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Project Introduction

This project aims to analyze traffic flow data to identify patterns, predict traffic conditions, and provide actionable insights for stakeholders. The analysis involves exploratory data analysis (EDA) and machine learning models to achieve these objectives.

```
Preprocessing: The Time and Date columns are converted to
appropriate formats, and relevant features like Hour, Month, and Day
are extracted.

Label Encoding: Categorical features like Day of the week and
Traffic Situation are encoded to numerical values. Feature
Selection: The features (Time, Day of the week, CarCount, etc.) are
selected for training.

Model Training: A RandomForestClassifier is used to predict the
traffic situation.

Evaluation: The model’s performance is evaluated using confusion
matrix, classification report, and accuracy score.

Feature Importance: A plot showing the importance of each feature in
predicting the traffic situation is generated.
```

In [5]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler,OneHotEncoder,LabelEncoder
```

```
df
=pd.read_csv(r"C:\Users\HP\Downloads\TrafficDataset.csv")
```

```
df.head()
```

	Time	Date	Day of the week	CarCount	BikeCount	BusCount	TruckCount	Total	Tr Sit
0	12:00:00 AM	10-10-2023	Tuesday	13	2	2	24	41	no
1	12:15:00 AM	10-10-2023	Tuesday	14	1	1	36	52	no
2	12:30:00 AM	10-10-2023	Tuesday	10	2	2	32	46	no
3	12:45:00 AM	10-10-2023	Tuesday	10	2	2	36	50	no
4	1:00:00 AM	10-10-2023	Tuesday	11	2	1	34	48	no

```
#Data Preprocessing
df.shape
```

```
(2976, 9)
```

```
df.dtypes
```

In [6]:

In [7]:

Out[7]:

```
Time                   object
Date                   object
Day of the week        object
CarCount                int64
BikeCount               int64
BusCount                int64
TruckCount              int64
Total                  int64
Traffic Situation    object
dtype: object
```

dtype: object

data type. But first, I am checking thuation has (
column floa

```python
df['Time'].unique()
```

In [8]:

Out[8]:

In [9]:

Out[9]:

In [10]:

Out[10]:

```
array(['12:00:00 AM', '12:15:00 AM', '12:30:00 AM', '12:45:00 AM',
       '1:00:00 AM', '1:15:00 AM', '1:30:00 AM', '1:45:00 AM',
       '2:00:00 AM', '2:15:00 AM', '2:30:00 AM', '2:45:00 AM',
       '3:00:00 AM', '3:15:00 AM', '3:30:00 AM', '3:45:00 AM',
```

```
               '4:00:00 AM', '4:15:00 AM', '4:30:00 AM', '4:45:00 AM',
               '5:00:00 AM', '5:15:00 AM', '5:30:00 AM', '5:45:00 AM',
               '6:00:00 AM', '6:15:00 AM', '6:30:00 AM', '6:45:00 AM',
               '7:00:00 AM', '7:15:00 AM', '7:30:00 AM', '7:45:00 AM',
               '8:00:00 AM', '8:15:00 AM', '8:30:00 AM', '8:45:00 AM',
               '9:00:00 AM', '9:15:00 AM', '9:30:00 AM', '9:45:00 AM',
               '10:00:00 AM', '10:15:00 AM', '10:30:00 AM', '10:45:00 AM',
               '11:00:00 AM', '11:15:00 AM', '11:30:00 AM', '11:45:00 AM',
               '12:00:00 PM', '12:15:00 PM', '12:30:00 PM', '12:45:00 PM',
               '1:00:00 PM', '1:15:00 PM', '1:30:00 PM', '1:45:00 PM',
               '2:00:00 PM', '2:15:00 PM', '2:30:00 PM', '2:45:00 PM',
               '3:00:00 PM', '3:15:00 PM', '3:30:00 PM', '3:45:00 PM',
               '4:00:00 PM', '4:15:00 PM', '4:30:00 PM', '4:45:00 PM',
               '5:00:00 PM', '5:15:00 PM', '5:30:00 PM', '5:45:00 PM',
               '6:00:00 PM', '6:15:00 PM', '6:30:00 PM', '6:45:00 PM',
               '7:00:00 PM', '7:15:00 PM', '7:30:00 PM', '7:45:00 PM',
               '8:00:00 PM', '8:15:00 PM', '8:30:00 PM', '8:45:00 PM',
               '9:00:00 PM', '9:15:00 PM', '9:30:00 PM', '9:45:00 PM',
               '10:00:00 PM', '10:15:00 PM', '10:30:00 PM', '10:45:00 PM',
       '11:00:00 PM', '11:15:00 PM', '11:30:00 PM', '11:45:00 PM'],
       dtype=object)
```

```
In [11]: # Convert 'Time' to minutes df['Time'] = pd.to_datetime(df['Time'],
         format='%I:%M:%S %p').dt.hour * 60 + pd.to_ df['Time'].unique()
```

```
Out[11]: array([   0,   15,   30,   45,   60,   75,   90,  105,  120,  135,  150,
         165,  180,  195,  210,  225,  240,  255,  270,  285,  300,  315,
                330,  345,  360,  375,  390,  405,  420,  435,  450,  465,  480,
                495,  510,  525,  540,  555,  570,  585,  600,  615,  630,  645,
                660,  675,  690,  705,  720,  735,  750,  765,  780,  795,  810,
                825,  840,  855,  870,  885,  900,  915,  930,  945,  960,  975,
                990, 1005, 1020, 1035, 1050, 1065, 1080, 1095, 1110, 1125, 1140,
               1155, 1170, 1185, 1200, 1215, 1230, 1245, 1260, 1275, 1290, 1305,
               1320, 1335, 1350, 1365, 1380, 1395, 1410, 1425])
```

In this code:

%I is the hour (01-12) for 12-hour clocks.

%p is AM or PM.

```
In [12]: df['Date'].unique()
```

```
     Out[12]: array(['10-10-2023', '11-10-2023', '12-10-2023', '13-10-
 2023',        '14-10-2023', '15-10-2023', '16-10-2023', '17-10-2023',
               '18-10-2023', '19-10-2023', '20-10-2023', '21-10-2023',
               '22-10-2023', '23-10-2023', '24-10-2023', '25-10-2023',
               '26-10-2023', '27-10-2023', '28-10-2023', '29-10-2023',
               '30-10-2023', '31-10-2023', '01-11-2023', '02-11-2023',
               '03-11-2023', '04-11-2023', '05-11-2023', '06-11-2023',
               '07-11-2023', '08-11-2023', '09-11-2023'], dtype=object)
```

In [13]:
```
# Inspect the raw 'Date' column
print("Raw Date Data:")
print(df['Date'].head(10))

# Convert 'Date' to datetime format (dd-mm-yyyy)
df['Date'] = pd.to_datetime(df['Date'], format='%d-%m-%Y', errors='coerce')

# Check for any missing values or incorrect parsing
print("\nConverted Date Data:")
print(df['Date'].head(10))
print("Missing values in 'Date':", df['Date'].isna().sum())

# Convert to days since a reference date
reference_date = pd.Timestamp('2023-10-09')
df['Date'] = (df['Date'] - reference_date).dt.days

# Verify the final result
print("\nFinal Date Data:")
print(df.dtypes)
print(df.head())
print(df.tail())
```

```
Raw Date Data:
0    10-10-2023
1    10-10-2023
2    10-10-2023
3    10-10-2023
4    10-10-2023
5    10-10-2023
6    10-10-2023
7    10-10-2023
8    10-10-2023
9    10-10-2023 Name: Date, dtype: object

Converted Date Data:
0   2023-10-10
1   2023-10-10
2   2023-10-10
3   2023-10-10
4   2023-10-10
5   2023-10-10
6   2023-10-10
7   2023-10-10
8   2023-10-10
9   2023-10-10
Name: Date, dtype: datetime64[ns]
Missing values in 'Date': 0

Final Date Data:
Time                  int32
Date                  int64
Day of the week      object
CarCount              int64
BikeCount             int64
BusCount              int64
TruckCount            int64
Total                 int64
Traffic Situation    object
dtype: object
   Time  Date Day of the week  CarCount  BikeCount  BusCount  TruckCount  \
0     0     1         Tuesday        13          2         2          24
1    15     1         Tuesday        14          1         1          36
2    30     1         Tuesday        10          2         2          32
3    45     1         Tuesday        10          2         2          36
4    60     1         Tuesday        11          2         1          34

   Total Traffic Situation
0     41            normal
1     52            normal
2     46            normal
3     50            normal
4     48            normal
      Time  Date Day of the week  CarCount  BikeCount  BusCount  TruckCount  \
2971  1365    31        Thursday         6          0         2          34
2972  1380    31        Thursday         5          0         2          24
2973  1395    31        Thursday        11          2         2          32
```

```
2974  1410    31        Thursday         5           2           2          37    2975
      1425    31        Thursday        10           1           0          25

       Total Traffic Situation
2971     42            normal
2972     31            normal
2973     47            normal
2974     46            normal
2975     36            normal
```

In [14]:
```
df['Traffic Situation'].unique()
```

Out[14]:
```
array(['normal', 'low', 'heavy', 'high'], dtype=object)
```

In [15]:
```
from sklearn.preprocessing import LabelEncoder

label_encoder =LabelEncoder()
df['Traffic Situation']=label_encoder.fit_transform(df['Traffic Situation'])
```

In [16]:
```
df.head()
```

Out[16]:

	Time	Date	Day of the week	CarCount	BikeCount	BusCount	TruckCount	Total	Traffic Situation
0	0	1	Tuesday	13	2	2	24	41	3
1	15	1	Tuesday	14	1	1	36	52	3
2	30	1	Tuesday	10	2	2	32	46	3
3	45	1	Tuesday	10	2	2	36	50	3
4	60	1	Tuesday	11	2	1	34	48	3

In [17]:
```
df['Date'].unique()
```

Out[17]:
```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31],
      dtype=int64)
```

In [18]:
```
df['Date'].head(10)
```

Out[18]:
```
0    1
1    1
2    1
3    1
4    1
5    1
6    1
7    1
8    1
9    1
```

```
Name: Date, dtype: int64
```

In [19]:
```
df['Traffic Situation'].unique()
```

Out[19]:
```
array([3, 2, 0, 1])
```

In [20]:
```
#Descriptive Statistics
df.describe()
```

Out[20]:

	Time	Date	CarCount	BikeCount	BusCount	TruckCount	
count	2976.000000	2976.000000	2976.000000	2976.000000	2976.000000	2976.000000	2976.
mean	712.500000	16.000000	62.184812	9.405578	10.546371	21.967742	104.
std	415.739495	8.945775	43.384148	9.275747	9.774527	10.312510	50.
min	0.000000	1.000000	5.000000	0.000000	0.000000	5.000000	25.
25%	356.250000	8.000000	15.000000	2.000000	2.000000	13.000000	53.
50%	712.500000	16.000000	61.000000	7.000000	8.000000	21.000000	101.
75%	1068.750000	24.000000	97.000000	15.000000	17.000000	30.000000	144.
max	1425.000000	31.000000	150.000000	50.000000	40.000000	60.000000	227.

In [21]:
```
df.isnull().sum()
```

Out[21]:
```
Time                 0
Date                 0
Day of the week      0
CarCount             0
BikeCount            0
BusCount             0
TruckCount           0
Total                0
Traffic Situation    0
dtype: int64
```

In [22]:
```
df.info()
```

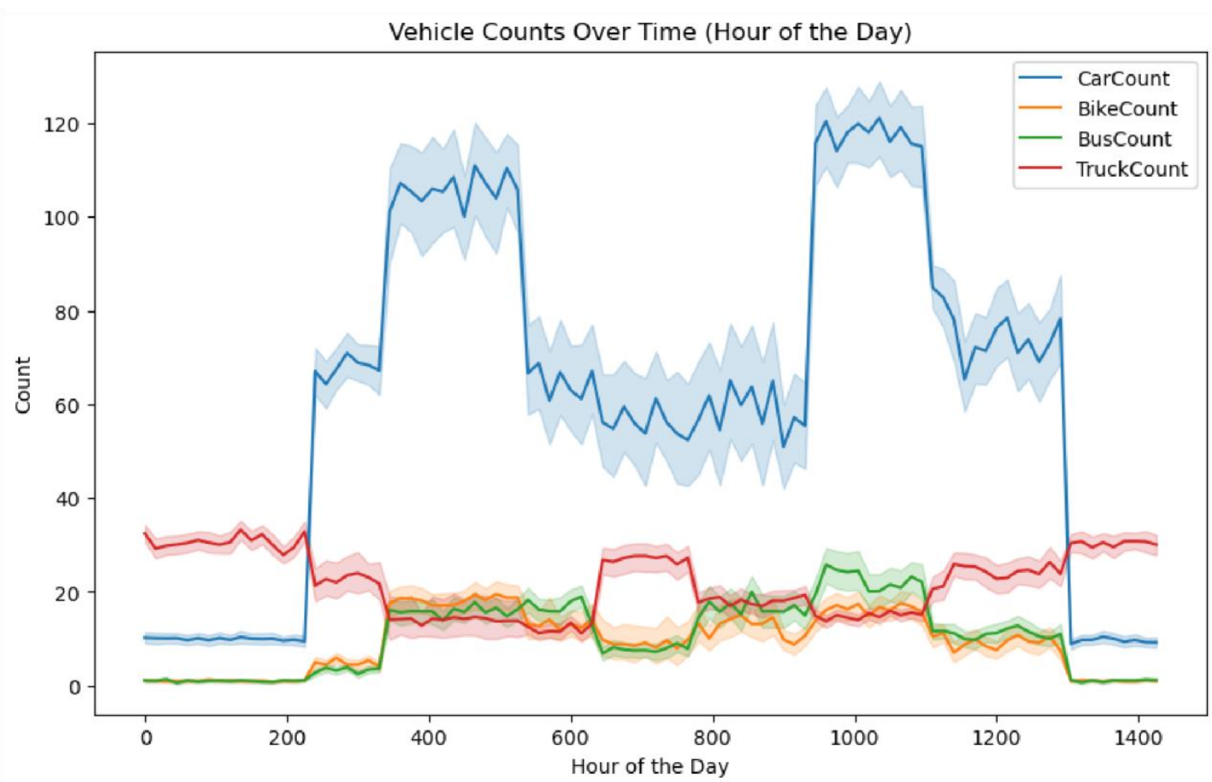
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2976 entries, 0 to 2975
Data columns (total 9 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
0    Time               2976 non-null   int32
1    Date               2976 non-null   int64
2    Day of the week    2976 non-null   object
```

```
3     CarCount            2976 non-null   int64
4     BikeCount           2976 non-null   int64
5     BusCount            2976 non-null   int64
6     TruckCount          2976 non-null   int64
7     Total               2976 non-null   int64   8    Traffic Situation   2976 non-
```

```
plt.figure(figsize=(10, 6))
sns.lineplot(data=df, x='Time', y='CarCount', label='CarCount')
sns.lineplot(data=df, x='Time', y='BikeCount', label='BikeCount')
sns.lineplot(data=df, x='Time', y='BusCount', label='BusCount')
sns.lineplot(data=df, x='Time', y='TruckCount',
label='TruckCount') plt.title('Vehicle Counts Over Time (Hour of
the Day)') plt.xlabel('Hour of the Day') plt.ylabel('Count')
plt.legend() plt.show()
```

```
null   int32 dtypes: int32(2), int64(6), object(1) memory usage: 186.1+ KB
```

In [23]:

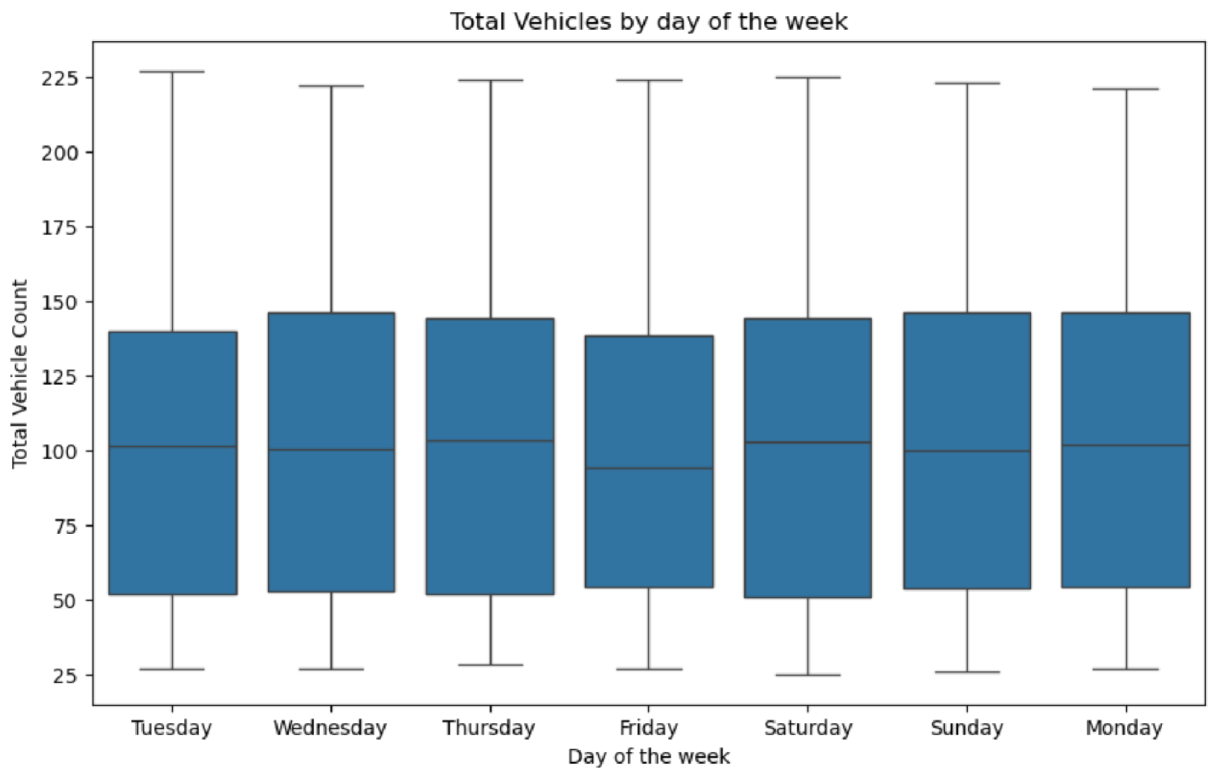


Graph Description

The graph shows vehicle traffic patterns over time. Cars have the highest volume, followed by bikes, buses, and trucks. There are two peak periods: morning and evening. Bikes and cars increase significantly during these times. Buses are relatively consistent, while trucks are lower overall.

