```
# import libraries
import torch
import torch.nn as nn
import torch.optim as optim
import torchvision
import torchvision.transforms as transforms
import matplotlib.pyplot as plt
import numpy as np
import random
import time
import math
import seaborn as sns
from torchsummary import summary
from sklearn.metrics import classification_report, confusion_matrix
```

Downloading the MNIST digit datasets

```
transform = transforms.Compose([transforms.ToTensor()])   # combines a list of trar
train_dataset = torchvision.datasets.MNIST(root='./data', train=True, transform=tra
test_dataset = torchvision.datasets.MNIST(root='./data', train=False, transform=tra
```

```
Downloading http://yann.lecun.com/exdb/mnist/train-images-idx3-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-idx3-ul
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-images-idx3-ul
100%|██████████| 9912422/9912422 [00:03<00:00, 3193275.64it/s]
Extracting ./data/MNIST/raw/train-images-idx3-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/train-labels-idx1-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-idx1-ul
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/train-labels-idx1-ul
100%|██████████| 28881/28881 [00:00<00:00, 499493.62it/s]
Extracting ./data/MNIST/raw/train-labels-idx1-ubyte.gz to ./data/MNIST/raw

Downloading http://yann.lecun.com/exdb/mnist/t10k-images-idx3-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-idx3-uby
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-images-idx3-uby
100%|██████████| 1648877/1648877 [00:00<00:00, 4050458.99it/s]
Extracting ./data/MNIST/raw/t10k-images-idx3-ubyte.gz to ./data/MNIST/raw
```

```
Downloading http://yann.lecun.com/exdb/mnist/t10k-labels-idx1-ubyte.gz
Failed to download (trying next):
HTTP Error 403: Forbidden

Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-idx1-uby
Downloading https://ossci-datasets.s3.amazonaws.com/mnist/t10k-labels-idx1-uby
100%|██████████| 4542/4542 [00:00<00:00, 10021319.71it/s]Extracting ./data/MN
```

```
train_dataset, val_dataset = torch.utils.data.random_split(train_dataset, [50000,
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=64, shuffle=
val_loader = torch.utils.data.DataLoader(val_dataset, batch_size=64, shuffle=Fals
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=64, shuffle=Fa
```

```
len(train_dataset), len(val_dataset), len(test_dataset)
```

```
(50000, 10000, 10000)
```

Visualizing the data

```
# Get a batch of data
data_iter = iter(train_loader)
images, labels = next(data_iter)

# Display the first 5 images
for i in range(5):
    plt.subplot(1, 5, i+1)
    plt.imshow(images[i].squeeze(), cmap='gray')
    plt.title(f'Label: {labels[i].item()}')
    plt.axis('off')

plt.show()
```

CNN Architecture

```
class CNN(nn.Module):
  def __init__(self, use_batch_norm=False):
    super(CNN, self).__init__()

    # convolutional layers
    self.conv1 = nn.Conv2d(in_channels=1, out_channels=32, kernel_size=3, stride=
    self.conv1_bn = nn.BatchNorm2d(32) if use_batch_norm else None
    self.relu1 = nn.ReLU()
    self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2) # 14x14

    self.conv2 = nn.Conv2d(in_channels=32, out_channels=32, kernel_size=3, stride
    self.conv2_bn = nn.BatchNorm2d(32) if use_batch_norm else None
    self.relu2 = nn.ReLU()
    self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2) # 7x7

    # Fully connected layers
    self.fc1 = nn.Linear(32 * 7 * 7, 500)
    self.fc1_bn = nn.BatchNorm1d(500) if use_batch_norm else None
    self.relu_fc1 = nn.ReLU()
    self.fc2 = nn.Linear(500, 10)

    # Softmax for output layer
    self.softmax = nn.Softmax(dim=1)

  def forward(self, x):
    # First Conv Block
    x = self.conv1(x)
    x = self.relu1(x)
    x = self.pool1(x)

    # Second Conv Block
    x = self.conv2(x)
    x = self.relu2(x)
    x = self.pool2(x)

    # Flatten the output for fully connected layers
    x = x.view(x.size(0), -1)

    # Fully connected layers
    x = self.fc1(x)
    x = self.relu_fc1(x)
    x = self.fc2(x)
    return x



# Optimizer selection

def optimizer_list(optimizer_type, parameters, lr=0.001, momentum=0.9, weight_dec
```

```
def optimizer_list(optimizer_type, parameters, lr=0.001, momentum=0.9, weight_dec
    if optimizer_type == "SGD":
        return optim.SGD(parameters, lr=lr, momentum=momentum)
    elif optimizer_type == "Adam":
        return optim.Adam(parameters, lr=lr, weight_decay=weight_decay)
    else:
        raise ValueError(f"Optimizer type {optimizer_type} not recognized.")
```

Training the model

```
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
criterion = nn.CrossEntropyLoss().to(device)
```

```
# Training plotting save the best model
def training_model(optimizer_type, use_batch_norm=False, update_best_model=True):
    net = CNN(use_batch_norm=use_batch_norm).to(device) # initialize the model
    optimizer = optimizer_list(optimizer_type, net.parameters()) # initilaize the

    num_epochs = 10
    train_losses, val_losses, accuracies = [], [], []

    start_time = time.time() # training time calculator

    # training loop
    for epoch in range(num_epochs):
        train_loss = 0.0
        for inputs, labels in train_loader:   # training batches
            inputs, labels = inputs.to(device), labels.to(device)
            optimizer.zero_grad()             # reset the gradients
            outputs = net(inputs)             # Forward pass through the network
            loss = criterion(outputs, labels) # Compute loss
            loss.backward()                   # Backpropagate to compute gradient
            optimizer.step()                  # Update weights using the optimize
            train_loss += loss.item()         # Accumulate batch loss

        # validation phase
        val_loss = 0.0
        correct = 0
        total = 0
        with torch.no_grad():
            for inputs, labels in val_loader:
                inputs, labels = inputs.to(device), labels.to(device)
                outputs = net(inputs)
                val_loss += criterion(outputs, labels).item()  # Compute validati
                _, predicted = outputs.max(1)                  # Get predictions
```

```
            total += labels.size(0)                        # Total number of
            correct += predicted.eq(labels).sum().item()   # Count correct pr

    # Calculate average train and validation losses for the epoch
    epoch_train_loss = train_loss / len(train_loader)
    epoch_val_loss = val_loss / len(val_loader)
    epoch_val_accuracy = 100. * correct / total   # Calculate validation accu

    print(f'Epoch: {epoch+1}/{num_epochs}, Train Loss: {epoch_train_loss:.4f}

    # Store the training and validation losses and accuracy for plotting
    train_losses.append(epoch_train_loss)
    val_losses.append(epoch_val_loss)
    accuracies.append(epoch_val_accuracy)

# end time and compute the total training duration
end_time = time.time()
elapsed_time = end_time - start_time
print(f"Training using {optimizer_type} with BatchNorm={use_batch_norm} took

# Training and validation losses, and validation accuracy plot
plt.figure(figsize=(12, 4))
plt.subplot(1, 3, 1)
plt.plot(train_losses, label='Train Loss')
plt.plot(val_losses, label='Validation Loss')
plt.legend()
plt.title(f'{optimizer_type} - Train and Validation Losses')

plt.subplot(1, 3, 2)
plt.plot(accuracies, label='Validation Accuracy')
plt.legend()
plt.title(f'{optimizer_type} - Validation Accuracy')

plt.tight_layout()
plt.show()

# Testing the model
test_preds, test_true = [], []
with torch.no_grad():
    for inputs, labels in test_loader:
        inputs, labels = inputs.to(device), labels.to(device)
        outputs = net(inputs)
        _, predicted = outputs.max(1) # Get predictions
        test_true.extend(labels.cpu().numpy())   # Store true labels
        test_preds.extend(predicted.cpu().numpy()) # Store predicted labels

 # Test accuracy calculation
acc = 100. * sum(np.array(test_true) == np.array(test_preds)) / len(test_true

# Track the best model and optimizer based on accuracy
global best_accuracy, best_optimizer, best_model
```

```
    if update_best_model and acc > best_accuracy:
        best_accuracy = acc
        best_optimizer = optimizer_type
        best_model = net

    return acc, classification_report(test_true, test_preds, zero_division=0), co
```

Plot randomly selected test images

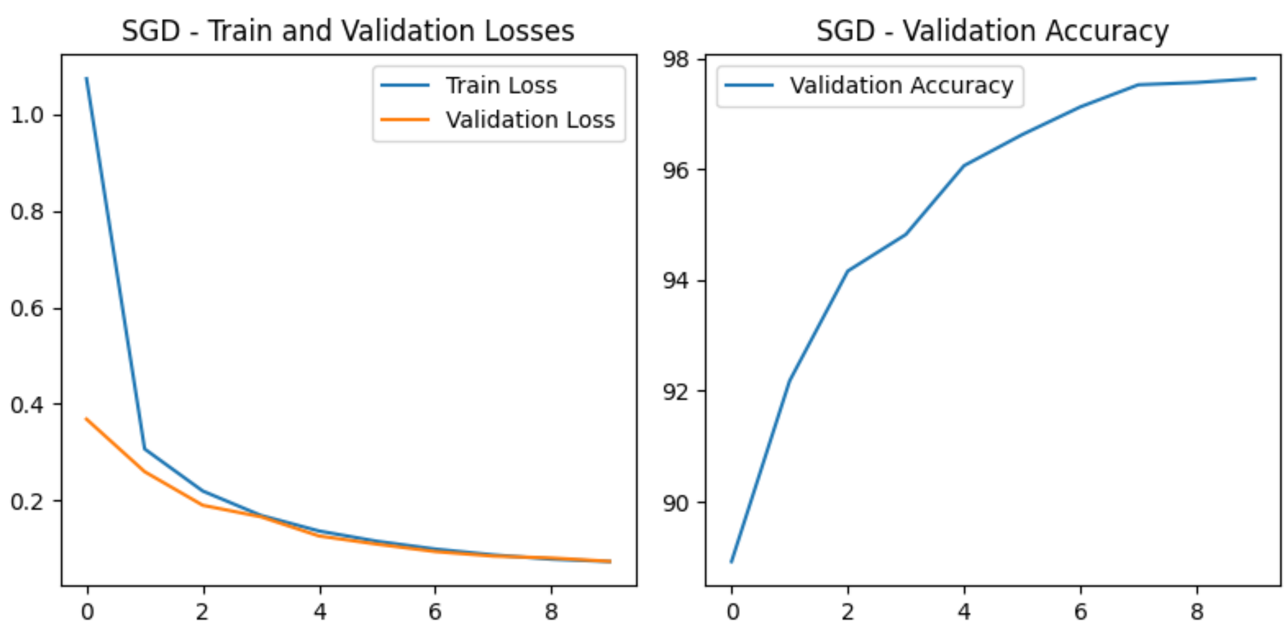
```
# Plot randomly selected images, their true labels and predicted labels from the
def plot_predictions(model, loader, num_samples=9):
    random_images, random_labels = [], []

    for images, labels in loader:     # Loop over the data loader
        random_images.append(images)  # Append the images batch to the list
        random_labels.append(labels)

    # Concatenate all collected batches of images and labels into a single tensor
    random_images = torch.cat(random_images)
    random_labels = torch.cat(random_labels)
    random_indices = random.sample(range(len(random_images)), num_samples) # rand
    images = random_images[random_indices]
    labels = random_labels[random_indices]

    outputs = model(images.to(device)) # model prediction
    _, predictions = outputs.max(1)

    grid_size = int(math.ceil(math.sqrt(num_samples))) # grid size for plotting

    plt.figure(figsize=(6, 6))

    # Loop over selected images, their true labels, and model predictions
    for i, (img, label, pred) in enumerate(zip(images, labels, predictions)):
        plt.subplot(grid_size, grid_size, i+1)
        plt.imshow(img[0].numpy(), cmap='gray')
        plt.title(f"True: {label.item()}, Pred: {pred.item()}", fontsize=10)
        plt.axis('off')
    plt.tight_layout()
    plt.show()
```

Count number of parameters and neurons

```
def count_parameters_and_neurons(model):
    total_params = 0
    fc_params = 0
    conv_params = 0

    total_neurons = 0
    fc_neurons = 0
    conv_neurons = 0

    height, width = 28, 28

    # child layers of a neural network mode
    for layer in model.children(): # Iterate over each layer in the model
        if isinstance(layer, nn.Conv2d): #  # Check if the layer is a convolution
            conv_params += sum(p.numel() for p in layer.parameters()) # Add the n

            # o/p dimensions after convolution
            height = (height + 2*layer.padding[0] - layer.kernel_size[0]) // laye
            width = (width + 2*layer.padding[1] - layer.kernel_size[1]) // layer.

            conv_neurons += layer.out_channels * height * width # o/p size after

        # For MaxPool2d layer
        elif isinstance(layer, nn.MaxPool2d): # Update the o/p dimensions after M
            height = (height - layer.kernel_size) // layer.stride + 1
            width = (width - layer.kernel_size) // layer.stride + 1

        # For Linear (fully connected) layer
        elif isinstance(layer, nn.Linear):
            fc_params += sum(p.numel() for p in layer.parameters())
            fc_neurons += layer.out_features

    # calculate total parameters and neurons
    total_params = conv_params + fc_params
    total_neurons = conv_neurons + fc_neurons

    print(f"Total parameters: {total_params}")
    print(f"Parameters in FC layers: {fc_params}")
    print(f"Parameters in Conv layers: {conv_params}")

    print(f"Total neurons: {total_neurons}")
    print(f"Neurons in FC layers: {fc_neurons}")
    print(f"Neurons in Conv layers: {conv_neurons}")

    return {
        "total_parameters": total_params,
        "fc_parameters": fc_params,
        "conv_parameters": conv_params,
        "total_neurons": total_neurons,
        "fc_neurons": fc_neurons,
        "conv_neurons": conv_neurons
```

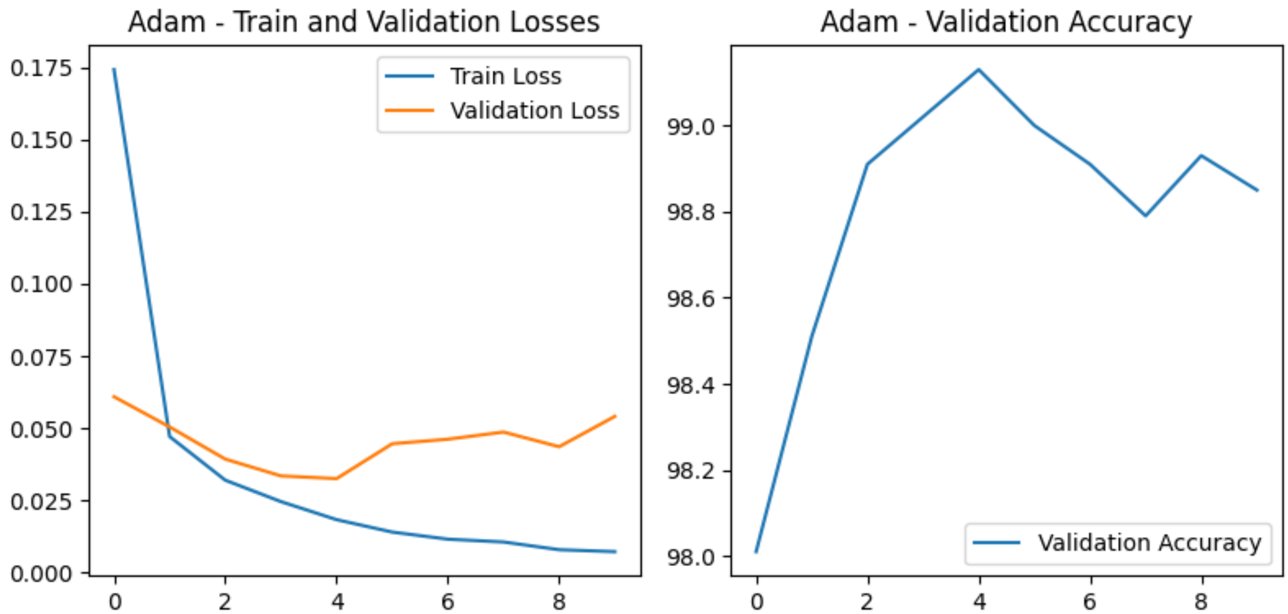
```
            conv_neurons : conv_neurons
    }


# List of optimizer types
optimizer_types = ["SGD", "Adam"]
results = {}  # store results of different optimizers
best_accuracy = 0
best_optimizer = None
best_model = None



# Loop through each optimizer type
for opt in optimizer_types:
    accuracy, class_report, conf_matrix, _ = training_model(opt) # train the mode
    results[opt] = {                                # store the results in dictiona
        "Accuracy": accuracy,
        "Classification Report": class_report,
        "Confusion Matrix": conf_matrix
    }
```

```
Epoch: 1/10, Train Loss: 1.0738, Val Loss: 0.3685, Val Accuracy: 88.92%
Epoch: 2/10, Train Loss: 0.3068, Val Loss: 0.2597, Val Accuracy: 92.18%
Epoch: 3/10, Train Loss: 0.2196, Val Loss: 0.1901, Val Accuracy: 94.16%
Epoch: 4/10, Train Loss: 0.1691, Val Loss: 0.1662, Val Accuracy: 94.82%
Epoch: 5/10, Train Loss: 0.1369, Val Loss: 0.1265, Val Accuracy: 96.06%
Epoch: 6/10, Train Loss: 0.1155, Val Loss: 0.1096, Val Accuracy: 96.62%
Epoch: 7/10, Train Loss: 0.0994, Val Loss: 0.0942, Val Accuracy: 97.12%
Epoch: 8/10, Train Loss: 0.0873, Val Loss: 0.0848, Val Accuracy: 97.52%
Epoch: 9/10, Train Loss: 0.0784, Val Loss: 0.0810, Val Accuracy: 97.56%
Epoch: 10/10, Train Loss: 0.0736, Val Loss: 0.0740, Val Accuracy: 97.63%
Training using SGD with BatchNorm=False took 98.45 seconds.
```




```
Epoch: 1/10, Train Loss: 0.1742, Val Loss: 0.0609, Val Accuracy: 98.01%
Epoch: 2/10, Train Loss: 0.0471, Val Loss: 0.0504, Val Accuracy: 98.51%
Epoch: 3/10, Train Loss: 0.0320, Val Loss: 0.0393, Val Accuracy: 98.91%
```

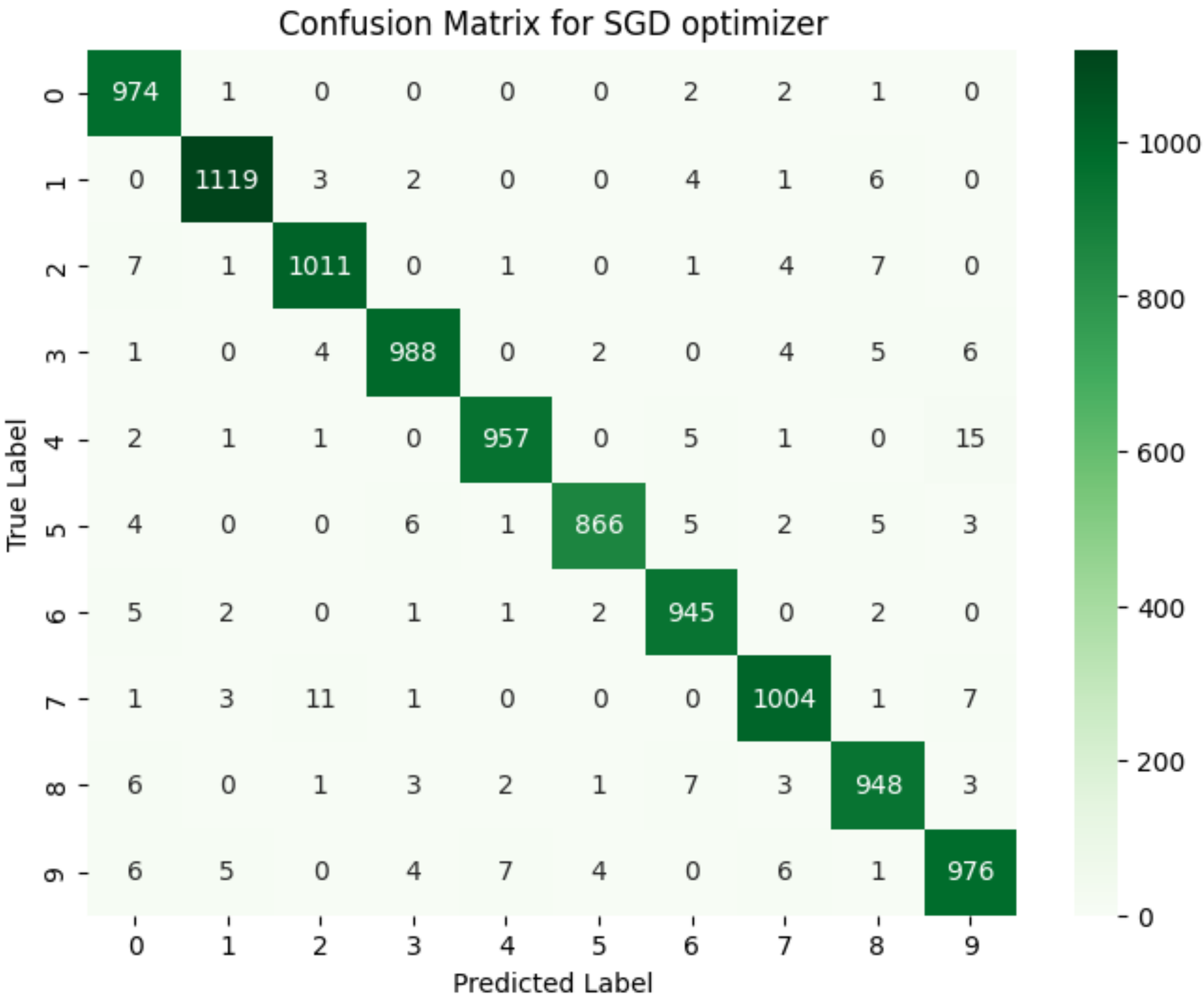
```
Epoch: 3/10, Train Loss: 0.0320, Val Loss: 0.0393, Val Accuracy: 98.91%
Epoch: 4/10, Train Loss: 0.0246, Val Loss: 0.0335, Val Accuracy: 99.02%
Epoch: 5/10, Train Loss: 0.0184, Val Loss: 0.0326, Val Accuracy: 99.13%
Epoch: 6/10, Train Loss: 0.0141, Val Loss: 0.0446, Val Accuracy: 99.00%
Epoch: 7/10, Train Loss: 0.0116, Val Loss: 0.0462, Val Accuracy: 98.91%
Epoch: 8/10, Train Loss: 0.0106, Val Loss: 0.0487, Val Accuracy: 98.79%
Epoch: 9/10, Train Loss: 0.0080, Val Loss: 0.0436, Val Accuracy: 98.93%
Epoch: 10/10, Train Loss: 0.0073, Val Loss: 0.0541, Val Accuracy: 98.85%
Training using Adam with BatchNorm=False took 86.69 seconds.
```




```
# Display accuracy, test loss,and a heatmap for the confusion matrix.

def results_display(optimizer_type, results):
  print(f"\nResults for {optimizer_type} optimizer:")
  print(f"Accuracy: {results['Accuracy']:.2f}%")
  #print(f"\nClassification Report:\n{results['Classification Report']}")

  plt.figure(figsize=(8, 6))
  sns.heatmap(results["Confusion Matrix"], annot=True, fmt="d", cmap="Greens")
  plt.title(f"Confusion Matrix for {optimizer_type} optimizer")
  plt.xlabel("Predicted Label")
  plt.ylabel("True Label")
  plt.show()
```

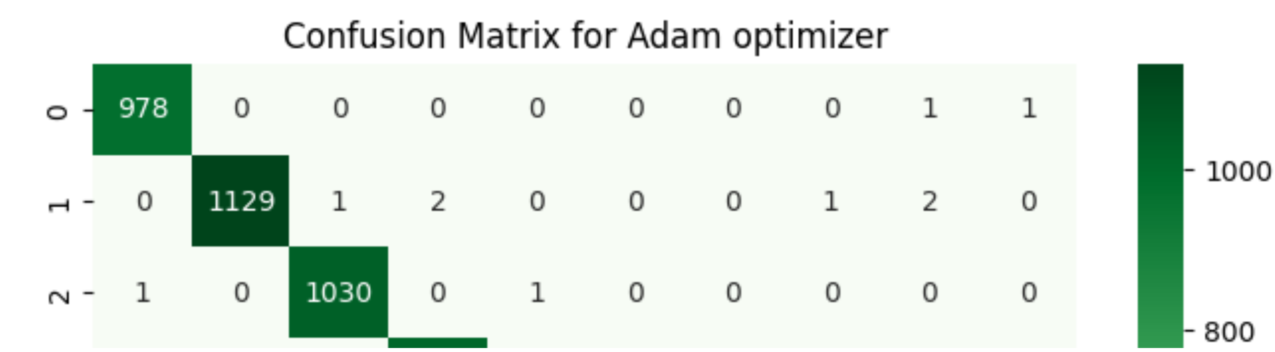
```
results_display("SGD", results["SGD"])
```

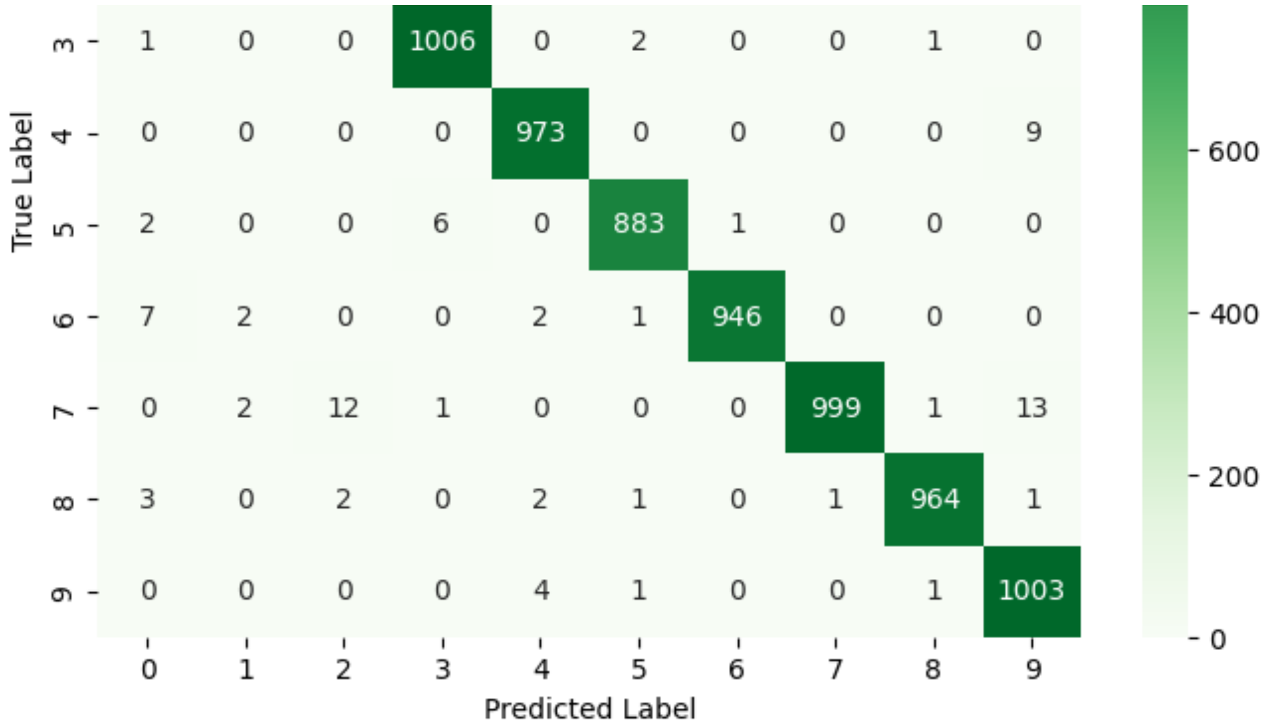
```
Results for SGD optimizer:
Accuracy: 97.88%
```




```
results_display("Adam", results["Adam"])
```

```
Results for Adam optimizer:
Accuracy: 99.11%
```





Save the best model

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
save_path = "/content/drive/MyDrive/PhD/SEM_2/DL/LAB/LAB2/best_model_{}_optimizer
torch.save(best_model.state_dict(), save_path)
print(f"Best model saved to Google Drive with {best_optimizer} optimizer, achieve
```

```
Best model saved to Google Drive with Adam optimizer, achieved accuracy: 99.1
```

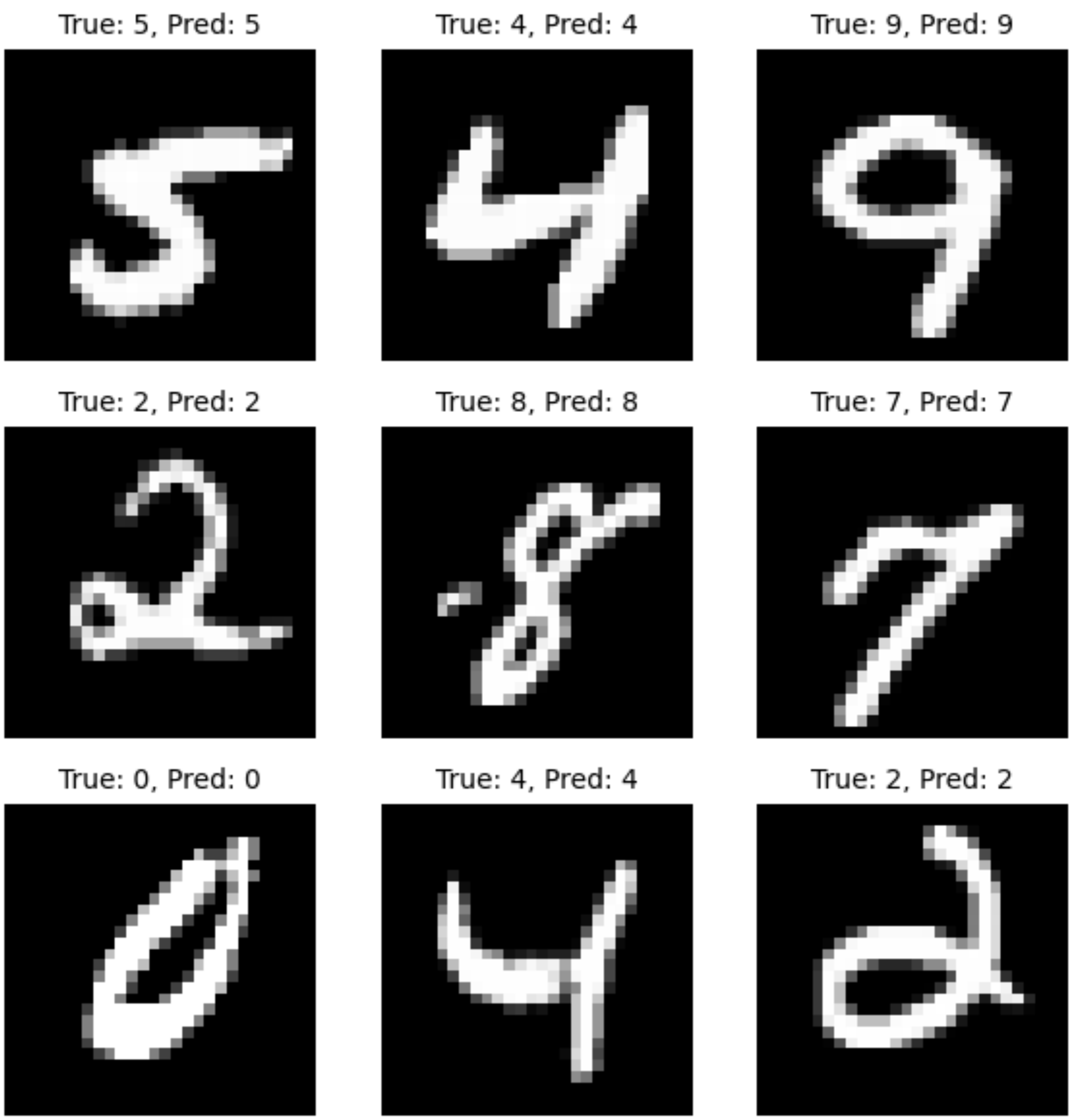
```
# Best model
top_model = CNN() # include the architecture of network
top_model.load_state_dict(torch.load(save_path)) # load_state_dict loads weights
top_model.eval()
```

```
<ipython-input-19-2c5601d762cb>:3: FutureWarning: You are using `torch.load` w
  top_model.load_state_dict(torch.load(save_path)) # load_state_dict loads we
CNN(
  (conv1): Conv2d(1, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (relu1): ReLU()
```

```
  (pool1): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (conv2): Conv2d(32, 32, kernel_size=(3, 3), stride=(1, 1), padding=(1, 1))
  (relu2): ReLU()
  (pool2): MaxPool2d(kernel_size=2, stride=2, padding=0, dilation=1,
ceil_mode=False)
  (fc1): Linear(in_features=1568, out_features=500, bias=True)
  (relu_fc1): ReLU()
  (fc2): Linear(in_features=500, out_features=10, bias=True)
  (softmax): Softmax(dim=1)
)
```

Plotting random images

```
top_model = top_model.to(device)
plot_predictions(top_model, test_loader)
```



Dimensions of the input and output at each layer.

```
summary(top_model, input_size=(1, 28, 28))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 32, 28, 28]             320
              ReLU-2           [-1, 32, 28, 28]               0
         MaxPool2d-3           [-1, 32, 14, 14]               0
            Conv2d-4           [-1, 32, 14, 14]           9,248
              ReLU-5           [-1, 32, 14, 14]               0
         MaxPool2d-6             [-1, 32, 7, 7]               0
            Linear-7                  [-1, 500]         784,500
              ReLU-8                  [-1, 500]               0
            Linear-9                   [-1, 10]           5,010
================================================================
Total params: 799,078
Trainable params: 799,078
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 0.55
Params size (MB): 3.05
Estimated Total Size (MB): 3.60
----------------------------------------------------------------
```

Number of parameters and neurons

```
count_parameters_and_neurons(top_model)
```

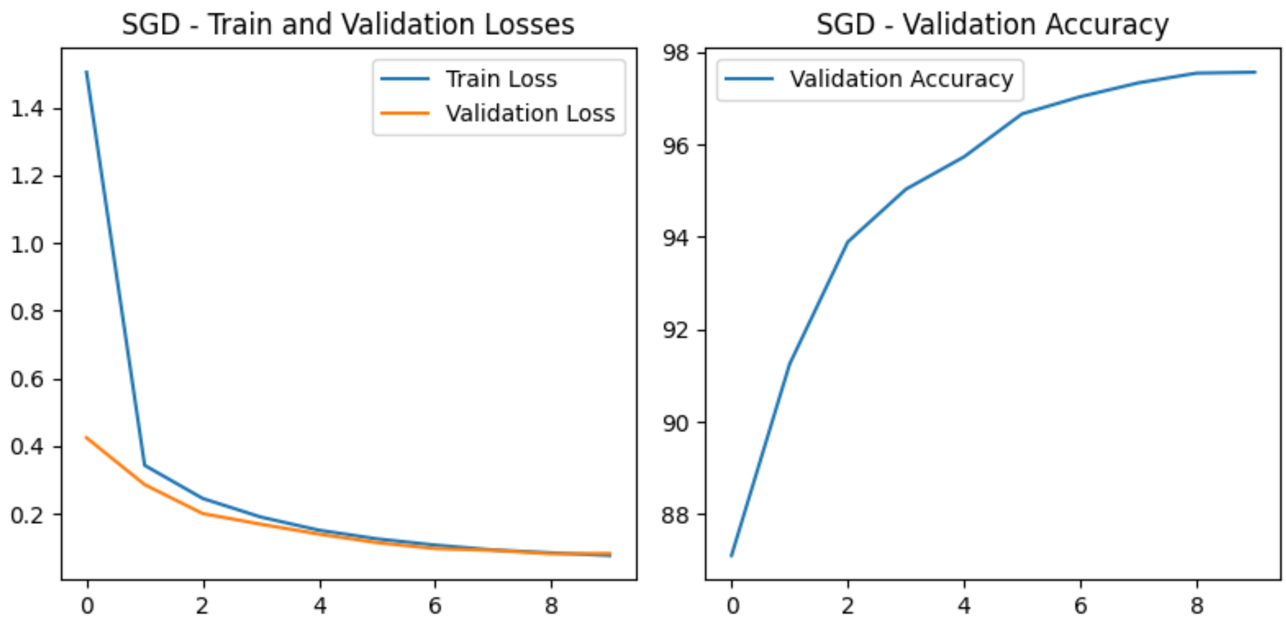
```
Total parameters: 799078
Parameters in FC layers: 789510
Parameters in Conv layers: 9568
Total neurons: 31870
Neurons in FC layers: 510
Neurons in Conv layers: 31360
{'total_parameters': 799078,
 'fc_parameters': 789510,
 'conv_parameters': 9568,
 'total_neurons': 31870,
 'fc_neurons': 510,
 'conv_neurons': 31360}
```

Batch Normalization

Batch Normalization

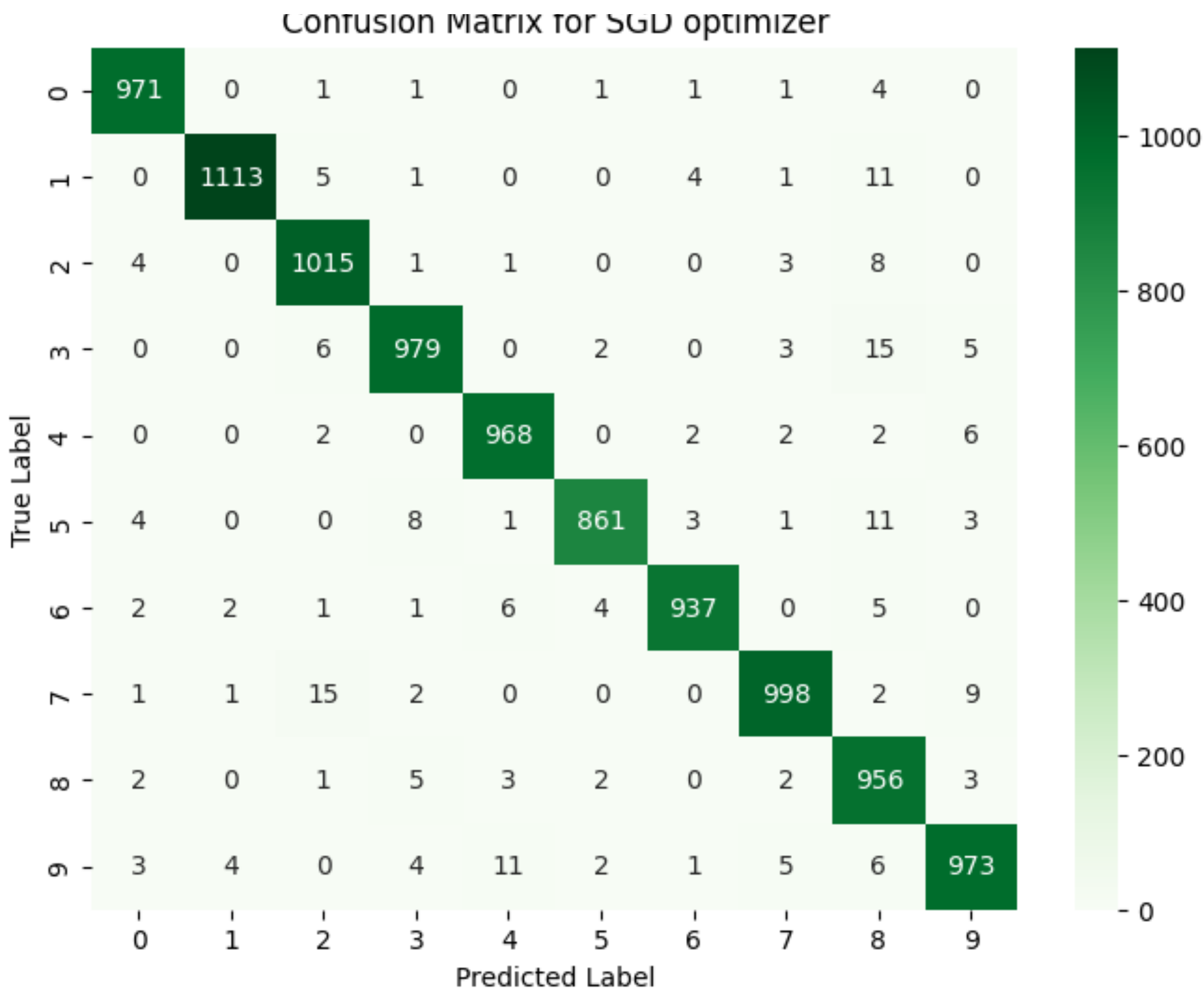
```
sgd_batch_acc, sgd_batch_classrepo, sgd_batch_confmat, sgd_batch_model = training
sgd_batch_results = {
        "Accuracy": sgd_batch_acc,
        "Classification Report": sgd_batch_classrepo,
        "Confusion Matrix": sgd_batch_confmat
    }
```

```
Epoch: 1/10, Train Loss: 1.5040, Val Loss: 0.4241, Val Accuracy: 87.11%
Epoch: 2/10, Train Loss: 0.3426, Val Loss: 0.2857, Val Accuracy: 91.25%
Epoch: 3/10, Train Loss: 0.2446, Val Loss: 0.2000, Val Accuracy: 93.89%
Epoch: 4/10, Train Loss: 0.1897, Val Loss: 0.1685, Val Accuracy: 95.03%
Epoch: 5/10, Train Loss: 0.1509, Val Loss: 0.1393, Val Accuracy: 95.73%
Epoch: 6/10, Train Loss: 0.1253, Val Loss: 0.1141, Val Accuracy: 96.66%
Epoch: 7/10, Train Loss: 0.1069, Val Loss: 0.0965, Val Accuracy: 97.03%
Epoch: 8/10, Train Loss: 0.0924, Val Loss: 0.0913, Val Accuracy: 97.33%
Epoch: 9/10, Train Loss: 0.0839, Val Loss: 0.0812, Val Accuracy: 97.54%
Epoch: 10/10, Train Loss: 0.0761, Val Loss: 0.0822, Val Accuracy: 97.56%
Training using SGD with BatchNorm=True took 88.57 seconds.
```



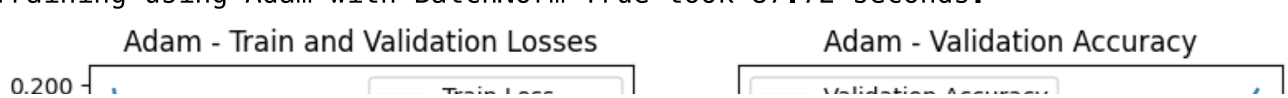

```
results_display(optimizer_type = "SGD", results = sgd_batch_results)
```

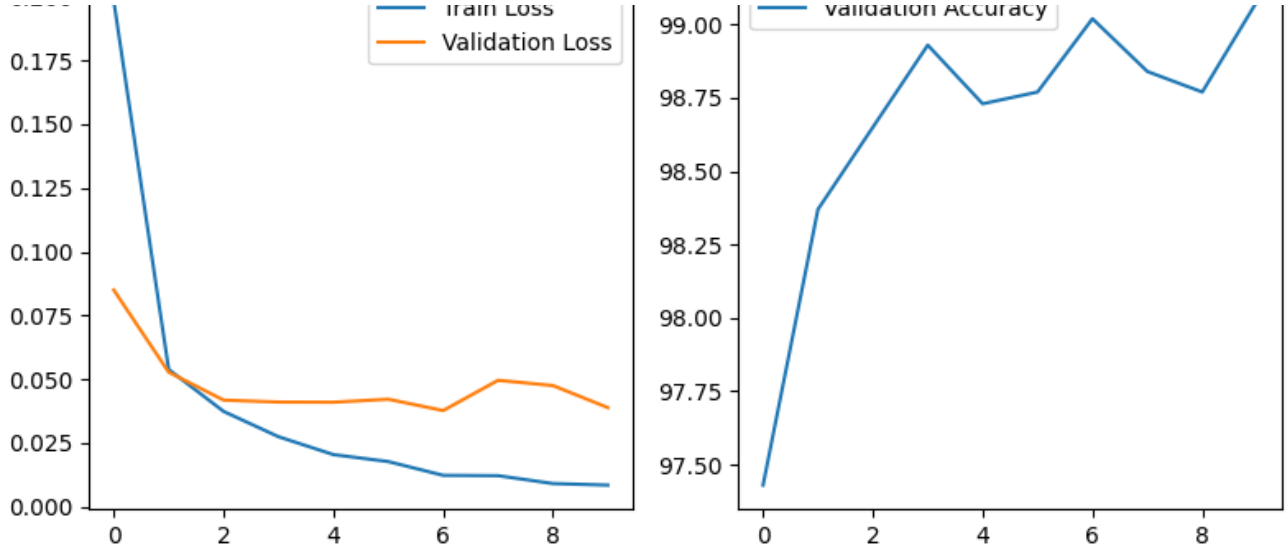
```
Results for SGD optimizer:
Accuracy: 97.71%
```




```
adam_batch_acc, adam_batch_classrepo, adam_batch_confmat, adam_batch_model = trai
adam_batch_results = {
        "Accuracy": adam_batch_acc,
        "Classification Report": adam_batch_classrepo,
        "Confusion Matrix": adam_batch_confmat
    }
```

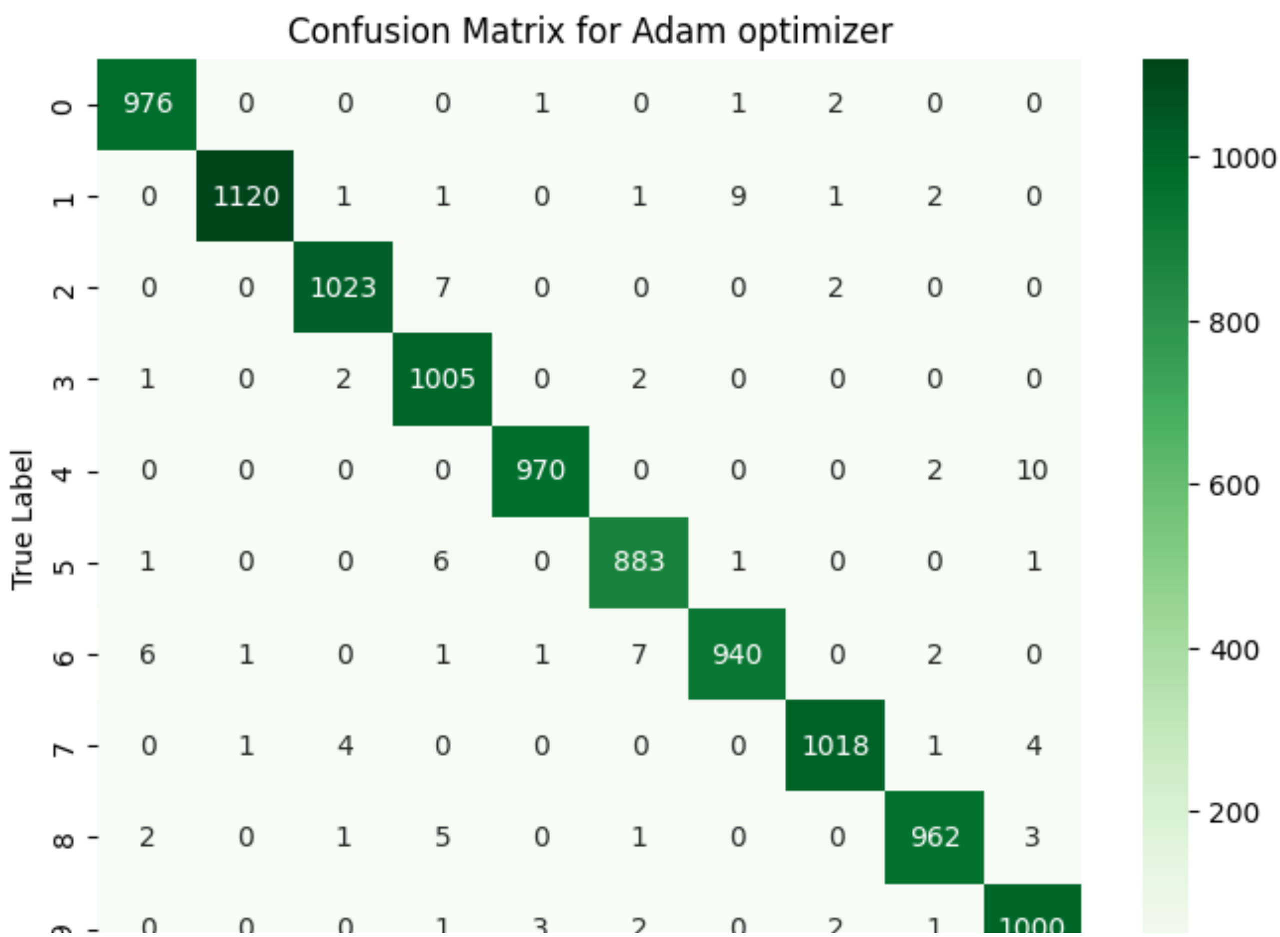
```
Epoch: 1/10, Train Loss: 0.1983, Val Loss: 0.0849, Val Accuracy: 97.43%
Epoch: 2/10, Train Loss: 0.0538, Val Loss: 0.0527, Val Accuracy: 98.37%
Epoch: 3/10, Train Loss: 0.0373, Val Loss: 0.0418, Val Accuracy: 98.65%
Epoch: 4/10, Train Loss: 0.0274, Val Loss: 0.0410, Val Accuracy: 98.93%
Epoch: 5/10, Train Loss: 0.0204, Val Loss: 0.0409, Val Accuracy: 98.73%
Epoch: 6/10, Train Loss: 0.0176, Val Loss: 0.0421, Val Accuracy: 98.77%
Epoch: 7/10, Train Loss: 0.0122, Val Loss: 0.0377, Val Accuracy: 99.02%
Epoch: 8/10, Train Loss: 0.0121, Val Loss: 0.0495, Val Accuracy: 98.84%
Epoch: 9/10, Train Loss: 0.0090, Val Loss: 0.0475, Val Accuracy: 98.77%
Epoch: 10/10, Train Loss: 0.0084, Val Loss: 0.0388, Val Accuracy: 99.08%
Training using Adam with BatchNorm=True took 87.72 seconds.
```

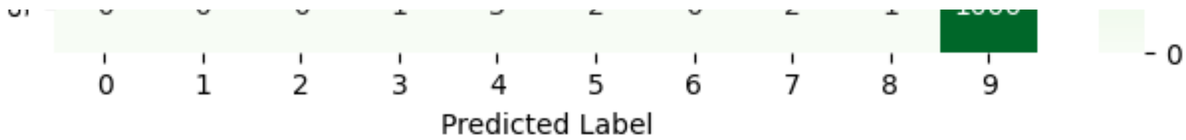





```
results_display(optimizer_type = "Adam", results = adam_batch_results)
```

```
Results for Adam optimizer:
Accuracy: 98.97%
```

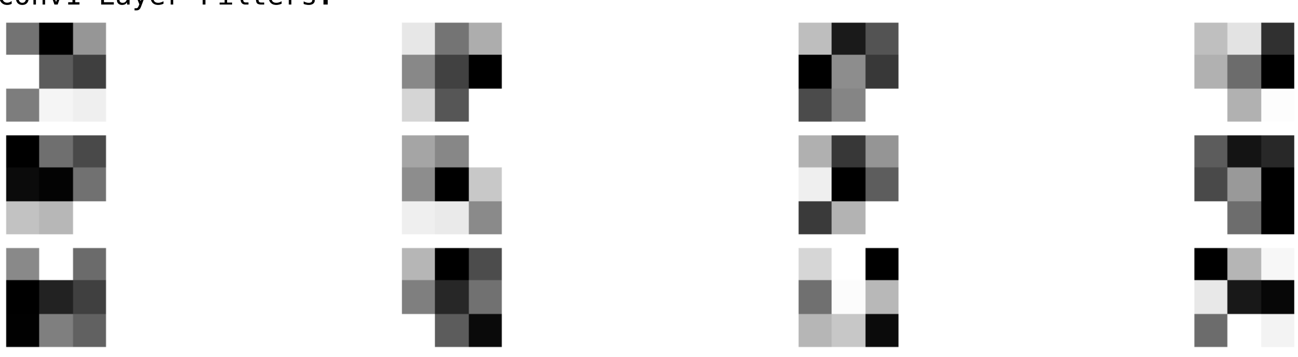


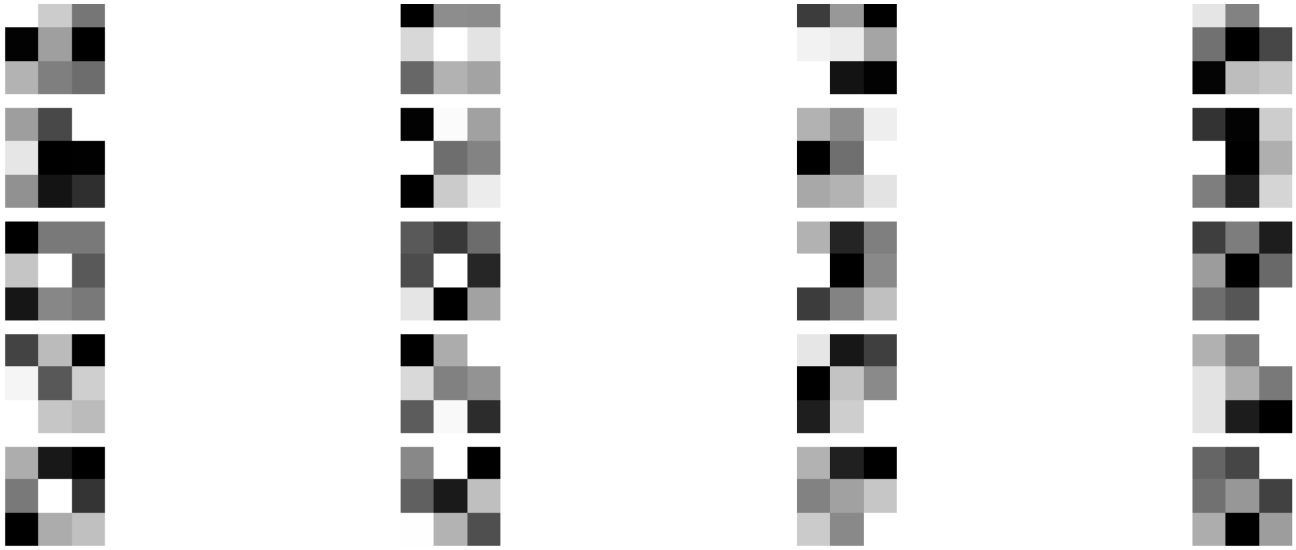


Visualizing Convolutional Neural Networks

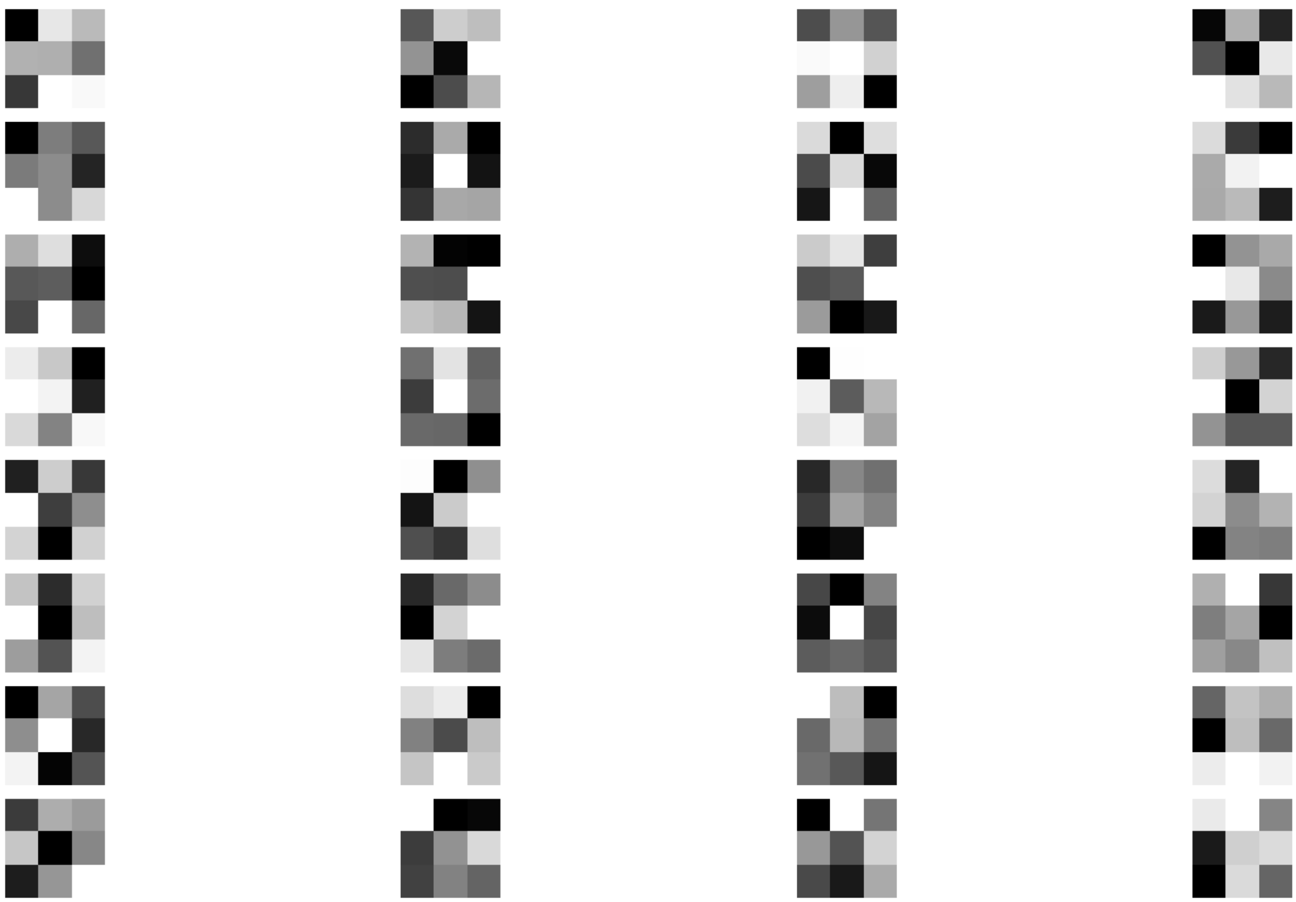
```
# Function to visualize filters
def plot_filters(layer, num_columns=4):
    filters = layer.weight.data.cpu()  # Get filters (weights)
    num_filters = filters.shape[0]     # No: of filters (kernels)
    num_rows = (num_filters + num_columns - 1) // num_columns  # No: of rows in t

    fig, axes = plt.subplots(num_rows, num_columns, figsize=(20, 10))

    # Loop through filters and plot them
    for i, ax in enumerate(axes.flat):
        if i < num_filters:
            ax.imshow(filters[i, 0], cmap="gray")  # first channel of each filter
        ax.axis('off')

    plt.tight_layout()
    plt.show()

model = CNN()
model.eval()

# Plot filters of conv1 layer
print("Conv1 Layer Filters:")
plot_filters(model.conv1)

# Plot filters of conv2 layer
print("Conv2 Layer Filters:")
plot_filters(model.conv2)
```

Conv1 Layer Filters:





Conv2 Layer Filters:



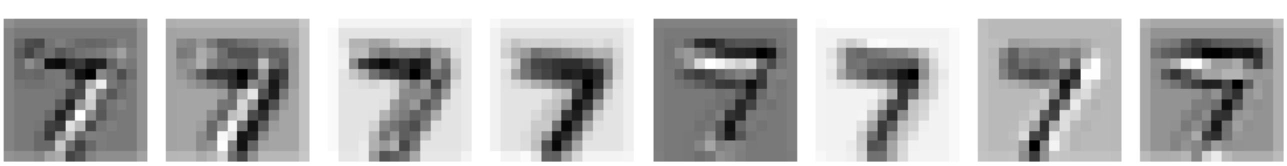
Visualize the activations of the convolutional layers.

```
def activations(model, image, layer_name, num_columns=8):
    # Store activations
    activations = []

    # Hook function to store layer output
    def hook(module, input, output):
        activations.append(output)

    # Register the hook for the specified layer (e.g., 'conv1', 'conv2')
    layer = getattr(model, layer_name)  # Access the layer by name
    handle = layer.register_forward_hook(hook)

    # Pass the image through the model to get activations
    model.eval()
    with torch.no_grad():
        model(image.unsqueeze(0))  # Add batch dimension

    # Remove the hook
    handle.remove()

    # Process activations
    act = activations[0].squeeze().cpu().detach().numpy()  # Get the activation d
    num_filters = act.shape[0]
    num_rows = int(np.ceil(num_filters / num_columns))

    # Plot activations
    fig, axes = plt.subplots(num_rows, num_columns, figsize=(10, 10))
    for i, ax in enumerate(axes.flat):
        if i < num_filters:
            ax.imshow(act[i], cmap="gray")
        ax.axis('off')

    plt.tight_layout()
    plt.show()

    return act
```

```
sample_img, _ = next(iter(test_loader))
sample_img = sample_img.to(device)
```

```
# Visualize activations from the first convolutional layer (conv1)
activation_val_conv1 = activations(model=adam_batch_model, image=sample_img[0], l
```

```
# Visualize activations from the second convolutional layer (conv2)
activation_val_conv2 = activations(model=adam_batch_model, image=sample_img[0], l
```

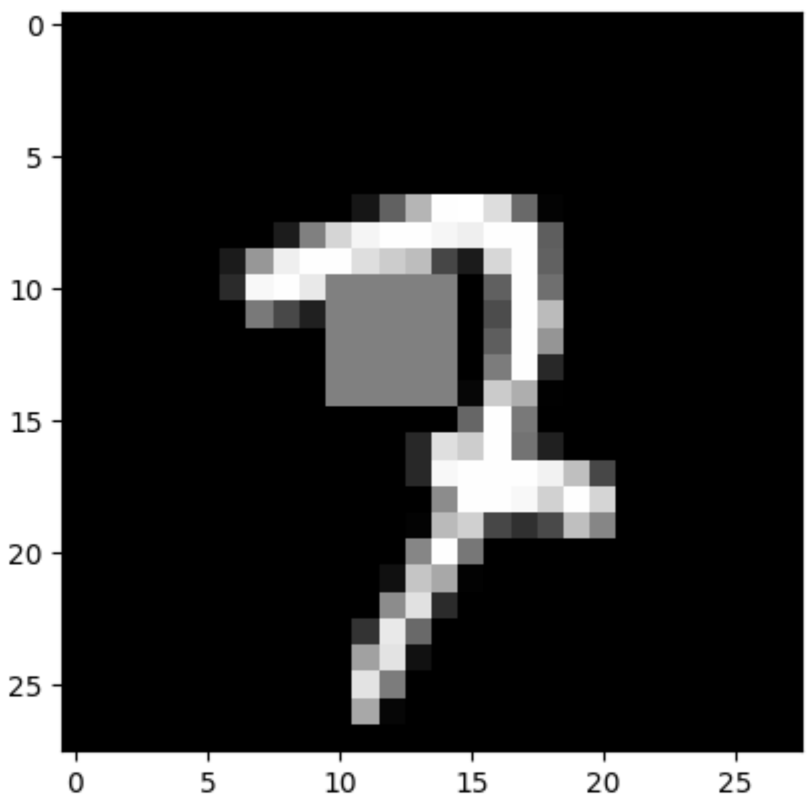


Occluding parts of the image

