LOK NAYAK JAI PRAKASH INSTITUE OF TECHNOLOGY, CHAPRA

Dept. Of Computer Science & Engineering

MINOR PROJECT SYNOPSIS

ON

"Digit Classification Using Deep Learning on MNIST Dataset "

Submitted in partial fulfilment of the requirements for

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In

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By

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Project Title:
Digit Classification using Deep Learning on MNIST Dataset

1. Introduction:

Handwritten digit recognition is crucial in tasks like postal code reading and cheque verification but remains challenging due to diverse writing styles and noise.
This project leverages the MNIST dataset, a widely-used collection of grayscale digit images, to develop a reliable recognition system using Convolutional Neural Networks (CNNs). CNNs, known for their effectiveness in image classification, will be used to create a robust model for handwritten digit recognition, demonstrating deep learning's potential in real-world applications.

2. Literature Review:

Handwritten digit recognition has been a key problem in machine learning. Traditional methods like Support Vector Machines (SVMs) and k-Nearest Neighbors (k-NN) relied heavily on feature engineering but often struggled with variations in handwriting and noisy data.

The introduction of Convolutional Neural Networks (CNNs) by Yann LeCun in the late 1980s marked a significant breakthrough. CNNs excel at automatically learning hierarchical features from pixel data, making them ideal for image classification. LeCun's LeNet-5 demonstrated high accuracy on the MNIST dataset, setting a foundation for modern deep learning models.

Later advancements such as AlexNet (2012), VGGNet (2014), and ResNet (2015) improved CNN performance by introducing deeper architectures, ReLU activation, and residual connections. These innovations enabled CNNs to tackle more complex tasks effectively. Techniques like data augmentation, batch normalization, and adaptive optimizers have further enhanced training efficiency and accuracy.

The MNIST dataset remains a benchmark for evaluating algorithms, where CNNs consistently outperform traditional methods. Their success on MNIST has extended to real-world applications, including facial recognition, object detection, and medical imaging, underscoring their versatility.

In summary, CNNs are recognized as the most effective solution for handwritten digit recognition, combining high accuracy with adaptability to various image recognition tasks.

3. Motivation:

Accurate digit recognition is vital in tasks like cheque verification and automated data entry, yet traditional systems face challenges with handwriting diversity.
CNNs, with their ability to learn complex patterns from images, offer a promising solution. This project aims to build a reliable CNN-based system, addressing these challenges and advancing practical applications in real-world scenarios.

4. Objectives of Work:

- Understand and preprocess the MNIST dataset.
- Design and implement a CNN for digit recognition.
- Optimize the model for accuracy and robustness.
- Evaluate using metrics like accuracy and confusion matrix.
- Showcase CNNs' effectiveness in real-world digit recognition.

5. Proposed Methodologies:

1. **Dataset Preprocessing**: Normalize and resize MNIST images for CNN input using NumPy and PIL.
2. **Model Design**: Build a CNN with convolutional, pooling, and dense layers using TensorFlow/Keras.
3. **Model Training**: Use Adam optimizer and cross-entropy loss for training.
4. **Hyperparameter Tuning**: Adjust learning rate, batch size, and epochs for better performance.
5. **Model Evaluation**: Assess metrics like accuracy and F1-score; visualize results with Matplotlib.
6. **Optimization**: Apply data augmentation, dropout, and batch normalization for robustness.

Technologies Used

- **Language**: Python
- **Libraries**: TensorFlow, Keras, NumPy, PIL, Matplotlib
- **Tool**: Jupyter Notebook

6. Analysis of the Result:

The anticipated performance of the CNN model will be evaluated after training it on the MNIST dataset.

1. **Expected Accuracy**: High test accuracy, indicating good generalization on unseen data.
2. **Accuracy and Loss Trends**: Training and validation accuracy should improve steadily; loss should decrease consistently.
3. **Custom Image Testing**: The model is expected to handle new digit images accurately after preprocessing.
4. **Model Reusability**: The saved model will reliably perform predictions on custom datasets.

This project aims to build a robust CNN capable of recognizing handwritten digits with high accuracy, paving the way for real-world applications like postal code reading and data automation.