This experimental report investigates the application of Principal Component Analysis (PCA) for dimensionality reduction in Multi-Layer Perceptron (MLP) classification of the MNIST handwritten digit dataset. We compare the performance and computational efficiency of the original and PCA-reduced data representations.

1 Experimental Setup

1.1 Dataset

- Dataset: MNIST Handwritten Digit Classification(Under the Data Folder)
- Dimensionality Reduction: Principal Component Analysis (PCA)
- Machine Learning Model: Multi-Layer Perceptron (MLP)

1.2 Configuration

- Input Size: 28×28 pixels (784 features)
- PCA Components: Reduced to 50 features
- Neural Network Architecture:
  - Input Layer: 784 neurons (original) / 50 neurons (PCA)
  - Hidden Layer: 128 neurons with ReLU activation
  - Output Layer: 10 neurons (digit classes)
- Training Parameters:
  - Optimizer: Adam
  - Learning Rate: 0.001
  - Epochs: 5
  - Loss Function: Cross-Entropy

2 Performance Analysis

2.1 Performance Comparison

Model	Accuracy	Time
Original Data	96.44%	40.17s
PCA-Reduced Data	97.69%	5.82s

Table 1: Performance Comparison

2.2 Data Loss Progression

$$\text{MLP Loss: } [0.3893, 0.2037, 0.1436, 0.1162, 0.1002]$$

$$\text{PCA Loss: } [0.3618, 0.1344, 0.0935, 0.0734, 0.0606]$$

3 Conclusion

PCA effectively captured the essential features of the MNIST dataset. It slightly improved the classification accuracy, converged faster, and was more efficient. Therefore, 50 principal components are sufficient to maintain high classification performance.

MLP and PCA

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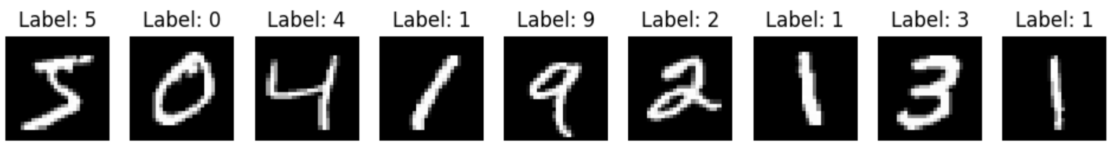
[1]:
```python
import os
import torch
import torch.nn as nn
import torch.optim as optim
from torchvision import datasets, transforms
import numpy as np
import time
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt

# Load the MNIST Dataset

data_dir = "./data"
transform = transforms.Compose([
    transforms.ToTensor(),
    transforms.Normalize((0.5,), (0.5,))
])

train_dataset = datasets.MNIST(root=data_dir, train=True, transform=transform,␣
 ↪download=False)
test_dataset = datasets.MNIST(root=data_dir, train=False, transform=transform,␣
 ↪download=False)

# Convert datasets to loaders
train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=64,␣
 ↪shuffle=True)
test_loader = torch.utils.data.DataLoader(test_dataset, batch_size=64,␣
 ↪shuffle=False)

# Visualize sample data
def visualize_samples(dataset, num_samples=9):
    fig, axes = plt.subplots(1, num_samples, figsize=(12, 4))
    for i, ax in enumerate(axes):
        image, label = dataset[i]
        ax.imshow(image.squeeze(), cmap="gray")
        ax.set_title(f"Label: {label}")
        ax.axis("off")
```

```python
    plt.show()

print("Visualizing Sample Data...")
visualize_samples(train_dataset)
```

Visualizing Sample Data…



[2]:
```python
# Flatten dataset to use with MLP
def flatten_data(loader):
    data, labels = [], []
    for images, lbls in loader:
        data.append(images.view(images.size(0), -1).numpy())
        labels.append(lbls.numpy())
    return np.vstack(data), np.hstack(labels)

X_train, y_train = flatten_data(train_loader)
X_test, y_test = flatten_data(test_loader)
```