Total Vehicles by day of the week

In [26]:
```
plt.figure(figsize=(10,6))
sns.boxplot(data=df,x ='Day of the week',y
='Total') plt.title('Total Vehicles by day of the
week') plt.xlabel('Day of the week')
plt.ylabel('Total Vehicle Count') plt.show()
```



Graph Description

The graph shows the total number of vehicles for each day of the week. The box plots indicate the median, quartiles, and outliers for each day. There is no significant difference in the overall vehicle count across the days. However, there is some variation in the spread of the data for each day.

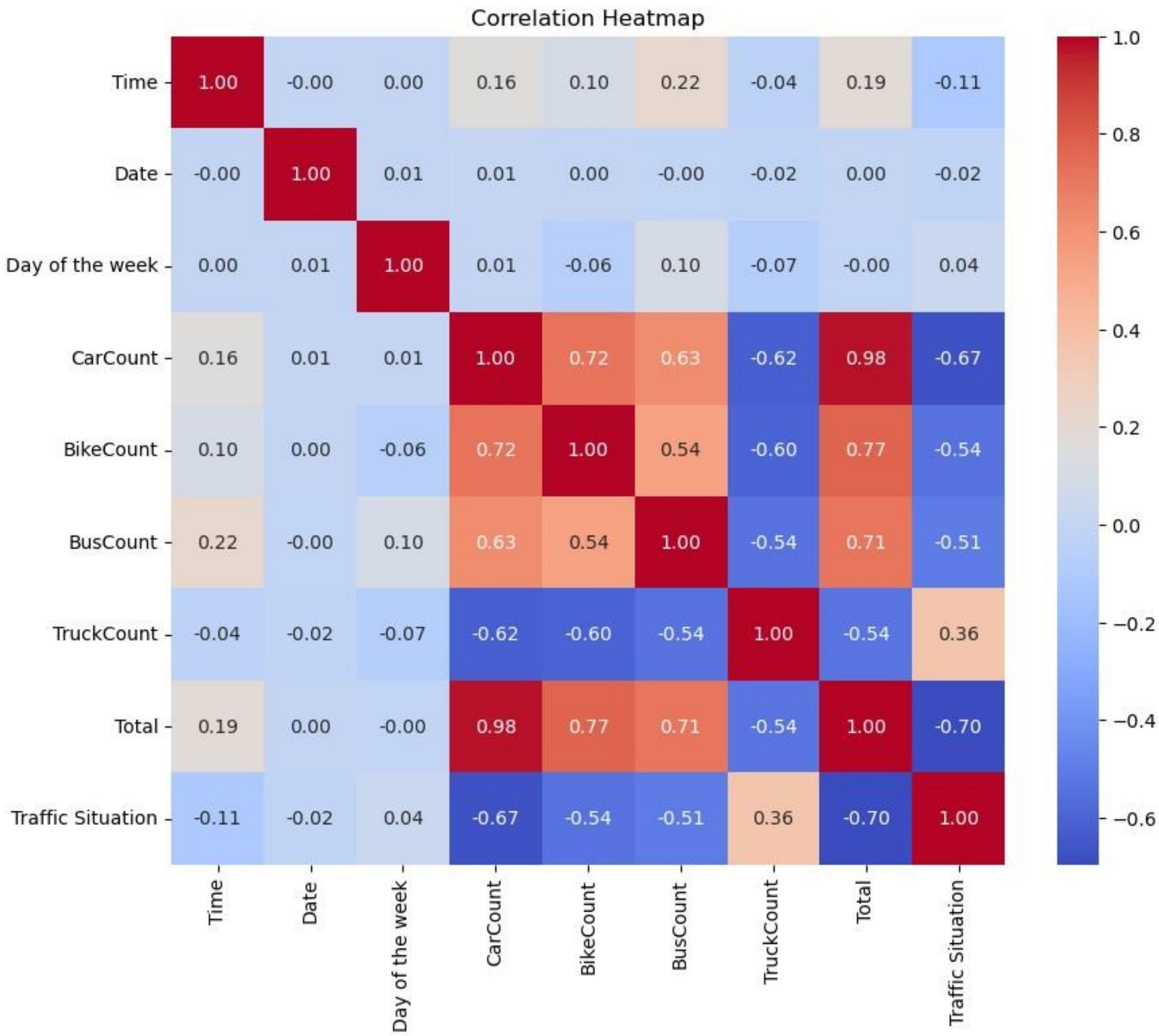
In [28]:
```
# Encoding categorical features
le = LabelEncoder()
df['Day of the week'] = le.fit_transform(df['Day of the week'])
```

In [29]:
```
df['Day of the week'].unique()
```

Out[29]: array([5, 6, 4, 0, 2, 3, 1])

Correlation Heatmap

In [31]:
```
plt.figure(figsize =(10,8))
sns.heatmap(df.corr(),annot =True,cmap ='coolwarm',fmt
='.2f') plt.title('Correlation Heatmap') plt.show()
```



Graph Description

The graph shows the correlation between different variables related to traffic data. The color scale indicates the strength and direction of the correlation. For example, a strong positive correlation is shown in red, while a strong negative correlation is shown in blue. Key observations include:

CarCount and BikeCount: These variables have a strong positive correlation, indicating that they tend to increase or decrease together. TruckCount and Traffic Situation: These variables have a strong negative correlation, suggesting that increased truck traffic is associated with lower traffic conditions. Time and Traffic Situation: There is a weak negative correlation between time and traffic situation, indicating that traffic tends to be better at certain times of the day.

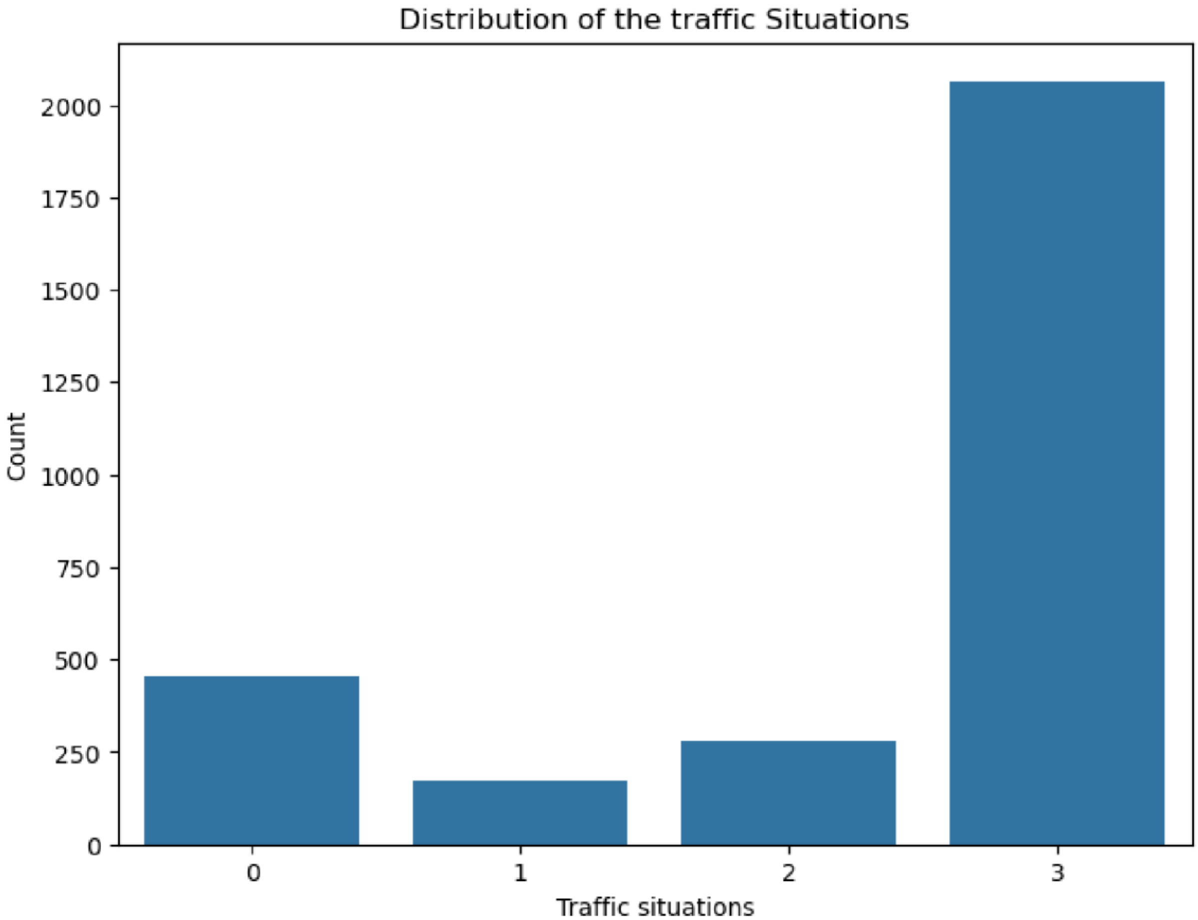
Hypothesis from the EDA

Based on the exploratory data analysis, we hypothesize that:

```
Traffic volume varies significantly by the time of day and day of

the week.
Certain vehicle types might dominate traffic at specific times
(e.g., more trucks at night).
The correlation between different vehicle types may indicate
patterns in traffic flow.
Predicting traffic situations might be feasible using machine
learning models based on vehicle counts.
```

Traffic situation distribution

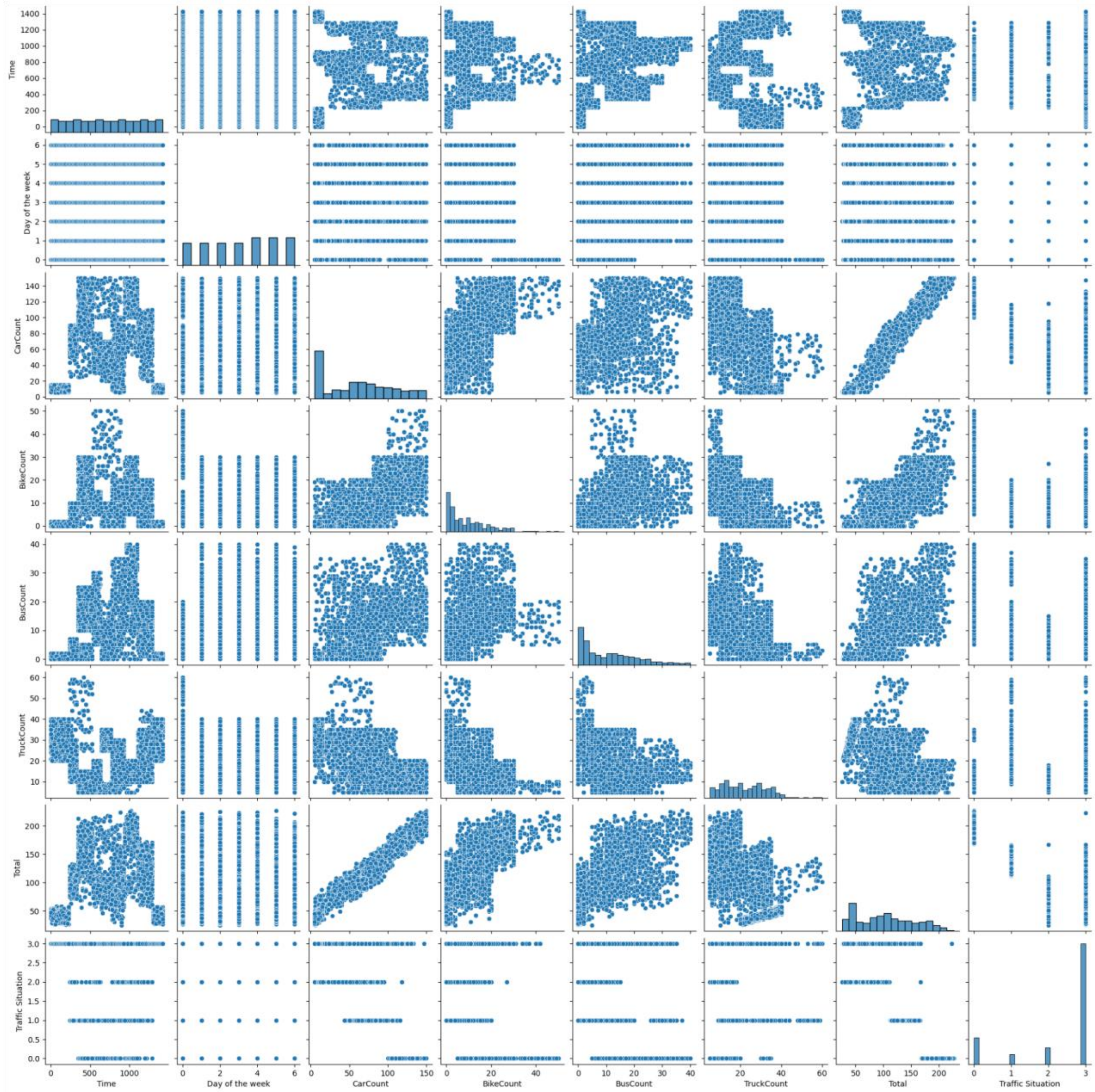
In [35]:
```
plt.figure(figsize =(8,6))
sns.countplot(x ='Traffic Situation',data =df)
plt.title('Distribution of the traffic
Situations') plt.xlabel('Traffic situations')
plt.ylabel('Count') plt.show()
```



Graph Description

The graph shows the distribution of traffic situations. The x-axis represents different traffic situations (0, 1, 2, 3), and the y-axis represents the count of each traffic situation. The majority of traffic situations fall into category 3, with significantly fewer occurrences in categories 0, 1, and 2.

In [37]:
```
#  Pairplot
sns.pairplot(df[['Time', 'Day of the week', 'CarCount', 'BikeCount', 'BusCount',
'T plt.show()
```



Graph Description

The graph is a pair plot that shows the relationships between different variables related to traffic data. Each subplot represents a pair of variables, with scatter plots showing the relationship between the two variables and histograms showing the distribution of each variable. Key observations include:

Positive correlation between CarCount and BikeCount: The scatter plot shows a clear upward trend, indicating that as CarCount increases, BikeCount also tends to increase.

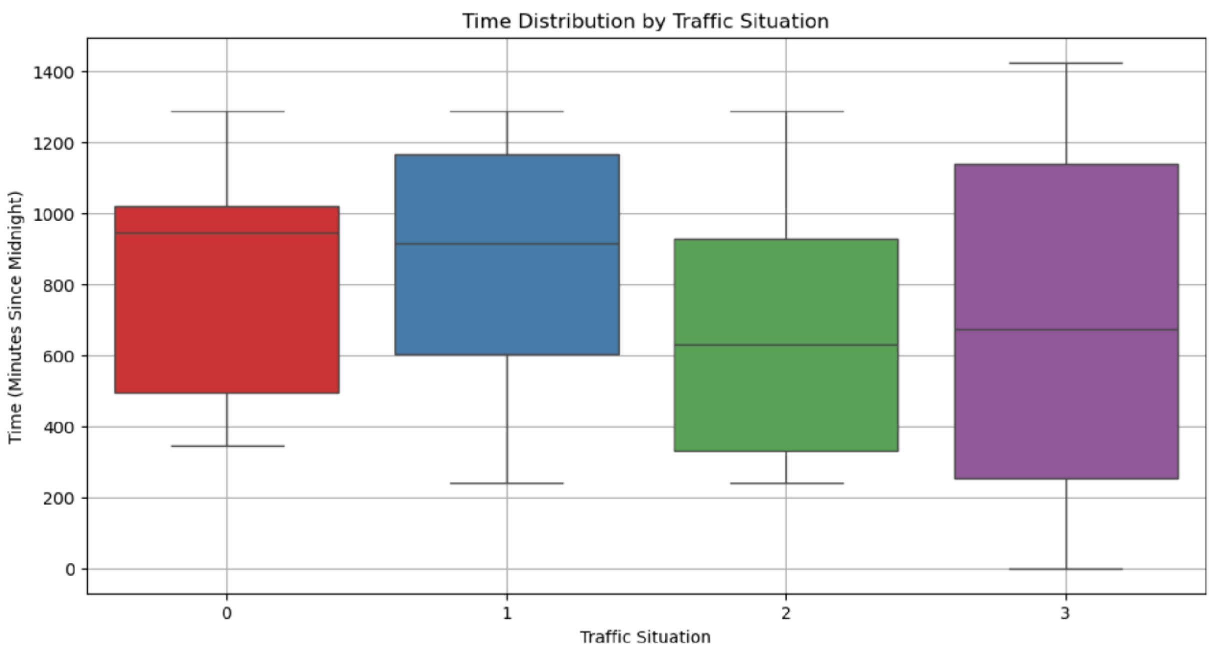
Negative correlation between TruckCount and Traffic Situation: The scatter plot shows a downward trend, suggesting that as TruckCount increases, Traffic Situation tends to decrease.

No clear relationship between Time and Traffic Situation: The scatter plot shows a random distribution of points, indicating that there is no strong correlation between these two variables.

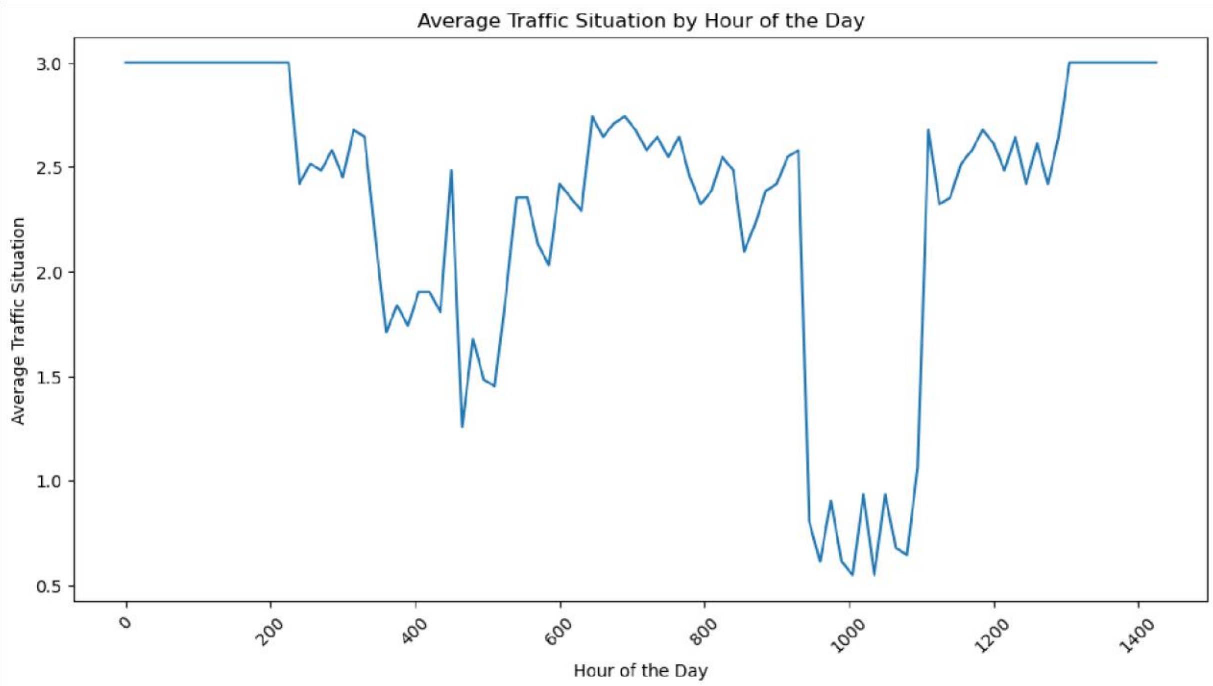
Time Vs Traffic situation

In [40]:
```
# Convert 'Traffic Situation' to categorical
df['Traffic Situation'] = pd.Categorical(df['Traffic Situation']).codes

# Create a box plot to show distribution
plt.figure(figsize=(12, 6))
sns.boxplot(x='Traffic Situation', y='Time', data=df,
palette='Set1') plt.title('Time Distribution by Traffic Situation')
plt.xlabel('Traffic Situation') plt.ylabel('Time (Minutes Since
Midnight)') plt.grid(True) plt.show()
```

```
C:\Users\HP\AppData\Local\Temp\ipykernel_16364\264837126.py:6: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in

v0.14 .0. Assign the `x` variable to `hue` and set `legend=False` for the same

effect.   sns.boxplot(x='Traffic Situation', y='Time', data=df, palette='Set1')
```



In [41]:
```
# Alternatively, a line plot to show average traffic situation over the hours
plt.figure(figsize=(12, 6))
avg_traffic_by_time = df.groupby('Time')['Traffic Situation'].mean()
sns.lineplot(x=avg_traffic_by_time.index,
y=avg_traffic_by_time.values) plt.title('Average Traffic Situation by
Hour of the Day') plt.xlabel('Hour of the Day') plt.ylabel('Average
Traffic Situation') plt.xticks(rotation=45)

plt.show()
```



In [42]:
```
df['Traffic Situation'].unique()
```

Out[42]:
```
array([3, 2, 0, 1], dtype=int8)
```

Explanation:

```
Boxplot:

Displays the distribution of Time for each Traffic Situation
category. Helps to visualize the range and median of Time values for
different traffic situations.

Line Plot:

The line plot shows the average traffic situation for each hour of
the day, providing a continuous view of traffic trends over time.
```

Model Training & Evaluation

The code trains a Random Forest Classifier model to predict traffic situations based on features like time, day of week, and vehicle counts. It splits data into training and testing sets, scales features, trains the model, and evaluates its performance using metrics like accuracy, precision, recall, and F1-score.

In [45]:
```
df.head()
```

Out[45]:

	Time	Date	Day of the	CarCount	BikeCount	BusCount	TruckCount	Total	Traffic Situation	week

```
#select features and target
X =df [['Time','Date','Day of the
week','CarCount','BikeCount','BusCount','TruckCou y =df['Traffic Situation']
```

0	0	1	5	13	2	2	24	41	3
1	15	1	5	14	1	1	36	52	3
2	30	1	5	10	2	2	32	46	3
3	45	1	5	10	2	2	36	50	3
4	60	1	5	11	2	1	34	48	3

In [76]:

In [78]:

```
#splitting the data into training and testing sets
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size    =0.2,random_state
=42)
```

In [80]:

```
from sklearn.preprocessing import StandardScaler

scaler =StandardScaler()
X_train =scaler.fit_transform(X_train)
X_test =scaler.transform(X_test)
```

In [84]:

```
#import RandomForest
from sklearn.ensemble import RandomForestClassifier
model =RandomForestClassifier(n_estimators =100,random_state =42)

model.fit(X_train,y_train)

#Make predictions y_pred
=model.predict(X_test)
```

In [86]:

```
from sklearn.metrics import confusion_matrix
from sklearn.metrics import
classification_report from sklearn.metrics
import accuracy_score

print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
print("Accuracy Score:", accuracy_score(y_test, y_pred))
```

```
Confusion Matrix:
 [[ 79   1   0   6]
```

```
 [  1  32   0   6]
 [  1   0  52   0]  [  6   2   3 407]]
Classification Report:               precision
recall  f1-score   support

0       0.91      0.92      0.91        86
1       0.91      0.82      0.86        39
2       0.95      0.98      0.96        53             3       0.97      0.97
        0.97       418

    accuracy                          0.96       596
macro avg       0.93      0.92      0.93       596
weighted avg       0.96      0.96      0.96       596

Accuracy Score: 0.9563758389261745
```

Report Description

The overall accuracy of the model is 0.95, which indicates that it correctly predicted 95% of the traffic situations in the testing set.

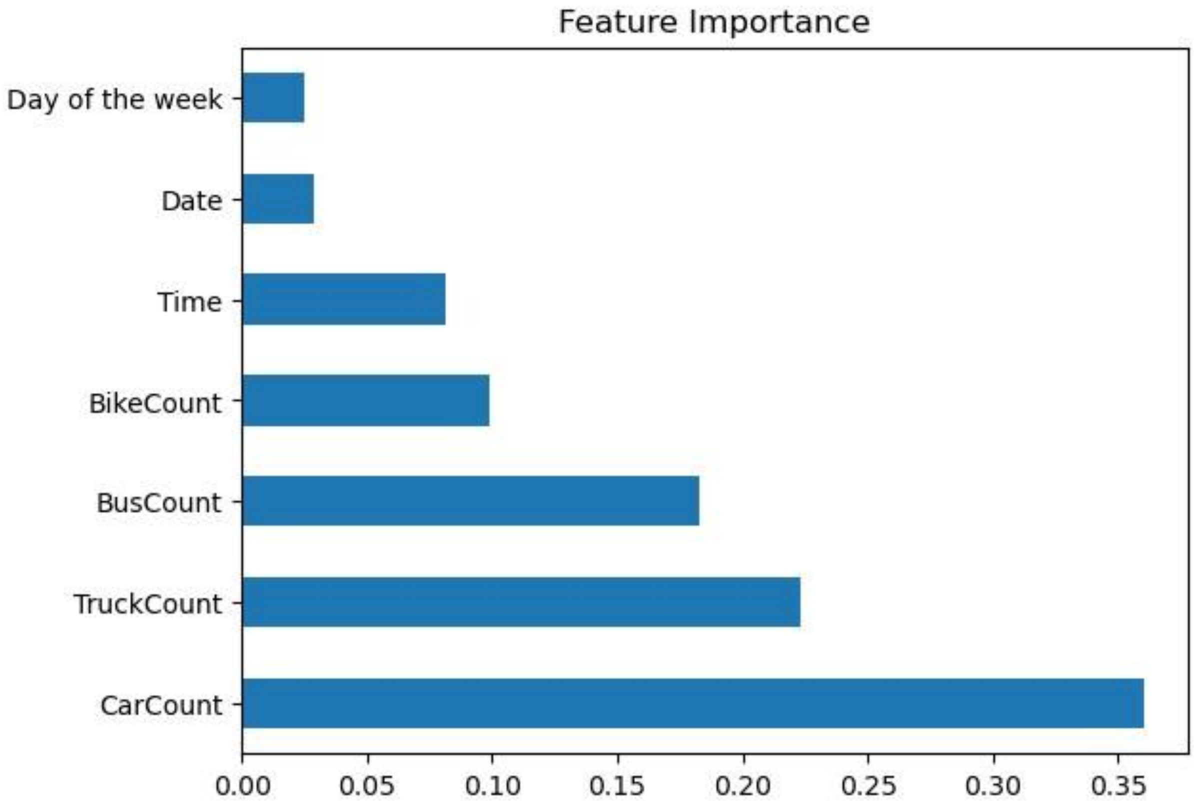
The precision, recall, and F1-score for each class are all relatively high, ranging from 0.89 to 0.99. This suggests that the model is able to accurately identify and predict different traffic situations.

Class 3 has the highest precision, recall, and F1-score, indicating that the model is particularly good at predicting this class.

Feature Importance

In [89]:

```
feature_importances =pd.Series(model.feature_importances_,index
=X.columns) feature_importances.nlargest(10).plot(kind ='barh')
plt.title('Feature Importance') plt.show()
```



Graph Description

The graph shows the feature importance for a machine learning model. The x-axis represents the feature importance, and the y-axis represents the features. The length of each bar indicates the importance of that feature in predicting the target variable. In this case, CarCount is the most important feature, followed by TruckCount and BusCount.

Summary of Insights

Sr. No.	**Parameters Taken from Dataset**	**Trend Observed**	**Insights or Outcomes**
1	Vehicle Type (Cars, Bikes, Buses, Trucks), Time	Cars have the highest volume, followed by bikes, with peak periods in the morning and evening. Trucks have the lowest volume.	Car and bike traffic increases significantly during rush hours. Consider measures to reduce congestion during peak times.
2	Vehicle Count per Day of the Week	No significant difference in total vehicle count across days. However, variation in spread for each day exists.	Traffic management remains consistent across the week, but detailed daily variations may require closer analysis.

Sr. No.	Parameters Taken from Dataset	Trend Observed	Insights or Outcomes
3	CarCount, BikeCount, TruckCount, Traffic Situation, Time	Strong positive correlation between CarCount and BikeCount. Negative correlation between TruckCount and Traffic Situation. Weak correlation between Time and Traffic Situation.	Higher truck traffic is associated with worse traffic conditions. Target traffic interventions based on vehicle type to improve flow.
4	Traffic Situation Categories (0, 1, 2, 3)	Category 3 dominates traffic situations, with fewer occurrences in categories 0, 1, and 2.	Category 3 represents the majority of traffic scenarios, implying that most traffic experiences fall under this range.
5	Pairwise Correlation (CarCount, BikeCount, TruckCount, Traffic Situation)	Positive correlation between CarCount and BikeCount. Negative correlation between TruckCount and Traffic Situation.	These correlations indicate that increases in certain vehicle types affect overall traffic conditions predictably.
6	Time Distribution for Traffic Situation	Different traffic situations show distinct time distributions with varying ranges and medians.	Certain traffic conditions (e.g., congestion) may be time-dependent. Interventions could be optimized for these times.

Conclusion

The Traffic Flow Prediction project provides critical insights into traffic patterns, highlighting peak congestion times and the impact of external factors such as weather or road conditions. By analyzing time-based traffic situations, the model identifies trends that can assist traffic authorities in managing congestion more effectively. The ability to predict traffic flow enables stakeholders to implement proactive measures, such as optimizing signal timings, adjusting public transport schedules, and planning road maintenance during low-traffic periods. These predictions can also support real-time traffic monitoring and alert systems, allowing for dynamic rerouting and minimizing disruptions during high-traffic periods.

Moreover, this project has broader implications for smart city integration and sustainability. By incorporating predictive traffic data, city planners can design more efficient road networks and reduce congestion, which in turn lowers vehicle emissions and fuel consumption. This contributes to environmental goals while also boosting economic productivity by reducing time spent in traffic. Ultimately, the traffic flow prediction model offers a data-driven approach to improving urban mobility, enhancing resource allocation, and fostering a more efficient and sustainable transportation ecosystem.

In [ ]:
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