time for accu
```

```
    accuracy = 100 * top1_correct / total
    top5_accuracy = 100 * top5_correct/ total
    print(f'TOP-1 Accuracy: {accuracy:.2f}%')
    print(f'TOP-5 Accuracy: {top5_accuracy:.2f}%')
```

The accuracies are already very high! Top-5 is close to 100%. These results suggest that the pretrained model is very good at recognizing the images.

In [87]:
```
evaluate_set(model, dataset, dataloader)
```

```
TOP-1 Accuracy: 76.00%
TOP-5 Accuracy: 94.20%
```

Task 2: Pixel-Wise Attacks

Fast Gradient Sign Method (FGSM) is implemented. This method implements a single step of gradient descent in the pixel space and truncates values of the gradients by epsilon. The raw epsilon value cannot exceed 0.02. This means that each pixel can change their value by at most +1/-1. A copy of the original dataset is made. FGSM is applied to the new dataset which is labeled Adversarial Test Set 1.

Making adversarial test set 1: This cell makes a list of the images to be made. Each original image is then cloned and applied PGD. The result is then added to the list. Afterwards, the list is converted to a tensor and then the dataset and loader are created.

In [88]:
```
import torch
import torch.nn.functional as F

# Per-channel epsilon (scaled for normalized ImageNet images)
epsilon = torch.tensor([0.0873, 0.0893, 0.0889]).view(3, 1, 1).to(device)

adversarial_images = [] #form of a list, not a tensor

model.eval() #ensure model is in evaluation mode

for images, labels in dataloader: #for each image and label (as a batch of 32)
    images = images.to(device)
    labels = labels.to(device)

    # Enable gradient wrt input
    images_adv = images.clone().detach().requires_grad_(True)

    # Forward pass
    outputs = model(images_adv)
    loss = F.cross_entropy(outputs, labels)

    # Backward pass: gradient wrt input image
    model.zero_grad()
    loss.backward()
```

```
    # Sign of gradient
    grad_sign = images_adv.grad.sign()

    # FGSM attack
    perturbed = images_adv + epsilon * grad_sign

    # Clamp to valid normalized range ([-3, 3] safe for ImageNet)
    perturbed = torch.clamp(perturbed, -3, 3)

    # Save perturbed image (copy)
    adversarial_images.append(perturbed.detach())
```

Extract all the labels from the original dataset. Convert the images that are in a list to a tensor. Convert the labels which are in a list to a tensor. Then connect the label and image tensor together with Tensor Dataset. Then make the data loader with that Tensor Dataset.

In [91]:
```
from torch.utils.data import TensorDataset, DataLoader
adv_images_tensor = torch.cat(adversarial_images, dim=0)
#extract all the labels from the original dataset so that they can be added to the
all_labels = []
for _, labels in dataloader:
    all_labels.append(labels)
all_labels = torch.cat(all_labels, dim=0)

# Now make a dataset
adversarial_test_set1 = TensorDataset(adv_images_tensor, all_labels)

# Wrap into a DataLoader
adversarial_loader1 = DataLoader(adversarial_test_set1, batch_size=32, shuffle=Fals
```

In order to plot the images, the images need to be unnormalized. This unnormalize function takes a tensor, the std and mean value specified in the beginning of the program and then clips the image to display it properly. The image is then returned. This function is normally used within other functions to print an image with matplotlib.

In [92]:
```
import matplotlib.pyplot as plt
import numpy as np

# Unnormalize and convert to numpy
def unnormalize(img_tensor, mean, std):
    img = img_tensor.cpu().clone()  # clone to avoid modifying original
    img = img.permute(1, 2, 0).numpy()  # [C, H, W] → [H, W, C]
    img = img * std + mean  # Unnormalize
    img = np.clip(img, 0, 1)  # Clamp to [0, 1] for display
    return img
```

This is the function that takes in the original image of the dataset and the new attacked image, printing them both out side by side for comparision.

In [145…
```
# Unnormalize both
def display_og_adv(dataset, adversarial_dataset, n, mean_norms, std_norms):
    image, label = dataset[n]
```

```
    perturbed, perturbed_label = adversarial_dataset[n]
    img_orig = unnormalize(image, mean_norms, std_norms)
    img_adv  = unnormalize(perturbed, mean_norms, std_norms)

    # Plot side by side
    plt.figure(figsize=(8,4))

    plt.subplot(1,2,1)
    plt.title("Original Image")
    plt.imshow(img_orig)
    plt.axis('off')

    plt.subplot(1,2,2)
    plt.title("Adversarial Image")
    plt.imshow(img_adv)
    plt.axis('off')

    plt.show()
```

For this task, each of the accuracies had to be less than 30% which is achieved. Evaluate_set function evaluated the new pixel attacked dataset with the pretrained resnet-34 model.

In [94]:
```
evaluate_set(model, adversarial_test_set1, adversarial_loader1)
```

