1. INTRODUCTION

1.1 Project Overview

Machine Learning (ML) is one of the most important and popular emerging branches these days as it is a part of Artificial Intelligence (AI). In recent times, machine learning becomes an essential and upcoming research area for transportation engineering, especially in traffic prediction. Traffic congestion affects the country's economy directly or indirectly by its means. Traffic congestion also takes people's valuable time, cost of fuel every single day. As traffic congestion is a major problem for all classes in society, there has to be a small-scale traffic prediction for the people's sake of living their lives without frustration or tension. For ensuring the country's economic growth, the road user's ease is required in the first place. This is possible only when the traffic flow is smooth. To deal with this, Traffic prediction is needed so that we can estimate or predict the future traffic to some extent.

In addition to the country's economy, pollution can also be reduced. The government is also investing in the intelligent transportation system (ITS) to solve these issues. The plot of this research paper is to find different machine learning algorithms and speculating the models by utilizing python3.The goal of traffic flow prediction is to predict the traffic to the users as soon as possible. Nowadays the traffic becomes really hectic and this cannot be determined by the people when they are on roads.

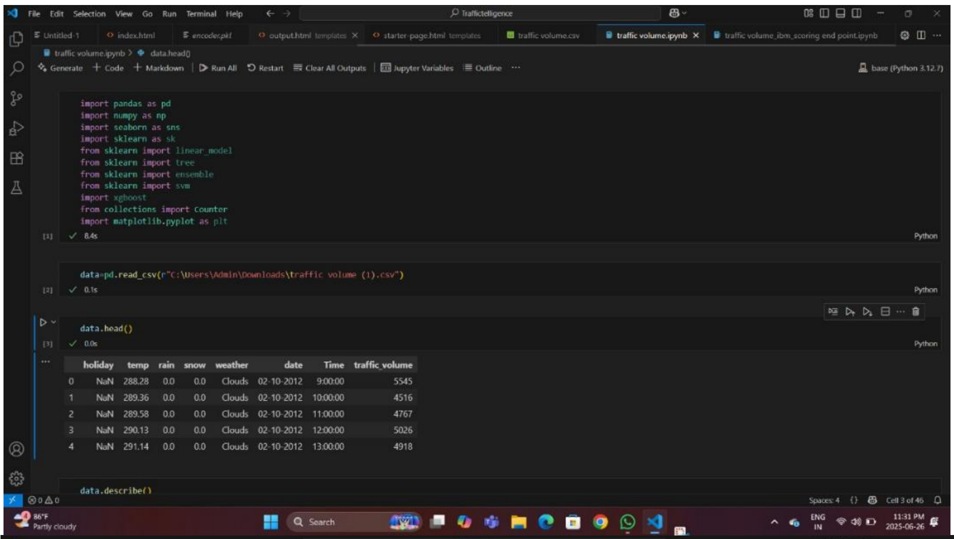
So, this research can be helpful to predict traffic. Machine learning is usually done using anaconda software but, in this paper, I have used the python program using command prompt window which is much easier than the usual way of predicting the data. In summary, the constructs of this paper consist of ten major sections. These are: Introduction, Purpose of Traffic Prediction, Problem Statement, Related Work, Overview, Methodology, Software Implementation and Conclusion with Future work.

1.2Purpose of the Project

Many reports of the traffic data are of actual time but it is not favorable and ccessible to many users as we need to have prior decision in which route we need to travel. For example, During working days, we need to have daily traffic information or at times we need hourly traffic information but then the traffic congestion occurs; for solving this issue the user need to have actual time traffic prediction. Many factors are responsible forthe traffic congestion. This can be predicted by taking two datasets; one with the past year and one with the recent year's data set. If traffic is so heavy then the traffic can be predicted by referring the same time in the past year's data set and analyzing how congested the traffic would be. With the increasing cost of the fuel, the traffic congestion changes drastically. The goal of this prediction is to provide real-time gridlock and snarl up information. The traffic on the city becomes complex and are out of control these days, so such kind of systems are not sufficient for prediction. Therefore, research on traffic flow prediction plays a major role in ITS.

7. RESULTS

7.1 Output Screenshots

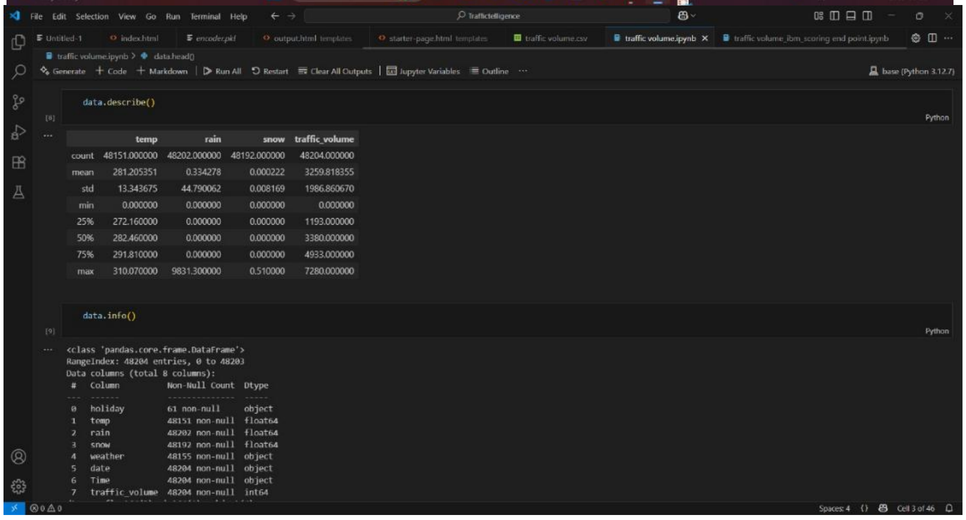


```
import pandas as pd
import numpy as np
import seaborn as sns
import sklearn as sk
from sklearn import linear_model
from sklearn import tree
from sklearn import ensemble
from sklearn import svm
import xgboost
from collections import Counter
import matplotlib.pyplot as plt
```

```
data=pd.read_csv(r"C:\Users\Admin\Downloads\traffic volume (1).csv")
```

```
data.head()
```

	holiday	temp	rain	snow	weather	date	Time	traffic_volume
0	NaN	288.28	0.0	0.0	Clouds	02-10-2012	9:00:00	5545
1	NaN	289.36	0.0	0.0	Clouds	02-10-2012	10:00:00	4516
2	NaN	289.58	0.0	0.0	Clouds	02-10-2012	11:00:00	4767
3	NaN	290.13	0.0	0.0	Clouds	02-10-2012	12:00:00	5026
4	NaN	291.14	0.0	0.0	Clouds	02-10-2012	13:00:00	4918

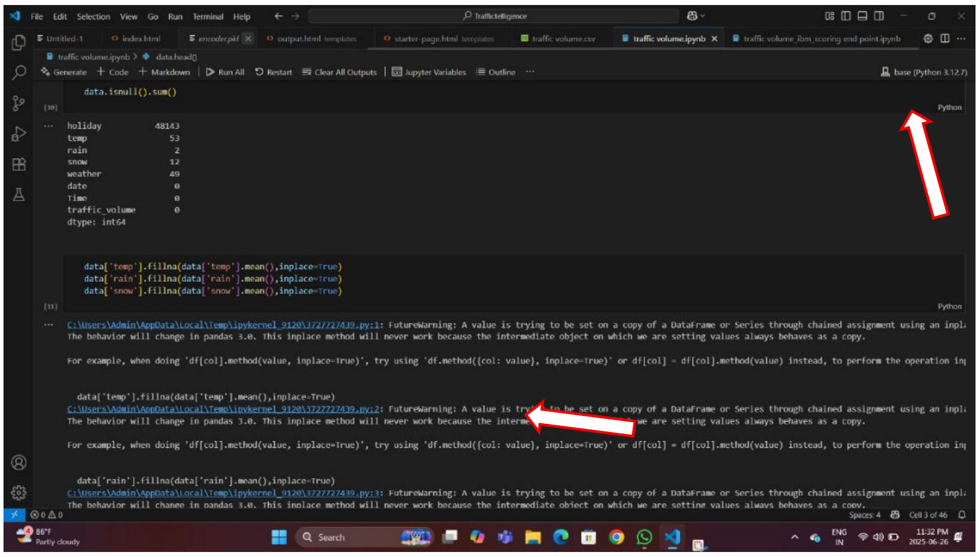


```
data.describe()
```

	temp	rain	snow	traffic_volume
count	48151.000000	48202.000000	48192.000000	48204.000000
mean	281.205351	0.334278	0.000222	3259.818355
std	13.343675	44.790062	0.008169	1986.860670
min	0.000000	0.000000	0.000000	0.000000
25%	272.160000	0.000000	0.000000	1193.000000
50%	282.460000	0.000000	0.000000	3380.000000
75%	291.810000	0.000000	0.000000	4933.000000
max	310.070000	9831.300000	0.510000	7280.000000

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48204 entries, 0 to 48203
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   holiday         61 non-null     object
 1   temp            48151 non-null  float64
 2   rain            48202 non-null  float64
 3   snow            48192 non-null  float64
 4   weather         48155 non-null  object
 5   date            48204 non-null  object
 6   Time            48204 non-null  object
 7   traffic_volume  48204 non-null  int64
```

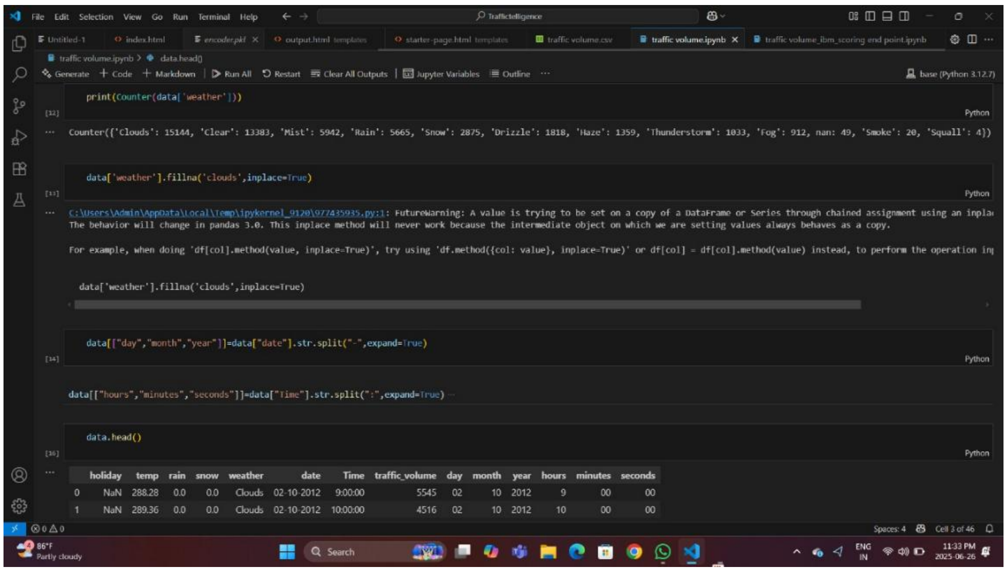


```
data.isnull().sum()
```

```
holiday           48143
temp                 53
rain                  2
snow                 12
weather              49
date                  0
Time                  0
traffic_volume        0
dtype: int64
```

```
data['temp'].fillna(data['temp'].mean(),inplace=True)
data['rain'].fillna(data['rain'].mean(),inplace=True)
data['snow'].fillna(data['snow'].mean(),inplace=True)
```

```
C:\Users\Admin\AppData\Local\Temp\ipykernel_9120\3727727439.py:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inpl
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation in

  data['temp'].fillna(data['temp'].mean(),inplace=True)
C:\Users\Admin\AppData\Local\Temp\ipykernel_9120\3727727439.py:2: FutureWarning: A value is try[illegible] to be set on a copy of a DataFrame or Series through chained assignment using an inpl
The behavior will change in pandas 3.0. This inplace method will never work because the interme[illegible] we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation in

  data['rain'].fillna(data['rain'].mean(),inplace=True)
C:\Users\Admin\AppData\Local\Temp\ipykernel_9120\3727727439.py:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inpl
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.
```



```
print(Counter(data['weather']))
```

```
Counter({'Clouds': 15144, 'Clear': 13383, 'Mist': 5942, 'Rain': 5665, 'Snow': 2875, 'Drizzle': 1818, 'Haze': 1359, 'Thunderstorm': 1033, 'Fog': 912, nan: 49, 'Smoke': 20, 'Squall': 4})
```

```
data['weather'].fillna('clouds',inplace=True)
```

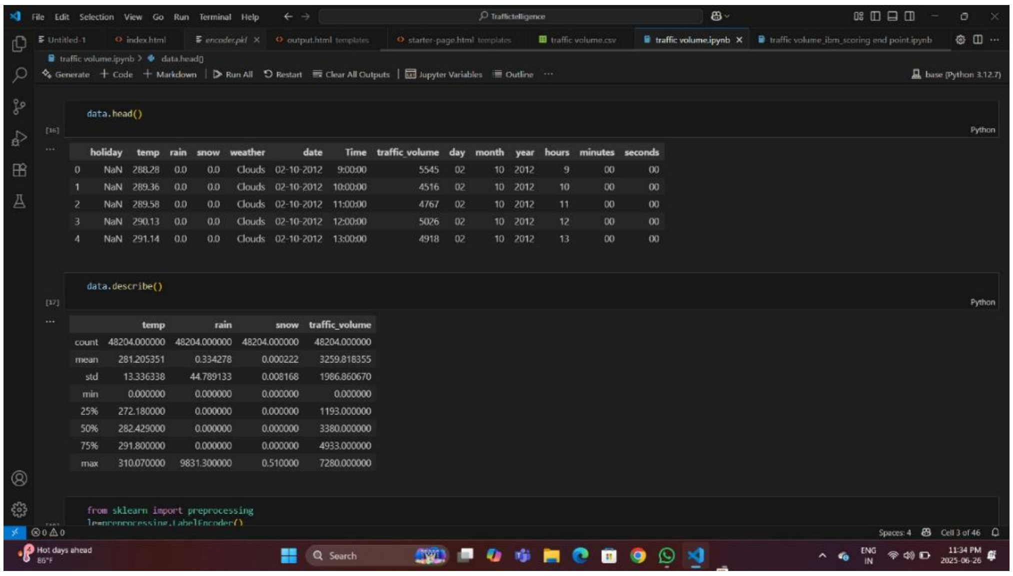
```
C:\Users\Admin\AppData\Local\Temp\ipykernel_9120\977435935.py:1: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inpla
The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation in

  data['weather'].fillna('clouds',inplace=True)
```

```
data[["day","month","year"]]=data["date"].str.split("-",expand=True)
```

```
data[["hours","minutes","seconds"]]=data["Time"].str.split(":",expand=True)
```

```
data.head()
```

	holiday	temp	rain	snow	weather	date	Time	traffic_volume	day	month	year	hours	minutes	seconds
0	NaN	288.28	0.0	0.0	Clouds	02-10-2012	9:00:00	5545	02	10	2012	9	00	00
1	NaN	289.36	0.0	0.0	Clouds	02-10-2012	10:00:00	4516	02	10	2012	10	00	00



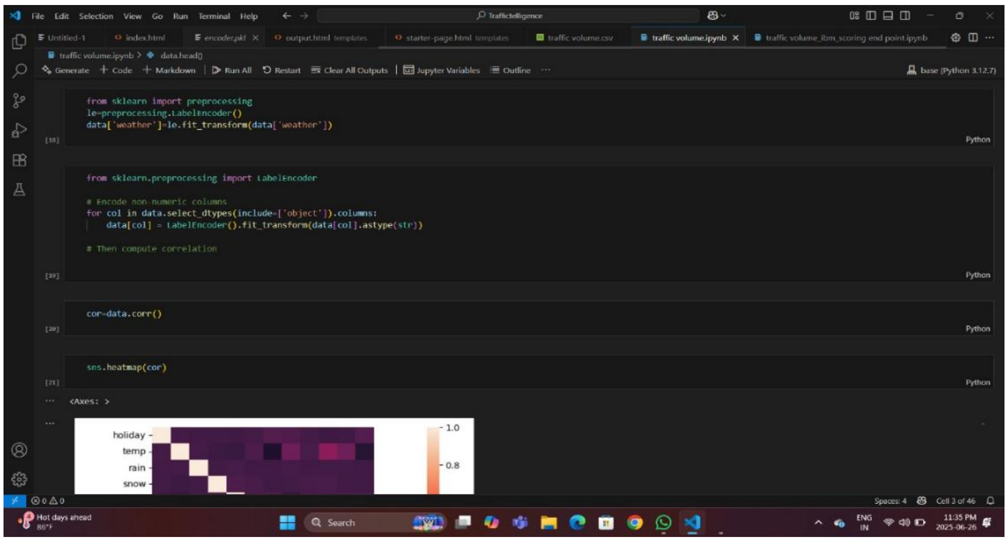
```
data.head()
```

	holiday	temp	rain	snow	weather	date	Time	traffic_volume	day	month	year	hours	minutes	seconds
0	NaN	288.28	0.0	0.0	Clouds	02-10-2012	9:00:00	5545	02	10	2012	9	00	00
1	NaN	289.36	0.0	0.0	Clouds	02-10-2012	10:00:00	4516	02	10	2012	10	00	00
2	NaN	289.58	0.0	0.0	Clouds	02-10-2012	11:00:00	4767	02	10	2012	11	00	00
3	NaN	290.13	0.0	0.0	Clouds	02-10-2012	12:00:00	5026	02	10	2012	12	00	00
4	NaN	291.14	0.0	0.0	Clouds	02-10-2012	13:00:00	4918	02	10	2012	13	00	00

```
data.describe()
```

	temp	rain	snow	traffic_volume
count	48204.000000	48204.000000	48204.000000	48204.000000
mean	281.205351	0.334278	0.000222	3259.818355
std	13.336338	44.789133	0.008168	1986.860670
min	0.000000	0.000000	0.000000	0.000000
25%	272.180000	0.000000	0.000000	1193.000000
50%	282.429000	0.000000	0.000000	3380.000000
75%	291.800000	0.000000	0.000000	4933.000000
max	310.070000	9831.300000	0.510000	7280.000000

```
from sklearn import preprocessing
le=preprocessing.LabelEncoder()
```



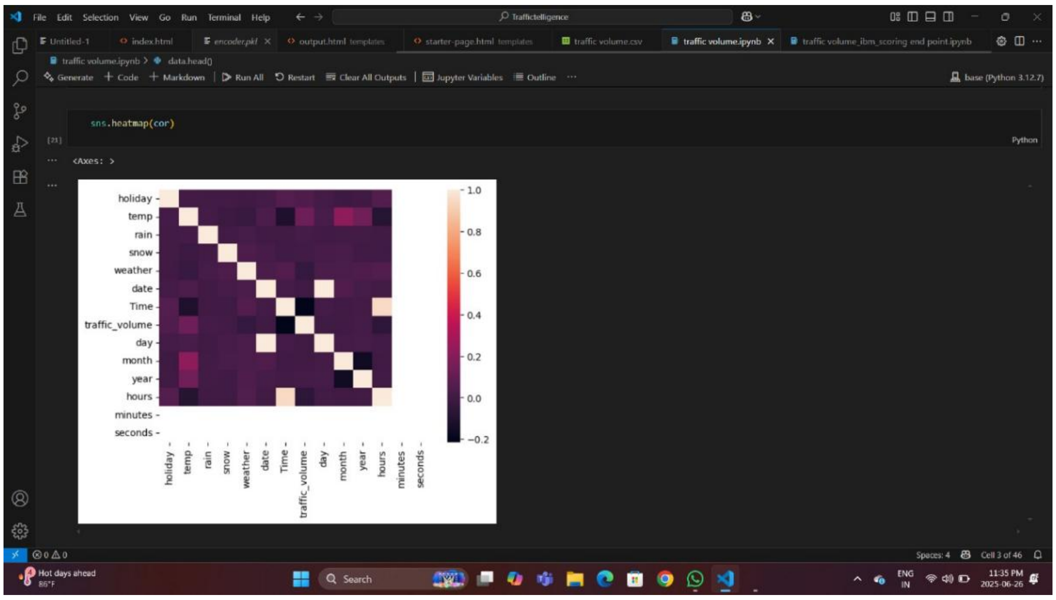
```
from sklearn import preprocessing
le=preprocessing.LabelEncoder()
data['weather']=le.fit_transform(data['weather'])
```

```
from sklearn.preprocessing import LabelEncoder

# Encode non-numeric columns
for col in data.select_dtypes(include=['object']).columns:
    data[col] = LabelEncoder().fit_transform(data[col].astype(str))

# Then compute correlation
```

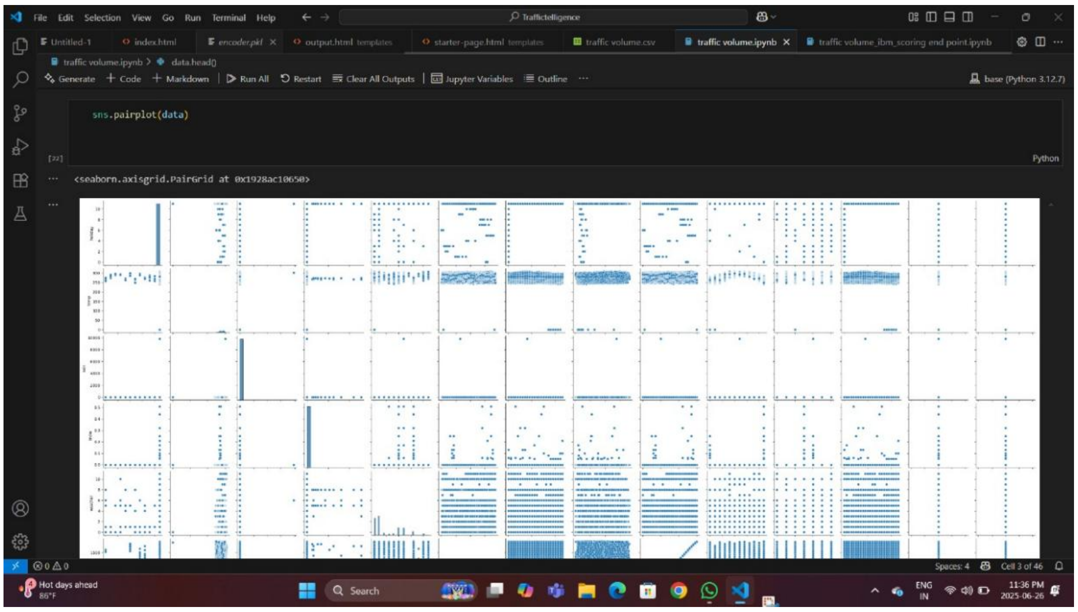
```
cor=data.corr()
```

```
sns.heatmap(cor)
```

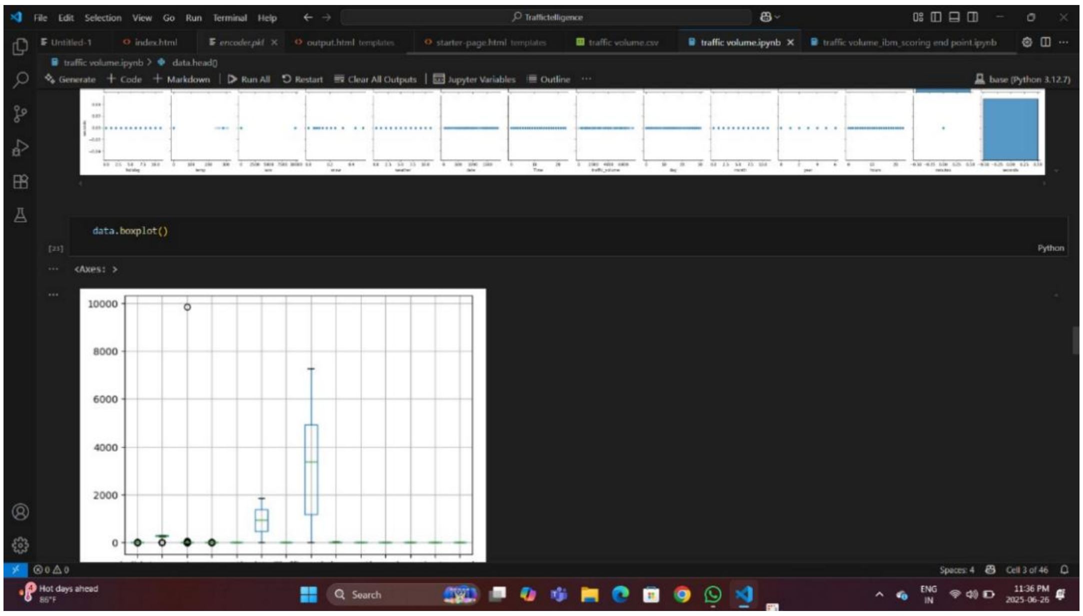
```
<Axes: >
```



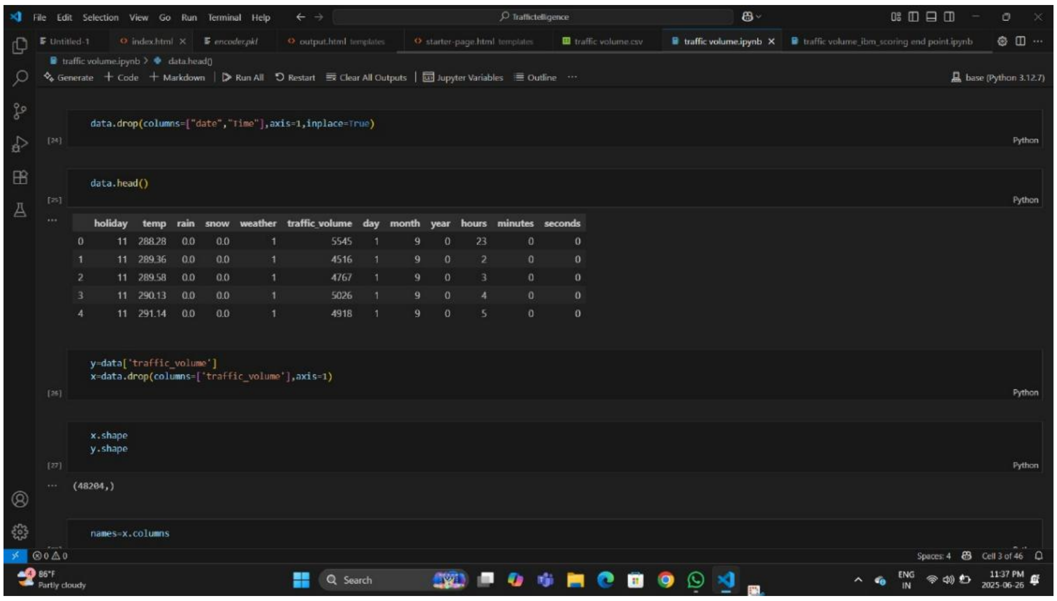
```
[21]  sns.heatmap(cor)

<Axes: >
```



```
[22]  sns.pairplot(data)

<seaborn.axisgrid.PairGrid at 0x1928ac10650>
```



```
[23]  data.boxplot()

<Axes: >
```



```python
data.drop(columns=["date","Time"],axis=1,inplace=True)
```
[24]

```python
data.head()
```
[25]

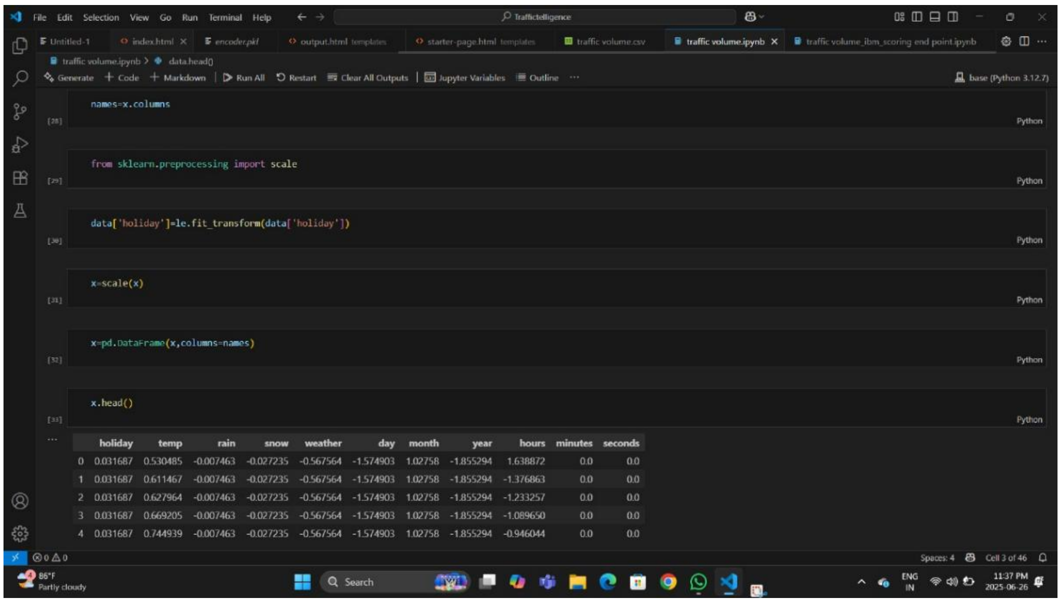
	holiday	temp	rain	snow	weather	traffic_volume	day	month	year	hours	minutes	seconds
0	11	288.28	0.0	0.0	1	5545	1	9	0	23	0	0
1	11	289.36	0.0	0.0	1	4516	1	9	0	2	0	0
2	11	289.58	0.0	0.0	1	4767	1	9	0	3	0	0
3	11	290.13	0.0	0.0	1	5026	1	9	0	4	0	0
4	11	291.14	0.0	0.0	1	4918	1	9	0	5	0	0

```python
y=data['traffic_volume']
x=data.drop(columns=['traffic_volume'],axis=1)
```
[26]

```python
x.shape
y.shape
```
[27]

```
(48204,)
```

```python
names=x.columns
```



```python
names=x.columns
```
[28]

```python
from sklearn.preprocessing import scale
```
[29]

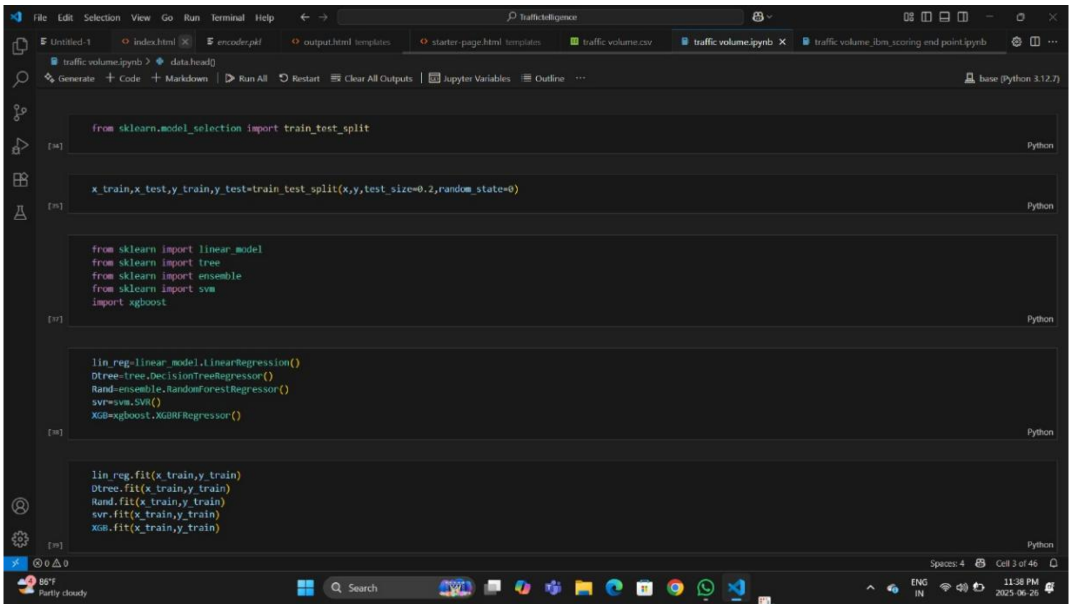
```python
data['holiday']=le.fit_transform(data['holiday'])
```
[30]

```python
x=scale(x)
```
[31]

```python
x=pd.DataFrame(x,columns=names)
```
[32]

```python
x.head()
```
[33]

	holiday	temp	rain	snow	weather	day	month	year	hours	minutes	seconds
0	0.031687	0.530485	-0.007463	-0.027235	-0.567564	-1.574903	1.02758	-1.855294	1.638872	0.0	0.0
1	0.031687	0.611467	-0.007463	-0.027235	-0.567564	-1.574903	1.02758	-1.855294	-1.376863	0.0	0.0
2	0.031687	0.627964	-0.007463	-0.027235	-0.567564	-1.574903	1.02758	-1.855294	-1.233257	0.0	0.0
3	0.031687	0.669205	-0.007463	-0.027235	-0.567564	-1.574903	1.02758	-1.855294	-1.089650	0.0	0.0
4	0.031687	0.744939	-0.007463	-0.027235	-0.567564	-1.574903	1.02758	-1.855294	-0.946044	0.0	0.0



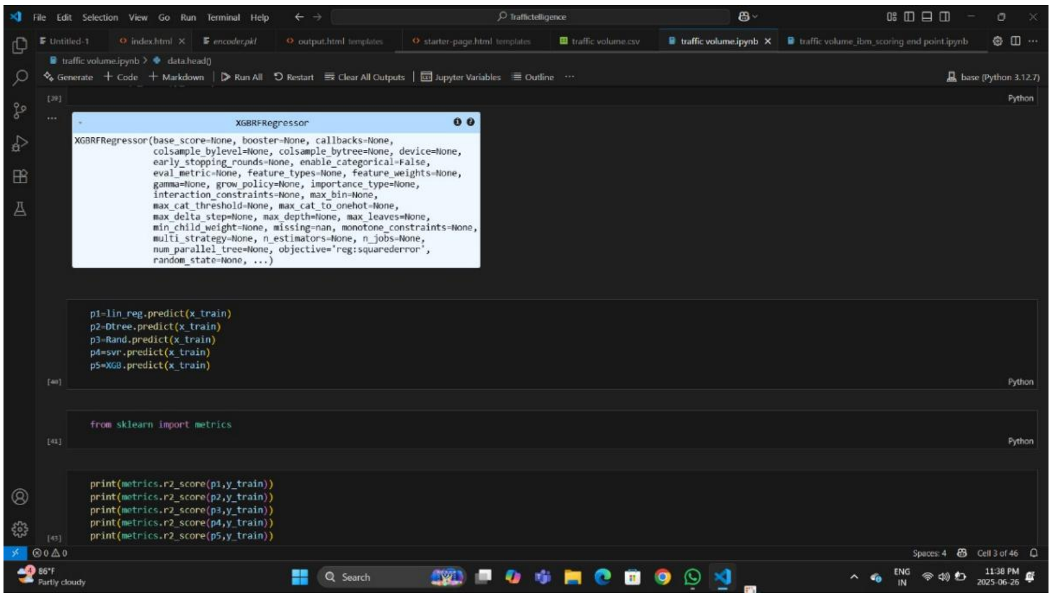
```python
from sklearn.model_selection import train_test_split
```
[34]

```python
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=0)
```
[35]

```python
from sklearn import linear_model
from sklearn import tree
from sklearn import ensemble
from sklearn import svm
import xgboost
```
[37]

```python
lin_reg=linear_model.LinearRegression()
Dtree=tree.DecisionTreeRegressor()
Rand=ensemble.RandomForestRegressor()
svr=svm.SVR()
XGB=xgboost.XGBRFRegressor()
```
[38]

```python
lin_reg.fit(x_train,y_train)
Dtree.fit(x_train,y_train)
Rand.fit(x_train,y_train)
svr.fit(x_train,y_train)
XGB.fit(x_train,y_train)
```
[39]

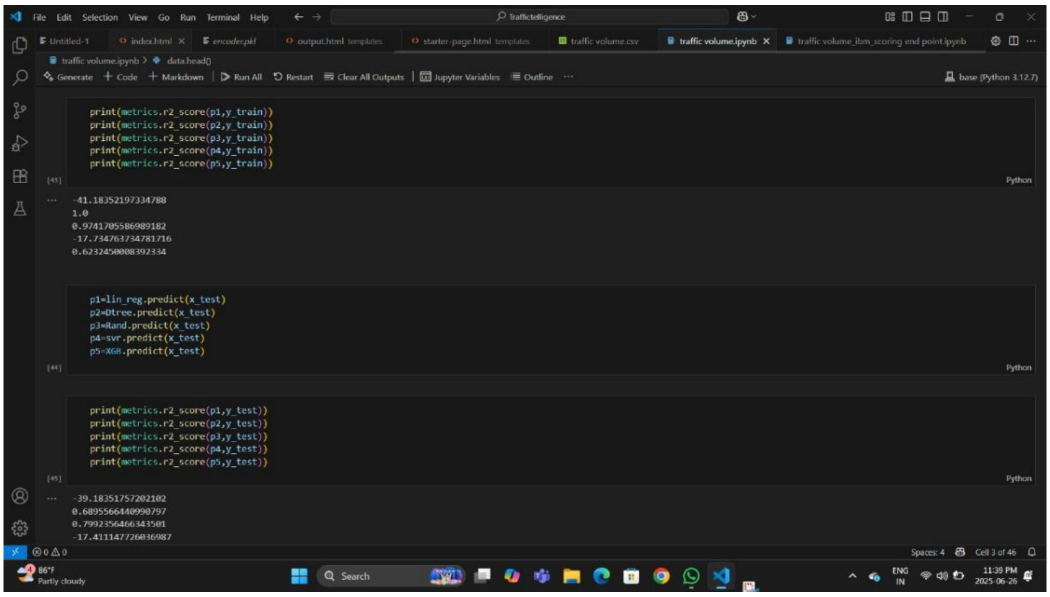


```
XGBRFRegressor(base_score=None, booster=None, callbacks=None,
               colsample_bylevel=None, colsample_bytree=None, device=None,
               early_stopping_rounds=None, enable_categorical=False,
               eval_metric=None, feature_types=None, feature_weights=None,
               gamma=None, grow_policy=None, importance_type=None,
               interaction_constraints=None, max_bin=None,
               max_cat_threshold=None, max_cat_to_onehot=None,
               max_delta_step=None, max_depth=None, max_leaves=None,
               min_child_weight=None, missing=nan, monotone_constraints=None,
               multi_strategy=None, n_estimators=None, n_jobs=None,
               num_parallel_tree=None, objective='reg:squarederror',
               random_state=None, ...)
```

```
p1=lin_reg.predict(x_train)
p2=Dtree.predict(x_train)
p3=Rand.predict(x_train)
p4=svr.predict(x_train)
p5=XGB.predict(x_train)
```

```
from sklearn import metrics
```

```
print(metrics.r2_score(p1,y_train))
print(metrics.r2_score(p2,y_train))
print(metrics.r2_score(p3,y_train))
print(metrics.r2_score(p4,y_train))
print(metrics.r2_score(p5,y_train))
```



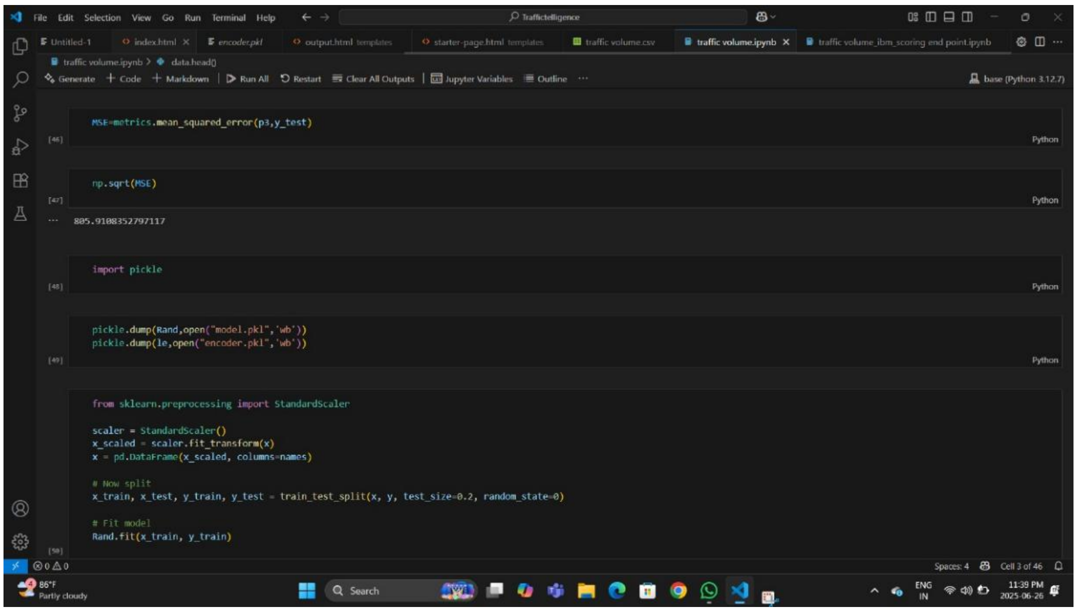
```
print(metrics.r2_score(p1,y_train))
print(metrics.r2_score(p2,y_train))
print(metrics.r2_score(p3,y_train))
print(metrics.r2_score(p4,y_train))
print(metrics.r2_score(p5,y_train))
```

```
-41.18352197334788
1.0
0.9741705586989182
-17.734763734781716
0.6232450008392334
```

```
p1=lin_reg.predict(x_test)
p2=Dtree.predict(x_test)
p3=Rand.predict(x_test)
p4=svr.predict(x_test)
p5=XGB.predict(x_test)
```

```
print(metrics.r2_score(p1,y_test))
print(metrics.r2_score(p2,y_test))
print(metrics.r2_score(p3,y_test))
print(metrics.r2_score(p4,y_test))
print(metrics.r2_score(p5,y_test))
```

```
-39.18351757202102
0.6895566440990797
0.7992356466343501
-17.411147726036987
```



```
MSE=metrics.mean_squared_error(p3,y_test)
```

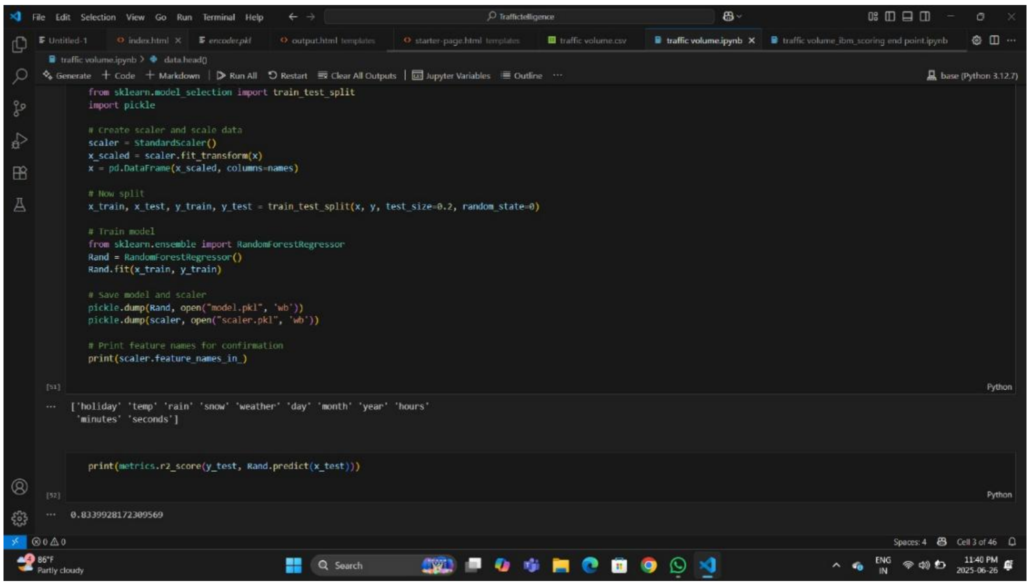
```
np.sqrt(MSE)
```

```
805.9108352797117
```

```
import pickle
```

```
pickle.dump(Rand,open("model.pkl",'wb'))
pickle.dump(le,open("encoder.pkl",'wb'))
```

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
x = pd.DataFrame(x_scaled, columns=names)

# Now split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=0)

# Fit model
Rand.fit(x_train, y_train)
```

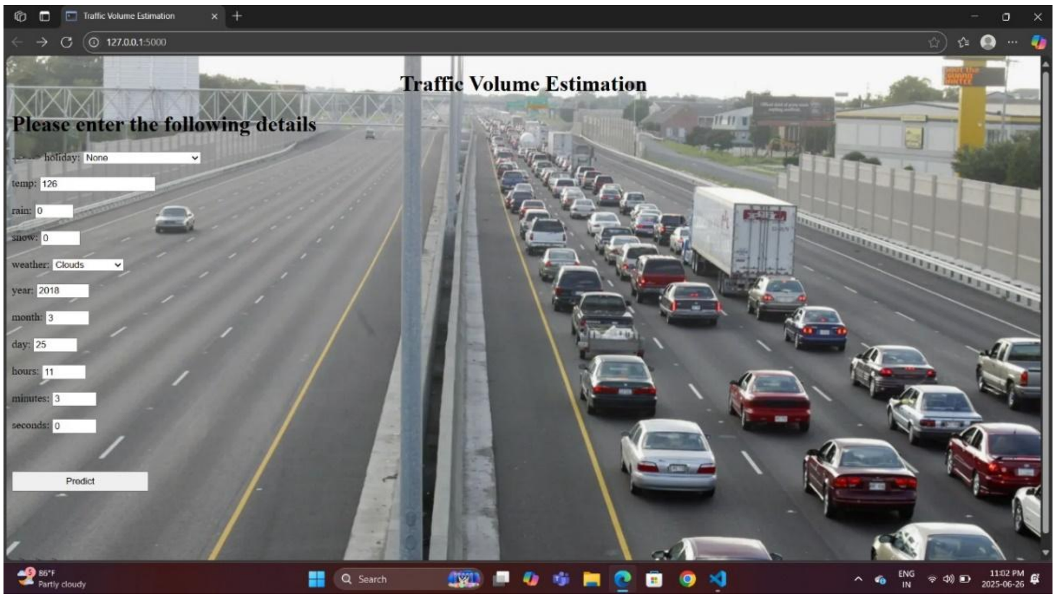


```
from sklearn.model_selection import train_test_split
import pickle

# Create scaler and scale data
scaler = StandardScaler()
x_scaled = scaler.fit_transform(x)
x = pd.DataFrame(x_scaled, columns=names)

# Now split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=0)

# Train model
from sklearn.ensemble import RandomForestRegressor
Rand = RandomForestRegressor()
Rand.fit(x_train, y_train)

# Save model and scaler
pickle.dump(Rand, open("model.pkl", 'wb'))
pickle.dump(scaler, open("scaler.pkl", 'wb'))

# Print feature names for confirmation
print(scaler.feature_names_in_)
```

```
['holiday' 'temp' 'rain' 'snow' 'weather' 'day' 'month' 'year' 'hours'
 'minutes' 'seconds']
```

```
print(metrics.r2_score(y_test, Rand.predict(x_test)))
```

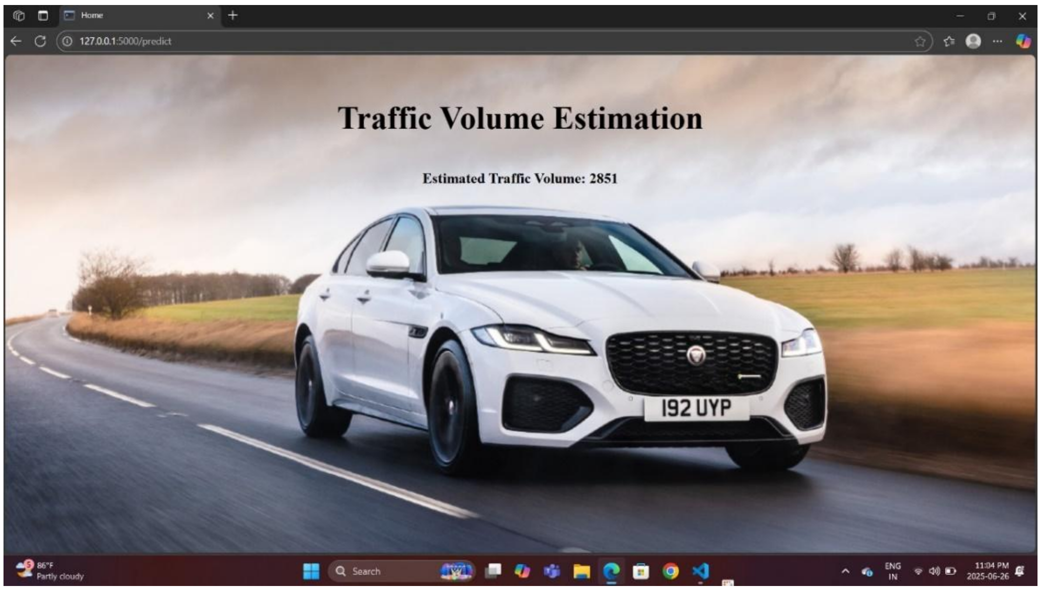
```
0.8339928172309569
```



Traffic Volume Estimation

Please enter the following details

holiday:	None
temp:	126
rain:	0
snow:	0
weather:	Clouds
year:	2018
month:	3
day:	25
hours:	11
minutes:	3
seconds:	0



Traffic Volume Estimation

Estimated Traffic Volume: 2851

8. ADVANTAGES & DISADVANTAGES

8.1 Advantages

Advantage	Description
High Accuracy	ML models can learn complex patterns and deliver more accurate traffic volume predictions than traditional methods.
Real-Time Capability	With proper integration of GPS, IoT, and streaming data, predictions can be updated in real-time.
Scalability	The system can be easily scaled to cover different cities or road networks by retraining or fine-tuning models.
Cost-Effective Over Time	Reduces the need for expensive physical infrastructure (e.g., loop detectors, manual counting).
Data-Driven Decision Making	Authorities can use insights from the model to improve traffic signal timings, road planning, and congestion control.
Adaptability	Can be retrained or updated based on changing traffic conditions, events, or new data sources.

Table 8.1: Advantages

8.2 Disadvantages / Limitations

Disadvantage	Description
Data Dependency	Requires large volumes of quality data (e.g., GPS traces, historical traffic) to train accurate models.
Complexity in Implementation	Integrating various data sources and building models requires technical expertise.
Real-Time Infrastructure	Real-time predictions need high-speed data processing pipelines and infrastructure, which can be costly initially.
Model Interpretability	Deep learning models (e.g., LSTM, GNN) may act as black boxes, making it hard to explain predictions.
Generalization Issues	A model trained for one city or area may not perform well in another without retraining.

Table 8.2: Disadvantages

9.CONCLUSION

In the system, it has been concluded that we develop the traffic flow prediction system by using a machine learning algorithm. By using regression model, the prediction is done. The public gets the benefits such as the current situation of the traffic flow, they can also check what will be the flow of traffic on the right after one hour of the situation and they can also know how the roads are as they can know mean of the vehicles passing though a particular junction that is 4 here. The weather conditions have been changing from years to years. The cost of fuel is also playing a major role in the transportation system. Many people are not able to afford the vehicle because of the fuel cost. So, there can be many variations in the traffic data. There is one more scenario where people prefer going on their own vehicle without car-pooling, this also matters in the traffic congestion. So, this prediction can help judging the traffic flow by comparing them with these 2 years data sets. The forecasting or the prediction can help people or the users in judging the road traffic easier beforehand and even they can decide which way to go using their navigator and also this will prediction will be also helpful.

10. FUTURE SCOPE

In the future, the system are often further improved using more factors that affect traffic management using other methods like deep learning, artificial neural network, and even big data. The users can then use this technique to seek out which route would be easiest to achieve on destination. The system can help in suggesting the users with their choice of search and also it can help to find the simplest choice where traffic isn't in any crowded environment. Many forecasting methods have already been applied in road traffic jam forecasting. While there's more scope to create the congestion prediction more precise, there are more methods that give precise and accurate results from the prediction. Also, during this period, the employment of the increased available traffic data by applying the newly developed forecasting models can improve the prediction accuracy. These days, traffic prediction is extremely necessary for pretty much a part of the state and also worldwide. So, this method of prediction would be helpful in predicting the traffic before and beforehand. For better congestion prediction, the grade and accuracy are prominent in traffic prediction. within the future, the expectation are going to be the estimation of established order accuracy prediction with much easier and user-friendly methods so people would find the prediction model useful and that they won't be wasting their time and energy to predict the information. There will be some more accessibility like weather outlook, GPS that's the road and accident-prone areas will be highlighted in order that people wouldn't prefer using the paths which aren't safe and simultaneously they'll predict the traffic. This will be done by deep learning, big data, and artificial neural networks.

11. APPENDIX

Source Code:

All codes are submitted in Git-Hub Repository

Git-Hub Repository Link:

https://github.com/Sireesha992/Traffictelligence-Advanced-Traffic-Volume-Estimation-With-Machine/tree/main

Dataset Link:

https://drive.google.com/file/d/1AAvFlqZfhti5GhotjYfoXJ6beOEbckpM/view?usp=drivesdk

Project Demo Link:

https://drive.google.com/file/d/19xI-ej1W4tuvOWGD6MYk3hHvjFtnxmjP/view?usp=drivesdk