Homework 5

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Problem 1

1 System Description

The neural network constructed for this assignment represents an evolution of the model developed in Homework 4, now tailored to leverage pre-trained weights. Utilizing the MNIST dataset, this network is structured with a fixed architecture of 784 input neurons, 150 hidden neurons, and 10 output neurons, conforming to the configuration from the Homework 4 Problem 1. Key hyperparameters include a learning rate of 0.01 and momentum of 0.9 The system is enhanced to support two distinct operational cases: Case I, where only the weights from the hidden-to output layer are trained while keeping the input-to-hidden layer weights fixed, and Case II, which involves training both layers. Training is conducted using backpropagation with momentum up to 200 epochs or until early stopping criteria are met. The network showcases adaptability and improved performance, leveraging pre-trained features for digit classification

2 Results

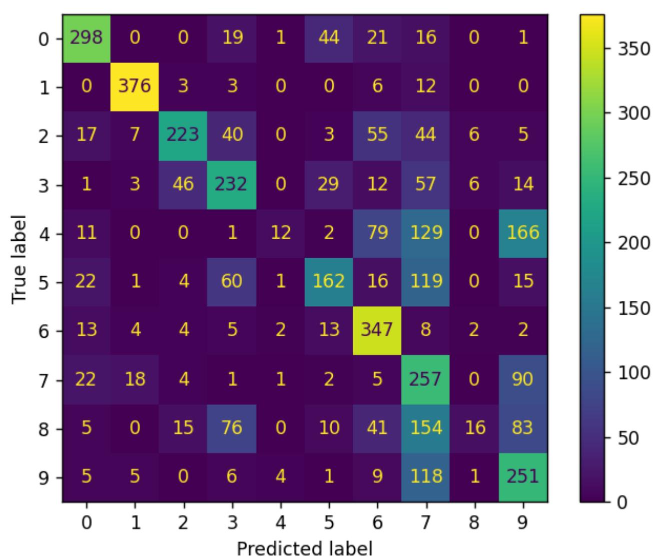

Figure 1: Case I Confusion Matrix displaying the classification of labels during model training

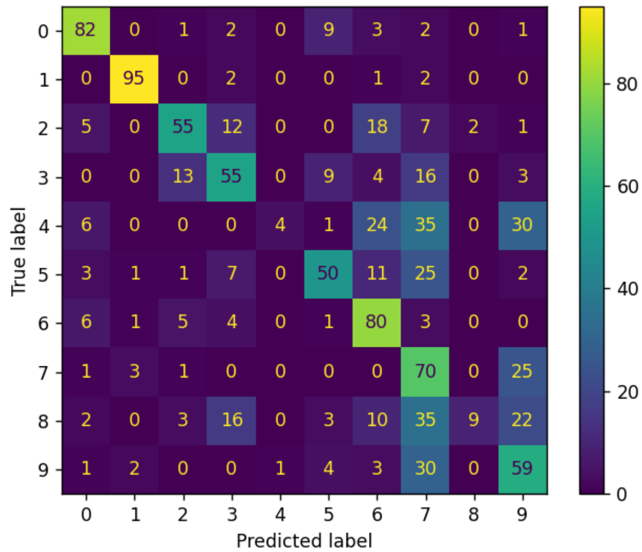

Figure 2: Case I Confusion Matrix displaying the classification of labels during model testing

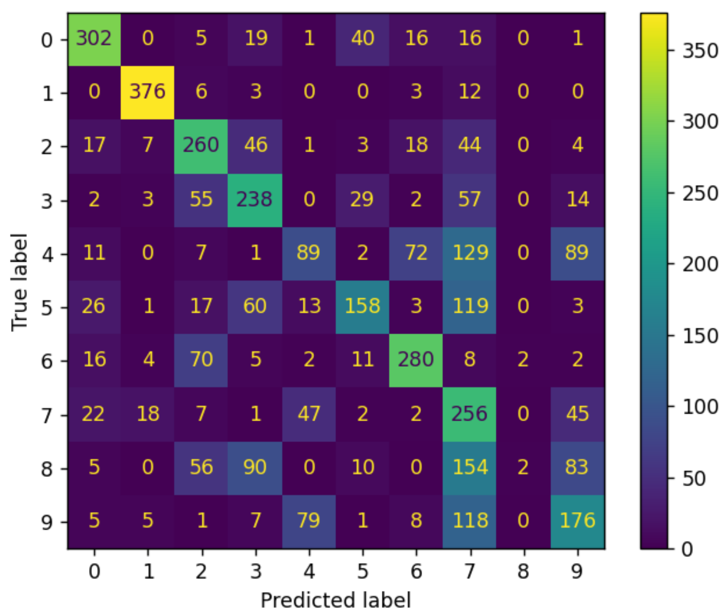

Figure 3: Case II Confusion Matrix displaying the classification of labels during model training

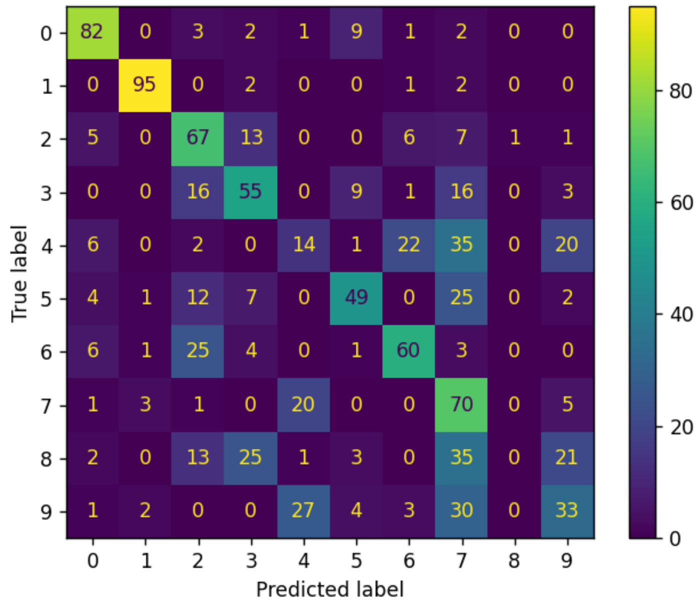

Figure 4: Case II Confusion Matrix displaying the classification of labels during model testing

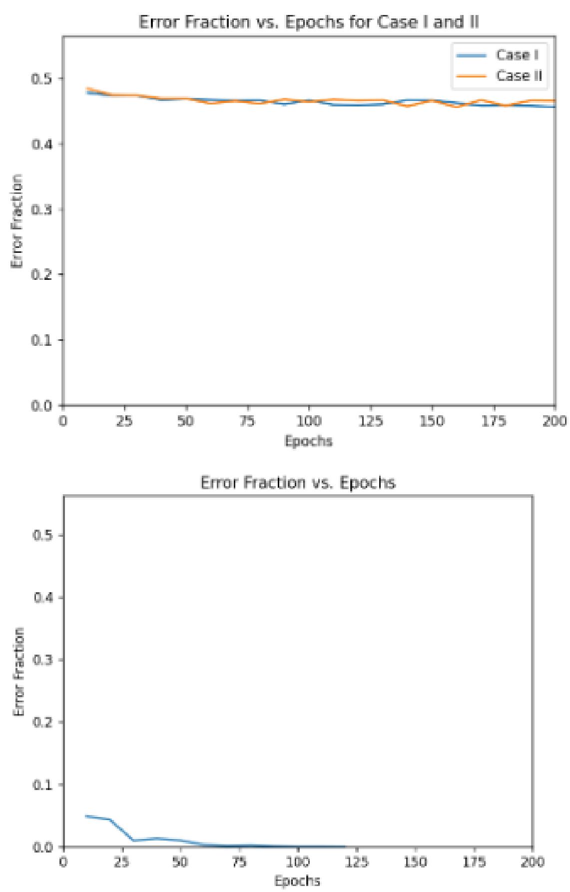

Figure 5: Displays the Error Fraction from Case I and II compared to Homework 4

3 Analysis of Results

The results from the experiments reveal insightful differences in the performance of the neural network across Homework 4 and Homework 5. Comparing the error fractions, it's evident that initializing the hidden weights from the autoencoder in Homework 5 didn't significantly enhance the training process when compared to Homework 4 (Figure 5). While Homework 4 showed a rapid decrease in error fraction, reaching near-zero values by 100 epochs, both cases in Homework 5 maintained relatively higher error fractions throughout the 200 epochs. This suggests that the pre-trained weights, while potentially providing a good starting point, didn't drastically accelerate the training process in the context of this specific classification task. In terms of performance, training both layers in Case II didn't substantially outperform training only the output layer in Case I (Figures 1 & 3). The error fractions, accuracy, recall, precision, and F1 score are relatively similar across both cases, with Case I even slightly outperforming Case II in terms of test accuracy (0.559 vs. 0.525) (Figure 2 & 4). This outcome indicates that the features learned by the autoencoder and used in Case I were sufficiently informative for classification, and further tuning of these features in Case II did not yield significant improvements.

Problem 2

1 System Description

This Self-Organizing Feature Map (SOFM) system is designed to classify and visualize the MNIST dataset of handwritten digits. The SOFM architecture consists of a 12x12 grid, each node having 784 inputs corresponding to the pixel values of 28x28 images. The system employs a dynamic learning rate and radius decay over 50 epochs, starting with an initial learning rate of 0.05, to adapt the neuron weights towards the data features. The learning utilizes the Euclidean distance for neuron competition and updates the weights based on the neighborhood function. Post-training, the system assesses classification performance through activity matrices, which reveal the neuron response to each digit class, and visualizes the neuron weights, illustrating the feature map of the trained network. This SOFM model demonstrates an unsupervised learning approach to extract patterns and features intrinsic to the MNIST digit data.

2 Results

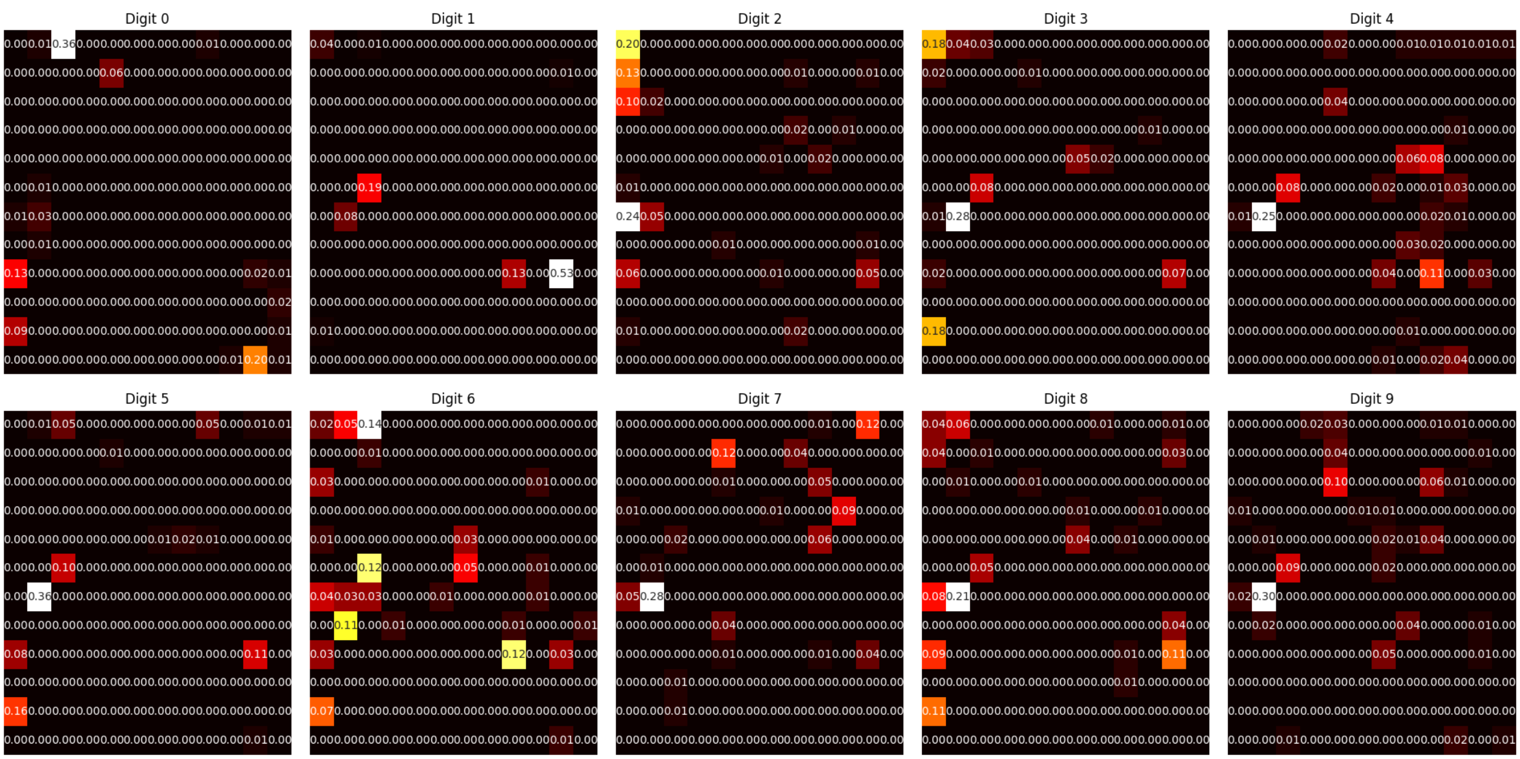

Figure 1: Heatmap of Activity Matrices for Digits 0 - 9

Figure 2: Final weights for the neurons of a 12 x 12 SOFM

3 Analysis of Results

The analysis of the activity matrices in digits 0-9 reveals varying degrees of neuron activation concentration. Notably, in digit 1, the highest winning fraction was found to be 0.53, whereas for all other digits, no value exceeded 0.36 (Figure 1). Interestingly, the heatmaps for digits 8 and 9 exhibited similar clustering patterns, suggesting a potential shared feature space. Furthermore, an observation from the final weights of the SOFM is that they significantly favored digits 8 and 9, with these two digits being the only ones distinguishable on the plot (Figure 2). This bias in favor of 8 and 9 in the SOFM's weight distribution could indeed explain why these two digits are easily distinguished in the network. The network's capacity to differentiate between these digits might be attributed to the distinct clusters created by the SOFM, leading to a more accurate representation and recognition of digits 8 and 9. This insight highlights the importance of understanding the network's weight distribution and its impact on classification performance.

Problem 3

1 System Description

This Integrated Neural Network system, enhanced with a Self-Organizing Feature Map, is engineered for efficient classification of the MNIST dataset of handwritten digits. The SOFM, forming the core of the system, features a 12x12 grid with each neuron connected to 784 inputs, matching the pixel count of 28x28 images. This setup undergoes training over 50 epochs with a dynamically adjusting learning rate, starting from 0.05. The innovative aspect of this system lies in its integration of SOFMs output with a neural network layer, forming a hybrid model. This design leverages the SOFM's feature extraction capabilities. The neural network, with an output layer of 10 neurons, further processes these features to classify the digits. The system's efficacy is demonstrated through metrics like accuracy, precision, recall, and F1 score, alongside a confusion matrix, offering a comprehensive evaluation of its performance on the MNIST dataset.

2 Results

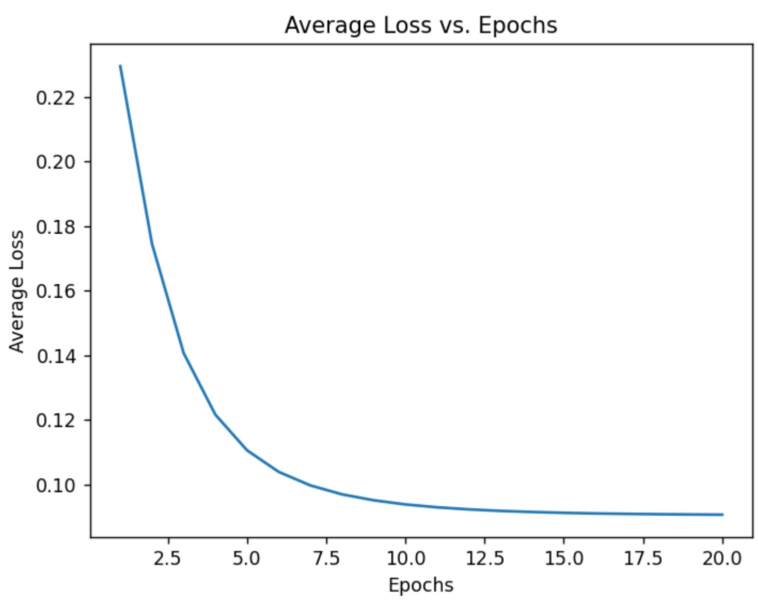

Figure 1: Displays the Average Loss vs Epochs

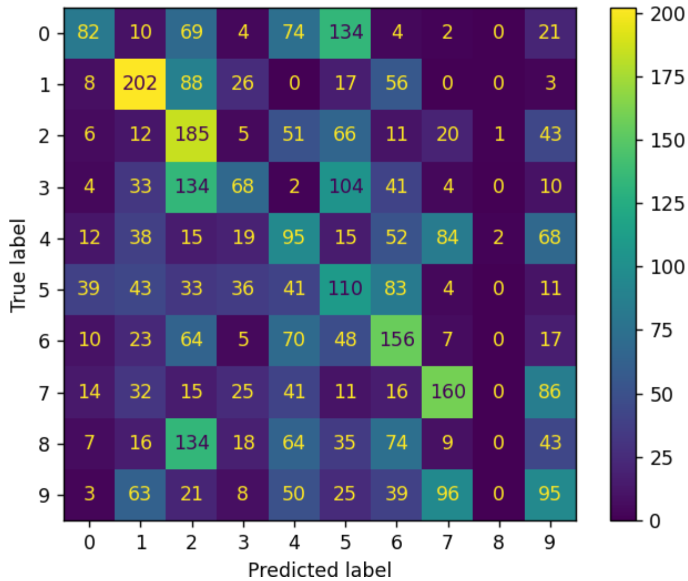

Figure 2: Confusion Matrix displaying the classification of labels during model training

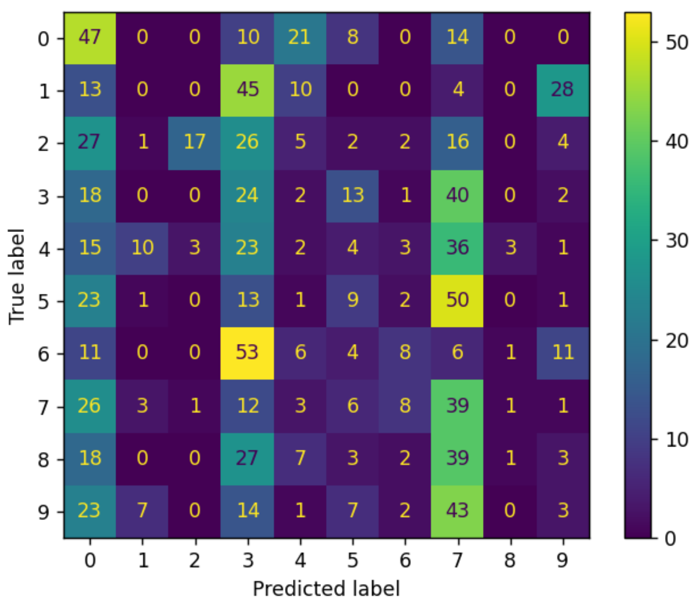

Figure 3: Confusion Matrix displaying the classification of labels during model testing

3 Analysis of Results

The results of the Integrated Neural Network system using Self-Organizing Feature Maps for the MNIST dataset demonstrate a progressive learning approach over 50 epochs for SOFM training and 20 epochs for the neural network. The SOFM training shows a gradual decrease in learning rate and radius, indicative of the network's adaptation to the dataset's features. However, the system's performance in classification, as indicated by the confusion matrix and accuracy metrics, suggests room for improvement (Figure 2). The accuracy on the training set stands at around 28.8%, with a similar F1 score, reflecting a moderate level of recognition capability. In the testing phase, the accuracy drops to 15%, highlighting a potential overfitting issue or an inadequacy in the training process to generalize well on unseen data. The confusion matrix from both training and testing phases reveals that certain digits are more challenging for the system to classify correctly, leading to a significant number of misclassifications (Figure 3). These results underscore the need for further optimization of the network's parameters, a potential increase in training epochs, or adjustments to enhance the model's generalization capabilities and overall accuracy in digit classification