***Discussion of Hyperparameter Tuning on CNN and MLP***

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# 1. Introduction

In this project, we will discuss the performance of different hyper-parameters tuning methods on two distinct models, i.e. Convolutional neural network Neural Network (CNN) and Multilayer Perceptrons (MLP). We will discuss in-depth the effects of hyper-parameters of neural networks on the converge rate and accuracy. Ranging from different optimizers and learning rates, we would also like to determine which is the most suitable parameters for CNN and MLP in terms of the training speed, test accuracy and test loss. We would like to discuss the impact of hyperparameters in terms of model accuracy and computation cost We would like to discuss the impact of hyperparameters in terms of model accuracy and computation cost

# 2. Data Description

In this study, an image dataset is selected. This image data set is called ‘Intel Image’ and it is available on Kaggle:

<https://www.kaggle.com/puneet6060/intel-image-classification>

Basically, it is a dataset for classification. Following are some details:

***Intel Image***

This dataset originally contains around 25000 pieces of Natural scenes images with all sizes equal pixels. The images are distributed under 6 categories:

0 for buildings, 1 for forests, 2 for glaciers,

3 for mountains, 4 for sea, 5 for streets.

However, due to the time and computational constraint, in this study, only mountains and buildings will be regarded as the data being processed.

The number of training image = 4703 and the number of testing image = 962.

Chart, bar chart

Description automatically generated

Proportion of train data and test data (0.8:0.2)

We will further discuss the background information of the Neural Networks below.

# 3. Neural Network Models

A neural network is a statistical technique for classification which mimics the functioning and mechanism of the human brain. There are several workable and useful models of neural networks for both classification and image recognizing. Mentioned before, we would use MLP and CNN only in this study.

## 3.1 Artificial Neural Network (ANN)

The most important component of ANNs is artificial neurons which are determined by the nature(s) of the problem. Every neuron received inputs from several other neurons, multiplied by assigned corresponding weights, then added to the sum and passed to one or more neurons. Usually, an activation function will be applied to the artificial neurons to the output then passing to the following variable. These mathematical computations are what happens in one single node. ([1.1](#A1))

ANNs are composed of a few layers which are made up of rows of artificial neurons, including an input layer, which receives data from data sources; one or at most two (sometimes can be zero) hidden layers which process the data; And an output layer which provides data point(s) based on the variables of the network. In between each layer, neurons are not connected but connected to neurons in the forward next layer, it is called feed-forward network. ([1.2](#A2))

## 3.2 Multilayer Perceptron (MLP)

MLP is a class of feedforward artificial neural network (ANN) which is composed of more than one perceptron. Perceptron is a similar but more general computational model than artificial neurons (McCulloch-Pitts neurons) by applying numerical weights for inputs and a mechanism for learning the weights. Perceptron also supports real inputs not just Boolean values. ([1.3](#A3))

The MLP consists of at least three types of layers which are an input layer, an output layer, and one or more hidden layers. The function of layers is the same as ANNs which also a feed-forward neural network. In between the other two layers, the hidden layers will be the true computational engine of MLP. The most significant difference between MLP and ANN is that MLP is a fully connected architecture. ([1.4](#A4))

***3.2.1 Hidden Layers***

Hidden layers are the most crucial part of NN which not visible but involves decent numbers of computations. Thus, in developing ANN and MLP, dealing with hidden layers will be one of the confusing tasks. There are two main components in adjusting the hidden layers, which are the choosing number of hidden layers and determining the optimal or reasonable neurons in a single hidden layer.

***3.2.2 Choosing Number of Hidden Layers***

If the data is separable linearly then no hidden layer is needed at all, but the situation usually will not happen. On the other hand, if the data is less complex with few dimensions or features, 1 to 2 hidden layers will probably work well in NN. Else, if the dataset consists of large dimensions or features, then to get an optimum solution, more than 5 hidden layers will be applied for an optimum value. More hidden layers will increase the model complexity accordingly, however, it does not equal to more hidden layers will obtain better results, sometimes it will lead to an overfitting problem.

***3.2.3 Choosing Nodes in Hidden Layers***

Deciding the number of neurons in the hidden layers is an important part that is unignorable to the overall neural network architecture. Thus, determined the number of neurons in each hidden layer must be considered carefully.

There are two situations when the number of neurons decided wrong. 1) Underfitting occurs when there are too few neurons in the hidden layers to adequately detect the signals in a complicated data set. 2) Overfitting occurs when the neural network has too many neurons in the single hidden layer for the training set.

