22AIE304 Deep Learning Lab Sheet 5

Fifth Semester BTech CSE(AI)

Department of Computer Science and Engineering

Amrita School of Computing

Training a Feedforward Neural Network on the MNIST Dataset Using PyTorch

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Exercise 1: Use this sample ipynb file for training and do the following:

- Part 1: Setting Up the Environment
  - Installing Required Libraries
  - Loading the MNIST Dataset
- Part 2: Defining the Feedforward Neural Network
  - Input layer (784 units)
  - 1 or 2 hidden layers (try different configurations like 128, 256, 512 units)
  - Output layer (10 units corresponding to the 10 classes in MNIST)
- Part 3: Training the Model - Use sigmoid activation

```
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import DataLoader, random_split
import torchvision
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
```

```
class FeedForwardNN(nn.Module):
    def __init__(self, input_size=784, output_size=10, hidden_sizes=[128], activation_fn=nn.ReLU):
        super(FeedForwardNN, self).__init__()
        layers = []
        for hidden_size in hidden_sizes:
            layers.append(nn.Linear(input_size, hidden_size))
            layers.append(activation_fn())
            input_size = hidden_size
        layers.append(nn.Linear(input_size, output_size))
        self.model = nn.Sequential(*layers)

    def forward(self, x):
        return self.model(x)
```

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

    for epoch in range(epochs):
        model.train()
```

```
        epoch_train_loss, correct, total = 0, 0, 0

        for inputs, labels in train_loader:
            inputs, labels = inputs.view(inputs.size(0), -1).to(device), labels.to(device)
            optimizer.zero_grad()
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            epoch_train_loss += loss.item() * inputs.size(0)
            _, predicted = torch.max(outputs, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

        train_loss.append(epoch_train_loss / total)
        train_acc.append(correct / total)

        model.eval()
        epoch_val_loss, correct, total = 0, 0, 0

        with torch.no_grad():
            for inputs, labels in val_loader:
                inputs, labels = inputs.view(inputs.size(0), -1).to(device), labels.to(device)
                outputs = model(inputs)
                loss = criterion(outputs, labels)
                epoch_val_loss += loss.item() * inputs.size(0)
                _, predicted = torch.max(outputs, 1)
                total += labels.size(0)
                correct += (predicted == labels).sum().item()

        val_loss.append(epoch_val_loss / total)
        val_acc.append(correct / total)

    return train_loss, val_loss, train_acc, val_acc
```

```
transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize((0.5,), (0.5,))])
train_set = torchvision.datasets.MNIST(root='./data', train=True, download=True, transform=transform)
test_set = torchvision.datasets.MNIST(root='./data', train=False, download=True, transform=transform)

train_size = int(0.8 * len(train_set))
val_size = len(train_set) - train_size
train_subset, val_subset = random_split(train_set, [train_size, val_size])

HLayers = [1, 2]
hidden_sizes = [64, 128, 256, 512]
activations = [nn.ReLU, nn.Sigmoid, nn.Tanh, nn.LeakyReLU]
learning_rates = [0.1, 0.01, 0.001]
batch_sizes = [16, 32, 64, 128]
optimizers = {"SGD": optim.SGD, "Adam": optim.Adam, "RMSprop": optim.RMSprop}
epochs = 10
```

```
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HTTP Error 403: Forbidden

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Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-idx3-ubyte.gz to ./data/MNIST/raw/train-images-idx3
100%|██████████| 9.91M/9.91M [00:00<00:00, 22.0MB/s]
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Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
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Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-idx1-ubyte.gz to ./data/MNIST/raw/train-labels-idx1
100%|██████████| 28.9k/28.9k [00:00<00:00, 627kB/s]
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Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-idx3-ubyte.gz to ./data/MNIST/raw/t10k-images-idx3-u
100%|██████████| 1.65M/1.65M [00:00<00:00, 5.60MB/s]
```

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100%|██████████| 4.54k/4.54k [00:00<00:00, 2.72MB/s]Extracting ./data/MNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/MNIST/
```

```python
confusion_matrices = []

def compute_confusion_matrix(model, data_loader, device):
    """Compute confusion matrix for the given model and data_loader."""
    model.eval()
    all_preds, all_labels = [], []

    with torch.no_grad():
        for inputs, labels in data_loader:
            inputs, labels = inputs.view(inputs.size(0), -1).to(device), labels.to(device)
            outputs = model(inputs)
            _, predicted = torch.max(outputs, 1)
            all_preds.extend(predicted.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())

    return confusion_matrix(all_labels, all_preds)
```

```python
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

transform = transforms.Compose([transforms.ToTensor(), transforms.Normalize((0.5,), (0.5,))])
train_set = torchvision.datasets.MNIST(root='./data', train=True, download=True, transform=transform)
test_set = torchvision.datasets.MNIST(root='./data', train=False, download=True, transform=transform)

train_size = int(0.8 * len(train_set))
val_size = len(train_set) - train_size
train_subset, val_subset = random_split(train_set, [train_size, val_size])

train_loader = DataLoader(train_subset, batch_size=64, shuffle=True)
val_loader = DataLoader(val_subset, batch_size=64, shuffle=False)
test_loader = DataLoader(test_set, batch_size=64, shuffle=False)
```

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Exercise 2: Visualizing the Training Process

- Plot the Training Loss Curve: Modify your code to store the training loss at each epoch and plot a curve that shows how the loss decreases over time. How does the loss change as the model trains? Does the loss converge as the number of epochs increases?
- Plot the Accuracy Curve: Track the training accuracy after each epoch and plot a graph showing how accuracy improves over time (comparing predictions with true labels). How does training accuracy change during training? Does the accuracy saturate after a certain number of epochs?
- Visualize Weight Updates: Visualize the changes in the weights of the hidden layer during training. After each epoch, store the values of the weights and plot them. How do weights evolve throughout training? Are there any patterns in the weight changes?

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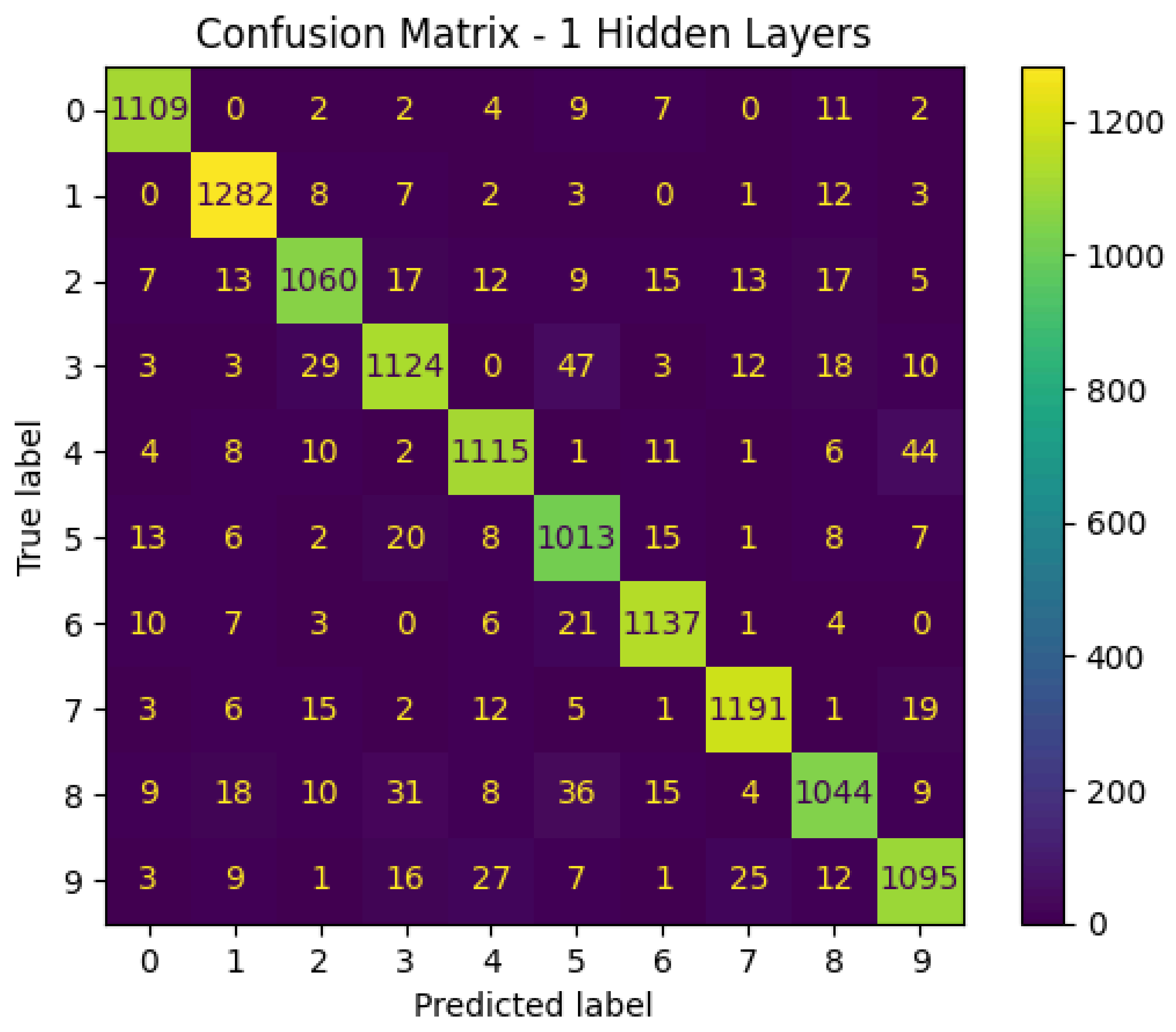
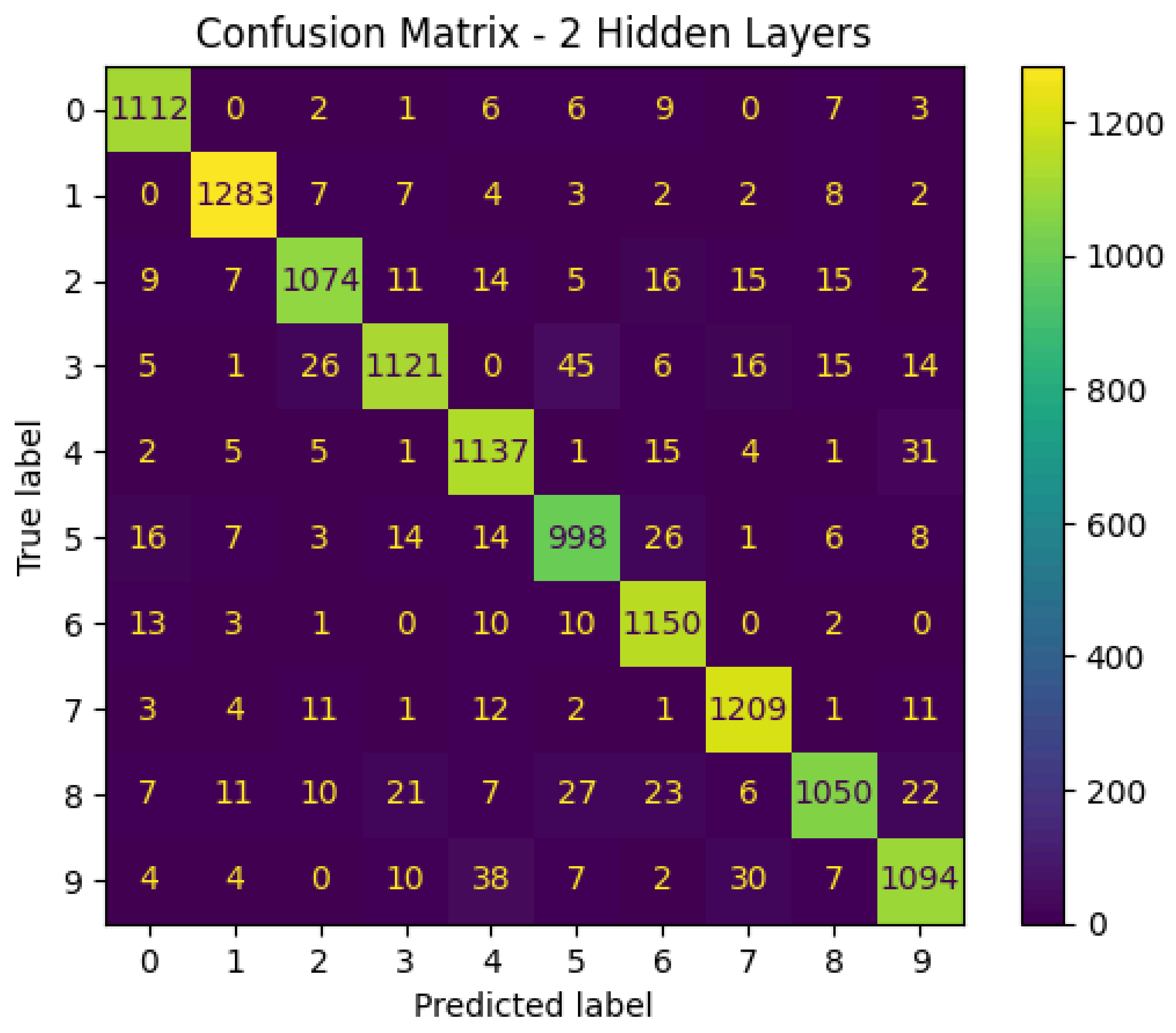
Exercise 3: Visualizing Validation/Testing results

a. Plot confusion Matrix on validation/test set: After the model is trained, plot a confusion matrix to show how well the model classifies each digit (0-9). Which digits does the model classify well, and which ones are more often confused with others
b. Plot validation accuracy and validation error for each epoch. How does the validation accuracy compare to the training accuracy
c. Compare training and validation loss

```
for entry in confusion_matrices:
    experiment_name = entry["experiment"]
    cm = entry["confusion_matrix"]

    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=range(cm.shape[0]))
    disp.plot(cmap="viridis")
    plt.title(f"Confusion Matrix - {experiment_name}")
    plt.show()
```





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Exercise 4: Explore different Activation Functions

Replace the activation functions (ReLU, Sigmoid, Tanh, Leaky ReLU) in your network and observe the effect on convergence and accuracy. Plot the performance for different activation functions.

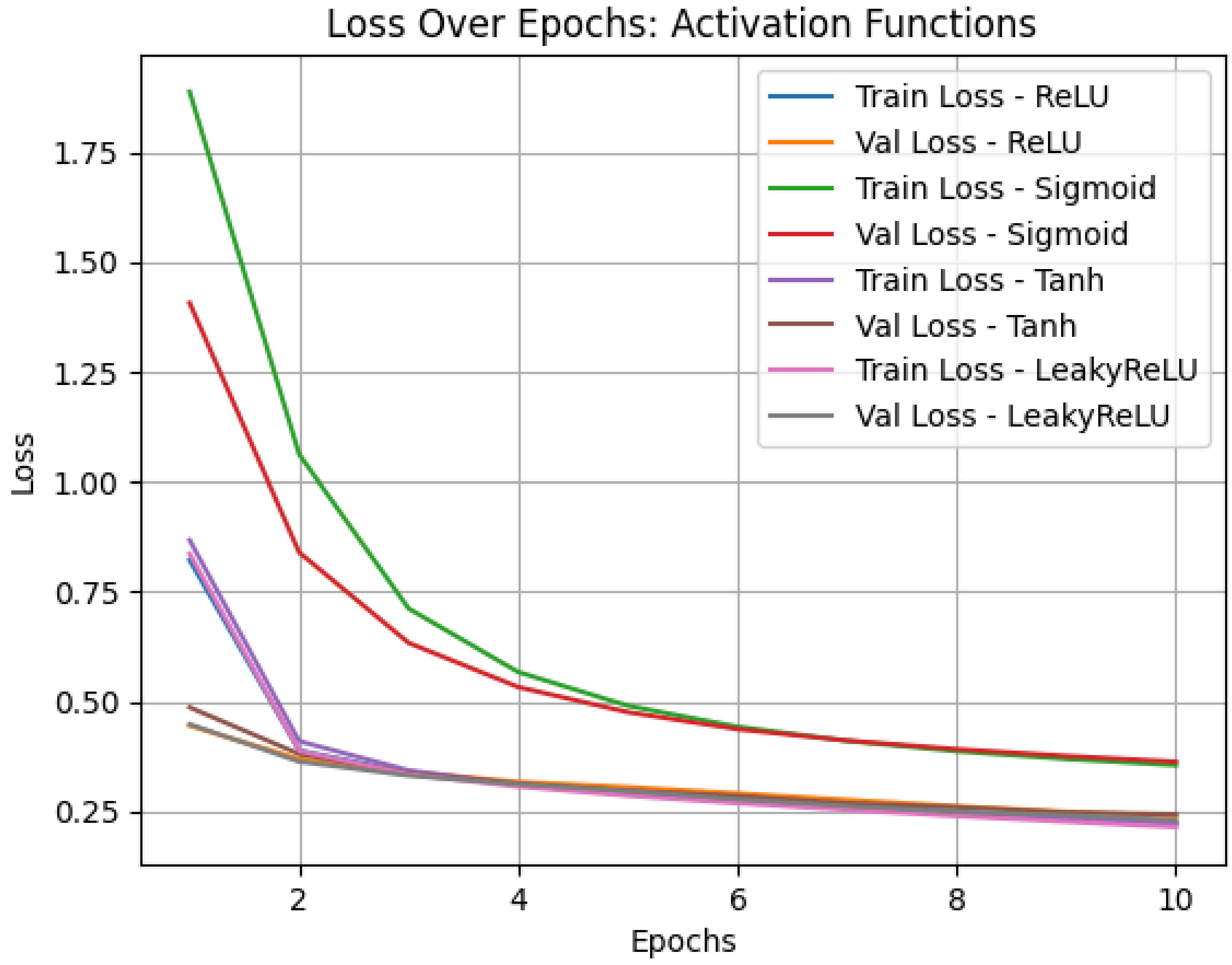
```
for activation_fn in activations:
    model = FeedForwardNN(
        hidden_sizes=[128],
        activation_fn=activation_fn
    ).to(device)

    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=0.01)

    train_loss, val_loss, train_acc, val_acc = train_model(
        model, train_loader, val_loader, epochs, criterion, optimizer, device
    )
```

```
    # Plot results
    plt.plot(range(1, epochs + 1), train_loss, label=f"Train Loss - {activation_fn.__name__}")
    plt.plot(range(1, epochs + 1), val_loss, label=f"Val Loss - {activation_fn.__name__}")

plt.title("Loss Over Epochs: Activation Functions")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.grid()
plt.show()
```



