PREDICT THE CRYPTOCURRENCY PRICE

In [3]:

```
## Loading the required libraries and dependencies
#================================================
import json
import requests
from keras.models import Sequential
from keras.layers import Activation, Dense, Dropout, LSTM
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.metrics import mean_absolute_error
%matplotlib inline
```

In [53]:

```
## Data set
#================================================
endpoint = 'https://min-api.cryptocompare.com/data/histoday'
res = requests.get(endpoint + '?fsym=BTC&tsym=USD&limit=1000') # Getting the Bitcoin price
hist = pd.DataFrame(json.loads(res.content)['Data'])
hist = hist.set_index('time')
hist.index = pd.to_datetime(hist.index, unit='s') # To convert string Date time into Python
target_col = 'close'
```

In [54]:

```
hist.drop(["conversionType", "conversionSymbol"], axis = 'columns', inplace = True)
```

In [55]:

```
## To look at the data set with headings
#============================================
hist.head(5)
```

Out[55]:

time	high	low	open	volumefrom	volumeto	close
2019-07-27	10202.95	9310.47	9847.45	53081.42	5.126121e+08	9478.32
2019-07-28	9591.52	9135.64	9478.32	28313.55	2.672438e+08	9531.77
2019-07-29	9717.69	9386.90	9531.77	31434.40	2.999364e+08	9506.93
2019-07-30	9749.53	9391.78	9506.93	28856.19	2.764023e+08	9595.52
2019-07-31	10123.94	9581.60	9595.52	42030.01	4.163431e+08	10089.25

The dataset contains total of 6 features. The details for them are as follows: High Price — It is highest price of currency for the day. Low Price — It is the lowest price for currency for that day. Open Price — It is market open price for currency for that day. Volume from and to — The volume of currency that is being in trade for that day.

price for currency for that day. Volume from and to — The volume of currency that is being in trade for that day.
Close Price — It is the market close price for currency for that particular day.

In [57]:

```
## Splitting data into two sets — training set and test set with 80% and 20%
#=====================================================
def train_test_split(df, test_size=0.2): # A function in Sklearn model selection for splitt
    split_row = len(df) - int(test_size * len(df))
    train_data = df.iloc[:split_row]
    test_data = df.iloc[split_row:]
    return train_data, test_data
```

In [58]:

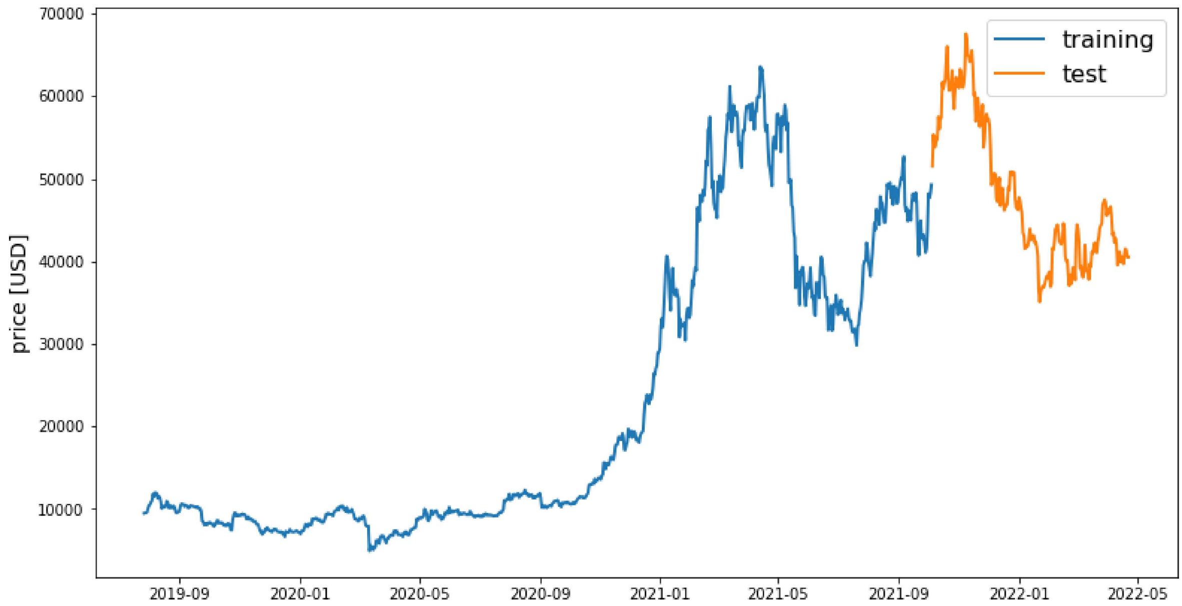
```
train, test = train_test_split(hist, test_size=0.2)
```

