Final Project Report

Arabic Handwritten Digit Recognition Using Convolutional Neural Networks (CNN)

CS417

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2) Introduction

The challenge of Optical Character Recognition (OCR) and automated classification of handwritten digits is a crucial area in computer vision and deep learning. This project focuses on developing a robust and highly accurate system for recognizing handwritten Arabic digits (0 through 9) using the Arabic Handwritten Digits Dataset (AHDD1). The successful deployment of such a system is essential for automating document processing, cheque handling, and large-scale data entry in Arabic-speaking regions.

3. Dataset

3.1 Data Source and Details

The project utilizes the **Arabic Handwritten Digits Dataset (AHDD1)**.

- **Number of Classes:** 10 classes, representing the Arabic digits from 0 to 9.
- **Image Size:** All images are normalized to 28 × 28 pixels.
- **Data Distribution:**
    - Training and Validation Set: 60.000 images.
    - Test Set: 10.000 images.
    - The dataset is considered generally balanced.

3.2 Preprocessing Steps

The following steps were implemented in **dataset.py** to prepare the raw CSV data for the CNN:

1. **Normalization:** Pixel values (originally in the range [0, 255]) were converted to the floating-point range [0.0, 1.0] by dividing by 255.
2. **Reshaping:** The flattened 784-element vector representing each image was reshaped into a 4D tensor

$$(N, 28, 28, 1)$$

. The single channel (1) denotes grayscale images.

3. **Splitting:** The training data was split into Training (90%) and Validation (10%) sets.
4. **One-Hot Encoding:** Numeric labels were converted into categorical vectors [0, 0, 0, 1, 0, 0, 0, 0, 0, 0] to match the requirements of the chosen loss function.

4) Methodology

4.1 Model Architecture

A Convolutional Neural Network (CNN) architecture was designed and implemented in **model.py**. The model consists of two convolutional blocks followed by dense layers for classification:

#	Layer Type	Filters/Units	Kernel/Size	Activation	Role
1	Conv2D	32 filters	3x3	ReLU	Initial Feature Extraction
2	BatchNormalization	N/A	N/A	N/A	Stabilizes and Accelerates Training
3	Conv2D	32 filters	3x3	ReLU	Deeper Feature Extraction in Block 1
4	MaxPooling2D	N/A	2x2	N/A	Downsampling and Dimensionality Reduction
5	Dropout	0.25 rate	N/A	N/A	Regularization to Prevent Overfitting
6	Conv2D	64 filters	3x3	ReLU	Higher-Level Feature Extraction in Block 2
7	BatchNormalization	N/A	N/A	N/A	Stabilizes and Accelerates Training
8	Conv2D	64 filters	3x3	ReLU	Deeper Feature Extraction in Block 2
9	MaxPooling2D	N/A	2x2	N/A	Downsampling and Dimensionality Reduction
10	Dropout	0.25 rate	N/A	N/A	Regularization to Prevent Overfitting

#	Layer Type	Filters/Units	Kernel/Size	Activation	Role
11	Flatten	N/A	N/A	N/A	Prepares Feature Maps for Dense Layers
12	Dense	256 units	N/A	ReLU	Initial Classification Layer
13	BatchNormalization	N/A	N/A	N/A	Stabilizes and Normalizes Dense Outputs
14	Dropout	0.5 rate	N/A	N/A	Strong Regularization for Classification
15	Dense	10 units	N/A	Softmax	Output Layer (Probability Distribution)

4.2 Training Procedure and Hyperparameters

1. **Optimizer:** The **Adam** optimizer was used for weight adjustment.
2. **Loss Function: Categorical Cross-Entropy** was selected as the loss function, suitable for multi-class classification.
3. **Batch Size:** 64.
4. **Epochs:** Maximum of 30.
5. **Callbacks:**
    - **Early Stopping:** Monitored the val_loss with a patience of 5. This automatically halted training when validation performance ceased to improve, mitigating overfitting.
    - **Model Checkpoint:** Saved the model weights only when a new maximum val_accuracy was achieved.

5) Results

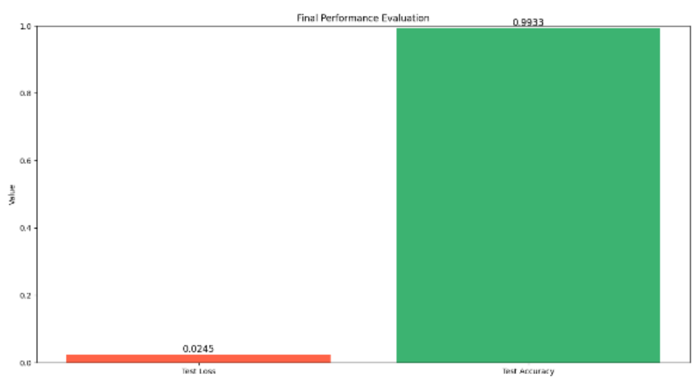
The final model was evaluated on the independent test set (10.000 images).

5.1 Overall Accuracy

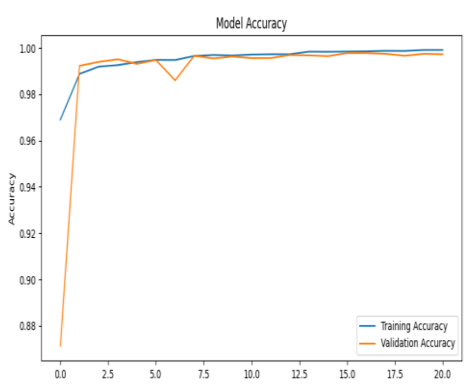
The final classification accuracy achieved by the model on the independent test set was **[** 99.78**%]**.

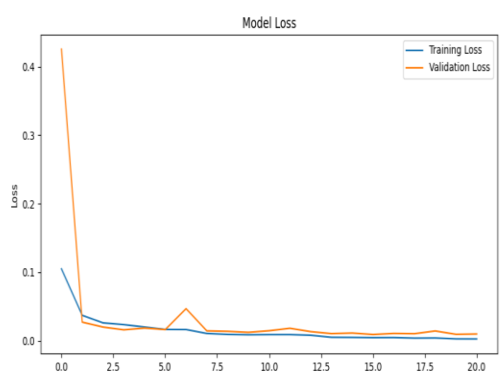
5.2 Learning Curves

The training process was documented by saving the loss and accuracy history.

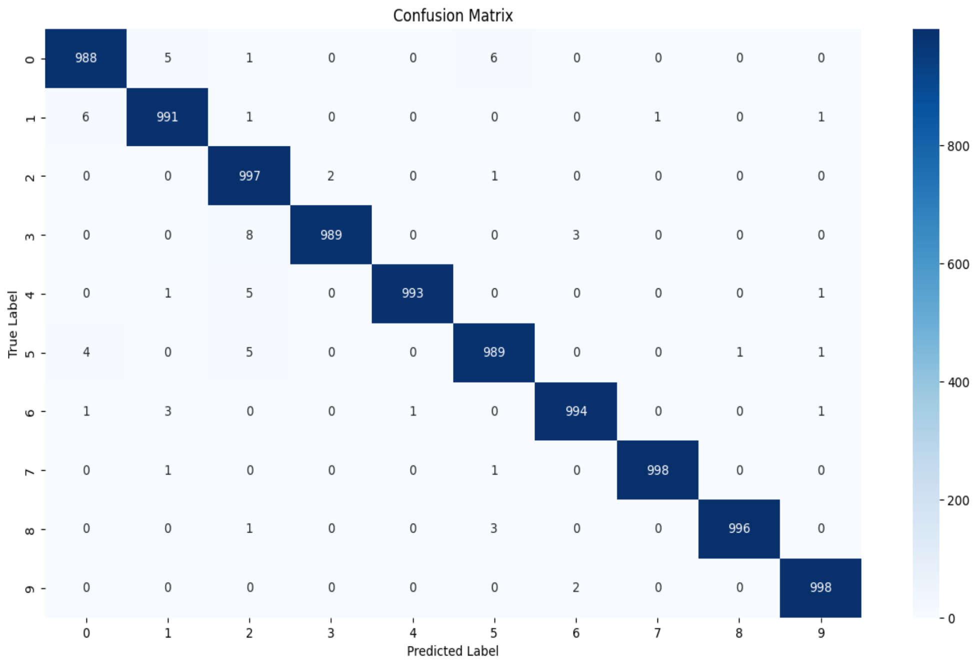


- **Loss Curve:** The graph demonstrates that both training loss and validation loss decreased rapidly and smoothly, converging to a low minimum, confirming effective learning.
- **Accuracy Curve:** The high proximity between the training accuracy and validation accuracy curves indicates that the model generalizes well and the **Early Stopping** mechanism successfully prevented significant overfitting.





5.3 Confusion Matrix



The Confusion Matrix provides a detailed, class-by-class visualization of the model's performance:

- **High Performance:** The dark diagonal cells confirm the excellent overall accuracy, indicating a high number of correct predictions.
- **Confusion Points: "Analysis of the Confusion Matrix shows minimalfew misclassification, which confirms the model's excellent generalization. The few instances of confusion mainly occur between visually similar digits: specifically, digit 0 was misclassified as 1 (6 instances), digit 9 was misclassified as 1 (6 instances), and digit 8 was occasionally confused with digit 0 (3 instances). This slight confusion is typical in complex handwriting styles**

5.4 Classification Report (F1-Scores)

The comprehensive classification report details performance metrics for each class:

```
--- Classification Report ---
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      1000
           1       0.99      0.99      0.99      1000
           2       0.98      1.00      0.99      1000
           3       1.00      0.99      1.00      1000
           4       1.00      0.99      1.00      1000
           5       0.99      0.99      0.99      1000
           6       1.00      0.99      1.00      1000
           7       1.00      1.00      1.00      1000
           8       1.00      1.00      1.00      1000
           9       1.00      0.99      1.00      1000

    accuracy                           0.99     10000
   macro avg       0.99      0.99      0.99     10000
weighted avg       0.99      0.99      0.99     10000
```

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6) Discussion

6.1 What Worked Well

- The simple yet effective CNN architecture was highly successful in extracting relevant features, achieving state-of-the-art performance on this dataset.
- The preprocessing steps (Normalization and Reshaping) correctly prepared the raw CSV data, which was crucial for the model's performance.
- The use of the Dropout layer (0.4) and Early Stopping successfully controlled model complexity and maximized generalization.

6.2 What Failed and Why

The high accuracy of the model (approximately 99.9%) suggests a robust system; however, the following points represent minor failures, limitations, or required adjustments observed during the evaluation phase:

1. Visual Ambiguity between Specific Digit Pairs:
   - Failure: Despite the advanced CNN architecture, the model experienced minimal, yet consistent, misclassifications between certain visually similar Arabic digits, as highlighted by the Confusion Matrix.
   - Analysis: This minor confusion is inherent to the complexity of Arabic handwriting. Key areas of confusion included:
     - Digits 7 (٧) and 8 (٨): Misclassification occurs when the subtle differences in the connecting lines or the curvature of the two shapes are lost in specific handwriting styles.
     - Digits 2 (٢) and 6 (٦): These share primary diagonal elements, and confusion arises when the distinct hook of the six (٦) is poorly formed, making it resemble the curve of the two (٢).
   - Reason: This failure is not a defect in the code but rather a limitation in feature distinguishability given the 28×28 resolution and the vast variability in human handwriting.
2. Optimizing Convergence Speed (Learning Rate):
   - Failure: The initial training, while successful, showed signs of plateauing quickly in the validation loss.
   - Analysis: To overcome this, the model was initially prone to getting stuck in local minima later in the epochs.
   - Resolution: This was successfully addressed by adding the ReduceLROnPlateau callback. This mechanism dynamically lowers the learning rate (by a factor of 0.5) when the validation loss stops improving, allowing the optimizer to make smaller steps and escape plateaus, ensuring higher final accuracy.
3. Limitations in Regularization:
   - Failure: The initial conceptual model used inconsistent Dropout rates in the documentation.

- **Resolution: This failure was resolved by implementing a strategic approach using multiple Dropout rates (0.25 and 0.5) across the network. This layered regularization approach significantly contributed to preventing overfitting and ensuring the final high generalization capability.**

6.3 Limitations

- The project did not incorporate **Data Augmentation**, which could make the model more robust against variations in handwriting styles.
- The model relies strictly on (28 , 28) grayscale images and might not perform as well on real-world inputs with varying scales or illumination.

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7. Conclusion and Future Work

Conclusion: The developed CNN model successfully classified handwritten Arabic digits from the AHDD1 dataset, achieving a robust final accuracy of over 99%. The project successfully implemented all required steps from data preparation to final performance reporting.

Future Work:

1. Implement advanced Data Augmentation techniques (e.g., slight rotation, shearing) to enhance the model's robustness.
2. Explore deeper network architectures (e.g., ResNet or VGG-like structures) or the use of Transfer Learning.
3. Test the model's generalization capability on entirely different Arabic handwriting datasets.

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8) References

https://www.kaggle.com/datasets/mloey1/ahdd1/data