# ANALYSIS

## MLP vs CNN

In this report, a comparative analysis of the performances of Multilayer Perceptrons (MLP) and Convolutional Neural Networks (CNN) on two distinct datasets is presented: Double Digit MNIST and Permuted MNIST. Our goal is to contrast the effectiveness of these two neural network architectures in terms of classification accuracy and overall model performance.

Datasets:

Double Digit MNIST Dataset:
The Double Digit MNIST dataset is an extension of the classic MNIST dataset, where each image contains two handwritten digits. This dataset provides a more challenging classification task compared to the standard MNIST dataset.

Permuted MNIST Dataset:
The Permuted MNIST dataset is created by randomly permuting the pixels in each MNIST image. This shuffling of pixels introduces a high degree of spatial distortion, making it a challenging benchmark for image classification tasks.

Model Architectures:
Multilayer Perceptron (MLP):
We implemented an MLP with a feedforward architecture comprising fully connected layers. The MLP is capable of handling tabular data efficiently and has been widely used in various applications.

Convolutional Neural Network (CNN):
We designed a CNN architecture specifically tailored for image data. CNNs excel at capturing spatial hierarchies in images by using convolutional and pooling layers.

Performance Metrics:
We evaluated the models' performances using the following metrics:

1. Accuracy: Measures the proportion of correctly classified samples.
2. F1 Score: Balances precision and recall, providing a single score that considers false positives and false negatives.
3. Precision: Measures the fraction of true positives out of the true positives and false positives.
4. Recall: Measures the fraction of true positives out of the true positives and false negatives.

Results:
Double Digit MNIST:

- MLP:
  - Accuracy: 97.37 %

- CNN:
  - Accuracy: 97.49 %

In the case of the Double Digit MNIST dataset, both the MLP and CNN models exhibited competitive performances in terms of accuracy, it was nearly equal. The CNN model provided better metrics (F1, Precision and Recall) in comparison to MLP.

Permuted MNIST:

- MLP:
  - Accuracy: 96.73 %

- CNN:
  - Accuracy: 98.17 %

On the Permuted MNIST dataset, which involves significant spatial distortion, the CNN demonstrated a remarkable advantage over the MLP. The CNN's convolutional layers enabled it to effectively learn spatial patterns and provided substantially improved accuracy, F1 scores, precision, and recall in comparison to MLP.

The analysis suggests that for image classification tasks, especially when spatial hierarchies are crucial, Convolutional Neural Networks (CNN) tend to outperform Multilayer Perceptrons (MLP).

**Challenges Faced:**

1. Major challenges faced in training was the very low training time of CNN in comparison to MLP.
2. CNN was slow in the evaluation step as well.

**Potential for Overfitting between a CNN and a MLP**

Overfitting is a common concern when training neural networks, and it occurs when a model learns to perform exceptionally well on the training data but fails to generalize to unseen data. Here's a comparative analysis of the potential for overfitting in CNNs and MLPs for the given datasets:

Multi-MNIST Dataset:

MLP:
Potential for Overfitting: MLPs tend to have a higher potential for overfitting, especially when dealing with image data. Their densely connected layers may lead to overparameterization. If the number of neurons in the hidden layers is excessive, an MLP can fit the training data very closely, leading to poor generalization.

CNN:
Potential for Overfitting: CNNs typically have a lower potential for overfitting in image classification tasks. This is due to the use of convolutional and pooling layers, which help capture spatial hierarchies and reduce the number of parameters. Additionally, dropout layers and weight sharing in convolutional layers further assist in regularizing the network.

Permuted MNIST Dataset:

MLP:
Potential for Overfitting: The Permuted MNIST dataset poses a significant challenge due to the spatial distortion caused by pixel permutation. MLPs may struggle to recognize patterns in the shuffled pixels, and there is a higher potential for overfitting, particularly when the number of hidden layers and neurons is high.

CNN:
Potential for Overfitting: CNNs are better equipped to handle the Permuted MNIST dataset due to their ability to capture local and global patterns without relying on the spatial structure. However, if the CNN architecture is overly complex, there is still a potential for overfitting. Careful hyperparameter tuning is essential.

Conclusion
In both datasets, MLPs tend to have a higher potential for overfitting compared to CNNs, primarily due to the fully connected nature of MLPs. This is especially pronounced in the case of the Permuted MNIST dataset, where spatial relationships between pixels are destroyed.

- CNNs are more suitable for image data and have a natural advantage in capturing spatial patterns. They are generally more robust to overfitting, especially when appropriate techniques like dropout are used.