

CSE 574 Project2 Report

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1. Experimental Environment

Hardware

CPU 14900K 24 Core

Memory 128G

No GPU

Software

OS: Ubuntu 22.04

Running **NN**: Python 3.12.7

Running **CNN & DNN**: Python 3.7.12, Tensorflow: 1.15.0

2. Implement MLP

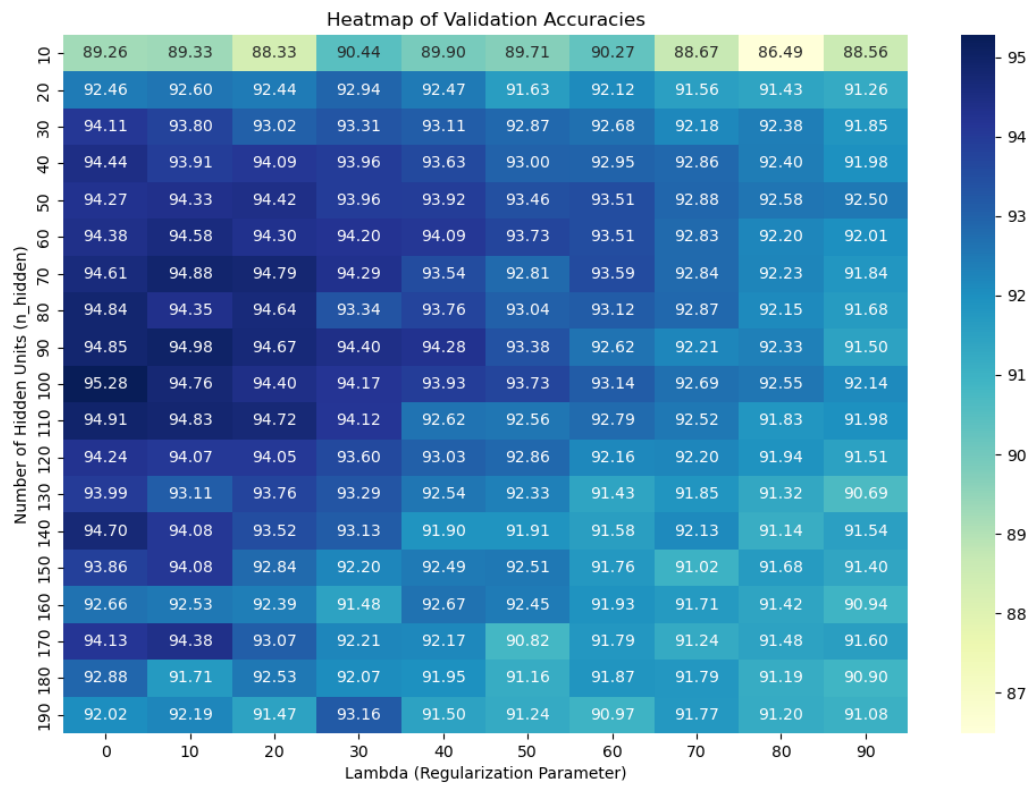
2.1 Accuracy

We tried different **n_hidden** and **lambda** hyper-params to train this MLP, and get such result:

We use the **validation accuracy** for hyper-parmas.

