In [1]:

#### LSTM ON TimeSeries DATA

#### NAME- PRABAL GHOSH

import matplotlib.pyplot as plt

```
import numpy as np
          import pandas as pd
In [2]:
          ### Load dataset
          from sklearn import datasets
          import tensorflow as tf
          import keras
          from tensorflow.keras.models import Model
          from tensorflow.keras.layers import Input, Dense
          from tensorflow.keras.losses import MeanSquaredLogarithmicError
In [3]:
          # filename = pd.read csv("C:\\Users\\praba\\Desktop\\uca1\\M1\\deep learning\\class
          # df_1 = pd.read_csv(filename, sep="\t", engine="python", on_bad_lines="skip")
          filename = "http://www.i3s.unice.fr/~riveill/dataset/precipitation.csv.zip"
          df = pd.read_csv(filename, sep="\t", engine="python", on_bad_lines="skip")
In [4]:
          df.describe()
Out[4]:
                        Year
                                   Jan
                                              Feb
                                                        Mar
                                                                   Apr
                                                                             May
                                                                                          Jun
                                                                                                      Jul
                   38.000000
                              38.000000
                                        38.000000
                                                   38.000000
                                                              38.000000
                                                                        38.000000
                                                                                    38.000000
                                                                                                38.000000
          count
          mean
                 1983.500000
                               0.294368
                                         1.101132
                                                    1.677184
                                                              12.381237
                                                                        25.059789
                                                                                   337.096395
                                                                                               430.010395 2
                               0.640510
                                          1.741219
            std
                   11.113055
                                                    2.486516
                                                              13.671071
                                                                        22.451708
                                                                                   171.666565
                                                                                               177.976444
                 1965.000000
                               0.000000
                                         0.000000
                                                    0.000000
                                                               0.061000
                                                                          0.508000
                                                                                    94.088000
                                                                                                84.936000
           min
                 1974.250000
                               0.000000
                                          0.000000
                                                    0.000000
                                                               2.291750
                                                                                   226.180250
           25%
                                                                          7.005250
                                                                                               322.461000
                               0.008000
           50%
                 1983.500000
                                         0.247500
                                                    0.596000
                                                               5.489500
                                                                         18.144500
                                                                                   312.100000
                                                                                               415.079500
                 1992.750000
                               0.248000
                                          1.948500
                                                    2.076000
                                                                         33.066000
                                                              19.796500
                                                                                   412.568250
                                                                                               555.284250
                 2002.000000
                               3.013000
                                          8.410000
                                                    9.619000
                                                              53.266000
                                                                        80.539000
                                                                                   773.737000
                                                                                               780.006000
                                                                                                          5
           max
In [5]:
          df.head()
                                                                                                          De
Out[5]:
                           Feb
                                                                  Jul
                                                                                           Oct
             Year
                    Jan
                                 Mar
                                         Apr
                                                May
                                                         Jun
                                                                          Aug
                                                                                   Sep
                                                                                                  Nov
             1965
                   0.029
                         0.069
                                0.000
                                      21.667
                                              17.859
                                                     102.111
                                                              606.071
                                                                       402.521
                                                                                 69.511
                                                                                         5.249
                                                                                                16.232
                                                                                                       22.07
             1966
                   0.905
                         0.000
                                0.000
                                       2.981
                                              63.008
                                                       94.088
                                                              481.942
                                                                        59.386
                                                                                150.624
                                                                                         1.308
                                                                                               41.214
                                                                                                        4.13
             1967
                  0.248
                         3.390
                                1.320
                                      13.482
                                              11.116
                                                     251.314
                                                              780.006
                                                                       181.069
                                                                                        50.404
                                                                                                 8.393
                                                                                                       37.68
          2
                                                                                183.757
            1968 0.318
                        3.035
                               1.704
                                      23.307
                                               7.441 179.872 379.354
                                                                      171.979
                                                                               219.884
                                                                                        73.997
                                                                                               23.326
                                                                                                        2.02
```

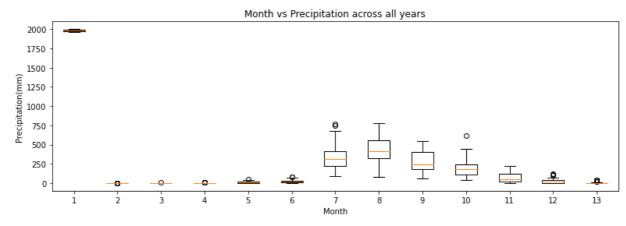
|   | Year | Jan   | Feb   | Mar   | Apr   | May   | Jun     | Jul     | Aug     | Sep     | Oct    | Nov    | De   |
|---|------|-------|-------|-------|-------|-------|---------|---------|---------|---------|--------|--------|------|
| 4 | 1969 | 0.248 | 2.524 | 0.334 | 4.569 | 6.213 | 393.682 | 678.354 | 397.335 | 205.413 | 24.014 | 24.385 | 1.95 |

```
import sklearn
from sklearn.model_selection import TimeSeriesSplit
```

```
import matplotlib.pyplot as plt

# df.set_index('Year', inplace=True)
plt.figure(figsize=(13,4))
plt.boxplot(df)
plt.xlabel('Month')
plt.ylabel('Precipitation(mm)')
plt.title('Month vs Precipitation across all years')

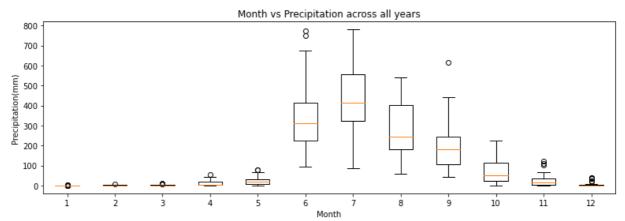
data = df.to_numpy().ravel()
```



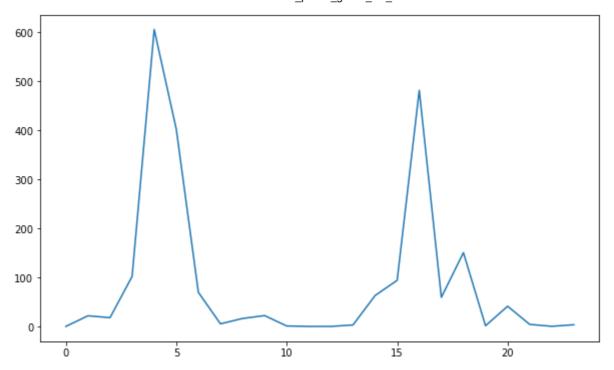
```
import matplotlib.pyplot as plt

df.set_index('Year', inplace=True)
  plt.figure(figsize=(13,4))
  plt.boxplot(df)
  plt.xlabel('Month')
  plt.ylabel('Precipitation(mm)')
  plt.title('Month vs Precipitation across all years')

data = df.to_numpy().ravel()
```



```
In [9]:
          #Prepare X and y
          input_with = 24
          offset = 0
          X = [data[i:i+input_with] for i in range(len(data)-input_with)]
          X = np.array(X)
          y = [data[i+input_with+offset] for i in range(len(data)-input_with)]
          y = np.array(y)
 In [ ]:
In [10]:
          X.shape, y.shape
          ((432, 24), (432,))
Out[10]:
In [11]:
          plt.figure(figsize=(16,8))
          plt.plot(data)
          [<matplotlib.lines.Line2D at 0x2688e17e460>]
Out[11]:
          800
          700
          500
          400
          300
          200
          100
           0
In [12]:
          plt.figure(figsize=(10,6))
          plt.plot(X[2])
          [<matplotlib.lines.Line2D at 0x268901d65e0>]
Out[12]:
```



```
import numpy as np
import tensorflow as tf
import keras
from keras import layers
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense
%matplotlib inline
```

# SOLUTION USING LSTM And CROSS VALIDATION ON TIME SERIES DATA

```
def plot_result(trainY, testY, train_predict, test_predict):
    actual = np.append(trainY, testY)
    predictions = np.append(train_predict, test_predict)
    rows = len(actual)
    plt.figure(figsize=(15, 6), dpi=80)
    plt.plot(range(rows), actual)
    plt.plot(range(rows), predictions)
    plt.axvline(x=len(trainY), color='r')
    plt.legend(['Actual', 'Predictions'])
    plt.xlabel('Observation number after given time steps')
    plt.ylabel('Sunspots scaled')
    plt.title('Actual and Predicted Values. The Red Line Separates The Training And
```

```
In [15]:
# def plot_loss(history):
# plt.plot(history.history["loss"])
# plt.plot(history.history["val_loss"])
# plt.title("validation loss & training loss")
# plt.xlabel("epochs")
# plt.ylabel("loss")
# leg = plt.legend(["training loss", "validation loss"],loc ="upper right");
# plt.show()
```

```
In [16]: # from sklearn.metrics import classification_report, confusion_matrix
# def plot_confusion_matrix(y_test,y_pred):
# conf_matrix = confusion_matrix(y_test,y_pred)
# plt.figure(figsize=(8, 6))
# plt.imshow(conf_matrix, cmap=plt.cm.Blues)
# plt.title('Confusion Matrix')
# plt.colorbar()
```

```
In [17]:
          import numpy as np
          from sklearn.model_selection import TimeSeriesSplit
          from sklearn.metrics import mean_squared_error
          from sklearn.preprocessing import MinMaxScaler
          from tensorflow.keras.models import Sequential
          from tensorflow.keras.layers import LSTM, Dense
          from tensorflow.keras.losses import MeanSquaredLogarithmicError
                                                               7 input 5; ze are conxnown
          # Build the LSTM model
          def build_model(input_shape):
              inputs =tf.keras.layers.Input(shape=(None,1)) 
              inputs_norm = tf.keras.layers.BatchNormalization()(inputs)
              lstm= tf.keras.layers.LSTM(128, return_sequences=False)(inputs_norm)
              outputs = tf.keras.layers.Dense(1, activation='linear')(lstm)
              model = Model(inputs, outputs)
              model.summary()
              optimizer = keras.optimizers.Adam(learning_rate=0.1)
              model.compile(optimizer=optimizer, loss=MeanSquaredLogarithmicError())
              return model
          #TimeSeriesSplit for cross-validation
          tscv = TimeSeriesSplit(n_splits=5)
          cv scores = []
          model = build model(input shape=(1, X.shape[1]))
          # callback = tf.keras.callbacks.EarlyStopping(monitor='val loss', patience=)
          print(tscv)
          history=[]
          for i, (train index, test index) in enumerate(tscv.split(X)):
              print(f"Fold {i}:")
              X train, X test = X[train index], X[test index]
              y_train, y_test = y[train_index], y[test_index]
              history.append(model.fit(X_train, y_train, epochs=100, validation_data=(X_test,y
```

Model: "model"

| Layer (type)   | Output Shape      | Param # |
|--|-------------------|---------|
| input_1 (InputLayer)                                 | [(None, None, 1)] | 0       |
| <pre>batch_normalization (BatchN ormalization)</pre> | (None, None, 1)   | 4       |
| lstm (LSTM)  | (None, 128)       | 66560   |

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Total params: 66,693 Trainable params: 66,691 Non-trainable params: 2

```
TimeSeriesSplit(gap=0, max_train_size=None, n_splits=5, test_size=None)
Fold 0:
Epoch 1/100
Epoch 2/100
Epoch 3/100
Epoch 4/100
Epoch 5/100
3/3 [============= - 0s 43ms/step - loss: 7.0774 - val loss: 11.282
Epoch 6/100
Epoch 7/100
Epoch 8/100
Epoch 9/100
Epoch 10/100
Epoch 11/100
Epoch 12/100
Epoch 13/100
3/3 [===========] - 0s 40ms/step - loss: 3.9706 - val loss: 3.2843
Epoch 14/100
3/3 [===========] - 0s 41ms/step - loss: 4.0015 - val loss: 3.3512
Epoch 15/100
3/3 [=========== ] - 0s 56ms/step - loss: 4.0057 - val loss: 3.3447
Epoch 16/100
Epoch 17/100
Epoch 18/100
3/3 [============ - 0s 42ms/step - loss: 4.0607 - val loss: 3.5851
Epoch 19/100
3/3 [============ - 0s 55ms/step - loss: 4.1620 - val loss: 3.6067
Epoch 20/100
Epoch 21/100
3/3 [============= ] - 0s 39ms/step - loss: 4.1405 - val_loss: 3.6648
Epoch 22/100
Epoch 23/100
Epoch 24/100
3/3 [============ - 0s 38ms/step - loss: 4.1389 - val loss: 3.4642
Epoch 25/100
```

```
Epoch 26/100
3/3 [===========] - 0s 41ms/step - loss: 3.8497 - val_loss: 3.4270
Epoch 28/100
3/3 [===========] - 0s 53ms/step - loss: 3.6362 - val_loss: 3.1118
Epoch 29/100
Epoch 30/100
Epoch 31/100
Epoch 32/100
3/3 [===========] - 0s 50ms/step - loss: 3.2357 - val_loss: 3.2757
Epoch 33/100
3/3 [===========] - 0s 44ms/step - loss: 3.8056 - val_loss: 2.8577
Epoch 34/100
3/3 [============= ] - 0s 43ms/step - loss: 3.1657 - val_loss: 2.7948
Epoch 35/100
Epoch 36/100
Epoch 37/100
Epoch 38/100
Epoch 39/100
Epoch 40/100
Epoch 41/100
Epoch 42/100
Epoch 43/100
Epoch 44/100
Epoch 45/100
3/3 [===========] - 0s 41ms/step - loss: 7.6401 - val loss: 7.7723
Epoch 46/100
Epoch 47/100
3/3 [==========] - 0s 42ms/step - loss: 7.9534 - val loss: 6.9655
Epoch 48/100
Epoch 49/100
Epoch 50/100
3/3 [===========] - 0s 39ms/step - loss: 5.6215 - val loss: 5.0673
Epoch 51/100
Epoch 52/100
Epoch 53/100
3/3 [===========] - 0s 44ms/step - loss: 4.9612 - val_loss: 5.0970
Epoch 54/100
Epoch 55/100
Epoch 56/100
3/3 [===========] - 0s 41ms/step - loss: 4.9036 - val loss: 5.0624
Epoch 57/100
```

```
Epoch 58/100
Epoch 59/100
Epoch 60/100
Epoch 61/100
Epoch 62/100
Epoch 63/100
Epoch 64/100
Epoch 65/100
Epoch 66/100
3/3 [============ ] - 0s 65ms/step - loss: 3.7905 - val_loss: 3.7848
Epoch 67/100
3/3 [===========] - 0s 67ms/step - loss: 3.6787 - val_loss: 3.6914
Epoch 68/100
3/3 [===========] - 0s 51ms/step - loss: 3.6227 - val_loss: 3.5693
Epoch 69/100
Epoch 70/100
Epoch 71/100
Epoch 72/100
Epoch 73/100
Epoch 74/100
Epoch 75/100
Epoch 76/100
Epoch 77/100
3/3 [=========== - 0s 51ms/step - loss: 5.3919 - val loss: 5.2198
Epoch 78/100
Epoch 79/100
3/3 [===========] - 0s 48ms/step - loss: 5.0886 - val loss: 5.0076
Epoch 80/100
Epoch 81/100
3/3 [===========] - 0s 47ms/step - loss: 4.8111 - val_loss: 4.9529
Epoch 82/100
3/3 [=========== ] - 0s 46ms/step - loss: 4.7225 - val loss: 5.0287
Epoch 83/100
Epoch 84/100
Epoch 85/100
Epoch 86/100
3/3 [=========== - 0s 37ms/step - loss: 4.7249 - val loss: 4.9382
Epoch 87/100
Epoch 88/100
3/3 [===========] - 0s 36ms/step - loss: 4.4562 - val loss: 4.5881
Epoch 89/100
```

```
Epoch 90/100
Epoch 91/100
3/3 [===========] - 0s 47ms/step - loss: 3.9167 - val_loss: 4.2727
Epoch 92/100
3/3 [===========] - 0s 47ms/step - loss: 3.8623 - val_loss: 3.8475
Epoch 93/100
3/3 [===========] - 0s 45ms/step - loss: 3.4269 - val_loss: 3.9413
Epoch 94/100
3/3 [===========] - 0s 42ms/step - loss: 3.4394 - val_loss: 3.9813
Epoch 95/100
Epoch 96/100
3/3 [===========] - 0s 38ms/step - loss: 3.1093 - val_loss: 3.2764
Epoch 97/100
3/3 [===========] - 0s 37ms/step - loss: 3.9212 - val_loss: 3.5875
Epoch 98/100
Epoch 99/100
Epoch 100/100
3/3 [===========] - 0s 48ms/step - loss: 4.0620 - val_loss: 3.9497
Fold 1:
Epoch 1/100
5/5 [===========] - 0s 39ms/step - loss: 3.8936 - val_loss: 3.9651
Epoch 2/100
5/5 [==========] - 0s 31ms/step - loss: 3.5640 - val_loss: 3.2679
Epoch 3/100
5/5 [===========] - 0s 31ms/step - loss: 2.9737 - val_loss: 2.5856
Epoch 4/100
5/5 [===========] - 0s 29ms/step - loss: 2.5543 - val_loss: 2.9232
Epoch 5/100
5/5 [=========== - 0s 33ms/step - loss: 2.3818 - val loss: 2.4831
Epoch 6/100
5/5 [============ ] - 0s 30ms/step - loss: 2.4282 - val_loss: 2.7243
Epoch 7/100
5/5 [===========] - 0s 29ms/step - loss: 2.4159 - val_loss: 2.3802
Epoch 8/100
5/5 [==========] - 0s 29ms/step - loss: 2.4446 - val_loss: 2.2925
Epoch 9/100
Epoch 10/100
5/5 [==========] - 0s 29ms/step - loss: 2.5609 - val_loss: 2.4358
Epoch 11/100
5/5 [==========] - 0s 29ms/step - loss: 2.4019 - val_loss: 2.9203
Epoch 12/100
5/5 [==========] - 0s 30ms/step - loss: 2.4459 - val_loss: 2.3429
Epoch 13/100
5/5 [=========== ] - 0s 29ms/step - loss: 2.2247 - val loss: 2.3740
Epoch 14/100
5/5 [==========] - 0s 29ms/step - loss: 2.0865 - val loss: 2.2945
Epoch 15/100
Epoch 16/100
Epoch 17/100
5/5 [==========] - 0s 28ms/step - loss: 2.0441 - val_loss: 2.1892
Epoch 18/100
5/5 [==========] - 0s 29ms/step - loss: 2.0488 - val loss: 3.0345
Epoch 19/100
Epoch 20/100
5/5 [===========] - 0s 30ms/step - loss: 2.2930 - val_loss: 2.3663
Epoch 21/100
```

```
5/5 [===========] - 0s 29ms/step - loss: 2.3586 - val_loss: 2.7413
Epoch 22/100
Epoch 23/100
5/5 [===========] - 0s 27ms/step - loss: 2.7323 - val_loss: 3.6878
Epoch 24/100
5/5 [===========] - 0s 25ms/step - loss: 2.6122 - val_loss: 2.9172
Epoch 25/100
5/5 [===========] - 0s 29ms/step - loss: 2.3756 - val_loss: 2.2375
Epoch 26/100
Epoch 27/100
5/5 [===========] - 0s 32ms/step - loss: 2.9155 - val_loss: 2.7355
Epoch 28/100
5/5 [=========== - 0s 28ms/step - loss: 2.7482 - val loss: 2.9143
Epoch 29/100
Epoch 30/100
Epoch 31/100
5/5 [===========] - 0s 27ms/step - loss: 5.6168 - val_loss: 6.3357
Epoch 32/100
5/5 [============ - 0s 28ms/step - loss: 5.6447 - val loss: 5.9107
Epoch 33/100
5/5 [===========] - 0s 29ms/step - loss: 5.5074 - val_loss: 5.6384
Epoch 34/100
Epoch 35/100
5/5 [===========] - 0s 28ms/step - loss: 5.1477 - val_loss: 5.4953
Epoch 36/100
5/5 [==========] - 0s 29ms/step - loss: 5.1699 - val_loss: 5.4517
Epoch 37/100
5/5 [=========== - 0s 27ms/step - loss: 5.0677 - val loss: 5.4457
Epoch 38/100
5/5 [===========] - 0s 27ms/step - loss: 5.1378 - val_loss: 5.5050
Epoch 39/100
5/5 [===========] - 0s 28ms/step - loss: 5.0833 - val_loss: 5.4792
Epoch 40/100
5/5 [===========] - 0s 30ms/step - loss: 5.0578 - val_loss: 5.4457
Epoch 41/100
5/5 [=========== - 0s 35ms/step - loss: 5.0536 - val loss: 5.4285
Epoch 42/100
5/5 [===========] - 0s 35ms/step - loss: 5.0802 - val_loss: 5.3810
Epoch 43/100
5/5 [===========] - 0s 34ms/step - loss: 5.0858 - val_loss: 5.3426
Epoch 44/100
5/5 [===========] - 0s 35ms/step - loss: 4.9881 - val_loss: 5.3923
Epoch 45/100
5/5 [=========== - 0s 33ms/step - loss: 4.9571 - val loss: 5.6751
Epoch 46/100
5/5 [==========] - 0s 33ms/step - loss: 5.1858 - val loss: 5.3443
Epoch 47/100
5/5 [==========] - 0s 30ms/step - loss: 4.9448 - val loss: 5.2768
Epoch 48/100
5/5 [============= ] - 0s 29ms/step - loss: 4.9203 - val_loss: 5.2714
Epoch 49/100
5/5 [==========] - 0s 27ms/step - loss: 4.8837 - val_loss: 5.2389
Epoch 50/100
5/5 [==========] - 0s 29ms/step - loss: 4.8303 - val loss: 5.1841
Epoch 51/100
Epoch 52/100
5/5 [===========] - 0s 28ms/step - loss: 4.8243 - val_loss: 5.2013
Epoch 53/100
```

```
5/5 [===========] - 0s 27ms/step - loss: 4.7941 - val_loss: 5.1996
Epoch 54/100
5/5 [===========] - 0s 30ms/step - loss: 4.9078 - val_loss: 5.3078
Epoch 55/100
5/5 [===========] - 0s 31ms/step - loss: 4.8332 - val_loss: 5.1384
Epoch 56/100
5/5 [===========] - 0s 30ms/step - loss: 4.7739 - val_loss: 5.1289
Epoch 57/100
5/5 [=========== ] - 0s 29ms/step - loss: 4.7376 - val_loss: 5.0994
Epoch 58/100
5/5 [=========== ] - 0s 30ms/step - loss: 4.7258 - val_loss: 5.0505
Epoch 59/100
5/5 [===========] - 0s 34ms/step - loss: 4.6905 - val_loss: 5.0129
Epoch 60/100
5/5 [==========] - 0s 31ms/step - loss: 4.7087 - val loss: 5.0099
Epoch 61/100
5/5 [==========] - 0s 29ms/step - loss: 4.6635 - val_loss: 4.9309
Epoch 62/100
Epoch 63/100
5/5 [===========] - 0s 28ms/step - loss: 4.5379 - val_loss: 4.8128
Epoch 64/100
5/5 [============ - 0s 30ms/step - loss: 4.4724 - val loss: 4.7913
Epoch 65/100
5/5 [==========] - 0s 29ms/step - loss: 4.4715 - val_loss: 4.6409
Epoch 66/100
5/5 [===========] - 0s 29ms/step - loss: 4.3060 - val_loss: 4.5174
Epoch 67/100
5/5 [===========] - 0s 29ms/step - loss: 4.2471 - val_loss: 4.4606
Epoch 68/100
5/5 [===========] - 0s 30ms/step - loss: 4.3227 - val_loss: 4.5835
Epoch 69/100
5/5 [=========== - 0s 29ms/step - loss: 4.4901 - val loss: 4.7700
Epoch 70/100
5/5 [===========] - 0s 28ms/step - loss: 4.3629 - val_loss: 4.5211
Epoch 71/100
Epoch 72/100
5/5 [==========] - 0s 28ms/step - loss: 4.3014 - val_loss: 4.2108
Epoch 73/100
5/5 [==========] - 0s 33ms/step - loss: 4.1055 - val loss: 4.4017
Epoch 74/100
5/5 [=========== - 0s 32ms/step - loss: 4.0197 - val loss: 4.0267
Epoch 75/100
5/5 [===========] - 0s 30ms/step - loss: 3.8563 - val_loss: 3.6726
Epoch 76/100
5/5 [==========] - 0s 29ms/step - loss: 3.4882 - val_loss: 3.8020
Epoch 77/100
5/5 [==========] - 0s 30ms/step - loss: 3.8619 - val loss: 3.3459
Epoch 78/100
5/5 [==========] - 0s 29ms/step - loss: 3.6292 - val loss: 3.5664
Epoch 79/100
Epoch 80/100
Epoch 81/100
5/5 [==========] - 0s 27ms/step - loss: 3.4200 - val_loss: 3.1112
Epoch 82/100
5/5 [===========] - 0s 30ms/step - loss: 2.8675 - val loss: 3.1052
Epoch 83/100
Epoch 84/100
5/5 [===========] - 0s 27ms/step - loss: 2.8395 - val_loss: 2.9787
Epoch 85/100
```

```
5/5 [===========] - 0s 28ms/step - loss: 3.5715 - val_loss: 4.7167
Epoch 86/100
5/5 [===========] - 0s 27ms/step - loss: 4.2993 - val_loss: 4.4631
Epoch 87/100
5/5 [===========] - 0s 26ms/step - loss: 4.0594 - val_loss: 3.8368
Epoch 88/100
5/5 [===========] - 0s 27ms/step - loss: 3.7937 - val_loss: 3.6079
Epoch 89/100
5/5 [==========] - 0s 28ms/step - loss: 3.5125 - val_loss: 4.0239
Epoch 90/100
5/5 [==========] - 0s 32ms/step - loss: 3.7586 - val_loss: 3.6399
Epoch 91/100
5/5 [===========] - 0s 30ms/step - loss: 3.3873 - val_loss: 3.0842
Epoch 92/100
5/5 [==========] - 0s 30ms/step - loss: 3.3885 - val loss: 3.6399
Epoch 93/100
5/5 [===========] - 0s 31ms/step - loss: 3.4000 - val_loss: 4.4841
Epoch 94/100
5/5 [===========] - 0s 32ms/step - loss: 3.3567 - val_loss: 3.0700
Epoch 95/100
Epoch 96/100
5/5 [=========== - 0s 33ms/step - loss: 2.4805 - val loss: 3.0375
Epoch 97/100
5/5 [===========] - 0s 32ms/step - loss: 3.3937 - val_loss: 3.5333
Epoch 98/100
5/5 [===========] - 0s 32ms/step - loss: 3.2631 - val_loss: 3.2215
Epoch 99/100
5/5 [============ ] - 0s 31ms/step - loss: 2.7398 - val_loss: 2.4361
Epoch 100/100
5/5 [===========] - 0s 30ms/step - loss: 2.7714 - val_loss: 3.0526
Fold 2:
Epoch 1/100
7/7 [==========] - 0s 32ms/step - loss: 3.0948 - val_loss: 3.2973
Epoch 2/100
7/7 [==========] - 0s 27ms/step - loss: 3.0683 - val_loss: 2.3011
Epoch 3/100
Epoch 4/100
7/7 [=========] - 0s 28ms/step - loss: 2.6853 - val loss: 2.2804
Epoch 5/100
7/7 [==========] - 0s 30ms/step - loss: 2.2625 - val loss: 2.1454
Epoch 6/100
7/7 [==========] - 0s 27ms/step - loss: 2.1445 - val loss: 3.1710
Epoch 7/100
7/7 [==========] - 0s 27ms/step - loss: 2.8023 - val_loss: 2.4865
Epoch 8/100
7/7 [==========] - 0s 27ms/step - loss: 2.2422 - val_loss: 2.2137
Epoch 9/100
7/7 [=========] - 0s 27ms/step - loss: 2.0824 - val loss: 2.9695
Epoch 10/100
7/7 [==========] - 0s 26ms/step - loss: 2.9683 - val loss: 2.8457
Epoch 11/100
7/7 [==========] - 0s 27ms/step - loss: 2.5426 - val_loss: 2.2180
Epoch 12/100
7/7 [==========] - 0s 27ms/step - loss: 2.1267 - val_loss: 2.5433
Epoch 13/100
7/7 [=========] - 0s 27ms/step - loss: 2.2596 - val loss: 2.7559
Epoch 14/100
7/7 [==========] - 0s 27ms/step - loss: 2.6882 - val_loss: 2.8341
Epoch 15/100
7/7 [=========] - 0s 27ms/step - loss: 2.6030 - val loss: 2.4468
Epoch 16/100
7/7 [===========] - 0s 27ms/step - loss: 2.1261 - val_loss: 2.6443
```

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Epoch 17/100
7/7 [==========] - 0s 27ms/step - loss: 2.4896 - val_loss: 2.6332
Epoch 18/100
7/7 [==========] - 0s 27ms/step - loss: 2.4935 - val_loss: 2.6991
Epoch 19/100
7/7 [==========] - 0s 28ms/step - loss: 2.6978 - val_loss: 3.3368
Epoch 20/100
7/7 [==========] - 0s 27ms/step - loss: 2.8214 - val_loss: 2.7079
Epoch 21/100
7/7 [==========] - 0s 28ms/step - loss: 2.5499 - val_loss: 2.8502
Epoch 22/100
7/7 [==========] - 0s 25ms/step - loss: 2.5698 - val_loss: 2.4512
Epoch 23/100
7/7 [==========] - 0s 26ms/step - loss: 2.5324 - val_loss: 2.5072
Epoch 24/100
7/7 [==========] - 0s 28ms/step - loss: 2.1281 - val_loss: 2.0684
Epoch 25/100
7/7 [==========] - 0s 31ms/step - loss: 1.9468 - val_loss: 3.3380
Epoch 26/100
7/7 [==========] - 0s 26ms/step - loss: 2.4315 - val_loss: 2.3507
Epoch 27/100
7/7 [==========] - 0s 24ms/step - loss: 2.1185 - val_loss: 1.9778
Epoch 28/100
7/7 [==========] - 0s 24ms/step - loss: 1.9646 - val_loss: 2.1393
Epoch 29/100
7/7 [==========] - 0s 28ms/step - loss: 2.0008 - val_loss: 2.2421
Epoch 30/100
7/7 [==========] - 0s 27ms/step - loss: 2.0599 - val_loss: 2.1157
Epoch 31/100
7/7 [==========] - 0s 28ms/step - loss: 2.0415 - val_loss: 2.8587
Epoch 32/100
7/7 [==========] - 0s 29ms/step - loss: 2.5469 - val_loss: 2.3986
Epoch 33/100
7/7 [=========] - 0s 27ms/step - loss: 2.3897 - val_loss: 2.5025
Epoch 34/100
7/7 [==========] - 0s 27ms/step - loss: 2.2386 - val_loss: 2.3658
Epoch 35/100
Epoch 36/100
7/7 [=========] - 0s 28ms/step - loss: 1.9762 - val loss: 3.0035
Epoch 37/100
7/7 [=========] - 0s 27ms/step - loss: 3.5990 - val_loss: 3.0889
Epoch 38/100
7/7 [==========] - 0s 27ms/step - loss: 2.7957 - val loss: 3.4747
Epoch 39/100
7/7 [==========] - 0s 28ms/step - loss: 3.2466 - val_loss: 3.0078
Epoch 40/100
7/7 [==========] - 0s 27ms/step - loss: 2.9446 - val_loss: 2.9464
Epoch 41/100
7/7 [=========] - 0s 27ms/step - loss: 2.9410 - val loss: 2.8565
Epoch 42/100
7/7 [==========] - 0s 27ms/step - loss: 2.5329 - val_loss: 3.0004
Epoch 43/100
Epoch 44/100
7/7 [==========] - 0s 27ms/step - loss: 2.4794 - val_loss: 2.8455
Epoch 45/100
7/7 [=========] - 0s 26ms/step - loss: 2.3370 - val loss: 2.5393
Epoch 46/100
7/7 [==========] - 0s 27ms/step - loss: 2.2643 - val_loss: 2.6842
Epoch 47/100
7/7 [==========] - 0s 28ms/step - loss: 2.3742 - val loss: 2.3956
Epoch 48/100
7/7 [===========] - 0s 29ms/step - loss: 2.1351 - val_loss: 2.5849
```

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Epoch 49/100
7/7 [==========] - 0s 27ms/step - loss: 2.0781 - val_loss: 2.2982
Epoch 50/100
7/7 [==========] - 0s 27ms/step - loss: 2.0757 - val_loss: 2.5739
Epoch 51/100
7/7 [==========] - 0s 27ms/step - loss: 2.0368 - val_loss: 2.6054
Epoch 52/100
7/7 [==========] - 0s 30ms/step - loss: 3.1404 - val_loss: 3.4278
Epoch 53/100
7/7 [==========] - 0s 28ms/step - loss: 3.5039 - val_loss: 2.8397
Epoch 54/100
7/7 [==========] - 0s 27ms/step - loss: 2.8471 - val_loss: 3.8260
Epoch 55/100
7/7 [==========] - 0s 27ms/step - loss: 2.4250 - val_loss: 2.2902
Epoch 56/100
7/7 [==========] - 0s 27ms/step - loss: 1.9254 - val_loss: 2.2315
Epoch 57/100
7/7 [==========] - 0s 30ms/step - loss: 2.2205 - val_loss: 2.5485
Epoch 58/100
7/7 [==========] - 0s 30ms/step - loss: 2.6187 - val_loss: 2.6864
Epoch 59/100
7/7 [==========] - 0s 27ms/step - loss: 2.5918 - val_loss: 2.5176
Epoch 60/100
7/7 [==========] - 0s 29ms/step - loss: 3.0066 - val_loss: 2.2837
Epoch 61/100
7/7 [==========] - 0s 27ms/step - loss: 2.5190 - val_loss: 3.2522
Epoch 62/100
7/7 [==========] - 0s 40ms/step - loss: 3.1531 - val_loss: 2.7940
Epoch 63/100
7/7 [==========] - 0s 37ms/step - loss: 2.4899 - val_loss: 2.3928
Epoch 64/100
7/7 [==========] - 0s 29ms/step - loss: 2.9910 - val_loss: 2.9242
Epoch 65/100
7/7 [==========] - 0s 29ms/step - loss: 2.7111 - val_loss: 2.8194
Epoch 66/100
7/7 [==========] - 0s 28ms/step - loss: 2.6559 - val_loss: 2.6329
Epoch 67/100
Epoch 68/100
7/7 [=========] - 0s 27ms/step - loss: 2.2795 - val loss: 3.2950
Epoch 69/100
7/7 [==========] - 0s 27ms/step - loss: 3.2899 - val_loss: 3.2116
Epoch 70/100
7/7 [=========] - 0s 26ms/step - loss: 2.6260 - val loss: 3.5478
Epoch 71/100
7/7 [==========] - 0s 28ms/step - loss: 2.8592 - val_loss: 3.2732
Epoch 72/100
7/7 [==========] - 0s 32ms/step - loss: 3.5701 - val_loss: 3.4925
Epoch 73/100
7/7 [==========] - 0s 27ms/step - loss: 3.2543 - val loss: 2.6324
Epoch 74/100
7/7 [==========] - 0s 29ms/step - loss: 2.6384 - val_loss: 6.0407
Epoch 75/100
7/7 [===========] - 0s 27ms/step - loss: 5.2042 - val_loss: 4.9478
Epoch 76/100
7/7 [==========] - 0s 26ms/step - loss: 3.5298 - val_loss: 3.6625
Epoch 77/100
7/7 [=========] - 0s 24ms/step - loss: 3.9782 - val loss: 3.5687
Epoch 78/100
7/7 [==========] - 0s 30ms/step - loss: 3.4687 - val_loss: 3.7367
Epoch 79/100
7/7 [=========] - 0s 26ms/step - loss: 3.2190 - val loss: 3.0060
Epoch 80/100
7/7 [==========] - 0s 24ms/step - loss: 2.6691 - val_loss: 3.3269
```

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Epoch 81/100
7/7 [==========] - 0s 26ms/step - loss: 2.3845 - val_loss: 3.2842
Epoch 82/100
7/7 [==========] - 0s 27ms/step - loss: 2.2791 - val_loss: 2.7360
Epoch 83/100
7/7 [==========] - 0s 26ms/step - loss: 2.3414 - val_loss: 2.7522
Epoch 84/100
7/7 [==========] - 0s 26ms/step - loss: 3.0671 - val_loss: 2.6676
Epoch 85/100
7/7 [==========] - 0s 24ms/step - loss: 2.2446 - val_loss: 2.7433
Epoch 86/100
7/7 [==========] - 0s 27ms/step - loss: 2.3732 - val_loss: 2.5512
Epoch 87/100
7/7 [==========] - 0s 32ms/step - loss: 2.2859 - val_loss: 2.5756
Epoch 88/100
7/7 [==========] - 0s 26ms/step - loss: 2.1740 - val_loss: 2.6735
Epoch 89/100
7/7 [==========] - 0s 27ms/step - loss: 2.9110 - val_loss: 2.6771
Epoch 90/100
7/7 [==========] - 0s 26ms/step - loss: 2.5594 - val_loss: 3.3647
Epoch 91/100
7/7 [==========] - 0s 25ms/step - loss: 2.6728 - val_loss: 3.1901
Epoch 92/100
7/7 [==========] - 0s 25ms/step - loss: 2.1615 - val_loss: 2.4087
Epoch 93/100
7/7 [==========] - 0s 26ms/step - loss: 1.9807 - val_loss: 2.6836
Epoch 94/100
7/7 [==========] - 0s 27ms/step - loss: 2.0427 - val_loss: 3.0950
Epoch 95/100
7/7 [==========] - 0s 28ms/step - loss: 2.2485 - val_loss: 2.8673
Epoch 96/100
7/7 [==========] - 0s 27ms/step - loss: 2.4800 - val_loss: 2.6092
Epoch 97/100
7/7 [==========] - 0s 26ms/step - loss: 2.3387 - val_loss: 2.4755
Epoch 98/100
7/7 [==========] - 0s 26ms/step - loss: 2.1373 - val_loss: 2.5074
Epoch 99/100
Epoch 100/100
7/7 [=========] - 0s 28ms/step - loss: 2.0302 - val loss: 2.7357
Fold 3:
Epoch 1/100
9/9 [==========] - 0s 31ms/step - loss: 2.4017 - val_loss: 2.7540
Epoch 2/100
9/9 [==========] - 0s 25ms/step - loss: 2.1853 - val_loss: 2.4017
Epoch 3/100
9/9 [==========] - 0s 24ms/step - loss: 2.1034 - val_loss: 2.0272
Epoch 4/100
9/9 [==========] - 0s 25ms/step - loss: 2.3644 - val loss: 5.7156
Epoch 5/100
9/9 [==========] - 0s 38ms/step - loss: 5.7082 - val_loss: 5.6067
Epoch 6/100
Epoch 7/100
9/9 [============= ] - 0s 30ms/step - loss: 3.2327 - val_loss: 3.4900
Epoch 8/100
9/9 [==========] - 0s 29ms/step - loss: 2.8862 - val_loss: 2.8901
Epoch 9/100
9/9 [=========] - 0s 32ms/step - loss: 2.9091 - val loss: 2.9636
Epoch 10/100
Epoch 11/100
Epoch 12/100
```

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9/9 [==========] - 0s 26ms/step - loss: 1.9342 - val_loss: 1.9460
Epoch 13/100
9/9 [==========] - 0s 24ms/step - loss: 2.2154 - val_loss: 2.8685
Epoch 14/100
9/9 [==========] - 0s 25ms/step - loss: 2.2410 - val_loss: 1.9680
Epoch 15/100
9/9 [==========] - Os 26ms/step - loss: 1.8896 - val_loss: 1.6646
Epoch 16/100
9/9 [==========] - 0s 23ms/step - loss: 2.1183 - val_loss: 1.9381
Epoch 17/100
9/9 [==========] - 0s 25ms/step - loss: 1.7313 - val_loss: 1.7857
Epoch 18/100
9/9 [===========] - 0s 28ms/step - loss: 2.0467 - val_loss: 1.8983
Epoch 19/100
9/9 [=========] - 0s 28ms/step - loss: 2.6430 - val loss: 2.9999
Epoch 20/100
9/9 [==========] - 0s 27ms/step - loss: 2.1987 - val_loss: 2.1931
Epoch 21/100
9/9 [==========] - 0s 24ms/step - loss: 2.1759 - val_loss: 2.0849
Epoch 22/100
9/9 [==========] - 0s 27ms/step - loss: 1.7009 - val_loss: 2.2392
Epoch 23/100
Epoch 24/100
9/9 [==========] - 0s 30ms/step - loss: 1.8653 - val_loss: 1.8000
Epoch 25/100
9/9 [==========] - 0s 28ms/step - loss: 2.4652 - val_loss: 3.0757
Epoch 26/100
9/9 [==========] - 0s 27ms/step - loss: 2.5600 - val_loss: 1.9881
Epoch 27/100
9/9 [===========] - Os 26ms/step - loss: 1.6478 - val_loss: 1.4858
Epoch 28/100
9/9 [==========] - 0s 26ms/step - loss: 1.5366 - val loss: 1.8258
Epoch 29/100
9/9 [==========] - 0s 26ms/step - loss: 2.0490 - val_loss: 2.7516
Epoch 30/100
Epoch 31/100
9/9 [==========] - 0s 25ms/step - loss: 5.4851 - val_loss: 6.3963
Epoch 32/100
9/9 [==========] - 0s 28ms/step - loss: 5.6154 - val loss: 5.3128
Epoch 33/100
9/9 [==========] - 0s 28ms/step - loss: 5.2119 - val_loss: 5.4329
Epoch 34/100
9/9 [==========] - 0s 25ms/step - loss: 5.2598 - val_loss: 5.4008
Epoch 35/100
9/9 [==========] - 0s 26ms/step - loss: 5.1727 - val_loss: 5.3255
Epoch 36/100
9/9 [==========] - 0s 26ms/step - loss: 5.1388 - val loss: 5.3076
Epoch 37/100
9/9 [==========] - 0s 30ms/step - loss: 5.1450 - val loss: 5.3132
Epoch 38/100
9/9 [==========] - 0s 30ms/step - loss: 5.1436 - val loss: 5.2801
Epoch 39/100
Epoch 40/100
9/9 [==========] - 0s 27ms/step - loss: 5.1165 - val_loss: 5.3284
Epoch 41/100
9/9 [=========] - 0s 28ms/step - loss: 5.2018 - val loss: 5.3490
Epoch 42/100
Epoch 43/100
9/9 [===========] - 0s 25ms/step - loss: 5.1484 - val_loss: 5.3080
Epoch 44/100
```

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9/9 [===========] - 0s 26ms/step - loss: 5.1584 - val_loss: 5.3084
Epoch 45/100
9/9 [==========] - 0s 26ms/step - loss: 5.1480 - val_loss: 5.3025
Epoch 46/100
9/9 [==========] - 0s 26ms/step - loss: 5.1360 - val_loss: 5.3017
Epoch 47/100
9/9 [===========] - 0s 25ms/step - loss: 5.1399 - val_loss: 5.3005
Epoch 48/100
9/9 [==========] - 0s 26ms/step - loss: 5.1364 - val_loss: 5.2899
Epoch 49/100
9/9 [===========] - 0s 26ms/step - loss: 5.1520 - val_loss: 5.3160
Epoch 50/100
9/9 [===========] - 0s 25ms/step - loss: 5.1410 - val_loss: 5.3028
Epoch 51/100
9/9 [==========] - 0s 25ms/step - loss: 5.1423 - val loss: 5.3021
Epoch 52/100
9/9 [==========] - 0s 26ms/step - loss: 5.1477 - val_loss: 5.2901
Epoch 53/100
9/9 [==========] - 0s 26ms/step - loss: 5.1304 - val_loss: 5.2860
Epoch 54/100
9/9 [==========] - 0s 29ms/step - loss: 5.1230 - val_loss: 5.2748
Epoch 55/100
9/9 [=========== - 0s 27ms/step - loss: 5.1145 - val loss: 5.2696
Epoch 56/100
9/9 [==========] - 0s 25ms/step - loss: 5.1293 - val_loss: 5.2786
Epoch 57/100
9/9 [===========] - 0s 26ms/step - loss: 5.1153 - val_loss: 5.2740
Epoch 58/100
9/9 [==========] - 0s 27ms/step - loss: 5.1201 - val_loss: 5.2689
Epoch 59/100
9/9 [==========] - 0s 27ms/step - loss: 5.1120 - val_loss: 5.2565
Epoch 60/100
9/9 [==========] - 0s 28ms/step - loss: 5.1152 - val loss: 5.2644
Epoch 61/100
9/9 [==========] - 0s 32ms/step - loss: 5.1116 - val_loss: 5.2593
Epoch 62/100
Epoch 63/100
9/9 [==========] - 0s 31ms/step - loss: 5.1149 - val_loss: 5.2620
Epoch 64/100
9/9 [==========] - 0s 32ms/step - loss: 5.1107 - val loss: 5.2515
Epoch 65/100
9/9 [==========] - 0s 32ms/step - loss: 5.1127 - val_loss: 5.2526
Epoch 66/100
9/9 [==========] - 0s 29ms/step - loss: 5.1020 - val_loss: 5.2515
Epoch 67/100
9/9 [===========] - 0s 25ms/step - loss: 5.0893 - val_loss: 5.2366
Epoch 68/100
9/9 [=========] - 0s 28ms/step - loss: 5.0622 - val loss: 5.2089
Epoch 69/100
9/9 [==========] - 0s 27ms/step - loss: 5.0606 - val loss: 5.2192
Epoch 70/100
9/9 [==========] - 0s 23ms/step - loss: 5.0481 - val loss: 5.1911
Epoch 71/100
Epoch 72/100
9/9 [==========] - 0s 24ms/step - loss: 5.1428 - val_loss: 5.0311
Epoch 73/100
9/9 [==========] - 0s 25ms/step - loss: 5.0310 - val loss: 5.1258
Epoch 74/100
Epoch 75/100
9/9 [===========] - 0s 23ms/step - loss: 5.1155 - val_loss: 5.3320
Epoch 76/100
```

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9/9 [==========] - 0s 26ms/step - loss: 5.1521 - val_loss: 5.3128
Epoch 77/100
9/9 [==========] - 0s 24ms/step - loss: 5.1514 - val_loss: 5.3208
Epoch 78/100
9/9 [==========] - 0s 23ms/step - loss: 5.1478 - val_loss: 5.3192
Epoch 79/100
9/9 [==========] - 0s 24ms/step - loss: 5.1560 - val_loss: 5.2844
Epoch 80/100
9/9 [==========] - 0s 23ms/step - loss: 5.1217 - val_loss: 5.2625
Epoch 81/100
9/9 [==========] - 0s 22ms/step - loss: 5.1810 - val_loss: 5.2698
Epoch 82/100
9/9 [===========] - 0s 27ms/step - loss: 5.1123 - val_loss: 5.2723
Epoch 83/100
9/9 [==========] - 0s 26ms/step - loss: 5.0847 - val loss: 5.2208
Epoch 84/100
9/9 [==========] - 0s 29ms/step - loss: 5.0540 - val_loss: 5.2165
Epoch 85/100
9/9 [===========] - 0s 25ms/step - loss: 5.0191 - val_loss: 5.1395
Epoch 86/100
9/9 [===========] - 0s 27ms/step - loss: 4.9547 - val_loss: 5.0661
Epoch 87/100
Epoch 88/100
9/9 [==========] - 0s 26ms/step - loss: 4.9560 - val_loss: 5.1980
Epoch 89/100
9/9 [==========] - 0s 26ms/step - loss: 4.9624 - val_loss: 5.1127
Epoch 90/100
9/9 [==========] - 0s 29ms/step - loss: 4.9449 - val_loss: 5.0438
Epoch 91/100
9/9 [==========] - 0s 29ms/step - loss: 5.0549 - val_loss: 5.0202
Epoch 92/100
9/9 [==========] - 0s 30ms/step - loss: 4.9386 - val loss: 4.9688
Epoch 93/100
9/9 [==========] - 0s 28ms/step - loss: 4.8132 - val_loss: 4.8960
Epoch 94/100
Epoch 95/100
9/9 [==========] - 0s 29ms/step - loss: 4.6038 - val_loss: 4.5746
Epoch 96/100
9/9 [=========] - 0s 29ms/step - loss: 4.5553 - val loss: 4.7144
Epoch 97/100
9/9 [==========] - 0s 27ms/step - loss: 4.5992 - val loss: 4.7457
Epoch 98/100
9/9 [==========] - 0s 26ms/step - loss: 4.7660 - val_loss: 4.7587
Epoch 99/100
9/9 [==========] - 0s 26ms/step - loss: 4.5925 - val_loss: 4.7553
Epoch 100/100
9/9 [==========] - 0s 25ms/step - loss: 4.5928 - val loss: 4.4966
Fold 4:
Epoch 1/100
43
Epoch 2/100
Epoch 3/100
76
Epoch 4/100
Epoch 5/100
```

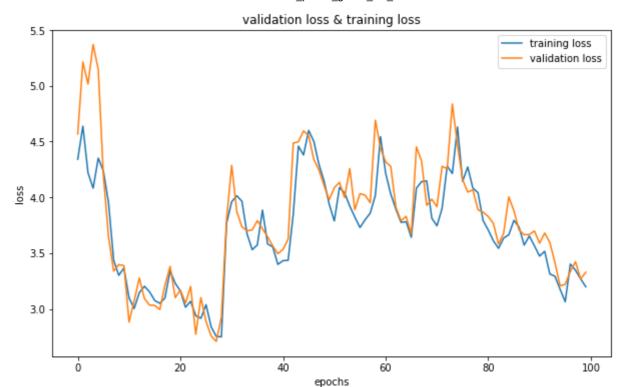
```
Epoch 6/100
57
Epoch 7/100
Epoch 8/100
Epoch 9/100
Epoch 10/100
Epoch 11/100
78
Epoch 12/100
Epoch 13/100
Epoch 14/100
80
Epoch 15/100
91
Epoch 16/100
Epoch 17/100
84
Epoch 18/100
77
Epoch 19/100
63
Epoch 20/100
44
Epoch 21/100
Epoch 22/100
62
Epoch 23/100
87
Epoch 24/100
Epoch 25/100
27
Epoch 26/100
```

```
Epoch 27/100
Epoch 28/100
56
Fnoch 29/100
33
Epoch 30/100
Epoch 31/100
Epoch 32/100
95
Epoch 33/100
77
Epoch 34/100
Epoch 35/100
Epoch 36/100
02
Epoch 37/100
Epoch 38/100
Epoch 39/100
12
Epoch 40/100
Epoch 41/100
Epoch 42/100
35
Epoch 43/100
Epoch 44/100
42
Epoch 45/100
84
Epoch 46/100
Epoch 47/100
61
Epoch 48/100
```

```
Epoch 49/100
97
Epoch 50/100
19
Epoch 51/100
Epoch 52/100
Epoch 53/100
15
Epoch 54/100
62
Epoch 55/100
Epoch 56/100
47
Epoch 57/100
Epoch 58/100
44
Epoch 59/100
Epoch 60/100
Epoch 61/100
02
Epoch 62/100
59
Epoch 63/100
Epoch 64/100
48
Epoch 65/100
Epoch 66/100
Epoch 67/100
Epoch 68/100
Epoch 69/100
```

```
Epoch 70/100
Epoch 71/100
Epoch 72/100
Epoch 73/100
Epoch 74/100
Epoch 75/100
47
Epoch 76/100
Epoch 77/100
Epoch 78/100
03
Epoch 79/100
08
Epoch 80/100
Epoch 81/100
Epoch 82/100
96
Epoch 83/100
46
Epoch 84/100
Epoch 85/100
Epoch 86/100
16
Epoch 87/100
01
Epoch 88/100
Epoch 89/100
98
Epoch 90/100
```

```
Epoch 91/100
    Epoch 92/100
    56
    Epoch 93/100
    75
    Epoch 94/100
    Epoch 95/100
    Epoch 96/100
    67
    Epoch 97/100
    26
    Epoch 98/100
    Epoch 99/100
    Epoch 100/100
    13
In [18]:
     history_train_loss=[i.history['loss'] for i in history]
     train_loss= np.mean(history_train_loss,axis=0) -> Mean of train_less
In [19]:
In [20]:
     history validation loss= [i.history['val loss'] for i in history]
     validation_loss= np.mean(history_validation_loss,axis=0) — mean of Validation_loss
In [21]:
In [40]:
     def plot loss(*history):
       plt.figure(figsize=(10,6))
       plt.plot(train_loss)
       plt.plot(validation_loss)
       plt.title("validation loss & training loss")
       plt.xlabel("epochs")
       plt.ylabel("loss")
       leg = plt.legend(["training loss", "validation loss"],loc ="upper right");
       plt.show()
In [41]:
     # loss plot with epochs
     plot_loss(train_loss,validation_loss)
```



```
In [24]: # plt.plot(train_loss)
    # plt.plot(validation_loss)
    # plt.title("validation loss & training loss")
    # plt.xlabel("epochs")
    # plt.ylabel("loss")
    # leg = plt.legend(["training loss", "validation loss"],loc ="upper right");
    # plt.show()
In []:
```

1.

# SOLUTION USING Sqquesntial model(LSTM) NEURAL NETWORK

```
In [25]:
         multi step dense 1 lstm = tf.keras.Sequential(
             tf.keras.layers.Input(shape=(None,1)),
                tf.keras.layers.BatchNormalization(),
          tf.keras.layers.LSTM(128, return_sequences=False),
             tf.keras.layers.Dense(1, activation='linear')
                                 ])
In [26]:
         multi_step_dense_1_lstm.summary()
        Model: "sequential"
         Layer (type)
                                  Output Shape
                                                          Param #
        ______
         batch normalization 1 (Batc (None, None, 1)
         hNormalization)
         lstm_1 (LSTM)
                                   (None, 128)
                                                          66560
```

129

(None, 1)

dense\_1 (Dense)

```
______
   Total params: 66,693
   Trainable params: 66,691
   Non-trainable params: 2
In [27]:
   # optimizer = keras.optimizers.Adam(learning rate=0.09)
   # multi_step_dense_1_lstm.compile(optimizer=optimizer, loss=MeanSquaredLogarithmicEr
   multi_step_dense_1_lstm.compile(optimizer='adam', loss=MeanSquaredLogarithmicError()
In [28]:
   callback = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=5)
In [29]:
   history = multi_step_dense_1_lstm.fit(X, y, epochs=500, validation_split=0.2,callbac
   Epoch 1/500
   Epoch 2/500
   84
   Epoch 3/500
   Epoch 4/500
   Epoch 5/500
   75
   Epoch 6/500
   47
   Epoch 7/500
   Epoch 8/500
   Epoch 9/500
   Epoch 10/500
   63
   Epoch 11/500
   Epoch 12/500
   Epoch 13/500
   44
   Epoch 14/500
   45
   Epoch 15/500
```

```
94
Epoch 16/500
17
Epoch 17/500
Epoch 18/500
Epoch 19/500
Epoch 20/500
Epoch 21/500
05
Epoch 22/500
Epoch 23/500
Epoch 24/500
12
Epoch 25/500
70
Epoch 26/500
Epoch 27/500
58
Epoch 28/500
Epoch 29/500
37
Epoch 30/500
Epoch 31/500
Epoch 32/500
04
Epoch 33/500
18
Epoch 34/500
Epoch 35/500
81
Epoch 36/500
```

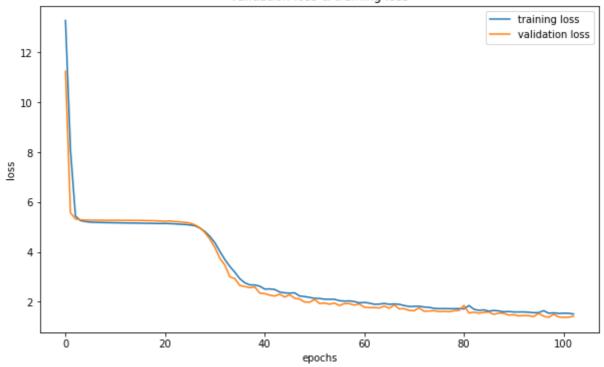
```
Epoch 37/500
Epoch 38/500
59
Epoch 39/500
Epoch 40/500
Epoch 41/500
Epoch 42/500
45
Epoch 43/500
96
Epoch 44/500
47
Epoch 45/500
Epoch 46/500
09
Epoch 47/500
Epoch 48/500
Epoch 49/500
09
Epoch 50/500
Epoch 51/500
Epoch 52/500
84
Epoch 53/500
Epoch 54/500
13
Epoch 55/500
95
Epoch 56/500
Epoch 57/500
95
Epoch 58/500
```

```
63
Epoch 59/500
Epoch 60/500
22
Epoch 61/500
Epoch 62/500
Epoch 63/500
57
Epoch 64/500
99
Epoch 65/500
Epoch 66/500
99
Epoch 67/500
10
Epoch 68/500
60
Epoch 69/500
Epoch 70/500
Epoch 71/500
15
Epoch 72/500
73
Epoch 73/500
Epoch 74/500
72
Epoch 75/500
Epoch 76/500
Epoch 77/500
Epoch 78/500
Epoch 79/500
```

```
Epoch 80/500
47
Epoch 81/500
Epoch 82/500
Epoch 83/500
Epoch 84/500
Epoch 85/500
50
Epoch 86/500
Epoch 87/500
Epoch 88/500
71
Epoch 89/500
50
Epoch 90/500
Epoch 91/500
99
Epoch 92/500
Epoch 93/500
67
Epoch 94/500
Epoch 95/500
Epoch 96/500
77
Epoch 97/500
22
Epoch 98/500
Epoch 99/500
87
Epoch 100/500
```

```
Epoch 101/500
        11/11 [=====
                            ========] - 0s 25ms/step - loss: 1.5406 - val_loss: 1.37
        Epoch 102/500
        89
        Epoch 103/500
                          =========] - 0s 26ms/step - loss: 1.5081 - val_loss: 1.42
        11/11 [========
In [30]:
        # history.history['loss']
In [ ]:
In [31]:
        plt.figure(figsize=(10,6))
        plt.plot(history.history["loss"])
        plt.plot(history.history["val_loss"])
        plt.title("validation loss & training loss")
        plt.xlabel("epochs")
        plt.ylabel("loss")
        leg = plt.legend(["training loss", "validation loss"],loc ="upper right");
        plt.show()
```

#### validation loss & training loss



```
In [ ]:
```

### **SOLUTION USING LSTM**

```
inputs =tf.keras.layers.Input(shape=(None,1))
inputs_norm = tf.keras.layers.BatchNormalization()(inputs)
lstm= tf.keras.layers.LSTM(128, return_sequences=False)(inputs_norm)
```

```
outputs = tf.keras.layers.Dense(1, activation='linear')(lstm)
model = Model(inputs, outputs)
model.summary()
```

Model: "model\_1"

```
Output Shape
                            Param #
    Layer (type)
    ______
                [(None, None, 1)]
    input_3 (InputLayer)
                            0
    batch_normalization_2 (Batc (None, None, 1)
    hNormalization)
    1stm_2 (LSTM)
                (None, 128)
                            66560
                (None, 1)
    dense_2 (Dense)
                            129
    _____
    Total params: 66,693
    Trainable params: 66,691
    Non-trainable params: 2
In [33]:
    from tensorflow.keras.losses import MeanSquaredLogarithmicError
    model.compile(optimizer='adam', loss=MeanSquaredLogarithmicError())
In [34]:
    callback = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=5)
In [35]:
    history = model.fit(X, y, epochs=500, validation_split=0.2,callbacks=[callback])
    Epoch 1/500
    9213
    Epoch 2/500
    Epoch 3/500
    17
    Epoch 4/500
    Epoch 5/500
    Epoch 6/500
    76
    Epoch 7/500
    42
    Epoch 8/500
    Epoch 9/500
    50
    Epoch 10/500
```

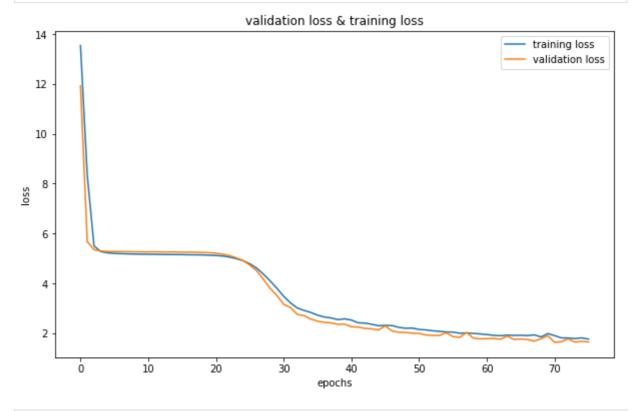
```
Epoch 11/500
Epoch 12/500
53
Epoch 13/500
92
Epoch 14/500
Epoch 15/500
Epoch 16/500
27
Epoch 17/500
05
Epoch 18/500
Epoch 19/500
Epoch 20/500
85
Epoch 21/500
Epoch 22/500
Epoch 23/500
67
Epoch 24/500
Epoch 25/500
Epoch 26/500
23
Epoch 27/500
Epoch 28/500
73
Epoch 29/500
12
Epoch 30/500
Epoch 31/500
27
Epoch 32/500
```

```
Epoch 33/500
57
Epoch 34/500
59
Epoch 35/500
Epoch 36/500
Epoch 37/500
79
Epoch 38/500
39
Epoch 39/500
Epoch 40/500
Epoch 41/500
72
Epoch 42/500
82
Epoch 43/500
Epoch 44/500
Epoch 45/500
08
Epoch 46/500
Epoch 47/500
Epoch 48/500
86
Epoch 49/500
Epoch 50/500
Epoch 51/500
Epoch 52/500
Epoch 53/500
```

```
Epoch 54/500
Epoch 55/500
Epoch 56/500
47
Epoch 57/500
Epoch 58/500
Epoch 59/500
24
Epoch 60/500
Epoch 61/500
Epoch 62/500
14
Epoch 63/500
73
Epoch 64/500
Epoch 65/500
99
Epoch 66/500
59
Epoch 67/500
58
Epoch 68/500
Epoch 69/500
Epoch 70/500
35
Epoch 71/500
12
Epoch 72/500
Epoch 73/500
31
Epoch 74/500
```

```
In [36]:
    plt.figure(figsize=(10,6))

    plt.plot(history.history["loss"])
    plt.plot(history.history["val_loss"])
    plt.title("validation loss & training loss")
    plt.xlabel("epochs")
    plt.ylabel("loss")
    leg = plt.legend(["training loss", "validation loss"],loc ="upper right");
    plt.show()
```



In [ ]:

## SOLUTION USING NORMAL NEURAL NETWORK

```
multi_step_dense = tf.keras.Sequential([
    tf.keras.layers.Input(shape=(24,1)),
    tf.keras.layers.Flatten(),
    tf.keras.layers.BatchNormalization(),

# Shape: (time, features) => (time*features)
    tf.keras.layers.Dense(units=32, activation='relu'),
    tf.keras.layers.Dense(units=1),
])
```

```
multi_step_dense.summary()
from tensorflow.keras.losses import MeanSquaredLogarithmicError
multi_step_dense.compile(optimizer='adam', loss=MeanSquaredLogarithmicError())
```

Model: "sequential\_1"

| Layer (type)                            | Output Shape | Param # |  |  |  |  |  |
|---|--------------|---------|--|--|--|--|--|
| ======================================= |              | ======= |  |  |  |  |  |
| flatten (Flatten)                       | (None, 24)   | 0       |  |  |  |  |  |
|   |              |         |  |  |  |  |  |
| batch_normalization_3 (Batc             | (None, 24)   | 96      |  |  |  |  |  |
| hNormalization)                         |              |         |  |  |  |  |  |
| •                                       |              |         |  |  |  |  |  |
| dense 3 (Dense)                         | (None, 32)   | 800     |  |  |  |  |  |
| dense_5 (sense)                         | (, 52)       |         |  |  |  |  |  |
| dense 4 (Dense)                         | (None, 1)    | 33      |  |  |  |  |  |
| dense_4 (bense)                         | (None; 1)    | 33      |  |  |  |  |  |
|   |              |         |  |  |  |  |  |
| T-+-1 020                               |              |         |  |  |  |  |  |
| Total params: 929                       |              |         |  |  |  |  |  |
| Trainable narams: 881                   |              |         |  |  |  |  |  |

Trainable params: 881
Non-trainable params: 48

```
In [38]:
```

```
callback = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=3)
history = multi_step_dense.fit(X, y, epochs=350, validation_split=0.2,callbacks=[cal
```

```
Epoch 1/350
Epoch 2/350
44
Epoch 3/350
Epoch 4/350
Epoch 5/350
Epoch 6/350
Epoch 7/350
Epoch 8/350
Epoch 9/350
Epoch 10/350
Epoch 11/350
8
Epoch 12/350
```

```
Epoch 13/350
Epoch 14/350
Epoch 15/350
Epoch 16/350
Epoch 17/350
Epoch 18/350
Epoch 19/350
Epoch 20/350
Epoch 21/350
Epoch 22/350
Epoch 23/350
Epoch 24/350
Epoch 25/350
Epoch 26/350
Epoch 27/350
Epoch 28/350
Epoch 29/350
Epoch 30/350
Epoch 31/350
Epoch 32/350
Epoch 33/350
```

```
Epoch 34/350
Epoch 35/350
Epoch 36/350
Epoch 37/350
Epoch 38/350
Epoch 39/350
Epoch 40/350
Epoch 41/350
Epoch 42/350
Epoch 43/350
Epoch 44/350
Epoch 45/350
Epoch 46/350
Epoch 47/350
Epoch 48/350
Epoch 49/350
Epoch 50/350
Epoch 51/350
Epoch 52/350
Epoch 53/350
Epoch 54/350
Epoch 55/350
```

```
Epoch 56/350
Epoch 57/350
Epoch 58/350
Epoch 59/350
Epoch 60/350
Epoch 61/350
Epoch 62/350
Epoch 63/350
Epoch 64/350
Epoch 65/350
Epoch 66/350
Epoch 67/350
Epoch 68/350
Epoch 69/350
Epoch 70/350
Epoch 71/350
Epoch 72/350
Epoch 73/350
11/11 [============] - 0s 5ms/step - loss: 1.5427 - val_loss: 1.514
Epoch 74/350
Epoch 75/350
Epoch 76/350
```

```
Epoch 77/350
Epoch 78/350
Epoch 79/350
Epoch 80/350
Epoch 81/350
Epoch 82/350
Epoch 83/350
Epoch 84/350
Epoch 85/350
Epoch 86/350
Epoch 87/350
Epoch 88/350
Epoch 89/350
Epoch 90/350
Epoch 91/350
Epoch 92/350
Epoch 93/350
Epoch 94/350
Epoch 95/350
Epoch 96/350
Epoch 97/350
```

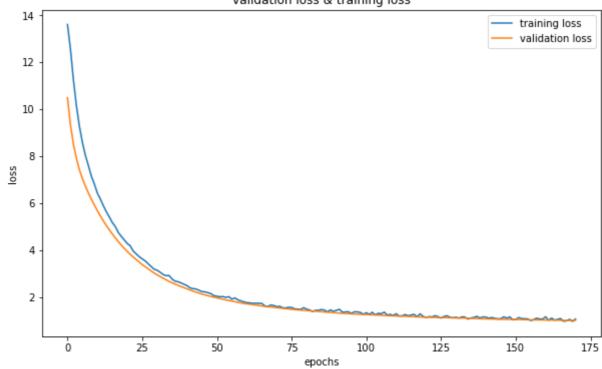
```
Epoch 98/350
Epoch 99/350
Epoch 100/350
Epoch 101/350
Epoch 102/350
Epoch 103/350
Epoch 104/350
Epoch 105/350
Epoch 106/350
Epoch 107/350
Epoch 108/350
Epoch 109/350
Epoch 110/350
Epoch 111/350
Epoch 112/350
Epoch 113/350
Epoch 114/350
Epoch 115/350
Epoch 116/350
Epoch 117/350
Epoch 118/350
Epoch 119/350
```

```
Epoch 120/350
Epoch 121/350
Epoch 122/350
Epoch 123/350
Epoch 124/350
Epoch 125/350
Epoch 126/350
Epoch 127/350
Epoch 128/350
Epoch 129/350
Epoch 130/350
Epoch 131/350
Epoch 132/350
Epoch 133/350
Epoch 134/350
Epoch 135/350
Epoch 136/350
Epoch 137/350
Epoch 138/350
Epoch 139/350
Epoch 140/350
```

```
Epoch 141/350
Epoch 142/350
Epoch 143/350
Epoch 144/350
Epoch 145/350
Epoch 146/350
Epoch 147/350
Epoch 148/350
Epoch 149/350
Epoch 150/350
Epoch 151/350
Epoch 152/350
Epoch 153/350
Epoch 154/350
Epoch 155/350
Epoch 156/350
Epoch 157/350
Epoch 158/350
Epoch 159/350
Epoch 160/350
Epoch 161/350
```

```
Epoch 162/350
   Epoch 163/350
   Epoch 164/350
   Epoch 165/350
   Epoch 166/350
   Epoch 167/350
   Epoch 168/350
   Epoch 169/350
   Epoch 170/350
   Epoch 171/350
   In [39]:
   plt.figure(figsize=(10,6))
   plt.plot(history.history["loss"])
   plt.plot(history.history["val_loss"])
   plt.title("validation loss & training loss")
   plt.xlabel("epochs")
   plt.ylabel("loss")
   leg = plt.legend(["training loss", "validation loss"],loc ="upper right");
   plt.show()
```





In [ ]: