In [5]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
```

In [6]:
```
data = pd.read_csv('BTC-USD.csv', date_parser = True)
data.tail()
```

Out[6]:

	Date	Open	High	Low	Close	Adj Close	Volume
2075	2020-05-23	9185.062500	9302.501953	9118.108398	9209.287109	9209.287109	2.772787e+10
2076	2020-05-24	9212.283203	9288.404297	8787.250977	8790.368164	8790.368164	3.251880e+10
2077	2020-05-25	8786.107422	8951.005859	8719.667969	8906.934570	8906.934570	3.128816e+10
2078	2020-05-26	NaN	NaN	NaN	NaN	NaN	NaN
2079	2020-05-27	8834.157227	8859.578125	8834.157227	8856.885742	8856.885742	2.914432e+10

In [7]:
```
data_training = data[data['Date']< '2020-01-01'].copy()
data_training
```

Out[7]:

	Date	Open	High	Low	Close	Adj Close	Volume
0	2014-09-17	465.864014	468.174011	452.421997	457.334015	457.334015	2.105680e+07
1	2014-09-18	456.859985	456.859985	413.104004	424.440002	424.440002	3.448320e+07
2	2014-09-19	424.102997	427.834991	384.532013	394.795990	394.795990	3.791970e+07
3	2014-09-20	394.673004	423.295990	389.882996	408.903992	408.903992	3.686360e+07
4	2014-09-21	408.084991	412.425995	393.181000	398.821014	398.821014	2.658010e+07
...	...	...	...	...	...	...	...
1927	2019-12-27	7238.141113	7363.529297	7189.934082	7290.088379	7290.088379	2.277736e+10
1928	2019-12-28	7289.031250	7399.041016	7286.905273	7317.990234	7317.990234	2.136567e+10
1929	2019-12-29	7317.647461	7513.948242	7279.865234	7422.652832	7422.652832	2.244526e+10
1930	2019-12-30	7420.272949	7454.824219	7276.308105	7292.995117	7292.995117	2.287413e+10
1931	2019-12-31	7294.438965	7335.290039	7169.777832	7193.599121	7193.599121	2.116795e+10

1932 rows × 7 columns

In [8]:
```
data_test = data[data['Date']> '2020-01-01'].copy()
data_test
```

Out[8]:

	Date	Open	High	Low	Close	Adj Close	Volume
1933	2020-01-02	7202.551270	7212.155273	6935.270020	6985.470215	6985.470215	2.080208e+10
1934	2020-01-03	6984.428711	7413.715332	6914.996094	7344.884277	7344.884277	2.811148e+10
1935	2020-01-04	7345.375488	7427.385742	7309.514160	7410.656738	7410.656738	1.844427e+10
1936	2020-01-05	7410.451660	7544.497070	7400.535645	7411.317383	7411.317383	1.972507e+10
1937	2020-01-06	7410.452148	7781.867188	7409.292969	7769.219238	7769.219238	2.327626e+10
...	...	...	...	...	...	...	...
2075	2020-05-23	9185.062500	9302.501953	9118.108398	9209.287109	9209.287109	2.772787e+10
2076	2020-05-24	9212.283203	9288.404297	8787.250977	8790.368164	8790.368164	3.251880e+10
2077	2020-05-25	8786.107422	8951.005859	8719.667969	8906.934570	8906.934570	3.128816e+10
2078	2020-05-26	NaN	NaN	NaN	NaN	NaN	NaN
2079	2020-05-27	8834.157227	8859.578125	8834.157227	8856.885742	8856.885742	2.914432e+10

147 rows × 7 columns

In [9]:
```
training_data = data_training.drop(['Date', 'Adj Close'], axis = 1)
training_data.head()
```

Out[9]:

	Open	High	Low	Close	Volume
0	465.864014	468.174011	452.421997	457.334015	21056800.0
1	456.859985	456.859985	413.104004	424.440002	34483200.0
2	424.102997	427.834991	384.532013	394.795990	37919700.0
3	394.673004	423.295990	389.882996	408.903992	36863600.0
4	408.084991	412.425995	393.181000	398.821014	26580100.0

In [10]:
```
scaler = MinMaxScaler()
training_data = scaler.fit_transform(training_data)
training_data
```

Out[10]:
```
array([[1.49732345e-02, 1.29013200e-02, 1.49400698e-02, 1.44534769e-02,
        3.35749244e-04],
       [1.45066780e-02, 1.23321258e-02, 1.28489753e-02, 1.27508263e-02,
        6.33453324e-04],
       [1.28093283e-02, 1.08719155e-02, 1.13293978e-02, 1.12164013e-02,
        7.09650970e-04],
       ...,
       [3.70008086e-01, 3.67365217e-01, 3.78051927e-01, 3.74990337e-01,
        4.97548412e-01],
       [3.75325771e-01, 3.64390763e-01, 3.77862744e-01, 3.68279031e-01,
        5.07057851e-01],
       [3.68805505e-01, 3.58377151e-01, 3.72197021e-01, 3.63134123e-01,
        4.69226533e-01]])
```

In [11]:
```
X_train = []
Y_train = []
```

In [12]:
```
training_data.shape[0]
```

Out[12]:
```
1932
```

In [13]:
```
for i in range(60, training_data.shape[0]):
    X_train.append(training_data[i-60:i])
    Y_train.append(training_data[i,0])
```

In [14]:
```
X_train, Y_train = np.array(X_train), np.array(Y_train)
```

In [15]:
```
X_train.shape
```

Out[15]:
```
(1872, 60, 5)
```

Building LSTM

In [16]:
```
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense, LSTM, Dropout
```

In [78]:
```
regressor = Sequential()
regressor.add(LSTM(units = 50, activation = 'relu', return_sequences = True, input_sha
regressor.add(Dropout(0.2))
```

In [79]:
```
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 [80]:
```
regressor.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_31 (LSTM)               (None, 60, 50)            11200
_________________________________________________________________
dropout_16 (Dropout)         (None, 60, 50)            0
_________________________________________________________________
lstm_32 (LSTM)               (None, 60, 60)            26640
_________________________________________________________________
dropout_17 (Dropout)         (None, 60, 60)            0
_________________________________________________________________
lstm_33 (LSTM)               (None, 60, 80)            45120
_________________________________________________________________
dropout_18 (Dropout)         (None, 60, 80)            0
_________________________________________________________________
lstm_34 (LSTM)               (None, 120)               96480
_________________________________________________________________
dropout_19 (Dropout)         (None, 120)               0
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 121
=================================================================
Total params: 179,561
Trainable params: 179,561
Non-trainable params: 0
_________________________________________________________________
```

