Import required liberaries

```
#import liberaries
import numpy as np
import pandas as pd
from pandas import read_csv
from numpy import nan
from numpy import isnan
from pandas import to_numeric
import matplotlib.pyplot as plt
```

load dataset

```
# load data
dataset = read_csv('heart-rate-time-series.csv')
dataset.columns=['HR'] #make heading for the column
dataset.head()
```

```
        HR
0  91.4634
1  91.1834
2  91.8788
3  91.1772
4  89.7992
```

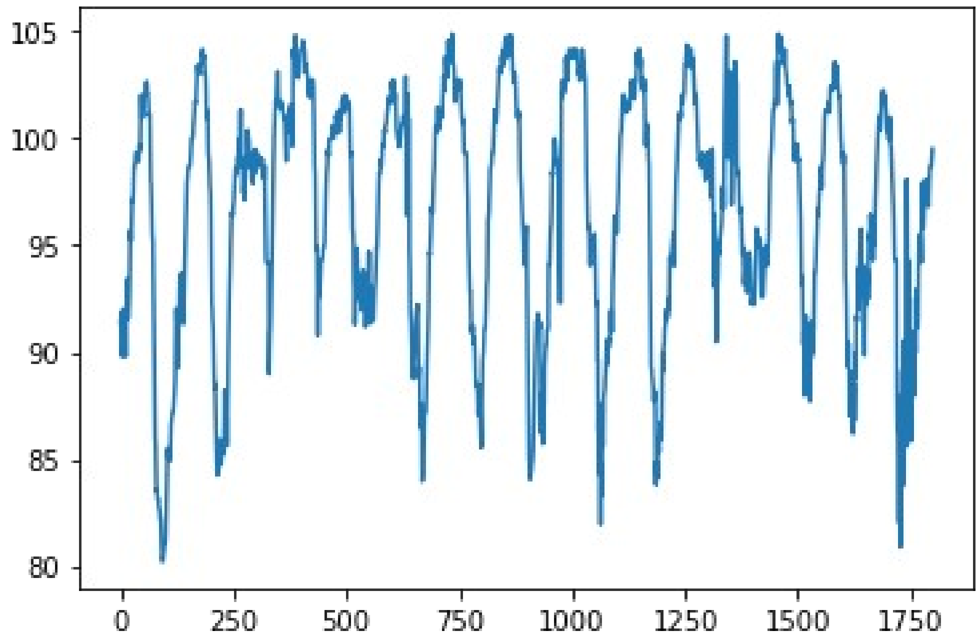
```
from numpy import nan
from numpy import isnan
from pandas import to_numeric
# mark all missing values
dataset.replace('?', nan, inplace=True)
# make dataset numeric
dataset = dataset.astype('float32')
dataset.head()
```

```
          HR
0  91.463402
1  91.183403
2  91.878799
3  91.177200
4  89.799202
```

Plot dataset to get more information about dataset

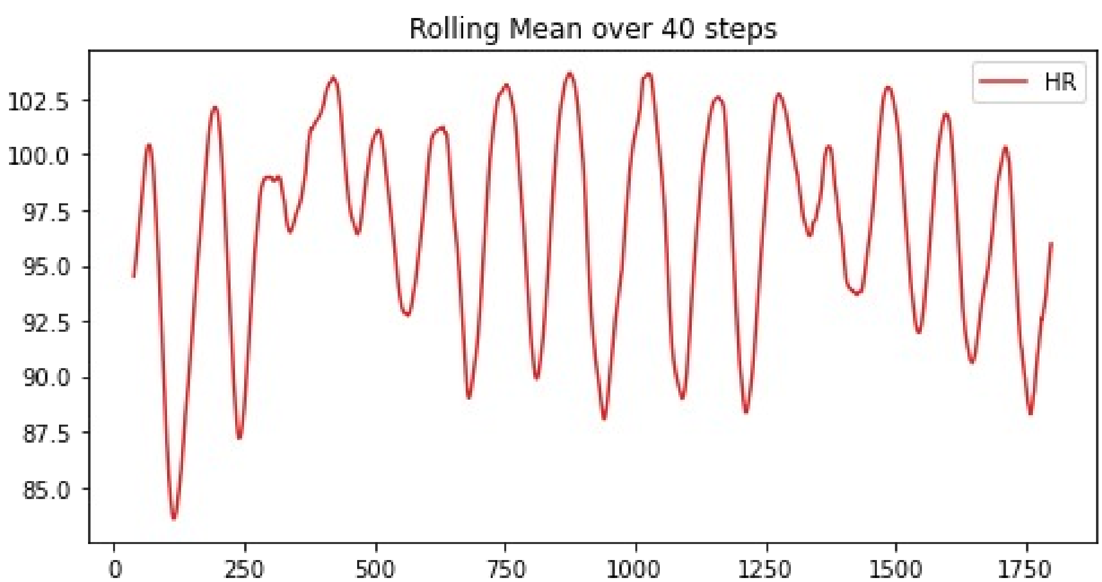
```
plt.plot(dataset)
```

```
[<matplotlib.lines.Line2D at 0xd89007fc70>]
```



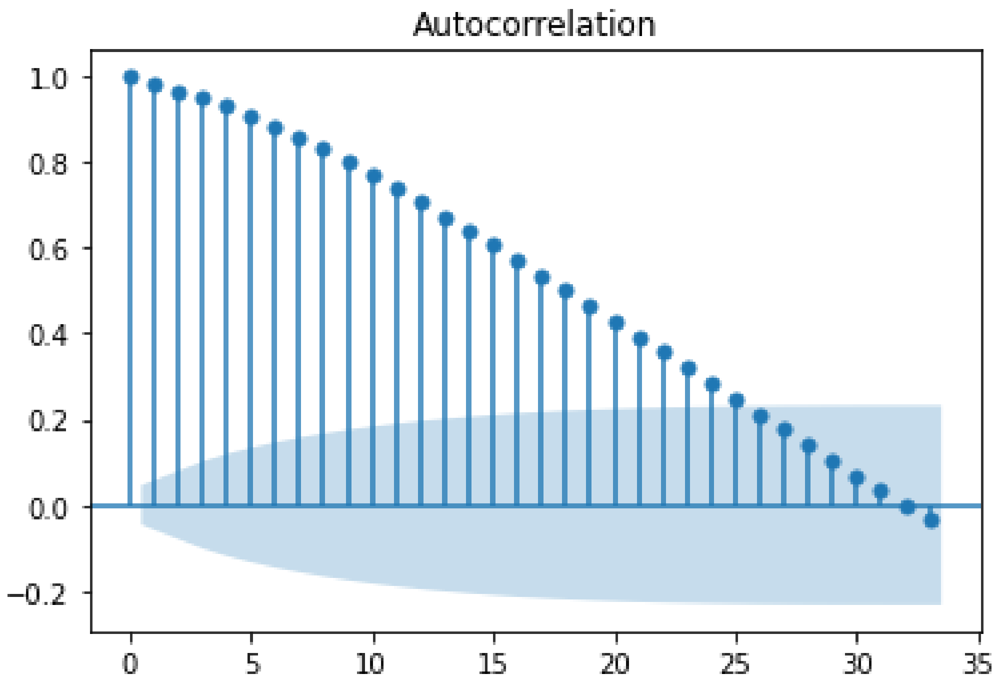
Moving averaging over the dataset to make it smoother

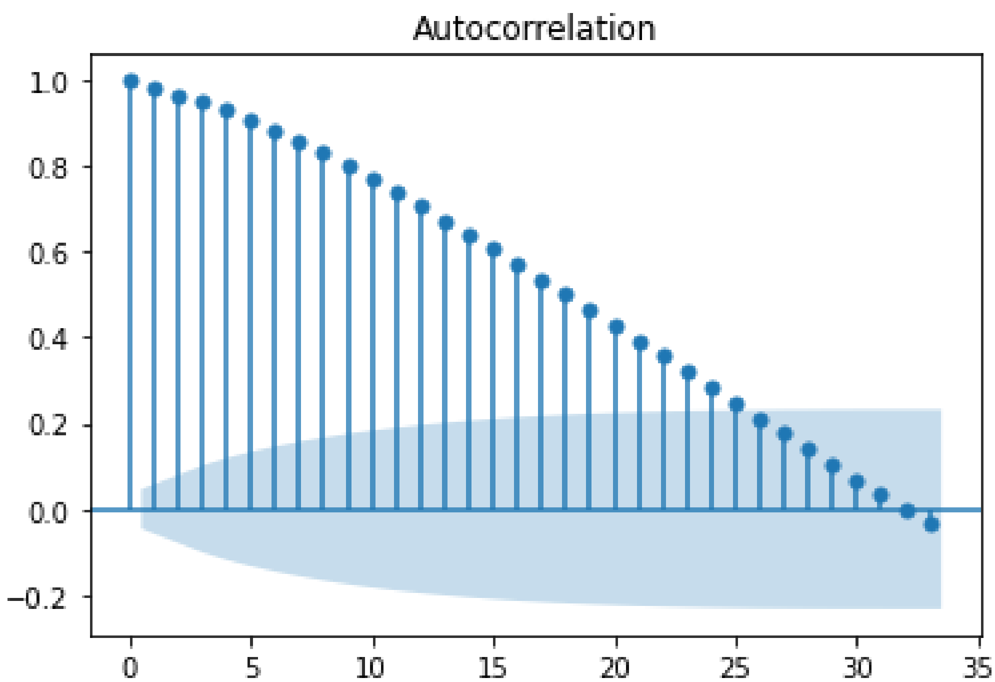
```
dataset.rolling(window = 40).mean().plot(figsize=(8,4),
color="tab:red", title="Rolling Mean over 40 steps");
```



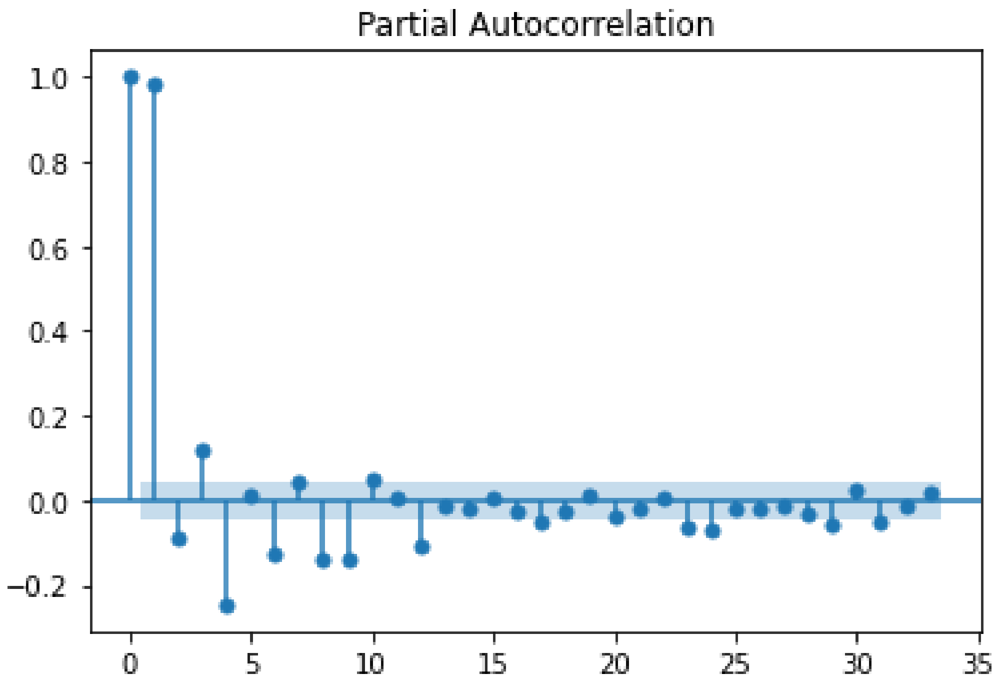
Do some statistics to got more insights

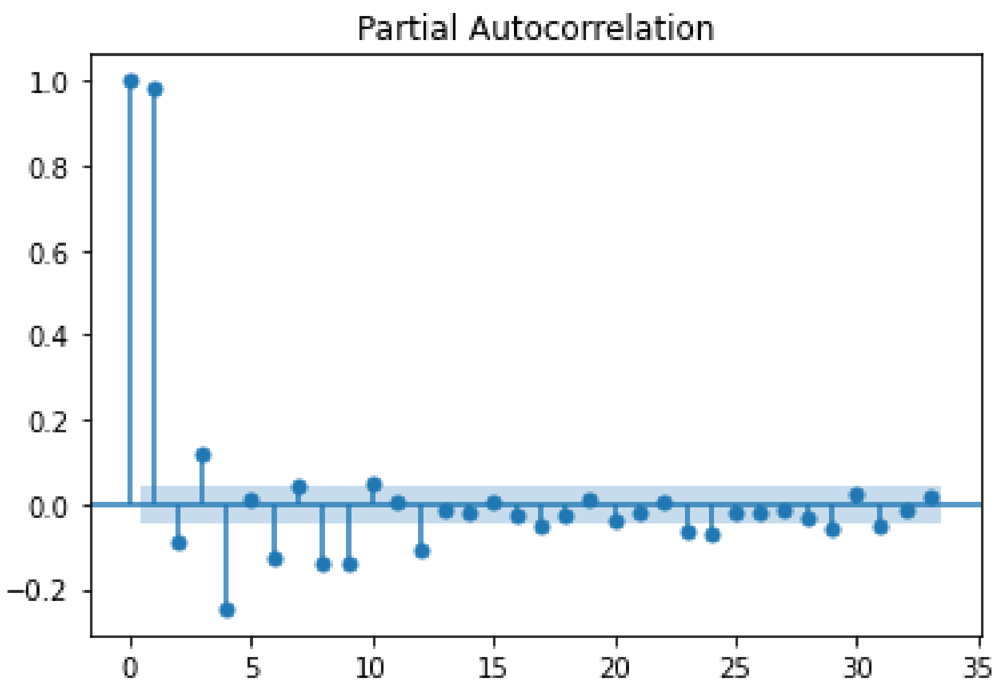
```
from statsmodels.graphics.tsaplots import plot_acf

plot_acf(dataset) #Auto Correlation Function ACF Plot or
Autocorrelation plot
```






```
from statsmodels.graphics.tsaplots import plot_pacf
plot_pacf(dataset) #partial autocorrelation function (PACF) plot
```





Dicky Fuller test to see whether the time series is stationary or not

```
from statsmodels.tsa.stattools import adfuller

dftest = adfuller(dataset['HR'], autolag = 'AIC')

print("1. ADF : ",dftest[0])
```

```python
print("2. P-Value : ", dftest[1])
print("3. Num Of Lags : ", dftest[2])
print("4. Num Of Observations Used For ADF Regression and Critical Values Calculation :", dftest[3])
print("5. Critical Values :")
for key, val in dftest[4].items():
    print("\t",key, ": ", val)
```

```
1. ADF :  -7.457988233959135
2. P-Value :  5.447866825089469e-11
3. Num Of Lags :  23
4. Num Of Observations Used For ADF Regression and Critical Values Calculation : 1775
5. Critical Values :
	 1% :  -3.4340394547116797
	 5% :  -2.863169689048283
	 10% :  -2.5676375957944853
```

Differencing to make the time series stationary

```python
# from pandas import Series
# # create a differenced series
# def difference(dataset, interval=10):
#     diff = list()
#     for i in range(interval, len(dataset)):
#         value = dataset[i] - dataset[i - interval]
#         diff.append(value)
#     return Series(diff)

# dataset=difference(dataset, interval=10)
```

Normalizing the dataset

```python
# Normalize time series data
from sklearn.preprocessing import MinMaxScaler
# prepare data for normalization
values=dataset.to_numpy()
values = values.reshape((len(values), 1))
# train the normalization
scaler = MinMaxScaler(feature_range=(-1, 1))
scaler = scaler.fit(values)
print('Min: %f, Max: %f' % (scaler.data_min_, scaler.data_max_))
# normalize the dataset
dataset = scaler.transform(values)
dataset
```

```
Min: 80.213898, Max: 104.894997
```

```
array([[-0.08841181],
       [-0.11110115],
```

```
        [-0.05475044],
        ...,
        [ 0.52234745],
        [ 0.5488291 ],
        [ 0.5644846 ]], dtype=float32)
```

```
dataset.shape
```

```
(1799, 1)
```

Transform time series data to supervised data

```
from pandas import DataFrame
from pandas import concat

def series_to_supervised(data, n_in=360, n_out=600, dropnan=True):
    """
    Frame a time series as a supervised learning dataset.
    Arguments:
        data: Sequence of observations as a list or NumPy array.
        n_in: Number of lag observations as input (X).
        n_out: Number of observations as output (y).
        dropnan: Boolean whether or not to drop rows with NaN values.
    Returns:
        Pandas DataFrame of series framed for supervised learning.
    """
    n_vars = 1 if type(data) is list else data.shape[1]
    df = DataFrame(data)
    cols, names = list(), list()
    # input sequence (t-n, ... t-1)
    for i in range(n_in, 0, -1):
        cols.append(df.shift(i))
        names += [('var%d(t-%d)' % (j+1, i)) for j in range(n_vars)]
    # forecast sequence (t, t+1, ... t+n)
    for i in range(0, n_out):
        cols.append(df.shift(-i))
        if i == 0:
            names += [('var%d(t)' % (j+1)) for j in range(n_vars)]
        else:
            names += [('var%d(t+%d)' % (j+1, i)) for j in
range(n_vars)]
    # put it all together
    agg = concat(cols, axis=1)
    agg.columns = names
    # drop rows with NaN values
    if dropnan:
        agg.dropna(inplace=True)
    return agg
```

```python
data = series_to_supervised(dataset, 360, 600) #transform time series dataset to supervised datasets
print(data)
```

```
      var1(t-360)  var1(t-359)  var1(t-358)  var1(t-357)  var1(t-356)  \
360     -0.088412    -0.111101    -0.054750    -0.111604    -0.223268   

361     -0.111101    -0.054750    -0.111604    -0.223268    -0.178059   

362     -0.054750    -0.111604    -0.223268    -0.178059    -0.043090   

363     -0.111604    -0.223268    -0.178059    -0.043090    -0.052182   

364     -0.223268    -0.178059    -0.043090    -0.052182    -0.114537   

...           ...          ...          ...          ...          ...   

1195     0.740126     0.790689     0.837852     0.872210     0.873831   

1196     0.790689     0.837852     0.872210     0.873831     0.849196   

1197     0.837852     0.872210     0.873831     0.849196     0.858191   

1198     0.872210     0.873831     0.849196     0.858191     0.882744   

1199     0.873831     0.849196     0.858191     0.882744     0.906731   


      var1(t-355)  var1(t-354)  var1(t-353)  var1(t-352)  var1(t-351)  ...  \
360     -0.178059    -0.043090    -0.052182    -0.114537    -0.048406  ...   
361     -0.043090    -0.052182    -0.114537    -0.048406    -0.055107  ...   
362     -0.052182    -0.114537    -0.048406    -0.055107    -0.193666  ...   
363     -0.114537    -0.048406    -0.055107    -0.193666    -0.222822  ...   
364     -0.048406    -0.055107    -0.193666    -0.222822    -0.073583  ...   
...           ...          ...          ...          ...          ...  ...   
1195     0.849196     0.858191     0.882744     0.906731     0.916292  ...   
1196     0.858191     0.882744     0.906731     0.916292     0.892306  ...   
1197     0.882744     0.906731     0.916292     0.892306     0.893035  ...   
```

1198	0.906731	0.916292	0.892306	0.893035	0.922127
...					
1199	0.916292	0.892306	0.893035	0.922127	0.938171
...					

	var1(t+590)	var1(t+591)	var1(t+592)	var1(t+593)	var1(t+594) \
360	0.127251	0.211470	0.248275	0.279165	0.291668
361	0.211470	0.248275	0.279165	0.291668	0.394192
362	0.248275	0.279165	0.291668	0.394192	0.476231
363	0.279165	0.291668	0.394192	0.476231	0.464732
364	0.291668	0.394192	0.476231	0.464732	0.503555
...	...	...	...	...	...
1195	0.418243	0.444036	0.416979	0.365726	0.344810
1196	0.444036	0.416979	0.365726	0.344810	0.396064
1197	0.416979	0.365726	0.344810	0.396064	0.466191
1198	0.365726	0.344810	0.396064	0.466191	0.492324
1199	0.344810	0.396064	0.466191	0.492324	0.496716

	var1(t+595)	var1(t+596)	var1(t+597)	var1(t+598)	var1(t+599)
360	0.394192	0.476231	0.464732	0.503555	0.568366
361	0.476231	0.464732	0.503555	0.568366	0.603340
362	0.464732	0.503555	0.568366	0.603340	0.603340
363	0.503555	0.568366	0.603340	0.603340	0.603340
364	0.568366	0.603340	0.603340	0.603340	0.588746
...	...	...	...	...	...
1195	0.396064	0.466191	0.492324	0.496716	0.496716
1196	0.466191	0.492324	0.496716	0.496716	0.496716

1197	0.492324	0.496716	0.496716	0.496716	0.522347
1198	0.496716	0.496716	0.496716	0.522347	0.548829
1199	0.496716	0.496716	0.522347	0.548829	0.564485

```
[840 rows x 960 columns]
```

split dataset into train and test sets

```
# split into train and test sets
values = data.values
n_train = int(len(values)*0.8) # 80% of data for training
train = values[:n_train, :]
test = values[n_train:, :]
n_train, train.shape, test.shape
```

```
(672, (672, 960), (168, 960))
```

```
np.info(train)
```

```
class:  ndarray
shape:  (672, 960)
strides:  (4, 3360)
itemsize:  4
aligned:  True
contiguous:  False
fortran:  False
data pointer: 0xd895a89040
byteorder:  little
byteswap:  False
type: float32
```

```
np.info(test)
```

```
class:  ndarray
shape:  (168, 960)
strides:  (4, 3360)
itemsize:  4
aligned:  True
contiguous:  False
fortran:  False
data pointer: 0xd895a89ac0
byteorder:  little
byteswap:  False
type: float32
```

```
np.info(train[:, -600:])
```

```
class:  ndarray
shape:  (672, 600)
strides:  (4, 3360)
itemsize:  4
aligned:  True
contiguous:  False
fortran:  False
data pointer: 0xd895bb0540
byteorder:  little
byteswap:  False
type: float32
```

split train and test sets into input and outputs

```
# split into input and outputs
train_X, train_y = train[:, :-600], train[:, -600:] #600 is the number
of outpout
test_X, test_y = test[:, :-600], test[:, -600:]
train_X.shape, train_y.shape
```

```
((672, 360), (672, 600))
```

prepare data to enter the network

```
# reshape input to be 3D [samples, timesteps, features]
features =1
train_X = train_X.reshape((train_X.shape[0],
train_X.shape[1],features))
test_X = test_X.reshape((test_X.shape[0], test_X.shape[1],features))
print(train_X.shape, train_y.shape, test_X.shape, test_y.shape)
```

```
(672, 360, 1) (672, 600) (168, 360, 1) (168, 600)
```

build the model

```
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Flatten
from keras.layers import LSTM
from keras.layers import Dropout
from keras import layers, callbacks
from keras.layers import Dense, LSTM, Dropout, GRU, Bidirectional

dropout=0.5
units=10
nout=600

# Create BiLSTM model
def create_model_bilstm(units):
```

```
    model = Sequential()
    # First layer of BiLSTM
    model.add(Bidirectional(LSTM(units = units, activation='relu',
return_sequences=True),input_shape=(train_X.shape[1],
train_X.shape[2])))
    model.add(Dropout(dropout))
    # Second layer of BiLSTM
    #model.add(Bidirectional(LSTM(units = units)))
    model.add(Dense(nout))
    #Compile model
    model.compile(loss='mse', optimizer='adam')
    return model


# Create LSTM or GRU model
def create_model(units, m):
    model = Sequential()
    # First layer of LSTM
    model.add(m (units = units, activation='relu', input_shape =
[train_X.shape[1], train_X.shape[2]]))
    model.add(Dropout(dropout))
    # Second layer of LSTM
    #model.add(m (units = units))
    #model.add(Dropout(dropout))
    model.add(Dense(nout))
    #Compile model
    model.compile(loss='mse', optimizer='adam')
    return model


# BiLSTM
model_bilstm = create_model_bilstm(units)

# GRU and LSTM
model_gru = create_model(units, GRU)
model_lstm = create_model(units, LSTM)
```

define a function to fit the model

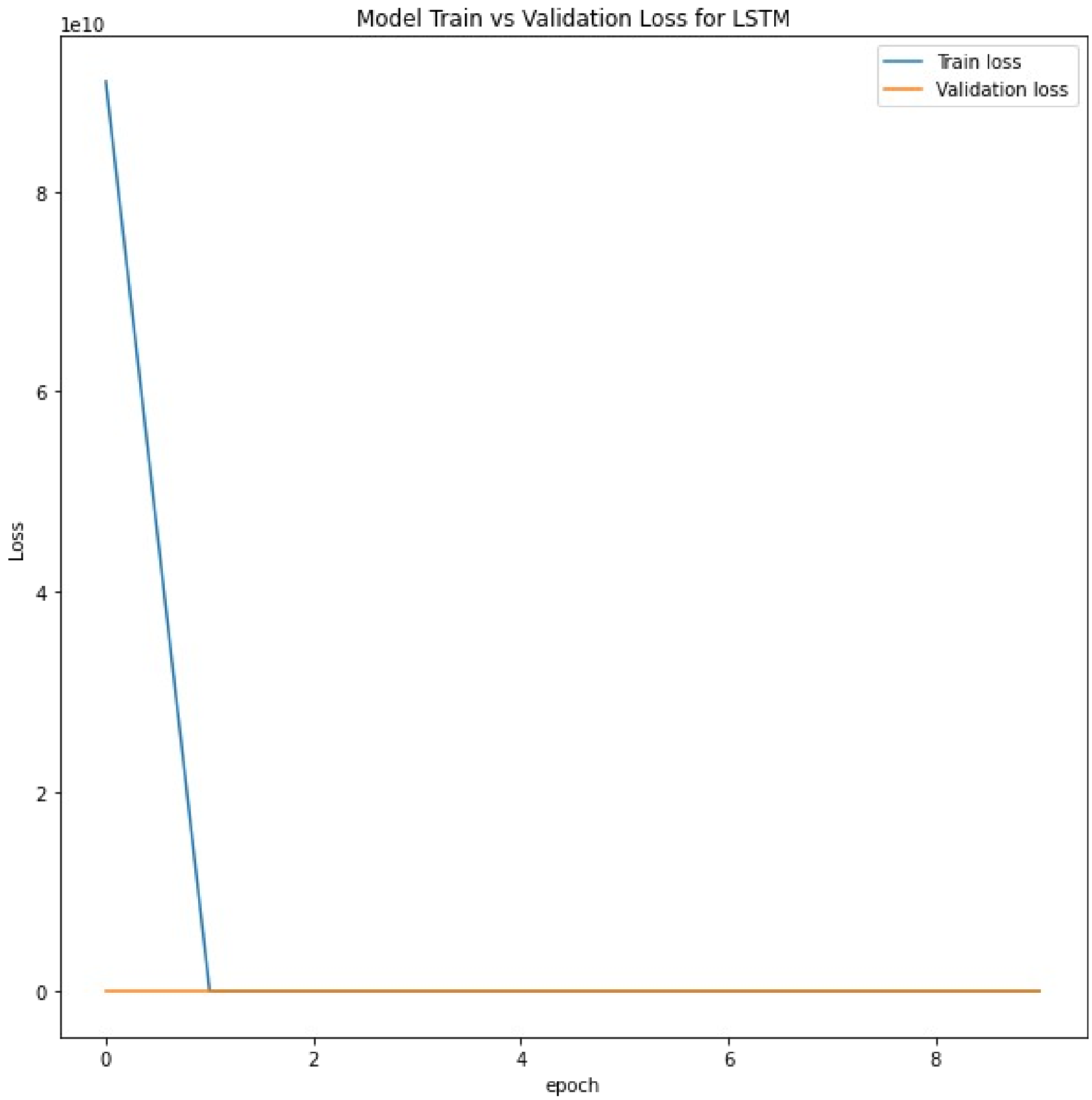
```
#fit models
epoch, batch= 10,1
def fit_model(model):
    history = model.fit(train_X, train_y, epochs=epoch,
batch_size=batch, validation_data=(test_X, test_y), verbose=1,
shuffle=False)
    return history

#history_bilstm = fit_model(model_bilstm)
```

```
history_lstm = fit_model(model_lstm)
#history_gru = fit_model(model_gru)
```

```
Epoch 1/10
672/672 [==============================] - 41s 60ms/step - loss:
91032895488.0000 - val_loss: 0.2115
Epoch 2/10
672/672 [==============================] - 40s 60ms/step - loss:
0.2500 - val_loss: 0.2057
Epoch 3/10
672/672 [==============================] - 46s 68ms/step - loss:
0.2412 - val_loss: 0.2029
Epoch 4/10
672/672 [==============================] - 49s 73ms/step - loss:
0.2398 - val_loss: 0.2033
Epoch 5/10
672/672 [==============================] - 50s 75ms/step - loss:
0.2356 - val_loss: 0.2037
Epoch 6/10
672/672 [==============================] - 52s 78ms/step - loss:
0.2353 - val_loss: 0.2054
Epoch 7/10
672/672 [==============================] - 52s 77ms/step - loss:
0.2343 - val_loss: 0.2066
Epoch 8/10
672/672 [==============================] - 53s 79ms/step - loss:
0.2294 - val_loss: 0.2091
Epoch 9/10
672/672 [==============================] - 54s 80ms/step - loss:
0.2324 - val_loss: 0.2093
Epoch 10/10
672/672 [==============================] - 53s 79ms/step - loss:
0.2303 - val_loss: 0.2098
```

plot the results

```
#plot train loss and validation loss
def plot_loss (history, model_name):
    plt.figure(figsize = (10, 10))
    plt.plot(history.history['loss'])
    plt.plot(history.history['val_loss'])
    plt.title('Model Train vs Validation Loss for ' + model_name)
    plt.ylabel('Loss')
    plt.xlabel('epoch')
    plt.legend(['Train loss', 'Validation loss'], loc='upper right')

#plot_loss (history_bilstm, 'BiLSTM')
plot_loss (history_lstm, 'LSTM')
#plot_loss (history_gru, 'GRU')
```




```
#model_bilstm.summary()
model_lstm.summary()
#model_gru.summary()

Model: "sequential_8"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_5 (LSTM)               (None, 10)                480

 dropout_8 (Dropout)         (None, 10)                0

 dense_8 (Dense)             (None, 600)               6600

=================================================================
Total params: 7,080
Trainable params: 7,080
```

```
Non-trainable params: 0
_________________________________________________________________
```

make prediction

```
#make prediction
def prediction(model):
    prediction = model.predict(test_X)
    return prediction

#prediction_bilstm = prediction(model_bilstm)
prediction_lstm = prediction(model_lstm)
prediction_gru = prediction(model_gru)
test_X = test_X.reshape((test_X.shape[0], test_X.shape[1]))
prediction_lstm.shape, prediction_gru.shape ,test_X.shape
```

```
((168, 600), (168, 600), (168, 360))
```

rescale the predictions into actual scale and calculate RMSE

```
from numpy import concatenate
from math import sqrt
from sklearn.metrics import mean_squared_error

# invert scaling lstm
inv_yhat_lstm = concatenate((prediction_lstm, test_X[:, 1:]), axis=1)
inv_yhat_lstm = scaler.inverse_transform(inv_yhat_lstm)
inv_yhat_lstm = inv_yhat_lstm[:,0]

# invert scaling gru
#inv_yhat_gru = concatenate((prediction_gru, test_X[:, 1:]), axis=1)
#inv_yhat_gru = scaler.inverse_transform(inv_yhat_gru)
#inv_yhat_gru = inv_yhat_gru[:,0]

# invert scaling for actual
test_y = test_y.reshape((len(test_y), nout))
inv_y = concatenate((test_y, test_X[:, 1:]), axis=1)
inv_y = scaler.inverse_transform(inv_y)
inv_y = inv_y[:,0]

# calculate RMSE
rmse_lstm = sqrt(mean_squared_error(inv_y, inv_yhat_lstm))
#rmse_gru = sqrt(mean_squared_error(inv_y, inv_yhat_gru))
print('Test RMSE lstm: %.3f' % rmse_lstm)
#print('Test RMSE gru: %.3f' % rmse_gru)
inv_yhat_lstm.shape
```

```
Test RMSE lstm: 2.939
```

```
(168,)
```

Define a function to calculate MAE and RMSE

```
# Define a function to calculate MAE and RMSE
def evaluate_prediction(predictions, actual, model_name):
    errors = predictions - actual
    mse = np.square(errors).mean()
    rmse = np.sqrt(mse)
    mae = np.abs(errors).mean()

    print(model_name + ':')
    #print('Mean Absolute Error: {:.4f}'.format(mae))
    print('Root Mean Square Error: {:.4f}'.format(rmse))
    print('')


#evaluate_prediction(prediction_bilstm, test_y, 'Bidirectional LSTM')
evaluate_prediction(prediction_lstm, test_y, 'LSTM')
#evaluate_prediction(prediction_gru, test_y, 'GRU')
```

```
LSTM:
Root Mean Square Error: 0.4580
```

```
inv_yhat_lstm.shape, inv_y.shape
```

```
((168,), (168,))
```

put actual values and predicted values alltogether in a dataframe and plot them

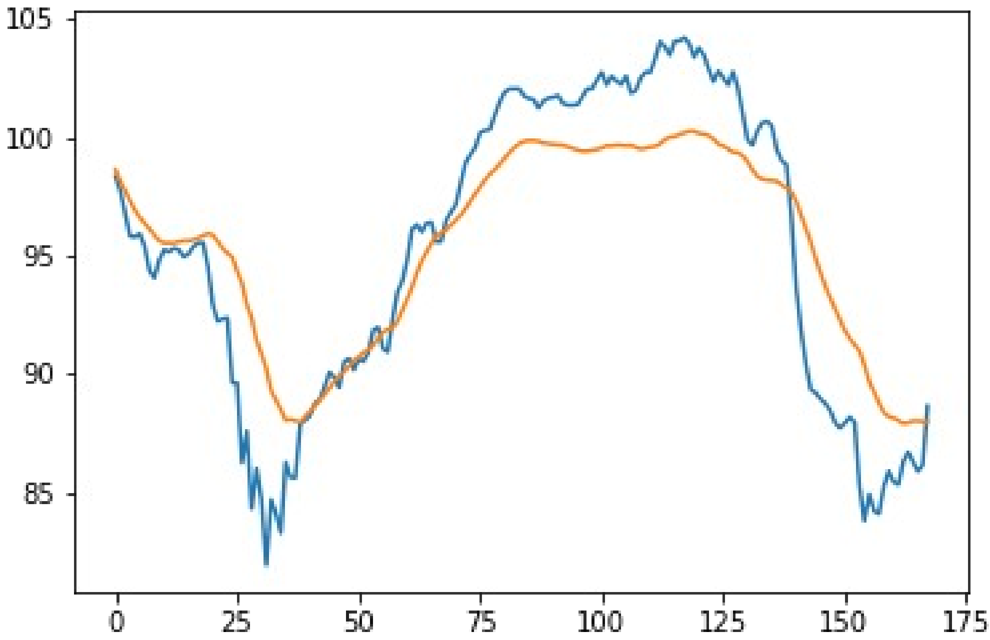
```
df = pd.DataFrame({'observation': inv_y, 'prediction':
inv_yhat_lstm} , columns=['observation', 'prediction']) #'gru
prediction2': inv_yhat_gru, 'bilstm prediction': inv_yhat_bilstm
df.head(20)
```

	observation	prediction
0	98.344498	98.624763
1	97.737602	98.139389
2	96.772797	97.718750
3	95.825600	97.314781
4	95.791298	96.922714
5	95.923599	96.610977
6	95.394203	96.367989
7	94.375702	96.128822
8	94.054199	95.862381
9	94.796303	95.629387
10	95.244797	95.533890

```
11    95.159203   95.535057
12    95.311600   95.539604
13    95.243896   95.583015
14    94.941498   95.622971
15    95.074600   95.627090
16    95.376900   95.663689
17    95.541397   95.746010
18    95.541397   95.843689
19    94.527000   95.930412
```

```
plt.plot(df)
```

```
[<matplotlib.lines.Line2D at 0xd89e3e8c10>,
 <matplotlib.lines.Line2D at 0xd89e3fe040>]
```



Result Interpretion:

We can see from the above plot and dataframe that the predictions are very close to the actual values which is reasonable and shows that the network works correctly but it still could be more optimized