

# Sri Lanka Institute of Information Technology

# Assignment-02

# Machine Learning (IT4060)

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# Stock Price Prediction using Different Machine Learning Models and Compare the Performance of the Models

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## 1 DESCRIPTION OF THE PROBLEM ADDRESSED

The stock price forecast is one of the most preferred topics and most interesting topics in the science industry. However, stock market price forecasts are challenging compared to other price forecasting case studies. Many scholars and industry experts have come to a greater consensus a decade. They have studied stocks in various fields such as Computer Science, Economics, Business Arithmetic, and Marketing price forecasts. The stock has been identified according to them as a random walking behavior at market prices. The sudden rises and falls have been the main reason behind stock market price forecasting being a big challenge. An efficient and accurate.

stock market forecasting model will help managers, investors, and decision-makers make the right decisions regarding their investments. Machine learning techniques used to predict stock prices include the analysis of historical data to predict the likelihood of a future event or to predict future performance. This is done by looking at patterns of data that include current and past information and finding the most suitable predictive models.

#### 1.1 What is the Stock Market?

A stock market is a public market where you can buy and sell shares for publicly listed companies. Shares, also known as shares, represent the ownership of a company. A stock exchange is an intermediary that allows you to buy and sell shares.

# 1.2 Importance of Stock Market

- Stock markets help companies to raise capital.
- It helps generate personal wealth.
- Stock markets serve as an indicator of the state of the economy.
- It is a widely used source for people to invest money in companies with high growth potential.

#### 1.3 Stock Price Prediction

Stock Price Prediction using machine learning helps you discover the future value of company stock and other financial assets traded on an exchange. The entire idea of predicting stock prices is to gain significant profits. Predicting how the stock market will perform is a hard task to do. There are other factors involved in the prediction, such as physical and psychological factors, rational and irrational behavior, and so on. All these factors combine to make share prices dynamic and volatile. This makes it very difficult to predict stock prices with high accuracy.

#### 2 DATASET

# 2.1 Description of the Data Set

The yahoo finance data has information from 2014 to 218. There are ten columns. Yahoo! Finance is a media property that is part of the Yahoo! network. It provides financial news, data and commentary including stock quotes, press releases, financial reports, and original content. It also offers some online tools for personal finance management.

The Open column tells the price at which a stock started trading when the market opened on a particular day. The Close column refers to the price of an individual stock when the stock exchange closed the market for the day. The High column depicts the highest price at which a stock traded during a period. The Low column tells the lowest price of the period. Volume is the total amount of trading activity during a period of time.

Description	This dataset is contain in yahoo finance site.
Data Set Link	https://finance.yahoo.com/quotes/OCR,dataset/view/v1/
Size of Data	12570
Related Task	Stock Market Prediction
Data Set Stored In	Github

#### 2.2 Data Set Parameters

Characteristic	Information
Number of columns	10
Number of rows	1257
Columns	Open, High, Low, Close, Adj Close, Volume, Increase/Decrease, Buy Sell on Open, Buy Sell, Return

# 2.3 Sample Images of the Dataset

#View Datas dataset	et									
	Open	High	Low	Close	Adj Close	Volume	Increase/Decrease	Buy_Sell_on_Open	Buy_Sell	Return
Date										
2014-01-03	3.980000	4.000000	3.880000	4.000000	4.000000	22887200	1	1	1	0.012658
2014-01-06	4.010000	4.180000	3.990000	4.130000	4.130000	42398300	1	1	1	0.032500
2014-01-07	4.190000	4.250000	4.110000	4.180000	4.180000	42932100	0	1	-1	0.012106
2014-01-08	4.230000	4.260000	4.140000	4.180000	4.180000	30678700	0	-1	-1	0.000000
2014-01-09	4.200000	4.230000	4.050000	4.090000	4.090000	30667600	0	-1	1	-0.021531
2018-12-24	16.520000	17.219999	16.370001	16.650000	16.650000	62933100	1	1	1	-0.016539
2018-12-26	16.879999	17.910000	16.030001	17.900000	17.900000	108811800	1	1	-1	0.075075
2018-12-27	17.430000	17.740000	16.440001	17.490000	17.490000	111373000	0	1	1	-0.022905
2018-12-28	17.530001	18.309999	17.139999	17.820000	17.820000	109214400	0	1	1	0.018868
2018-12-31	18.150000	18.510000	17.850000	18.459999	18.459999	84732200	0	-1	-1	0.035915
1257 rows × 1	0 columns									

# See data types o	of the Columns
dataset.dtypes	
Open High Low Close Adj Close Volume Increase/Decrease Buy_Sell_on_Open Buy_Sell Return dtype: object	float64 float64 float64 float64 int64 int64 int64 float64

#### 3 SELECTED MACHINE LEARNING ARCHITECTURES

To predict the stock price, we use the Machine Learning Models below and finally compare the accuracy values and the loss function values to find the best model.

- 1. Linear Regression
- 2. Decision Tree Regression
- 3. Logistic Regression
- 4. Bayesian Ridge Regression

**Linear Regression:** Linear regression attempts to model the relationship between two variables by fitting a linear equation to observed data. One variable is considered to be an explanatory variable, and the other is considered to be a dependent variable. For example, a modeler might want to relate the weights of individuals to their heights using a linear regression model.

**Decision Tree Regression:** Decision tree builds regression or classification models in the form of a tree structure. It breaks down a dataset into smaller and smaller subsets while at the same time an associated decision tree is incrementally developed. The final result is a tree with decision nodes and leaf nodes.

**Logistic Regression:** In statistics, the logistic model is a statistical model that models the probability of one event taking place by having the log-odds for the event be a linear combination of one or more independent variables. In regression analysis, logistic regression is estimating the parameters of a logistic model.

**Bayesian Ridge Regression:** Bayesian regression allows a natural mechanism to survive insufficient data or poorly distributed data by formulating linear regression using probability distributors rather than point estimates.

# 4 METHODOLOGY

We used TensorFlow, Keras as main framework for this and use normal python libraries like matplotlib, NumPy, pandas, sklearn to other purposes. They are an open-source machine learning library for Python, mainly developed by the Facebook AI Research team. These are the main steps we followed to build and train the models.

