Optimizing Handwritten Digit Recognition with Deep Learning

Farah Walid Abdelsalam

Software Engineer

Uneeq interns Machine learning task 3

***Abstract*— This report details the development and optimization of a deep learning model for handwritten digit recognition using the MNIST dataset. The model is based on a fully connected neural network architecture and was refined through manual hyperparameter tuning to enhance performance. After training and evaluation, the final model achieved a high test accuracy of 98.12%, with precision, recall, and F1-score metrics also reaching 98.12%. These results underscore the model's capability in effectively and accurately classifying handwritten digits, demonstrating its potential for applications in optical character recognition and similar fields.**

Keywords— Deep learning, MNIST, handwritten digits, accuracy, precision, recall, f1-score, classifying, Neural Networks.

I. Introduction

A well-known computer vision benchmark for assessing machine learning systems is handwritten digit recognition. One of the most often used datasets for this task is the MNIST dataset, which has 10,000 test images and 60,000 training images representing the numbers 0 through 9. The goal of this project is to use deep learning methods and hyperparameter tuning to create a neural network model that can recognise these digits with accuracy.

II. Data Description and Preprocessing Steps

The MNIST dataset consists of 70,000 grayscale images of handwritten digits, each of size 28x28 pixels. The data was split into 60,000 training images and 10,000 test images. The pixel values were normalized to the range [0, 1] by dividing by 255. The images were then flattened into vectors of size 784 (28x28) to serve as input to the fully connected neural network. The labels were one-hot encoded to represent the 10-digit classes.

III. Using Methodology/Approach

The model is a fully connected neural network with the following architecture:

- Input layer: 784 neurons (one for each pixel)
- Hidden layer 1: 512 neurons with ReLU activation
- Dropout layer 1: 20-30% dropout rate
- Hidden layer 2: 256 neurons with ReLU activation
- Dropout layer 2: 20-30% dropout rate
- Output layer: 10 neurons with softmax activation (one for each digit class)

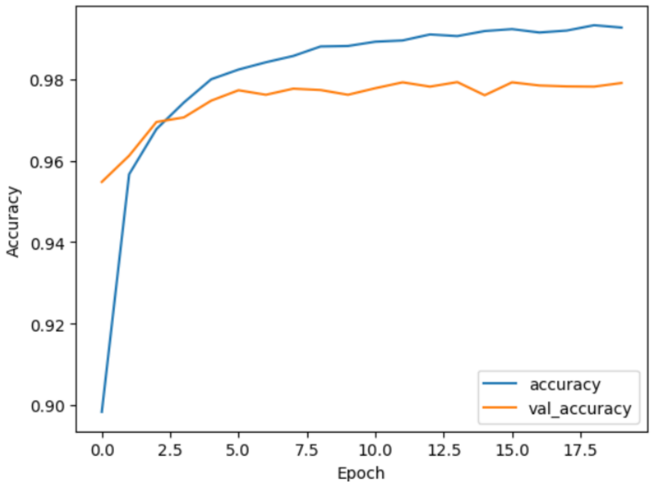
The model was compiled using the Adam optimizer and categorical cross-entropy as the loss function. Hyperparameters such as batch size, number of epochs, and dropout rate were manually tuned to optimize model performance.

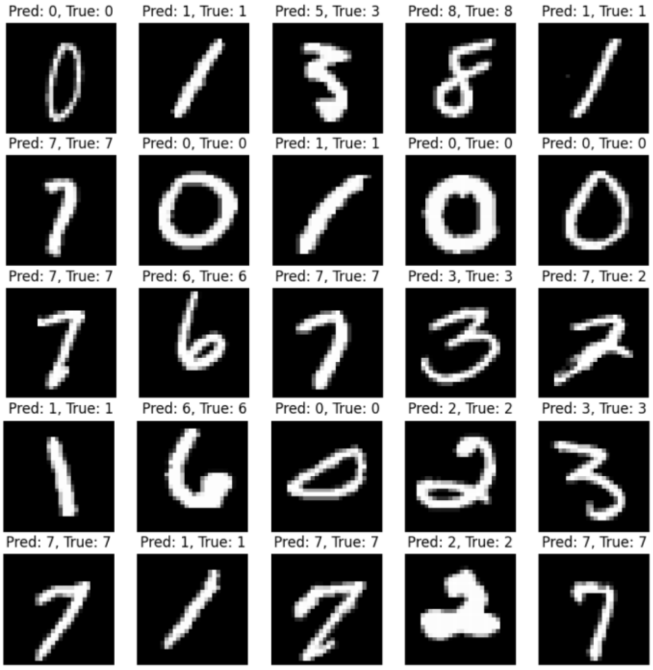
IV. Results

The final model was trained and evaluated on the MNIST test set, achieving the following performance metrics:

Final Model	
Accuracy	98.12%
Recall	98.12%
Precision	98.12%
F1-Score	98.12%

The model demonstrated strong generalization ability, achieving high accuracy on unseen test data. Additionally, the accuracy and loss curves during training indicated that the model was well-fitted without significant overfitting.





V. Conclusion

This project successfully developed a deep learning model capable of recognizing handwritten digits with high accuracy. The manual hyperparameter tuning process was effective in optimizing the model, resulting in a robust and reliable classifier. For future work, I could experiment more advanced architectures like CNNs or explore with different optimization techniques to further enhanced performance.