PHASE 1: PROJECT SETUP

Step 1.1 Load All Three CSVs

```
from google.colab import files
uploaded = files.upload()
```

Choose Files 3 files

- **TCS_stock_action.csv**(text/csv) - 1404 bytes, last modified: 7/13/2025 - 100% done
- **TCS_stock_history.csv**(text/csv) - 447231 bytes, last modified: 7/13/2025 - 100% done
- **TCS_stock_info.csv**(text/csv) - 5357 bytes, last modified: 7/13/2025 - 100% done

```
Saving TCS_stock_action.csv to TCS_stock_action.csv
Saving TCS_stock_history.csv to TCS_stock_history.csv
Saving TCS_stock_info.csv to TCS_stock_info.csv
```

Step 1.2 Clean & Prepare df_history (TCS_stock_history.csv : Primary Dataset)

```
import pandas as pd

# Use the actual uploaded filenames (check them from the files dictionary)
df_history = pd.read_csv('TCS_stock_history.csv')
df_info = pd.read_csv('TCS_stock_info.csv')
df_action = pd.read_csv('TCS_stock_action.csv')
```

```
df_history.head()
```

	Date	Open	High	Low	Close	Volume	Dividends	Stock Splits
0	2002-08-12	28.794172	29.742206	28.794172	29.519140	212976	0.0	0.0
1	2002-08-13	29.556316	30.030333	28.905705	29.119476	153576	0.0	0.0
2	2002-08-14	29.184536	29.184536	26.563503	27.111877	822776	0.0	0.0
3	2002-08-15	27.111877	27.111877	27.111877	27.111877	0	0.0	0.0
4	2002-08-16	26.972458	28.255089	26.582090	27.046812	811856	0.0	0.0

Next steps: Generate code with `df_history` | View recommended plots | New interactive sheet

```
# Convert Date to datetime
df_history['Date'] = pd.to_datetime(df_history['Date'])

# Sort by date
df_history = df_history.sort_values(by='Date')
df_history.reset_index(drop=True, inplace=True)

# Check data types and nulls
print(df_history.info())
print(df_history.isnull().sum())
```

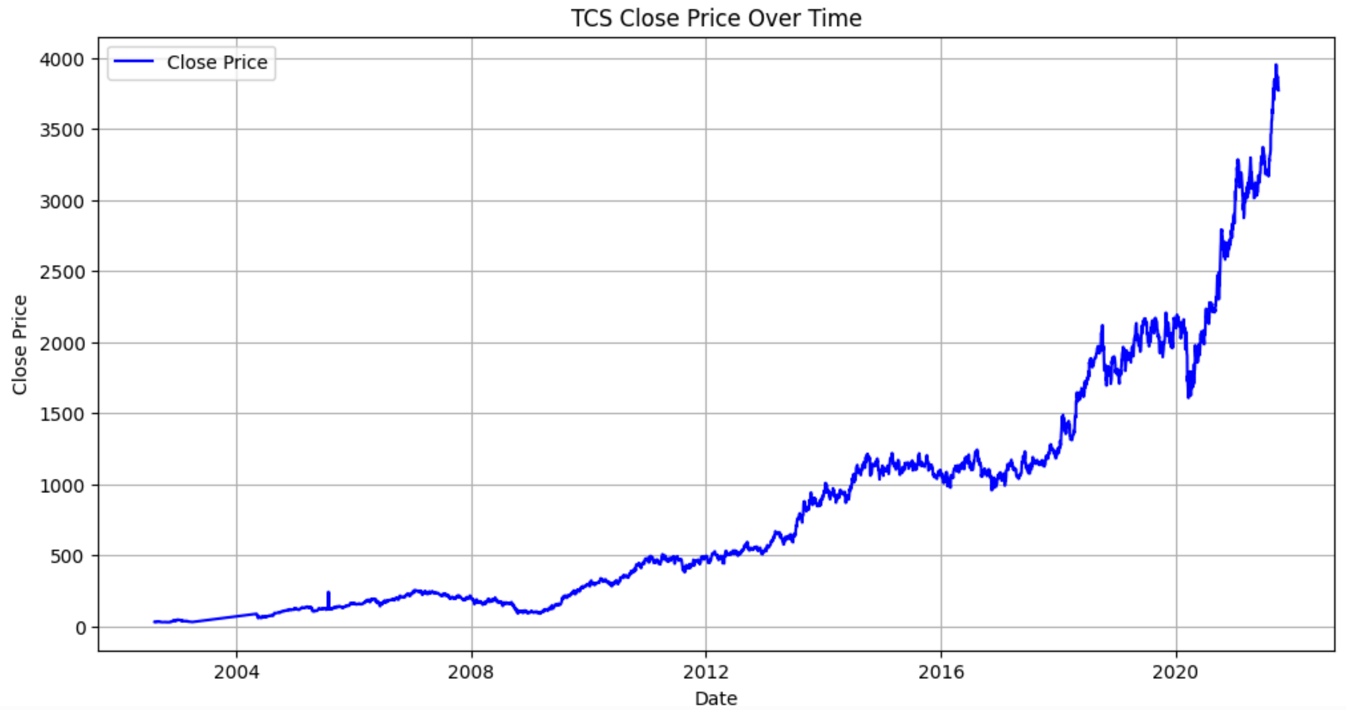
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4463 entries, 0 to 4462
Data columns (total 8 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Date          4463 non-null   datetime64[ns]
 1   Open          4463 non-null   float64
 2   High          4463 non-null   float64
 3   Low           4463 non-null   float64
 4   Close         4463 non-null   float64
 5   Volume        4463 non-null   int64
 6   Dividends     4463 non-null   float64
 7   Stock Splits  4463 non-null   float64
dtypes: datetime64[ns](1), float64(6), int64(1)
memory usage: 279.1 KB
None
Date            0
Open            0
High            0
Low             0
Close           0
Volume          0
Dividends       0
Stock Splits    0
```

What can I help you build?

