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OPEN-ENDED PROJECT REPORT

FUNDAMENTALS OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING LAB

COURSE CODE: 5139C

TOPIC :

STOCK PRICE PREDICTION

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ABSTRACT

Stock price prediction is a critical challenge in financial markets, and the application of Artificial Intelligence (AI) and Machine Learning (ML) techniques has gained significant attention in recent years. This abstract provides a concise overview of the utilization of AI and ML in stock price prediction, emphasizing its key components and implications.

The integration of AI and ML in stock price prediction involves the analysis of vast volumes of historical data, real-time market information, and textual sources such as news articles and social media sentiment. AI models leverage complex algorithms and data-driven insights to identify patterns and relationships within this data, enabling more accurate predictions. These models can adapt to evolving market conditions and provide valuable insights into investment decisions.

AI and ML models used in stock price prediction encompass a variety of algorithms, including linear regression, decision trees, neural networks, and deep learning techniques. Feature engineering, model training, and rigorous evaluation of model performance are fundamental aspects of the process. While these models offer the potential for improved forecasting accuracy, challenges such as data quality, model interpretability, and the dynamic nature of financial markets remain important areas of consideration. Effective use of AI and ML in stock price prediction requires a balance of advanced technology and human expertise, with an emphasis on informed decision-making.

PROGRAM CODE AND OUTPUT

#Importing all the required libraries

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

 # Importing dataset

```
data = pd.read_csv("../input/nyse/prices-split-adjusted.csv")
df = pd.DataFrame(data)
```

```
df.head()
```

	date	symbol	open	close	low	high	volume
0	2016-01-05	WLTW	123.430000	125.839996	122.309998	126.250000	2163600.0
1	2016-01-06	WLTW	125.239998	119.980003	119.940002	125.540001	2386400.0
2	2016-01-07	WLTW	116.379997	114.949997	114.930000	119.739998	2489500.0
3	2016-01-08	WLTW	115.480003	116.620003	113.500000	117.440002	2006300.0
4	2016-01-11	WLTW	117.010002	114.970001	114.089996	117.330002	1408600.0

Data Information :

```
df.describe()
```

	open	close	low	high	volume
count	851264.000000	851264.000000	851264.000000	851264.000000	8.512640e+05
mean	64.993618	65.011913	64.336541	65.639748	5.415113e+06
std	75.203893	75.201216	74.459518	75.906861	1.249468e+07
min	1.660000	1.590000	1.500000	1.810000	0.000000e+00
25%	31.270000	31.292776	30.940001	31.620001	1.221500e+06
50%	48.459999	48.480000	47.970001	48.959999	2.476250e+06
75%	75.120003	75.139999	74.400002	75.849998	5.222500e+06
max	1584.439941	1578.130005	1549.939941	1600.930054	8.596434e+08

 # showing column wise %ge of NaN values they contains

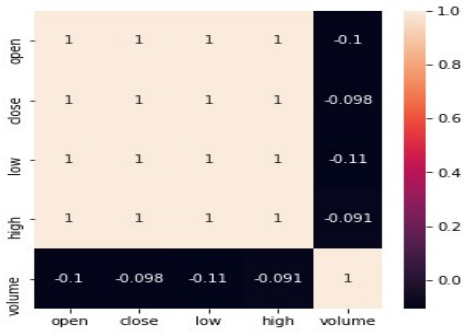
```
for i in df.columns:
  print(i,"\t-\t", df[i].isna().mean()*100)
```

```
date    -        0.0
symbol  -        0.0
open    -        0.0
close   -        0.0
low     -        0.0
high    -        0.0
volume  -        0.0
```

Since there is no null values, we can move further

```
df = df[df['symbol']=='AAP']  # Choosin stock values for any company

cormap = df.corr()
fig, ax = plt.subplots(figsize=(5,5))
sns.heatmap(cormap, annot = True)
```




```
def get_corelated_col(cor_dat, threshold):

  # Cor_data to be column along which corelation to be measured
  #Threshold be the value above which of corelation to considered
  feature=[]
  value=[]

  for i ,index in enumerate(cor_dat.index):
    if abs(cor_dat[index]) > threshold:
      feature.append(index)
      value.append(cor_dat[index])

  df = pd.DataFrame(data = value, index = feature, columns=['corr value'])
  return df

top_corelated_values = get_corelated_col(cormap['close'], 0.60)

top_corelated_values
```

	corr value
open	0.999382
close	1.000000
low	0.999615
high	0.999737

Looks like all columns except *volume* are *highly co-related*. Using them for predictions_

```
df = df[top_corelated_values.index]
```

```
df.head()
```

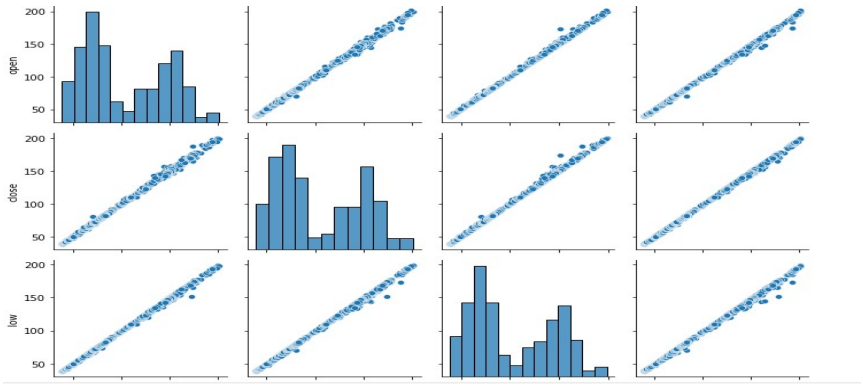
	open	close	low	high
253	40.700001	40.380001	40.360001	41.040001
720	40.299999	40.139999	39.720001	40.310001
1188	40.049999	40.490002	40.049999	40.779999
1656	39.549999	40.480000	39.549999	40.540001
2124	40.250000	40.639999	40.110001	40.820000

```
df.shape
```

```
(1762, 4)
```

```
sns.pairplot(df)
```

```
plt.tight_layout()
```



Since other parameters have linear relationship with close, we are using some linear models fore prediction

```
X = df.drop(['close'], axis=1)
```

```
y = df['close']
```

Since range of data in different columns varies significantly we need to scale the independent variable i.e. X. For this we will use Min-Max Scaling.

```
from sklearn.preprocessing import MinMaxScaler
```

```
scaler = MinMaxScaler()
X = pd.DataFrame(scaler.fit_transform(X), columns=X.columns)
X.head()
```

	open	low	high
0	0.012001	0.012392	0.010256
1	0.009539	0.008387	0.005746
2	0.008000	0.010452	0.008649
3	0.004923	0.007323	0.007167
4	0.009231	0.010827	0.008897

Prediction Model :

#now lets split data in test train pairs

```
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, shuffle=False)
Acc = []
```

1.Linear Regression :

```
from sklearn.linear_model import LinearRegression
```

 # model training

```
model_1 = LinearRegression()
model_1.fit(X_train, y_train)
```

```
LinearRegression()
```

 # prediction

```
y_pred_1 = model_1.predict(X_test)
pred_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_1})
pred_df.head()
```

	Actual	Predicted
675111	173.660004	173.682489
675608	171.919998	172.593759
676105	172.000000	171.182789
676602	187.789993	187.980305
677099	187.029999	188.440838

 # Measure the Accuracy Score

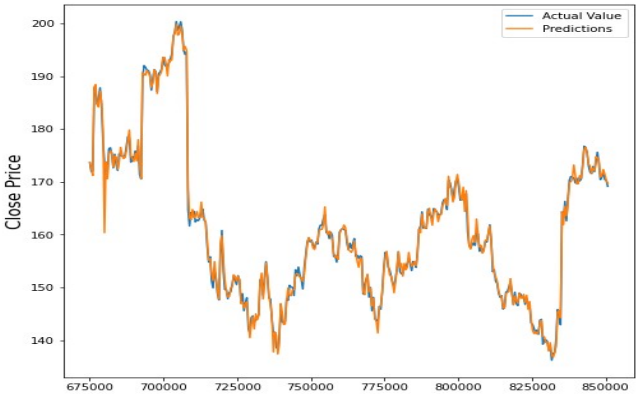
```
from sklearn.metrics import r2_score

print("Accuracy score of the predictions: {0}".format(r2_score(y_test, y_pred_1)))
Acc.append(r2_score(y_test, y_pred_1))
```

```
Accuracy score of the predictions: 0.9931342019332019
```

```
plt.figure(figsize=(8,8))

plt.ylabel('Close Price', fontsize=16)
plt.plot(pred_df)
plt.legend(['Actual Value', 'Predictions'])
plt.show()
```



2. ANN :

 # Model Creation

```
from keras.models import Sequential
from keras.layers import Dense

def regressor(inp_dim):

    model = Sequential()

    model.add(Dense(20, input_dim=inp_dim, kernel_initializer='normal',
activation='relu'))
    model.add(Dense(25, kernel_initializer='normal', activation='relu'))
    model.add(Dense(10, kernel_initializer='normal', activation='relu'))
    model.add(Dense(1, kernel_initializer='normal'))

    model.compile(loss='mean_squared_error', optimizer='adam')

    return model
```

 # Model Training

```
model_2 = regressor(inp_dim=3)
model_2.fit(X_train, y_train, epochs=70, validation_split=0.2)
```

```
Epoch 1/70
36/36 [==============================] - 1s 12ms/step - loss: 6039.9136 - val_loss: 22082.7910
Epoch 2/70
36/36 [==============================] - 0s 3ms/step - loss: 6148.0490 - val_loss: 21983.5176
Epoch 3/70
36/36 [==============================] - 0s 4ms/step - loss: 6048.6005 - val_loss: 21526.3438
Epoch 4/70
36/36 [==============================] - 0s 4ms/step - loss: 5898.5889 - val_loss: 20082.7168
Epoch 5/70
36/36 [==============================] - 0s 4ms/step - loss: 5210.5215 - val_loss: 16763.3730
Epoch 6/70
36/36 [==============================] - 0s 4ms/step - loss: 4012.6616 - val_loss: 11200.8164
Epoch 7/70
36/36 [==============================] - 0s 4ms/step - loss: 2315.5936 - val_loss: 4884.3481
Epoch 8/70
36/36 [==============================] - 0s 4ms/step - loss: 729.7410 - val_loss: 1114.4911
Epoch 9/70
```

Prediction

```
y_pred_2 = model_2.predict(X_test)

pred_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_2.flatten()})

pred_df.head()
```

	Actual	Predicted
675111	173.660004	174.118927
675608	171.919998	172.438049
676105	172.000000	170.655121
676602	187.789993	179.478363
677099	187.029999	188.179977

Measure the Accuracy Score

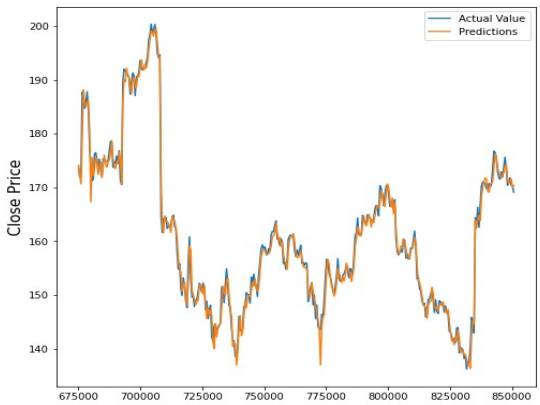
```
from sklearn.metrics import r2_score

print("Accuracy score of the predictions: {0}".format(r2_score(y_test, y_pred_2)))
Acc.append(r2_score(y_test, y_pred_2))
```

```
Accuracy score of the predictions: 0.9877609818668082
```

```
plt.figure(figsize=(8,8))

plt.ylabel('Close Price', fontsize=16)
plt.plot(pred_df)
plt.legend(['Actual Value', 'Predictions'])
plt.show()
```



3.CNN :

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

X_test = np.array(X_test).reshape(X_test.shape[0], X_test.shape[1], 1)


from tensorflow.keras import Sequential,utils

from tensorflow.keras.layers import Flatten, Dense, Conv1D, MaxPool1D, Dropout

def reg():

    model = Sequential()

    model.add(Conv1D(32, kernel_size=(3,), padding='same', activation='relu',
input_shape = (X_train.shape[1],1)))
    model.add(Conv1D(64, kernel_size=(3,), padding='same', activation='relu'))
    model.add(Conv1D(128, kernel_size=(5,), padding='same', activation='relu'))

    model.add(Flatten())

    model.add(Dense(50, activation='relu'))
    model.add(Dense(20, activation='relu'))
    model.add(Dense(units = 1))

    model.compile(loss='mean_squared_error', optimizer='adam')

    return model
```

 # Model Training

```
model_3 = reg()
model_3.fit(X_train, y_train, epochs=100, validation_split=0.2)
```

```
Epoch 1/100
36/36 [==============================] - 1s 11ms/step - loss: 5823.3276 - val_loss: 11471.756
Epoch 2/100
36/36 [==============================] - 0s 6ms/step - loss: 1123.1389 - val_loss: 171.6087
Epoch 3/100
36/36 [==============================] - 0s 7ms/step - loss: 15.3328 - val_loss: 8.5728
Epoch 4/100
36/36 [==============================] - 0s 7ms/step - loss: 2.9474 - val_loss: 8.8803
Epoch 5/100
36/36 [==============================] - 0s 7ms/step - loss: 1.0818 - val_loss: 4.4193
Epoch 6/100
36/36 [==============================] - 0s 6ms/step - loss: 0.6523 - val_loss: 1.8011
Epoch 7/100
36/36 [==============================] - 0s 7ms/step - loss: 0.4726 - val_loss: 1.4435
Epoch 8/100
36/36 [==============================] - 0s 6ms/step - loss: 0.4215 - val_loss: 1.4433
Epoch 9/100
36/36 [==============================] - 0s 6ms/step - loss: 0.4324 - val_loss: 1.4659
```

 # Prediction

```
y_pred_3 = model_3.predict(X_test)
```

```
pred_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_3.flatten()})
pred_df.head()
```

	Actual	Predicted
675111	173.660004	174.413849
675608	171.919998	172.824112
676105	172.000000	171.037766
676602	187.789993	182.193436
677099	187.029999	188.761780

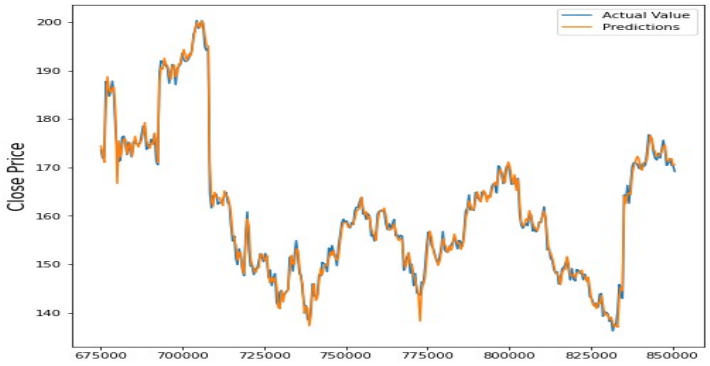
Measure the Accuracy Score

```
from sklearn.metrics import r2_score

print("Accuracy score of the predictions: {0}".format(r2_score(y_test, y_pred_3)))
Acc.append(r2_score(y_test, y_pred_3))
```

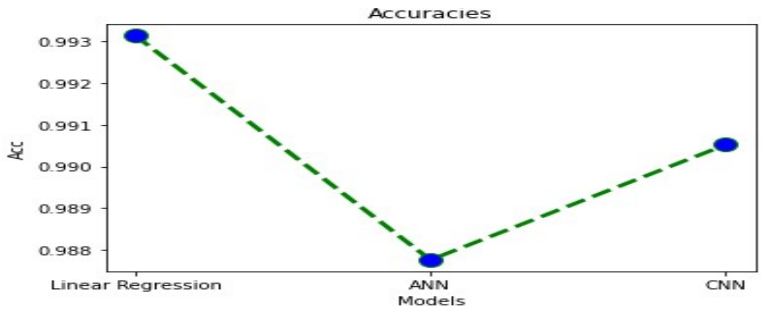
```
Accuracy score of the predictions: 0.9905183812120758
```

```
plt.figure(figsize=(8,8))
plt.ylabel('Close Price', fontsize=16)
plt.plot(pred_df)
plt.legend(['Actual Value', 'Predictions'])
plt.show()
```



Comparison of Accuracies of different models

```
plt.plot(range(3), Acc, color='green', linestyle='dashed', linewidth = 3,
         marker='o', markerfacecolor='blue', markersize=12)
plt.ylabel('Acc')
plt.xlabel('Models')
plt.title("Accuracies")
plt.xticks(range(3), ['Linear Regression', 'ANN', 'CNN'])
plt.show()
```



Now converting data in a time series data and applying some models :

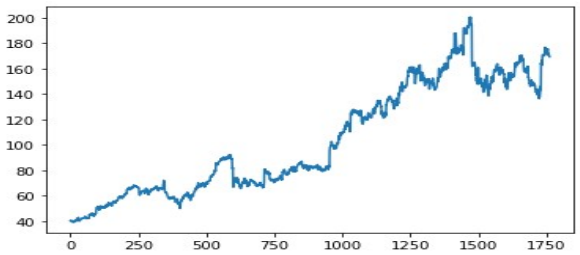
close = df.reset_index()['close']

close.head()

```
0    40.380001
1    40.139999
2    40.490002
3    40.480000
4    40.639999
Name: close, dtype: float64
```

plt.plot(close)

plt.show()



time_step = 30

X, y = [], []

```
for i in range(len(close)-time_step-1):
    X.append(close[i:(i+time_step)])
    y.append(close[(i+time_step)])
```

X = np.array(X)
y = np.array(y)

X[:5]

```
array([[40.380001, 40.139999, 40.490002, 40.48    , 40.639999, 40.240002,
        39.540001, 40.09    , 39.560001, 39.310001, 39.5     , 39.16    ,
        39.23    , 39.740002, 40.5     , 40.549999, 40.59    , 39.77    ,
        39.450001, 40.490002, 41.189999, 41.189999, 40.93    , 40.720001,
        40.810001, 41.57    , 42.330002, 42.549999, 42.810001, 42.630001],
       [40.139999, 40.490002, 40.48    , 40.639999, 40.240002, 39.540001,
        40.09    , 39.560001, 39.310001, 39.5     , 39.16    , 39.23    ,
        39.740002, 40.5     , 40.549999, 40.59    , 39.77    , 39.450001,
        40.490002, 41.189999, 41.189999, 40.93    , 40.720001, 40.810001,
        41.57    , 42.330002, 42.549999, 42.810001, 42.630001, 42.880001],
       [40.490002, 40.48    , 40.639999, 40.240002, 39.540001, 40.09    ,
        39.560001, 39.310001, 39.5     , 39.16    , 39.23    , 39.740002,
        40.5     , 40.549999, 40.59    , 39.77    , 39.450001, 40.490002,
        41.189999, 41.189999, 40.93    , 40.720001, 40.810001, 41.57    ,
        42.330002, 42.549999, 42.810001, 42.630001, 42.880001, 40.150002],
       [40.48    , 40.639999, 40.240002, 39.540001, 40.09    , 39.560001,
        39.310001, 39.5     , 39.16    , 39.23    , 39.740002, 40.5     ,
        40.549999, 40.59    , 39.77    , 39.450001, 40.490002, 41.189999,
        41.189999, 40.93    , 40.720001, 40.810001, 41.57    , 42.330002,
        42.549999, 42.810001, 42.630001, 42.880001, 40.150002, 40.        ],
       [40.639999, 40.240002, 39.540001, 40.09    , 39.560001, 39.310001,
        39.5     , 39.16    , 39.23    , 39.740002, 40.5     , 40.549999,
        40.59    , 39.77    , 39.450001, 40.490002, 41.189999, 41.189999,
        40.93    , 40.720001, 40.810001, 41.57    , 42.330002, 42.549999,
        42.810001, 42.630001, 42.880001, 40.150002, 40.        , 40.240002]])
```

```
y[:5]
```

```
array([42.880001, 40.150002, 40.      , 40.240002, 40.220001])
```

```
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler()
X = scaler.fit_transform(X)
pd.DataFrame(X).head()
```

	0	1	2	3	4	5	6	7	8	9	...	20	21	22	23	24	25	
0	0.007567	0.006079	0.008250	0.008188	0.009180	0.006699	0.002357	0.005769	0.002481	0.000930	...	0.007420	0.007420	0.005799	0.004489	0.005051	0.009789	0.0
1	0.006079	0.008250	0.008188	0.009180	0.006699	0.002357	0.005769	0.002481	0.000930	0.002109	...	0.007420	0.005799	0.004489	0.005051	0.009789	0.014528	0.0
2	0.008250	0.008188	0.009180	0.006699	0.002357	0.005769	0.002481	0.000930	0.002109	0.000000	...	0.005799	0.004489	0.005051	0.009789	0.014528	0.015900	0.0
3	0.008188	0.009180	0.006699	0.002357	0.005769	0.002481	0.000930	0.002109	0.000000	0.000434	...	0.004489	0.005051	0.009789	0.014528	0.015900	0.017521	0.0
4	0.009180	0.006699	0.002357	0.005769	0.002481	0.000930	0.002109	0.000000	0.000434	0.003598	...	0.005051	0.009789	0.014528	0.015900	0.017521	0.016399	0.0

5 rows × 30 columns

Prediction :

#now lets split data in test train pairs

```
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, shuffle=False)

Acc = []
```

1.LSTM :

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

X_test_ = X_test.reshape(X_test.shape[0],X_test.shape[1],1)


from tensorflow.keras.layers import LSTM

def Reg():
    model = Sequential()
    model.add(LSTM(70, return_sequences=True, input_shape=(30,1)))
    model.add(LSTM(70, return_sequences=True))
    model.add(LSTM(70))
    model.add(Dense(1))
    model.compile(loss='mean_squared_error', optimizer='adam')
    return model
```

 # Model Training

```
model_1 = reg()

model_1.fit(X_train_, y_train, epochs=100, validation_split=0.2)
```

```
Epoch 1/100
35/35 [==============================] - 1s 20ms/step - loss: 5263.1816 - val_loss: 374.2244
Epoch 2/100
35/35 [==============================] - 0s 13ms/step - loss: 143.8724 - val_loss: 69.1650
Epoch 3/100
35/35 [==============================] - 0s 13ms/step - loss: 18.9093 - val_loss: 32.3330
Epoch 4/100
35/35 [==============================] - 0s 12ms/step - loss: 17.6992 - val_loss: 36.9906
Epoch 5/100
35/35 [==============================] - 0s 13ms/step - loss: 15.3594 - val_loss: 46.4716
Epoch 6/100
35/35 [==============================] - 0s 14ms/step - loss: 18.0349 - val_loss: 43.0336
Epoch 7/100
35/35 [==============================] - 0s 14ms/step - loss: 17.1972 - val_loss: 44.4252
Epoch 8/100
35/35 [==============================] - 0s 14ms/step - loss: 15.8552 - val_loss: 35.6157
Epoch 9/100
35/35 [==============================] - 0s 14ms/step - loss: 16.4335 - val_loss: 32.1757
Epoch 10/100
35/35 [==============================] - 0s 13ms/step - loss: 16.0581 - val_loss: 33.8946
```

Prediction

```
y_pred_1 = model_1.predict(X_test_)
```

```
pred_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_1.flatten()})

pred_df.head()
```

	Actual	Predicted
0	184.690002	187.363693
1	185.770004	188.112045
2	187.839996	188.959335
3	184.449997	190.631851
4	177.539993	190.848419

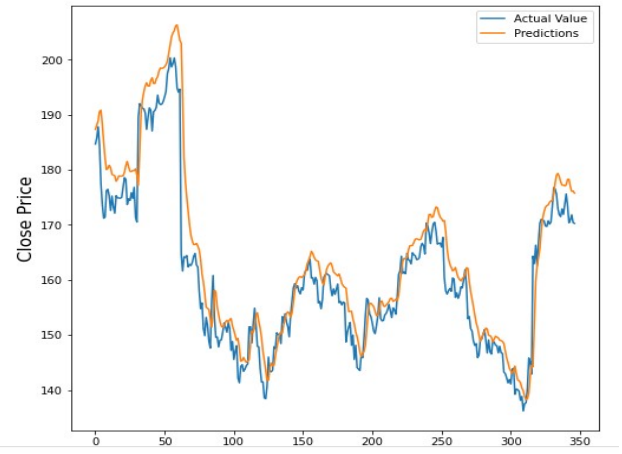
Measure the Accuracy Score

```
from sklearn.metrics import r2_score
print("Accuracy score of the predictions: {0}".format(r2_score(y_test, y_pred_1)))
Acc.append(r2_score(y_test, y_pred_1))
```

```
Accuracy score of the predictions: 0.8540723542553025
```

```
plt.figure(figsize=(8,8))

plt.ylabel('Close Price', fontsize=16)
plt.plot(pred_df)
plt.legend(['Actual Value', 'Predictions'])
plt.show()
```



2.ANN :

Model Training

```
model_2 = regressor(inp_dim=30)
model_2.fit(X_train, y_train, epochs=100, validation_split=0.2)
```

```
Epoch 1/100
35/35 [==============================] - 1s 10ms/step - loss: 6247.7302 - val_loss: 22389.2695
Epoch 2/100
35/35 [==============================] - 0s 4ms/step - loss: 6476.4340 - val_loss: 21955.1543
Epoch 3/100
35/35 [==============================] - 0s 5ms/step - loss: 6220.2017 - val_loss: 19594.3984
Epoch 4/100
35/35 [==============================] - 0s 4ms/step - loss: 5375.9773 - val_loss: 12539.9854
Epoch 5/100
35/35 [==============================] - 0s 4ms/step - loss: 3518.0683 - val_loss: 2452.4004
Epoch 6/100
35/35 [==============================] - 0s 4ms/step - loss: 1050.2850 - val_loss: 773.7950
Epoch 7/100
35/35 [==============================] - 0s 4ms/step - loss: 232.8285 - val_loss: 1657.7784
Epoch 8/100
35/35 [==============================] - 0s 4ms/step - loss: 208.3441 - val_loss: 1392.7090
Epoch 9/100
35/35 [==============================] - 0s 4ms/step - loss: 207.8356 - val_loss: 1325.0494
Epoch 10/100
35/35 [==============================] - 0s 4ms/step - loss: 193.5805 - val_loss: 1298.0989
Epoch 11/100
35/35 [==============================] - 0s 4ms/step - loss: 190.8307 - val_loss: 1227.8551
```

Prediction

```
y_pred_2 = model_2.predict(X_test)
```

Measure the Accuracy Score

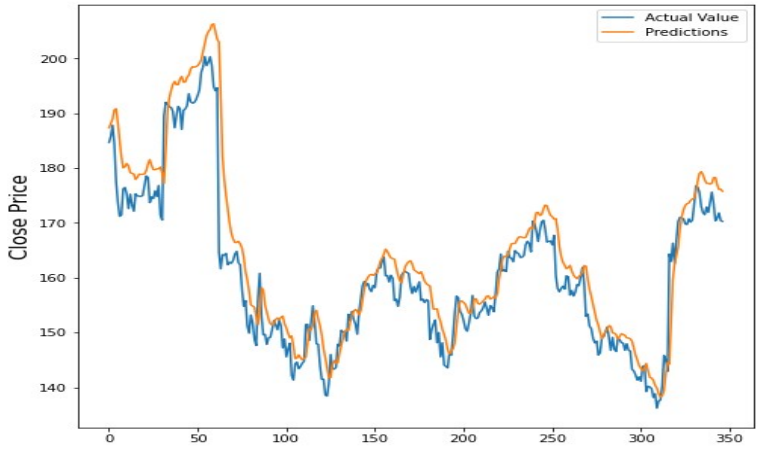
```
from sklearn.metrics import r2_score

print("Accuracy score of the predictions: {0}".format(r2_score(y_test, y_pred_2)))
Acc.append(r2_score(y_test, y_pred_2))
```

```
Accuracy score of the predictions: 0.7776921663567443
```

```
plt.figure(figsize=(8,8))

plt.ylabel('Close Price', fontsize=16)
plt.plot(pred_df)
plt.legend(['Actual Value', 'Predictions'])
plt.show()
```



3.CNN :

Model Training

```
model_3 = reg()
model_3.fit(X_train_, y_train, epochs=100, validation_split=0.2)
```

```
35/35 [==============================] - 0s 13ms/step - loss: 16.2593 - val_loss: 36.0084
Epoch 4/100
35/35 [==============================] - 0s 14ms/step - loss: 15.8262 - val_loss: 41.0867
Epoch 5/100
35/35 [==============================] - 0s 13ms/step - loss: 14.8779 - val_loss: 46.3527
Epoch 6/100
35/35 [==============================] - 0s 13ms/step - loss: 16.6008 - val_loss: 33.8264
Epoch 7/100
35/35 [==============================] - 0s 13ms/step - loss: 16.1398 - val_loss: 32.5189
Epoch 8/100
35/35 [==============================] - 0s 13ms/step - loss: 13.0114 - val_loss: 37.8520
Epoch 9/100
35/35 [==============================] - 0s 13ms/step - loss: 15.3161 - val_loss: 31.2398
Epoch 10/100
35/35 [==============================] - 0s 13ms/step - loss: 13.8654 - val_loss: 29.7689
Epoch 11/100
35/35 [==============================] - 0s 13ms/step - loss: 15.0773 - val_loss: 34.0495
Epoch 12/100
35/35 [==============================] - 0s 13ms/step - loss: 15.6380 - val_loss: 31.7314
Epoch 13/100
35/35 [==============================] - 0s 13ms/step - loss: 16.9460 - val_loss: 37.0163
Epoch 14/100
35/35 [==============================] - 0s 13ms/step - loss: 14.1666 - val_loss: 30.7477
```

Prediction

```
y_pred_3 = model_3.predict(X_test_)
```

```
pred_df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred_3.flatten()})
```

```
pred_df.head()
```

	Actual	Predicted
0	184.690002	187.443634
1	185.770004	187.687561
2	187.839996	189.151138
3	184.449997	190.904144
4	177.539993	189.504868

Measure the Accuracy Score

```
from sklearn.metrics import r2_score
```

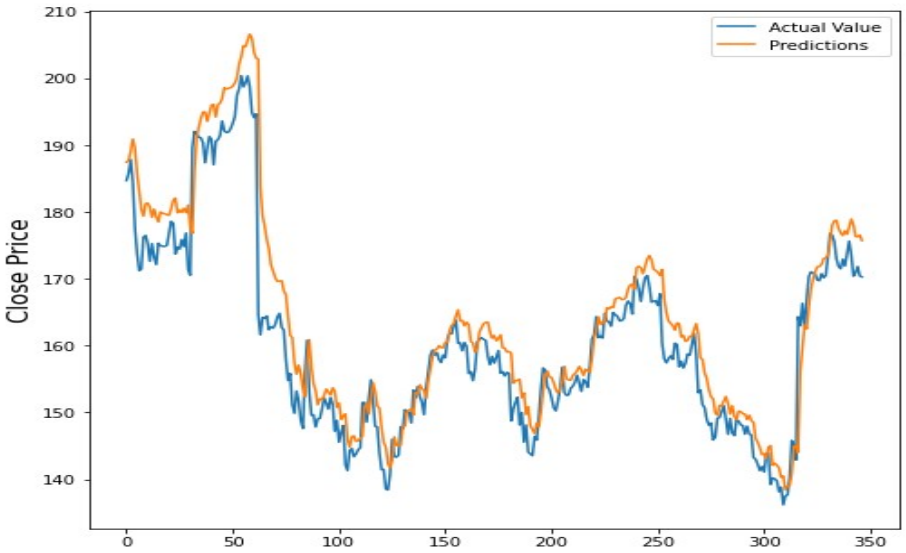
```
print("Accuracy score of the predictions: {0}".format(r2_score(y_test, y_pred_3)))
Acc.append(r2_score(y_test, y_pred_3))
```

```
Accuracy score of the predictions: 0.8647900448552586
```

```
plt.figure(figsize=(8,8))
```

```
plt.ylabel('Close Price', fontsize=16)
plt.plot(pred_df)
plt.legend(['Actual Value', 'Predictions'])
```

```
plt.show()
```



Comparison of Accuracies of different models

```
plt.plot(range(3), Acc, color='green', linestyle='dashed', linewidth = 3,
         marker='o', markerfacecolor='blue', markersize=12)
plt.ylabel('Acc')
plt.xlabel('Models')
plt.title("Accuracies")
plt.xticks(range(3), ['LSTM', 'ANN', 'CNN'])
plt.show()
```