Stock Price Prediction Utilizing LSTM Techniques

A stock price prediction project using Long Short-Term Memory model.

Import Libraries

In [1]:

```
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

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 [2]:

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

Data Exploration

In [3]:

```
Data = yf.download(Company,Date1, Date2)
Data =Data.reset_index()
Data
```

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

Out[3]:

	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 [4]:

```
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 [5]:

```
Data.isnull().sum()
```

Out[5]:

```
Date         0
Open         0
High         0
Low          0
Close        0
Adj Close    0
Volume       0
dtype: int64
```

Data Visualization

Stock Price

In [6]:

```
fig, ax = plt.subplots(figsize=(12,6))
plt.title("Stock Price", fontsize="20")
ax.plot(Data["Date"], Data["Close"], color="Blue")
ax.set_ylabel("Stock Price")
plt.grid()
plt.show()
```

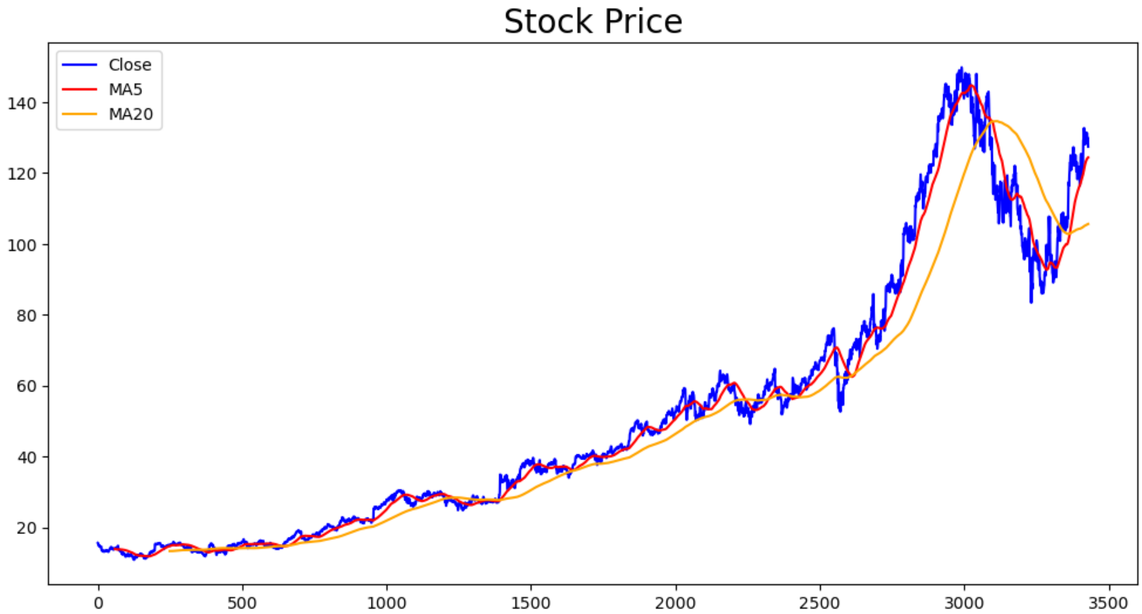
Moving Average

In [7]:

```
MA60=Data.Close.rolling(60).mean()
MA250=Data.Close.rolling(250).mean()
fig, ax = plt.subplots(figsize=(12,6))
plt.title("Stock Price",fontsize= 20)
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[7]:

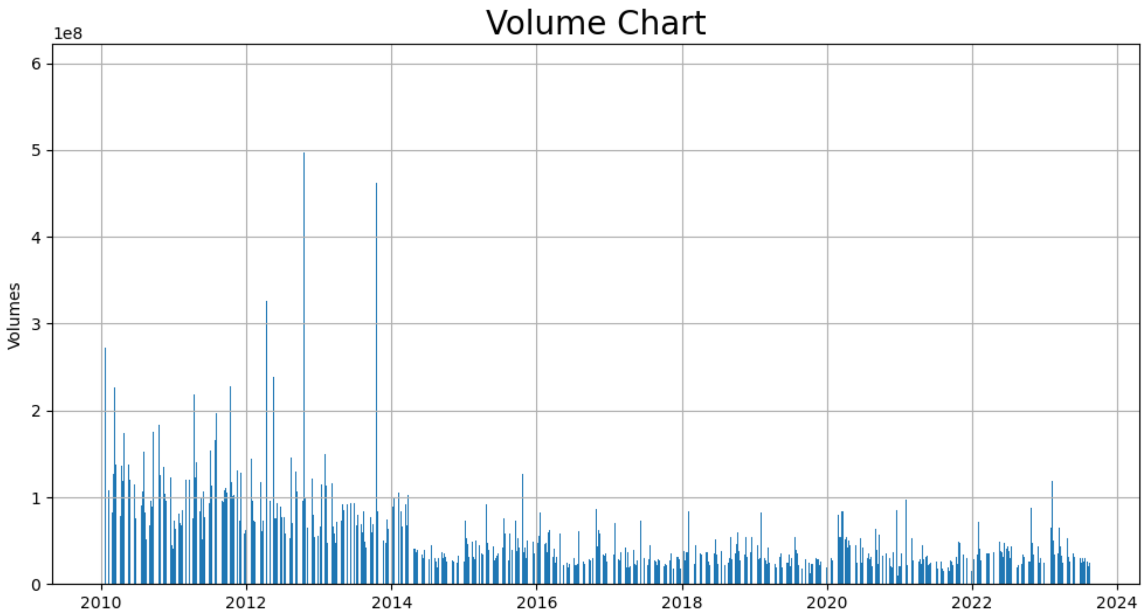
```
<matplotlib.legend.Legend at 0x1c431346b20>
```



Volume

In [8]:

```
fig, ax = plt.subplots(figsize=(12,6))
plt.title("Volume Chart", fontsize="20")
ax.bar(Data["Date"], Data["Volume"])
ax.set_ylabel("Volumes")
plt.grid()
plt.show()
```



Daily Return

In [9]:

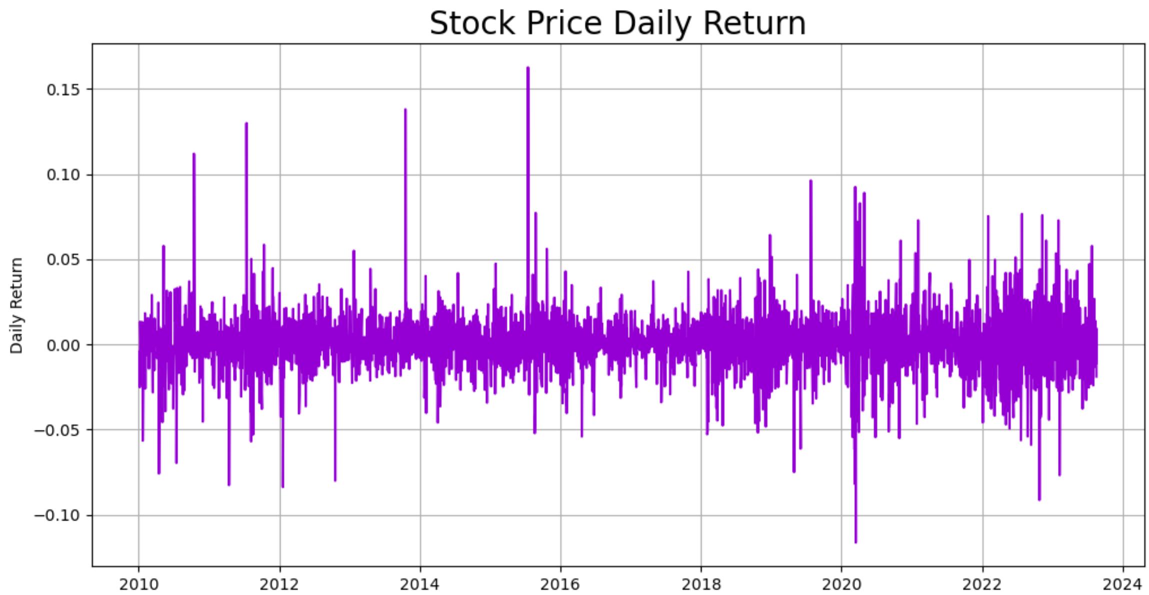
```
Data["Daily Return"] = Data["Close"].pct_change(1)
Data["Daily Return"]
```

Out[9]:

```
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 [10]:

```
fig, ax = plt.subplots(figsize=(12,6))
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()
```

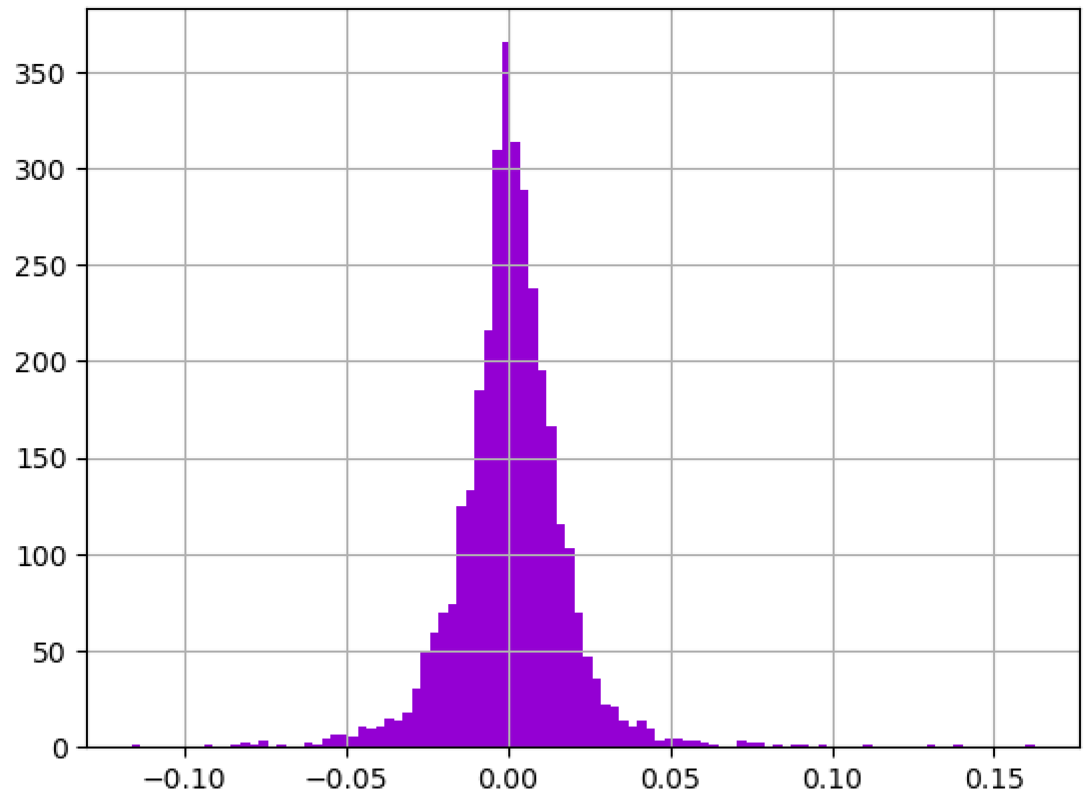


In [11]:

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

Out[11]:

```
<AxesSubplot:>
```



Cumulative Return

In [12]:

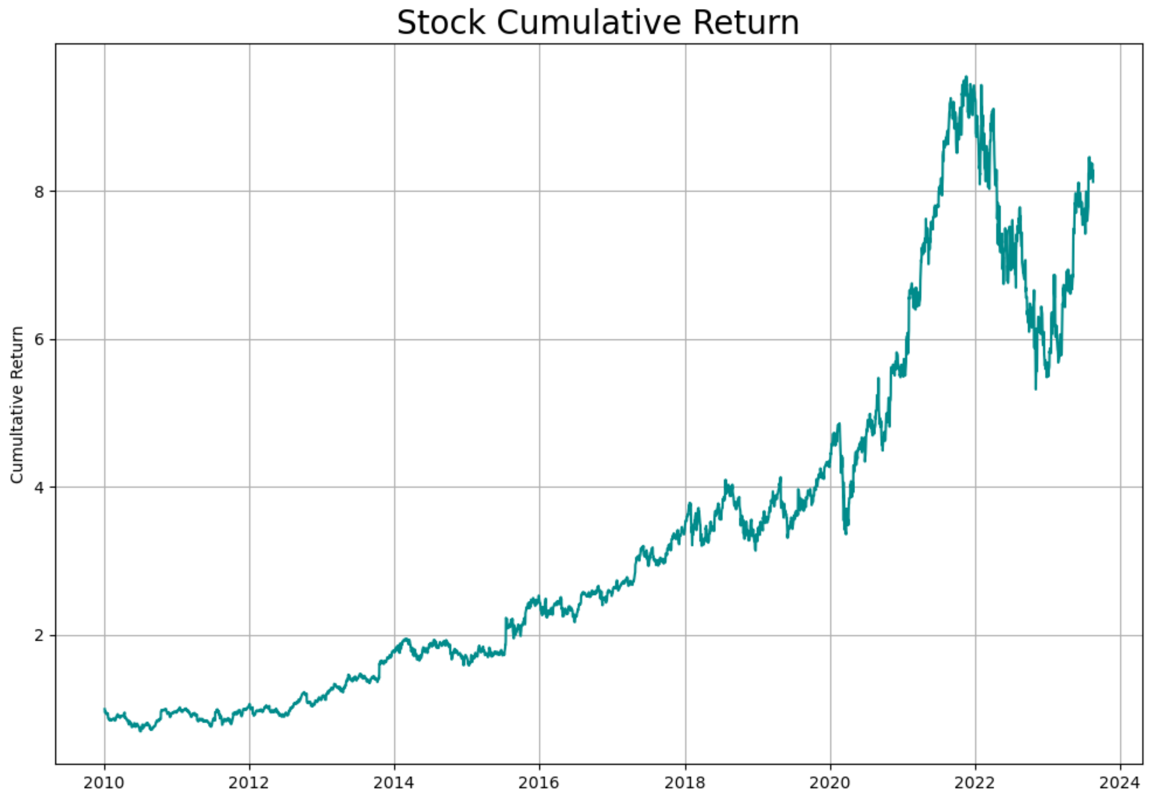
```
Data["Cumulative Return"] = (1+Data["Daily Return"]).cumprod()
Data["Cumulative Return"]
```

Out[12]:

```
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 [13]:

```
#Cumulative Return of the stock during the given period
fig, ax = plt.subplots(figsize=(12,8))
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()
```



Data Preprocessing

Splitting Data into Training and Validation Sets

In [14]:

```
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[14]:

```
2744
```

Scaling Data

In [15]:

```
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[15]:

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

Creating Sequences

In [16]:

```
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, 0.0298929
5,
       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 [17]:

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

Out[17]:

```
(2684, 60, 1)
```

LSTM Model Building, Compiling, and Training

In [18]:

```
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 [==============================] - 7s 38ms/step - loss: 0.0036
Epoch 2/10
84/84 [==============================] - 3s 38ms/step - loss: 4.3697e-04
Epoch 3/10
84/84 [==============================] - 3s 38ms/step - loss: 3.9763e-04
Epoch 4/10
84/84 [==============================] - 3s 40ms/step - loss: 4.2687e-04
Epoch 5/10
84/84 [==============================] - 3s 41ms/step - loss: 3.1408e-04
Epoch 6/10
84/84 [==============================] - 3s 41ms/step - loss: 2.9001e-04
Epoch 7/10
84/84 [==============================] - 3s 40ms/step - loss: 2.9207e-04
Epoch 8/10
84/84 [==============================] - 3s 39ms/step - loss: 2.4339e-04
Epoch 9/10
84/84 [==============================] - 3s 38ms/step - loss: 2.2306e-04
Epoch 10/10
84/84 [==============================] - 3s 38ms/step - loss: 2.3047e-04
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 60, 50)            10400

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

 lstm_1 (LSTM)               (None, 50)                20200

 dropout_1 (Dropout)         (None, 50)                0

 dense (Dense)               (None, 32)                1632

 dense_1 (Dense)             (None, 1)                 33

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

In [19]:

```
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[19]:

```
(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 [20]:

```
Pred = Model.predict(x_test)
Pred = scaler.inverse_transform(Pred)
RMSE = np.sqrt(np.mean(Pred - y_test)**2)
RMSE
```

```
22/22 [==============================] - 1s 14ms/step
```

Out[20]:

```
0.9098903778343089
```

Prediction Results

In [21]:

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

Out[21]:

Date	Close	Predictions
2020-11-25	88.206497	89.604225
2020-11-27	89.350998	89.595543
2020-11-30	87.720001	89.695320
2020-12-01	89.767998	89.730164
2020-12-02	91.248497	89.878944
...	...	...
2023-08-14	131.330002	131.449432
2023-08-15	129.779999	131.544281
2023-08-16	128.699997	131.547073
2023-08-17	129.919998	131.413315
2023-08-18	127.459999	131.300659

686 rows × 2 columns

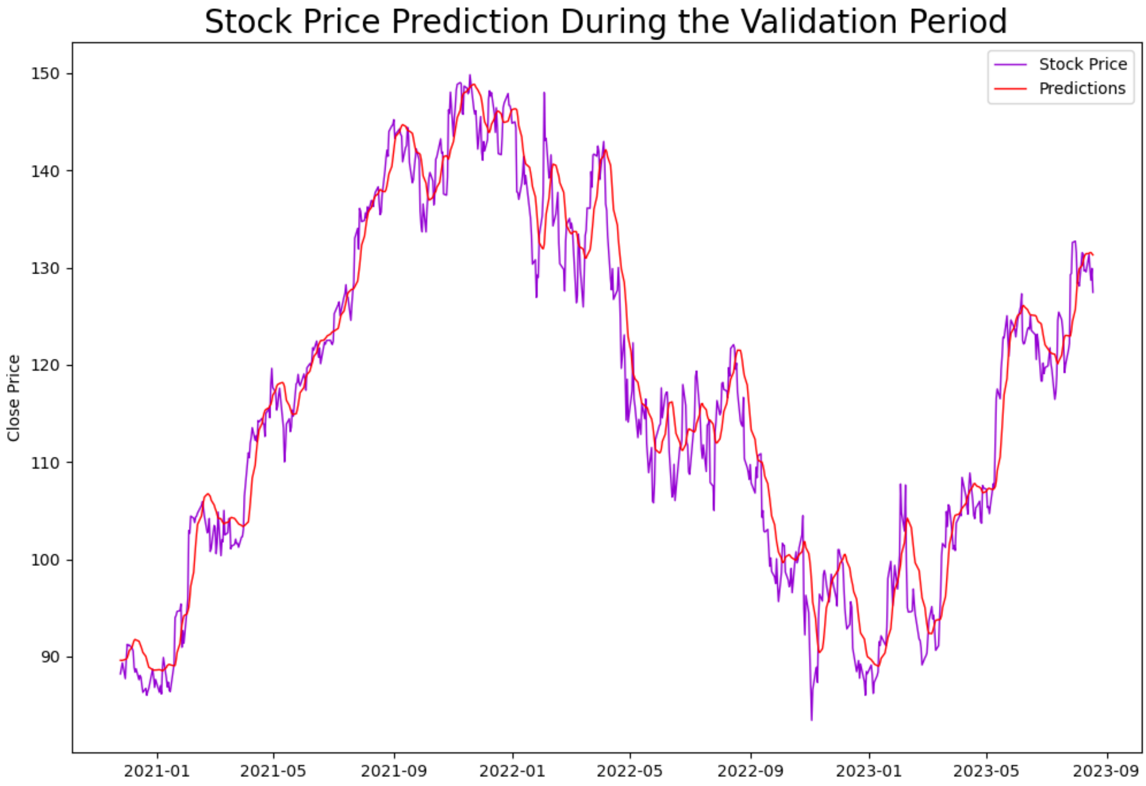
Visualization

In [22]:

```
plt.figure(figsize=(12,8))
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[22]:

```
<matplotlib.legend.Legend at 0x1c434f4c280>
```



In [23]:

```
plt.figure(figsize=(20,8))
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[23]:

```
<matplotlib.legend.Legend at 0x1c4335d2370>
```

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 extrapolation. You'll find out it doesn’t work in real-life (The prediction seems accurate because 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.