In [82]:
```
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')
```

In [97]:
```
regressor.fit(X_train, Y_train, epochs = 20, batch_size =50)
```

```
Epoch 1/20
38/38 [==============================] - 6s 148ms/step - loss: 0.0018
Epoch 2/20
38/38 [==============================] - 5s 141ms/step - loss: 0.0017
Epoch 3/20
38/38 [==============================] - 6s 151ms/step - loss: 0.0018
Epoch 4/20
38/38 [==============================] - 6s 169ms/step - loss: 0.0020
Epoch 5/20
38/38 [==============================] - 7s 184ms/step - loss: 0.0017
Epoch 6/20
38/38 [==============================] - 6s 149ms/step - loss: 0.0016
Epoch 7/20
38/38 [==============================] - 6s 147ms/step - loss: 0.0016
Epoch 8/20
38/38 [==============================] - 7s 175ms/step - loss: 0.0016
Epoch 9/20
38/38 [==============================] - 6s 166ms/step - loss: 0.0017
Epoch 10/20
38/38 [==============================] - 6s 152ms/step - loss: 0.0017
Epoch 11/20
38/38 [==============================] - 6s 151ms/step - loss: 0.0016
Epoch 12/20
38/38 [==============================] - 7s 188ms/step - loss: 0.0017
Epoch 13/20
38/38 [==============================] - 6s 167ms/step - loss: 0.0017 0s - loss: 0.00
Epoch 14/20
38/38 [==============================] - 6s 154ms/step - loss: 0.0017
Epoch 15/20
38/38 [==============================] - 6s 160ms/step - loss: 0.0015
Epoch 16/20
38/38 [==============================] - 6s 166ms/step - loss: 0.0017
Epoch 17/20
38/38 [==============================] - 6s 148ms/step - loss: 0.0016
Epoch 18/20
38/38 [==============================] - 6s 146ms/step - loss: 0.0018
Epoch 19/20
38/38 [==============================] - 7s 184ms/step - loss: 0.0019
Epoch 20/20
38/38 [==============================] - 6s 167ms/step - loss: 0.0016
```

