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Handwritten Digit Recognition Using Convolutional Neural Networks

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ABSTRACT

With the advent of artificial intelligence, handwritten digit recognition has come to be an essential computer vision problem with applications in postal automation, cheque processing, and form digitization. This work describes the implementation of a recognition model based on Convolutional Neural Networks (CNNs). The MNIST dataset with 70,000 grayscale digit images was employed for model training and testing. Preprocessing involved normalization, reshaping, and augmentation to enhance generalization. A CNN model with convolutional, pooling, dropout, and dense layers was defined with TensorFlow and Keras. The model's high accuracy on unobserved test data was confirmed with confusion matrices and prediction visualization. Results emphasize the efficacy of CNNs in optical character recognition (OCR) and the ease of their integration into real-world applications.

Keywords: CNN, Handwritten Digit Recognition, MNIST, Deep Learning, Optical Character Recognition

1.0 INTRODUCTION

Handwritten digit recognition is a traditional pattern recognition problem and computer vision. Handwriting style variations and noise were difficult to process using traditional methods of feature engineering. Deep learning, and especially CNNs, offer automatic feature extraction and classification.

The project involved designing and implementing a CNN-based digit recognition model from handwritten digits based on the MNIST dataset. The project interfaced academic knowledge in deep learning with its practical application in real-world automation contexts like postal sorting and banking operations.

2.0 SYSTEM STUDY / REQUIREMENT ANALYSIS

2.1 Problem Statement

Manual reading of handwritten data is tedious and error prone. The task is to construct an effective recognition model that can identify handwritten digits (0–9) with high accuracy under diverse handwriting styles.

2.2 Functional Requirements

Input: MNIST dataset of 28×28 grayscale images of digits.

Processing: Normalization of data, training using CNN-based approach, and testing.

Output: Predicted digit along with probability scores.

2.3 Non-Functional Requirements

Performance: High accuracy with low overfitting.

Usability: Good visualizations of results and prediction outputs.

Scalability: Can be extended to bigger OCR problems.

2.4 Technology Stack

Languages/Libraries: Python, TensorFlow, Keras, NumPy, Pandas, Matplotlib, Seaborn

IDE: Jupyter Notebook, Google Colab

Algorithm: Convolutional Neural Network (CNN)

Evaluation Metrics: Accuracy, Loss Curves, Confusion Matrix

3.0 SYSTEM DESIGN AND IMPLEMENTATION

The model pipeline was split into four modules:

Data Preprocessing Module: Normalized pixel values, image reshaping, and data splitting into training/validation/test sets.

CNN Model Building Module: Built convolutional + pooling layers for feature extraction, dropout for regularization, and softmax output layer for classification.

Evaluation Module: Checked accuracy, graphed training/validation loss curves, and confusion matrices.

Visualization Module: Shown predictions, probability distributions, and interpretability maps.

The CNN architecture was trained with Adam optimizer and categorical cross-entropy loss function, with performance monitored over epochs.

4.0 RESULTS AND DISCUSSION

The learnt CNN resulted in high accuracy on the MNIST test data. Visual inspection of learning curves validated strong convergence and negligible overfitting thanks to dropout and batch normalization.

Individual predictions demonstrated the model's capability to confidently identify the correct digit with more than 98% probability. Misidentifications predominantly arose between visually indistinguishable digits (e.g., 4 and 9).

Outputs:

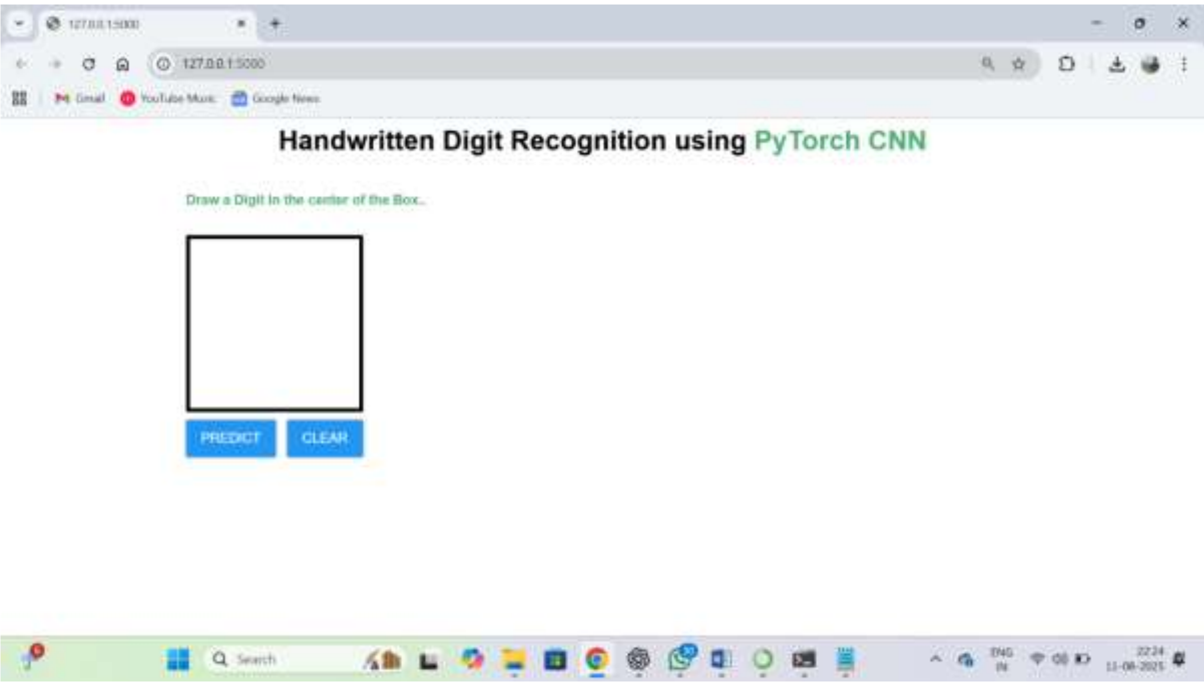

Fig 4.1 Digit prediction

A web interface for handwritten digit recognition using PyTorch CNN, featuring a drawing box and buttons to predict or clear the input.

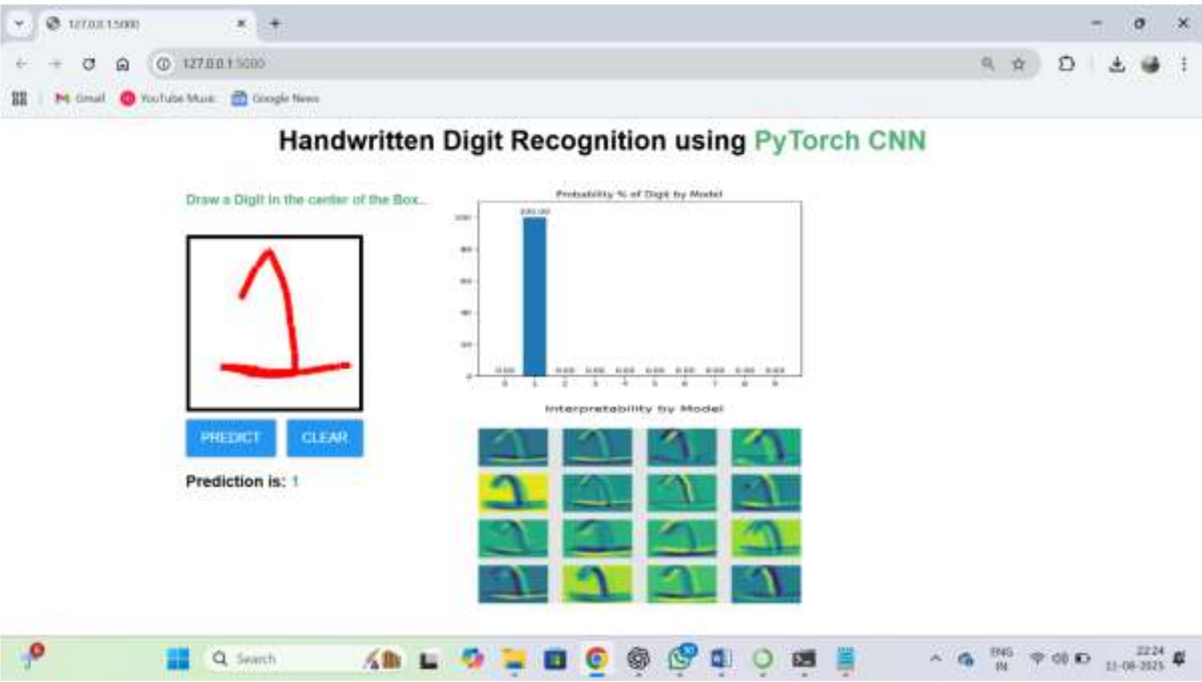

Fig 4.2 Digit Prediction Result

A PyTorch CNN web app predicting the drawn digit "1" with 100% confidence, along with model interpretability visualizations.

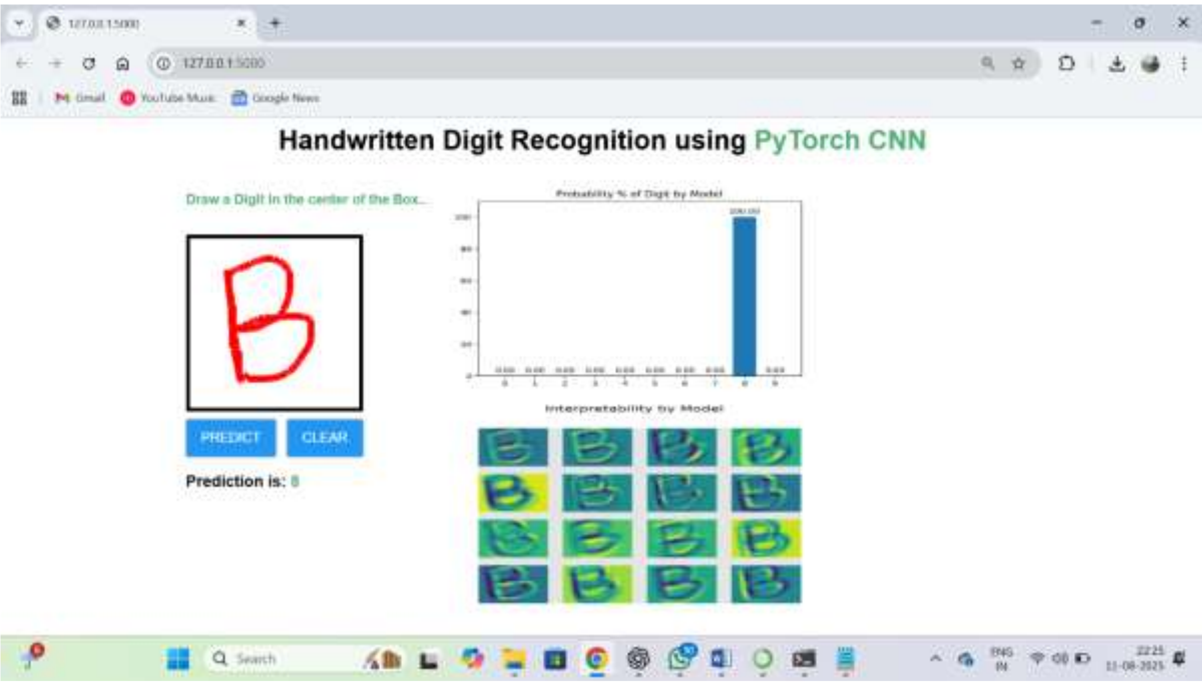

Fig 4.3 Digit Prediction 8

A PyTorch CNN web app predicting the drawn digit "8" with 100% confidence, displaying probability and interpretability maps.

5.0 CONCLUSION

The project was able to demonstrate handwritten digit recognition with CNNs on the MNIST dataset effectively. The system was well able to process preprocessing, training, and testing, exhibiting high classification accuracy.

Key Findings:

Spatial features were automatically extracted by CNNs without the need for manual feature engineering.

Dropout and batch normalization improved generalization.

Visualization methods enhanced interpretability and identified error cases.

Future Scope:

Extension to bigger datasets such as EMNIST or CIFAR-10.

Deployment as a real-time web/mobile OCR application.

Integration into mail and bank automation workflows.

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