ZIDIO INTERNSHIP 2025 TIME SERIES ANALYSIS TASK LIST

PHASE-1 WEEK(1-2)

1. INSTALLING LIBRAIES AND DATA COLLECTION FROM TCS STOCK DATA

```
import yfinance as yf
import pandas as pd
import matplotlib.pyplot as plt

# Download TCS data from Yahoo Finance
tcs = yf.download("TCS.NS", start="2015-01-01", end="2024-12-31")

# View the first few rows
tcs.head()
```

```
/tmp/ipython-input-2-1777239112.py:6: FutureWarning: YF.download() has changed argument auto_adjust default to True
  tcs = yf.download("TCS.NS", start="2015-01-01", end="2024-12-31")
[*********************100%***********************]  1 of 1 completed
```

Price	Close	High	Low	Open	Volume
Ticker	TCS.NS	TCS.NS	TCS.NS	TCS.NS	TCS.NS
Date					
2015-01-01	1073.510498	1082.556381	1071.591649	1082.556381	366830
2015-01-02	1087.806519	1092.656303	1075.639948	1075.808595	925740
2015-01-05	1071.275024	1096.430600	1064.696146	1088.460127	1754242
2015-01-06	1031.781006	1066.572933	1028.997610	1066.572933	2423784
2015-01-07	1019.593262	1045.507956	1015.270628	1041.649256	2636332

PHASE-2 (WEEK 3-4)

2.DATA PREPROCESSING AND VISUALIZATION-- (load data and check missing values)

```
tcs.to_csv("tcs_stock_data.csv") # this is the tcs stock data csv
tcs
```

Price	Close	High	Low	Open	Volume
Ticker	TCS.NS	TCS.NS	TCS.NS	TCS.NS	TCS.NS
Date					
2015-01-01	1073.510498	1082.556381	1071.591649	1082.556381	366830
2015-01-02	1087.806519	1092.656303	1075.639948	1075.808595	925740
2015-01-05	1071.275024	1096.430600	1064.696146	1088.460127	1754242
2015-01-06	1031.781006	1066.572933	1028.997610	1066.572933	2423784
2015-01-07	1019.593262	1045.507956	1015.270628	1041.649256	2636332
...	...	...	...	...	...
2024-12-23	4097.958984	4155.807385	4055.188855	4139.103153	2195338
2024-12-24	4118.851562	4156.792892	4097.959002	4097.959002	1181886
2024-12-26	4108.602539	4139.004973	4083.028905	4118.851529	1208464
2024-12-27	4104.414062	4120.280532	4087.069359	4102.590812	858100
2024-12-30	4098.452148	4138.364460	4052.331448	4090.765525	1527169

2466 rows × 5 columns

```
# Check basic info
tcs.info()

# Check for missing/null values
```

```
print("\nMissing Values:\n", tcs.isnull().sum())
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 2466 entries, 2015-01-01 to 2024-12-30
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   (Close, TCS.NS)   2466 non-null   float64
 1   (High, TCS.NS)    2466 non-null   float64
 2   (Low, TCS.NS)     2466 non-null   float64
 3   (Open, TCS.NS)    2466 non-null   float64
 4   (Volume, TCS.NS)  2466 non-null   int64
dtypes: float64(4), int64(1)
memory usage: 115.6 KB

Missing Values:
 Price   Ticker
Close   TCS.NS    0
High    TCS.NS    0
Low     TCS.NS    0
Open    TCS.NS    0
Volume  TCS.NS    0
dtype: int64
```

(filling missing values if any) implace=True

```
# Forward fill missing values (if any)
tcs.fillna(method='ffill', inplace=True)
print(tcs)
```

