```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.preprocessing import MinMaxScaler
from xgboost import XGBClassifier
from sklearn import metrics

from keras.models import Sequential
from keras.layers import LSTM
from keras.layers import Dense
from keras.layers import Dropout

import warnings
warnings.filterwarnings('ignore')
```

```
from google.colab import drive
drive.mount('/content/drive')
df = pd.read_csv('drive/My Drive/AAPLmain.csv')
df.head()
```

```
Mounted at /content/drive
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	1980-12-12	0.128348	0.128906	0.128348	0.128348	0.099722	469033600
1	1980-12-15	0.122210	0.122210	0.121652	0.121652	0.094519	175884800
2	1980-12-16	0.113281	0.113281	0.112723	0.112723	0.087582	105728000
3	1980-12-17	0.115513	0.116071	0.115513	0.115513	0.089749	86441600
4	1980-12-18	0.118862	0.119420	0.118862	0.118862	0.092351	73449600

```
df.shape
```

```
(10664, 7)
```

```
df.describe()
```

	Open	High	Low	Close	Adj Close	Volume
count	10664.000000	10664.000000	10664.000000	10664.000000	10664.000000	1.066400e+04
mean	17.214226	17.411780	17.021893	17.224528	16.533494	3.261870e+08
std	36.387008	36.832052	35.965057	36.417573	36.066055	3.374503e+08
min	0.049665	0.049665	0.049107	0.049107	0.038154	0.000000e+00
25%	0.287946	0.296875	0.282366	0.289063	0.238623	1.201032e+08
50%	0.491071	0.498884	0.483962	0.491071	0.407027	2.135056e+08
75%	16.693303	16.851606	16.577144	16.695893	14.498148	4.058439e+08
max	182.630005	182.940002	179.119995	182.009995	180.683868	7.421641e+09

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10664 entries, 0 to 10663
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Date       10664 non-null  object 
 1   Open       10664 non-null  float64
 2   High       10664 non-null  float64
 3   Low        10664 non-null  float64
 4   Close      10664 non-null  float64
 5   Adj Close  10664 non-null  float64
 6   Volume     10664 non-null  int64  
dtypes: float64(5), int64(1), object(1)
memory usage: 583.3+ KB
```

```
plt.figure(figsize=(15,5))
plt.plot(df['Close'])
plt.title('Tesla Close price.', fontsize=15)
```

```
plt.title('Tesla Close price.', fontsize=15)
plt.ylabel('Price in dollars.')
plt.show()
```


```
df.head()
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	1980-12-12	0.128348	0.128906	0.128348	0.128348	0.099722	469033600
1	1980-12-15	0.122210	0.122210	0.121652	0.121652	0.094519	175884800
2	1980-12-16	0.113281	0.113281	0.112723	0.112723	0.087582	105728000
3	1980-12-17	0.115513	0.116071	0.115513	0.115513	0.089749	86441600
4	1980-12-18	0.118862	0.119420	0.118862	0.118862	0.092351	73449600

```
df[df['Close'] == df['Adj Close']].shape
```

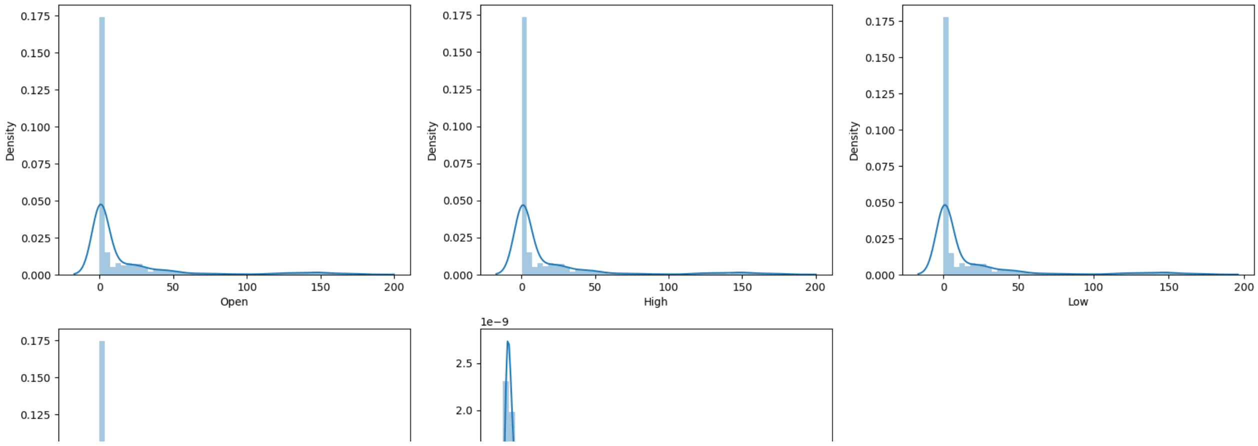
```
(34, 7)
```

