CMPS261 Final Proeject

Bashar Karaja, Ebaa Ibrahim, Hasan Hammoud

April 17, 2023

1 Introduction

By examining the structure of matter and the laws regulating its interactions, the field of high-energy physics seeks to understand the basic principles of the cosmos. The main equipment used by experimental high-energy physicists to smash protons and/or antiprotons and produce exotic particles that only exist at extremely high energy density is modern accelerators. Solving challenging signal-versus-background classification issues, for which machine-learning methods are frequently applied, is necessary in order to find these uncommon particles. This research deals with a classification challenge that separates a signal process that generates hypothetical new Higgs bosons from a background process that has similar decay products but different kinematic characteristics. As part of our project we have used multiple types of model to solve this classification problem such as tree ensemble using XGBOOST, Neural Networks using MLPClassifiers and Tensor flow, as well as Logistic Regression

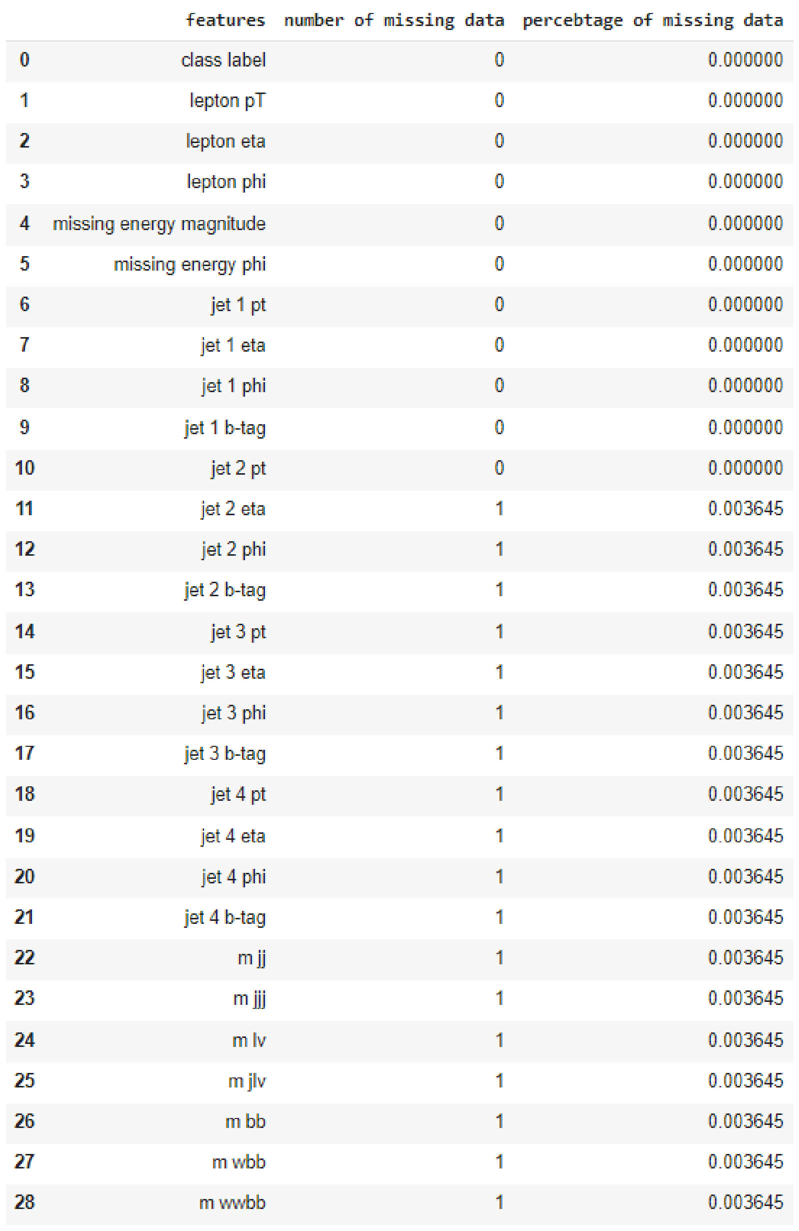
2 Manipulation of data

2.1 Data Characteristics

After Loading the data set, we can see that the data consists of 600000 data point where each data point have 27 features of which 21 of them are raw measurements and the rest are human made features using feature engineering. Some of the characteristics of the data

2.2 Missing data and cleaning

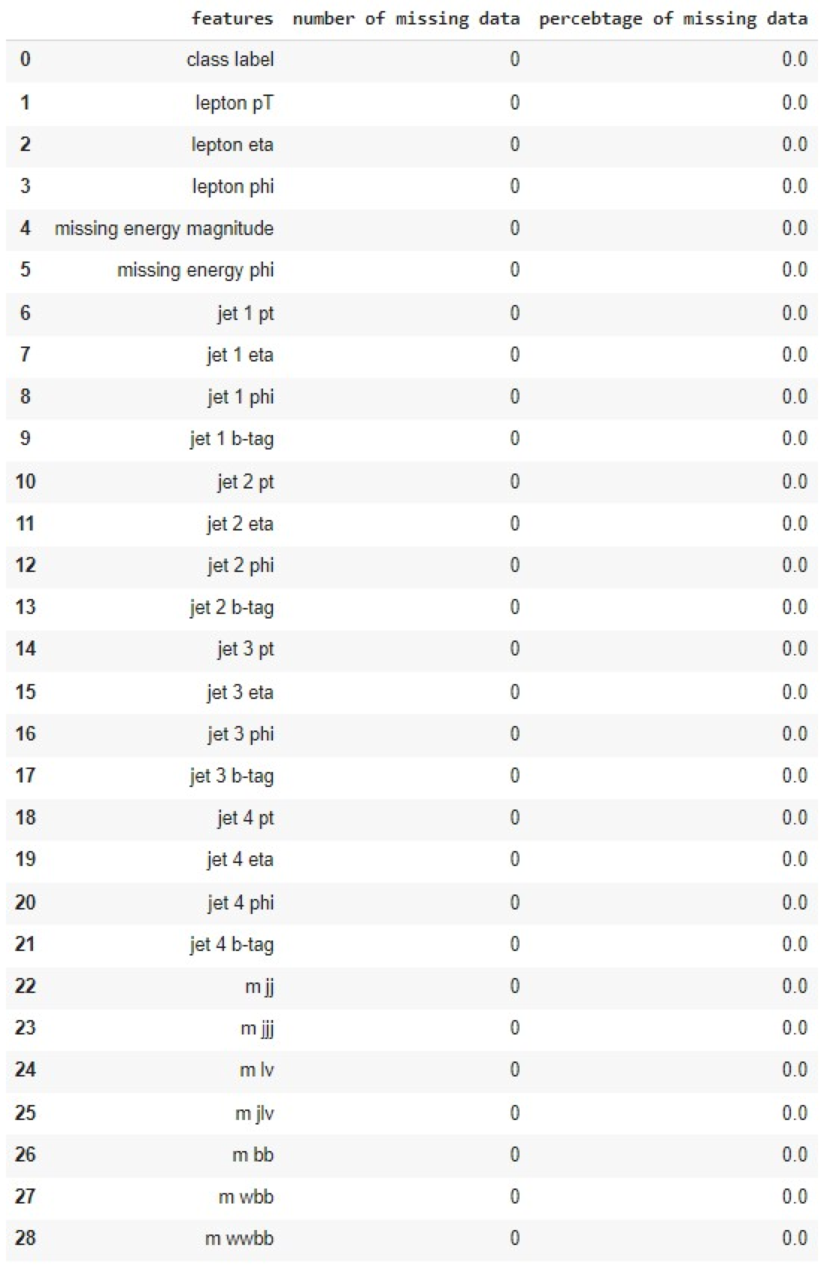
First we need to identify any missing data in the data set so that we can either remove the point or adjust encoded accordingly, Fig.1 shows summarizes the above:



	features	number of missing data	percebtage of missing data
0	class label	0	0.000000
1	lepton pT	0	0.000000
2	lepton eta	0	0.000000
3	lepton phi	0	0.000000
4	missing energy magnitude	0	0.000000
5	missing energy phi	0	0.000000
6	jet 1 pt	0	0.000000
7	jet 1 eta	0	0.000000
8	jet 1 phi	0	0.000000
9	jet 1 b-tag	0	0.000000
10	jet 2 pt	0	0.000000
11	jet 2 eta	1	0.003645
12	jet 2 phi	1	0.003645
13	jet 2 b-tag	1	0.003645
14	jet 3 pt	1	0.003645
15	jet 3 eta	1	0.003645
16	jet 3 phi	1	0.003645
17	jet 3 b-tag	1	0.003645
18	jet 4 pt	1	0.003645
19	jet 4 eta	1	0.003645
20	jet 4 phi	1	0.003645
21	jet 4 b-tag	1	0.003645
22	m jj	1	0.003645
23	m jjj	1	0.003645
24	m lv	1	0.003645
25	m jlv	1	0.003645
26	m bb	1	0.003645
27	m wbb	1	0.003645
28	m wwbb	1	0.003645

Figure 1: shows the summary of missing data.

After cleaning and removing any strings or NA the data summary becomes as in fig.2:



	features	number of missing data	percebtage of missing data
0	class label	0	0.0
1	lepton pT	0	0.0
2	lepton eta	0	0.0
3	lepton phi	0	0.0
4	missing energy magnitude	0	0.0
5	missing energy phi	0	0.0
6	jet 1 pt	0	0.0
7	jet 1 eta	0	0.0
8	jet 1 phi	0	0.0
9	jet 1 b-tag	0	0.0
10	jet 2 pt	0	0.0
11	jet 2 eta	0	0.0
12	jet 2 phi	0	0.0
13	jet 2 b-tag	0	0.0
14	jet 3 pt	0	0.0
15	jet 3 eta	0	0.0
16	jet 3 phi	0	0.0
17	jet 3 b-tag	0	0.0
18	jet 4 pt	0	0.0
19	jet 4 eta	0	0.0
20	jet 4 phi	0	0.0
21	jet 4 b-tag	0	0.0
22	m jj	0	0.0
23	m jjj	0	0.0
24	m lv	0	0.0
25	m jlv	0	0.0
26	m bb	0	0.0
27	m wbb	0	0.0
28	m wwbb	0	0.0

Figure 2: shows the summary of missing data after cleaning

3 Models

3.1 XGBOOST

NoW that our data is ready we will start implementing our models. The first model we impleemented was tree ensemble using XGBOOST.