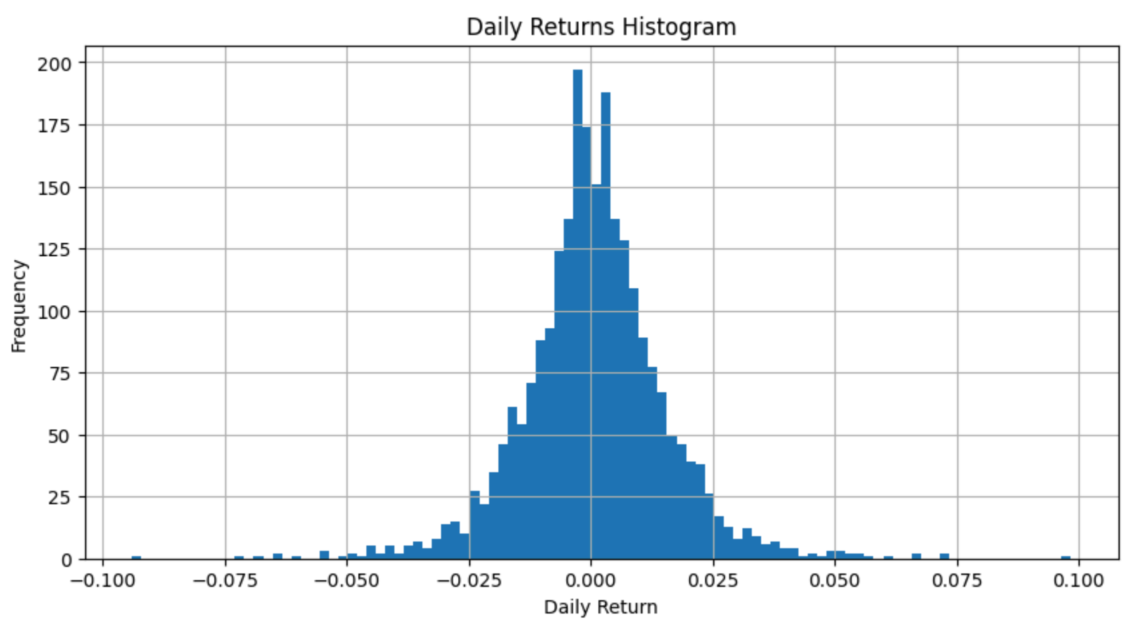
```
Price             Close         High          Low         Open   Volume
Ticker           TCS.NS       TCS.NS       TCS.NS       TCS.NS   TCS.NS
Date
2015-01-01  1073.510376  1082.556258  1071.591528  1082.556258   366830
2015-01-02  1087.806152  1092.655935  1075.639586  1075.808233   925740
2015-01-05  1071.275146  1096.430725  1064.696268  1088.460251  1754242
2015-01-06  1031.780762  1066.572681  1028.997367  1066.572681  2423784
2015-01-07  1019.593872  1045.508582  1015.271236  1041.649880  2636332
...                 ...          ...          ...          ...      ...
2024-12-23  4097.958984  4155.807385  4055.188855  4139.103153  2195338
2024-12-24  4118.851562  4156.792892  4097.959002  4097.959002  1181886
2024-12-26  4108.602539  4139.004973  4083.028905  4118.851529  1208464
2024-12-27  4104.414062  4120.280532  4087.069359  4102.590812   858100
2024-12-30  4098.452148  4138.364460  4052.331448  4090.765525  1527169

[2466 rows x 5 columns]
/tmp/ipython-input-16-2480750985.py:2: FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a future version. U
  tcs.fillna(method='ffill', inplace=True)
```

((Plot the Closing Price))

```
import matplotlib.pyplot as plt

plt.figure(figsize=(9, 6))
plt.plot(tcs['Close'], label='TCS Closing Price', color='red')
plt.title("TCS Stock Closing Prices (2015–2024)")
plt.xlabel("Date")
plt.ylabel("Price (INR)")
plt.legend()
plt.grid(True)
plt.show()
```

((plotting daily returns (volatility)))

```
# Calculate daily returns
tcs['Daily Return'] = tcs['Close'].pct_change()

# Plot histogram of returns
tcs['Daily Return'].hist(bins=100, figsize=(10, 5))
plt.title('Daily Returns Histogram')
plt.xlabel('Daily Return')
plt.ylabel('Frequency')
plt.grid(True)
plt.show()
```



-------XXXXXXXX-------------------XXXXXXXXX------------------------

PHASE-3a (WEEK 5-9) MODELLING ARIMA statemodels,LSTM

1. ADF test checking for staionary

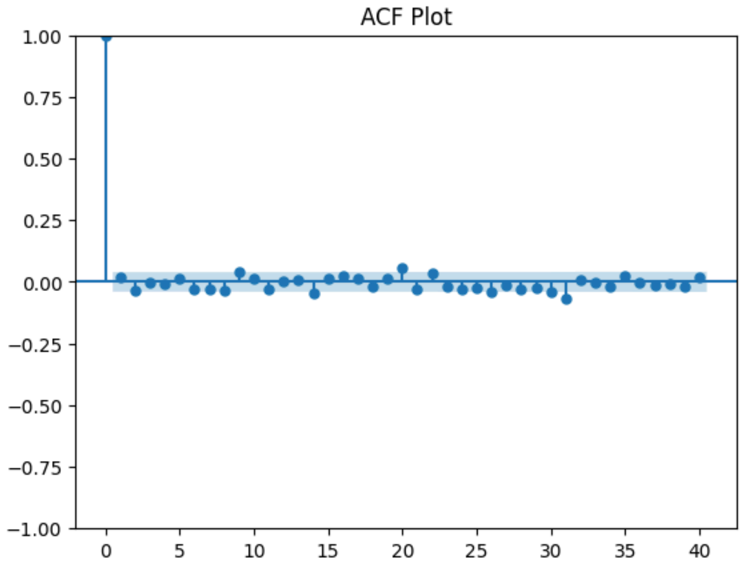
```
from statsmodels.tsa.stattools import adfuller

# ADF Test
result = adfuller(ts)
print("ADF Statistic:", result[0])
print("p-value:", result[1])

if result[1] <= 0.05:
    print(" Data is stationary (d=0)")
else:
    print(" Data is not stationary (use d=1)")
```

```
ADF Statistic: -0.2563561532590817
p-value: 0.9314621886932883
 Data is not stationary (use d=1)
```

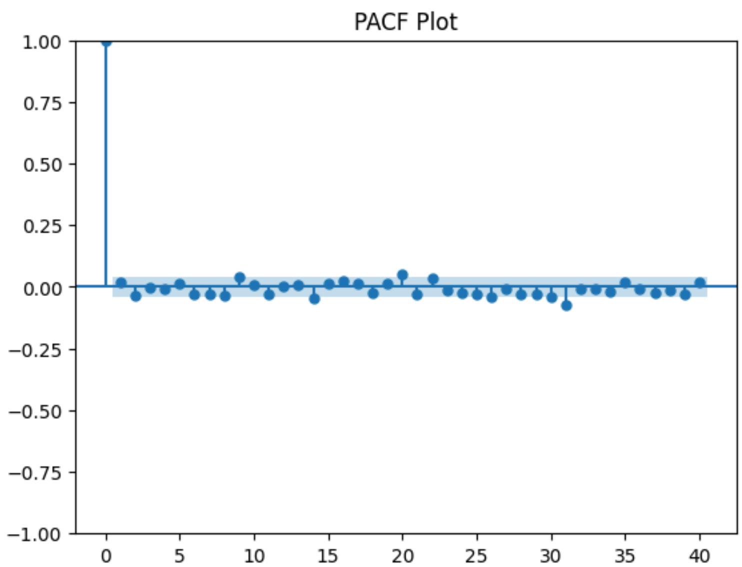
2.plotting ACF and PACF to estimate p and q

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
import matplotlib.pyplot as plt

plt.figure(figsize=(9,5))
plot_acf(ts.diff().dropna(), lags=40)
plt.title('ACF Plot')                                        # PACF first sharp drop → p   ACF first sharp drop → q
plt.show()
plt.figure(figsize=(12,5))
plot_pacf(ts.diff().dropna(), lags=40)
plt.title('PACF Plot')
plt.show()
```

<Figure size 900x500 with 0 Axes>



<Figure size 1200x500 with 0 Axes>



3. Fit ARIMA model using statesmodels