```
TOP-1 Accuracy: 3.80%
TOP-5 Accuracy: 21.40%
```

Sometimes, we want to only find the prediction for a single image. This function makes that happen by setting the image to evaluation mode; making sure the model is set to GPU; and then predicting the label with the model from the parameter. The predicted and actual label is printed.

In [95]:
```
def evaluate_single_image(model, image, label):
    model.eval()  # switch model to evaluation mode
    model = model.to(device)  # move model to gpu

    # Add a batch dimension to the single image tensor (since model expects batches
    image = image.unsqueeze(0).to(device)  # shape [1, C, H, W]

    with torch.no_grad():  # turn off gradients since evaluating
        outputs = model(image)  # pass image through model
        _, predicted = torch.max(outputs, 1)  # find prediction for top1

    # Print the predicted label and the actual label
    predicted_label = predicted.item()
    actual_label = label

    print(f"Predicted Label: {predicted_label}, Actual Label: {actual_label}")
```

In order to find meaningful cases where the predicted labels for the adversarial testset differ from the original dataset, the first 10 images and their predictions are printed. We can see that sometimes the prediction differs from the actual label; however, if the model misclassified the image with the original dataset, I ignored that result and tried to find where the predicted labels differed. I specifically tried to find casess where the original image was correctly classified while the attacked image was misclassified. Selected image 1, 3, and 6

In [18]:
```python
for n in range(0, 10):
    print(f"For {n}th image in set: ")
    test_image, test_label = adversarial_test_set1[n]
    og_image, og_label = dataset[n]
    evaluate_single_image(model, og_image, og_label)
    evaluate_single_image(model, test_image, test_label)
    print("------------------------")
```

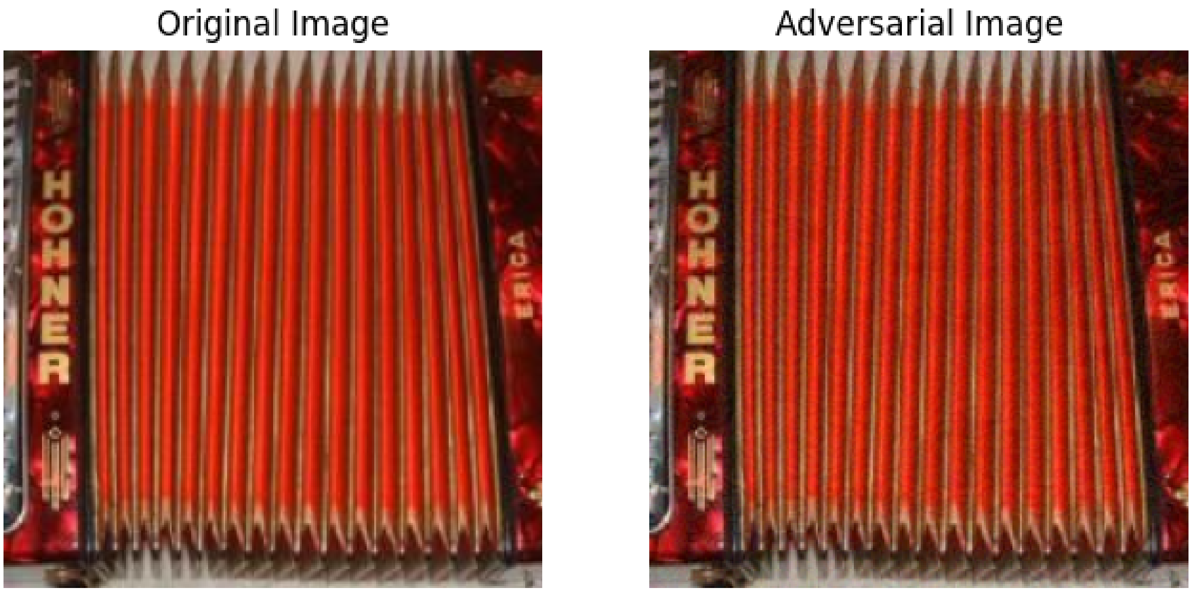
```
For 0th image in set:
Predicted Label: 401, Actual Label: 401
Predicted Label: 401, Actual Label: 401
------------------------
For 1th image in set:
Predicted Label: 401, Actual Label: 401
Predicted Label: 753, Actual Label: 401
------------------------
For 2th image in set:
Predicted Label: 819, Actual Label: 401
Predicted Label: 819, Actual Label: 401
------------------------
For 3th image in set:
Predicted Label: 401, Actual Label: 401
Predicted Label: 772, Actual Label: 401
------------------------
For 4th image in set:
Predicted Label: 398, Actual Label: 401
Predicted Label: 398, Actual Label: 401
------------------------
For 5th image in set:
Predicted Label: 546, Actual Label: 402
Predicted Label: 546, Actual Label: 402
------------------------
For 6th image in set:
Predicted Label: 402, Actual Label: 402
Predicted Label: 551, Actual Label: 402
------------------------
For 7th image in set:
Predicted Label: 402, Actual Label: 402
Predicted Label: 546, Actual Label: 402
------------------------
For 8th image in set:
Predicted Label: 402, Actual Label: 402
Predicted Label: 641, Actual Label: 402
------------------------
For 9th image in set:
Predicted Label: 402, Actual Label: 402
Predicted Label: 546, Actual Label: 402
------------------------
```

For the following example images, it is hard to find the differences between the original and adversarial case even by zooming in. This suggests that even slightly affecting the pixels can change the overall pattern of the image the model was designed to find.

In [98]:
```
test_image, test_label = adversarial_test_set1[1]
og_image, og_label = dataset[1]
evaluate_single_image(model, og_image, og_label)
evaluate_single_image(model, test_image, test_label)
```

