Stock Price Analysis-Tesla

In [695…

```
#import the libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.simplefilter('ignore')
import yfinance as yf
```

Section 1: The data is non stationary and non mean reverting. The variance is also non stationary and trend is upward and there is a steep change at the end. We have decomposed the data into trend, variance and seasonality and found the similar results

In [696…

```
startdate='2015-01-01'
enddate='2020-12-31'
df=yf.download('TSLA',start=startdate,end=enddate)
```

```
[*********************100%***********************]  1 of 1 completed
```

In [697…

```
df.head(15)
df.tail(15)
```

Out[697…

	Open	High	Low	Close	Adj Close	Volume
Date						
2020-12-09	653.690002	654.320007	588.000000	604.479980	604.479980	71291200
2020-12-10	574.369995	627.750000	566.340027	627.070007	627.070007	67083200
2020-12-11	615.010010	624.000000	596.799988	609.989990	609.989990	46475000
2020-12-14	619.000000	642.750000	610.200012	639.830017	639.830017	52040600
2020-12-15	643.280029	646.900024	623.799988	633.250000	633.250000	45071500
2020-12-16	628.229980	632.500000	605.000000	622.770020	622.770020	42095800
2020-12-17	628.190002	658.820007	619.500000	655.900024	655.900024	56270100
2020-12-18	668.900024	695.000000	628.539978	695.000000	695.000000	222126200
2020-12-21	666.239990	668.500000	646.070007	649.859985	649.859985	58045300
2020-12-22	648.000000	649.880005	614.229980	640.340027	640.340027	51716000
2020-12-23	632.200012	651.500000	622.570007	645.979980	645.979980	33173000
2020-12-24	642.989990	666.090027	641.000000	661.770020	661.770020	22865600
2020-12-28	674.510010	681.400024	660.799988	663.690002	663.690002	32278600
2020-12-29	661.000000	669.900024	655.000000	665.989990	665.989990	22910800

	Open	High	Low	Close	Adj Close	Volume
Date						
2020-12-30	672.000000	696.599976	668.359985	694.780029	694.780029	42846000

In [698…

```
df=df['Close'].reset_index()
```

In [699…

```
df.head(2)
```

Out[699…

	Date	Close
0	2015-01-02	43.862000
1	2015-01-05	42.018002

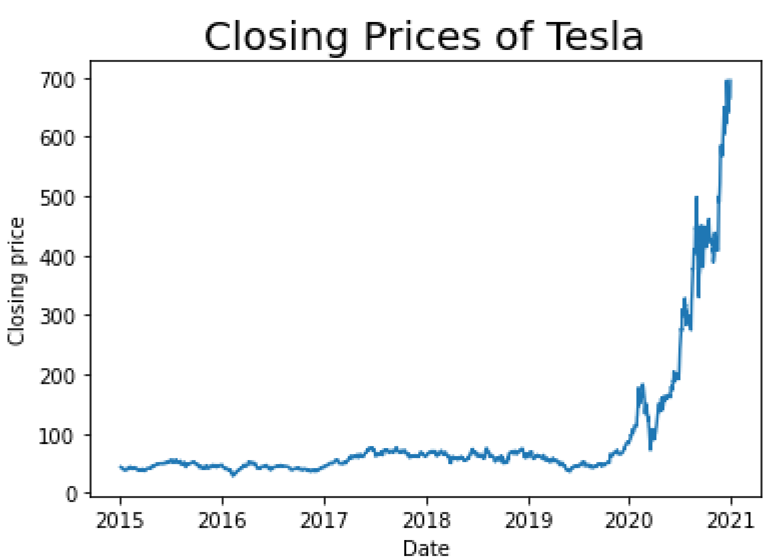
In [700…

```
df['Date'] = pd.to_datetime(df['Date'],infer_datetime_format=True)
df = df.set_index(['Date'])
```

Plot the Trend of Stock Price over the Years

In [701…

```
plt.title("Closing Prices of Tesla",fontsize=20)
plt.xlabel('Date')
plt.ylabel('Closing price')
plt.plot(df['Close'])
plt.show()
```



Compare with rolling statistics

In [702…

```
#Mean Stock price on a window of 365 days
df["rolling_avg"] = df["Close"].rolling(window=365).mean()
```

```
#Standard Deviation of stock price on 365 days wimdow
df["rolling_std"] = df["Close"].rolling(window=365).std()
```

