his 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
- 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

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

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

3 Conclusion

PCA effectively captured the essential features of the MNIST dataset. It slightly improved classification accuracy and substantial computational efficiency gains. Therefore, 50 principal components are sufficient to maintain high classification performance.