```
Predicted Label: 401, Actual Label: 401
Predicted Label: 753, Actual Label: 401
```

In [146…
```
display_og_adv(dataset, adversarial_test_set1, 1, mean_norms, std_norms)
```



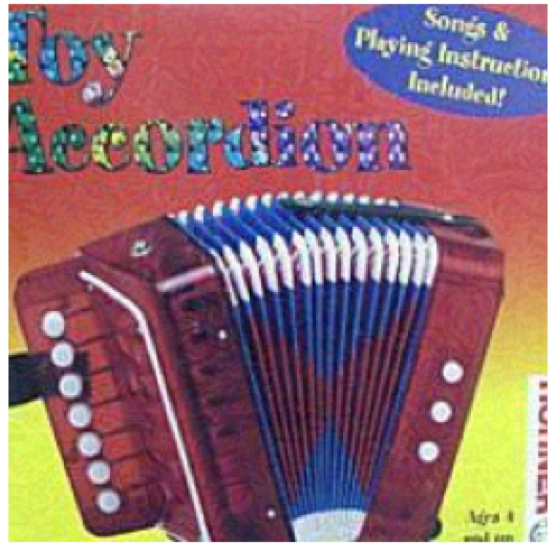
In [99]:
```
test_image, test_label = adversarial_test_set1[3]
og_image, og_label = dataset[3]
evaluate_single_image(model, og_image, og_label)
evaluate_single_image(model, test_image, test_label)
```

```
Predicted Label: 401, Actual Label: 401
Predicted Label: 772, Actual Label: 401
```

In [147…
```
display_og_adv(dataset, adversarial_test_set1, 3, mean_norms, std_norms)
```

Original Image

Adversarial Image



In [100…

```
test_image, test_label = adversarial_test_set1[6]
og_image, og_label = dataset[6]
evaluate_single_image(model, og_image, og_label)
evaluate_single_image(model, test_image, test_label)
```

```
Predicted Label: 402, Actual Label: 402
Predicted Label: 551, Actual Label: 402
```

In [148…

```
display_og_adv(dataset, adversarial_test_set1, 6, mean_norms, std_norms)
```

Original Image

Adversarial Image

Task 3: Improved Attacks

After applying a pixel-wise attack in the previous task, another attack was implemented to a fresh clone of the original dataset. This attack is known as Progressive Gradient Descent

(PGD) where contraints are taken into account while updating the gradients. The top1 and top5 accuracies must be 70% lower than those of the original dataset.

The following cell holds the pdg_attack_loader function. The dataloader loads the images and labels so that the gradients can be computed. The gradients are adjusted with respect to alpha and epsilon. The final results are applied to each image and returned at the end of the function.

The epsilon values were found by dividing the raw epsilon by the original std values. The raw epsilon is 0.02. Thus, 0.02/original std = 0.0873 for example.

In [22]:
```
epsilon_norm = torch.tensor([0.0873, 0.0893, 0.0889]).view(3,1,1).to(device)  # nor
alpha = epsilon / 9
num_iter = 2


def pgd_attack_loader(model, dataloader, epsilon, alpha, num_iter):
    model.eval()  # set to eval mode
    adv_images_list = []
    labels_list = []

    for images, labels in dataloader:
        images = images.to(device)
        labels = labels.to(device)

        # Initialize adv_images as clean image
        adv_images = images.clone().detach()
        # for each image
        for i in range(num_iter):
            adv_images.requires_grad = True
            outputs = model(adv_images) #find the prediction for that image

            loss = F.cross_entropy(outputs, labels) #compute the loss
            model.zero_grad()
            loss.backward() #backpropogate

            # Gradient sign step
            grad_sign = adv_images.grad.sign()
            adv_images = adv_images + alpha * grad_sign #essential step for PGD, ap

            # Projection: clamp perturbation within epsilon of original image
            perturbation = torch.clamp(adv_images - images, min=-epsilon, max=epsil
            adv_images = torch.clamp(images + perturbation, min=-3, max=3).detach()
        #add images to the list and labels
        adv_images_list.append(adv_images)
        labels_list.append(labels)

    # Stack into tensors
    adv_images_tensor = torch.cat(adv_images_list, dim=0)
    labels_tensor = torch.cat(labels_list, dim=0)

    return adv_images_tensor, labels_tensor
```

After defining the function, the function is used to make the new images and label tensors.|

In [23]:
```
adv_set2_images_tensor, adv_set2_labels_tensor = pgd_attack_loader(model,
                                                                    dataloader,
                                                                    epsilon_norm,
                                                                    alpha, num_iter)
```

Joining the image and label tensors to make a dataset. Using that dataset to make a dataloader.

In [24]:
```
# Now make a dataset
adversarial_test_set2 = TensorDataset(adv_set2_images_tensor, all_labels)

# Wrap into a DataLoader
adversarial_loader2 = DataLoader(adversarial_test_set2, batch_size=32, shuffle=Fals
```

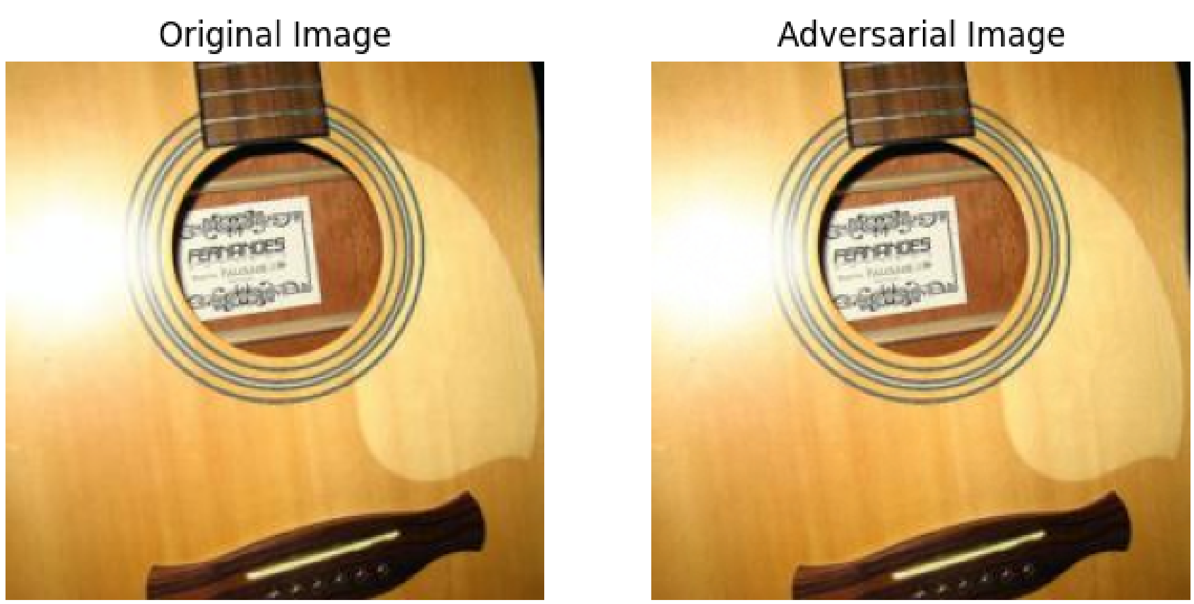
The results were supposed to be atleast 70% less than those of the original dataset. This goal has been achieved. The accuracy for top1 is close to zero; however, the top5 accuracy is significantly higher. This suggests that the attack is not super strong but still prevents the first guess from being correct.

In [25]:
```
evaluate_set(model, adversarial_test_set2, adversarial_loader2)
```