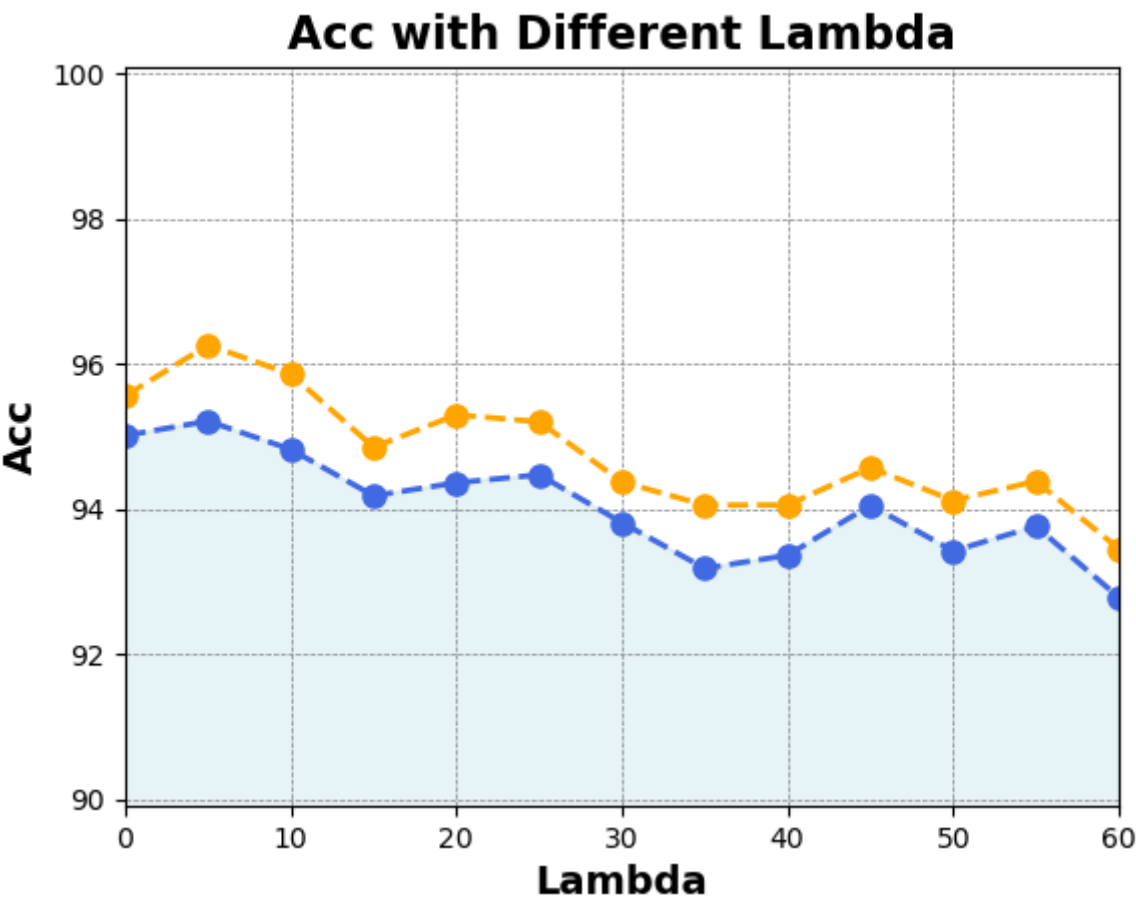
During initial debugging, a grid search approach was employed to identify the optimal parameters. We began by exploring a broad range for n_hidden ([0, 200] with step size 10) and lambdaval ([0, 100] with step size 10). As n_hidden and lambdaval increase, the model's accuracy quickly converges, reaching its peak when n_hidden is 100 and lambdaval is 0. After parameters optimization, the best validation accruary for

NN on the handwritten digits is 95.28%.