3.1.1 XGBOOST and its parameters

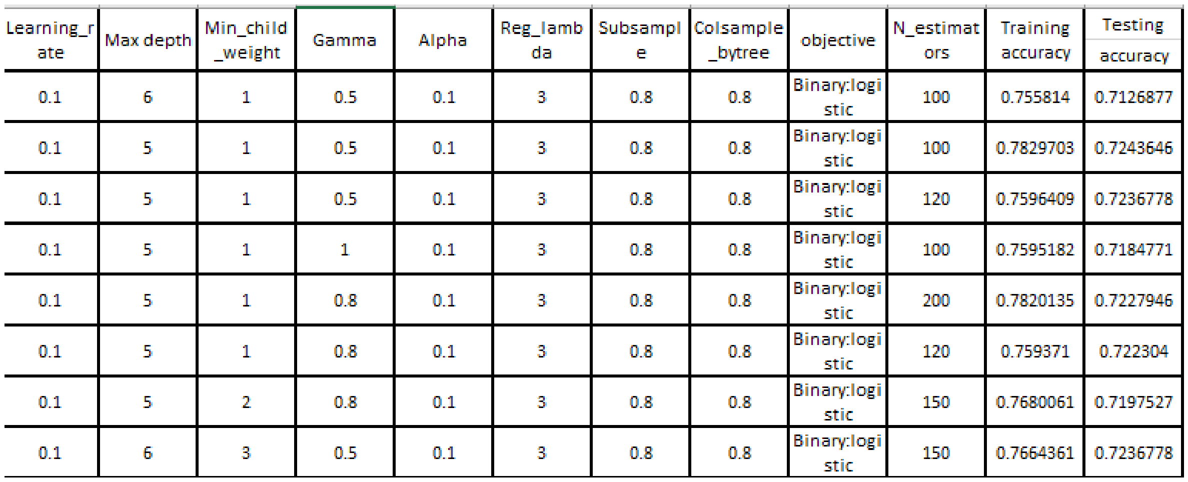
XGBoost is an acronym for ”Extreme Gradient Boosting,” a well-known and strong machine learning technique for regression, classification, and ranking applications. It is an ensemble learning approach that integrates numerous weak predictive models into a single, powerful model.

XGBoost is notably effective in the setting of large-scale, complicated data sets with numerous features, as it can handle missing values, regularization, and feature selection automatically. It leverages a gradient boosting strategy to repeatedly train decision trees using the residual errors of prior trees, while also including regularization to prevent over fitting.

it consists of the following parameters:

```
n_estimators: controls number of decision trees used

learning_rate: controls the step size at each iteration of the gradient boosting process.

max_depth: controls the maximum depth of each decision tree in the ensemble

subsample: This parameter controls the fraction of training examples that are used to
train each tree. Setting this parameter to a value less than 1 can help to reduce overfitting.

colsample_bytree: This parameter controls the fraction of features that are used to train
each tree. Setting this parameter to a value less than 1 can help to reduce overfitting.

gamma: This parameter controls the minimum reduction in the loss required to split a node
during the tree building process. Increasing this parameter can help to reduce overfitting.

min_child_weight: This parameter controls the minimum sum of instance weight (hessian) needed
in a child. Increasing this parameter can help to reduce overfitting.

reg_alpha: This parameter controls L1 regularization on the weights of the decision trees.
Increasing this parameter can help to reduce overfitting.

reg_lambda: This parameter controls L2 regularization on the weights of the decision trees.
Increasing this parameter can help to reduce overfitting.

objective: This parameter defines the loss function to be optimized during training.
XGBoost supports a wide range of loss functions for different types of problems, such as
binary classification, multiclass classification, and regression.
```

While training our XGBOOST Model, we have been tuning the different hyper parameters , the table below summarizes the change of accuracy as a function of these parameters:



Learning_rate	Max depth	Min_child_weight	Gamma	Alpha	Reg_lambda	Subsample	Colsample_bytree	objective	N_estimators	Training accuracy	Testing accuracy
0.1	6	1	0.5	0.1	3	0.8	0.8	Binary:logistic	100	0.755814	0.7126877
0.1	5	1	0.5	0.1	3	0.8	0.8	Binary:logistic	100	0.7829703	0.7243646
0.1	5	1	0.5	0.1	3	0.8	0.8	Binary:logistic	120	0.7596409	0.7236778
0.1	5	1	1	0.1	3	0.8	0.8	Binary:logistic	100	0.7595182	0.7184771
0.1	5	1	0.8	0.1	3	0.8	0.8	Binary:logistic	200	0.7820135	0.7227946
0.1	5	1	0.8	0.1	3	0.8	0.8	Binary:logistic	120	0.759371	0.722304
0.1	5	2	0.8	0.1	3	0.8	0.8	Binary:logistic	150	0.7680061	0.7197527
0.1	6	3	0.5	0.1	3	0.8	0.8	Binary:logistic	150	0.7664361	0.7236778

Figure 3: shows the variation of training and testing accuries as a fcuntion of XGBOOST Hyper parameters

3.1.2 testing effect of hyper parameters

we will now test the effect of some parameters to try to see what are the best values for each one that would give us the highest accuracy.

the below graphs summarizes the results:

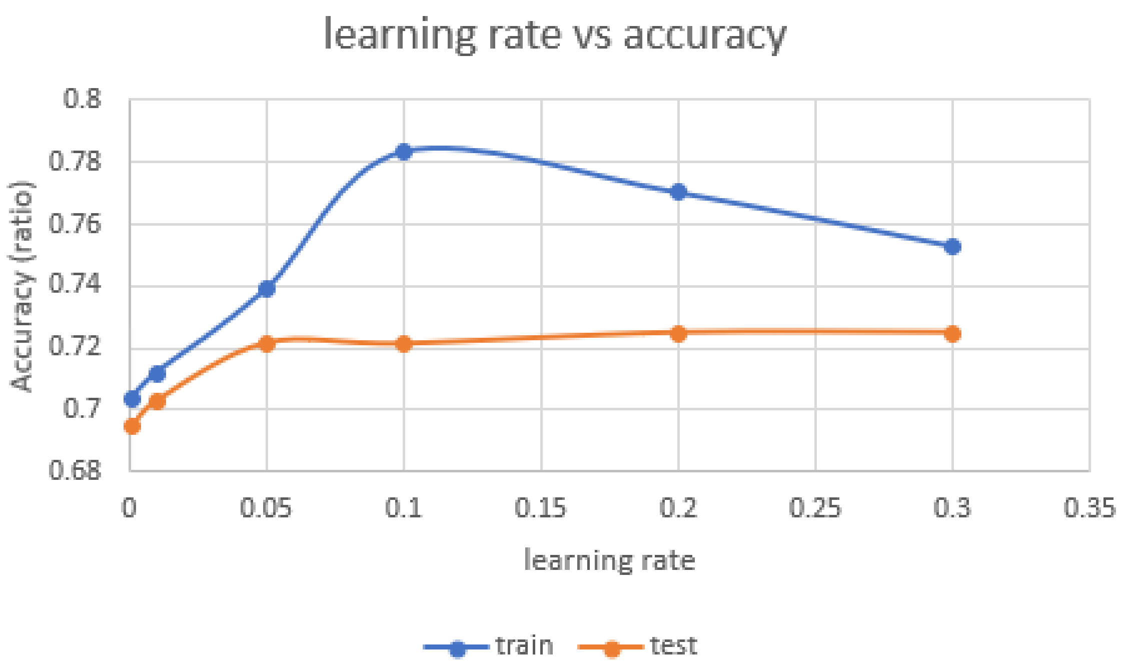


Figure 4: shows the variation of training and testing accuries as a fcuntion the learning rate

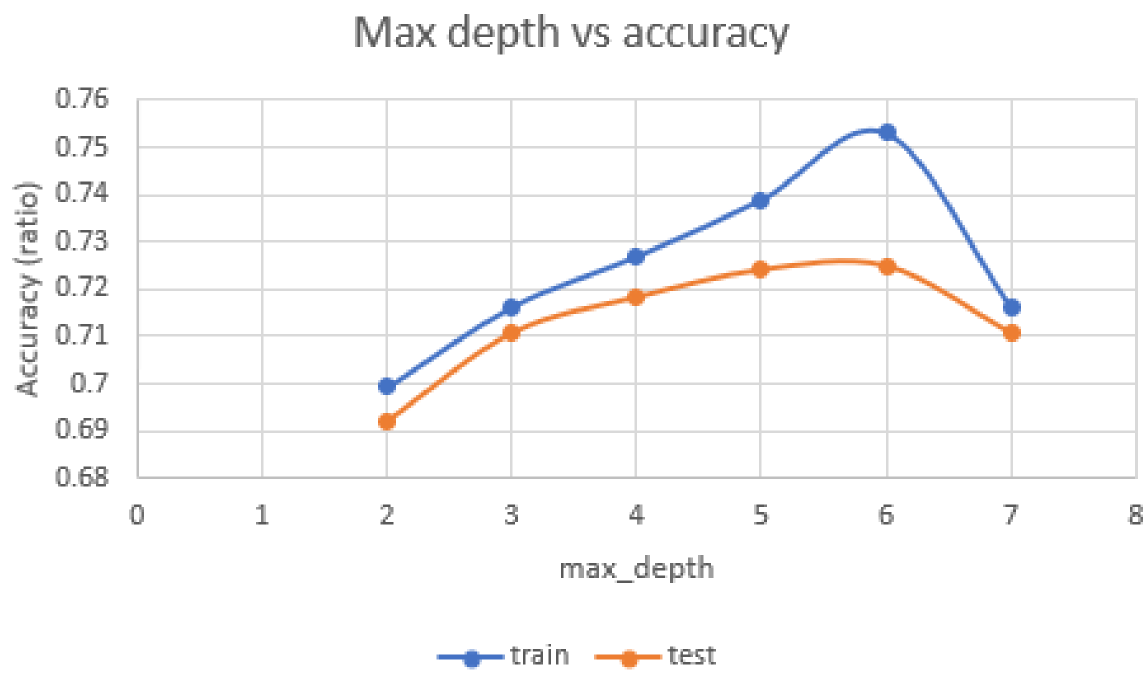


Figure 5: shows the variation of training and testing accuries as a fcuntion of XGBOOST the max depth

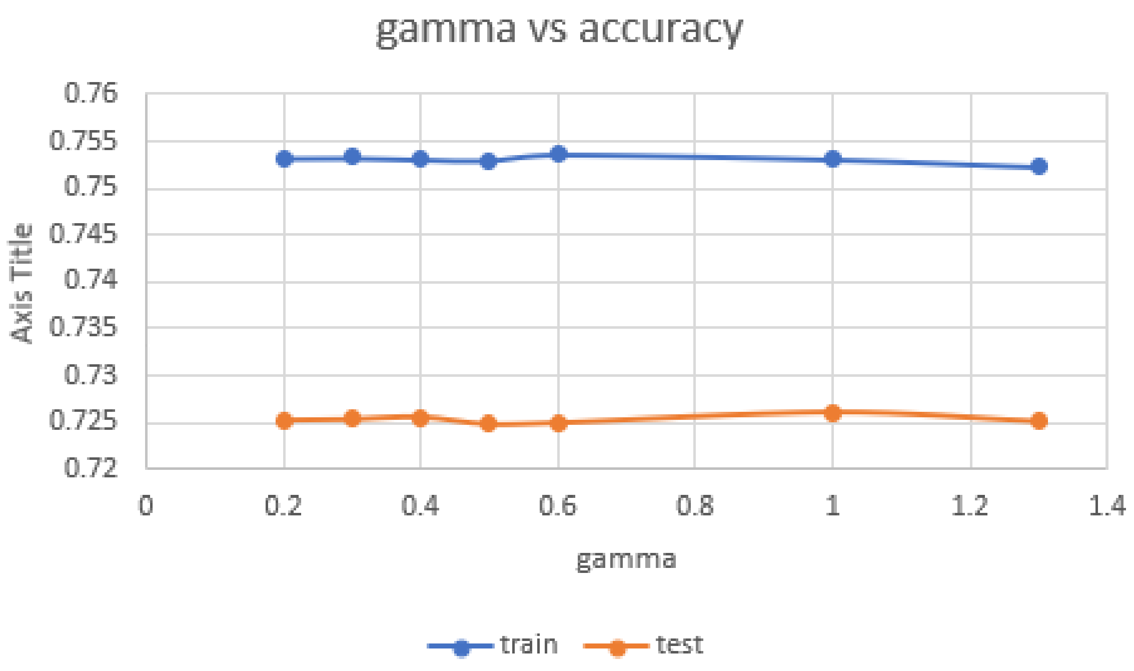


Figure 6: shows the variation of training and testing accuries as a fcuntion ofgamma

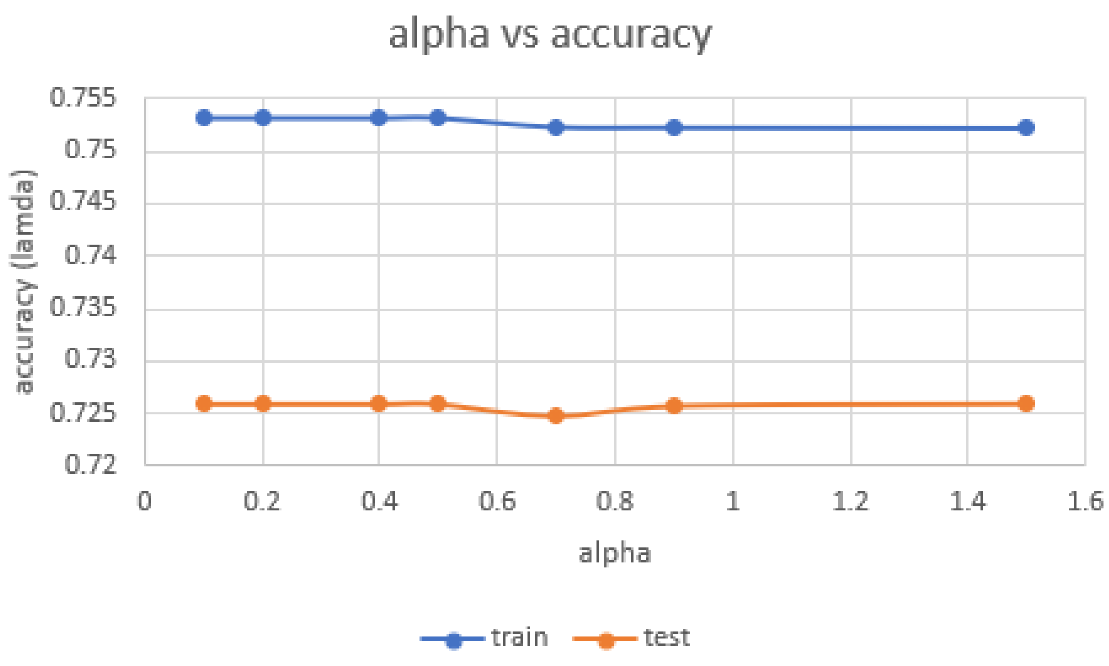


Figure 7: shows the variation of training and testing accuries as a fcuntion of alpha

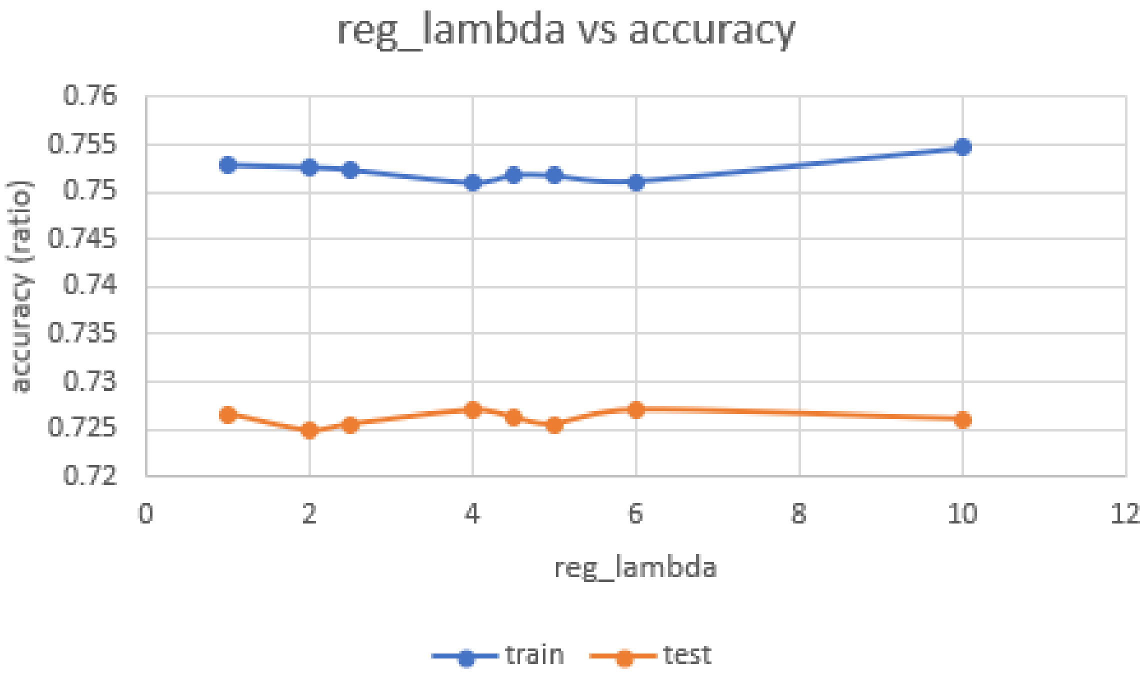


Figure 8: shows the variation of training and testing accuries as a fcuntion of reg$_{l}ambda$

3.2 MLPClassifier

3.2.1 MLPClassifier and its parameters

MLPClassifier is a class in the scikit-learn Python library that implements a multi-layer perceptron (MLP) algorithm for classification tasks.

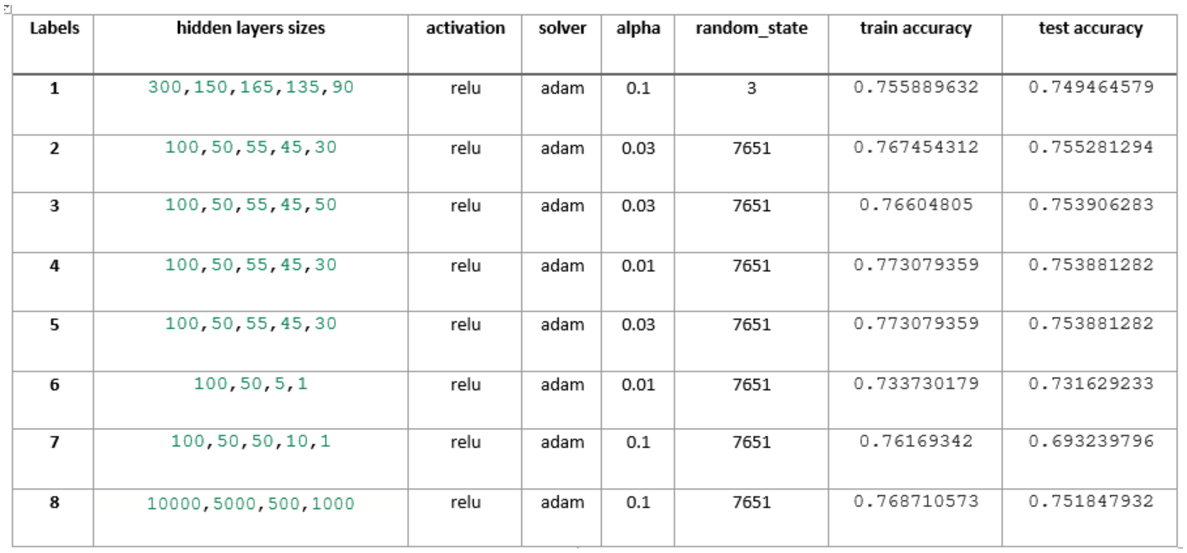
An MLP is a type of neural network that consists of multiple layers of interconnected nodes, each of which applies a non-linear activation function to the weighted sum of its inputs. The MLP algorithm is trained using backpropagation, which adjusts the weights in each layer to minimize the error between the predicted and actual outputs.

The MLPClassifier in sci kit-learn allows you to create an MLP model with customizable parameters, including the number of hidden layers, the number of nodes in each layer, and the activation function used in each layer

it consists of the following parameters:

```
hidden_layer_sizes: A tuple that specifies the number of nodes in each hidden layer of the neural
network. For example, if you set hidden_layer_sizes=(50, 20), the neural network will have two
hidden layers, the first with 50 nodes and the second with 20 nodes.

activation: The activation function used for the hidden layers. Popular choices include ’relu’,
’tanh’, and ’logistic’.

solver: The optimization algorithm used to update the weights of the neural network. Popular
choices include ’sgd’ (stochastic gradient descent), ’adam’ (a variant of stochastic gradient
descent),and ’lbfgs’ (a quasi-Newton method).

alpha: The regularization parameter that controls the amount of L2 regularization applied to the
weights. Larger values of alpha result in more regularization.

batch_size: The size of the minibatch used for stochastic gradient descent. Larger minibatches
typically result in faster convergence, but smaller minibatches may lead to better generalization.

learning_rate: The learning rate used for stochastic gradient descent. This controls the step size
used for updating the weights.

random_state: a random initial conditions of parameters to start with
```

the table below summarizes the change of accuracy as a function of different parameters:



Labels	hidden layers sizes	activation	solver	alpha	random_state	train accuracy	test accuracy
1	300,150,165,135,90	relu	adam	0.1	3	0.755889632	0.749464579
2	100,50,55,45,30	relu	adam	0.03	7651	0.767454312	0.755281294
3	100,50,55,45,50	relu	adam	0.03	7651	0.76604805	0.753906283
4	100,50,55,45,30	relu	adam	0.01	7651	0.773079359	0.753881282
5	100,50,55,45,30	relu	adam	0.03	7651	0.773079359	0.753881282
6	100,50,5,1	relu	adam	0.01	7651	0.733730179	0.731629233
7	100,50,50,10,1	relu	adam	0.1	7651	0.76169342	0.693239796
8	10000,5000,500,1000	relu	adam	0.1	7651	0.768710573	0.751847932

Figure 9: shows the variation of training and testing accuracies as a function of mlpclassifier parameters

NOTE: in our coming graph, we will be showing the effect of different hidden layers sizes on the accuracies, however we have labeled the different choices as in the table in fig.9 so that it would be easier to visualize.

3.2.2 Graphs

This section shows the different relations and effects of the different hypar parameters individualy on th testing and training accuracies.

The graphs below summarizes the results

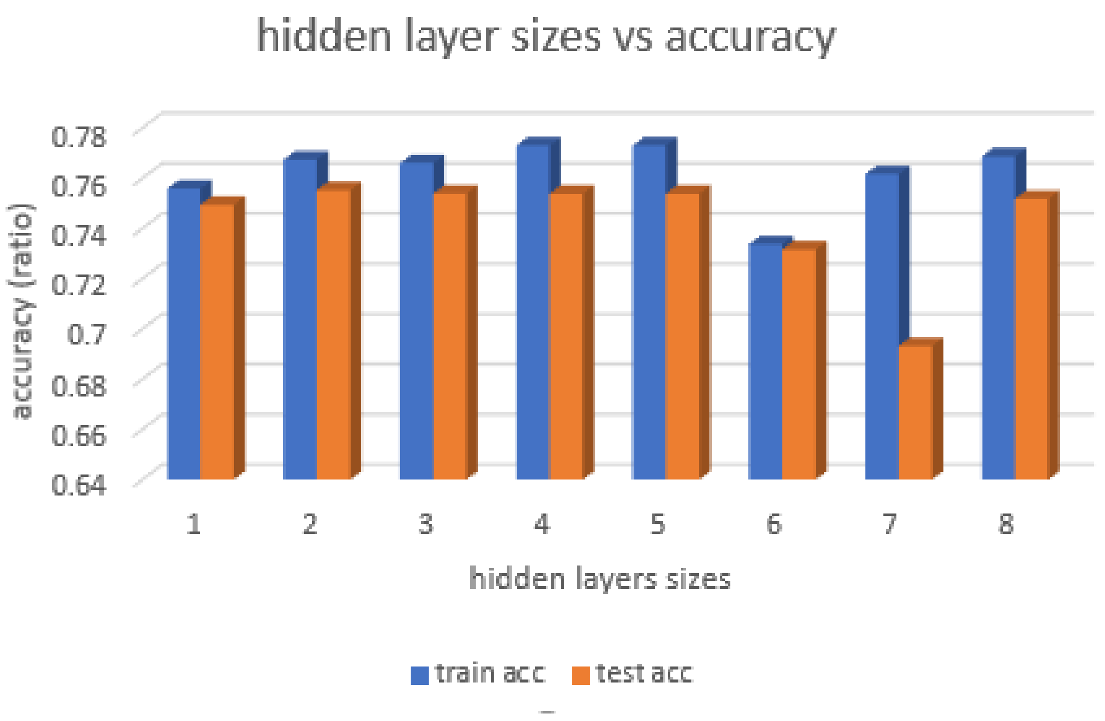


Figure 10: shows the variation of training and testing accuracies as a function of hidden layers sizes

3.2.3 Analysis

During the training process, we have tried over a 100 MLPClassifer models with different parameters, and as we have noticed that the best number of layers to go with is 5 hidden layers and a regularization parameter of 0.03. The number of Neurons of each of the 5 hidden layers for our model of the best performance is: 100, 50, 55, 45 ,30, where the training accuracies was 0.76645 ratio while the testing accuracy was 0.75528 by ratio.

3.3 Logistic Regression

3.3.1 Logistic Regression and its parameters

Logistic regression is a statistical method for predicting whether an observation belongs to one of two categories. It is a type of regression analysis in which the likelihood of a binary response variable (either 0 or 1) is modeled using one or more predictor variables.

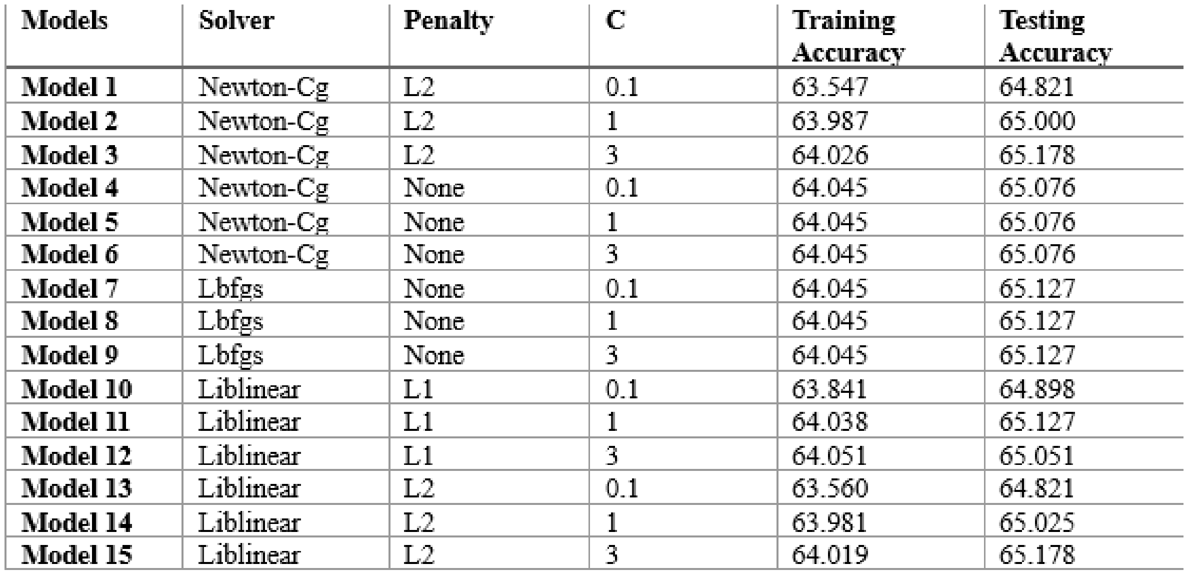
In logistic regression, the logistic function (also known as the sigmoid function) is used to depict the relationship between the predictor variables and the response variable. Every real-valued input is converted to a value between 0 and 1. The logistic function is used to determine the likelihood of an observation belonging to the positive class given the predictor factors.

it consists of the following parameters:

```
penalty: This parameter determines the type of regularization to be applied to the model
. The default is 'l2', which corresponds to Ridge regularization.

C: This parameter controls the strength of the regularization. A smaller value of C leads
to stronger regularization, and a larger value leads to weaker regularization.
```

```
The default value is 1.0.

solver: This parameter determines the algorithm to be used for optimization. The default
is 'lbfgs', which is a quasi-Newton method.
```

the table below summarizes the change of accuracy as a function of the different Logistic Regression models:



Models	**Solver**	**Penalty**	**C**	**Training Accuracy**	**Testing Accuracy**
Model 1	Newton-Cg	L2	0.1	63.547	64.821
Model 2	Newton-Cg	L2	1	63.987	65.000
Model 3	Newton-Cg	L2	3	64.026	65.178
Model 4	Newton-Cg	None	0.1	64.045	65.076
Model 5	Newton-Cg	None	1	64.045	65.076
Model 6	Newton-Cg	None	3	64.045	65.076
Model 7	Lbfgs	None	0.1	64.045	65.127
Model 8	Lbfgs	None	1	64.045	65.127
Model 9	Lbfgs	None	3	64.045	65.127
Model 10	Liblinear	L1	0.1	63.841	64.898
Model 11	Liblinear	L1	1	64.038	65.127
Model 12	Liblinear	L1	3	64.051	65.051
Model 13	Liblinear	L2	0.1	63.560	64.821
Model 14	Liblinear	L2	1	63.981	65.025
Model 15	Liblinear	L2	3	64.019	65.178

Figure 11: shows the variation of training and testing accuracies as a function of Logistic Regression Model's parameters

3.3.2 Graphs

This section shows the different relations and effects of the different hypar parameters individualy on th testing and training accuracies.