```
# Sample batch from the test_loader
test_features, test_labels = next(iter(test_loader))
rand_samples = np.random.choice(test_features.shape[0], 10) # select 10 samples f

# Set occluder size and position
size = 5
```

```
x = y = 10
# Sample with occlusion
temp = torch.clone(test_features[rand_samples[0]].cpu().reshape(28, 28))
temp[x:x + size, y:y + size] = torch.full((size, size), 0.5)  # Set the occluded

plt.imshow(temp, cmap='gray')
```

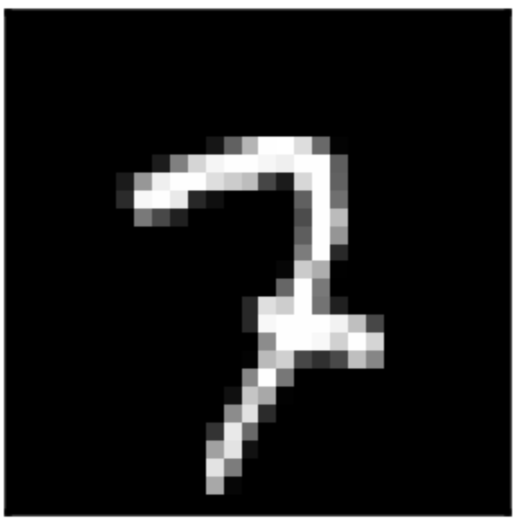
```
<matplotlib.image.AxesImage at 0x7f1ec4616fb0>
```

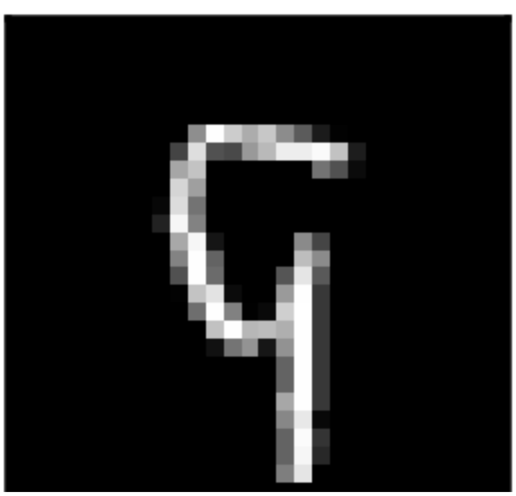


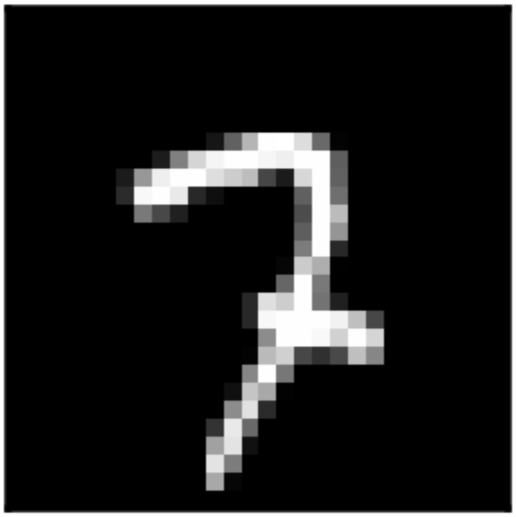

```
# probability of the target class before occlusion
predicted_prob = model.forward(temp.reshape(1, 1, 28, 28).cpu()).detach()[0][test
print(predicted_prob)

size = 7 # Probability map initialization
prob = np.zeros((len(range(0, 28 - size)), len(range(0, 28 - size)), 10))

# Iterate over positions for occlusion
for i in range(0, 28 - size):
    for j in range(0, 28 - size):
        for k in range(10):
            # occluded image for the current sample
            temp = torch.clone(test_features[rand_samples[k]].reshape(28, 28))
            temp[i:i + size, j:j + size] = torch.full((size, size), 1)  # Occlude

            # predicted probability for the target class
            prob[i, j, k] = model.forward(temp.reshape(1, 1, 28, 28).cpu()).detac
```

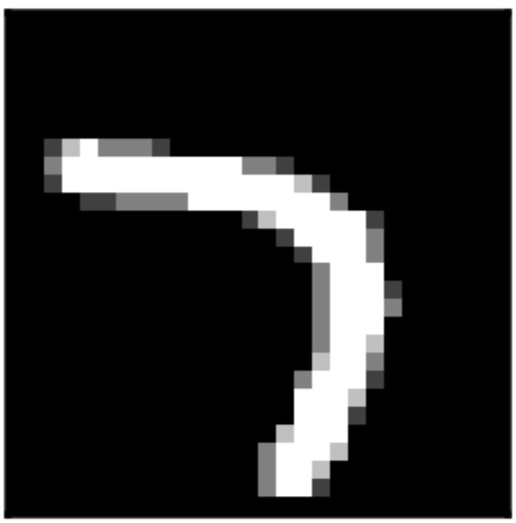
```
# original images and probability maps
fig, axs = plt.subplots(10, 2, figsize=(5, 10), dpi=320)
for i in range(10):
    # Original image
    axs[i, 0].xaxis.set_visible(False)
    axs[i, 0].yaxis.set_visible(False)
    axs[i, 0].imshow(test_features[rand_samples[i]].reshape(28, 28), cmap="gray")

    # Probability map
    axs[i, 1].xaxis.set_visible(False)
    axs[i, 1].yaxis.set_visible(False)
    im = axs[i, 1].imshow(prob[:, :, i], cmap='jet')
    plt.colorbar(im, ax=axs[i, 1])

plt.tight_layout()
plt.show()
```

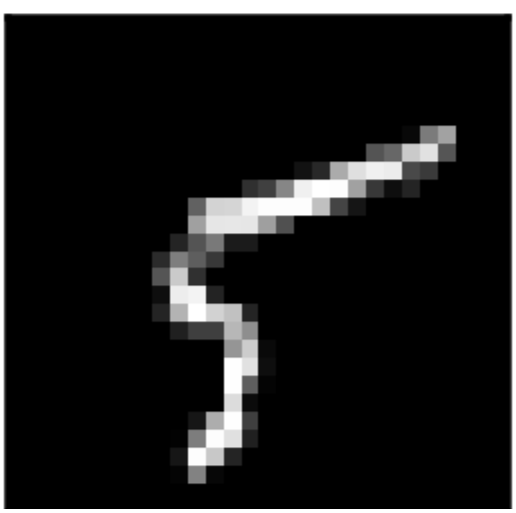
```
0.015031811781227589
```

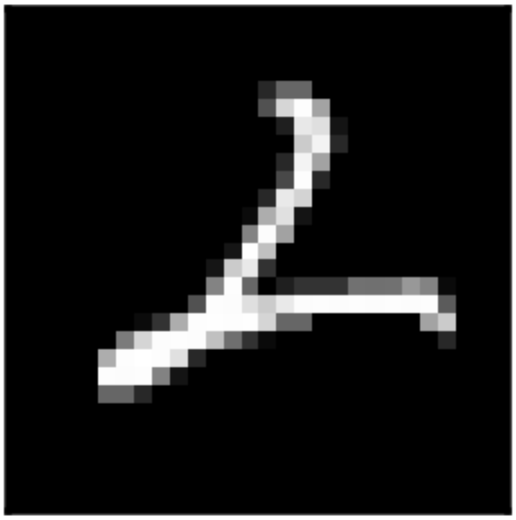


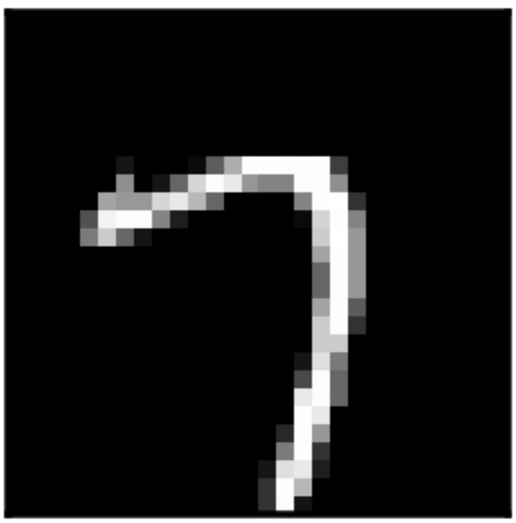


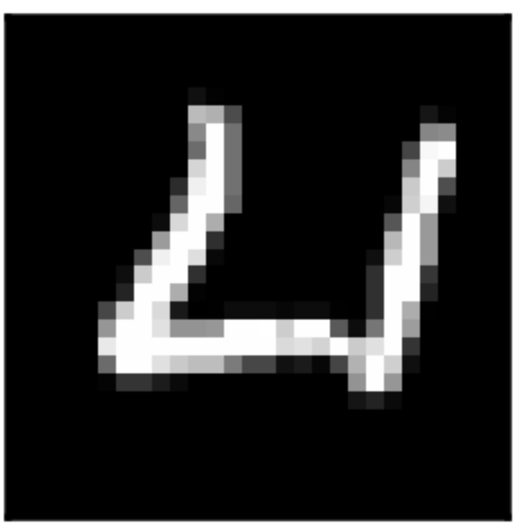


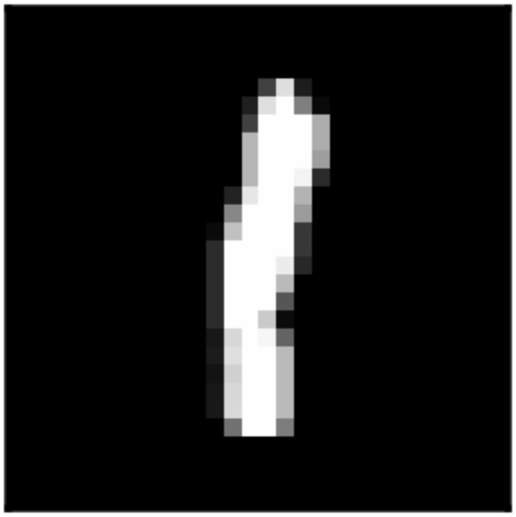


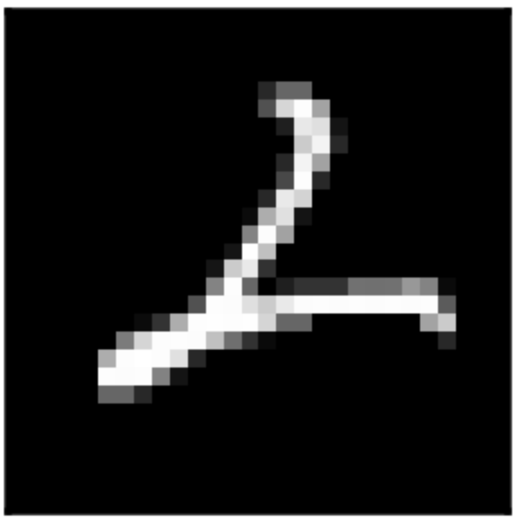








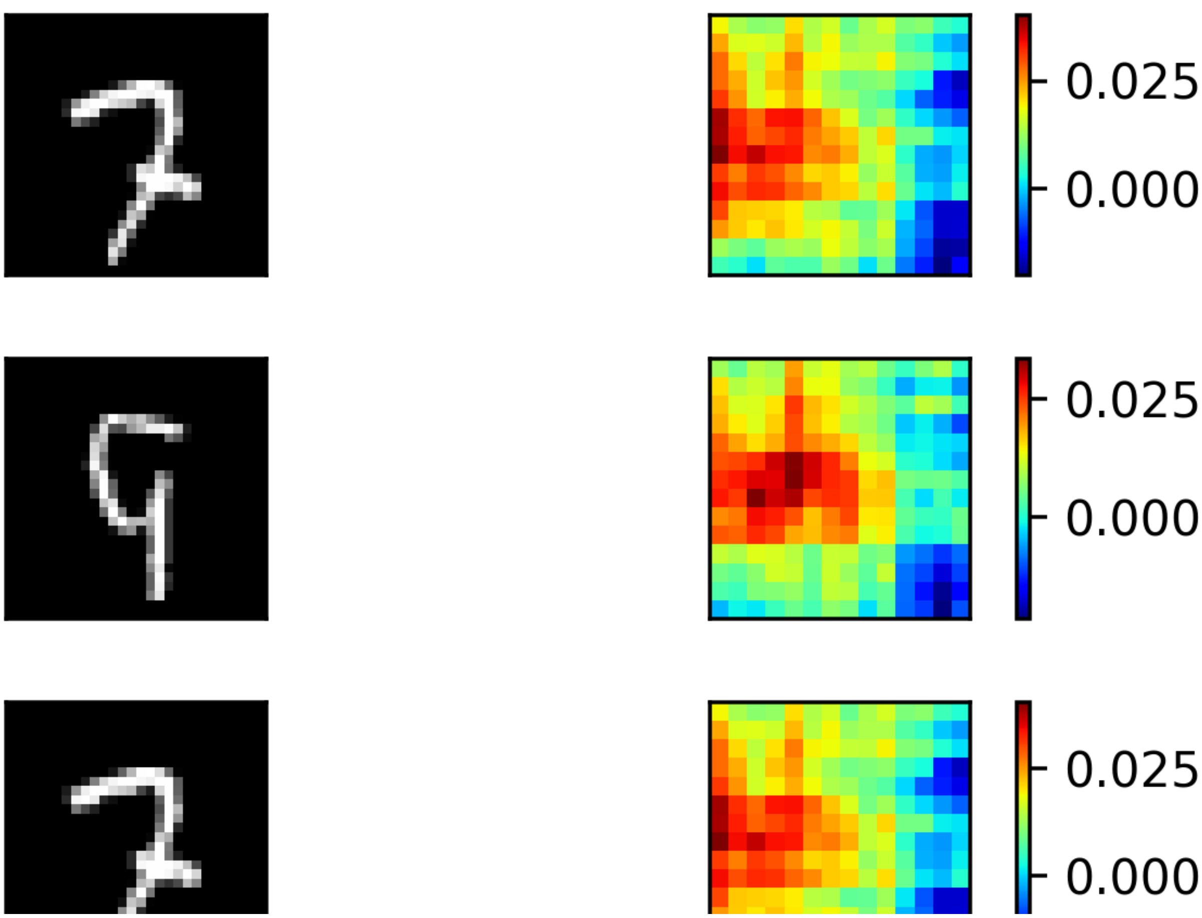


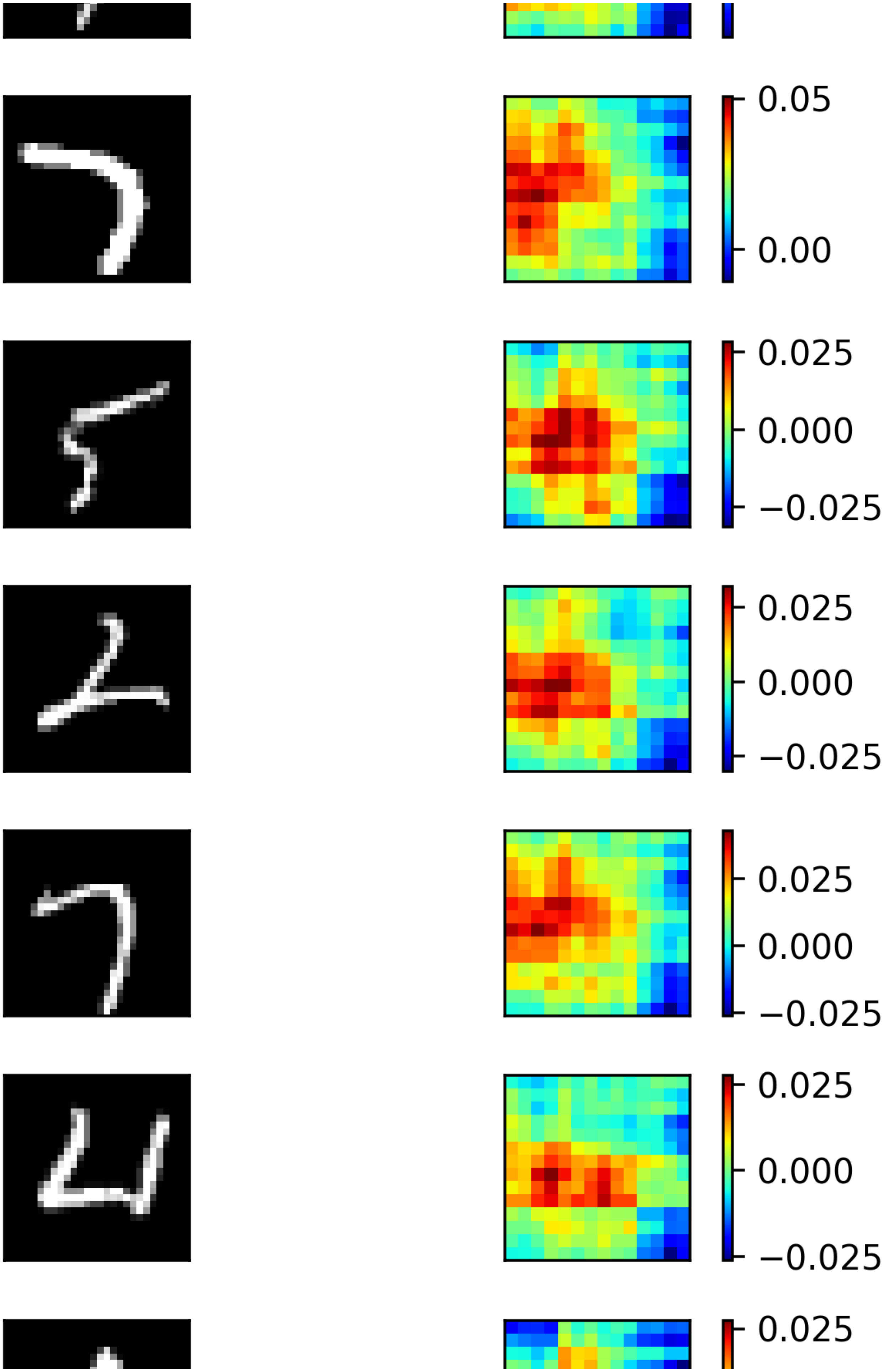


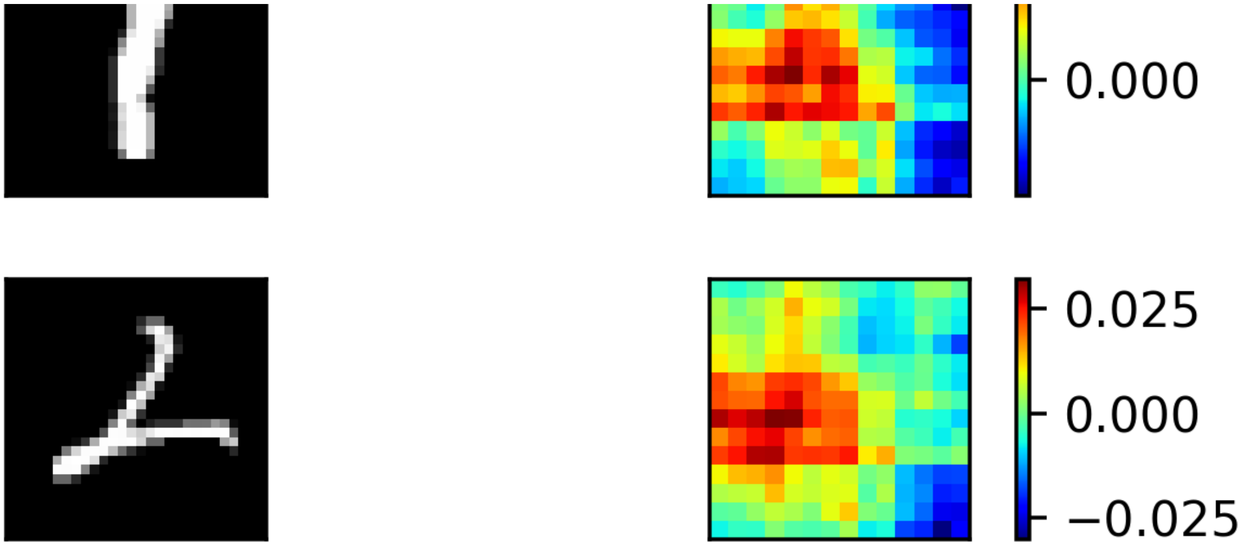
```
# Probability of the target class before occlusion
predicted_prob = model.forward(temp.reshape(1, 1, 28, 28).cpu()).detach()[0][test
print(predicted_prob)

size = 14  # Updated size for the occlusion patch

# Probability map initialization
prob = np.zeros((len(range(0, 28 - size)), len(range(0, 28 - size)), 10))

# Iterate over positions for occlusion
for i in range(0, 28 - size):
    for j in range(0, 28 - size):
        for k in range(10):
```

```
            # Occluded image for the current sample
            temp = torch.clone(test_features[rand_samples[k]].reshape(28, 28))
            temp[i:i + size, j:j + size] = torch.full((size, size), 1)  # Occlude

            # Predicted probability for the target class
            prob[i, j, k] = model.forward(temp.reshape(1, 1, 28, 28).cpu()).detac

# Original images and probability maps
fig, axs = plt.subplots(10, 2, figsize=(5, 10), dpi=320)
for i in range(10):
    # Original image
    axs[i, 0].xaxis.set_visible(False)
    axs[i, 0].yaxis.set_visible(False)
    axs[i, 0].imshow(test_features[rand_samples[i]].reshape(28, 28), cmap="gray")

    # Probability map
    axs[i, 1].xaxis.set_visible(False)
    axs[i, 1].yaxis.set_visible(False)
    im = axs[i, 1].imshow(prob[:, :, i], cmap='jet')
    plt.colorbar(im, ax=axs[i, 1])

plt.tight_layout()
plt.show()
```

```
-0.029278360307216644
```




0.05
0.00
0.025
0.000
−0.025
0.025
0.000
−0.025
0.025
0.000
−0.025
0.025
0.000
−0.025
0.025


0.000
0.025
0.000
−0.025

Adversarial Examples

Non-Targeted Attack

```
# Adversarial example generation

def generate_adversarial_example_with_costs(model, target_class, stepsize=0.05, m
  model.eval() # evaluate model

  X = torch.normal(128, 1, (1, 1, 28, 28)).to(device) # normal distribution cente
  X.requires_grad = True
  costs = [] # store the cost

  for iteration in range(max_iterations):
    logits = model(X) # output of the model before applying softmax
    cost = logits[0, target_class] # Output for the target class
    costs.append(cost.item())

    model.zero_grad() # Clear previous gradients
    cost.backward()  # Compute gradients w.r.t. X

    perturbation = stepsize * X.grad.data # Scale the gradient by stepsize
    if use_epsilon:
      perturbation = torch.clamp(perturbation, -epsilon, epsilon)
    X.data = X.data + perturbation # update the image

    X.data = torch.clamp(X.data, 0, 255)
    X.grad.data.zero_() # Clear the gradient for the next iteration

  return X.detach(), costs


def plot_costs_for_target_class(generated_examples, target_class):
  costs = generated_examples['cost'][target_class] # Extract the cost values for

  plt.figure(figsize=(8, 6))
  plt.plot(costs)
  plt.xlabel('Iterations')
  plt.ylabel('Cost Value')
  plt.title(f"Cost Function for Target Class {target_class} over Iterations")
  plt.grid(True)
  plt.show()



def display_adversarial_images(generated_examples):
  plt.figure(figsize=(10, 5))

  # Iterate over the generated adversarial examples
  for i, img in generated_examples['gen_egs'].items():
    plt.subplot(2, 5, i+1)
    plt.imshow(img.cpu().squeeze().numpy(), cmap='gray')
    plt.title(f"Target: {i}")
```

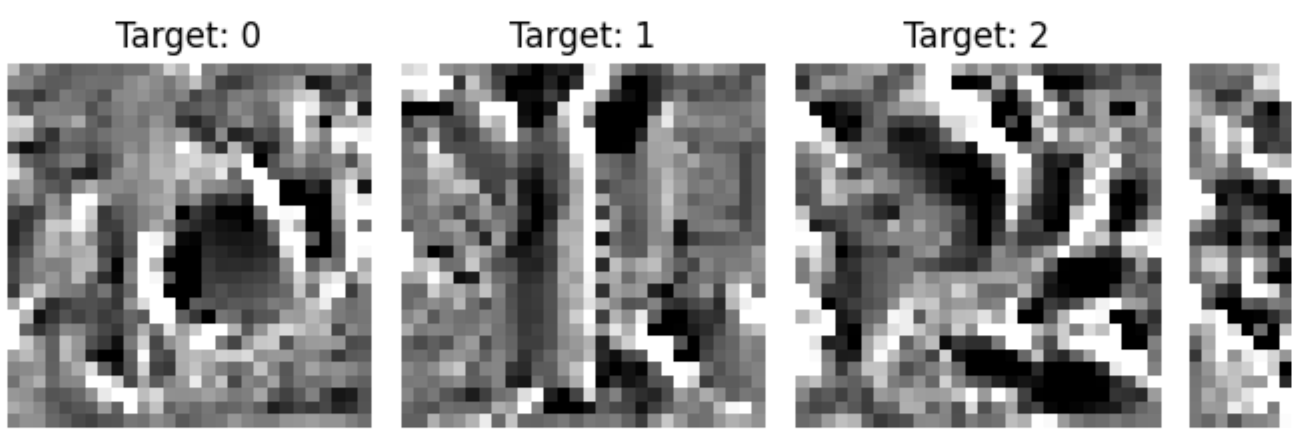
```
    plt.axis('off')
  plt.tight_layout()
  plt.show()


def check_network_predictions(model, generated_examples):
    for i, img in generated_examples['gen_egs'].items():
        logits = model(img)
        probs = torch.nn.functional.softmax(logits, dim=1)
        pred_class = torch.argmax(probs, dim=1).item()
        confidence = probs[0, pred_class].item()

        print(f"Target Class: {i}, Predicted Class: {pred_class}, Confidence: {co
```

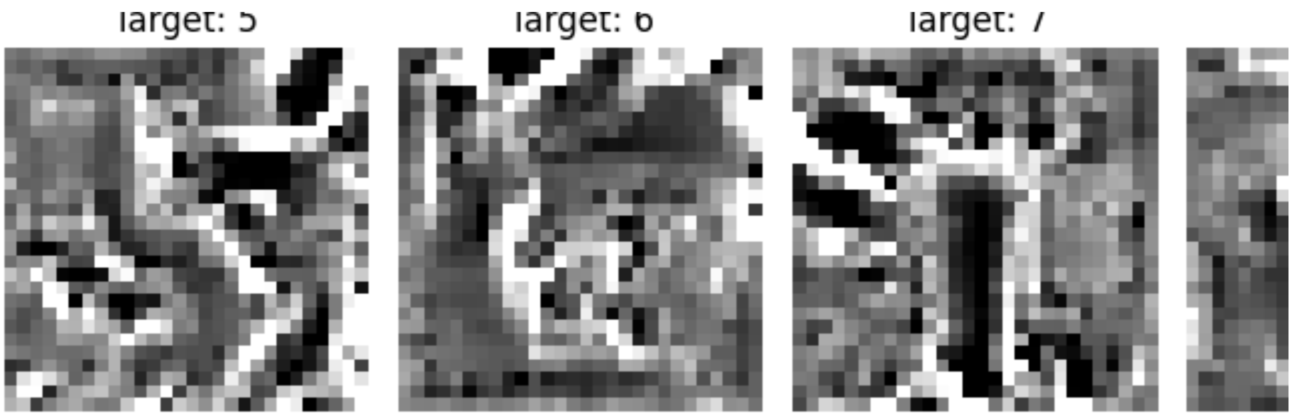
```
# dictionary to store generated adversarial examples ('gen_egs') and their associ
generated_examples = {'gen_egs': {}, 'cost': {}}
for i in range(10):
  gen_eg, cost = generate_adversarial_example_with_costs(adam_batch_model, i) # G
  generated_examples['gen_egs'][i] = gen_eg # Store the generated adversarial eg
  generated_examples['cost'][i] = cost # Store the cost function values for the c
```