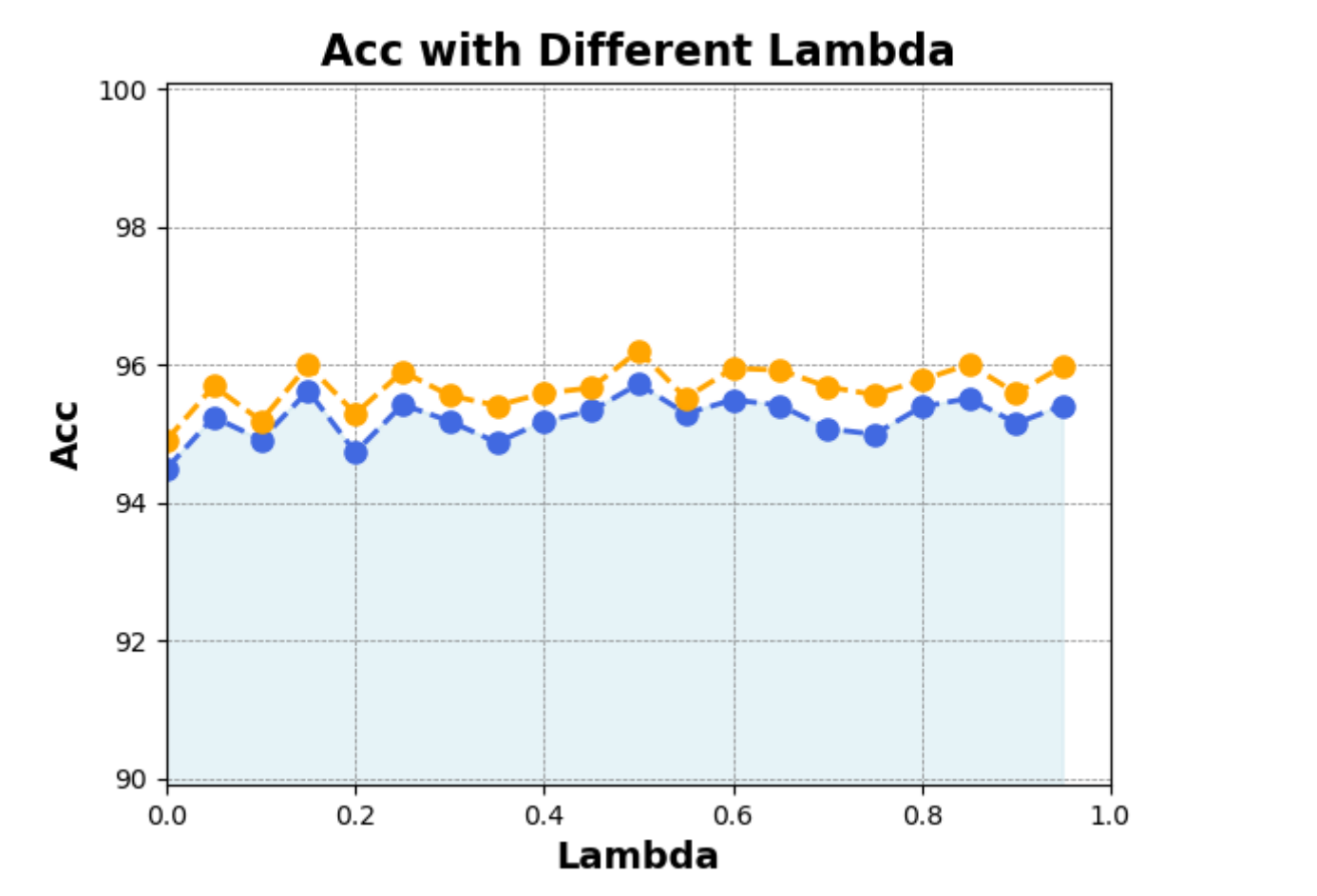


With this chart, we found that using around 100 as `n_hidden` can lead to better performance.

About the regularization parms `lambda`, we test other range of lambda with a fixed `n_hidden(100)`



Firstly, we try a big range from 0 to 60, and we find that when lambda is around 5, the accuracy is better. So we run other experiments from 0 to 10



After that, we chose `lambda=0.5` for better accuracy We got such result:

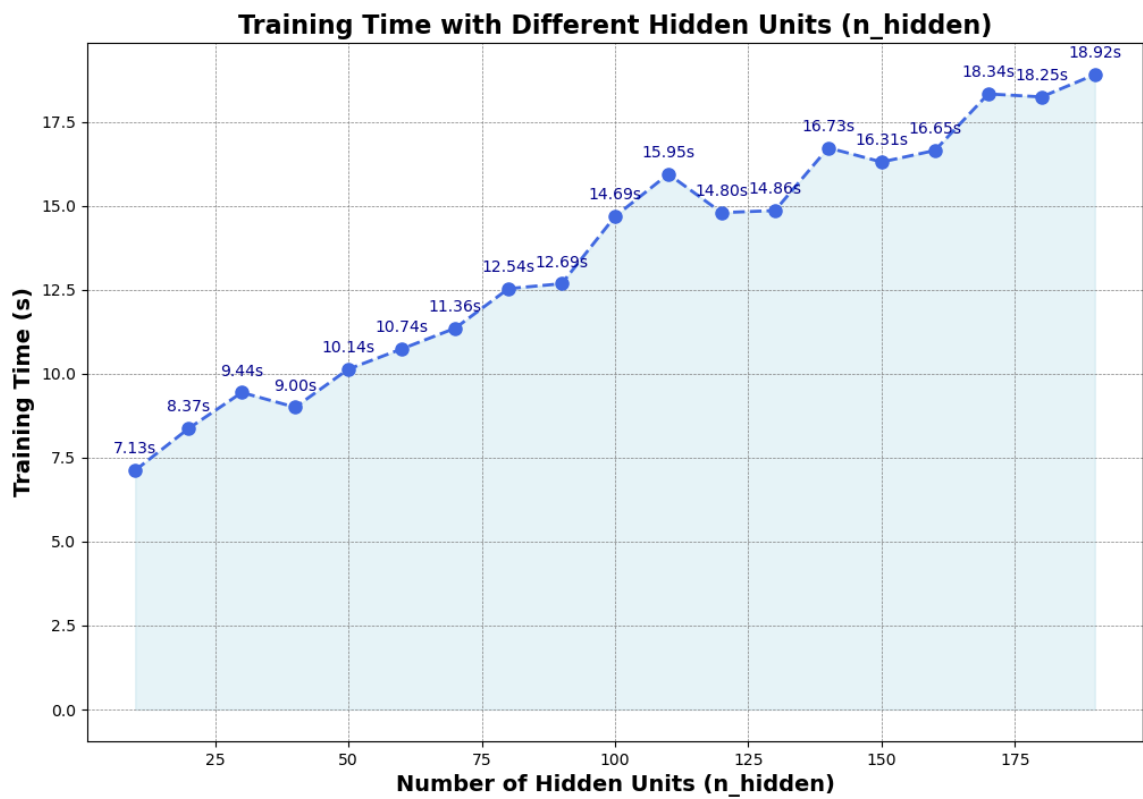
```
Training set Accuracy:95.65599999999999%  
Validation set Accuracy:95.1%  
Test set Accuracy:95.11%
```

2.2 Regularization of underfitting and overfitting

It is a means or operation to impose a priori restrictions or constraints on a problem in order to achieve a specific purpose. The purpose of using regularization in the algorithm is to prevent the model from overfitting.

We can find that, when `lambda` is small like 5, the accuracy of both training data and validation data is high, which means the model is overfitting. However with a big `lambda > 30`, the model is underfitting which leads to a poor performance.

2.3 Train Time



Refer to this chart, we can find that the tarin time will increase by increasing `n_hidden`. This makes sense because more hidden node in this MLP, more computing is needed.

3. Compare with CNN

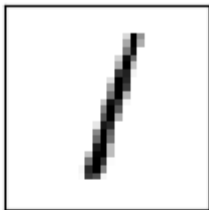
After 1000 iter, the cnn has such result:



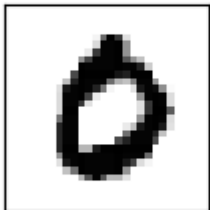
True: 7, Pred: 4



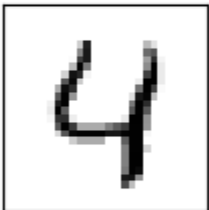
True: 2, Pred: 4



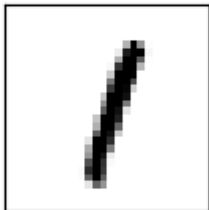