```
dtype: int64
```

Step 1.3: Initial Visualization

```
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 6))
plt.plot(df_history['Date'], df_history['Close'], label='Close Price', color='blue')
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.title('TCS Close Price Over Time')
plt.grid(True)
plt.legend()
plt.show()
```



Phase 2: Data Preprocessing

Objective: Clean and prepare the data so it's ready for EDA and modeling.

Step 2.1: Check for Nulls

```
df_history.isnull().sum()
```

	0
Date	0
Open	0
High	0
Low	0
Close	0
Volume	0
Dividends	0
Stock Splits	0

```
# Fill missing values using forward fill
df_history.fillna(method='ffill', inplace=True)
```

```
/tmp/ipython-input-9-2135942139.py:2: FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a future versior
  df_history.fillna(method='ffill', inplace=True)
```

Step 2.2: Ensure Correct Data Types

```
df_history.dtypes
```

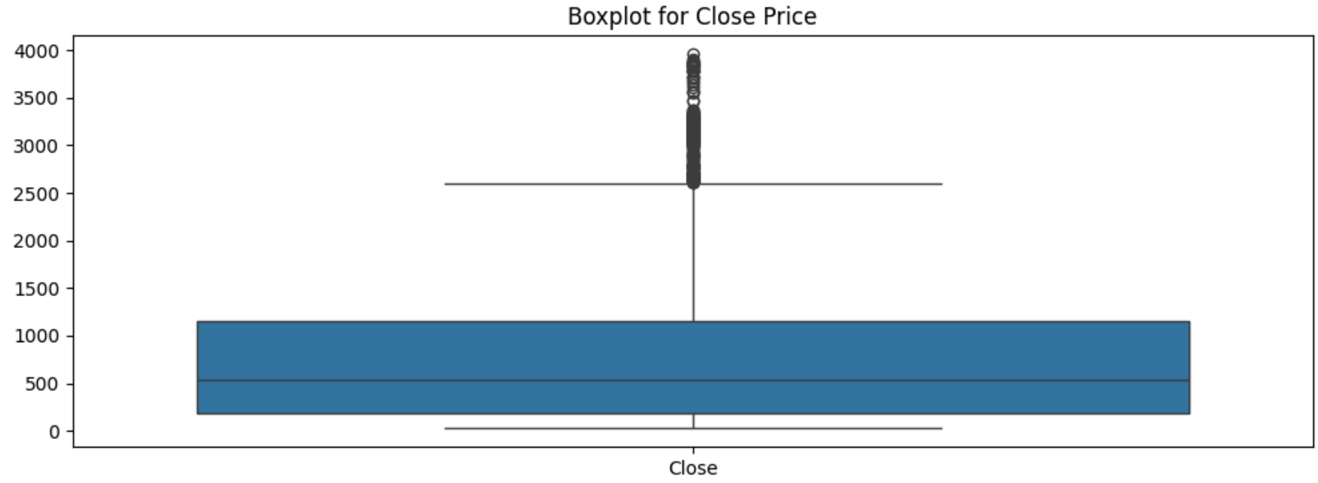
	0
Date	datetime64[ns]
Open	float64
High	float64
Low	float64
Close	float64
Volume	int64
Dividends	float64
Stock Splits	float64

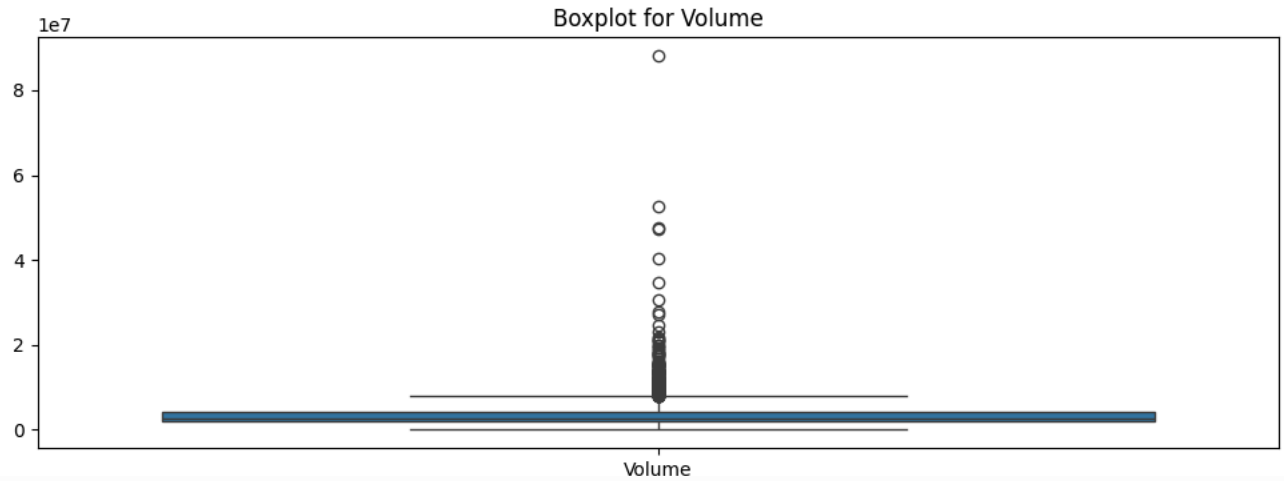
```
cols_to_convert = ['Open', 'High', 'Low', 'Close', 'Volume', 'Dividends', 'Stock Splits']
for col in cols_to_convert:
    df_history[col] = pd.to_numeric(df_history[col], errors='coerce')

df_history.fillna(method='ffill', inplace=True)  # Just in case new NaNs appear
```

```
/tmp/ipython-input-11-54204086.py:5: FutureWarning: DataFrame.fillna with 'method' is deprecated and will raise in a future version
  df_history.fillna(method='ffill', inplace=True)  # Just in case new NaNs appear
```

Step 2.3: Check for Outliers

```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 4))
sns.boxplot(data=df_history[['Close']])
plt.title('Boxplot for Close Price')
plt.show()

plt.figure(figsize=(12, 4))
sns.boxplot(data=df_history[['Volume']])
plt.title('Boxplot for Volume')
plt.show()
```





Step 2.4: Create Useful Columns

```
df_history['Year'] = df_history['Date'].dt.year
df_history['Month'] = df_history['Date'].dt.month
df_history['Day'] = df_history['Date'].dt.day
df_history['DayOfWeek'] = df_history['Date'].dt.dayofweek
```

Step 2.5: Add Daily Change %

```
# Calculate daily percentage change
df_history['Daily_Change_Pct'] = df_history['Close'].pct_change() * 100

# Fill NaN created from first row
df_history['Daily_Change_Pct'] = df_history['Daily_Change_Pct'].fillna(0)
```

Phase 3: Exploratory Data Analysis (EDA)

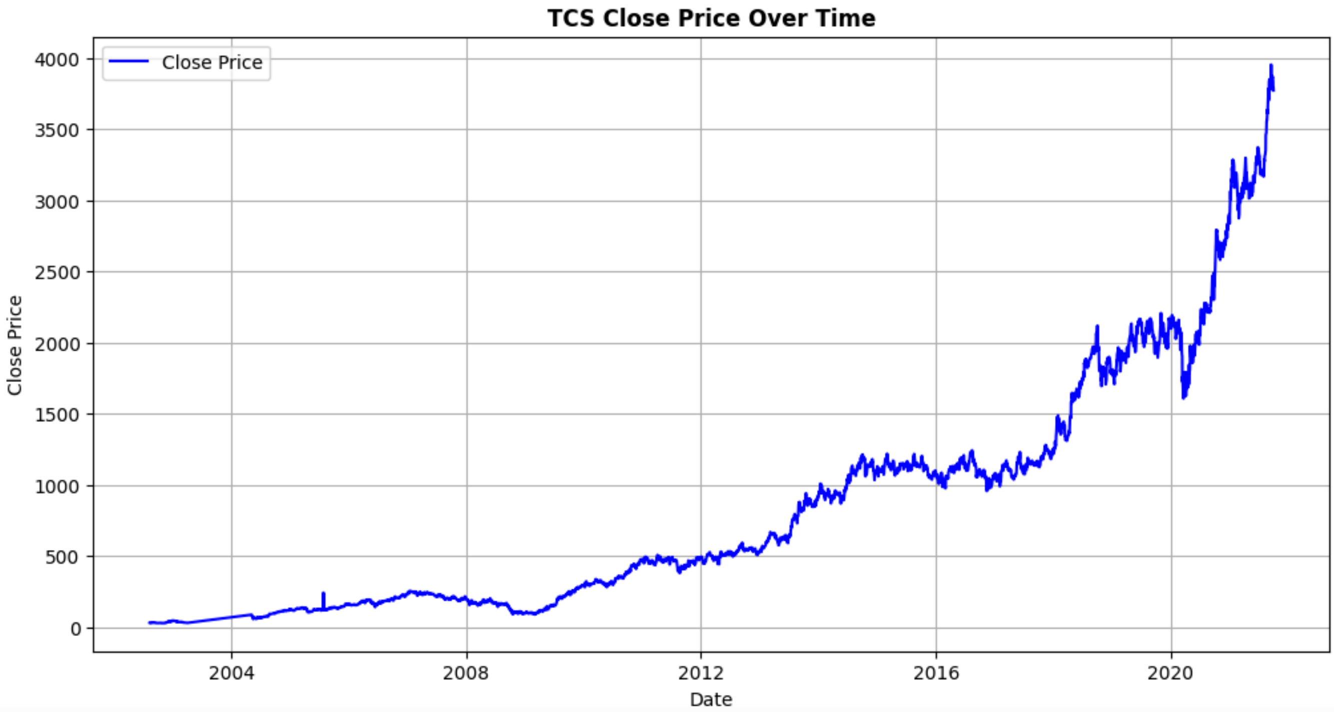
Understand historical stock behavior of TCS using visualizations and stats:

- Trends
- Volume Analysis
- Price Volatility
- Correlation
- Moving Averages

Step 3.1: Line Plot of Close Price Over Time

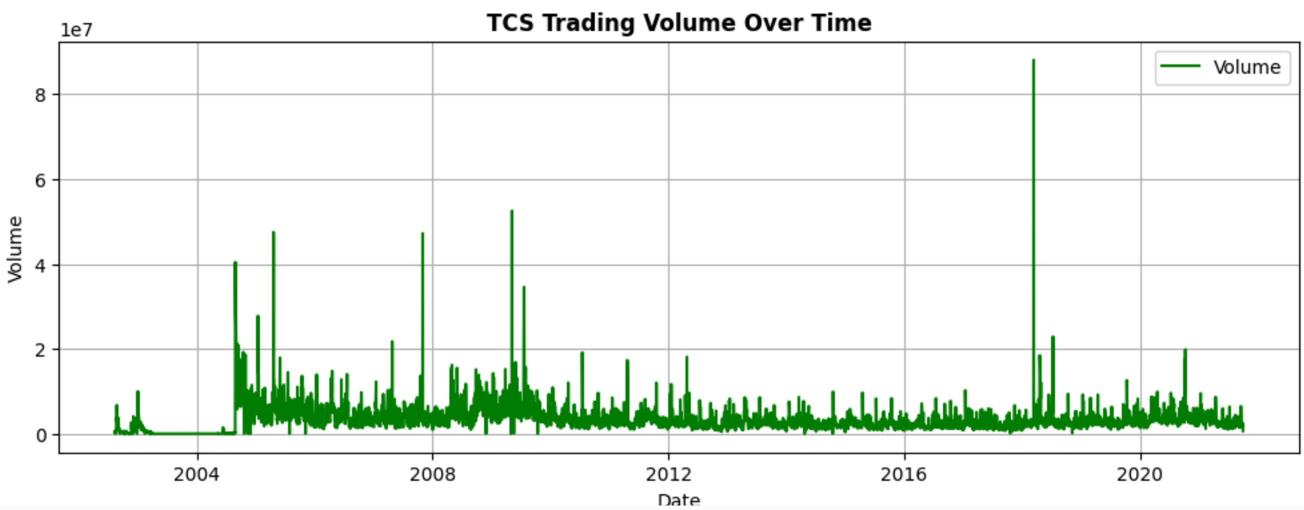
```
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 6))
plt.plot(df_history['Date'], df_history['Close'], label='Close Price', color='blue')
```

