Problem 8

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, classification_report
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import LabelEncoder

path = '/content/drive/MyDrive/sem 7/ID5055/Assignment 4/Traffic_data.csv'
```

```
data = pd.read_csv(path)
```

```
data.head(10)
```

	Time	Date	Day of the week	CarCount	BikeCount	BusCount	TruckCount	Total	Traffic Situation
0	12:00:00 AM	10	Tuesday	31	0	4	4	39	low
1	12:15:00 AM	10	Tuesday	49	0	3	3	55	low
2	12:30:00 AM	10	Tuesday	46	0	3	6	55	low
3	12:45:00 AM	10	Tuesday	51	0	2	5	58	low
4	1:00:00 AM	10	Tuesday	57	6	15	16	94	normal
5	1:15:00 AM	10	Tuesday	44	0	5	4	53	low
6	1:30:00 AM	10	Tuesday	37	0	1	4	42	low
7	1:45:00 AM	10	Tuesday	42	4	4	5	55	low
8	2:00:00 AM	10	Tuesday	51	0	9	7	67	low
9	2:15:00 AM	10	Tuesday	34	0	4	7	45	low

```
data.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   object
 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-null   object
dtypes: int64(6), object(3)
memory usage: 209.4+ KB
```

```
df = data
```

```
# Converting string values to numeric, Monday = 0 and Sunday = 6

df['Day of the week cat'] = LabelEncoder().fit_transform(df['Day of the week'])
col = df.pop('Day of the week cat')
data.insert(2, col.name, col)
```

```
df['Time'] = pd.to_datetime(df['Time']).apply(lambda x: x.hour)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2976 entries, 0 to 2975
Data columns (total 10 columns):
 #   Column               Non-Null Count  Dtype 
---  ------               --------------  ----- 
 0   Time                 2976 non-null   int64 
 1   Date                 2976 non-null   int64 
 2   Day of the week cat  2976 non-null   int64 
```

```
 3   Day of the week      2976 non-null   object
 4   CarCount             2976 non-null   int64
 5   BikeCount            2976 non-null   int64
 6   BusCount             2976 non-null   int64
 7   TruckCount           2976 non-null   int64
 8   Total                2976 non-null   int64
 9   Traffic Situation    2976 non-null   object
dtypes: int64(8), object(2)
memory usage: 232.6+ KB
```

```
X = df.drop(['Traffic Situation', 'Day of the week'], axis = 1)
Y = df['Traffic Situation']
```

1. Split the dataset into train and test set (train size= 0.8, random state = 42) and train a random forest classifier using the train set. Plot a confusion matrix using the test set for prediction.

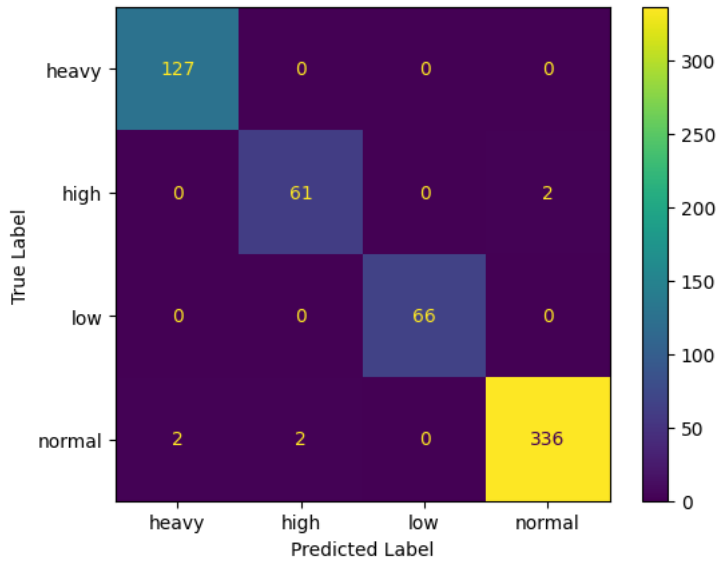
```
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, train_size= 0.8, random_state = 42)
```

```
rf = RandomForestClassifier()
rf.fit(X_train, Y_train)
Y_pred = rf.predict(X_test)
```

```
cm = confusion_matrix(Y_test, Y_pred)
cm_display = ConfusionMatrixDisplay(cm, display_labels = rf.classes_).plot()
plt.rcParams.update({'font.size': 14})
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()

print('\n*********************************************************************************\n')

print(classification_report(Y_test, Y_pred))
```




```
*********************************************************************************
              precision    recall  f1-score   support

       heavy       0.98      1.00      0.99       127
        high       0.97      0.97      0.97        63
         low       1.00      1.00      1.00        66
      normal       0.99      0.99      0.99       340

    accuracy                           0.99       596
   macro avg       0.99      0.99      0.99       596
weighted avg       0.99      0.99      0.99       596
```

2. Use a weighted random forest classifier with weights based on the frequency of the corresponding class. Plot a confusion matrix and report your observation by comparing the results with the previous results.

```
print(f'The classes are:\n{rf.classes_}')
```

```
The classes are:
['heavy' 'high' 'low' 'normal']
```

```
freq = dict(Y.value_counts())
print(freq)
```

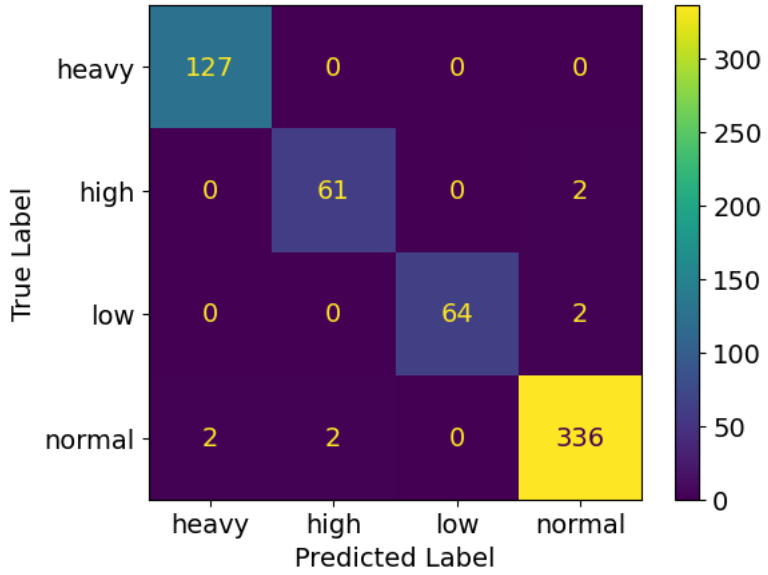
```
{'normal': 1669, 'heavy': 682, 'high': 321, 'low': 304}
```

```
rf_weighted = RandomForestClassifier(class_weight = freq)
rf_weighted.fit(X_train, Y_train)
Y_pred_weighted = rf_weighted.predict(X_test)
```

```
cm = confusion_matrix(Y_test, Y_pred_weighted)
cm_display = ConfusionMatrixDisplay(cm, display_labels = rf_weighted.classes_).plot()
plt.rcParams.update({'font.size': 14})
plt.xlabel("Predicted Label")
plt.ylabel("True Label")
plt.show()

print('\n*********************************************************************************\n')

print(classification_report(Y_test, Y_pred_weighted))
```




```
*********************************************************************************

              precision    recall  f1-score   support

       heavy       0.98      1.00      0.99       127
        high       0.97      0.97      0.97        63
         low       1.00      0.97      0.98        66
      normal       0.99      0.99      0.99       340

    accuracy                           0.99       596
   macro avg       0.99      0.98      0.98       596
weighted avg       0.99      0.99      0.99       596
```

3. Use the trained classifier model to report the important features based on impurity metric

```
rf.feature_importances_
```

```
array([0.04223248, 0.0091661 , 0.01331356, 0.14465027, 0.05917621,
       0.15528884, 0.22902063, 0.3471519 ])
```

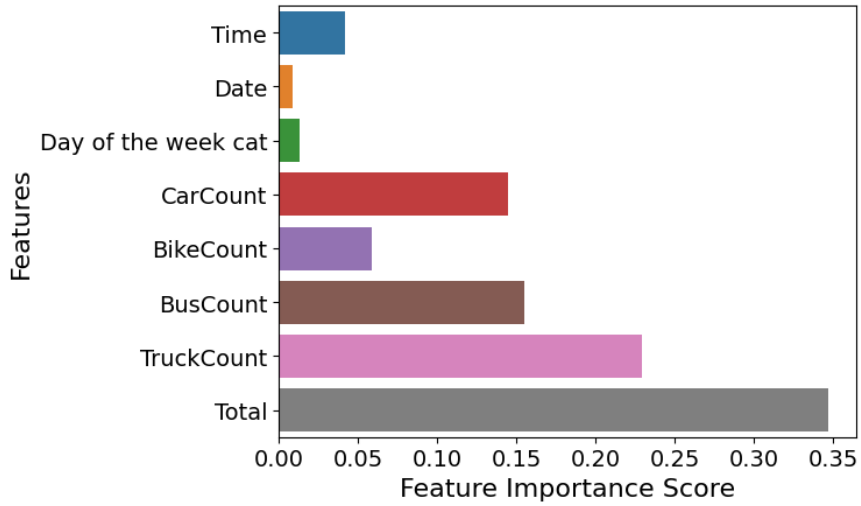
```
# Model 1
feature_scores = pd.Series(rf.feature_importances_, index = X_train.columns)
print(feature_scores)
```

```
Time                  0.042232
Date                  0.009166
Day of the week cat   0.013314
CarCount              0.144650
BikeCount             0.059176
BusCount              0.155289
```

```
TruckCount              0.229021
Total                   0.347152
dtype: float64
```

```
sns.barplot(x = feature_scores, y = feature_scores.index)
plt.xlabel('Feature Importance Score', fontsize = 16)
plt.ylabel('Features', fontsize = 16)
```

```
Text(0, 0.5, 'Features')
```

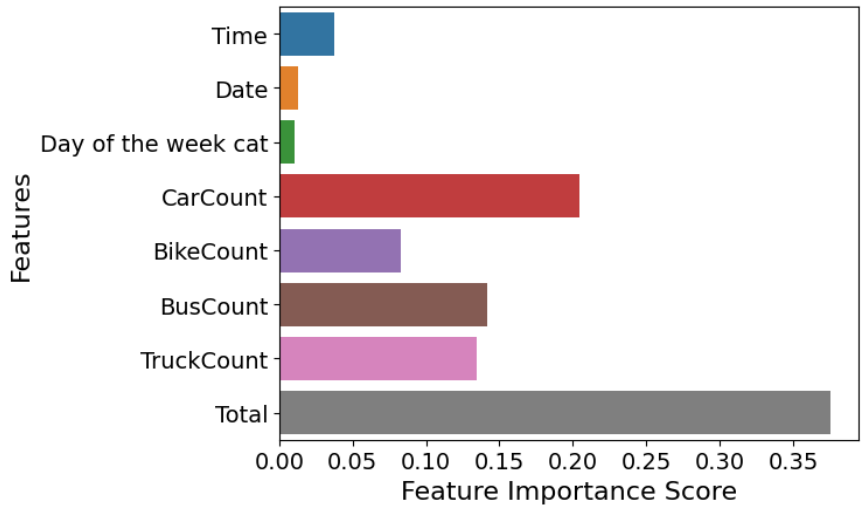



```
# Model 2
feature_scores_w = pd.Series(rf_weighted.feature_importances_, index = X_train.columns)
print(feature_scores)
```

```
Time                    0.037775
Date                    0.012922
Day of the week cat     0.010682
CarCount                0.204475
BikeCount               0.082924
BusCount                0.141365
TruckCount              0.134151
Total                   0.375706
dtype: float64
```

```
sns.barplot(x = feature_scores_w, y = feature_scores.index)
plt.xlabel('Feature Importance Score', fontsize = 16)
plt.ylabel('Features', fontsize = 16)
```

```
Text(0, 0.5, 'Features')
```



Observations

1. Since we are predicting the traffic condition, so it is reasonable why 'Total' feature has the highest feature importance.

2. Other important features are the count of heavy vehicles like cars, buses, and trucks, as they are main reason for traffic.
3. Time, Date, and Day of week got low feature score, however time is also an important feature in determining the traffic condition.