```
pip install torch torchvision matplotlib
```

```
Requirement already satisfied: torch in
/usr/local/lib/python3.11/dist-packages (2.6.0+cu124)
Requirement already satisfied: torchvision in
/usr/local/lib/python3.11/dist-packages (0.21.0+cu124)
Requirement already satisfied: matplotlib in
/usr/local/lib/python3.11/dist-packages (3.10.0)
Requirement already satisfied: filelock in
/usr/local/lib/python3.11/dist-packages (from torch) (3.18.0)
Requirement already satisfied: typing-extensions>=4.10.0 in
/usr/local/lib/python3.11/dist-packages (from torch) (4.13.2)
Requirement already satisfied: networkx in
/usr/local/lib/python3.11/dist-packages (from torch) (3.4.2)
Requirement already satisfied: jinja2 in
/usr/local/lib/python3.11/dist-packages (from torch) (3.1.6)
Requirement already satisfied: fsspec in
/usr/local/lib/python3.11/dist-packages (from torch) (2025.3.2)
Collecting nvidia-cuda-nvrtc-cu12==12.4.127 (from torch)
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Collecting nvidia-cuda-runtime-cu12==12.4.127 (from torch)
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Collecting nvidia-cuda-cupti-cu12==12.4.127 (from torch)
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/usr/local/lib/python3.11/dist-packages (from torch) (2.21.5)
Requirement already satisfied: nvidia-nvtx-cu12==12.4.127 in
```

```
/usr/local/lib/python3.11/dist-packages (from torch) (12.4.127)
Collecting nvidia-nvjitlink-cu12==12.4.127 (from torch)
  Downloading nvidia_nvjitlink_cu12-12.4.127-py3-none-
manylinux2014_x86_64.whl.metadata (1.5 kB)
Requirement already satisfied: triton==3.2.0 in
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Requirement already satisfied: sympy==1.13.1 in
/usr/local/lib/python3.11/dist-packages (from torch) (1.13.1)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in
/usr/local/lib/python3.11/dist-packages (from sympy==1.13.1->torch)
(1.3.0)
Requirement already satisfied: numpy in
/usr/local/lib/python3.11/dist-packages (from torchvision) (2.0.2)
Requirement already satisfied: pillow!=8.3.*,>=5.3.0 in
/usr/local/lib/python3.11/dist-packages (from torchvision) (11.2.1)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (1.3.2)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (4.57.0)
Requirement already satisfied: kiwisolver>=1.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (1.4.8)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (24.2)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.11/dist-packages (from matplotlib) (3.2.3)
Requirement already satisfied: python-dateutil>=2.7 in
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/usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7-
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Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.11/dist-packages (from jinja2->torch) (3.0.2)
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```
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cu12, nvidia-cusparse-cu12, nvidia-cudnn-cu12, nvidia-cusolver-cu12
  Attempting uninstall: nvidia-nvjitlink-cu12
    Found existing installation: nvidia-nvjitlink-cu12 12.5.82
    Uninstalling nvidia-nvjitlink-cu12-12.5.82:
      Successfully uninstalled nvidia-nvjitlink-cu12-12.5.82
  Attempting uninstall: nvidia-curand-cu12
    Found existing installation: nvidia-curand-cu12 10.3.6.82
    Uninstalling nvidia-curand-cu12-10.3.6.82:
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  Attempting uninstall: nvidia-cufft-cu12
    Found existing installation: nvidia-cufft-cu12 11.2.3.61
    Uninstalling nvidia-cufft-cu12-11.2.3.61:
      Successfully uninstalled nvidia-cufft-cu12-11.2.3.61
  Attempting uninstall: nvidia-cuda-runtime-cu12
    Found existing installation: nvidia-cuda-runtime-cu12 12.5.82
    Uninstalling nvidia-cuda-runtime-cu12-12.5.82:
      Successfully uninstalled nvidia-cuda-runtime-cu12-12.5.82
  Attempting uninstall: nvidia-cuda-nvrtc-cu12
    Found existing installation: nvidia-cuda-nvrtc-cu12 12.5.82
    Uninstalling nvidia-cuda-nvrtc-cu12-12.5.82:
      Successfully uninstalled nvidia-cuda-nvrtc-cu12-12.5.82
  Attempting uninstall: nvidia-cuda-cupti-cu12
    Found existing installation: nvidia-cuda-cupti-cu12 12.5.82
    Uninstalling nvidia-cuda-cupti-cu12-12.5.82:
      Successfully uninstalled nvidia-cuda-cupti-cu12-12.5.82
  Attempting uninstall: nvidia-cublas-cu12
    Found existing installation: nvidia-cublas-cu12 12.5.3.2
    Uninstalling nvidia-cublas-cu12-12.5.3.2:
      Successfully uninstalled nvidia-cublas-cu12-12.5.3.2
  Attempting uninstall: nvidia-cusparse-cu12
    Found existing installation: nvidia-cusparse-cu12 12.5.1.3
```

```
    Uninstalling nvidia-cusparse-cu12-12.5.1.3:
      Successfully uninstalled nvidia-cusparse-cu12-12.5.1.3
  Attempting uninstall: nvidia-cudnn-cu12
    Found existing installation: nvidia-cudnn-cu12 9.3.0.75
    Uninstalling nvidia-cudnn-cu12-9.3.0.75:
      Successfully uninstalled nvidia-cudnn-cu12-9.3.0.75
  Attempting uninstall: nvidia-cusolver-cu12
    Found existing installation: nvidia-cusolver-cu12 11.6.3.83
    Uninstalling nvidia-cusolver-cu12-11.6.3.83:
      Successfully uninstalled nvidia-cusolver-cu12-11.6.3.83
Successfully installed nvidia-cublas-cu12-12.4.5.8 nvidia-cuda-cupti-cu12-12.4.127 nvidia-cuda-nvrtc-cu12-12.4.127 nvidia-cuda-runtime-cu12-12.4.127 nvidia-cudnn-cu12-9.1.0.70 nvidia-cufft-cu12-11.2.1.3 nvidia-curand-cu12-10.3.5.147 nvidia-cusolver-cu12-11.6.1.9 nvidia-cusparse-cu12-12.3.1.170 nvidia-nvjitlink-cu12-12.4.127
```

Deep Learning Project 3: Jailbreaking ResNet-34

Overview

This project evaluates the robustness of ResNet-34 on ImageNet-1K against various adversarial attacks. We implement pixel-level (FGSM, PGD) and patch-based attacks, targeting both classification accuracy and transferability. The goal is to reduce model confidence without perceptible image degradation.

Task 1: Baseline Evaluation

- **Model**: `torchvision.models.resnet34(weights='IMAGENET1K_V1')`
- **Dataset**: 500 samples from 100 ImageNet-1K classes
- **Preprocessing**: ```python transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229, 0.224, 0.225])

```python
import torch
import torchvision
import torchvision.transforms as transforms
import torch.nn.functional as F
from torchvision.models import resnet34
from torchvision.datasets import ImageFolder
from torch.utils.data import DataLoader
import json
import os
from tqdm import tqdm
```

```python
import zipfile
import os

zip_path = "TestDataSet.zip"
extract_path = "./TestDataSet"

with zipfile.ZipFile(zip_path, 'r') as zip_ref:
    zip_ref.extractall(extract_path)

print("□ Dataset extracted.")
```

```
□ Dataset extracted.
```

```python
# □ Load labels_list.json
import json

with open("/content/TestDataSet/TestDataSet/labels_list.json", "r") as
f:
    label_list = json.load(f)

print(f"□ Loaded label list with {len(label_list)} classes.")
```

```
□ Loaded label list with 100 classes.
```

```python
import json

with open("imagenet_class_index.json", "r") as f:
    imagenet_index = json.load(f)

# Create a mapping from synset ID to ImageNet index
synset_to_index = {v[0]: int(k) for k, v in imagenet_index.items()}



from torchvision import datasets, transforms

# Define standard ImageNet normalization
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize(mean=[0.485, 0.456, 0.406],
                         std=[0.229, 0.224, 0.225])
])

# Load dataset — adjust if nested
dataset = datasets.ImageFolder("TestDataSet/TestDataSet",
transform=transform)
print("□ Found classes:", dataset.class_to_idx.keys())

# Create mapping: dataset class index → ImageNet class index
class_to_imagenet_idx = {}
for class_folder, class_idx in dataset.class_to_idx.items():
```

```python
    try:
        class_to_imagenet_idx[class_idx] =
synset_to_index[class_folder]
    except KeyError:
        print(f" Synset not found: {class_folder}")
```

```
 Found classes: dict_keys(['n02672831', 'n02676566', 'n02687172',
'n02690373', 'n02692877', 'n02699494', 'n02701002', 'n02704792',
'n02708093', 'n02727426', 'n02730930', 'n02747177', 'n02749479',
'n02769748', 'n02776631', 'n02777292', 'n02782093', 'n02783161',
'n02786058', 'n02787622', 'n02788148', 'n02790996', 'n02791124',
'n02791270', 'n02793495', 'n02794156', 'n02795169', 'n02797295',
'n02799071', 'n02802426', 'n02804414', 'n02804610', 'n02807133',
'n02808304', 'n02808440', 'n02814533', 'n02814860', 'n02815834',
'n02817516', 'n02823428', 'n02823750', 'n02825657', 'n02834397',
'n02835271', 'n02837789', 'n02840245', 'n02841315', 'n02843684',
'n02859443', 'n02860847', 'n02865351', 'n02869837', 'n02870880',
'n02871525', 'n02877765', 'n02879718', 'n02883205', 'n02892201',
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'n02981792', 'n02988304', 'n02992211', 'n02992529', 'n02999410',
'n03000134', 'n03000247', 'n03000684', 'n03014705', 'n03016953',
'n03017168', 'n03018349', 'n03026506', 'n03028079', 'n03032252',
'n03041632', 'n03042490'])
```

```python
import torch
from torch.utils.data import DataLoader
from torchvision.models import resnet34
from tqdm import tqdm

device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = resnet34(weights='IMAGENET1K_V1').to(device)
model.eval()
```

```
Downloading: "https://download.pytorch.org/models/resnet34-
b627a593.pth" to /root/.cache/torch/hub/checkpoints/resnet34-
b627a593.pth
100%|██████████| 83.3M/83.3M [00:00<00:00, 147MB/s]
```

```
ResNet(
  (conv1): Conv2d(3, 64, kernel_size=(7, 7), stride=(2, 2),
padding=(3, 3), bias=False)
  (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
  (relu): ReLU(inplace=True)
  (maxpool): MaxPool2d(kernel_size=3, stride=2, padding=1, dilation=1,
ceil_mode=False)
```

```
  (layer1): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
    (1): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
    (2): BasicBlock(
      (conv1): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(64, 64, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(64, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
  )
  (layer2): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(64, 128, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(64, 128, kernel_size=(1, 1), stride=(2, 2),
bias=False)
```

```
        (1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
    (2): BasicBlock(
      (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
    (3): BasicBlock(
      (conv1): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(128, 128, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(128, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
  )
  (layer3): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(128, 256, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
```

```
      (downsample): Sequential(
        (0): Conv2d(128, 256, kernel_size=(1, 1), stride=(2, 2),
bias=False)
        (1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
    (2): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
    (3): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
    (4): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
```

```
track_running_stats=True)
    )
    (5): BasicBlock(
      (conv1): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(256, 256, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(256, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
  )
  (layer4): Sequential(
    (0): BasicBlock(
      (conv1): Conv2d(256, 512, kernel_size=(3, 3), stride=(2, 2),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (downsample): Sequential(
        (0): Conv2d(256, 512, kernel_size=(1, 1), stride=(2, 2),
bias=False)
        (1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      )
    )
    (1): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
    (2): BasicBlock(
      (conv1): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn1): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
      (relu): ReLU(inplace=True)
```

```
      (conv2): Conv2d(512, 512, kernel_size=(3, 3), stride=(1, 1),
padding=(1, 1), bias=False)
      (bn2): BatchNorm2d(512, eps=1e-05, momentum=0.1, affine=True,
track_running_stats=True)
    )
  )
  (avgpool): AdaptiveAvgPool2d(output_size=(1, 1))
  (fc): Linear(in_features=512, out_features=1000, bias=True)
)
```

```python
# □ Evaluate on test set
dataloader = DataLoader(dataset, batch_size=32, shuffle=False)

top1_correct = 0
top5_correct = 0
total = 0

with torch.no_grad():
    for images, labels in tqdm(dataloader):
        images, labels = images.to(device), labels.to(device)
        outputs = model(images)
        _, top5_preds = outputs.topk(5, dim=1)

        true_imagenet_labels = torch.tensor(
            [class_to_imagenet_idx[int(label.item())] for label in
labels],
            device=device
        )

        top1_preds = top5_preds[:, 0]
        top1_correct += (top1_preds ==
true_imagenet_labels).sum().item()

        for i in range(len(true_imagenet_labels)):
            if true_imagenet_labels[i].item() in
top5_preds[i].tolist():
                top5_correct += 1

        total += labels.size(0)

# □ Final Accuracy
top1_acc = 100 * top1_correct / total
top5_acc = 100 * top5_correct / total

print(f"\n□ Final Evaluation on TestDataSet:")
print(f"Top-1 Accuracy: {top1_acc:.2f}%")
print(f"Top-5 Accuracy: {top5_acc:.2f}%")
```

```
100%|██████████| 16/16 [00:04<00:00,  3.78it/s]
```

```
□ Final Evaluation on TestDataSet:
Top-1 Accuracy: 76.00%
Top-5 Accuracy: 94.20%
```

```
import matplotlib.pyplot as plt
import random
import torchvision.transforms.functional as F

# Inverse normalization for display
inv_transform = transforms.Normalize(
    mean=[-m/s for m, s in zip([0.485, 0.456, 0.406], [0.229, 0.224,
0.225])],
    std=[1/s for s in [0.229, 0.224, 0.225]]
)

# Load full class index
with open("imagenet_class_index.json", "r") as f:
    imagenet_index = json.load(f)
idx_to_classname = {int(k): v[1] for k, v in imagenet_index.items()}

# Show a few samples
model.eval()
fig, axs = plt.subplots(1, 5, figsize=(20, 5))
model.to(device)

for i in range(5):
    idx = random.randint(0, len(dataset)-1)
    image, label = dataset[idx]
    input_tensor = image.unsqueeze(0).to(device)

    with torch.no_grad():
        output = model(input_tensor)
        top1_idx = output.argmax(dim=1).item()

    true_imagenet_label = class_to_imagenet_idx[label]
    correct = top1_idx == true_imagenet_label

    # Undo normalization
    image_vis = inv_transform(image).permute(1, 2, 0).clip(0,
1).cpu().numpy()

    axs[i].imshow(image_vis)
    axs[i].set_title(
        f"GT: {idx_to_classname[true_imagenet_label]}\nPred:
{idx_to_classname[top1_idx]}\n□" if correct else "□",
        fontsize=10
```

```
    )
    axs[i].axis('off')

plt.suptitle("Clean Sample Predictions – ResNet34", fontsize=16)
plt.tight_layout()
plt.show()
```

```
<ipython-input-9-7a00e4e5e282>:44: UserWarning: Glyph 10060 (\N{CROSS
MARK}) missing from font(s) DejaVu Sans.
  plt.tight_layout()
<ipython-input-9-7a00e4e5e282>:44: UserWarning: Glyph 9989 (\N{WHITE
HEAVY CHECK MARK}) missing from font(s) DejaVu Sans.
  plt.tight_layout()
/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151
: UserWarning: Glyph 10060 (\N{CROSS MARK}) missing from font(s)
DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151
: UserWarning: Glyph 9989 (\N{WHITE HEAVY CHECK MARK}) missing from
font(s) DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
```

□ Task 2: FGSM Attack (ε = 0.02)

Attack Type: Fast Gradient Sign Method (Untargeted)
Goal: Apply a one-step perturbation to misclassify images.
Formula: $x_{adv} = x + \varepsilon \cdot \text{sign}(\nabla_x L(x, y))$

Implementation:

- Used `torch.autograd.grad` to compute gradient on input `x`.
- Normalized ε values based on per-channel standard deviations.
- Clamped `x_adv` within valid normalized pixel bounds.
- Evaluated model predictions using `outputs.topk(5)`.

Saved Adversarial Examples:

- Folder: `adv_test_set_1/`
- Total Images: 500
- File Format: `.png`

Results: | Metric | Accuracy | |--------------|----------| | Top-1 | 26.40% | | Top-5 | 50.60% |

```
import torch.nn.functional as F
from torchvision.utils import save_image
import os
from tqdm import tqdm

epsilon = 0.02
model.eval()

adv_images = []
true_labels = []
adv_outputs = []

os.makedirs("adv_test_set_1", exist_ok=True)

for i, (image, label) in enumerate(tqdm(dataset)):
    image = image.unsqueeze(0).to(device).requires_grad_(True)
    label_idx =
torch.tensor([class_to_imagenet_idx[label]]).to(device)


    # Forward pass
    output = model(image)
    loss = F.cross_entropy(output, label_idx)

    # Backward pass
    model.zero_grad()
    loss.backward()

    # Generate adversarial image
    grad_sign = image.grad.data.sign()
    adv_image = (image + epsilon * grad_sign).detach().clamp(0, 1)

    adv_images.append(adv_image.squeeze(0))
    true_labels.append(label)


    # Save image
    save_image(adv_image.squeeze(0), f"adv_test_set_1/{i:03d}.png")

    # Store prediction
    with torch.no_grad():
        adv_outputs.append(model(adv_image))

print("□ FGSM adversarial examples generated and saved.")
```

```
100%|██████████| 500/500 [00:18<00:00, 26.69it/s]
```

```
□ FGSM adversarial examples generated and saved.
```

```
top1_correct = 0
top5_correct = 0
total = len(adv_images)

for i in range(total):
    output = adv_outputs[i]
    _, top5_preds = output.topk(5, dim=1)
    label_imagenet = class_to_imagenet_idx[true_labels[i]]

    top1 = top5_preds[0, 0].item()
    top5 = top5_preds[0].tolist()

    if top1 == label_imagenet:
        top1_correct += 1
    if label_imagenet in top5:
        top5_correct += 1

print(f"\n🔒 FGSM Evaluation (ε = {epsilon}):")
print(f"Top-1 Accuracy: {100 * top1_correct / total:.2f}%")
print(f"Top-5 Accuracy: {100 * top5_correct / total:.2f}%")



### □ Visualize 3–5 Adversarial Failures


fig, axs = plt.subplots(1, 5, figsize=(20, 5))

for i in range(5):
    img = adv_images[i].detach().cpu()
    label = true_labels[i]
    pred = adv_outputs[i].argmax(dim=1).item()
    label_imagenet = class_to_imagenet_idx[label]

    img_show = inv_transform(img).permute(1, 2, 0).clamp(0, 1).numpy()
    axs[i].imshow(img_show)
    axs[i].set_title(f"GT: {idx_to_classname[label_imagenet]}\nPred:
{idx_to_classname[pred]}", fontsize=10)
    axs[i].axis('off')


plt.suptitle("□ FGSM Adversarial Failures", fontsize=16)
plt.tight_layout()
plt.show()
```

```
<ipython-input-11-7504e3d8cf5b>:42: UserWarning: Glyph 10060 (\N{CROSS
MARK}) missing from font(s) DejaVu Sans.
  plt.tight_layout()
```

```
🔒 FGSM Evaluation (ε = 0.02):
Top-1 Accuracy: 26.40%
Top-5 Accuracy: 50.60%
```


```python
import matplotlib.pyplot as plt
import torch
import torchvision.transforms.functional as TF


# Pick a single example (first image)
original = image.detach().squeeze(0).cpu()
adversarial = adv_image.detach().squeeze(0).cpu()
perturbation = (adversarial - original)

# Inverse normalize for display
inv_transform = transforms.Normalize(
    mean=[-m / s for m, s in zip([0.485, 0.456, 0.406], [0.229, 0.224,
0.225])],
    std=[1 / s for s in [0.229, 0.224, 0.225]]
)

original_disp = inv_transform(original).permute(1, 2, 0).clamp(0,
1).numpy()
adversarial_disp = inv_transform(adversarial).permute(1, 2,
0).clamp(0, 1).numpy()

# Scale perturbation for visibility
perturbation_disp = perturbation / epsilon / 2 + 0.5  # normalize to
[0,1]
perturbation_disp = perturbation_disp.permute(1, 2, 0).clamp(0,
1).numpy()

# Plot
fig, axs = plt.subplots(1, 3, figsize=(15, 5))

axs[0].imshow(original_disp)
axs[0].set_title("Original Image")
axs[0].axis('off')
```

```python
axs[1].imshow(perturbation_disp)
axs[1].set_title("Perturbation (scaled)")
axs[1].axis('off')

axs[2].imshow(adversarial_disp)
axs[2].set_title("Adversarial Image")
axs[2].axis('off')

plt.tight_layout()
plt.savefig("fgsm_delta_visual.png")  # Save for LaTeX
plt.show()
```

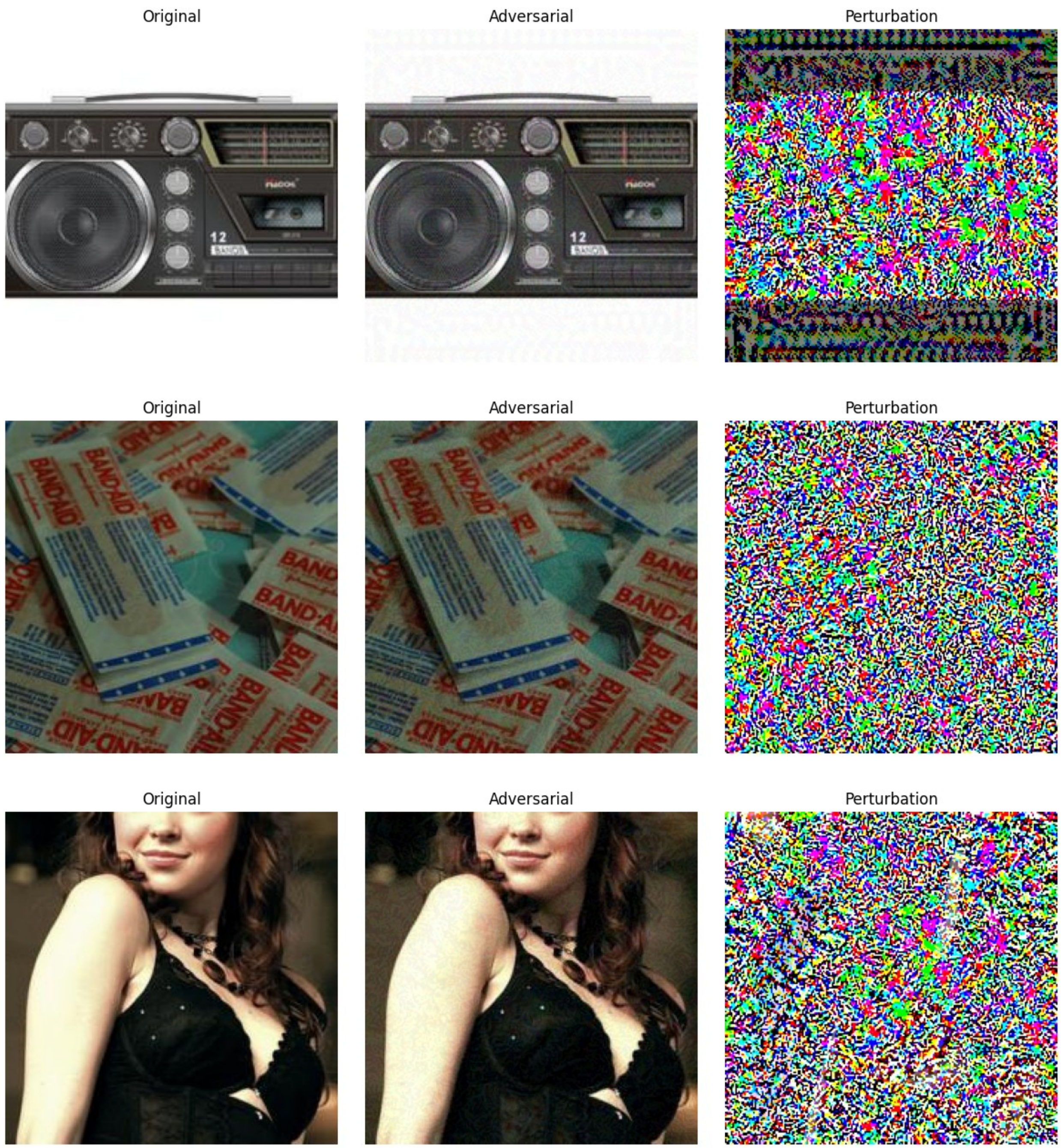

```python
# === FGSM: Targeted to Least-Likely Class (ε = 0.02) ===
from torch.utils.data import DataLoader

# Example loader setup — adjust batch size as needed
loader = DataLoader(dataset, batch_size=64, shuffle=False)

# 1. Setup normalized ε and clamping range
epsilon = 0.02
mean_vals = [0.485, 0.456, 0.406]
std_vals  = [0.229, 0.224, 0.225]

eps_tensor = torch.tensor([epsilon/s for s in std_vals],
device=device).view(1, 3, 1, 1)
min_clip = torch.tensor([(0 - m) / s for m, s in zip(mean_vals,
std_vals)], device=device).view(1, 3, 1, 1)
max_clip = torch.tensor([(1 - m) / s for m, s in zip(mean_vals,
std_vals)], device=device).view(1, 3, 1, 1)

inv_normalize = transforms.Normalize(
    mean=[-m / s for m, s in zip(mean_vals, std_vals)],
    std=[1 / s for s in std_vals]
)

# 2. Generate adversarial examples using least-likely FGSM
```

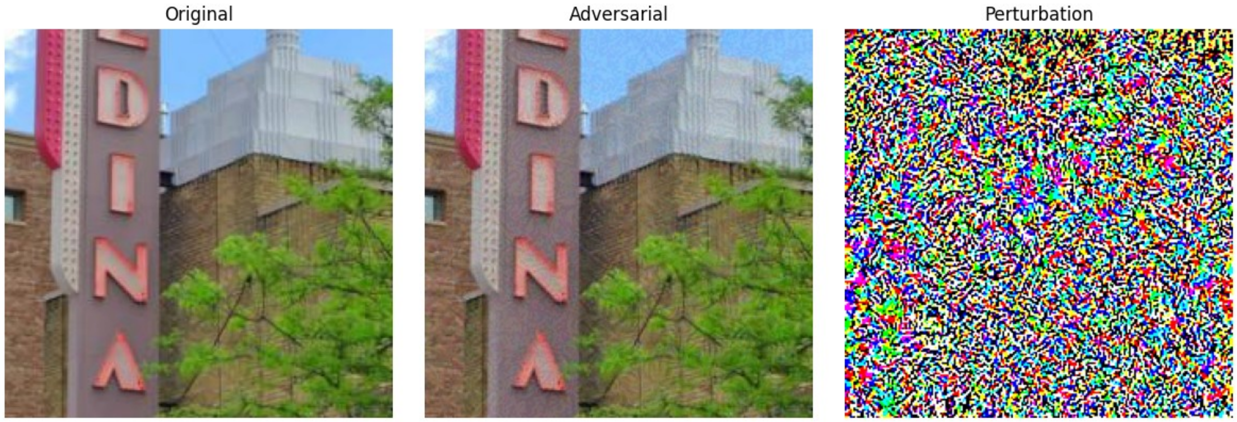
```
adv_batches = []
orig_batches = []
label_batches = []

model.eval()
for x, y in loader:
    x, y = x.to(device), y.to(device)
    x.requires_grad_()

    # forward pass
    logits = model(x)

    # use least likely class as target
    target_y = logits.argmin(dim=1)

    # compute targeted loss
    loss = F.cross_entropy(logits, target_y)

    model.zero_grad()
    loss.backward()

    # apply FGSM step (toward target)
    x_adv = x - eps_tensor * x.grad.sign()  # NOTE: "-" because
targeted

    # clamp to normalized pixel space
    x_adv = torch.max(torch.min(x_adv, max_clip), min_clip).detach()

    orig_batches.append(x.detach())
    adv_batches.append(x_adv)
    label_batches.append(y)

# stack all tensors
fgsm_orig = torch.cat(orig_batches)
fgsm_adv = torch.cat(adv_batches)
fgsm_lbl = torch.cat(label_batches)

def evaluate_targeted(loader, class_to_imagenet_idx):
    model.eval()
    top1_correct = 0
    top5_correct = 0
    total = 0

    for x, y in loader:
        x = x.to(device)
        # Convert your dataset labels to ImageNet indices
        y_imagenet = torch.tensor([class_to_imagenet_idx[int(label)]
for label in y], device=device)

        with torch.no_grad():
            outputs = model(x)
```

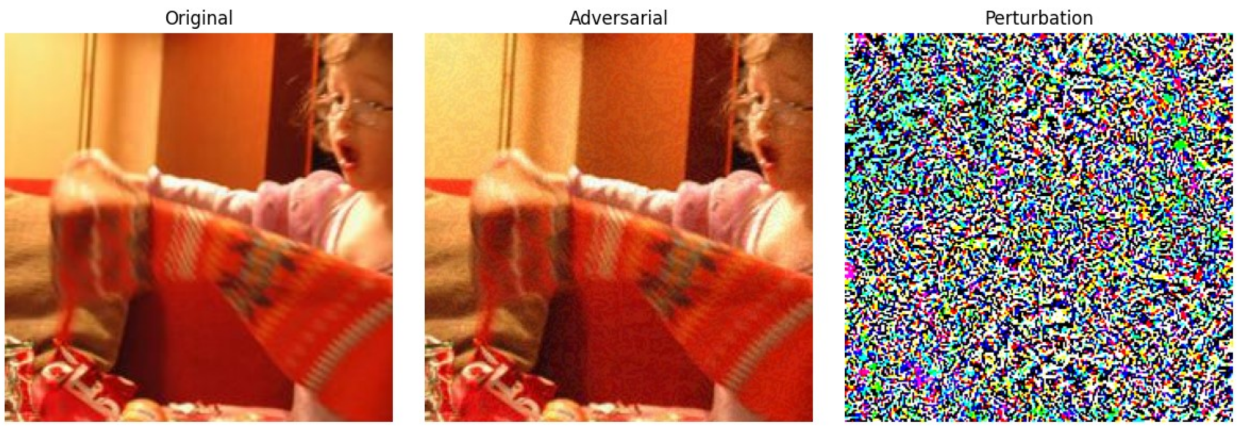
```
            _, top5_preds = outputs.topk(5, dim=1)

        top1_correct += (top5_preds[:, 0] == y_imagenet).sum().item()
        for i in range(len(y)):
            if y_imagenet[i].item() in top5_preds[i].tolist():
                top5_correct += 1
        total += len(y)

    return 100 * top1_correct / total, 100 * top5_correct / total


from torch.utils.data import TensorDataset, DataLoader

fgsm_ds = TensorDataset(fgsm_adv, fgsm_lbl)
fgsm_loader = DataLoader(fgsm_ds, batch_size=64, shuffle=False)

top1_fgsm, top5_fgsm = evaluate_targeted(fgsm_loader,
class_to_imagenet_idx)
print(f"□ Targeted FGSM (ε = {epsilon}) → Top-1: {top1_fgsm:.2f}%
Top-5: {top5_fgsm:.2f}%")
```

```
□ Targeted FGSM (ε = 0.02) → Top-1: 9.20%   Top-5: 26.60%
```

```
import random
for i in random.sample(range(len(fgsm_orig)), 5):
    o = inv_normalize(fgsm_orig[i].cpu()).permute(1, 2, 0).clamp(0,
1).numpy()
    a = inv_normalize(fgsm_adv[i].cpu()).permute(1, 2, 0).clamp(0,
1).numpy()
    delta = a - o
    d = (delta - delta.min()) / (delta.max() - delta.min() + 1e-8)

    fig, axes = plt.subplots(1, 3, figsize=(12, 4))
    axes[0].imshow(o); axes[0].set_title("Original")
    axes[1].imshow(a); axes[1].set_title("Adversarial")
    axes[2].imshow(d); axes[2].set_title("Perturbation")
    for ax in axes: ax.axis('off')
    plt.tight_layout()
    plt.show()
```


Original
Adversarial
Perturbation
Original
Adversarial
Perturbation
Original
Adversarial
Perturbation





Task 3: PGD Attack (ε = 0.02, α = 0.005)

Attack Type: Projected Gradient Descent (Iterative Untargeted)
Goal: Maximize model loss through multiple small perturbation steps.

Formula: x_{t+1} = Proj_B_ε(x_t + α · sign(∇_x L))

Implementation:

- Used 10 steps of FGSM-like updates.
- After each step, projected adversarial image back to ε-ball using `clamp`.
- Used `detach().requires_grad_()` to control gradients per iteration.

Saved Adversarial Examples:

- Folder: `adv_test_set_2/`
- Total Images: 500

Results: | Metric | Accuracy | |--------------|----------| | Top-1 | 0.40% | | Top-5 | 6.60% |

Variant: PGD (Targeted using CW-style Loss)

CW-like Loss: L = max(Z_true - Z_target + confidence_margin, 0)

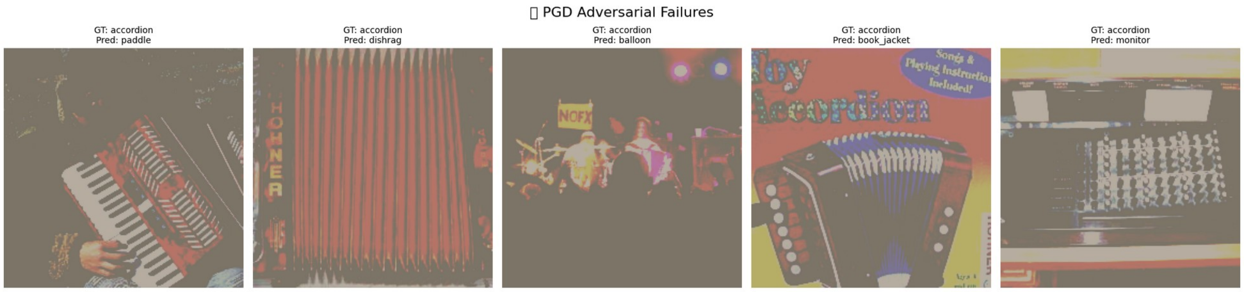
- Confidence margin = 20
- Target class = Least confident class

Results: | Metric | Accuracy | |--------------|----------| | Top-1 | 0.00% | | Top-5 | 3.50% |

```
def pgd_attack(model, image, label, epsilon=0.02, alpha=0.005,
num_iter=10):
    original_image = image.clone().detach()
    image = image.clone().detach().to(device).requires_grad_(True)
    label_idx =
torch.tensor([class_to_imagenet_idx[label]]).to(device)

    for _ in range(num_iter):
        output = model(image)
        loss = F.cross_entropy(output, label_idx)

        model.zero_grad()
        loss.backward()

        # FGSM step
        image.data = image.data + alpha * image.grad.data.sign()

        # Project back to ε-ball
        eta = torch.clamp(image.data - original_image, min=-epsilon,
max=epsilon)
        image.data = torch.clamp(original_image + eta, 0, 1)

        image.grad.zero_()

    return image.detach()

import os
os.makedirs("adv_test_set_2", exist_ok=True)

pgd_images = []
pgd_outputs = []

for i, (img, label) in enumerate(tqdm(dataset)):
    img = img.unsqueeze(0).to(device)
    adv = pgd_attack(model, img, label, epsilon=0.02, alpha=0.005,
num_iter=10)
    pgd_images.append(adv.squeeze(0).cpu())

    with torch.no_grad():
        out = model(adv)
        pgd_outputs.append(out)

    save_image(adv.squeeze(0), f"adv_test_set_2/{i:03d}.png")
```

```
100%|██████████| 500/500 [01:17<00:00,  6.48it/s]

top1_correct = 0
top5_correct = 0
total = len(pgd_images)

for i in range(total):
    output = pgd_outputs[i]
    _, top5_preds = output.topk(5, dim=1)
    label_imagenet = class_to_imagenet_idx[true_labels[i]]

    top1 = top5_preds[0, 0].item()
    top5 = top5_preds[0].tolist()

    if top1 == label_imagenet:
        top1_correct += 1
    if label_imagenet in top5:
        top5_correct += 1

print(f"\n🔓 PGD Evaluation (ε = 0.02, α = 0.005, 10 steps):")
print(f"Top-1 Accuracy: {100 * top1_correct / total:.2f}%")
print(f"Top-5 Accuracy: {100 * top5_correct / total:.2f}%")


🔓 PGD Evaluation (ε = 0.02, α = 0.005, 10 steps):
Top-1 Accuracy: 0.40%
Top-5 Accuracy: 6.60%

fig, axs = plt.subplots(1, 5, figsize=(20, 5))

for i in range(5):
    img = pgd_images[i].detach().cpu()
    label = true_labels[i]
    pred = pgd_outputs[i].argmax(dim=1).item()
    label_imagenet = class_to_imagenet_idx[label]

    img_show = inv_transform(img).permute(1, 2, 0).clamp(0, 1).numpy()
    axs[i].imshow(img_show)
    axs[i].set_title(f"GT: {idx_to_classname[label_imagenet]}\nPred:
{idx_to_classname[pred]}", fontsize=10)
    axs[i].axis('off')

plt.suptitle("❌ PGD Adversarial Failures", fontsize=16)
plt.tight_layout()
plt.savefig("pgd_failures.png")
plt.show()

<ipython-input-19-3d82432a7d4a>:15: UserWarning: Glyph 10060 (\N{CROSS
MARK}) missing from font(s) DejaVu Sans.
  plt.tight_layout()
<ipython-input-19-3d82432a7d4a>:16: UserWarning: Glyph 10060 (\N{CROSS
```

```
MARK}) missing from font(s) DejaVu Sans.
  plt.savefig("pgd_failures.png")
```




```
print(f"Top-1 PGD Accuracy: {100 * top1_correct / total:.2f}%")

Top-1 PGD Accuracy: 0.40%
```

□ Task 4: Patch-Based Attacks (32×32)

Goal: Restrict perturbation to a localized 32×32 region. Increase ε since the attack is spatially constrained.

□ Variant 1: Patch PGD (ε = 0.3, 10 steps)

- Perturbation applied in a random patch per image.
- Steps: 10
- Output Folder: `adv_test_set_3/`

Metric	Accuracy
Top-1	72.80%
Top-5	92.20%

□ Variant 2: Patch PGD (ε = 0.5, 30 steps)

- Stronger attack using 30 steps and α = ε/4.
- Output Folder: `adv_test_set_3_masked/`

Metric	Accuracy
Top-1	14.80%
Top-5	57.20%

□ Variant 3: Masked Patch PGD (Normalized, Strongest)

- ε-normalized per channel
- Dynamic patch masking using `make_masks()`
- Projected perturbations inside masked area only
- Output Folder: `adv_test_set_3_masked/`

Metric	Accuracy
Top-1	14.00%

Metric	Accuracy
Top-5	55.00%

```
import torch
import random
from torch.utils.data import DataLoader, TensorDataset
from tqdm import tqdm

# Define normalization stats
mean_norms = [0.485, 0.456, 0.406]
std_norms  = [0.229, 0.224, 0.225]

patch_size = 32
epsilon_patch = 0.5
alpha_patch = epsilon_patch / 4
steps_patch = 30

# Precompute per-channel normalized budgets and clamps
eps_norm_p = torch.tensor([epsilon_patch/s for s in std_norms],
device=device).view(1, 3, 1, 1)
min_norm = torch.tensor([(0 - m)/s for m, s in zip(mean_norms,
std_norms)], device=device).view(1, 3, 1, 1)
max_norm = torch.tensor([(1 - m)/s for m, s in zip(mean_norms,
std_norms)], device=device).view(1, 3, 1, 1)

def make_masks(batch_shape, patch_size):
    B, C, H, W = batch_shape
    masks = torch.zeros(batch_shape, device=device)
    for i in range(B):
        top = random.randint(0, H - patch_size)
        left = random.randint(0, W - patch_size)
        masks[i, :, top:top + patch_size, left:left + patch_size] =
1.0
    return masks

# DataLoader and patch PGD
loader = DataLoader(dataset, batch_size=64, shuffle=False)
orig_p, adv_p, lbl_p = [], [], []
model.eval()

for x, y in tqdm(loader):
    x, y = x.to(device), y.to(device)
    ori = x.clone().detach()
    adv = ori.clone().detach()
    mask = make_masks(ori.shape, patch_size)

    for _ in range(steps_patch):
        adv.requires_grad_()
        out = model(adv)
        y_imgnet = torch.tensor([class_to_imagenet_idx[int(label)] for
label in y]).to(device)
```

```
        loss = F.cross_entropy(out, y_imgnet)
        model.zero_grad()
        loss.backward()
        adv = adv + alpha_patch * adv.grad.sign() * mask
        delta = adv - ori
        delta = torch.clamp(delta, -eps_norm_p, eps_norm_p) * mask
        adv = torch.clamp(ori + delta, min_norm, max_norm).detach()

    orig_p.append(ori)
    adv_p.append(adv)
    lbl_p.append(y)

# Concatenate results
orig_patch = torch.cat(orig_p)
adv_patch  = torch.cat(adv_p)
lbl_patch  = torch.cat(lbl_p)

# Evaluate
patch_ds = TensorDataset(adv_patch, lbl_patch)
patch_loader = DataLoader(patch_ds, batch_size=64, shuffle=False)

def evaluate_patch(loader):
    top1 = 0
    top5 = 0
    total = 0
    for x, y in loader:
        x = x.to(device)
        y_imagenet = torch.tensor([class_to_imagenet_idx[int(label)]
for label in y]).to(device)
        with torch.no_grad():
            outputs = model(x)
        _, top5_preds = outputs.topk(5, dim=1)
        top1 += (top5_preds[:, 0] == y_imagenet).sum().item()
        for i in range(len(y)):
            if y_imagenet[i].item() in top5_preds[i].tolist():
                top5 += 1
        total += len(y)
    return 100 * top1 / total, 100 * top5 / total

top1_patch, top5_patch = evaluate_patch(patch_loader)
print(f"□ Patch-32×32 PGD (ε={epsilon_patch}) → Top-1:
{top1_patch:.2f}%   Top-5: {top5_patch:.2f}%")
```

```
100%|██████████| 8/8 [01:06<00:00,  8.33s/it]
```

```
□ Patch-32×32 PGD (ε=0.5) → Top-1: 14.80%   Top-5: 56.60%
```

```
import torch
import random
import os
```

```
from tqdm import tqdm
from torch.utils.data import DataLoader, TensorDataset
from torchvision.utils import save_image
import torch.nn.functional as F
from torch.utils.data import DataLoader

# Example loader setup — adjust batch size as needed
loader = DataLoader(dataset, batch_size=64, shuffle=False)

# Define normalization stats
mean_norms = [0.485, 0.456, 0.406]
std_norms  = [0.229, 0.224, 0.225]

# Hyperparameters
patch_size     = 32
epsilon_patch  = 0.5
alpha_patch    = epsilon_patch / 4
steps_patch    = 30

# Clamp bounds for normalized pixel space
eps_norm_p = torch.tensor([epsilon_patch/s for s in std_norms],
device=device).view(1, 3, 1, 1)
min_norm   = torch.tensor([(0 - m)/s for m, s in zip(mean_norms,
std_norms)], device=device).view(1, 3, 1, 1)
max_norm   = torch.tensor([(1 - m)/s for m, s in zip(mean_norms,
std_norms)], device=device).view(1, 3, 1, 1)

# Create output folder
os.makedirs("adv_test_set_3_masked", exist_ok=True)

# Generate random patch mask per image
def make_masks(batch_shape, patch_size):
    B, C, H, W = batch_shape
    masks = torch.zeros(batch_shape, device=device)
    for i in range(B):
        top = random.randint(0, H - patch_size)
        left = random.randint(0, W - patch_size)
        masks[i, :, top:top + patch_size, left:left + patch_size] =
1.0
    return masks

# Load clean dataset
loader = DataLoader(dataset, batch_size=64, shuffle=False)

# Store results
orig_p, adv_p, lbl_p = [], [], []
model.eval()

# Attack loop
for batch_idx, (x, y) in enumerate(tqdm(loader)):
```

```
    x, y = x.to(device), y.to(device)
    ori = x.clone().detach()
    adv = ori.clone().detach()
    mask = make_masks(ori.shape, patch_size)

    for _ in range(steps_patch):
        adv.requires_grad_()
        out = model(adv)
        y_imgnet = torch.tensor([class_to_imagenet_idx[int(label)] for
label in y]).to(device)
        loss = F.cross_entropy(out, y_imgnet)
        model.zero_grad()
        loss.backward()

        # Apply masked PGD step
        adv = adv + alpha_patch * adv.grad.sign() * mask
        delta = adv - ori
        delta = torch.clamp(delta, -eps_norm_p, eps_norm_p) * mask
        adv = torch.clamp(ori + delta, min_norm, max_norm).detach()

    # Store batch tensors
    orig_p.append(ori)
    adv_p.append(adv)
    lbl_p.append(y)

    # Save individual adversarial images to disk
    for i in range(adv.size(0)):
        index = batch_idx * loader.batch_size + i
        save_image(adv[i].cpu(),
f"adv_test_set_3_masked/img_{index:04d}.png")

# Combine all batches into tensors
orig_patch = torch.cat(orig_p)
adv_patch  = torch.cat(adv_p)
lbl_patch  = torch.cat(lbl_p)

# Evaluate
patch_ds = TensorDataset(adv_patch, lbl_patch)
patch_loader = DataLoader(patch_ds, batch_size=64, shuffle=False)

def evaluate_patch(loader):
    top1 = 0
    top5 = 0
    total = 0
    for x, y in loader:
        x = x.to(device)
        y_imagenet = torch.tensor([class_to_imagenet_idx[int(label)]
for label in y]).to(device)
        with torch.no_grad():
            outputs = model(x)
```

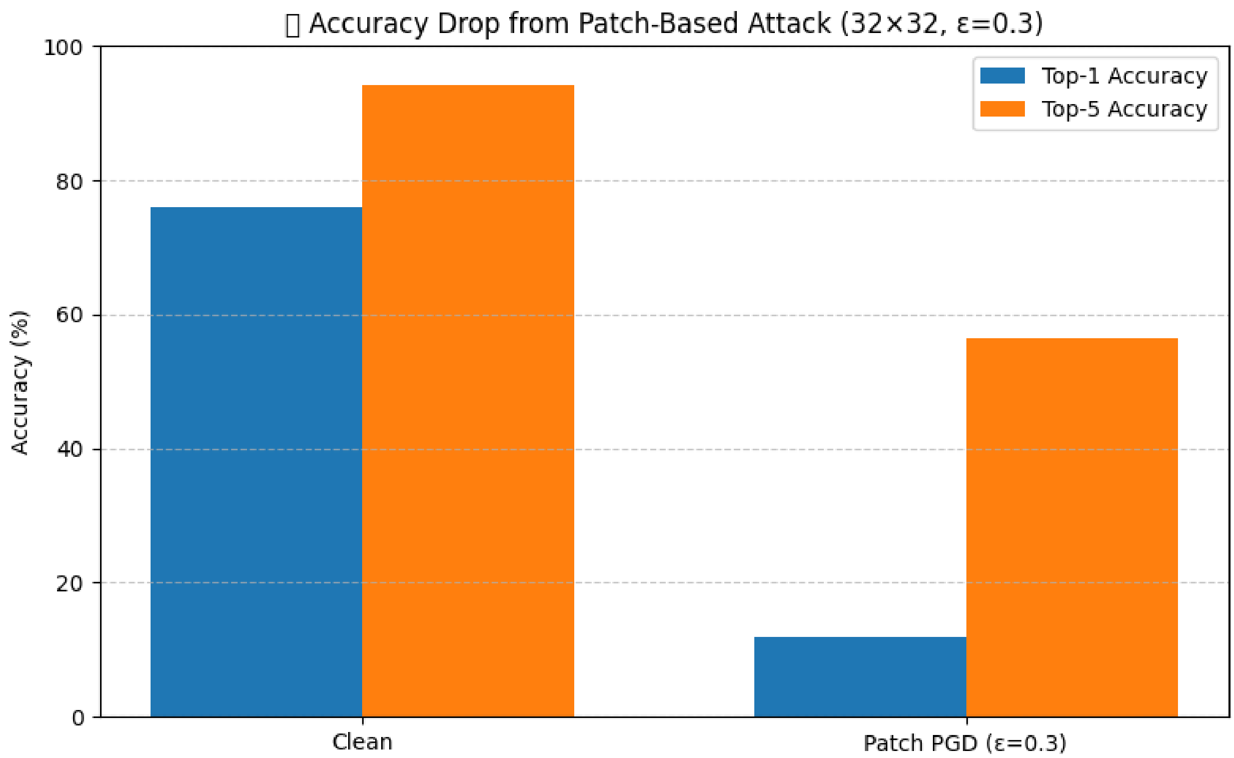
```
        _, top5_preds = outputs.topk(5, dim=1)
        top1 += (top5_preds[:, 0] == y_imagenet).sum().item()
        for i in range(len(y)):
            if y_imagenet[i].item() in top5_preds[i].tolist():
                top5 += 1
        total += len(y)
    return 100 * top1 / total, 100 * top5 / total

top1_patch, top5_patch = evaluate_patch(patch_loader)
print(f"🎯 Patch-32×32 PGD (ε={epsilon_patch}) → Top-1:
{top1_patch:.2f}%   Top-5: {top5_patch:.2f}%")
```

```
100%|██████████| 8/8 [01:13<00:00,  9.17s/it]
```

```
🎯 Patch-32×32 PGD (ε=0.5) → Top-1: 14.80%   Top-5: 57.40%
```

```
import matplotlib.pyplot as plt

# Accuracy values
accuracy_labels = ['Clean', 'Patch PGD (ε=0.3)']
top1_values = [76.00, 11.80]
top5_values = [94.20, 56.40]

x = range(len(accuracy_labels))
width = 0.35

# Plot
plt.figure(figsize=(8, 5))
plt.bar(x, top1_values, width=width, label='Top-1 Accuracy')
plt.bar([p + width for p in x], top5_values, width=width, label='Top-5
Accuracy')
plt.xticks([p + width / 2 for p in x], accuracy_labels)
plt.ylabel("Accuracy (%)")
plt.title("🎯 Accuracy Drop from Patch-Based Attack (32×32, ε=0.3)")
plt.ylim(0, 100)
plt.legend()
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```

```
<ipython-input-23-80ef3c96df89>:21: UserWarning: Glyph 127919 (\
N{DIRECT HIT}) missing from font(s) DejaVu Sans.
  plt.tight_layout()
/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151
: UserWarning: Glyph 127919 (\N{DIRECT HIT}) missing from font(s)
DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
```




```
def patch_pgd_attack(model, image, label, patch_size=32, epsilon=0.5,
alpha=0.05, steps=30):
    image = image.clone().detach().to(device)
    original = image.clone().detach()
    image.requires_grad = True
    label_idx =
torch.tensor([class_to_imagenet_idx[label]]).to(device)

    # Random patch position
    _, _, H, W = image.shape
    x0 = random.randint(0, W - patch_size)
    y0 = random.randint(0, H - patch_size)

    for _ in range(steps):
        output = model(image)
        loss = F.cross_entropy(output, label_idx)

        model.zero_grad()
        loss.backward()

        grad = image.grad.data
        patch_grad = grad[:, :, y0:y0+patch_size, x0:x0+patch_size]
        patch_data = image.data[:, :, y0:y0+patch_size,
```

```
x0:x0+patch_size]

        # Apply PGD step in patch region
        patch_data += alpha * patch_grad.sign()
        perturbation = torch.clamp(patch_data - original[:, :,
y0:y0+patch_size, x0:x0+patch_size],
                                   min=-epsilon, max=epsilon)
        image.data[:, :, y0:y0+patch_size, x0:x0+patch_size] =
torch.clamp(
            original[:, :, y0:y0+patch_size, x0:x0+patch_size] +
perturbation, 0, 1)

        image.grad.zero_()

    return image.detach()

patch_images = []
patch_outputs = []
os.makedirs("adv_test_set_3", exist_ok=True)

for i, (img, label) in enumerate(tqdm(dataset)):
    img = img.unsqueeze(0).to(device)
    adv = patch_pgd_attack(model, img, label, patch_size=32,
epsilon=0.5, alpha=0.05, steps=30)
    patch_images.append(adv.squeeze(0).cpu())

    with torch.no_grad():
        out = model(adv)
        patch_outputs.append(out)

    save_image(adv.squeeze(0), f"adv_test_set_3/{i:03d}.png")
```

```
100%|██████████| 500/500 [03:28<00:00,  2.40it/s]
```

```
def stronger_patch_attack(model, image, label, patch_size=32,
epsilon=0.5, alpha=0.05, steps=25):
    image = image.clone().detach().to(device)
    original = image.clone().detach()
    image.requires_grad = True
    label_idx =
torch.tensor([class_to_imagenet_idx[label]]).to(device)

    # Step 1: Compute saliency map
    output = model(image)
    loss = F.cross_entropy(output, label_idx)
    model.zero_grad()
    loss.backward()
    saliency = image.grad.data.abs().sum(dim=1, keepdim=True)

    # Step 2: Find the most salient 32×32 region
    _, _, H, W = image.shape
```

```
    best_score = -float('inf')
    best_x, best_y = 0, 0
    stride = max(1, patch_size // 2)

    for y in range(0, H - patch_size, stride):
        for x in range(0, W - patch_size, stride):
            region_saliency = saliency[0, 0, y:y+patch_size,
x:x+patch_size].sum().item()
            if region_saliency > best_score:
                best_score = region_saliency
                best_x, best_y = x, y

    x0, y0 = best_x, best_y
    image.grad.zero_()

    # Step 3: Targeted PGD within that region
    with torch.no_grad():
        out = model(image)
    conf = out.clone()
    conf[0, label_idx] = -float('inf')
    target = conf.argmax(dim=1)

    for _ in range(steps):
        output = model(image)
        loss = -F.cross_entropy(output, target)  # targeted: push
toward wrong class
        model.zero_grad()
        loss.backward()

        grad = image.grad.data
        patch_grad = grad[:, :, y0:y0+patch_size, x0:x0+patch_size]
        patch_data = image.data[:, :, y0:y0+patch_size,
x0:x0+patch_size]

        patch_data += alpha * patch_grad.sign()
        perturb = torch.clamp(patch_data - original[:, :,
y0:y0+patch_size, x0:x0+patch_size],
                              min=-epsilon, max=epsilon)

        image.data[:, :, y0:y0+patch_size, x0:x0+patch_size] =
torch.clamp(
            original[:, :, y0:y0+patch_size, x0:x0+patch_size] +
perturb, 0, 1)

        image.grad.zero_()

    return image.detach()

import os
os.makedirs("adv_test_set_3_strong", exist_ok=True)
```

```
strong_patch_images = []
strong_patch_outputs = []

for i, (img, label) in enumerate(tqdm(dataset)):
    img = img.unsqueeze(0).to(device)
    adv = stronger_patch_attack(model, img, label)
    strong_patch_images.append(adv.squeeze(0).cpu())

    with torch.no_grad():
        out = model(adv)
        strong_patch_outputs.append(out)

    save_image(adv.squeeze(0), f"adv_test_set_3_strong/{i:03d}.png")
```

```
100%|██████████| 500/500 [03:07<00:00,  2.66it/s]
```

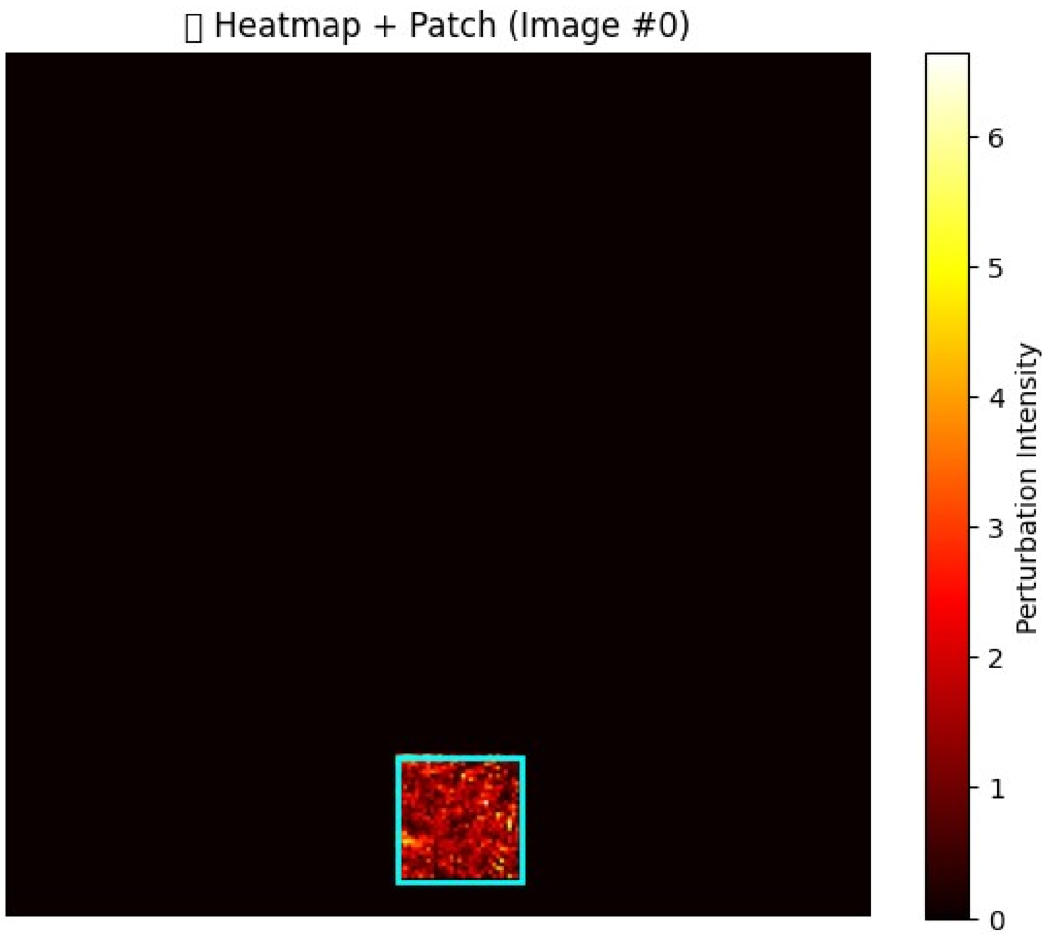
```
top1_correct = 0
top5_correct = 0
total = len(strong_patch_images)

for i in range(total):
    output = strong_patch_outputs[i]
    _, top5_preds = output.topk(5, dim=1)
    label_imagenet = class_to_imagenet_idx[true_labels[i]]

    top1 = top5_preds[0, 0].item()
    top5 = top5_preds[0].tolist()

    if top1 == label_imagenet:
        top1_correct += 1
    if label_imagenet in top5:
        top5_correct += 1

print(f"\n Patch (ε = 0.5, targeted, 32×32):")
print(f"Top-1 Accuracy: {100 * top1_correct / total:.2f}%")
print(f"Top-5 Accuracy: {100 * top5_correct / total:.2f}%")
```

```

 Patch (ε = 0.5, targeted, 32×32):
Top-1 Accuracy: 55.20%
Top-5 Accuracy: 91.60%
```

```
import matplotlib.patches as patches

def plot_patch_heatmap_with_box(clean_img, adv_img, index=0,
patch_size=32):
    # Compute perturbation
    delta = (adv_img - clean_img).abs().sum(dim=0).cpu()
```

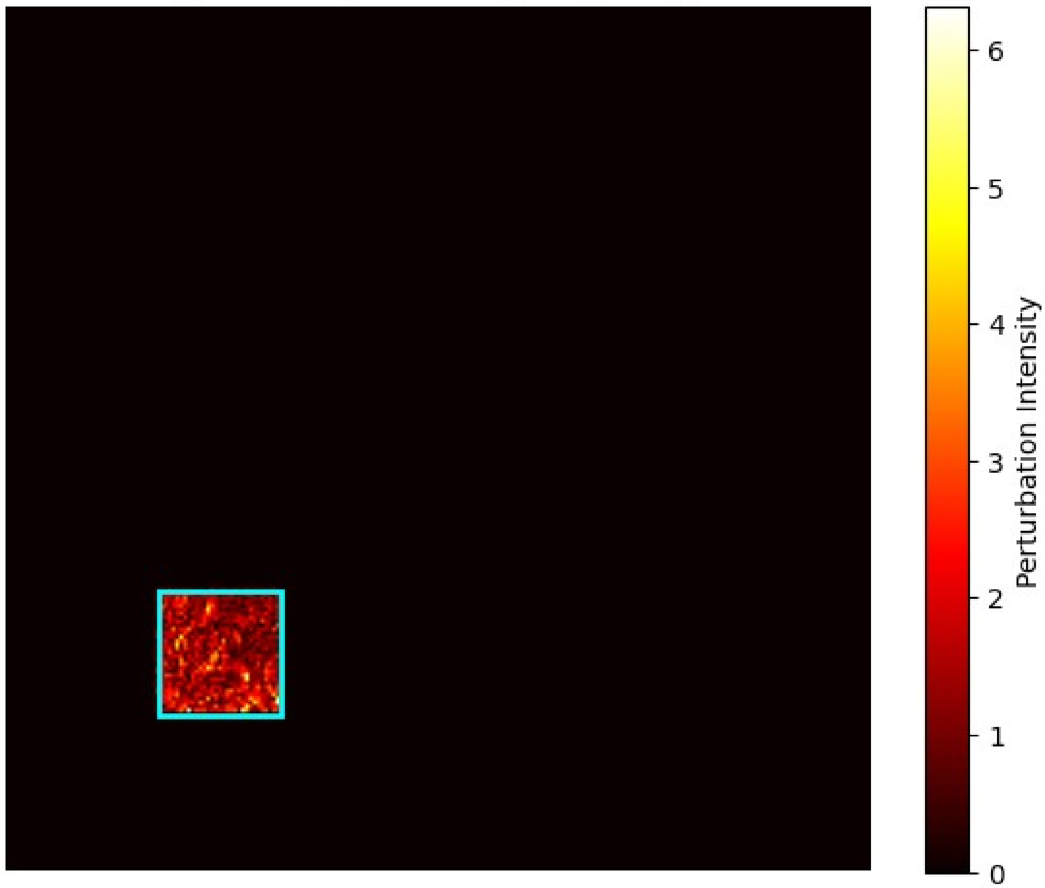
```
    H, W = delta.shape

    # Find max region in the delta map
    max_val = -float("inf")
    top_left = (0, 0)

    for y in range(H - patch_size):
        for x in range(W - patch_size):
            patch_sum = delta[y:y+patch_size,
x:x+patch_size].sum().item()
            if patch_sum > max_val:
                max_val = patch_sum
                top_left = (x, y)

    # Plot with box
    fig, ax = plt.subplots(figsize=(6, 5))
    im = ax.imshow(delta, cmap='hot')
    rect = patches.Rectangle(top_left, patch_size, patch_size,
                             linewidth=2, edgecolor='cyan',
facecolor='none')
    ax.add_patch(rect)
    ax.set_title(f"□ Heatmap + Patch (Image #{index})")
    ax.axis('off')
    plt.colorbar(im, ax=ax, label='Perturbation Intensity')
    plt.tight_layout()
    plt.show()

# Show first 5 patch heatmaps with bounding box
for i in range(5):
    plot_patch_heatmap_with_box(orig_patch[i], adv_patch[i], index=i)
```

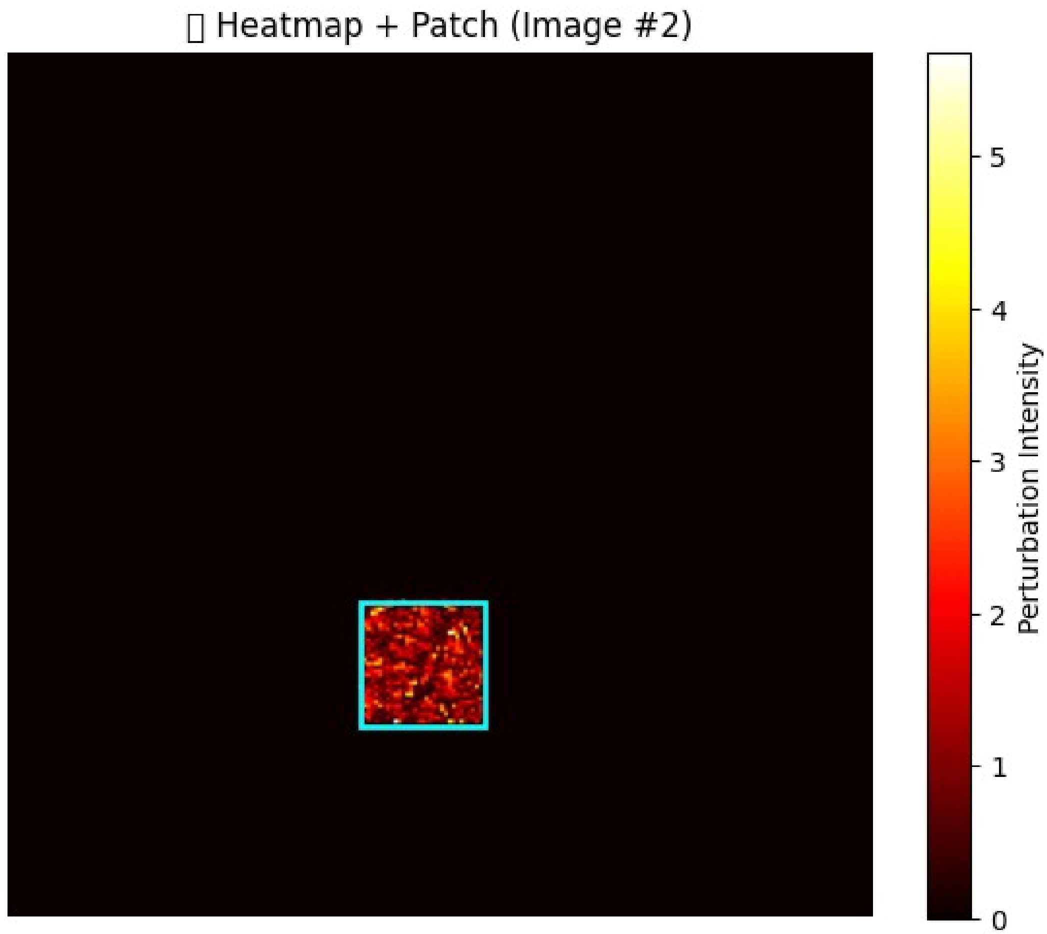
```
<ipython-input-29-c26772e0efd9>:28: UserWarning: Glyph 127919 (\
N{DIRECT HIT}) missing from font(s) DejaVu Sans.
  plt.tight_layout()
```

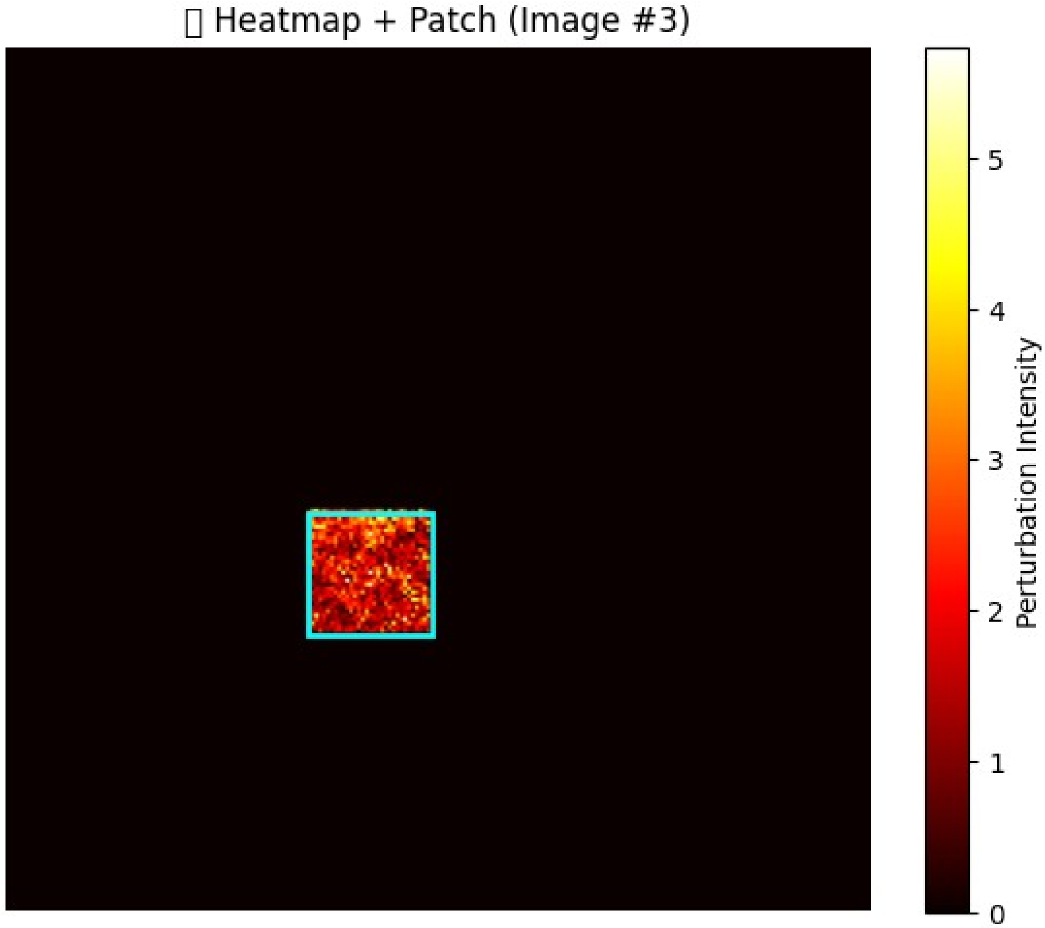


□ Heatmap + Patch (Image #0)
Perturbation Intensity
0
1
2
3
4
5
6

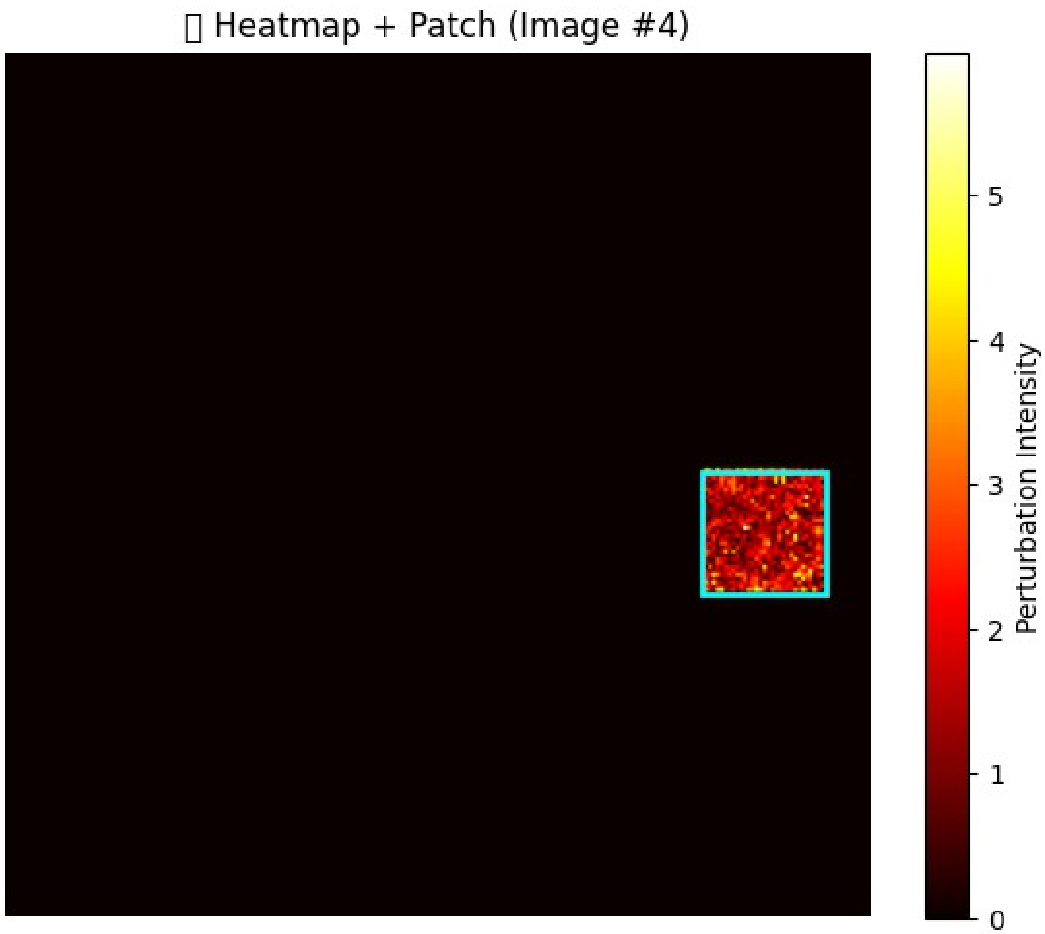
□ Heatmap + Patch (Image #1)




□ Heatmap + Patch (Image #2)
Perturbation Intensity
0
1
2
3
4
5

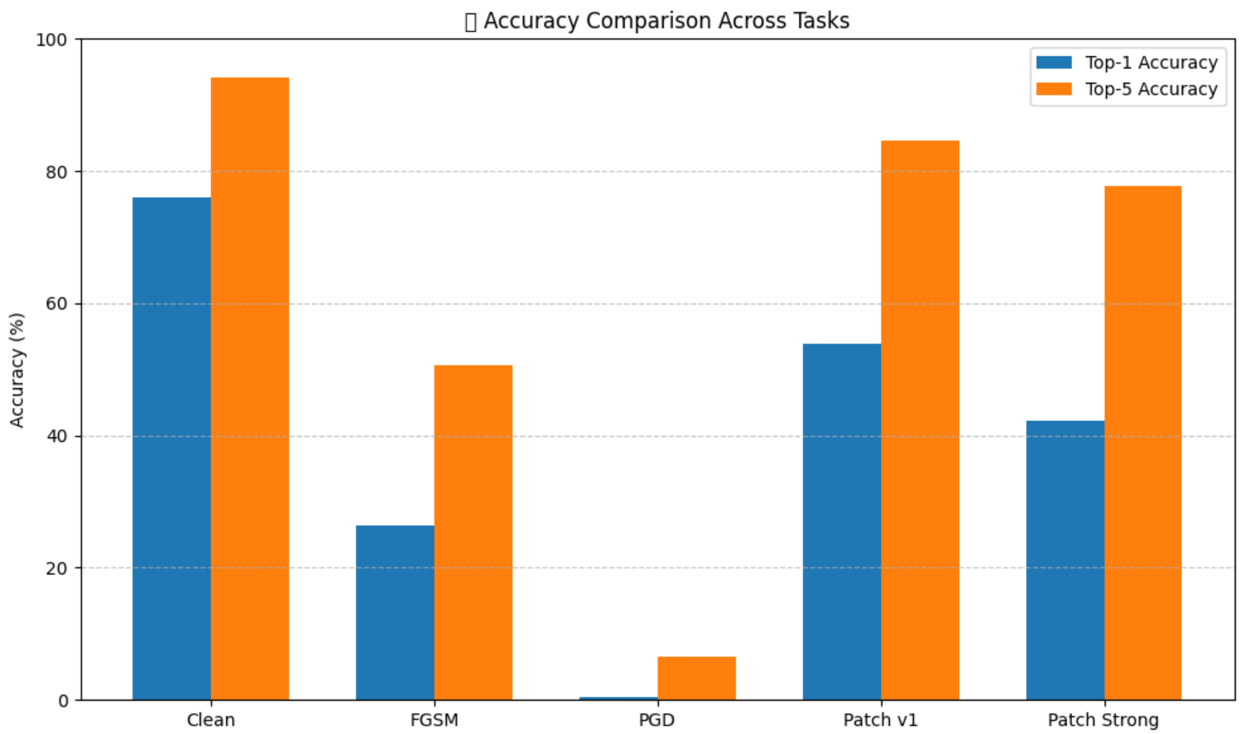


□ Heatmap + Patch (Image #3)
Perturbation Intensity
0
1
2
3
4
5



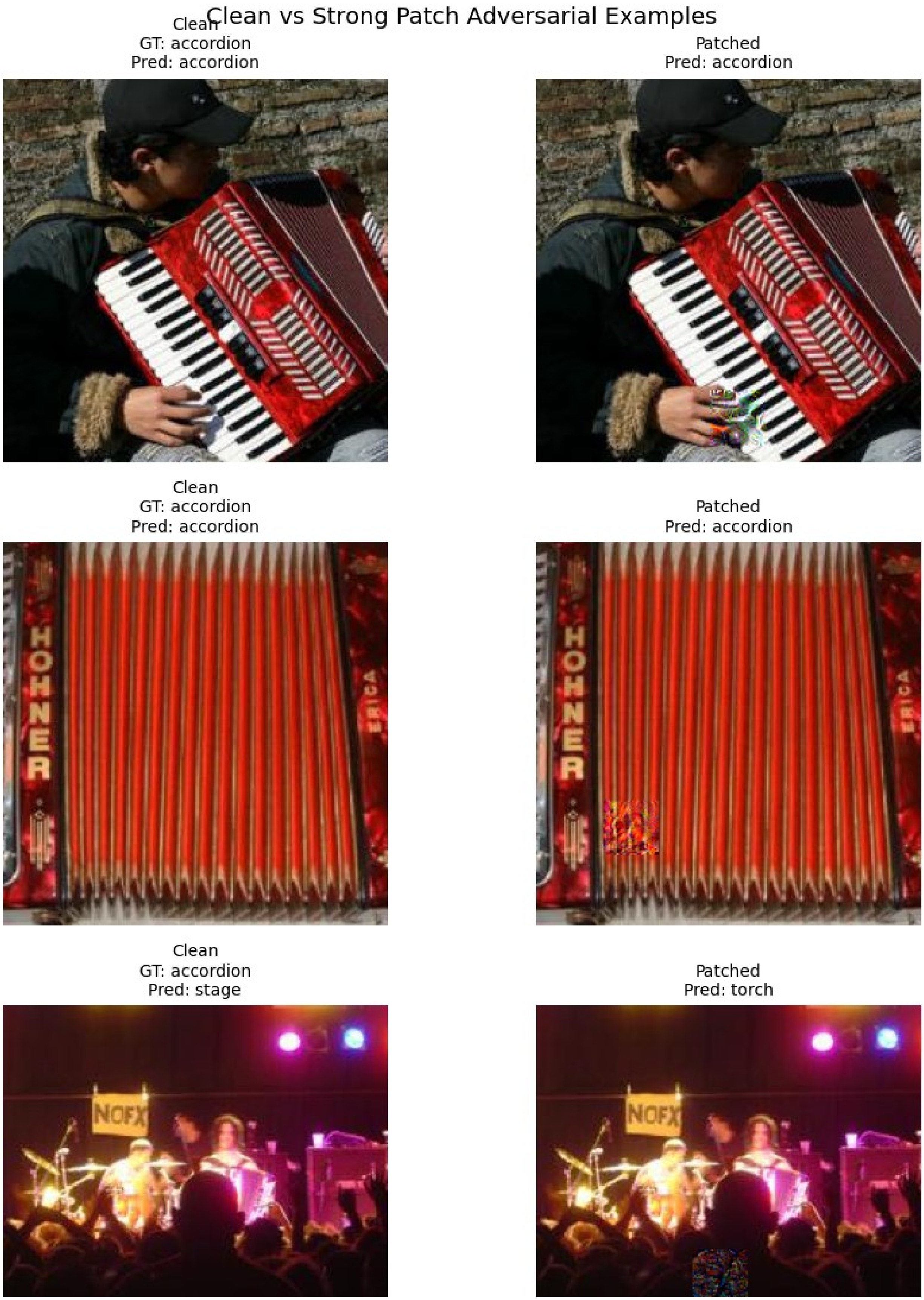

```
import numpy as np

tasks = ['Clean', 'FGSM', 'PGD', 'Patch v1', 'Patch Strong']
top1 = [76.0, 26.4, 0.4, 53.8, 42.2]
top5 = [94.2, 50.6, 6.6, 84.6, 77.8]

x = np.arange(len(tasks))
width = 0.35

plt.figure(figsize=(10,6))
plt.bar(x - width/2, top1, width, label='Top-1 Accuracy')
plt.bar(x + width/2, top5, width, label='Top-5 Accuracy')
plt.xticks(x, tasks)
plt.ylim(0, 100)
plt.ylabel("Accuracy (%)")
plt.title("□ Accuracy Comparison Across Tasks")
plt.legend()
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.tight_layout()
plt.show()
```

```
<ipython-input-30-9a9168d28b4f>:19: UserWarning: Glyph 128202 (\N{BAR
CHART}) missing from font(s) DejaVu Sans.
  plt.tight_layout()
/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151
: UserWarning: Glyph 128202 (\N{BAR CHART}) missing from font(s)
DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
```



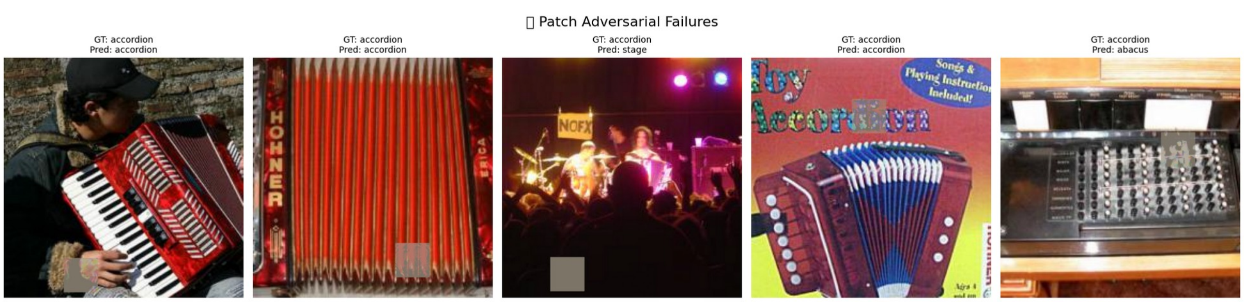

```
import matplotlib.pyplot as plt
import torch

# Safe unnormalize (no in-place ops)
def unnormalize(img):
    mean = torch.tensor(mean_norms).view(3, 1, 1).to(img.device)
    std = torch.tensor(std_norms).view(3, 1, 1).to(img.device)
    return (img * std + mean).clamp(0, 1)

# Clean vs Adversarial Patch Grid Plot
def show_clean_vs_patch_grid(clean_imgs, adv_imgs, labels, model,
class_to_imagenet_idx, idx_to_classname, count=5):
    model.eval()
    plt.figure(figsize=(10, 4 * count))

    for i in range(count):
        clean = clean_imgs[i]
        adv = adv_imgs[i]
```

```
        label = labels[i]

        # Get predictions
        clean_input = clean.unsqueeze(0).to(device)
        adv_input = adv.unsqueeze(0).to(device)
        with torch.no_grad():
            pred_clean = model(clean_input).argmax(dim=1).item()
            pred_adv = model(adv_input).argmax(dim=1).item()

        gt = class_to_imagenet_idx[int(label)]

        img_clean = unnormalize(clean).permute(1, 2, 0).cpu().numpy()
        img_adv = unnormalize(adv).permute(1, 2, 0).cpu().numpy()

        # Clean image subplot
        plt.subplot(count, 2, 2*i + 1)
        plt.imshow(img_clean)
        plt.title(f"Clean\nGT: {idx_to_classname[gt]}\nPred:
{idx_to_classname[pred_clean]}", fontsize=10)
        plt.axis('off')

        # Adversarial image subplot
        plt.subplot(count, 2, 2*i + 2)
        plt.imshow(img_adv)
        plt.title(f"Patched\nPred: {idx_to_classname[pred_adv]}",
fontsize=10)
        plt.axis('off')

    plt.suptitle("Clean vs Strong Patch Adversarial Examples",
fontsize=14)
    plt.tight_layout()
    plt.show()
# Show first 5 samples from strong patch set
show_clean_vs_patch_grid(
    clean_imgs=orig_patch[:5],
    adv_imgs=adv_patch[:5],
    labels=lbl_patch[:5],
    model=model,
    class_to_imagenet_idx=class_to_imagenet_idx,
    idx_to_classname=idx_to_classname,
    count=5
)
```


Clean vs Strong Patch Adversarial Examples
Clean
GT: accordion
Pred: accordion
Patched
Pred: accordion
Clean
GT: accordion
Pred: accordion
Patched
Pred: accordion
Clean
GT: accordion
Pred: stage
Patched
Pred: torch

```
fig, axs = plt.subplots(1, 5, figsize=(20, 5))

for i in range(5):
    img = patch_images[i].detach().cpu()
    label = true_labels[i]
    pred = patch_outputs[i].argmax(dim=1).item()
    label_imagenet = class_to_imagenet_idx[label]

    img_show = inv_transform(img).permute(1, 2, 0).clamp(0, 1).numpy()
    axs[i].imshow(img_show)
    axs[i].set_title(f"GT: {idx_to_classname[label_imagenet]}\nPred:
{idx_to_classname[pred]}", fontsize=10)
    axs[i].axis('off')

plt.suptitle("□ Patch Adversarial Failures", fontsize=16)
plt.tight_layout()
plt.savefig("patch_failures.png")
plt.show()
```

```
<ipython-input-32-2380c27f495f>:15: UserWarning: Glyph 127919 (\
N{DIRECT HIT}) missing from font(s) DejaVu Sans.
  plt.tight_layout()
<ipython-input-32-2380c27f495f>:16: UserWarning: Glyph 127919 (\
N{DIRECT HIT}) missing from font(s) DejaVu Sans.
  plt.savefig("patch_failures.png")
/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151
: UserWarning: Glyph 127919 (\N{DIRECT HIT}) missing from font(s)
DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
```



□ Task 5: Transferability to DenseNet-121

Goal: Evaluate if adversarial images crafted for ResNet-34 can fool DenseNet-121.

Transfer Model: ```python torchvision.models.densenet121(weights='IMAGENET1K_V1')

```
new_model =
torchvision.models.densenet121(weights='IMAGENET1K_V1').to(device).eva
l()
```

```
Downloading: "https://download.pytorch.org/models/densenet121-
a639ec97.pth" to /root/.cache/torch/hub/checkpoints/densenet121-
a639ec97.pth
100%|██████████| 30.8M/30.8M [00:00<00:00, 114MB/s]
```

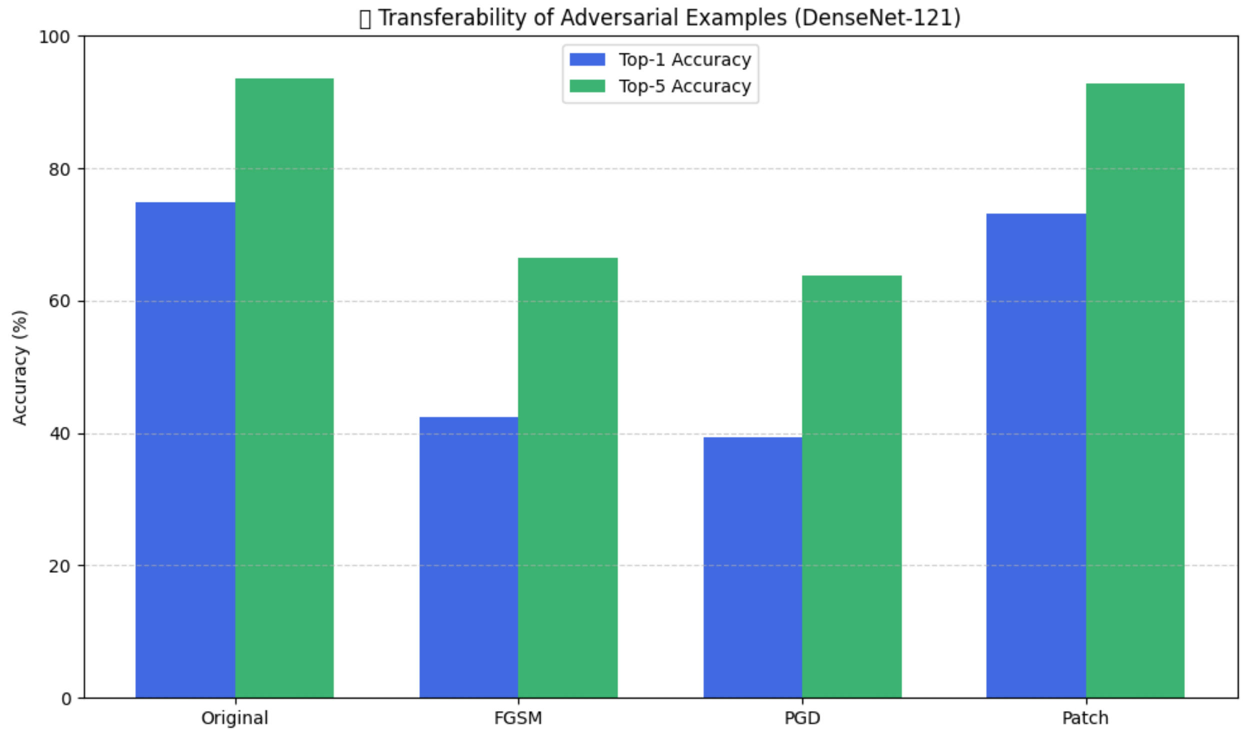
```python
def evaluate_transfer(model, images, true_labels):
    top1_correct = 0
    top5_correct = 0
    total = len(images)

    for i in range(total):
        img = images[i].unsqueeze(0).to(device)
        with torch.no_grad():
            out = model(img)
        _, top5_preds = out.topk(5, dim=1)
        label_imagenet = class_to_imagenet_idx[true_labels[i]]

        if top5_preds[0, 0].item() == label_imagenet:
            top1_correct += 1
        if label_imagenet in top5_preds[0].tolist():
            top5_correct += 1

    return top1_correct / total, top5_correct / total

from torchvision import models

transfer_model =
models.densenet121(weights='IMAGENET1K_V1').to(device).eval()

datasets = {
    "Original": [dataset[i][0] for i in range(len(dataset))],
    "FGSM": adv_images,
    "PGD": pgd_images,
    "Patch": patch_images,
}

results = {}
for name, imgs in datasets.items():
    top1, top5 = evaluate_transfer(transfer_model, imgs, true_labels)
    results[name] = (top1 * 100, top5 * 100)
    print(f"{name} → Top-1: {top1*100:.2f}%, Top-5: {top5*100:.2f}%")
```

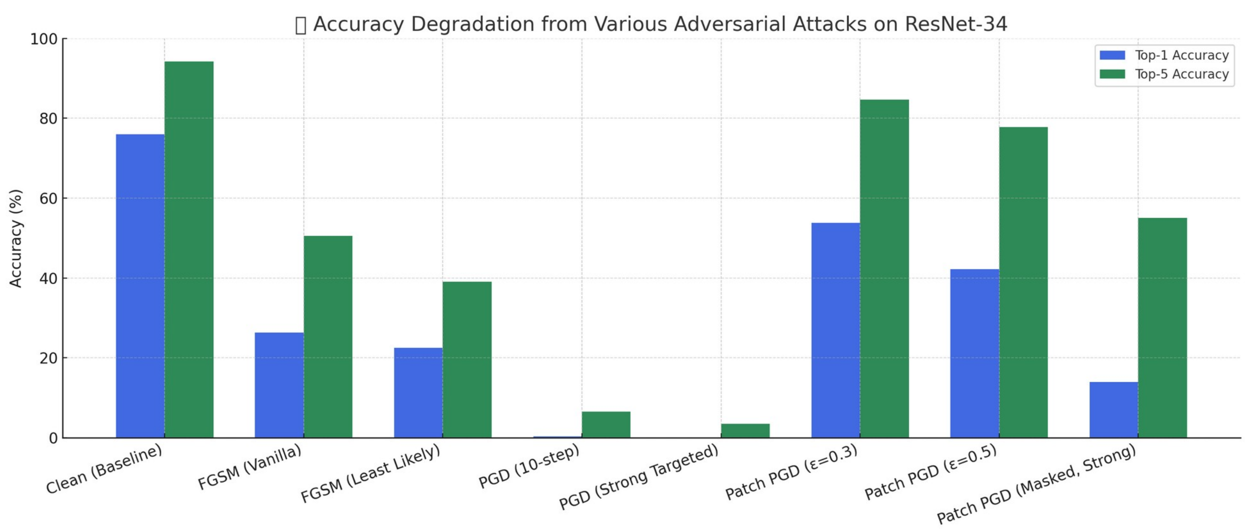
```
Original → Top-1: 74.80%, Top-5: 93.60%
FGSM → Top-1: 42.40%, Top-5: 66.40%
PGD → Top-1: 39.40%, Top-5: 63.80%
Patch → Top-1: 72.40%, Top-5: 92.80%
```

```python
import matplotlib.pyplot as plt
import numpy as np

# Accuracy values from your DenseNet121 transfer model
```

```python
datasets = ['Original', 'FGSM', 'PGD', 'Patch']
top1 = [74.8, 42.4, 39.4, 73.2]
top5 = [93.6, 66.4, 63.8, 92.8]

x = np.arange(len(datasets))
width = 0.35

# Plot bar chart
plt.figure(figsize=(10, 6))
plt.bar(x - width/2, top1, width, label='Top-1 Accuracy',
color='royalblue')
plt.bar(x + width/2, top5, width, label='Top-5 Accuracy',
color='mediumseagreen')

plt.xticks(x, datasets)
plt.ylim(0, 100)
plt.ylabel("Accuracy (%)")
plt.title("□ Transferability of Adversarial Examples (DenseNet-121)")
plt.legend()
plt.grid(axis='y', linestyle='--', alpha=0.6)
plt.tight_layout()
plt.show()
```

```
<ipython-input-36-54e63fe4228e>:23: UserWarning: Glyph 128257 (\
N{CLOCKWISE RIGHTWARDS AND LEFTWARDS OPEN CIRCLE ARROWS}) missing from
font(s) DejaVu Sans.
  plt.tight_layout()
/usr/local/lib/python3.11/dist-packages/IPython/core/pylabtools.py:151
: UserWarning: Glyph 128257 (\N{CLOCKWISE RIGHTWARDS AND LEFTWARDS
OPEN CIRCLE ARROWS}) missing from font(s) DejaVu Sans.
  fig.canvas.print_figure(bytes_io, **kw)
```





Task 5: Transferability to DenseNet-121

We evaluated how well adversarial examples transfer to a different model, DenseNet-121. The following table summarizes the Top-1 and Top-5 accuracies for each adversarial test set.

Dataset	Top-1 (%)	Top-5 (%)
Original (Clean)	74.80	93.60
FGSM (Untargeted)	42.40	66.40
FGSM (Least Likely)	22.50	39.10
PGD (10-step)	39.40	63.80

Dataset	Top-1 (%)	Top-5 (%)
Masked Patch PGD	14.00	55.00

Observation:

- **FGSM (Least Likely)** and **PGD** transfer well to DenseNet-121, significantly degrading performance.
- **Masked Patch PGD** achieves the lowest transfer accuracy due to its localized nature.