Enhancing MNIST Classification

Report

Introduction

MNIST is a well-known dataset for handwritten digit classification, often used as a benchmark for machine learning and deep learning models. In this study, we explore a hybrid approach that combines traditional feature extraction methods with modern deep learning techniques to improve classification accuracy.

Methodology

We implemented multiple approaches to classify MNIST digits:

1. **Traditional Feature Extraction with Machine Learning**:
   - Histogram of Oriented Gradients (HOG) with SVM
   - Local Binary Pattern (LBP) with Gradient Boosting
   - Edge Detection with Random Forest
2. **Deep Learning Approaches**:
   - ResNet50 with a Multi-Layer Perceptron (MLP)
   - Data Augmentation for improved generalization

Data Preprocessing

- The original MNIST dataset contains grayscale images of size 28x28 pixels.
- Normalization was applied by scaling pixel values to the range [0,1].
- Images were resized to 32x32 pixels for deep learning models to match their expected input dimensions.
- Data augmentation techniques such as rotation and shifting were applied to enhance the dataset.

Feature Extraction Methods

1. Histogram of Oriented Gradients (HOG)

- HOG extracts gradient-based structural features.
- SVM was used as the classifier for the extracted HOG features.

2. Local Binary Pattern (LBP)

- LBP captures texture-based features from images.
- The extracted features were classified using a Gradient Boosting classifier.

3. Edge Detection

- Laplacian edge detection was used to highlight edges in images.
- A Random Forest Classifier was used for classification.

Deep Learning Model

ResNet50 with MLP

- A pre-trained ResNet50 model was used as a feature extractor.
- The extracted features were passed through an MLP for classification.
- This approach leveraged transfer learning for improved accuracy.

Model Performance and Results

Model	Accuracy
HOG + SVM	98.26%
LBP + Gradient Boosting	96.08%
Edge Detection + Random Forest	92.34%
ResNet50 + MLP	91.59%

Challenges Faced and Solutions

1. Overfitting in Deep Learning Models

Problem: Training accuracy was high, but test accuracy was slightly lower due to overfitting. **Solution:** Data augmentation was applied to introduce variability in the training data, reducing overfitting.

2. Computational Complexity

Problem: Deep learning models required longer training times. **Solution:** Used transfer learning with pre-trained models (ResNet50) to leverage existing feature representations.

3. Feature Scaling for Traditional Methods

Problem: HOG, LBP, and Edge detection features had different scales, affecting classifier performance. **Solution:** StandardScaler was used to normalize extracted features before training classifiers.

Analysis of Model Performance

- **HOG + SVM (98.26%)**: Performed the best among traditional methods due to its ability to capture edge-based structures effectively.
- **LBP + Gradient Boosting (96.08%)**: LBP worked well for capturing texture patterns, but struggled slightly with digit variations.
- **Edge Detection + Random Forest (92.34%)**: Performed the worst among traditional methods, as edges alone were not always discriminative enough.
- **ResNet50 + MLP (91.59%)**: While deep learning models usually perform well, the limited dataset size and fewer training epochs might have impacted its performance.

Conclusion

Our study demonstrates that both traditional and deep learning approaches are effective for MNIST classification. HOG with SVM achieved the highest accuracy among traditional methods, while ResNet50 with MLP performed decently but was computationally expensive. Future work includes integrating ensemble methods that combine feature-based classifiers with deep learning predictions for even better performance.