Besides, Dropout is a regularization method to prevent the NN from overfitting, which can be applied to any or even all hidden layers. The method is to randomly drop out some nodes in the hidden layers, perform better in wide NN with a decent number of nodes. A hyperparameter is implemented to hidden layers, which ranges from 1-0 usually 0.8-0.5, which means the probability of dropping the output of each node in a hidden layer. The objective is to prevent overfitting problems not just from selecting the nodes in the first hidden layer, but all following hidden layers.

## 3.3 Convolutional Neural Network (CNN)

CNN is also a type of deep neural network, which usually CNN is a type of deep learning model utilized for analyzing visual imagery (data with a grid pattern). CNN is designed to learn spatial hierarchies of features automatically and adaptively. The architecture of CNN is similar but not the same as MLP. It consists of three layers: convolution, pooling, and fully connected layers. The convolution and pooling layers perform feature extraction, while the fully connected layer converts the extracted features into output.

***3.3.1 Convolutional Layer***

The convolutional layer is the core of a CNN, and most of the computation occurs in this layer. It consists of a few components: input data, filter, and feature map. In the convolution process, filters are a feature detector, which moves across the receptive fields of the image to check if the feature is present. The filter is typically a 3x3 matrix that equivalent to the size of the receptive field. The filter is then applied to the image, and a dot product between the input pixels and the filter is calculated and projected into an output array. After that, the filter shifts by a stride, repeating the previous process until the filter has reached every pixel in the entire image. The so-called feature map is a matrix with all the calculated dot products, also known as weight.

There are three key parameters in a convolutional layer, which are: filters, stride size, and padding, that will affect the output volume size. 1) *Filters* are simply a 3x3 matrix, but the type and number of filters applied to the input image determine the features and the depth of the output. 2) *Stride size* is the distance or number of pixels for the filters to move on the input after every calculation. 3) *Padding* is to add more dummy cells (0 in value to avoid noise problem) to the input along the side which is to enable the CNN to get a larger output matrix size and enough information for edges.

***3.3.2 Pooling Layer***

The Pooling layers treat the output from the convolutional layer as input, and it is introduced to reduce the number of parameters in the input. Therefore, the amount of calculation will also decrease, which also reduces the overfitting to a certain extent. There are two main types of pooling: 1) Max pooling: As the filter moves across the input, it selects the pixel with the maximum value and returns it as an output. 2) Average pooling: As the filter moves across the input, it calculates the average value within the moving window and returns as an output.

# 4. Hyper Parameters in Training Neural Network Models

In training the neural network models, there are several hyper-parameters that worth tuning, our main focus in this study is the optimizers, learning rate, and the activation function.

## 4.1 Optimizers

***Gradient Descent (GD)***

Gradient descent is a popular iterative optimization algorithm that minimizes the loss function , where by updating the parameters in the opposite direction of the gradient of the loss function. The learning rate determines the size of the steps taken to reach a local minimum. Thus, we follow the direction of the slope of the surface created by the loss function downhill until we reach threshold.

There are three types of gradient descent, which differ in the amount of data used to compute the gradient of the loss function. Depending on the amount of data, we make a trade-off between the accuracy of updates and the time consumed for updates. The major difference between GD, BGD and SGD is the sample sizes (batch size) for parameter update in each time.

BGD generally refers to use the whole dataset at once, i.e. n=N, whereas MBGD uses a partial dataset as a part for each epoch, i.e. and for SGD, it uses only one sample for each epoch, i.e. )

***4.1.1 Batch Gradient Descent***

Classical (batch) gradient descent, computes the gradient of the loss function with respect to for the entire training set:

As the gradients need to be calculated for the entire dataset to perform a single update () which is one iteration, thus batch gradient descent can be very time-consuming and space-consuming for datasets that are considerably large. However, Batch gradient descent is guaranteed to converge to the global minimum for convex error surfaces as well as a local minimum for non-convex surfaces.

***4.1.2 Mini-Batch Gradient Descent***

Mini-batch gradient descent is taken to adopt the benefits of SGD and batch gradient descent. Mini-batch reduces the variance of the parameter updates, which results in more stable convergence. It performs an update for every Mini-batch (fraction of samples) of n (batch size) training examples:

The mini-batch sizes range from but when batch size is 1 it is an SGD. Mini-batch gradient descent is typically the algorithm of choice when training a neural network.