- 1. Import Libraries
- 2. Load data into a Data Frame
- 3. Data set Cleaning
- 4. Data set Preposing
- 5. Analyze the Data
- 6. Prepare Dataset
- 7. Create Model
- 8. Instantiate Model
- 9. Instantiate Loss
- 10. Instantiate Optimizer
- 11. Training the Model
- 12. Prediction

#### **5 IMPLEMENTATION**

# **5.1 Import Libraries**

## **Linear Regression**

```
# yahoo_finance is used to fetch data
!pip install yfinance
```

```
# Import Libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import warnings
warnings.filterwarnings("ignore")

# yahoo_finance is used to fetch data
import yfinance as yf
yf.pdr_override()
```

# **Decision Tree Regression**

```
# yahoo_finance is used to fetch data
!pip install yfinance
```

```
# Import Libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

import warnings
warnings.filterwarnings("ignore")

# yahoo_finance is used to fetch data
import yfinance as yf
yf.pdr_override()

# MATPLOTLIB & SEABORN FOR GRAPH-PLOTTING
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

#### **Logistic Regression**

```
# yahoo_finance is used to fetch data
!pip install yfinance
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

import warnings
warnings.filterwarnings("ignore")

!pip install yfinance
import yfinance as yf
yf.pdr_override()
```

```
# MATPLOTLIB & SEABORN FOR GRAPH-PLOTTING
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

## **Bayesian Ridge Regression**

```
# yahoo_finance is used to fetch data
!pip install yfinance

import numpy as np
import matplotlib.pyplot as plt
import pandas as pd

import warnings
warnings.filterwarnings("ignore")

!pip install yfinance
import yfinance as yf
yf.pdr_override()

# MATPLOTLIB & SEABORN FOR GRAPH-PLOTTING
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

#### 5.2 Load data into a Data Frame

```
# input
symbol = 'AMD'
start = '2014-01-01'
end = '2019-01-01'

# Read data
dataset = yf.download(symbol, start, end)

# View data set
dataset.head()
```

# View data dataset.hea							
[********	*****	*****1	.00%**	******	*******	***] 1 of	1 completed
	0pen	High	Low	Close	Adj Close	Volume	7
Date							
2014-01-02	3.85	3.98	3.84	3.95	3.95	20548400	
2014-01-03	3.98	4.00	3.88	4.00	4.00	22887200	
2014-01-06	4.01	4.18	3.99	4.13	4.13	42398300	
2014-01-07	4.19	4.25	4.11	4.18	4.18	42932100	
2014-01-08	4.23	4.26	4.14	4.18	4.18	30678700	

## **5.3 Data Preprocessing**

Data pre-processing is the practice of processing raw data using a machine learning model. It is similar to the most important stages in data cleaning and building a machine learning model.

```
# Create more data
dataset['Increase/Decrease'] = np.where(dataset['Volume'].shift(-
1) > dataset['Volume'],1,0)
dataset['Buy_Sell_on_Open'] = np.where(dataset['Open'].shift(-
1) > dataset['Open'],1,-1)
dataset['Buy_Sell'] = np.where(dataset['Adj Close'].shift(-
1) > dataset['Adj Close'],1,-1)
dataset['Return'] = dataset['Adj Close'].pct_change()
dataset = dataset.dropna()
dataset.head()
```

	0pen	High	Low	Close	Adj Close	Volume	Increase/Decrease	Buy_Sell_on_Open	Buy_Sell	Return	1
Date											
2014-01-03	3.98	4.00	3.88	4.00	4.00	22887200	1	1	1	0.012658	
2014-01-06	4.01	4.18	3.99	4.13	4.13	42398300	1	1	1	0.032500	
2014-01-07	4.19	4.25	4.11	4.18	4.18	42932100	0	1	-1	0.012106	
2014-01-08	4.23	4.26	4.14	4.18	4.18	30678700	0	-1	-1	0.000000	
2014-01-09	4.20	4.23	4.05	4.09	4.09	30667600	0	-1	1	-0.021531	

# **5.4 View Dataset**

#View Dataset

Dataset

#View Datas dataset	et										
	Open	High	Low	Close	Adj Close	Volume	Increase/Decrease	Buy_Sell_on_Open	Buy_Sell	Return	7
Date											
2014-01-03	3.980000	4.000000	3.880000	4.000000	4.000000	22887200	1	1	1	0.012658	
2014-01-06	4.010000	4.180000	3.990000	4.130000	4.130000	42398300	1	1	1	0.032500	
2014-01-07	4.190000	4.250000	4.110000	4.180000	4.180000	42932100	0	1	-1	0.012106	
2014-01-08	4.230000	4.260000	4.140000	4.180000	4.180000	30678700	0	-1	-1	0.000000	
2014-01-09	4.200000	4.230000	4.050000	4.090000	4.090000	30667600	0	-1	1	-0.021531	
2018-12-24	16.520000	17.219999	16.370001	16.650000	16.650000	62933100	1	1	1	-0.016539	
2018-12-26	16.879999	17.910000	16.030001	17.900000	17.900000	108811800	1	1	-1	0.075075	
2018-12-27	17.430000	17.740000	16.440001	17.490000	17.490000	111373000	0	1	1	-0.022905	
2018-12-28	17.530001	18.309999	17.139999	17.820000	17.820000	109214400	0	1	1	0.018868	
2018-12-31	18.150000	18.510000	17.850000	18.459999	18.459999	84732200	0	-1	-1	0.035915	
1257 rows × 1	0 columns										

#### 5.5 Null value testing and data clearance

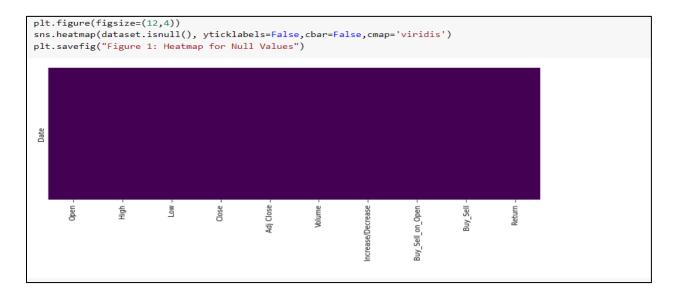
We check for null values in the data frame to ensure that there are none. The existence of null values in the dataset causes issues during training since they function as outliers, creating a wide variance in the training process.

Data cleaning is the method of finding the parts of data that are faulty, incomplete, unreliable, obsolete, or unavailable, and then updating, removing, or replacing them, as necessary. Data cleaning is considered as a fundamental component of model training on machine learning. As a good practice when doing modification on data frames, we done the modifications to new data frames.

```
# See how many null values in each column
dataset.isnull().sum()
```

```
# See how many null values in each column
dataset.isnull().sum()
0pen
                    0
High
                    0
Low
Close
                    0
Adj Close
                    0
Volume
Increase/Decrease
Buy_Sell_on_Open
                    0
Buy_Sell
                    0
Return
dtype: int64
```

```
plt.figure(figsize=(12,4))
sns.heatmap(dataset.isnull(), yticklabels=False,cbar=False,cmap='viridis')
plt.savefig("Figure 1: Heatmap for Null Values")
```



## 5.6 Analyze the Data

Before doing anything with the data it is better to have an analysis on them. Get the size of the data. This shows 1257 rows and 10 columns. We can say this dataset is large enough to use to train a machine learning model.

```
# see number of rows, number of columns
dataset.shape
```

```
# see number of rows, number of columns
dataset.shape

(1257, 10)
```

```
#TOTAL NUMBER OF RECORDS
dataset.size
print("Total number of records = ",dataset.size)
```

```
#TOTAL NUMBER OF RECORDS

dataset.size

print("Total number of records = ",dataset.size)

Total number of records = 12570
```

```
# see columns names
dataset.columns
```

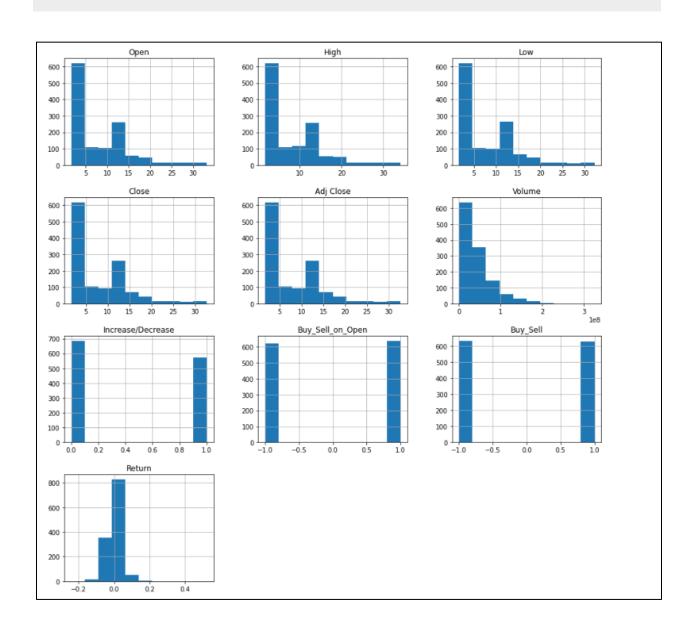
```
# See data types of the Columns
dataset.dtypes
```

```
# See data types of the Columns
dataset.dtypes
                  float64
0pen
High
                  float64
                  float64
Low
Close
                  float64
Adj Close
                  float64
Volume
                   int64
Increase/Decrease
                   int64
Buy_Sell_on_Open int64
Buy_Sell
                   int64
                  float64
Return
dtype: object
```

```
#View Data Info
dataset.info()
```

```
#View Data Info
dataset.info()
 <class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1257 entries, 2014-01-03 to 2018-12-31
Data columns (total 10 columns):
   # Column Non-Null Count Dtype
                                                                                                      1257 non-null float64
1257 non-null float64
1257 non-null float64
  ---
   0 Open
   1 High
   2 Low
  | 1257 | 1011 | 1016164 | 1257 | 1011 | 1016164 | 1257 | 1011 | 1016164 | 1257 | 1011 | 1016164 | 1257 | 1011 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016164 | 1016
   7 Buy_Sell_on_Open 1257 non-null int64
   8 Buy_Sell 1257 non-null int64
                                                                                                              1257 non-null float64
    9 Return
 dtypes: float64(6), int64(4)
memory usage: 108.0 KB
```

```
# Histogram per each numerical column
dataset.hist(figsize=(15, 15))
```



```
# The statistics per each column
dataset.describe()
```

# The statistics per each column dataset.describe()												
	Open	High	Low	Close	Adj Close	Volume	Increase/Decrease	Buy_Sell_on_Open	Buy_Sell	Return		
count	1257.000000	1257.000000	1257.000000	1257.000000	1257.000000	1.257000e+03	1257.000000	1257.000000	1257.000000	1257.000000		
mean	8.169578	8.358266	7.972641	8.167780	8.167780	4.353588e+07	0.455052	0.011933	-0.003978	0.001971		
std	6.482962	6.659404	6.280754	6.476459	6.476459	4.089003e+07	0.498174	1.000327	1.000390	0.039211		
min	1.620000	1.690000	1.610000	1.620000	1.620000	0.000000e+00	0.000000	-1.000000	-1.000000	-0.242291		
25%	2.760000	2.800000	2.710000	2.760000	2.760000	1.374570e+07	0.000000	-1.000000	-1.000000	-0.016523		
50%	5.100000	5.190000	5.000000	5.100000	5.100000	3.179370e+07	0.000000	1.000000	-1.000000	0.000000		
75%	12.400000	12.660000	12.120000	12.300000	12.300000	5.820150e+07	1.000000	1.000000	1.000000	0.018692		
max	33.180000	34.139999	32.189999	32.720001	32.720001	3.250584e+08	1.000000	1.000000	1.000000	0.522901		

#### 5.7 Define X and Y

## **Linear Regression**

```
X = dataset[['Open', 'High', 'Low','Volume', 'Open_Close', 'High_Low', 'Re
turns']]
y = dataset['Adj Close']
```

#### **Decision Tree Regression**

```
X = dataset.drop(['Adj Close', 'Close'], axis=1)
y = dataset['Adj Close']
```

#### **Logistic Regression**

```
# Define X
X = np.asarray(dataset[['Open', 'High', 'Low', 'Adj Close', 'Volume']])
X[0:5]
# Define y
y = np.asarray(dataset['Buy_Sell'])
y[0:5]
```

#### **Bayesian Ridge Regression**

```
X = dataset['Open'].values.reshape(1170,-1)
y = dataset['Adj Close'].values.reshape(1170,-1)
```

#### 5.8 Split Train data and Test data

#### **Linear Regression**

#### **Decision Tree Regression**

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, r
andom_state=0)
```

#### **Logistic Regression**

```
# Splitting the dataset into the Training set and Test set
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25
, random_state = 0)
print ('Train set:', X_train.shape, y_train.shape)
print ('Test set:', X_test.shape, y_test.shape)
```

#### **Bayesian Ridge Regression**

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,
  random_state = 0)
```

#### 5.9 Dataset Training and Model Training

#### **Linear Regression**

```
from sklearn.linear_model import LinearRegression
lm = LinearRegression()
lm.fit(X train,y train)
```

#### **Decision Tree Regression**

```
from sklearn.tree import DecisionTreeRegressor
regressor = DecisionTreeRegressor()
regressor.fit(X_train, y_train)
```

#### **Logistic Regression**

```
# Fitting Logistic Regression to the Training set
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
LR = LogisticRegression(C=0.01, solver='liblinear').fit(X_train,y_train)
LR
```

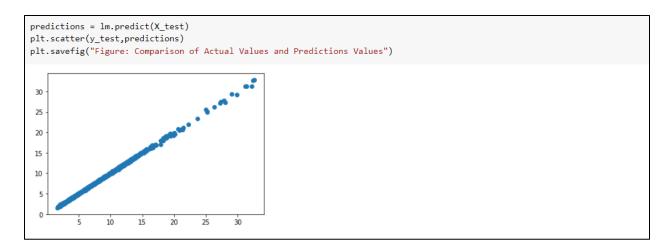
## **Bayesian Ridge Regression**

```
model = BayesianRidge(compute_score=True)
model.fit(X_train, y_train)
```

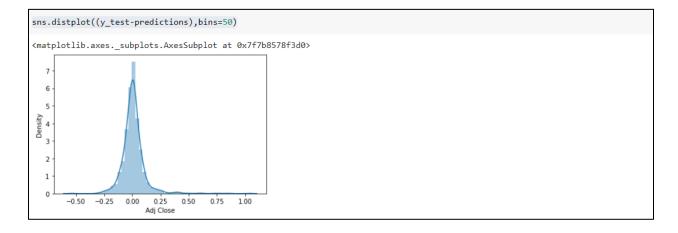
# 5.10 Comparison of Actual Values and Predictions Values

# **Linear Regression**

```
predictions = lm.predict(X_test)
plt.scatter(y_test,predictions)
plt.savefig("Figure: Comparison of Actual Values and Predictions Values")
```



sns.distplot((y\_test-predictions),bins=50)



#### **Decision Tree Regression**

```
y_pred = regressor.predict(X_test)

df = pd.DataFrame({'Actual':y_test, 'Predicted':y_pred})
print(df.head())
print(df.tail())
```

```
y_pred = regressor.predict(X_test)
df = pd.DataFrame({'Actual':y_test, 'Predicted':y_pred})
print(df.head())
print(df.tail())
           Actual Predicted
Date
2017-08-04 13.12
                      13.02
2017-06-22 14.38
                    14.29
2016-05-17
            3.79
                       3.86
2015-04-24
           2.30
2.01
                     2.32
2015-09-11
                       2.09
             Actual Predicted
Date
2017-04-20 13.110000
                         13.00
2014-03-11 3.850000
                          3.82
2018-07-09 16.610001
                         16.66
2018-02-21 11.720000
                         11.88
2018-08-20 19.980000
                         19.58
```

#### **Logistic Regression**

```
# Predicting the Test set results
yhat = LR.predict(X_test)
yhat
```

```
# Predicting the Test set results
yhat = LR.predict(X_test)
yhat
-1, 1, -1, -1, -1, -1, 1, -1, -1, 1, 1, 1, 1, 1, 1, 1, -1,
   1, 1, -1, -1, -1, 1, -1, 1, 1, 1, -1, 1, -1, 1, 1,
   1, 1, -1, -1, -1, -1, 1, 1, 1, -1, 1, -1, 1, 1, 1,
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   1, -1, 1, -1, 1, -1, 1, 1, -1, 1, 1, -1, 1, 1, 1,
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   1, -1, -1, 1, 1, -1, 1, -1, 1, -1, 1, 1, -1, 1, 1, -1, 1,
   -1, 1, 1, -1, 1, -1, -1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
```

#### **Bayesian Ridge Regression**

```
y pred = model.predict(X test)
```

## 5.11 Accuracy and Loss Function Values of the Model

#### **Linear Regression**

```
from sklearn import metrics
print('Mean_Absolute_Error(MAE):', metrics.mean_absolute_error(y_test, pre
dictions))
print('Mean_Squared_Error(MSE):', metrics.mean_squared_error(y_test, predictions))
print('Root_Mean_Squared_Error(RMSE):', np.sqrt(metrics.mean_squared_error
(y_test, predictions)))
print('Accuracy score: {:.7f}''.format(lm.score(X_test, y_test)))
```

```
from sklearn import metrics

print('Mean_Absolute_Error(MAE):', metrics.mean_absolute_error(y_test, predictions))

print('Mean_Squared_Error(MSE):', metrics.mean_squared_error(y_test, predictions))

print('Root_Mean_Squared_Error(RMSE):', np.sqrt(metrics.mean_squared_error(y_test, predictions)))

Mean_Absolute_Error(MAE): 0.0617037525685526

Mean_Squared_Error(MSE): 0.010497023921536569

Root_Mean_Squared_Error(RMSE): 0.10245498485450363

print("Accuracy_score: {:.7f}".format(lm.score(X_test, y_test)))

Accuracy_score: 0.9995713
```

#### **Decision Tree Regression**

```
from sklearn import metrics
print('Mean_Absolute_Error(MAE):', metrics.mean_absolute_error(y_test, dt_
fit.predict(X_test)))
print('Mean_Squared_Error(MSE):', metrics.mean_squared_error(y_test, dt_fit.predict(X_test)))
print('Root_Mean_Squared_Error(RMSE):', np.sqrt(metrics.mean_squared_error(y_test, dt_fit.predict(X_test))))
print('Accuracy_score: {:.7f}".format(regressor.score(X_test, y_test)))
```

```
from sklearn import metrics
print('Mean_Absolute_Error(MAE):', metrics.mean_absolute_error(y_test, dt_fit.predict(X_test)))
print('Mean_Squared_Error(MSE):', metrics.mean_squared_error(y_test, dt_fit.predict(X_test)))
print('Root_Mean_Squared_Error(RMSE):', np.sqrt(metrics.mean_squared_error(y_test, dt_fit.predict(X_test)))

Mean_Absolute_Error(MAE): 0.10346154015288393
Mean_Squared_Error(MSE): 0.034138895615638154
Root_Mean_Squared_Error(RMSE): 0.1847671388955248

print("Accuracy score: {:.7f}".format(regressor.score(X_test, y_test)))

Accuracy score: 0.9985958
```

#### **Logistic Regression**

```
print ("LogLoss: : %.2f" % log_loss(y_test, yhat_prob2))
print("Accuracy:", metrics.accuracy_score(y_test, yhat))
```

```
print ("LogLoss: : %.2f" % log_loss(y_test, yhat_prob2))
LogLoss: : 0.70
print("Accuracy:",metrics.accuracy_score(y_test, yhat))
Accuracy: 0.5426621160409556
```

## **Bayesian Ridge Regression**

```
from sklearn import metrics
print('Mean_Absolute_Error(MAE):', metrics.mean_absolute_error(y_test, y_p
red))
print('Mean_Squared_Error(MSE):', metrics.mean_squared_error(y_test, y_pre
d))
print('Root_Mean_Squared_Error(RMSE):', np.sqrt(metrics.mean_squared_error
(y_test, y_pred)))
print('Accuracy Score:', model.score(X_test, y_test))
```

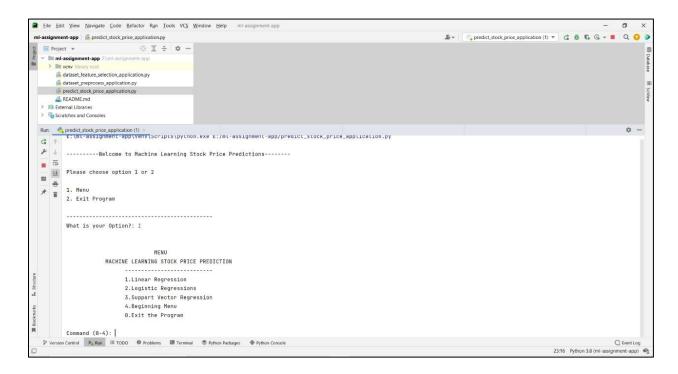
```
from sklearn import metrics
print('Mean_Absolute_Error(MAE):', metrics.mean_absolute_error(y_test, y_pred))
print('Mean_Squared_Error(MSE):', metrics.mean_squared_error(y_test, y_pred))
print('Root_Mean_Squared_Error(RMSE):', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))

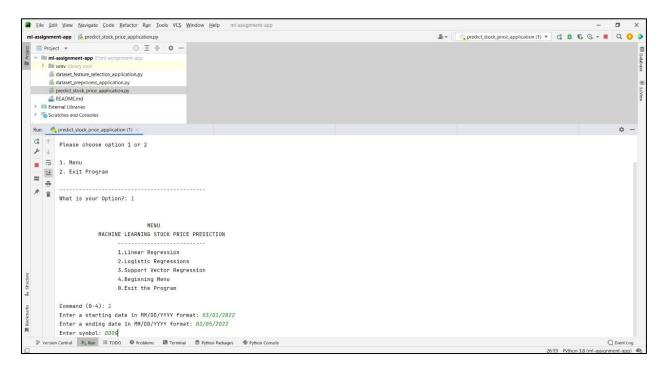
Mean_Absolute_Error(MAE): 0.1466702616961777
Mean_Squared_Error(MSE): 0.051846556663474076
Root_Mean_Squared_Error(RMSE): 0.22769838968133718

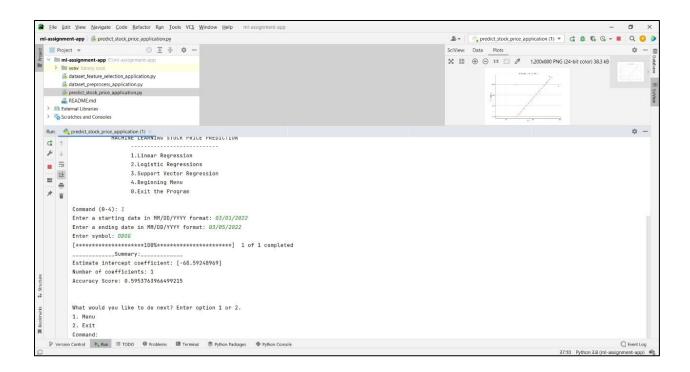
print('Accuracy_Score:', model.score(X_test, y_test))

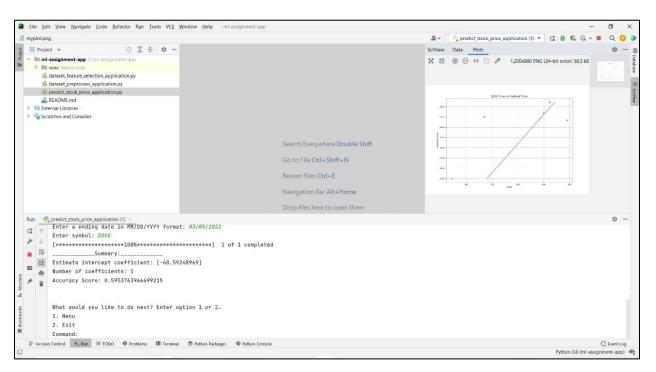
Accuracy_Score: 0.9978674317701605
```

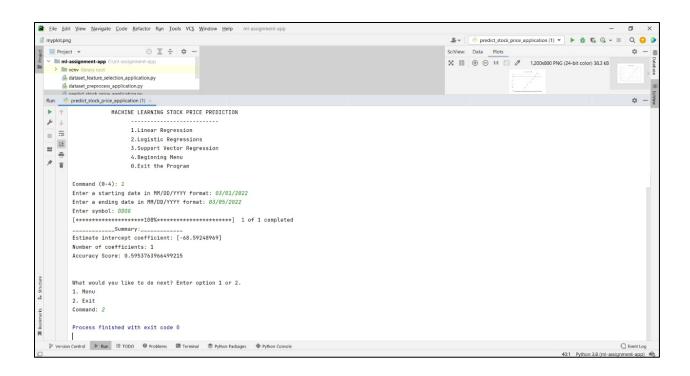
# **6 OUTPUT APPLICATION SCREENSHOTS**

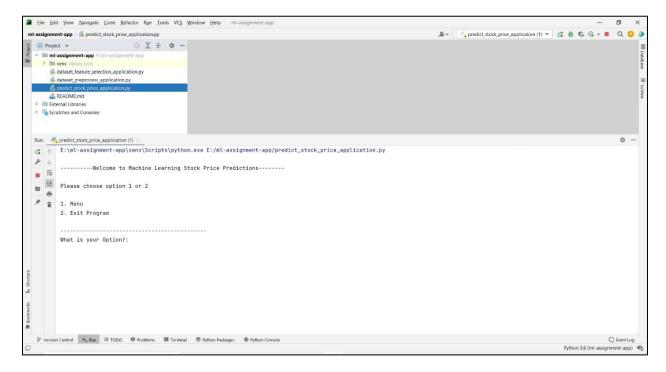












#### 7 RESULTS AND DISCUSSION

## 7.1 Accuracy Comparison of the Models

The performance of a model depends on its loss function values and accuracy values.

Three common loss functions:

- Mean Absolute Error (MAE) is the mean of the absolute value of the errors. MAE is the easiest to understand because it's the average error
- Mean Squared Error (MSE) is the mean of the squared errors. MSE is more popular than MAE, because MSE "punishes" larger errors, which tends to be useful in the real world
- Root Mean Squared Error (RMSE) is the square root of the mean of the squared errors. RMSE is even more popular than MSE, because RMSE is interpretable in the "y" units

All of these are loss functions because we want to minimize them to increase the performance of model.

Machine learning model accuracy is the measurement used to determine which model is best at identifying relationships and patterns between variables in a dataset based on the input, or training, data.

The table below compares the values and accuracy of the loss functions applicable to the models we used.

Model	MAE	MSE	RMSE	Log Loss	Accuracy
Linear Regression	0.061703	0.010497	0.102454	-	0.999571
Decision Tree Regression	0.103461	0.034138	0.184767	-	0.998595
Logistic Regression	-	-	-	0.70	0.542662
Bayesian Ridge Regression	0.146670	0.051846	0.227698	-	0.997867

Based on the results of both loss functions value and accuracy values approaches, we can say that Linear Regression, Decision Tree Regression and Bayesian Ridge Regression give better prediction in this scenario. Comparing loss functions value and accuracy value shows that the Linear Regression Model is best suited for stock price prediction.

#### 8 CRITICAL ANALYSIS & DISCUSSION

#### **8.1 Possible Limitations**

Model that are being trained and maintained for one business does not fit another business. When considering the studies have done most of the studies does not use a large dataset which compromises different types of data. Some studies used only one company database for more than 14 years. One of the biggest challenges in this research area is an accurate prediction. It is due to multiple reasons, mainly micro and macro, such as global economic conditions, unforeseen events, the financial performance of a company, and politics. However, there is a huge load of data, which we can use the identify trends and patterns. Therefore, researchers, analysts in finance, data science, and data scientists use this data to explore different analytical techniques. We Can't Predict All Contingencies. For example, predicting that something will rise when prices fall can disrupt a trader's finances, especially since we do not know exactly how the market will react to ongoing news or information. When prices fall, even the good news is that prices will not rise significantly, and when prices rise, even bad news does not have a long-term negative impact on prices. Individual stocks do not necessarily follow the overall market. Unexpected changes in stuff price prediction can occur all at once. In such a case, a previously trained model may make some mistakes in making decisions.

#### 8.2 Challenges in Stock Price Prediction

- Biggest challenge is achieving a higher accuracy amid the different reasons and problems.
- Unexpected global and local situation like COVID-19, and war will lead to less accuracy of the models even we trained models to predict profit, gain, and loss.
- Most of the models are overmounting.
- Difficulties introduced on identifying quality data because fake databases and bot generated datasets.
- When using binary features sometimes important data might be lost while converting to binary features.

#### **8.3** Future Work (Areas of Possible Improvement)

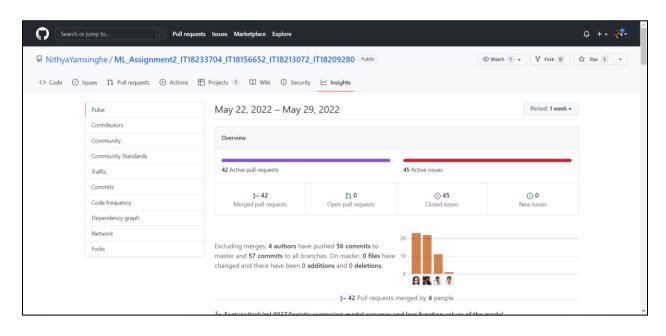
- Adding important information from the original database an enrich the research database while improving forecast accuracy.
- Although we have many models predict stock prices, there are a smaller number of models to predict the changes in stock prices.
- Use the approaches to predict the inventory costs in the future.
- Using hybrid forecast models can improve the accuracy.
- Most of the times different variables of dataset considered for training model can be unique
  to relevant country, income, and education of that country. Therefore, training a universal
  accurate model is really challenging.
- Use more feature selection and feature engineering to help enrich the database and mine important information from the original database to improve forecast accuracy.

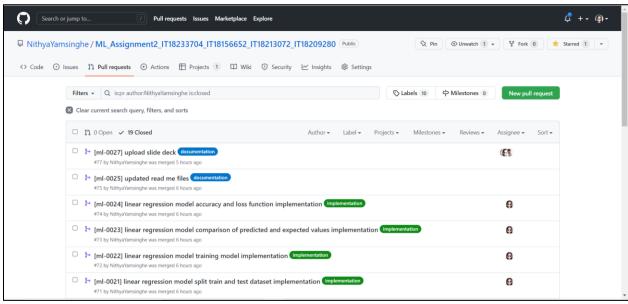
#### **8.4 Solutions for Stock Price Prediction**

- Determining stock patterns
- Construct pattern networks
- Extract essential characteristic variables
- Determine the optimal parameter values for best suitable model
- Implement in the real market

## 9 INDIVIDUAL CONTRIBUTION

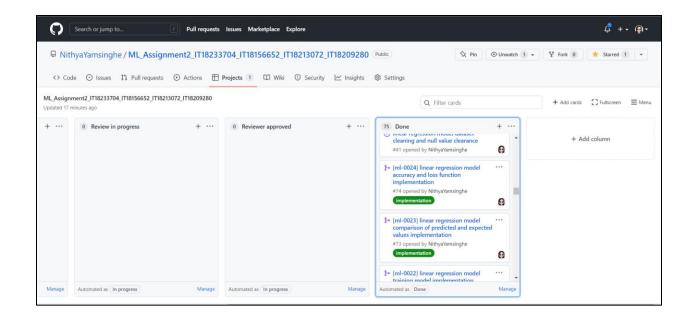
## 9.1 GitHub Commits Screenshots - IT18233704 | Yamasinghe N.R





□	0
Im-0018] linear regression model dataset cleaning and null value clearance implementation   enhancement   Implementation   enhancement   enh	9
□ I* [ml-0005] linear regression model view dataset implementation (implementation) #54 by NithyaYamsinghe was merged 20 hours ago	9
□ 1* [ml-0004] linear regression model dataset preprocessing implementation (implementation #53 by NithyaYamsinghe was merged 20 hours ago	9
□ I* [mI-0003] linear regression model load dataset into data frame implementation enhancement #52 by NithyaYamsinghe was merged yesterday	9
□ I* [ml-0002] linear regression model import libraries implementation enhancement #51 by Nithya/Yamsinghe was merged yesterday	9
□ ► [ml-0001] project readme file updated documentation #50 by NithyaYamsinghe was merged 2 days ago	0
□ I*• [ml-0001] project readme file updated documentation #49 by NithyaYamsinghe was merged 2 days ago	0
□ I→ [ml-0001] project readme file updated documentation #48 by Nithys/Yamsinghe was merged 2 days ago	0
#47 by Nithys/ramsinghe was merged 2 days ago  #47 by Nithys/ramsinghe was merged 2 days ago	9
□ I*• [mI-0001] project readme file updated enhancement #46 by NithyaYamsinghe was merged 2 days ago	9

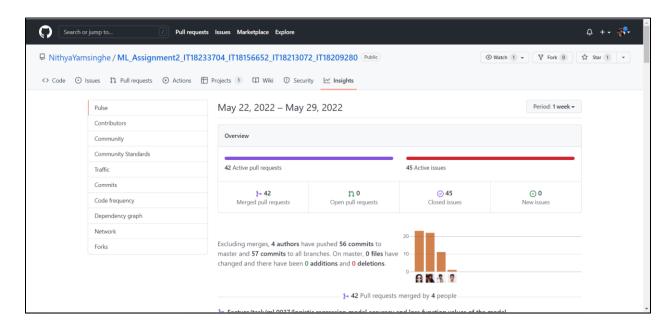
C	[ml-0024] linear regression model accuracy and loss function implementation (implementation) #74 by NithyaYamsinghe was merged 6 hours ago	0	•
C	[ml-0023] linear regression model comparison of predicted and expected values implementation (mplementation) #73 by NithyaYamsinghe was merged 6 hours ago	0	
C	Im-0022] linear regression model training model implementation (implementation) (implementa	0	
С	[ml-0021] linear regression model split train and test dataset implementation mplementation #71 by NithyaYamsinghe was merged 6 hours ago	0	
	[ml-0021] linear regression model define x and y implementation implementation #70 by NithyaYamsinghe was merged 6 hours ago	Θ	
C	[ml-0020] linear regression model view dataset implementation (implementation) (implementation) (implementation)	0	
	[ml-0019] linear regression model analyze dataset implementation enhancement implementation #68 by NithyaYamsinghe was merged 7 hours ago	0	
C	[ml-0018] linear regression model dataset cleaning and null value clearance implementation enhancement implementation enhancement implementation enhancement implementation enhancement implementation.	9	
	[ml-0005] linear regression model view dataset implementation (implementation) (implementation) (implementation)	0	
	[ml-0004] linear regression model dataset preprocessing implementation (implementation) e53 by NithyaYamsinghe was merged 20 hours ago	0	
	* [ml-0003] linear regression model load dataset into data frame implementation enhancement #52 by NithyaYamsinghe was merged yesterday	0	Sunday, May 29, 2022

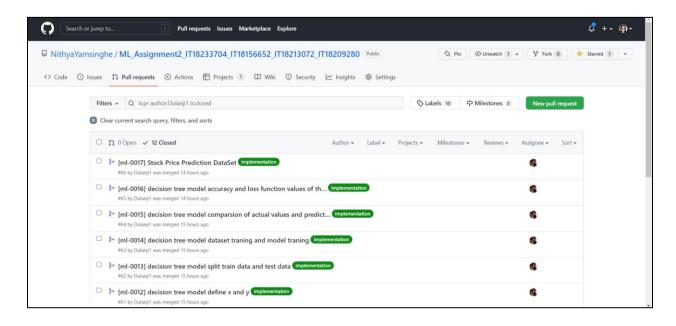


## 9.2 Individual References - IT18233704 | Yamasinghe N.R

- [01] https://vitalflux.com/popular-machine-learning-techniques-for-stock-price-movement-prediction/#:~:text=Machine%20learning%20techniques%20used%20for%20predicting%20stock%20prices%20involve%20analyzing,the%20best%20fit%20predictive%20models.
- [02] https://www.projectpro.io/article/stock-price-prediction-using-machine-learning-project/571
- [03] https://www.sciencedirect.com/science/article/pii/S1877050918307828
- [04] https://towardsdatascience.com/5-reasons-why-stock-prediction-projects-fail-a3dddf30d242
- [05] https://www.android-examples.com/category/phpmyadmin/
- [06] https://hbr.org/2009/01/why-we-cant-predict-financial
- [07] https://github.com/CYBERDEVILZ/Stock-Market-Prediction

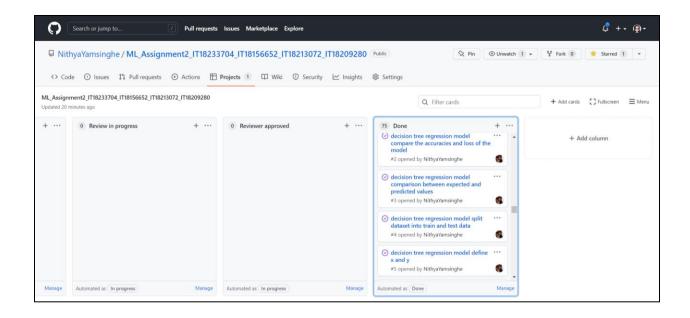
## 9.3 GitHub Commits Screenshots - IT18156652 | Cooray M.D.D.M





#66 by Dulanji1 was merged 14 hours ago		
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[ml-0015] decision tree model comparsion of actual values and predict [implementation] #64 by Dulanji1 was merged 15 hours ago	•	
☐ ► [ml-0014] decision tree model dataset traning and model traning (implementation) #63 by Dulanji1 was merged 15 hours ago	•	
[ml-0013] decision tree model split train data and test data [mplementation]  #62 by Dulanji1 was merged 15 hours ago	•	
[ml-0012] decision tree model define x and y implementation  #61 by Dulanji1 was merged 15 hours ago	•	
☐	•	
[ml-0010] decision tree model null value testing and data clearance (implementation) #59 by Dulanji1 was merged 15 hours ago	•	
[ml-0009] decision tree model view data set (implementation) #58 by Dulanji1 was merged 15 hours ago	•	
Iml-0008  decision tree model data preprocessing   Implementation   #57 by Dulanji1 was merged 15 hours ago	•	
☐ ► [ml-0007] decision tree model load data into a data frame (implementation) #56 by Dulanji1 was merged 15 hours ago	•	
☐	•	

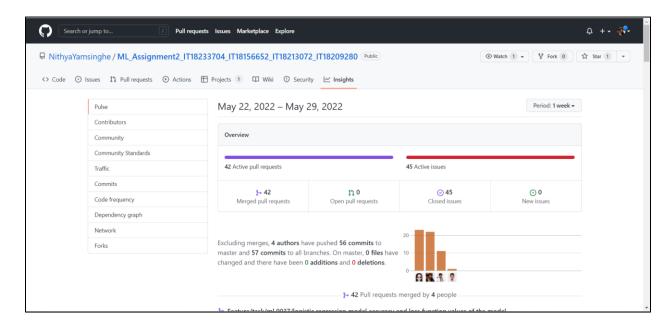
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	* [ml-0016] decision tree model accuracy and loss function values of th melementation #65 by Dulanji1 was merged 14 hours ago	4
	* [ml-0015] decision tree model comparsion of actual values and predict implementation #64 by Dulanji1 was merged 15 hours ago	4
	* [ml-0014] decision tree model dataset traning and model traning implementation #63 by Dulanji1 was merged 15 hours ago	4
0	[m]-0013] decision tree model split train data and test data [mp/ementation] #62 by Dulanji1 was merged 15 hours ago	4
	[m-0012] decision tree model define x and y implementation #61 by Dulanji1 was merged 15 hours ago	4
	[* [ml-001]] decision tree model analyze data set [implementation] #60 by Dulanji1 was merged 15 hours ago	4
0	I* [mI-0010] decision tree model null value testing and data clearance € [implementation] #59 by Dulanji1 was merged 15 hours ago	4
	[* [ml-0009] decision tree model view data set implementation #58 by Dulanji1 was merged 15 hours ago	4
0	[m-0008] decision tree model data preprocessing (mplementation) #57 by Dulanji1 was merged 15 hours ago	4
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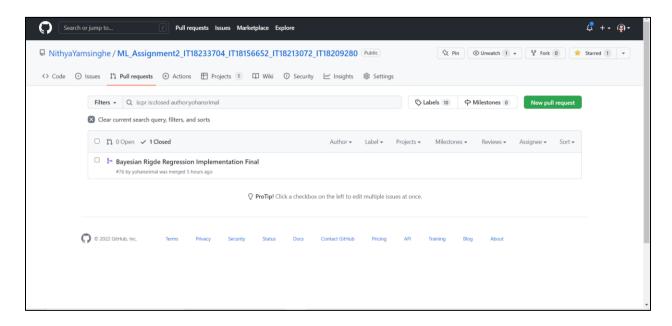


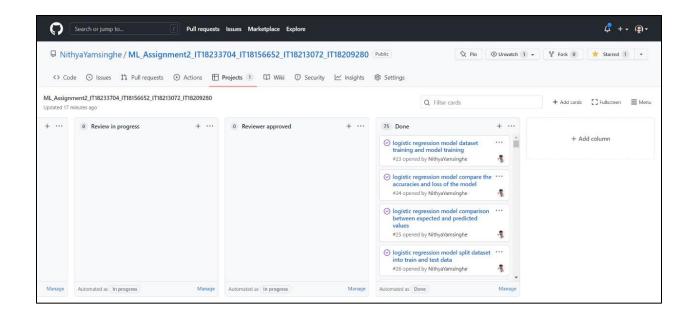
## 9.4 Individual References - IT18156652 | Cooray M.D.D.M

- [01] https://vitalflux.com/popular-machine-learning-techniques-for-stock-price-movement-prediction/#:~:text=Machine%20learning%20techniques%20used%20for%20predicting%20stock%20prices%20involve%20analyzing,the%20best%20fit%20predictive%20models.
- [02] https://www.projectpro.io/article/stock-price-prediction-using-machine-learning-project/571
- [03] https://github.com/LastAncientOne/Deep-Learning-Machine-Learning-Stock/tree/master/Stock\_Algorithms
- [04] https://towardsdatascience.com/5-reasons-why-stock-prediction-projects-fail-a3dddf30d242
- [05] https://github.com/NourozR/Stock-Price-Prediction-LSTM
- [06] https://www.sciencedirect.com/science/article/pii/S1877050918307828
- [07] https://github.com/CYBERDEVILZ/Stock-Market-Prediction

# 9.5 GitHub Commits Screenshots - IT18213072 | Ranasinghe Y.S



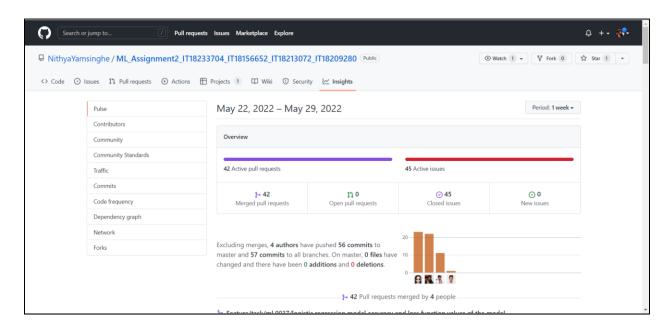


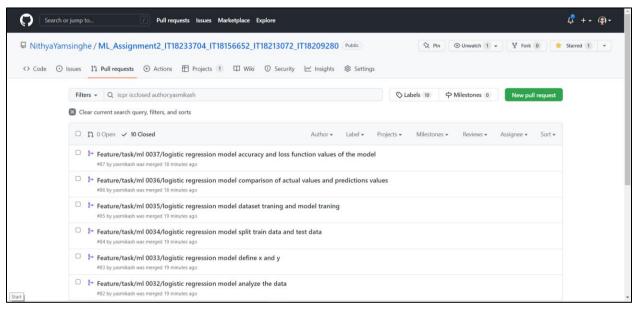


## 9.6 Individual References - IT18213072 | Ranasinghe Y.S

- [01] https://vitalflux.com/popular-machine-learning-techniques-for-stock-price-movement-prediction/#:~:text=Machine%20learning%20techniques%20used%20for%20predicting%20stock%20prices%20involve%20analyzing,the%20best%20fit%20predictive%20models.
- [02] https://www.projectpro.io/article/stock-price-prediction-using-machine-learning-project/571
- [03] https://github.com/LastAncientOne/Deep-Learning-Machine-Learning-Stock/tree/master/Stock\_Algorithms
- [04] https://towardsdatascience.com/5-reasons-why-stock-prediction-projects-fail-a3dddf30d242
- [05] https://www.android-examples.com/category/phpmyadmin/
- [06] https://hbr.org/2009/01/why-we-cant-predict-financial
- [07] https://github.com/CYBERDEVILZ/Stock-Market-Prediction

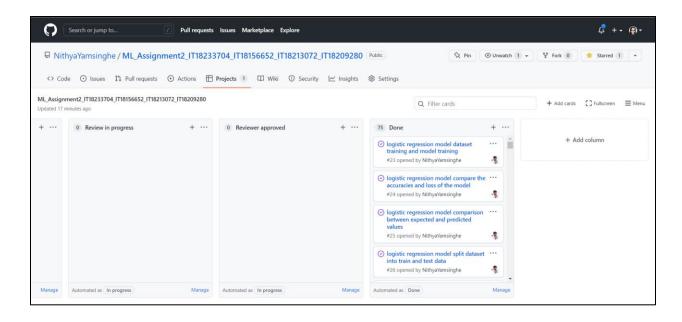
## 9.7 GitHub Commits Screenshots - IT18209280 | Dissanayake D.M.Y.S





0	1 0 Open 🗸 10 Closed Author + Label + Projects + Milestones + Reviews + Assignee - Sort +
0	Feature/task/ml 0037/logistic regression model accuracy and loss function values of the model #87 by yasmikash was merged 21 minutes ago
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0	Feature/task/ml 0035/logistic regression model dataset traning and model traning #85 by yasmikash was merged 21 minutes ago
0	Feature/task/ml 0034/logistic regression model split train data and test data #84 by yasmikash was merged 21 minutes ago
0	Feature/task/ml 0033/logistic regression model define x and y  #83 by yasmikash was merged 22 minutes ago
0	Feature/task/ml 0032/logistic regression model analyze the data #82 by yasmikash was merged 22 minutes ago
0	Feature/task/ml 0031/logistic regression model null value testing and data clearance #81 by yasmikash was merged 22 minutes ago
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	Feature/task/ml 0033/logistic regression model define x and y #83 by yasmikash was merged 19 minutes ago							
	Feature/task/ml 0032/logistic regression model analyze the da #82 by yasmikash was merged 19 minutes ago	ta						
	Feature/task/ml 0031/logistic regression model null value testi #81 by yasmikash was merged 20 minutes ago	ng and data clearar	ice					
	Feature/task/ml 0030/logistic regression model data preproce #80 by yasmikash was merged 20 minutes ago	ssing						
0	Feature/task/ml 0029/logistic regression model load data into #79 by yasmikash was merged 20 minutes ago	a dataframe						
	Feature/task/ml 0028/logistic regression model import librarie #78 by vasmikash was merged 20 minutes ago	s						



## 9.8 Individual References - IT18209280 | Dissanayake D.M.Y.S

- [01] https://vitalflux.com/popular-machine-learning-techniques-for-stock-price-movement-prediction/#:~:text=Machine%20learning%20techniques%20used%20for%20predicting%20stock%20prices%20involve%20analyzing,the%20best%20fit%20predictive%20models.
- [02] https://www.projectpro.io/article/stock-price-prediction-using-machine-learning-project/571
- [03] https://github.com/LastAncientOne/Deep-Learning-Machine-Learning-Stock/tree/master/Stock\_Algorithms
- [04] https://towardsdatascience.com/5-reasons-why-stock-prediction-projects-fail-a3dddf30d242
- [05] https://www.android-examples.com/category/phpmyadmin/
- [06] https://hbr.org/2009/01/why-we-cant-predict-financial
- [07] https://github.com/CYBERDEVILZ/Stock-Market-Prediction

#### 10 REFERANCES

- [01] https://vitalflux.com/popular-machine-learning-techniques-for-stock-price-movement-prediction/#:~:text=Machine%20learning%20techniques%20used%20for%20predicting%20stock%20prices%20involve%20analyzing,the%20best%20fit%20predictive%20models.
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- [03] https://github.com/LastAncientOne/Deep-Learning-Machine-Learning-Stock/tree/master/Stock\_Algorithms
- [04] https://github.com/NourozR/Stock-Price-Prediction-LSTM
- [05] https://www.projectpro.io/article/stock-price-prediction-using-machine-learning-project/571
- [06] https://github.com/CYBERDEVILZ/Stock-Market-Prediction
- [07] https://towardsdatascience.com/5-reasons-why-stock-prediction-projects-fail-a3dddf30d242
- [08] https://www.android-examples.com/category/phpmyadmin/
- [09] https://hbr.org/2009/01/why-we-cant-predict-financial
- [10] https://www.emerald.com/insight/content/doi/10.1108/IJCS-05-2020-0012/full/html

#### 11 APPENDICES

### 11.1 GitHub Repository Link

https://github.com/NithyaYamsinghe/ML\_Assignment2\_IT18233704\_IT18156652\_IT18213072\_IT18209280

#### 11.2 GitHub Project Link

https://github.com/NithyaYamsinghe/ML Assignment2 IT18233704 IT18156652 IT18213072 IT18209280/projects/1

#### 11.3 Video Demonstration One Drive Link

https://mysliit-

my.sharepoint.com/:f:/g/personal/it18233704\_my\_sliit\_lk/EnHh4V5KZRdHtu4bcQ35rE8BFxawz Ym7JimFbU-U7kpD9g?e=kLjNb3

#### 11.4 Video Demonstration Slide Deck Link

https://drive.google.com/drive/folders/1ehb3EBDx0ZLjNj6vViHEMRR1itQnbyPS?usp=sharing

#### 11.5 Report

https://drive.google.com/drive/folders/10k7yfftiB1OSyvz1aK9jlmL5dyDEK5U\_?usp=sharing

#### 11.6 Complete Project Link

https://drive.google.com/drive/folders/1Ppob\_fOveAhjWn7MG2GwCE2tDiltQ\_I1?usp=sharing