```
import tensorflow as tf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
from sklearn.preprocessing import MinMaxScaler
from tensorflow import keras
import keras.backend as K
from keras.models import Sequential
from keras.layers import Dense, Dropout, LSTM, Layer, Bidirectional,
Attention
from keras import optimizers
from sklearn.metrics import mean squared error
seed = 1234
np.random.seed(seed)
plt.style.use('ggplot')
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
data raw = pd.read csv("VNM.csv", index col="Date",
parse dates=["Date"])
data raw = data raw.dropna()
dataset = pd.DataFrame(data raw['Close'])
print(' Count row of data: ',len(dataset))
fig = plt.figure(figsize=(14, 6))
plt.plot(dataset)
plt.xlabel('Date')
plt.ylabel('Stock Price')
plt.gca().xaxis.set major formatter(mdates.DateFormatter("%Y-%m"))
plt.title('Stock Price')
plt.show()
 Count row of data:
                     988
```

```
Stock Price
   22 -
   20
   18
  Stock Price
   14
   12
              2019-07
                                     2021-01
                                             2021-07
                                                     2022-01
      2019-01
                     2020-01
                             2020-07
                                                            2022-07
                                                                    2023-01
                                     Date
dataset norm = dataset.copy()
dataset[['Close']]
scaler = MinMaxScaler()
dataset norm['Close'] = scaler.fit transform(dataset[['Close']])
dataset norm
                Close
Date
             0.426881
2018-12-31
2019-01-02
             0.439560
2019-01-03
             0.404057
2019-01-04
             0.440406
2019-01-07
             0.451395
2022-11-23
             0.120034
2022 - 11 - 25
             0.158073
2022-11-28
             0.177515
2022-11-29
             0.211327
2022-11-30
             0.260355
[988 rows x 1 columns]
totaldata = dataset.values
totaldatatrain = int(len(totaldata)*0.75)
totaldataval = int(len(totaldata)*0.1)
totaldatatest = int(len(totaldata)*0.15)
# Store data into each partition
training set = dataset norm[0:totaldatatrain]
val set=dataset norm[totaldatatrain:totaldatatrain+totaldataval]
test set = dataset norm[totaldatatrain+totaldataval:]
```

Initiaton value of lag

lag = 2

```
# sliding windows function
def create sliding windows(data,len data,lag):
    x=[]
    y=[]
    for i in range(lag,len data):
        x.append(data[i-lag:i,0])
        y.append(data[i,0])
    return np.array(x),np.array(y)
# Formating data into array for create sliding windows
array training set = np.array(training set)
array val set = np.array(val set)
array test set = np.array(test set)
# Create sliding windows into training data
x train, y train =
create sliding windows(array training set,len(array training set),
lag)
x_train = np.reshape(x_train, (x_train.shape[0],x_train.shape[1],1))
# Create sliding windows into validation data
x val,y val =
create sliding windows(array val set,len(array val set),lag)
x_val = np.reshape(x_val, (x_val.shape[0],x_val.shape[1],1))
# Create sliding windows into test data
x test,y test =
create_sliding_windows(array_test_set,len(array_test_set),lag)
x \text{ test} = \text{np.reshape}(x \text{ test}, (x \text{ test.shape}[0], x \text{ test.shape}[1], 1))
# Hyperparameters
learning rate = 0.0001
hidden unit = 64
batch size=64
epoch = 100
# Architecture Gated Recurrent Unit
model = Sequential()
# First GRU layer with dropout
model.add(Bidirectional(LSTM(units=hidden unit, return sequences=True,
input shape=(x train.shape[1],1), activation = 'relu')))
model.add(Dropout(0.2))
# Second GRU layer with dropout
model.add(Bidirectional(LSTM(units=hidden unit, return sequences=True,
activation = 'relu')))
model.add(Dropout(0.2))
# Third GRU layer with dropout
model.add(Bidirectional(LSTM(units=hidden unit,
return sequences=False, activation = 'relu')))
model.add(Dropout(0.2))
```

```
# Output layer
model.add(Dense(units=1))
# Compiling the Gated Recurrent Unit
model.compile(optimizer=tf.keras.optimizers.Adam(lr=learning rate),los
s='mean squared error')
# Fitting ke data training dan data validation
pred = model.fit(x train, y train, validation data=(x val,y val),
batch_size=batch_size, epochs=epoch)
WARNING:absl:`lr` is deprecated, please use `learning rate` instead,
or use the legacy optimizer, e.g., tf.keras.optimizers.legacy.Adam.
