STOCK PREDICTION

0. LIBRARY :

In [ ]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import datetime
import mysql.connector
import tensorflow as tf
from tensorflow.keras.layers import Dense, LSTM , GRU
from tensorflow.keras.models import Sequential
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
import seaborn as sns
pd.options.mode.chained_assignment = None
tf.random.set_seed(0)
```

1. FUNCTION :

1.Connect and get database from MySQL

In [ ]:

```
def get_database_from_MySQL_after_query(host, user, password, database, sql_query):
    config = {
        "host": host,
        "user": user,
        "password": password,
        "database": database
    }
    conn = mysql.connector.connect(**config)
    cursor = conn.cursor()
    cursor.execute(sql_query)
    results = cursor.fetchall()
    column_names = [i[0] for i in cursor.description]
    conn.close()
    df = pd.DataFrame(results, columns=column_names)
    return df
```

2.Full data

In [ ]:

```
def Full_data():
    query = ''' select * from msn'''
    return query
```

3.Data query timeframe H1

In [ ]:

```
def Query_data_H1():
    query = '''
        SELECT
            DATE_FORMAT(open_time, '%Y-%m-%d %H') as open_time,
            MIN(Low) as low,
            MAX(High) AS high,
            AVG(Volume) as volume
        FROM stock.msn
        GROUP BY DATE_FORMAT(open_time, '%Y-%m-%d %H');
        '''
    return query
```

4.Data query highest price during the day timeframe H1

In [ ]:

```
def Query_highest_price_H1():
    query = '''
        WITH CTE AS
        (
            SELECT
                DATE_FORMAT(open_time, '%Y-%m-%d %H') as open_time,
                MIN(Low) as low,
                MAX(High) AS high,
                AVG(Volume) as volume
            FROM stock.msn
            GROUP BY DATE_FORMAT(open_time, '%Y-%m-%d %H')
        ),
        latest_table AS
        (
            WITH CTE1 AS
            (
                SELECT DATE(open_time) as ngay , MAX(high) AS gia
                FROM CTE
                GROUP BY DATE(open_time)
            )
            SELECT b.open_time AS OPEN_TIME, n.gia AS PRICE
            FROM CTE1 AS n
            INNER JOIN CTE AS b
            ON n.ngay = DATE(b.open_time) AND n.gia = b.high
        )
        SELECT HOUR(OPEN_TIME) AS "Thời Gian", COUNT(PRICE) AS "Số Lần"
        FROM latest_table
        GROUP BY HOUR(OPEN_TIME)
        ORDER BY HOUR(OPEN_TIME) ASC;
        '''
    return query
```

5.Data query lowest price during the day timeframe H1

In [ ]:

```
def Query_lowest_price_H1():
    query = '''
        WITH CTE AS
        (
            SELECT
                DATE_FORMAT(open_time, '%Y-%m-%d %H') AS open_time,
                MIN(Low) AS low,
                MAX(High) AS high,
                AVG(Volume) AS volume
            FROM stock.msn
            GROUP BY DATE_FORMAT(open_time, '%Y-%m-%d %H')
        ),
        latest_table AS
        (
            WITH CTE1 AS
            (
                SELECT DATE(open_time) AS ngay , MIN(low) AS gia
                FROM CTE
                GROUP BY DATE(open_time)
            )
            SELECT b.open_time AS OPEN_TIME, n.gia AS PRICE
            FROM CTE1 AS n
            INNER JOIN CTE AS b
            ON n.ngay = DATE(b.open_time) AND n.gia = b.low
        )
        SELECT HOUR(OPEN_TIME) AS "Thời Gian", COUNT(PRICE) AS "Số Lần"
        FROM latest_table
        GROUP BY HOUR(OPEN_TIME)
        ORDER BY HOUR(OPEN_TIME) ASC;
        '''
    return query
```

6.Create sequences

In [ ]:

```
def create_sequences(data, sequence_length):
    sequences = []
    for i in range(len(data) - sequence_length):
        seq = data[i:i+sequence_length]
        sequences.append(seq)
    return np.array(sequences)
```

2. DATA PREPARATION :

1.Full data info:

In [ ]:

```
df = get_database_from_MySQL_after_query("localhost","root","Khanhbg2522003","stock
```

In [ ]:

```
df.head(5)
```

Out[ ]:

	Ticker	open_time	Open	High	Low	Close	Volume	Open Interest
0	MSN	2017-12-25 09:15:00	73.1	73.1	73.1	73.1	4210	0
1	MSN	2017-12-25 09:16:00	73.0	73.0	73.0	73.0	5000	0
2	MSN	2017-12-25 09:18:00	73.5	73.5	73.5	73.5	210	0
3	MSN	2017-12-25 09:20:00	73.2	73.5	73.1	73.1	2050	0
4	MSN	2017-12-25 09:21:00	73.0	73.0	73.0	73.0	1380	0

In [ ]:

```
df.tail(5)
```

Out[ ]:

	Ticker	open_time	Open	High	Low	Close	Volume	Open Interest
135349	MSN	2020-12-22 14:23:00	82.8	82.8	82.8	82.8	700	0
135350	MSN	2020-12-22 14:24:00	82.7	82.8	82.7	82.8	4660	0
135351	MSN	2020-12-22 14:25:00	82.8	82.8	82.8	82.8	50	0
135352	MSN	2020-12-22 14:27:00	82.8	82.8	82.8	82.8	300	0
135353	MSN	2020-12-22 14:46:00	82.8	82.8	82.8	82.8	200	0

In [ ]:

```
df.dtypes
```

```
Out[ ]: Ticker            object
        open_time         object
        Open             float64
        High             float64
        Low              float64
        Close            float64
        Volume             int64
        Open Interest      int64
        dtype: object
```

```
In [ ]: df.isna().sum().sort_values(ascending=False)
```

```
Out[ ]: Ticker           0
        open_time        0
        Open             0
        High             0
        Low              0
        Close            0
        Volume           0
        Open Interest    0
        dtype: int64
```

```
In [ ]: df.isna().sum().sort_values(ascending=False)
```

```
Out[ ]: Ticker           0
        open_time        0
        Open             0
        High             0
        Low              0
        Close            0
        Volume           0
        Open Interest    0
        dtype: int64
```

```
In [ ]: df.describe()
```

Out[ ]:

	Open	High	Low	Close	Volume	Open Interest
count	135354.000000	135354.000000	135354.000000	135354.000000	1.353540e+05	135354.0
mean	74.878809	74.931668	74.834625	74.880759	5.683578e+03	0.0
std	15.418074	15.426954	15.412677	15.418857	2.798513e+04	0.0
min	46.500000	46.500000	46.400000	46.400000	1.000000e+01	0.0
25%	57.900000	57.900000	57.800000	57.800000	5.000000e+02	0.0
50%	79.100000	79.200000	79.100000	79.100000	2.000000e+03	0.0
75%	86.000000	86.100000	86.000000	86.000000	5.560000e+03	0.0
max	117.800000	118.000000	117.700000	118.000000	3.300680e+06	0.0

In [ ]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 135354 entries, 0 to 135353
Data columns (total 8 columns):
 #   Column         Non-Null Count   Dtype  
---  ------         --------------   -----  
 0   Ticker         135354 non-null  object 
 1   open_time      135354 non-null  object 
 2   Open           135354 non-null  float64
 3   High           135354 non-null  float64
 4   Low            135354 non-null  float64
 5   Close          135354 non-null  float64
 6   Volume         135354 non-null  int64  
 7   Open Interest  135354 non-null  int64  
dtypes: float64(4), int64(2), object(2)
memory usage: 8.3+ MB
```

2.Data timeframe H1:

In [ ]:

```
df2 = get_database_from_MySQL_after_query("localhost","root","Khanhbg2522003","stoc
```

In [ ]:

```
df2["open_time"] = pd.to_datetime(df2["open_time"])
df2.set_index('open_time', inplace=True)
df2.head(5)
```

Out[ ]:

	low	high	volume
open_time			
2017-12-25 09:00:00	73.0	73.5	2016.9565
2017-12-25 10:00:00	73.0	74.2	1705.3333
2017-12-25 11:00:00	73.5	74.1	2300.0000
2017-12-25 13:00:00	73.3	74.2	815.8621
2017-12-25 14:00:00	74.2	75.4	2928.0000

In [ ]:

```
df2.tail(5)
```

Out[ ]:

	low	high	volume
open_time			
2020-12-22 09:00:00	82.8	84.0	5368.8372
2020-12-22 10:00:00	83.1	83.5	1960.5556
2020-12-22 11:00:00	82.8	83.3	5269.3103
2020-12-22 13:00:00	82.5	82.9	4460.6780
2020-12-22 14:00:00	82.6	82.9	1876.0714

In [ ]:

```
df2.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 3733 entries, 2017-12-25 09:00:00 to 2020-12-22 14:00:00
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   low     3733 non-null   float64
 1   high    3733 non-null   float64
 2   volume  3733 non-null   object 
dtypes: float64(2), object(1)
memory usage: 116.7+ KB
```

3. DATA ANALYSIS :

1.Frequency of highest price during the day:

In [ ]:

```
df_highest = get_database_from_MySQL_after_query("localhost","root","Khanhbg2522003
```

In [ ]:

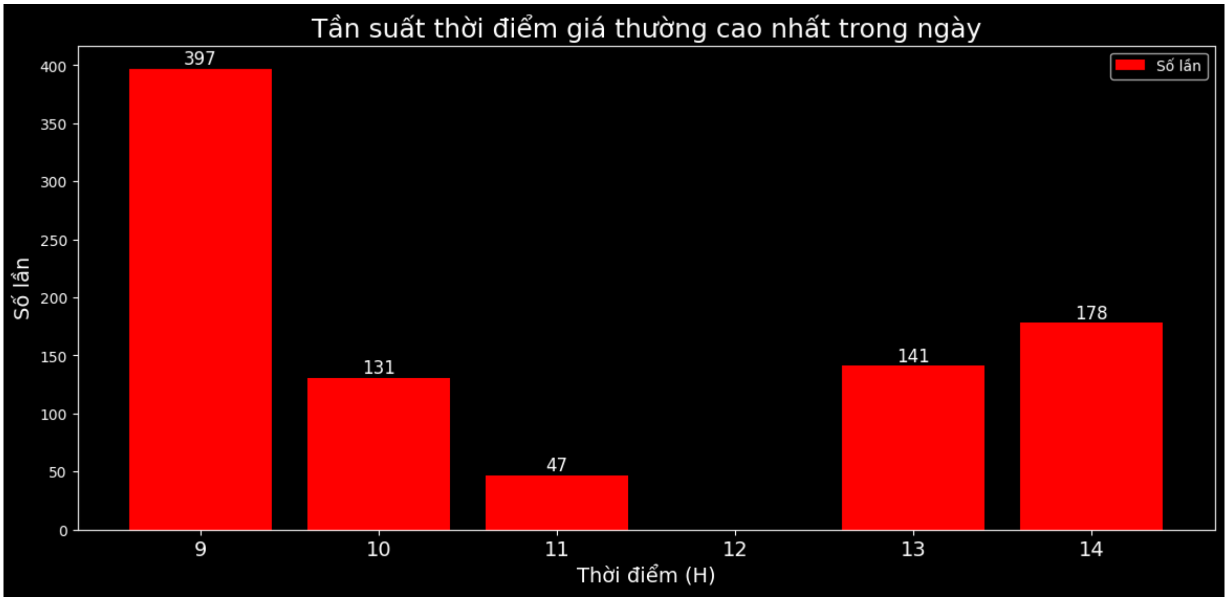
```
df_highest.head()
```

Out[ ]:

	Thời Gian	Số Lần
0	9	397
1	10	131
2	11	47
3	13	141
4	14	178

In [ ]:

```
plt.figure(figsize=(14,6))
bars = plt.bar(df_highest["Thời Gian"], df_highest["Số Lần"], label="Số lần",color=
plt.title("Tần suất thời điểm giá thường cao nhất trong ngày", fontsize=18)
plt.xlabel("Thời điểm (H)",fontsize=14)
plt.ylabel("Số lần",fontsize=14)
plt.xticks(fontsize=14)
plt.legend()
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, yval, round(yval, 2), ha='center',
```



2.Frequency of lowest price during the day:

In [ ]:

```
df_lowest = get_database_from_MySQL_after_query("localhost","root","Khanhbg2522003"
```

In [ ]:

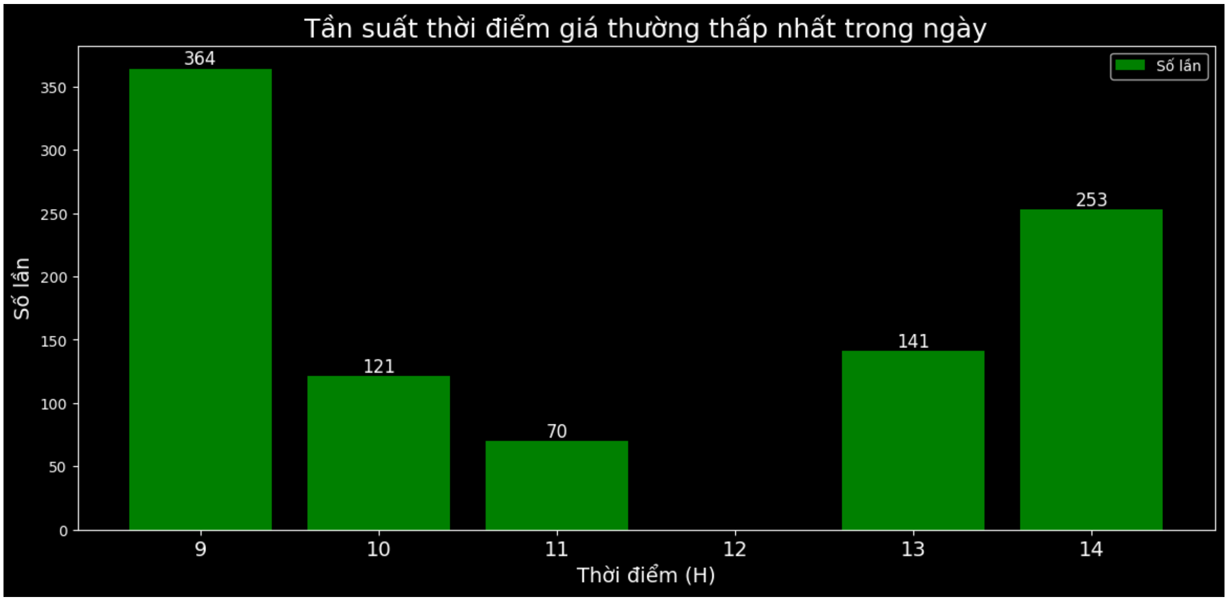
```
df_lowest
```

Out[ ]:

	Thời Gian	Số Lần
0	9	364
1	10	121
2	11	70
3	13	141
4	14	253

In [ ]:

```
plt.figure(figsize=(14,6))
bars = plt.bar(df_lowest["Thời Gian"], df_lowest["Số Lần"], label="Số lần",color="g
plt.title("Tần suất thời điểm giá thường thấp nhất trong ngày", fontsize=18)
plt.xlabel("Thời điểm (H)",fontsize=14)
plt.ylabel("Số lần",fontsize=14)
plt.xticks(fontsize=14)
plt.legend()
for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width() / 2, yval, round(yval, 2), ha='center',
```



4. MODEL PREDICTION :

1.Scale and split data:

In [ ]:

```
high_price = df2['high'].values.reshape(-1, 1)
scaler = MinMaxScaler()
scaled_prices = scaler.fit_transform(high_price)
train_size = int(len(scaled_prices) * 0.8)
train_data = scaled_prices[:train_size]
test_data = scaled_prices[train_size:]

sequence_length = 60
```

2.LSTM:

In [ ]:

```
X_train_lstm = create_sequences(train_data, sequence_length)
X_test_lstm = create_sequences(test_data, sequence_length)
lstm_model = tf.keras.Sequential([
    tf.keras.layers.LSTM(50, activation='relu', input_shape=(sequence_length, 1), r
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.LSTM(50, activation='relu'),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(1)
])

lstm_model.compile(optimizer='adam', loss='mean_squared_error')

lstm_model.fit(X_train_lstm, train_data[sequence_length:], epochs=80, batch_size=32

y_test_lstm = lstm_model.predict(X_test_lstm).reshape(-1, 1)
mse_lstm = mean_squared_error(y_test_actual, y_test_lstm)

predicted_scaled_prices_lstm = lstm_model.predict(X_test_lstm)
predicted_prices_lstm = scaler.inverse_transform(predicted_scaled_prices_lstm)
```

```
Epoch 1/80
92/92 [==============================] - 8s 55ms/step - loss: 0.0312
Epoch 2/80
92/92 [==============================] - 5s 54ms/step - loss: 0.0043
Epoch 3/80
92/92 [==============================] - 5s 52ms/step - loss: 0.0041
Epoch 4/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0037
Epoch 5/80
92/92 [==============================] - 5s 51ms/step - loss: 0.0033
Epoch 6/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0034
Epoch 7/80
92/92 [==============================] - 5s 53ms/step - loss: 0.0031
Epoch 8/80
92/92 [==============================] - 5s 53ms/step - loss: 0.0031
Epoch 9/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0031
Epoch 10/80
92/92 [==============================] - 5s 53ms/step - loss: 0.0028
Epoch 11/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0025
Epoch 12/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0026
Epoch 13/80
92/92 [==============================] - 5s 49ms/step - loss: 0.0025
Epoch 14/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0024
Epoch 15/80
92/92 [==============================] - 5s 49ms/step - loss: 0.0024
Epoch 16/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0023
Epoch 17/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0021
Epoch 18/80
92/92 [==============================] - 5s 51ms/step - loss: 0.0020
Epoch 19/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0021
Epoch 20/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0021
Epoch 21/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0020
Epoch 22/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0018
Epoch 23/80
92/92 [==============================] - 5s 51ms/step - loss: 0.0019
Epoch 24/80
92/92 [==============================] - 5s 52ms/step - loss: 0.0017
Epoch 25/80
92/92 [==============================] - 5s 52ms/step - loss: 0.0017
Epoch 26/80
92/92 [==============================] - 5s 49ms/step - loss: 0.0018
Epoch 27/80
92/92 [==============================] - 4s 49ms/step - loss: 0.0016
Epoch 28/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0016
```

```
Epoch 29/80
92/92 [==============================] - 5s 49ms/step - loss: 0.0014
Epoch 30/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0014
Epoch 31/80
92/92 [==============================] - 5s 49ms/step - loss: 0.0014
Epoch 32/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0014
Epoch 33/80
92/92 [==============================] - 5s 49ms/step - loss: 0.0014
Epoch 34/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0013
Epoch 35/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0014
Epoch 36/80
92/92 [==============================] - 5s 49ms/step - loss: 0.0012
Epoch 37/80
92/92 [==============================] - 5s 49ms/step - loss: 0.0013
