Predicting stock prices is an uncertain task which is modelled using machine learning to predict the return on stocks. In this task, the future stock prices of BlackRock (BLK) are predicted using the LSTM and GRU Recurrent Neural Network.

Loading Stock Market Data

In [1]:

```
# Required Packages
import time
import math
import warnings
import numpy as np
import pandas as pd
import tensorflow as tf
import pandas_datareader as pdr
import matplotlib.pyplot as plt

from sklearn.preprocessing import MinMaxScaler

warnings.filterwarnings('ignore')
print(f'Tensorflow version: {tf.__version__}')
```

```
Tensorflow version: 2.5.0
```

In [2]:

```
# Fetch Stock Prices
dataset = pdr.DataReader('BLK', data_source='yahoo', start='2013-01-01', end='2019-12-31'
)
dataset.head()
```

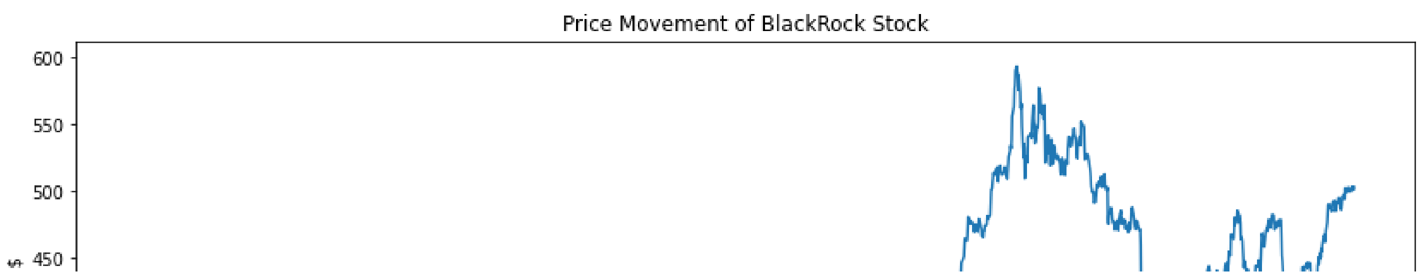
Out[2]:

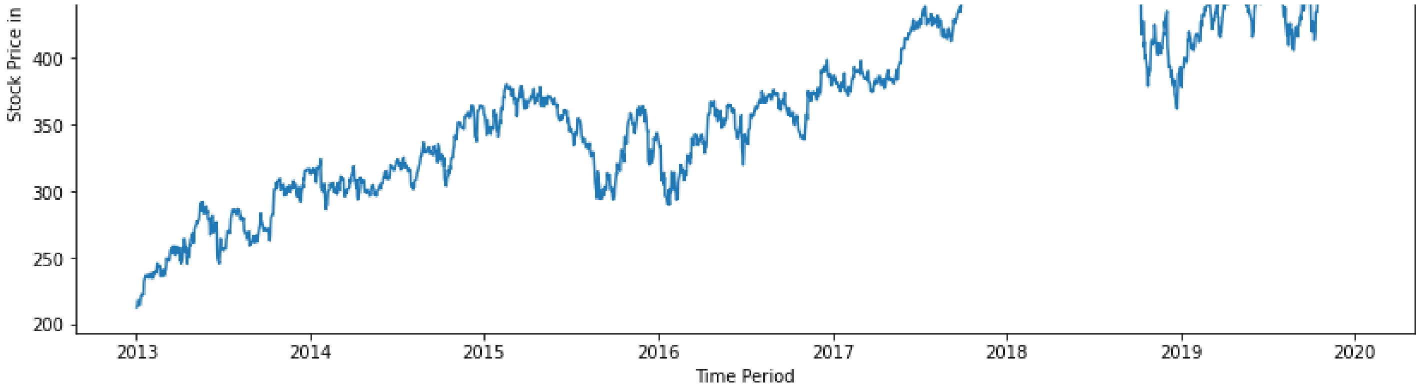
Date	High	Low	Open	Close	Volume	Adj Close
2013-01-02	212.869995	208.770004	210.619995	212.770004	951600.0	171.830475
2013-01-03	215.990005	212.169998	213.309998	213.350006	596200.0	172.298859
2013-01-04	218.860001	213.020004	213.029999	218.029999	805200.0	176.078369
2013-01-07	218.289993	215.250000	217.679993	217.630005	722300.0	175.755356
2013-01-08	217.440002	214.050003	217.020004	214.259995	630400.0	173.033798

We are going to consider the close price of BlackRock stock.