```
TOP-1 Accuracy: 1.20%
TOP-5 Accuracy: 21.40%
```

Verification that the new images are similar to the original images as requested.

In [149…
```
display_og_adv(dataset, adversarial_test_set2, 6, mean_norms, std_norms)
```



The three example images: The adversarial image again does not appear to be very different from the original. However, each case's prediction is not accurate to the ground truth. Additionally, the results for the misclassifications appear to match to those of the pixel attacked images.

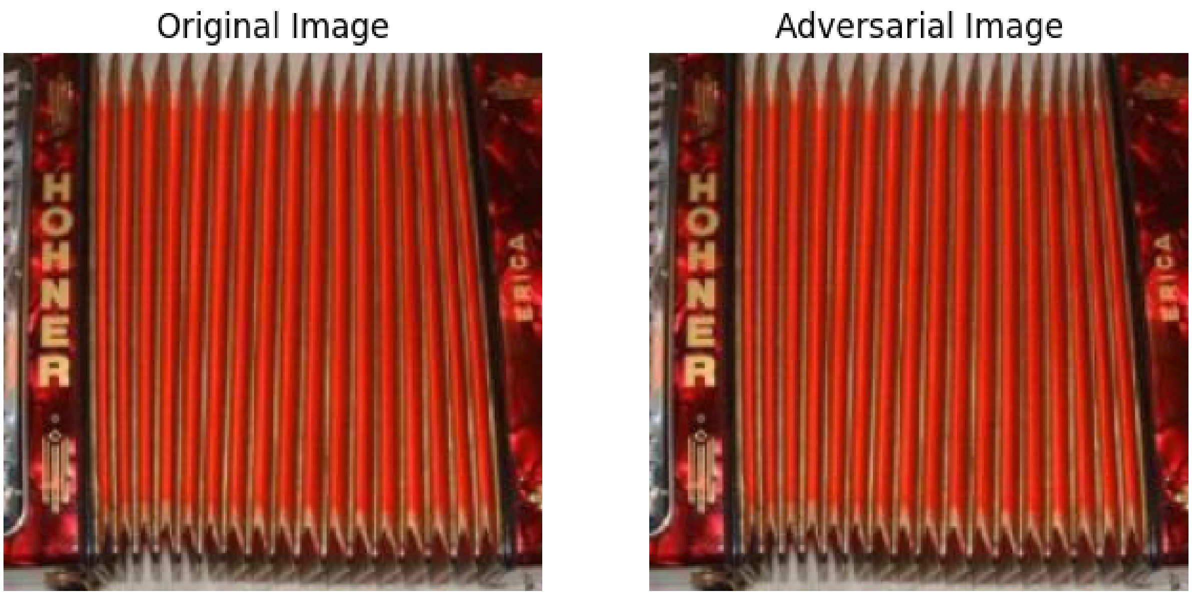
In [120…

```
test_image, test_label = adversarial_test_set2[1]
og_image, og_label = dataset[1]
evaluate_single_image(model, og_image, og_label)
evaluate_single_image(model, test_image, test_label)
```

```
Predicted Label: 401, Actual Label: 401
Predicted Label: 753, Actual Label: 401
```

In [150…

```
display_og_adv(dataset, adversarial_test_set2, 1, mean_norms, std_norms)
```



In [121…

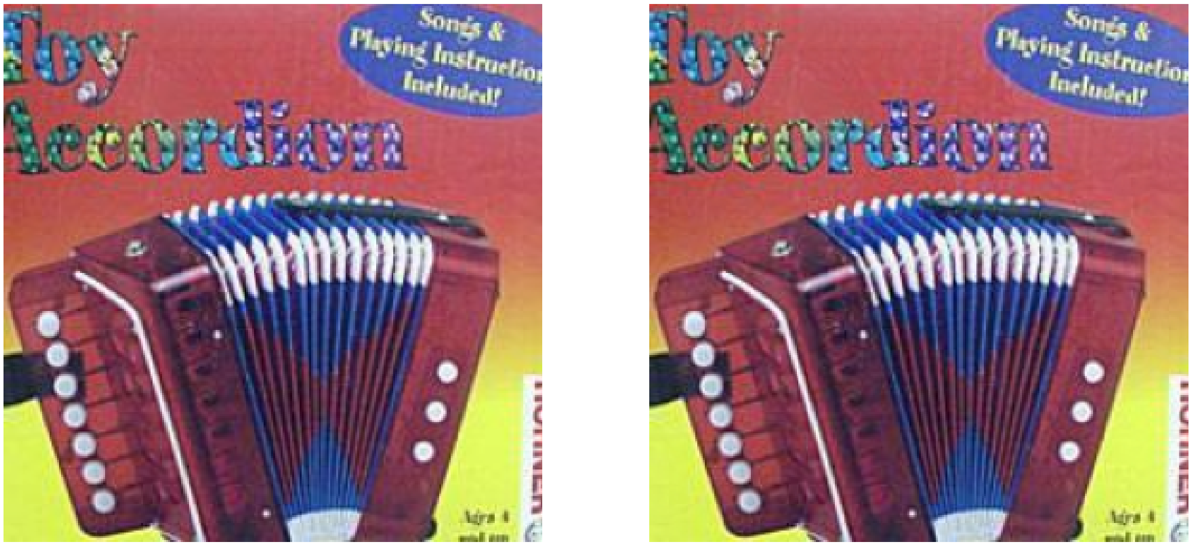
```
test_image, test_label = adversarial_test_set2[3]
og_image, og_label = dataset[3]
evaluate_single_image(model, og_image, og_label)
evaluate_single_image(model, test_image, test_label)
```

```
Predicted Label: 401, Actual Label: 401
Predicted Label: 772, Actual Label: 401
```

In [151…

```
display_og_adv(dataset, adversarial_test_set2, 3, mean_norms, std_norms)
```

Original Image Adversarial Image



In [122…
```
test_image, test_label = adversarial_test_set2[6]
og_image, og_label = dataset[6]
evaluate_single_image(model, og_image, og_label)
evaluate_single_image(model, test_image, test_label)
```

```
Predicted Label: 402, Actual Label: 402
Predicted Label: 551, Actual Label: 402
```

In [152…
```
display_og_adv(dataset, adversarial_test_set2, 6, mean_norms, std_norms)
```

Original Image Adversarial Image

Task 4: Patch Attacks

This time, an attack is not applied to the entire image. It must cover only 32x32. This is challenging because 32x32 is only around 10% of the image, and yet, it is supposed to trick the model into predicting incorrectly. Targetted attacks were used by training the patch. The patch would then trick the model into classifying the images as class 859. This trend is observed for the first and second example image where the predicted classes are 859. A new dataset was created labeled Adversarial Test Set 3 which hosts a copy of the patch on each image.

The following cell uses regular gradient descent to train a 32 by 32 patch with the original dataset. The patch is placed in the center and trained to exploit the weaknesses of the mode. The target_class variable will ensure that the model appears to be of that class (859).

In [73]:
```
import random
import torch
import torch.nn.functional as F

# Settings
patch_size = 32
num_epochs = 300 # Can be just 270 since the results appear to plateau after that
target_class = 859
alpha = 0.1  # Learning rate
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Initialize patch
patch = torch.randn(3, patch_size, patch_size, device=device, requires_grad=True)

optimizer = torch.optim.Adam([patch], lr=alpha)

# Ensure model is in evaluation mode
model.eval()

# For clamping
image_min = -3
image_max = 3

for epoch in range(num_epochs):
    for images, _ in dataloader:
        images = images.to(device)
        B, C, H, W = images.shape

        # Randomly select placement location for each image
        x_start = (W - patch_size) // 2  # OR random.randint(0, W - patch_size)
        y_start = (H - patch_size) // 2  # OR random.randint(0, H - patch_size)

        # Clone images and paste patch
        patched_images = images.clone()
        patched_images[:, :, y_start:y_start+patch_size, x_start:x_start+patch_size

        # Forward pass
        outputs = model(patched_images)

        # Targeted loss (we want outputs to predict target_class)
        target_labels = torch.full((B,), target_class, dtype=torch.long, device=dev
        loss = F.cross_entropy(outputs, target_labels)

        # Backprop and optimize patch
```

```
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

        #Clip patch pixel values
        patch.data.clamp_(min=image_min, max=image_max)

    if epoch % 5 == 0:
        print(f"Epoch {epoch}/{num_epochs}, Loss: {loss.item():.4f}")

# Now patch is optimized!
torch.save(patch.detach().cpu(), "optimized_patch.pt")
```

```
Epoch 0/300, Loss: 12.2892
Epoch 5/300, Loss: 1.3996
Epoch 10/300, Loss: 0.5141
Epoch 15/300, Loss: 0.3342
Epoch 20/300, Loss: 0.2532
Epoch 25/300, Loss: 0.2101
Epoch 30/300, Loss: 0.1855
Epoch 35/300, Loss: 0.1748
Epoch 40/300, Loss: 0.1634
Epoch 45/300, Loss: 0.1583
Epoch 50/300, Loss: 0.1555
Epoch 55/300, Loss: 0.1497
Epoch 60/300, Loss: 0.1465
Epoch 65/300, Loss: 0.1441
Epoch 70/300, Loss: 0.1376
Epoch 75/300, Loss: 0.1336
Epoch 80/300, Loss: 0.1292
Epoch 85/300, Loss: 0.1277
Epoch 90/300, Loss: 0.1226
Epoch 95/300, Loss: 0.1215
Epoch 100/300, Loss: 0.1177
Epoch 105/300, Loss: 0.1166
Epoch 110/300, Loss: 0.1161
Epoch 115/300, Loss: 0.1153
Epoch 120/300, Loss: 0.1114
Epoch 125/300, Loss: 0.1108
Epoch 130/300, Loss: 0.1110
Epoch 135/300, Loss: 0.1087
Epoch 140/300, Loss: 0.1093
Epoch 145/300, Loss: 0.1087
Epoch 150/300, Loss: 0.1072
Epoch 155/300, Loss: 0.1062
Epoch 160/300, Loss: 0.1070
Epoch 165/300, Loss: 0.1079
Epoch 170/300, Loss: 0.1070
Epoch 175/300, Loss: 0.1067
Epoch 180/300, Loss: 0.1072
Epoch 185/300, Loss: 0.1075
Epoch 190/300, Loss: 0.1051
Epoch 195/300, Loss: 0.1059
Epoch 200/300, Loss: 0.1060
Epoch 205/300, Loss: 0.1042
Epoch 210/300, Loss: 0.1045
Epoch 215/300, Loss: 0.1050
Epoch 220/300, Loss: 0.1039
Epoch 225/300, Loss: 0.1049
Epoch 230/300, Loss: 0.1038
Epoch 235/300, Loss: 0.1038
Epoch 240/300, Loss: 0.1027
Epoch 245/300, Loss: 0.1040
Epoch 250/300, Loss: 0.1025
Epoch 255/300, Loss: 0.1025
Epoch 260/300, Loss: 0.1033
Epoch 265/300, Loss: 0.1027
Epoch 270/300, Loss: 0.1035
Epoch 275/300, Loss: 0.1028
```

```
Epoch 280/300, Loss: 0.1027
Epoch 285/300, Loss: 0.1043
Epoch 290/300, Loss: 0.1032
Epoch 295/300, Loss: 0.1033
```

Save the patch so that it can be applied to each image later.

In [74]:
```
# After training, save the optimized patch
torch.save(patch.detach().cpu(), "optimized_patch.pt")

# 2. Apply the optimized patch to all images in the dataset
patch = torch.load("optimized_patch.pt").to(device)
```

Apply the patch to each image.

In [75]:
```
all_patched_images = []
all_patched_labels = []

# Assuming you want to apply the patch to the entire dataset
for images, labels in dataloader:
    images = images.to(device)
    B, C, H, W = images.shape

    # Ensure patch stays in the same place
    x_start = (W - patch_size) // 2
    y_start = (H - patch_size) // 2

    # Clone images and paste patch
    patched_images = images.clone()
    patched_images[:, :, y_start:y_start+patch_size, x_start:x_start+patch_size] =

    all_patched_images.append(patched_images)
    all_labels.append(labels)

# Convert to a single tensor for easy saving
all_patched_images = torch.cat(all_patched_images, dim=0)
all_labels = torch.cat(all_labels, dim=0)
```

Convert the image and label tensor to dataset and make the dataloader as well.

In [77]:
```
# Now make a dataset
adversarial_test_set3 = TensorDataset(all_patched_images, all_labels)
# Wrap into a DataLoader
adversarial_loader3 = DataLoader(adversarial_test_set3, batch_size=32, shuffle=Fals
```

TOP1 is less than 10%. Had difficulties with making top5 accuracy less than 10%

In [158…
```
evaluate_set(model, adversarial_test_set3, adversarial_loader3)
```

```
TOP-1 Accuracy: 5.80%
TOP-5 Accuracy: 31.80%
```

The final three test cases. The patch is very visible and appears to be a distorted twisted mixture of color (kind of like how mixed paint appears on a palette. This effect shows that the patch was trained to trick the model. The other part of the image is unchanged as requested.

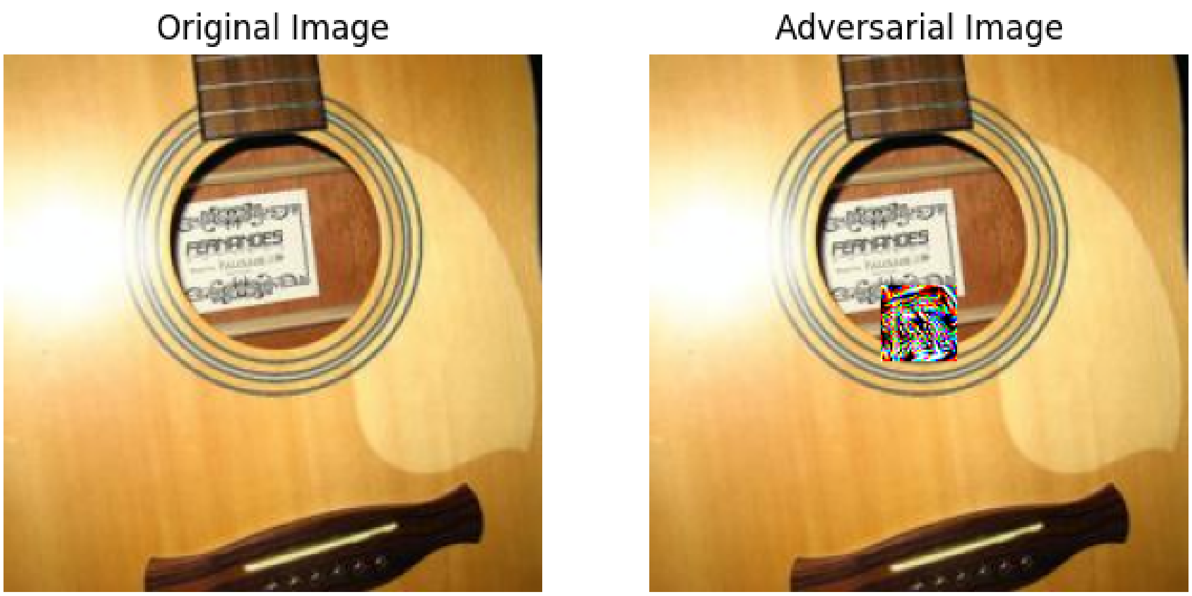
In [139...

```
m = 6
test_image, test_label = adversarial_test_set3[m]
og_image, og_label = dataset[m]
evaluate_single_image(model, og_image, og_label)
evaluate_single_image(model, test_image, test_label)
```

```
Predicted Label: 402, Actual Label: 402
Predicted Label: 859, Actual Label: 402
```

In [153...

```
display_og_adv(dataset, adversarial_test_set3, 6, mean_norms, std_norms)
```



In [141...

```
m = 3
test_image, test_label = adversarial_test_set3[m]
og_image, og_label = dataset[m]
evaluate_single_image(model, og_image, og_label)
evaluate_single_image(model, test_image, test_label)
```

```
Predicted Label: 401, Actual Label: 401
Predicted Label: 859, Actual Label: 401
```

In [154...

```
display_og_adv(dataset, adversarial_test_set3, 3, mean_norms, std_norms)
```

Original Image

Adversarial Image

In [143…

```
m = 1
test_image, test_label = adversarial_test_set3[m]
og_image, og_label = dataset[m]
evaluate_single_image(model, og_image, og_label)
evaluate_single_image(model, test_image, test_label)
```

```
Predicted Label: 401, Actual Label: 401
Predicted Label: 401, Actual Label: 401
```

In [155…

```
display_og_adv(dataset, adversarial_test_set3, 1, mean_norms, std_norms)
```

Original Image

Adversarial Image

Task 5

After finding the top1 and top5 results for each dataset with the resnet34 model, another model known as the densenet121 was evaluated with the same datasets. This excercise was used to demonstrate how the effects of the attacks can transfer from different architectures. The top1 and top5 results are printed for the new model. As observed the original dataset accuracies appear very close to those with the resnet34 model. However, The rest of the accuracies boosted up from their resnet-34 results. This suggests that the densenet121 model possibly prepared for attacks during training.

In [102…

```
new_model = torchvision.models.densenet121(weights='IMAGENET1K_V1')
```

```
Downloading: "https://download.pytorch.org/models/densenet121-a639ec97.pth" to C:\Users\nehag/.cache\torch\hub\checkpoints\densenet121-a639ec97.pth
100%|██████████| 30.8M/30.8M [00:03<00:00, 9.79MB/s]
```

In [109…

```
evaluate_set(new_model, dataset, dataloader)
```

```
TOP-1 Accuracy: 74.60%
TOP-5 Accuracy: 93.60%
```

In [106…

```
evaluate_set(new_model, adversarial_test_set1, adversarial_loader1)
```

```
TOP-1 Accuracy: 45.20%
TOP-5 Accuracy: 75.80%
```

In [107…

```
evaluate_set(new_model, adversarial_test_set2, adversarial_loader2)
```

```
TOP-1 Accuracy: 63.60%
TOP-5 Accuracy: 89.60%
```

In [108…

```
evaluate_set(new_model, adversarial_test_set3, adversarial_loader3)
```

```
TOP-1 Accuracy: 62.20%
TOP-5 Accuracy: 86.00%
```

Comments on Findings

By checking the accuracy of the Densenet model of predicting the labels for the datasets, the top1 and top5 accuracies for all are very cloes to one another. The original dataset has the highest accuracies. Surprisingly, the pixelwise attack had the lowest accuracies by around 15-20% compared to adversarial dataset 2 and 3. This shows that pixelwise attacks are very effective despite the effects looking negligible. When I compared the original image to that of the pixel attacked image, they both looked identical. This is because each pixel's values changed and the model was not prepared such random changes to an image. The values possibly felt artificial to the model because the patterns it learned was no longer present, leading to the lower accuracy.

Another finding was that the simple addition of a 32 by 32 noise patch was not an effective attack. This is because the pretrained model was possibly prepared for noisy patches, so it ignored that portion. The random placement also helped keep a high accuracy because the patches were placed in areas that were not important for classification. I eventually came up with the idea to train the patch to target a specific class. However, by adding grad-cam, the accuracies were back to being high.

Trends Observed

Task 2 and 3's classifications of the images appeared identical despite misclassifying the image. This suggests that there is a trend where the attacks guide the image to appear to be of a different class when a light attack is placed on the entire image.

Lessons Learned

The lessons I learned are that patch attacks do not have to be simply noise. They can be an imported image, a trained image, or even a pattern (such as checkered). I learned that a patch can be trained and placed in a specific spot to exploit a model's weaknesses. I also learned that a light pixel attack or PGD can make the image appear to be identical to the original and yet significantly affect predicitions.

Potential Ways Mitigating Transferability

To prevent attacks from signficantly affecting one model to another with different architectures, adversarial images can be fed to a model to quickly recognize attacks and classify them separately. Adding random transformations can also help models handle attacks. Processing data before transfering them to a model for evaluation can also lessen the attack's effect.