

Bangladesh University of Engineering and Technology

Machine Learning Sessional CSE 472

Assignment 3

Function Approximation with Neural Network and Backpropagation

Report

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1 Introduction

This report covers the training and evaluation of three neural network architectures on the Fashion-MNIST dataset using four learning rates. Performance is measured by training/validation loss, accuracy, and F1 scores. The model with the highest validation macro-F1 score is chosen and tested on an independent set.

2 Running the Code

To run the code provided, please follow these steps:

- 1. Install Necessary Libraries
- 2. Set Up the Dataset
- 3. Execute the Training Script
- 4. Save the Best Model
- 5. Test the Best Model on Independent Dataset

All these steps can be completed by running the 1905027.ipynb file following the order of the cells in the ipynb file.

3 Data Loading and Preprocessing

The dataset for this report is the Fashion-MNIST, a common benchmark for computer vision tasks. It is loaded and preprocessed using torchvision, with normalization applied to the input images. The images are flattened into $28 \times 28 = 784$ -dimensional vectors for use in the fully connected neural networks.

```
# Data Loading and Preprocessing
def preprocess(dataset):
    images = []
    labels = []
    for image, label in dataset:
        image = np.array(image).flatten() / 255.0 # Flatten and normalize to [0, 1]
        label_onehot = np.zeros(10) # One-hot encoding
        label_onehot[label] = 1
        images.append(image)
        labels.append(label_onehot)

# Convert lists to NumPy arrays
    images = np.array(images)
    labels = np.array(labels)
    return images, labels
```

```
# Load Data Function

def load_data():
    train_dataset = ds.FashionMNIST(root='./data', train=True, transform=transforms.ToTensor(), download=True)
    test_dataset = ds.FashionMNIST(root='./data', train=False, transform=transforms.ToTensor(), download=True)

X_train, Y_train = preprocess(train_dataset)
    X_test, Y_test = preprocess(test_dataset)
    return X_train, Y_train, X_test, Y_test

✓ 0.0s
```

4 Model Architectures

We implemented three different neural network architectures to compare performance:

- 1. **Model 1:** A simple two-layer network with 256 neurons in the hidden layer, followed by a ReLU activation and a 10-class Softmax output layer.
- 2. Model 2: A deeper network with two hidden layers, first with 128 neurons and then 256 neurons, both using ReLU activation, followed by a Softmax output.
- 3. Model 3: The most complex model with three hidden layers, progressively increasing in size (64, 128, and 256 neurons), each followed by ReLU, and a Softmax output layer for classification.

Each model aims to classify the 28x28 input images into 10 categories.

5 Training and Validation Metrics

For each training epoch, the following metrics are recorded:

- Train Loss
- Train Accuracy
- Val Loss (Validation Loss)
- Val Accuracy (Validation Accuracy)

For each learning rate of a model, the following metrics are recorded:

- Accuracy
- Validation Macro-F1 Score

6 Results for Different Models and Learning Rates

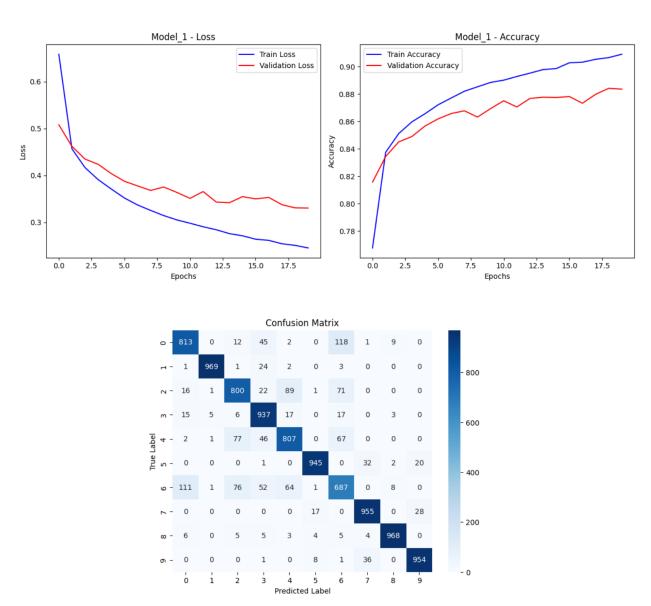
For each model, we tested four learning rates: 0.005, 0.001, 0.0005, and 0.0001. Below are the results showing the effect of these learning rates on performance metrics.

