Technical Report:

Convolutional Neural Network for MNIST Digit Classification

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1. Introduction:

Handwritten digit recognition is a foundational problem in machine learning and computer vision.
The MNIST dataset provides 70,000 grayscale images of digits (0–9) and serves as a standard benchmark for evaluating image classification models.
This project implements a Convolutional Neural Network (CNN) using TensorFlow/Keras to classify handwritten digits.
The model is trained with data augmentation, uses regularization techniques such as dropout and batch normalization, and finally performs real-time predictions on user-provided images.

2. Dataset and Preprocessing:

The MNIST dataset consists of 60,000 training images and 10,000 test images, each 28×28 pixels in grayscale. Images are reshaped to include a channel dimension and normalized to the range [0,1] to improve convergence stability.

Preprocessing includes:

-Reshaping: converting images to (28,28,1)
- Normalization: scaling pixel values to float32 / 255.0
- Augmentation: rotation, zoom, width/height shifts using ImageDataGenerator

3. Model Architecture

The CNN contains three convolutional blocks followed by dense layers:
- Conv2D layers with ReLU activation extract hierarchical spatial features.
- Batch Normalization stabilizes training.
- MaxPooling reduces spatial size and computational complexity.
- Dropout reduces overfitting in fully connected layers.
- A final softmax layer outputs a 10 class probability distribution.

4. Training Procedure

    The model uses the Adam optimizer and sparse categorical cross entropy loss.

    Two callbacks improve training:

    - ModelCheckpoint: saves the best model based on validation accuracy.
    - EarlyStopping: halts training when validation loss stops improving.

    Training uses augmented batches for 50 epochs with validation on the test set. The model typically reaches 98–99% accuracy.

5. External Image Prediction

    A custom preprocessing function converts user provided images to MNIST format:

    - Convert to grayscale
    - Resize to 28×28 pixels
    - Invert colors to match MNIST style
    - Normalize and reshape A prediction loop displays the processed image and a probability bar chart for digits 0–9.

6. Results
7. The trained CNN achieves:
8. - ~99% test accuracy
9. - High robustness due to augmentation
10. - Effective generalization to external images
11. - Low latency predictions suitable for interactive use

7. Conclusion

This project demonstrates a complete deep learning pipeline for handwritten digit recognition, including data preprocessing, augmentation, CNN architecture design, training with callbacks, and interactive prediction. The system is extendable to other datasets and real world applications