Epoch 1/100
val loss: 0.5151
Epoch 2/100
val loss: 0.1053
Epoch 3/100
val loss: 0.0032
Epoch 4/100
val loss: 0.0484
Epoch 5/100
val loss: 0.0071
Epoch 6/100
val loss: 0.0155
Epoch 7/100
val loss: 0.0035
Epoch 8/100
val loss: 0.0036
Epoch 9/100
val loss: 6.0298e-04
Epoch 10/100
val loss: 9.1905e-04
Epoch 11/100
val loss: 5.5649e-04
Epoch 12/100
val loss: 8.0275e-04
```

```
Epoch 13/100
val loss: 7.0017e-04
Epoch 14/100
val loss: 5.0966e-04
Epoch 15/100
val loss: 5.5732e-04
Epoch 16/100
val loss: 5.5892e-04
Epoch 17/100
val loss: 5.7585e-04
Epoch 18/100
val loss: 6.4938e-04
Epoch 19/100
val loss: 8.1603e-04
Epoch 20/100
val loss: 8.5383e-04
Epoch 21/100
val_loss: 7.6687e-04
Epoch 22/100
val loss: 6.2468e-04
Epoch 23/100
val loss: 5.5692e-04
Epoch 24/100
val loss: 7.0514e-04
Epoch 25/100
val loss: 7.8985e-04
Epoch 26/100
val loss: 7.8555e-04
Epoch 27/100
val loss: 0.0011
Epoch 28/100
val loss: 7.6222e-04
Epoch 29/100
```

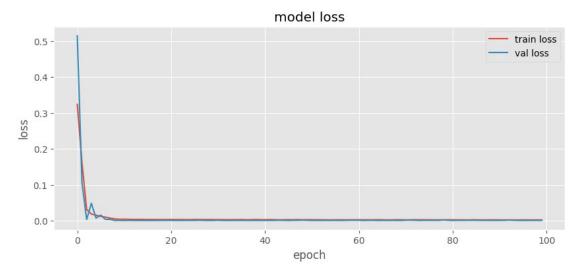
```
val loss: 6.4975e-04
Epoch 30/100
val loss: 6.2320e-04
Epoch 31/100
12/12 [============== ] - Os 14ms/step - loss: 0.0028 -
val loss: 0.0011
Epoch 32/100
val loss: 7.0678e-04
Epoch 33/100
val loss: 5.7406e-04
Epoch 34/100
val_loss: 6.1102e-04
Epoch 35/100
val loss: 7.0406e-04
Epoch 36/100
val loss: 6.5866e-04
Epoch 37/100
val loss: 6.8819e-04
Epoch 38/100
val loss: 6.5058e-04
Epoch 39/100
val loss: 6.6101e-04
Epoch 40/100
val loss: 5.8701e-04
Epoch 41/100
val loss: 5.9732e-04
Epoch 42/100
val loss: 7.8076e-04
Epoch 43/100
val loss: 6.4241e-04
Epoch 44/100
val loss: 0.0012
Epoch 45/100
val loss: 8.5488e-04
Epoch 46/100
```

```
val loss: 6.5623e-04
Epoch 47/100
val loss: 9.3385e-04
Epoch 48/100
12/12 [============== ] - Os 15ms/step - loss: 0.0030 -
val loss: 0.0010
Epoch 49/100
val loss: 0.0015
Epoch 50/100
val loss: 0.0011
Epoch 51/100
val loss: 6.2857e-04
Epoch 52/100
val loss: 6.3086e-04
Epoch 53/100
val loss: 6.9913e-04
Epoch 54/100
val loss: 6.9443e-04
Epoch 55/100
val loss: 6.5038e-04
Epoch 56/100
val loss: 8.1234e-04
Epoch 57/100
val loss: 6.2960e-04
Epoch 58/100
val loss: 8.4343e-04
Epoch 59/100
val loss: 0.0011
Epoch 60/100
val loss: 0.0012
Epoch 61/100
val loss: 0.0012
Epoch 62/100
val loss: 6.3914e-04
```

```
Epoch 63/100
val loss: 9.1721e-04
Epoch 64/100
val loss: 9.2544e-04
Epoch 65/100
val loss: 6.1067e-04
Epoch 66/100
val loss: 6.4710e-04
Epoch 67/100
val loss: 6.2876e-04
Epoch 68/100
val loss: 7.4592e-04
Epoch 69/100
val loss: 6.6616e-04
Epoch 70/100
val loss: 6.1225e-04
Epoch 71/100
val loss: 0.0012
Epoch 72/100
val loss: 0.0015
Epoch 73/100
val loss: 0.0011
Epoch 74/100
val loss: 6.3207e-04
Epoch 75/100
val loss: 9.4824e-04
Epoch 76/100
val loss: 9.2989e-04
Epoch 77/100
val loss: 0.0010
Epoch 78/100
val loss: 7.5611e-04
Epoch 79/100
```

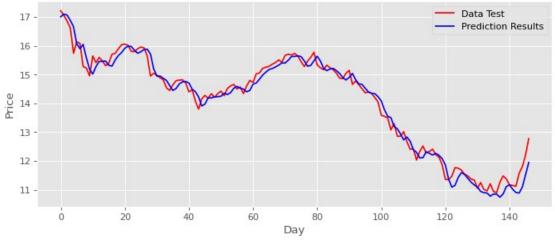
```
val loss: 0.0019
Epoch 80/100
val loss: 0.0011
Epoch 81/100
val loss: 6.3124e-04
Epoch 82/100
val loss: 8.7704e-04
Epoch 83/100
val loss: 8.2500e-04
Epoch 84/100
val loss: 0.0010
Epoch 85/100
val loss: 0.0010
Epoch 86/100
val loss: 0.0011
Epoch 87/100
val loss: 7.9519e-04
Epoch 88/100
val loss: 7.7954e-04
Epoch 89/100
val loss: 7.2426e-04
Epoch 90/100
val loss: 7.7557e-04
Epoch 91/100
val loss: 7.0264e-04
Epoch 92/100
val loss: 9.4707e-04
Epoch 93/100
val loss: 0.0017
Epoch 94/100
val loss: 0.0011
Epoch 95/100
val loss: 6.6568e-04
Epoch 96/100
```

```
======= ] - 0s 12ms/step - loss: 0.0021 -
12/12 [======
val loss: 6.4345e-04
Epoch 97/100
val loss: 7.8933e-04
Epoch 98/100
val loss: 7.2604e-04
Epoch 99/100
val loss: 7.7786e-04
Epoch 100/100
val loss: 7.4949e-04
fig = plt.figure(figsize=(10, 4))
plt.plot(pred.history['loss'], label='train loss')
plt.plot(pred.history['val loss'], label='val loss')
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(loc='upper right')
plt.show()
```



```
Training Loss Validation Loss
Learning Rate
0.0001
                   0.002097
                                   0.000749
y pred test = model.predict(x test)
# Invert normalization min-max
y pred invert norm = scaler.inverse transform(y pred test)
set test = dataset["Close"]
datacompare = pd.DataFrame()
datatest=np.array(set test[totaldatatrain+totaldataval+lag:])
datapred= y_pred_invert_norm
datacompare['Data Test'] = datatest
datacompare['Prediction Results'] = datapred
datacompare
    Data Test Prediction Results
0
    17.219999
                        17.010592
1
    17.059999
                        17.104795
2
    16.860001
                        17.069622
3
    16.620001
                        16.885792
    15.740000
4
                        16.662764
142 11.120000
                        10.905536
   11.570000
143
                        10.884079
                        11.092619
144 11.800000
145
    12.200000
                        11.515539
146 12.780000
                        11.951453
[147 rows x 2 columns]
plt.figure(num=None, figsize=(10, 4), dpi=80, facecolor='w',
edgecolor='k')
plt.title('Graph Comparison Data Actual and Data Prediction')
plt.plot(datacompare['Data Test'], color='red',label='Data Test')
plt.plot(datacompare['Prediction Results'],
color='blue',label='Prediction Results')
plt.xlabel('Day')
plt.ylabel('Price')
plt.legend()
plt.show()
```

Graph Comparison Data Actual and Data Prediction



```
def MAPE(datatest,datapred):
    mape = np.mean(np.abs((datatest - datapred)/datatest))*100
    return mape
mape = MAPE(datatest, datapred)
print(mape)
13.738295078642611
from sklearn.metrics import mean_squared_error
import math
MSE = mean_squared_error(datatest, datapred)
RMSE = math.sqrt(MSE)
print(RMSE)
0.2761624981131313
from sklearn.metrics import mean absolute error
mean absolute error(
    y_true=datatest,
    y_pred=datapred
)
0.2076929376191639
n ahead=input("How many values do you want to predict ?");
n_ahead=int(n_ahead)
# Making the prediction list
def predict ahead(n ahead, X train):
   yhat = []
   for in range(n ahead):
   # Making the prediction
       fc = model.predict(X train)
       yhat.append(fc)
```

```
# Creating a new input matrix for forecasting
    X train = np.append(X train, fc)
 # Ommitting the first variable
    X train = np.delete(X train, 0)
 # Reshaping for the next iteration
    X train = np.reshape(X train, (1, len(X train), 1))
 return yhat
y30 = predict ahead(n ahead, x test[len(x test)-30:])
1/1 [======] - 0s 86ms/step
1/1 [======] - 2s 2s/step
1/1 [======] - 0s 38ms/step
1/1 [=======] - 0s 46ms/step
1/1 [======] - 0s 44ms/step
1/1 [=======] - 0s 45ms/step
1/1 [======= ] - 0s 43ms/step
1/1 [======] - 0s 42ms/step
1/1 [======= ] - 0s 44ms/step
1/1 [======] - Os 39ms/step
1/1 [======] - 0s 40ms/step
1/1 [======= ] - 0s 43ms/step
1/1 [======= ] - 0s 44ms/step
1/1 [======] - 0s 37ms/step
1/1 [======] - 0s 38ms/step
1/1 [======] - 0s 36ms/step
1/1 [=======] - 0s 43ms/step
1/1 [======] - 0s 45ms/step
1/1 [=======] - 0s 45ms/step
1/1 [======] - 0s 40ms/step
1/1 [======] - 0s 38ms/step
1/1 [======] - 0s 39ms/step
1/1 [=======] - 0s 48ms/step
1/1 [======] - 0s 42ms/step
1/1 [======] - 0s 40ms/step
1/1 [======] - 0s 37ms/step
1/1 [=======] - 0s 39ms/step
v30
[array([[0.21674204],
    [0.21097781],
    [0.20105417],
    [0.18288219],
```

```
[0.14114706],
       [0.11761088],
       [0.12266176],
       [0.14602378],
       [0.16010551],
       [0.15469024],
       [0.14323843],
       [0.13223785],
       [0.12397379],
       [0.11763855],
       [0.1049497],
       [0.1013751],
       [0.1002242],
       [0.0910664],
       [0.09719525],
       [0.09686133],
       [0.08795277],
       [0.09734835],
       [0.11907981],
       [0.12442023].
       [0.11102837],
       [0.10190491],
       [0.10009122],
       [0.11771923],
       [0.15346901],
       [0.19031721]], dtype=float32),
array([[7.3751546e+19]], dtype=float32),
array([[nan]], dtype=float32),
```

```
array([[nan]], dtype=float32),
 array([[nan]], dtype=float32),
 array([[nan]], dtype=float32),
 array([[nan]], dtype=float32),
 array([[nan]], dtype=float32)]
y30 = [[0.21674204],
        [0.21097781],
        [0.20105417],
        [0.18288219],
        [0.14114706],
        [0.11761088],
        [0.12266176],
        [0.14602378],
        [0.16010551],
        [0.15469024],
        [0.14323843],
        [0.13223785],
        [0.12397379],
        [0.11763855],
        [0.1049497],
        [0.1013751]
        [0.1002242],
        [0.0910664],
        [0.09719525],
        [0.09686133],
        [0.08795277]
        [0.09734835],
        [0.11907981],
        [0.12442023],
        [0.11102837]
        [0.10190491],
        [0.10009122],
        [0.11771923]
        [0.15346901],
        [0.19031721]]
y30 = scaler.inverse_transform(y30)
from numpy import savetxt
savetxt('Bi-LSTM.csv', y30, delimiter=',')
```