In [59]:

```
## Plot the cryptocurrency prices in USD
#=============================================
def line_plot(line1, line2, label1=None, label2=None, title='', lw=2):
    fig, ax = plt.subplots(1, figsize=(13, 7))
    ax.plot(line1, label=label1, linewidth=lw)
    ax.plot(line2, label=label2, linewidth=lw)
    ax.set_ylabel('price [USD]', fontsize=14)
    ax.set_title(title, fontsize=16)
    ax.legend(loc='best', fontsize=16);
```

In [60]:

```
line_plot(train[target_col], test[target_col], 'training', 'test', title='')
```



In [61]:

```
## Normalize the values
#===================================
def normalise_zero_base(df):
    return df / df.iloc[0] - 1

def normalise_min_max(df):
    return (df - df.min()) / (data.max() - df.min())
```

Normalization is a technique often applied as part of data preparation for machine learning.

In [62]:

```
## Extract data
#============================================
def extract_window_data(df, window_len=5, zero_base=True):
    window_data = []
    for idx in range(len(df) - window_len):
        tmp = df[idx: (idx + window_len)].copy()
        if zero_base:
            tmp = normalise_zero_base(tmp)
        window_data.append(tmp.values)
    return np.array(window_data)
```

In [63]:

```
## Prepare the data
#============================================
def prepare_data(df, target_col, window_len=10, zero_base=True, test_size=0.2):
    train_data, test_data = train_test_split(df, test_size=test_size)
    X_train = extract_window_data(train_data, window_len, zero_base)
    X_test = extract_window_data(test_data, window_len, zero_base)
    y_train = train_data[target_col][window_len:].values
    y_test = test_data[target_col][window_len:].values
    if zero_base:
        y_train = y_train / train_data[target_col][:-window_len].values - 1
        y_test = y_test / test_data[target_col][:-window_len].values - 1

    return train_data, test_data, X_train, X_test, y_train, y_test
```

In [64]:

```
##Building the LSTM model
#============================================
def build_lstm_model(input_data, output_size, neurons=100, activ_func='linear',
                     dropout=0.2, loss='mse', optimizer='adam'):
    model = Sequential()
    model.add(LSTM(neurons, input_shape=(input_data.shape[1], input_data.shape[2])))
    model.add(Dropout(dropout))
    model.add(Dense(units=output_size))
    model.add(Activation(activ_func))

    model.compile(loss=loss, optimizer=optimizer)
    return model
```

In [65]:

```
## Setting up some of the parameters to be used
#====================================================
np.random.seed(42) # Makes the random numbers predictable
window_len = 5
test_size = 0.2
zero_base = True
lstm_neurons = 100 # Increasing the network's depth lets it to learn a more powerful functi
epochs = 20
batch_size = 32
loss = 'mse' # Mean squared error (MSE) is the most commonly used loss function for regress
dropout = 0.2
optimizer = 'adam' # Adam optimization is a stochastic gradient descent method that is base
```

In [66]:

```
## Train the model using inputs x_train and labels y_train
#==============================================================
train, test, X_train, X_test, y_train, y_test = prepare_data(
    hist, target_col, window_len=window_len, zero_base=zero_base, test_size=test_size)
```

