

Stock Prediction

By Swagata Naskar

```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import datetime
from datetime import date
import math
import pandas_datareader as web
```

```
In [2]: from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout
```

```
In [3]: data = web.get_data_yahoo('^NSEBANK', start = datetime.datetime(2010, 1, 2),
                                     end = date.today())

data = data[['Adj Close']]
data.columns = ['Price']
data.head()
```

```
Out[3]:
```

	Price
Date	
2010-01-04	9112.349609
2010-01-05	9192.150391
2010-01-06	9223.000000
2010-01-07	9192.950195
2010-01-08	9160.700195

```
In [4]: data.tail()
```

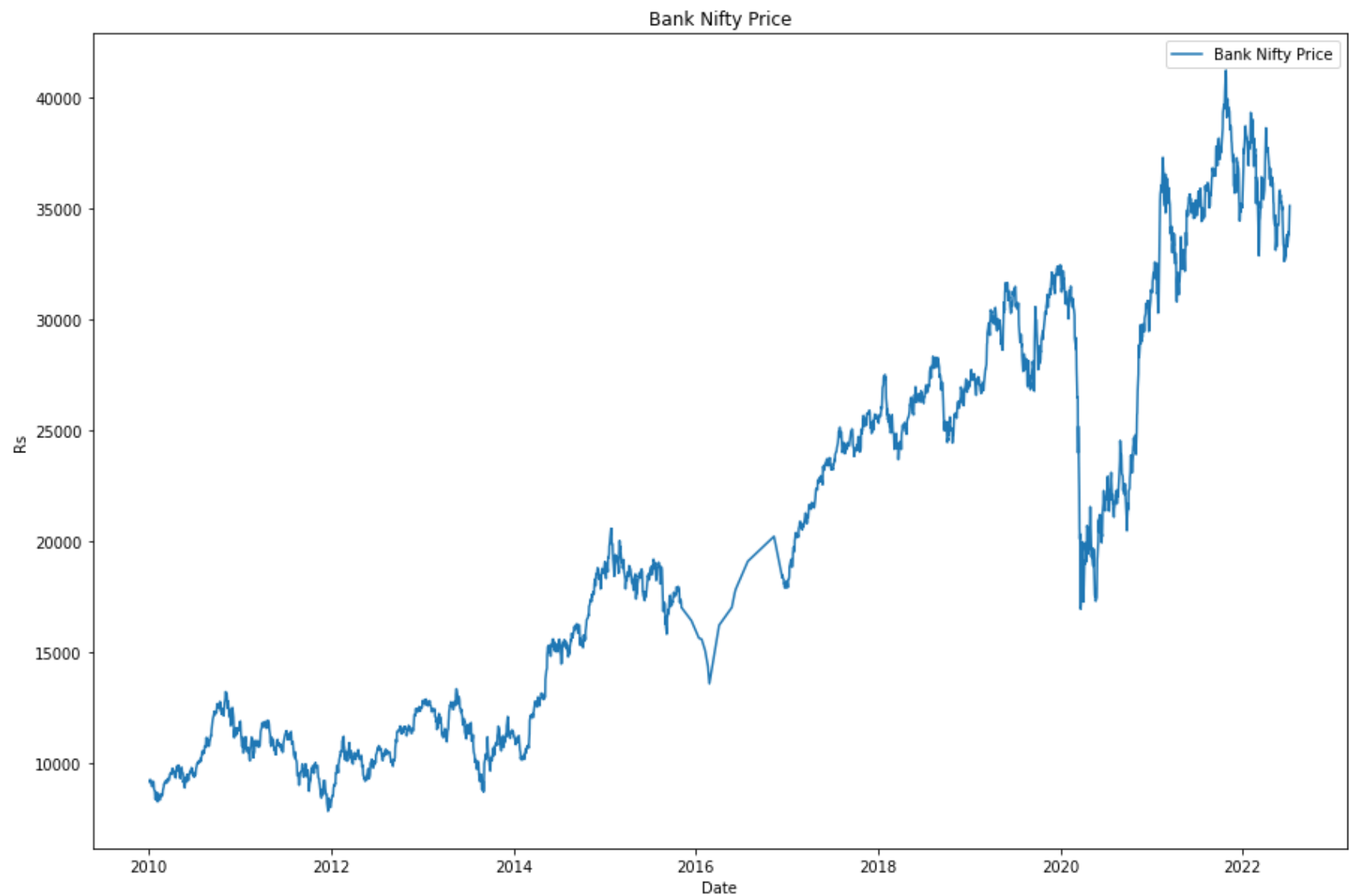
```
Out[4]:
```

	Price
Date	
2022-07-04	33940.898438
2022-07-05	33815.898438
2022-07-06	34324.250000
2022-07-07	34920.300781
2022-07-08	35124.050781

```
In [5]: print('There are {} number of days in the dataset.'.format(data.shape[0]))
```