Out[97]:
```
<tensorflow.python.keras.callbacks.History at 0x221ab8fb988>
```

Test Dataset

In [100…
```
past_60_days = data_training.tail(60)
df= past_60_days.append(data_test, ignore_index = True)
df = df.drop(['Date', 'Adj Close'], axis = 1)
df.head()
```

Out[100]:

	Open	High	Low	Close	Volume
0	9259.783203	9377.486328	9249.587891	9324.717773	2.124268e+10
1	9324.787109	9379.806641	9141.251953	9235.354492	2.113222e+10
2	9235.607422	9505.051758	9191.485352	9412.612305	2.617026e+10
3	9413.004883	9457.417969	9256.931641	9342.527344	2.619861e+10
4	9340.864258	9423.237305	9305.909180	9360.879883	2.313390e+10

In [101…
```
inputs = scaler.transform(df)
inputs
```

Out[101]:
```
array([[0.4706426 , 0.46111744, 0.48280998, 0.47344448, 0.47088353],
       [0.47401087, 0.46123417, 0.47704822, 0.46881889, 0.4684344 ],
       [0.4693899 , 0.46753509, 0.47971984, 0.47799406, 0.58014293],
       ...,
       [0.44609842, 0.43966175, 0.45462663, 0.45181931, 0.69362236],
       [       nan,        nan,        nan,        nan,        nan],
       [0.44858819, 0.43506214, 0.46071565, 0.44922869, 0.64608693]])
```

In [102…
```
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])
```

In [103…
```
X_test, Y_test = np.array(X_test), np.array(Y_test)
X_test.shape, Y_test.shape
```

Out[103]:
```
((147, 60, 5), (147,))
```

In [1]:
```
Y_pred = regressor.predict(X_test)
Y_pred, Y_test
```

In [105…
```
scaler.scale_
```

Out[105]:
```
array([5.18164146e-05, 5.03087220e-05, 5.31841635e-05, 5.17617168e-05,
       2.21730382e-11])
```

In [106…
```
scale = 1/5.18164146e-05
scale
```

Out[106]:
```
19298.903787912797
```

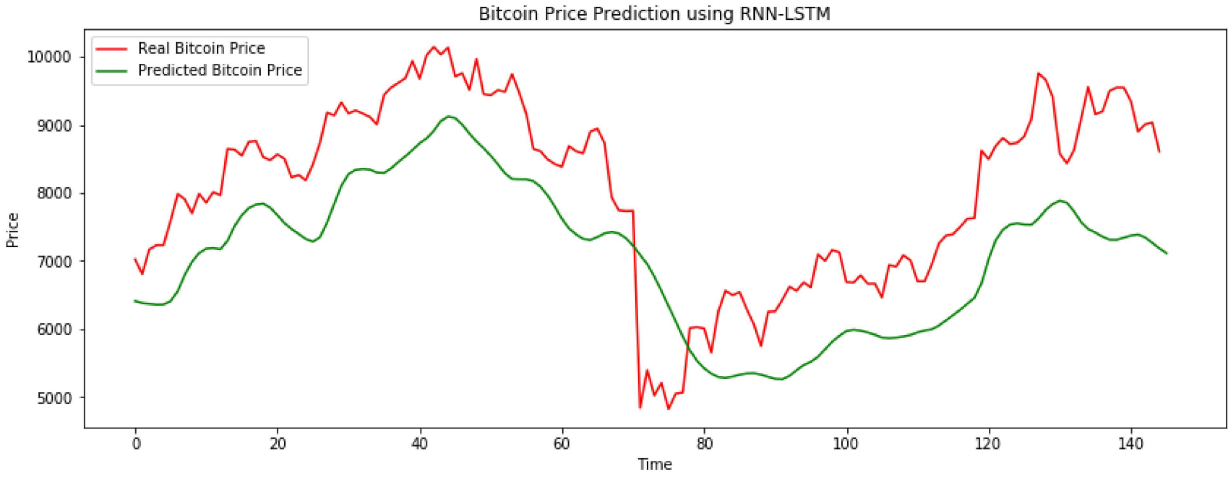
In [107…
```
Y_test = Y_test*scale
Y_pred = Y_pred*scale
```

In [2]:
```
Y_pred
```

In [95]:
```
Y_test
```

Out[95]:
```
array([ 7025.65427061,  6807.5317115 ,  7168.47848868,  7233.55466072,
        7233.55514872,  7591.7851299 ,  7985.0385481 ,  7905.39889906,
        7701.41061796,  7985.2939191 ,  7856.36472004,  8012.87497412,
        7964.03610609,  8648.44675144,  8635.58444644,  8548.31296239,
        8750.31491549,  8764.5483145 ,  8527.73483738,  8482.09421236,
        8567.3139394 ,  8503.75339237,  8228.67038423,  8263.22214224,
        8187.51315721,  8420.41159533,  8735.62741549,  9180.57370472,
        9139.11960369,  9331.41647879,  9169.46042371,  9212.92331473,
        9167.78659571,  9115.94479868,  9006.51901763,  9440.92429085,
        9549.1059319 ,  9616.17331494,  9686.99753298,  9938.6625721 ,
        9678.99460397, 10025.49069715, 10147.06394021, 10034.65378315,
       10136.95944721,  9712.28268999,  9759.66354901,  9514.33347089,
        9966.90183012,  9452.42819686,  9434.88522885,  9510.81003289,
        9486.42136087,  9744.68601001,  9474.41550187,  9161.39304071,
        8648.19675144,  8611.83151742,  8494.31589236,  8422.86179033,
        8386.36764931,  8688.49069646,  8611.64499342,  8583.38815741,
        8901.41159557,  8944.70358759,  8731.30905648,  7934.24948508,
        7745.24997398,  7733.19284497,  7736.71921197,  4840.93405449,
        5396.18063677,  5024.16989458,  5208.33249168,  4825.68112448,
        5050.21676959,  5068.5195036 ,  6014.75680909,  6029.6244841 ,
        6008.66110509,  5654.4775119 ,  6259.74557822,  6561.81979737,
        6498.27389834,  6542.49216036,  6290.35690623,  6068.72751212,
        5748.64157395,  6253.70944521,  6260.42233622,  6429.8793673 ,
        6620.4994844 ,  6561.48581337,  6685.64059843,  6611.1528054 ,
        7096.74704365,  7002.3862036 ,  7161.06930968,  7126.91843066,
        6690.54343044,  6681.17087143,  6788.71969949,  6666.38473842,
        6668.66452343,  6463.55710232,  6939.65573456,  6915.39450455,
        7084.02536364,  7009.9765356 ,  6702.88718044,  6702.54343044,
        6944.40915257,  7257.28464173,  7373.58591079,  7393.2421608 ,
        7502.52194585,  7620.07321591,  7629.81540292,  8620.77292343,
        8495.88522836,  8692.16061846,  8806.71725952,  8718.84811848,
        8735.93503249,  8830.54440754,  9084.99850967,  9759.26511101,
        9664.00925196,  9414.27194684,  8578.63815741,  8433.48874333,
        8628.49069643,  9094.43210367,  9557.39401791,  9156.3432357 ,
        9198.03268972,  9498.79831488,  9550.16647891,  9548.4321039 ,
        9345.8432358 ,  8903.43796257,  9008.16550163,  9035.38620464,
        8609.21042342,            nan,  8657.26022845])
```

In [109…
```
plt.figure(figsize=(14,5))
plt.plot(Y_test, color = 'red', label = 'Real Bitcoin Price')
plt.plot(Y_pred, color = 'green', label = 'Predicted Bitcoin Price')
plt.title('Bitcoin Price Prediction using RNN-LSTM')
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend()
plt.show()
```


Bitcoin Price Prediction using RNN-LSTM
Real Bitcoin Price
Predicted Bitcoin Price
Price
Time
10000
9000
8000
7000
6000
5000
0
20
40
60
80
100
120
140