In [3]:

```
# Plotting the prices
plt.figure(figsize=(14, 6))
plt.plot(dataset['Close']);
plt.xlabel('Time Period');
plt.ylabel('Stock Price in $');
plt.title('Price Movement of BlackRock Stock');
```





In [4]:

```
data = dataset.filter(['Close'])
data = data.values
```

In [5]:

```
# Scaling the close price of BlackRock
scaler = MinMaxScaler()
scaled_price = scaler.fit_transform(data)
# Top 10 scaled values
print(f'Scaled values: \n {scaled_price[:10]}')
```

```
Scaled values:
 [[0.        ]
 [0.00152435]
 [0.01382426]
 [0.012773  ]
 [0.00391598]
 [0.0053878 ]
 [0.01571656]
 [0.02165626]
 [0.02475754]
 [0.02754342]]
```

In [6]:

```
train_size = math.ceil(len(data)*0.7)

train_data = scaled_price[0:train_size, :]

X_train = []
y_train = []

for i in range(60, train_size):
  X_train.append(train_data[i-60:i, 0])
  y_train.append(train_data[i, 0])

print(f'X_train: \n{X_train[0]}')  # Should have 60 values in each list
print(f'y_train: {y_train[0]}')     # Single valued y label
print(f'X_train size: {len(X_train)}')   # Total length of X_train column
print(f'y_train size: {len(y_train)}')   # Total length of y_train column
```

```
X_train:
[0.         0.00152435 0.01382426 0.012773   0.00391598 0.0053878
 0.01571656 0.02165626 0.02475754 0.02754342 0.02488896 0.05054008
 0.05561247 0.06357592 0.06102657 0.06192015 0.06215668 0.05805671
 0.06633549 0.06473229 0.06178873 0.06339193 0.05705798 0.06856947
 0.06841178 0.06320798 0.06672974 0.07012009 0.06856947 0.07818865
 0.08620464 0.07931875 0.08239373 0.06925278 0.06163105 0.07385211
 0.06236694 0.06144705 0.07437778 0.07090855 0.06323424 0.07490341
 0.08310335 0.0967174  0.09382637 0.09330074 0.09224944 0.09637572
 0.10757179 0.11372179 0.11556147 0.1116455  0.10620512 0.12071278
 0.10573207 0.10607375 0.10263082 0.11995059 0.11511473 0.11592946]
y_train: 0.10562695960782165
X_train size: 1174
y_train size: 1174
```

In [7]:

```
test_data = scaled_price[train_size-60:, :]

X_test = []
y_test = data[train_size:, :]

for i in range(60, len(test_data)):
  X_test.append(test_data[i-60:i, 0])

print(f'X_test: \n{X_test[0]}')  # Should have 60 values in each list
print(f'X_test size: {len(X_test)}')  # Total length of X_train column
print(f'y_test size: {len(y_test)}')  # Total length of y_train column
```

```
X_test:
[0.5346527  0.54203791 0.54931796 0.52795077 0.52411363 0.5295277
 0.53399565 0.5552577  0.56716339 0.55914737 0.55959419 0.56755761
 0.56944991 0.5772031  0.58161844 0.58046203 0.58535042 0.59097479
 0.58248571 0.59299847 0.61326179 0.61583744 0.62335411 0.62556178
 0.64427448 0.66141025 0.65823016 0.65620648 0.66419612 0.68637805
 0.70388181 0.69047802 0.69696965 0.69063571 0.69576071 0.69389472
 0.69344789 0.68758708 0.68582615 0.67381531 0.68519541 0.68953191
 0.68206786 0.67823065 0.67418329 0.68898001 0.69999206 0.69079339
 0.68490627 0.68183133 0.66711345 0.6650897  0.6631974  0.677232
 0.67736338 0.68661458 0.68653574 0.68858572 0.70590548 0.69954531]
X_test size: 528
y_test size: 528
```

In [8]:

```
# Converting array as sequential model takes array data type as input
X_train = np.array(X_train)
y_train = np.array(X_train)
X_test = np.array(X_test)
```

In [9]:

```
# Reshaping the X_train and X_test to 3D tensor as sequential model takes 3D tensor as in
put
new_shape_train = (X_train.shape[0], X_train.shape[1], 1)
X_train = np.reshape(X_train, newshape=new_shape_train)
X_train.shape
```

Out[9]:

```
(1174, 60, 1)
```

In [10]:

```
new_shape_test = (X_test.shape[0], X_test.shape[1], 1)
X_test = np.reshape(X_test, newshape=new_shape_test)
X_test.shape
```

Out[10]:

```
(528, 60, 1)
```

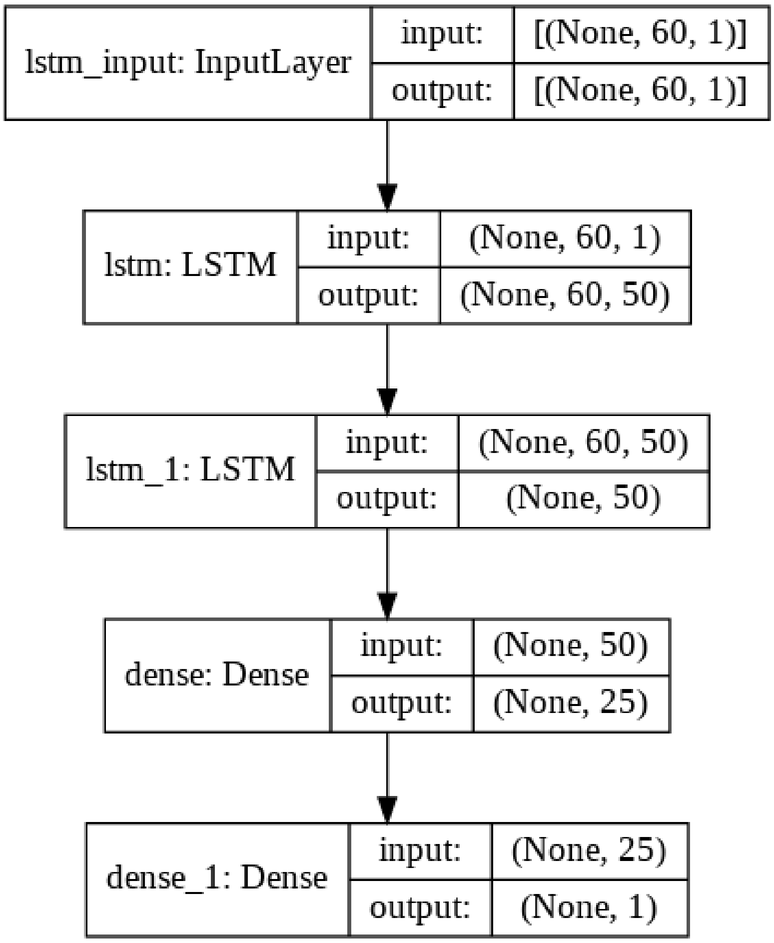
LSTM

In [11]:

```
model = tf.keras.Sequential()
model.add(tf.keras.layers.LSTM(units=50, return_sequences=True, input_shape=(X_train.sha
pe[1], 1)))
model.add(tf.keras.layers.LSTM(units=50, return_sequences=False))
model.add(tf.keras.layers.Dense(25))
model.add(tf.keras.layers.Dense(1))

tf.keras.utils.plot_model(model, show_shapes=True)
```

Out[11]:



In [12]:

```
start = time.time()
model.compile(optimizer='adam', loss='mean_squared_error')
model.fit(X_train, y_train, batch_size=100, epochs=20)
end = time.time()
print(f'Time taken: {round((end - start)/60, 1)} minutes.')
```

```
Epoch 1/20
12/12 [==============================] - 5s 93ms/step - loss: 0.0276
Epoch 2/20
12/12 [==============================] - 1s 93ms/step - loss: 0.0057
Epoch 3/20
12/12 [==============================] - 1s 93ms/step - loss: 0.0040
Epoch 4/20
12/12 [==============================] - 1s 92ms/step - loss: 0.0031
Epoch 5/20
12/12 [==============================] - 1s 92ms/step - loss: 0.0025
Epoch 6/20
12/12 [==============================] - 1s 92ms/step - loss: 0.0021
Epoch 7/20
12/12 [==============================] - 1s 90ms/step - loss: 0.0020
Epoch 8/20
12/12 [==============================] - 1s 91ms/step - loss: 0.0020
Epoch 9/20
12/12 [==============================] - 1s 93ms/step - loss: 0.0019
Epoch 10/20
12/12 [==============================] - 1s 92ms/step - loss: 0.0019
Epoch 11/20
12/12 [==============================] - 1s 90ms/step - loss: 0.0019
Epoch 12/20
12/12 [==============================] - 1s 89ms/step - loss: 0.0019
Epoch 13/20
12/12 [==============================] - 1s 92ms/step - loss: 0.0018
Epoch 14/20
12/12 [==============================] - 1s 89ms/step - loss: 0.0018
Epoch 15/20
12/12 [==============================] - 1s 94ms/step - loss: 0.0018
Epoch 16/20
12/12 [==============================] - 1s 92ms/step - loss: 0.0017
```

```
Epoch 17/20
12/12 [==============================] - 1s 91ms/step - loss: 0.0017
Epoch 18/20
12/12 [==============================] - 1s 94ms/step - loss: 0.0016
Epoch 19/20
12/12 [==============================] - 1s 92ms/step - loss: 0.0016
Epoch 20/20
12/12 [==============================] - 1s 91ms/step - loss: 0.0015
Time taken: 0.7 minutes.
```

In [13]:

```
predictions_lstm = model.predict(X_test)
predictions_lstm = scaler.inverse_transform(predictions_lstm)   # It inverts the transform
for you when you make predictions. Returns predictions in original form
```

In [14]:

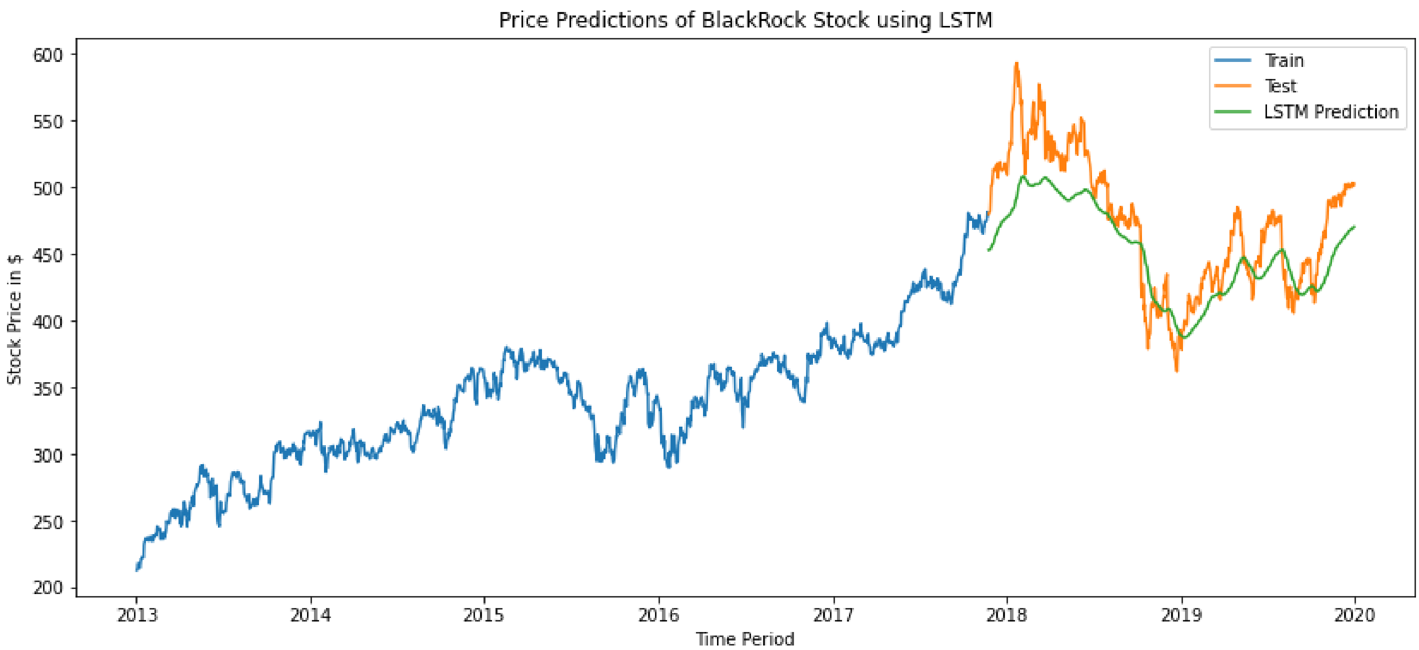
```
# Root Mean Square Error
rmse_lstm = np.sqrt(np.mean(predictions_lstm - y_test)**2)
rmse_lstm
```

Out[14]:

```
20.89255338726622
```

In [15]:

```
train = dataset.iloc[:train_size, :]
test = dataset.iloc[train_size:, :]
test.loc[:,'LSTM Predictions'] = predictions_lstm
plt.figure(figsize=(14, 6))
plt.plot(train['Close']);
plt.plot(test[['Close', 'LSTM Predictions']]);
plt.xlabel('Time Period');
plt.ylabel('Stock Price in $');
plt.legend(['Train', 'Test', 'LSTM Prediction'], loc='best')
plt.title('Price Predictions of BlackRock Stock using LSTM');
```



GRU

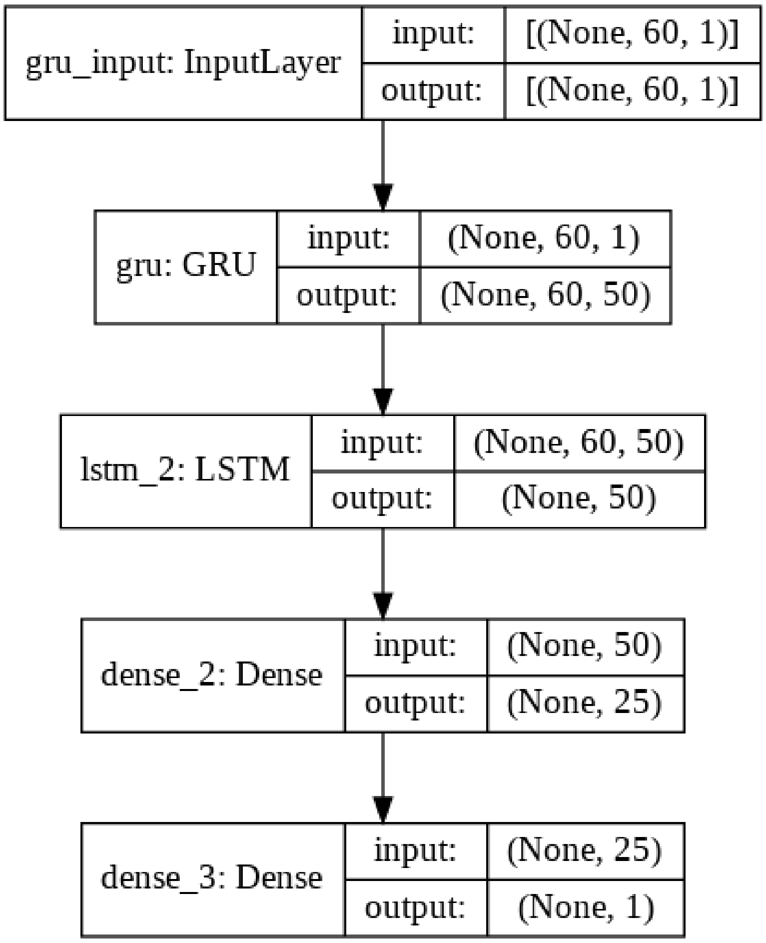
In [16]:

```
model = tf.keras.Sequential()
model.add(tf.keras.layers.GRU(units=50, return_sequences=True, input_shape=(X_train.shap
e[1], 1)))
model.add(tf.keras.layers.LSTM(units=50, return_sequences=False))
```

```
model.add(tf.keras.layers.Dense(25))
model.add(tf.keras.layers.Dense(1))

tf.keras.utils.plot_model(model, show_shapes=True)
```

Out[16]:



In [17]:

```
start = time.time()
model.compile(optimizer='adam', loss='mean_squared_error')
model.fit(X_train, y_train, batch_size=100, epochs=20)
end = time.time()
print(f'Time taken: {round((end - start)/60, 1)} minutes.')
```

```
Epoch 1/20
12/12 [==============================] - 5s 93ms/step - loss: 0.0436
Epoch 2/20
12/12 [==============================] - 1s 91ms/step - loss: 0.0065
Epoch 3/20
12/12 [==============================] - 1s 93ms/step - loss: 0.0041
Epoch 4/20
12/12 [==============================] - 1s 95ms/step - loss: 0.0031
Epoch 5/20
12/12 [==============================] - 1s 92ms/step - loss: 0.0026
Epoch 6/20
12/12 [==============================] - 1s 92ms/step - loss: 0.0023
Epoch 7/20
12/12 [==============================] - 1s 90ms/step - loss: 0.0022
Epoch 8/20
12/12 [==============================] - 1s 94ms/step - loss: 0.0022
Epoch 9/20
12/12 [==============================] - 1s 92ms/step - loss: 0.0022
Epoch 10/20
12/12 [==============================] - 1s 89ms/step - loss: 0.0022
Epoch 11/20
12/12 [==============================] - 1s 90ms/step - loss: 0.0022
Epoch 12/20
12/12 [==============================] - 1s 91ms/step - loss: 0.0021
Epoch 13/20
12/12 [==============================] - 1s 95ms/step - loss: 0.0021
```

```
Epoch 14/20
12/12 [==============================] - 1s 92ms/step - loss: 0.0021
Epoch 15/20
12/12 [==============================] - 1s 91ms/step - loss: 0.0021
Epoch 16/20
12/12 [==============================] - 1s 91ms/step - loss: 0.0021
Epoch 17/20
12/12 [==============================] - 1s 92ms/step - loss: 0.0021
Epoch 18/20
12/12 [==============================] - 1s 92ms/step - loss: 0.0020
Epoch 19/20
12/12 [==============================] - 1s 93ms/step - loss: 0.0020
Epoch 20/20
12/12 [==============================] - 1s 92ms/step - loss: 0.0020
Time taken: 0.4 minutes.
```

In [18]:

```
predictions_gru = model.predict(X_test)
predictions_gru = scaler.inverse_transform(predictions_gru)
```

In [19]:

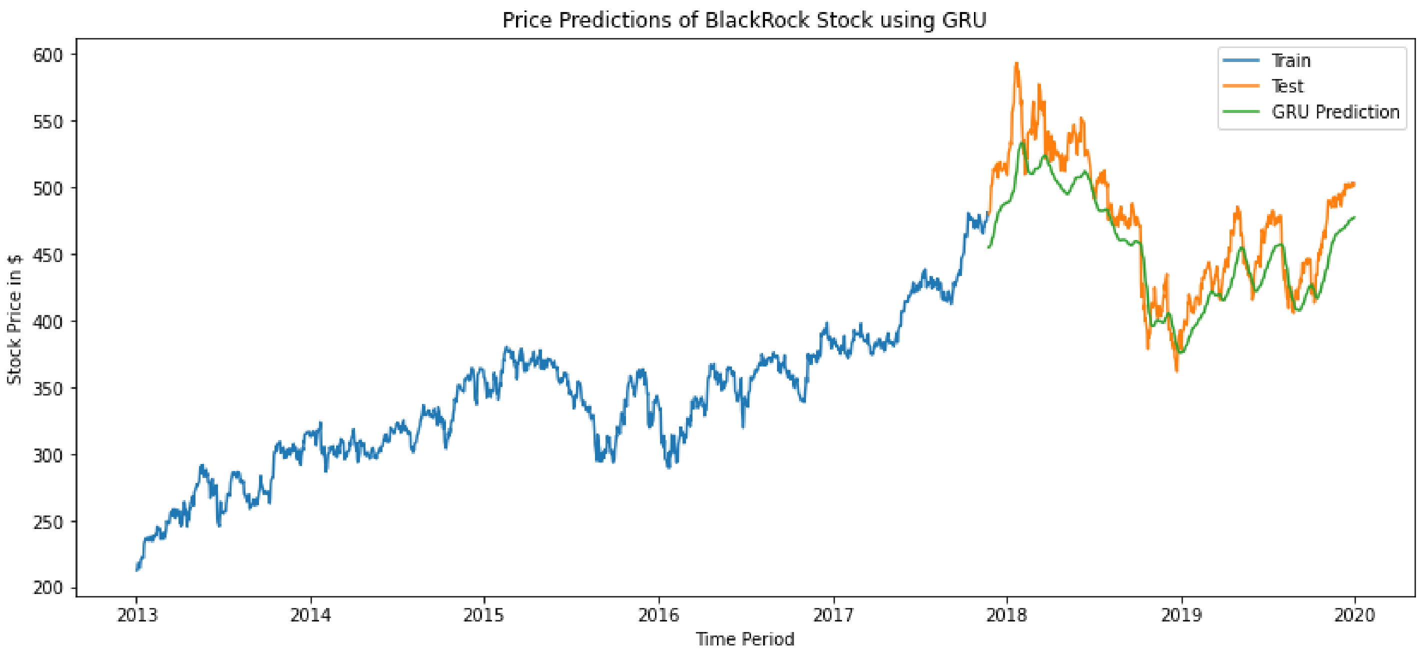
```
# Root Mean Square Error
rmse_gru = np.sqrt(np.mean(predictions_gru - y_test)**2)
rmse_gru
```

Out[19]:

```
18.987350868456293
```

In [20]:

```
test.loc[:,'GRU Predictions'] = predictions_gru
plt.figure(figsize=(14, 6))
plt.plot(train['Close']);
plt.plot(test[['Close', 'GRU Predictions']]);
plt.xlabel('Time Period');
plt.ylabel('Stock Price in $');
plt.legend(['Train', 'Test', 'GRU Prediction'], loc='best')
plt.title('Price Predictions of BlackRock Stock using GRU');
```



- **It can be observed that training time was much less in case of GRU (0.4 mins) as compared to LSTM (0.7 mins).**
- **Similarly RMSE was less for GRU (20) as compared to LSTM (18)**
- **We can say that GRUs are better approximations to LSTM considering both time complexity wise and performance wise.**