The graphs show:

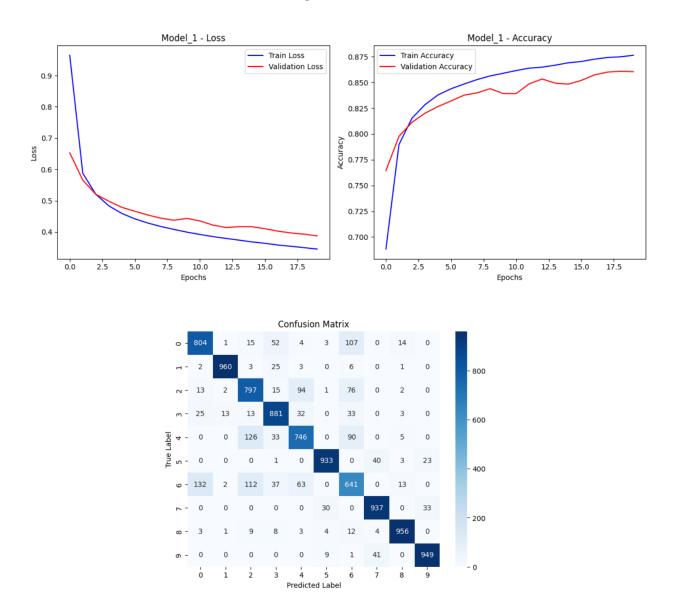
- Training and validation loss against number of epochs
- Training and validation accuracy against number of epochs
- Confusion matrix

Model 1 (One Layer, Hidden Dimension = 256)

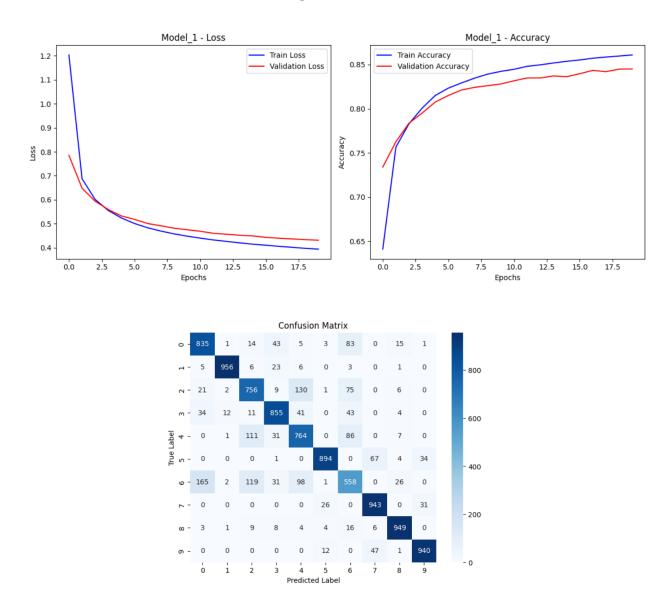
Learning Rate = 0.005



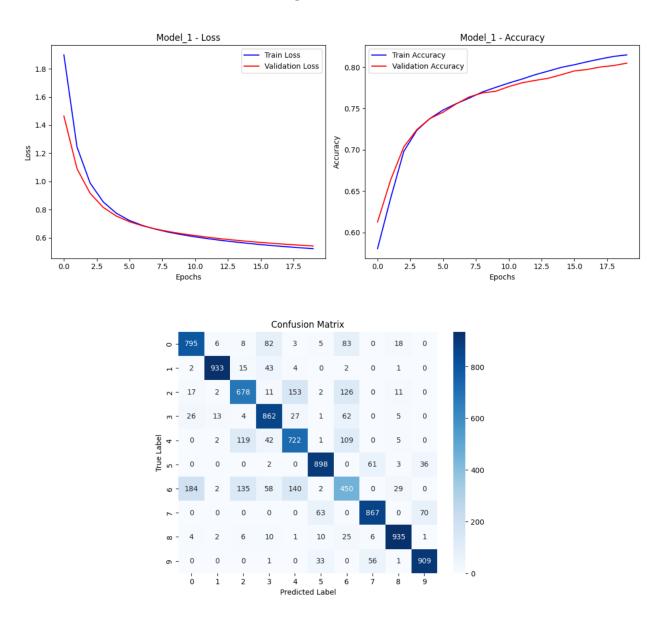
Accuracy: 88.35% Validation Macro-F1 Score: 0.8832