The graphs below summarizes the results

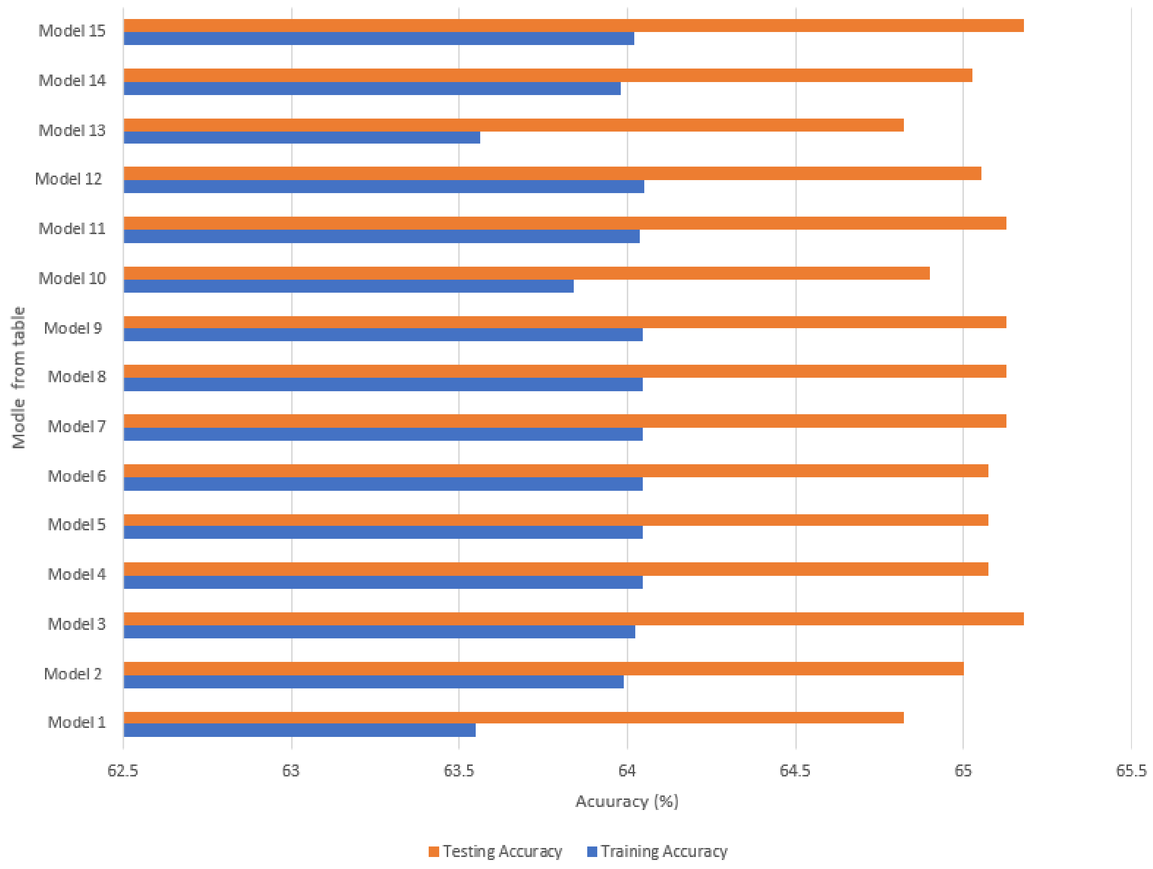


Figure 12: shows the variation of training and testing accuracies as a function of the models in the table of fig.11

3.3.3 Analysis

Upon implementing the model, we got a training accuracy of 0.64 using a ratio of 0.8 of the training examples that we were provided. And by testing the model on the other 0.2 by ratio of the data we got a testing accuracy of 0.65127 by ratio. Those numbers were close so there were no indications of over fitting. However, a ratio of 0.65127 accuracy is relatively low considering that in the research paper provided they were able to reach 0.78.

4 Summary of Results of the Different Models Best Performance

In this section we will be showing the a table of the best accuracy achieved by each model. and then we will uinclude each models parameter for the best performance

Models	Best Training Accuracy (Train)	Best Training Accuracy (Test)
MLPClassifier	0.77	0.75
Logistic Regression	0.77	0.74
xGBOOST	0.7	0.65

Table 1: Table caption goes here.

```
MLPClassifier best performence parameters:
```

number of hidden layers: 5
number of neurons in each: 100,50,55,45,30 respectively.
activation='relu',
solver='adam',
alpha=.03,
random_state = 7651

XGBOOST best performence parameters:

learning_rate=0.1,
max_depth=5,
min_child_weight=3,
gamma=.8,
alpha=0.1,
reg_lambda=3.0,
subsample=0.8,
colsample_bytree=0.8,
objective='binary:logistic',
n_estimators=1500,
scale_pos_weight=1

Logistic Regression:

solver:Lbfgs
penalty:None
C:1

Therefore, our best model implementation is MLPClassifier which give us the best accuracy of 75.52%