In [67]:

```
model = build_lstm_model(
    X_train, output_size=1, neurons=lstm_neurons, dropout=dropout, loss=loss,
    optimizer=optimizer)
history = model.fit(
    X_train, y_train, validation_data=(X_test, y_test), epochs=epochs, batch_size=batch_siz
```

```
Epoch 1/20
25/25 [==============================] - 3s 27ms/step - loss: 0.0060 - val_l
oss: 0.0057
Epoch 2/20
25/25 [==============================] - 0s 6ms/step - loss: 0.0049 - val_lo
ss: 0.0022
Epoch 3/20
25/25 [==============================] - 0s 6ms/step - loss: 0.0041 - val_lo
ss: 0.0020
Epoch 4/20
25/25 [==============================] - 0s 6ms/step - loss: 0.0032 - val_lo
ss: 0.0026
Epoch 5/20
25/25 [==============================] - 0s 5ms/step - loss: 0.0033 - val_lo
ss: 0.0023
Epoch 6/20
25/25 [==============================] - 0s 6ms/step - loss: 0.0030 - val_lo
ss: 0.0017
Epoch 7/20
25/25 [==============================] - 0s 6ms/step - loss: 0.0027 - val_lo
ss: 0.0019
Epoch 8/20
25/25 [==============================] - 0s 6ms/step - loss: 0.0024 - val_lo
ss: 0.0017
Epoch 9/20
25/25 [==============================] - 0s 6ms/step - loss: 0.0023 - val_lo
ss: 0.0016
Epoch 10/20
25/25 [==============================] - 0s 6ms/step - loss: 0.0025 - val_lo
ss: 0.0016
Epoch 11/20
25/25 [==============================] - 0s 6ms/step - loss: 0.0023 - val_lo
ss: 0.0018
Epoch 12/20
25/25 [==============================] - 0s 6ms/step - loss: 0.0022 - val_lo
ss: 0.0019
Epoch 13/20
25/25 [==============================] - 0s 5ms/step - loss: 0.0022 - val_lo
ss: 0.0015
Epoch 14/20
25/25 [==============================] - 0s 8ms/step - loss: 0.0020 - val_lo
ss: 0.0015
Epoch 15/20
25/25 [==============================] - 0s 6ms/step - loss: 0.0022 - val_lo
ss: 0.0014
Epoch 16/20
25/25 [==============================] - 0s 5ms/step - loss: 0.0021 - val_lo
ss: 0.0015
Epoch 17/20
25/25 [==============================] - 0s 7ms/step - loss: 0.0020 - val_lo
ss: 0.0017
Epoch 18/20
25/25 [==============================] - 0s 6ms/step - loss: 0.0019 - val_lo
```

```
ss: 0.0014
Epoch 19/20
25/25 [==============================] - 0s 6ms/step - loss: 0.0020 - val_lo
ss: 0.0015
Epoch 20/20
25/25 [==============================] - 0s 6ms/step - loss: 0.0019 - val_lo
ss: 0.0014
```

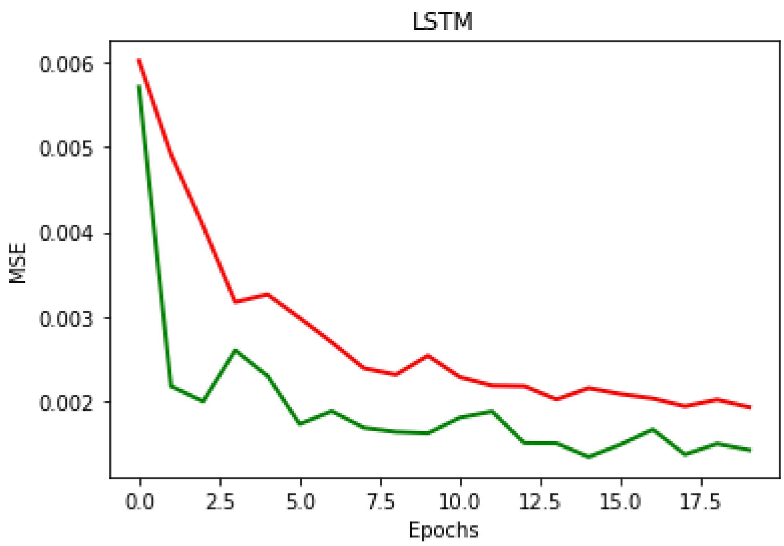
The evaluation statistic I used is Mean Absolute Error (MAE). MAE is preferred over Root Mean Squared Error (RMSE) because it is more interpretable. Because RMSE does not only convey average error, it is significantly more difficult to comprehend.