Accuracy: 86.04% Validation Macro-F1 Score: 0.8602



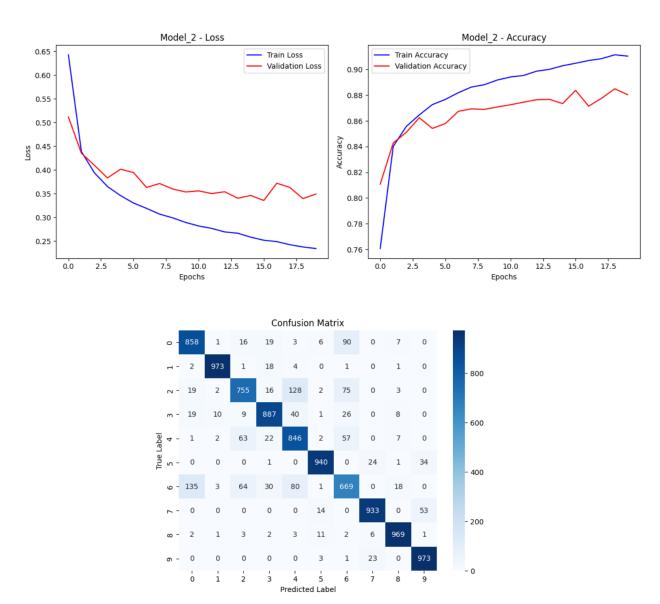
Accuracy: 84.50% Validation Macro-F1 Score: 0.8439



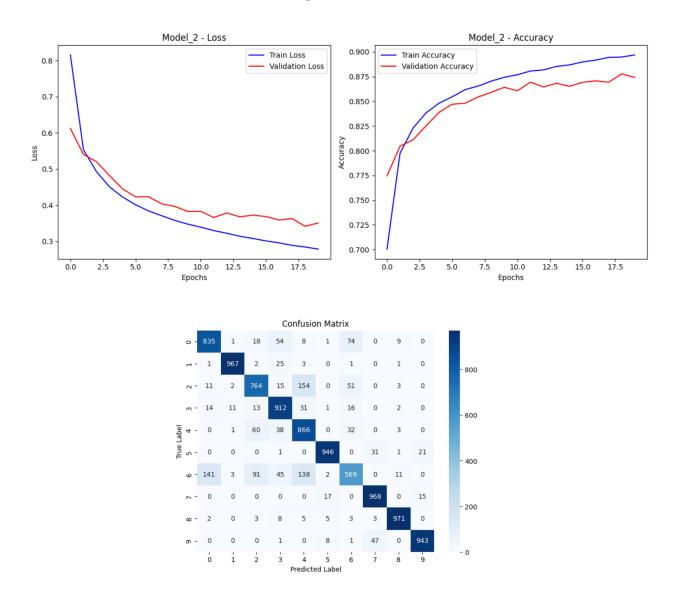
Accuracy: 80.49% Validation Macro-F1 Score: 0.8028

Model 2 (Two Layer, Hidden Dimension-1 = 128, Hidden Dimension-2 = 256)

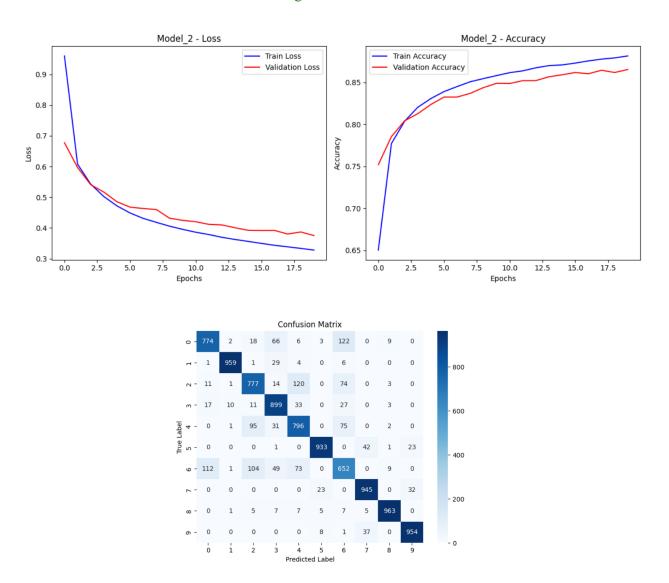
Learning Rate = 0.005



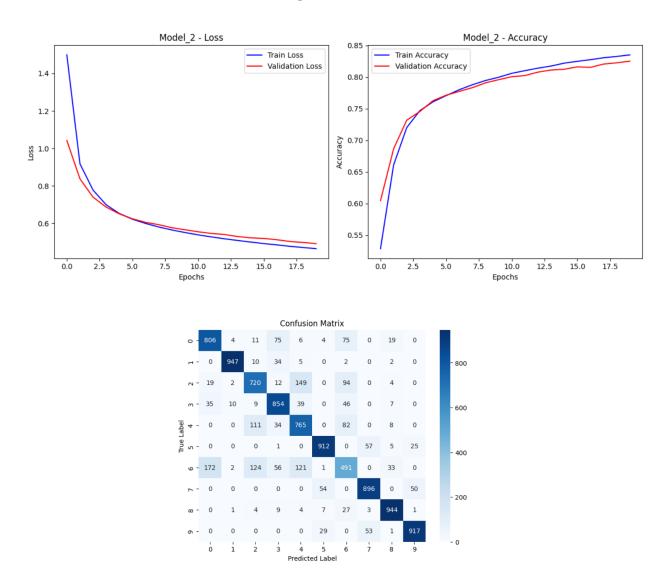
Accuracy: 88.03% Validation Macro-F1 Score: 0.8795



Accuracy: 87.41% Validation Macro-F1 Score: 0.8721



Accuracy: 86.52% Validation Macro-F1 Score: 0.8650

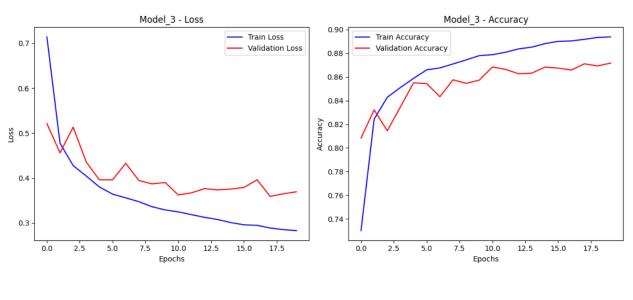


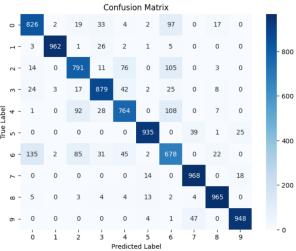
Accuracy: 82.52% Validation Macro-F1 Score: 0.8231

Model 3 (Three Layer)

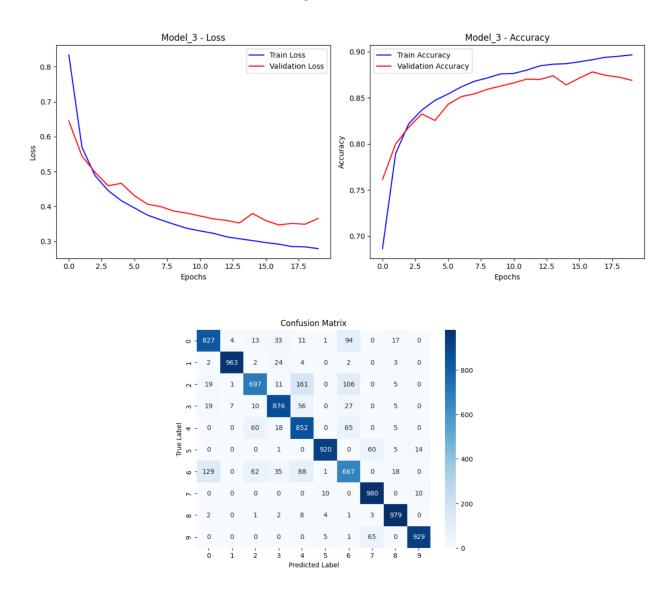
(Hidden Dimension-1 = 64, Hidden Dimension-2 = 128, Hidden Dimension-3 = 256)

Learning Rate = 0.005

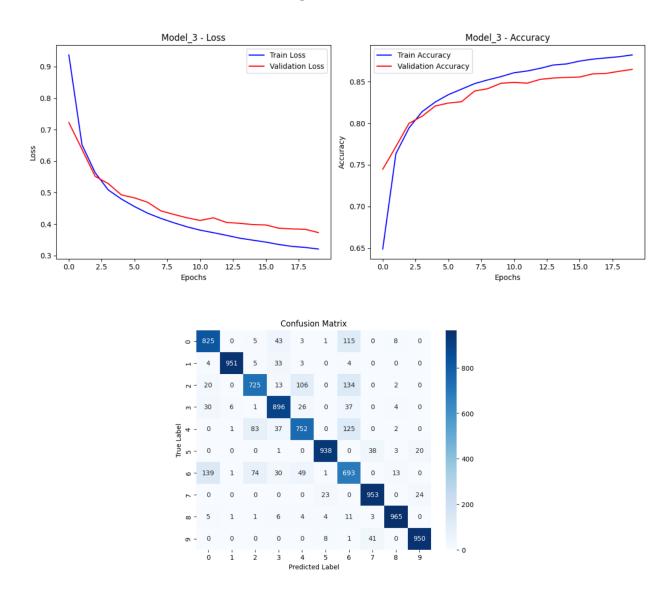




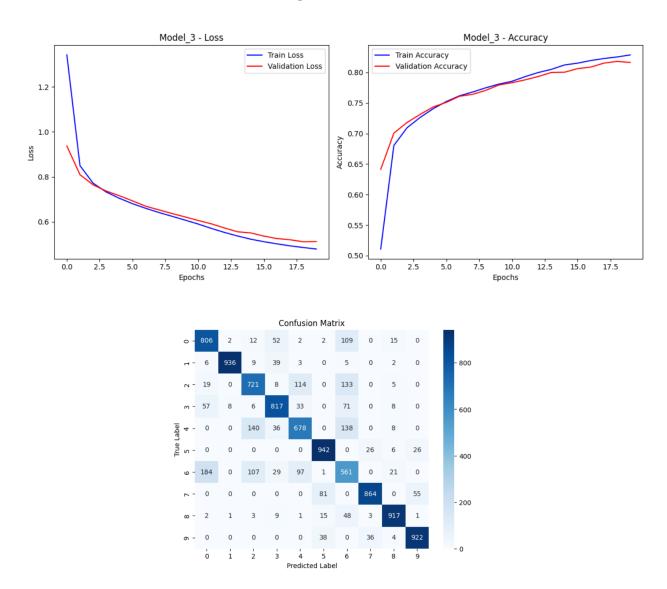
Accuracy: 87.16% Validation Macro-F1 Score: 0.8716



Accuracy: 86.90% Validation Macro-F1 Score: 0.8686



Accuracy: 86.48% Validation Macro-F1 Score: 0.8656



Accuracy: 81.64% Validation Macro-F1 Score: 0.8174

7 Best Model Selection

The process tracks the model with the highest F1 score during training. If a model's F1 score surpasses the previous best, the model, its name, and the learning rate are updated to ensure the top-performing model is selected.

Initialization:

```
best_score = 0.0
best_model = None
best_model_name = None
best_model_learning_rate = None
```

Update:

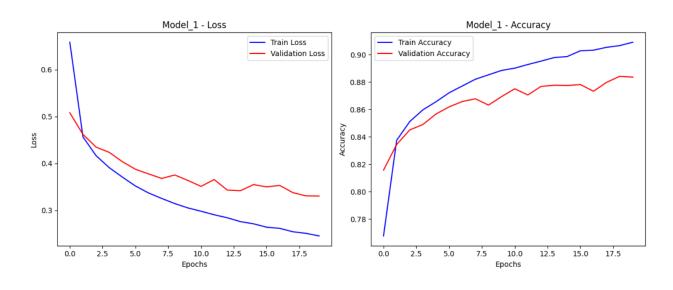
8 Best Model Performance Statistics

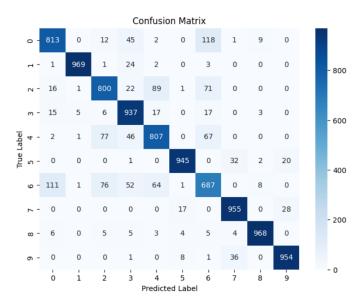
The best model is model-1 (One Layer, Hidden Dimension = 256) with a learning rate of 0.005. Its validation micro-F1 score is 0.8832.

Best_Model: Model_1, Learning_Rate: 0.005

Model 1 (One Layer, Hidden Dimension = 256)

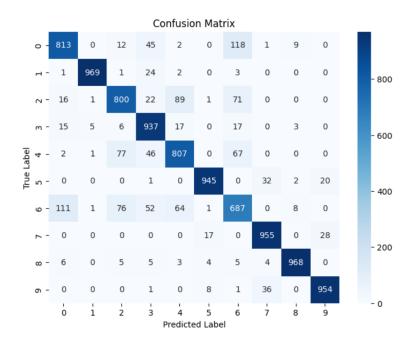
Learning Rate = 0.005





Accuracy: 88.35% Validation Macro-F1 Score: 0.8832

9 Best Model Performance on an Independent Test Set



Accuracy: 88.35%, F1 Score: 0.8832

10 Conclusion

This report compares three neural network models across four learning rates. **model-1** (One Layer, Hidden Dimension = 256) with a learning rate of 0.005 performed the best, achieving a validation macro-F1 score of 0.8832. Future improvements could focus on further tuning, testing different architectures, increasing number of epochs and exploring alternative optimization techniques.