In [703…

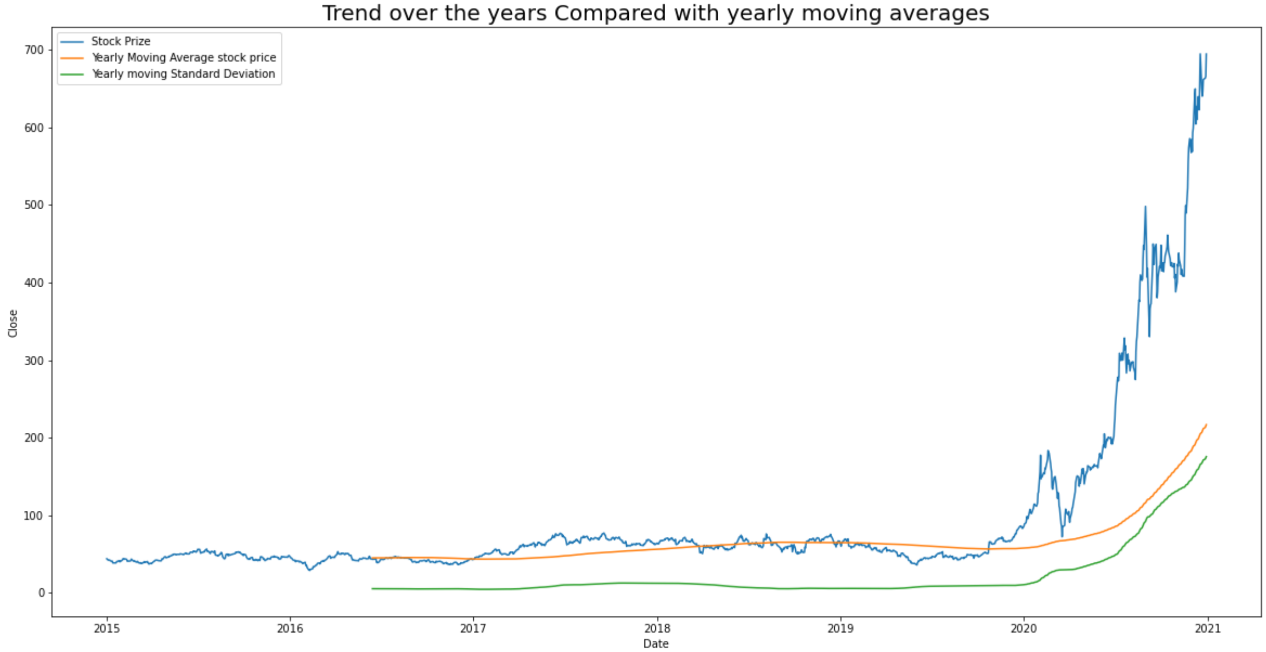
```
df=df.reset_index()
```

In [704…

```
plt.figure(figsize=(20,10))
plt.title('Trend over the years Compared with yearly moving averages',size=20)
sns.lineplot(data=df, x='Date',y='Close',label='Stock Prize ')
sns.lineplot(data=df,x='Date',y='rolling_avg',label='Yearly Moving Average stock price'
sns.lineplot(data=df,x='Date',y='rolling_std',label='Yearly moving Standard Deviation')
```

Out[704…

```
<AxesSubplot:title={'center':'Trend over the years Compared with yearly moving average
s'}, xlabel='Date', ylabel='Close'>
```



Augmented Dickey–Fuller Test

Checking for non-stationarity

Null Hypothesis: The data is not stationary.

Alternative Hypothesis:The data is stationary.

In [705…

```
from statsmodels.tsa.stattools import adfuller,kpss
```

In [706…

```
dftest = adfuller(df['Close'], autolag='AIC')

dfoutput = pd.Series(dftest[0:4], index=['Test Statistic','p-value','#Lags Used','Numbe
for key,value in dftest[4].items():
    dfoutput['Critical Value (%s)'%key] = value

print(dfoutput)
```

```
Test Statistic                    6.314977
```

```
p-value                          1.000000
#Lags Used                      23.000000
Number of Observations Used   1486.000000
Critical Value (1%)             -3.434758
Critical Value (5%)             -2.863487
Critical Value (10%)            -2.567807
dtype: float64
```

Based on such high P values, we fail to reject the Null so the data is not Stationary

Kwiatkowski-Phillips-Schmidt-Shin (KPSS)

Here the null hypothesis is that the series is stationary

Null Hypothesis: The data is stationary

Alternate Hypothesis:: The data is not stationary

In [707…

```
statistic, p_value, n_lags, critical_values = kpss(df['Close'])
```

In [708…

```
print(f'KPSS Statistic: {statistic}')
print(f'p-value: {p_value}')
print(f'num lags: {n_lags}')
print('Critial Values:')
```

```
KPSS Statistic: 2.342020314039496
p-value: 0.01
num lags: 24
Critial Values:
```

Based on a lower p value, we reject the null , the data is non stationary

Box Cox Transformation

For making variance constant

In [709…

```
from scipy import stats
```

In [710…

```
Boxcox=list(stats.boxcox(df['Close'])[0])
```

In [711…

```
transformed_data, best_lambda = stats.boxcox(df['Close'])
best_lambda
```

Out[711…

```
-1.3625118729824754
```

In [712…

```
logged=np.log(df['Close'])
```

```
df.insert(len(df.columns), 'logged values',logged)
```

In [713…

```
df.insert(len(df.columns), 'Boxcox',transformed_data)
```

In [714…

```
df_copy=df.copy()
```

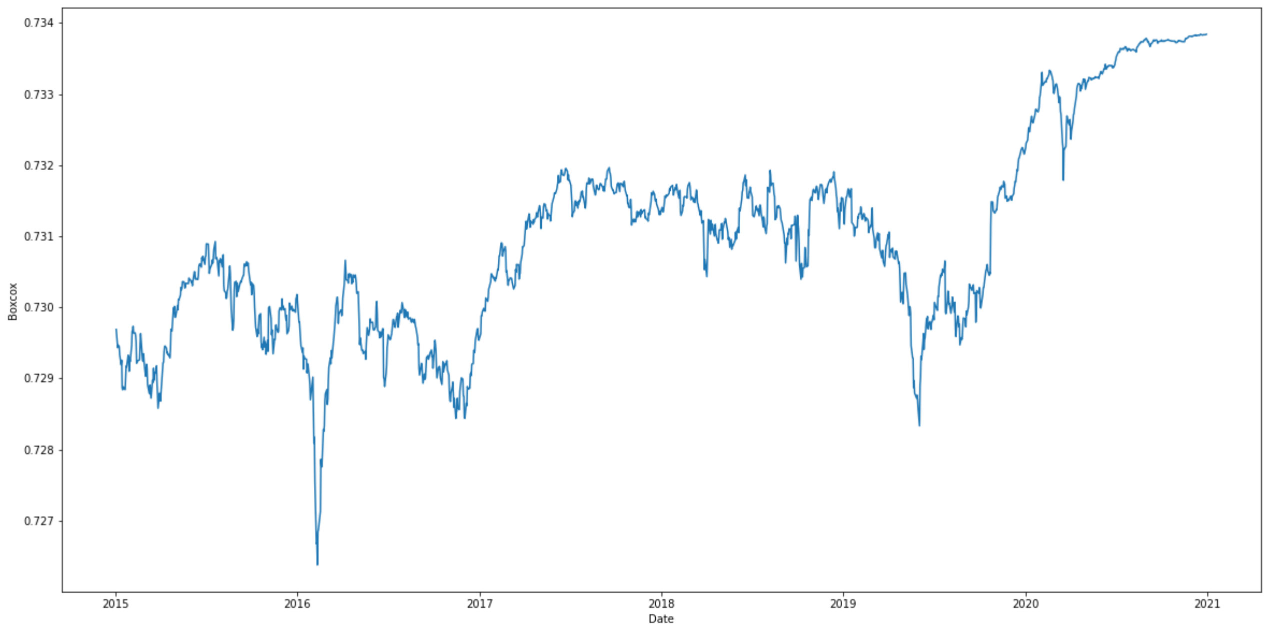
Plot the values after Box Cox Transformation

In [715…

```
plt.figure(figsize=(20,10))
sns.lineplot(data=df,x='Date',y='Boxcox')
```

Out[715…

```
<AxesSubplot:xlabel='Date', ylabel='Boxcox'>
```



Augemented Dicky Fuller Test to check if the data is stationary for box-cox transformed values

Null Hypothesis: The data is not stationary.

Alternative Hypothesis: The data is stationary.

In [716…

```
test= adfuller(df['Boxcox'], autolag='AIC')

output = pd.Series(test[0:4], index=['Test Statistic','p-value','#Lags Used','Number of
for key,value in test[4].items():
    output['Critical Value (%s)'%key] = value

print(output)
```

```
Test Statistic                  -1.285773
```

```
p-value                          0.635656
#Lags Used                       0.000000
Number of Observations Used   1509.000000
Critical Value (1%)             -3.434691
Critical Value (5%)             -2.863457
Critical Value (10%)            -2.567791
dtype: float64
```

Based on the high p values, we Fail to reject the Null ,data is not stationary

Autocorrelation

Since the Mean of data is non Stationary, calculating the first difference of data, the 3rd difference and the 6th difference

Calculating values of AutoCorrelation, a measure of how correlated time series data is at a given point in time with past values

First lag autocorrelation

In [717…

```
autocorrelation_lag1=df['Close'].autocorr(lag=30) ## lag taken for 30 days
print("1 month Lag:", autocorrelation_lag1)
```

```
1 month Lag: 0.9624867552011044
```

Second lag autocorrelation value of Data: 0.9601946480498523

In [718…

```
autocorrelation_lag2=df['Close'].autocorr(lag=60) ## lag taken for 60 days
print("2 month Lag:", autocorrelation_lag2)
```

```
2 month Lag: 0.9456946549894001
```

Third lag autocorrelation value of Data: 0.8956753113926396

In [719…

```
autocorrelation_lag3=df['Close'].autocorr(lag=120) ## lag taken for 120 days
print(" 3 month lag:", autocorrelation_lag3)
```

```
 3 month lag: 0.8959107176901502
```

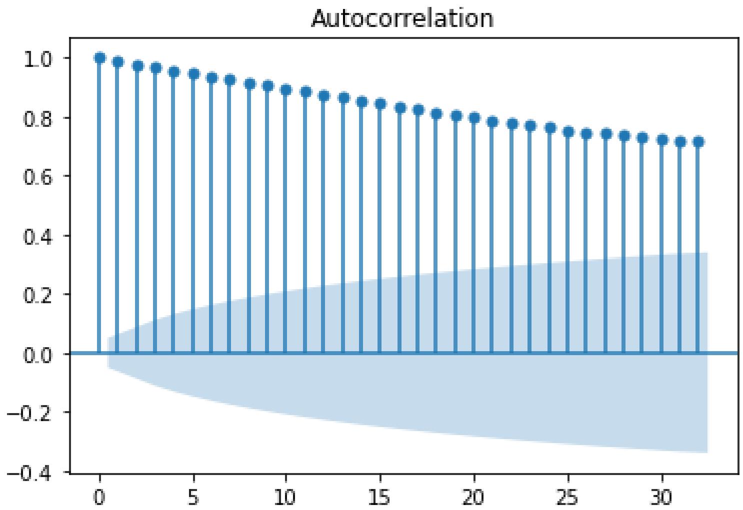
Inference : even after giving lag of 3 months the data is highly correlated

ACF/PACF Plots for closing price value

In [720…

```
from statsmodels.graphics.tsaplots import plot_acf
fig1=plt.figure(figsize=(30,10))
fig1=plot_acf(df['Close'])
```

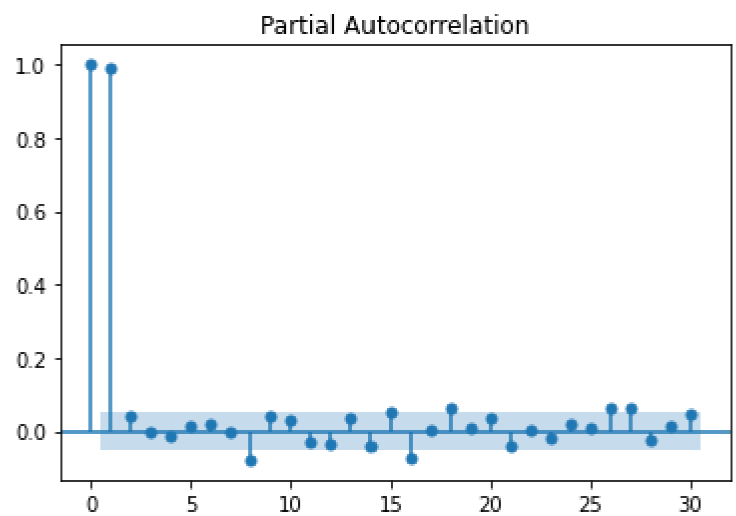
```
<Figure size 2160x720 with 0 Axes>
```



In [721…

```
from statsmodels.graphics.tsaplots import plot_pacf
fig=plt.figure(figsize=(30,10))
fig=plot_pacf(df['Close'],lags=30)
```

```
<Figure size 2160x720 with 0 Axes>
```



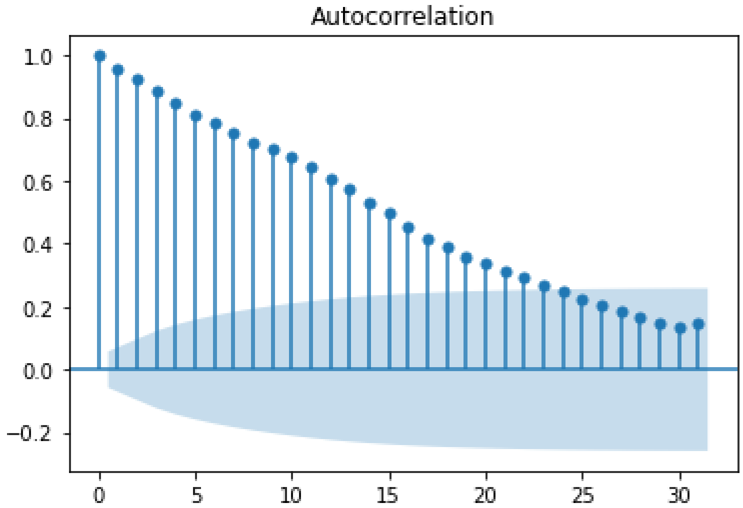
From ACF and PACF plots it looks like AR of 2nd order

ACF PACF plot using 1st Lag-(1 month lag approx 30 days)

In [722…

```
df['lagprice'] = df['Close'].shift(30)
df['1st Differencing']=df['lagprice']-df['Close']
df.dropna(inplace=True)
fig4=plt.figure(figsize=(30,10))
fig4=plot_acf(df['1st Differencing'])
```

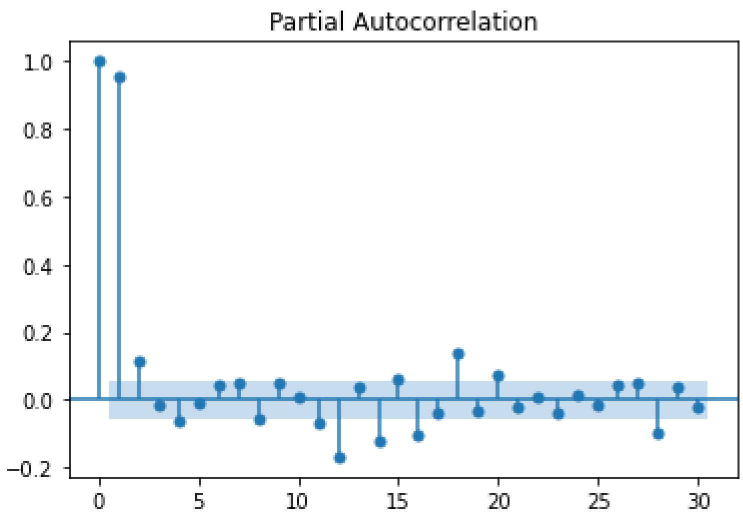
```
<Figure size 2160x720 with 0 Axes>
```



In [723…

```
fig=plt.figure(figsize=(30,10))
fig=plot_pacf(df['1st Differencing'],lags=30)
```

```
<Figure size 2160x720 with 0 Axes>
```

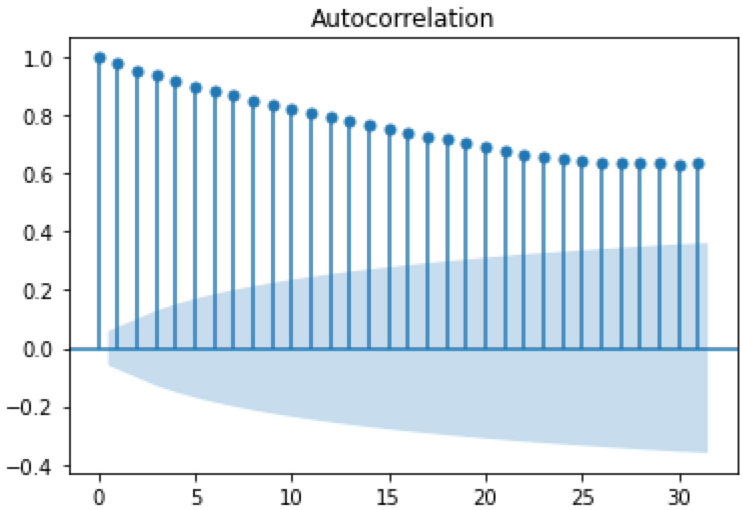


ACF PACF plot using 2nd Lag

In [724…

```
df['lagprice'] = df['Close'].shift(60)
df['1st Differencing']=df['lagprice']-df['Close']
df.dropna(inplace=True)
fig4=plt.figure(figsize=(30,10))
fig4=plot_acf(df['1st Differencing'])
```

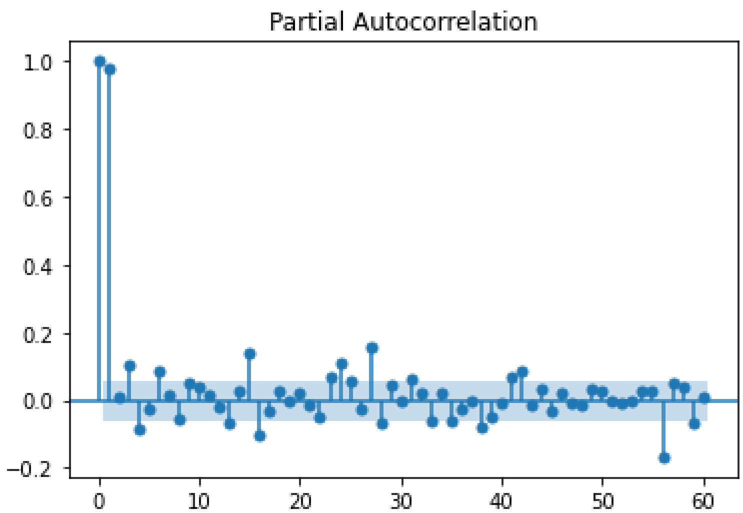
```
<Figure size 2160x720 with 0 Axes>
```



In [725…

```
fig=plt.figure(figsize=(30,10))
fig=plot_pacf(df['1st Differencing'],lags=60)
```

```
<Figure size 2160x720 with 0 Axes>
```

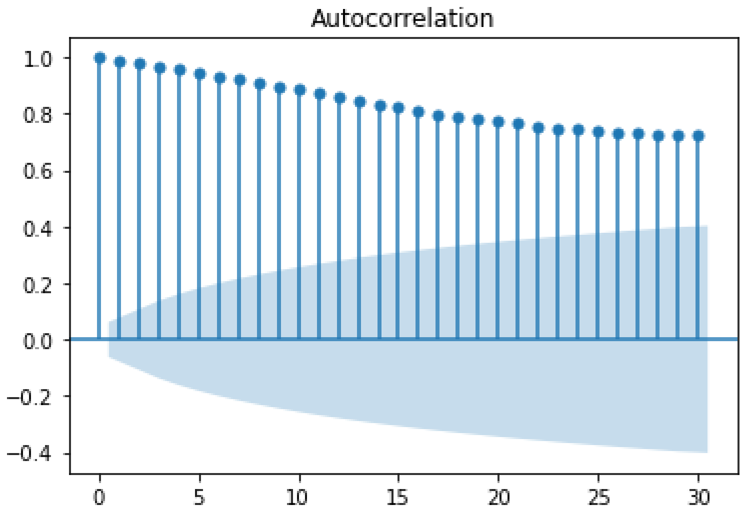


ACF PACF plot using 3rd Lag- approx 3 months

In [726…

```
df['lagprice'] = df['Close'].shift(90)
df['1st Differencing']=df['lagprice']-df['Close']
df.dropna(inplace=True)
fig4=plt.figure(figsize=(30,10))
fig4=plot_acf(df['1st Differencing'])
```

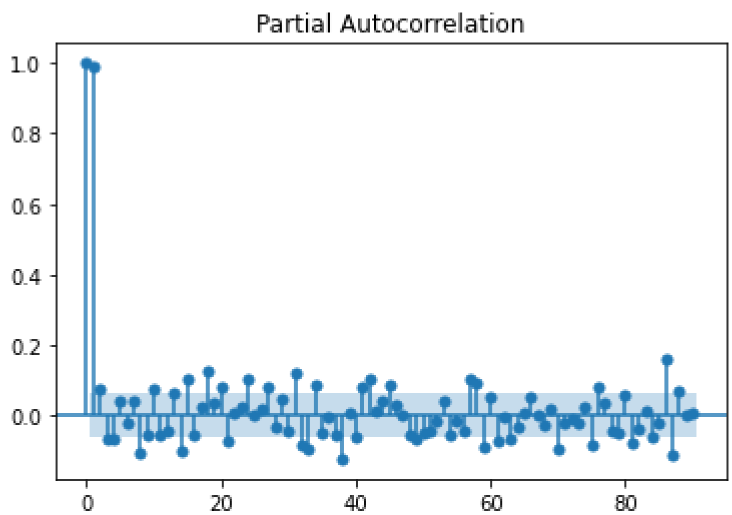
```
<Figure size 2160x720 with 0 Axes>
```



In [727…

```
fig=plt.figure(figsize=(30,10))
fig=plot_pacf(df['1st Differencing'],lags=90)
```

```
<Figure size 2160x720 with 0 Axes>
```



In [728…

```
dftest1 = adfuller(df['1st Differencing'], autolag='AIC')

dfoutput = pd.Series(dftest1[0:4], index=['Test Statistic','p-value','#Lags Used','Numb
for key,value in dftest[4].items():
    dfoutput['Critical Value (%s)'%key] = value

print(dfoutput)
```

```
Test Statistic                   0.235194
p-value                          0.974168
#Lags Used                      19.000000
Number of Observations Used    976.000000
Critical Value (1%)             -3.434758
Critical Value (5%)             -2.863487
Critical Value (10%)            -2.567807
dtype: float64
```

Inference: Even after taking a lag of 3 months , the p value is high and is greater than 0.05 so the data is not stationary

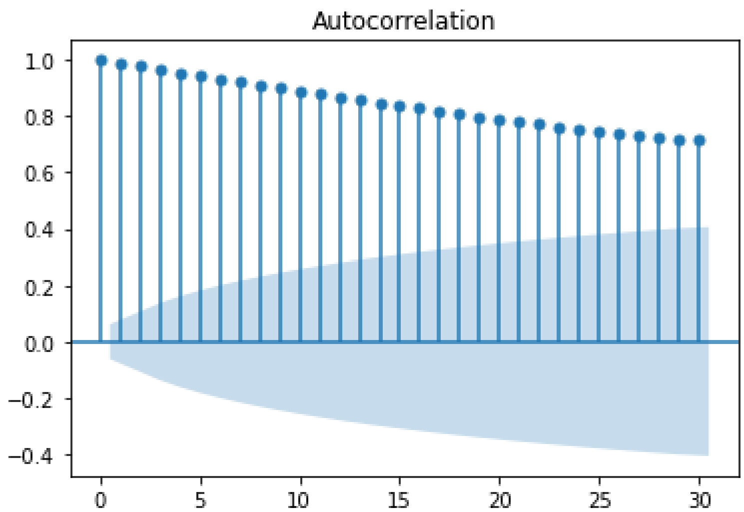
---

ACF PACF plots for Lagged differencing on BoxCox transformed Values

In [729…

```
df['lagprice'] = df['Boxcox'].shift(3)
df['3rd lag Differencing']=df['lagprice']-df['Close']
df.dropna(inplace=True)
fig4=plt.figure(figsize=(30,10))
fig4=plot_acf(df['3rd lag Differencing'])
```

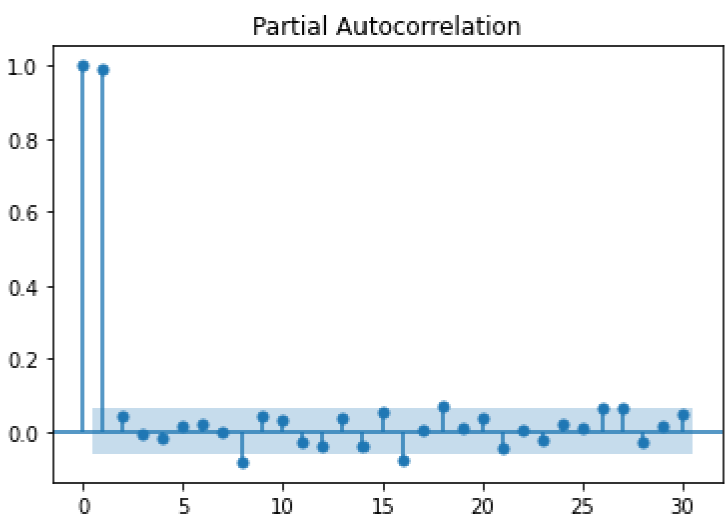
```
<Figure size 2160x720 with 0 Axes>
```



In [730…

```
fig5=plt.figure(figsize=(30,10))
fig5=plot_pacf(df['3rd lag Differencing'],lags=30)
```

```
<Figure size 2160x720 with 0 Axes>
```



from the ACF and PACF plots it looks like AR of 2nd order

Trend Decomposition

In [731...

```
from statsmodels.tsa.seasonal import seasonal_decompose
```

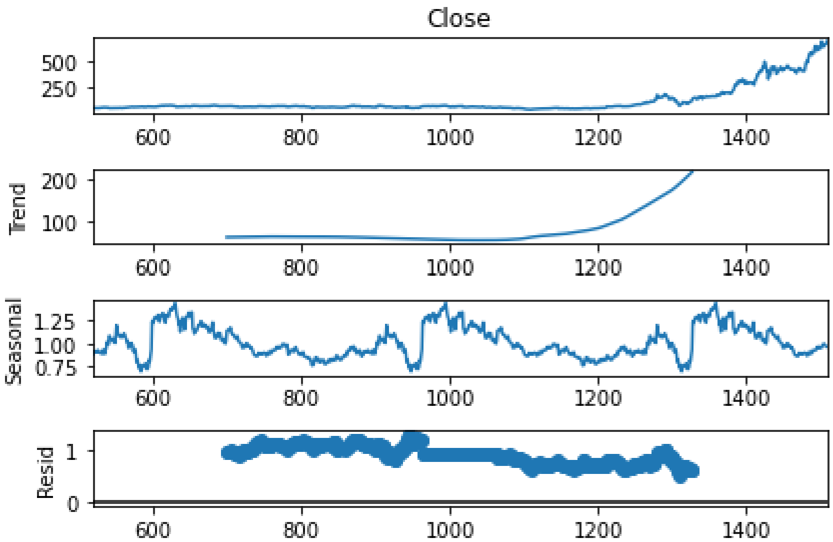
In [732...

```
decompose=seasonal_decompose(df['Close'],model='multiplicative',period=365) ## period i
```

In [733...

```
fig3=plt.figure(figsize=(30,20))
fig3=decompose.plot()
```

<Figure size 2160x1440 with 0 Axes>



Inference: Yes, there are seasonal fluctuations in the data as can be seen from the seasonal spikes in the figure above but overall there is no seasonality since there is a high spike at the end

Section 2

Fitting Several Arima Models and the using Auto Arima to obtain the best model

In [734...

```
import pmdarima
from pmdarima.arima import auto_arima
```

In [735...

```
from statsmodels.tsa.arima.model import ARIMA
import statsmodels.api as sm
```

In [736...

```
model1=ARIMA(df_copy['Boxcox'],order=(2,0,1))
model1 = model1.fit()
model1.summary()
print(model1.bic)
```

```
-15497.180506688877
```

In [737…

```
model2=ARIMA(df_copy['Boxcox'],order=(1,1,1))
model2 = model2.fit()
model2.summary()
print(model2.bic)
```

```
-22753.742733672225
```

In [738…

```
model3=ARIMA(df_copy['Boxcox'],order=(2,1,3))
model3 = model3.fit()
model3.summary()
print(model3.bic)
```

```
-22731.962556627073
```

Based on the above findings, we select the ARIMA(1,1,1) model as it has the least AIC and BIC

In [739…

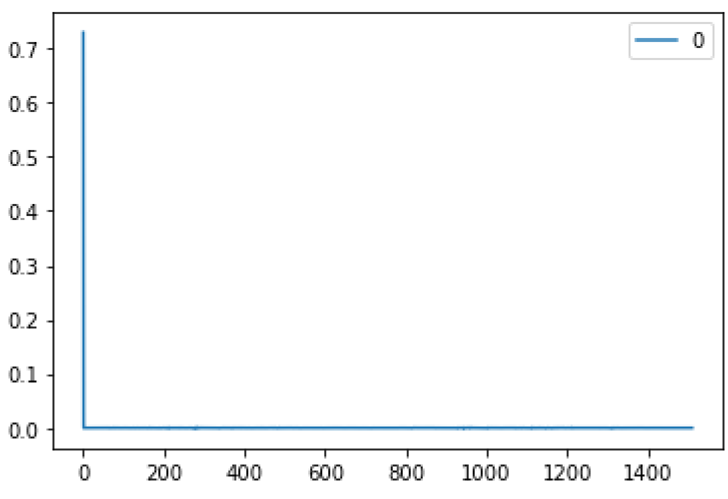
```
model_best=ARIMA(df_copy['Boxcox'],order=(1,1,1))
```

In [740…

```
model_fit_best = model_best.fit()
residuals_best = pd.DataFrame(model_fit_best.resid)
residuals_best.plot()
```

Out[740…

```
<AxesSubplot:>
```



In [741…

```
residuals_best.describe()
```

Out[741…

	0
count	1510.000000
mean	0.000486
std	0.018778
min	-0.000858

	0
25%	-0.000045
50%	0.000002
75%	0.000060
max	0.729689

Auto Arima to find the best fit model

In [742…

```
import pmdarima as pm
```

In [743…

```
model_autoarima = pm.auto_arima(df_copy['Boxcox'], start_p=0, start_q=0,
                      test='adf',       # use adftest to find optimal 'd'
                      max_p=5, max_q=5, # maximum p and q
                      m=5,              # frequency of series
                      d=None,           # let model determine 'd'

                      start_P=0,
                      D=0,
                      trace=True,
                      error_action='ignore',
                      suppress_warnings=True,
                      stepwise=True)
```

```
Performing stepwise search to minimize aic
 ARIMA(0,1,0)(0,0,1)[5] intercept   : AIC=-22769.073, Time=1.09 sec
 ARIMA(0,1,0)(0,0,0)[5] intercept   : AIC=-22770.545, Time=0.74 sec
 ARIMA(1,1,0)(1,0,0)[5] intercept   : AIC=-22767.703, Time=1.06 sec
 ARIMA(0,1,1)(0,0,1)[5] intercept   : AIC=-22767.648, Time=1.63 sec
 ARIMA(0,1,0)(0,0,0)[5]             : AIC=-22771.844, Time=0.11 sec
 ARIMA(0,1,0)(1,0,0)[5] intercept   : AIC=-22769.058, Time=0.87 sec
 ARIMA(0,1,0)(1,0,1)[5] intercept   : AIC=-22767.284, Time=1.63 sec
 ARIMA(1,1,0)(0,0,0)[5] intercept   : AIC=-22769.267, Time=0.53 sec
 ARIMA(0,1,1)(0,0,0)[5] intercept   : AIC=-22769.208, Time=1.19 sec
 ARIMA(1,1,1)(0,0,0)[5] intercept   : AIC=-22768.237, Time=2.54 sec

Best model:  ARIMA(0,1,0)(0,0,0)[5]
Total fit time: 11.412 seconds
```

