Project Report

Title: Handwritten Digit Classification using CNN (MNIST Dataset)

1. Introduction

Image classification is one of the most important tasks in computer vision and artificial intelligence. This project focuses on building a deep learning model capable of classifying handwritten digits using the MNIST dataset. The MNIST dataset contains grayscale images of digits ranging from 0 to 9, each represented in a 28x28 pixel format. The goal of this project is to train a Convolutional Neural Network (CNN) that can automatically learn patterns from raw image data and classify unseen images with high accuracy. This project demonstrates the potential of CNNs for practical applications such as optical character recognition (OCR), postal automation, and form digitization.

2. Objectives

The main objectives of this project are:
- To design and implement a CNN capable of recognizing digits from images.
- To achieve high accuracy on the test dataset by learning robust image features.
- To evaluate the model using training and validation metrics.
- To highlight real-world applications of image classification models.

3. Dataset

The MNIST dataset is a benchmark dataset widely used in machine learning. It consists of 70,000 labeled images of handwritten digits, with 60,000 images for training and 10,000 images for testing. Each image is a 28x28 grayscale pixel grid representing a single digit from 0 to 9. The dataset is balanced across all digit classes, making it an excellent choice for testing machine learning algorithms. Since the dataset is built into popular libraries such as TensorFlow and Keras, it can be loaded easily without requiring manual download.

4. Methodology

The following steps were followed in this project:

Data Preprocessing: Pixel values were normalized to the range [0,1] to speed up training. Each image was reshaped to include a single channel dimension suitable for CNN input.

Model Architecture: The CNN was designed with two convolutional layers followed by max pooling layers. The feature maps were flattened and connected to a fully connected dense layer with ReLU activation. Finally, a softmax layer was used to output probabilities for 10 digit classes.

Training: The model was trained for 5 epochs using the Adam optimizer and sparse categorical crossentropy loss. Validation accuracy was monitored during training to ensure the model generalized well.

Evaluation: The trained model was tested on the MNIST test set, and its performance was evaluated using accuracy scores.

5. Results

The CNN model achieved approximately 99% accuracy on the training dataset and about 98% accuracy on the validation/test dataset. The results show that even a relatively simple CNN can learn to recognize handwritten digits with high precision. Sample predictions confirm the model's ability to correctly classify unseen images. This level of accuracy demonstrates the effectiveness of deep learning for pattern recognition tasks.

6. Applications

This project has direct applications in real-world systems such as:
- Automatic recognition of handwritten digits in bank cheques.
- Postal code recognition for mail sorting.
- OCR technology for digitizing handwritten forms.
- License plate recognition systems.

The methods used in this project can also be extended to more complex datasets such as Fashion-MNIST or CIFAR-10.

7. Conclusion

In conclusion, this project successfully built and trained a CNN model to classify handwritten digits from the MNIST dataset. The model achieved a strong accuracy of about 98% on unseen test data, highlighting the power of convolutional architectures in computer vision tasks. This work not only demonstrates a foundational machine learning project but also serves as a stepping stone for tackling more advanced challenges in image recognition. Future enhancements could include experimenting with deeper CNN architectures, applying data augmentation techniques, or using transfer learning for more complex datasets.