# Stock Price Prediction Using Deep Learning Technique

A stock price prediction project utilizing Long Short-Term Memory model. Leveraging the yfinance library, you have the flexibility to select your target stock and the time frame.

## Import Library

In [126]:
```
import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import math
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense, LSTM, Dropout
import warnings
warnings.filterwarnings('ignore')
```

## Access Data and Input Variables

Enter the stock ticker, date, and the epoch times. Noted that the first 80% of the date will be used for training, and the remaining 20% will be used for validation.

Example Inputs : "googl", "2010-01-01", "2023-08-20"

In [127]:
```
Company = input("Ticker of the Stock:")
Date1 = input("Start(YYYY-MM-DD):")
Date2 = input("End(YYYY-MM-DD):")
```

## Data Exploration

In [128]:
```
Data = yf.download(Company,Date1, Date2)
Data =Data.reset_index()
Data
```

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

Out[128]:

| | Date | Open | High | Low | Close | Adj Close | Volume |
|---|---|---|---|---|---|---|---|
| **0** | 2010-01-04 | 15.689439 | 15.753504 | 15.621622 | 15.684434 | 15.684434 | 78169752 |
| **1** | 2010-01-05 | 15.695195 | 15.711712 | 15.554054 | 15.615365 | 15.615365 | 120067812 |
| **2** | 2010-01-06 | 15.662162 | 15.662162 | 15.174174 | 15.221722 | 15.221722 | 158988852 |
| **3** | 2010-01-07 | 15.250250 | 15.265265 | 14.831081 | 14.867367 | 14.867367 | 256315428 |
| **4** | 2010-01-08 | 14.814815 | 15.096346 | 14.742492 | 15.065566 | 15.065566 | 188783028 |
| **...** | ... | ... | ... | ... | ... | ... | ... |
| **3425** | 2023-08-14 | 129.389999 | 131.369995 | 128.960007 | 131.330002 | 131.330002 | 24695600 |
| **3426** | 2023-08-15 | 131.100006 | 131.419998 | 129.279999 | 129.779999 | 129.779999 | 19770700 |
| **3427** | 2023-08-16 | 128.699997 | 130.279999 | 127.870003 | 128.699997 | 128.699997 | 25216100 |
| **3428** | 2023-08-17 | 129.800003 | 131.990005 | 129.289993 | 129.919998 | 129.919998 | 33446300 |
| **3429** | 2023-08-18 | 128.509995 | 129.250000 | 126.379997 | 127.459999 | 127.459999 | 30491300 |

3430 rows × 7 columns

In [129]:
```
Data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3430 entries, 0 to 3429
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   Date       3430 non-null   datetime64[ns]
 1   Open       3430 non-null   float64
 2   High       3430 non-null   float64
 3   Low        3430 non-null   float64
 4   Close      3430 non-null   float64
 5   Adj Close  3430 non-null   float64
 6   Volume     3430 non-null   int64
dtypes: datetime64[ns](1), float64(5), int64(1)
memory usage: 187.7 KB
```