```
check_network_predictions(adam_batch_model, generated_examples)
```

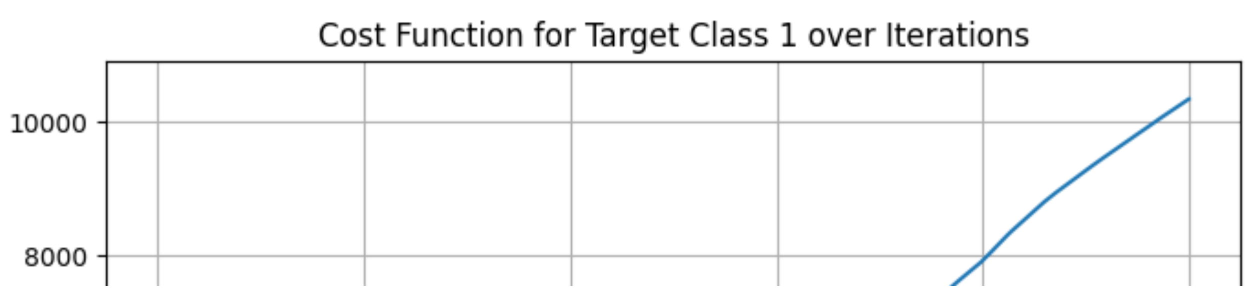
```
Target Class: 0, Predicted Class: 0, Confidence: 1.0000
Target Class: 1, Predicted Class: 1, Confidence: 1.0000
Target Class: 2, Predicted Class: 2, Confidence: 1.0000
Target Class: 3, Predicted Class: 3, Confidence: 1.0000
Target Class: 4, Predicted Class: 4, Confidence: 1.0000
Target Class: 5, Predicted Class: 5, Confidence: 1.0000
Target Class: 6, Predicted Class: 6, Confidence: 1.0000
Target Class: 7, Predicted Class: 7, Confidence: 1.0000
Target Class: 8, Predicted Class: 8, Confidence: 1.0000
Target Class: 9, Predicted Class: 9, Confidence: 1.0000
```

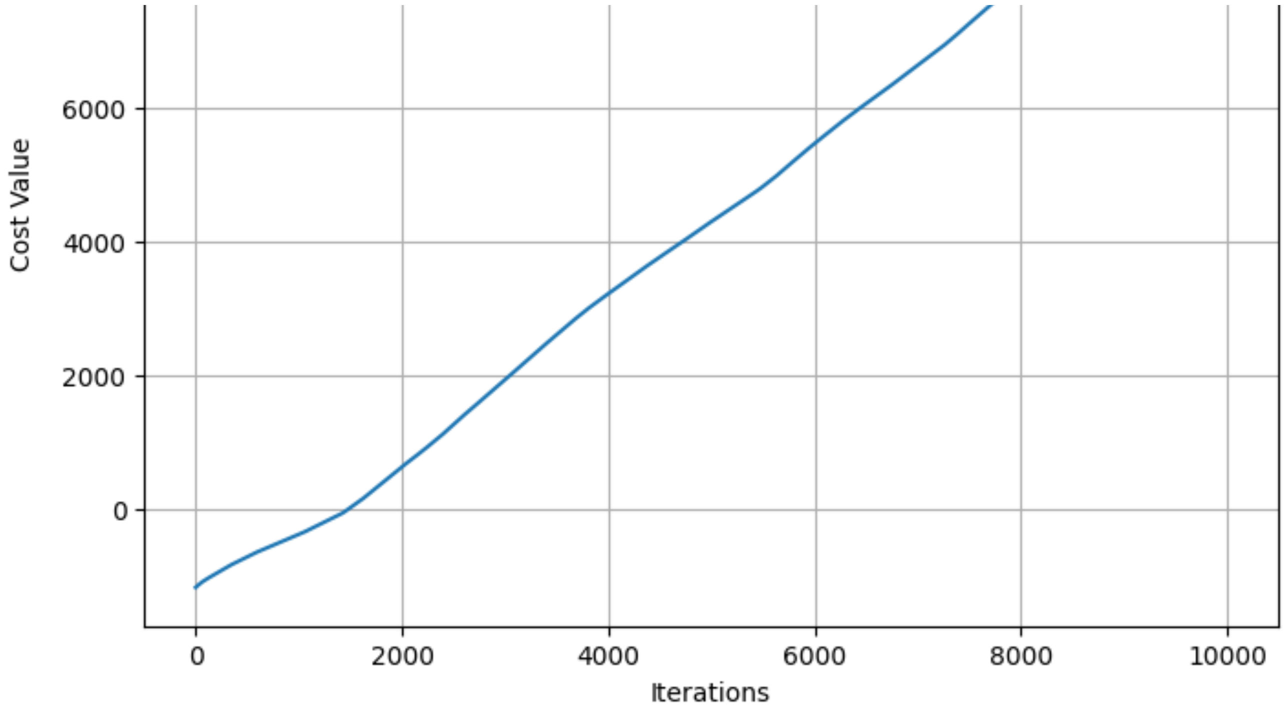
```
display_adversarial_images(generated_examples)
```



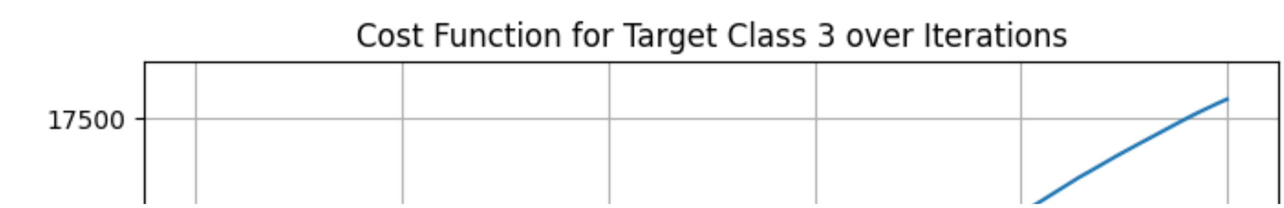


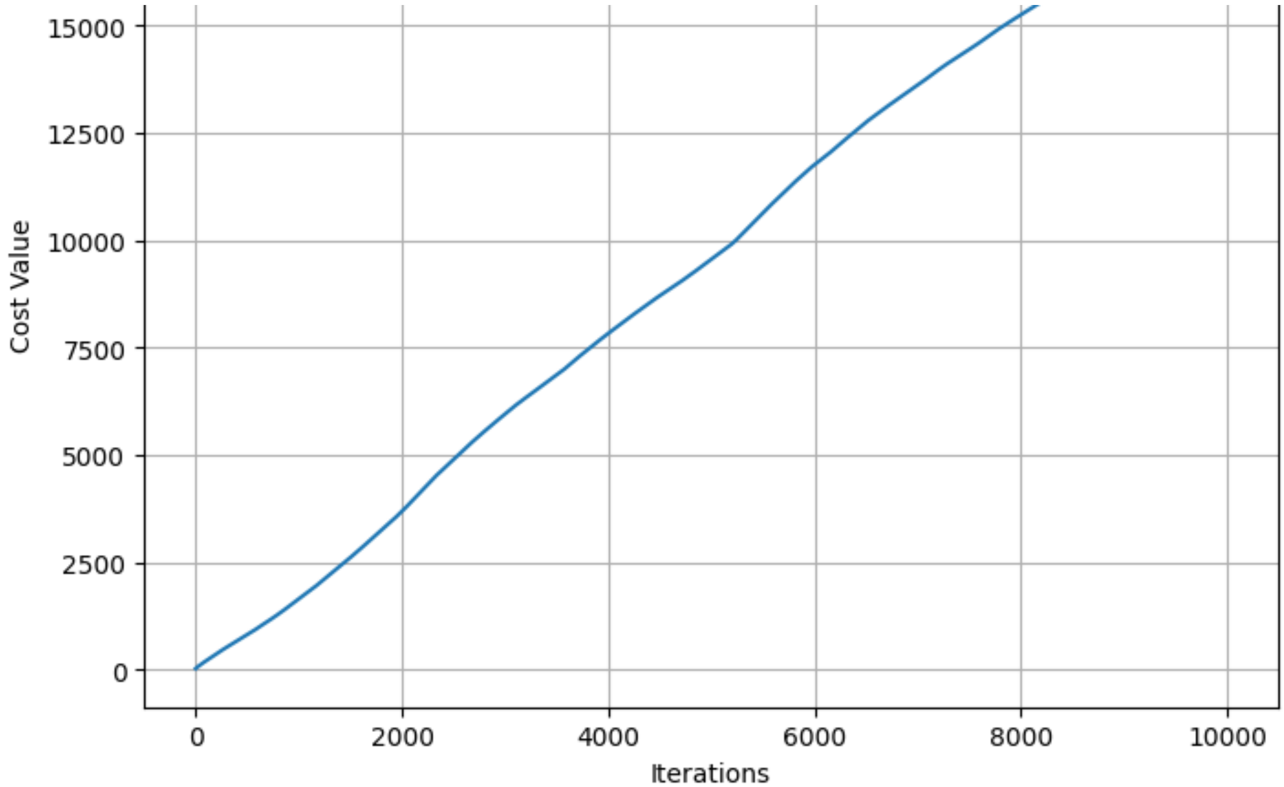

