Stock Prediction using RNN's

Loading the required Libraries

In [1]:
```
import numpy as np
import string as str
import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import Dense, LSTM, Dropout, GRU
from keras.optimizers import SGD
import math
from sklearn.metrics import mean_squared_error
```

Loading the Data

In [2]:
```
data = pd.read_csv('C:/Users/LEGION/Downloads/GOOG.csv', index_col='Date', parse_dates=[
#data.head()
data.tail()
```

Out[2]:

	Open	High	Low	Close	Adj Close	Volume
Date						
2023-11-13	133.360001	134.110001	132.770004	133.639999	133.639999	16409900
2023-11-14	135.649994	137.240005	135.100006	135.429993	135.429993	22317300
2023-11-15	136.639999	136.839996	135.330002	136.380005	136.380005	15840900
2023-11-16	136.960007	138.880005	136.080002	138.699997	138.699997	17615100
2023-11-17	137.820007	138.000000	135.479996	136.940002	136.940002	25565300

In [3]:
```
data.info()
```

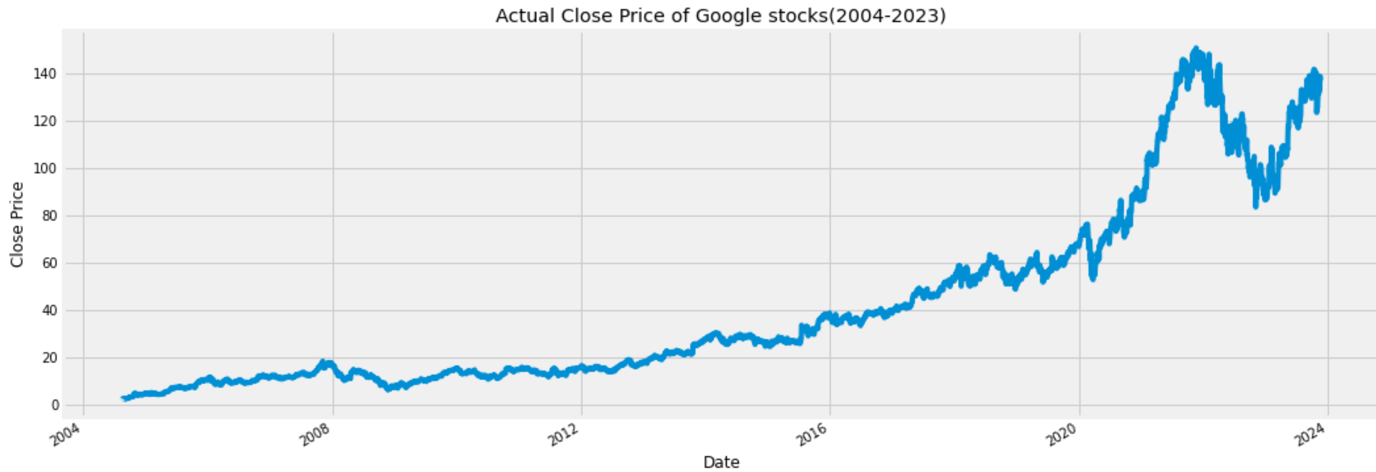
```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 4847 entries, 2004-08-19 to 2023-11-17
Data columns (total 6 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Open       4847 non-null   float64
 1   High       4847 non-null   float64
 2   Low        4847 non-null   float64
 3   Close      4847 non-null   float64
 4   Adj Close  4847 non-null   float64
 5   Volume     4847 non-null   int64  
dtypes: float64(5), int64(1)
memory usage: 265.1 KB
```

In [4]:
```
len(data)
```

Out[4]:
```
4847
```

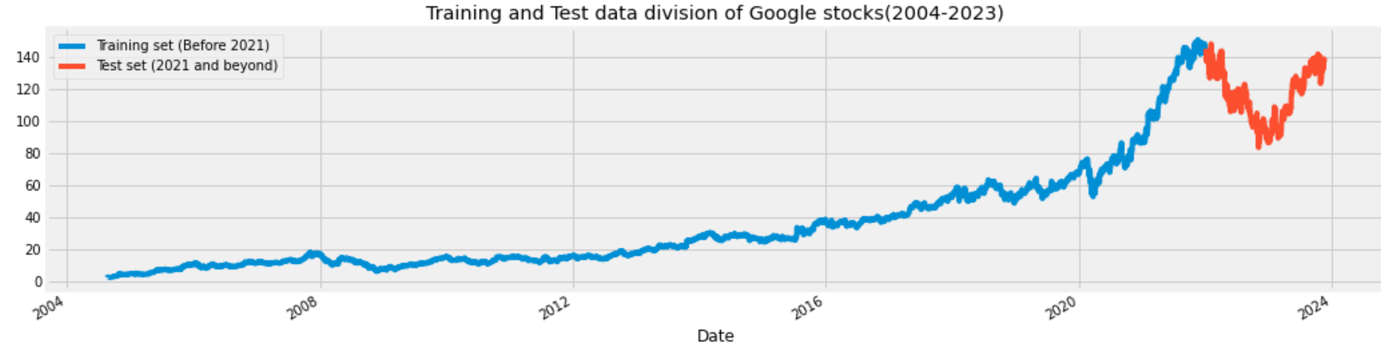
In [5]:
```
data["Close"].plot(figsize=(16, 6))
plt.title("Actual Close Price of Google stocks(2004-2023)")
plt.xlabel("Date")
```

```python
plt.ylabel("Close Price")
plt.show()
# Plotting a histogram
plt.figure(figsize=(14, 6))
plt.hist(data["Close"], bins=10, color='skyblue', edgecolor='black')
plt.title("Histogram of Close Prices")
plt.xlabel("Close Price")
plt.ylabel("Frequency")
plt.show()
```



Displaying the division of data into Training and Test set over time

In [6]:
```python
# We have chosen 'Close' attribute for prices. Let's see what it looks like
data["Close"][:'2021'].plot(figsize=(16,4),legend=True)
data["Close"]['2022':].plot(figsize=(16,4),legend=True)
plt.legend(['Training set (Before 2021)','Test set (2021 and beyond)'])
plt.title('Training and Test data division of Google stocks(2004-2023)')
plt.show()
```



In [7]:
```
data = data.filter(['Close'])
# Convert the dataframe to a numpy array
dataset = data.values
# Get the number of rows to train the model on
training_data_len = int(np.ceil( len(dataset) * .95 ))

training_data_len
```

Out[7]:
```
4605
```

In [8]:
```
# Scale the data
from sklearn.preprocessing import MinMaxScaler

scaler = MinMaxScaler(feature_range=(0,1))
scaled_data = scaler.fit_transform(dataset)

scaled_data
```

Out[8]:
```
array([[5.54588186e-05],
       [1.39474206e-03],
       [1.57790459e-03],
       ...,
       [9.03324923e-01],
       [9.18977479e-01],
       [9.07103119e-01]])
```

In [9]:
```
# Create the training data set
# Create the scaled training data set
train_data = scaled_data[0:int(training_data_len), :]
# Split the data into x_train and y_train data sets
x_train = []
y_train = []

for i in range(60, len(train_data)):
    x_train.append(train_data[i-60:i, 0])
    y_train.append(train_data[i, 0])
    if i<= 61:
        print(x_train)
        print(y_train)
        print()

# Convert the x_train and y_train to numpy arrays
x_train, y_train = np.array(x_train), np.array(y_train)

# Reshape the data
x_train = np.reshape(x_train, (x_train.shape[0], x_train.shape[1], 1))
# x_train.shape
```

```
[array([5.54588186e-05, 1.39474206e-03, 1.57790459e-03, 8.16681705e-04,
       1.00656406e-03, 1.32752354e-03, 1.03177016e-03, 3.36085838e-04,
       3.96577781e-04, 4.03324596e-05, 2.52061005e-04, 0.00000000e+00,
       2.63827450e-04, 3.84818082e-04, 3.86498039e-04, 8.93979963e-04,
       1.25862507e-03, 1.92911004e-03, 2.01480808e-03, 2.34584731e-03,
```

```
       2.93735406e-03, 3.25158697e-03, 2.99616605e-03, 3.08690396e-03,
       3.49692814e-03, 3.33056518e-03, 3.06674448e-03, 4.51189199e-03,
       5.22102272e-03, 4.97232163e-03, 5.47308373e-03, 5.88982099e-03,
       6.44603516e-03, 6.22926674e-03, 6.52669333e-03, 6.33849093e-03,
       5.92343362e-03, 6.28303886e-03, 6.87117895e-03, 7.05602144e-03,
       7.41058681e-03, 8.25919444e-03, 8.05418572e-03, 6.80228048e-03,
       8.29616024e-03, 1.21694999e-02, 1.46850634e-02, 1.37440379e-02,
       1.44447688e-02, 1.56765011e-02, 1.52295178e-02, 1.61352508e-02,
       1.59403285e-02, 1.54025939e-02, 1.42313536e-02, 1.16519315e-02,
       1.21896594e-02, 1.15427073e-02, 1.14015505e-02, 1.39490466e-02])]
[0.013777643750050559]

[array([5.54588186e-05, 1.39474206e-03, 1.57790459e-03, 8.16681705e-04,
       1.00656406e-03, 1.32752354e-03, 1.03177016e-03, 3.36085838e-04,
       3.96577781e-04, 4.03324596e-05, 2.52061005e-04, 0.00000000e+00,
       2.63827450e-04, 3.84818082e-04, 3.86498039e-04, 8.93979963e-04,
       1.25862507e-03, 1.92911004e-03, 2.01480808e-03, 2.34584731e-03,
       2.93735406e-03, 3.25158697e-03, 2.99616605e-03, 3.08690396e-03,
       3.49692814e-03, 3.33056518e-03, 3.06674448e-03, 4.51189199e-03,
       5.22102272e-03, 4.97232163e-03, 5.47308373e-03, 5.88982099e-03,
       6.44603516e-03, 6.22926674e-03, 6.52669333e-03, 6.33849093e-03,
       5.92343362e-03, 6.28303886e-03, 6.87117895e-03, 7.05602144e-03,
       7.41058681e-03, 8.25919444e-03, 8.05418572e-03, 6.80228048e-03,
       8.29616024e-03, 1.21694999e-02, 1.46850634e-02, 1.37440379e-02,
       1.44447688e-02, 1.56765011e-02, 1.52295178e-02, 1.61352508e-02,
       1.59403285e-02, 1.54025939e-02, 1.42313536e-02, 1.16519315e-02,
       1.21896594e-02, 1.15427073e-02, 1.14015505e-02, 1.39490466e-02]), array([1.394742
06e-03, 1.57790459e-03, 8.16681705e-04, 1.00656406e-03,
       1.32752354e-03, 1.03177016e-03, 3.36085838e-04, 3.96577781e-04,
       4.03324596e-05, 2.52061005e-04, 0.00000000e+00, 2.63827450e-04,
       3.84818082e-04, 3.86498039e-04, 8.93979963e-04, 1.25862507e-03,
       1.92911004e-03, 2.01480808e-03, 2.34584731e-03, 2.93735406e-03,
       3.25158697e-03, 2.99616605e-03, 3.08690396e-03, 3.49692814e-03,
       3.33056518e-03, 3.06674448e-03, 4.51189199e-03, 5.22102272e-03,
       4.97232163e-03, 5.47308373e-03, 5.88982099e-03, 6.44603516e-03,
       6.22926674e-03, 6.52669333e-03, 6.33849093e-03, 5.92343362e-03,
       6.28303886e-03, 6.87117895e-03, 7.05602144e-03, 7.41058681e-03,
       8.25919444e-03, 8.05418572e-03, 6.80228048e-03, 8.29616024e-03,
       1.21694999e-02, 1.46850634e-02, 1.37440379e-02, 1.44447688e-02,
       1.56765011e-02, 1.52295178e-02, 1.61352508e-02, 1.59403285e-02,
       1.54025939e-02, 1.42313536e-02, 1.16519315e-02, 1.21896594e-02,
       1.15427073e-02, 1.14015505e-02, 1.39490466e-02, 1.37776438e-02])]
[0.013777643750050559, 0.014259919573783194]
```

Using LSTM Network

In [10]:
```
from keras.models import Sequential
from keras.layers import Dense, LSTM

regressor = Sequential()

# # add first layer with dropout

regressor.add(LSTM(units=50,activation="relu", return_sequences=True, input_shape=(x_tra
#regressor.add(BatchNormalization())
regressor.add(Dropout(0.2))

# # add second layer

regressor.add(LSTM(units=60,activation="relu", return_sequences=True))
#regressor.add(BatchNormalization())
regressor.add(Dropout(0.2))
```

```
# # add third layer

regressor.add(LSTM(units=80,activation="relu", return_sequences=True))
#regressor.add(BatchNormalization())
regressor.add(Dropout(0.2))

# # add fourth layer

regressor.add(LSTM(units=120,activation="relu"))
#regressor.add(BatchNormalization())
regressor.add(Dropout(0.2))

# # the output layer
regressor.add(Dense(units=1))

# Compile the model
regressor.compile(optimizer='rmsprop', loss='mean_squared_error')
```

In [11]:
```
regressor.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 60, 50)            10400

 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: 178761 (698.29 KB)
Trainable params: 178761 (698.29 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [12]:
```
# Train the model
regressor.fit(x_train, y_train, batch_size=32, epochs=50)
```

```
Epoch 1/50
143/143 [==============================] - 15s 86ms/step - loss: 0.0082
Epoch 2/50
143/143 [==============================] - 12s 85ms/step - loss: 0.0032
Epoch 3/50
143/143 [==============================] - 12s 81ms/step - loss: 0.0027
Epoch 4/50
143/143 [==============================] - 12s 82ms/step - loss: 0.0028
Epoch 5/50
143/143 [==============================] - 12s 81ms/step - loss: 0.0025
Epoch 6/50
143/143 [==============================] - 12s 83ms/step - loss: 0.0021
Epoch 7/50
143/143 [==============================] - 12s 83ms/step - loss: 0.0020
```

