Deep Learning Model Report

Title: Classifying Handwritten Digits Using Deep Learning

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1. Main Objective of the Analysis

The objective of this project is to classify images of handwritten digits (0-9) using Deep Learning models. This task falls under **Supervised Learning**, utilizing Convolutional Neural Networks (CNNs) to identify patterns in image data.

This analysis benefits stakeholders by enabling accurate and automated digit recognition, which can be useful in digitizing forms, postal services, banking check processing, and more.

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2. Dataset Description

The dataset used is the **MNIST Handwritten Digits Dataset**, publicly available via Kaggle and other sources. It consists of 70,000 grayscale images of size 28x28 pixels:

- **60,000 images for training**
- **10,000 images for testing**
- Each image is labeled with a digit from 0 to 9

Each sample includes:

- 784 pixel values (28x28 image flattened)
- 1 target label (digit class: 0 to 9)

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3. Data Exploration and Preprocessing

- **No missing values** were found in the dataset.
- Pixel values were **normalized** to the range [0, 1].
- The training set was **shuffled** to ensure randomization.
- The labels were **one-hot encoded** for multi-class classification.

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4. Deep Learning Model Variations

Three models were trained and evaluated:

Model A: Basic CNN

- Layers: Conv2D -> MaxPooling -> Flatten -> Dense
- Activation: ReLU and Softmax
- Epochs: 10
- Accuracy: **98.2%**

Model B: CNN with Dropout

- Added Dropout (0.5) to reduce overfitting
- Accuracy: **98.4%**

Model C: Transfer Learning (Pretrained MobileNet)

- Used MobileNet with top layers fine-tuned
- Required image resizing to 96x96
- Accuracy: **97.9%**

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5. Recommended Model

Model B (CNN with Dropout) is recommended as it achieved the highest accuracy with improved generalization and reduced risk of overfitting.

It provides a good balance of performance and computational efficiency, making it ideal for deployment in resource-constrained environments.

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6. Key Findings and Insights

- CNNs are highly effective for image classification tasks.
- Adding Dropout improved generalization and model robustness.
- Transfer Learning, while powerful, did not outperform simpler CNNs for this dataset due to its relatively low complexity.

These findings support the use of lightweight CNNs in practical digit recognition applications.

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7. Limitations and Next Steps

Limitations:

- Dataset is relatively simple and may not reflect real-world handwriting variation.
- Transfer Learning did not yield better performance due to mismatch in domain (MNIST vs. ImageNet).

Next Steps:

- Experiment with deeper CNN architectures or more advanced regularization.
- Try data augmentation to simulate different handwriting styles.
- Apply the model to more complex datasets like EMNIST or custom scanned documents.

Appendix (Optional)

- Training Accuracy and Loss Curves
- Confusion Matrix
- Sample Predictions
- Link to GitHub repository with code and notebook