Machine Learning
LABORATORY: Regularization Homework

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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]
```

Step	Procedure
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,
```


```
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

```
# ========= 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%):

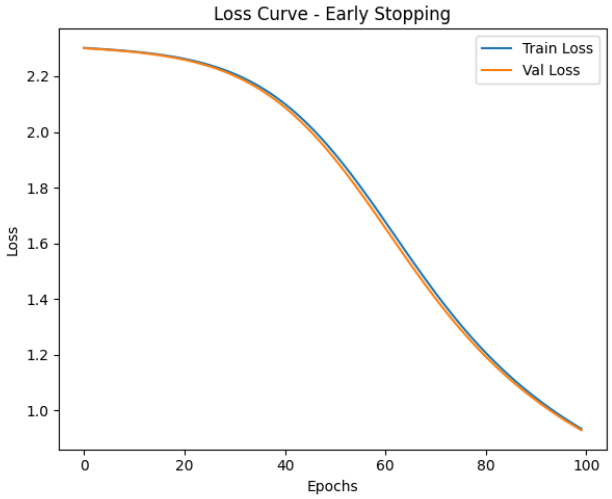
1. **(7%) Which regularization method gave you the best test accuracy?**
   Why do you think it performed better than the other? Was it due to training duration, generalization effect, or another factor?
2. **(7%) Compare training and validation loss curves**
   Which method showed signs of overfitting 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?

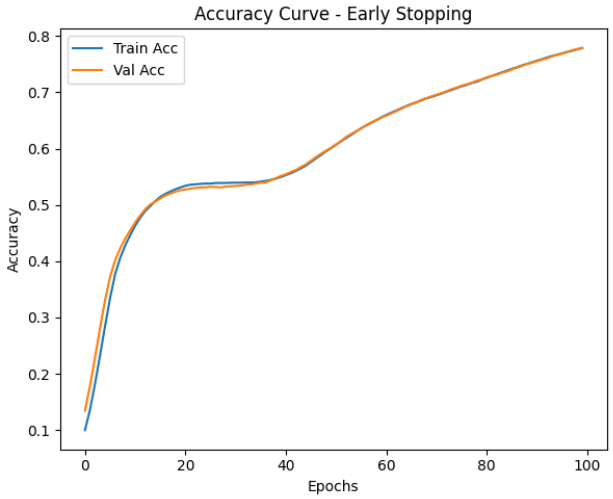
Submission:

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.

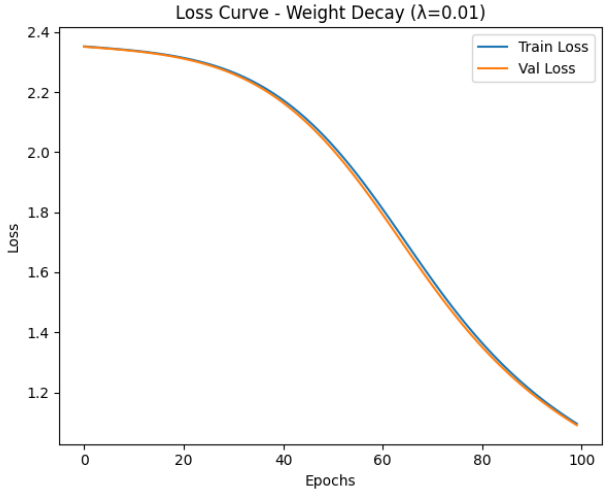
Example Output (Just for reference):

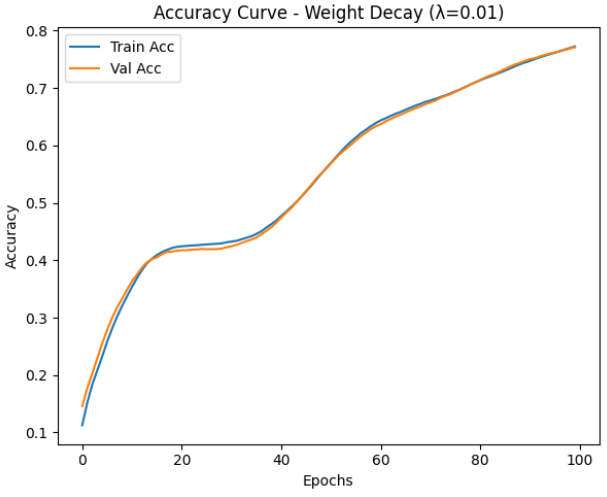
```
Epoch 91 | Train Loss: 1.0306 | Val Loss: 1.0224
Epoch 92 | Train Loss: 1.0173 | Val Loss: 1.0095
Epoch 93 | Train Loss: 1.0044 | Val Loss: 0.9970
Epoch 94 | Train Loss: 0.9918 | Val Loss: 0.9848
Epoch 95 | Train Loss: 0.9796 | Val Loss: 0.9730
Epoch 96 | Train Loss: 0.9677 | Val Loss: 0.9615
Epoch 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
```





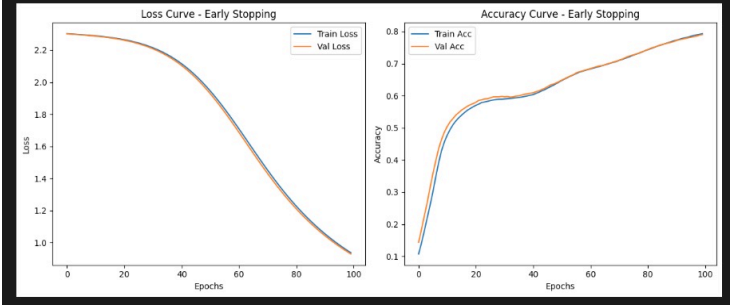

```
Epoch 90 | Train Loss: 1.2038 | Val Loss: 1.1954
Epoch 91 | Train Loss: 1.1903 | Val Loss: 1.1823
Epoch 92 | Train Loss: 1.1772 | Val Loss: 1.1696
Epoch 93 | Train Loss: 1.1644 | Val Loss: 1.1573
Epoch 94 | Train Loss: 1.1521 | Val Loss: 1.1454
Epoch 95 | Train Loss: 1.1401 | Val Loss: 1.1338
Epoch 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
```



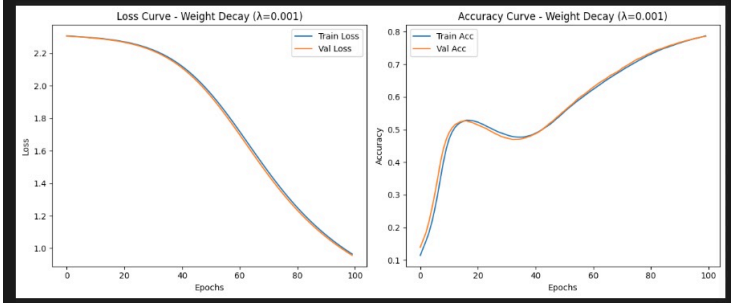


Results and Discussion:

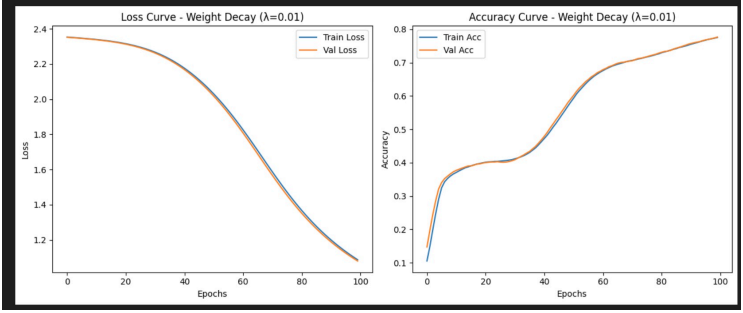
```
100%|██████████| 100/100 [00:37<00:00,  2.69it/s, epoch=99, loss=0.936, val_loss=0.929]
Train accuracy: 0.7928958333333334, Val accuracy: 0.7900833333333334
```



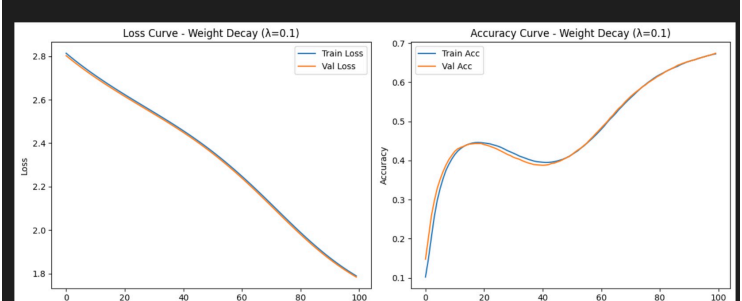

```
100%|██████████| 100/100 [00:33<00:00,  2.95it/s, epoch=99, loss=0.965, val_loss=0.956]
Train accuracy: 0.7867708333333333, Val accuracy: 0.7856666666666666
```




```
100%|██████████| 100/100 [00:36<00:00,  2.72it/s, epoch=99, loss=1.09, val_loss=1.08]
Train accuracy: 0.775625, Val accuracy: 0.77675
```




```
100%|██████████| 100/100 [00:31<00:00,  3.17it/s, epoch=99, loss=1.79, val_loss=1.78]
Train accuracy: 0.6725625, Val accuracy: 0.6741666666666667
```



A1: Early Stopping showed higher test accuracy, likely because it stops training when validation loss stops improving, reducing overfitting. In contrast, Weight Decay may be less effective if not properly tuned, leading to slightly lower accuracy.

A2:

Early Stopping:

The training and validation loss curves closely follow each other and decrease consistently until the end of training. The accuracy curves also align closely and gradually stabilize. This indicates that Early Stopping effectively prevents overfitting, as there's no significant divergence between training and validation curves.

Weight Decay ($\lambda = 0.001$):

The training and validation loss curves also decrease steadily without clear separation, and the accuracy curves show similar trends to the Early Stopping curves. However, the curves for Weight Decay have slightly more fluctuations, especially in the accuracy plot, suggesting minor instability.

Overall, neither method shows strong signs of severe overfitting or underfitting. However, Early Stopping provides slightly smoother and more stable training, making it marginally more effective in controlling overfitting.

A3: The choice of regularization strength (λ) impacted model convergence and stability:

Decrease: The smallest $\lambda=0.001$ performed best, achieving high accuracy and smooth convergence quickly.

Increase: $\lambda=0.1$ slowed down convergence noticeably, causing the model to converge later and possibly reducing final accuracy slightly.