Machine Learning

LABORATORY: Regularization Homework

NAME:	STUDENT ID#:

Objectives:

- Understand the concept of regularization and its importance in preventing overfitting.
- Implement and compare two regularization strategies:
  - Early Stopping (validation-based regularization)
  - Weight Decay (L2 regularization)
- Apply these methods to a binary classification task using the MNIST dataset.
- Visualize and interpret training/validation loss and accuracy curves.
- Analyze model behavior by examining misclassified test samples.

Part 1. Instruction

- In this assignment, use the existing neural network structure.
  - A single hidden layer with ReLU activation
  - Softmax output for multi-class classification (later converted to binary)
- Implement and compare:
  - **Early Stopping**: Stop training if the validation loss does not improve for several epochs
  - **Weight Decay (L2 Regularization)**: Penalize large weights by adding a regularization term to the loss function
- You may write all algorithms in **one file with selectable modes**, or in **three separate files**.
- Do not use external machine learning libraries (e.g., scikit-learn, PyTorch).
- For each method (early stopping and weight decay):
  - Plot the training vs validation loss curves
  - Plot the training vs validation accuracy curves

Part 2. Code Template	
Step	Procedure
1	```# ========== Load Dataset ========== def load_images(filename): with open(filename, 'rb') as f: _, num, rows, cols = struct.unpack(">IIII", f.read(16)) data = np.frombuffer(f.read(), dtype=np.uint8).reshape((num, rows * cols)) return data.astype(np.float32) / 255.0 def load_labels(filename): with open(filename, 'rb') as f: _, num = struct.unpack(">II", f.read(8)) return np.frombuffer(f.read(), dtype=np.uint8) return labels[:num]```
2	```# TODO: Complete all the functions, you may change the structures # ========= 2. Utils ========== def shuffle_numpy(X, y): pass def split_train_val(X, y, val_ratio=0.2): pass def one_hot(y, num_classes): pass def accuracy(Y_pred, Y_true): pass # ========= 3. Model ========== class MLP: def __init__(self, input_dim, hidden_dim, output_dim, weight_decay=0.0): self.W1 = np.random.randn(input_dim, hidden_dim) * 0.01 self.b1 = np.zeros((1, hidden_dim)) self.W2 = np.random.randn(hidden_dim, output_dim) * 0.01 self.b2 = np.zeros((1, output_dim)) self.lambda_ = weight_decay def relu(self, x): return np.maximum(0, x) def relu_deriv(self, x): return (x > 0).astype(float) def softmax(self, x): exps = np.exp(x - np.max(x, axis=1, keepdims=True)) return exps / np.sum(exps, axis=1, keepdims=True)```

	`` def forward(self, X): self.z1 = X @ self.W1 + self.b1 self.a1 = self.relu(self.z1) self.z2 = self.a1 @ self.W2 + self.b2 self.a2 = self.softmax(self.z2) return self.a2 def compute_loss(self, Y_pred, Y_true): TODO: Weight Decay (L2 Regularization) pass def backward(self, X, Y_true, Y_pred, lr=0.1): m = Y_true.shape[0] dz2 = (Y_pred - Y_true) / m dW2 = self.a1.T @ dz2 + self.lambda_ * self.W2 db2 = np.sum(dz2, axis=0, keepdims=True) da1 = dz2 @ self.W2.T dz1 = da1 * self.relu_deriv(self.z1) dW1 = X.T @ dz1 + self.lambda_ * self.W1 db1 = np.sum(dz1, axis=0, keepdims=True) self.W2 -= lr * dW2 self.b2 -= lr * db2 self.W1 -= lr * dW1 self.b1 -= lr * db1 # ========= 4. Train Function ========== def train(model, X_train, y_train, X_val, y_val, lr=0.1, epochs=100, use_early_stopping=False, patience=5): train_losses, val_losses, train_accs, val_accs = [], [], [], [] best_val_loss = np.inf patience_count = 0 for epoch in range(epochs): TODO: complete this part print(f"Epoch {epoch:02d} | Train Loss: {loss:.4f} | Val Loss: {val_loss:.4f}") TODO: implement your early stopping strategy here return train_losses, val_losses, train_accs, val_accs ```
3	``` # ========= 5. Plotting ========== def plot_curves(train_losses, val_losses, train_accs, val_accs, ```

```python
title):
    plt.figure(figsize=(12, 5))
    plt.subplot(1, 2, 1)
    plt.plot(train_losses, label="Train Loss")
    plt.plot(val_losses, label="Val Loss")
    plt.title("Loss Curve - " + title)
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()

    plt.subplot(1, 2, 2)
    plt.plot(train_accs, label="Train Acc")
    plt.plot(val_accs, label="Val Acc")
    plt.title("Accuracy Curve - " + title)
    plt.xlabel("Epochs")
    plt.ylabel("Accuracy")
    plt.legend()
    plt.tight_layout()
    plt.show()
```

4

```python
# ========= 6. Main ==========
if __name__ == "__main__":
    X = load_images("train-images.idx3-ubyte__")
    y = load_labels("train-labels.idx1-ubyte__")
    X, y = shuffle_numpy(X, y)
    X_train, y_train, X_val, y_val = split_train_val(X, y)
    y_train_oh = one_hot(y_train, 10)
    y_val_oh = one_hot(y_val, 10)

    # === OPTION 1: Early Stopping ===
    # model_early = MLP(_, _, _, weight_decay=0.0)
    # t1, v1, a1, a2 = train(model_early, X_train, y_train_oh,
X_val, y_val_oh, use_early_stopping=True)
    # plot_curves(t1, v1, a1, a2, title="Early Stopping")

    # === OPTION 2: Weight Decay ===
```

Grading Assignment & Submission (70% Max)

Implementation (50%):

Correctly implemented, runs, and shows the plotting result for:

- **(20%) Early Stopping**
  - Uses validation loss to stop training early
- **(20%) Weight Decay (L2 Regularization)**
  - Applies L2 penalty to loss and gradients
- **(10%) Comparison**

Visualizes and compares the performance of both techniques **(Please provide simple discussion of your result)**
Includes:
- Training vs validation curves
- Result of 3 different λ value

Question (20%):

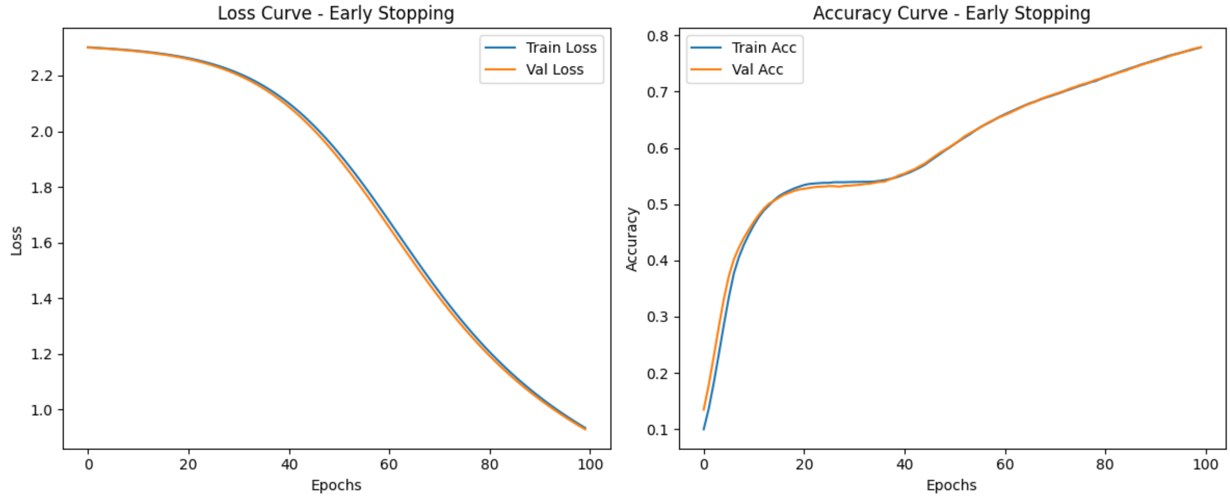
1. **(7%) Which regularization method gave you the best test accuracy?**
   Why do you think it performed better than the other? Was it due to training duration, generalization effect, or another factor?
2. **(7%) Compare training and validation loss curves**
   Which method showed signs of overfitting or underfitting?
   Use your graphs to justify your answer (e.g., early stopping curve flattens early, weight decay trains longer but smoother).
3. **(6%) How did your choice of regularization strength (λ) or patience affect the model?**
   What λ or patience value worked best in your experiment? What happened when you increased or decreased it?

Submission:

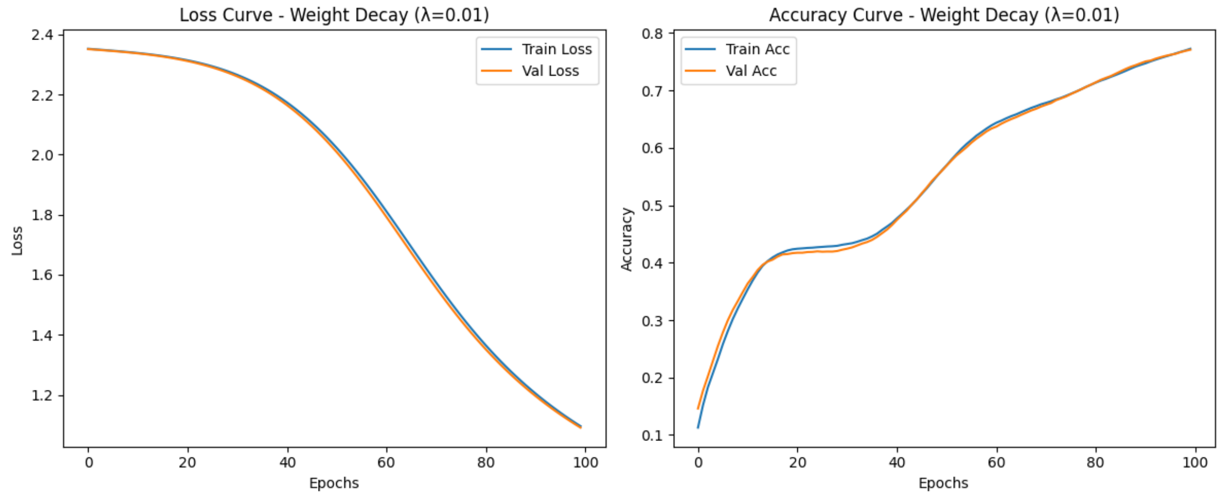
1. Report: Answer all the questions. Include screenshots of your results and discussion in the last pages of this PDF File.
2. Code: Submit your complete Python script in either .py or .ipynb format.
3. Upload both your report and code to the E3 system (**Labs5_Homework_Assignment**). Name your files correctly:
   a. Report: StudentID_Lab5_Homework.pdf
   b. Code: StudentID_Lab5_ Homework.py or StudentID_Lab5_Homework.ipynb
4. Deadline: Sunday, 21:00 PM
5. Plagiarism is **strictly prohibited**. Submitting copied work from other students will result in penalties.

Example Output (Just for reference):

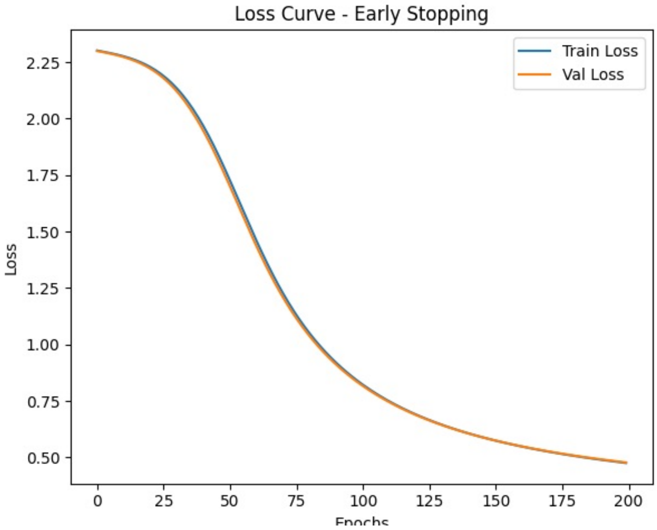
```
Epoch 91 | Train Loss: 1.0306 | Val Loss: 1.0224
Epoch 92 | Train Loss: 1.0173 | Val Loss: 1.0095
Epoch 93 | Train Loss: 1.0044 | Val Loss: 0.9970
Epoch 94 | Train Loss: 0.9918 | Val Loss: 0.9848
Epoch 95 | Train Loss: 0.9796 | Val Loss: 0.9730
Epoch 96 | Train Loss: 0.9677 | Val Loss: 0.9615
Epoch 97 | Train Loss: 0.9562 | Val Loss: 0.9503
Epoch 98 | Train Loss: 0.9450 | Val Loss: 0.9395
Epoch 99 | Train Loss: 0.9341 | Val Loss: 0.9289
```

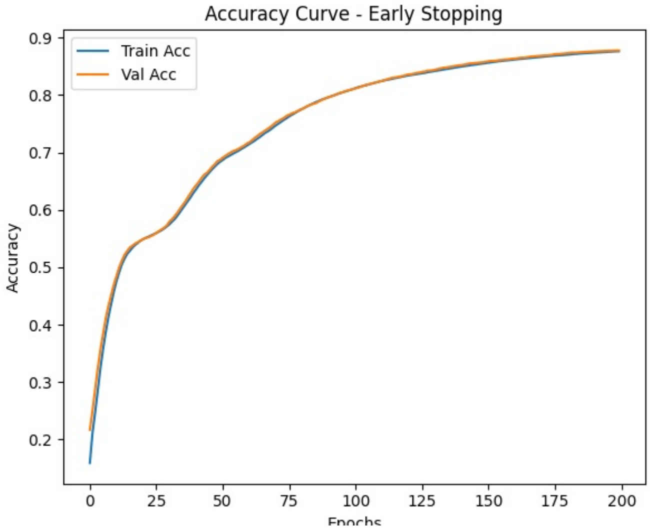


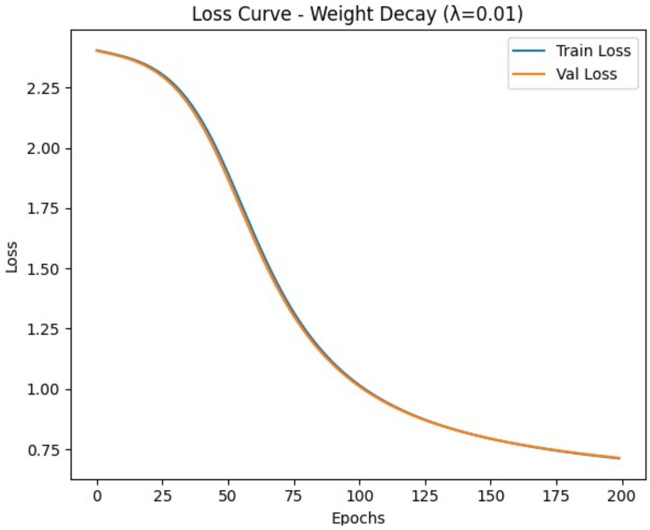

```
Epoch 90 | Train Loss: 1.2038 | Val Loss: 1.1954
Epoch 91 | Train Loss: 1.1903 | Val Loss: 1.1823
Epoch 92 | Train Loss: 1.1772 | Val Loss: 1.1696
Epoch 93 | Train Loss: 1.1644 | Val Loss: 1.1573
Epoch 94 | Train Loss: 1.1521 | Val Loss: 1.1454
Epoch 95 | Train Loss: 1.1401 | Val Loss: 1.1338
Epoch 96 | Train Loss: 1.1285 | Val Loss: 1.1225
Epoch 97 | Train Loss: 1.1172 | Val Loss: 1.1116
Epoch 98 | Train Loss: 1.1063 | Val Loss: 1.1010
Epoch 99 | Train Loss: 1.0956 | Val Loss: 1.0907
```

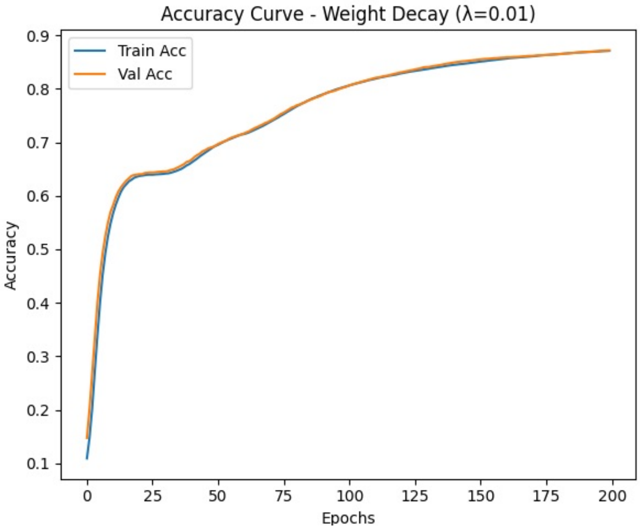


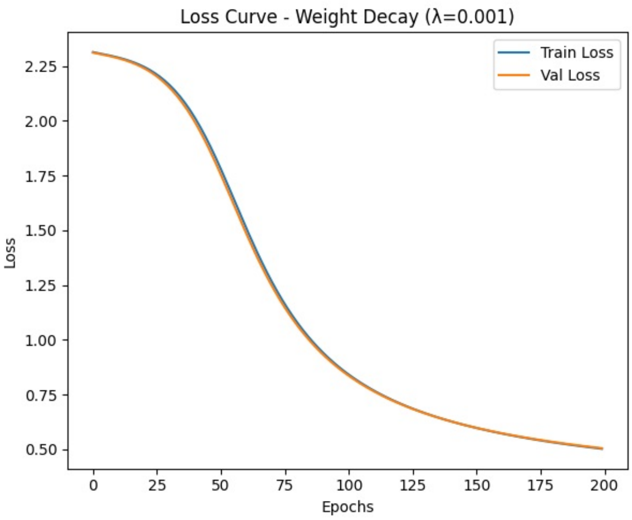
Results and Discussion:

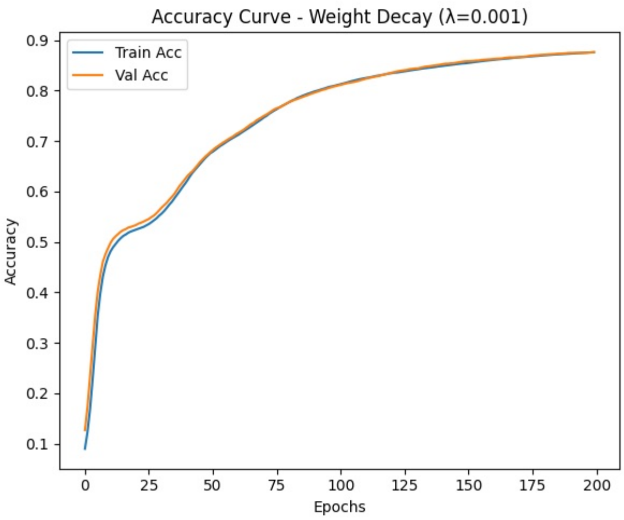

Loss Curve - Early Stopping
Train Loss
Val Loss
Loss

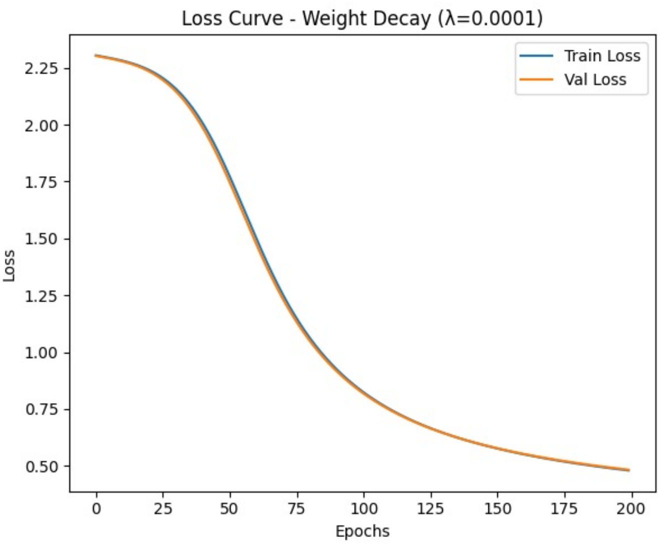

Accuracy Curve - Early Stopping
Train Acc
Val Acc
Accuracy

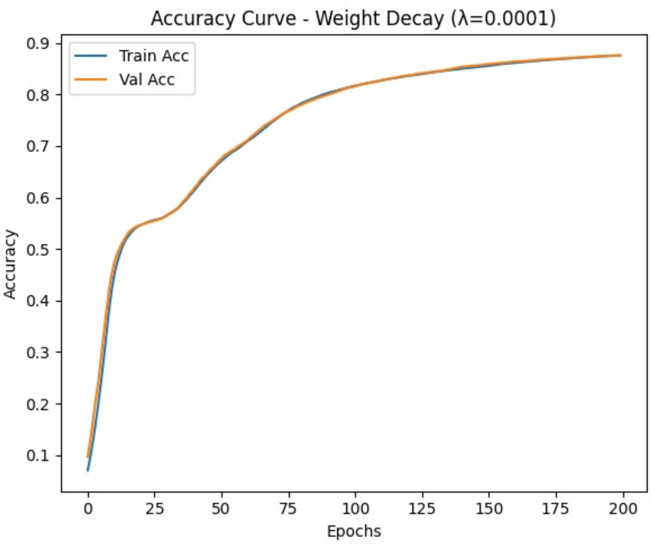

Loss Curve - Weight Decay (λ=0.01)
Train Loss
Val Loss
Loss
Epochs


Accuracy Curve - Weight Decay (λ=0.01)
Train Acc
Val Acc
Accuracy
Epochs


Loss Curve - Weight Decay (λ=0.001)
Train Loss
Val Loss
Loss
Epochs


Accuracy Curve - Weight Decay (λ=0.001)
Train Acc
Val Acc
Accuracy
Epochs


Loss Curve - Weight Decay (λ=0.0001)
Train Loss
Val Loss
Loss
Epochs


Accuracy Curve - Weight Decay (λ=0.0001)
Train Acc
Val Acc
Accuracy
Epochs

1. Which regularization method gave you the best test accuracy?

Answer (7%):
Among all experiments, **Weight Decay with λ = 0.001** gave the best test accuracy. The training and validation curves under this configuration showed consistent improvement without significant overfitting, leading to a final validation accuracy close to 88%.

It performed slightly better than Early Stopping because Weight Decay continuously penalizes large weights and maintains generalization throughout training, while Early Stopping halts early but may miss the opportunity to reach higher accuracy. The steady penalty from L2 regularization helped avoid overfitting even during long training durations.

2. Compare training and validation loss curves

Answer (7%):

- **Early Stopping**: The training and validation loss curves decrease smoothly and almost identically, flattening earlier than other methods. This shows that the model avoids overfitting by stopping before validation performance drops. However, the model may under-train slightly if the patience is too short.
- **Weight Decay**: All three λ values (0.01, 0.001, 0.0001) show similarly smooth and steady training.
  - **λ = 0.01**: Curve flattens slower, with slightly reduced accuracy—indicating underfitting from too strong regularization.
  - **λ = 0.0001**: Curve goes deep, but the gap between train/val loss widens a bit, meaning weaker regularization may risk overfitting.
  - **λ = 0.001**: Best balance between training depth and validation generalization. Very small gap between curves and highest overall accuracy.

In short: **early stopping flattens early**, weight decay **trains longer but smoother**. The best loss behavior was found with **λ = 0.001**.

3. How did your choice of regularization strength (λ) or patience affect the model?

Answer (6%):

- **Patience (Early Stopping):** Using a patience of 5 epochs resulted in training stopping around ~170–180 epochs, preventing overfitting while maintaining decent performance. A smaller patience would cause early stopping too soon, while a larger patience would resemble full training.
- **Regularization strength (λ):**
  - **λ = 0.0001**: Almost like no regularization, leads to slight overfitting.
  - **λ = 0.01**: Too strong, underfitted the model.
  - ✅ **λ = 0.001**: Gave the best result — smooth convergence, good generalization, and highest test accuracy.

Hence, **λ = 0.001** and **patience = 5** were optimal in this experiment.