# Spaced Learning

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## 1. Introduction

Ensemble learning techniques have been widely adopted in the realm of machine learning, with decision trees as a focal point, largely due to their fast training speed. However, when it comes to ensemble learning methods tailored for neural networks, there remains a notable void in research and practical application. This void can be primarily attributed to the considerable computational demands, including the consumption of processing time and memory resources. The primary objective of this research is to test a new kind of ensemble learning technique for neural networks that takes up less memory and faster training time in comparison to other ensemble techniques. This study involves a comprehensive comparative analysis between our proposed ensemble learning technique and established methods within the context of neural networks. The goal is to assess its efficiency, performance, and potential advantages over existing ensemble learning techniques.

## 2. Research Methodology

We used three datasets to train different model which include:

1. MNIST : images of handwritten numbers
2. Fashion MNIST : clothing images
3. CIFAR10 : Image dataset with 10 classes

We compared their accuracy, memory, and training-time to find out which model performed better. We used google colab to program spaced learning which can be found in this link : SpacedLearning_Delfino&Fhillip.ipynb

## 3. Result and Analysis

By checking at table 1, we can see that Spaced learning & CNN, and CNN performs the best. On complex datasets like Cifar10, Spaced learning & CNN outperform CNN but on other datasets Spaced Learning & CNN have the same accuracy as CNN but require more memory than CNN.

*Table 1. Comparison Table.*

| | MNIST | | | Fashion MNIST | | | Cifar10 | | |
|---|---|---|---|---|---|---|---|---|---|
| **Model** | **Accuracy (%)** | **Tim e(s)** | **Memory (mb)** | **Accuracy (%)** | **Time (s)** | **Memory (mb)** | **Accuracy (%)** | **Time (s)** | **Memory (mb)** |
| **Spaced Learning & CNN** | **98** | **118** | **2252** | **90** | **499** | **1128** | **70** | **1774** | **2506** |
| **CNN** | **98** | **189** | **22** | **90** | **378** | **528** | **56** | **1284** | **82** |
| **Random Forest** | **94** | **45** | **2200** | **87** | **95** | **2200** | **46** | **22** | **3200** |
| **Bagging & CNN** | **96** | **1680** | **11558** | **79** | **1680** | **7168** | **MEMORY EXCEED** | | |

However, after checking the confusion matrix of Fashion MNIST provided on figure 1 and 2 we noticed that Spaced learning & CNN is able to learn data that looks similar much better compared to pure CNN. Such as t-shirts, pullover, and coat.

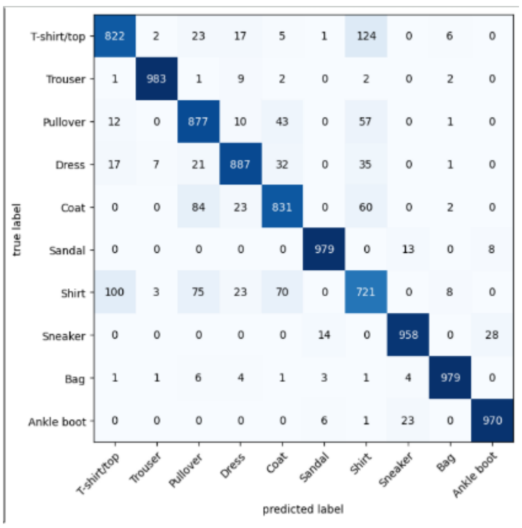


*Figure 1. FashionMNIST confusion matrix(Spaced Learning)*

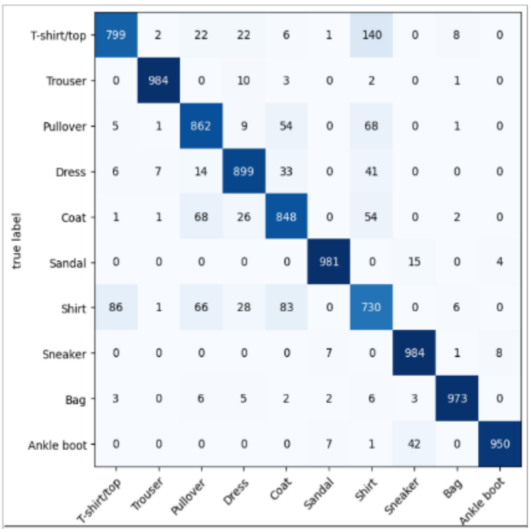


*Figure 2. FashionMNIST confusion matrix(CNN)*

## 4. Conclusions and Future Works

In summary, as data complexity grows, neural network accuracy tends to decline. We've found that ensemble techniques, despite time and memory trade-offs, are effective in mitigating this decline. Notably, Spaced Learning has demonstrated exceptional results.

Looking ahead, we plan to further explore Spaced Learning and its integration with additional concepts for improved performance. We also aim to refine ensemble technique combinations to strike a better balance between accuracy and resource usage. This ongoing research holds the promise of enhancing the processing of complex data with neural networks.

## References

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