```
plt.title('TCS Close Price Over Time', weight='bold')
plt.xlabel('Date')
plt.ylabel('Close Price')
plt.legend()
plt.grid(True)
plt.show()
```



Step 3.2: Trading Volume Over Time

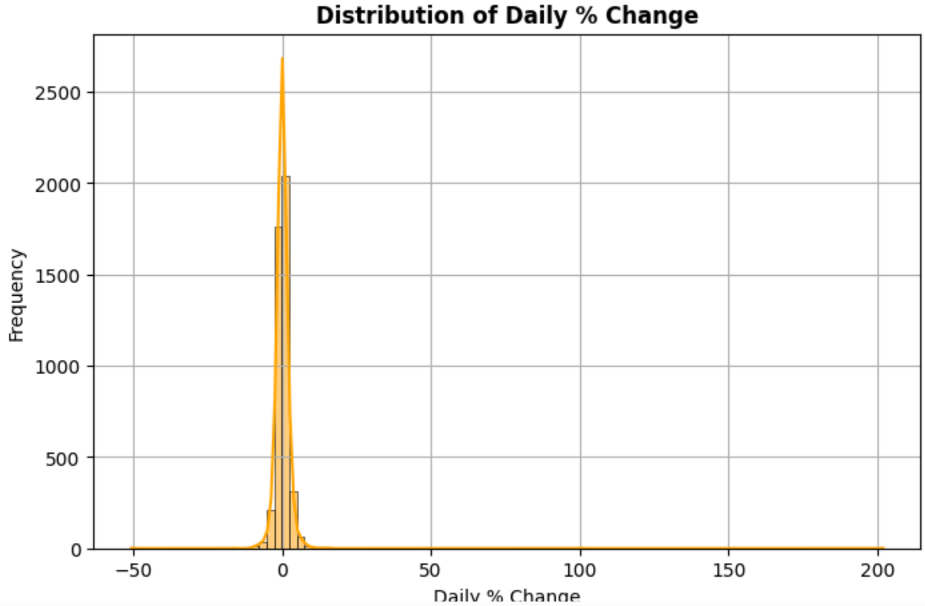
```
plt.figure(figsize=(12, 4))
plt.plot(df_history['Date'], df_history['Volume'], label='Volume', color='green')
plt.title('TCS Trading Volume Over Time', weight='bold')
plt.xlabel('Date')
plt.ylabel('Volume')
plt.legend()
plt.grid(True)
plt.show()
```



Step 3.3: Daily Percentage Change Distribution

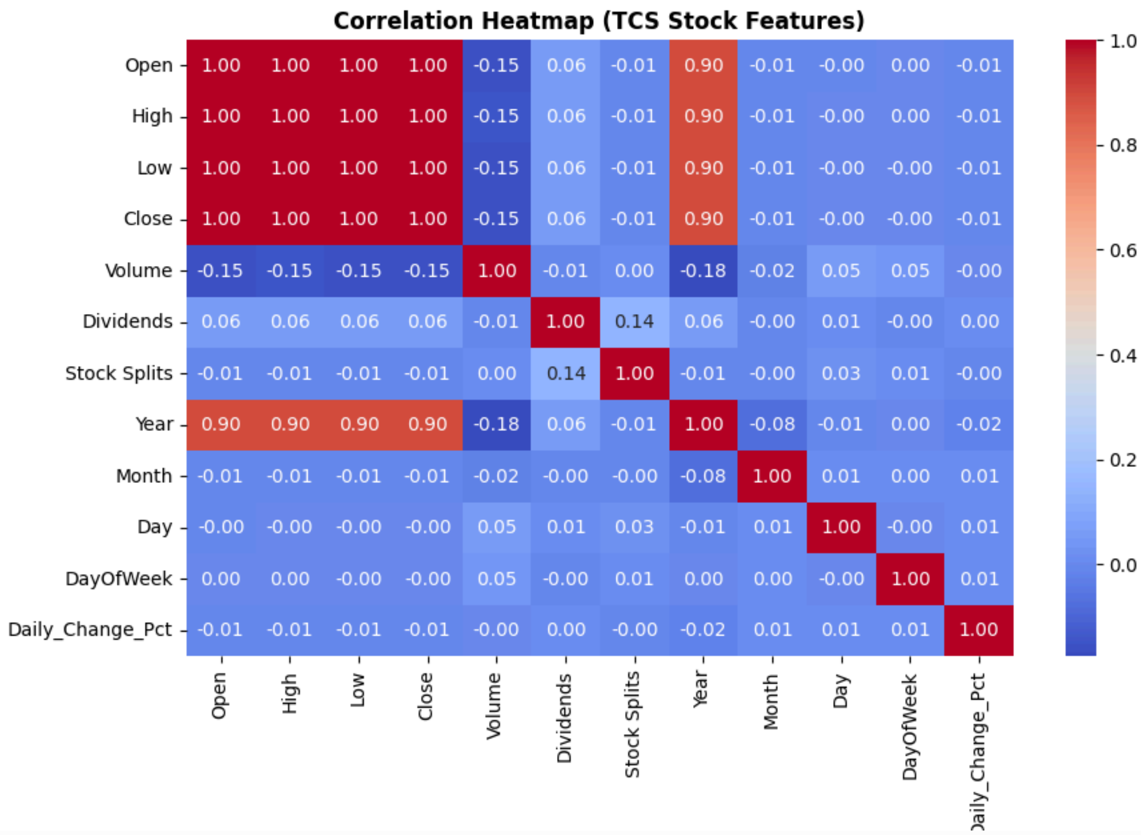
```
import seaborn as sns

plt.figure(figsize=(8, 5))
sns.histplot(df_history['Daily_Change_Pct'], bins=100, kde=True, color='orange')
plt.title("Distribution of Daily % Change", weight='bold')
plt.xlabel("Daily % Change")
```

```
plt.ylabel("Frequency")
plt.grid(True)
plt.show()
```



Step 3.4: Correlation Heatmap (Numerical Features)

```
plt.figure(figsize=(10, 6))
sns.heatmap(df_history.corr(numeric_only=True), annot=True, fmt=".2f", cmap='coolwarm')
plt.title("Correlation Heatmap (TCS Stock Features)", weight='bold')
plt.show()
```

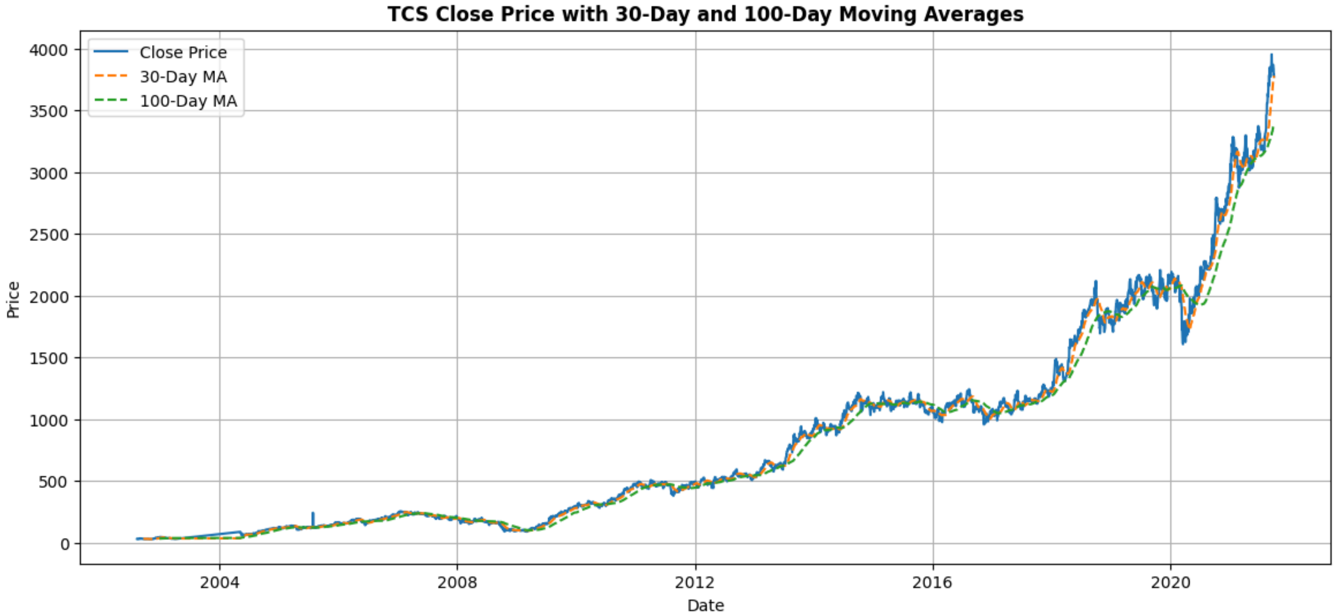


	Open	High	Low	Close	Volume	Dividends	Stock Splits	Year	Month	Day	DayOfWeek	Daily_Change_Pct
Open	1.00	1.00	1.00	1.00	-0.15	0.06	-0.01	0.90	-0.01	-0.00	0.00	-0.01
High	1.00	1.00	1.00	1.00	-0.15	0.06	-0.01	0.90	-0.01	-0.00	0.00	-0.01
Low	1.00	1.00	1.00	1.00	-0.15	0.06	-0.01	0.90	-0.01	-0.00	-0.00	-0.01
Close	1.00	1.00	1.00	1.00	-0.15	0.06	-0.01	0.90	-0.01	-0.00	-0.00	-0.01
Volume	-0.15	-0.15	-0.15	-0.15	1.00	-0.01	0.00	-0.18	-0.02	0.05	0.05	-0.00
Dividends	0.06	0.06	0.06	0.06	-0.01	1.00	0.14	0.06	-0.00	0.01	-0.00	0.00
Stock Splits	-0.01	-0.01	-0.01	-0.01	0.00	0.14	1.00	-0.01	-0.00	0.03	0.01	-0.00
Year	0.90	0.90	0.90	0.90	-0.18	0.06	-0.01	1.00	-0.08	-0.01	0.00	-0.02
Month	-0.01	-0.01	-0.01	-0.01	-0.02	-0.00	-0.00	-0.08	1.00	0.01	0.00	0.01
Day	-0.00	-0.00	-0.00	-0.00	0.05	0.01	0.03	-0.01	0.01	1.00	-0.00	0.01
DayOfWeek	0.00	0.00	-0.00	-0.00	0.05	-0.00	0.01	0.00	0.00	-0.00	1.00	0.01
Daily_Change_Pct	-0.01	-0.01	-0.01	-0.01	-0.00	0.00	-0.00	-0.02	0.01	0.01	0.01	1.00

Step 3.5: Close Price with Moving Averages

```
df_history['MA30'] = df_history['Close'].rolling(window=30).mean()
df_history['MA100'] = df_history['Close'].rolling(window=100).mean()

plt.figure(figsize=(14, 6))
```

```
plt.plot(df_history['Date'], df_history['Close'], label='Close Price')
plt.plot(df_history['Date'], df_history['MA30'], label='30-Day MA', linestyle='--')
plt.plot(df_history['Date'], df_history['MA100'], label='100-Day MA', linestyle='--')
plt.title("TCS Close Price with 30-Day and 100-Day Moving Averages", weight='bold')
plt.xlabel("Date")
plt.ylabel("Price")
plt.legend()
plt.grid(True)
plt.show()
```



Phase 4: Feature Engineering

Objective: Extract new features from existing columns (especially Date and Close) to improve the model's ability to detect patterns and trends.

Step 4.1: Reconfirm Date Column and Dataset

```
df_history['Date'] = pd.to_datetime(df_history['Date'])
df_history = df_history.sort_values(by='Date').reset_index(drop=True)
```

Step 4.2: Time-Based Features

```
df_history['Year'] = df_history['Date'].dt.year
df_history['Month'] = df_history['Date'].dt.month
df_history['Day'] = df_history['Date'].dt.day
df_history['DayOfWeek'] = df_history['Date'].dt.dayofweek  # Monday=0, Sunday=6
```

Step 4.3: Lag Features (Previous Day's Values)

```
# Previous day's closing price
df_history['Prev_Close'] = df_history['Close'].shift(1)

# Previous day's high and low (optional)
df_history['Prev_High'] = df_history['High'].shift(1)
df_history['Prev_Low'] = df_history['Low'].shift(1)
```

Step 4.4: Rolling Statistics (Moving Averages & Volatility)

```
# Rolling means (trend)
df_history['MA7'] = df_history['Close'].rolling(window=7).mean()
df_history['MA21'] = df_history['Close'].rolling(window=21).mean()

# Rolling std deviation (volatility)
df_history['Volatility_7'] = df_history['Close'].rolling(window=7).std()
```

Step 4.5: Drop NaNs from Rolling/Lag Features

```
df_history.dropna(inplace=True)
```

PHASE 5: MODEL BUILDING (LINEAR REGRESSION)

Objective: Build a predictive model using Linear Regression to forecast TCS's closing stock price.

Step 5.1: Select Features & Target Variable

```
# Features (independent variables)
features = ['Open', 'High', 'Low', 'Volume', 'Prev_Close', 'DayOfWeek', 'MA7', 'MA21', 'Volatility_7']

# Target (dependent variable)
target = 'Close'

# X = inputs, y = output
X = df_history[features]
y = df_history[target]
```

Step 5.2: Train-Test Split

```
from sklearn.model_selection import train_test_split

# 80% train, 20% test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Step 5.3: Train Linear Regression Model

```
from sklearn.linear_model import LinearRegression

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

```
▾ LinearRegression
LinearRegression()
```

Step 5.4: Make Predictions

```
y_pred = model.predict(X_test)
```

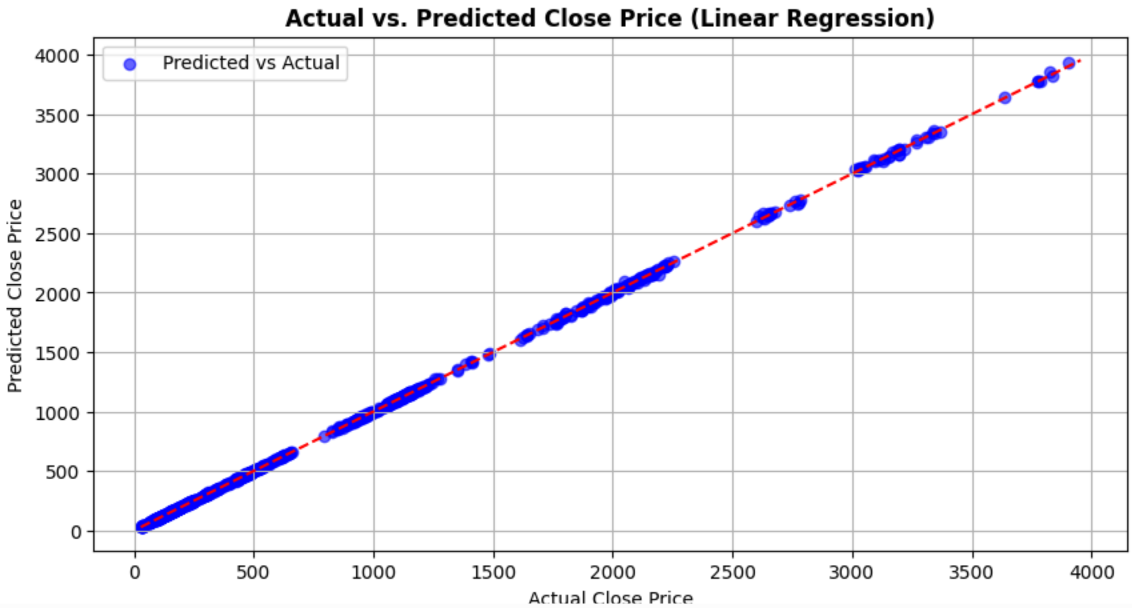
Step 5.5: Evaluate the Model

```
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error

print("Mean Absolute Error (MAE):", mean_absolute_error(y_test, y_pred))
print("Mean Squared Error (MSE):", mean_squared_error(y_test, y_pred))
print("R² Score:", r2_score(y_test, y_pred))
```

```
Mean Absolute Error (MAE): 4.058993623288566
Mean Squared Error (MSE): 48.40126319919669
R² Score: 0.9999318503007047
```

Step 5.6: Plot Predicted vs. Actual Prices

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 5))
plt.scatter(y_test, y_pred, color='blue', alpha=0.6, label='Predicted vs Actual')
plt.plot([y.min(), y.max()], [y.min(), y.max()], color='red', linestyle='--')  # Diagonal line
plt.xlabel('Actual Close Price')
plt.ylabel('Predicted Close Price')
plt.title('Actual vs. Predicted Close Price (Linear Regression)', weight='bold')
plt.legend()
plt.grid(True)
plt.show()
```



Phase 6: LSTM Model – Time Series Forecasting

Objective: Use a Long Short-Term Memory (LSTM) neural network to model and predict the Close price based on past values — capturing temporal patterns better than linear models.

Step 6.1: Install TensorFlow

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense
from sklearn.preprocessing import MinMaxScaler
import numpy as np
```

Step 6.2: Prepare the Data for LSTM

```
# Use only the 'Close' column for time-series modeling
close_data = df_history['Close'].values.reshape(-1, 1)

# Scale the data
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_close = scaler.fit_transform(close_data)
```

Step 6.3: Create Sequences (Windowed Data)

```
sequence_length = 60
X = []
y = []

for i in range(sequence_length, len(scaled_close)):
    X.append(scaled_close[i - sequence_length:i, 0])
    y.append(scaled_close[i, 0])
```

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

# Reshape to 3D for LSTM [samples, time steps, features]
X = np.reshape(X, (X.shape[0], X.shape[1], 1))
```

Step 6.4: Build the 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))  # Output layer

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

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim` argum
  super().__init__(**kwargs)
```

Step 6.5: Train the Model