In [744…

```
model_autoarima.summary()
```

Out[744…

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	1510
Model:	SARIMAX(0, 1, 0)	**Log Likelihood**	11386.922
Date:	Sat, 05 Feb 2022	**AIC**	-22771.844
Time:	17:26:06	**BIC**	-22766.525
Sample:	0	**HQIC**	-22769.863
	- 1510		

Covariance Type:	opg

	coef	std err	z	P>|z|	[0.025	0.975]
sigma2	1.633e-08	2.89e-10	56.537	0.000	1.58e-08	1.69e-08

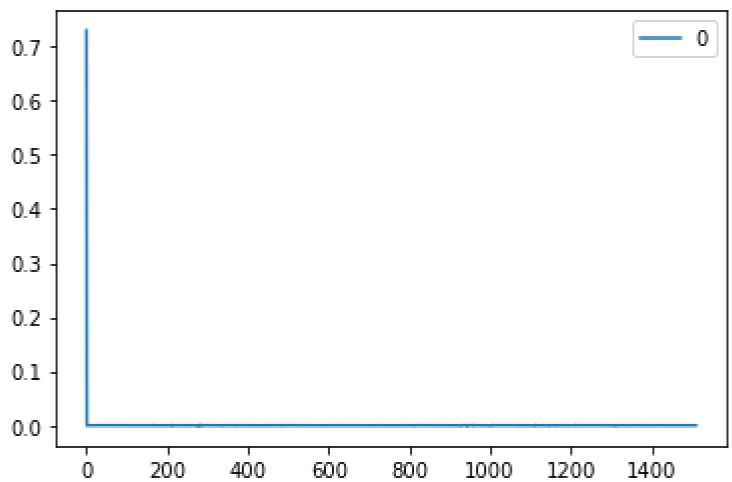
Ljung-Box (L1) (Q):	0.72	**Jarque-Bera (JB):**	2738.83
Prob(Q):	0.40	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.56	**Skew:**	-0.28
Prob(H) (two-sided):	0.00	**Kurtosis:**	9.58

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

Ljung-Box test for residuals

In [745...

```
# line plot of residuals
model=ARIMA(df['Boxcox'],order=(0,1,0))
residuals = pd.DataFrame(model_fit_best.resid)
residuals.plot()
plt.show()
```



H0: The residuals are independently distributed.

HA: The residuals are not independently distributed; they exhibit serial correlation.

In [746...

```
import statsmodels.api as sm
sm.stats.acorr_ljungbox(residuals, lags=[5], return_df=True)
```

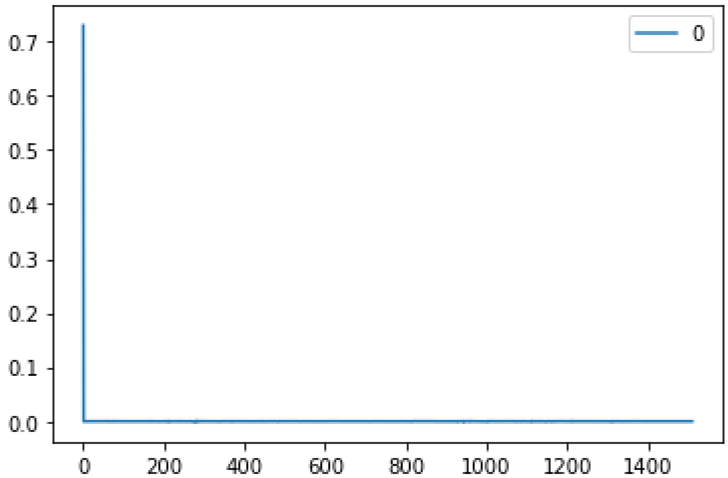
Out[746...

	lb_stat	lb_pvalue
5	0.000238	1.0

Inference : We cannot reject null hypothesis which means residuals are independently distributed

In [747…

```
# line plot of residuals
model=ARIMA(df_copy['Boxcox'],order=(0,1,0))
residuals = pd.DataFrame(model_fit_best.resid)
residuals.plot()
plt.show()
```



In [761…

```
from scipy.special import boxcox, inv_boxcox
prediction1=model_fit_best.predict(start=0, end=1509)
pred1=inv_boxcox(prediction1,-1.36)
```

In [762…

```
prediction=model_fit_best.predict(start=0, end=1509)
from sklearn.metrics import mean_squared_error
np.sqrt(mean_squared_error(df_copy['Close'],pred1))
```

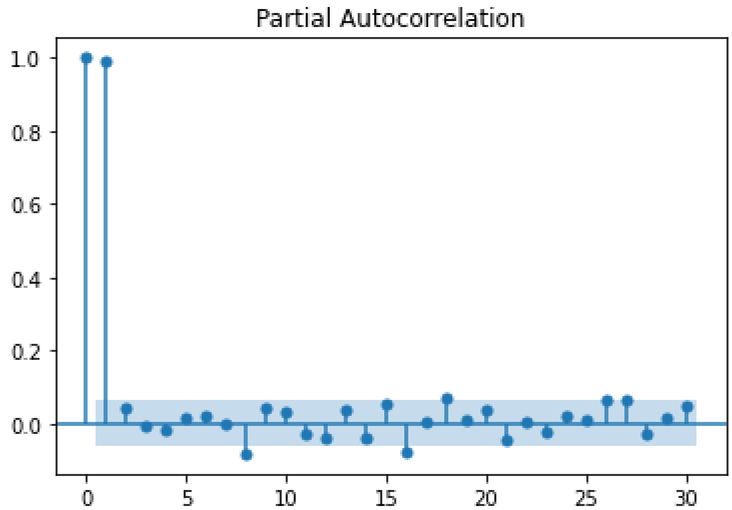
Out[762…

```
106.5792299366475
```

In [763…

```
from statsmodels.graphics.tsaplots import plot_pacf
fig=plt.figure(figsize=(30,10))
fig=plot_pacf(df['Close'],lags=30)
```

```
<Figure size 2160x720 with 0 Axes>
```

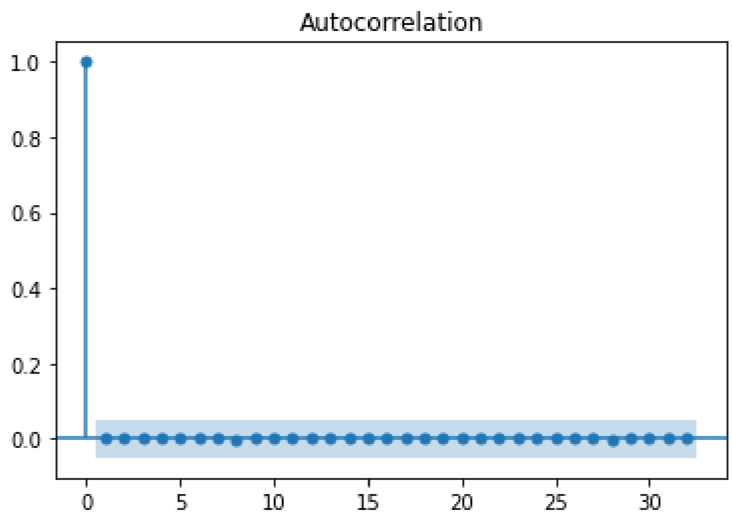


ACF PACF plots for residual

In [764…

```
fig4=plt.figure(figsize=(30,10))
fig4=plot_acf(residuals)
```

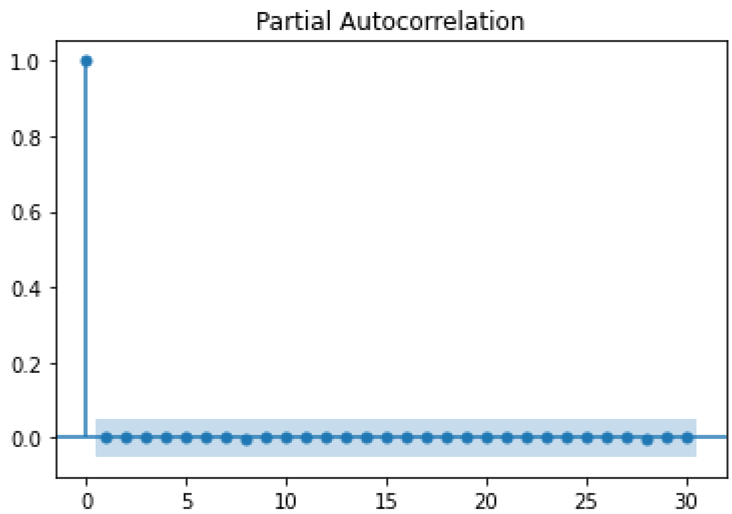
```
<Figure size 2160x720 with 0 Axes>
```



In [765…

```
fig5=plt.figure(figsize=(30,10))
fig5=plot_pacf(residuals,lags=30)
```

```
<Figure size 2160x720 with 0 Axes>
```



From ACF PACF figures, it can be inferred that there is no autocorrelation in the residuals and it is a white noise process

RMSE value is 106.58

Predicted values for the next 5 periods

In [766…

```
prediction2=model_fit_best.predict(start=1510, end=1514)
pred2=inv_boxcox(prediction2, -1.362)
```

In [767…

```
pred2
```

Out[767…

```
1510    261.541310
1511    261.583308
1512    261.606839
1513    261.620021
1514    261.627405
Name: predicted_mean, dtype: float64
```

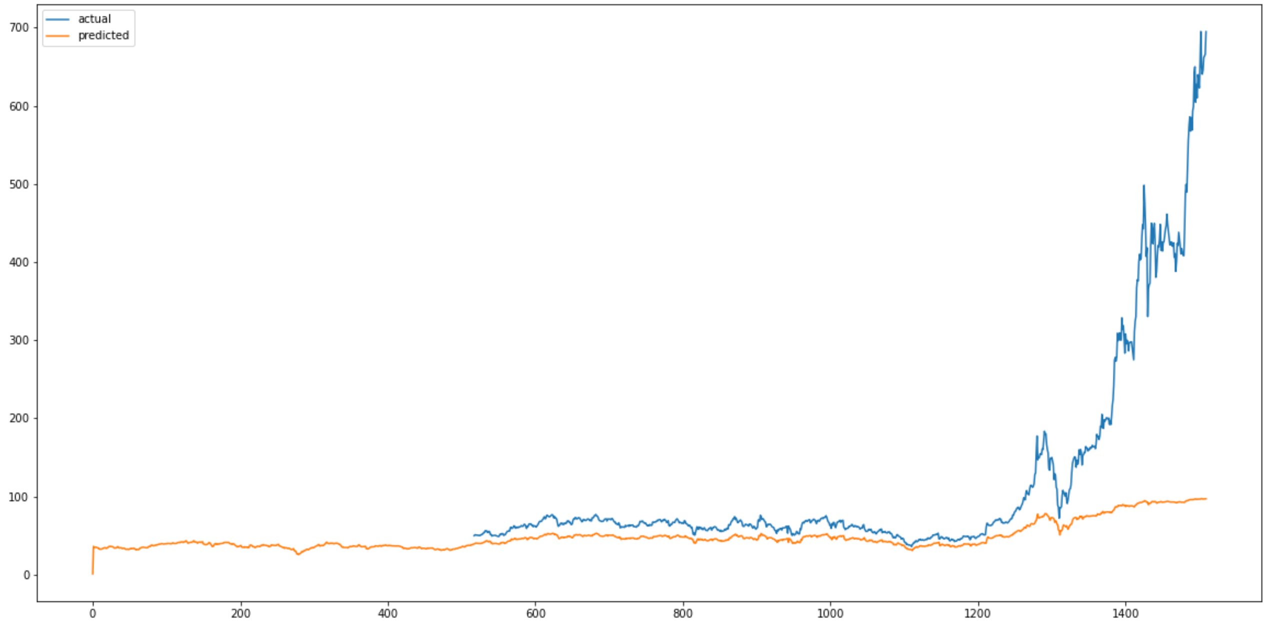
The Predicted values are reasonable and comparable to the original values

In [768…

```
plt.figure(figsize=(20,10))
plt.plot(df['Close'],label='actual')
plt.plot(pred1,label='predicted')
plt.legend()
```

Out[768…

```
<matplotlib.legend.Legend at 0x25148adb100>
```



Yes in sample predicted values follow approximately the same trend as the original data

In [ ]:

```

```

In [ ]:

```

```