```
from statsmodels.tsa.arima.model import ARIMA

# Example ARIMA(5,1,0) — adjust if needed
model = ARIMA(ts, order=(5, 1, 0))
model_fit = model.fit()

# Summary of the model
print(model_fit.summary())
```

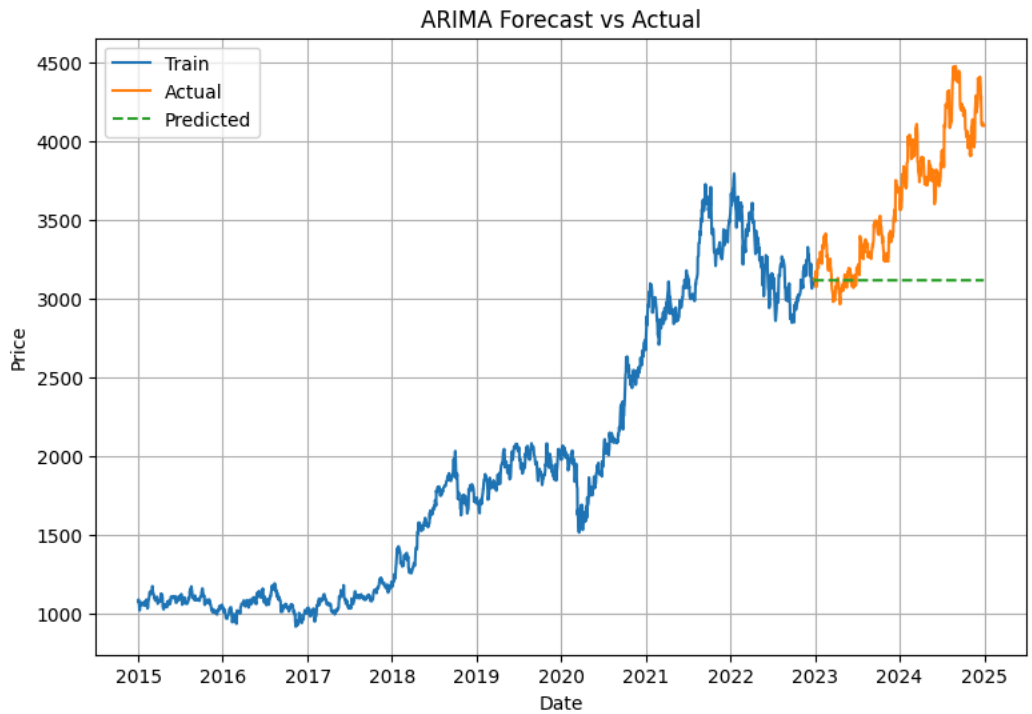
```
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has
  self._init_dates(dates, freq)
                               SARIMAX Results
==============================================================================
Dep. Variable:                 TCS.NS   No. Observations:                 2466
Model:                 ARIMA(5, 1, 0)   Log Likelihood              -12238.181
Date:                Thu, 24 Jul 2025   AIC                          24488.361
Time:                        10:22:17   BIC                          24523.221
Sample:                             0   HQIC                         24501.026
                               - 2466
Covariance Type:                  opg
==============================================================================
```

```
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1          0.0180      0.016      1.123      0.261      -0.013       0.049
ar.L2         -0.0322      0.015     -2.141      0.032      -0.062      -0.003
ar.L3         -0.0007      0.015     -0.044      0.965      -0.031       0.029
ar.L4         -0.0067      0.017     -0.395      0.693      -0.040       0.026
ar.L5          0.0128      0.017      0.761      0.447      -0.020       0.046
sigma2      1203.4564     18.086     66.542      0.000    1168.009    1238.904
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):              3156.86
Prob(Q):                              0.96   Prob(JB):                         0.00
Heteroskedasticity (H):               8.71   Skew:                             0.06
Prob(H) (two-sided):                  0.00   Kurtosis:                         8.54
===================================================================================