Mean Absolute Error

It measures the average magnitude of the errors in a set of predictions, without considering their direction. It's the average over the test sample of the absolute differences between actual and predicted observations where all individual differences have equal weight.

In [68]:

```
import matplotlib.pyplot as plt
plt.plot(history.history['loss'],'r',linewidth=2, label='Train loss')
plt.plot(history.history['val_loss'], 'g',linewidth=2, label='Validation loss')
plt.title('LSTM')
plt.xlabel('Epochs')
plt.ylabel('MSE')
plt.show()
```



In [69]:

```
targets = test[target_col][window_len:]
preds = model.predict(X_test).squeeze()
mean_absolute_error(preds, y_test)
```

Out[69]:

```
0.02828603976896899
```

The MAE value obtained looks good.

In [70]:

```
from sklearn.metrics import mean_squared_error
MAE=mean_squared_error(preds, y_test)
MAE
```

Out[70]:

0.0014361100338639461

In [71]:

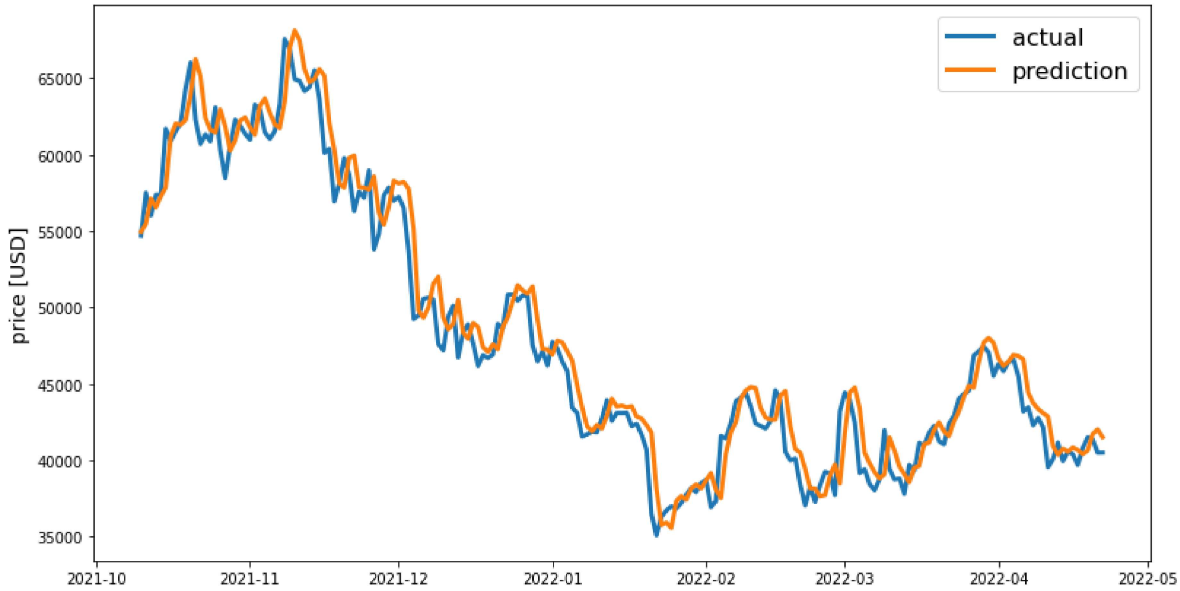
```
from sklearn.metrics import r2_score
R2=r2_score(y_test, preds)
R2
```

Out[71]:

0.690062685813517

In [72]:

```
## Plot the actual and predicted prices
#==========================================
preds = test[target_col].values[:-window_len] * (preds + 1)
preds = pd.Series(index=targets.index, data=preds)
line_plot(targets, preds, 'actual', 'prediction', lw=3)
```



We can use the LSTM neural network in this project to predict cryptocurrency prices in real time. Here I have used a four-step process that included gathering real-time cryptocurrency data, preparing data for training and testing, implementing an LSTM neural network to predict prices, and visualising the findings.

In [ ]: