Exploring and Manipulating Linear Classifier Templates

This project will teach you how to create a linear classifier using visual templates. You will:

1. **Load and preprocess a combined weights image** containing all 10 weights (0-9)
2. **Convert the image into a weight matrix** for a linear classifier
3. **Test the classifier on MNIST dataset** and achieve >20% accuracy

Important: You need to provide your own combined weights image named all_weights_combined_(YOUR CUID).png in the Project 1 folder. This image should contain all 10 weight templates stacked vertically, with each template being approximately 28x28 pixels when resized.

Weight template Generator: You can use this temporary website to generate and download your image: https://nianyi-li.github.io/CPSC-6430-fall25/P1_GUI/

After downloading, rename your file as instructed, all_weights_combined_(YOUR CUID).png, and place it in the Project 1 folder.

NOTE: When filling in the code, please REMOVE the `pass` statement. DO NOT remove the TODO coding highlight in your submission.

Grading Criteria:

- Test accuracy must be >20% (60% points)
- Code quality and implementation (8% points)
- Analysis and answers to questions (32% points)
- **Total: 5 points (50% of project score)**

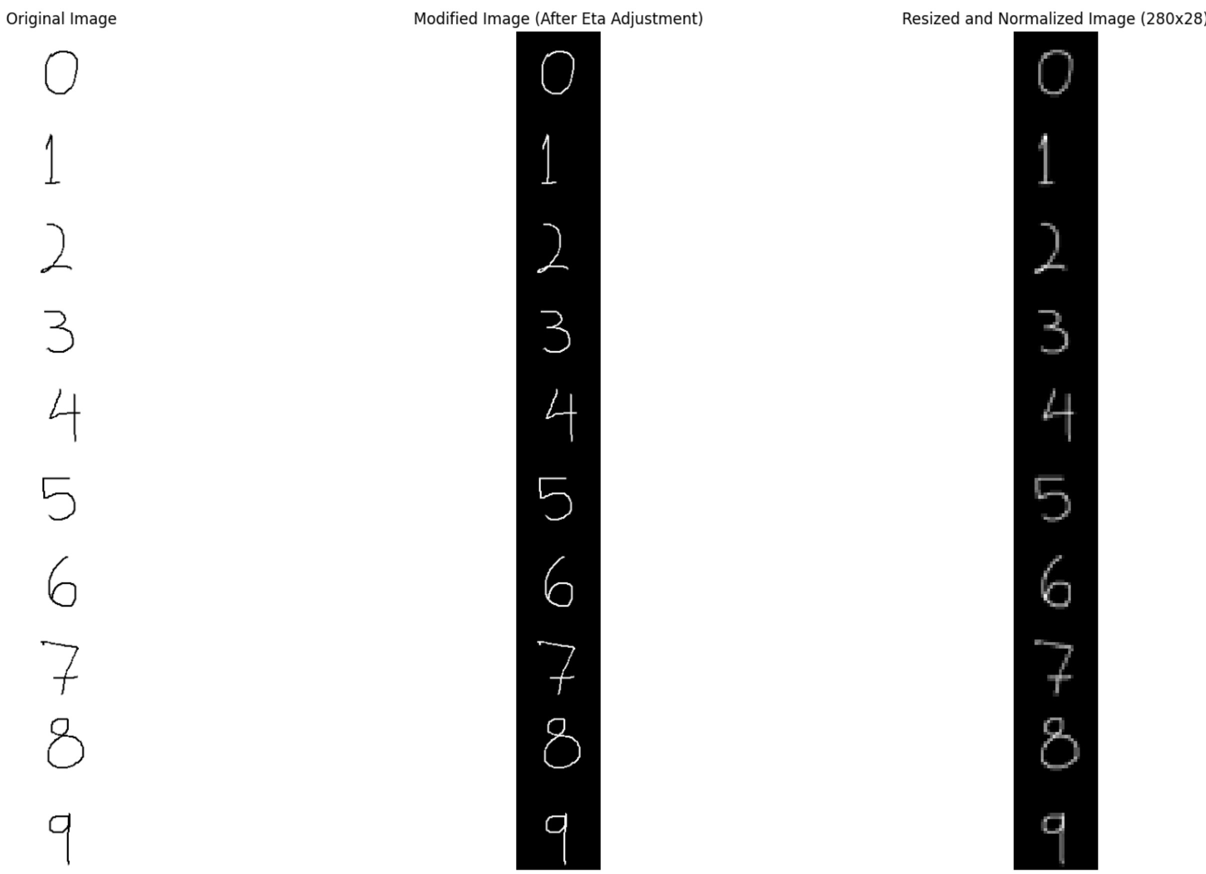
In [13]:
```
# # Google Colab Setup (Comment out for local computer running)
############################################################################
# Uncomment and set the path to your project folder in Google Drive
############################################################################
# from google.colab import drive
# drive.mount('/content/drive')

# FOLDERNAME = 'cpsc8430/assignments/project1/'
# assert FOLDERNAME is not None, "[!] Enter the foldername."

# # Now that we've mounted your Drive, this ensures that
# # the Python interpreter of the Colab VM can load
# # python files from within it.
```

```
# import sys
# sys.path.append('/content/drive/My Drive/{}'.format(FOLDERNAME))
# %cd /content/drive/My\ Drive/$FOLDERNAME
```