[3]:
```python
# Define the MLP Classifier
class MLP(nn.Module):
    def __init__(self, input_size, hidden_size, output_size):
        super(MLP, self).__init__()
        self.fc1 = nn.Linear(input_size, hidden_size)
        self.relu = nn.ReLU()
        self.fc2 = nn.Linear(hidden_size, output_size)

    def forward(self, x):
        x = self.fc1(x)
        x = self.relu(x)
        x = self.fc2(x)
        return x

# should work with gpu but i dont have one
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

# Helper function to train and evaluate the model
def train_and_evaluate(model, train_loader, test_loader, num_epochs=5, learning_rate=0.001):
    criterion = nn.CrossEntropyLoss()
    optimizer = optim.Adam(model.parameters(), lr=learning_rate)
```

```
    model.to(device)

    # Perform MLP
    for epoch in range(num_epochs):
        model.train()
        running_loss = 0.0
        for images, labels in train_loader:
            images, labels = images.view(images.size(0), -1).to(device), labels.
↪to(device)

            optimizer.zero_grad()
            outputs = model(images)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            running_loss += loss.item()

        print(f"Epoch [{epoch + 1}/{num_epochs}], Loss: {running_loss /␣
↪len(train_loader):.4f}")

    # Evaluate
    model.eval()
    correct = 0
    total = 0
    with torch.no_grad():
        for images, labels in test_loader:
            images, labels = images.view(images.size(0), -1).to(device), labels.
↪to(device)
            outputs = model(images)
            _, predicted = torch.max(outputs, 1)
            total += labels.size(0)
            correct += (predicted == labels).sum().item()

    accuracy = correct / total
    print(f"Accuracy: {accuracy:.4f}")
    return accuracy
```

[4]:
```
# Train and evaluate MLP on original data
input_size = 28 * 28
hidden_size = 128
output_size = 10

print("Training MLP on Original Data")
mlp_original = MLP(input_size, hidden_size, output_size)
start_time_original = time.time()
```

```
accuracy_original = train_and_evaluate(mlp_original, train_loader, test_loader)
time_original = time.time() - start_time_original
```

```
Training MLP on Original Data…
Epoch [1/5], Loss: 0.3893
Epoch [2/5], Loss: 0.2037
Epoch [3/5], Loss: 0.1436
Epoch [4/5], Loss: 0.1162
Epoch [5/5], Loss: 0.1002
Accuracy: 0.9644
```

[5]:

```
# Apply PCA using sklearn

n_components = 50
pca = PCA(n_components=n_components)
X_train_pca = pca.fit_transform(X_train)
X_test_pca = pca.transform(X_test)

# Convert PCA data to PyTorch loaders
train_pca_loader = torch.utils.data.DataLoader(
    torch.utils.data.TensorDataset(torch.tensor(X_train_pca, dtype=torch.
 ↪float32), torch.tensor(y_train)),
    batch_size=64,
    shuffle=True
)

test_pca_loader = torch.utils.data.DataLoader(
    torch.utils.data.TensorDataset(torch.tensor(X_test_pca, dtype=torch.
 ↪float32), torch.tensor(y_test)),
    batch_size=64,
    shuffle=False
)

# Train and evaluate MLP on PCA-reduced data
print("Training MLP on PCA-Reduced Data")
mlp_pca = MLP(n_components, hidden_size, output_size)
start_time_pca = time.time()
accuracy_pca = train_and_evaluate(mlp_pca, train_pca_loader, test_pca_loader)
time_pca = time.time() - start_time_pca
```

```
Applying PCA to reduce dimensionality…
Training MLP on PCA-Reduced Data…
Epoch [1/5], Loss: 0.3618
Epoch [2/5], Loss: 0.1344
Epoch [3/5], Loss: 0.0935
Epoch [4/5], Loss: 0.0734
Epoch [5/5], Loss: 0.0606
Accuracy: 0.9769
```

[6]:

```
# Compare Results
print("\nComparison of Results:")
print(f"Accuracy on Original Data: {accuracy_original:.4f}")
print(f"Accuracy on PCA-Reduced Data: {accuracy_pca:.4f}")
print(f"Time taken on Original Data: {time_original:.2f} seconds")
print(f"Time taken on PCA-Reduced Data: {time_pca:.2f} seconds")
```

```
Comparison of Results:
Accuracy on Original Data: 0.9644
Accuracy on PCA-Reduced Data: 0.9769
Time taken on Original Data: 40.17 seconds
Time taken on PCA-Reduced Data: 5.82 seconds
```