**Report on Handwritten Character Recognition**

**Introduction:** Handwritten character recognition is a fascinating field within machine learning and computer vision. It involves the automatic identification and interpretation of handwritten characters from images. This technology has numerous applications, including digitizing handwritten notes, automating form processing, and enhancing accessibility for individuals with disabilities.

**Objective:** The primary objective of this project is to develop a system that can accurately recognize handwritten characters. This report outlines the steps taken to build and evaluate a Convolutional Neural Network (CNN) model for this purpose, using the MNIST dataset as a starting point.

**Dataset:** The MNIST dataset is a well-known benchmark in the field of machine learning. It consists of 60,000 training images and 10,000 test images of handwritten digits, each of size 28x28 pixels. The dataset is labeled, with each image corresponding to a digit from 0 to 9.

**Methodology:**

**Data Preprocessing**:

**Normalization**: The pixel values of the images were normalized to the range [0, 1] to facilitate faster and more efficient training.

**Reshaping**: The images were reshaped to include a single channel, making them compatible with the input requirements of the CNN model.

**Model Architecture**:

**Convolutional Layers**: The model includes two convolutional layers with ReLU activation functions. These layers are responsible for extracting features from the input images.

**Pooling Layers**: MaxPooling layers were used to reduce the spatial dimensions of the feature maps, thereby reducing the computational complexity.

**Dropout Layers**: Dropout was applied to prevent overfitting by randomly setting a fraction of input units to zero during training.

**Fully Connected Layers**: The flattened feature maps were passed through fully connected layers to perform the final classification.

**Training:**

The model was trained using the Adam optimizer and categorical cross-entropy loss function.

The training process involved 10 epochs with a batch size of 200.

The training and validation accuracy and loss were monitored to ensure proper learning.

**Evaluation:**

The model’s performance was evaluated on the test dataset.

Metrics such as accuracy, confusion matrix, and classification report were used to assess the model’s effectiveness.

**Results:** The trained CNN model achieved a high level of accuracy on the test dataset, demonstrating its ability to correctly recognize handwritten digits. The confusion matrix and classification report provided insights into the model’s performance across different classes.

**Conclusion:** The handwritten character recognition system developed in this project showcases the potential of deep learning in solving real-world problems. By accurately recognizing handwritten characters, this system can be extended to recognize entire words or sentences, opening up a wide range of applications.