In [35]:
```python
import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt

from sklearn.preprocessing import MinMaxScaler, StandardScaler, RobustScaler, MaxAbsScaler
from keras.models import Sequential
from keras.layers import LSTM, Dense, Dropout

import datetime as dt
import time

import pandas as pd
import pandas_ta as ta
import yfinance as yf

from collections import deque
```

In [36]:
```python
tf.__version__
```

Out[36]:
```
'2.10.1'
```

In [37]:
```python
# check that the GPU is being used to accelerate training
len(tf.config.list_physical_devices('GPU')) > 0
```

Out[37]:
```
True
```

In [38]:
```python
STOCKS = pd.read_html('https://en.wikipedia.org/wiki/List_of_S%26P_500_companies')[0]
```

In [39]:
```python
STOCKS
```

Out[39]:

	Symbol	Security	GICS Sector	GICS Sub-Industry	Headquarters Location	Date added	CIK	Founded
0	MMM	3M	Industrials	Industrial Conglomerates	Saint Paul, Minnesota	1957-03-04	66740	1902
1	AOS	A. O. Smith	Industrials	Building Products	Milwaukee, Wisconsin	2017-07-26	91142	1916
2	ABT	Abbott	Health Care	Health Care Equipment	North Chicago, Illinois	1957-03-04	1800	1888
3	ABBV	AbbVie	Health Care	Biotechnology	North Chicago, Illinois	2012-12-31	1551152	2013 (1888)
4	ACN	Accenture	Information Technology	IT Consulting & Other Services	Dublin, Ireland	2011-07-06	1467373	1989
...	...	...	...	...	...	...	...	...
498	YUM	Yum! Brands	Consumer Discretionary	Restaurants	Louisville, Kentucky	1997-10-06	1041061	1997
499	ZBRA	Zebra Technologies	Information Technology	Electronic Equipment & Instruments	Lincolnshire, Illinois	2019-12-23	877212	1969
500	ZBH	Zimmer Biomet	Health Care	Health Care Equipment	Warsaw, Indiana	2001-08-07	1136869	1927
501	ZION	Zions Bancorporation	Financials	Regional Banks	Salt Lake City, Utah	2001-06-22	109380	1873
502	ZTS	Zoetis	Health Care	Pharmaceuticals	Parsippany, New Jersey	2013-06-21	1555280	1952

503 rows × 8 columns

In [7]:
```python
# create a list of unique stock tickers from the data in STOCKS
ST_list = STOCKS['Symbol'].unique().tolist()

cur_date = (dt.date.today() - dt.timedelta(days=8)).strftime('%Y-%m-%d')
init_date = (dt.date.today() - dt.timedelta(days=(365*5)+8)).strftime('%Y-%m-%d')

init_date, cur_date
```

Out[7]:
```
('2019-01-11', '2024-01-10')
```

In [8]:
```python
# get data on all tickers
df = yf.download(tickers = ST_list,
                 start = init_date,
                 end = cur_date).stack()

# label the index columsn
df.index.names = ['date', 'ticker']
df
```

```
[*********************100%%**********************]  503 of 503 completed

2 Failed downloads:
['BF.B']: Exception('%ticker%: No price data found, symbol may be delisted (1d 2019-01-11 -> 2024-01-10)')
['BRK.B']: Exception('%ticker%: No timezone found, symbol may be delisted')
```

Out[8]:

		Adj Close	Close	High	Low	Open	Volume
date	**ticker**						
2019-01-11	**A**	67.906906	70.379997	70.410004	68.940002	69.290001	1210800.0
	AAL	31.293978	31.799999	31.990000	31.100000	31.799999	6900100.0
	AAPL	36.542397	38.072498	38.424999	37.877499	38.220001	108092800.0
	ABBV	69.256439	88.309998	88.309998	87.540001	87.540001	5318100.0
	ABT	63.445335	69.330002	69.360001	68.449997	68.599998	6583000.0
...	**...**	...	...	...	...	...	...
2024-01-09	**YUM**	128.220001	128.220001	128.300003	127.260002	127.860001	968400.0
	ZBH	121.870003	121.870003	124.269997	120.660004	121.629997	2921800.0
	ZBRA	256.440002	256.440002	259.660004	255.000000	255.820007	326600.0
	ZION	44.040001	44.040001	44.590000	43.380001	43.840000	1388200.0
	ZTS	195.940002	195.940002	199.830002	194.050003	195.550003	1983200.0

624351 rows × 6 columns

In [40]:

```python
# BRK.B and BF.B have a '.' but they need a '-' to be correctly called from yfinance
STOCKS['Symbol'] = STOCKS['Symbol'].str.replace('.', '-')
ST_list = STOCKS['Symbol'].unique().tolist()
```

In [41]:

```python
# get data on all tickers
df = yf.download(tickers = ST_list,
                 start = init_date,
                 end = cur_date).stack()

# label the index columsn
df.index.names = ['date', 'ticker']
df
```

```
[*********************100%%**********************]  503 of 503 completed
```

Out[41]:

		Adj Close	Close	High	Low	Open	Volume
date	**ticker**						
2019-01-11	**A**	67.906891	70.379997	70.410004	68.940002	69.290001	1210800.0
	AAL	31.293976	31.799999	31.990000	31.100000	31.799999	6900100.0
	AAPL	36.542393	38.072498	38.424999	37.877499	38.220001	108092800.0
	ABBV	69.256447	88.309998	88.309998	87.540001	87.540001	5318100.0
	ABT	63.445354	69.330002	69.360001	68.449997	68.599998	6583000.0
...	**...**	...	...	...	...	...	...
2024-01-09	**YUM**	128.220001	128.220001	128.300003	127.260002	127.860001	968400.0
	ZBH	121.870003	121.870003	124.269997	120.660004	121.629997	2921800.0
	ZBRA	256.440002	256.440002	259.660004	255.000000	255.820007	326600.0
	ZION	44.040001	44.040001	44.590000	43.380001	43.840000	1388200.0
	ZTS	195.496597	195.940002	199.830002	194.050003	195.550003	1983200.0

626865 rows × 6 columns

In [42]:

```python
# calculate RSI
df['Rsi'] = df.groupby(level=1)['Adj Close'].transform(ta.rsi, length=15)

#calculate MACD
def compute_macd(closing_prices):
    macd_values = ta.macd(close=closing_prices, length=15).iloc[:,0]
    return(macd_values - macd_values.mean())/macd_values.std()
df['Macd'] = df.groupby(level=1, group_keys=False)['Adj Close'].transform(compute_macd)

# Calculate ATR
def compute_atr(price_data):
    avg_true_range = ta.atr(
        high = price_data['High'],
        low = price_data['Low'],
        close = price_data['Close'],
        length = 14)
    return (avg_true_range - avg_true_range.mean()) / avg_true_range.std()
df['Atr'] = df.groupby(level=1, group_keys=False).apply(compute_atr)
```

In [43]:
```
df
```

Out[43]:

date	ticker	Adj Close	Close	High	Low	Open	Volume	Rsi	Macd	Atr
2019-01-11	**A**	67.906891	70.379997	70.410004	68.940002	69.290001	1210800.0	NaN	NaN	NaN
	AAL	31.293976	31.799999	31.990000	31.100000	31.799999	6900100.0	NaN	NaN	NaN
	AAPL	36.542393	38.072498	38.424999	37.877499	38.220001	108092800.0	NaN	NaN	NaN
	ABBV	69.256447	88.309998	88.309998	87.540001	87.540001	5318100.0	NaN	NaN	NaN
	ABT	63.445354	69.330002	69.360001	68.449997	68.599998	6583000.0	NaN	NaN	NaN
...	**...**	...	...	...	...	...	...	...	...	...
2024-01-09	**YUM**	128.220001	128.220001	128.300003	127.260002	127.860001	968400.0	49.700200	0.181875	-0.649722
	ZBH	121.870003	121.870003	124.269997	120.660004	121.629997	2921800.0	68.057421	0.651897	-1.167871
	ZBRA	256.440002	256.440002	259.660004	255.000000	255.820007	326600.0	52.530807	0.534541	-0.806302
	ZION	44.040001	44.040001	44.590000	43.380001	43.840000	1388200.0	59.810270	1.275825	-0.164497
	ZTS	195.496597	195.940002	199.830002	194.050003	195.550003	1983200.0	62.085004	1.042856	-0.120530

626865 rows × 9 columns

In [44]:
```
# make a copy of df to freely manipulate
df_copy = df.copy()

# pick the stock to analyse
STOCK = 'PG'
df_individual = df_copy.loc[(df_copy.index.get_level_values('ticker') == STOCK)]
df_individual
```

Out[44]:

date	ticker	Adj Close	Close	High	Low	Open	Volume	Rsi	Macd	Atr
2019-01-11	**PG**	80.352509	91.769997	91.980003	91.110001	91.669998	7166600.0	NaN	NaN	NaN
2019-01-14	**PG**	79.809669	91.150002	91.910004	90.849998	91.500000	7952000.0	NaN	NaN	NaN
2019-01-15	**PG**	80.562660	92.010002	92.610001	91.139999	91.150002	7834500.0	NaN	NaN	NaN
2019-01-16	**PG**	80.002289	91.370003	92.150002	90.989998	91.739998	7964500.0	NaN	NaN	NaN
2019-01-17	**PG**	79.990822	90.639999	91.559998	90.349998	90.709999	8044500.0	NaN	NaN	NaN
...	**...**	...	...	...	...	...	...	...	...	...
2024-01-03	**PG**	146.912170	147.839996	149.199997	147.179993	148.339996	7697500.0	51.634256	-0.593247	-0.413326
2024-01-04	**PG**	147.717087	148.649994	149.270004	147.770004	148.050003	7067400.0	53.993175	-0.463807	-0.447110
2024-01-05	**PG**	146.494812	147.419998	148.869995	146.550003	148.720001	5294200.0	50.023706	-0.423339	-0.410806
2024-01-08	**PG**	147.756851	148.690002	148.919998	147.649994	147.910004	8255300.0	53.782650	-0.323971	-0.444771
2024-01-09	**PG**	148.363022	149.300003	149.399994	148.050003	148.570007	9786800.0	55.504911	-0.213665	-0.488689

1257 rows × 9 columns

In [45]:
```
# remove index labels to later remove ticker
df_individual = df_individual.reset_index()

# remove ticker column
df_individual = df_individual.drop('ticker', axis=1)
df_individual
```

Out[45]:

	date	Adj Close	Close	High	Low	Open	Volume	Rsi	Macd	Atr
0	2019-01-11	80.352509	91.769997	91.980003	91.110001	91.669998	7166600.0	NaN	NaN	NaN
1	2019-01-14	79.809669	91.150002	91.910004	90.849998	91.500000	7952000.0	NaN	NaN	NaN
2	2019-01-15	80.562660	92.010002	92.610001	91.139999	91.150002	7834500.0	NaN	NaN	NaN
3	2019-01-16	80.002289	91.370003	92.150002	90.989998	91.739998	7964500.0	NaN	NaN	NaN
4	2019-01-17	79.990822	90.639999	91.559998	90.349998	90.709999	8044500.0	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...
1252	2024-01-03	146.912170	147.839996	149.199997	147.179993	148.339996	7697500.0	51.634256	-0.593247	-0.413326
1253	2024-01-04	147.717087	148.649994	149.270004	147.770004	148.050003	7067400.0	53.993175	-0.463807	-0.447110
1254	2024-01-05	146.494812	147.419998	148.869995	146.550003	148.720001	5294200.0	50.023706	-0.423339	-0.410806
1255	2024-01-08	147.756851	148.690002	148.919998	147.649994	147.910004	8255300.0	53.782650	-0.323971	-0.444771
1256	2024-01-09	148.363022	149.300003	149.399994	148.050003	148.570007	9786800.0	55.504911	-0.213665	-0.488689

1257 rows × 10 columns

In [46]:
```
# calculate an intra day average from price highs and lows
df_individual['Average'] = (df_individual['High'] + df_individual['Low'])/2
df_individual
```

Out[46]:

	date	Adj Close	Close	High	Low	Open	Volume	Rsi	Macd	Atr	Average
0	2019-01-11	80.352509	91.769997	91.980003	91.110001	91.669998	7166600.0	NaN	NaN	NaN	91.545002
1	2019-01-14	79.809669	91.150002	91.910004	90.849998	91.500000	7952000.0	NaN	NaN	NaN	91.380001
2	2019-01-15	80.562660	92.010002	92.610001	91.139999	91.150002	7834500.0	NaN	NaN	NaN	91.875000
3	2019-01-16	80.002289	91.370003	92.150002	90.989998	91.739998	7964500.0	NaN	NaN	NaN	91.570000
4	2019-01-17	79.990822	90.639999	91.559998	90.349998	90.709999	8044500.0	NaN	NaN	NaN	90.954998
...	...	...	...	...	...	...	...	...	...	...	...
1252	2024-01-03	146.912170	147.839996	149.199997	147.179993	148.339996	7697500.0	51.634256	-0.593247	-0.413326	148.189995
1253	2024-01-04	147.717087	148.649994	149.270004	147.770004	148.050003	7067400.0	53.993175	-0.463807	-0.447110	148.520004
1254	2024-01-05	146.494812	147.419998	148.869995	146.550003	148.720001	5294200.0	50.023706	-0.423339	-0.410806	147.709999
1255	2024-01-08	147.756851	148.690002	148.919998	147.649994	147.910004	8255300.0	53.782650	-0.323971	-0.444771	148.284996
1256	2024-01-09	148.363022	149.300003	149.399994	148.050003	148.570007	9786800.0	55.504911	-0.213665	-0.488689	148.724998

1257 rows × 11 columns

In [47]:
```
# set date as an index again
df_individual = df_individual.set_index(['date'])
df_individual
```

Out[47]:

	Adj Close	Close	High	Low	Open	Volume	Rsi	Macd	Atr	Average
date										
2019-01-11	80.352509	91.769997	91.980003	91.110001	91.669998	7166600.0	NaN	NaN	NaN	91.545002
2019-01-14	79.809669	91.150002	91.910004	90.849998	91.500000	7952000.0	NaN	NaN	NaN	91.380001
2019-01-15	80.562660	92.010002	92.610001	91.139999	91.150002	7834500.0	NaN	NaN	NaN	91.875000
2019-01-16	80.002289	91.370003	92.150002	90.989998	91.739998	7964500.0	NaN	NaN	NaN	91.570000
2019-01-17	79.990822	90.639999	91.559998	90.349998	90.709999	8044500.0	NaN	NaN	NaN	90.954998
...	...	...	...	...	...	...	...	...	...	...
2024-01-03	146.912170	147.839996	149.199997	147.179993	148.339996	7697500.0	51.634256	-0.593247	-0.413326	148.189995
2024-01-04	147.717087	148.649994	149.270004	147.770004	148.050003	7067400.0	53.993175	-0.463807	-0.447110	148.520004
2024-01-05	146.494812	147.419998	148.869995	146.550003	148.720001	5294200.0	50.023706	-0.423339	-0.410806	147.709999
2024-01-08	147.756851	148.690002	148.919998	147.649994	147.910004	8255300.0	53.782650	-0.323971	-0.444771	148.284996
2024-01-09	148.363022	149.300003	149.399994	148.050003	148.570007	9786800.0	55.504911	-0.213665	-0.488689	148.724998

1257 rows × 10 columns

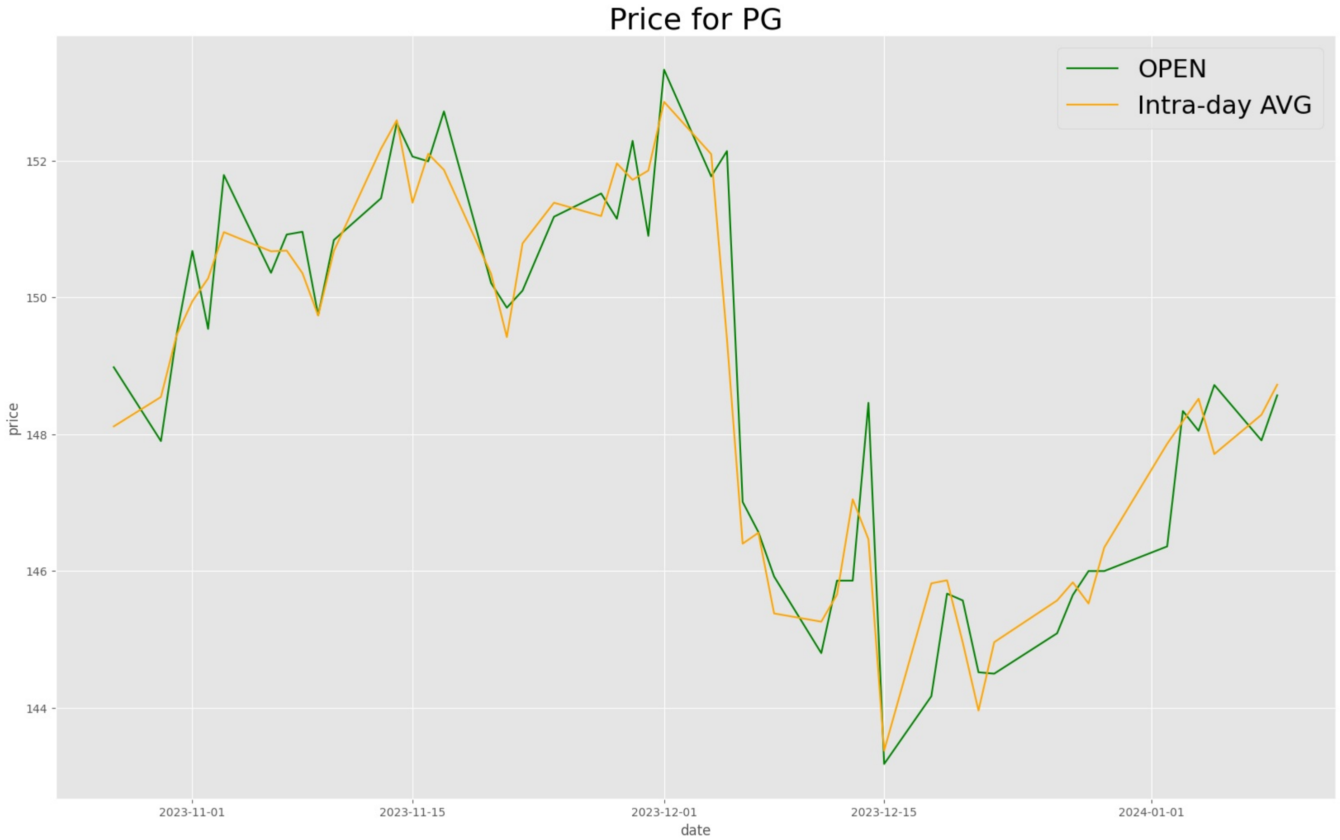
In [48]:
```
# check entries
total_rows = len(df_individual)
total_rows
```

Out[48]: 1257

In [49]:
```
# Plot the price on open to compare against the intra-day average
```

```
DAYS = 50

plt.style.use(style='ggplot')
plt.figure(figsize=(20,12))
plt.title(f'Price for {STOCK}', fontsize=26)
plt.plot(df_individual['Open'][-DAYS:], color='g', label='OPEN')
plt.plot(df_individual['Average'][-DAYS:], color='orange', label='Intra-day AVG')
plt.xlabel('date')
plt.ylabel('price')
plt.legend(fontsize=22)
plt.show()
```



TIME SERIES ANALYSIS ON PRICE ALONE

In [50]:

```
# pick Scaler (MinMaxScaler, StandardScaler, RobustScaler, MaxAbsScaler)
scaler = MinMaxScaler()
# change the transformed column from CLose to Average to check on the middle ground between daily lows and high
df_individual['Scaled'] = scaler.fit_transform(np.expand_dims(df_individual['Close'].values, axis=1))
df_individual
```

Out[50]:

date	Adj Close	Close	High	Low	Open	Volume	Rsi	Macd	Atr	Average	Scaled
2019-01-11	80.352509	91.769997	91.980003	91.110001	91.669998	7166600.0	NaN	NaN	NaN	91.545002	0.018029
2019-01-14	79.809669	91.150002	91.910004	90.849998	91.500000	7952000.0	NaN	NaN	NaN	91.380001	0.009624
2019-01-15	80.562660	92.010002	92.610001	91.139999	91.150002	7834500.0	NaN	NaN	NaN	91.875000	0.021282
2019-01-16	80.002289	91.370003	92.150002	90.989998	91.739998	7964500.0	NaN	NaN	NaN	91.570000	0.012607
2019-01-17	79.990822	90.639999	91.559998	90.349998	90.709999	8044500.0	NaN	NaN	NaN	90.954998	0.002711
...	...	...	...	...	...	...	...	...	...	...	...
2024-01-03	146.912170	147.839996	149.199997	147.179993	148.339996	7697500.0	51.634256	-0.593247	-0.413326	148.189995	0.778094
2024-01-04	147.717087	148.649994	149.270004	147.770004	148.050003	7067400.0	53.993175	-0.463807	-0.447110	148.520004	0.789074
2024-01-05	146.494812	147.419998	148.869995	146.550003	148.720001	5294200.0	50.023706	-0.423339	-0.410806	147.709999	0.772401
2024-01-08	147.756851	148.690002	148.919998	147.649994	147.910004	8255300.0	53.782650	-0.323971	-0.444771	148.284996	0.789616
2024-01-09	148.363022	149.300003	149.399994	148.050003	148.570007	9786800.0	55.504911	-0.213665	-0.488689	148.724998	0.797885

1257 rows × 11 columns

In [51]:
```
df_individual['Date'] = df_individual.index
df_individual
```

Out[51]:

	Adj Close	Close	High	Low	Open	Volume	Rsi	Macd	Atr	Average	Scaled	Date
date												
2019-01-11	80.352509	91.769997	91.980003	91.110001	91.669998	7166600.0	NaN	NaN	NaN	91.545002	0.018029	2019-01-11
2019-01-14	79.809669	91.150002	91.910004	90.849998	91.500000	7952000.0	NaN	NaN	NaN	91.380001	0.009624	2019-01-14
2019-01-15	80.562660	92.010002	92.610001	91.139999	91.150002	7834500.0	NaN	NaN	NaN	91.875000	0.021282	2019-01-15
2019-01-16	80.002289	91.370003	92.150002	90.989998	91.739998	7964500.0	NaN	NaN	NaN	91.570000	0.012607	2019-01-16
2019-01-17	79.990822	90.639999	91.559998	90.349998	90.709999	8044500.0	NaN	NaN	NaN	90.954998	0.002711	2019-01-17
...	...	...	...	...	...	...	...	...	...	...	...	...
2024-01-03	146.912170	147.839996	149.199997	147.179993	148.339996	7697500.0	51.634256	-0.593247	-0.413326	148.189995	0.778094	2024-01-03
2024-01-04	147.717087	148.649994	149.270004	147.770004	148.050003	7067400.0	53.993175	-0.463807	-0.447110	148.520004	0.789074	2024-01-04
2024-01-05	146.494812	147.419998	148.869995	146.550003	148.720001	5294200.0	50.023706	-0.423339	-0.410806	147.709999	0.772401	2024-01-05
2024-01-08	147.756851	148.690002	148.919998	147.649994	147.910004	8255300.0	53.782650	-0.323971	-0.444771	148.284996	0.789616	2024-01-08
2024-01-09	148.363022	149.300003	149.399994	148.050003	148.570007	9786800.0	55.504911	-0.213665	-0.488689	148.724998	0.797885	2024-01-09

1257 rows × 12 columns

In [22]:
```
# Set up number of days for window size
N_days = 15
# set the sequence of days to predict for
STEPS = [1,2,3,4,5]
```

In [23]:
```
def prepare_data_for_prediction(initial_data, prediction_window_size):
    # Avoid modifying the original DataFrame
    data = initial_data.copy()

    # Efficiently create 'Future_scaled' column using vectorized operations
    data["Future_scaled"] = data["Scaled"].shift(-prediction_window_size)

    # Pre-allocate lst_seq with correct shape and dtype for efficiency
    lst_seq = np.empty((prediction_window_size + N_days, 1), dtype=np.float32)
    lst_seq[-prediction_window_size:] = data[["Scaled"]].tail(prediction_window_size).values

    # Drop null values efficiently
    data.dropna(inplace=True)

    sequences = deque(maxlen=N_days)
    input_sequences = np.zeros((len(data) - N_days, N_days, 1), dtype=np.float32)  # Pre-allocate with correct
    target_values = np.empty_like(data["Future_scaled"].iloc[N_days:])  # Pre-allocate with correct shape

    for i, (scaled_entries, future_value) in enumerate(zip(data[["Scaled"]].values, data["Future_scaled"].value
        sequences.append(scaled_entries)

        if len(sequences) == N_days:
            input_sequences[i - N_days] = np.array(sequences)
            target_values[i - N_days] = future_value

    # Fill remaining values in lst_seq efficiently
    lst_seq[:N_days] = np.array([s[0] for s in sequences])

    return data, lst_seq, input_sequences, target_values
```

In [24]:
```
temp = prepare_data_for_prediction(df_individual,1)
temp
```

Out[24]:
```
(             Adj Close       Close        High         Low        Open   \
 date
 2019-02-19   88.799568   99.989998  100.000000   98.470001   98.559998
 2019-02-20   88.169037   99.279999  100.220001   98.940002   99.779999
 2019-02-21   88.613075   99.779999   99.860001   98.589996   99.099998
 2019-02-22   89.030472  100.250000  100.400002   99.400002   99.690002
 2019-02-25   88.426582   99.570000  100.449997   99.330002  100.360001
 ...               ...         ...         ...         ...         ...
 2024-01-02  148.740005  148.740005  149.410004  146.309998  146.360001
 2024-01-03  147.839996  147.839996  149.199997  147.179993  148.339996
 2024-01-04  148.649994  148.649994  149.270004  147.770004  148.050003
 2024-01-05  147.419998  147.419998  148.869995  146.550003  148.720001
```

```
2024-01-08  148.690002  148.690002  148.919998  147.649994  147.910004

                Volume        Rsi      Macd       Atr     Average    Scaled  \
date
2019-02-19  10098200.0  74.053542  1.293404 -0.989746   99.235001  0.129456
2019-02-20   8947400.0  68.523198  1.242998 -1.002349   99.580002  0.119832
2019-02-21   7444800.0  70.202260  1.209535 -1.014714   99.224998  0.126610
2019-02-22   7925400.0  71.721492  1.188353 -1.051415   99.900002  0.132981
2019-02-25   7436100.0  66.468256  1.124308 -1.073566   99.889999  0.123763
...                ...        ...       ...       ...         ...       ...
2024-01-02   7238400.0  54.534001 -0.699941 -0.423160  147.860001  0.790294
2024-01-03   7697500.0  51.634274 -0.593247 -0.413326  148.189995  0.778094
2024-01-04   7067400.0  53.993187 -0.463806 -0.447110  148.520004  0.789074
2024-01-05   5294200.0  50.023710 -0.423338 -0.410806  147.709999  0.772401
2024-01-08   8255300.0  53.782640 -0.323971 -0.444771  148.284996  0.789616

                 Date  Future_scaled
date
2019-02-19 2019-02-19       0.119832
2019-02-20 2019-02-20       0.126610
2019-02-21 2019-02-21       0.132981
2019-02-22 2019-02-22       0.123763
2019-02-25 2019-02-25       0.127287
...               ...            ...
2024-01-02 2024-01-02       0.778094
2024-01-03 2024-01-03       0.789074
2024-01-04 2024-01-04       0.772401
2024-01-05 2024-01-05       0.789616
2024-01-08 2024-01-08       0.797885

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       [0.75545603],
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       [0.7295647 ],
       [0.7433915 ],
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       [0.7539649 ],
       [0.7494915 ],
       [0.7604716 ],
       [0.7902942 ],
       [0.77809393],
       [0.789074  ],
       [0.7724006 ],
       [0.78961635],
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        ...,
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       [[0.11983185340807534, Timestamp('2019-02-20 00:00:00')],
        [0.12660967597879536, Timestamp('2019-02-21 00:00:00')],
        [0.13298084574269042, Timestamp('2019-02-22 00:00:00')],
        ...,
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       [[0.12660967597879536, Timestamp('2019-02-21 00:00:00')],
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        [0.1455875998610845, Timestamp('2019-03-13 00:00:00')]],

       ...,

       [[0.7881252002496177, Timestamp('2023-12-13 00:00:00')],
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       [[0.7349870961163001, Timestamp('2023-12-14 00:00:00')],
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        [0.7554560458164921, Timestamp('2023-12-18 00:00:00')],
        ...,
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        [0.7890739878512991, Timestamp('2024-01-04 00:00:00')],
        [0.7724006022432921, Timestamp('2024-01-05 00:00:00')]],
```

```
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        [0.7554560458164921, Timestamp('2023-12-18 00:00:00')],
        [0.7554560458164921, Timestamp('2023-12-19 00:00:00')],
        ...,
        [0.7890739878512991, Timestamp('2024-01-04 00:00:00')],
        [0.7724006022432921, Timestamp('2024-01-05 00:00:00')],
        [0.7896163294888852, Timestamp('2024-01-08 00:00:00')]]],
      dtype=object),
 array([0.13026976, 0.1455876 , 0.14748538, ..., 0.7724006 , 0.78961633,
       0.79788528]))
```

In [25]:

```
def build_and_train_time_series_model(input_sequences, target_values):

    model = Sequential()
    model.add(LSTM(85, return_sequences=True, input_shape=(N_days, len(['Scaled']))))
    model.add(Dropout(0.2))
    model.add(LSTM(170, return_sequences=False))
    model.add(Dropout(0.35))
    model.add(LSTM(40, return_sequences=False))
    model.add(Dropout(0.3)
    model.add(Dense(35))
    model.add(Dense(20))
    model.add(Dense(1))

    '''
    model = tf.keras.models.Sequential([
        tf.keras.layers.LSTM(85, return_sequences=True, input_shape=(N_days, len(['Scaled']))),
        tf.keras.layers.Dropout(0.2),
        tf.keras.layers.LSTM(170, return_sequences=False),
        tf.keras.layers.Dropout(0.35),
        tf.keras.layers.LSTM(0, return_sequences=False),
        tf.keras.layers.Dropout(0.35),
        # ReLU activation for dense layers
        tf.keras.layers.Dense(35, activation='relu'),
        tf.keras.layers.Dense(20, activation='relu'),
         # Single output for prediction
        tf.keras.layers.Dense(1)
    ])
    '''

    model.compile(loss='mean_squared_error', optimizer='adam')
    model.fit(input_sequences, target_values, batch_size=8, epochs=120, verbose=2)
    model.summary()

    return model
```

In [52]:

```
all_predictions = []

# Pre-allocate arrays for efficiency
input_sequences = np.empty((0, N_days, 1), dtype=np.float32)  # Shape for all prediction steps
target_values = np.empty(0, dtype=np.float32)  # Shape for all prediction steps

for prediction_horizon in STEPS:
    data, lst_seq, step_input_sequences, step_target_values = prepare_data_for_prediction(df_individual, predic

    # Concatenate data for all prediction steps (avoiding redundant model building)
    input_sequences = np.concatenate((input_sequences, step_input_sequences), axis=0)
    target_values = np.concatenate((target_values, step_target_values), axis=0)

# Build and train the model once for all prediction steps
model = build_and_train_time_series_model(input_sequences, target_values)

for prediction_horizon in STEPS:
    # Get relevant recent data for the current prediction step
    recent_data = lst_seq[-N_days:]
    prediction_input = np.expand_dims(recent_data, axis=0)

    predicted_value = model.predict(prediction_input)
    predicted_price = scaler.inverse_transform(predicted_value)[0][0]
    all_predictions.append(round(float(predicted_price), 2))
```

```
(1217, 15, 1)
(1217,)
Epoch 1/120
153/153 - 3s - loss: 0.0171 - 3s/epoch - 22ms/step
Epoch 2/120
153/153 - 1s - loss: 0.0042 - 934ms/epoch - 6ms/step
Epoch 3/120
153/153 - 1s - loss: 0.0037 - 927ms/epoch - 6ms/step
Epoch 4/120
153/153 - 1s - loss: 0.0028 - 921ms/epoch - 6ms/step
Epoch 5/120
153/153 - 1s - loss: 0.0024 - 924ms/epoch - 6ms/step
Epoch 6/120
153/153 - 1s - loss: 0.0021 - 929ms/epoch - 6ms/step
Epoch 7/120
153/153 - 1s - loss: 0.0020 - 914ms/epoch - 6ms/step
Epoch 8/120
```

```
153/153 - 1s - loss: 0.0020 - 936ms/epoch - 6ms/step
Epoch 9/120
153/153 - 1s - loss: 0.0018 - 1s/epoch - 7ms/step
Epoch 10/120
153/153 - 1s - loss: 0.0019 - 978ms/epoch - 6ms/step
Epoch 11/120
153/153 - 1s - loss: 0.0017 - 982ms/epoch - 6ms/step
Epoch 12/120
153/153 - 1s - loss: 0.0018 - 976ms/epoch - 6ms/step
Epoch 13/120
153/153 - 1s - loss: 0.0017 - 948ms/epoch - 6ms/step
Epoch 14/120
153/153 - 1s - loss: 0.0016 - 923ms/epoch - 6ms/step
Epoch 15/120
153/153 - 1s - loss: 0.0018 - 941ms/epoch - 6ms/step
Epoch 16/120
153/153 - 1s - loss: 0.0016 - 931ms/epoch - 6ms/step
Epoch 17/120
153/153 - 1s - loss: 0.0015 - 928ms/epoch - 6ms/step
Epoch 18/120
153/153 - 1s - loss: 0.0015 - 959ms/epoch - 6ms/step
Epoch 19/120
153/153 - 1s - loss: 0.0014 - 1s/epoch - 7ms/step
Epoch 20/120
153/153 - 1s - loss: 0.0015 - 962ms/epoch - 6ms/step
Epoch 21/120
153/153 - 1s - loss: 0.0018 - 976ms/epoch - 6ms/step
Epoch 22/120
153/153 - 1s - loss: 0.0014 - 949ms/epoch - 6ms/step
Epoch 23/120
153/153 - 1s - loss: 0.0015 - 963ms/epoch - 6ms/step
Epoch 24/120
153/153 - 1s - loss: 0.0014 - 939ms/epoch - 6ms/step
Epoch 25/120
153/153 - 1s - loss: 0.0013 - 977ms/epoch - 6ms/step
Epoch 26/120
153/153 - 1s - loss: 0.0015 - 992ms/epoch - 6ms/step
Epoch 27/120
153/153 - 1s - loss: 0.0013 - 953ms/epoch - 6ms/step
Epoch 28/120
153/153 - 1s - loss: 0.0014 - 933ms/epoch - 6ms/step
Epoch 29/120
153/153 - 1s - loss: 0.0012 - 946ms/epoch - 6ms/step
Epoch 30/120
153/153 - 1s - loss: 0.0012 - 988ms/epoch - 6ms/step
Epoch 31/120
153/153 - 1s - loss: 0.0013 - 1s/epoch - 7ms/step
Epoch 32/120
153/153 - 1s - loss: 0.0013 - 978ms/epoch - 6ms/step
Epoch 33/120
153/153 - 1s - loss: 0.0013 - 1s/epoch - 7ms/step
Epoch 34/120
153/153 - 1s - loss: 0.0013 - 965ms/epoch - 6ms/step
Epoch 35/120
153/153 - 1s - loss: 0.0012 - 1s/epoch - 7ms/step
Epoch 36/120
153/153 - 1s - loss: 0.0014 - 982ms/epoch - 6ms/step
Epoch 37/120
153/153 - 1s - loss: 0.0015 - 1s/epoch - 7ms/step
Epoch 38/120
153/153 - 1s - loss: 0.0013 - 1s/epoch - 7ms/step
Epoch 39/120
153/153 - 1s - loss: 0.0014 - 1s/epoch - 7ms/step
Epoch 40/120
153/153 - 1s - loss: 0.0014 - 986ms/epoch - 6ms/step
Epoch 41/120
153/153 - 1s - loss: 0.0011 - 934ms/epoch - 6ms/step
Epoch 42/120
153/153 - 1s - loss: 0.0012 - 942ms/epoch - 6ms/step
Epoch 43/120
153/153 - 1s - loss: 0.0012 - 925ms/epoch - 6ms/step
Epoch 44/120
153/153 - 1s - loss: 0.0013 - 938ms/epoch - 6ms/step
Epoch 45/120
153/153 - 1s - loss: 0.0012 - 981ms/epoch - 6ms/step
Epoch 46/120
153/153 - 1s - loss: 0.0013 - 979ms/epoch - 6ms/step
Epoch 47/120
153/153 - 1s - loss: 0.0014 - 949ms/epoch - 6ms/step
Epoch 48/120
153/153 - 1s - loss: 0.0012 - 948ms/epoch - 6ms/step
Epoch 49/120
153/153 - 1s - loss: 0.0010 - 966ms/epoch - 6ms/step
Epoch 50/120
153/153 - 1s - loss: 0.0012 - 945ms/epoch - 6ms/step
Epoch 51/120
153/153 - 1s - loss: 0.0016 - 947ms/epoch - 6ms/step
Epoch 52/120
153/153 - 1s - loss: 0.0012 - 956ms/epoch - 6ms/step
```

```
Epoch 53/120
153/153 - 1s - loss: 0.0011 - 943ms/epoch - 6ms/step
Epoch 54/120
153/153 - 1s - loss: 0.0012 - 939ms/epoch - 6ms/step
Epoch 55/120
153/153 - 1s - loss: 0.0010 - 924ms/epoch - 6ms/step
Epoch 56/120
153/153 - 1s - loss: 0.0012 - 910ms/epoch - 6ms/step
Epoch 57/120
153/153 - 1s - loss: 0.0011 - 909ms/epoch - 6ms/step
Epoch 58/120
153/153 - 1s - loss: 0.0012 - 928ms/epoch - 6ms/step
Epoch 59/120
153/153 - 1s - loss: 0.0011 - 941ms/epoch - 6ms/step
Epoch 60/120
153/153 - 1s - loss: 0.0012 - 939ms/epoch - 6ms/step
Epoch 61/120
153/153 - 1s - loss: 0.0013 - 918ms/epoch - 6ms/step
Epoch 62/120
153/153 - 1s - loss: 0.0012 - 910ms/epoch - 6ms/step
Epoch 63/120
153/153 - 1s - loss: 0.0012 - 901ms/epoch - 6ms/step
Epoch 64/120
153/153 - 1s - loss: 0.0010 - 903ms/epoch - 6ms/step
Epoch 65/120
153/153 - 1s - loss: 0.0011 - 907ms/epoch - 6ms/step
Epoch 66/120
153/153 - 1s - loss: 0.0011 - 937ms/epoch - 6ms/step
Epoch 67/120
153/153 - 1s - loss: 0.0011 - 916ms/epoch - 6ms/step
Epoch 68/120
153/153 - 1s - loss: 0.0011 - 911ms/epoch - 6ms/step
Epoch 69/120
153/153 - 1s - loss: 0.0011 - 912ms/epoch - 6ms/step
Epoch 70/120
153/153 - 1s - loss: 0.0011 - 908ms/epoch - 6ms/step
Epoch 71/120
153/153 - 1s - loss: 0.0012 - 913ms/epoch - 6ms/step
Epoch 72/120
153/153 - 1s - loss: 0.0010 - 909ms/epoch - 6ms/step
Epoch 73/120
153/153 - 1s - loss: 0.0011 - 902ms/epoch - 6ms/step
Epoch 74/120
153/153 - 1s - loss: 0.0011 - 902ms/epoch - 6ms/step
Epoch 75/120
153/153 - 1s - loss: 0.0011 - 916ms/epoch - 6ms/step
Epoch 76/120
153/153 - 1s - loss: 0.0011 - 937ms/epoch - 6ms/step
Epoch 77/120
153/153 - 1s - loss: 9.8946e-04 - 974ms/epoch - 6ms/step
Epoch 78/120
153/153 - 1s - loss: 0.0011 - 934ms/epoch - 6ms/step
Epoch 79/120
153/153 - 1s - loss: 0.0011 - 908ms/epoch - 6ms/step
Epoch 80/120
153/153 - 1s - loss: 0.0012 - 923ms/epoch - 6ms/step
Epoch 81/120
153/153 - 1s - loss: 0.0011 - 953ms/epoch - 6ms/step
Epoch 82/120
153/153 - 1s - loss: 0.0011 - 1s/epoch - 7ms/step
Epoch 83/120
153/153 - 1s - loss: 0.0010 - 960ms/epoch - 6ms/step
Epoch 84/120
153/153 - 1s - loss: 0.0012 - 951ms/epoch - 6ms/step
Epoch 85/120
153/153 - 1s - loss: 0.0012 - 914ms/epoch - 6ms/step
Epoch 86/120
153/153 - 1s - loss: 0.0011 - 915ms/epoch - 6ms/step
Epoch 87/120
153/153 - 1s - loss: 0.0010 - 934ms/epoch - 6ms/step
Epoch 88/120
153/153 - 1s - loss: 0.0011 - 948ms/epoch - 6ms/step
Epoch 89/120
153/153 - 1s - loss: 0.0011 - 934ms/epoch - 6ms/step
Epoch 90/120
153/153 - 1s - loss: 0.0010 - 913ms/epoch - 6ms/step
Epoch 91/120
153/153 - 1s - loss: 0.0011 - 906ms/epoch - 6ms/step
Epoch 92/120
153/153 - 1s - loss: 0.0011 - 907ms/epoch - 6ms/step
Epoch 93/120
153/153 - 1s - loss: 0.0011 - 921ms/epoch - 6ms/step
Epoch 94/120
153/153 - 1s - loss: 9.7067e-04 - 919ms/epoch - 6ms/step
Epoch 95/120
153/153 - 1s - loss: 0.0011 - 917ms/epoch - 6ms/step
Epoch 96/120
153/153 - 1s - loss: 0.0013 - 1s/epoch - 7ms/step
Epoch 97/120
```

```
153/153 - 1s - loss: 0.0011 - 959ms/epoch - 6ms/step
Epoch 98/120
153/153 - 1s - loss: 9.9286e-04 - 935ms/epoch - 6ms/step
Epoch 99/120
153/153 - 1s - loss: 0.0011 - 925ms/epoch - 6ms/step
Epoch 100/120
153/153 - 1s - loss: 9.4695e-04 - 929ms/epoch - 6ms/step
Epoch 101/120
153/153 - 1s - loss: 0.0011 - 936ms/epoch - 6ms/step
Epoch 102/120
153/153 - 1s - loss: 0.0011 - 940ms/epoch - 6ms/step
Epoch 103/120
153/153 - 1s - loss: 9.6505e-04 - 963ms/epoch - 6ms/step
Epoch 104/120
153/153 - 1s - loss: 0.0010 - 928ms/epoch - 6ms/step
Epoch 105/120
153/153 - 1s - loss: 0.0011 - 903ms/epoch - 6ms/step
Epoch 106/120
153/153 - 1s - loss: 0.0014 - 917ms/epoch - 6ms/step
Epoch 107/120
153/153 - 1s - loss: 0.0011 - 931ms/epoch - 6ms/step
Epoch 108/120
153/153 - 1s - loss: 0.0010 - 912ms/epoch - 6ms/step
Epoch 109/120
153/153 - 1s - loss: 0.0010 - 914ms/epoch - 6ms/step
Epoch 110/120
153/153 - 1s - loss: 0.0010 - 953ms/epoch - 6ms/step
Epoch 111/120
153/153 - 1s - loss: 9.7171e-04 - 951ms/epoch - 6ms/step
Epoch 112/120
153/153 - 1s - loss: 0.0010 - 916ms/epoch - 6ms/step
Epoch 113/120
153/153 - 1s - loss: 0.0011 - 911ms/epoch - 6ms/step
Epoch 114/120
153/153 - 1s - loss: 9.9229e-04 - 934ms/epoch - 6ms/step
Epoch 115/120
153/153 - 1s - loss: 0.0010 - 936ms/epoch - 6ms/step
Epoch 116/120
153/153 - 1s - loss: 0.0011 - 932ms/epoch - 6ms/step
Epoch 117/120
153/153 - 1s - loss: 0.0011 - 947ms/epoch - 6ms/step
Epoch 118/120
153/153 - 1s - loss: 9.9028e-04 - 943ms/epoch - 6ms/step
Epoch 119/120
153/153 - 1s - loss: 0.0010 - 929ms/epoch - 6ms/step
Epoch 120/120
153/153 - 1s - loss: 0.0011 - 972ms/epoch - 6ms/step
Model: "sequential_7"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_14 (LSTM)              (None, 15, 85)            29580

 dropout_14 (Dropout)        (None, 15, 85)            0

 lstm_15 (LSTM)              (None, 130)               112320

 dropout_15 (Dropout)        (None, 130)               0

 dense_21 (Dense)            (None, 35)                4585

 dense_22 (Dense)            (None, 20)                720

 dense_23 (Dense)            (None, 1)                 21

=================================================================
Total params: 147,226
Trainable params: 147,226
Non-trainable params: 0
_________________________________________________________________
WARNING:tensorflow:6 out of the last 6 calls to <function Model.make_predict_function.<locals>.predict_function
at 0x0000017AC7A31990> triggered tf.function retracing. Tracing is expensive and the excessive number of tracin
gs could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (
3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For
(2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer
to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/pyth
on/tf/function for  more details.
1/1 [==============================] - 1s 526ms/step
(1216, 15, 1)
(1216,)
Epoch 1/120
152/152 - 3s - loss: 0.0145 - 3s/epoch - 19ms/step
Epoch 2/120
152/152 - 1s - loss: 0.0047 - 803ms/epoch - 5ms/step
Epoch 3/120
152/152 - 1s - loss: 0.0039 - 803ms/epoch - 5ms/step
Epoch 4/120
152/152 - 1s - loss: 0.0032 - 841ms/epoch - 6ms/step
Epoch 5/120
```

```
152/152 - 1s - loss: 0.0030 - 869ms/epoch - 6ms/step
Epoch 6/120
152/152 - 1s - loss: 0.0023 - 830ms/epoch - 5ms/step
Epoch 7/120
152/152 - 1s - loss: 0.0026 - 805ms/epoch - 5ms/step
Epoch 8/120
152/152 - 1s - loss: 0.0025 - 816ms/epoch - 5ms/step
Epoch 9/120
152/152 - 1s - loss: 0.0021 - 823ms/epoch - 5ms/step
Epoch 10/120
152/152 - 1s - loss: 0.0019 - 804ms/epoch - 5ms/step
Epoch 11/120
152/152 - 1s - loss: 0.0020 - 796ms/epoch - 5ms/step
Epoch 12/120
152/152 - 1s - loss: 0.0021 - 800ms/epoch - 5ms/step
Epoch 13/120
152/152 - 1s - loss: 0.0020 - 797ms/epoch - 5ms/step
Epoch 14/120
152/152 - 1s - loss: 0.0020 - 795ms/epoch - 5ms/step
Epoch 15/120
152/152 - 1s - loss: 0.0020 - 805ms/epoch - 5ms/step
Epoch 16/120
152/152 - 1s - loss: 0.0020 - 787ms/epoch - 5ms/step
Epoch 17/120
152/152 - 1s - loss: 0.0020 - 794ms/epoch - 5ms/step
Epoch 18/120
152/152 - 1s - loss: 0.0020 - 794ms/epoch - 5ms/step
Epoch 19/120
152/152 - 1s - loss: 0.0020 - 787ms/epoch - 5ms/step
Epoch 20/120
152/152 - 1s - loss: 0.0019 - 790ms/epoch - 5ms/step
Epoch 21/120
152/152 - 1s - loss: 0.0021 - 793ms/epoch - 5ms/step
Epoch 22/120
152/152 - 1s - loss: 0.0020 - 792ms/epoch - 5ms/step
Epoch 23/120
152/152 - 1s - loss: 0.0018 - 793ms/epoch - 5ms/step
Epoch 24/120
152/152 - 1s - loss: 0.0019 - 807ms/epoch - 5ms/step
Epoch 25/120
152/152 - 1s - loss: 0.0019 - 808ms/epoch - 5ms/step
Epoch 26/120
152/152 - 1s - loss: 0.0019 - 801ms/epoch - 5ms/step
Epoch 27/120
152/152 - 1s - loss: 0.0018 - 802ms/epoch - 5ms/step
Epoch 28/120
152/152 - 1s - loss: 0.0017 - 793ms/epoch - 5ms/step
Epoch 29/120
152/152 - 1s - loss: 0.0019 - 798ms/epoch - 5ms/step
Epoch 30/120
152/152 - 1s - loss: 0.0019 - 798ms/epoch - 5ms/step
Epoch 31/120
152/152 - 1s - loss: 0.0017 - 804ms/epoch - 5ms/step
Epoch 32/120
152/152 - 1s - loss: 0.0017 - 798ms/epoch - 5ms/step
Epoch 33/120
152/152 - 1s - loss: 0.0018 - 805ms/epoch - 5ms/step
Epoch 34/120
152/152 - 1s - loss: 0.0019 - 798ms/epoch - 5ms/step
Epoch 35/120
152/152 - 1s - loss: 0.0017 - 800ms/epoch - 5ms/step
Epoch 36/120
152/152 - 1s - loss: 0.0017 - 802ms/epoch - 5ms/step
Epoch 37/120
152/152 - 1s - loss: 0.0018 - 801ms/epoch - 5ms/step
Epoch 38/120
152/152 - 1s - loss: 0.0018 - 798ms/epoch - 5ms/step
Epoch 39/120
152/152 - 1s - loss: 0.0019 - 800ms/epoch - 5ms/step
Epoch 40/120
152/152 - 1s - loss: 0.0017 - 795ms/epoch - 5ms/step
Epoch 41/120
152/152 - 1s - loss: 0.0019 - 793ms/epoch - 5ms/step
Epoch 42/120
152/152 - 1s - loss: 0.0017 - 829ms/epoch - 5ms/step
Epoch 43/120
152/152 - 1s - loss: 0.0016 - 797ms/epoch - 5ms/step
Epoch 44/120
152/152 - 1s - loss: 0.0017 - 809ms/epoch - 5ms/step
Epoch 45/120
152/152 - 1s - loss: 0.0017 - 798ms/epoch - 5ms/step
Epoch 46/120
152/152 - 1s - loss: 0.0019 - 795ms/epoch - 5ms/step
Epoch 47/120
152/152 - 1s - loss: 0.0019 - 798ms/epoch - 5ms/step
Epoch 48/120
152/152 - 1s - loss: 0.0018 - 794ms/epoch - 5ms/step
Epoch 49/120
152/152 - 1s - loss: 0.0016 - 797ms/epoch - 5ms/step
```

```
Epoch 50/120
152/152 - 1s - loss: 0.0020 - 801ms/epoch - 5ms/step
Epoch 51/120
152/152 - 1s - loss: 0.0016 - 801ms/epoch - 5ms/step
Epoch 52/120
152/152 - 1s - loss: 0.0017 - 800ms/epoch - 5ms/step
Epoch 53/120
152/152 - 1s - loss: 0.0017 - 795ms/epoch - 5ms/step
Epoch 54/120
152/152 - 1s - loss: 0.0016 - 797ms/epoch - 5ms/step
Epoch 55/120
152/152 - 1s - loss: 0.0017 - 794ms/epoch - 5ms/step
Epoch 56/120
152/152 - 1s - loss: 0.0016 - 791ms/epoch - 5ms/step
Epoch 57/120
152/152 - 1s - loss: 0.0016 - 793ms/epoch - 5ms/step
Epoch 58/120
152/152 - 1s - loss: 0.0016 - 790ms/epoch - 5ms/step
Epoch 59/120
152/152 - 1s - loss: 0.0017 - 789ms/epoch - 5ms/step
Epoch 60/120
152/152 - 1s - loss: 0.0015 - 792ms/epoch - 5ms/step
Epoch 61/120
152/152 - 1s - loss: 0.0017 - 826ms/epoch - 5ms/step
Epoch 62/120
152/152 - 1s - loss: 0.0015 - 811ms/epoch - 5ms/step
Epoch 63/120
152/152 - 1s - loss: 0.0016 - 824ms/epoch - 5ms/step
Epoch 64/120
152/152 - 1s - loss: 0.0017 - 829ms/epoch - 5ms/step
Epoch 65/120
152/152 - 1s - loss: 0.0017 - 820ms/epoch - 5ms/step
Epoch 66/120
152/152 - 1s - loss: 0.0016 - 810ms/epoch - 5ms/step
Epoch 67/120
152/152 - 1s - loss: 0.0015 - 789ms/epoch - 5ms/step
Epoch 68/120
152/152 - 1s - loss: 0.0015 - 803ms/epoch - 5ms/step
Epoch 69/120
152/152 - 1s - loss: 0.0016 - 795ms/epoch - 5ms/step
Epoch 70/120
152/152 - 1s - loss: 0.0016 - 793ms/epoch - 5ms/step
Epoch 71/120
152/152 - 1s - loss: 0.0014 - 793ms/epoch - 5ms/step
Epoch 72/120
152/152 - 1s - loss: 0.0016 - 800ms/epoch - 5ms/step
Epoch 73/120
152/152 - 1s - loss: 0.0015 - 798ms/epoch - 5ms/step
Epoch 74/120
152/152 - 1s - loss: 0.0018 - 793ms/epoch - 5ms/step
Epoch 75/120
152/152 - 1s - loss: 0.0017 - 789ms/epoch - 5ms/step
Epoch 76/120
152/152 - 1s - loss: 0.0016 - 794ms/epoch - 5ms/step
Epoch 77/120
152/152 - 1s - loss: 0.0016 - 805ms/epoch - 5ms/step
Epoch 78/120
152/152 - 1s - loss: 0.0015 - 801ms/epoch - 5ms/step
Epoch 79/120
152/152 - 1s - loss: 0.0016 - 802ms/epoch - 5ms/step
Epoch 80/120
152/152 - 1s - loss: 0.0016 - 804ms/epoch - 5ms/step
Epoch 81/120
152/152 - 1s - loss: 0.0016 - 806ms/epoch - 5ms/step
Epoch 82/120
152/152 - 1s - loss: 0.0016 - 795ms/epoch - 5ms/step
Epoch 83/120
152/152 - 1s - loss: 0.0015 - 793ms/epoch - 5ms/step
Epoch 84/120
152/152 - 1s - loss: 0.0014 - 813ms/epoch - 5ms/step
Epoch 85/120
152/152 - 1s - loss: 0.0015 - 801ms/epoch - 5ms/step
Epoch 86/120
152/152 - 1s - loss: 0.0015 - 795ms/epoch - 5ms/step
Epoch 87/120
152/152 - 1s - loss: 0.0015 - 794ms/epoch - 5ms/step
Epoch 88/120
152/152 - 1s - loss: 0.0015 - 790ms/epoch - 5ms/step
Epoch 89/120
152/152 - 1s - loss: 0.0016 - 805ms/epoch - 5ms/step
Epoch 90/120
152/152 - 1s - loss: 0.0016 - 798ms/epoch - 5ms/step
Epoch 91/120
152/152 - 1s - loss: 0.0014 - 798ms/epoch - 5ms/step
Epoch 92/120
152/152 - 1s - loss: 0.0017 - 792ms/epoch - 5ms/step
Epoch 93/120
152/152 - 1s - loss: 0.0015 - 792ms/epoch - 5ms/step
Epoch 94/120
```

```
152/152 - 1s - loss: 0.0014 - 798ms/epoch - 5ms/step
Epoch 95/120
152/152 - 1s - loss: 0.0015 - 796ms/epoch - 5ms/step
Epoch 96/120
152/152 - 1s - loss: 0.0015 - 795ms/epoch - 5ms/step
Epoch 97/120
152/152 - 1s - loss: 0.0016 - 791ms/epoch - 5ms/step
Epoch 98/120
152/152 - 1s - loss: 0.0015 - 797ms/epoch - 5ms/step
Epoch 99/120
152/152 - 1s - loss: 0.0015 - 792ms/epoch - 5ms/step
Epoch 100/120
152/152 - 1s - loss: 0.0015 - 798ms/epoch - 5ms/step
Epoch 101/120
152/152 - 1s - loss: 0.0016 - 794ms/epoch - 5ms/step
Epoch 102/120
152/152 - 1s - loss: 0.0015 - 796ms/epoch - 5ms/step
Epoch 103/120
152/152 - 1s - loss: 0.0016 - 794ms/epoch - 5ms/step
Epoch 104/120
152/152 - 1s - loss: 0.0015 - 811ms/epoch - 5ms/step
Epoch 105/120
152/152 - 1s - loss: 0.0016 - 803ms/epoch - 5ms/step
Epoch 106/120
152/152 - 1s - loss: 0.0014 - 793ms/epoch - 5ms/step
Epoch 107/120
152/152 - 1s - loss: 0.0014 - 794ms/epoch - 5ms/step
Epoch 108/120
152/152 - 1s - loss: 0.0016 - 791ms/epoch - 5ms/step
Epoch 109/120
152/152 - 1s - loss: 0.0014 - 789ms/epoch - 5ms/step
Epoch 110/120
152/152 - 1s - loss: 0.0015 - 794ms/epoch - 5ms/step
Epoch 111/120
152/152 - 1s - loss: 0.0016 - 794ms/epoch - 5ms/step
Epoch 112/120
152/152 - 1s - loss: 0.0015 - 789ms/epoch - 5ms/step
Epoch 113/120
152/152 - 1s - loss: 0.0015 - 796ms/epoch - 5ms/step
Epoch 114/120
152/152 - 1s - loss: 0.0015 - 790ms/epoch - 5ms/step
Epoch 115/120
152/152 - 1s - loss: 0.0015 - 803ms/epoch - 5ms/step
Epoch 116/120
152/152 - 1s - loss: 0.0015 - 787ms/epoch - 5ms/step
Epoch 117/120
152/152 - 1s - loss: 0.0015 - 789ms/epoch - 5ms/step
Epoch 118/120
152/152 - 1s - loss: 0.0013 - 787ms/epoch - 5ms/step
Epoch 119/120
152/152 - 1s - loss: 0.0014 - 790ms/epoch - 5ms/step
Epoch 120/120
152/152 - 1s - loss: 0.0014 - 788ms/epoch - 5ms/step
Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_16 (LSTM)              (None, 15, 85)            29580

 dropout_16 (Dropout)        (None, 15, 85)            0

 lstm_17 (LSTM)              (None, 130)               112320

 dropout_17 (Dropout)        (None, 130)               0

 dense_24 (Dense)            (None, 35)                4585

 dense_25 (Dense)            (None, 20)                720

 dense_26 (Dense)            (None, 1)                 21

=================================================================
Total params: 147,226
Trainable params: 147,226
Non-trainable params: 0
_________________________________________________________________
1/1 [==============================] - 1s 510ms/step
(1215, 15, 1)
(1215,)
Epoch 1/120
152/152 - 3s - loss: 0.0126 - 3s/epoch - 21ms/step
Epoch 2/120
152/152 - 1s - loss: 0.0051 - 918ms/epoch - 6ms/step
Epoch 3/120
152/152 - 1s - loss: 0.0044 - 924ms/epoch - 6ms/step
Epoch 4/120
152/152 - 1s - loss: 0.0037 - 937ms/epoch - 6ms/step
Epoch 5/120
152/152 - 1s - loss: 0.0036 - 922ms/epoch - 6ms/step
```

```
Epoch 6/120
152/152 - 1s - loss: 0.0031 - 923ms/epoch - 6ms/step
Epoch 7/120
152/152 - 1s - loss: 0.0029 - 944ms/epoch - 6ms/step
Epoch 8/120
152/152 - 1s - loss: 0.0026 - 941ms/epoch - 6ms/step
Epoch 9/120
152/152 - 1s - loss: 0.0027 - 930ms/epoch - 6ms/step
Epoch 10/120
152/152 - 1s - loss: 0.0029 - 903ms/epoch - 6ms/step
Epoch 11/120
152/152 - 1s - loss: 0.0022 - 906ms/epoch - 6ms/step
Epoch 12/120
152/152 - 1s - loss: 0.0025 - 930ms/epoch - 6ms/step
Epoch 13/120
152/152 - 1s - loss: 0.0026 - 918ms/epoch - 6ms/step
Epoch 14/120
152/152 - 1s - loss: 0.0027 - 960ms/epoch - 6ms/step
Epoch 15/120
152/152 - 1s - loss: 0.0023 - 939ms/epoch - 6ms/step
Epoch 16/120
152/152 - 1s - loss: 0.0024 - 923ms/epoch - 6ms/step
Epoch 17/120
152/152 - 1s - loss: 0.0022 - 933ms/epoch - 6ms/step
Epoch 18/120
152/152 - 1s - loss: 0.0023 - 954ms/epoch - 6ms/step
Epoch 19/120
152/152 - 1s - loss: 0.0026 - 921ms/epoch - 6ms/step
Epoch 20/120
152/152 - 1s - loss: 0.0024 - 905ms/epoch - 6ms/step
Epoch 21/120
152/152 - 1s - loss: 0.0022 - 899ms/epoch - 6ms/step
Epoch 22/120
152/152 - 1s - loss: 0.0023 - 905ms/epoch - 6ms/step
Epoch 23/120
152/152 - 1s - loss: 0.0024 - 906ms/epoch - 6ms/step
Epoch 24/120
152/152 - 1s - loss: 0.0023 - 902ms/epoch - 6ms/step
Epoch 25/120
152/152 - 1s - loss: 0.0022 - 910ms/epoch - 6ms/step
Epoch 26/120
152/152 - 1s - loss: 0.0023 - 909ms/epoch - 6ms/step
Epoch 27/120
152/152 - 1s - loss: 0.0023 - 900ms/epoch - 6ms/step
Epoch 28/120
152/152 - 1s - loss: 0.0023 - 921ms/epoch - 6ms/step
Epoch 29/120
152/152 - 1s - loss: 0.0022 - 930ms/epoch - 6ms/step
Epoch 30/120
152/152 - 1s - loss: 0.0023 - 980ms/epoch - 6ms/step
Epoch 31/120
152/152 - 1s - loss: 0.0022 - 909ms/epoch - 6ms/step
Epoch 32/120
152/152 - 1s - loss: 0.0024 - 942ms/epoch - 6ms/step
Epoch 33/120
152/152 - 1s - loss: 0.0023 - 958ms/epoch - 6ms/step
Epoch 34/120
152/152 - 1s - loss: 0.0023 - 964ms/epoch - 6ms/step
Epoch 35/120
152/152 - 1s - loss: 0.0024 - 960ms/epoch - 6ms/step
Epoch 36/120
152/152 - 1s - loss: 0.0021 - 916ms/epoch - 6ms/step
Epoch 37/120
152/152 - 1s - loss: 0.0022 - 914ms/epoch - 6ms/step
Epoch 38/120
152/152 - 1s - loss: 0.0020 - 924ms/epoch - 6ms/step
Epoch 39/120
152/152 - 1s - loss: 0.0024 - 932ms/epoch - 6ms/step
Epoch 40/120
152/152 - 1s - loss: 0.0023 - 913ms/epoch - 6ms/step
Epoch 41/120
152/152 - 1s - loss: 0.0022 - 911ms/epoch - 6ms/step
Epoch 42/120
152/152 - 1s - loss: 0.0022 - 912ms/epoch - 6ms/step
Epoch 43/120
152/152 - 1s - loss: 0.0021 - 909ms/epoch - 6ms/step
Epoch 44/120
152/152 - 1s - loss: 0.0024 - 910ms/epoch - 6ms/step
Epoch 45/120
152/152 - 1s - loss: 0.0022 - 923ms/epoch - 6ms/step
Epoch 46/120
152/152 - 1s - loss: 0.0021 - 904ms/epoch - 6ms/step
Epoch 47/120
152/152 - 1s - loss: 0.0022 - 915ms/epoch - 6ms/step
Epoch 48/120
152/152 - 1s - loss: 0.0021 - 936ms/epoch - 6ms/step
Epoch 49/120
152/152 - 1s - loss: 0.0021 - 921ms/epoch - 6ms/step
Epoch 50/120
```

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152/152 - 1s - loss: 0.0021 - 920ms/epoch - 6ms/step
Epoch 51/120
152/152 - 1s - loss: 0.0020 - 918ms/epoch - 6ms/step
Epoch 52/120
152/152 - 1s - loss: 0.0021 - 926ms/epoch - 6ms/step
Epoch 53/120
152/152 - 1s - loss: 0.0022 - 922ms/epoch - 6ms/step
Epoch 54/120
152/152 - 1s - loss: 0.0021 - 918ms/epoch - 6ms/step
Epoch 55/120
152/152 - 1s - loss: 0.0022 - 924ms/epoch - 6ms/step
Epoch 56/120
152/152 - 1s - loss: 0.0022 - 916ms/epoch - 6ms/step
Epoch 57/120
152/152 - 1s - loss: 0.0021 - 902ms/epoch - 6ms/step
Epoch 58/120
152/152 - 1s - loss: 0.0021 - 920ms/epoch - 6ms/step
Epoch 59/120
152/152 - 1s - loss: 0.0021 - 908ms/epoch - 6ms/step
Epoch 60/120
152/152 - 1s - loss: 0.0022 - 904ms/epoch - 6ms/step
Epoch 61/120
152/152 - 1s - loss: 0.0021 - 911ms/epoch - 6ms/step
Epoch 62/120
152/152 - 1s - loss: 0.0020 - 910ms/epoch - 6ms/step
Epoch 63/120
152/152 - 1s - loss: 0.0020 - 905ms/epoch - 6ms/step
Epoch 64/120
152/152 - 1s - loss: 0.0020 - 912ms/epoch - 6ms/step
Epoch 65/120
152/152 - 1s - loss: 0.0021 - 903ms/epoch - 6ms/step
Epoch 66/120
152/152 - 1s - loss: 0.0022 - 900ms/epoch - 6ms/step
Epoch 67/120
152/152 - 1s - loss: 0.0021 - 900ms/epoch - 6ms/step
Epoch 68/120
152/152 - 1s - loss: 0.0021 - 908ms/epoch - 6ms/step
Epoch 69/120
152/152 - 1s - loss: 0.0021 - 914ms/epoch - 6ms/step
Epoch 70/120
152/152 - 1s - loss: 0.0021 - 924ms/epoch - 6ms/step
Epoch 71/120
152/152 - 1s - loss: 0.0021 - 900ms/epoch - 6ms/step
Epoch 72/120
152/152 - 1s - loss: 0.0021 - 911ms/epoch - 6ms/step
Epoch 73/120
152/152 - 1s - loss: 0.0020 - 907ms/epoch - 6ms/step
Epoch 74/120
152/152 - 1s - loss: 0.0020 - 896ms/epoch - 6ms/step
Epoch 75/120
152/152 - 1s - loss: 0.0021 - 902ms/epoch - 6ms/step
Epoch 76/120
152/152 - 1s - loss: 0.0021 - 903ms/epoch - 6ms/step
Epoch 77/120
152/152 - 1s - loss: 0.0021 - 902ms/epoch - 6ms/step
Epoch 78/120
152/152 - 1s - loss: 0.0021 - 908ms/epoch - 6ms/step
Epoch 79/120
152/152 - 1s - loss: 0.0020 - 901ms/epoch - 6ms/step
Epoch 80/120
152/152 - 1s - loss: 0.0020 - 910ms/epoch - 6ms/step
Epoch 81/120
152/152 - 1s - loss: 0.0019 - 899ms/epoch - 6ms/step
Epoch 82/120
152/152 - 1s - loss: 0.0019 - 931ms/epoch - 6ms/step
Epoch 83/120
152/152 - 1s - loss: 0.0020 - 965ms/epoch - 6ms/step
Epoch 84/120
152/152 - 1s - loss: 0.0018 - 953ms/epoch - 6ms/step
Epoch 85/120
152/152 - 1s - loss: 0.0019 - 912ms/epoch - 6ms/step
Epoch 86/120
152/152 - 1s - loss: 0.0019 - 921ms/epoch - 6ms/step
Epoch 87/120
152/152 - 1s - loss: 0.0021 - 929ms/epoch - 6ms/step
Epoch 88/120
152/152 - 1s - loss: 0.0020 - 952ms/epoch - 6ms/step
Epoch 89/120
152/152 - 1s - loss: 0.0020 - 938ms/epoch - 6ms/step
Epoch 90/120
152/152 - 1s - loss: 0.0020 - 941ms/epoch - 6ms/step
Epoch 91/120
152/152 - 1s - loss: 0.0019 - 967ms/epoch - 6ms/step
Epoch 92/120
152/152 - 1s - loss: 0.0018 - 934ms/epoch - 6ms/step
Epoch 93/120
152/152 - 1s - loss: 0.0021 - 906ms/epoch - 6ms/step
Epoch 94/120
152/152 - 1s - loss: 0.0020 - 901ms/epoch - 6ms/step
```

```
Epoch 95/120
152/152 - 1s - loss: 0.0019 - 931ms/epoch - 6ms/step
Epoch 96/120
152/152 - 1s - loss: 0.0018 - 910ms/epoch - 6ms/step
Epoch 97/120
152/152 - 1s - loss: 0.0020 - 923ms/epoch - 6ms/step
Epoch 98/120
152/152 - 1s - loss: 0.0021 - 910ms/epoch - 6ms/step
Epoch 99/120
152/152 - 1s - loss: 0.0018 - 917ms/epoch - 6ms/step
Epoch 100/120
152/152 - 1s - loss: 0.0019 - 912ms/epoch - 6ms/step
Epoch 101/120
152/152 - 1s - loss: 0.0019 - 924ms/epoch - 6ms/step
Epoch 102/120
152/152 - 1s - loss: 0.0019 - 909ms/epoch - 6ms/step
Epoch 103/120
152/152 - 1s - loss: 0.0020 - 911ms/epoch - 6ms/step
Epoch 104/120
152/152 - 1s - loss: 0.0019 - 918ms/epoch - 6ms/step
Epoch 105/120
152/152 - 1s - loss: 0.0019 - 931ms/epoch - 6ms/step
Epoch 106/120
152/152 - 1s - loss: 0.0020 - 909ms/epoch - 6ms/step
Epoch 107/120
152/152 - 1s - loss: 0.0019 - 910ms/epoch - 6ms/step
Epoch 108/120
152/152 - 1s - loss: 0.0018 - 907ms/epoch - 6ms/step
Epoch 109/120
152/152 - 1s - loss: 0.0020 - 916ms/epoch - 6ms/step
Epoch 110/120
152/152 - 1s - loss: 0.0018 - 915ms/epoch - 6ms/step
Epoch 111/120
152/152 - 1s - loss: 0.0019 - 912ms/epoch - 6ms/step
Epoch 112/120
152/152 - 1s - loss: 0.0018 - 921ms/epoch - 6ms/step
Epoch 113/120
152/152 - 1s - loss: 0.0022 - 912ms/epoch - 6ms/step
Epoch 114/120
152/152 - 1s - loss: 0.0021 - 913ms/epoch - 6ms/step
Epoch 115/120
152/152 - 1s - loss: 0.0019 - 904ms/epoch - 6ms/step
Epoch 116/120
152/152 - 1s - loss: 0.0018 - 917ms/epoch - 6ms/step
Epoch 117/120
152/152 - 1s - loss: 0.0019 - 906ms/epoch - 6ms/step
Epoch 118/120
152/152 - 1s - loss: 0.0021 - 905ms/epoch - 6ms/step
Epoch 119/120
152/152 - 1s - loss: 0.0017 - 897ms/epoch - 6ms/step
Epoch 120/120
152/152 - 1s - loss: 0.0017 - 903ms/epoch - 6ms/step
Model: "sequential_9"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_18 (LSTM)              (None, 15, 85)            29580

 dropout_18 (Dropout)        (None, 15, 85)            0

 lstm_19 (LSTM)              (None, 130)               112320

 dropout_19 (Dropout)        (None, 130)               0

 dense_27 (Dense)            (None, 35)                4585

 dense_28 (Dense)            (None, 20)                720

 dense_29 (Dense)            (None, 1)                 21

=================================================================
Total params: 147,226
Trainable params: 147,226
Non-trainable params: 0
_________________________________________________________________
1/1 [==============================] - 1s 568ms/step
(1214, 15, 1)
(1214,)
Epoch 1/120
152/152 - 3s - loss: 0.0169 - 3s/epoch - 21ms/step
Epoch 2/120
152/152 - 1s - loss: 0.0058 - 906ms/epoch - 6ms/step
Epoch 3/120
152/152 - 1s - loss: 0.0052 - 903ms/epoch - 6ms/step
Epoch 4/120
152/152 - 1s - loss: 0.0043 - 906ms/epoch - 6ms/step
Epoch 5/120
152/152 - 1s - loss: 0.0038 - 902ms/epoch - 6ms/step
Epoch 6/120
```