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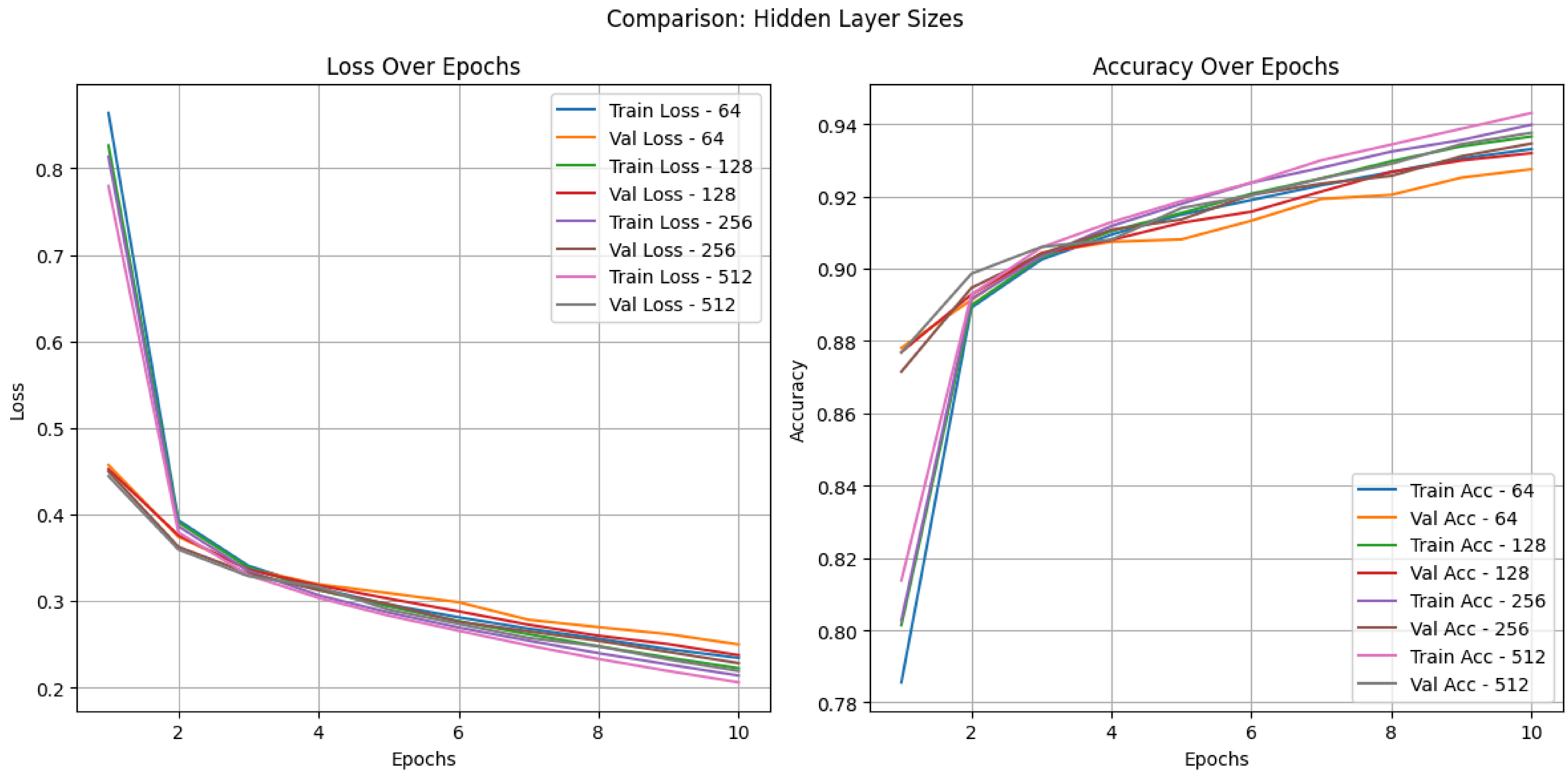
Exercise 5: Experimenting with Hyperparameters

a. Experiment with different learning rates (e.g., 0.1, 0.01, 0.001). Plot the effect of learning rate on training loss and accuracy.
b. Experiment with different batch sizes (e.g., 16, 32, 64, 128). Plot the training time and accuracy for each batch size.
c. Experiment with different numbers of hidden units in the hidden layers (e.g., 64, 128, 256). Plot the validation accuracy as a function of the number of hidden units.
d. Try different optimizers (SGD, Adam, RMSprop) and compare the convergence speed and final performance.

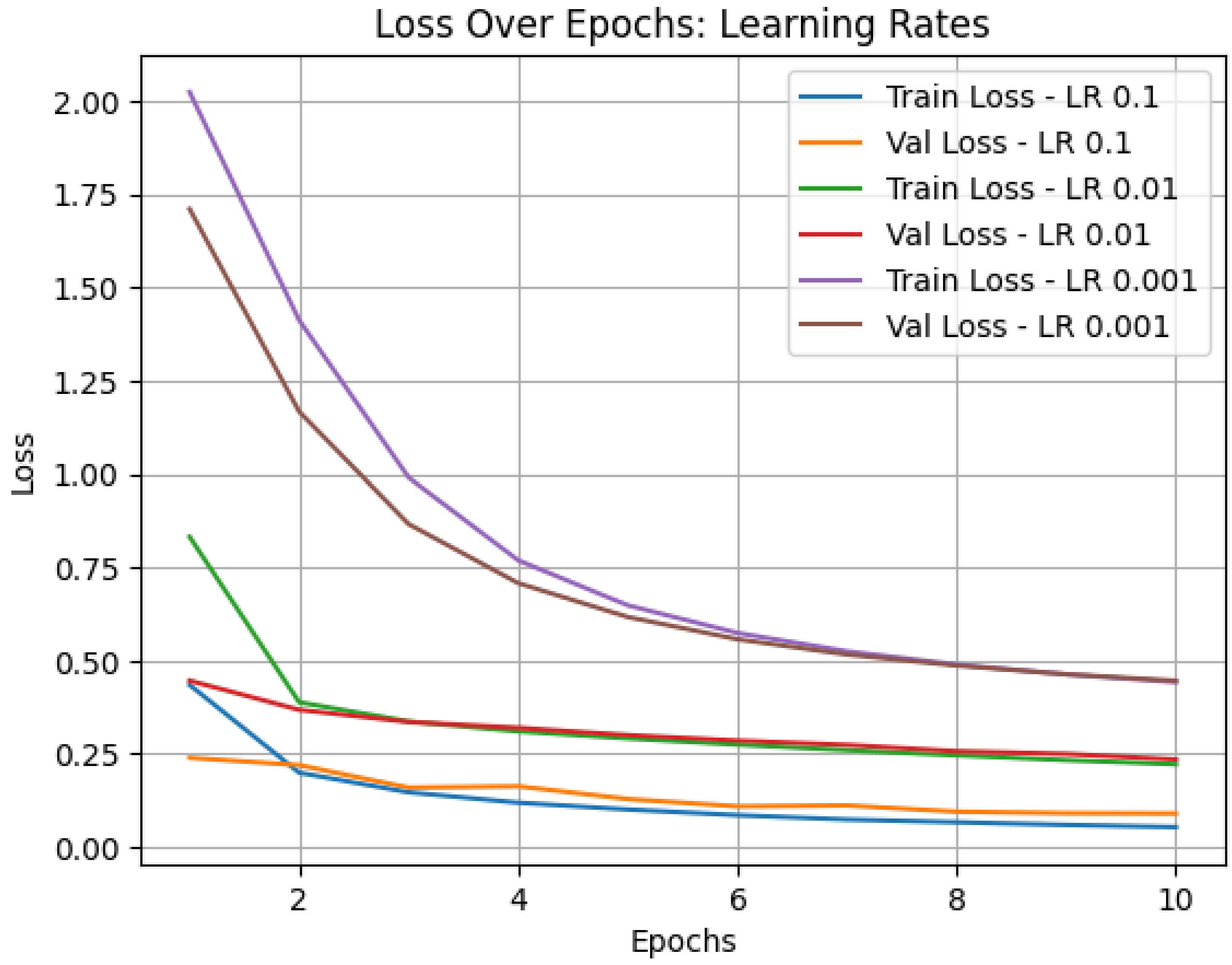
```
results = []
for hidden_size in hidden_sizes:
    model = FeedForwardNN(
        hidden_sizes=[hidden_size] * 1,
        activation_fn=nn.ReLU
    ).to(device)

    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=0.01)

    train_loss, val_loss, train_acc, val_acc = train_model(
        model, train_loader, val_loader, epochs, criterion, optimizer, device
    )
    results.append((train_loss, val_loss, train_acc, val_acc))

# Plot results
fig, axs = plt.subplots(1, 2, figsize=(12, 6))
for i, hidden_size in enumerate(hidden_sizes):
```

```
    axs[0].plot(range(1, epochs + 1), results[i][0], label=f"Train Loss - {hidden_size}")
    axs[0].plot(range(1, epochs + 1), results[i][1], label=f"Val Loss - {hidden_size}")
    axs[1].plot(range(1, epochs + 1), results[i][2], label=f"Train Acc - {hidden_size}")
    axs[1].plot(range(1, epochs + 1), results[i][3], label=f"Val Acc - {hidden_size}")

axs[0].set_title("Loss Over Epochs")
axs[0].set_xlabel("Epochs")
axs[0].set_ylabel("Loss")
axs[0].legend()
axs[0].grid()

axs[1].set_title("Accuracy Over Epochs")
axs[1].set_xlabel("Epochs")
axs[1].set_ylabel("Accuracy")
axs[1].legend()
axs[1].grid()

plt.suptitle("Comparison: Hidden Layer Sizes")
plt.tight_layout()
plt.show()
```