Epoch 38/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0012
Epoch 39/80
92/92 [==============================] - 5s 52ms/step - loss: 0.0011
Epoch 40/80
92/92 [==============================] - 4s 49ms/step - loss: 0.0011
Epoch 41/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0011
Epoch 42/80
92/92 [==============================] - 5s 49ms/step - loss: 0.0011
Epoch 43/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0011
Epoch 44/80
92/92 [==============================] - 4s 49ms/step - loss: 0.0011
Epoch 45/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0010
Epoch 46/80
92/92 [==============================] - 4s 49ms/step - loss: 0.0011
Epoch 47/80
92/92 [==============================] - 5s 49ms/step - loss: 0.0012
Epoch 48/80
92/92 [==============================] - 4s 49ms/step - loss: 0.0011
Epoch 49/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0010
Epoch 50/80
92/92 [==============================] - 5s 52ms/step - loss: 9.8410e-04
Epoch 51/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0010
Epoch 52/80
92/92 [==============================] - 5s 50ms/step - loss: 0.0012
Epoch 53/80
92/92 [==============================] - 5s 52ms/step - loss: 9.8279e-04
Epoch 54/80
92/92 [==============================] - 5s 51ms/step - loss: 0.0011
Epoch 55/80
92/92 [==============================] - 5s 52ms/step - loss: 0.0010
Epoch 56/80
92/92 [==============================] - 5s 50ms/step - loss: 9.9475e-04
```

```
Epoch 57/80
92/92 [==============================] - 5s 50ms/step - loss: 9.8980e-04
Epoch 58/80
92/92 [==============================] - 5s 51ms/step - loss: 9.6141e-04
Epoch 59/80
92/92 [==============================] - 5s 50ms/step - loss: 9.3093e-04
Epoch 60/80
92/92 [==============================] - 5s 52ms/step - loss: 0.0010
Epoch 61/80
92/92 [==============================] - 5s 51ms/step - loss: 9.6702e-04
Epoch 62/80
92/92 [==============================] - 5s 51ms/step - loss: 9.9850e-04
Epoch 63/80
92/92 [==============================] - 5s 51ms/step - loss: 0.0011
Epoch 64/80
92/92 [==============================] - 5s 50ms/step - loss: 9.2582e-04
Epoch 65/80
92/92 [==============================] - 5s 51ms/step - loss: 9.2703e-04
Epoch 66/80
92/92 [==============================] - 5s 51ms/step - loss: 0.0011
Epoch 67/80
92/92 [==============================] - 5s 54ms/step - loss: 0.0011
Epoch 68/80
92/92 [==============================] - 5s 51ms/step - loss: 9.8592e-04
Epoch 69/80
92/92 [==============================] - 5s 49ms/step - loss: 9.7557e-04
Epoch 70/80
92/92 [==============================] - 5s 50ms/step - loss: 9.4388e-04
Epoch 71/80
92/92 [==============================] - 5s 51ms/step - loss: 0.0010
Epoch 72/80
92/92 [==============================] - 5s 58ms/step - loss: 9.7224e-04
Epoch 73/80
92/92 [==============================] - 5s 53ms/step - loss: 9.3360e-04
Epoch 74/80
92/92 [==============================] - 5s 54ms/step - loss: 9.3623e-04
Epoch 75/80
92/92 [==============================] - 5s 55ms/step - loss: 9.2143e-04
Epoch 76/80
92/92 [==============================] - 5s 53ms/step - loss: 8.9388e-04
Epoch 77/80
92/92 [==============================] - 5s 52ms/step - loss: 8.9992e-04
Epoch 78/80
92/92 [==============================] - 5s 53ms/step - loss: 8.9383e-04
Epoch 79/80
92/92 [==============================] - 5s 53ms/step - loss: 0.0010
Epoch 80/80
92/92 [==============================] - 5s 55ms/step - loss: 9.2091e-04
22/22 [==============================] - 1s 22ms/step
22/22 [==============================] - 1s 22ms/step
```