In [14]:
```
import torch
import torch.nn as nn
import torchvision
import matplotlib.pyplot as plt
import numpy as np
from PIL import Image
import os

# Set random seed for reproducibility
torch.manual_seed(42)
np.random.seed(42)
```

In [15]:
```
# Load and preprocess the combined digits image
image_path = 'all_weights_combined_szinn.png' # all_digits_combined_4
img = Image.open(image_path)
img_array = np.array(img)

# Convert to grayscale if image is RGB, White is 255, Black is 0
if len(img_array.shape) == 3:
    img_array = img_array.mean(axis=2)


##########################################################################
# TODO: Try different eta values to control the grayscale inversion of the i
# eta = 0.0 -> original image, eta = 1.0 -> fully inverted (255 - img_array)

eta = 1  # Change this value between 0.0 and 1.0 to experiment
img_modified = (1 - eta) * img_array + eta * (255 - img_array)
##########################################################################

# Resize to height 280 and width 28 (10 blocks of 28x28 stacked vertically)
target_size = (28, 280)  # Note: PIL uses (width, height)
img_resized = Image.fromarray(img_modified.astype(np.uint8)).resize(target_s
img_tensor = torch.tensor(np.array(img_resized), dtype=torch.float32)

# Normalize to [-1, 1]
img_min = img_tensor.min()
img_max = img_tensor.max()
img_normalized = 2.0 * (img_tensor - img_min) / (img_max - img_min) - 1.0

# Display original, modified, and resized images
plt.figure(figsize=(20, 10))
plt.subplot(1, 3, 1)
plt.imshow(img_array, cmap='gray')
plt.title('Original Image')
plt.axis('off')
plt.subplot(1, 3, 2)
plt.imshow(img_modified, cmap='gray')
plt.title('Modified Image (After Eta Adjustment)')
plt.axis('off')
```

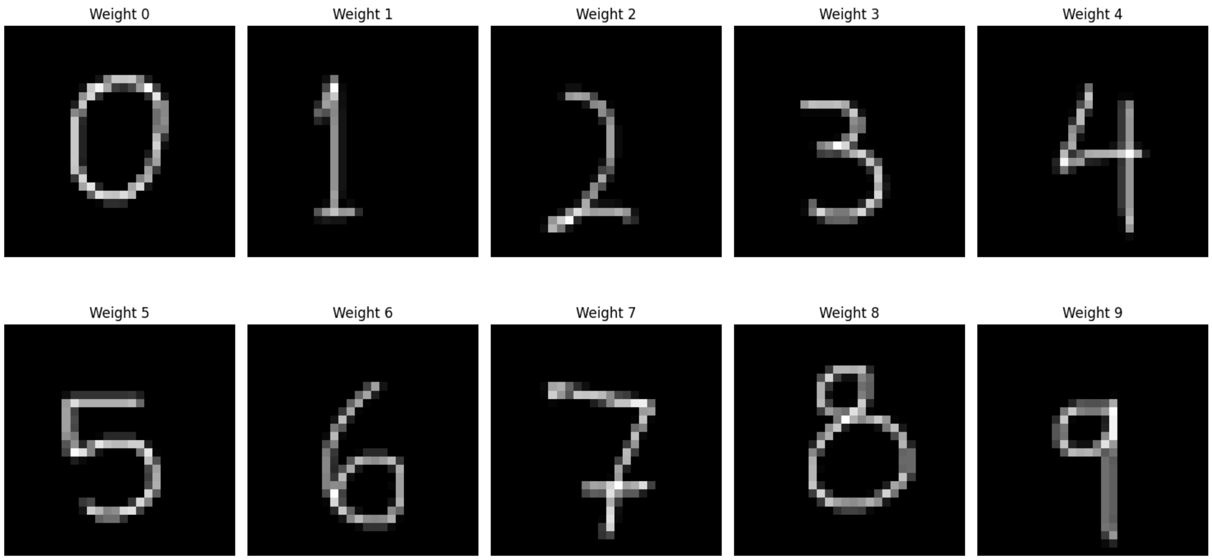
```python
plt.subplot(1, 3, 3)
plt.imshow(img_normalized.numpy(), cmap='gray')
plt.title('Resized and Normalized Image (280x28)')
plt.tight_layout()
plt.axis('off')
plt.show()

print(f"Normalized image tensor shape: {img_normalized.shape}")
print(f"Value range: [{img_normalized.min():.2f}, {img_normalized.max():.2f}
```




```
Normalized image tensor shape: torch.Size([280, 28])
Value range: [-1.00, 1.00]
```

