Analysis Report: MNIST Classification with Feature Extraction Methods

Executive Summary

This report analyzes the performance of different feature extraction techniques on the MNIST handwritten digit dataset when used with a Random Forest classifier. The methods evaluated include traditional computer vision techniques (HOG, LBP, Edge Detection) and deep learning-based features (MobileNetV2). HOG features achieved the highest accuracy (97.09%), significantly outperforming other methods, while LBP features performed the worst (60.77%).

Performance Analysis

Accuracy Comparison

1. **HOG Features**: 97.09% accuracy
2. **Edge Detection**: 87.30% accuracy
3. **Deep Features**: 78.71% accuracy
4. **LBP Features**: 60.77% accuracy

The HOG method demonstrated superior performance, achieving near state-of-the-art results on MNIST without using deep learning. This suggests that for simple, well-defined shapes like handwritten digits, carefully designed traditional features can outperform more complex deep learning approaches.

Training Time Analysis

- **Fastest Training**: LBP (16.23s) and Edge Detection (17.04s)
- **Slowest Training**: HOG (66.34s) and Deep Features (64.89s)

While HOG required the longest training time, its superior accuracy justifies the additional computational cost for this application.

Method-Specific Observations

1. HOG (Histogram of Oriented Gradients)

- **Strengths**:
  - Excellent performance (97.09% accuracy)
  - Captures gradient information crucial for digit recognition
  - Robust to small variations in digit positioning
- **Weaknesses**:
  - Longest feature extraction and training time
  - May be less effective with more complex image datasets

2. LBP (Local Binary Patterns)

- **Strengths**:
    - Fastest feature extraction and training
    - Computationally inexpensive
- **Weaknesses**:
    - Poor performance (60.77% accuracy)
    - Texture-based features less discriminative for digits
    - Loses structural information critical for digit recognition

3. Edge Detection

- **Strengths**:
    - Reasonable performance (87.30% accuracy)
    - Fast computation
    - Preserves basic shape information
- **Weaknesses**:
    - Loses internal structure of digits
    - Sensitive to noise and edge discontinuities

4. Deep Features (MobileNetV2)

- **Strengths**:
    - Automatic feature learning
    - Potential for better generalization to other datasets
- **Weaknesses**:
    - Surprisingly poor performance (78.71%) compared to HOG
    - Requires image resizing and channel conversion
    - Computationally intensive feature extraction

Unexpected Findings

1. **Deep Features Underperformance**: The MobileNetV2 features performed worse than expected (78.71% vs HOG's 97.09%). Possible reasons:
    - Pre-trained on natural images (ImageNet) which differ significantly from MNIST digits
    - Input size modification (28x28 → 32x32) may have introduced artifacts
    - Grayscale to RGB conversion didn't provide meaningful additional information
2. **HOG Superiority**: The exceptional performance of HOG suggests that:
    - Handcrafted features can be highly effective for constrained problems

- Gradient information is particularly discriminative for digit recognition
- The Random Forest classifier works exceptionally well with HOG features for this task

Recommendations

1. **For MNIST Classification**:
    - Use HOG features for best performance
    - Consider Edge Detection if faster processing is required and slightly lower accuracy is acceptable
    - Avoid LBP for this specific task
2. **For General Image Classification**:
    - Deep learning features would likely perform better on more complex datasets
    - Consider fine-tuning the pre-trained model rather than just using it for feature extraction
    - Experiment with different pre-trained models (e.g., ResNet, VGG)
3. **Future Work**:
    - Combine HOG with other features to potentially improve performance
    - Experiment with different classifiers (e.g., SVM for HOG features)
    - Try domain-adapted deep learning approaches for better feature extraction

Conclusion

This analysis demonstrates that for the MNIST dataset, traditional feature extraction methods—particularly HOG—can outperform deep learning-based approaches when combined with a Random Forest classifier. The results highlight the importance of selecting appropriate feature extraction methods tailored to the specific characteristics of the dataset, rather than automatically opting for more complex deep learning solutions.

The superior performance of HOG suggests that for problems with clear, well-defined shapes and limited variability, carefully designed traditional computer vision techniques can provide excellent results with reasonable computational requirements.