22AIE304 Deep Learning Labsheet 6

Name: Aniketh Vijesh

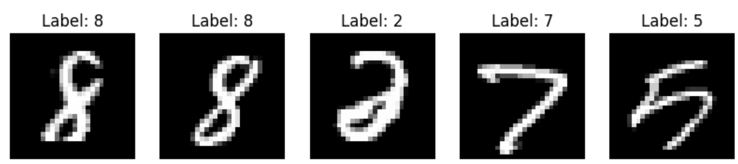
Roll No: AM.EN.U4AIE22009

```
import os
import matplotlib.pyplot as plt
import numpy as np
import random

import torch
from torch.utils.data import DataLoader, random_split
import torchvision.transforms as transforms
from torchvision import datasets
import torch.nn as nn
import torch.nn.functional as F

# Device configuration
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
```

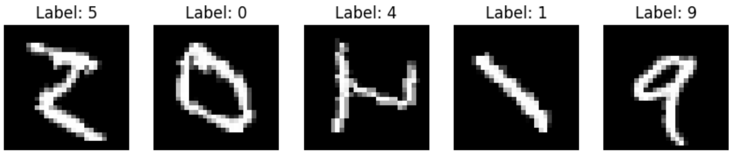
Exercise 1: Custom Convolutional Neural Network

1. **Dataset Selection**
   1.1 Each student is required to select a publicly available image dataset for classification. Students working on an image dataset for a case study may use the same dataset.
2. **Dataset Preprocessing and Splitting**
   2.1 Normalize and resize the images as needed for the CNN input.
   2.2 Apply data augmentation techniques to enhance the dataset.
   2.3 Divide the dataset into training and validation sets with an appropriate split ratio
3. **Visualization**
   3.1 Visualize sample images from the dataset before transformations.
   3.2 Visualize sample images after applying transformations to understand preprocessing effects.
4. **Model Design**
   4.1 Create a custom CNN architecture suitable for the chosen dataset.
   4.2 Display the model summary to verify the architecture.
5. **Model Training**
   5.1 Define the loss function as Cross Entropy Loss.
   5.2 Train the model using an appropriate optimizer.
   5.3 Plot the training and validation loss and accuracy over epochs.
6. **Feature Map Visualization**
   6.1 Visualize feature maps from the first convolutional layer to understand what features the CNN is learning.
7. **Hyperparameter Tuning**
   7.1 Experiment with the following hyperparameters and compare the results:
   - 7.1.1 **Number of Filters, Kernel Size, and Stride**: Test different configurations and evaluate the model's performance.
   - 7.1.2 **Learning Rate and Batch Size**: Adjust these parameters and compare the training curves (loss and accuracy).
   - 7.1.3 **Number of Layers and Hidden Neurons**: Experiment with deeper architectures and denser layers.
   - 7.1.4 **Activation Functions**: Compare learning curves for activation functions like ReLU, Sigmoid, and Tanh.
   - 7.1.5 **Optimizers**: Use different optimizers and evaluate their impact.
   7.2 For each experiment, plot and discuss the training and validation curves.

```
transform = transforms.Compose([
    transforms.Resize((28, 28)),
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

train_dataset = datasets.QMNIST(root='./data', train=True, transform=transform, download=True)
test_dataset = datasets.QMNIST(root='./data', train=False, transform=transform, download=True)

train_size = int(0.8 * len(train_dataset))
val_size = len(train_dataset) - train_size
train_dataset, val_dataset = random_split(train_dataset, [train_size, val_size])

batch_size = 64
train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=batch_size, shuffle=False)
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)

def show_images(dataset, num_images=5):
    plt.figure(figsize=(10, 5))
    for i in range(num_images):
        image, label = dataset[i]
        plt.subplot(1, num_images, i + 1)
        plt.imshow(image.squeeze(), cmap='gray')
        plt.title(f"Label: {label}")
        plt.axis('off')
    plt.show()

show_images(train_dataset)
```




```
aug_transform = transforms.Compose([
    transforms.RandomRotation(20),
    transforms.RandomHorizontalFlip(),
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

augmented_dataset = datasets.QMNIST(root='./data', train=True, transform=aug_transform)
show_images(augmented_dataset)
```




```
class CustomCNN(nn.Module):
    def __init__(self):
        super(CustomCNN, self).__init__()
        self.conv1 = nn.Conv2d(1, 32, kernel_size=3, stride=1, padding=1)
        self.conv2 = nn.Conv2d(32, 64, kernel_size=3, stride=1, padding=1)
        self.pool = nn.MaxPool2d(2, 2)
        self.fc1 = nn.Linear(64 * 7 * 7, 128)
        self.fc2 = nn.Linear(128, 10)

    def forward(self, x):
        x = self.pool(F.relu(self.conv1(x)))
        x = self.pool(F.relu(self.conv2(x)))
        x = x.view(-1, 64 * 7 * 7)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x

model = CustomCNN().to(device)
print(model)
```

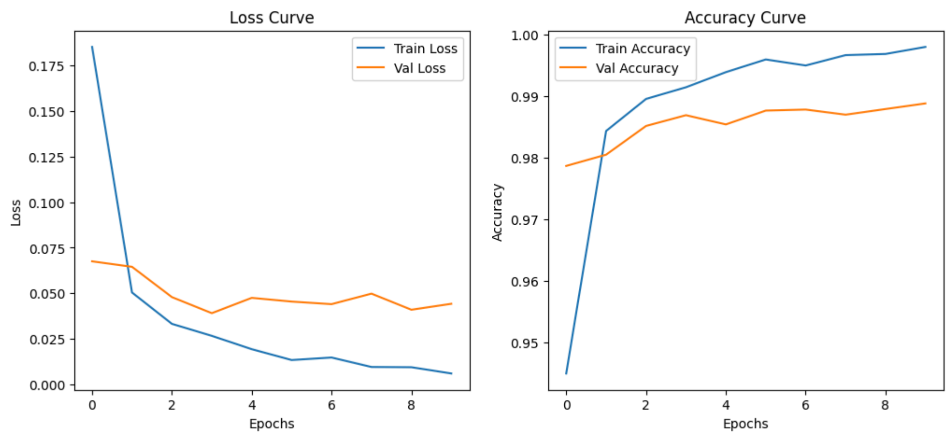
```
CustomCNN(
  (conv1): Conv2d(1, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (conv2): Conv2d(32, 64, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (pool): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1, ceil_mode=False)
  (fc1): Linear(in_features=3136, out_features=128, bias=True)
  (fc2): Linear(in_features=128, out_features=10, bias=True)
)
```

```
criterion = nn.CrossEntropyLoss()
optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
```

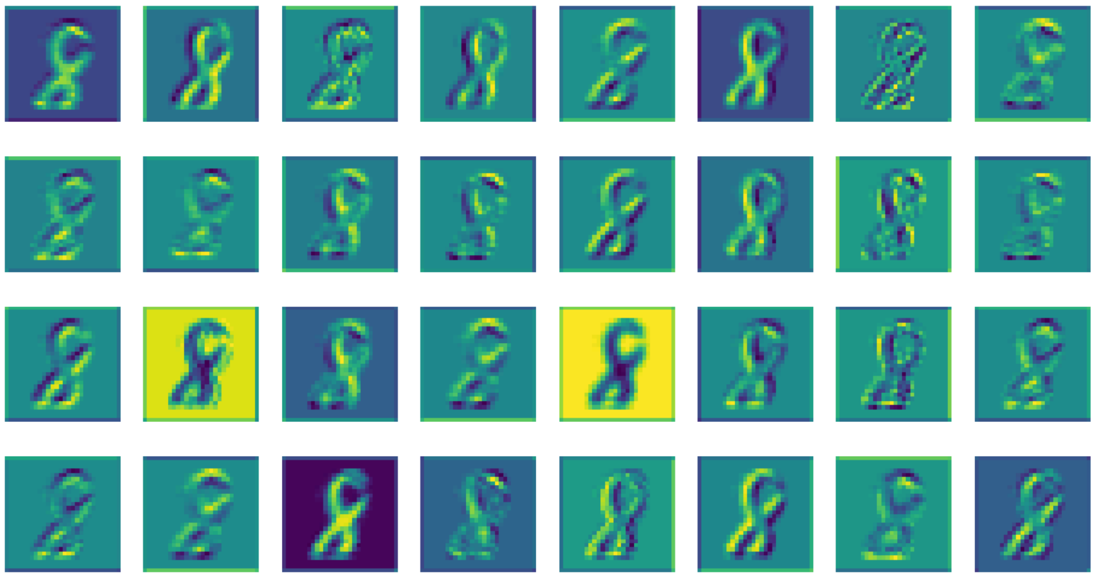
```
def train_model(model, train_loader, val_loader, epochs=10):
    train_loss, val_loss, train_acc, val_acc = [], [], [], []

    for epoch in range(epochs):
        model.train()
        running_loss, correct = 0, 0
        for images, labels in train_loader:
            images, labels = images.to(device), labels.to(device)

            # Forward pass
            outputs = model(images)
            loss = criterion(outputs, labels)

            # Backward pass
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()

            running_loss += loss.item()
            _, predicted = torch.max(outputs, 1)
            correct += (predicted == labels).sum().item()

        train_loss.append(running_loss / len(train_loader))
        train_acc.append(correct / len(train_dataset))

        # Validation
        model.eval()
        val_running_loss, val_correct = 0, 0
        with torch.no_grad():
            for images, labels in val_loader:
                images, labels = images.to(device), labels.to(device)
                outputs = model(images)
                loss = criterion(outputs, labels)

                val_running_loss += loss.item()
                _, predicted = torch.max(outputs, 1)
                val_correct += (predicted == labels).sum().item()

        val_loss.append(val_running_loss / len(val_loader))
        val_acc.append(val_correct / len(val_dataset))

        print(f"Epoch [{epoch+1}/{epochs}], Train Loss: {train_loss[-1]:.4f}, Val Loss: {val_loss[-1]:.4f}, Train Acc: {train_acc[-1]:.4f}, Val Acc: {val_acc[-1]:.4f}")

    return train_loss, val_loss, train_acc, val_acc

train_loss, val_loss, train_acc, val_acc = train_model(model, train_loader, val_loader)
```

```
Epoch [1/10], Train Loss: 0.1850, Val Loss: 0.0675, Train Acc: 0.9449, Val Acc: 0.9787
Epoch [2/10], Train Loss: 0.0505, Val Loss: 0.0645, Train Acc: 0.9844, Val Acc: 0.9805
Epoch [3/10], Train Loss: 0.0333, Val Loss: 0.0479, Train Acc: 0.9896, Val Acc: 0.9852
Epoch [4/10], Train Loss: 0.0267, Val Loss: 0.0391, Train Acc: 0.9915, Val Acc: 0.9869
Epoch [5/10], Train Loss: 0.0194, Val Loss: 0.0475, Train Acc: 0.9939, Val Acc: 0.9854
Epoch [6/10], Train Loss: 0.0135, Val Loss: 0.0455, Train Acc: 0.9960, Val Acc: 0.9877
Epoch [7/10], Train Loss: 0.0148, Val Loss: 0.0441, Train Acc: 0.9950, Val Acc: 0.9878
Epoch [8/10], Train Loss: 0.0096, Val Loss: 0.0498, Train Acc: 0.9967, Val Acc: 0.9870
Epoch [9/10], Train Loss: 0.0095, Val Loss: 0.0410, Train Acc: 0.9969, Val Acc: 0.9879
Epoch [10/10], Train Loss: 0.0061, Val Loss: 0.0443, Train Acc: 0.9980, Val Acc: 0.9888
```

```
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(train_loss, label='Train Loss')
plt.plot(val_loss, label='Val Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.title('Loss Curve')

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




```
def visualize_feature_maps(model, image):
    model.eval()
    with torch.no_grad():
        image = image.unsqueeze(0).to(device)
        feature_maps = model.conv1(image)
        feature_maps = feature_maps.cpu().squeeze().detach()

    fig, axs = plt.subplots(4, 8, figsize=(15, 8))
    for i, ax in enumerate(axs.flatten()):
        if i < feature_maps.size(0):
            ax.imshow(feature_maps[i], cmap='viridis')
        ax.axis('off')
    plt.show()

sample_image, _ = train_dataset[0]
visualize_feature_maps(model, sample_image)
```



7

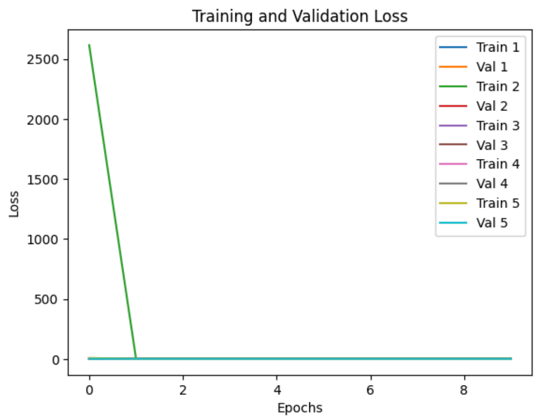
Creating an adjustable network so thats its easier to fine tune and mess around with the hyperparams

```
hyperparams = {
    "num_filters": [16, 32, 64],
    "kernel_size": [3],
    "stride": [1],
    "num_layers": [2, 3, 4],
    "hidden_neurons": [64, 128, 256],
    "activation_fn": [F.relu, F.sigmoid, F.tanh],
    "batch_size": [32, 64, 128],
    "learning_rate": [0.1, 0.01, 0.001],
    "optimizer": ["SGD", "Adam", "RMSprop"]
}


# Custom CNN class
class CustomCNN(nn.Module):
    def __init__(self, num_filters, kernel_size, stride, num_layers, hidden_neurons, activation_fn):
        super(CustomCNN, self).__init__()
        layers = []
        in_channels = 1  # Assuming grayscale input
        for i in range(num_layers):
            layers.append(nn.Conv2d(in_channels, num_filters, kernel_size=kernel_size, stride=stride, padding=1))
            layers.append(nn.ReLU() if activation_fn == F.relu else nn.Tanh() if activation_fn == F.tanh else nn.Sigmoid())
            layers.append(nn.MaxPool2d(2, 2))
            in_channels = num_filters
            num_filters *= 2
        self.conv_layers = nn.Sequential(*layers)
        self.fc1 = nn.Linear(in_channels * (28 // (2 ** num_layers)) ** 2, hidden_neurons)
        self.fc2 = nn.Linear(hidden_neurons, 10)

    def forward(self, x):
        x = self.conv_layers(x)
        x = x.view(x.size(0), -1)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x
```

```
def random_hyperparams(hyperparams):
    return {k: random.choice(v) for k, v in hyperparams.items()}


def train_model(model, train_loader, val_loader, optimizer, criterion, epochs=10):
    train_losses, val_losses = [], []
    for epoch in range(epochs):
        model.train()
        running_loss = 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()
        train_losses.append(running_loss / len(train_loader))

        # Validation
        model.eval()
        val_loss = 0
        with torch.no_grad():
            for images, labels in val_loader:
                images, labels = images.to(device), labels.to(device)
                outputs = model(images)
                loss = criterion(outputs, labels)
                val_loss += loss.item()
        val_losses.append(val_loss / len(val_loader))

    return train_losses, val_losses



device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
results = []

for i in range(5):  # Run 5 random experiments
    params = random_hyperparams(hyperparams)
    print(f"Experiment {i+1}: {params}")

    # Initialize model and optimizer
    model = CustomCNN(
        num_filters=params["num_filters"],
        kernel_size=params["kernel_size"],
        stride=params["stride"],
        num_layers=params["num_layers"],
        hidden_neurons=params["hidden_neurons"],
        activation_fn=params["activation_fn"]
    ).to(device)

    optimizer_class = torch.optim.SGD if params["optimizer"] == "SGD" else \
                      torch.optim.Adam if params["optimizer"] == "Adam" else \
                      torch.optim.RMSprop
    optimizer = optimizer_class(model.parameters(), lr=params["learning_rate"])
    criterion = nn.CrossEntropyLoss()

    # Create data loaders
    train_loader = DataLoader(train_dataset, batch_size=params["batch_size"], shuffle=True)
    val_loader = DataLoader(val_dataset, batch_size=params["batch_size"], shuffle=False)