```
model.fit(X, y, epochs=20, batch_size=32)
```

```
Epoch 1/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 10s 46ms/step - loss: 0.0201
Epoch 2/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 10s 45ms/step - loss: 1.6399e-04
Epoch 3/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 11s 49ms/step - loss: 1.4748e-04
Epoch 4/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 7s 51ms/step - loss: 1.5496e-04
Epoch 5/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 9s 46ms/step - loss: 1.5705e-04
Epoch 6/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 11s 49ms/step - loss: 1.4301e-04
Epoch 7/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 10s 45ms/step - loss: 1.2816e-04
Epoch 8/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 11s 52ms/step - loss: 1.2399e-04
Epoch 9/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 11s 54ms/step - loss: 1.3347e-04
Epoch 10/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 6s 45ms/step - loss: 1.2618e-04
Epoch 11/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 10s 46ms/step - loss: 1.3350e-04
Epoch 12/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 10s 47ms/step - loss: 1.0918e-04
Epoch 13/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 7s 53ms/step - loss: 8.0820e-05
Epoch 14/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 6s 46ms/step - loss: 9.4008e-05
Epoch 15/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 7s 53ms/step - loss: 8.7626e-05
Epoch 16/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 9s 46ms/step - loss: 9.0974e-05
Epoch 17/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 7s 53ms/step - loss: 8.9141e-05
Epoch 18/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 11s 56ms/step - loss: 1.0770e-04
Epoch 19/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 10s 52ms/step - loss: 8.4506e-05
Epoch 20/20
135/135 ━━━━━━━━━━━━━━━━━━━━ 7s 48ms/step - loss: 6.2605e-05
<keras.src.callbacks.history.History at 0x7b82c8a51790>
```

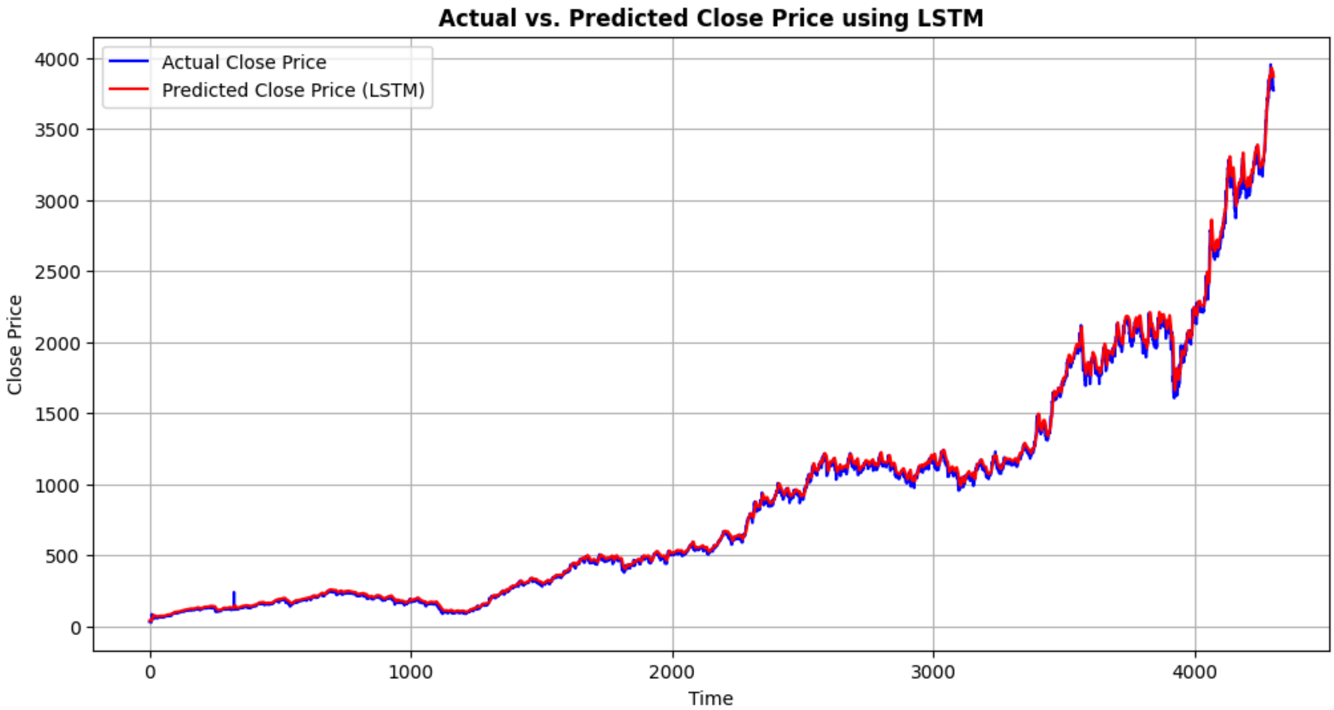
Step 6.6: Predict and Visualize

```
# Predict on the last X (same data for simplicity)
predicted_prices = model.predict(X)

# Inverse scale to get actual prices
predicted_prices = scaler.inverse_transform(predicted_prices)
actual_prices = scaler.inverse_transform(y.reshape(-1, 1))
```

```
135/135 ━━━━━━━━━━━━━━━━━━━━ 4s 22ms/step
```

Step 6.7: Plot Actual vs Predicted

```
import matplotlib.pyplot as plt

plt.figure(figsize=(12,6))
plt.plot(actual_prices, label='Actual Close Price', color='blue')
plt.plot(predicted_prices, label='Predicted Close Price (LSTM)', color='red')
plt.title('Actual vs. Predicted Close Price using LSTM', weight='bold')
plt.xlabel('Time')
plt.ylabel('Close Price')
plt.legend()
plt.grid(True)
plt.show()
```



Step 6.8: Evaluate Model Performance

```
from sklearn.metrics import mean_absolute_error

mae = mean_absolute_error(actual_prices, predicted_prices)
print("LSTM Mean Absolute Error (MAE):", round(mae, 2))
```

```
LSTM Mean Absolute Error (MAE): 22.51
```

Phase 7: Save Models & Export Excel Dashboard Data

Step 7.1: Save the Linear Regression Model

```
import pickle

# Save Linear Regression model
with open('tcs_linear_model.pkl', 'wb') as file:
    pickle.dump(model, file)

# Download the model file
from google.colab import files
files.download('tcs_linear_model.pkl')
```

Step 7.2: Save the LSTM Model

```
# Save the LSTM model
model.save('tcs_lstm_model.h5')

# Download the model file
```

```
files.download('tcs_lstm_model.h5')
```

```
WARNING:absl:You are saving your model as an HDF5 file via `model.save()` or `keras.saving.save_model(model)`. This file format is c
```

Step 7.3: Save LSTM Predictions

```
import pandas as pd

# Create DataFrame with predictions and actual values
pred_df = pd.DataFrame({
    'Date': df_history['Date'].iloc[-len(predicted_prices):].values,
    'Actual_Close': actual_prices.flatten(),
    'Predicted_Close_LSTM': predicted_prices.flatten()
})

# Save to CSV
pred_df.to_csv('tcs_lstm_predictions_with_dates.csv', index=False)

# Download the CSV
files.download('tcs_lstm_predictions_with_dates.csv')
```

Step 7.4: Save Final Cleaned Data for Excel Dashboard