***4.1.3 Stochastic Gradient Descent (SGD)***

SGD is proposed to improve the batch gradient descent method which the main idea is to perform a parameter update for each training exampleand label. i.e.

Batch gradient descent performs excessive computations for large datasets since it computes gradients for similar examples repeatedly before each parameter update. SGD opposes redundancy by performing only one update at a time. Therefore, SGD is usually much faster than batch gradient descent. SGD performs frequent updates with a high variance that cause the loss function to fluctuate. While batch gradient descent converges to the minimum of the pool of the parameters. On the one hand, the fluctuation in SGD enables it to change to new and potentially better local minima. Although this complicates the convergence to the exact minimum, it has been known that when the learning rate increase slowly, SGD will have the same convergence behavior as batch gradient descent, almost certainly converging to either local or the global minimum for non-convex and convex optimization correspondingly.

***4.1.4 Adaptive Moment Estimation (Adam)***

In practice, it is too sensitive to decide the hyperparameter learning rate , thus Adam is implemented as a gradient descent optimization algorithm. Adam incorporates the idea of RMSprop and Momentum with a bias correction which is to store an exponentially decaying average of past squared gradients, also keep an exponentially decaying average of past gradients. i.e.

,

and are estimates of the first moment and the second moment of the gradients, respectively. As and are initialized as zero vectors, so under the initial condition both and are biased towards zero. By computing the unbiased first and second moment estimates

,

Using the above-unbiased estimator, the Adam update rule is introduced as:

***4.1.5 Root Mean Squared Propagation (RMSprop)***

RMSprop is an adaptive learning rate optimization algorithm which is to avoid the vanishing learning rate by replacing the sum of the square of the historic gradient with a weighted average i.e.

RMSprop as well divides the learning rate by an exponentially decaying average of squared gradients. Hinton in his lecture 6e suggests that  and  would be good values for the algorithm.

***4.2 Learning Rate***

The learning rate is a hyperparameter that controls the amount of apportioned error when the weights of the model are updated each time it updates. Thus, the learning rate could be one of the most important hyperparameters when configuring the NN. Therefore, it is vital to know the effects of the learning rate on model performance when deciding the learning rate for the NN model.

The learning rate controls the adaption speed of the model to the problem. Smaller learning rates require more training epochs given the smaller changes made to the weights of each update. Hence required a longer training process. Whereas larger learning rates result in more rapid changes as well as require fewer training epochs.

When a learning rate is too large, it can cause the model to converge too fast to a suboptimal solution, i.e. The gradient may oscillate back and forth around the minimum and may not even converge. Whereas a learning rate that is too small can cause the process stuck in training.

Since learning rate is a configurable parameter, the challenge of training NNs involves careful selection of the learning rate. A traditional default value for the learning rate is either 0.1 or 0.01, and this may represent a good starting point on most of the problems. (It is common to grid search learning rates on a log scale . But very time-consuming.) In this study, we decide our learning rates to be 0.01,0.005 and 0.001.

## 4.3 Activation Function (AF)

Activation functions are a critical part of the design of a neural network. AFs act like a switch in a circuit depending on the input. If AF is not used, there will be a linear relationship between input and output variables. Thus, many complex problems are not able to be solved as a linear relationship has some limitations. The main purpose of introducing an activation function is to introduce non-linearity to solve complex problems. The choice of activation function in the hidden layer will determine how well the network model learns the training dataset. In the output layer, AFs will define the type of predictions the model can make. In our project, several AFs will be applied to hidden layers.

***4.3.1 Sigmoid***

In mathematical definition, the sigmoid function takes any range of real numbers and returns the output value which is within the range of . Based on the convention, we can expect the output value is within the range of {-1,1}.

The property of the sigmoid function is that it returns a real-valued output. The first derivative of the sigmoid function will be non-negative or non-positive. Illustrate as:

The Sigmoid function is used for**binary classification**in a logistic regression model. While creating artificial neurons, a sigmoid function is used as the **activation function**. In statistics, the **sigmoid function graphs** are common as a cumulative distribution function.

**4.3.2 Rectified Linear Unit (ReLU)**

A ReLU has output 0 if the input is less than 0, and *raw* output otherwise. That is, if the input is greater than 0, the output equals the input. The operation of ReLU is closer to the way our *biological neurons* work. i.e.