3.GRU:

In [ ]:

```python
X_train_gru = create_sequences(train_data, sequence_length)
X_test_gru = create_sequences(test_data, sequence_length)
gru_model = tf.keras.Sequential([
    tf.keras.layers.GRU(50, activation='relu', input_shape=(sequence_length, 1), re
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.GRU(50, activation='relu'),
    tf.keras.layers.Dropout(0.2),
    tf.keras.layers.Dense(1)
])

gru_model.compile(optimizer='adam', loss='mean_squared_error')

gru_model.fit(X_train_gru, train_data[sequence_length:], epochs=100, batch_size=32,

X_test_gru = create_sequences(test_data, sequence_length)
y_test_actual = test_data[sequence_length:]
y_test_gru = gru_model.predict(X_test_gru).reshape(-1, 1)


mse_gru = mean_squared_error(y_test_actual, y_test_gru)

predicted_scaled_prices_gru = gru_model.predict(X_test_gru)
predicted_prices_gru = scaler.inverse_transform(predicted_scaled_prices_gru)
```

```
22/22 [==============================] - 1s 17ms/step
22/22 [==============================] - 0s 15ms/step
```

4.ERROR:

In [ ]:

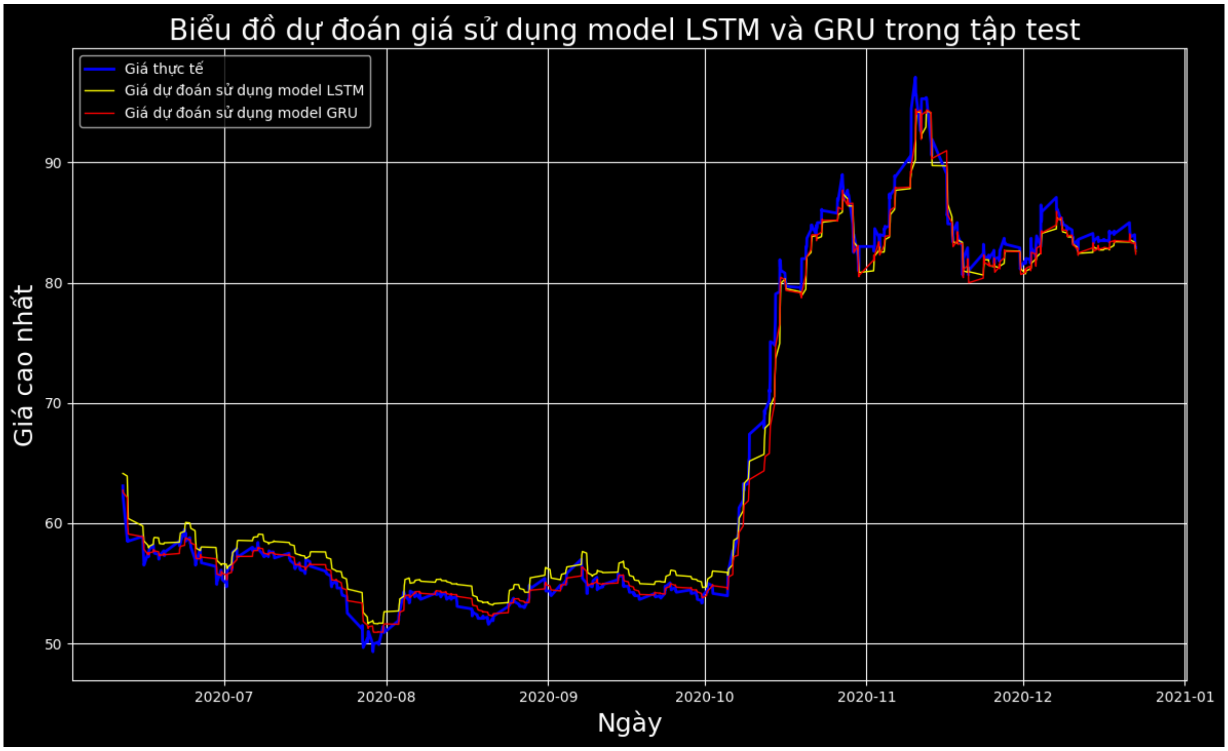
```
print(f'Mean Squared Error (LSTM): {mse_lstm}')
print(f'Mean Squared Error (GRU): {mse_gru}')
```

```
Mean Squared Error (LSTM): 0.0004328345509141703
Mean Squared Error (GRU): 0.000248389563732974
```

5.Testing parameter:

In [ ]:

```
plt.style.use('dark_background')
plt.figure(figsize=(14, 8))
plt.plot(df2.index[train_size+sequence_length:], high_price[train_size+sequence_len
plt.plot(df2.index[train_size+sequence_length:], predicted_prices_lstm, label='Giá
plt.plot(df2.index[train_size+sequence_length:], predicted_prices_gru, label='Giá d
plt.title('Biểu đồ dự đoán giá sử dụng model LSTM và GRU trong tập test ',fontsize=
plt.xlabel('Ngày',fontsize=18)
plt.ylabel('Giá cao nhất',fontsize=18)
plt.legend(loc='upper left')
plt.grid(True)
plt.show()
```

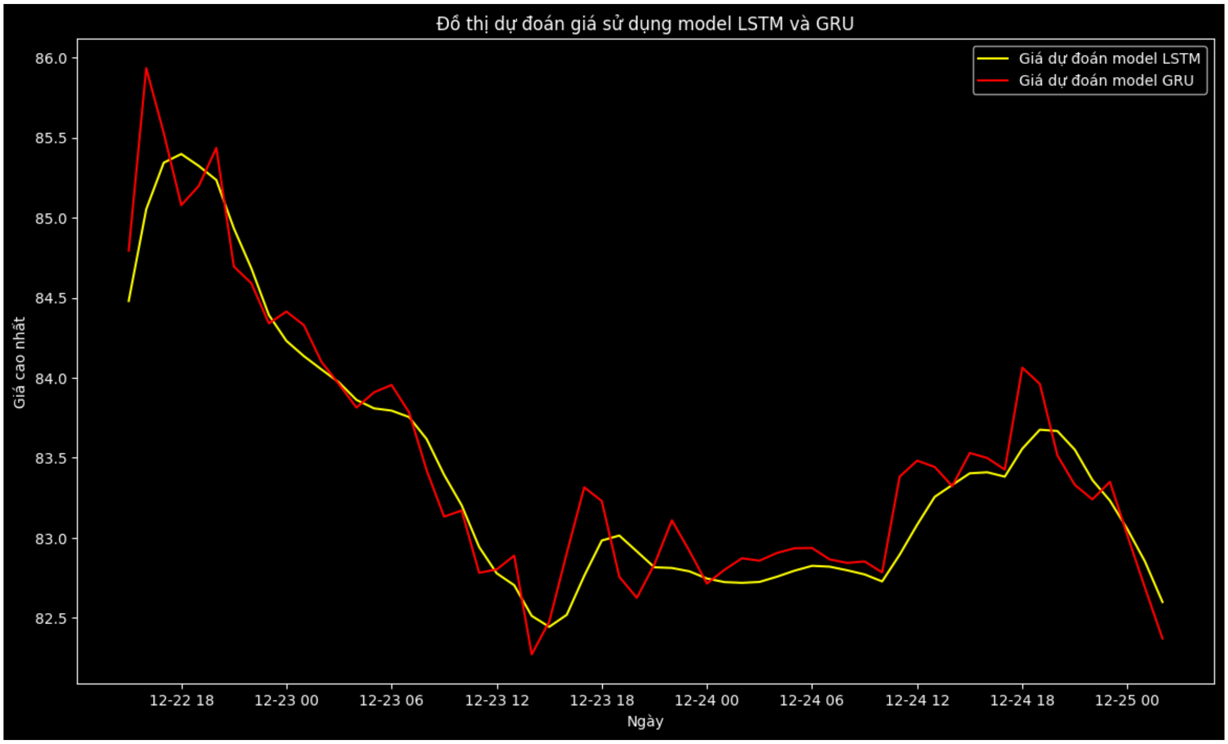


6.Prediction:

In [ ]:

```
full_train_data = scaled_prices
X_full_train = create_sequences(full_train_data, sequence_length)
future_predictions_scaled_lstm = lstm_model.predict(X_full_train[-60:])
future_predictions_scaled_gru = gru_model.predict(X_full_train[-60:])

full_train_data = scaled_prices

X_full_train = create_sequences(full_train_data, sequence_length)

future_predictions_scaled_lstm = lstm_model.predict(X_full_train[-60:])
future_predictions_scaled_gru = gru_model.predict(X_full_train[-60:])
future_predictions_lstm = scaler.inverse_transform(future_predictions_scaled_lstm)
future_predictions_gru = scaler.inverse_transform(future_predictions_scaled_gru)

plt.figure(figsize=(14, 8))
plt.plot(pd.date_range(start=df2.index[-1], periods=61, freq='H')[1:], future_predi
plt.plot(pd.date_range(start=df2.index[-1], periods=61, freq='H')[1:], future_predi
plt.title('Đồ thị dự đoán giá sử dụng model LSTM và GRU')
plt.xlabel('Ngày')
plt.ylabel('Giá cao nhất')
plt.legend()
plt.show()
```

```
2/2 [==============================] - 0s 23ms/step
2/2 [==============================] - 0s 19ms/step
2/2 [==============================] - 0s 23ms/step
2/2 [==============================] - 0s 16ms/step
```


Đồ thị dự đoán giá sử dụng model LSTM và GRU
Giá dự đoán model LSTM
Giá dự đoán model GRU
Giá cao nhất
86.0
85.5
85.0
84.5
84.0
83.5
83.0
82.5
Ngày
12-22 18
12-23 00
12-23 06
12-23 12
12-23 18
12-24 00
12-24 06
12-24 12
12-24 18
12-25 00