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

4.Forecast & Compare to Actual Data

```
# Split into train and test
train_size = int(len(ts) * 0.8)
train, test = ts[:train_size], ts[train_size:]

# Re-fit on training data
model = ARIMA(train, order=(5, 1, 0))
model_fit = model.fit()

# Forecast next steps (same length as test)
forecast = model_fit.forecast(steps=len(test))

# Plot
plt.figure(figsize=(9,6))
plt.plot(train, label='Train')
plt.plot(test, label='Actual')
plt.plot(test.index, forecast, label='Predicted', linestyle='--')
plt.title("ARIMA Forecast vs Actual")
plt.xlabel("Date")
plt.ylabel("Price")
plt.legend()
plt.grid(True)
plt.show()
```

```
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has
  self._init_dates(dates, freq)
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:837: ValueWarning: No supported index is available. Prediction
  return get_prediction_index(
/usr/local/lib/python3.11/dist-packages/statsmodels/tsa/base/tsa_model.py:837: FutureWarning: No supported index is available. In the ne
  return get_prediction_index(
```



5. Evaluate the acuracy

```
from sklearn.metrics import mean_squared_error, mean_absolute_error
import numpy as np

rmse = np.sqrt(mean_squared_error(test, forecast))
mae = mean_absolute_error(test, forecast)

print(f"RMSE: {rmse}")
print(f"MAE: {mae}")
```

```
RMSE: 669.6622862260131
MAE: 530.8764176723853
```

PHASE-3b Prophets model (Facebook's time forcasting)

1.prepare data for prophet in tcs stock analysis

```
from prophet import Prophet

# Prepare DataFrame
df_prophet = tcs.reset_index()[['Date', 'Close']]
df_prophet.columns = ['ds', 'y']
df_prophet = df_prophet.dropna()
df_prophet.head()
```

	ds	y
0	2015-01-01	1073.510376
1	2015-01-02	1087.806152
2	2015-01-05	1071.275146
3	2015-01-06	1031.780762
4	2015-01-07	1019.593872

2.Train Prophet Model & plot the forcast

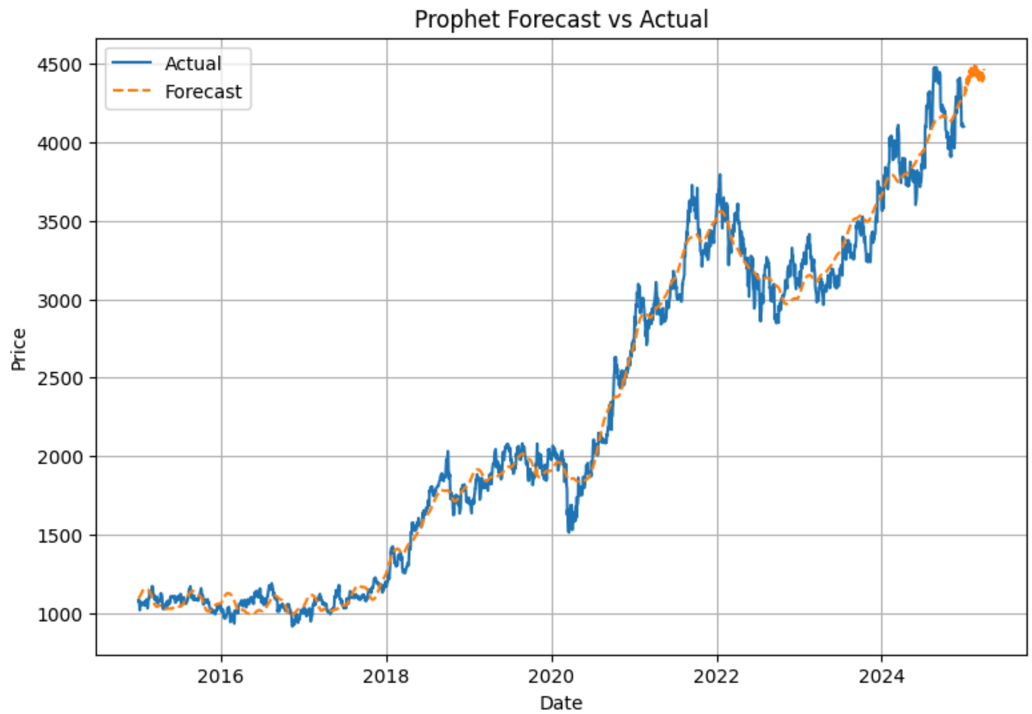
```
model = Prophet()
model.fit(df_prophet)

# Create future dataframe (e.g., 90 days ahead)
future = model.make_future_dataframe(periods=90)
forecast = model.predict(future)
# Plot forecast
fig1 = model.plot(forecast)
```

```
INFO:prophet:Disabling daily seasonality. Run prophet with daily_seasonality=True to override this.
DEBUG:cmdstanpy:input tempfile: /tmp/tmpnfmt4k3_/kho0oce7.json
DEBUG:cmdstanpy:input tempfile: /tmp/tmpnfmt4k3_/dv7x60w2.json
DEBUG:cmdstanpy:idx 0
DEBUG:cmdstanpy:running CmdStan, num_threads: None
DEBUG:cmdstanpy:CmdStan args: ['/usr/local/lib/python3.11/dist-packages/prophet/stan_model/prophet_model.bin', 'random', 'seed=95963', '
10:41:54 - cmdstanpy - INFO - Chain [1] start processing
INFO:cmdstanpy:Chain [1] start processing
10:41:55 - cmdstanpy - INFO - Chain [1] done processing
INFO:cmdstanpy:Chain [1] done processing
```

3.compare actual data with prophets forcasting and plotting

```
import matplotlib.pyplot as plt

plt.figure(figsize=(9,6))
plt.plot(df_prophet['ds'], df_prophet['y'], label='Actual')
plt.plot(forecast['ds'], forecast['yhat'], label='Forecast', linestyle='--')
plt.title("Prophet Forecast vs Actual")
```

```
plt.xlabel("Date")
plt.ylabel("Price")
plt.legend()
plt.grid(True)
plt.show()
```



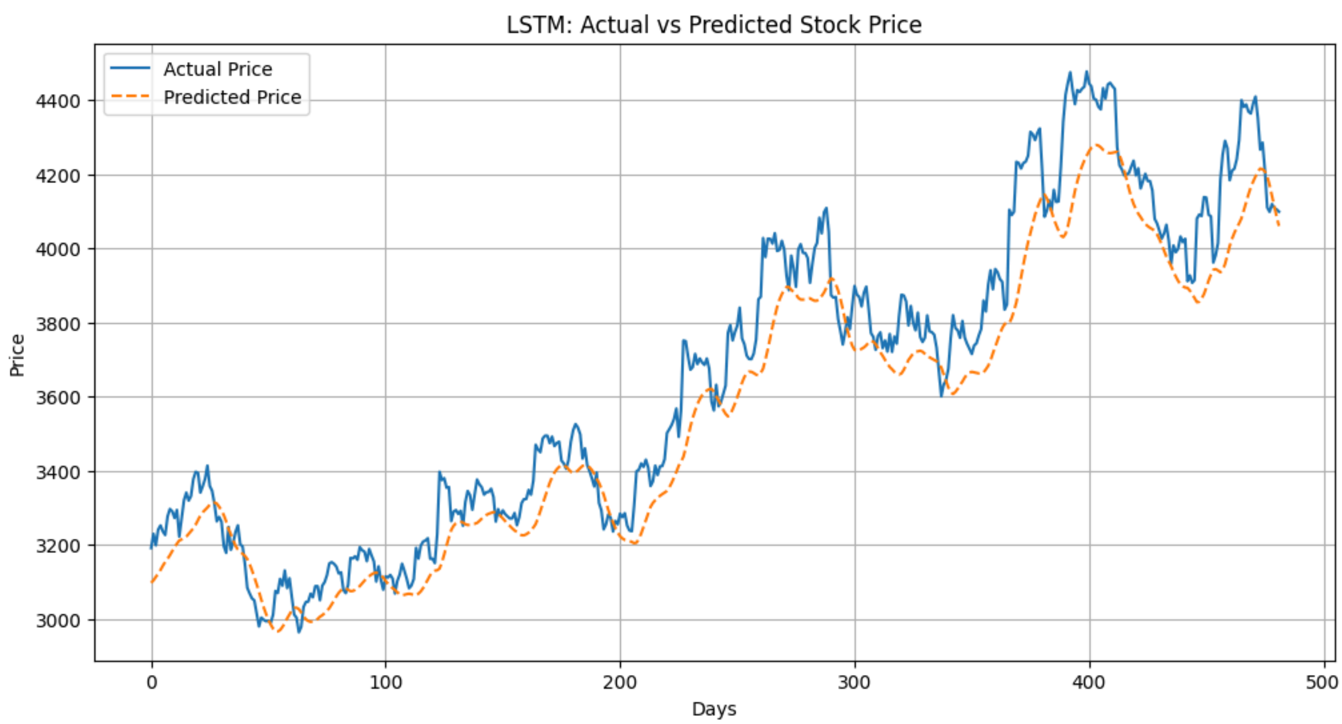
PHASE 3c (LSTM MODEL) its DL model in which it learns time series in form of temporal patterns

1.Importing library and prepare the data for lstm

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
# Use only the Close prices
data = tcs[['Close']].values

# Normalize
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(data)

# Set sequence length
sequence_len = 60

X = []
y = []

for i in range(sequence_len, len(scaled_data)):
    X.append(scaled_data[i-sequence_len:i])
    y.append(scaled_data[i])
X, y = np.array(X), np.array(y)
#train-test split
train_size = int(len(X) * 0.8)

X_train, X_test = X[:train_size], X[train_size:]
y_train, y_test = y[:train_size], y[train_size:]
#build lstm model
model = Sequential()
model.add(LSTM(units=50, return_sequences=True, input_shape=(X.shape[1], 1)))
model.add(LSTM(units=50))
model.add(Dense(1))
```

```
model.compile(optimizer='adam', loss='mean_squared_error')
#train the model
history = model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_test, y_test))
#make prediction and plot
predicted_prices = model.predict(X_test)
predicted_prices = scaler.inverse_transform(predicted_prices)
real_prices = scaler.inverse_transform(y_test)

# Plot actual vs predicted
plt.figure(figsize=(12,6))
plt.plot(real_prices, label='Actual Price')
plt.plot(predicted_prices, label='Predicted Price', linestyle='--')
plt.title("LSTM: Actual vs Predicted Stock Price")
plt.xlabel("Days")
plt.ylabel("Price")
plt.legend()
plt.grid(True)
plt.show()
```

```
Epoch 1/10
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim` argumen
  super().__init__(**kwargs)
61/61 ━━━━━━━━━━━━━━━━━━━━ 7s 57ms/step - loss: 0.0414 - val_loss: 0.0013
Epoch 2/10
61/61 ━━━━━━━━━━━━━━━━━━━━ 4s 65ms/step - loss: 4.5642e-04 - val_loss: 0.0015
Epoch 3/10
61/61 ━━━━━━━━━━━━━━━━━━━━ 4s 50ms/step - loss: 4.3153e-04 - val_loss: 0.0014
Epoch 4/10
61/61 ━━━━━━━━━━━━━━━━━━━━ 3s 49ms/step - loss: 4.0732e-04 - val_loss: 8.5659e-04
Epoch 5/10
61/61 ━━━━━━━━━━━━━━━━━━━━ 3s 57ms/step - loss: 3.6301e-04 - val_loss: 8.9182e-04
Epoch 6/10
61/61 ━━━━━━━━━━━━━━━━━━━━ 5s 51ms/step - loss: 3.6967e-04 - val_loss: 7.5341e-04
Epoch 7/10
61/61 ━━━━━━━━━━━━━━━━━━━━ 5s 50ms/step - loss: 3.8319e-04 - val_loss: 9.5784e-04
Epoch 8/10
61/61 ━━━━━━━━━━━━━━━━━━━━ 5s 56ms/step - loss: 3.6978e-04 - val_loss: 9.6043e-04
Epoch 9/10
61/61 ━━━━━━━━━━━━━━━━━━━━ 3s 49ms/step - loss: 3.4091e-04 - val_loss: 6.8194e-04
Epoch 10/10
61/61 ━━━━━━━━━━━━━━━━━━━━ 5s 52ms/step - loss: 3.3954e-04 - val_loss: 0.0014
16/16 ━━━━━━━━━━━━━━━━━━━━ 1s 33ms/step
```



7. evaluate lstm accuracy

```
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

```
rmse = np.sqrt(mean_squared_error(real_prices, predicted_prices))
mae = mean_absolute_error(real_prices, predicted_prices)

print(f"RMSE (LSTM): {rmse}")
print(f"MAE (LSTM): {mae}")
```

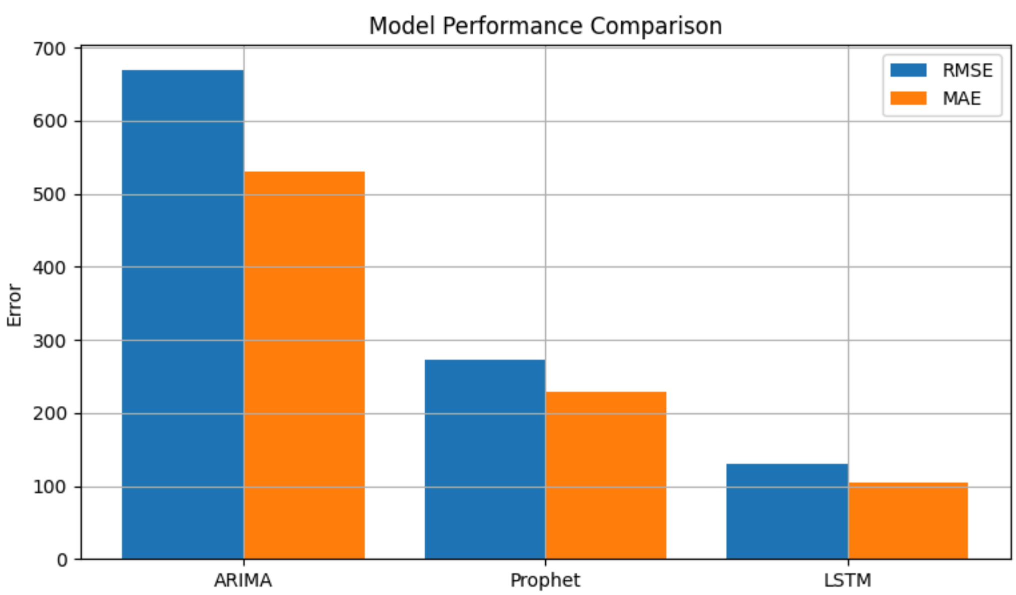
```
RMSE (LSTM): 130.85567553348727
MAE (LSTM): 103.81856299435944
```

PHASE 4 model camparison and tuning (week 9)

```
# 1.collecting ARIMA,Prophets, LSTM evaluation metrics

#ARIMA- RMSE: 669.6622862260131,MAE: 530.8764176723853
#Propehts-RMSE (Prophet): 273.5245539421691,MAE (Prophet): 228.63656673269716
#RMSE (LSTM): 130.85567553348727,MAE (LSTM): 103.81856299435944
```

2.plot comparison graph for three models

```
import matplotlib.pyplot as plt

models = ['ARIMA', 'Prophet', 'LSTM']
rmse_values = [669.6622862260131,273.5245539421691,130.85567553348727] # Replace with your actual values
mae_values = [ 530.8764176723853,228.63656673269716,103.81856299435944]

x = range(len(models))

plt.figure(figsize=(9, 5))

plt.bar(x, rmse_values, width=0.4, label='RMSE', align='center')
plt.bar([i + 0.4 for i in x], mae_values, width=0.4, label='MAE', align='center')

plt.xticks([i + 0.2 for i in x], models)
plt.ylabel('Error')
plt.title('Model Performance Comparison')
plt.legend()
plt.grid(True)
plt.show()
```



3. Tuning for each models means changing the value parameter to get better accuracy

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
model = ARIMA(train, order=(2,1,1))        # changing p,d,q with diff value
model_fit = model.fit()
  #for arima sarima
```

```
# Summary of the model
```