True: 1, Pred: 4



True: 0, Pred: 4



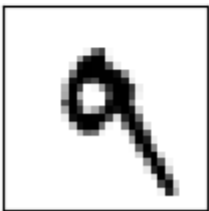
True: 4, Pred: 5



True: 1, Pred: 4



True: 4, Pred: 5

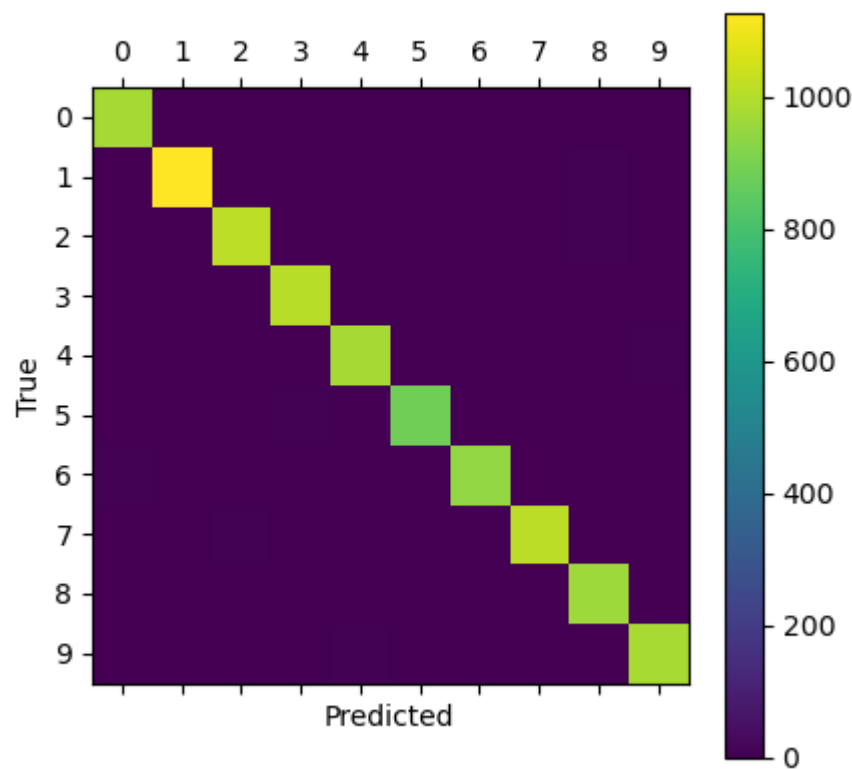


True: 9, Pred: 5



True: 9, Pred: 5

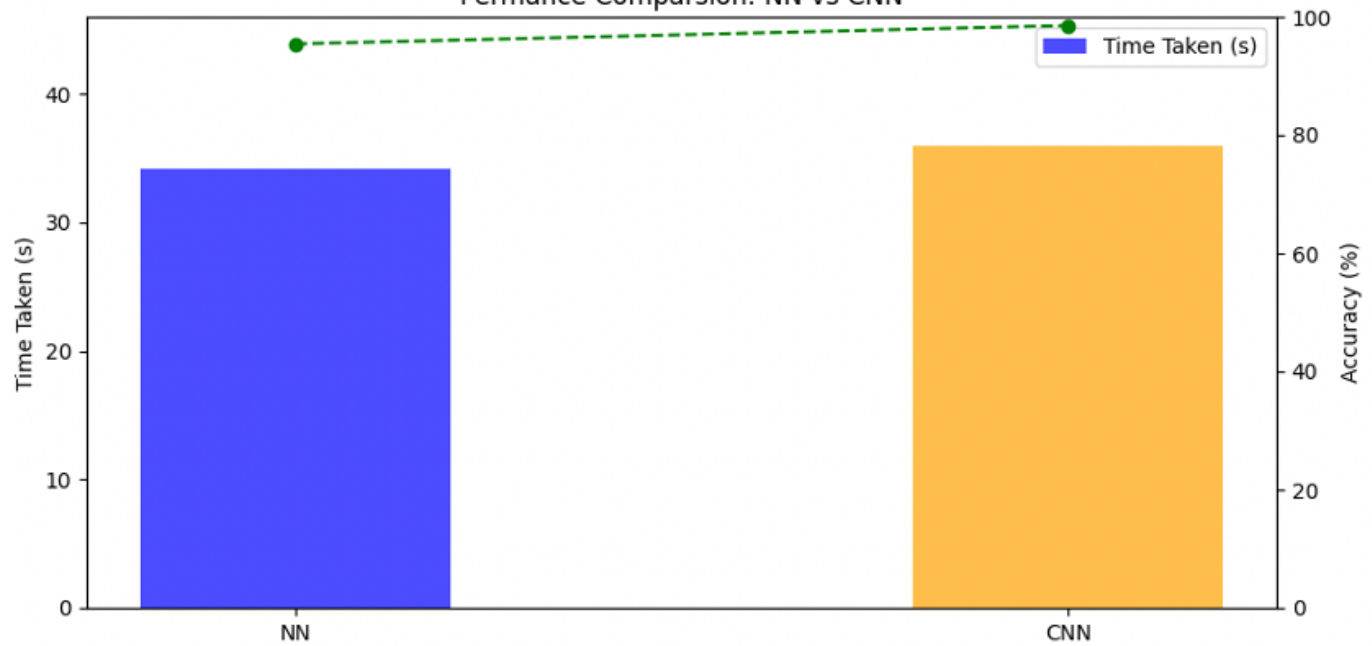
And the confusion matrix is like this:



Time usage: 0:00:36
Accuracy on Test-Set: 98.5% (9853 / 10000)

Compared to NN, CNN achieves higher accuracy with a similar training time.

Permanance Comparsion: NN vs CNN



4. Compare with DNN

We adopt the `nnScript.py` to the CelebA dataset, and get such result:

```
Training set Accuracy:86.32701421800948%  
  
Validation set Accuracy:85.29080675422139%  
  
Test set Accuracy:86.41180923542771%  
  
Time taken: 22.72310185432434
```

After that, we test this dataset with DNN

```
Time taken: 22.835124015808105  
Accuracy: 0.8186979
```

The DNN has similar training time and worse accuracy. We think this is because the model has so many hidden and is overfitting

