**REPORT**

**Introduction**

This project focuses on developing a robust classifier capable of recognizing handwritten digits with high accuracy using the Modified National Institute of Standards and Technology (MNIST) database. The MNIST dataset is one of the most widely recognized benchmarks in the fields of machine learning, computer vision and artificial intelligence, consisting of over 70,000 grayscale images of handwritten digits (0-9), split into 60,000 training images and 10,000 testing images. Each image is 28x28 pixels in size, which makes it manageable for training and testing image-based machine learning models while still providing enough complexity to challenge classification models [1]. Handwritten digit classification is a fundamental task in the fields of computer vision and artificial intelligence, with applications that extend from postal code recognition in mail sorting to automated digitization of handwritten forms. Solving this problem effectively requires a model capable of distinguishing subtle variations in writing styles across different samples of the same digit. Neural networks, particularly deep learning architectures, have proven to be well-suited for such image classification tasks due to their capacity for learning complex patterns and features from data [2].

For the implementation, we used Keras, a high-level neural network library that runs on top of TensorFlow. Keras is highly regarded for its simplicity and flexibility, making it suitable for both rapid experimentation and large-scale applications. By using Keras, we aimed to implement and fine-tune a multi-layer neural network specifically optimized for the MNIST digit classification task [3]. Our target performance metric was a minimum testing accuracy in excess of 99.0%. Achieving this level of accuracy not only validates the robustness of the model in recognizing handwritten digits but also demonstrates the practical capabilities of neural networks to handle variability in handwriting styles and noise. This project builds on foundational research in machine learning and neural networks, particularly in convolutional neural networks (CNNs) for image classification. Early CNN models, such as LeNet-5, demonstrated the effectiveness of neural network architectures specifically tailored for digit recognition tasks, setting the stage for future advancements in pattern recognition and classification accuracy [4]. By applying modern neural network techniques and optimization strategies, we aim to enhance the performance of our model, pushing it closer to the benchmarks established by state-of-the-art classifiers [5].

In this report, we document each phase of the project, from data preprocessing and model design to hyperparameter tuning and evaluation. This structured approach enables us to achieve both high accuracy on the MNIST dataset and reproducibility of our results, providing a foundation for future projects and continued exploration in neural network-based classifications.

**Scope of the project**

The scope of this project encompasses the complete end-to-end development of a high-performance classification model, from initial data exploration and preprocessing through model training, tuning, and evaluation. Th team has collaborated on all stages of the project, including design, data preparation, model configuration, and testing, with the shared goal of creating an accurate and efficient classifier with high accuracy (99%). The MNIST dataset, being both manageable in size and complex in content, is an ideal choice for benchmarking our learning models [6].

To achieve the target minimum testing accuracy of >99%, our approach includes several key components:

**1.** *Data Preparation*: This stage involves loading, visualizing, and preprocessing the MNIST dataset. Image data preprocessing includes normalization, which scales pixel values to a range that optimizes the neural network performance, and reshaping, which configures image data to match the input structure expected by Keras models [7, 8]

**2.** *Model Design and Implementation*: We utilize the Keras library to build a neural network model specifically tailored to the MNIST classification. The model architecture includes multiple layers aimed at progressively extracting features from the input data, and we incorporate various optimization techniques to enhance training efficiency and model accuracy [8].

**3.** *Evaluation and Optimization*: After building and training the model, we conduct a rigorous performance evaluation to assess accuracy, precision, and recall. Using these metrics, we identify potential areas for improvement, such as hyperparameter tuning, and then refine the model accordingly. Model optimization includes experimenting with different layer configurations, activation functions, number of epochs and dropout rates to prevent overfitting and ensure robust generalization on unseen data [9].

**4.** *Documentation and Presentation*: A key aspect of the project involves documenting our process, results, and insights to ensure reproducibility and transparency. This includes detailed explanations of our methodology, along with a comprehensive analysis of the model performance metrics. Through this documentation, we aim to contribute to the growing body of research on neural networks and provide a foundation for future projects in classification models [10].

**Approach/Methodology**

**Data Processing**

**Challenges and Solutions**

**Results and Discussion**

**Conclusion**

**Outlook/Future Work**

**References**

1. Deng, L. (2012). The MNIST database of handwritten digit images for machine learning research [Best of the Web]. IEEE Signal Processing Magazine, 29(6), 141-142.

2. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

3. Chollet, F. (2015). Keras. Retrieved from https://keras.io

4. Lecun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324.

5. Lecun, Y., & Cortes, C. (2010). MNIST handwritten digit database. Retrieved from http://yann.lecun.com/exdb/mnist/

References

6. Deng, L. (2012). The MNIST database of handwritten digit images for machine learning research [Best of the Web]. IEEE Signal Processing Magazine, 29(6), 141-142.

7. Lecun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324.

8. Chollet, F. (2015). Keras. Retrieved from https://keras.io

9. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

10. Lecun, Y., & Cortes, C. (2010). MNIST handwritten digit database. Retrieved from http://yann.lecun.com/exdb/mnist/

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