```
for i in range(10):
  plot_costs_for_target_class(generated_examples, i)
```



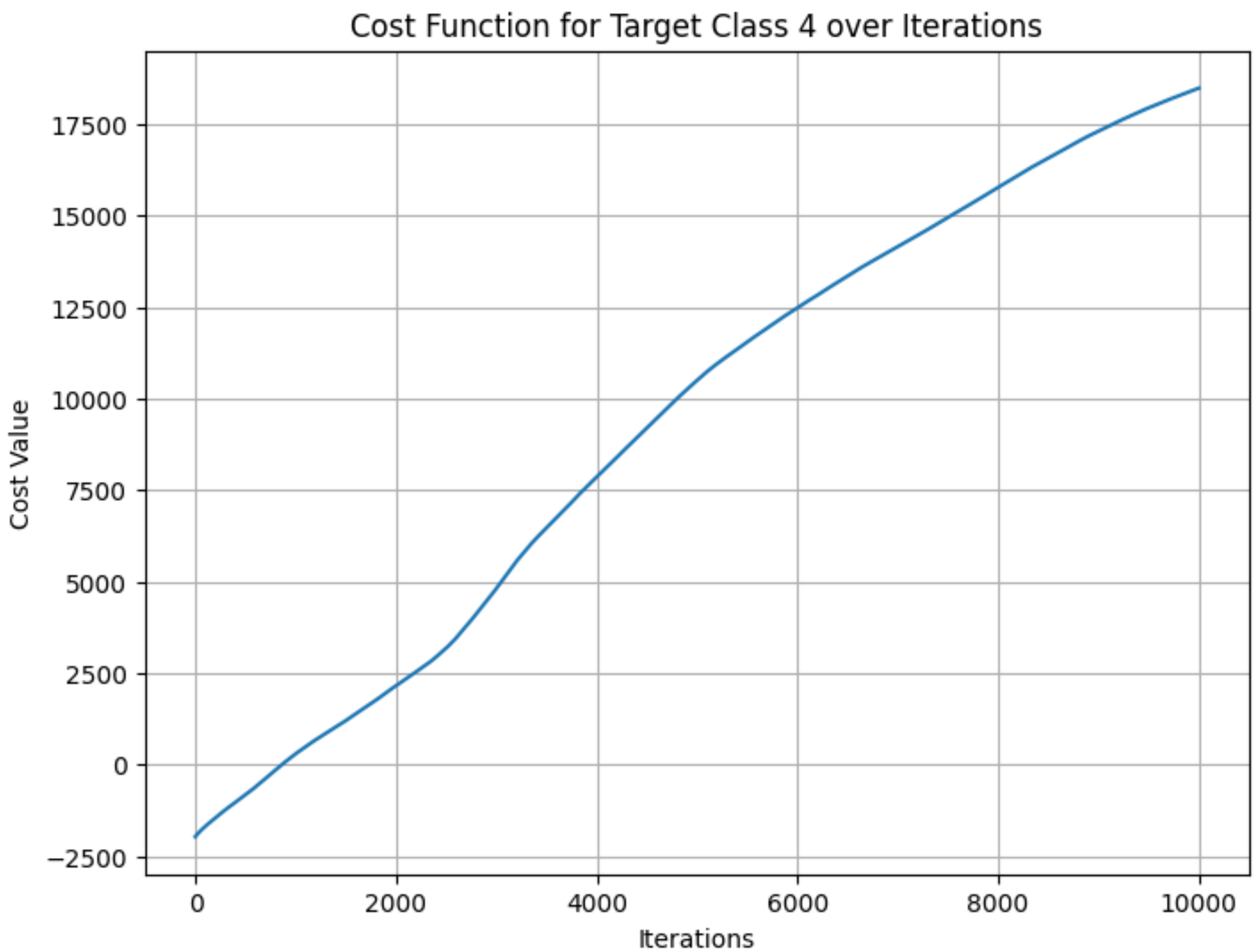

Cost Value
6000
4000
2000
0
0
2000
4000
6000
8000
10000
Iterations


Cost Function for Target Class 2 over Iterations
Cost Value
17500
15000
12500
10000
7500
5000
2500
0
0
2000
4000
6000
8000
10000
Iterations

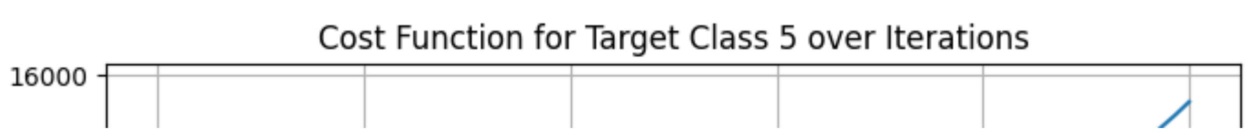

Cost Function for Target Class 3 over Iterations
17500



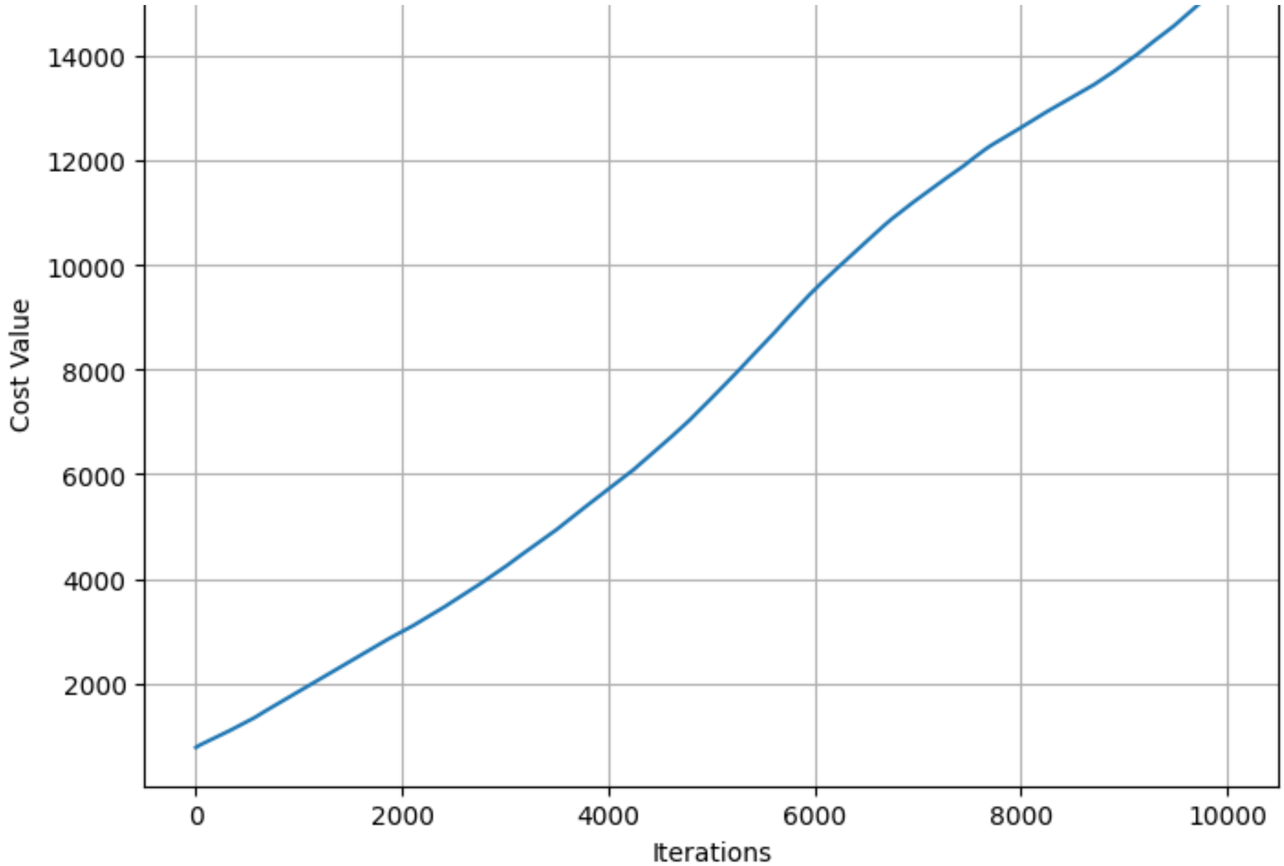
Cost Value
Iterations
0
2500
5000
7500
10000
12500
15000
0
2000
4000
6000
8000
10000



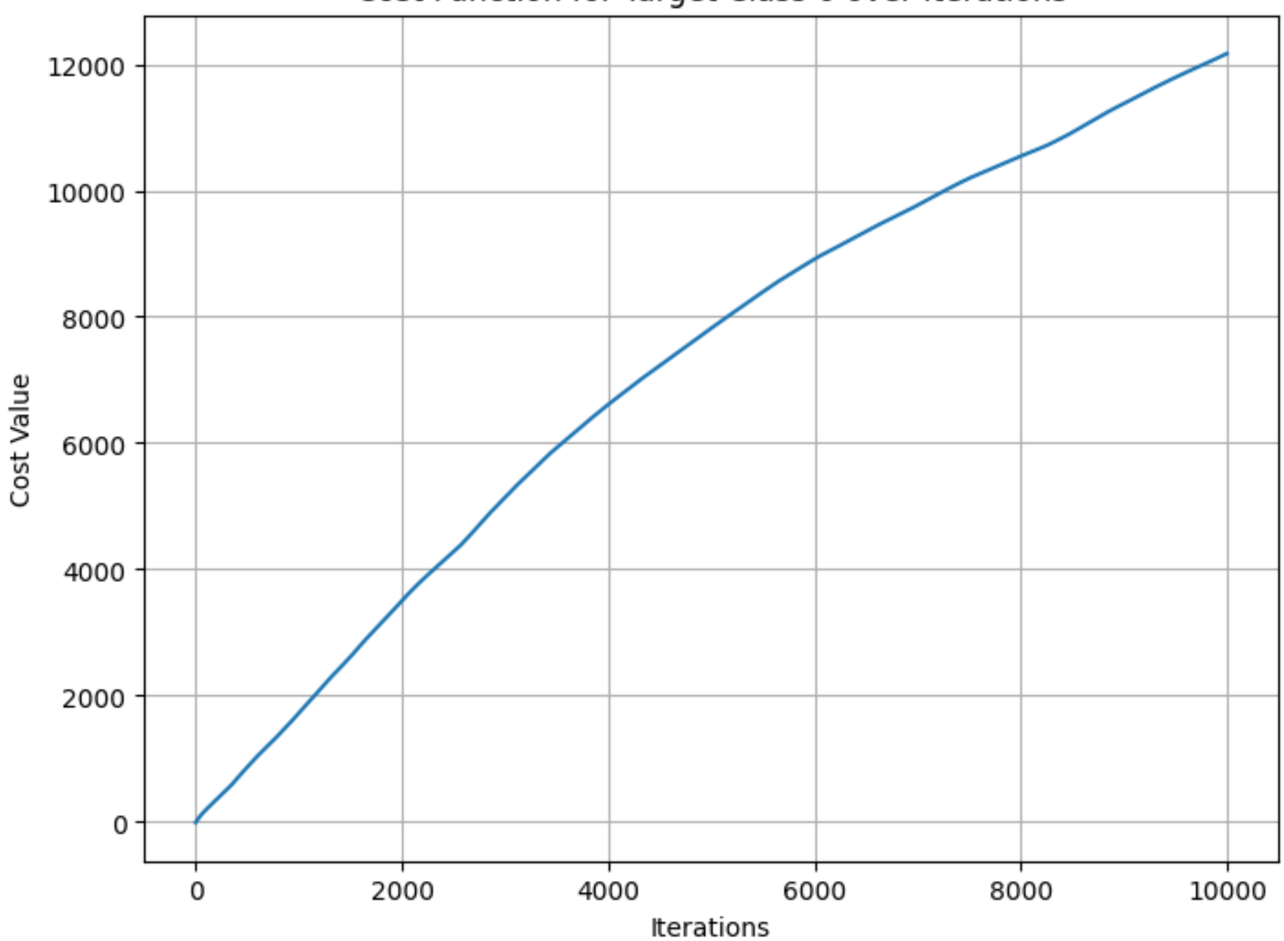
Cost Function for Target Class 4 over Iterations
Cost Value
Iterations
−2500
0
2500
5000
7500
10000
12500
15000
17500
0
2000
4000
6000
8000
10000



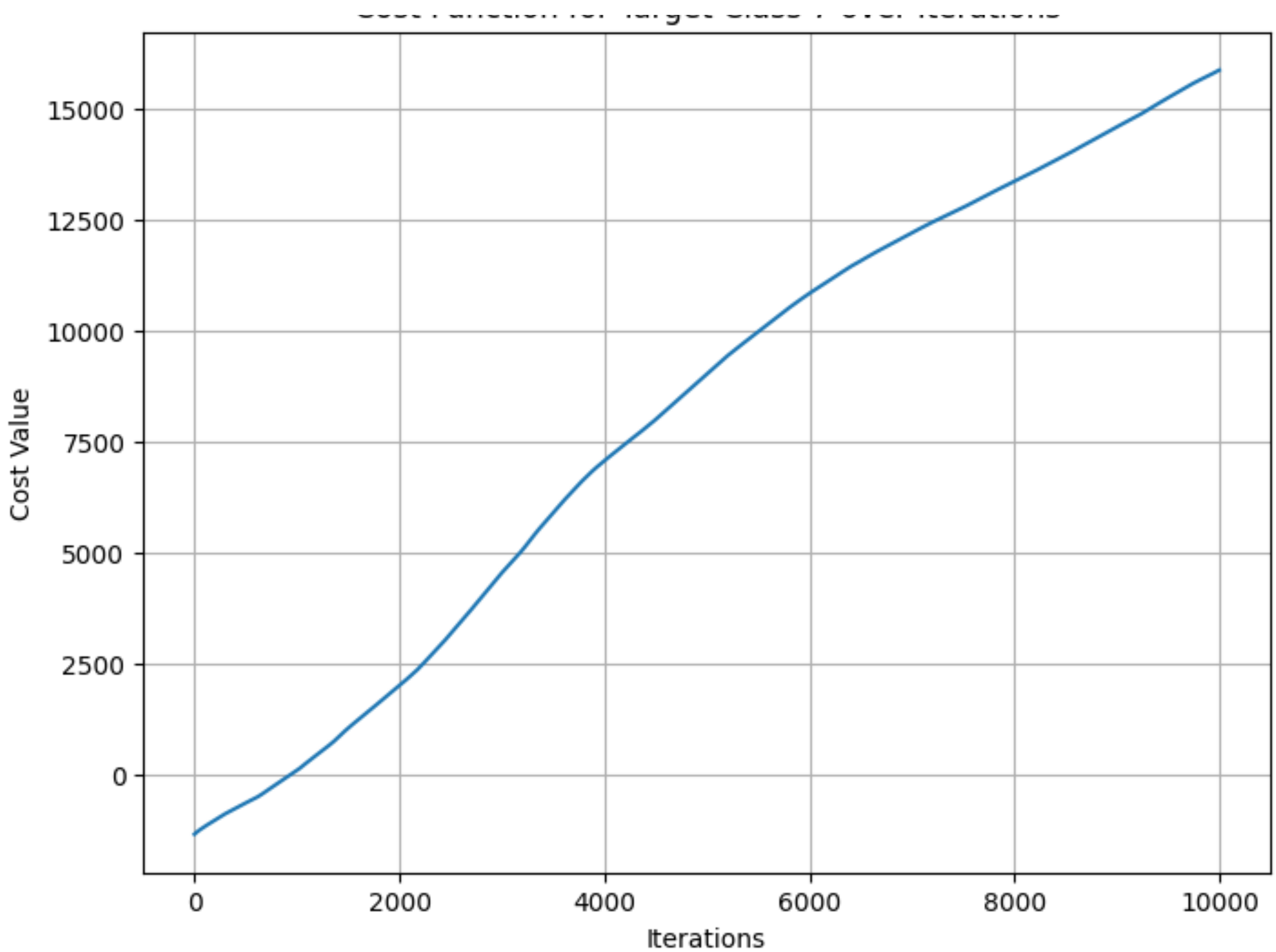
Cost Function for Target Class 5 over Iterations
16000

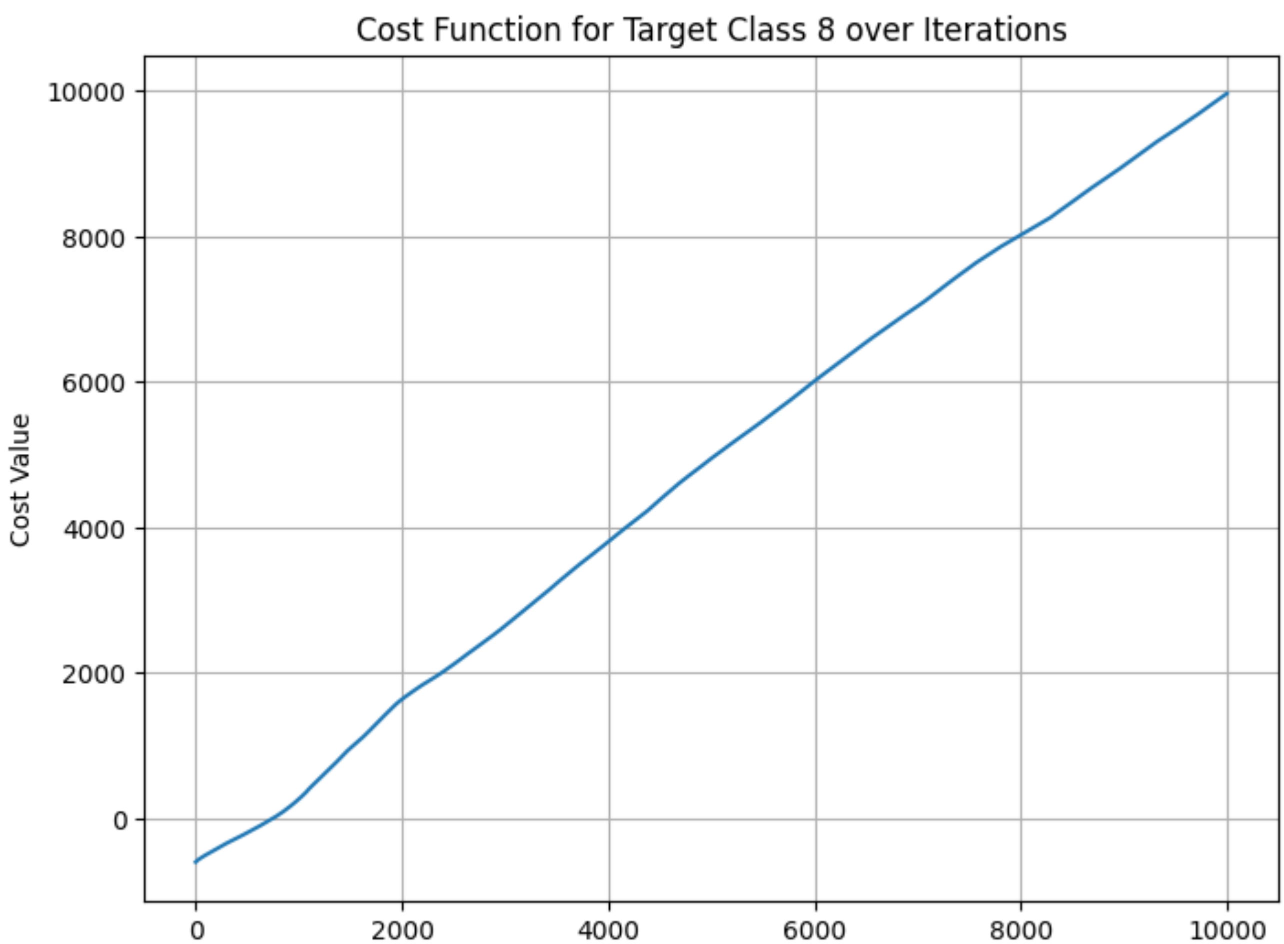


Cost Function for Target Class 6 over Iterations

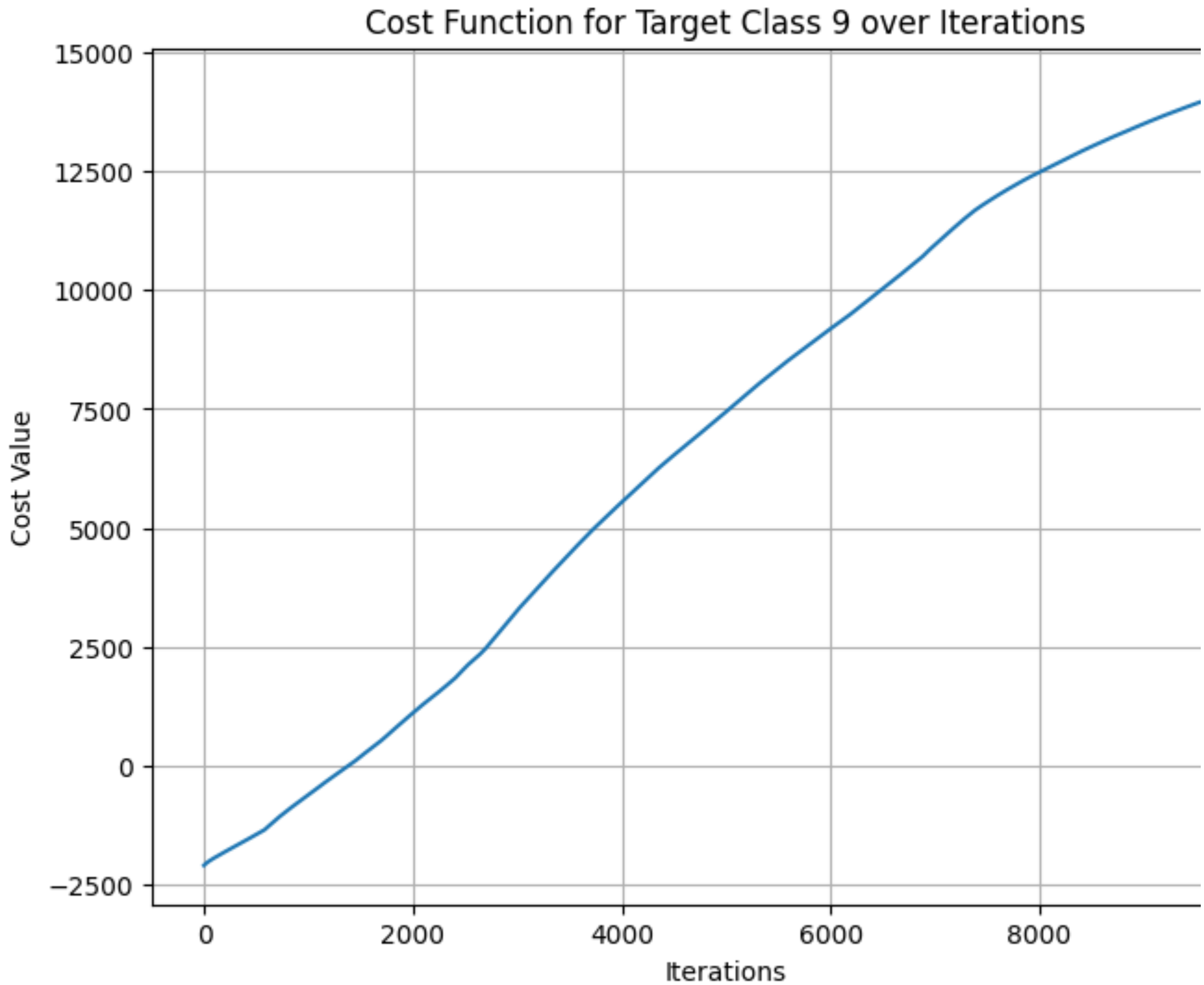


Cost Function for Target Class 7 over Iterations


15000
12500
10000
7500
5000
2500
0
Cost Value
0
2000
4000
6000
8000
10000
Iterations


Cost Function for Target Class 8 over Iterations
10000
8000
6000
4000
2000
0
Cost Value
0
2000
4000
6000
8000
10000

Iterations


Cost Function for Target Class 9 over Iterations
15000
12500
10000
7500
5000
2500
0
−2500
Cost Value
0
2000
4000
6000
8000
Iterations

Targeted Attack

```
def generate_target_adversarial_example(model, target_class, target_image, stepsi
  model.eval() # model to evaluation

  X = torch.normal(128, 1, (1, 1, 28, 28)).to(device) # normal distribution cente
  X.requires_grad = True # gradient computation for X
  mse_loss = nn.MSELoss() # Mean Squared Error (MSE) loss

  for iteration in range(max_iterations):
    logits = model(X)
    cost = logits[0, target_class] - beta * mse_loss(X, target_image) # aversaria

    model.zero_grad()
    cost.backward() # Backpropagate to compute the gradients

    perturbation = stepsize * X.grad.data # Compute the perturbation to add to X
    if use_epsilon:
      perturbation = torch.clamp(perturbation, -epsilon, epsilon) # perturbation
    X.data = X.data + perturbation

    X.data = torch.clamp(X.data, 0, 255)
    X.grad.data.zero_()

  return X.detach()


def classwise_adversarial_example(model, dataset, beta=0.001):
  target_images = {} # dictionary to store target images

  # Iterate through the dataset to collect one image for each class (0-9)
  for _, (images, labels) in enumerate(dataset):
    for img, label in zip(images, labels):
      if label.item() not in target_images:
        target_images[label.item()] = img.to(device)
      if len(target_images) == 10: # Stop if we collected images for all 10 class
        break
    if len(target_images) == 10:
      break

  adversarial_images = {} # dictionary to store the adversarial images
  for true_digit, target_img in target_images.items(): # Create adversarial image
    for target_digit in range(10):
      if true_digit != target_digit:
```

```
        adv_img = generate_target_adversarial_example(model, target_digit, target
        adversarial_images[(true_digit, target_digit)] = adv_img

  # Displaying the generated images
  plt.figure(figsize=(20, 20))
  for i, ((true_digit, target_digit), img) in enumerate(adversarial_images.items(
    plt.subplot(10, 9, i+1)
    plt.imshow(img[0,0].cpu().numpy(), cmap='gray')
    plt.title(f"Looks: {true_digit}, Predicted: {target_digit}", fontsize=10)
    plt.axis('off')
  plt.tight_layout()
  plt.show()
```

```
classwise_adversarial_example(adam_batch_model, test_loader)
```