There are 2800 number of days in the dataset.

```
In [6]: plt.figure(figsize=(15, 10))#, dpi=100)
plt.plot(data.index, data['Price'], label='Bank Nifty Price')
plt.xlabel('Date')
plt.ylabel('Rs')
plt.title('Bank Nifty Price')
plt.legend()
plt.show()
```



```
In [7]: def get_technical_indicators(dataset):  
        # Create 7 and 21 days Moving Average  
        dataset['ma7'] = dataset['Price'].rolling(window=7).mean()  
        dataset['ma21'] = dataset['Price'].rolling(window=21).mean()  
  
        # Create MACD  
        dataset['26ema'] = dataset['Price'].ewm(span=26).mean()  
        dataset['12ema'] = dataset['Price'].ewm(span=12).mean()
```

```

dataset['MACD'] = dataset['12ema']-dataset['26ema']

# Create Bollinger Bands
dataset['20sd'] = dataset['Price'].rolling(window = 21).std()
dataset['upper_band'] = dataset['ma21'] + (dataset['20sd']*2)
dataset['lower_band'] = dataset['ma21'] - (dataset['20sd']*2)

# Create Exponential moving average
dataset['ema'] = dataset['Price'].ewm(com=0.5).mean()

# Create Momentum
dataset['momentum'] = dataset['Price']-1
dataset['log_momentum'] = np.log(dataset['momentum'])
return dataset

```

In [8]: df = get_technical_indicators(data)

In [9]: df = df.dropna()
df.head()

Out[9]:

	Price	ma7	ma21	26ema	12ema	MACD	20sd	upper_band	lower_band	ema	mo
Date											
2010-02-02	8468.150391	8570.264230	8907.354678	8801.227916	8697.663730	-103.564187	277.087495	9461.529668	8353.179688	8520.889180	846
2010-02-03	8631.849609	8550.149833	8884.473726	8785.853374	8687.275187	-98.578187	279.144713	9442.763152	8326.184299	8594.862800	863
2010-02-04	8471.099609	8517.935547	8850.137974	8757.752225	8653.288548	-104.463677	283.715600	9417.569174	8282.706775	8512.354006	847
2010-02-05	8223.250000	8502.714146	8802.530831	8710.746733	8585.906040	-124.840693	301.351790	9405.234412	8199.827251	8319.618002	822
2010-02-08	8342.200195	8491.049944	8762.018927	8678.779150	8547.828169	-130.950980	303.419639	9368.858204	8155.179649	8334.672798	834

In [10]:

```

def plot_technical_indicators(dataset, last_days):
    plt.figure(figsize=(16, 10), dpi=100)
    shape_0 = dataset.shape[0]
    xmacd_ = shape_0-last_days

```

```

dataset = dataset.iloc[-last_days:, :]
x_ = range(3, dataset.shape[0])
x_ = list(dataset.index)

plt.figure(figsize=(30,20))
# Plot first subplot
plt.subplot(2, 1, 1)
plt.plot(dataset['ma7'],label='MA 7', color='g',linestyle='--')
plt.plot(dataset['Price'],label='Closing Price', color='b')
plt.plot(dataset['ma21'],label='MA 21', color='r',linestyle='--')
plt.plot(dataset['upper_band'],label='Upper Band', color='c')
plt.plot(dataset['lower_band'],label='Lower Band', color='c')
plt.fill_between(x_, dataset['lower_band'], dataset['upper_band'], alpha=0.35)
plt.title('Technical indicators for Goldman Sachs - last {} days.'.format(last_days))
plt.ylabel('USD')
plt.legend()

# Plot second subplot

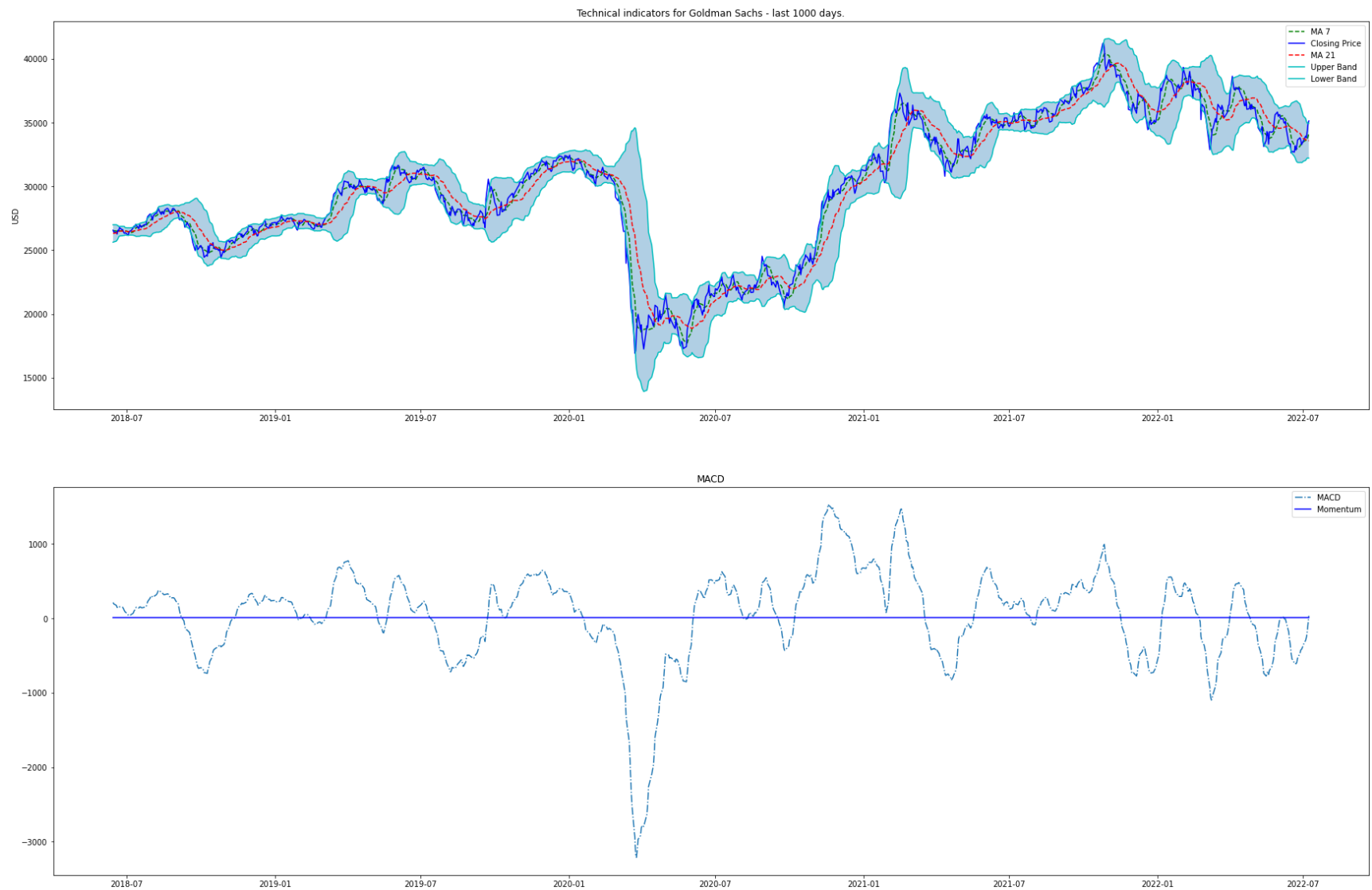
plt.subplot(2, 1, 2)
plt.title('MACD')
plt.plot(dataset['MACD'],label='MACD', linestyle='-.')
# plt.hlines(15, xmacd_, shape_0, colors='g', linestyle='--')
# plt.hlines(-15, xmacd_, shape_0, colors='g', linestyle='--')
plt.plot(dataset['log_momentum'],label='Momentum', color='b',linestyle='-.')

plt.legend()
plt.show()

```

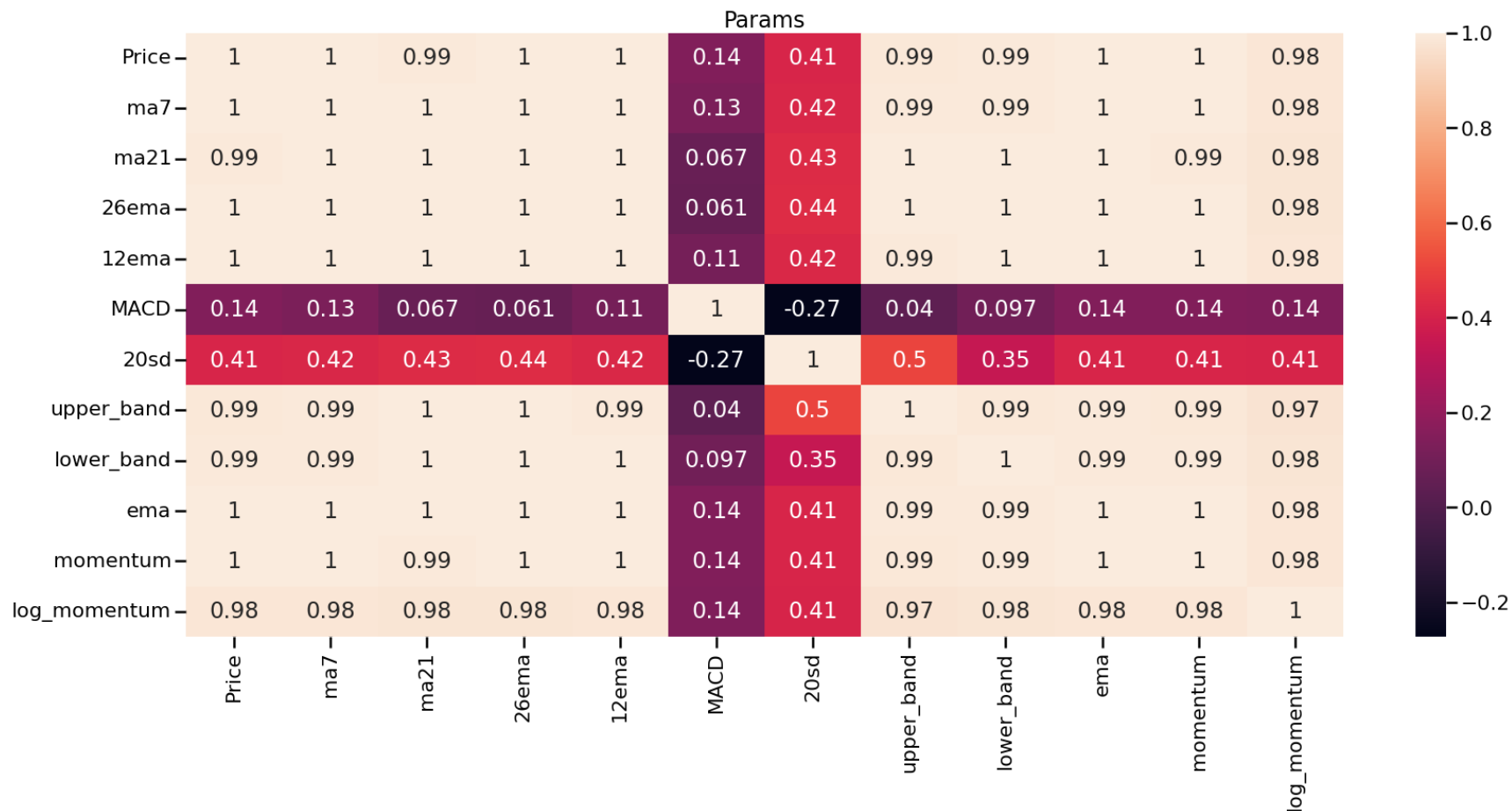
In [11]: plot_technical_indicators(df, 1000)

<Figure size 1600x1000 with 0 Axes>



```
In [12]: plt.figure(figsize = (28,12))  
sns.set_context('poster',font_scale=1)  
sns.heatmap(df.corr(), annot = True).set_title('Params')
```

```
Out[12]: Text(0.5, 1.0, 'Params')
```



```
In [13]: print('Total dataset has {} samples, and {} features.'.format(df.shape[0], \
                                                                    df.shape[1]))
```

Total dataset has 2780 samples, and 12 features.

```
In [14]: df.columns
```

```
Out[14]: Index(['Price', 'ma7', 'ma21', '26ema', '12ema', 'MACD', '20sd', 'upper_band',
               'lower_band', 'ema', 'momentum', 'log_momentum'],
              dtype='object')
```

```
In [15]: df
```

Out[15]:

	Price	ma7	ma21	26ema	12ema	MACD	20sd	upper_band	lower_band	€
Date										
2010-02-02	8468.150391	8570.264230	8907.354678	8801.227916	8697.663730	-103.564187	277.087495	9461.529668	8353.179688	8520.889
2010-02-03	8631.849609	8550.149833	8884.473726	8785.853374	8687.275187	-98.578187	279.144713	9442.763152	8326.184299	8594.862
2010-02-04	8471.099609	8517.935547	8850.137974	8757.752225	8653.288548	-104.463677	283.715600	9417.569174	8282.706775	8512.354
2010-02-05	8223.250000	8502.714146	8802.530831	8710.746733	8585.906040	-124.840693	301.351790	9405.234412	8199.827251	8319.618
2010-02-08	8342.200195	8491.049944	8762.018927	8678.779150	8547.828169	-130.950980	303.419639	9368.858204	8155.179649	8334.672
...
2022-07-04	33940.898438	33608.070871	33683.395182	33860.420558	33564.752226	-295.668331	821.997085	35327.389353	32039.401012	33793.410
2022-07-05	33815.898438	33634.992188	33612.238002	33857.122623	33603.390105	-253.732518	734.108973	35080.455948	32144.020057	33808.402
2022-07-06	34324.250000	33708.277902	33580.249907	33891.724651	33714.291627	-177.433024	683.702987	34947.655881	32212.843933	34152.300
2022-07-07	34920.300781	33890.828125	33579.019066	33967.915475	33899.831497	-68.083978	681.139532	34941.298129	32216.740003	34664.300
2022-07-08	35124.050781	34155.707031	33580.857236	34053.555127	34088.172925	34.617798	685.446623	34951.750482	32209.963989	34970.800

2780 rows × 12 columns



```
In [16]: data_training = df[df.index < '2019-01-31'].copy()
          data_training
```


Out[16]:

	Price	ma7	ma21	26ema	12ema	MACD	20sd	upper_band	lower_band	€
Date										
2010-02-02	8468.150391	8570.264230	8907.354678	8801.227916	8697.663730	-103.564187	277.087495	9461.529668	8353.179688	8520.889
2010-02-03	8631.849609	8550.149833	8884.473726	8785.853374	8687.275187	-98.578187	279.144713	9442.763152	8326.184299	8594.862
2010-02-04	8471.099609	8517.935547	8850.137974	8757.752225	8653.288548	-104.463677	283.715600	9417.569174	8282.706775	8512.354
2010-02-05	8223.250000	8502.714146	8802.530831	8710.746733	8585.906040	-124.840693	301.351790	9405.234412	8199.827251	8319.618
2010-02-08	8342.200195	8491.049944	8762.018927	8678.779150	8547.828169	-130.950980	303.419639	9368.858204	8155.179649	8334.672
...
2019-01-24	27266.400391	27428.878348	27316.590495	27208.914029	27369.590681	160.676652	220.658590	27757.907674	26875.273315	27288.044
2019-01-25	27115.300781	27376.250000	27322.709542	27201.979714	27330.469158	128.489444	212.693942	27748.097427	26897.321658	27172.881
2019-01-28	26653.050781	27251.150112	27311.971447	27161.318312	27226.250946	64.932634	240.158143	27792.287733	26831.655162	26826.327
2019-01-29	26573.400391	27124.964565	27285.692894	27117.768836	27125.812399	8.043563	287.196724	27860.086343	26711.299446	26657.709
2019-01-30	26825.500000	27023.807478	27269.754836	27096.119293	27079.610492	-16.508801	303.342509	27876.439854	26663.069819	26769.569

1935 rows × 12 columns

```
In [17]: data_testing = df[df.index >= '2019-01-31'].copy()
          data_testing
```

Out[17]:

	Price	ma7	ma21	26ema	12ema	MACD	20sd	upper_band	lower_band	€
Date										
2019-01-31	27295.449219	26997.121652	27275.504836	27110.884472	27112.816450	1.931977	302.594107	27880.693050	26670.316623	27120.156
2019-02-01	27085.949219	26973.578683	27281.509580	27109.037417	27108.683029	-0.354387	297.220439	27875.950457	26687.068702	27097.351
2019-02-04	27186.599609	26962.178571	27281.109561	27114.782764	27120.670196	5.887431	297.348316	27875.806193	26686.412929	27156.850
2019-02-05	27271.699219	26984.521205	27279.545201	27126.406205	27143.905430	17.499225	297.305238	27874.155677	26684.934725	27233.416
2019-02-06	27402.349609	27091.563895	27274.442801	27146.846457	27183.666073	36.819615	294.063180	27862.569162	26686.316441	27346.038
...
2022-07-04	33940.898438	33608.070871	33683.395182	33860.420558	33564.752226	-295.668331	821.997085	35327.389353	32039.401012	33793.410
2022-07-05	33815.898438	33634.992188	33612.238002	33857.122623	33603.390105	-253.732518	734.108973	35080.455948	32144.020057	33808.402
2022-07-06	34324.250000	33708.277902	33580.249907	33891.724651	33714.291627	-177.433024	683.702987	34947.655881	32212.843933	34152.300
2022-07-07	34920.300781	33890.828125	33579.019066	33967.915475	33899.831497	-68.083978	681.139532	34941.298129	32216.740003	34664.300
2022-07-08	35124.050781	34155.707031	33580.857236	34053.555127	34088.172925	34.617798	685.446623	34951.750482	32209.963989	34970.800

845 rows × 12 columns

```
In [18]: scalar = MinMaxScaler()

data_training_scaled = scalar.fit_transform(data_training)
print(data_training_scaled.shape)
data_training_scaled
```

(1935, 12)

```
Out[18]: array([[0.0326293 , 0.02151149, 0.02926575, ..., 0.03154458, 0.0326293 ,
          0.06387762],
          [0.04060628, 0.02050703, 0.02810332, ..., 0.03517799, 0.04060628,
          0.07872494],
          [0.03277302, 0.01889834, 0.02635895, ..., 0.03112535, 0.03277302,
          0.06414764],
          ...,
          [0.9187704 , 0.95438137, 0.96428198, ..., 0.93066481, 0.9187704 ,
          0.95296134],
          [0.91488907, 0.94808003, 0.96294694, ..., 0.92238268, 0.91488907,
          0.95064069],
          [0.92717376, 0.94302853, 0.96213723, ..., 0.92787699, 0.92717376,
          0.95796207]])
```

```
In [19]: X_train = []
         y_train = []
```

```
In [20]: for i in range(60, data_training.shape[0]):
         X_train.append(data_training_scaled[i-60: i])
         y_train.append(data_training_scaled[i, 0])
```

```
In [21]: X_train, y_train = np.array(X_train), np.array(y_train)
         X_train.shape, y_train.shape
```

```
Out[21]: ((1875, 60, 12), (1875,))
```

```
In [22]: regressor = Sequential()

         regressor.add(LSTM(units = 50, activation = 'relu', return_sequences = True, input_shape = (X_train.shape[1], 12)))
         regressor.add(Dropout(0.2))

         regressor.add(LSTM(units = 60, activation = 'relu', return_sequences = True))
         regressor.add(Dropout(0.3))

         regressor.add(LSTM(units = 80, activation = 'relu', return_sequences = True))
         regressor.add(Dropout(0.4))

         regressor.add(LSTM(units = 120, activation = 'relu'))
         regressor.add(Dropout(0.5))

         regressor.add(Dense(units = 1))
```

```
In [23]: regressor.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 60, 50)	12600
dropout (Dropout)	(None, 60, 50)	0
lstm_1 (LSTM)	(None, 60, 60)	26640
dropout_1 (Dropout)	(None, 60, 60)	0
lstm_2 (LSTM)	(None, 60, 80)	45120
dropout_2 (Dropout)	(None, 60, 80)	0
lstm_3 (LSTM)	(None, 120)	96480
dropout_3 (Dropout)	(None, 120)	0
dense (Dense)	(None, 1)	121
=====		
Total params: 180,961		
Trainable params: 180,961		
Non-trainable params: 0		

```
In [24]: # Compiling the RNN
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')
```

```
In [25]: regressor.fit(X_train, y_train, epochs=50, batch_size = 64)
```

```
Epoch 1/50
30/30 [=====] - 9s 175ms/step - loss: 0.0867
Epoch 2/50
30/30 [=====] - 5s 173ms/step - loss: 0.0151
Epoch 3/50
30/30 [=====] - 5s 173ms/step - loss: 0.0107
Epoch 4/50
30/30 [=====] - 5s 177ms/step - loss: 0.0087
Epoch 5/50
30/30 [=====] - 5s 174ms/step - loss: 0.0091
Epoch 6/50
30/30 [=====] - 5s 174ms/step - loss: 0.0087
Epoch 7/50
30/30 [=====] - 5s 174ms/step - loss: 0.0073
Epoch 8/50
30/30 [=====] - 5s 175ms/step - loss: 0.0072
Epoch 9/50
30/30 [=====] - 5s 174ms/step - loss: 0.0065
Epoch 10/50
30/30 [=====] - 5s 175ms/step - loss: 0.0061
Epoch 11/50
30/30 [=====] - 5s 175ms/step - loss: 0.0061
Epoch 12/50
30/30 [=====] - 5s 175ms/step - loss: 0.0058
Epoch 13/50
30/30 [=====] - 5s 179ms/step - loss: 0.0059
Epoch 14/50
30/30 [=====] - 5s 178ms/step - loss: 0.0057
Epoch 15/50
30/30 [=====] - 5s 179ms/step - loss: 0.0057
Epoch 16/50
30/30 [=====] - 5s 180ms/step - loss: 0.0059
Epoch 17/50
30/30 [=====] - 5s 179ms/step - loss: 0.0053
Epoch 18/50
30/30 [=====] - 5s 177ms/step - loss: 0.0054
Epoch 19/50
30/30 [=====] - 5s 179ms/step - loss: 0.0054
Epoch 20/50
30/30 [=====] - 5s 179ms/step - loss: 0.0050
Epoch 21/50
30/30 [=====] - 5s 178ms/step - loss: 0.0049
Epoch 22/50
30/30 [=====] - 5s 178ms/step - loss: 0.0057
Epoch 23/50
```

```
30/30 [=====] - 5s 180ms/step - loss: 0.0048
Epoch 24/50
30/30 [=====] - 5s 179ms/step - loss: 0.0046
Epoch 25/50
30/30 [=====] - 5s 181ms/step - loss: 0.0047
Epoch 26/50
30/30 [=====] - 5s 181ms/step - loss: 0.0046
Epoch 27/50
30/30 [=====] - 5s 181ms/step - loss: 0.0046
Epoch 28/50
30/30 [=====] - 5s 179ms/step - loss: 0.0046
Epoch 29/50
30/30 [=====] - 5s 179ms/step - loss: 0.0041
Epoch 30/50
30/30 [=====] - 5s 179ms/step - loss: 0.0045
Epoch 31/50
30/30 [=====] - 5s 182ms/step - loss: 0.0041
Epoch 32/50
30/30 [=====] - 5s 179ms/step - loss: 0.0045
Epoch 33/50
30/30 [=====] - 5s 181ms/step - loss: 0.0044
Epoch 34/50
30/30 [=====] - 6s 184ms/step - loss: 0.0040
Epoch 35/50
30/30 [=====] - 5s 182ms/step - loss: 0.0041
Epoch 36/50
30/30 [=====] - 5s 181ms/step - loss: 0.0041
Epoch 37/50
30/30 [=====] - 5s 181ms/step - loss: 0.0036
Epoch 38/50
30/30 [=====] - 5s 181ms/step - loss: 0.0039
Epoch 39/50
30/30 [=====] - 6s 201ms/step - loss: 0.0038
Epoch 40/50
30/30 [=====] - 6s 204ms/step - loss: 0.0041
Epoch 41/50
30/30 [=====] - 6s 200ms/step - loss: 0.0039
Epoch 42/50
30/30 [=====] - 6s 191ms/step - loss: 0.0037
Epoch 43/50
30/30 [=====] - 6s 192ms/step - loss: 0.0039
Epoch 44/50
30/30 [=====] - 6s 192ms/step - loss: 0.0040
Epoch 45/50
30/30 [=====] - 6s 191ms/step - loss: 0.0040
```

```
Epoch 46/50
30/30 [=====] - 6s 200ms/step - loss: 0.0037
Epoch 47/50
30/30 [=====] - 6s 192ms/step - loss: 0.0034
Epoch 48/50
30/30 [=====] - 6s 201ms/step - loss: 0.0032
Epoch 49/50
30/30 [=====] - 6s 193ms/step - loss: 0.0032
Epoch 50/50
30/30 [=====] - 6s 191ms/step - loss: 0.0035
```

Out[25]: <keras.callbacks.History at 0x2ceba6ec970>

```
In [26]: past_100 = data_training.tail(100)

dt = past_100.append(data_testing, ignore_index = True)
dt
```

C:\Users\US\AppData\Local\Temp\ipykernel_1828\1412723301.py:3: FutureWarning: The frame.append method is deprecated and will be removed from pandas in a future version. Use pandas.concat instead.

```
dt = past_100.append(data_testing, ignore_index = True)
```

Out[26]:

	Price	ma7	ma21	26ema	12ema	MACD	20sd	upper_band	lower_band	em
0	27819.500000	28082.449777	28011.473772	27843.299406	28038.335626	195.036220	239.913058	28491.299888	27531.647656	27909.40813
1	27430.750000	28024.742746	28015.035714	27812.740190	27944.860914	132.120724	230.046379	28475.128473	27554.942956	27590.30271
2	27376.050781	27897.864397	27999.823847	27780.392827	27857.351663	76.958836	260.745660	28521.315167	27478.332527	27447.46809
3	27468.699219	27783.442801	27979.357143	27757.304411	27797.558979	40.254568	284.850507	28549.058157	27409.656129	27461.62217
4	27481.449219	27677.349888	27960.573754	27736.870693	27748.926708	12.056015	304.351450	28569.276653	27351.870854	27474.84020
...
940	33940.898438	33608.070871	33683.395182	33860.420558	33564.752226	-295.668331	821.997085	35327.389353	32039.401012	33793.41065
941	33815.898438	33634.992188	33612.238002	33857.122623	33603.390105	-253.732518	734.108973	35080.455948	32144.020057	33808.40251
942	34324.250000	33708.277902	33580.249907	33891.724651	33714.291627	-177.433024	683.702987	34947.655881	32212.843933	34152.30083
943	34920.300781	33890.828125	33579.019066	33967.915475	33899.831497	-68.083978	681.139532	34941.298129	32216.740003	34664.30080
944	35124.050781	34155.707031	33580.857236	34053.555127	34088.172925	34.617798	685.446623	34951.750482	32209.963989	34970.80078

945 rows × 12 columns

```
In [27]: inputs = scalar.fit_transform(dt)
print(inputs.shape)
inputs
```

```
Out[27]: (945, 12)
array([[0.44825485, 0.45705141, 0.44013283, ..., 0.44260293, 0.44825485,
        0.55822432],
       [0.4322705 , 0.45450529, 0.44030402, ..., 0.42912793, 0.4322705 ,
        0.54243042],
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```

```
In [28]: X_test = []
y_test = []

for i in range(60, inputs.shape[0]):
    X_test.append(inputs[i-60:i])
    y_test.append(inputs[i, 0])

X_test, y_test = np.array(X_test), np.array(y_test)
X_test.shape, y_test.shape
```

```
Out[28]: ((885, 60, 12), (885,))
```

```
In [29]: y_pred = regressor.predict(X_test)
```

```
28/28 [=====] - 2s 47ms/step
```

```
In [30]: y_pred
```



```
Out[30]: array([[0.30307862],  
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```

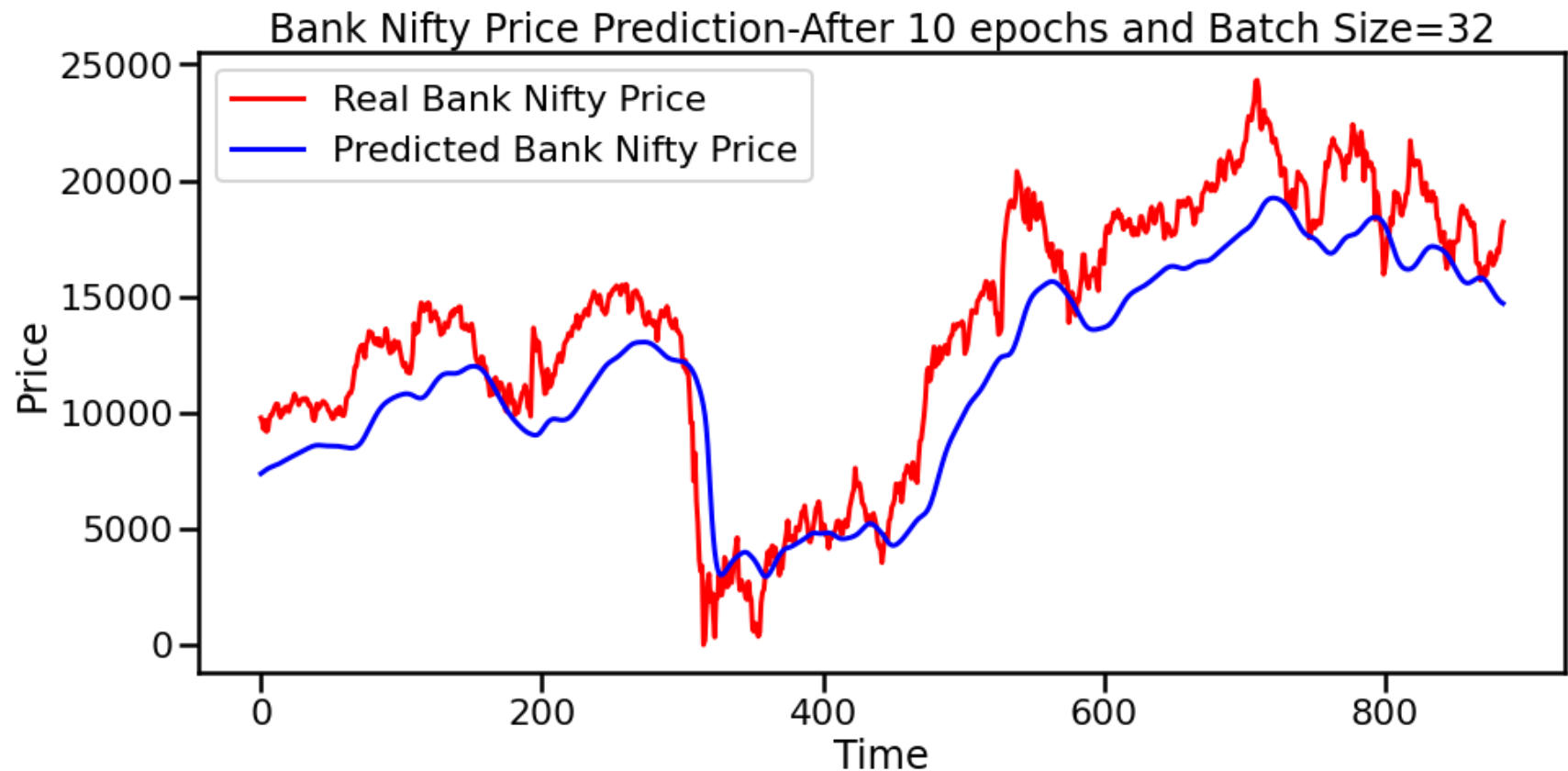
```
In [31]: scale = 1/scalar.scale_[0]
```

```
In [32]: y_pred = y_pred*scale  
y_test = y_test*scale
```

```
In [33]: # Visualising the results
```

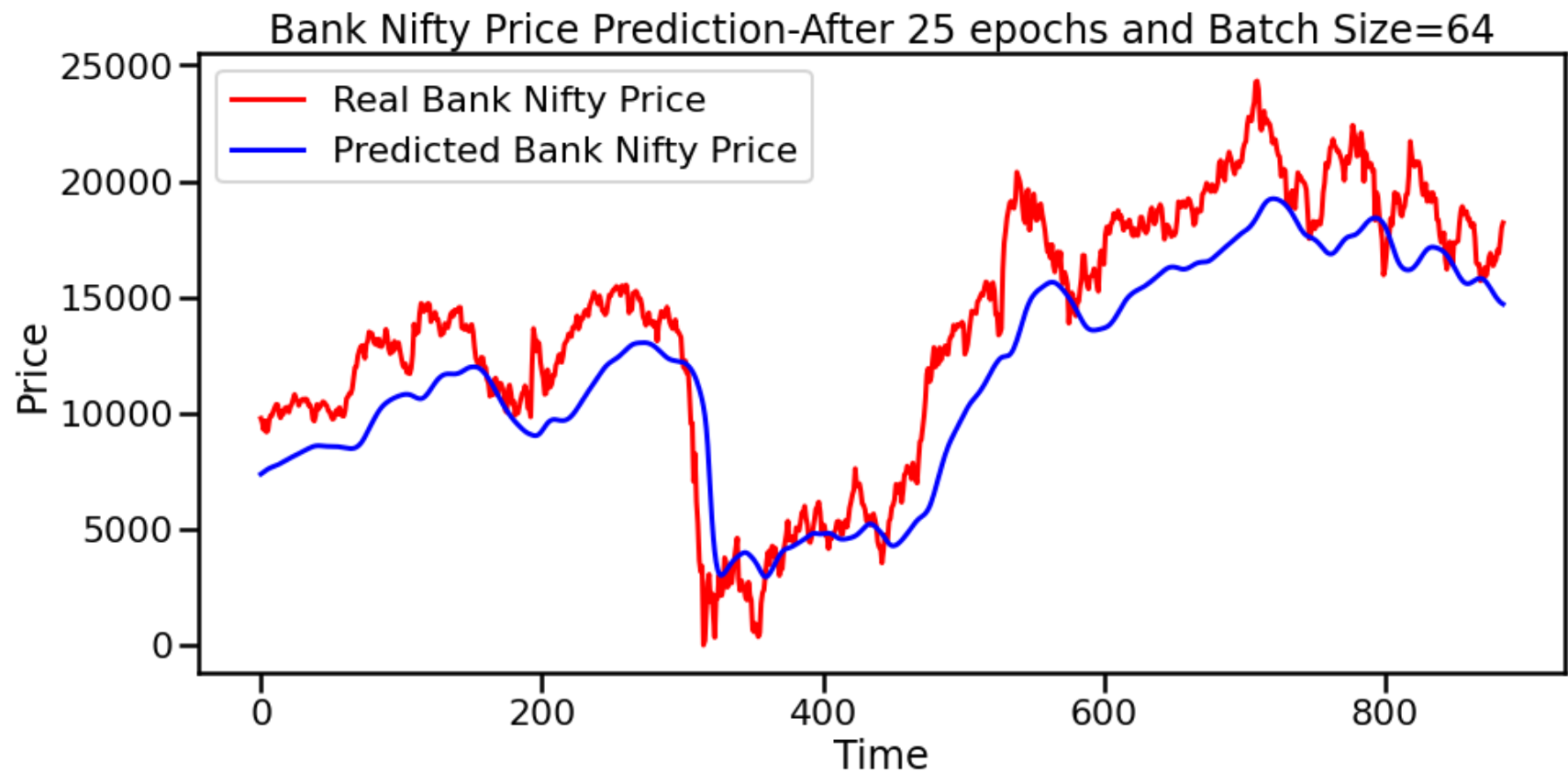
```
plt.figure(figsize=(15,7))  
plt.plot(y_test, color = 'red', label = 'Real Bank Nifty Price')  
plt.plot(y_pred, color = 'blue', label = 'Predicted Bank Nifty Price')  
plt.title('Bank Nifty Price Prediction-After 10 epochs and Batch Size=32')  
plt.xlabel('Time')  
plt.ylabel('Price')
```

```
plt.legend()  
plt.show()
```



In [34]: *# Visualising the results*

```
plt.figure(figsize=(15,7))  
plt.plot(y_test, color = 'red', label = 'Real Bank Nifty Price')  
plt.plot(y_pred, color = 'blue', label = 'Predicted Bank Nifty Price')  
plt.title('Bank Nifty Price Prediction-After 25 epochs and Batch Size=64')  
plt.xlabel('Time')  
plt.ylabel('Price')  
plt.legend()  
plt.show()
```



In [35]: *# Visualising the results*

```
plt.figure(figsize=(15,7))
plt.plot(y_test, color = 'red', label = 'Real Bank Nifty Price')
plt.plot(y_pred, color = 'blue', label = 'Predicted Bank Nifty Price')
plt.title('Bank Nifty Price Prediction-After 50 epochs and Batch Size=32')
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend()
plt.show()
```