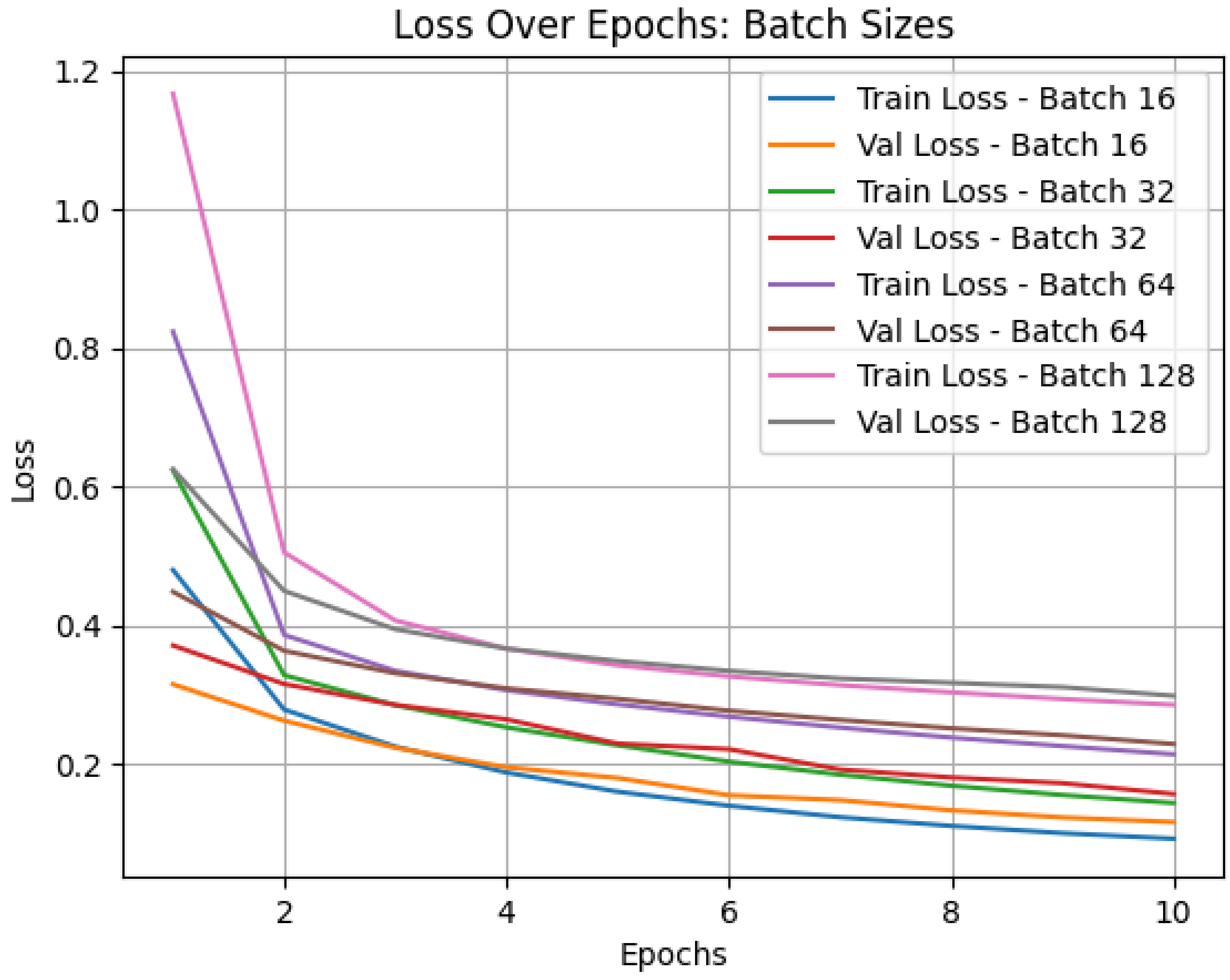



```
for lr in learning_rates:
    model = FeedForwardNN(
        hidden_sizes=[128],
        activation_fn=nn.ReLU
    ).to(device)

    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=lr)

    train_loss, val_loss, train_acc, val_acc = train_model(
        model, train_loader, val_loader, epochs, criterion, optimizer, device
    )

    # Plot results
    plt.plot(range(1, epochs + 1), train_loss, label=f"Train Loss - LR {lr}")
    plt.plot(range(1, epochs + 1), val_loss, label=f"Val Loss - LR {lr}")

plt.title("Loss Over Epochs: Learning Rates")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
```

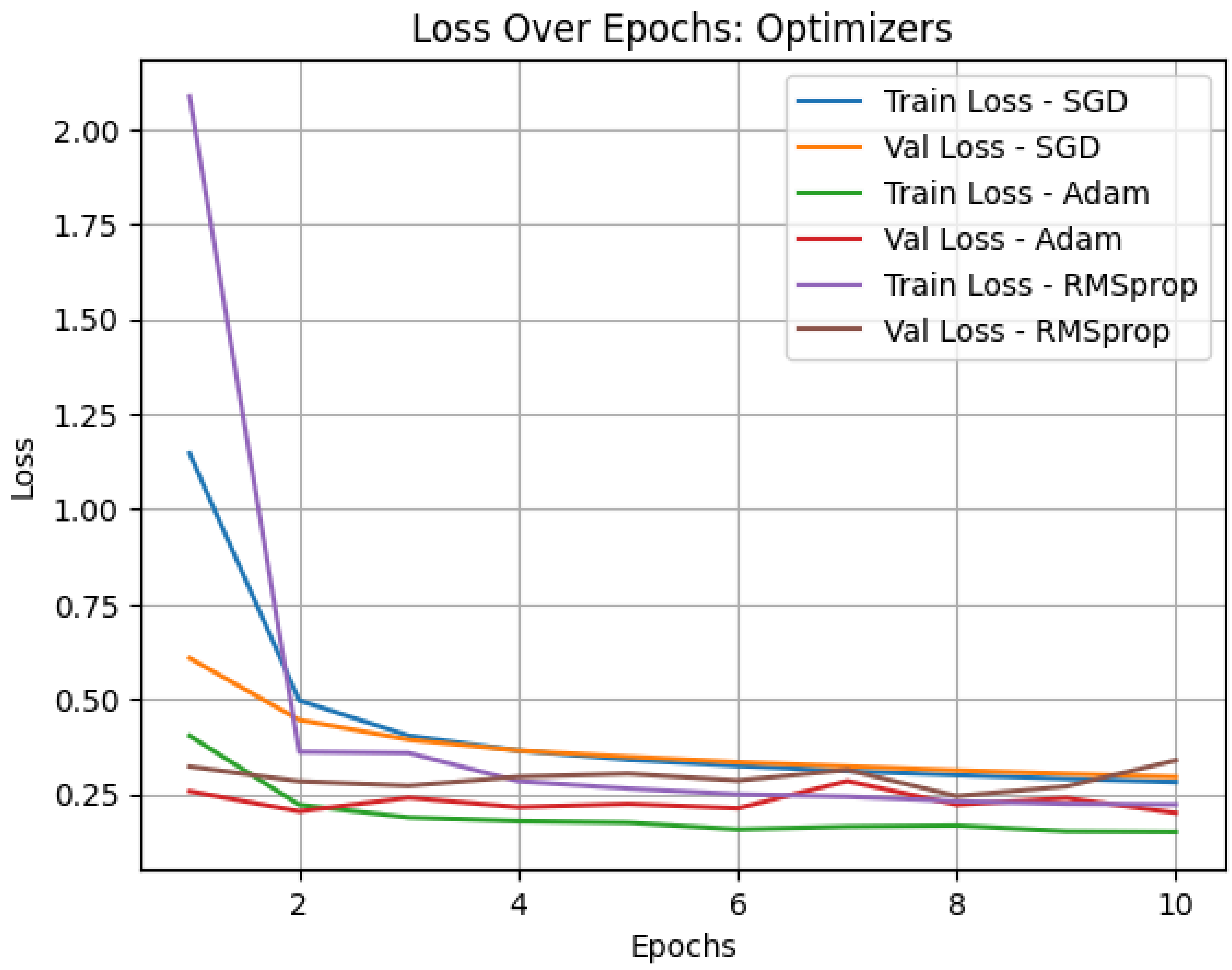
```
plt.grid()
plt.show()
```




```
for batch_size in batch_sizes:
    train_loader = DataLoader(train_subset, batch_size=batch_size, shuffle=True)
    val_loader = DataLoader(val_subset, batch_size=batch_size, shuffle=False)

    model = FeedForwardNN(
        hidden_sizes=[128],
        activation_fn=nn.ReLU
    ).to(device)

    criterion = nn.CrossEntropyLoss()
    optimizer = optim.SGD(model.parameters(), lr=0.01)

    train_loss, val_loss, train_acc, val_acc = train_model(
        model, train_loader, val_loader, epochs, criterion, optimizer, device
    )

    # Plot results
    plt.plot(range(1, epochs + 1), train_loss, label=f"Train Loss - Batch {batch_size}")
    plt.plot(range(1, epochs + 1), val_loss, label=f"Val Loss - Batch {batch_size}")

plt.title("Loss Over Epochs: Batch Sizes")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.grid()
plt.show()
```




```
for name, optimizer_fn in optimizers.items():
    model = FeedForwardNN(
        hidden_sizes=[128],
        activation_fn=nn.ReLU
    ).to(device)

    criterion = nn.CrossEntropyLoss()
    optimizer = optimizer_fn(model.parameters(), lr=0.01)

    train_loss, val_loss, train_acc, val_acc = train_model(
        model, train_loader, val_loader, epochs, criterion, optimizer, device
    )

    # Plot results
    plt.plot(range(1, epochs + 1), train_loss, label=f"Train Loss - {name}")
    plt.plot(range(1, epochs + 1), val_loss, label=f"Val Loss - {name}")

plt.title("Loss Over Epochs: Optimizers")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
plt.grid()
plt.show()
```



```
import pandas as pd

performance_data = []

for idx, (train_loss, val_loss, train_acc, val_acc) in enumerate(results):
    performance_data.append({
        "Experiment": f"Experiment {idx + 1}",
        "Train Loss": train_loss[-1],
        "Validation Loss": val_loss[-1],
        "Train Accuracy (%)": train_acc[-1] * 100,
        "Validation Accuracy (%)": val_acc[-1] * 100
    })

performance_df = pd.DataFrame(performance_data)
print("Model Performance Summary")
print(performance_df)
```

```
Model Performance Summary
     Experiment  Train Loss  Validation Loss  Train Accuracy (%)  \
0  Experiment 1    0.228985         0.229270           93.481250
1  Experiment 2    0.220583         0.223019           93.764583
2  Experiment 3    0.216583         0.217687           93.879167
3  Experiment 4    0.208605         0.208130           94.150000

   Validation Accuracy (%)
0                93.433333
1                93.483333
2                93.850000
3                94.166667
```

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