Mini project Report

Predicting Traffic Flow Project

Author by:

Saleh Alanazi

Anas Alwohaib

Khuzama Alsenan

Alyaa Bajaber

EDA:

LSTM

Import libraries

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import SimpleRNN,LSTM,GRU, Dense,Dropout
from keras.optimizers import SGD
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error
from google.colab import drive
import math
from tensorflow.keras.preprocessing.sequence import TimeseriesGenerator
from keras.utils import timeseries_dataset_from_array
```

Random seed

```
# fix random seed for reproducibility
tf.random.set_seed(23)
```

Load dataset

```
df = pd.read_csv('/content/telraam.csv',parse_dates=['Date'],index_col=['Date'])
df.head()
```

	Bike	Car	Lorry	speed_00	speed_10	speed_20	speed_30	speed_40	speed_50	speed_60
Date										
2020-06-11 16:00:00+00:00	0.0	24.0	0.0	12.0	12.0	NaN	NaN	NaN	NaN	NaN
2020-06-16 10:00:00+00:00	63.0	682.0	0.0	210.0	242.0	158.0	53.0	11.0	11.0	NaN
2020-06-16 11:00:00+00:00	56.0	747.0	0.0	131.0	230.0	266.0	92.0	11.0	4.0	4.0
2020-06-16 12:00:00+00:00	45.0	539.0	0.0	171.0	92.0	168.0	68.0	15.0	13.0	8.0
2020-06-16 14:00:00+00:00	125.0	820.0	0.0	322.0	365.0	102.0	15.0	8.0	5.0	3.0

Exploratory Data Analysis (EDA)

```
[ ] df.head()
```

Date	Bike	Car	Lorry	speed_00	speed_10	speed_20	speed_30	speed_40	speed_50	speed_60
2020-06-11 16:00:00+00:00	0.0	24.0	0.0	12.0	12.0	NaN	NaN	NaN	NaN	NaN
2020-06-16 10:00:00+00:00	63.0	682.0	0.0	210.0	242.0	158.0	53.0	11.0	11.0	NaN
2020-06-16 11:00:00+00:00	56.0	747.0	0.0	131.0	230.0	266.0	92.0	11.0	4.0	4.0
2020-06-16 12:00:00+00:00	45.0	539.0	0.0	171.0	92.0	168.0	68.0	15.0	13.0	8.0
2020-06-16 14:00:00+00:00	125.0	820.0	0.0	322.0	365.0	102.0	15.0	8.0	5.0	3.0

```
[ ] df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 971 entries, 2020-06-11 16:00:00+00:00 to 2020-08-10 10:00:00+00:00
Data columns (total 10 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Bike      971 non-null    float64
 1   Car       971 non-null    float64
 2   Lorry     971 non-null    float64
 3   speed_00  674 non-null    float64
```

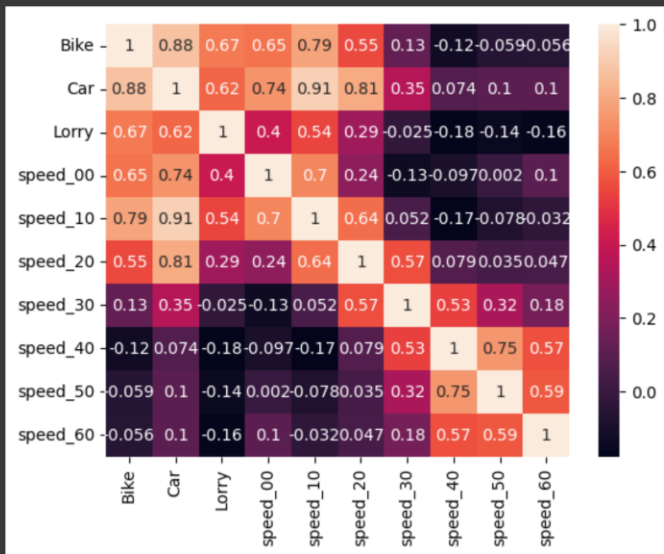
```
[ ] df.describe()
```

	Bike	Car	Lorry	speed_00	speed_10	speed_20	speed_30	speed_40	speed_50	speed_60
count	971.000000	971.000000	971.000000	674.000000	672.000000	678.000000	667.000000	612.000000	525.000000	440.000000
mean	41.112130	302.804337	28.282472	98.398547	142.900248	134.265817	39.943424	10.241764	5.296795	3.989924
std	42.401791	279.531658	40.646932	87.620351	96.127674	81.860653	29.069642	10.802235	5.530055	3.673575
min	0.000000	0.000000	0.000000	1.271635	1.298233	1.281139	1.298233	1.260063	1.259182	1.268052
25%	0.000000	0.000000	0.000000	19.917127	56.441863	72.371838	18.480058	3.995931	2.455662	1.545735
50%	30.953271	283.296214	0.000000	74.291481	134.858440	141.629697	34.532374	7.567878	3.868195	2.864533
75%	71.587284	574.128713	54.915412	167.852593	227.082172	201.140949	54.000000	13.191330	6.498195	5.000000
max	167.142857	920.000000	208.862494	347.088315	408.199872	303.000000	164.258555	125.000000	51.891892	41.379310

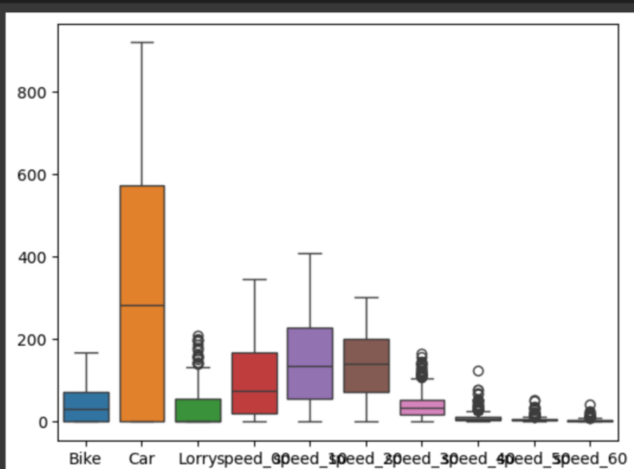
```
[ ] df.isnull().sum()
```

	0
Bike	0
Car	0
Lorry	0
speed_00	297

```
num_columns = df.select_dtypes(include=['number','float64'])
sns.heatmap(num_columns.corr(),annot=True)
plt.show()
```



```
sns.boxplot(df)
plt.show()
```



Data processing:

Data Preprocessing

```
miss_val_col = ['speed_00','speed_10','speed_20','speed_30','speed_40','speed_50','speed_60']

for col in miss_val_col:
    df[col].fillna(0, inplace=True)

df.isnull().sum()
```

	0
Bike	0
Car	0
Lorry	0
speed_00	0
speed_10	0
speed_20	0
speed_30	0
speed_40	0
speed_50	0
speed_60	0

```
def remove_outliers(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return df[(df[column] >= lower_bound) & (df[column] <= upper_bound)]

    for col in df.columns:
     df = remove_outliers(df,df.col)
```

```
df.duplicated().sum()
```

```
277
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 971 entries, 2020-06-11 16:00:00+00:00 to 2020-08-10 10:00:00+00:00
Data columns (total 10 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Bike      971 non-null    float64
 1   Car       971 non-null    float64
 2   Lorry     971 non-null    float64
 3   speed_00  971 non-null    float64
 4   speed_10  971 non-null    float64
 5   speed_20  971 non-null    float64
 6   speed_30  971 non-null    float64
 7   speed_40  971 non-null    float64
```

Feature engineering:

Feature Engineering

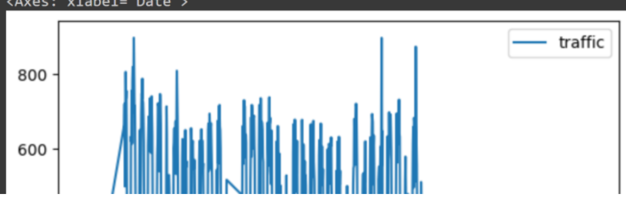
```python
df['traffic'] = df['speed_00'] + df['speed_10'] + df['speed_20'] + df['speed_30']
```

```python
[ ] df.drop(columns=['Bike','Car',
                    'Lorry','speed_00',
                    'speed_10','speed_20',
                    'speed_30','speed_40',
                    'speed_50','speed_60'], inplace=True)
```

Plot Data

```python
[ ] df.plot()
```

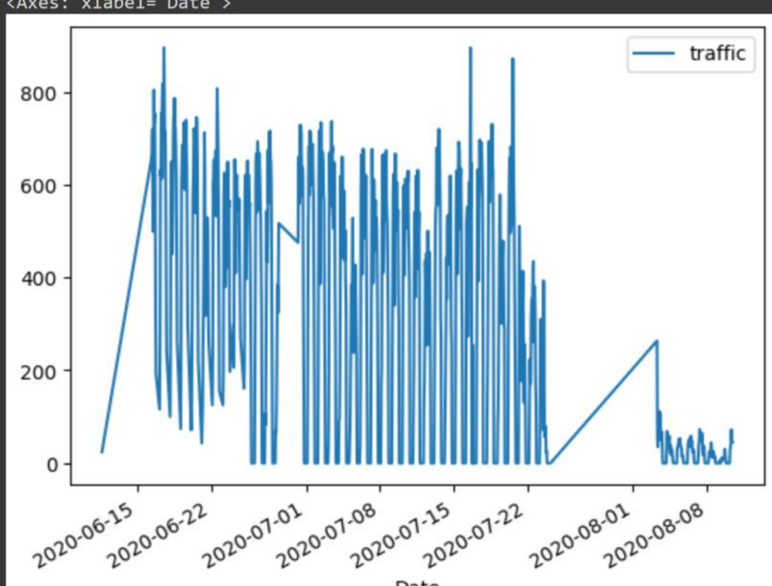
<Axes: xlabel='Date'>



Plot Data

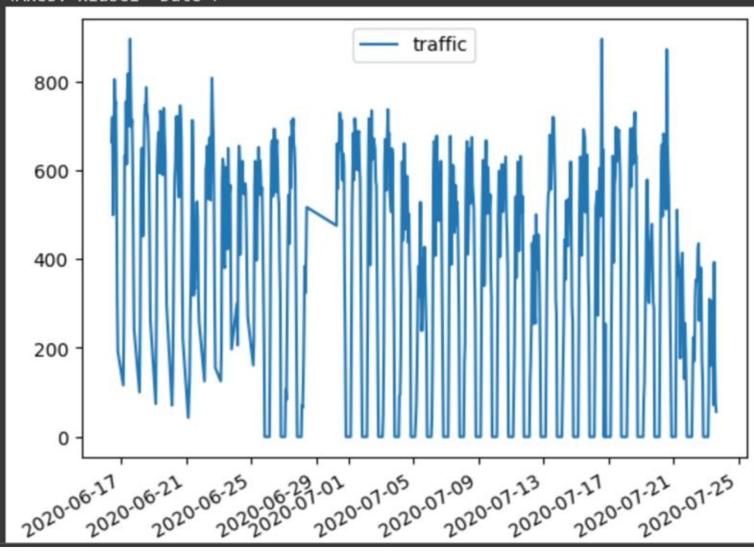
```python
[ ] df.plot()
```

<Axes: xlabel='Date'>



```
df.sort_index(inplace=True)
df.drop(index=df[:'2020-06-16 00:00:00+00:00'].index,inplace=True)

df.drop(index=df['2020-07-23 16:00:00+00:00':].index,inplace=True)

df.plot()
```

```
<Axes: xlabel='Date'>
```



Train test split:

Train-Test Split

```
splitindex = int(len(df)*0.7)
splitdate = df.index[splitindex]

train = df.loc[:splitdate]

valindex = int(len(df) * 0.85)
valdate = df.index[valindex]
val = df.loc[splitdate:valdate]

test = df.loc[valdate:]
```

Feature scalling:

Feature Scaling

```
[ ] sc = MinMaxScaler()

    sc.fit(train) # scale for just train
    train_scaled = sc.transform(train) # train
    val_scaled = sc.transform(val) # val
    test_scaled = sc.transform(test) # test
```

```
[ ] Window_size = 2

    trainxy =timeseries_dataset_from_array(train_scaled, targets = train_scaled[2:], sequence_length =Window_size)
    valxy =timeseries_dataset_from_array(val_scaled, targets = val_scaled[2:], sequence_length =Window_size)
    testxy =timeseries_dataset_from_array(test_scaled, targets = test_scaled[2:], sequence_length =Window_size)
```

1-Using RNN model:

Using RNN Model

Building the RNN Model

```
[ ] model_RNN = Sequential([SimpleRNN(units=32, activation='tanh', return_sequences=True), # 1st Hidden layer
                            SimpleRNN(units=64, activation='tanh', return_sequences=True),  # 2nd Hidden layer
                            SimpleRNN(units=128, activation='tanh'),  # 3rd Hidden layer
                            Dropout(0.2),
                           Dense(units=1, activation='relu')]) # Output

    model_RNN.compile(optimizer='adam', loss='mae', metrics=['mae'] )
```

Fit the RNN Model

```
[ ] RNN_History = model_RNN.fit(trainxy, validation_data=valxy, epochs=20)
```

```
Epoch 1/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 6s 144ms/step - loss: 0.2064 - mae: 0.2064 - val_loss: 0.1585 - val_mae: 0.1585
Epoch 2/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - loss: 0.1825 - mae: 0.1825 - val_loss: 0.1678 - val_mae: 0.1678
Epoch 3/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step - loss: 0.1901 - mae: 0.1901 - val_loss: 0.1613 - val_mae: 0.1613
```

```
Model: "sequential"
```

Layer (type)	Output Shape	Param #
simple_rnn (SimpleRNN)	(None, None, 32)	1,088
simple_rnn_1 (SimpleRNN)	(None, None, 64)	6,208
simple_rnn_2 (SimpleRNN)	(None, 128)	24,704
dropout (Dropout)	(None, 128)	0
dense (Dense)	(None, 1)	129

```
Total params: 96,389 (376.52 KB)
Trainable params: 32,129 (125.50 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 64,260 (251.02 KB)
```

RNN prediction and evaluation:

```
Epoch 17/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step - loss: 0.1087 - mae: 0.1087 - val_loss: 0.0997 - val_mae: 0.0997
Epoch 18/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 32ms/step - loss: 0.1056 - mae: 0.1056 - val_loss: 0.0992 - val_mae: 0.0992
Epoch 19/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step - loss: 0.1095 - mae: 0.1095 - val_loss: 0.1005 - val_mae: 0.1005
Epoch 20/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step - loss: 0.1045 - mae: 0.1045 - val_loss: 0.0993 - val_mae: 0.0993
```

Make preductuion RNN Model

```
for b in testxy:
    test_X, test_y = b
    pred_RNN = model_RNN.predict(test_X)
```

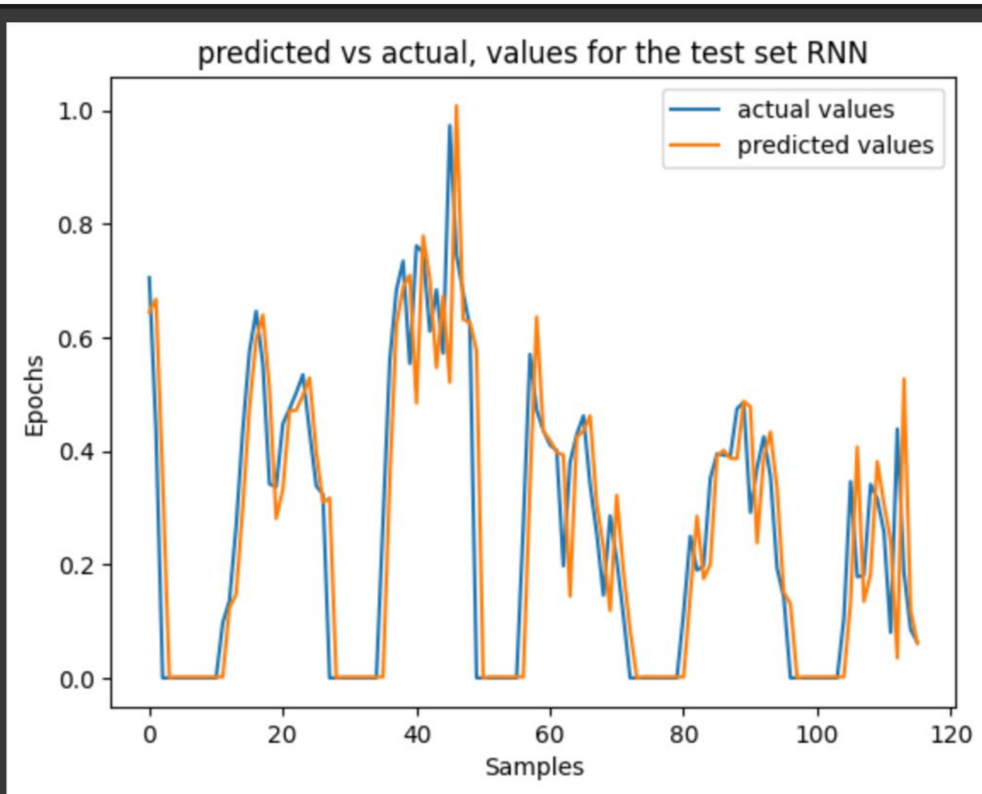
```
4/4 ━━━━━━━━━━━━━━━━━━━━ 1s 117ms/step
```

Make Evaluation RNN Model

```
MAE_val = RNN_History.history['val_mae']

final_MAEval = MAE_val[-1]
print(f'The value of MAE for RNN: {final_MAEval:.4f}')
```

```
The value of MAE for RNN: 0.0993
```

```
predits = []
act_val = []

predits.extend(pred_RNN.flatten())
act_val.extend(test_y.numpy().flatten())

plt.plot(act_val, label='actual values')
plt.plot(predits, label='predicted values')
plt.title('predicted vs actual, values for the test set RNN')
plt.legend()
plt.xlabel('Samples')
plt.ylabel('Epochs')
plt.show()
```




```
plt.plot(RNN_History.history['mae'], label='Training MAE')
plt.plot(RNN_History.history['val_mae'], label='Validation MAE')
plt.legend()
plt.show()
```

2-Using LSTM model:

Using LSTM Model

Building the LSTM Model

```
[ ] model_LSTM = Sequential([LSTM(units=32, activation='tanh', return_sequences=True), # 1st Hidden layer
                             LSTM(units=64, activation='tanh', return_sequences=True), # 2nd Hidden layer
                             LSTM(units=128, activation='tanh'), # 3ed Hidden layer
                             Dropout(0.2),
                            Dense(units=1, activation='relu')]) # Output

    model_LSTM.compile(optimizer='adam', loss='mse', metrics=['mae'] )
```

Fit the LSTM Model

```
[ ] history_LSTM = model_LSTM.fit(trainxy, validation_data=valxy, epochs=20)
```

```
Epoch 1/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 7s 342ms/step - loss: 0.3032 - mae: 0.4709 - val_loss: 0.2236 - val_mae: 0.3573
Epoch 2/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 36ms/step - loss: 0.3023 - mae: 0.4706 - val_loss: 0.2099 - val_mae: 0.3517
Epoch 3/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step - loss: 0.2782 - mae: 0.4532 - val_loss: 0.1775 - val_mae: 0.3359
Epoch 4/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step - loss: 0.2312 - mae: 0.4150 - val_loss: 0.1352 - val_mae: 0.3106
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
lstm_3 (LSTM)	(None, None, 32)	4,352
lstm_4 (LSTM)	(None, None, 64)	24,832
lstm_5 (LSTM)	(None, 128)	98,816
dropout_4 (Dropout)	(None, 128)	0
dense_4 (Dense)	(None, 1)	129

Total params: 384,389 (1.47 MB)
Trainable params: 128,129 (500.50 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 256,260 (1001.02 KB)

LTSM prediction and evaluation:

```
5/5 ━━━━━━━━━━━━━━━━━━━━ 1s 71ms/step - loss: 0.0372 - mae: 0.1536 - val_loss: 0.0391 - val_mae: 0.1564
Epoch 20/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 44ms/step - loss: 0.0377 - mae: 0.1533 - val_loss: 0.0391 - val_mae: 0.1552
```

Make preductuion LSTM Model

```
for b in testxy:
  test_X, test_y = b
  pred_LSTM = model_LSTM.predict(test_X)
```

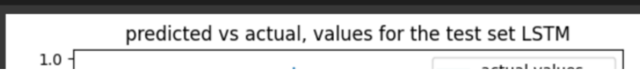
```
WARNING:tensorflow:5 out of the last 9 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at
1/4 ━━━━━━━━━━━━━━━━━━━━ 1s 407ms/stepWARNING:tensorflow:6 out of the last 12 calls to <function TensorFlowTrainer.make_predict_function.<
4/4 ━━━━━━━━━━━━━━━━━━━━ 1s 143ms/step
```

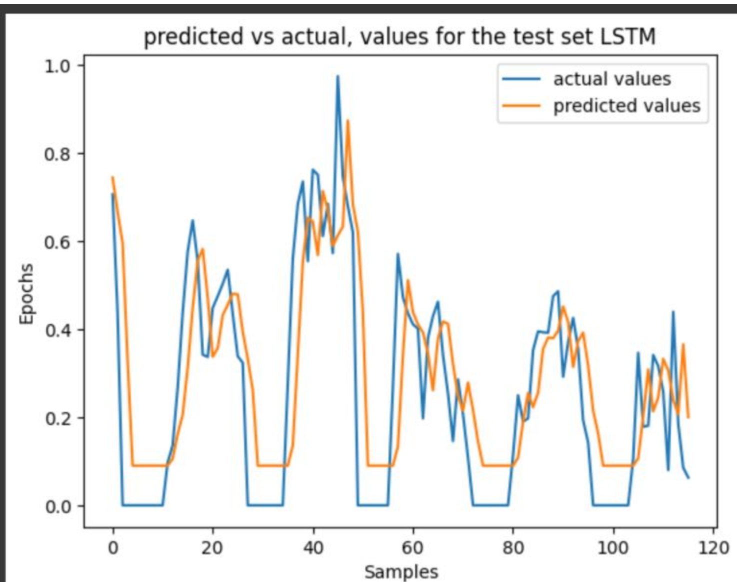
Make Evaluation LSTM Model

```
MAE_val = history_LSTM.history['val_mae']

final_MAEval = MAE_val[-1]
print(f'The value of MAE for LSTM: {final_MAEval:.4f}')
```

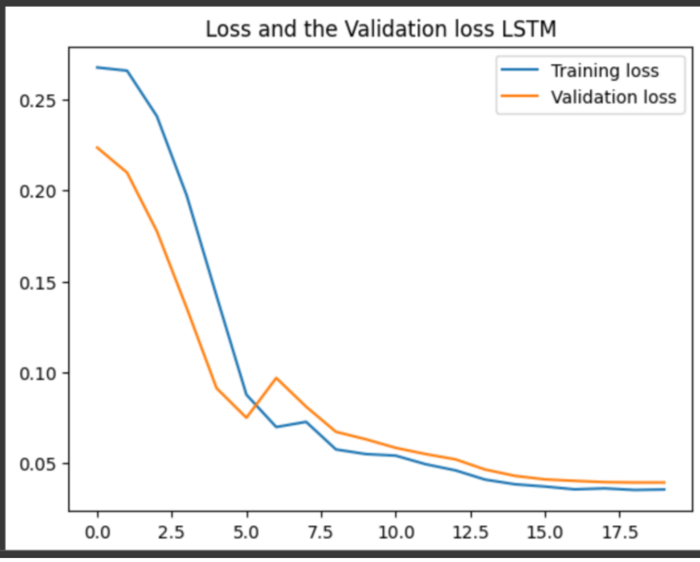
```
The value of MAE for LSTM: 0.1552
```

```
predits = []
act_val = []

predits.extend(pred_LSTM.flatten())
act_val.extend(test_y.numpy().flatten())

plt.plot(act_val, label='actual values')
plt.plot(predits, label='predicted values')
plt.title('predicted vs actual, values for the test set LSTM')
plt.legend()
plt.xlabel('Samples')
plt.ylabel('Epochs')
plt.show()
```





```
[ ] plt.plot(history_LSTM.history['loss'], label='Training loss')
    plt.plot(history_LSTM.history['val_loss'], label='Validation loss')
    plt.legend()
    plt.title('Loss and the Validation loss LSTM')
    plt.show()
```



3-Using GRU model:

Using GRU Model

Building the GRU Model

```
[ ] model_GRU = Sequential([GRU(units=32, activation='tanh', return_sequences=True), # 1st Hidden layer
                         GRU(units=64, activation='tanh', return_sequences=True), # 2nd Hidden layer
                         GRU(units=128, activation='tanh'), # 3ed Hidden layer
                         Dropout(0.2),
                       Dense(units=1, activation='relu')]) # Output

    model_GRU.compile(optimizer='adam', loss='mse', metrics=['mae'] )
```

fit the GRU model

```
[ ] history_GRU = model_GRU.fit(trainxy, validation_data=valxy, epochs=20)

    Epoch 1/20
    5/5 ━━━━━━━━━━━━━━━━━━━━ 7s 186ms/step - loss: 0.2736 - mae: 0.4497 - val_loss: 0.1069 - val_mae: 0.2795
    Epoch 2/20
    5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 52ms/step - loss: 0.1199 - mae: 0.2981 - val_loss: 0.0572 - val_mae: 0.2077
    Epoch 3/20
    5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 37ms/step - loss: 0.0552 - mae: 0.1978 - val_loss: 0.0815 - val_mae: 0.2282
```

```
Model: "sequential_5"
```

Layer (type)	Output Shape	Param #
gru_3 (GRU)	(None, None, 32)	3,360
gru_4 (GRU)	(None, None, 64)	18,816
gru_5 (GRU)	(None, 128)	74,496
dropout_5 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 1)	129

```
Total params: 290,405 (1.11 MB)
Trainable params: 96,801 (378.13 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 193,604 (756.27 KB)
```

GRU prediction and evaluation:

```
Epoch 19/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 38ms/step - loss: 0.0323 - mae: 0.1416 - val_loss: 0.0332 - val_mae: 0.1432
Epoch 20/20
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step - loss: 0.0316 - mae: 0.1406 - val_loss: 0.0329 - val_mae: 0.1422
```

Make preductuion with Model GRU

```
for b in testxy:
  test_X, test_y = b
  pred_GRU = model_GRU.predict(test_X)
```

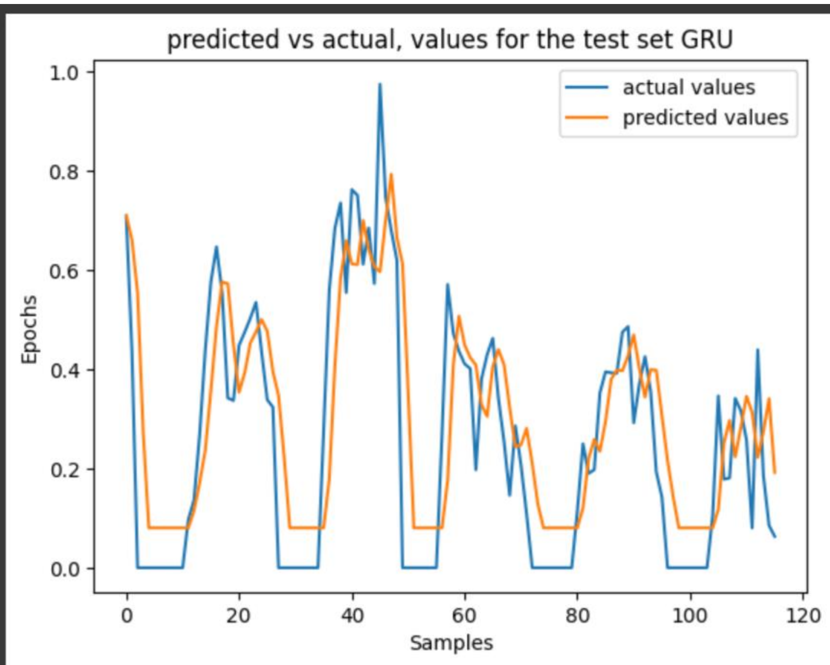
```
4/4 ━━━━━━━━━━━━━━━━━━━━ 1s 209ms/step
```

Make Evaluation GRU Model

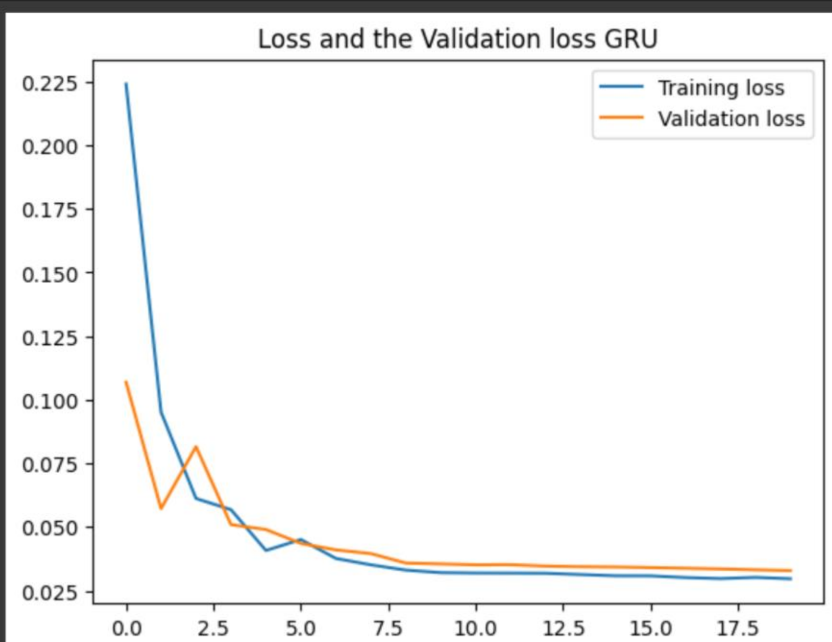
```
MAE_val = history_GRU.history['val_mae']

final_MAEval = MAE_val[-1]
print(f'The value of MAE for GRU: {final_MAEval:.4f}')
```

```
The value of MAE for GRU: 0.1422
```

```
predits = []
act_val = []

predits.extend(pred_GRU.flatten())
act_val.extend(test_y.numpy().flatten())

plt.plot(act_val, label='actual values')
plt.plot(predits, label='predicted values')
plt.title('predicted vs actual, values for the test set GRU')
plt.legend()
plt.xlabel('Samples')
plt.ylabel('Epochs')
plt.show()
```




```python
plt.plot(history_GRU.history['loss'], label='Training loss')
plt.plot(history_GRU.history['val_loss'], label='Validation loss')
plt.legend()
plt.title('Loss and the Validation loss GRU')
plt.show()
```



Conclusion:

By comparing the models' performance on Mean Absolute Error, We see the most suitable model for our traffic speed prediction task is RNN Model.