    # Train model
    train_loss, val_loss = train_model(model, train_loader, val_loader, optimizer, criterion, epochs=10)

    # Store results
    results.append((params, train_loss, val_loss))
```

```
Experiment 1: {'num_filters': 64, 'kernel_size': 3, 'stride': 1, 'num_layers': 2, 'hidden_neurons': 128, 'activation_fn': <function sigmoid at 0x7cf6381a1c60>, 'batch_size': 128, 'learning_rate'
Experiment 2: {'num_filters': 16, 'kernel_size': 3, 'stride': 1, 'num_layers': 2, 'hidden_neurons': 128, 'activation_fn': <function relu at 0x7cf6381a11b0>, 'batch_size': 64, 'learning_rate': 0.
Experiment 3: {'num_filters': 16, 'kernel_size': 3, 'stride': 1, 'num_layers': 2, 'hidden_neurons': 256, 'activation_fn': <function relu at 0x7cf6381a11b0>, 'batch_size': 128, 'learning_rate': 0
Experiment 4: {'num_filters': 16, 'kernel_size': 3, 'stride': 1, 'num_layers': 3, 'hidden_neurons': 64, 'activation_fn': <function sigmoid at 0x7cf6381a1c60>, 'batch_size': 32, 'learning_rate':
Experiment 5: {'num_filters': 64, 'kernel_size': 3, 'stride': 1, 'num_layers': 2, 'hidden_neurons': 64, 'activation_fn': <function relu at 0x7cf6381a11b0>, 'batch_size': 32, 'learning_rate': 0.0
```

```
for i, (params, train_loss, val_loss) in enumerate(results):
    plt.plot(train_loss, label=f"Train {i+1}")
    plt.plot(val_loss, label=f"Val {i+1}")
plt.title("Training and Validation Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.show()
```



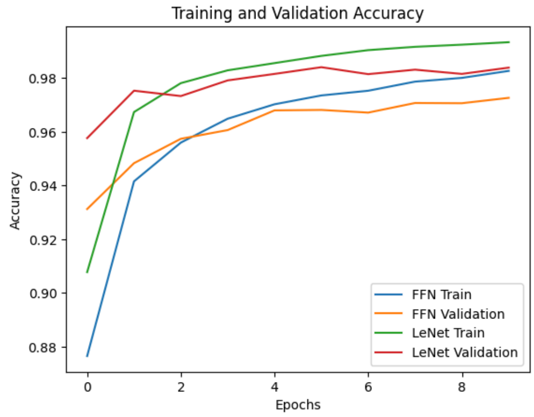
Exercise 2: Comparing Neural Networks

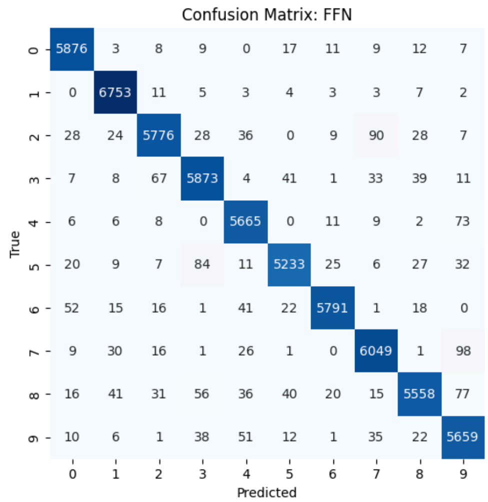
1. **Apply a Feedforward Neural Network (FFN)**
   - Use the same dataset and apply the Feedforward Neural Network (FFN) model implemented in **Lab Sheet 5** for classification.
   - Compare the performance of the FFN with the CNN trained in Exercise 1.
2. **Predefined Architectures**
   - Train and evaluate the chosen dataset using pre-defined architectures like **VGG** and **LeNet**.
   - Compare the performance of the custom CNN, FFN, VGG, and LeNet models using metrics such as accuracy, loss, and confusion matrix.

```python
import torch
import torch.nn as nn
from torchvision import models, transforms
from torch.utils.data import DataLoader
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, accuracy_score
import seaborn as sns

class FeedforwardNeuralNet(nn.Module):
    def __init__(self, input_size=784, hidden_size=128, output_size=10, num_hidden_layers=2, activation=nn.ReLU()):
        super(FeedforwardNeuralNet, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.hidden_layers = nn.ModuleList([nn.Linear(hidden_size, hidden_size) for _ in range(num_hidden_layers - 1)])
        self.output = nn.Linear(hidden_size, output_size)
        self.activation = activation

    def forward(self, x):
        x = x.view(x.size(0), -1)
        x = self.activation(self.fc1(x))
        for layer in self.hidden_layers:
            x = self.activation(layer(x))
        x = self.output(x)
        return x

# Train a model
def train_model(model, train_loader, val_loader, criterion, optimizer, epochs=10):
    train_acc, val_acc = [], []
    for epoch in range(epochs):
        model.train()
        correct, total = 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()

            _, preds = torch.max(outputs, 1)
            correct += (preds == labels).sum().item()
            total += labels.size(0)
        train_acc.append(correct / total)

        # Validation
        model.eval()
        correct, total = 0, 0
        with torch.no_grad():
            for images, labels in val_loader:
                images, labels = images.to(device), labels.to(device)
                outputs = model(images)
                _, preds = torch.max(outputs, 1)
                correct += (preds == labels).sum().item()
                total += labels.size(0)
        val_acc.append(correct / total)

    return train_acc, val_acc

# Function to evaluate models
def evaluate_model(model, test_loader):
    model.eval()
    all_preds, all_labels = [], []
    with torch.no_grad():
        for images, labels in test_loader:
            images, labels = images.to(device), labels.to(device)
            outputs = model(images)
            _, preds = torch.max(outputs, 1)
            all_preds.extend(preds.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())
    acc = accuracy_score(all_labels, all_preds)
    cm = confusion_matrix(all_labels, all_preds)
    return acc, cm



def get_predefined_model(arch):
    if arch == "VGG":
        model = models.vgg11(pretrained=False)
        model.features[0] = nn.Conv2d(1, 64, kernel_size=3, stride=1, padding=1)  # Adjust for 1-channel input
        model.classifier[6] = nn.Linear(4096, 10)  # Adjust output layer for 10 classes

        # Modify the feature extractor for smaller inputs
        model.features = nn.Sequential(
            *[layer for i, layer in enumerate(model.features) if i not in [16, 23]]  # Remove some pooling layers
        )
    elif arch == "LeNet":
        model = nn.Sequential(
            nn.Conv2d(1, 6, kernel_size=5),
            nn.Tanh(),
            nn.AvgPool2d(kernel_size=2, stride=2),
            nn.Conv2d(6, 16, kernel_size=5),
            nn.Tanh(),
            nn.AvgPool2d(kernel_size=2, stride=2),
            nn.Flatten(),
            nn.Linear(256, 120),
            nn.Tanh(),
            nn.Linear(120, 84),
            nn.Tanh(),
            nn.Linear(84, 10),
        )
    return model



models_to_train = {
    "FFN": FeedforwardNeuralNet(),
    "LeNet": get_predefined_model("LeNet")
}


results = {}
for model_name, model in models_to_train.items():
    model = model.to(device)
    optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
    criterion = nn.CrossEntropyLoss()

    print(f"Training {model_name}...")
    train_acc, val_acc = train_model(model, train_loader, val_loader, criterion, optimizer, epochs=10)
    test_acc, cm = evaluate_model(model, test_loader)

    results[model_name] = {
        "train_acc": train_acc,
        "val_acc": val_acc,
        "test_acc": test_acc,
```

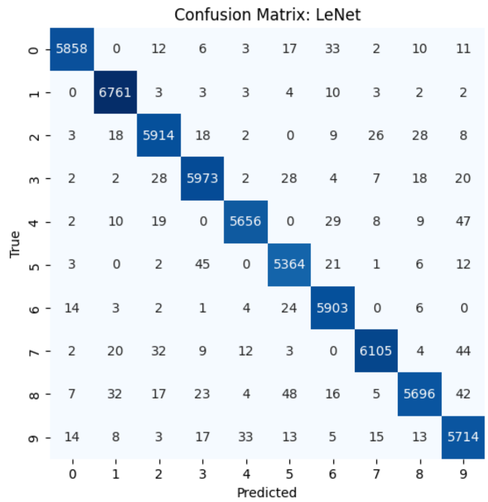
```
        "confusion_matrix": cm
    }

# Plot and compare
for model_name, result in results.items():
    plt.plot(result["train_acc"], label=f"{model_name} Train")
    plt.plot(result["val_acc"], label=f"{model_name} Validation")
plt.title("Training and Validation Accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
plt.show()

# Display confusion matrices
for model_name, result in results.items():
    plt.figure(figsize=(6, 6))
    sns.heatmap(result["confusion_matrix"], annot=True, fmt="d", cmap="Blues", cbar=False)
    plt.title(f"Confusion Matrix: {model_name}")
    plt.xlabel("Predicted")
    plt.ylabel("True")
    plt.show()
    print(f"Test Accuracy for {model_name}: {result['test_acc']:.2f}")
```

```
Training FFN...
Training LeNet...
```






```
Test Accuracy for FFN: 0.97
```




```
Test Accuracy for LeNet: 0.98
```