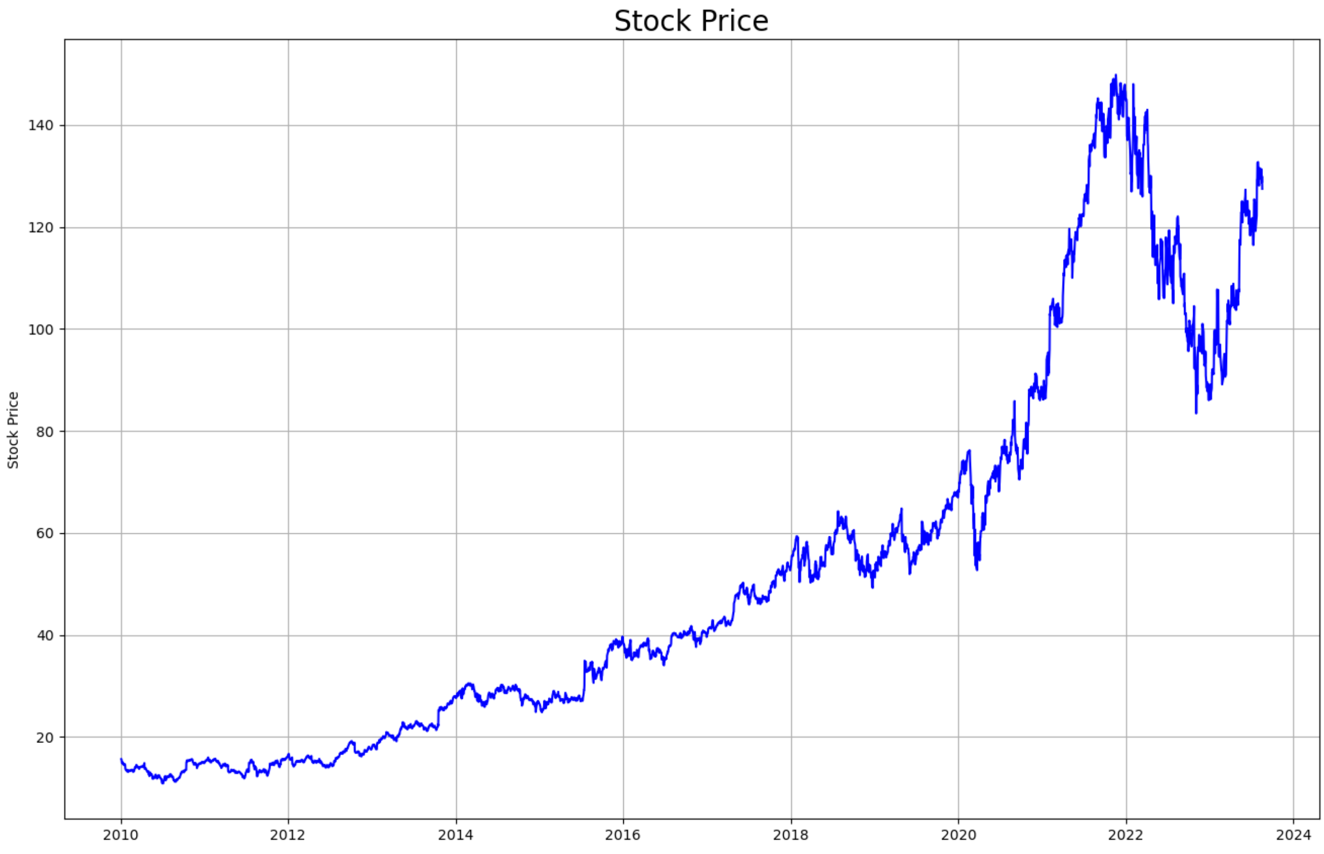
In [130]:
```
Data.isnull().sum()
```

Out[130]:
```
Date         0
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
dtype: int64
```

# Data Visualization

## Stock Price

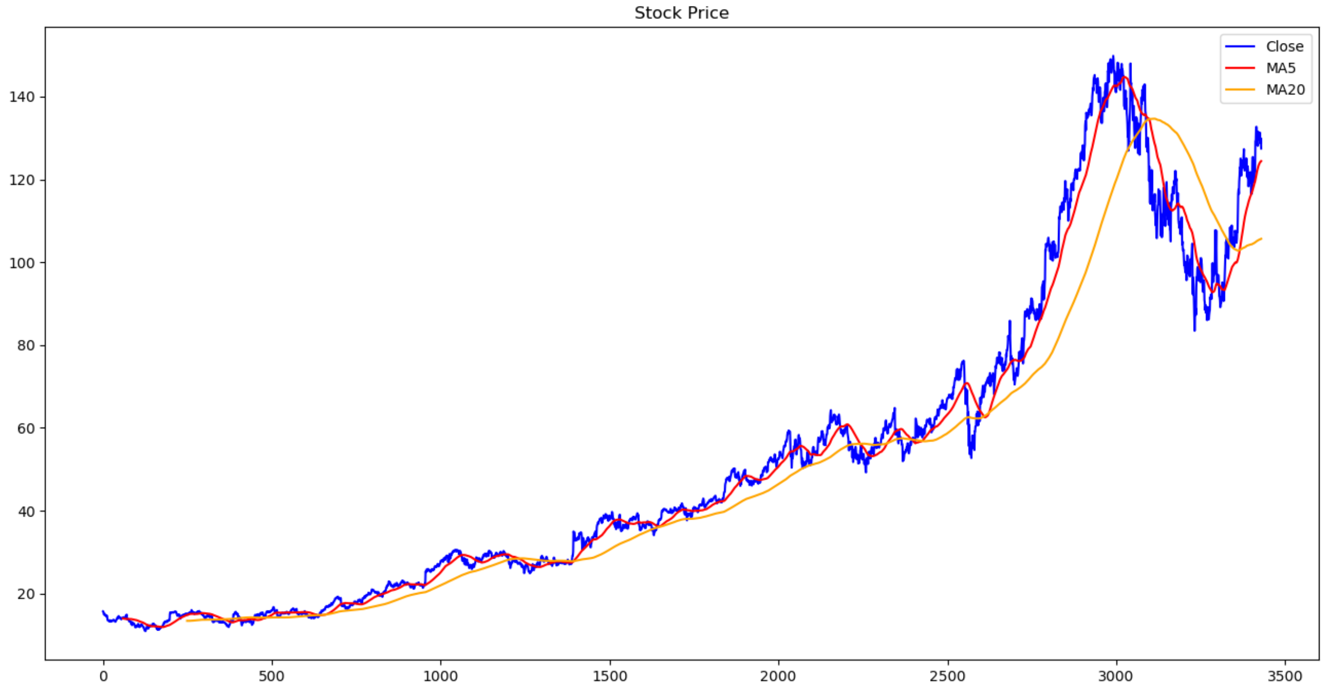
In [131]:
```
fig, ax = plt.subplots(figsize=(16,10))
plt.title("Stock Price", fontsize="20")
ax.plot(Data["Date"], Data["Close"], color="Blue")
ax.set_ylabel("Stock Price")
plt.grid()
plt.show()
```



## Moving Average

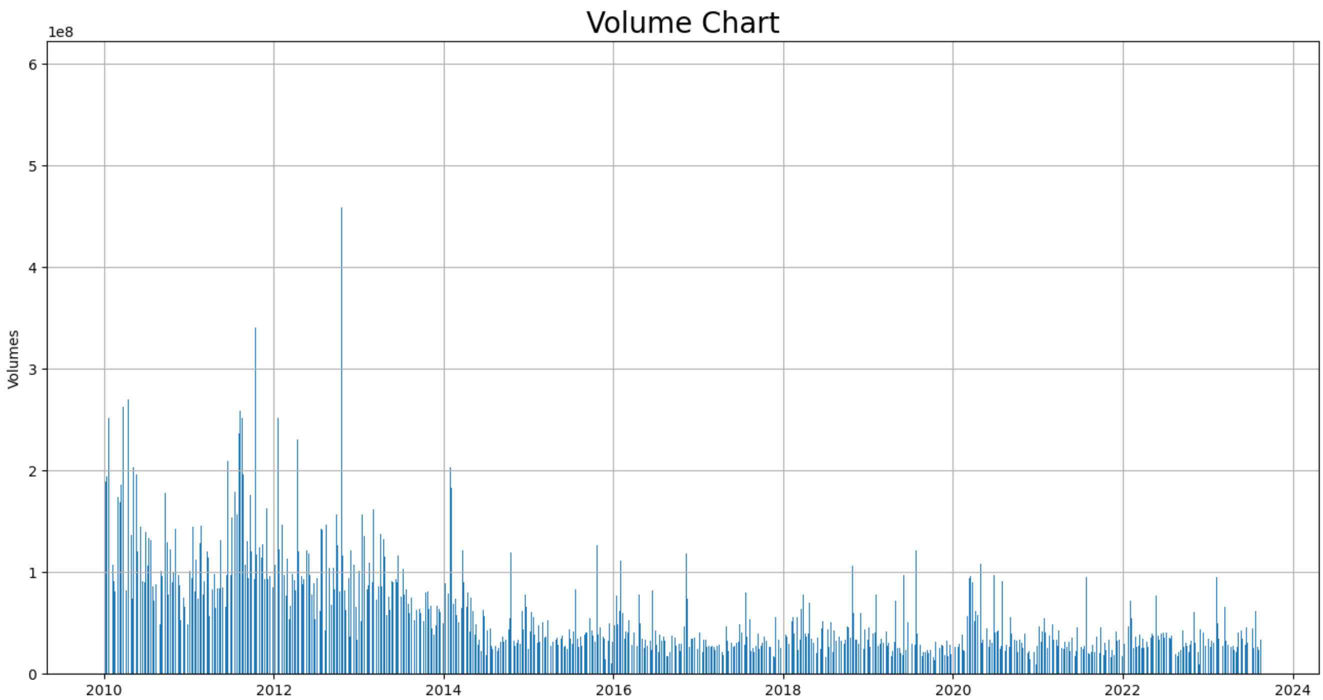
In [132]:
```
MA60=Data.Close.rolling(60).mean()
MA250=Data.Close.rolling(250).mean()
fig, ax = plt.subplots(figsize=(16,8))
plt.title("Stock Price")
plt.plot(Data.Close, color="Blue", label="Close")
plt.plot(MA60, color = 'Red', label = "MA5")
plt.plot(MA250, color = 'Orange', label = "MA20")
plt.legend()
```

Out[132]: <matplotlib.legend.Legend at 0x2bcf39f5160>




## Volume

In [133]:
```
fig, ax = plt.subplots(figsize=(16,8))
plt.title("Volume Chart", fontsize="20")
ax.bar(Data["Date"], Data["Volume"])
ax.set_ylabel("Volumes")
plt.grid()
plt.show()
```

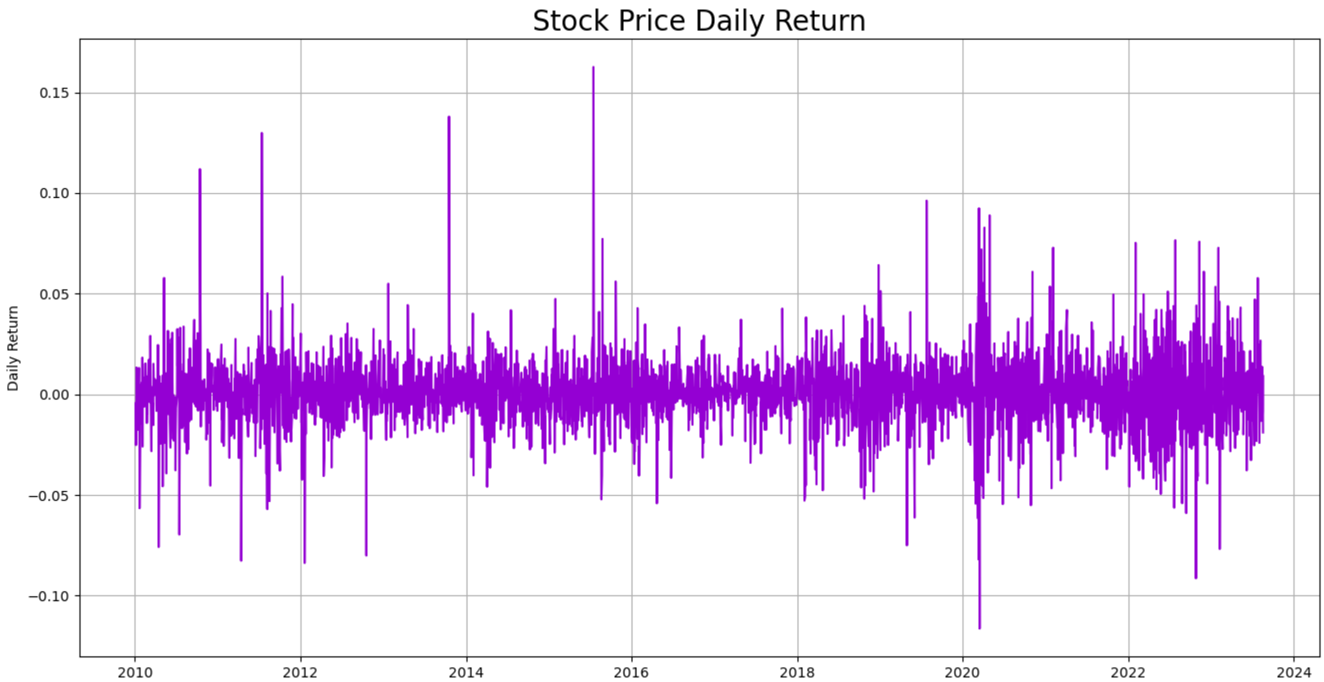


## Daily Return

In [134]:
```
Data["Daily Return"] = Data["Close"].pct_change(1)
Data["Daily Return"]
```

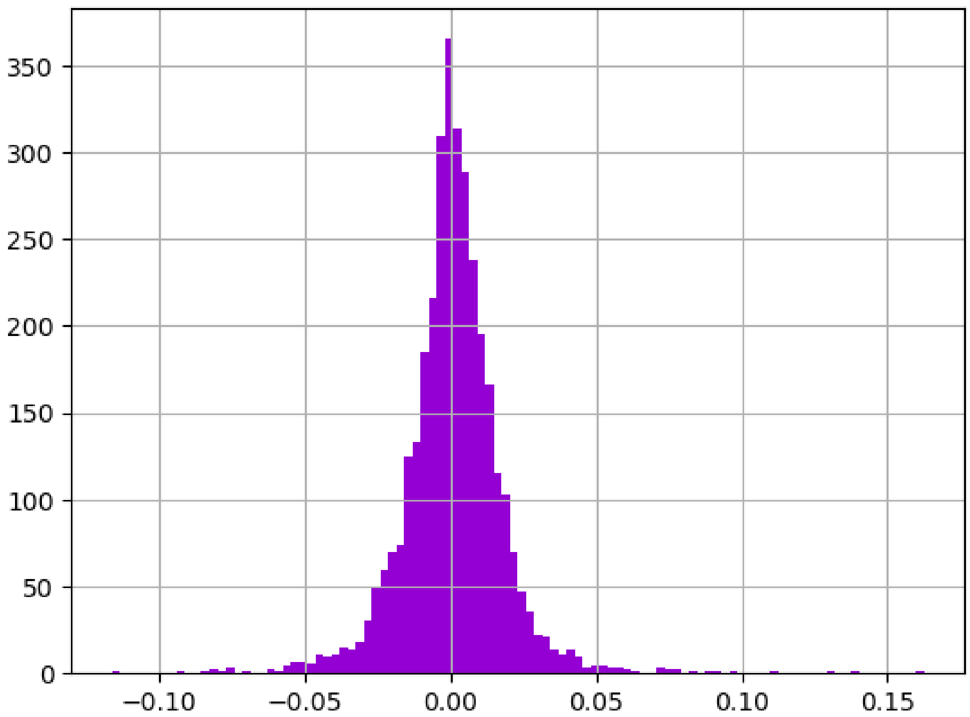
Out[134]:
```
0            NaN
1      -0.004404
2      -0.025209
3      -0.023280
4       0.013331
          ...
3425    0.013662
3426   -0.011802
3427   -0.008322
3428    0.009479
3429   -0.018935
Name: Daily Return, Length: 3430, dtype: float64
```

In [135]:
```
fig, ax = plt.subplots(figsize=(16,8))
plt.title("Stock Price Daily Return",fontsize="20")
ax.plot(Data["Date"], Data["Daily Return"], color="Darkviolet")
ax.set_ylabel("Daily Return")
plt.grid()
plt.show()
```



In [136]:
```
#Distribution of Daily Return(Volatility)
Data.iloc[Data["Daily Return"].argmax()]
Data["Daily Return"].hist(bins=100, color='Darkviolet')
```

Out[136]: <AxesSubplot:>

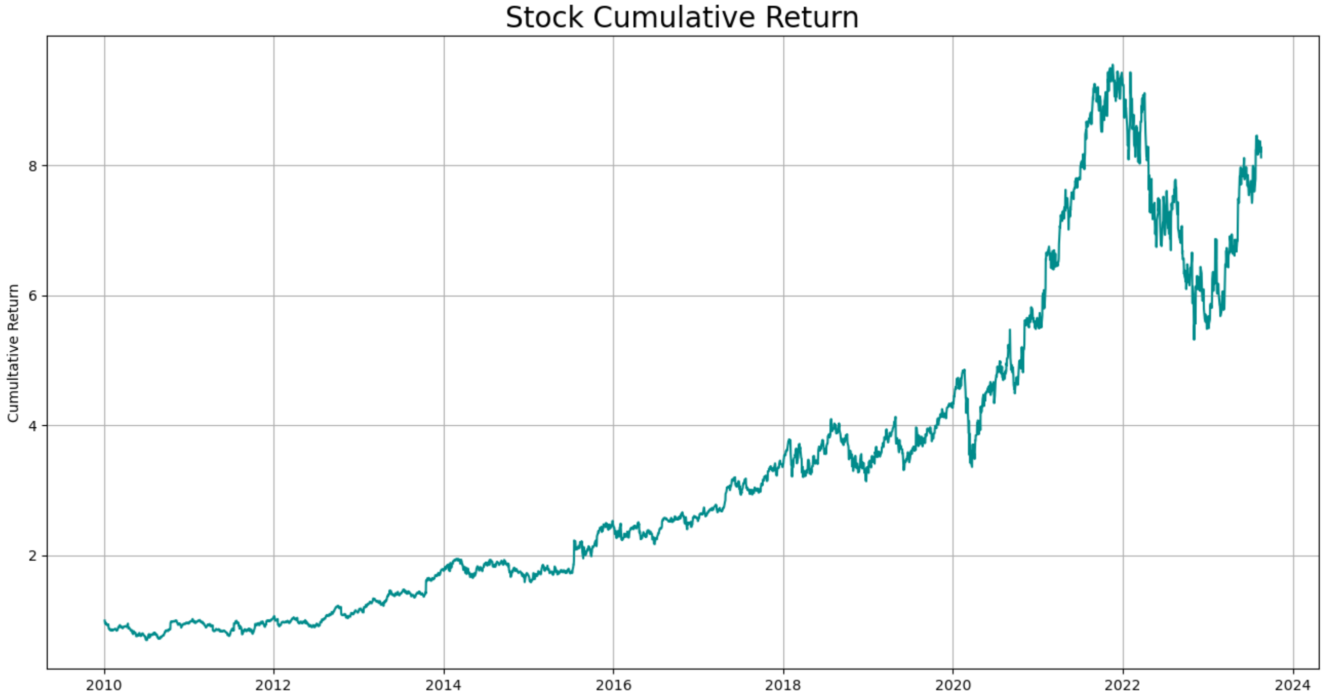



## Cumulative Return

In [137]:
```
Data["Cumulative Return"] = (1+Data["Daily Return"]).cumprod()
Data["Cumulative Return"]
```

Out[137]:
```
0            NaN
1       0.995596
2       0.970499
3       0.947906
4       0.960543
          ...
3425    8.373270
3426    8.274446
3427    8.205588
3428    8.283372
3429    8.126528
Name: Cumulative Return, Length: 3430, dtype: float64
```

In [138]:
```
#Cumultative Return of the stock during the given period
fig, ax = plt.subplots(figsize=(16,8))
plt.title("Stock Cumulative Return",fontsize="20")
ax.plot(Data["Date"], Data["Cumulative Return"], color="Darkcyan")
ax.set_ylabel("Cumultative Return")
plt.grid()
plt.show()
```




### Splitting Data into Training and Validation Sets

In [139]:
```
Data['Date'] = pd.to_datetime(Data['Date'])
Data.set_index('Date',inplace=True)
Close = Data.filter(['Close'])
CloseValue = Close.values
TrainingDataLength = math.ceil(len(CloseValue)*.8)
TrainingDataLength
```

Out[139]:
```
2744
```

### Scaling data

In [140]:
```
scaler = MinMaxScaler(feature_range=(0,1))
PriceData = scaler.fit_transform(CloseValue)
PriceData
## Customized the function:
# def Rank(data):
#     feature_range = data.max() - data.min()
#     scaled_data = (data - data.min()) / feature_range
#     return scaled_data
# PriceData = Rank(CloseValue)
# Rank(CloseValue)
```

Out[140]:
```
array([[0.03434761],
       [0.03385045],
       [0.03101697],
       ...,
       [0.84784325],
       [0.85662492],
       [0.83891764]])
```

In [141]:
```
X_train, Y_train = [],[]
Backcandles = 60
TrainData = PriceData[0:TrainingDataLength]
for i in range(Backcandles,len(TrainData)):
    X_train.append(TrainData[i-Backcandles:i, 0])
    Y_train.append(TrainData[i,0])
    if i<= Backcandles:
        print("X_train:",X_train,"\nY_train:",Y_train)
X_train,Y_train = np.array(X_train), np.array(Y_train)
```

```
X_train: [array([0.03434761, 0.03385045, 0.03101697, 0.02846629, 0.02989295,
       0.02972903, 0.02781422, 0.02720357, 0.02770073, 0.02592643,
       0.02729904, 0.02600028, 0.02646323, 0.02052427, 0.01872114,
       0.01915706, 0.01909942, 0.01769259, 0.01690901, 0.01746381,
       0.01712157, 0.01886885, 0.01633979, 0.01715219, 0.01754487,
       0.01807987, 0.01772141, 0.01807266, 0.01748183, 0.01895531,
       0.0183987 , 0.01930117, 0.01885804, 0.01922551, 0.01783308,
       0.01718461, 0.01627675, 0.01634339, 0.01740437, 0.01891208,
       0.01967945, 0.02134927, 0.02308214, 0.02277051, 0.02235801,
       0.02528697, 0.02613178, 0.02584357, 0.02289661, 0.02326047,
       0.02332532, 0.02347663, 0.02232379, 0.02187345, 0.02034233,
       0.02184283, 0.02284257, 0.02280834, 0.02276511, 0.02353248])]
Y_train: [0.023606326054810806]
```

In [142]:
```
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_train.shape
```

Out[142]:
```
(2684, 60, 1)
```

### LSTM Model Building, Compiling, and Training

In [143]:
```
Model = Sequential([
    LSTM(50, return_sequences = True, input_shape = (X_train.shape[1], 1)),
    (Dropout(0.2)),
    LSTM((50)),
    (Dropout(0.2)),
    (Dense(32)),
    (Dense(1))
])

Model.compile(optimizer="adam", loss="mean_squared_error")
Model.fit(X_train, Y_train, batch_size=32, epochs=10)
Model.summary()
```

```
Epoch 1/10
84/84 [==============================] - 8s 41ms/step - loss: 0.0037
Epoch 2/10
84/84 [==============================] - 3s 41ms/step - loss: 5.1302e-04
Epoch 3/10
84/84 [==============================] - 3s 40ms/step - loss: 4.1107e-04
Epoch 4/10
84/84 [==============================] - 4s 43ms/step - loss: 3.5053e-04
Epoch 5/10
84/84 [==============================] - 4s 44ms/step - loss: 3.4685e-04
Epoch 6/10
84/84 [==============================] - 4s 43ms/step - loss: 3.3997e-04
Epoch 7/10
84/84 [==============================] - 4s 43ms/step - loss: 3.3205e-04
Epoch 8/10
84/84 [==============================] - 4s 43ms/step - loss: 2.5720e-04
Epoch 9/10
84/84 [==============================] - 3s 42ms/step - loss: 2.6947e-04
Epoch 10/10
84/84 [==============================] - 3s 40ms/step - loss: 2.4330e-04
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_8 (LSTM)               (None, 60, 50)            10400

 dropout_8 (Dropout)         (None, 60, 50)            0

 lstm_9 (LSTM)               (None, 50)                20200

 dropout_9 (Dropout)         (None, 50)                0

 dense_8 (Dense)             (None, 32)                1632

 dense_9 (Dense)             (None, 1)                 33

=================================================================
Total params: 32265 (126.04 KB)
Trainable params: 32265 (126.04 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [144]:
```
test_data= PriceData[TrainingDataLength-Backcandles:, :]
x_test, y_test = [], CloseValue[TrainingDataLength:,:]
for i in range(Backcandles,len(test_data)):
    x_test.append(test_data[i-Backcandles:i,0])
x_test = np.array(x_test)
x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1],1))
x_test.shape
```

Out[144]:
```
(686, 60, 1)
```

# Results of the Prediction

## Root-Mean-Square Error

A higher RMSE value generally indicates poorer predictive performance. Hence, our training objective is to "minimize RMSE".

In [145]:
```
Pred = Model.predict(x_test)
Pred = scaler.inverse_transform(Pred)
RMSE = np.sqrt(np.mean(Pred - y_test)**2)
RMSE
```

```
22/22 [==============================] - 1s 15ms/step
```

Out[145]:
```
1.8634645779000774
```

## Prediction Results

In [146]:
```
TrainingSet,ValidationSet = Close[:TrainingDataLength],Close[TrainingDataLength:]
ValidationSet["Predictions"] = Pred
ValidationSet
```

Out[146]:

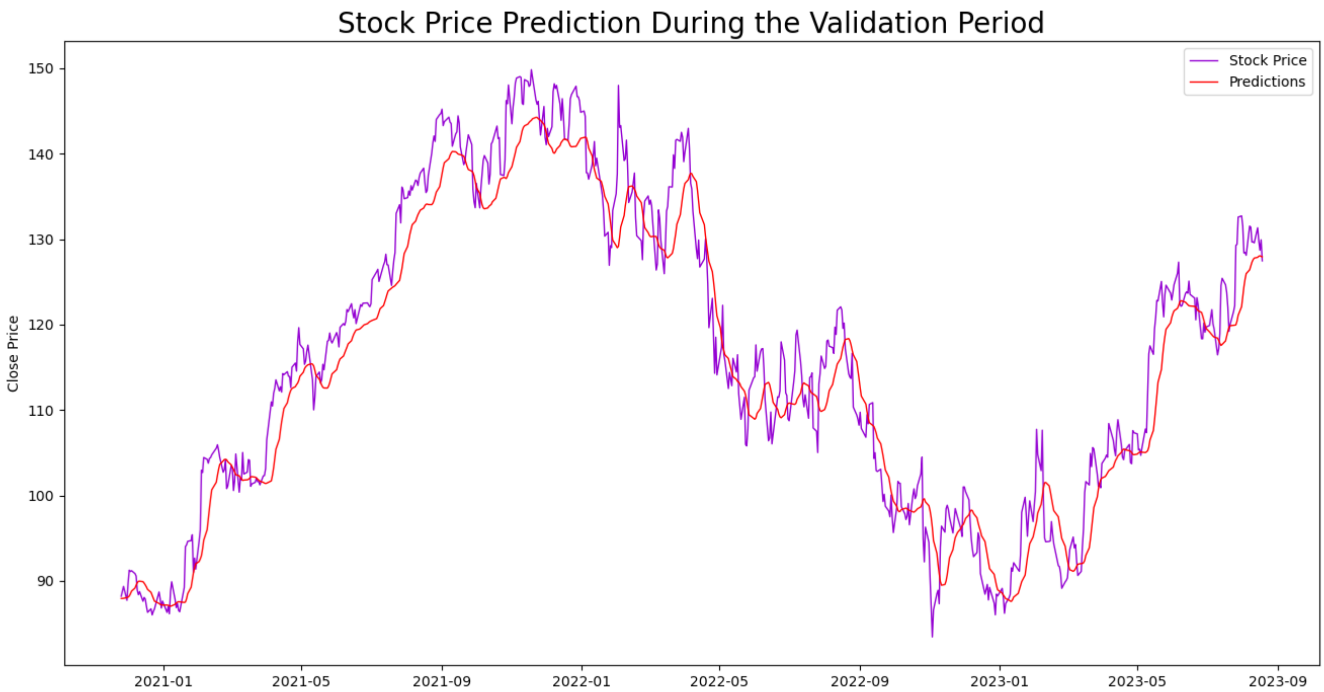
| | Close | Predictions |
|---|---|---|
| **Date** | | |
| **2020-11-25** | 88.206497 | 87.938492 |
| **2020-11-27** | 89.350998 | 87.956757 |
| **2020-11-30** | 87.720001 | 88.047287 |
| **2020-12-01** | 89.767998 | 88.097267 |
| **2020-12-02** | 91.248497 | 88.225983 |
| **...** | ... | ... |
| **2023-08-14** | 131.330002 | 127.871643 |
| **2023-08-15** | 129.779999 | 127.996346 |
| **2023-08-16** | 128.699997 | 128.046631 |
| **2023-08-17** | 129.919998 | 127.986809 |
| **2023-08-18** | 127.459999 | 127.922981 |

686 rows × 2 columns

## Visualization

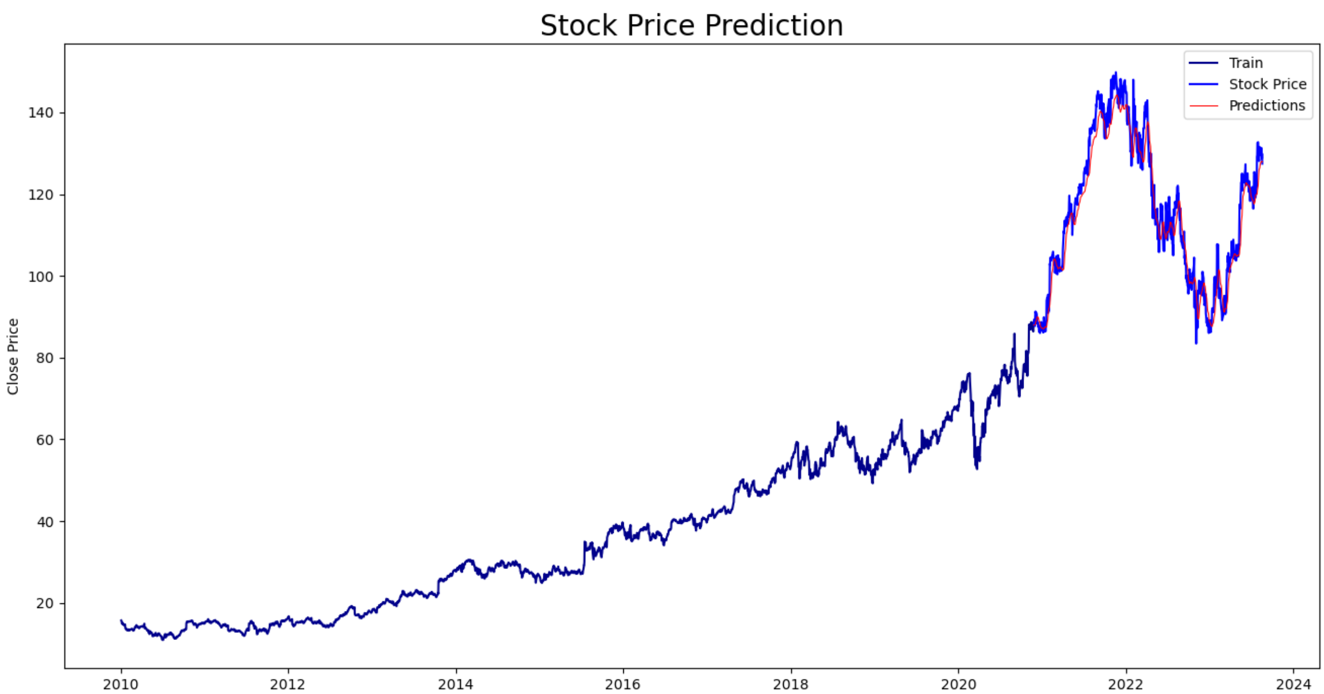
In [147]:
```
plt.figure(figsize=(16,8))
plt.title("Stock Price Prediction During the Validation Period", fontsize = 20)
plt.ylabel("Close Price")
plt.plot(ValidationSet["Close"],linewidth=1,color = "Darkviolet")
plt.plot(ValidationSet["Predictions"],linewidth=1,color = "Red")
plt.legend(["Stock Price","Predictions"])
```

Out[147]:
```
<matplotlib.legend.Legend at 0x2bcf77b77c0>
```




In [148]:
```
plt.figure(figsize=(16,8))
plt.title("Stock Price Prediction", fontsize=20)
plt.ylabel("Close Price" )
plt.plot(TrainingSet["Close"], color = "Darkblue")
plt.plot(ValidationSet["Close"],color = "Blue")
plt.plot(ValidationSet["Predictions"],linewidth=0.75,color = "Red")
plt.legend(["Train","Stock Price","Predictions"])
```

Out[148]:
```
<matplotlib.legend.Legend at 0x2bc888228b0>
```



**Please note that using LSTM with raw stock price data is impractical and using min-max scaler to scale the price data is also unreasonable, since the raw stock price data is neither stationarity nor extrpolation. You'll find out it doesn’t work in real-life (The prediction results seems accurate becuase it's nothing but a delay curve :P).**

**When utilizing LSTM for financial data prediction, forecasting "Log Return" might be a better option. This project is better suited as a programming example for basic machine learning rather than a precise stock price prediction.**