

HW6_1

June 5, 2021

1 HW6

1.0.1 2015129053 Hyoung Chul KIm

1.

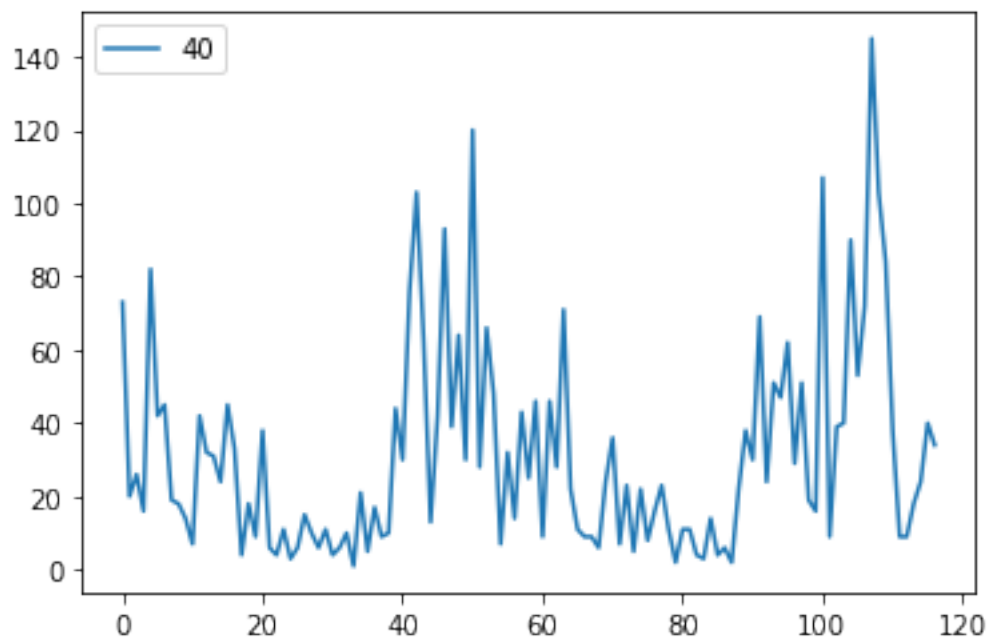
(a) I used following codes to plot the time series of the reported cases:

```
[1]: #data preprocessing stage

#import the library
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

```
[2]: #(a) drawing the time series plot of the reported cases.

data=pd.read_csv("case.csv")
data.plot()
plt.show()
```



There does not seem to be a strict pattern. But it seems that the reported cases of rotavirus were high around 50 week and 110 week. Also, as one year is made up of around 52 weeks, we can see that the shape of the time series is repeated every 52 weeks. (They are both U shape) Thus it might have some yearly patterns.

- (b) I constructed a LSTM model to estimate the reported cases by using the previous 30 weeks' information. I used following codes (**Keep in mind that I followed the procedure that I learned in the stock price prediction example**):

```
[3]: data=pd.DataFrame(data=data)
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler(feature_range = (0, 1))
data_scaled = sc.fit_transform(data)
```

```
[4]: #(b) previous 30 week's info

# Creating a data structure
X_train = []
y_train = []
for i in range(30, 117):
    X_train.append(data_scaled[i-30:i,0])
    y_train.append(data_scaled[i,0])
X_train, y_train = np.array(X_train), np.array(y_train)
X_train
```

```
[4]: array([[0.5          , 0.13194444, 0.17361111, ..., 0.0625      , 0.03472222,
            0.06944444],
            [0.13194444, 0.17361111, 0.10416667, ..., 0.03472222, 0.06944444,
            0.02083333],
            [0.17361111, 0.10416667, 0.5625      , ..., 0.06944444, 0.02083333,
            0.03472222],
            ...,
            [0.09027778, 0.02083333, 0.03472222, ..., 0.05555556, 0.05555556,
            0.11805556],
            [0.02083333, 0.03472222, 0.00694444, ..., 0.05555556, 0.11805556,
            0.15972222],
            [0.03472222, 0.00694444, 0.14583333, ..., 0.11805556, 0.15972222,
            0.27083333]])
```

```
[5]: # Reshaping
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
X_train
```

```
[5]: array([[[0.5          ],
            [0.13194444],
```

```

[0.17361111],
...,
[0.0625    ],
[0.03472222],
[0.06944444]],

[[0.13194444],
 [0.17361111],
 [0.10416667],
 ...,
 [0.03472222],
 [0.06944444],
 [0.02083333]],

[[0.17361111],
 [0.10416667],
 [0.5625    ],
 ...,
 [0.06944444],
 [0.02083333],
 [0.03472222]],

...,

[[0.09027778],
 [0.02083333],
 [0.03472222],
 ...,
 [0.05555556],
 [0.05555556],
 [0.11805556]],

[[0.02083333],
 [0.03472222],
 [0.00694444],
 ...,
 [0.05555556],
 [0.11805556],
 [0.15972222]],

[[0.03472222],
 [0.00694444],
 [0.14583333],
 ...,
 [0.11805556],
 [0.15972222],
 [0.27083333]]])

```

```
[6]: # Part 2 - Build the RNN
```

```
# Importing the libraries and packages
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers import Dropout
```

```
[7]: # Start the RNN
```

```
regressor = Sequential()

# Add the first LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 60, return_sequences = True, input_shape = (X_train.
↪shape[1], 1)))
regressor.add(Dropout(0.3))
```

```
[8]: # Adding a second LSTM layer and some Dropout regularisation
```

```
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.23))
```

```
[9]: # Adding a third LSTM layer and some Dropout regularisation
```

```
regressor.add(LSTM(units = 55, return_sequences = True))
regressor.add(Dropout(0.2))
```

```
[10]: # Adding a fourth LSTM layer and some Dropout regularisation
```

```
regressor.add(LSTM(units = 55))
regressor.add(Dropout(0.2))
```

```
[14]: # Adding the output layer
```

```
regressor.add(Dense(units = 1))

# Compiling the RNN
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')

# Fitting the RNN to the Training set
regressor.fit(X_train, y_train, epochs = 170, batch_size = 10)
```

Epoch 1/170

9/9 [=====] - 4s 39ms/step - loss: 0.0219

Epoch 2/170

9/9 [=====] - 0s 28ms/step - loss: 0.0221

Epoch 3/170

9/9 [=====] - 0s 27ms/step - loss: 0.0204

Epoch 4/170

9/9 [=====] - 0s 28ms/step - loss: 0.0190

Epoch 5/170

9/9 [=====] - 0s 28ms/step - loss: 0.0220

Epoch 6/170
9/9 [=====] - 0s 27ms/step - loss: 0.0220
Epoch 7/170
9/9 [=====] - 0s 27ms/step - loss: 0.0169
Epoch 8/170
9/9 [=====] - 0s 27ms/step - loss: 0.0238
Epoch 9/170
9/9 [=====] - 0s 28ms/step - loss: 0.0196
Epoch 10/170
9/9 [=====] - 0s 27ms/step - loss: 0.0219
Epoch 11/170
9/9 [=====] - 0s 27ms/step - loss: 0.0238
Epoch 12/170
9/9 [=====] - 0s 26ms/step - loss: 0.0189
Epoch 13/170
9/9 [=====] - 0s 27ms/step - loss: 0.0215
Epoch 14/170
9/9 [=====] - 0s 27ms/step - loss: 0.0254
Epoch 15/170
9/9 [=====] - 0s 27ms/step - loss: 0.0261
Epoch 16/170
9/9 [=====] - 0s 27ms/step - loss: 0.0173
Epoch 17/170
9/9 [=====] - 0s 27ms/step - loss: 0.0187
Epoch 18/170
9/9 [=====] - 0s 27ms/step - loss: 0.0217
Epoch 19/170
9/9 [=====] - 0s 27ms/step - loss: 0.0246
Epoch 20/170
9/9 [=====] - 0s 28ms/step - loss: 0.0177
Epoch 21/170
9/9 [=====] - 0s 28ms/step - loss: 0.0263
Epoch 22/170
9/9 [=====] - 0s 29ms/step - loss: 0.0139
Epoch 23/170
9/9 [=====] - 0s 31ms/step - loss: 0.0212
Epoch 24/170
9/9 [=====] - 0s 29ms/step - loss: 0.0213
Epoch 25/170
9/9 [=====] - 0s 30ms/step - loss: 0.0174
Epoch 26/170
9/9 [=====] - 0s 27ms/step - loss: 0.0216
Epoch 27/170
9/9 [=====] - 0s 27ms/step - loss: 0.0156
Epoch 28/170
9/9 [=====] - 0s 28ms/step - loss: 0.0259
Epoch 29/170
9/9 [=====] - 0s 29ms/step - loss: 0.0247

Epoch 30/170
9/9 [=====] - 0s 29ms/step - loss: 0.0216
Epoch 31/170
9/9 [=====] - 0s 27ms/step - loss: 0.0242
Epoch 32/170
9/9 [=====] - 0s 28ms/step - loss: 0.0245
Epoch 33/170
9/9 [=====] - 0s 29ms/step - loss: 0.0279
Epoch 34/170
9/9 [=====] - 0s 36ms/step - loss: 0.0175
Epoch 35/170
9/9 [=====] - 0s 29ms/step - loss: 0.0176
Epoch 36/170
9/9 [=====] - 0s 28ms/step - loss: 0.0236
Epoch 37/170
9/9 [=====] - 0s 29ms/step - loss: 0.0206
Epoch 38/170
9/9 [=====] - 0s 28ms/step - loss: 0.0182
Epoch 39/170
9/9 [=====] - 0s 28ms/step - loss: 0.0171
Epoch 40/170
9/9 [=====] - 0s 28ms/step - loss: 0.0169
Epoch 41/170
9/9 [=====] - 0s 29ms/step - loss: 0.0164
Epoch 42/170
9/9 [=====] - 0s 29ms/step - loss: 0.0243
Epoch 43/170
9/9 [=====] - 0s 28ms/step - loss: 0.0204
Epoch 44/170
9/9 [=====] - 0s 28ms/step - loss: 0.0216
Epoch 45/170
9/9 [=====] - 0s 28ms/step - loss: 0.0204
Epoch 46/170
9/9 [=====] - 0s 27ms/step - loss: 0.0185
Epoch 47/170
9/9 [=====] - 0s 28ms/step - loss: 0.0121
Epoch 48/170
9/9 [=====] - 0s 28ms/step - loss: 0.0153
Epoch 49/170
9/9 [=====] - 0s 28ms/step - loss: 0.0181
Epoch 50/170
9/9 [=====] - 0s 27ms/step - loss: 0.0170
Epoch 51/170
9/9 [=====] - 0s 27ms/step - loss: 0.0220
Epoch 52/170
9/9 [=====] - 0s 28ms/step - loss: 0.0149
Epoch 53/170
9/9 [=====] - 0s 27ms/step - loss: 0.0155

Epoch 54/170
9/9 [=====] - 0s 27ms/step - loss: 0.0171
Epoch 55/170
9/9 [=====] - 0s 28ms/step - loss: 0.0159
Epoch 56/170
9/9 [=====] - 0s 27ms/step - loss: 0.0144
Epoch 57/170
9/9 [=====] - 0s 28ms/step - loss: 0.0187
Epoch 58/170
9/9 [=====] - 0s 29ms/step - loss: 0.0136
Epoch 59/170
9/9 [=====] - 0s 28ms/step - loss: 0.0147
Epoch 60/170
9/9 [=====] - 0s 30ms/step - loss: 0.0162
Epoch 61/170
9/9 [=====] - 0s 28ms/step - loss: 0.0147
Epoch 62/170
9/9 [=====] - 0s 28ms/step - loss: 0.0140
Epoch 63/170
9/9 [=====] - 0s 30ms/step - loss: 0.0132
Epoch 64/170
9/9 [=====] - 0s 31ms/step - loss: 0.0167
Epoch 65/170
9/9 [=====] - 0s 29ms/step - loss: 0.0203
Epoch 66/170
9/9 [=====] - 0s 30ms/step - loss: 0.0221
Epoch 67/170
9/9 [=====] - 0s 31ms/step - loss: 0.0223
Epoch 68/170
9/9 [=====] - 0s 29ms/step - loss: 0.0185
Epoch 69/170
9/9 [=====] - 0s 28ms/step - loss: 0.0224
Epoch 70/170
9/9 [=====] - 0s 28ms/step - loss: 0.0116
Epoch 71/170
9/9 [=====] - 0s 32ms/step - loss: 0.0174
Epoch 72/170
9/9 [=====] - 0s 31ms/step - loss: 0.0116
Epoch 73/170
9/9 [=====] - 0s 28ms/step - loss: 0.0225
Epoch 74/170
9/9 [=====] - 0s 29ms/step - loss: 0.0164
Epoch 75/170
9/9 [=====] - 0s 27ms/step - loss: 0.0165
Epoch 76/170
9/9 [=====] - 0s 31ms/step - loss: 0.0159
Epoch 77/170
9/9 [=====] - 0s 28ms/step - loss: 0.0247

Epoch 78/170
9/9 [=====] - 0s 30ms/step - loss: 0.0160
Epoch 79/170
9/9 [=====] - 0s 28ms/step - loss: 0.0232
Epoch 80/170
9/9 [=====] - 0s 30ms/step - loss: 0.0116
Epoch 81/170
9/9 [=====] - 0s 28ms/step - loss: 0.0159
Epoch 82/170
9/9 [=====] - 0s 29ms/step - loss: 0.0185
Epoch 83/170
9/9 [=====] - 0s 28ms/step - loss: 0.0251
Epoch 84/170
9/9 [=====] - 0s 34ms/step - loss: 0.0179
Epoch 85/170
9/9 [=====] - 0s 27ms/step - loss: 0.0135
Epoch 86/170
9/9 [=====] - 0s 37ms/step - loss: 0.0157
Epoch 87/170
9/9 [=====] - 0s 31ms/step - loss: 0.0148
Epoch 88/170
9/9 [=====] - 0s 30ms/step - loss: 0.0154
Epoch 89/170
9/9 [=====] - 0s 32ms/step - loss: 0.0115
Epoch 90/170
9/9 [=====] - 0s 33ms/step - loss: 0.0107
Epoch 91/170
9/9 [=====] - 0s 34ms/step - loss: 0.0158
Epoch 92/170
9/9 [=====] - 0s 33ms/step - loss: 0.0118
Epoch 93/170
9/9 [=====] - 0s 29ms/step - loss: 0.0144
Epoch 94/170
9/9 [=====] - 0s 28ms/step - loss: 0.0121
Epoch 95/170
9/9 [=====] - 0s 29ms/step - loss: 0.0138
Epoch 96/170
9/9 [=====] - 0s 28ms/step - loss: 0.0147
Epoch 97/170
9/9 [=====] - 0s 28ms/step - loss: 0.0187
Epoch 98/170
9/9 [=====] - 0s 28ms/step - loss: 0.0203
Epoch 99/170
9/9 [=====] - 0s 28ms/step - loss: 0.0199
Epoch 100/170
9/9 [=====] - 0s 28ms/step - loss: 0.0167
Epoch 101/170
9/9 [=====] - 0s 35ms/step - loss: 0.0158

Epoch 102/170
9/9 [=====] - 0s 29ms/step - loss: 0.0182
Epoch 103/170
9/9 [=====] - 0s 30ms/step - loss: 0.0215
Epoch 104/170
9/9 [=====] - 0s 29ms/step - loss: 0.0183
Epoch 105/170
9/9 [=====] - 0s 33ms/step - loss: 0.0124
Epoch 106/170
9/9 [=====] - 0s 28ms/step - loss: 0.0153
Epoch 107/170
9/9 [=====] - 0s 30ms/step - loss: 0.0126
Epoch 108/170
9/9 [=====] - 0s 30ms/step - loss: 0.0128
Epoch 109/170
9/9 [=====] - 0s 28ms/step - loss: 0.0133
Epoch 110/170
9/9 [=====] - 0s 29ms/step - loss: 0.0187
Epoch 111/170
9/9 [=====] - 0s 29ms/step - loss: 0.0143
Epoch 112/170
9/9 [=====] - 0s 33ms/step - loss: 0.0134
Epoch 113/170
9/9 [=====] - 0s 30ms/step - loss: 0.0099
Epoch 114/170
9/9 [=====] - 0s 28ms/step - loss: 0.0149
Epoch 115/170
9/9 [=====] - 0s 30ms/step - loss: 0.0179
Epoch 116/170
9/9 [=====] - 0s 30ms/step - loss: 0.0119
Epoch 117/170
9/9 [=====] - 0s 27ms/step - loss: 0.0163
Epoch 118/170
9/9 [=====] - 0s 26ms/step - loss: 0.0162
Epoch 119/170
9/9 [=====] - 0s 27ms/step - loss: 0.0076
Epoch 120/170
9/9 [=====] - 0s 28ms/step - loss: 0.0122
Epoch 121/170
9/9 [=====] - 0s 27ms/step - loss: 0.0103
Epoch 122/170
9/9 [=====] - 0s 27ms/step - loss: 0.0099
Epoch 123/170
9/9 [=====] - 0s 30ms/step - loss: 0.0108
Epoch 124/170
9/9 [=====] - 0s 29ms/step - loss: 0.0134
Epoch 125/170
9/9 [=====] - 0s 33ms/step - loss: 0.0093

Epoch 126/170
9/9 [=====] - 0s 29ms/step - loss: 0.0168
Epoch 127/170
9/9 [=====] - 0s 29ms/step - loss: 0.0143
Epoch 128/170
9/9 [=====] - 0s 30ms/step - loss: 0.0147
Epoch 129/170
9/9 [=====] - 0s 28ms/step - loss: 0.0184
Epoch 130/170
9/9 [=====] - 0s 28ms/step - loss: 0.0202
Epoch 131/170
9/9 [=====] - 0s 29ms/step - loss: 0.0273
Epoch 132/170
9/9 [=====] - 0s 29ms/step - loss: 0.0190
Epoch 133/170
9/9 [=====] - 0s 28ms/step - loss: 0.0197
Epoch 134/170
9/9 [=====] - 0s 29ms/step - loss: 0.0158
Epoch 135/170
9/9 [=====] - 0s 29ms/step - loss: 0.0133
Epoch 136/170
9/9 [=====] - 0s 30ms/step - loss: 0.0118
Epoch 137/170
9/9 [=====] - 0s 28ms/step - loss: 0.0119
Epoch 138/170
9/9 [=====] - 0s 28ms/step - loss: 0.0115
Epoch 139/170
9/9 [=====] - 0s 29ms/step - loss: 0.0137
Epoch 140/170
9/9 [=====] - 0s 28ms/step - loss: 0.0116
Epoch 141/170
9/9 [=====] - 0s 28ms/step - loss: 0.0094
Epoch 142/170
9/9 [=====] - 0s 29ms/step - loss: 0.0114
Epoch 143/170
9/9 [=====] - 0s 28ms/step - loss: 0.0135
Epoch 144/170
9/9 [=====] - 0s 28ms/step - loss: 0.0095
Epoch 145/170
9/9 [=====] - 0s 31ms/step - loss: 0.0154
Epoch 146/170
9/9 [=====] - 0s 31ms/step - loss: 0.0096
Epoch 147/170
9/9 [=====] - 0s 33ms/step - loss: 0.0116
Epoch 148/170
9/9 [=====] - 0s 31ms/step - loss: 0.0134
Epoch 149/170
9/9 [=====] - 0s 29ms/step - loss: 0.0183

```

Epoch 150/170
9/9 [=====] - 0s 28ms/step - loss: 0.0122
Epoch 151/170
9/9 [=====] - 0s 28ms/step - loss: 0.0127
Epoch 152/170
9/9 [=====] - 0s 28ms/step - loss: 0.0132
Epoch 153/170
9/9 [=====] - 0s 29ms/step - loss: 0.0135
Epoch 154/170
9/9 [=====] - 0s 30ms/step - loss: 0.0160
Epoch 155/170
9/9 [=====] - 0s 30ms/step - loss: 0.0125
Epoch 156/170
9/9 [=====] - 0s 30ms/step - loss: 0.0148
Epoch 157/170
9/9 [=====] - 0s 29ms/step - loss: 0.0163
Epoch 158/170
9/9 [=====] - 0s 29ms/step - loss: 0.0163
Epoch 159/170
9/9 [=====] - 0s 28ms/step - loss: 0.0160
Epoch 160/170
9/9 [=====] - 0s 28ms/step - loss: 0.0118
Epoch 161/170
9/9 [=====] - 0s 29ms/step - loss: 0.0136
Epoch 162/170
9/9 [=====] - 0s 28ms/step - loss: 0.0155
Epoch 163/170
9/9 [=====] - 0s 28ms/step - loss: 0.0112
Epoch 164/170
9/9 [=====] - 0s 29ms/step - loss: 0.0102
Epoch 165/170
9/9 [=====] - 0s 30ms/step - loss: 0.0120
Epoch 166/170
9/9 [=====] - 0s 29ms/step - loss: 0.0098
Epoch 167/170
9/9 [=====] - 0s 27ms/step - loss: 0.0103
Epoch 168/170
9/9 [=====] - 0s 28ms/step - loss: 0.0087
Epoch 169/170
9/9 [=====] - 0s 28ms/step - loss: 0.0112
Epoch 170/170
9/9 [=====] - 0s 29ms/step - loss: 0.0080

```

[14]: <tensorflow.python.keras.callbacks.History at 0x7f85c0c63210>

From this, we can see that the MSE is **0.0080**

```
[15]: # Part 3 - Making the predictions and visualising the results
```

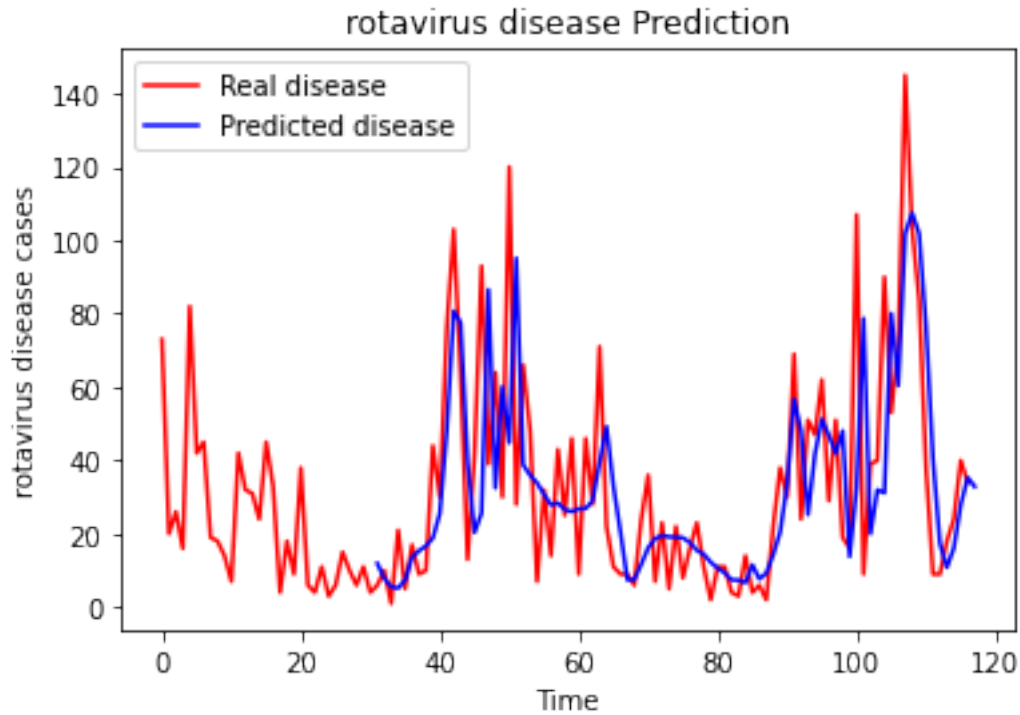
```
data_test = pd.read_csv('case.csv')
real_disease = data_test.values
```

```
[16]: inputs = data_test.values
inputs = inputs.reshape(-1,1)
inputs = sc.transform(inputs)
X_test = []
for i in range(30, 117):
    X_test.append(inputs[i-30:i, 0])
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
predicted_disease = regressor.predict(X_test)
predicted_disease = sc.inverse_transform(predicted_disease)
```

Now I visualize to compare the estimated and true reported cases:

```
[18]: # Visualizing the results
plt.plot(real_disease, color = 'red', label = 'Real disease')
plt.plot(range(31, 31+len(predicted_disease)), predicted_disease, color = 'blue', label = 'Predicted disease')

plt.title('rotavirus disease Prediction')
plt.xlabel('Time')
plt.ylabel('rotavirus disease cases')
plt.legend()
plt.show()
```



We can easily see that the prediction is quite accurate. So the RNN is fitted well. However, there could be some problem as the prediction fits the real data a bit **too** well. This could mean that there can be some overfitting issues. Still, the MSE changes (little bit) everytime I run the **regressor.fit function**. So there were also sometimes where the prediction graph was not this accurate. Also, the problem could be solved by applying more dropouts.

case60

June 5, 2021

(c) Similarly, we use following codes to construct LSTM model and compare the estimated and true reported cases.

```
[3]: data=pd.DataFrame(data=data)
      from sklearn.preprocessing import MinMaxScaler
      sc = MinMaxScaler(feature_range = (0, 1))
      data_scaled = sc.fit_transform(data)
```

```
[4]: #(b) previous 60 week's info

      X_train = []
      y_train = []
      for i in range(60, 117):
          X_train.append(data_scaled[i-60:i,0])
          y_train.append(data_scaled[i,0])
      X_train, y_train = np.array(X_train), np.array(y_train)
      X_train
```

```
[4]: array([[0.5          , 0.13194444, 0.17361111, ..., 0.29166667, 0.16666667,
            0.3125          ],
            [0.13194444, 0.17361111, 0.10416667, ..., 0.16666667, 0.3125          ,
            0.05555556],
            [0.17361111, 0.10416667, 0.5625          , ..., 0.3125          , 0.05555556,
            0.3125          ],
            ...,
            [0.04166667, 0.21527778, 0.09027778, ..., 0.05555556, 0.05555556,
            0.11805556],
            [0.21527778, 0.09027778, 0.29166667, ..., 0.05555556, 0.11805556,
            0.15972222],
            [0.09027778, 0.29166667, 0.16666667, ..., 0.11805556, 0.15972222,
            0.27083333]])
```

```
[5]: # Reshaping
      X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
      X_train
```

```
[5]: array([[[0.5          ],
            [0.13194444],
```

```

[0.17361111],
...,
[0.29166667],
[0.16666667],
[0.3125    ]],

[[0.13194444],
 [0.17361111],
 [0.10416667],
 ...,
 [0.16666667],
 [0.3125    ],
 [0.05555556]],

[[0.17361111],
 [0.10416667],
 [0.5625    ],
 ...,
 [0.3125    ],
 [0.05555556],
 [0.3125    ]],

...,

[[0.04166667],
 [0.21527778],
 [0.09027778],
 ...,
 [0.05555556],
 [0.05555556],
 [0.11805556]],

[[0.21527778],
 [0.09027778],
 [0.29166667],
 ...,
 [0.05555556],
 [0.11805556],
 [0.15972222]],

[[0.09027778],
 [0.29166667],
 [0.16666667],
 ...,
 [0.11805556],
 [0.15972222],
 [0.27083333]]])

```

```
[7]: # Initializing the RNN
regressor = Sequential()

# Adding the first LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 60, return_sequences = True, input_shape = (X_train.
    ↪shape[1], 1)))
regressor.add(Dropout(0.3))
```

```
[8]: # Adding a second LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.23))
```

```
[9]: # Adding a third LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 55, return_sequences = True))
regressor.add(Dropout(0.2))
```

```
[10]: # Adding a fourth LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 55))
regressor.add(Dropout(0.2))
```

```
[13]: # Adding the output layer
regressor.add(Dense(units = 1))

# Compiling the RNN
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')

# Fitting the RNN to the Training set
regressor.fit(X_train, y_train, epochs = 170, batch_size = 10)
```

```
Epoch 1/170
6/6 [=====] - 4s 59ms/step - loss: 0.0576
Epoch 2/170
6/6 [=====] - 0s 51ms/step - loss: 0.0436
Epoch 3/170
6/6 [=====] - 0s 50ms/step - loss: 0.0525
Epoch 4/170
6/6 [=====] - 0s 52ms/step - loss: 0.0459
Epoch 5/170
6/6 [=====] - 0s 52ms/step - loss: 0.0536
Epoch 6/170
6/6 [=====] - 0s 51ms/step - loss: 0.0295
Epoch 7/170
6/6 [=====] - 0s 52ms/step - loss: 0.0398
Epoch 8/170
6/6 [=====] - 0s 52ms/step - loss: 0.0300
Epoch 9/170
6/6 [=====] - 0s 52ms/step - loss: 0.0473
```


Epoch 10/170
6/6 [=====] - 0s 53ms/step - loss: 0.0353
Epoch 11/170
6/6 [=====] - 0s 53ms/step - loss: 0.0442
Epoch 12/170
6/6 [=====] - 0s 53ms/step - loss: 0.0405
Epoch 13/170
6/6 [=====] - 0s 52ms/step - loss: 0.0283
Epoch 14/170
6/6 [=====] - 0s 55ms/step - loss: 0.0285
Epoch 15/170
6/6 [=====] - 0s 53ms/step - loss: 0.0353
Epoch 16/170
6/6 [=====] - 0s 54ms/step - loss: 0.0322
Epoch 17/170
6/6 [=====] - 0s 52ms/step - loss: 0.0314
Epoch 18/170
6/6 [=====] - 0s 53ms/step - loss: 0.0276
Epoch 19/170
6/6 [=====] - 0s 54ms/step - loss: 0.0307
Epoch 20/170
6/6 [=====] - 0s 53ms/step - loss: 0.0231
Epoch 21/170
6/6 [=====] - 0s 53ms/step - loss: 0.0226
Epoch 22/170
6/6 [=====] - 0s 54ms/step - loss: 0.0446
Epoch 23/170
6/6 [=====] - 0s 55ms/step - loss: 0.0337
Epoch 24/170
6/6 [=====] - 0s 52ms/step - loss: 0.0320
Epoch 25/170
6/6 [=====] - 0s 52ms/step - loss: 0.0255
Epoch 26/170
6/6 [=====] - 0s 52ms/step - loss: 0.0438
Epoch 27/170
6/6 [=====] - 0s 52ms/step - loss: 0.0408
Epoch 28/170
6/6 [=====] - 0s 50ms/step - loss: 0.0386
Epoch 29/170
6/6 [=====] - 0s 52ms/step - loss: 0.0454
Epoch 30/170
6/6 [=====] - 0s 51ms/step - loss: 0.0236
Epoch 31/170
6/6 [=====] - 0s 53ms/step - loss: 0.0349
Epoch 32/170
6/6 [=====] - 0s 51ms/step - loss: 0.0343
Epoch 33/170
6/6 [=====] - 0s 51ms/step - loss: 0.0211

Epoch 34/170
6/6 [=====] - 0s 50ms/step - loss: 0.0228
Epoch 35/170
6/6 [=====] - 0s 52ms/step - loss: 0.0251
Epoch 36/170
6/6 [=====] - 0s 52ms/step - loss: 0.0257
Epoch 37/170
6/6 [=====] - 0s 52ms/step - loss: 0.0382
Epoch 38/170
6/6 [=====] - 0s 54ms/step - loss: 0.0277
Epoch 39/170
6/6 [=====] - 0s 50ms/step - loss: 0.0324
Epoch 40/170
6/6 [=====] - 0s 52ms/step - loss: 0.0238
Epoch 41/170
6/6 [=====] - 0s 53ms/step - loss: 0.0397
Epoch 42/170
6/6 [=====] - 0s 52ms/step - loss: 0.0383
Epoch 43/170
6/6 [=====] - 0s 52ms/step - loss: 0.0256
Epoch 44/170
6/6 [=====] - 0s 51ms/step - loss: 0.0304
Epoch 45/170
6/6 [=====] - 0s 51ms/step - loss: 0.0259
Epoch 46/170
6/6 [=====] - 0s 52ms/step - loss: 0.0378
Epoch 47/170
6/6 [=====] - 0s 57ms/step - loss: 0.0232
Epoch 48/170
6/6 [=====] - 0s 54ms/step - loss: 0.0301
Epoch 49/170
6/6 [=====] - 0s 55ms/step - loss: 0.0253
Epoch 50/170
6/6 [=====] - 0s 52ms/step - loss: 0.0337
Epoch 51/170
6/6 [=====] - 0s 52ms/step - loss: 0.0461
Epoch 52/170
6/6 [=====] - 0s 52ms/step - loss: 0.0324
Epoch 53/170
6/6 [=====] - 0s 54ms/step - loss: 0.0380
Epoch 54/170
6/6 [=====] - 0s 56ms/step - loss: 0.0289
Epoch 55/170
6/6 [=====] - 0s 54ms/step - loss: 0.0225
Epoch 56/170
6/6 [=====] - 0s 55ms/step - loss: 0.0213
Epoch 57/170
6/6 [=====] - 0s 55ms/step - loss: 0.0266

Epoch 58/170
6/6 [=====] - 0s 51ms/step - loss: 0.0191
Epoch 59/170
6/6 [=====] - 0s 52ms/step - loss: 0.0204
Epoch 60/170
6/6 [=====] - 0s 52ms/step - loss: 0.0374
Epoch 61/170
6/6 [=====] - 0s 52ms/step - loss: 0.0335
Epoch 62/170
6/6 [=====] - 0s 53ms/step - loss: 0.0297
Epoch 63/170
6/6 [=====] - 0s 52ms/step - loss: 0.0379
Epoch 64/170
6/6 [=====] - 0s 52ms/step - loss: 0.0237
Epoch 65/170
6/6 [=====] - 0s 52ms/step - loss: 0.0229
Epoch 66/170
6/6 [=====] - 0s 52ms/step - loss: 0.0351
Epoch 67/170
6/6 [=====] - 0s 52ms/step - loss: 0.0290
Epoch 68/170
6/6 [=====] - 0s 52ms/step - loss: 0.0274
Epoch 69/170
6/6 [=====] - 0s 51ms/step - loss: 0.0267
Epoch 70/170
6/6 [=====] - 0s 52ms/step - loss: 0.0321
Epoch 71/170
6/6 [=====] - 0s 54ms/step - loss: 0.0288
Epoch 72/170
6/6 [=====] - 0s 53ms/step - loss: 0.0347
Epoch 73/170
6/6 [=====] - 0s 54ms/step - loss: 0.0394
Epoch 74/170
6/6 [=====] - 0s 52ms/step - loss: 0.0346
Epoch 75/170
6/6 [=====] - 0s 56ms/step - loss: 0.0324
Epoch 76/170
6/6 [=====] - 0s 55ms/step - loss: 0.0300
Epoch 77/170
6/6 [=====] - 0s 53ms/step - loss: 0.0330
Epoch 78/170
6/6 [=====] - 0s 56ms/step - loss: 0.0250
Epoch 79/170
6/6 [=====] - 0s 57ms/step - loss: 0.0211
Epoch 80/170
6/6 [=====] - 0s 55ms/step - loss: 0.0350
Epoch 81/170
6/6 [=====] - 0s 53ms/step - loss: 0.0251

Epoch 82/170
6/6 [=====] - 0s 53ms/step - loss: 0.0275
Epoch 83/170
6/6 [=====] - 0s 53ms/step - loss: 0.0259
Epoch 84/170
6/6 [=====] - 0s 54ms/step - loss: 0.0226
Epoch 85/170
6/6 [=====] - 0s 55ms/step - loss: 0.0240
Epoch 86/170
6/6 [=====] - 0s 57ms/step - loss: 0.0235
Epoch 87/170
6/6 [=====] - 0s 55ms/step - loss: 0.0200
Epoch 88/170
6/6 [=====] - 0s 53ms/step - loss: 0.0336
Epoch 89/170
6/6 [=====] - 0s 54ms/step - loss: 0.0236
Epoch 90/170
6/6 [=====] - 0s 53ms/step - loss: 0.0379
Epoch 91/170
6/6 [=====] - 0s 53ms/step - loss: 0.0223
Epoch 92/170
6/6 [=====] - 0s 51ms/step - loss: 0.0224
Epoch 93/170
6/6 [=====] - 0s 53ms/step - loss: 0.0292
Epoch 94/170
6/6 [=====] - 0s 53ms/step - loss: 0.0349
Epoch 95/170
6/6 [=====] - 0s 53ms/step - loss: 0.0226
Epoch 96/170
6/6 [=====] - 0s 53ms/step - loss: 0.0358
Epoch 97/170
6/6 [=====] - 0s 52ms/step - loss: 0.0205
Epoch 98/170
6/6 [=====] - 0s 52ms/step - loss: 0.0267
Epoch 99/170
6/6 [=====] - 0s 52ms/step - loss: 0.0213
Epoch 100/170
6/6 [=====] - 0s 53ms/step - loss: 0.0234
Epoch 101/170
6/6 [=====] - 0s 53ms/step - loss: 0.0295
Epoch 102/170
6/6 [=====] - 0s 52ms/step - loss: 0.0201
Epoch 103/170
6/6 [=====] - 0s 52ms/step - loss: 0.0296
Epoch 104/170
6/6 [=====] - 0s 52ms/step - loss: 0.0266
Epoch 105/170
6/6 [=====] - 0s 52ms/step - loss: 0.0229

Epoch 106/170
6/6 [=====] - 0s 51ms/step - loss: 0.0187
Epoch 107/170
6/6 [=====] - 0s 52ms/step - loss: 0.0175
Epoch 108/170
6/6 [=====] - 0s 52ms/step - loss: 0.0424
Epoch 109/170
6/6 [=====] - 0s 51ms/step - loss: 0.0240
Epoch 110/170
6/6 [=====] - 0s 56ms/step - loss: 0.0222
Epoch 111/170
6/6 [=====] - 0s 55ms/step - loss: 0.0299
Epoch 112/170
6/6 [=====] - 0s 55ms/step - loss: 0.0270
Epoch 113/170
6/6 [=====] - 0s 51ms/step - loss: 0.0237
Epoch 114/170
6/6 [=====] - 0s 53ms/step - loss: 0.0213
Epoch 115/170
6/6 [=====] - 0s 53ms/step - loss: 0.0176
Epoch 116/170
6/6 [=====] - 0s 53ms/step - loss: 0.0216
Epoch 117/170
6/6 [=====] - 0s 55ms/step - loss: 0.0161
Epoch 118/170
6/6 [=====] - 0s 56ms/step - loss: 0.0151
Epoch 119/170
6/6 [=====] - 0s 56ms/step - loss: 0.0189
Epoch 120/170
6/6 [=====] - 0s 52ms/step - loss: 0.0216
Epoch 121/170
6/6 [=====] - 0s 54ms/step - loss: 0.0235
Epoch 122/170
6/6 [=====] - 0s 52ms/step - loss: 0.0283
Epoch 123/170
6/6 [=====] - 0s 52ms/step - loss: 0.0224
Epoch 124/170
6/6 [=====] - 0s 52ms/step - loss: 0.0187
Epoch 125/170
6/6 [=====] - 0s 53ms/step - loss: 0.0130
Epoch 126/170
6/6 [=====] - 0s 50ms/step - loss: 0.0213
Epoch 127/170
6/6 [=====] - 0s 52ms/step - loss: 0.0253
Epoch 128/170
6/6 [=====] - 0s 51ms/step - loss: 0.0189
Epoch 129/170
6/6 [=====] - 0s 51ms/step - loss: 0.0203

Epoch 130/170
6/6 [=====] - 0s 50ms/step - loss: 0.0220
Epoch 131/170
6/6 [=====] - 0s 51ms/step - loss: 0.0181
Epoch 132/170
6/6 [=====] - 0s 53ms/step - loss: 0.0214
Epoch 133/170
6/6 [=====] - 0s 53ms/step - loss: 0.0175
Epoch 134/170
6/6 [=====] - 0s 51ms/step - loss: 0.0299
Epoch 135/170
6/6 [=====] - 0s 53ms/step - loss: 0.0194
Epoch 136/170
6/6 [=====] - 0s 54ms/step - loss: 0.0212
Epoch 137/170
6/6 [=====] - 0s 52ms/step - loss: 0.0206
Epoch 138/170
6/6 [=====] - 0s 53ms/step - loss: 0.0177
Epoch 139/170
6/6 [=====] - 0s 53ms/step - loss: 0.0274
Epoch 140/170
6/6 [=====] - 0s 51ms/step - loss: 0.0202
Epoch 141/170
6/6 [=====] - 0s 52ms/step - loss: 0.0244
Epoch 142/170
6/6 [=====] - 0s 55ms/step - loss: 0.0176
Epoch 143/170
6/6 [=====] - 0s 55ms/step - loss: 0.0225
Epoch 144/170
6/6 [=====] - 0s 57ms/step - loss: 0.0191
Epoch 145/170
6/6 [=====] - 0s 51ms/step - loss: 0.0160
Epoch 146/170
6/6 [=====] - 0s 54ms/step - loss: 0.0166
Epoch 147/170
6/6 [=====] - 0s 54ms/step - loss: 0.0229
Epoch 148/170
6/6 [=====] - 0s 53ms/step - loss: 0.0155
Epoch 149/170
6/6 [=====] - 0s 52ms/step - loss: 0.0200
Epoch 150/170
6/6 [=====] - 0s 52ms/step - loss: 0.0141
Epoch 151/170
6/6 [=====] - 0s 56ms/step - loss: 0.0151
Epoch 152/170
6/6 [=====] - 0s 53ms/step - loss: 0.0240
Epoch 153/170
6/6 [=====] - 0s 52ms/step - loss: 0.0240

```

Epoch 154/170
6/6 [=====] - 0s 54ms/step - loss: 0.0240
Epoch 155/170
6/6 [=====] - 0s 52ms/step - loss: 0.0261
Epoch 156/170
6/6 [=====] - 0s 53ms/step - loss: 0.0121
Epoch 157/170
6/6 [=====] - 0s 53ms/step - loss: 0.0143
Epoch 158/170
6/6 [=====] - 0s 50ms/step - loss: 0.0166
Epoch 159/170
6/6 [=====] - 0s 52ms/step - loss: 0.0114
Epoch 160/170
6/6 [=====] - 0s 53ms/step - loss: 0.0213
Epoch 161/170
6/6 [=====] - 0s 50ms/step - loss: 0.0148
Epoch 162/170
6/6 [=====] - 0s 52ms/step - loss: 0.0149
Epoch 163/170
6/6 [=====] - 0s 52ms/step - loss: 0.0135
Epoch 164/170
6/6 [=====] - 0s 53ms/step - loss: 0.0146
Epoch 165/170
6/6 [=====] - 0s 53ms/step - loss: 0.0222
Epoch 166/170
6/6 [=====] - 0s 51ms/step - loss: 0.0153
Epoch 167/170
6/6 [=====] - 0s 53ms/step - loss: 0.0159
Epoch 168/170
6/6 [=====] - 0s 52ms/step - loss: 0.0179
Epoch 169/170
6/6 [=====] - 0s 52ms/step - loss: 0.0211
Epoch 170/170
6/6 [=====] - 0s 53ms/step - loss: 0.0147

```

[13]: <tensorflow.python.keras.callbacks.History at 0x7fb5a87cab50>

[16]: *# Part 3 - Making the predictions and visualizing the results*

```

data_test = pd.read_csv('case.csv')
real_disease = data_test.values

```

[17]:

```

inputs = data_test.values
inputs = inputs.reshape(-1,1)
inputs = sc.transform(inputs)
X_test = []
for i in range(60, 117):

```

```

X_test.append(inputs[i-60:i, 0])
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
predicted_disease = regressor.predict(X_test)
predicted_disease = sc.inverse_transform(predicted_disease)

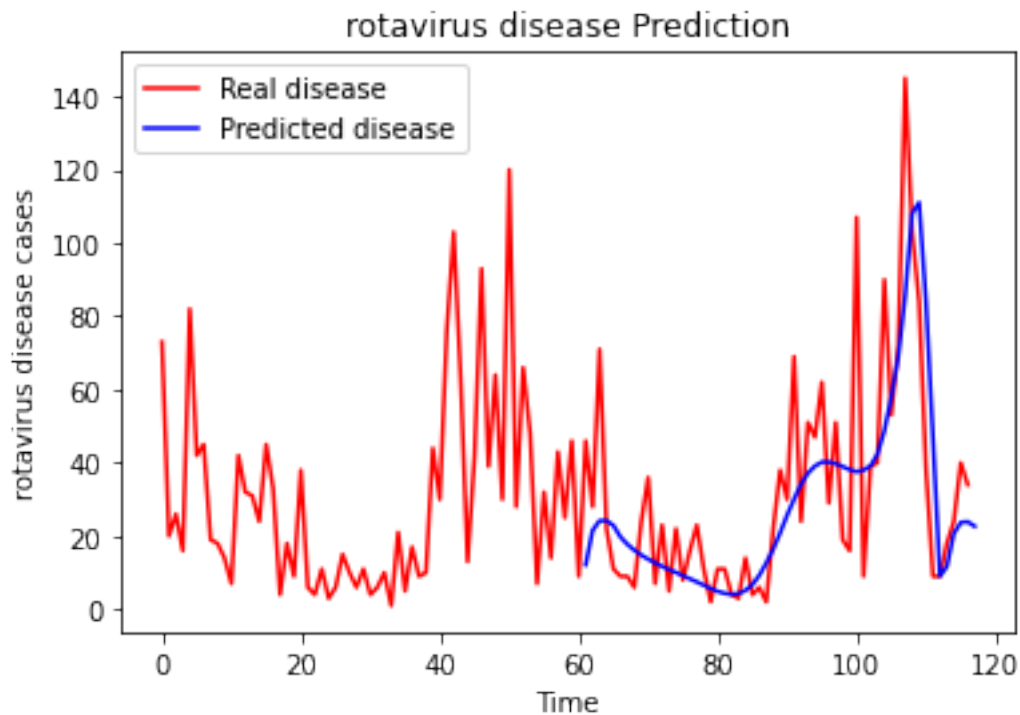
```

```

[19]: # Visualising the results
plt.plot(real_disease, color = 'red', label = 'Real disease')
plt.plot(range(61, 61+len(predicted_disease)), predicted_disease, color = 'blue', label = 'Predicted disease')

plt.title('rotavirus disease Prediction')
plt.xlabel('Time')
plt.ylabel('rotavirus disease cases')
plt.legend()
plt.show()

```



case90

June 5, 2021

(d) Again, we use following codes to construct LSTM and compare the data.

```
[3]: data=pd.DataFrame(data=data)
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler(feature_range = (0, 1))
data_scaled = sc.fit_transform(data)
```

```
[4]: #(b) previous 90 week's info

X_train = []
y_train = []
for i in range(90, 117):
    X_train.append(data_scaled[i-90:i,0])
    y_train.append(data_scaled[i,0])
X_train, y_train = np.array(X_train), np.array(y_train)
X_train
```

```
[4]: array([[0.5          , 0.13194444, 0.17361111, ..., 0.00694444, 0.14583333,
           0.25694444],
          [0.13194444, 0.17361111, 0.10416667, ..., 0.14583333, 0.25694444,
           0.20138889],
          [0.17361111, 0.10416667, 0.5625      , ..., 0.25694444, 0.20138889,
           0.47222222],
          ...,
          [0.01388889, 0.03472222, 0.09722222, ..., 0.05555556, 0.05555556,
           0.11805556],
          [0.03472222, 0.09722222, 0.0625      , ..., 0.05555556, 0.11805556,
           0.15972222],
          [0.09722222, 0.0625      , 0.03472222, ..., 0.11805556, 0.15972222,
           0.27083333]])
```

```
[5]: # Reshaping
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))
X_train
```

```
[5]: array([[[0.5          ],
             [0.13194444],
             [0.17361111],
```

```

...,
[0.00694444],
[0.14583333],
[0.25694444]],

[[0.13194444],
[0.17361111],
[0.10416667],
...,
[0.14583333],
[0.25694444],
[0.20138889]],

[[0.17361111],
[0.10416667],
[0.5625   ]],
...,
[0.25694444],
[0.20138889],
[0.47222222]],

...,

[[0.01388889],
[0.03472222],
[0.09722222],
...,
[0.05555556],
[0.05555556],
[0.11805556]],

[[0.03472222],
[0.09722222],
[0.0625   ]],
...,
[0.05555556],
[0.11805556],
[0.15972222]],

[[0.09722222],
[0.0625   ],
[0.03472222],
...,
[0.11805556],
[0.15972222],
[0.27083333]]])

```

```
[7]: # Initializing the RNN
regressor = Sequential()

# Adding the first LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 60, return_sequences = True, input_shape = (X_train.
    ↪shape[1], 1)))
regressor.add(Dropout(0.3))
```

```
[8]: # Adding a second LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.23))
```

```
[9]: # Adding a third LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 55, return_sequences = True))
regressor.add(Dropout(0.2))
```

```
[10]: # Adding a fourth LSTM layer and some Dropout regularisation
regressor.add(LSTM(units = 55))
regressor.add(Dropout(0.2))
```

```
[13]: # Adding the output layer
regressor.add(Dense(units = 1))

# Compiling the RNN
regressor.compile(optimizer = 'adam', loss = 'mean_squared_error')

# Fitting the RNN to the Training set
regressor.fit(X_train, y_train, epochs = 170, batch_size = 10)
```

```
Epoch 1/170
3/3 [=====] - 5s 101ms/step - loss: 0.1594
Epoch 2/170
3/3 [=====] - 0s 74ms/step - loss: 0.1263
Epoch 3/170
3/3 [=====] - 0s 73ms/step - loss: 0.0892
Epoch 4/170
3/3 [=====] - 0s 80ms/step - loss: 0.0612
Epoch 5/170
3/3 [=====] - 0s 74ms/step - loss: 0.0529
Epoch 6/170
3/3 [=====] - 0s 73ms/step - loss: 0.0819
Epoch 7/170
3/3 [=====] - 0s 73ms/step - loss: 0.0470
Epoch 8/170
3/3 [=====] - 0s 73ms/step - loss: 0.0652
Epoch 9/170
3/3 [=====] - 0s 73ms/step - loss: 0.0577
```

Epoch 10/170
3/3 [=====] - 0s 72ms/step - loss: 0.0585
Epoch 11/170
3/3 [=====] - 0s 74ms/step - loss: 0.0453
Epoch 12/170
3/3 [=====] - 0s 74ms/step - loss: 0.0634
Epoch 13/170
3/3 [=====] - 0s 74ms/step - loss: 0.0442
Epoch 14/170
3/3 [=====] - 0s 73ms/step - loss: 0.0451
Epoch 15/170
3/3 [=====] - 0s 81ms/step - loss: 0.0454
Epoch 16/170
3/3 [=====] - 0s 80ms/step - loss: 0.0711
Epoch 17/170
3/3 [=====] - 0s 80ms/step - loss: 0.0508
Epoch 18/170
3/3 [=====] - 0s 77ms/step - loss: 0.0511
Epoch 19/170
3/3 [=====] - 0s 74ms/step - loss: 0.0541
Epoch 20/170
3/3 [=====] - 0s 72ms/step - loss: 0.0604
Epoch 21/170
3/3 [=====] - 0s 73ms/step - loss: 0.0512
Epoch 22/170
3/3 [=====] - 0s 77ms/step - loss: 0.0464
Epoch 23/170
3/3 [=====] - 0s 74ms/step - loss: 0.0676
Epoch 24/170
3/3 [=====] - 0s 78ms/step - loss: 0.0485
Epoch 25/170
3/3 [=====] - 0s 79ms/step - loss: 0.0409
Epoch 26/170
3/3 [=====] - 0s 82ms/step - loss: 0.0454
Epoch 27/170
3/3 [=====] - 0s 78ms/step - loss: 0.0671
Epoch 28/170
3/3 [=====] - 0s 75ms/step - loss: 0.0454
Epoch 29/170
3/3 [=====] - 0s 75ms/step - loss: 0.0534
Epoch 30/170
3/3 [=====] - 0s 75ms/step - loss: 0.0637
Epoch 31/170
3/3 [=====] - 0s 75ms/step - loss: 0.0720
Epoch 32/170
3/3 [=====] - 0s 74ms/step - loss: 0.0590
Epoch 33/170
3/3 [=====] - 0s 73ms/step - loss: 0.0501

Epoch 34/170
3/3 [=====] - 0s 72ms/step - loss: 0.0614
Epoch 35/170
3/3 [=====] - 0s 75ms/step - loss: 0.0494
Epoch 36/170
3/3 [=====] - 0s 73ms/step - loss: 0.0602
Epoch 37/170
3/3 [=====] - 0s 74ms/step - loss: 0.0561
Epoch 38/170
3/3 [=====] - 0s 75ms/step - loss: 0.0524
Epoch 39/170
3/3 [=====] - 0s 74ms/step - loss: 0.0558
Epoch 40/170
3/3 [=====] - 0s 77ms/step - loss: 0.0529
Epoch 41/170
3/3 [=====] - 0s 72ms/step - loss: 0.0528
Epoch 42/170
3/3 [=====] - 0s 73ms/step - loss: 0.0630
Epoch 43/170
3/3 [=====] - 0s 76ms/step - loss: 0.0554
Epoch 44/170
3/3 [=====] - 0s 74ms/step - loss: 0.0625
Epoch 45/170
3/3 [=====] - 0s 74ms/step - loss: 0.0504
Epoch 46/170
3/3 [=====] - 0s 74ms/step - loss: 0.0655
Epoch 47/170
3/3 [=====] - 0s 74ms/step - loss: 0.0708
Epoch 48/170
3/3 [=====] - 0s 74ms/step - loss: 0.0652
Epoch 49/170
3/3 [=====] - 0s 75ms/step - loss: 0.0449
Epoch 50/170
3/3 [=====] - 0s 73ms/step - loss: 0.0383
Epoch 51/170
3/3 [=====] - 0s 79ms/step - loss: 0.0535
Epoch 52/170
3/3 [=====] - 0s 75ms/step - loss: 0.0647
Epoch 53/170
3/3 [=====] - 0s 77ms/step - loss: 0.0583
Epoch 54/170
3/3 [=====] - 0s 74ms/step - loss: 0.0517
Epoch 55/170
3/3 [=====] - 0s 72ms/step - loss: 0.0540
Epoch 56/170
3/3 [=====] - 0s 73ms/step - loss: 0.0481
Epoch 57/170
3/3 [=====] - 0s 82ms/step - loss: 0.0522

Epoch 58/170
3/3 [=====] - 0s 75ms/step - loss: 0.0431
Epoch 59/170
3/3 [=====] - 0s 71ms/step - loss: 0.0650
Epoch 60/170
3/3 [=====] - 0s 73ms/step - loss: 0.0561
Epoch 61/170
3/3 [=====] - 0s 73ms/step - loss: 0.0521
Epoch 62/170
3/3 [=====] - 0s 74ms/step - loss: 0.0509
Epoch 63/170
3/3 [=====] - 0s 81ms/step - loss: 0.0435
Epoch 64/170
3/3 [=====] - 0s 81ms/step - loss: 0.0610
Epoch 65/170
3/3 [=====] - 0s 79ms/step - loss: 0.0598
Epoch 66/170
3/3 [=====] - 0s 78ms/step - loss: 0.0617
Epoch 67/170
3/3 [=====] - 0s 73ms/step - loss: 0.0439
Epoch 68/170
3/3 [=====] - 0s 73ms/step - loss: 0.0661
Epoch 69/170
3/3 [=====] - 0s 73ms/step - loss: 0.0449
Epoch 70/170
3/3 [=====] - 0s 75ms/step - loss: 0.0407
Epoch 71/170
3/3 [=====] - 0s 78ms/step - loss: 0.0502
Epoch 72/170
3/3 [=====] - 0s 73ms/step - loss: 0.0590
Epoch 73/170
3/3 [=====] - 0s 77ms/step - loss: 0.0558
Epoch 74/170
3/3 [=====] - 0s 87ms/step - loss: 0.0502
Epoch 75/170
3/3 [=====] - 0s 83ms/step - loss: 0.0553
Epoch 76/170
3/3 [=====] - 0s 77ms/step - loss: 0.0471
Epoch 77/170
3/3 [=====] - 0s 74ms/step - loss: 0.0536
Epoch 78/170
3/3 [=====] - 0s 73ms/step - loss: 0.0588
Epoch 79/170
3/3 [=====] - 0s 72ms/step - loss: 0.0434
Epoch 80/170
3/3 [=====] - 0s 69ms/step - loss: 0.0500
Epoch 81/170
3/3 [=====] - 0s 75ms/step - loss: 0.0615

Epoch 82/170
3/3 [=====] - 0s 75ms/step - loss: 0.0549
Epoch 83/170
3/3 [=====] - 0s 76ms/step - loss: 0.0594
Epoch 84/170
3/3 [=====] - 0s 76ms/step - loss: 0.0424
Epoch 85/170
3/3 [=====] - 0s 78ms/step - loss: 0.0430
Epoch 86/170
3/3 [=====] - 0s 77ms/step - loss: 0.0556
Epoch 87/170
3/3 [=====] - 0s 74ms/step - loss: 0.0571
Epoch 88/170
3/3 [=====] - 0s 69ms/step - loss: 0.0467
Epoch 89/170
3/3 [=====] - 0s 72ms/step - loss: 0.0428
Epoch 90/170
3/3 [=====] - 0s 72ms/step - loss: 0.0567
Epoch 91/170
3/3 [=====] - 0s 71ms/step - loss: 0.0549
Epoch 92/170
3/3 [=====] - 0s 71ms/step - loss: 0.0508
Epoch 93/170
3/3 [=====] - 0s 71ms/step - loss: 0.0426
Epoch 94/170
3/3 [=====] - 0s 70ms/step - loss: 0.0371
Epoch 95/170
3/3 [=====] - 0s 71ms/step - loss: 0.0429
Epoch 96/170
3/3 [=====] - 0s 77ms/step - loss: 0.0421
Epoch 97/170
3/3 [=====] - 0s 70ms/step - loss: 0.0515
Epoch 98/170
3/3 [=====] - 0s 72ms/step - loss: 0.0386
Epoch 99/170
3/3 [=====] - 0s 72ms/step - loss: 0.0424
Epoch 100/170
3/3 [=====] - 0s 69ms/step - loss: 0.0452
Epoch 101/170
3/3 [=====] - 0s 73ms/step - loss: 0.0488
Epoch 102/170
3/3 [=====] - 0s 73ms/step - loss: 0.0507
Epoch 103/170
3/3 [=====] - 0s 76ms/step - loss: 0.0473
Epoch 104/170
3/3 [=====] - 0s 73ms/step - loss: 0.0453
Epoch 105/170
3/3 [=====] - 0s 71ms/step - loss: 0.0412

Epoch 106/170
3/3 [=====] - 0s 70ms/step - loss: 0.0388
Epoch 107/170
3/3 [=====] - 0s 78ms/step - loss: 0.0510
Epoch 108/170
3/3 [=====] - 0s 82ms/step - loss: 0.0503
Epoch 109/170
3/3 [=====] - 0s 85ms/step - loss: 0.0467
Epoch 110/170
3/3 [=====] - 0s 89ms/step - loss: 0.0459
Epoch 111/170
3/3 [=====] - 0s 75ms/step - loss: 0.0358
Epoch 112/170
3/3 [=====] - 0s 74ms/step - loss: 0.0438
Epoch 113/170
3/3 [=====] - 0s 75ms/step - loss: 0.0420
Epoch 114/170
3/3 [=====] - 0s 76ms/step - loss: 0.0418
Epoch 115/170
3/3 [=====] - 0s 83ms/step - loss: 0.0367
Epoch 116/170
3/3 [=====] - 0s 75ms/step - loss: 0.0408
Epoch 117/170
3/3 [=====] - 0s 73ms/step - loss: 0.0376
Epoch 118/170
3/3 [=====] - 0s 74ms/step - loss: 0.0399
Epoch 119/170
3/3 [=====] - 0s 87ms/step - loss: 0.0419
Epoch 120/170
3/3 [=====] - 0s 88ms/step - loss: 0.0347
Epoch 121/170
3/3 [=====] - 0s 75ms/step - loss: 0.0382
Epoch 122/170
3/3 [=====] - 0s 72ms/step - loss: 0.0359
Epoch 123/170
3/3 [=====] - 0s 80ms/step - loss: 0.0380
Epoch 124/170
3/3 [=====] - 0s 81ms/step - loss: 0.0330
Epoch 125/170
3/3 [=====] - 0s 80ms/step - loss: 0.0446
Epoch 126/170
3/3 [=====] - 0s 72ms/step - loss: 0.0302
Epoch 127/170
3/3 [=====] - 0s 71ms/step - loss: 0.0503
Epoch 128/170
3/3 [=====] - 0s 76ms/step - loss: 0.0286
Epoch 129/170
3/3 [=====] - 0s 78ms/step - loss: 0.0336

Epoch 130/170
3/3 [=====] - 0s 71ms/step - loss: 0.0345
Epoch 131/170
3/3 [=====] - 0s 78ms/step - loss: 0.0374
Epoch 132/170
3/3 [=====] - 0s 73ms/step - loss: 0.0280
Epoch 133/170
3/3 [=====] - 0s 81ms/step - loss: 0.0553
Epoch 134/170
3/3 [=====] - 0s 72ms/step - loss: 0.0373
Epoch 135/170
3/3 [=====] - 0s 72ms/step - loss: 0.0333
Epoch 136/170
3/3 [=====] - 0s 70ms/step - loss: 0.0295
Epoch 137/170
3/3 [=====] - 0s 73ms/step - loss: 0.0420
Epoch 138/170
3/3 [=====] - 0s 70ms/step - loss: 0.0263
Epoch 139/170
3/3 [=====] - 0s 70ms/step - loss: 0.0375
Epoch 140/170
3/3 [=====] - 0s 73ms/step - loss: 0.0250
Epoch 141/170
3/3 [=====] - 0s 69ms/step - loss: 0.0337
Epoch 142/170
3/3 [=====] - 0s 70ms/step - loss: 0.0414
Epoch 143/170
3/3 [=====] - 0s 72ms/step - loss: 0.0381
Epoch 144/170
3/3 [=====] - 0s 71ms/step - loss: 0.0455
Epoch 145/170
3/3 [=====] - 0s 72ms/step - loss: 0.0345
Epoch 146/170
3/3 [=====] - 0s 77ms/step - loss: 0.0369
Epoch 147/170
3/3 [=====] - 0s 75ms/step - loss: 0.0372
Epoch 148/170
3/3 [=====] - 0s 73ms/step - loss: 0.0419
Epoch 149/170
3/3 [=====] - 0s 72ms/step - loss: 0.0322
Epoch 150/170
3/3 [=====] - 0s 71ms/step - loss: 0.0376
Epoch 151/170
3/3 [=====] - 0s 75ms/step - loss: 0.0249
Epoch 152/170
3/3 [=====] - 0s 76ms/step - loss: 0.0312
Epoch 153/170
3/3 [=====] - 0s 84ms/step - loss: 0.0309

```

Epoch 154/170
3/3 [=====] - 0s 83ms/step - loss: 0.0299
Epoch 155/170
3/3 [=====] - 0s 77ms/step - loss: 0.0304
Epoch 156/170
3/3 [=====] - 0s 77ms/step - loss: 0.0315
Epoch 157/170
3/3 [=====] - 0s 71ms/step - loss: 0.0249
Epoch 158/170
3/3 [=====] - 0s 71ms/step - loss: 0.0234
Epoch 159/170
3/3 [=====] - 0s 73ms/step - loss: 0.0205
Epoch 160/170
3/3 [=====] - 0s 76ms/step - loss: 0.0296
Epoch 161/170
3/3 [=====] - 0s 78ms/step - loss: 0.0409
Epoch 162/170
3/3 [=====] - 0s 79ms/step - loss: 0.0355
Epoch 163/170
3/3 [=====] - 0s 75ms/step - loss: 0.0300
Epoch 164/170
3/3 [=====] - 0s 79ms/step - loss: 0.0284
Epoch 165/170
3/3 [=====] - 0s 82ms/step - loss: 0.0334
Epoch 166/170
3/3 [=====] - 0s 75ms/step - loss: 0.0393
Epoch 167/170
3/3 [=====] - 0s 85ms/step - loss: 0.0344
Epoch 168/170
3/3 [=====] - 0s 79ms/step - loss: 0.0234
Epoch 169/170
3/3 [=====] - 0s 82ms/step - loss: 0.0489
Epoch 170/170
3/3 [=====] - 0s 78ms/step - loss: 0.0372

```

[13]: <tensorflow.python.keras.callbacks.History at 0x7fb412c15dd0>

[14]: *# Part 3 - Making the predictions and visualizing the results*

```

data_test = pd.read_csv('case.csv')
real_disease = data_test.values

```

[15]:

```

inputs = data_test.values
inputs = inputs.reshape(-1,1)
inputs = sc.transform(inputs)
X_test = []
for i in range(90, 117):

```

```

X_test.append(inputs[i-90:i, 0])
X_test = np.array(X_test)
X_test = np.reshape(X_test, (X_test.shape[0], X_test.shape[1], 1))
predicted_disease = regressor.predict(X_test)
predicted_disease = sc.inverse_transform(predicted_disease)

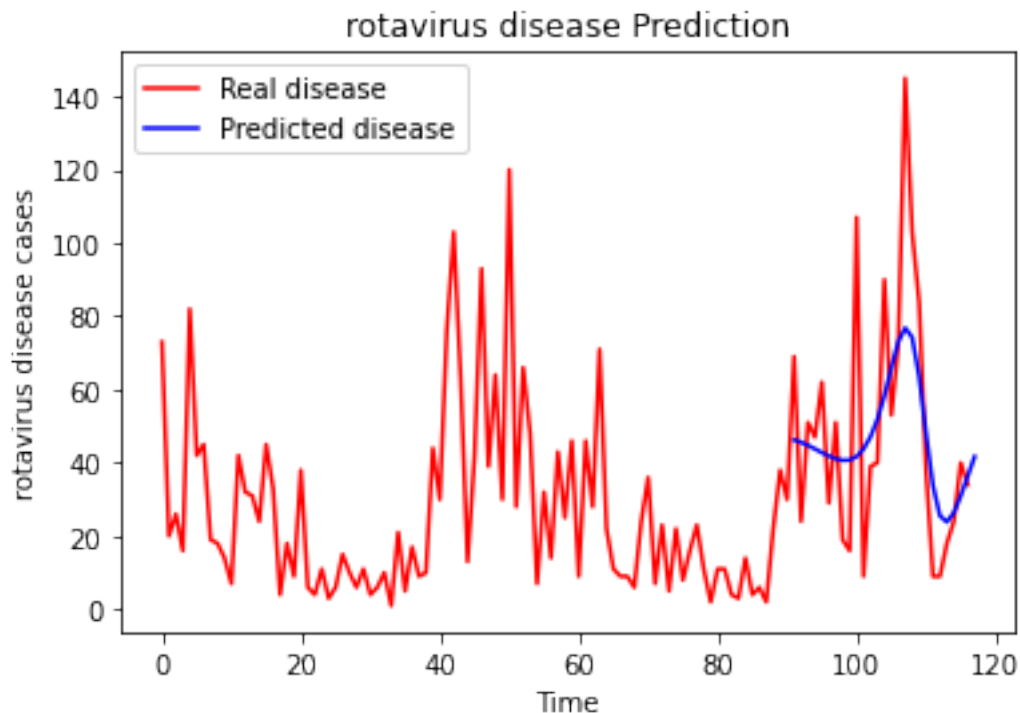
```

```

[17]: # Visualizing the results
plt.plot(real_disease, color = 'red', label = 'Real disease')
plt.plot(range(91, 91+len(predicted_disease)), predicted_disease, color = 'blue', label = 'Predicted disease')

plt.title('rotavirus disease Prediction')
plt.xlabel('Time')
plt.ylabel('rotavirus disease cases')
plt.legend()
plt.show()

```



- (e) We will compare the accuracy between LSTM models in (b), (c), (d) by checking the MSE. The MSE for (b), (c), (d) was 0.0080, 0.0147, 0.0372 respectively. From this, we see that (b) has the best accuracy and (d) has the lowest accuracy out of the three. This difference of MSE happens because (c), (d) considers past information more than (b). (b) only considered previous 30 weeks' information. So it is usually more accurate because present reported case of rotavirus disease is mostly affected by recent past. If the reported cases of rotavirus was low(high) in the recent past, the present and future cases of rotavirus will also be low(high).

In that sense, (b) is accurate as it only deals with the recent past. However, (c) and (d) also take into account “distant past” information. This is because they use previous 60 weeks’ and 90 weeks’ information respectively. Information about distant past might be good in capturing the long-term pattern, but it will dilute the information of the recent past by smoothing the case of rotavirus. This could be why there are such differences between three models.