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April 20, 2025

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[1]: # Aarya Admane
      # TEBD22630 B2 SL2 Prac 12th

import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torchvision import datasets, transforms
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score, confusion_matrix, \
    classification_report
import seaborn as sns
import numpy as np
from PIL import Image

[2]: # Data transformations
transform_train = transforms.Compose([
    transforms.RandomHorizontalFlip(),
    transforms.RandomCrop(32, padding=4),
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])
transform_test = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

# Load CIFAR-10 dataset
train_dataset = datasets.CIFAR10(root='./data', train=True, download=True, \
    transform=transform_train)
test_dataset = datasets.CIFAR10(root='./data', train=False, download=True, \
    transform=transform_test)
train_loader = DataLoader(train_dataset, batch_size=64, shuffle=True)
test_loader = DataLoader(test_dataset, batch_size=64, shuffle=False)

# CNN Model
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class CNN(nn.Module):
    def __init__(self):
        super(CNN, self).__init__()
        self.conv1 = nn.Conv2d(3, 32, kernel_size=3, padding=1)
        self.conv2 = nn.Conv2d(32, 64, kernel_size=3, padding=1)
        self.pool = nn.MaxPool2d(2, 2)
        self.dropout = nn.Dropout(0.3)
        self.fc1 = nn.Linear(64 * 8 * 8, 256)
        self.fc2 = nn.Linear(256, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x))) # 32x32 → 16x16
        x = self.pool(F.relu(self.conv2(x))) # 16x16 → 8x8
        x = x.view(-1, 64 * 8 * 8)
        x = self.dropout(x)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x

# Device and setup
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model = CNN().to(device)
criterion = nn.CrossEntropyLoss()
optimizer = optim.Adam(model.parameters(), lr=0.001)

train_losses, val_losses, train_acc, val_acc = [], [], [], []

# Training and Validation Loop
for epoch in range(10):
    model.train()
    running_loss, correct, total = 0.0, 0, 0
    for images, labels in train_loader:
        images, labels = images.to(device), labels.to(device)
        optimizer.zero_grad()
        outputs = model(images)
        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(train_loader))
    train_acc.append(100. * correct / total)

# Validation

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model.eval()
val_loss, correct, total = 0.0, 0, 0
with torch.no_grad():
    for images, labels in test_loader:
        images, labels = images.to(device), labels.to(device)
        outputs = model(images)
        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(test_loader))
val_acc.append(100. * correct / total)

print(f"Epoch {epoch+1}: Train Loss: {train_losses[-1]:.4f}, Train Acc: {train_acc[-1]:.2f}% | Val Loss: {val_losses[-1]:.4f}, Val Acc: {val_acc[-1]:.2f}%")

# Plotting Loss and Accuracy Curves
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.plot(train_losses, label='Train Loss')
plt.plot(val_losses, label='Validation Loss')
plt.title('Loss Curve')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(train_acc, label='Train Accuracy')
plt.plot(val_acc, label='Validation Accuracy')
plt.title('Accuracy Curve')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

# Final Evaluation
model.eval()
all_preds, all_labels = [], []
with torch.no_grad():
    for images, labels in test_loader:
        images = images.to(device)
        outputs = model(images)
        _, preds = torch.max(outputs, 1)
        all_preds.extend(preds.cpu().numpy())

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        all_labels.extend(labels.numpy())

acc = accuracy_score(all_labels, all_preds)
print(f"\nTest Accuracy: {acc * 100:.2f}%\n")
print("Classification Report:\n")
print(classification_report(all_labels, all_preds, target_names=test_dataset.
    ↪classes))

# Confusion Matrix
cm = confusion_matrix(all_labels, all_preds)
plt.figure(figsize=(10, 8))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=test_dataset.
    ↪classes, yticklabels=test_dataset.classes)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()

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Downloading <https://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz> to
./data/cifar-10-python.tar.gz

100%| | 170M/170M [00:05<00:00, 33.5MB/s]

Extracting ./data/cifar-10-python.tar.gz to ./data

Files already downloaded and verified

Epoch 1: Train Loss: 1.5492, Train Acc: 43.31% | Val Loss: 1.2300, Val Acc: 54.73%

Epoch 2: Train Loss: 1.2276, Train Acc: 55.89% | Val Loss: 1.0660, Val Acc: 62.09%

Epoch 3: Train Loss: 1.0897, Train Acc: 61.07% | Val Loss: 0.9432, Val Acc: 66.80%

Epoch 4: Train Loss: 1.0079, Train Acc: 64.19% | Val Loss: 0.8791, Val Acc: 69.64%

Epoch 5: Train Loss: 0.9470, Train Acc: 66.39% | Val Loss: 0.8250, Val Acc: 70.97%

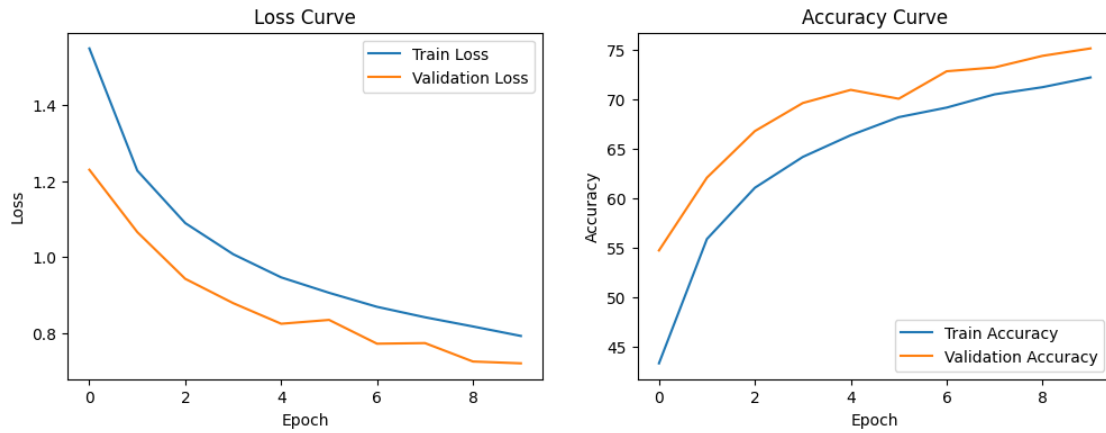
Epoch 6: Train Loss: 0.9064, Train Acc: 68.21% | Val Loss: 0.8351, Val Acc: 70.07%

Epoch 7: Train Loss: 0.8695, Train Acc: 69.18% | Val Loss: 0.7725, Val Acc: 72.85%

Epoch 8: Train Loss: 0.8420, Train Acc: 70.52% | Val Loss: 0.7741, Val Acc: 73.24%

Epoch 9: Train Loss: 0.8179, Train Acc: 71.24% | Val Loss: 0.7257, Val Acc: 74.41%

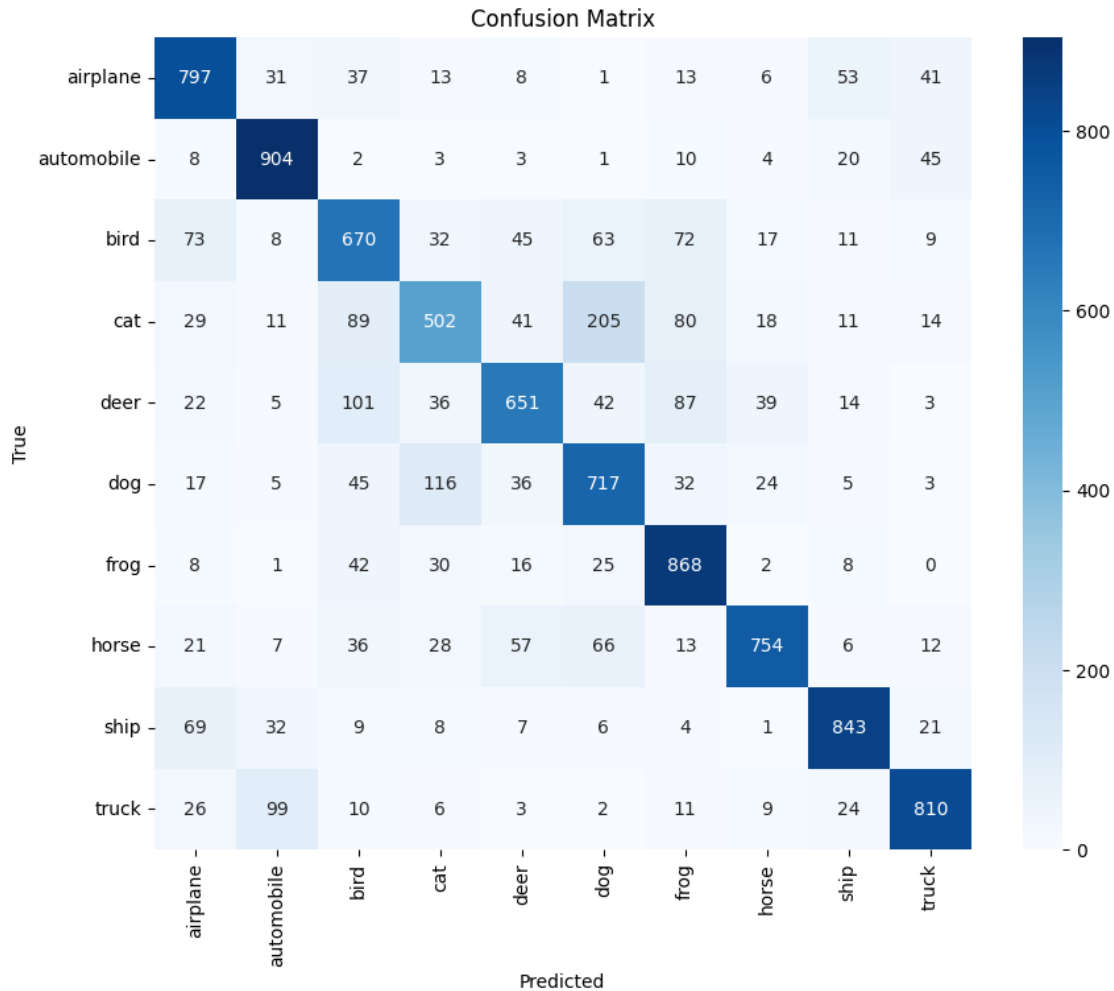
Epoch 10: Train Loss: 0.7929, Train Acc: 72.22% | Val Loss: 0.7209, Val Acc: 75.16%



Test Accuracy: 75.16%

Classification Report:

	precision	recall	f1-score	support
airplane	0.74	0.80	0.77	1000
automobile	0.82	0.90	0.86	1000
bird	0.64	0.67	0.66	1000
cat	0.65	0.50	0.57	1000
deer	0.75	0.65	0.70	1000
dog	0.64	0.72	0.67	1000
frog	0.73	0.87	0.79	1000
horse	0.86	0.75	0.80	1000
ship	0.85	0.84	0.85	1000
truck	0.85	0.81	0.83	1000
accuracy			0.75	10000
macro avg	0.75	0.75	0.75	10000
weighted avg	0.75	0.75	0.75	10000



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[ ]: # Show correct vs incorrect samples
correct_samples = np.array(all_preds) == np.array(all_labels)
fig, axs = plt.subplots(2, 5, figsize=(12, 5))
fig.suptitle('Correctly Classified vs Misclassified Samples')
correct_idx = np.where(correct_samples)[0][:5]
wrong_idx = np.where(~correct_samples)[0][:5]

for i, idx in enumerate(correct_idx):
    img, label = test_dataset[idx]
    axs[0, i].imshow(img.permute(1, 2, 0) * 0.5 + 0.5)
    axs[0, i].set_title(f"True: {test_dataset.classes[all_labels[idx]]}\nPred: {test_dataset.classes[all_preds[idx]]}")
    axs[0, i].axis('off')

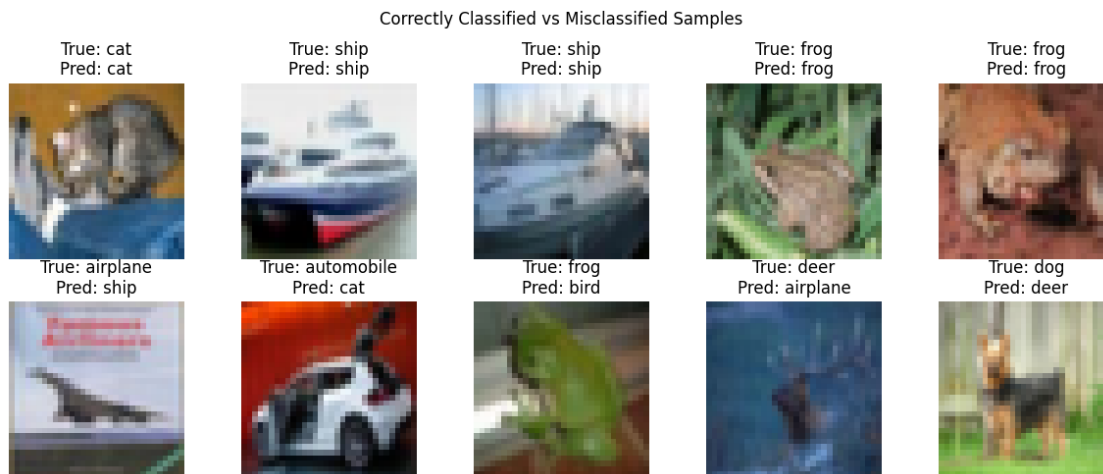
for i, idx in enumerate(wrong_idx):
    img, label = test_dataset[idx]
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    axs[1, i].imshow(img.permute(1, 2, 0) * 0.5 + 0.5)
    axs[1, i].set_title(f"True: {test_dataset.classes[all_labels[idx]]}\nPred: {test_dataset.classes[all_preds[idx]]}")
    axs[1, i].axis('off')

plt.tight_layout()
plt.show()

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[4]: # Predict custom image
user_transform = transforms.Compose([
    transforms.Resize((32, 32)),
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

def predict_user_image(img_path, model):
    img = Image.open(img_path).convert('RGB')
    input_tensor = user_transform(img).unsqueeze(0).to(device)
    model.eval()
    with torch.no_grad():
        output = model(input_tensor)
        _, predicted = torch.max(output, 1)
        pred_class = test_dataset.classes[predicted.item()]
    plt.imshow(img)
    plt.title(f"Model Prediction: {pred_class}")
    plt.axis('off')
    plt.show()

# Example usage
predict_user_image("car.jpg", model)

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Model Prediction: automobile