```
152/152 - 1s - loss: 0.0036 - 901ms/epoch - 6ms/step
Epoch 7/120
152/152 - 1s - loss: 0.0034 - 904ms/epoch - 6ms/step
Epoch 8/120
152/152 - 1s - loss: 0.0031 - 910ms/epoch - 6ms/step
Epoch 9/120
152/152 - 1s - loss: 0.0029 - 916ms/epoch - 6ms/step
Epoch 10/120
152/152 - 1s - loss: 0.0029 - 916ms/epoch - 6ms/step
Epoch 11/120
152/152 - 1s - loss: 0.0028 - 924ms/epoch - 6ms/step
Epoch 12/120
152/152 - 1s - loss: 0.0028 - 925ms/epoch - 6ms/step
Epoch 13/120
152/152 - 1s - loss: 0.0029 - 918ms/epoch - 6ms/step
Epoch 14/120
152/152 - 1s - loss: 0.0025 - 917ms/epoch - 6ms/step
Epoch 15/120
152/152 - 1s - loss: 0.0029 - 926ms/epoch - 6ms/step
Epoch 16/120
152/152 - 1s - loss: 0.0026 - 940ms/epoch - 6ms/step
Epoch 17/120
152/152 - 1s - loss: 0.0028 - 914ms/epoch - 6ms/step
Epoch 18/120
152/152 - 1s - loss: 0.0028 - 927ms/epoch - 6ms/step
Epoch 19/120
152/152 - 1s - loss: 0.0028 - 977ms/epoch - 6ms/step
Epoch 20/120
152/152 - 1s - loss: 0.0026 - 921ms/epoch - 6ms/step
Epoch 21/120
152/152 - 1s - loss: 0.0028 - 917ms/epoch - 6ms/step
Epoch 22/120
152/152 - 1s - loss: 0.0030 - 931ms/epoch - 6ms/step
Epoch 23/120
152/152 - 1s - loss: 0.0030 - 917ms/epoch - 6ms/step
Epoch 24/120
152/152 - 1s - loss: 0.0026 - 919ms/epoch - 6ms/step
Epoch 25/120
152/152 - 1s - loss: 0.0029 - 923ms/epoch - 6ms/step
Epoch 26/120
152/152 - 1s - loss: 0.0029 - 922ms/epoch - 6ms/step
Epoch 27/120
152/152 - 1s - loss: 0.0027 - 917ms/epoch - 6ms/step
Epoch 28/120
152/152 - 1s - loss: 0.0028 - 920ms/epoch - 6ms/step
Epoch 29/120
152/152 - 1s - loss: 0.0025 - 911ms/epoch - 6ms/step
Epoch 30/120
152/152 - 1s - loss: 0.0026 - 911ms/epoch - 6ms/step
Epoch 31/120
152/152 - 1s - loss: 0.0027 - 920ms/epoch - 6ms/step
Epoch 32/120
152/152 - 1s - loss: 0.0027 - 913ms/epoch - 6ms/step
Epoch 33/120
152/152 - 1s - loss: 0.0027 - 955ms/epoch - 6ms/step
Epoch 34/120
152/152 - 1s - loss: 0.0029 - 915ms/epoch - 6ms/step
Epoch 35/120
152/152 - 1s - loss: 0.0026 - 918ms/epoch - 6ms/step
Epoch 36/120
152/152 - 1s - loss: 0.0027 - 916ms/epoch - 6ms/step
Epoch 37/120
152/152 - 1s - loss: 0.0025 - 924ms/epoch - 6ms/step
Epoch 38/120
152/152 - 1s - loss: 0.0027 - 916ms/epoch - 6ms/step
Epoch 39/120
152/152 - 1s - loss: 0.0026 - 926ms/epoch - 6ms/step
Epoch 40/120
152/152 - 1s - loss: 0.0027 - 922ms/epoch - 6ms/step
Epoch 41/120
152/152 - 1s - loss: 0.0027 - 931ms/epoch - 6ms/step
Epoch 42/120
152/152 - 1s - loss: 0.0027 - 915ms/epoch - 6ms/step
Epoch 43/120
152/152 - 1s - loss: 0.0024 - 929ms/epoch - 6ms/step
Epoch 44/120
152/152 - 1s - loss: 0.0028 - 922ms/epoch - 6ms/step
Epoch 45/120
152/152 - 1s - loss: 0.0024 - 926ms/epoch - 6ms/step
Epoch 46/120
152/152 - 1s - loss: 0.0027 - 965ms/epoch - 6ms/step
Epoch 47/120
152/152 - 1s - loss: 0.0026 - 943ms/epoch - 6ms/step
Epoch 48/120
152/152 - 1s - loss: 0.0025 - 917ms/epoch - 6ms/step
Epoch 49/120
152/152 - 1s - loss: 0.0026 - 912ms/epoch - 6ms/step
Epoch 50/120
152/152 - 1s - loss: 0.0025 - 946ms/epoch - 6ms/step
```

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Epoch 51/120
152/152 - 1s - loss: 0.0025 - 926ms/epoch - 6ms/step
Epoch 52/120
152/152 - 1s - loss: 0.0025 - 920ms/epoch - 6ms/step
Epoch 53/120
152/152 - 1s - loss: 0.0026 - 914ms/epoch - 6ms/step
Epoch 54/120
152/152 - 1s - loss: 0.0027 - 929ms/epoch - 6ms/step
Epoch 55/120
152/152 - 1s - loss: 0.0024 - 915ms/epoch - 6ms/step
Epoch 56/120
152/152 - 1s - loss: 0.0025 - 913ms/epoch - 6ms/step
Epoch 57/120
152/152 - 1s - loss: 0.0025 - 916ms/epoch - 6ms/step
Epoch 58/120
152/152 - 1s - loss: 0.0026 - 925ms/epoch - 6ms/step
Epoch 59/120
152/152 - 1s - loss: 0.0028 - 910ms/epoch - 6ms/step
Epoch 60/120
152/152 - 1s - loss: 0.0023 - 910ms/epoch - 6ms/step
Epoch 61/120
152/152 - 1s - loss: 0.0026 - 907ms/epoch - 6ms/step
Epoch 62/120
152/152 - 1s - loss: 0.0026 - 906ms/epoch - 6ms/step
Epoch 63/120
152/152 - 1s - loss: 0.0023 - 915ms/epoch - 6ms/step
Epoch 64/120
152/152 - 1s - loss: 0.0025 - 920ms/epoch - 6ms/step
Epoch 65/120
152/152 - 1s - loss: 0.0024 - 920ms/epoch - 6ms/step
Epoch 66/120
152/152 - 1s - loss: 0.0024 - 908ms/epoch - 6ms/step
Epoch 67/120
152/152 - 1s - loss: 0.0026 - 914ms/epoch - 6ms/step
Epoch 68/120
152/152 - 1s - loss: 0.0026 - 930ms/epoch - 6ms/step
Epoch 69/120
152/152 - 1s - loss: 0.0024 - 904ms/epoch - 6ms/step
Epoch 70/120
152/152 - 1s - loss: 0.0024 - 910ms/epoch - 6ms/step
Epoch 71/120
152/152 - 1s - loss: 0.0022 - 914ms/epoch - 6ms/step
Epoch 72/120
152/152 - 1s - loss: 0.0024 - 912ms/epoch - 6ms/step
Epoch 73/120
152/152 - 1s - loss: 0.0024 - 922ms/epoch - 6ms/step
Epoch 74/120
152/152 - 1s - loss: 0.0025 - 917ms/epoch - 6ms/step
Epoch 75/120
152/152 - 1s - loss: 0.0023 - 918ms/epoch - 6ms/step
Epoch 76/120
152/152 - 1s - loss: 0.0023 - 917ms/epoch - 6ms/step
Epoch 77/120
152/152 - 1s - loss: 0.0023 - 925ms/epoch - 6ms/step
Epoch 78/120
152/152 - 1s - loss: 0.0022 - 915ms/epoch - 6ms/step
Epoch 79/120
152/152 - 1s - loss: 0.0024 - 917ms/epoch - 6ms/step
Epoch 80/120
152/152 - 1s - loss: 0.0023 - 908ms/epoch - 6ms/step
Epoch 81/120
152/152 - 1s - loss: 0.0023 - 905ms/epoch - 6ms/step
Epoch 82/120
152/152 - 1s - loss: 0.0023 - 905ms/epoch - 6ms/step
Epoch 83/120
152/152 - 1s - loss: 0.0023 - 903ms/epoch - 6ms/step
Epoch 84/120
152/152 - 1s - loss: 0.0025 - 914ms/epoch - 6ms/step
Epoch 85/120
152/152 - 1s - loss: 0.0024 - 944ms/epoch - 6ms/step
Epoch 86/120
152/152 - 1s - loss: 0.0024 - 921ms/epoch - 6ms/step
Epoch 87/120
152/152 - 1s - loss: 0.0024 - 923ms/epoch - 6ms/step
Epoch 88/120
152/152 - 1s - loss: 0.0022 - 916ms/epoch - 6ms/step
Epoch 89/120
152/152 - 1s - loss: 0.0024 - 917ms/epoch - 6ms/step
Epoch 90/120
152/152 - 1s - loss: 0.0023 - 913ms/epoch - 6ms/step
Epoch 91/120
152/152 - 1s - loss: 0.0024 - 920ms/epoch - 6ms/step
Epoch 92/120
152/152 - 1s - loss: 0.0022 - 911ms/epoch - 6ms/step
Epoch 93/120
152/152 - 1s - loss: 0.0024 - 929ms/epoch - 6ms/step
Epoch 94/120
152/152 - 1s - loss: 0.0023 - 917ms/epoch - 6ms/step
Epoch 95/120
```

```
152/152 - 1s - loss: 0.0022 - 916ms/epoch - 6ms/step
Epoch 96/120
152/152 - 1s - loss: 0.0024 - 925ms/epoch - 6ms/step
Epoch 97/120
152/152 - 1s - loss: 0.0024 - 927ms/epoch - 6ms/step
Epoch 98/120
152/152 - 1s - loss: 0.0023 - 925ms/epoch - 6ms/step
Epoch 99/120
152/152 - 1s - loss: 0.0023 - 919ms/epoch - 6ms/step
Epoch 100/120
152/152 - 1s - loss: 0.0023 - 916ms/epoch - 6ms/step
Epoch 101/120
152/152 - 1s - loss: 0.0022 - 957ms/epoch - 6ms/step
Epoch 102/120
152/152 - 1s - loss: 0.0023 - 954ms/epoch - 6ms/step
Epoch 103/120
152/152 - 1s - loss: 0.0023 - 979ms/epoch - 6ms/step
Epoch 104/120
152/152 - 1s - loss: 0.0022 - 936ms/epoch - 6ms/step
Epoch 105/120
152/152 - 1s - loss: 0.0022 - 920ms/epoch - 6ms/step
Epoch 106/120
152/152 - 1s - loss: 0.0023 - 972ms/epoch - 6ms/step
Epoch 107/120
152/152 - 1s - loss: 0.0022 - 954ms/epoch - 6ms/step
Epoch 108/120
152/152 - 1s - loss: 0.0022 - 935ms/epoch - 6ms/step
Epoch 109/120
152/152 - 1s - loss: 0.0024 - 932ms/epoch - 6ms/step
Epoch 110/120
152/152 - 1s - loss: 0.0023 - 947ms/epoch - 6ms/step
Epoch 111/120
152/152 - 1s - loss: 0.0021 - 933ms/epoch - 6ms/step
Epoch 112/120
152/152 - 1s - loss: 0.0022 - 914ms/epoch - 6ms/step
Epoch 113/120
152/152 - 1s - loss: 0.0022 - 917ms/epoch - 6ms/step
Epoch 114/120
152/152 - 1s - loss: 0.0022 - 919ms/epoch - 6ms/step
Epoch 115/120
152/152 - 1s - loss: 0.0022 - 916ms/epoch - 6ms/step
Epoch 116/120
152/152 - 1s - loss: 0.0024 - 925ms/epoch - 6ms/step
Epoch 117/120
152/152 - 1s - loss: 0.0023 - 916ms/epoch - 6ms/step
Epoch 118/120
152/152 - 1s - loss: 0.0022 - 919ms/epoch - 6ms/step
Epoch 119/120
152/152 - 1s - loss: 0.0022 - 924ms/epoch - 6ms/step
Epoch 120/120
152/152 - 1s - loss: 0.0022 - 944ms/epoch - 6ms/step
Model: "sequential_10"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_20 (LSTM)              (None, 15, 85)            29580

 dropout_20 (Dropout)        (None, 15, 85)            0

 lstm_21 (LSTM)              (None, 130)               112320

 dropout_21 (Dropout)        (None, 130)               0

 dense_30 (Dense)            (None, 35)                4585

 dense_31 (Dense)            (None, 20)                720

 dense_32 (Dense)            (None, 1)                 21

=================================================================
Total params: 147,226
Trainable params: 147,226
Non-trainable params: 0
_________________________________________________________________
1/1 [==============================] - 1s 533ms/step
(1213, 15, 1)
(1213,)
Epoch 1/120
152/152 - 3s - loss: 0.0143 - 3s/epoch - 22ms/step
Epoch 2/120
152/152 - 1s - loss: 0.0065 - 925ms/epoch - 6ms/step
Epoch 3/120
152/152 - 1s - loss: 0.0056 - 918ms/epoch - 6ms/step
Epoch 4/120
152/152 - 1s - loss: 0.0046 - 919ms/epoch - 6ms/step
Epoch 5/120
152/152 - 1s - loss: 0.0041 - 924ms/epoch - 6ms/step
Epoch 6/120
152/152 - 1s - loss: 0.0041 - 922ms/epoch - 6ms/step
```

```
Epoch 7/120
152/152 - 1s - loss: 0.0036 - 925ms/epoch - 6ms/step
Epoch 8/120
152/152 - 1s - loss: 0.0032 - 919ms/epoch - 6ms/step
Epoch 9/120
152/152 - 1s - loss: 0.0034 - 919ms/epoch - 6ms/step
Epoch 10/120
152/152 - 1s - loss: 0.0033 - 912ms/epoch - 6ms/step
Epoch 11/120
152/152 - 1s - loss: 0.0032 - 935ms/epoch - 6ms/step
Epoch 12/120
152/152 - 1s - loss: 0.0035 - 928ms/epoch - 6ms/step
Epoch 13/120
152/152 - 1s - loss: 0.0030 - 948ms/epoch - 6ms/step
Epoch 14/120
152/152 - 1s - loss: 0.0031 - 922ms/epoch - 6ms/step
Epoch 15/120
152/152 - 1s - loss: 0.0033 - 920ms/epoch - 6ms/step
Epoch 16/120
152/152 - 1s - loss: 0.0031 - 930ms/epoch - 6ms/step
Epoch 17/120
152/152 - 1s - loss: 0.0030 - 927ms/epoch - 6ms/step
Epoch 18/120
152/152 - 1s - loss: 0.0034 - 928ms/epoch - 6ms/step
Epoch 19/120
152/152 - 1s - loss: 0.0032 - 919ms/epoch - 6ms/step
Epoch 20/120
152/152 - 1s - loss: 0.0031 - 913ms/epoch - 6ms/step
Epoch 21/120
152/152 - 1s - loss: 0.0029 - 910ms/epoch - 6ms/step
Epoch 22/120
152/152 - 1s - loss: 0.0032 - 913ms/epoch - 6ms/step
Epoch 23/120
152/152 - 1s - loss: 0.0032 - 908ms/epoch - 6ms/step
Epoch 24/120
152/152 - 1s - loss: 0.0031 - 911ms/epoch - 6ms/step
Epoch 25/120
152/152 - 1s - loss: 0.0030 - 909ms/epoch - 6ms/step
Epoch 26/120
152/152 - 1s - loss: 0.0029 - 921ms/epoch - 6ms/step
Epoch 27/120
152/152 - 1s - loss: 0.0030 - 915ms/epoch - 6ms/step
Epoch 28/120
152/152 - 1s - loss: 0.0029 - 925ms/epoch - 6ms/step
Epoch 29/120
152/152 - 1s - loss: 0.0031 - 930ms/epoch - 6ms/step
Epoch 30/120
152/152 - 1s - loss: 0.0030 - 933ms/epoch - 6ms/step
Epoch 31/120
152/152 - 1s - loss: 0.0030 - 930ms/epoch - 6ms/step
Epoch 32/120
152/152 - 1s - loss: 0.0029 - 919ms/epoch - 6ms/step
Epoch 33/120
152/152 - 1s - loss: 0.0028 - 913ms/epoch - 6ms/step
Epoch 34/120
152/152 - 1s - loss: 0.0032 - 926ms/epoch - 6ms/step
Epoch 35/120
152/152 - 1s - loss: 0.0030 - 919ms/epoch - 6ms/step
Epoch 36/120
152/152 - 1s - loss: 0.0030 - 917ms/epoch - 6ms/step
Epoch 37/120
152/152 - 1s - loss: 0.0030 - 921ms/epoch - 6ms/step
Epoch 38/120
152/152 - 1s - loss: 0.0029 - 915ms/epoch - 6ms/step
Epoch 39/120
152/152 - 1s - loss: 0.0029 - 922ms/epoch - 6ms/step
Epoch 40/120
152/152 - 1s - loss: 0.0029 - 921ms/epoch - 6ms/step
Epoch 41/120
152/152 - 1s - loss: 0.0028 - 921ms/epoch - 6ms/step
Epoch 42/120
152/152 - 1s - loss: 0.0029 - 921ms/epoch - 6ms/step
Epoch 43/120
152/152 - 1s - loss: 0.0028 - 920ms/epoch - 6ms/step
Epoch 44/120
152/152 - 1s - loss: 0.0029 - 925ms/epoch - 6ms/step
Epoch 45/120
152/152 - 1s - loss: 0.0029 - 957ms/epoch - 6ms/step
Epoch 46/120
152/152 - 1s - loss: 0.0028 - 927ms/epoch - 6ms/step
Epoch 47/120
152/152 - 1s - loss: 0.0028 - 933ms/epoch - 6ms/step
Epoch 48/120
152/152 - 1s - loss: 0.0028 - 950ms/epoch - 6ms/step
Epoch 49/120
152/152 - 1s - loss: 0.0030 - 919ms/epoch - 6ms/step
Epoch 50/120
152/152 - 1s - loss: 0.0028 - 925ms/epoch - 6ms/step
Epoch 51/120
```

```
152/152 - 1s - loss: 0.0028 - 919ms/epoch - 6ms/step
Epoch 52/120
152/152 - 1s - loss: 0.0027 - 917ms/epoch - 6ms/step
Epoch 53/120
152/152 - 1s - loss: 0.0027 - 937ms/epoch - 6ms/step
Epoch 54/120
152/152 - 1s - loss: 0.0028 - 937ms/epoch - 6ms/step
Epoch 55/120
152/152 - 1s - loss: 0.0027 - 929ms/epoch - 6ms/step
Epoch 56/120
152/152 - 1s - loss: 0.0028 - 931ms/epoch - 6ms/step
Epoch 57/120
152/152 - 1s - loss: 0.0026 - 929ms/epoch - 6ms/step
Epoch 58/120
152/152 - 1s - loss: 0.0028 - 919ms/epoch - 6ms/step
Epoch 59/120
152/152 - 1s - loss: 0.0029 - 926ms/epoch - 6ms/step
Epoch 60/120
152/152 - 1s - loss: 0.0028 - 920ms/epoch - 6ms/step
Epoch 61/120
152/152 - 1s - loss: 0.0031 - 931ms/epoch - 6ms/step
Epoch 62/120
152/152 - 1s - loss: 0.0028 - 922ms/epoch - 6ms/step
Epoch 63/120
152/152 - 1s - loss: 0.0027 - 928ms/epoch - 6ms/step
Epoch 64/120
152/152 - 1s - loss: 0.0027 - 919ms/epoch - 6ms/step
Epoch 65/120
152/152 - 1s - loss: 0.0026 - 948ms/epoch - 6ms/step
Epoch 66/120
152/152 - 1s - loss: 0.0028 - 922ms/epoch - 6ms/step
Epoch 67/120
152/152 - 1s - loss: 0.0028 - 916ms/epoch - 6ms/step
Epoch 68/120
152/152 - 1s - loss: 0.0026 - 908ms/epoch - 6ms/step
Epoch 69/120
152/152 - 1s - loss: 0.0026 - 913ms/epoch - 6ms/step
Epoch 70/120
152/152 - 1s - loss: 0.0028 - 907ms/epoch - 6ms/step
Epoch 71/120
152/152 - 1s - loss: 0.0028 - 908ms/epoch - 6ms/step
Epoch 72/120
152/152 - 1s - loss: 0.0027 - 920ms/epoch - 6ms/step
Epoch 73/120
152/152 - 1s - loss: 0.0029 - 914ms/epoch - 6ms/step
Epoch 74/120
152/152 - 1s - loss: 0.0027 - 914ms/epoch - 6ms/step
Epoch 75/120
152/152 - 1s - loss: 0.0027 - 983ms/epoch - 6ms/step
Epoch 76/120
152/152 - 1s - loss: 0.0028 - 983ms/epoch - 6ms/step
Epoch 77/120
152/152 - 1s - loss: 0.0025 - 939ms/epoch - 6ms/step
Epoch 78/120
152/152 - 1s - loss: 0.0028 - 957ms/epoch - 6ms/step
Epoch 79/120
152/152 - 1s - loss: 0.0029 - 925ms/epoch - 6ms/step
Epoch 80/120
152/152 - 1s - loss: 0.0027 - 926ms/epoch - 6ms/step
Epoch 81/120
152/152 - 1s - loss: 0.0029 - 918ms/epoch - 6ms/step
Epoch 82/120
152/152 - 1s - loss: 0.0028 - 936ms/epoch - 6ms/step
Epoch 83/120
152/152 - 1s - loss: 0.0025 - 932ms/epoch - 6ms/step
Epoch 84/120
152/152 - 1s - loss: 0.0029 - 952ms/epoch - 6ms/step
Epoch 85/120
152/152 - 1s - loss: 0.0026 - 957ms/epoch - 6ms/step
Epoch 86/120
152/152 - 1s - loss: 0.0026 - 957ms/epoch - 6ms/step
Epoch 87/120
152/152 - 1s - loss: 0.0027 - 920ms/epoch - 6ms/step
Epoch 88/120
152/152 - 1s - loss: 0.0026 - 916ms/epoch - 6ms/step
Epoch 89/120
152/152 - 1s - loss: 0.0026 - 920ms/epoch - 6ms/step
Epoch 90/120
152/152 - 1s - loss: 0.0028 - 919ms/epoch - 6ms/step
Epoch 91/120
152/152 - 1s - loss: 0.0026 - 920ms/epoch - 6ms/step
Epoch 92/120
152/152 - 1s - loss: 0.0026 - 910ms/epoch - 6ms/step
Epoch 93/120
152/152 - 1s - loss: 0.0027 - 918ms/epoch - 6ms/step
Epoch 94/120
152/152 - 1s - loss: 0.0025 - 930ms/epoch - 6ms/step
Epoch 95/120
152/152 - 1s - loss: 0.0026 - 911ms/epoch - 6ms/step
```

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Epoch 96/120
152/152 - 1s - loss: 0.0026 - 910ms/epoch - 6ms/step
Epoch 97/120
152/152 - 1s - loss: 0.0026 - 951ms/epoch - 6ms/step
Epoch 98/120
152/152 - 1s - loss: 0.0026 - 959ms/epoch - 6ms/step
Epoch 99/120
152/152 - 1s - loss: 0.0027 - 1s/epoch - 7ms/step
Epoch 100/120
152/152 - 1s - loss: 0.0026 - 929ms/epoch - 6ms/step
Epoch 101/120
152/152 - 1s - loss: 0.0025 - 924ms/epoch - 6ms/step
Epoch 102/120
152/152 - 1s - loss: 0.0026 - 921ms/epoch - 6ms/step
Epoch 103/120
152/152 - 1s - loss: 0.0027 - 919ms/epoch - 6ms/step
Epoch 104/120
152/152 - 1s - loss: 0.0026 - 918ms/epoch - 6ms/step
Epoch 105/120
152/152 - 1s - loss: 0.0026 - 926ms/epoch - 6ms/step
Epoch 106/120
152/152 - 1s - loss: 0.0026 - 913ms/epoch - 6ms/step
Epoch 107/120
152/152 - 1s - loss: 0.0026 - 913ms/epoch - 6ms/step
Epoch 108/120
152/152 - 1s - loss: 0.0027 - 910ms/epoch - 6ms/step
Epoch 109/120
152/152 - 1s - loss: 0.0026 - 914ms/epoch - 6ms/step
Epoch 110/120
152/152 - 1s - loss: 0.0025 - 909ms/epoch - 6ms/step
Epoch 111/120
152/152 - 1s - loss: 0.0026 - 910ms/epoch - 6ms/step
Epoch 112/120
152/152 - 1s - loss: 0.0026 - 909ms/epoch - 6ms/step
Epoch 113/120
152/152 - 1s - loss: 0.0025 - 913ms/epoch - 6ms/step
Epoch 114/120
152/152 - 1s - loss: 0.0025 - 951ms/epoch - 6ms/step
Epoch 115/120
152/152 - 1s - loss: 0.0026 - 928ms/epoch - 6ms/step
Epoch 116/120
152/152 - 1s - loss: 0.0027 - 931ms/epoch - 6ms/step
Epoch 117/120
152/152 - 1s - loss: 0.0027 - 943ms/epoch - 6ms/step
Epoch 118/120
152/152 - 1s - loss: 0.0025 - 922ms/epoch - 6ms/step
Epoch 119/120
152/152 - 1s - loss: 0.0024 - 919ms/epoch - 6ms/step
Epoch 120/120
152/152 - 1s - loss: 0.0028 - 911ms/epoch - 6ms/step
Model: "sequential_11"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 lstm_22 (LSTM)              (None, 15, 85)            29580     
                                                                 
 dropout_22 (Dropout)        (None, 15, 85)            0         
                                                                 
 lstm_23 (LSTM)              (None, 130)               112320    
                                                                 
 dropout_23 (Dropout)        (None, 130)               0         
                                                                 
 dense_33 (Dense)            (None, 35)                4585      
                                                                 
 dense_34 (Dense)            (None, 20)                720       
                                                                 
 dense_35 (Dense)            (None, 1)                 21        
                                                                 
=================================================================
Total params: 147,226
Trainable params: 147,226
Non-trainable params: 0
_________________________________________________________________
1/1 [==============================] - 1s 547ms/step
```

In [162…

```python
if len(all_predictions) > 0:
    print(all_predictions)
```

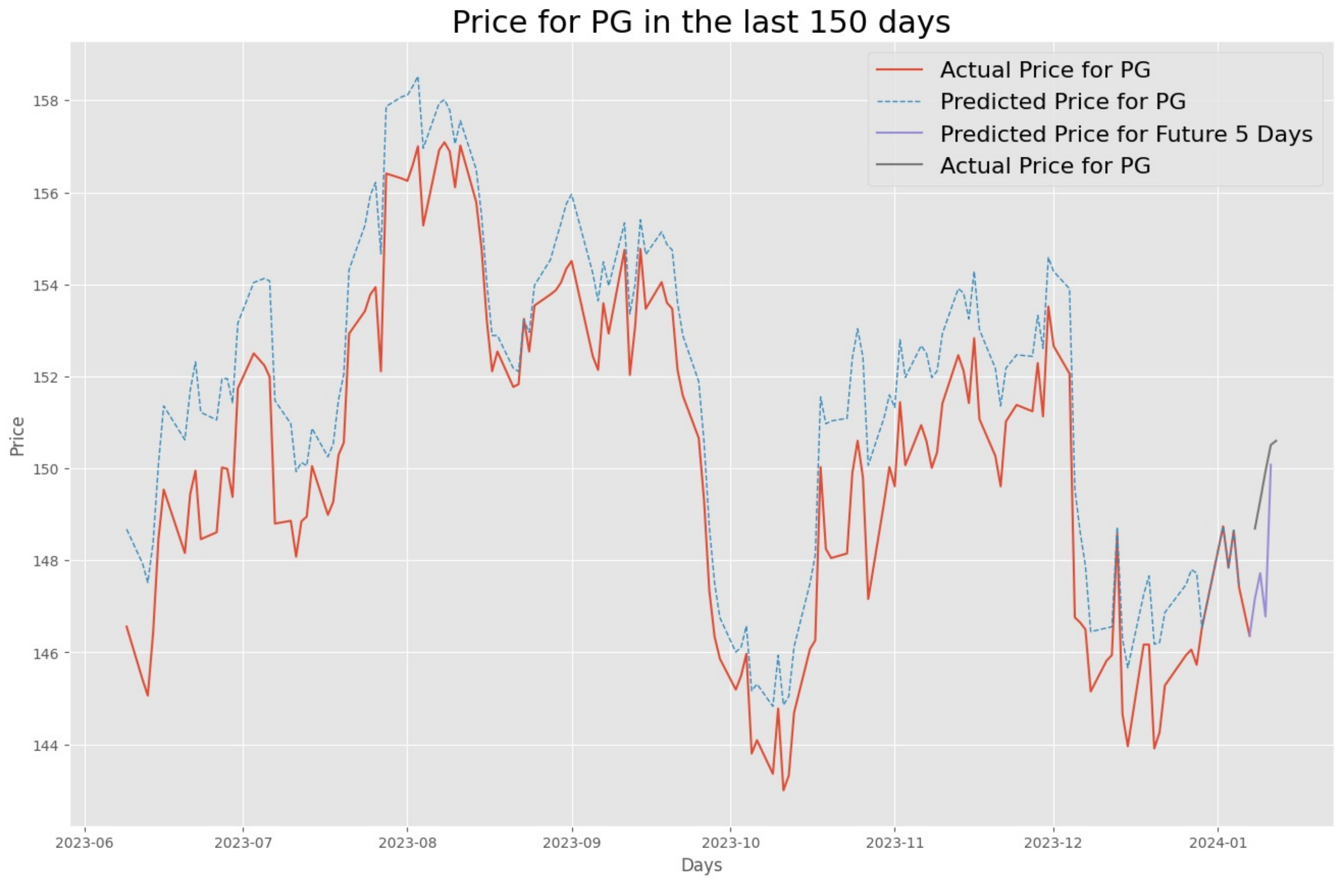
```
[146.36, 147.17, 147.72, 146.78, 150.08]
```

In [163…

```python
data_with_predictions = df_individual.copy()
data_with_predictions.dropna(inplace=True)
data_with_predictions = data_with_predictions.drop(['Adj Close', 'High', 'Low', 'Volume', 'Rsi', 'Macd', 'Atr']

red = len(STEPS)

# Generate model predictions
model_predictions = model.predict(input_sequences)
# print(len(model_predictions))
```

```
# print(len(data_with_predictions))
inverse_transformed_predictions = scaler.inverse_transform(model_predictions)

# Add edge predictions for a continuous sequence
inverse_transformed_predictions = np.concatenate([
    scaler.inverse_transform(target_values[:(N_days-1), np.newaxis]),
    inverse_transformed_predictions,
    scaler.inverse_transform(target_values[-len(STEPS):, np.newaxis])
])

# Add predictions to the DataFrame
data_with_predictions['Predicted_close'] = inverse_transformed_predictions

# Add predicted results for future dates
today = (dt.date.today() - dt.timedelta(days=8))
future_dates = [today + dt.timedelta(days=i) for i in range(red)]
future_predictions = all_predictions[:red]   # Assuming 'predictions' holds the 5 future values

# print(data_with_predictions)

for date, prediction in zip(future_dates, future_predictions):
    data_with_predictions.loc[date] = [prediction, 0, 0, 0, date.strftime('%Y-%m-%d'), 0]

# print(data_with_predictions)

# check the predictions against the actual price
check_cur_date = dt.date.today()
check_start_date = (dt.date.today() - dt.timedelta(days=8))

check_ind_stock_data = yf.download(STOCK, start = check_start_date, end = check_cur_date)

# Visualize results
plt.style.use('ggplot')
plt.figure(figsize=(16, 10))
plt.title(f'Price for {STOCK} in the last 150 days', fontsize=22)
plt.plot(data_with_predictions['Close'].tail(150).head(151 - red))
plt.plot(data_with_predictions['Predicted_close'].tail(150).head(150 - red), linewidth=1, linestyle='dashed')
plt.plot(data_with_predictions['Close'].tail(len(STEPS)))
plt.plot(check_ind_stock_data['Close'])
plt.xlabel('Days')
plt.ylabel('Price')
plt.legend([f'Actual Price for {STOCK}',
            f'Predicted Price for {STOCK}',
            f'Predicted Price for Future {len(STEPS)} Days',
            f'Actual Price for {STOCK}'], fontsize=16)
plt.show()
```

```
38/38 [==============================] - 0s 2ms/step
[*********************100%%**********************]  1 of 1 completed
```



In [164…

```
# get the error in a percentage
miss = []
```

```python
for acc_price, price in zip(check_ind_stock_data['Close'], all_predictions):
    print(acc_price, price)
    miss.append((abs(acc_price - price)*100)/price)
miss_avg = sum(miss)/len(miss)
print(f'The difference in % is {miss_avg}')
```

```
148.69000244140625 146.36
149.3000030517578 147.17
149.94000244140625 147.72
150.50999450683594 146.78
150.60000610351562 150.08
The difference in % is 1.4859639632446664
```

In [85]:
```python
check_ind_stock_data
```

Out[85]:

Date	Open	High	Low	Close	Adj Close	Volume
2024-01-08	495.119995	522.750000	494.790009	522.530029	522.530029	64251000
2024-01-09	524.010010	543.250000	516.900024	531.400024	531.400024	77310000
2024-01-10	536.159973	546.000000	534.890015	543.500000	543.500000	53379600
2024-01-11	549.989990	553.460022	535.599976	548.219971	548.219971	59675900
2024-01-12	546.200012	549.700012	543.299988	547.099976	547.099976	35247900

In [ ]: