HUCENROTIA LAB

Machine Learning
LABORATORY: Deep Neural Network

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Objectives:

- Understand and implement the forward pass of a neural network using matrix operations.
- Apply activation functions based on textbook equations to non-linearize the model.
- Use softmax and cross-entropy loss for multi-class classification tasks.
- Experiment with different layer configurations to observe the effect on model accuracy.
- Evaluate classifier performance using confusion matrix, ROC, and standard metrics (precision, recall, accuracy, F1-score).

Part 1. Instruction

- In this assignment, you will build a multilayer feedforward neural network using **only NumPy and Matplotlib** to solve a **multi-class classification** problem on the **MNIST dataset**. You **must** use the **dataset provided by the TA.** Use only **NumPy** for matrix operations and **Matplotlib/Seaborn** for plotting. Implement the forward pass only, without backpropagation.
- Follow the arithmetic instructions and code template provided in Part 3 of this lab. Evaluate your model using accuracy, confusion matrix, and ROC curves.
- You need to try experiment with different activation functions and network structures to **improve your model's performance.**

Part 2. Arithmetic Instructions.

Step | **Procedure**

1 Activation Function- Refer to equation 6.14 – 6.18

2 Multilayer Feedforward

- Refer to Equation 6.7-6.9
- Equation 6.19:

$$z^{(l)} = h^{(l)}(W^{(l)}z^{(l-1)})$$

3 Cross Entropy and one-hot encoding – Equation 6.36:

$$E(\mathbf{w}) = -\sum_{n=1}^{N}\sum_{k=1}^{K} t_{kn}\ln\, y_k(\mathbf{x}_n, \mathbf{w})$$

SoftMax Function – Equation 6.37:

$$y_k(\mathbf{x}, \mathbf{w}) = \frac{\exp\,(a_k(\mathbf{x}, \mathbf{w}))}{\sum_j\, \exp\,\left(a_j(\mathbf{x}, \mathbf{w})\right)}$$

5 Evaluation using Confusion Matrix, ROC, Accuracy, Precision, Recall
Refer to the previous Labs

Part 3. Data Transfer Instructions.

Step Procedure

1 #Load Dataset

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import struct
import pandas as pd

# === Step 1: Load MNIST Dataset ===
def load_mnist_images(filename):
    with open(filename, 'rb') as f:
        _, num, rows, cols = struct.unpack(">IIII", f.read(16))
        images = np.frombuffer(f.read(), dtype=np.uint8).reshape(num, rows * cols)
        return images / 255.0

def load_mnist_labels(filename):
    with open(filename, 'rb') as f:
        _, num = struct.unpack(">II", f.read(8))
        labels = np.frombuffer(f.read(), dtype=np.uint8)
        return labels
 # Students can experiment to modify number of Train
X_train = load_mnist_images("train-images.idx3-ubyte__")[:500]
y_train = load_mnist_labels("train-labels.idx1-ubyte__")[:500]
X_test = load_mnist_images("t10k-images.idx3-ubyte__")[:200]
y_test = load_mnist_labels("t10k-labels.idx1-ubyte__")[:200]
```

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```
# === Step 2: Activation Functions (Refer to Eq. 6.14 - 6.18) ===
def relu(x): return None
def tanh(x): return None
def softplus(x): return None
def leaky_relu(x, alpha=0.1): return None

def one_hot(y, num_classes=10): # Refer to Equation 6.36
    return None
def cross_entropy(y_pred, y_true): # Refer to Equation 6.36
    return None
def softmax(a): # Refer to Equation 6.37
    return None

def forward_pass(X, weights, activations): # Forward Pass (Eq. 6.19) ===
    return None
```

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```
# === Step 3: Training Loop === # Students can experiment to modify
np.random.seed(42)
input_size = 784
hidden1 = 64
hidden2 = 32
output_size = 10
epochs = 30
best_loss = float('inf')
best_weights = None
```

```
for epoch in range(epochs):
    # TODO: Randomly initialize weights for each layer
    W1 = None
    W2 = None
    W3 = None

    weights = [W1, W2, W3]
    activations = [relu, relu, softmax]  # Students can experiment to modify
```

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```
# === Step 4: Evaluation Metrics (Confusion Matrix, ROC, etc) ===
def compute_confusion_matrix(y_true, y_pred, num_classes=10): return None

# === ROC Curve ===
def compute_roc(y_true_oh, y_pred_proba):  return None

# === Classification Report === Print TP, FP, FN, TN, precision, recall, f1, accuracy
def compute_metrics(cm): return None

print("=== Classification Report === Print TP, FP, FN, TN, precision, recall, f1 for each
class and overall accuracy")
```

Grading Assignment & Submission (70% Max)

Implementation (50%):

1. (10%) Implement a Feedforward Neural Network with More Than One Hidden Layer.
2. (10%) Activation functions implemented from scratch (Eq. 6.14–6.18), and Softmax output and cross-entropy loss (Eq. 6.36 & 6.37).
3. (15%) Model runs correctly and generates prediction results.
4. Evaluation:
    a. (5%) Confusion matrix (plotted),
    b. (5%) ROC curve for 10 classes (plotted),
    c. (5%) Precision, Recall, F1, Overall Accuracy

Question (20%):

1. Explain how you designed your model (number of layers, neurons, and activation functions). What changes did you make to improve the accuracy, and how did those changes affect the results? *Please attach the performance results before and after your improvements.
2. Based on your evaluation results (confusion matrix, ROC, etc.), how well did the model perform? Which classes are harder to predict? Why do you think that happened?

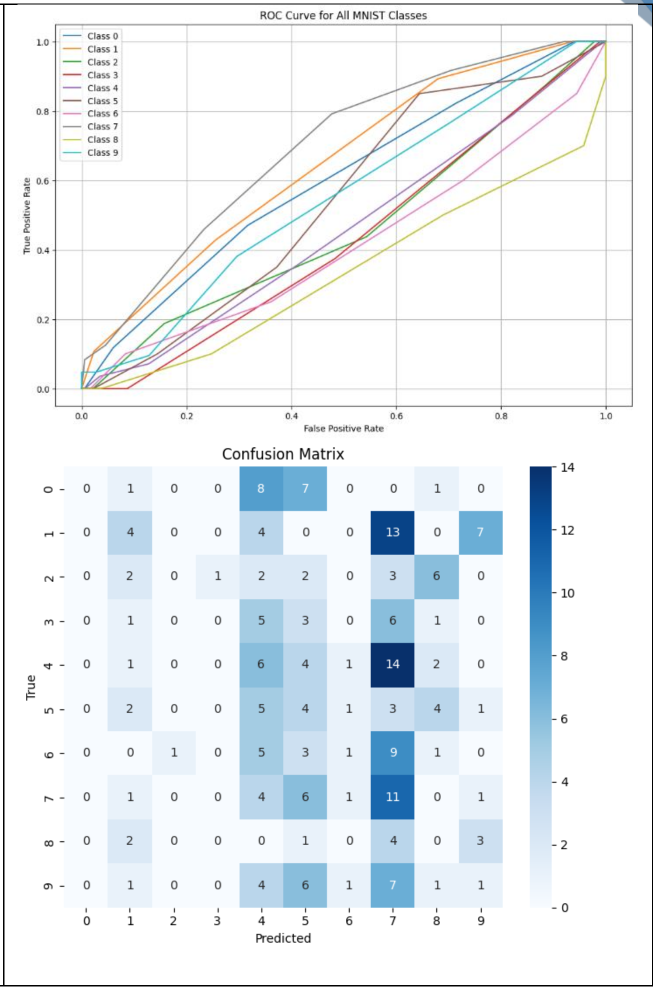
Submission :

1. Report: Answer all conceptual questions. Include screenshots of your results in the last pages of this PDF File.
2. Code: Submit your complete Python script in either .py or .ipynb format.
3. Upload both your report and code to the E3 system (**Labs3 Homework Assignment**). Name your files correctly:
    a. Report: StudentID_Lab3_Homework.pdf
    b. Code: StudentID_Lab3_ Homework.py or StudentID_Lab3_ Homework.ipynb
4. Deadline: Sunday – 21:00 PM
5. Plagiarism is **strictly prohibited**. Submitting copied work from other students will result in penalties.

Lecture: Prof. Hsien-I Lin
TA: Satrio Sanjaya and Muhammad Ahsan

Example Output (Just for reference):

```
Class 1:
  TP: 4, FP: 11, FN: 24, TN: 161
  Precision: 0.2667
  Recall:    0.1429
  F1 Score:  0.1860

Class 2:
  TP: 0, FP: 1, FN: 16, TN: 183
  Precision: 0.0000
  Recall:    0.0000
  F1 Score:  0.0000

Class 3:
  TP: 0, FP: 1, FN: 16, TN: 183
  Precision: 0.0000
  Recall:    0.0000
  F1 Score:  0.0000

Class 4:
  TP: 6, FP: 37, FN: 22, TN: 135
  Precision: 0.1395
  Recall:    0.2143
  F1 Score:  0.1690

Class 5:
  TP: 4, FP: 32, FN: 16, TN: 148
  Precision: 0.1111
  Recall:    0.2000
  F1 Score:  0.1429

Class 6:
  TP: 1, FP: 4, FN: 19, TN: 176
  Precision: 0.2000
  Recall:    0.0500
  F1 Score:  0.0800

Class 7:
  TP: 11, FP: 59, FN: 13, TN: 117
  Precision: 0.1571
  Recall:    0.4583
  F1 Score:  0.2340

Class 8:
  TP: 0, FP: 16, FN: 10, TN: 174
  Precision: 0.0000
  Recall:    0.0000
  F1 Score:  0.0000

Class 9:
  TP: 1, FP: 12, FN: 20, TN: 167
  Precision: 0.0769
  Recall:    0.0476
  F1 Score:  0.0588

Overall Accuracy: 0.1350
```



Code Results and Answer:

A1:

Default model settings:
Input size: 784
Hidden1: 64
Activation 1: relu
Hidden 2: 32
Activation 2: relu
Output size: 10
Activation 3: softmax

Hyperparameters:
Epochs: 30
learning_rate=0.01
seed=42

Improved model settings:
Input size: 784
Hidden1: 256
Activation 1: relu
Hidden 2: 128
Activation 2: relu
Output size: 10
Activation 3: softmax

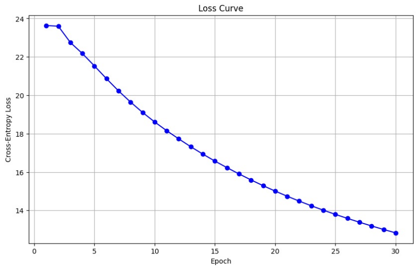
Hyperparameters:
Epochs: 60
learning_rate=0.01
seed=42

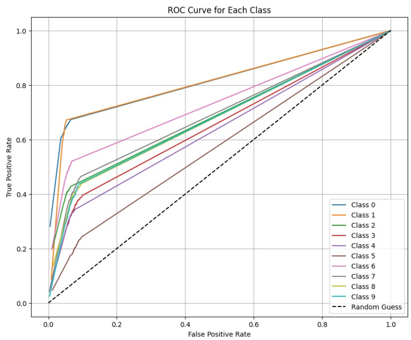
Increased hidden layer size, training epochs.
Overall accuracy significantly improved from 0.6133 (61.33%) to 0.7674 (76.74%).
The loss curve indicates better convergence, reaching a lower and more stable loss after improvements.

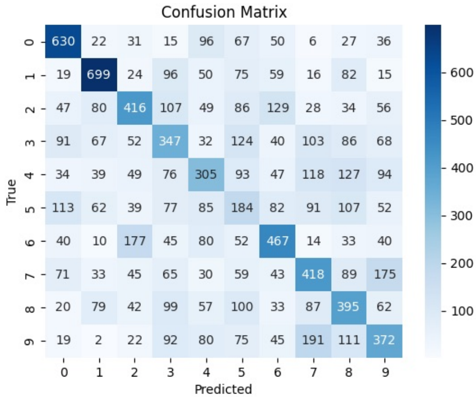
The results are presented on the next page.

Default model results:

```
=== Classification Report === Print TP, FP
Class 0:
TP: 630, FP: 454, FN: 350, TN: 8566
Precision: 0.5812
Recall: 0.6429
F1 Score: 0.6105
Class 1:
TP: 699, FP: 394, FN: 436, TN: 8471
Precision: 0.6395
Recall: 0.6159
F1 Score: 0.6275
Class 2:
TP: 416, FP: 481, FN: 616, TN: 8487
Precision: 0.4638
Recall: 0.4031
F1 Score: 0.4313
Class 3:
TP: 347, FP: 672, FN: 663, TN: 8318
Precision: 0.3405
Recall: 0.3436
F1 Score: 0.3420
Class 4:
TP: 305, FP: 559, FN: 677, TN: 8459
Precision: 0.3530
Recall: 0.3106
F1 Score: 0.3304
Class 5:
TP: 184, FP: 731, FN: 708, TN: 8377
Precision: 0.2011
Recall: 0.2063
F1 Score: 0.2037
Class 6:
TP: 467, FP: 528, FN: 491, TN: 8514
Precision: 0.4693
Recall: 0.4875
F1 Score: 0.4782
Class 7:
TP: 418, FP: 654, FN: 610, TN: 8318
Precision: 0.3899
Recall: 0.4066
F1 Score: 0.3981
Class 8:
TP: 395, FP: 696, FN: 579, TN: 8330
Precision: 0.3621
Recall: 0.4055
F1 Score: 0.3826
Class 9:
TP: 372, FP: 598, FN: 637, TN: 8393
Precision: 0.3835
Recall: 0.3687
F1 Score: 0.3759
Overall Accuracy: 0.4233
```

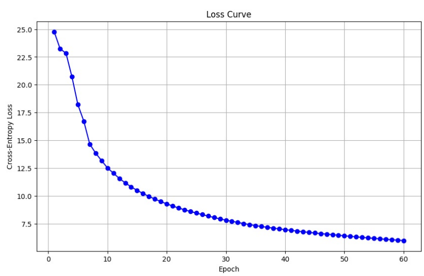


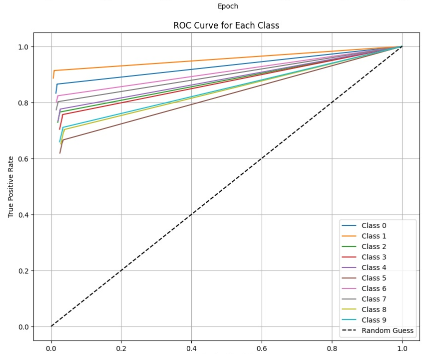


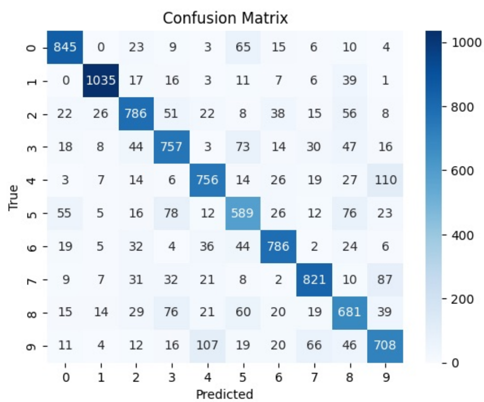


Improved model results:

```
=== Classification Report === Print TP, FP
Class 0:
TP: 845, FP: 152, FN: 135, TN: 8868
Precision: 0.8475
Recall: 0.8622
F1 Score: 0.8548
Class 1:
TP: 1035, FP: 76, FN: 100, TN: 8789
Precision: 0.9316
Recall: 0.9119
F1 Score: 0.9216
Class 2:
TP: 786, FP: 218, FN: 246, TN: 8750
Precision: 0.7829
Recall: 0.7616
F1 Score: 0.7721
Class 3:
TP: 757, FP: 288, FN: 253, TN: 8702
Precision: 0.7244
Recall: 0.7495
F1 Score: 0.7367
Class 4:
TP: 756, FP: 228, FN: 226, TN: 8790
Precision: 0.7683
Recall: 0.7699
F1 Score: 0.7691
Class 5:
TP: 589, FP: 302, FN: 303, TN: 8806
Precision: 0.6611
Recall: 0.6603
F1 Score: 0.6607
Class 6:
TP: 786, FP: 168, FN: 172, TN: 8874
Precision: 0.8239
Recall: 0.8205
F1 Score: 0.8222
Class 7:
TP: 821, FP: 175, FN: 207, TN: 8797
Precision: 0.8243
Recall: 0.7986
F1 Score: 0.8113
Class 8:
TP: 681, FP: 335, FN: 293, TN: 8691
Precision: 0.6703
Recall: 0.6992
F1 Score: 0.6844
Class 9:
TP: 708, FP: 294, FN: 301, TN: 8697
Precision: 0.7066
Recall: 0.7017
F1 Score: 0.7041
Overall Accuracy: 0.7764
```







A2:

Based on the evaluation results, the improved model performed significantly better overall, achieving approximately 76.74% accuracy, a clear enhancement compared to the original 61.33%.

Classes Harder to Predict:

- Class "5" showed the poorest performance, with lower precision, recall, and F1-score compared to other classes. The confusion matrix clearly indicates frequent misclassifications, particularly between "5" and similar digits such as "3", "6", or "8".

Possible Reasons for Class "5" Underperformance:

1. Similarity in shape with other digits:
   The digit "5" visually resembles digits like "3", "6", "8", and even "9", making it challenging for the model to distinguish these subtle differences.
2. Data Imbalance or quality:
   It could also result from the intrinsic nature of MNIST, where certain digits have slightly less consistent representations or more varied stroke patterns.