```
df = df.drop(['Adj Close'], axis=1)
```

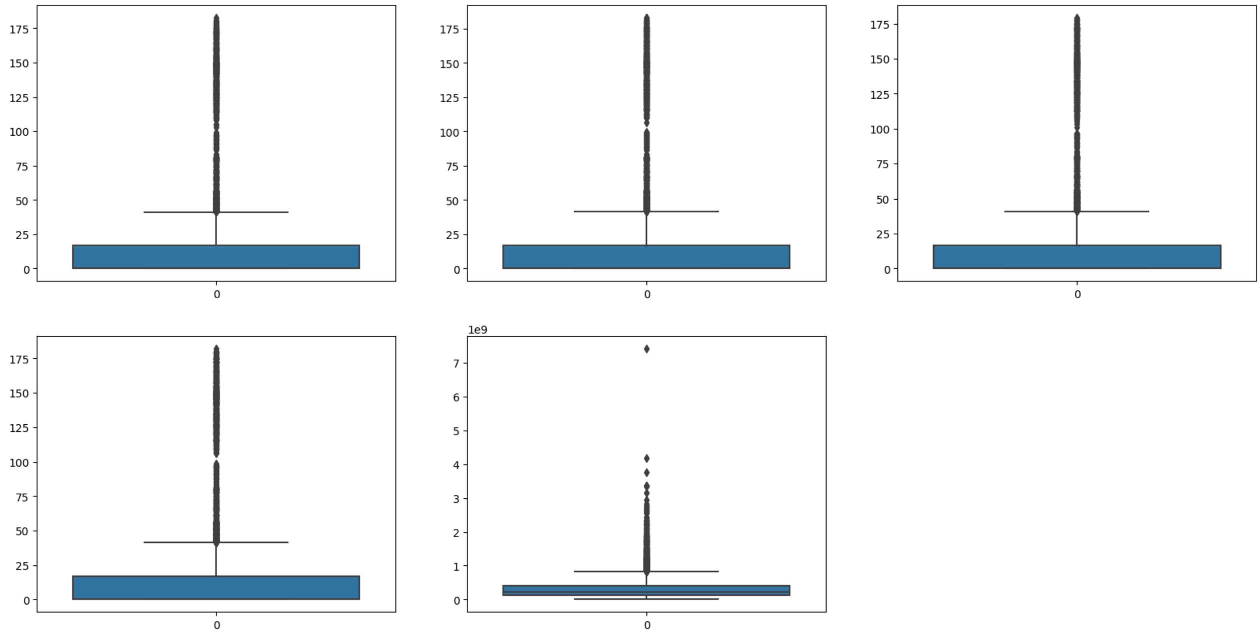
```
'''checking for null values'''
df.isnull().sum()
```

```
Date      0
Open      0
High      0
Low       0
Close     0
Volume    0
dtype: int64
```

```
features = ['Open', 'High', 'Low', 'Close', 'Volume']

plt.subplots(figsize=(20,10))

for i, col in enumerate(features):
  plt.subplot(2,3,i+1)
  sb.distplot(df[col])
plt.show()
```




```
plt.subplots(figsize=(20,10))
for i, col in enumerate(features):
  plt.subplot(2,3,i+1)
  sb.boxplot(df[col])
plt.show()
```



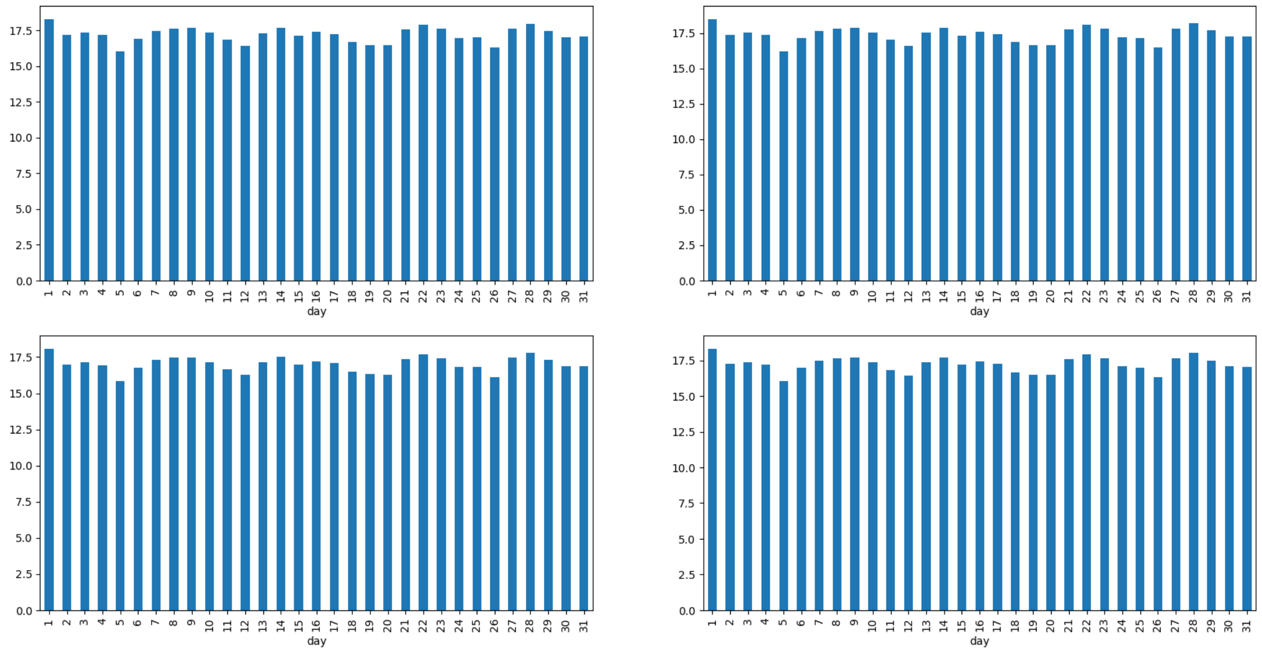

```
splitted = df['Date'].str.split('-', expand=True)

df['day'] = splitted[2].astype('int')
df['month'] = splitted[1].astype('int')
df['year'] = splitted[0].astype('int')

df.head()
```

	Date	Open	High	Low	Close	Volume	day	month	year
0	1980-12-12	0.128348	0.128906	0.128348	0.128348	469033600	12	12	1980
1	1980-12-15	0.122210	0.122210	0.121652	0.121652	175884800	15	12	1980
2	1980-12-16	0.113281	0.113281	0.112723	0.112723	105728000	16	12	1980
3	1980-12-17	0.115513	0.116071	0.115513	0.115513	86441600	17	12	1980
4	1980-12-18	0.118862	0.119420	0.118862	0.118862	73449600	18	12	1980

```
df['is_quarter_end'] = np.where(df['month']%3==0,1,0)
df.head()
```

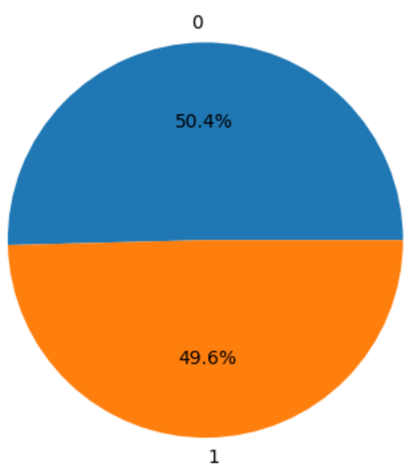
	Date	Open	High	Low	Close	Volume	day	month	year	is_quarter_end
0	1980-12-12	0.128348	0.128906	0.128348	0.128348	469033600	12	12	1980	1
1	1980-12-15	0.122210	0.122210	0.121652	0.121652	175884800	15	12	1980	1
2	1980-12-16	0.113281	0.113281	0.112723	0.112723	105728000	16	12	1980	1
3	1980-12-17	0.115513	0.116071	0.115513	0.115513	86441600	17	12	1980	1

```
data_grouped = df.groupby('day').mean()
plt.subplots(figsize=(20,10))

for i, col in enumerate(['Open', 'High', 'Low', 'Close']):
  plt.subplot(2,2,i+1)
  data_grouped[col].plot.bar()
plt.show()
```



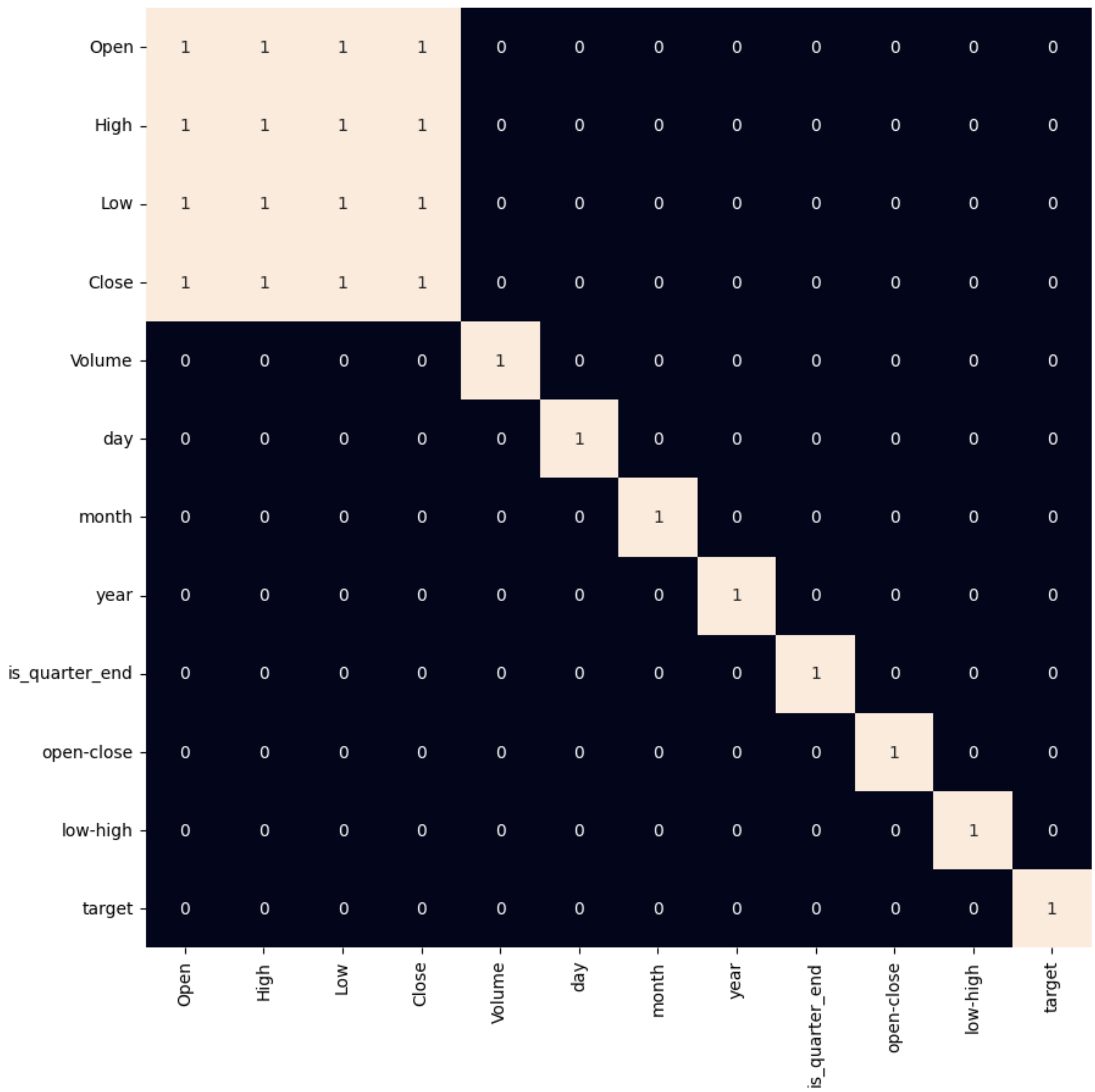

```
df['open-close']  = df['Open'] - df['Close']
df['low-high']  = df['Low'] - df['High']
df['target'] = np.where(df['Close'].shift(-1) > df['Close'], 1, 0)
```

```
plt.pie(df['target'].value_counts().values,
        labels=[0, 1], autopct='%1.1f%%')
plt.show()
```




```
plt.figure(figsize=(10, 10))

```

```
# As our concern is with the highly
# correlated features only so, we will visualize
# our heatmap as per that criteria only.
sb.heatmap(df.corr() > 0.9, annot=True, cbar=False)
plt.show()
```



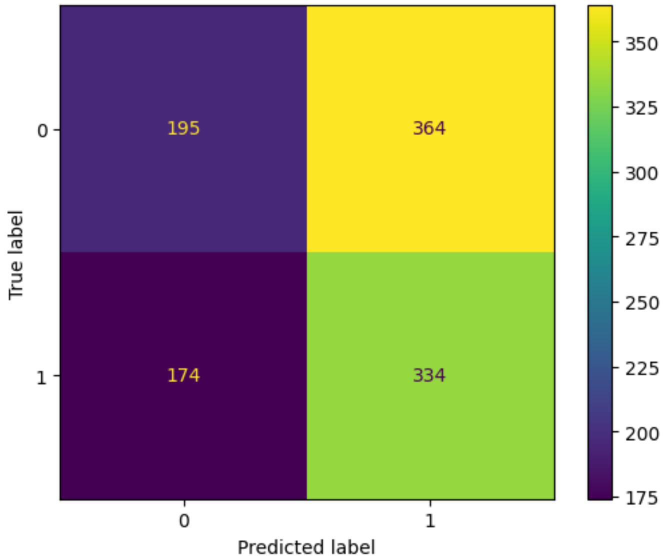

```
features = df[['open-close', 'low-high', 'is_quarter_end']]
target = df['target']

scaler = StandardScaler()
features = scaler.fit_transform(features)

X_train, X_valid, Y_train, Y_valid = train_test_split(
    features, target, test_size=0.1, random_state=2022)
print(X_train.shape, X_valid.shape)
```

```
(9597, 3) (1067, 3)
```

```
models = [LogisticRegression(), SVC(
  kernel='poly', probability=True), XGBClassifier()]

for i in range(3):
  models[i].fit(X_train, Y_train)

  print(f'{models[i]} : ')
  print('Training Accuracy : ', metrics.roc_auc_score(
    Y_train, models[i].predict_proba(X_train)[:,1]))
  print('Validation Accuracy : ', metrics.roc_auc_score(
    Y_valid, models[i].predict_proba(X_valid)[:,1]))
  print()
```

```
LogisticRegression() :
Training Accuracy :  0.5269174389766803
Validation Accuracy :  0.5309185412646317

SVC(kernel='poly', probability=True) :
Training Accuracy :  0.5174615996250385
Validation Accuracy :  0.5082983533587819

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...) :
Training Accuracy :  0.817039507331415
Validation Accuracy :  0.5100080289606017
```

```
1 metrics.ConfusionMatrixDisplay.from_estimator(models[0], X_valid, Y_valid)
2 plt.show()
```




```
1 dataset_train = pd.read_csv('drive/My Drive/AAPLmain.csv')
2 dataset_train.head()
```

	Date	Open	High	Low	Close	Adj Close	Volume
0	1980-12-12	0.128348	0.128906	0.128348	0.128348	0.099722	469033600
1	1980-12-15	0.122210	0.122210	0.121652	0.121652	0.094519	175884800
2	1980-12-16	0.113281	0.113281	0.112723	0.112723	0.087582	105728000
3	1980-12-17	0.115513	0.116071	0.115513	0.115513	0.089749	86441600
4	1980-12-18	0.118862	0.119420	0.118862	0.118862	0.092351	73449600

```
1 training_set = dataset_train.iloc[:,1:2].values
2 print(training_set)
3 print (training_set.shape)
```

```
[[1.28348000e-01]
 [1.22210000e-01]
 [1.13281000e-01]
 ...
 [1.57970001e+02]
 [1.59369995e+02]
 [1.61529999e+02]]
(10664, 1)
```

```
1 scaler = MinMaxScaler (feature_range = (0,1))
2 scaled_training_set = scaler.fit_transform(training_set)
3 scaled_training_set
```

```
array([[4.30950014e-04],
       [3.97331936e-04],
       [3.48427437e-04],
       ...,
       [8.64936148e-01],
       [8.72603973e-01],
       [8.84434403e-01]])
```

```
X_train = []
y_train = []
for i in range(60,10664):
    X_train.append(scaled_training_set[i-60:i, 0])
    y_train.append(scaled_training_set[i, 0])
X_train = np.array(X_train)
y_train = np.array(y_train)
```

```
print( X_train.shape)
print( y_train.shape)
```

```
(10604, 60)
(10604,)
```

```
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
X_train.shape
```

```
(10604, 60, 1)
```

```
regressor = Sequential()
regressor.add(LSTM(units = 50, return_sequences= True, input_shape = (X_train.shape[1], 1)))
regressor.add(Dropout (0.2))
regressor.add(LSTM(units = 50, return_sequences= True))
regressor.add(Dropout (0.2))
regressor.add(LSTM(units = 50, return_sequences=True))
regressor.add(Dropout (0.2))
regressor.add(LSTM(units = 50))
regressor.add (Dropout (0.2))
regressor.add(Dense (units=1))
```

```
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')
regressor.fit(X_train, y_train, epochs=100, batch_size=32)
```

```
332/332 [==============================] - 34s 103ms/step - loss: 3.2640e-04
Epoch 94/100
332/332 [==============================] - 34s 101ms/step - loss: 3.0982e-04
Epoch 95/100
332/332 [==============================] - 33s 100ms/step - loss: 3.1802e-04
Epoch 96/100
332/332 [==============================] - 32s 97ms/step - loss: 3.0795e-04
Epoch 97/100
332/332 [==============================] - 33s 99ms/step - loss: 3.0633e-04
Epoch 98/100
332/332 [==============================] - 33s 100ms/step - loss: 2.7265e-04
Epoch 99/100
332/332 [==============================] - 34s 102ms/step - loss: 3.2877e-04
Epoch 100/100
332/332 [==============================] - 34s 102ms/step - loss: 3.2680e-04
<keras.callbacks.History at 0x7f3235e66620>
```

```
dataset_test = pd.read_csv("drive/My Drive/TSLA2023-Jan-March.csv")
actual_stock_price = dataset_test.iloc[:,1:2].values
```

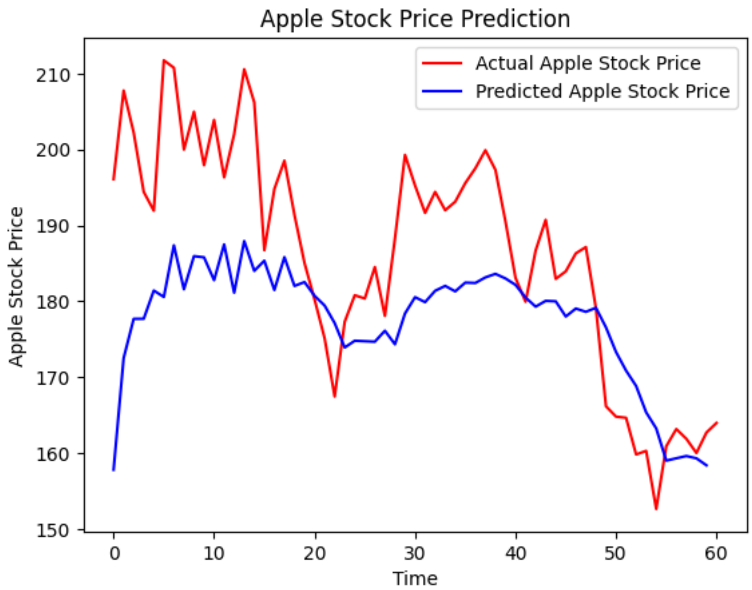
```
dataset_total = pd.concat((dataset_train [ 'Open'], dataset_test['Open']), axis = 0)
inputs = dataset_total[len(dataset_total)- len(dataset_test)-60:].values

inputs = inputs.reshape(-1,1)
inputs = scaler.transform(inputs)
inputs.shape

X_test = []
for i in range(60,120):
    X_test.append(inputs [i-60:i, 0])
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0],X_test.shape[1] , 1))
```

```
predicted_stock_price = regressor.predict(X_test)
predicted_stock_price = scaler.inverse_transform(predicted_stock_price)

```

```
2/2 [==============================] - 1s 28ms/step
```

```
plt.plot(actual_stock_price, color = 'red', label = 'Actual Apple Stock Price')
plt.plot(predicted_stock_price, color = 'blue', label = 'Predicted Apple Stock Price')
plt.title('Apple Stock Price Prediction')
plt.xlabel('Time')
plt.ylabel('Apple Stock Price')
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f32365063e0>
```



✓ 0s completed at 11:08 AM