In [16]:
```python
# Create weight matrix [10, 784] from the normalized image
weight_matrix = torch.zeros(10, 784)

# The image is 280x28, which means we have 10 blocks of 28x28 stacked vertic
for i in range(10):
    # Extract the i-th 28x28 block (vertically stacked)
    start_row = i * 28
    end_row = start_row + 28
    block = img_normalized[start_row:end_row, :]

    # Flatten the block and assign to the corresponding row in weight matrix
    weight_matrix[i] = block.flatten()

# Visualize each weight as a 28x28 image
plt.figure(figsize=(15, 8))
for i in range(10):
    plt.subplot(2, 5, i + 1)
```

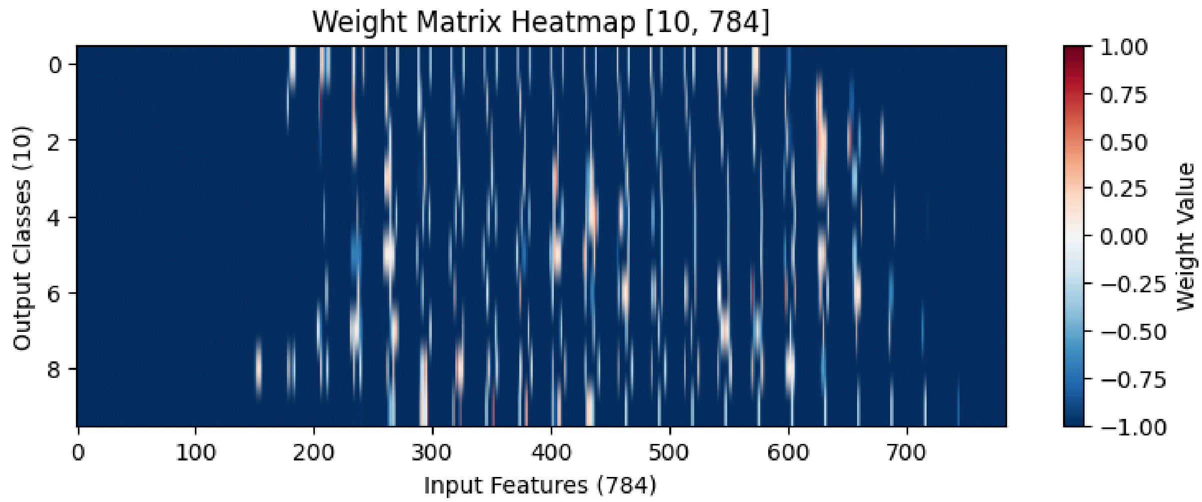
```python
    plt.imshow(weight_matrix[i].reshape(28, 28), cmap='gray')
    plt.title(f'Weight {i}')
    plt.axis('off')
plt.tight_layout()
plt.show()

print(f"Weight matrix shape: {weight_matrix.shape}")
```




```
Weight matrix shape: torch.Size([10, 784])
```

In [17]:
```python
# Visualize the large weight matrix [10, 784]
plt.figure(figsize=(20, 3))

# Create a heatmap of the entire weight matrix
plt.subplot(1, 2, 1)
weight_heatmap = plt.imshow(weight_matrix.numpy(), cmap='RdBu_r', aspect='au
plt.colorbar(weight_heatmap, label='Weight Value')
plt.title('Weight Matrix Heatmap [10, 784]')
plt.xlabel('Input Features (784)')
plt.ylabel('Output Classes (10)')


print("Weight matrix visualization complete!")
print(f"Matrix statistics:")
print(f"  Min value: {weight_matrix.min():.3f}")
print(f"  Max value: {weight_matrix.max():.3f}")
print(f"  Mean value: {weight_matrix.mean():.3f}")
print(f"  Std value: {weight_matrix.std():.3f}")
```

```
Weight matrix visualization complete!
Matrix statistics:
  Min value: -1.000
  Max value: 1.000
  Mean value: -0.935
  Std value: 0.244
```



In [ ]:
```
# Load MNIST test dataset
transform = torchvision.transforms.Compose([
    torchvision.transforms.ToTensor(),
    torchvision.transforms.Normalize((0.1307,), (0.3081,))  # MNIST mean and
])

test_dataset = torchvision.datasets.MNIST(
    root='cpsc8430/datasets/MNIST',
    train=False,
    download=True,
    transform=transform
)

test_loader = torch.utils.data.DataLoader(
    test_dataset,
    batch_size=1000,
    shuffle=False
)

# Create random bias
bias = torch.randn(10)

# Evaluation function
def evaluate():
    correct = 0
    total = 0

    with torch.no_grad():
        for images, labels in test_loader:
            # Flatten the images
            images = images.view(-1, 784)

            # Forward pass: compute scores
            scores = torch.mm(images, weight_matrix.t()) + bias

            # Get predictions
            _, predicted = torch.max(scores, 1)

            # Update statistics
            total += labels.size(0)
```

```
            correct += (predicted == labels).sum().item()

    return 100 * correct / total

# Test the classifier
accuracy = evaluate()
print(f"Test Accuracy: {accuracy:.2f}%")

# IMPORTANT: This accuracy should be greater than 20% for full credit
# assert accuracy > 20.0, f"Test accuracy {accuracy:.2f}% is below the requi
# print(f"✅ Test accuracy {accuracy:.2f}% meets the requirement of >20%!")

# Store the result for grading
test_accuracy_result = accuracy
```

```
Test Accuracy: 23.61%
```

Inline Questions

Question 1

Try adjusting the value of `eta` (located in the second code cell after "TODO") to each of the following values: {0, 0.25, 0.5, 0.75, 1}. For each value, run the code and report the resulting test accuracy. What do you observe as you change `eta`? Why do you think this happens?

$\textit{Your Answer:}$

- Testing accuracy for $\eta = 0$: 9.62%
- Testing accuracy for $\eta = 0.25$: 9.63%
- Testing accuracy for $\eta = 0.5$: 9.80%
- Testing accuracy for $\eta = 0.75$: 22.84%
- Testing accuracy for $\eta = 1$: 23.04%

As eta changes, so does the background and digit color through grayscale inversion. At `eta = 0`, the digits and their background are unchanged in color, while `eta = 1` is a complete inversion. The testing accuracy also changes, going from `9.62%` at `eta = 0` to `23.04%` at `eta = 1`. This probably happens because the weights change with the grayscale.

Question 2

Why do you think this approach achieves an accuracy above 20%? What are the advantages and limitations of using visual templates as weights?

$\textit{Your Answer:}$

I think it achieves an accuracy above `20%` because the weights minimize the loss at this level of inversion.

Advantages	Disadvantages
Weights are likely closer to what is expected as they follow the basic outlines of the training and test data set	By using visual templates, you limit the ability to change the weights for better predictions as they are fixed on the given template.
	If any digit is written weird, the model can't identify the digit

Question 3

How could you improve the performance of this classifier? What modifications would you make to achieve higher accuracy?

$\textit{Your Answer:}$

I would change the weight matrix so it isn't dependent on the visual templates and instead use gradient descent to improve the weights. I would play around with other hyperparameters such as batch size and bias.

Question 4

What does the weight matrix represent in this linear classifier? How does it relate to the original combined digits image?

$\textit{Your Answer:}$

The weight matrix is the combined digit input I gave. By decomposing the image, you can see the individual digits.