Assignment 7: Semi-Supervised Learning for Image Classification

Introduction

This report explores the implementation of a semi-supervised learning pipeline for image classification using the MNIST dataset. The primary objective was to utilize pseudo-labeling to enhance classification performance while minimizing reliance on labeled data. The model was trained in two stages: supervised training on labeled data and semi-supervised learning with pseudo-labels.

Dataset and Preprocessing

The [MNIST](#) dataset consists of 70,000 grayscale images of handwritten digits (0-9), each with a resolution of 28x28 pixels. The dataset was preprocessed using the following steps:

- **Normalization:** Pixel values were scaled to the range [0,1] to standardize inputs.
- **Resizing:** Images were resized to 28x28 pixels to ensure consistency.
- **Data Splitting:**
    - **Labeled Training Set:** 15% of the dataset was used for supervised training.
    - **Unlabeled Set:** 70% of the dataset was reserved for pseudo-labeling.
    - **Test Set:** 15% of the dataset was used for evaluation.
- **Data Augmentation:** Techniques such as random horizontal flips, rotations, and resized crops were applied. However, data augmentation did not significantly improve performance and led to a slight drop in the F1-score by 0.02%. This could be attributed to the simplicity and structured nature of MNIST, where transformations do not create additional meaningful variations, unlike more complex datasets such as CIFAR-10 or ImageNet.

Model and Training Process

A convolutional neural network (CNN) was employed for classification. The training process was divided into two main stages:

Supervised Training

- The model was trained using the labeled dataset.
- Loss Function: Cross-entropy loss.
- Optimizer: Adam optimizer with an initial learning rate of 0.01.
- Monitoring: Training loss and accuracy were plotted to track progress.
- Epochs: 40

Semi-Supervised Learning with Pseudo-Labeling

- The trained model generated predictions for the unlabeled dataset.
- Pseudo-labels with a confidence threshold of **85%** were added to the labeled dataset.

- The model was fine-tuned using only the pseudo-labeled samples that had a confidence score above the threshold.
- 48371 samples had a confidence above the threshold
- The learning rate was reduced to 0.005 for stability and better optimization.
- Epochs: 5

Evaluation and Results

The model was evaluated on the test set using various classification metrics and visualizations.

Classification Performance

- **Supervised Model:** Achieved an accuracy of **98%**.
- **Pseudo-Labeled Model:** Maintained the same **98%** accuracy, with minor improvements in precision and recall for certain classes.

Confusion Matrices

- Both models exhibited strong diagonal dominance, indicating high classification accuracy.
- Misclassifications were mainly observed in similar-looking digits, such as **4 vs. 9** and **3 vs. 5**.

Loss and Accuracy Trends

- **Supervised Training:** Loss decreased steadily and plateaued after 10 epochs, while accuracy reached around **98%** over 40 epochs.
- **Pseudo-Labeling Training:** Loss further decreased, reinforcing model confidence. Accuracy initially fluctuated but stabilized at approximately **97.5%**.

Insights and Conclusion

The semi-supervised learning approach effectively leveraged unlabeled data, demonstrating its potential in image classification. However, in this case, pseudo-labeling did not significantly boost performance, as the supervised model had already reached a high baseline accuracy. The minimal effect of data augmentation suggests that MNIST does not benefit much from transformations due to its structured and low-variance nature. Future improvements could include experimenting with different confidence thresholds and alternative semi-supervised techniques, such as consistency regularization or contrastive learning.