ReLU is non-linear and not having any backpropagation errors, unlike the

sigmoid function. Also, for larger NNs, the speed of building models based off on ReLU is very fast compared to Sigmoid (Krizhevsky et al), because 1. ReLU is One-sided, compared to the anti-symmetry of Tanh. 2. Sparse activation on hidden units. 3. Fewer vanishing gradient problems compared to sigmoid. 4. Only comparison, addition, and multiplication involved in the computation. 5. It is scale-invariant i.e.

# 5. Model selection

## 5.1 CNN

In our CNN model, the model structure is shown as the follows:

The 3 convolutional layers serve as the feature extraction layer for finding out the differences between the buildings and mountain in the training dataset. ReLU is chosen to be the activation function and Max Pooling is applied. The number of layers is selected to be 3 as it would be more secure for feature extraction. Whilst if we would like to have a faster training speed, # of convolutional layers could be equal to 2.

While the 4-layers MLP is served as the analysis layer for the classification. ReLU and Sigmoid (output layer) is chosen to be the activation function and Batch Normalization is applied.

## 5.1 MLP

In our MLP model, the model structure is shown as the follows:

We would like to test how would the image classification perform differently if we skipped the convolutional part. For the experimental manner, we designed a MLP model with the same number of layers as the CNN one. The activation function used are also ReLU and Sigmoid (output).

# 6. Result and Discussion

In this section, two important findings in our study would be presented. The first part is the hyper-parameter tuning result. The second part is the comparison of the performance of the CNN and MLP models.

## 6.1 Hyper-parameters tuning

***6.1.1 CNN***

In this section, we fixed the number of epochs = 10 for the optimizers **Adam**, **mini-batch SGD** and **RMSprop**. Moreover, the batch size is also fixed to be 128 for these three optimizers.

By considering the optimizing algorithm of **SGD**, we need to allow more than 10 epochs to it. Therefore, for **SGD**, we trained it with 10, 30 and 128 epochs.

Unfortunately, for the **Batch GD,** normal CPU cannot handle the computational process and we would not include this optimizer.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Optimizer | LR | Train acc | Train loss | Val acc | Val loss | Test acc | Test loss | Train time(s) |
| Adam | 0.01 | 0.9750 | 0.0766 | 0.9362 | 0.2131 | 0.9324 | 0.1565 | 434.9 |
| 0.005 | 0.9915 | 0.0315 | 0.907 | 0.4489 | 0.9210 | 0.3767 | 460.5 |
| 0.001 | 0.9984 | 0.0087 | 0.946 | 0.1682 | 0.9470 | 0.1446 | 472.6 |
| Mini-Batch  SGD | 0.01 | 0.9976 | 0.0410 | 0.8512 | 0.5054 | 0.8555 | 0.4996 | 473.8 |
| 0.005 | 0.9934 | 0.0731 | 0.7237 | 0.5444 | 0.7495 | 0.5323 | 451.6 |
| 0.001 | 0.9476 | 0.1904 | 0.6461 | 0.6079 | 0.6933 | 0.5988 | 451.7 |
| RMSprop | 0.01 | 0.9740 | 0.0651 | 0.9501 | 0.2935 | 0.9324 | 0.2984 | 448.6 |
| 0.005 | 0.9809 | 0.0515 | 0.9554 | 0.2057 | 0.9615 | 0.1539 | 457.7 |
| 0.001 | 0.9960 | 0.0155 | 0.8682 | 0.4442 | 0.8846 | 0.3999 | 466.9 |

*Assumption:*

Epoch = 10

Batch size = 128

For Adam, minibatch SGD, RMSprop:

For the SGD, learning rate (LR) is fixed at 0.01:

\*\*used GPU to accelerate the training process.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Optimizer | LR | **Epoch** | Train acc | Train loss | Val acc | Val loss | Test acc | Test loss | Train time(s) |
| SGD | 0.01 | 10 | 0.5245 | 0.6922 | 0.4378 | 242.5130 | **0.4563** | **315.6449** | **1643.8** |
| 0.01 | 30 | 0.5327 | 0.6913 | 0.4389 | 353.7512 | **0.4688** | **499.7157** | **7178.8** |
| 0.01 | 128 | 0.5331 | 0.6912 | 0.4580 | 374.1743 | **0.4574** | **358.6020** | **1982.2\*\*** |

From the above table, we have the following findings:

1. **Each Optimizers would have its own best learning rate combination**:

As the table shown, the three best (most accurate) optimizer-learning rate combinations are:

This implies that there is not a universal best learning rate. Each optimizer has its own algorithm to minimize the loss function. That is why by using different optimizers, we need to tune the learning rate vigorously to find out the best model. With the page limit of this report, we merely tune the learning rate with the optimizer. But in the actual practice, there are many hyperparameters are also need for the researcher to tune such as the momentum and the dropout ratio. Therefore, hyperparameter tuning is a complex and important work to be done every single time.

1. **SGD is poorly performed in this study:**

Among all the selected optimizers, Adam, minibatch SGD and RMSprop give similar results in terms of test accuracy, test loss and training time. Adam and RMSprop successfully predict the class label with above 90% accuracy. Minibatch SGD prediction is slightly less good than theirs due to underfitting with epoch = 10. Yet, it has around 70 – 80 accuracy. However, SGD cannot converge at epoch = 10, hence at epoch = 128. The accuracy is below 50% and the training time is a few times of others.

1. **Convergence rate:**

**Adam**

***Mini-batch SGD***

*Lr = 0.01*

*![Chart, line chart, scatter chart

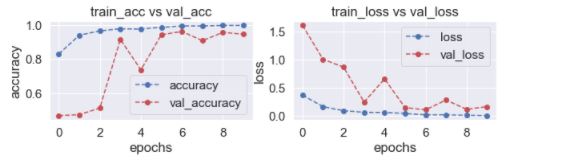
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*Lr = 0.005*

*![Chart

Description automatically 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*Lr = 0.001*

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*Lr = 0.01*

*Chart, scatter chart

Description automatically generated*

*Lr = 0.005*

*Chart, line chart, scatter chart

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*Lr = 0.001*

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***RMSprop***

*Lr = 0.01*

*![Chart, line chart

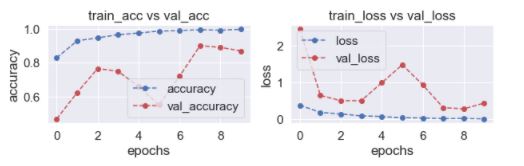
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*Lr = 0.005*

*![Chart, line chart

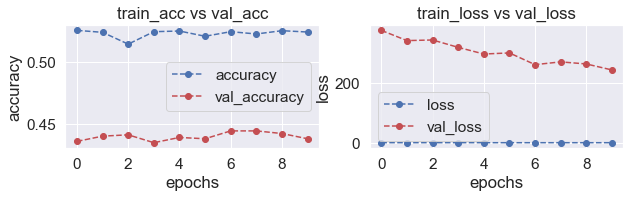
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*Lr = 0.001*

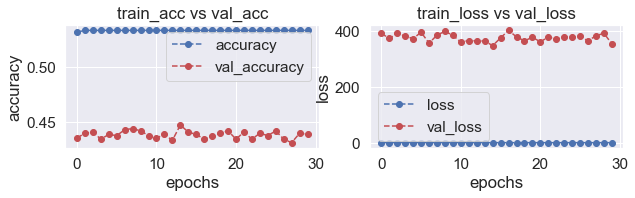
**

***SGD***

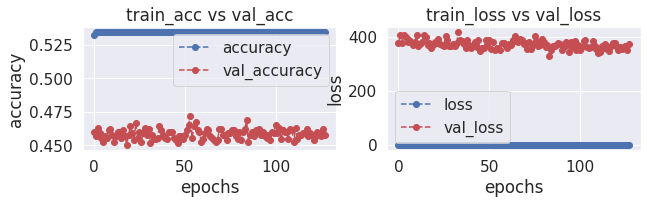
*Lr = 0.01, epoch = 10*



*Lr = 0.01, epoch = 30*



*Lr = 0.01, epoch = 128*



As we can see, Adam and RMSprop has the fastest convergence rate. Mini-batch SGD also show the tendency to converge. However, for the convergence rate of SGD, we can see that it still needs a lot of epoch (possibly 1000 epochs) to converge.

***6.1.2 MLP***

In this section, we fixed the number of epochs = 100 for the optimizers **Adam**, **mini-batch SGD** and **RMSprop**. Moreover, the batch size is also fixed to be 128 for these three optimizers.

For **SGD**, this time we also used epoch = 100 to see if it can converge in MLP. Also, **Batch GD** is not included.

And for the page constraint, this section will only consider 2 learning rates: 0.001 and 0.01 for Adam, Mini-batch SGD and RMSprop. For SGD, 0.01 and 0.05 is applied.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Optimizer | LR | Train acc | Train loss | Val acc | Val loss | Test acc | Test loss | Train time(s) |
| Adam | 0.01 | 0.9944 | 0.0139 | 0.7535 | 1.5605 | 0.7640 | 1.5778 | 105.4 |
| 0.001 | 0.9976 | 0.0075 | 0.7981 | 1.0592 | 0.7952 | 1.0800 | 101.5 |
| Mini-batch SGD | 0.01 | 1.0000 | 0.0020 | 0.8130 | 0.5858 | 0.8274 | 0.5371 | 87.1 |
| 0.001 | 1.0000 | 0.0192 | 0.7747 | 0.5373 | 0.7890 | 0.4526 | 88.9 |
| RMSprop | 0.01 | 0.9952 | 0.0169 | 0.7428 | 1.8303 | 0.7370 | 1.6390 | 151.7 |
| 0.001 | 0.9992 | 0.0016 | 0.7556 | 1.4258 | 0.7620 | 1.4443 | 153.0 |
| SGD | 0.01 | 0.5319 | 0.6920 | 0.4772 | 195057.2 | **0.4792** | **201612.2** | **3391.6** |
| 0.05 | 0.5040 | 0.7175 | 0.5058 | 1797195 | **0.5229** | **1755922** | **5125.7** |

From the above table, we have the following findings:

1. **Each Optimizers would have its own best learning rate combination:**

As the table shown, the three best (most accurate) optimizer-learning rate combinations are:

[Adam, 0.001], [Minibatch SGD, 0.01], [RMSprop, 0.001]

1. **SGD is poorly performed in this study again:**

Among all the selected optimizers, Adam, minibatch SGD and RMSprop give similar results in terms of test accuracy, test loss and training time. Adam, Mini-batch SGD and RMSprop successfully predict the class label with around 80% accuracy. However, SGD again, cannot converge at epoch = 100. The accuracy is around 50% and the training time is a more than 10 times of other’s. We believe that SGD is not the best in the small-middle dataset.

1. **Convergence rate:**

**Adam**

Lr = 0.01

Chart

Description automatically generated

Lr = 0.001

Graphical user interface, chart

Description automatically generated

**Mini-batch SGD**

Lr = 0.01

Graphical user interface, application

Description automatically generated

Lr = 0.001

Chart

Description automatically generated

**RMSprop**

Lr = 0.01

Chart, scatter chart

Description automatically generated

Lr = 0.001

Chart, scatter chart

Description automatically generated

**SGD**

Lr = 0.01

**Chart

Description automatically generated**

Lr = 0.05

Chart, scatter chart

Description automatically generated

Compared to CNN, Adam, Mini-batch SGD, and SGD has a more stable converge rate. For the SGD, Lr = 0.01, it presents a smooth curve of gradient descent. However, please note that the loss of the SGD is in scale 10^7. Even after 100 epochs, the loss is still extremely large (200000+). By giving 500 more epochs, it should have a lower loss and higher accuracy. In SGD, Lr =0.05, we naively expected a faster convergence will be seen, but instead it cannot be converged due to the too high learning rate. From this point of view, we can conclude that SGD still has the lowest convergence rate.

## 6.2 CNN vs MLP

From the tables and graphs shown in the above section, there are some apparent differences between CNN and MLP illustrated.

* CNN has a higher accuracy than MLP:

The best (most accurate) MLP model in this study is with hyper-parameters: optimizer = Mini-batch SGD with learning rate = 0.01. The corresponding test accuracy is 0.8274. Although this model is not the best tuned MLP, we can deduce that the accuracy ceiling of using MLP would be around 85%. Whilst the CNN models can always exceed this ceiling (if not underfitted). We can conclude that CNN handle image data better than the plain MLP.

* MLP has a faster training time than CNN.

# 7. Limitation and Conclusion

## 7.1 Limitations

***7.1.1 Time and Computational (hardware) Constraint:***

In this study, we decided to use the trimmed dataset to perform binary classification instead of the whole dataset to illustrate multiclass classification due to the computational constraint. By using merely CPU, the training time and the memory usage is overwhelming in CNN.

For the SGD part, we are also unable to deliver an epoch which the model is fully converged as the training time would be too long.

***7.1.2 Page and content limitation***

This project can have a deeper analysis on the hyperparameter tuning aspect. For instance, we could try to tune and see how the momentum, rho, dropout rate, different number of layers and neurons of CNN, MLP affecting the testing accuracy, loss, and the convergence speed. But due to the page limitation, we decided to choose optimizer, learning rate and activation function to be our main focus as we believed that these three hyperparameters has a prior place than the others mentioned above.

It is also unfortunate to have only one dataset in this study. Originally, we intended to use two datasets (small dataset vs big dataset to illustrate the fact that the size of the dataset is also a crucial point of choosing the hyperparameter such as optimizer. It has been shown that for a small dataset, batch GD would give the fastest convergence time. Alternatively, SGD should have a better performance on a big dataset (with 1Million+ record). However, due to the page limit and the content constraint of “exact 2 models”, we failed to include this comparison in this study.

## 7.2 Conclusion

In conclusion, we performed the hyperparameter tuning and model comparison in this study by using an image dataset.

Basically, there are three main findings.

First, SGD is shown to be poorly performed in the small-to-medium-size dataset. Despite different learning rates (0.01,0.05,0.001,0.005) and models (CNN and MLP). SGD performs the worst in terms of convergence speed, training time, accuracy, and loss.

Second, different optimizers should have different learning rates. As mentioned in 6.1.1 and 6.1.2. 1. Each Optimizers would have its own best learning rate combination. And as we believe, many people may not understand the importance of hyperparameter tuning and just call package as well as using the default settings in the package. We would like to point out that using the default setting must not lead to a satisfactory result in handling data in reality. Moreover, there are not only optimizer and learning rate, but also a lot of hyperparameters for users to adjust in order to get the best model. Therefore, hyperparameter tuning has been called the art of the deep learning.

Third, the performance of CNN is better than that of MLP. In section 6, we can see a huge difference (10%) between CNN and MLP models. Although the training time of MLP is faster than the CNN, the increase in accuracy by using CNN outweighs the longer training time. And the deficiency in training time of CNN can be overcome by GPU accelerator.

# Appendix

***Reference:***

ANN picture and infos

<https://wiki.pathmind.com/neural-network>/

MLP picture

<https://users.ics.aalto.fi/ahonkela/dippa/node41.html>

MLP perceptrons picture

<https://towardsdatascience.com/perceptron-the-artificial-neuron-4d8c70d5cc8d/>

learning rate

<https://www.jeremyjordan.me/nn-learning-rate/>

dropout

<https://machinelearningmastery.com/dropout-for-regularizing-deep-neural-networks/>

ReLU and leaky ReLU

<https://www.machinecurve.com/index.php/2019/10/15/leaky-relu-improving-traditional-relu/#introducing-leaky-relu/>

sigmoid

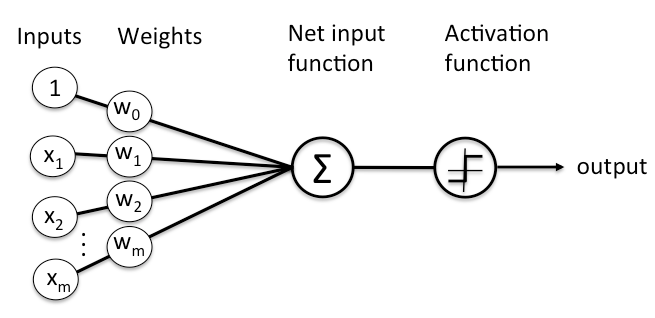
<https://dataaspirant.com/difference-between-softmax-function-and-sigmoid-function/>

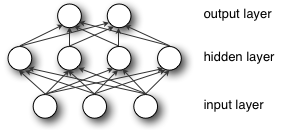
BGD SGD MiniBGD formula and info

<https://arxiv.org/pdf/1609.04747.pdf/>

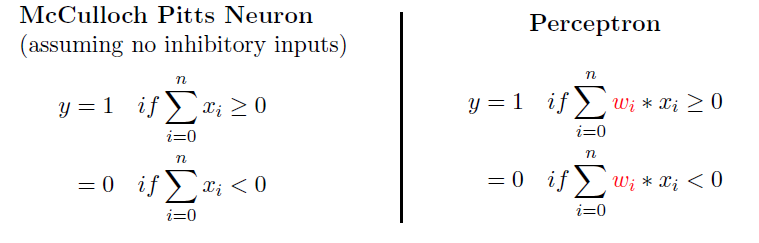
***Image illustrations***

1.1

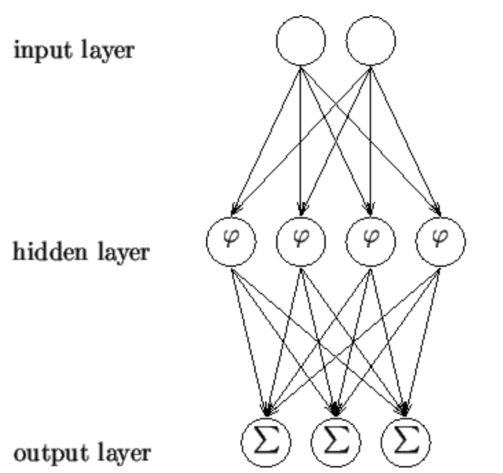
1.2

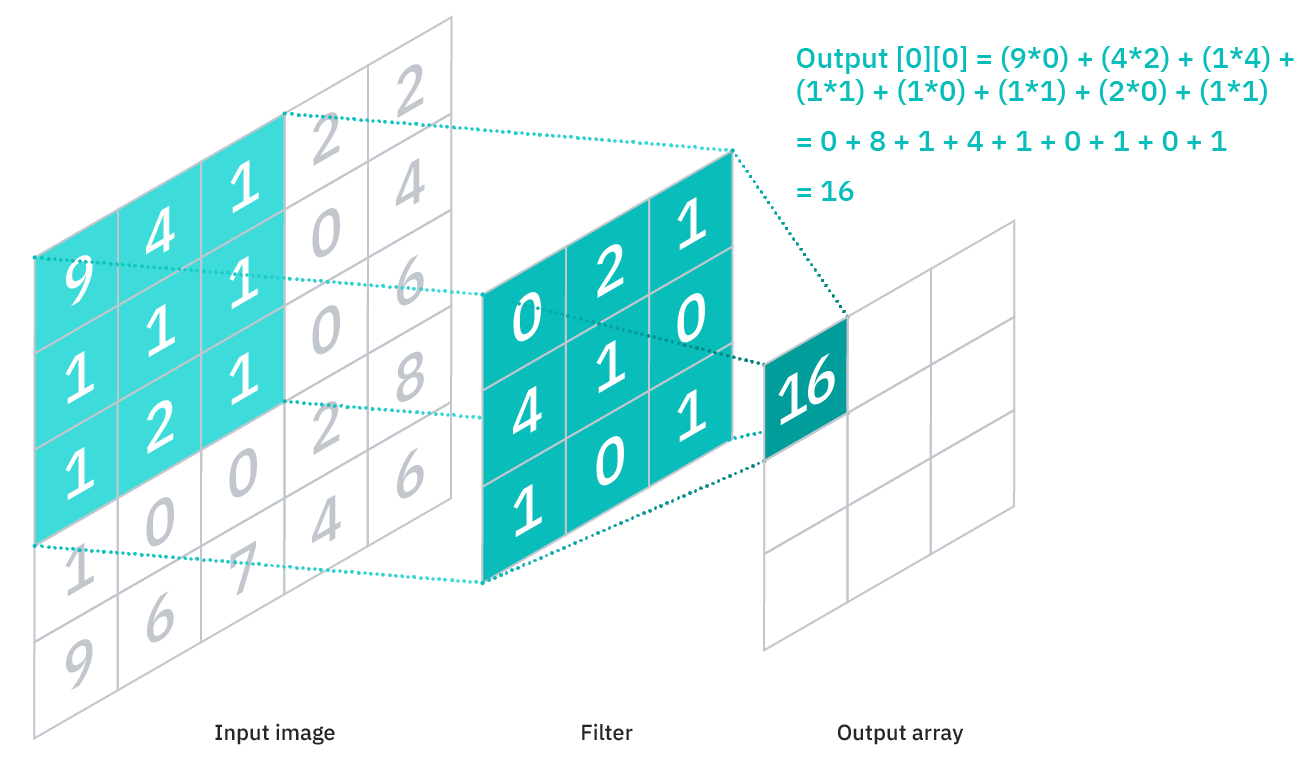


1.3



1.4





1.5 Examples of the images of the dataset:

Graphical user interface, application

Description automatically generated