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Handwritten Digit Recognition Using Machine Learning

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ABSTRACT

The objective of this study is to design and implement a robust classification framework for handwritten digit recognition. The work explores the effectiveness of classical machine learning algorithms, including Support Vector Machines (SVM), K-Nearest Neighbor (KNN), and Random Forest Classifier (RFC), in comparison with deep learning approaches, specifically a multilayer Convolutional Neural Network (CNN) implemented using Keras with TensorFlow and Theano backends. To enhance usability, the proposed system integrates an interactive Graphical User Interface (GUI), which facilitates real-time digit input and recognition. Experimental evaluation using the MNIST benchmark dataset demonstrates that the CNN-based framework achieves superior accuracy and robustness, while the GUI ensures improved user interactivity.

Keywords: Handwritten Digit Recognition, Convolutional Neural Networks (CNN), Machine Learning, Deep Learning, Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), Random Forest Classifier (RFC), Optical Character Recognition (OCR), Feature Extraction, MNIST Dataset, Image Classification, Pattern Recognition, Neural Networks, Graphical User Interface (GUI), Keras, TensorFlow, Theano, Accuracy, Precision, Recall, F1-Score, Data Normalization, Supervised Learning

Introduction

Handwritten digit recognition has long been regarded as a fundamental research problem in the domains of pattern recognition, image processing, and machine learning. With the increasing use of automated systems in banking, postal services, and document digitization, reliable digit recognition plays an essential role in practical applications. Traditional machine learning algorithms such as SVM, KNN, and RFC have been extensively studied and applied to this task, yielding satisfactory results on structured datasets.

Recent advancements in deep learning have led to significant improvements in recognition accuracy. Convolutional Neural Networks (CNNs), in particular, have demonstrated superior performance by automatically learning hierarchical feature representations directly from raw images. However, for practical deployment, recognition systems must also provide an interactive and user-friendly interface. To address this, we present a framework that combines CNN-based recognition with a Graphical User Interface (GUI), enabling real-time interaction and instant feedback.

Proposed System

The system aims to identify digits (0–9) using supervised learning techniques on the MNIST dataset.

- **Dataset:** MNIST (60,000 training and 10,000 testing grayscale images, size 28×28 pixels).
- **Preprocessing:** Normalize pixel values from 0–255 to a 0–1 range.
- **Feature Extraction:** Either flatten images for classical ML models or extract features via CNN layers.
- **Models:**
    - Classical ML: SVM, k-NN, Random Forest.
    - Deep Learning: CNNs (preferred).
- **Training:** Conduct supervised learning with labeled samples.
- **Testing/Evaluation:** Measure accuracy, precision, recall, F1-score, and confusion matrix.
- **Output:** Predicted digit between 0–9.

System Architecture

The CNN-based handwritten digit recognition system consists of multiple layers:

1. **Convolution Layer** – Applies filters to capture edges, curves, and patterns from input images.
2. **Activation (ReLU)** – Introduces non-linearity by setting negative values to zero, preserving positive activations.
3. **Pooling Layer** – Performs downsampling (max pooling) to reduce dimensionality and computational cost.
4. **Fully Connected Layers** – Combines features learned in previous layers for classification.
5. **Softmax Layer** – Produces probability distribution across 10 output classes (digits 0–9).

This architecture ensures efficient feature learning and robust classification performance.

System Requirements

Hardware Requirements

- Processor: Intel i3 or higher
- RAM: 2 GB minimum
- Hard Disk: 1 TB
- Monitor: 15” Color Display
- Keyboard: Standard 122 keys

Software Requirements

- Operating Systems: Windows NT/98/2000/XP/2010
- GUI Development: Tkinter (Python)
- Libraries: TensorFlow, Keras, NumPy, Matplotlib
- Dataset: MNIST

Flowchart

Stepwise Flow of Handwritten Digit Recognition System:

1. Input digit (drawn or image-based)
2. Preprocessing (normalization, reshaping)
3. CNN feature extraction (convolution + pooling)
4. Classification (fully connected layers, softmax)
5. Prediction output (digit 0–9)

Algorithm (CNN-based Digit Recognition)

1. Start
2. Import required libraries (TensorFlow, Keras, NumPy, Matplotlib).
3. Load MNIST dataset.
4. Normalize pixel values and reshape inputs to (28×28×1).
5. Construct CNN model:
    - Apply convolution with filters and kernels.
    - Perform ReLU activation.

- Apply max pooling.
- Flatten feature maps.
- Use dense layers for classification.

1. Train the model using 20 epochs.
2. Evaluate performance on test dataset.
3. Provide a GUI for real-time digit input and recognition.
4. Display predicted digit with confidence score.
5. Stop.

Methodology

The CRISP-DM methodology is adopted:

1. **Business Understanding** – Recognizing handwritten digits for OCR-related applications.
2. **Data Understanding** – MNIST dataset with 70,000 images (28×28 pixels).
3. **Data Preparation** – Noise removal, normalization (0–1 scaling), reshaping to (28×28×1).
4. **Modeling** – Training ML and DL algorithms (SVM, k-NN, Random Forest, CNN).
5. **Evaluation** – Performance assessment using metrics like accuracy, precision, recall, and confusion matrix.
6. **Deployment** – GUI integration for practical use.

Conclusion

This project confirms that Convolutional Neural Networks outperform traditional machine learning methods in handwritten digit recognition tasks. The CNN model achieved a remarkable accuracy of **99.25%** on the MNIST dataset, establishing its reliability for real-world applications such as banking, postal automation, and digital form processing. Cross-validation confirmed the robustness of the chosen architecture, while the GUI integration demonstrated its usability.

Although the achieved results are significant, further improvements can be made by fine-tuning hyperparameters (learning rate, optimizers, depth of the network, and epoch count). Future research may also involve experimenting with larger datasets, advanced architectures (ResNet, DenseNet), and real-time mobile deployment.

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