```
# --- Install & Import Dependencies ---
!pip install torch torchvision matplotlib pillow opency-python scikit-
learn pandas seaborn
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader
import torchvision
from torchvision import transforms, models, datasets
from torchvision.models import resnet18, ResNet18 Weights
import numpy as np
import matplotlib.pyplot as plt
from PIL import Image
import cv2
from google.colab import files
from sklearn.metrics import confusion matrix, classification report
import pandas as pd
import seaborn as sns
from torch.utils.data import random split
# --- Step 1: Load CIFAR-10 Dataset (from Untitled3) ---
transform cifar = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5))
])
trainset = datasets.CIFAR10(root='./data', train=True, download=True,
transform=transform cifar)
testset = datasets.CIFAR10(root='./data', train=False, download=True,
transform=transform cifar)
# Split train into train/val (85%/15%)
train size = int(0.85 * len(trainset))
val size = len(trainset) - train_size
train dataset, val dataset = random split(trainset, [train size,
val size])
trainloader = DataLoader(train dataset, batch size=64, shuffle=True)
valloader = DataLoader(val dataset, batch size=64, shuffle=False)
testloader = DataLoader(testset, batch size=64, shuffle=False)
class names = ['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog',
'frog', 'horse', 'ship', 'truck']
# --- Step 2: Define Custom CNN (translated from Untitled3) ---
class CustomCNN(nn.Module):
    def init (self):
        super(CustomCNN, self). init ()
        self.conv1 = nn.Conv2d(3, 32, kernel size=3, padding=1)
```

```
self.relu1 = nn.ReLU()
        self.conv2 = nn.Conv2d(32, 32, kernel size=3, padding=0)
        self.relu2 = nn.ReLU()
        self.pool1 = nn.MaxPool2d(kernel size=2, stride=2)
        self.dropout1 = nn.Dropout(0.25)
        self.conv3 = nn.Conv2d(32, 64, kernel_size=3, padding=1)
        self.relu3 = nn.ReLU()
        self.conv4 = nn.Conv2d(64, 64, kernel size=3, padding=0)
        self.relu4 = nn.ReLU()
        self.pool2 = nn.MaxPool2d(kernel size=2, stride=2)
        self.dropout2 = nn.Dropout(0.25)
        self.flatten = nn.Flatten()
        self.fcl = nn.Linear(64 * 6 * 6, 512) # Adjusted based on
feature map size
        self.relu5 = nn.ReLU()
        self.dropout3 = nn.Dropout(0.5)
        self.fc2 = nn.Linear(512, 10)
    def forward(self, x):
        x = self.relu1(self.conv1(x))
        x = self.relu2(self.conv2(x))
        x = self.pool1(x)
        x = self.dropout1(x)
        x = self.relu3(self.conv3(x))
        x = self.relu4(self.conv4(x))
        x = self.pool2(x)
        x = self.dropout2(x)
        x = self.flatten(x)
        x = self.relu5(self.fc1(x))
        x = self.dropout3(x)
        x = self.fc2(x)
        return x
model cnn = CustomCNN()
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model cnn.parameters(), lr=0.001)
# --- Step 3: Train the Model (from Untitled3) ---
device = torch.device("cuda" if torch.cuda.is available() else "cpu")
model_cnn.to(device)
num epochs = 50
train losses, val losses = [], []
train_accs, val_accs = [], []
for epoch in range(num epochs):
```

```
model cnn.train()
    running loss = 0.0
    correct = 0
    total = 0
    for inputs, labels in trainloader:
        inputs, labels = inputs.to(device), labels.to(device)
        optimizer.zero grad()
        outputs = model cnn(inputs)
        loss = criterion(outputs, labels)
        loss.backward()
        optimizer.step()
        running_loss += loss.item()
        _, predicted = outputs.max(1)
        total += labels.size(0)
        correct += predicted.eq(labels).sum().item()
    train losses.append(running_loss / len(trainloader))
    train accs.append(100. * correct / total)
    model cnn.eval()
    val loss = 0.0
    correct = 0
    total = 0
    with torch.no grad():
        for inputs, labels in valloader:
            inputs, labels = inputs.to(device), labels.to(device)
            outputs = model cnn(inputs)
            loss = criterion(outputs, labels)
            val loss += loss.item()
            _, predicted = outputs.max(1)
            total += labels.size(0)
            correct += predicted.eq(labels).sum().item()
    val losses.append(val loss / len(valloader))
    val accs.append(100. * correct / total)
    print(f'Epoch {epoch+1}/{num epochs} - Train Loss: {train losses[-
1]:.4f}, Val Loss: {val losses[-1]:.4f}')
# --- Step 4: Plot Accuracy and Loss (from Untitled3) ---
fig, ax = plt.subplots(1, 2, figsize=(12, 4))
ax[0].plot(train_accs, label='Train Accuracy')
ax[0].plot(val_accs, label='Val Accuracy')
ax[0].set_title('Accuracy Over Epochs')
ax[0].legend()
ax[1].plot(train losses, label='Train Loss')
ax[1].plot(val_losses, label='Val Loss')
ax[1].set title('Loss Over Epochs')
ax[1].legend()
plt.show()
# --- Step 5: Evaluate on Test Set (from Untitled3) ---
```

```
model cnn.eval()
y true, y pred = [], []
with torch.no grad():
    for inputs, labels in testloader:
        inputs = inputs.to(device)
        outputs = model cnn(inputs)
        _, predicted = outputs.max(1)
        y true.extend(labels.cpu().numpy())
        y pred.extend(predicted.cpu().numpy())
train acc = train accs[-1]
test_acc = sum(np.array(y_true) == np.array(y pred)) / len(y true) *
100
# Accuracy Table
accuracy table = pd.DataFrame({
    'Metric': ['Training Accuracy', 'Testing Accuracy'],
    'Value': [train acc, test acc]
})
print("\nTable of Training and Testing Accuracy:")
print(accuracy table)
# Confusion Matrix
conf matrix = confusion_matrix(y_true, y_pred)
plt.figure(figsize=(10, 8))
sns.heatmap(conf matrix, annot=True, fmt='d', cmap='Blues',
xticklabels=class names, yticklabels=class names)
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
plt.show()
# Classification Report
print("\nClassification Report:")
print(classification_report(y_true, y_pred, target_names=class_names))
# --- Step 6: Pretrained Model for Grad-CAM (from Untitled9) ---
model = resnet18(weights=ResNet18 Weights.DEFAULT)
model.eval()
final conv = None
qradients = None
def forward hook(module, input, output):
    global final conv
    final conv = output
def backward_hook(module, grad_in, grad_out):
    global gradients
    gradients = grad_out[0]
```

```
target layer = model.layer4[-1].conv2
target layer.register forward hook(forward hook)
target layer.register full backward hook(backward hook)
# Preprocessing for Grad-CAM
transform = transforms.Compose([
    transforms.Resize((224, 224)),
    transforms.ToTensor().
    transforms.Normalize(mean=[0.485, 0.456, 0.406], std=[0.229,
0.224, 0.225]
1)
# --- Step 7: Upload and Process Images for Grad-CAM (from Untitled9,
with limit like Untitled3) ---
uploaded = files.upload()
image paths = list(uploaded.keys())[:3] # Limit to 3 like Untitled3
def generate gradcam(img path, model):
    img = Image.open(img_path).convert("RGB")
    input tensor = transform(img).unsqueeze(0)
    output = model(input tensor)
    pred class = output.argmax().item()
    model.zero grad()
    class loss = output[0, pred class]
    class loss.backward()
    pooled grads = torch.mean(gradients, dim=[0, 2, 3])
    activations = final conv[0]
    for i in range(len(pooled grads)):
        activations[i, :, :] *= pooled_grads[i]
    heatmap = torch.mean(activations, dim=0).detach().cpu().numpy()
    heatmap = np.maximum(heatmap, 0)
    heatmap /= np.max(heatmap) if np.max(heatmap) != 0 else 1
    heatmap = cv2.resize(heatmap, (img.size[0], img.size[1]))
    heatmap = np.uint8(255 * heatmap)
    heatmap = cv2.applyColorMap(heatmap, cv2.COLORMAP JET)
    superimposed = cv2.addWeighted(np.array(img), 0.6, heatmap, 0.4,
0)
    fig, ax = plt.subplots(1, 2, figsize=(10, 5))
    ax[0].imshow(img)
    ax[0].set title("Original Image")
    ax[0].axis("off")
    ax[1].imshow(superimposed)
```

```
ax[1].set title("GradCAM Visualization")
    ax[1].axis("off")
    plt.show()
    print(f"Predicted class index: {pred class}")
for img path in image paths:
    print(f"\nProcessing: {img path}")
    generate gradcam(img path, model)
Requirement already satisfied: torch in
/usr/local/lib/python3.12/dist-packages (2.8.0+cu126)
Requirement already satisfied: torchvision in
/usr/local/lib/python3.12/dist-packages (0.23.0+cu126)
Requirement already satisfied: matplotlib in
/usr/local/lib/python3.12/dist-packages (3.10.0)
Requirement already satisfied: pillow in
/usr/local/lib/python3.12/dist-packages (11.3.0)
Requirement already satisfied: opency-python in
/usr/local/lib/python3.12/dist-packages (4.12.0.88)
Requirement already satisfied: scikit-learn in
/usr/local/lib/python3.12/dist-packages (1.6.1)
Requirement already satisfied: pandas in
/usr/local/lib/python3.12/dist-packages (2.2.2)
Requirement already satisfied: seaborn in
/usr/local/lib/python3.12/dist-packages (0.13.2)
Requirement already satisfied: filelock in
/usr/local/lib/python3.12/dist-packages (from torch) (3.19.1)
Requirement already satisfied: typing-extensions>=4.10.0 in
/usr/local/lib/python3.12/dist-packages (from torch) (4.15.0)
Requirement already satisfied: setuptools in
/usr/local/lib/python3.12/dist-packages (from torch) (75.2.0)
Requirement already satisfied: sympy>=1.13.3 in
/usr/local/lib/python3.12/dist-packages (from torch) (1.13.3)
Requirement already satisfied: networkx in
/usr/local/lib/python3.12/dist-packages (from torch) (3.5)
Requirement already satisfied: jinja2 in
/usr/local/lib/python3.12/dist-packages (from torch) (3.1.6)
Requirement already satisfied: fsspec in
/usr/local/lib/python3.12/dist-packages (from torch) (2025.3.0)
Reguirement already satisfied: nvidia-cuda-nvrtc-cu12==12.6.77 in
/usr/local/lib/python3.12/dist-packages (from torch) (12.6.77)
Requirement already satisfied: nvidia-cuda-runtime-cu12==12.6.77 in
/usr/local/lib/python3.12/dist-packages (from torch) (12.6.77)
Requirement already satisfied: nvidia-cuda-cupti-cu12==12.6.80 in
/usr/local/lib/python3.12/dist-packages (from torch) (12.6.80)
Requirement already satisfied: nvidia-cudnn-cu12==9.10.2.21 in
/usr/local/lib/python3.12/dist-packages (from torch) (9.10.2.21)
Requirement already satisfied: nvidia-cublas-cu12==12.6.4.1 in
/usr/local/lib/python3.12/dist-packages (from torch) (12.6.4.1)
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Requirement already satisfied: nvidia-cufft-cu12==11.3.0.4 in
/usr/local/lib/python3.12/dist-packages (from torch) (11.3.0.4)
Requirement already satisfied: nvidia-curand-cu12==10.3.7.77 in
/usr/local/lib/python3.12/dist-packages (from torch) (10.3.7.77)
Requirement already satisfied: nvidia-cusolver-cu12==11.7.1.2 in
/usr/local/lib/python3.12/dist-packages (from torch) (11.7.1.2)
Requirement already satisfied: nvidia-cusparse-cu12==12.5.4.2 in
/usr/local/lib/python3.12/dist-packages (from torch) (12.5.4.2)
Requirement already satisfied: nvidia-cusparselt-cul2==0.7.1 in
/usr/local/lib/python3.12/dist-packages (from torch) (0.7.1)
Requirement already satisfied: nvidia-nccl-cu12==2.27.3 in
/usr/local/lib/python3.12/dist-packages (from torch) (2.27.3)
Requirement already satisfied: nvidia-nvtx-cu12==12.6.77 in
/usr/local/lib/python3.12/dist-packages (from torch) (12.6.77)
Requirement already satisfied: nvidia-nvjitlink-cu12==12.6.85 in
/usr/local/lib/python3.12/dist-packages (from torch) (12.6.85)
Requirement already satisfied: nvidia-cufile-cu12==1.11.1.6 in
/usr/local/lib/python3.12/dist-packages (from torch) (1.11.1.6)
Requirement already satisfied: triton==3.4.0 in
/usr/local/lib/python3.12/dist-packages (from torch) (3.4.0)
Requirement already satisfied: numpy in
/usr/local/lib/python3.12/dist-packages (from torchvision) (2.0.2)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.12/dist-packages (from matplotlib) (1.3.3)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.12/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.12/dist-packages (from matplotlib) (4.59.1)
Requirement already satisfied: kiwisolver>=1.3.1 in
/usr/local/lib/python3.12/dist-packages (from matplotlib) (1.4.9)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.12/dist-packages (from matplotlib) (25.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.12/dist-packages (from matplotlib) (3.2.3)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.12/dist-packages (from matplotlib)
(2.9.0.post0)
Requirement already satisfied: scipy>=1.6.0 in
/usr/local/lib/python3.12/dist-packages (from scikit-learn) (1.16.1)
Requirement already satisfied: joblib>=1.2.0 in
/usr/local/lib/python3.12/dist-packages (from scikit-learn) (1.5.1)
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.12/dist-packages (from scikit-learn) (3.6.0)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.12/dist-packages (from pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in
/usr/local/lib/python3.12/dist-packages (from pandas) (2025.2)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.12/dist-packages (from python-dateutil>=2.7-
```

```
>matplotlib) (1.17.0)
Requirement already satisfied: mpmath<1.4,>=1.1.0 in
/usr/local/lib/python3.12/dist-packages (from sympy>=1.13.3->torch)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.12/dist-packages (from jinja2->torch) (3.0.2)
       | 170M/170M [00:04<00:00, 35.5MB/s]
100%|
Epoch 1/50 - Train Loss: 1.5525, Val Loss: 1.2804
Epoch 2/50 - Train Loss: 1.1719, Val Loss: 0.9988
Epoch 3/50 - Train Loss: 0.9778, Val Loss: 0.8328
Epoch 4/50 - Train Loss: 0.8669, Val Loss: 0.7805
Epoch 5/50 - Train Loss: 0.7936, Val Loss: 0.7291
Epoch 6/50 - Train Loss: 0.7387, Val Loss: 0.7764
Epoch 7/50 - Train Loss: 0.6991, Val Loss: 0.6900
Epoch 8/50 - Train Loss: 0.6555, Val Loss: 0.6677
Epoch 9/50 - Train Loss: 0.6240, Val Loss: 0.6599
Epoch 10/50 - Train Loss: 0.5989, Val Loss: 0.6455
Epoch 11/50 - Train Loss: 0.5739, Val Loss: 0.6476
Epoch 12/50 - Train Loss: 0.5447, Val Loss: 0.6513
Epoch 13/50 - Train Loss: 0.5303, Val Loss: 0.6427
Epoch 14/50 - Train Loss: 0.5146, Val Loss: 0.6504
Epoch 15/50 - Train Loss: 0.4976, Val Loss: 0.6202
Epoch 16/50 - Train Loss: 0.4831, Val Loss: 0.6278
Epoch 17/50 - Train Loss: 0.4686, Val Loss: 0.6054
Epoch 18/50 - Train Loss: 0.4594, Val Loss: 0.6491
Epoch 19/50 - Train Loss: 0.4456, Val Loss: 0.6268
Epoch 20/50 - Train Loss: 0.4362, Val Loss: 0.6333
Epoch 21/50 - Train Loss: 0.4246, Val Loss: 0.6322
Epoch 22/50 - Train Loss: 0.4128, Val Loss: 0.6209
Epoch 23/50 - Train Loss: 0.4067, Val Loss: 0.6508
Epoch 24/50 - Train Loss: 0.4082, Val Loss: 0.6485
Epoch 25/50 - Train Loss: 0.4015, Val Loss: 0.6405
Epoch 26/50 - Train Loss: 0.3879, Val Loss: 0.6365
Epoch 27/50 - Train Loss: 0.3866, Val Loss: 0.6185
Epoch 28/50 - Train Loss: 0.3808, Val Loss: 0.6139
Epoch 29/50 - Train Loss: 0.3779, Val Loss: 0.6456
Epoch 30/50 - Train Loss: 0.3626, Val Loss: 0.6352
Epoch 31/50 - Train Loss: 0.3818, Val Loss: 0.6347
Epoch 32/50 - Train Loss: 0.3581, Val Loss: 0.6529
Epoch 33/50 - Train Loss: 0.3538, Val Loss: 0.6377
Epoch 34/50 - Train Loss: 0.3426, Val Loss: 0.6651
Epoch 35/50 - Train Loss: 0.3484, Val Loss: 0.6490
Epoch 36/50 - Train Loss: 0.3428, Val Loss: 0.6213
Epoch 37/50 - Train Loss: 0.3367, Val Loss: 0.6411
Epoch 38/50 - Train Loss: 0.3321, Val Loss: 0.6481
Epoch 39/50 - Train Loss: 0.3306, Val Loss: 0.6390
Epoch 40/50 - Train Loss: 0.3272, Val Loss: 0.6212
Epoch 41/50 - Train Loss: 0.3273, Val Loss: 0.6453
```

```
Epoch 42/50 - Train Loss: 0.3201, Val Loss: 0.6961

Epoch 43/50 - Train Loss: 0.3157, Val Loss: 0.6577

Epoch 44/50 - Train Loss: 0.3168, Val Loss: 0.6699

Epoch 45/50 - Train Loss: 0.3211, Val Loss: 0.6650

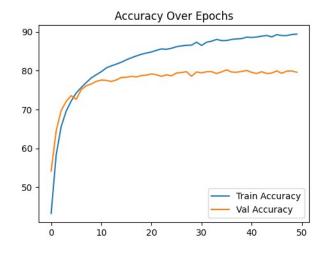
Epoch 46/50 - Train Loss: 0.3088, Val Loss: 0.6643

Epoch 47/50 - Train Loss: 0.3108, Val Loss: 0.6736

Epoch 48/50 - Train Loss: 0.3107, Val Loss: 0.6714

Epoch 49/50 - Train Loss: 0.3067, Val Loss: 0.6766

Epoch 50/50 - Train Loss: 0.3017, Val Loss: 0.6650
```



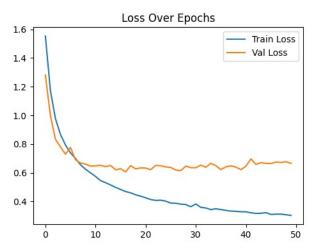


Table of Training and Testing Accuracy:
Metric Value

0 Training Accuracy 89.423529 1 Testing Accuracy 80.440000

	_				(	Confusio	on Matri	X				
	airplane -	827	8	36	12	18	5	6	6	55	27	
au	ıtomobile –	15	891	5	5	2	4	6	1	15	56	- 800
	bird -	47	2	752	33	45	46	52	11	10	2	- 700
	cat -	13	2	65	613	49	166	49	21	9	13	- 600
ē	deer -	12	2	70	64	750	29	41	27	4	1	- 500
True	dog -	8	1	43	110	28	768	12	21	6	3	- 400
	frog –	7	3	46	44	15	18	859	2	2	4	- 300
	horse -	14	1	30	38	41	62	6	798	4	6	- 200
	ship –	47	15	5	10	3	2	4	1	897	16	- 100
	truck -	14	48	6	9	2	1	8	2	21	889	
		airplane -	automobile -	bird -	cat -	deer -	- bop	- bou	horse -	- dihs	truck -	
						Pred	icted					

Classification Report:								
	precision	recall	f1-score	support				
airplane	0.82	0.83	0.83	1000				
automobile	0.92	0.89	0.90	1000				
bird	0.71	0.75	0.73	1000				
cat	0.65	0.61	0.63	1000				
deer	0.79	0.75	0.77	1000				
dog	0.70	0.77	0.73	1000				
frog	0.82	0.86	0.84	1000				
horse	0.90	0.80	0.84	1000				
ship	0.88	0.90	0.89	1000				
truck	0.87	0.89	0.88	1000				
accuracy			0.80	10000				

macro avg 0.81 0.80 0.80 10000 weighted avg 0.81 0.80 0.80 10000

Downloading: "https://download.pytorch.org/models/resnet18-f37072fd.pth" to /root/.cache/torch/hub/checkpoints/resnet18-

f37072fd.pth

100%| 44.7M/44.7M [00:00<00:00, 182MB/s]

<IPython.core.display.HTML object>

Saving airplane.jpg to airplane.jpg Saving dog.jpg to dog.jpg Saving ship.jpg to ship.jpg

Processing: airplane.jpg

Original Image



**GradCAM Visualization** 



Predicted class index: 908

Processing: dog.jpg

Original Image



**GradCAM Visualization** 



Predicted class index: 207

Processing: ship.jpg

Original Image



**GradCAM Visualization** 



Predicted class index: 628