```
Epoch 8/50
143/143 [==============================] - 12s 84ms/step - loss: 0.0019
Epoch 9/50
143/143 [==============================] - 12s 84ms/step - loss: 0.0019
Epoch 10/50
143/143 [==============================] - 12s 86ms/step - loss: 0.0019
Epoch 11/50
143/143 [==============================] - 12s 84ms/step - loss: 0.0017
Epoch 12/50
143/143 [==============================] - 12s 85ms/step - loss: 0.0017
Epoch 13/50
143/143 [==============================] - 12s 84ms/step - loss: 0.0016
Epoch 14/50
143/143 [==============================] - 12s 85ms/step - loss: 0.0017
Epoch 15/50
143/143 [==============================] - 12s 86ms/step - loss: 0.0016
Epoch 16/50
143/143 [==============================] - 12s 84ms/step - loss: 0.0014
Epoch 17/50
143/143 [==============================] - 12s 86ms/step - loss: 0.0014
Epoch 18/50
143/143 [==============================] - 12s 83ms/step - loss: 0.0014
Epoch 19/50
143/143 [==============================] - 12s 84ms/step - loss: 0.0014
Epoch 20/50
143/143 [==============================] - 12s 82ms/step - loss: 0.0015
Epoch 21/50
143/143 [==============================] - 12s 85ms/step - loss: 0.0013
Epoch 22/50
143/143 [==============================] - 12s 83ms/step - loss: 0.0011
Epoch 23/50
143/143 [==============================] - 12s 83ms/step - loss: 0.0011
Epoch 24/50
143/143 [==============================] - 12s 84ms/step - loss: 0.0012
Epoch 25/50
143/143 [==============================] - 12s 84ms/step - loss: 0.0011
Epoch 26/50
143/143 [==============================] - 12s 83ms/step - loss: 0.0011
Epoch 27/50
143/143 [==============================] - 12s 83ms/step - loss: 0.0012
Epoch 28/50
143/143 [==============================] - 12s 83ms/step - loss: 0.0011
Epoch 29/50
143/143 [==============================] - 12s 83ms/step - loss: 0.0011
Epoch 30/50
143/143 [==============================] - 12s 86ms/step - loss: 0.0010
Epoch 31/50
143/143 [==============================] - 12s 84ms/step - loss: 0.0011
Epoch 32/50
143/143 [==============================] - 12s 81ms/step - loss: 0.0010
Epoch 33/50
143/143 [==============================] - 12s 82ms/step - loss: 0.0010
Epoch 34/50
143/143 [==============================] - 12s 82ms/step - loss: 9.2351e-04
Epoch 35/50
143/143 [==============================] - 12s 84ms/step - loss: 9.9724e-04
Epoch 36/50
143/143 [==============================] - 12s 83ms/step - loss: 9.0745e-04
Epoch 37/50
143/143 [==============================] - 12s 81ms/step - loss: 0.0010
Epoch 38/50
143/143 [==============================] - 12s 83ms/step - loss: 9.2112e-04
Epoch 39/50
143/143 [==============================] - 12s 83ms/step - loss: 8.8355e-04
Epoch 40/50
143/143 [==============================] - 12s 85ms/step - loss: 9.6124e-04
```

```
Epoch 41/50
143/143 [==============================] - 12s 85ms/step - loss: 9.2582e-04
Epoch 42/50
143/143 [==============================] - 12s 84ms/step - loss: 9.0119e-04
Epoch 43/50
143/143 [==============================] - 12s 83ms/step - loss: 8.4469e-04
Epoch 44/50
143/143 [==============================] - 12s 84ms/step - loss: 9.4424e-04
Epoch 45/50
143/143 [==============================] - 12s 85ms/step - loss: 9.0712e-04
Epoch 46/50
143/143 [==============================] - 12s 84ms/step - loss: 8.9871e-04
Epoch 47/50
143/143 [==============================] - 12s 84ms/step - loss: 8.9171e-04
Epoch 48/50
143/143 [==============================] - 12s 83ms/step - loss: 8.3077e-04
Epoch 49/50
143/143 [==============================] - 12s 83ms/step - loss: 9.3319e-04
Epoch 50/50
143/143 [==============================] - 12s 83ms/step - loss: 8.9674e-04
```

Out[12]:

```
<keras.src.callbacks.History at 0x20d94be89a0>
```

In [13]:

```python
# Create the testing data set
2
test_data = scaled_data[training_data_len - 60: , :]
# Create the data sets x_test and y_test
x_test = []
y_test = dataset[training_data_len:, :]
for i in range(60, len(test_data)):
    x_test.append(test_data[i-60:i, 0])

# Convert the data to a numpy array
x_test = np.array(x_test)

# Reshape the data
x_test = np.reshape(x_test, (x_test.shape[0], x_test.shape[1], 1 ))

# Get the models predicted price values
predictions = regressor.predict(x_test)
predictions = scaler.inverse_transform(predictions)

# Get the root mean squared error (RMSE)
rmse = np.sqrt(np.mean(((predictions - y_test) ** 2)))
print("The RMSE when using LSTM network is :-",rmse)
```

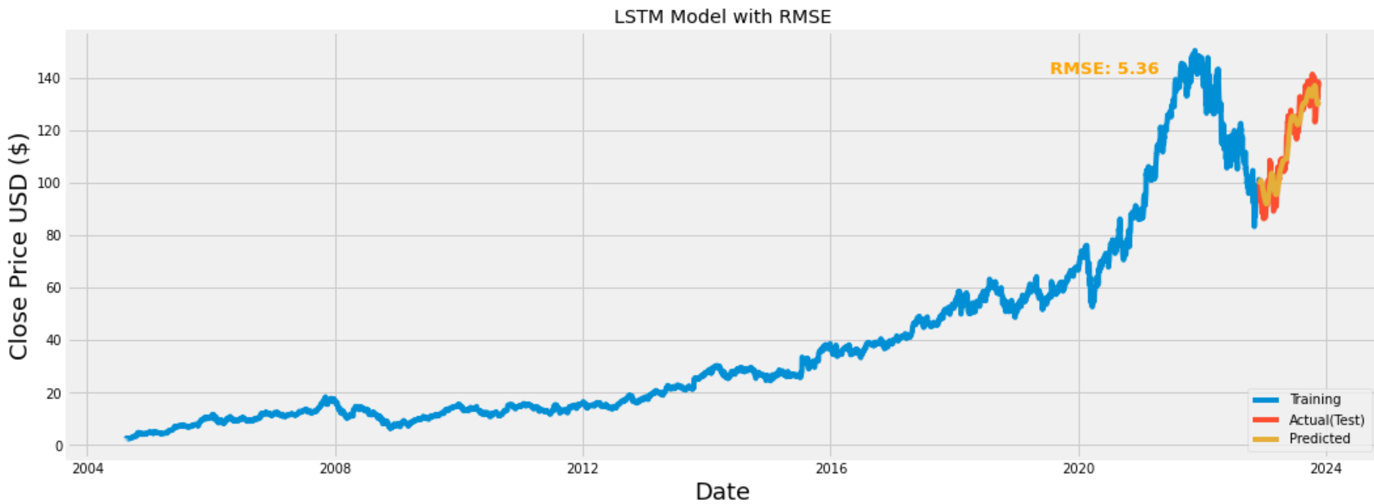
```
8/8 [==============================] - 1s 27ms/step
The RMSE when using LSTM network is :- 5.355018236923045
```

In [14]:

```python
# Plot the data
train = data[:training_data_len]
valid = data[training_data_len:]
valid['Predictions'] = predictions

# Visualize the data and RMSE
plt.figure(figsize=(16,6))
plt.title('LSTM Model with RMSE')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.plot(train['Close'])
plt.plot(valid[['Close','Predictions']])
plt.legend(['Training', 'Actual(Test)', 'Predicted'], loc='lower right')

# Add RMSE as a text annotation
plt.annotate(f'RMSE: {rmse:.2f}', xy=(0.75, 0.9), xycoords='axes fraction', fontsize=13,
```

```
plt.show()
```

```
C:\Users\LEGION\AppData\Local\Temp\ipykernel_16632\1652237224.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  valid['Predictions'] = predictions
```



Close Price comparison between Actual and Predicted

In [15]:
```
valid
```

Out[15]:

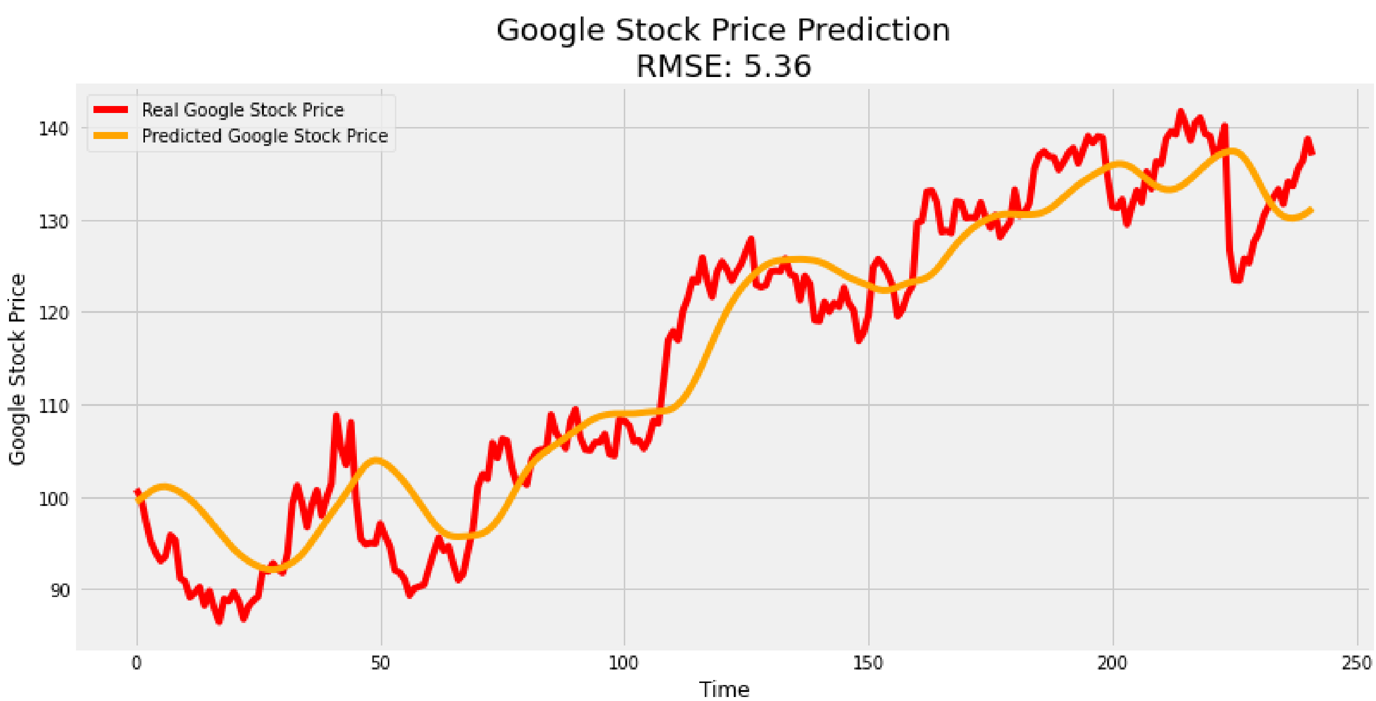
Date	Close	Predictions
2022-12-02	100.830002	99.441353
2022-12-05	99.870003	99.841202
2022-12-06	97.309998	100.243843
2022-12-07	95.150002	100.617989
2022-12-08	93.949997	100.915184
...	...	...
2023-11-13	133.639999	130.117935
2023-11-14	135.429993	130.222549
2023-11-15	136.380005	130.445786
2023-11-16	138.699997	130.771469
2023-11-17	136.940002	131.196060

242 rows × 2 columns

Better view of the Predicted Model

In [16]:
```
# def plot_predictions(test,predicted):
#     plt.plot(test, color='red',label='Real Google Stock Price')
```

```
#      plt.plot(predicted, color='orange',label='Predicted Google Stock Price')
#      plt.title('Google Stock Price Prediction')
#      plt.xlabel('time')
#      plt.ylabel('Google Stock Price')
#      plt.legend()
#      plt.show()
# plot_predictions(y_test,predictions)

def plot_predictions(test, predicted, rmse=None):
    plt.figure(figsize=(12, 6))

    # Plot actual stock prices
    plt.plot(test, color='red', label='Real Google Stock Price')

    # Plot predicted stock prices
    plt.plot(predicted, color='orange', label='Predicted Google Stock Price')

    # Add RMSE as text in the plot
    if rmse is not None:
        plt.title(f'Google Stock Price Prediction\nRMSE: {rmse:.2f}', fontsize=18)
    else:
        plt.title('Google Stock Price Prediction', fontsize=18)

    plt.xlabel('Time')
    plt.ylabel('Google Stock Price')
    plt.legend()
    plt.show()

# Call the function with RMSE
plot_predictions(y_test, predictions, rmse)
```



Using GRU Network

In [17]:
```
from keras.models import Sequential
from keras.layers import Dense, GRU, Dropout

regressor_gru = Sequential()

# add first GRU layer with dropout
regressor_gru.add(GRU(units=50, return_sequences=True, input_shape=(x_train.shape[1], 1)
```

```python
regressor_gru.add(Dropout(0.2))

# add second GRU layer with dropout
regressor_gru.add(GRU(units=60, return_sequences=True, activation='tanh'))
regressor_gru.add(Dropout(0.2))

# add third GRU layer with dropout
regressor_gru.add(GRU(units=80, return_sequences=True, activation='tanh'))
regressor_gru.add(Dropout(0.2))

# add fourth GRU layer with dropout
regressor_gru.add(GRU(units=120, activation='tanh'))
regressor_gru.add(Dropout(0.2))

# output layer
regressor_gru.add(Dense(units=1))

# Compile the model
regressor_gru.compile(optimizer='rmsprop',loss='mean_squared_error')

# Train the model
regressor_gru.fit(x_train, y_train, batch_size=32, epochs=50)
```

```
Epoch 1/50
143/143 [==============================] - 14s 64ms/step - loss: 0.0049
Epoch 2/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0025
Epoch 3/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0019
Epoch 4/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0018
Epoch 5/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0017
Epoch 6/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0015
Epoch 7/50
143/143 [==============================] - 9s 65ms/step - loss: 0.0014
Epoch 8/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0015
Epoch 9/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0013
Epoch 10/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0012
Epoch 11/50
143/143 [==============================] - 9s 65ms/step - loss: 0.0013
Epoch 12/50
143/143 [==============================] - 9s 65ms/step - loss: 0.0012
Epoch 13/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0011
Epoch 14/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0012
Epoch 15/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0011
Epoch 16/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0011
Epoch 17/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0011
Epoch 18/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0010
Epoch 19/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0010
Epoch 20/50
143/143 [==============================] - 9s 64ms/step - loss: 0.0010
Epoch 21/50
143/143 [==============================] - 9s 64ms/step - loss: 8.6703e-04
Epoch 22/50
```

```
143/143 [==============================] - 9s 65ms/step - loss: 9.6961e-04
Epoch 23/50
143/143 [==============================] - 9s 64ms/step - loss: 9.1353e-04
Epoch 24/50
143/143 [==============================] - 9s 64ms/step - loss: 8.2264e-04
Epoch 25/50
143/143 [==============================] - 9s 64ms/step - loss: 8.9070e-04
Epoch 26/50
143/143 [==============================] - 9s 64ms/step - loss: 8.4979e-04
Epoch 27/50
143/143 [==============================] - 9s 64ms/step - loss: 8.6238e-04
Epoch 28/50
143/143 [==============================] - 9s 64ms/step - loss: 8.0190e-04
Epoch 29/50
143/143 [==============================] - 9s 65ms/step - loss: 7.7021e-04
Epoch 30/50
143/143 [==============================] - 9s 65ms/step - loss: 7.4556e-04
Epoch 31/50
143/143 [==============================] - 9s 65ms/step - loss: 7.3761e-04
Epoch 32/50
143/143 [==============================] - 9s 65ms/step - loss: 8.0597e-04
Epoch 33/50
143/143 [==============================] - 9s 65ms/step - loss: 7.7037e-04
Epoch 34/50
143/143 [==============================] - 9s 63ms/step - loss: 6.8795e-04
Epoch 35/50
143/143 [==============================] - 9s 65ms/step - loss: 7.7414e-04
Epoch 36/50
143/143 [==============================] - 9s 65ms/step - loss: 6.8681e-04
Epoch 37/50
143/143 [==============================] - 164s 1s/step - loss: 7.3837e-04
Epoch 38/50
143/143 [==============================] - 10s 71ms/step - loss: 7.6438e-04
Epoch 39/50
143/143 [==============================] - 10s 67ms/step - loss: 7.1066e-04
Epoch 40/50
143/143 [==============================] - 10s 67ms/step - loss: 6.6468e-04
Epoch 41/50
143/143 [==============================] - 9s 65ms/step - loss: 7.0453e-04
Epoch 42/50
143/143 [==============================] - 10s 70ms/step - loss: 6.2223e-04
Epoch 43/50
143/143 [==============================] - 10s 71ms/step - loss: 6.8235e-04
Epoch 44/50
143/143 [==============================] - 10s 68ms/step - loss: 7.3754e-04
Epoch 45/50
143/143 [==============================] - 10s 69ms/step - loss: 7.1004e-04
Epoch 46/50
143/143 [==============================] - 10s 66ms/step - loss: 6.5130e-04
Epoch 47/50
143/143 [==============================] - 10s 70ms/step - loss: 6.3557e-04
Epoch 48/50
143/143 [==============================] - 10s 67ms/step - loss: 6.1692e-04
Epoch 49/50
143/143 [==============================] - 9s 66ms/step - loss: 6.2068e-04
Epoch 50/50
143/143 [==============================] - 10s 67ms/step - loss: 6.2628e-04
```

Out[17]:

```
<keras.src.callbacks.History at 0x20d9fee2640>
```

In [18]:

```
regressor_gru.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
```

```
 gru (GRU)                   (None, 60, 50)            7950

 dropout_4 (Dropout)         (None, 60, 50)            0

 gru_1 (GRU)                 (None, 60, 60)            20160

 dropout_5 (Dropout)         (None, 60, 60)            0

 gru_2 (GRU)                 (None, 60, 80)            34080

 dropout_6 (Dropout)         (None, 60, 80)            0

 gru_3 (GRU)                 (None, 120)               72720

 dropout_7 (Dropout)         (None, 120)               0

 dense_1 (Dense)             (None, 1)                 121

=================================================================
Total params: 135031 (527.46 KB)
Trainable params: 135031 (527.46 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

In [19]:

```
# Create the testing data set
test_data_gru = scaled_data[training_data_len - 60:, :]
x_test_gru = []

# Create the data sets x_test and y_test
for i in range(60, len(test_data_gru)):
    x_test_gru.append(test_data_gru[i-60:i, 0])

# Convert the data to a numpy array
x_test_gru = np.array(x_test_gru)

# Reshape the data
x_test_gru = np.reshape(x_test_gru, (x_test_gru.shape[0], x_test_gru.shape[1], 1))

# Get the models predicted price values
predictions_gru = regressor_gru.predict(x_test_gru)
predictions_gru = scaler.inverse_transform(predictions_gru)

# Get the root mean squared error (RMSE)
rmse_gru = np.sqrt(np.mean(((predictions_gru - y_test) ** 2)))
#rmse_gru
print("The RMSE when using GRU network is :-",rmse_gru)
```

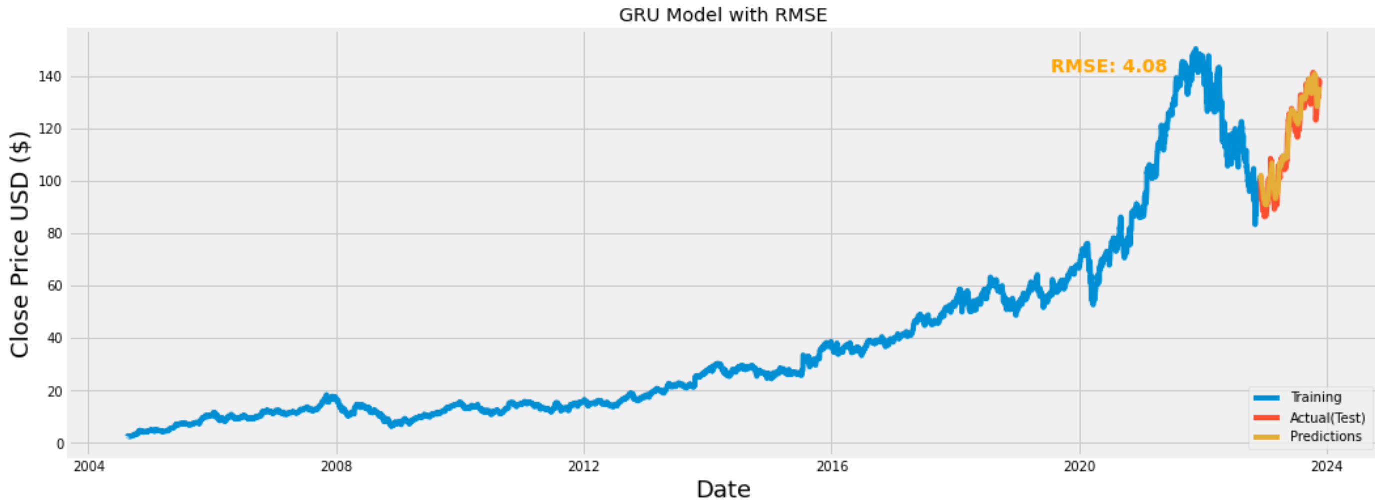
```
8/8 [==============================] - 1s 17ms/step
The RMSE when using GRU network is :- 4.083131934686538
```

In [20]:

```
# Plot the data
train = data[:training_data_len]
valid_gru = data[training_data_len:]
valid_gru['Predictions'] = predictions_gru

# Visualize the data and RMSE
plt.figure(figsize=(16,6))
plt.title('GRU Model with RMSE')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)
plt.plot(train['Close'])
plt.plot(valid_gru[['Close', 'Predictions']])
plt.legend(['Training', 'Actual(Test)', 'Predictions'], loc='lower right')

# Add RMSE as a text annotation
plt.annotate(f'RMSE: {rmse_gru:.2f}', xy=(0.75, 0.9), xycoords='axes fraction', fontsize
```

```
plt.show()
```

```
C:\Users\LEGION\AppData\Local\Temp\ipykernel_16632\2446099753.py:4: SettingWithCopyWarni
ng:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_
guide/indexing.html#returning-a-view-versus-a-copy
  valid_gru['Predictions'] = predictions_gru
```



Close price comparison between Actual and Predicted

In [21]:
```
valid_gru
```

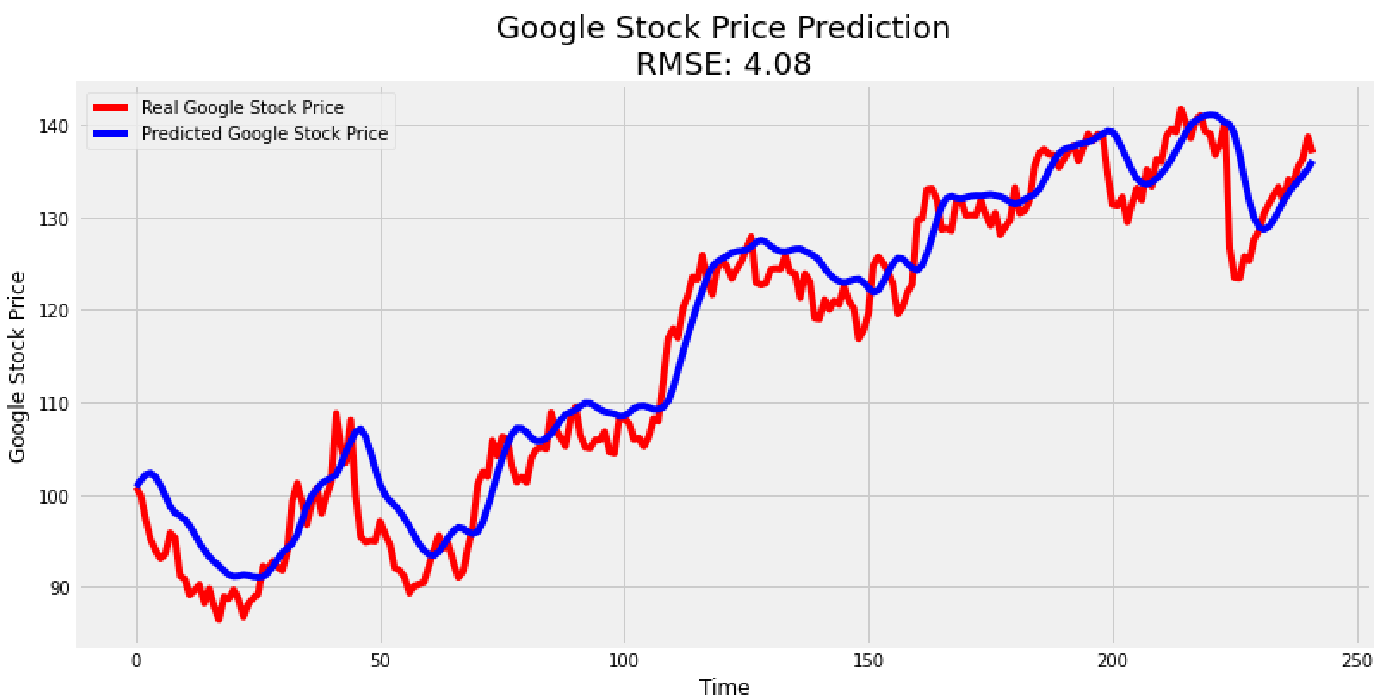
Out[21]:

Date	Close	Predictions
2022-12-02	100.830002	100.801277
2022-12-05	99.870003	101.543709
2022-12-06	97.309998	102.163353
2022-12-07	95.150002	102.334763
2022-12-08	93.949997	101.916710
...	...	...
2023-11-13	133.639999	133.295670
2023-11-14	135.429993	133.913788
2023-11-15	136.380005	134.541534
2023-11-16	138.699997	135.238373
2023-11-17	136.940002	136.118378

242 rows × 2 columns

Better view of the Predicted Model

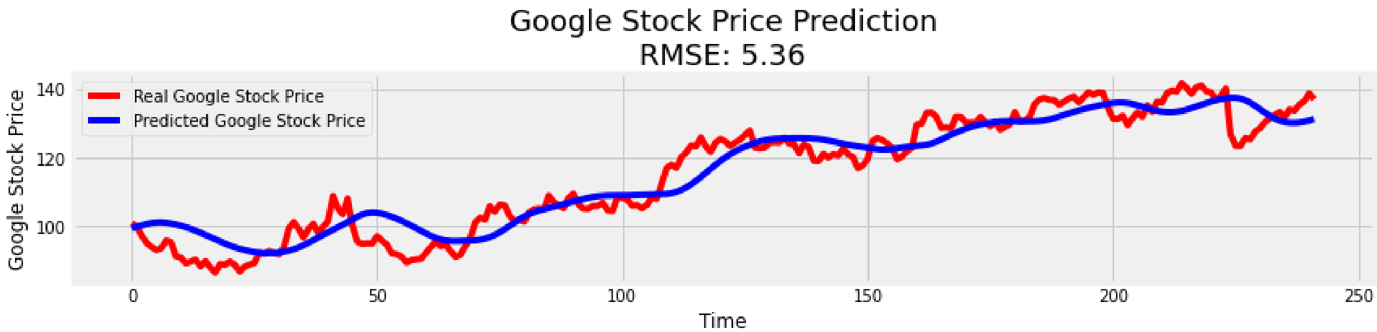
In [22]:
```python
def plot_predictions(test, predicted, rmse=None):
    plt.figure(figsize=(12, 6))

    # Plot actual stock prices
    plt.plot(test, color='red', label='Real Google Stock Price')

    # Plot predicted stock prices
    plt.plot(predicted, color='blue', label='Predicted Google Stock Price')

    # Add RMSE as text in the plot
    if rmse is not None:
        plt.title(f'Google Stock Price Prediction\nRMSE: {rmse:.2f}', fontsize=18)
    else:
        plt.title('Google Stock Price Prediction', fontsize=18)

    plt.xlabel('Time')
    plt.ylabel('Google Stock Price')
    plt.legend()
    plt.show()

# Call the function with RMSE
plot_predictions(y_test, predictions_gru, rmse_gru)
```

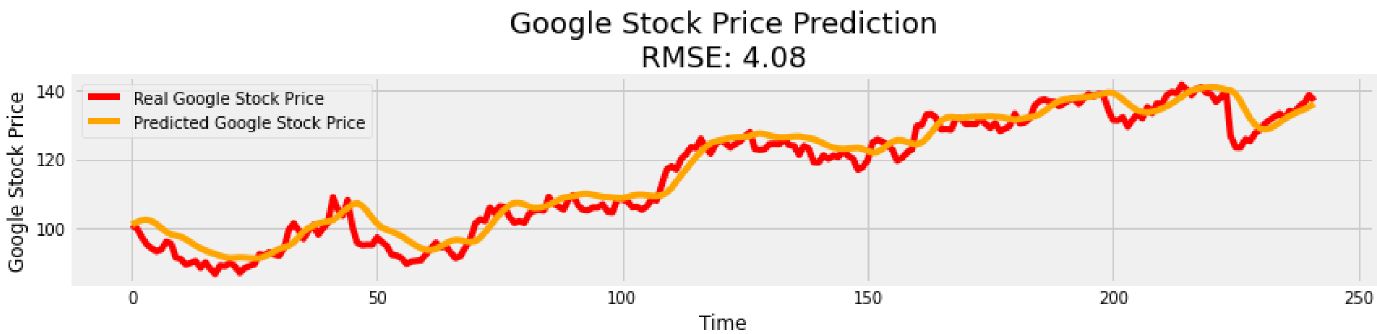


Model Comparison

In [23]:
```python
def plot_predictions(test, predicted, rmse=None, color='orange'):
    plt.plot(test, color='red', label='Real Google Stock Price')
    plt.plot(predicted, color=color, label='Predicted Google Stock Price')

    if rmse is not None:
        plt.title(f'Google Stock Price Prediction\nRMSE: {rmse:.2f}', fontsize=18)
    else:
        plt.title('Google Stock Price Prediction', fontsize=18)

    plt.xlabel('Time')
    plt.ylabel('Google Stock Price')
    plt.legend()


# Plot LSTM predictions
```

```
plt.figure(figsize=(12, 6))
plt.subplot(2, 1, 1)
plot_predictions(y_test, predictions, rmse, color='blue')

# Plot GRU predictions
plt.subplot(2, 1, 2)
plot_predictions(y_test, predictions_gru, rmse_gru, color='orange')

plt.tight_layout()  # Adjust layout for better spacing
plt.show()
```



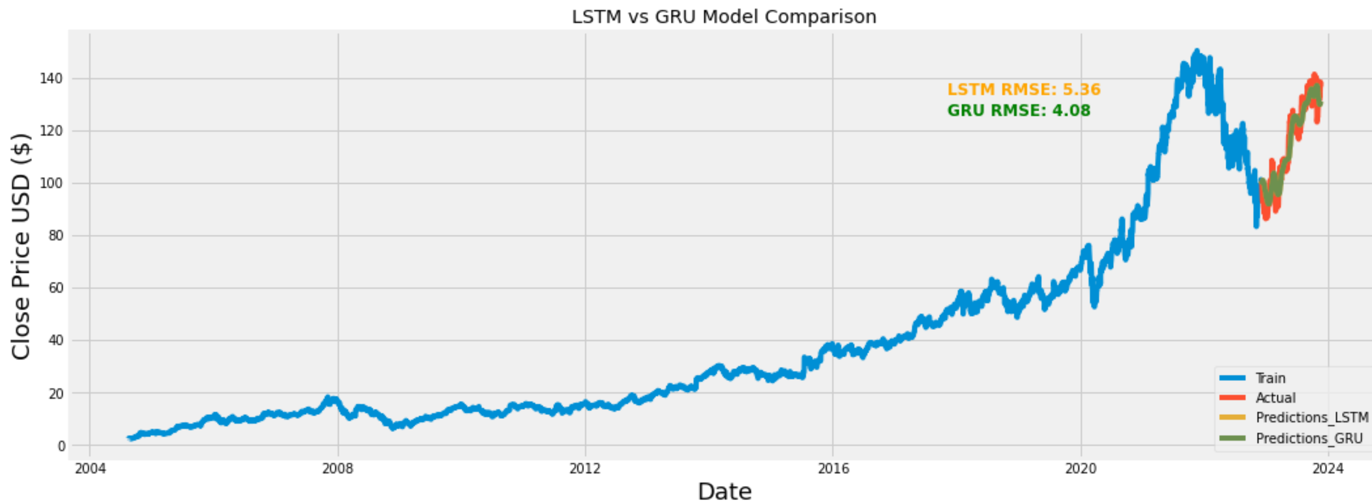


In [24]:

```
# Get the root mean squared error (RMSE) for LSTM and GRU
rmse_lstm = np.sqrt(np.mean(((predictions - y_test) ** 2)))
rmse_gru = np.sqrt(np.mean(((predictions_gru - y_test) ** 2)))

# Plot the data
train = data[:training_data_len]
valid = data[training_data_len:]
valid['Predictions'] = predictions
valid_gru['Predictions'] = predictions_gru

# Visualize the data, LSTM predictions, GRU predictions, and RMSE
plt.figure(figsize=(16, 6))
plt.title('LSTM vs GRU Model Comparison')
plt.xlabel('Date', fontsize=18)
plt.ylabel('Close Price USD ($)', fontsize=18)

# Plot actual values
plt.plot(train['Close'], label='Train')
plt.plot(valid[['Close', 'Predictions']], label=['Actual', 'Predictions_L

# Add RMSE values as text annotations
plt.annotate(f'LSTM RMSE: {rmse_lstm:.2f}', xy=(0.67, 0.85), xycoords='axes fraction', f
plt.annotate(f'GRU RMSE: {rmse_gru:.2f}', xy=(0.67, 0.80), xycoords='axes fraction', fon

plt.legend(loc='lower right')
plt.show()
```

```
C:\Users\LEGION\AppData\Local\Temp\ipykernel_16632\362990747.py:8: SettingWithCopyWarnin
g:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  valid['Predictions'] = predictions
C:\Users\LEGION\AppData\Local\Temp\ipykernel_16632\362990747.py:9: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  valid_gru['Predictions'] = predictions_gru
```



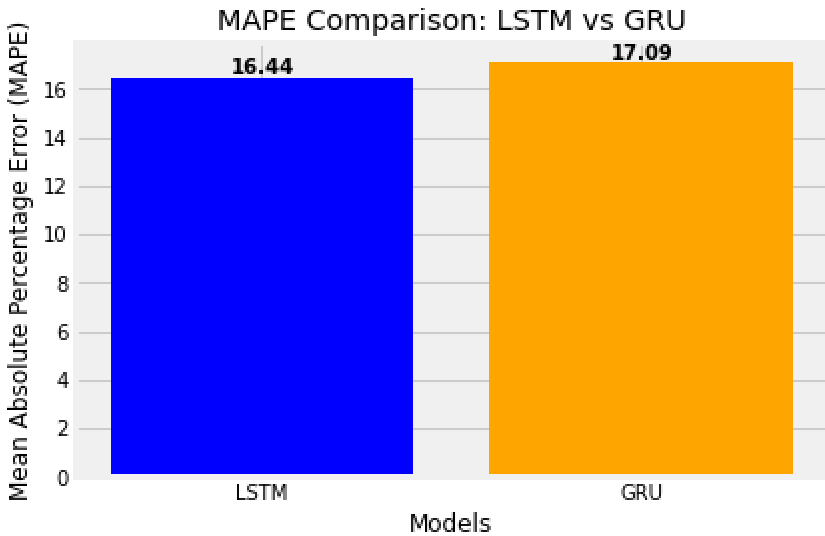
Calculating the Mean Bias Error

In [25]:
```python
# Calculate Mean Bias Error (MBE) for LSTM
mbe_lstm = np.mean(predictions - y_test)

# Calculate Mean Bias Error (MBE) for GRU
mbe_gru = np.mean(predictions_gru - y_test)

# Print MBE values
print("MBE for LSTM: {:.2f}".format(mbe_lstm))
print("MBE for GRU: {:.2f}".format(mbe_gru))


# Calculate MAPE for LSTM
mape_lstm = np.mean(np.abs((y_test - predictions.flatten()) / y_test)) * 100
print("Mean Absolute Percentage Error (MAPE) for LSTM: ", mape_lstm)

# Calculate MAPE for GRU
mape_gru = np.mean(np.abs((y_test - predictions_gru.flatten()) / y_test)) * 100
print("Mean Absolute Percentage Error (MAPE) for GRU: ", mape_gru)
```

```
MBE for LSTM: 0.26
MBE for GRU: 1.67
Mean Absolute Percentage Error (MAPE) for LSTM:  16.438492858225246
Mean Absolute Percentage Error (MAPE) for GRU:  17.0898645365201
```

In [26]:
```python
import matplotlib.pyplot as plt

# Plotting MAPE for LSTM and GRU
models = ['LSTM', 'GRU']
mape_values = [mape_lstm, mape_gru]

fig, ax = plt.subplots()
bars = ax.bar(models, mape_values, color=['blue', 'orange'])
```

```python
# Displaying MAPE values at the center of each bar
for bar, value in zip(bars, mape_values):
    yval = bar.get_height()
    ax.text(bar.get_x() + bar.get_width() / 2, yval, f'{value:.2f}', ha='center', va='bo

plt.xlabel('Models')
plt.ylabel('Mean Absolute Percentage Error (MAPE)')
plt.title('MAPE Comparison: LSTM vs GRU')
plt.show()
```

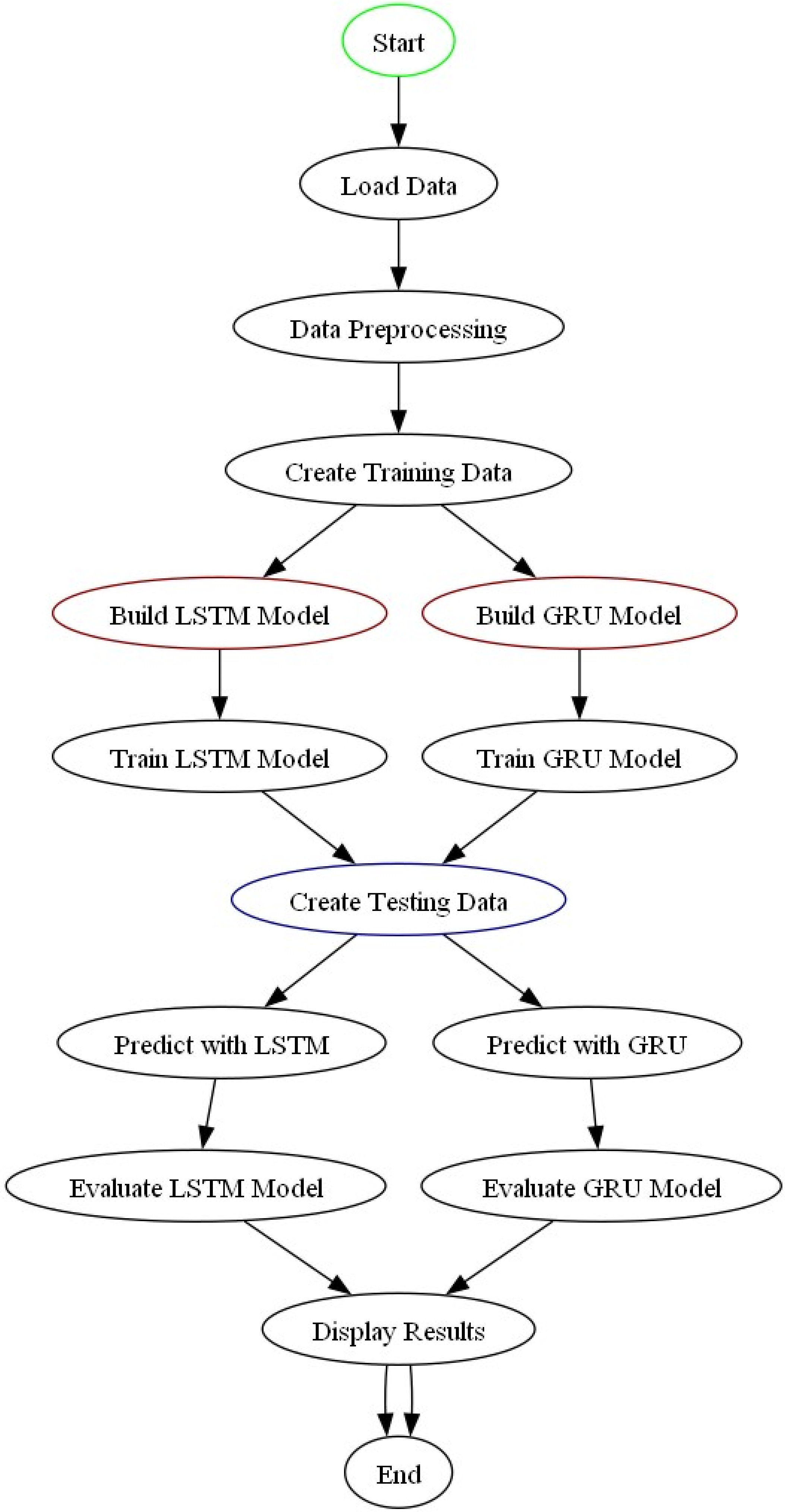


Methodology

In [27]:

```python
from graphviz import Digraph

# Create a Digraph object
flowchart = Digraph(comment='Stock Price Prediction Flowchart', format='png')

# Add nodes and edges
flowchart.node('A', 'Start', color='green')
flowchart.node('B', 'Load Data')
flowchart.node('C', 'Data Preprocessing')
flowchart.node('D', 'Create Training Data')
flowchart.node('E', 'Build LSTM Model', color ='darkred')
flowchart.node('F', 'Train LSTM Model')
flowchart.node('G', 'Create Testing Data', color ='darkblue')
flowchart.node('H', 'Predict with LSTM')
flowchart.node('I', 'Evaluate LSTM Model')
flowchart.node('J', 'Build GRU Model',color='darkred')
flowchart.node('K', 'Train GRU Model')
flowchart.node('L', 'Predict with GRU')
flowchart.node('M', 'Evaluate GRU Model')
flowchart.node('N', 'Display Results')
flowchart.node('O', 'End')

flowchart.edges(['AB', 'BC', 'CD', 'DE', 'EF', 'FG', 'GH', 'HI','IN','NO', 'DJ', 'JK', '

flowchart.render('flowchart', format='png', cleanup=True, directory='C:/Users/LEGION/Dow


print("Flowchart generated and saved as flowchart.png")
```

```
Flowchart generated and saved as flowchart.png
```


Start
Load Data
Data Preprocessing
Create Training Data
Build LSTM Model
Build GRU Model
Train LSTM Model
Train GRU Model
Create Testing Data
Predict with LSTM
Predict with GRU
Evaluate LSTM Model
Evaluate GRU Model
Display Results
End