

DIC_Project_Harshit_Malpani_50608809

November 5, 2024

1 Phase 1

1.1 1: Problem Statement

1.1.1 1.1.1 Problem Statement

This project's goal is to make a detailed analysis on why road accidents are occurring a lot and in what trend, will be helpful in improving road safety measures & make the policy options which can reduce the number of accidents. This research would help to know the impacts of accident severity on the driver attributes, vehicle conditions, surface conditions and environmental conditions.

1.1.2 1.1.2 Potential Contribution & Importance

Road accidents pose a threat to health globally by resulting in significant fatalities and injuries of individuals worldwide. This evaluation plays a role in finding factors that play a vital role in accident prevention. The evidence of this review may support the implementation of measures of safety, improvement of driver education programs, and modification of road systems that can reduce accidents and save lives.

1.2 2: Ask Questions

Harshit Malpani: 50608809

Question 1: What vehicles should the authorities focus more on to reduce the cases of road accidents and the severity of road accidents Analyzing the type of vehicle involved in road accidents can help identify what vehicle type needs improvement in the technology. More technologies like Airbags, ABS brakes etc. can be augmented in those vehicles to improve their safety ratings and reduce life loss due to accidents

Question 2: Does the service period of the vehicle and ownership of the vehicle have any correlation with the accidents. The state of vehicle and the person driving it plays an important role in road safety. We need to find out how the state of the vehicle and the ownership of the vehicle affect the possibility of a vehicle to be involved in an accident. This study will help in making policies and rules to reduce road accidents and related casualties.

1.3 3: Data Retrieval

The dataset has been taken from [KAGGLE](#). For this task, we have uploaded a copy of the dataset to a GitHub repository and downloaded the data from the GitHub repository directly to the data frame

```
[224]: import pandas as pd

dataset = pd.read_csv('https://raw.githubusercontent.com/hmalpani/RTA-Dataset/
↳main/RTA_Dataset.csv')
```

```
[225]: dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12316 entries, 0 to 12315
Data columns (total 32 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   Time                                  12316 non-null  object
1   Day_of_week                          12316 non-null  object
2   Age_band_of_driver                   12316 non-null  object
3   Sex_of_driver                        12316 non-null  object
4   Educational_level                    11575 non-null  object
5   Vehicle_driver_relation              11737 non-null  object
6   Driving_experience                   11487 non-null  object
7   Type_of_vehicle                      11366 non-null  object
8   Owner_of_vehicle                    11834 non-null  object
9   Service_year_of_vehicle              8388 non-null   object
10  Defect_of_vehicle                    7889 non-null   object
11  Area_accident_occured                12077 non-null  object
12  Lanes_or_Medians                    11931 non-null  object
13  Road_allignment                     12174 non-null  object
14  Types_of_Junction                   11429 non-null  object
15  Road_surface_type                   12144 non-null  object
16  Road_surface_conditions              12316 non-null  object
17  Light_conditions                    12316 non-null  object
18  Weather_conditions                  12316 non-null  object
19  Type_of_collision                   12161 non-null  object
20  Number_of_vehicles_involved          12316 non-null  int64
21  Number_of_casualties                 12316 non-null  int64
22  Vehicle_movement                     12008 non-null  object
23  Casualty_class                       12316 non-null  object
24  Sex_of_casualty                     12316 non-null  object
25  Age_band_of_casualty                 12316 non-null  object
26  Casualty_severity                    12316 non-null  object
27  Work_of_casualty                     9118 non-null   object
28  Fitness_of_casualty                  9681 non-null   object
29  Pedestrian_movement                 12316 non-null  object
30  Cause_of_accident                   12316 non-null  object
31  Accident_severity                    12316 non-null  object
dtypes: int64(2), object(30)
memory usage: 3.0+ MB
```

```
[226]: dataset.head()
```

[226]:

	Time	Day_of_week	Age_band_of_driver	Sex_of_driver	Educational_level	\
0	17:02:00	Monday	18-30	Male	Above high school	
1	17:02:00	Monday	31-50	Male	Junior high school	
2	17:02:00	Monday	18-30	Male	Junior high school	
3	1:06:00	Sunday	18-30	Male	Junior high school	
4	1:06:00	Sunday	18-30	Male	Junior high school	

	Vehicle_driver_relation	Driving_experience	Type_of_vehicle	\
0	Employee	1-2yr	Automobile	
1	Employee	Above 10yr	Public (> 45 seats)	
2	Employee	1-2yr	Lorry (41?100Q)	
3	Employee	5-10yr	Public (> 45 seats)	
4	Employee	2-5yr	NaN	

	Owner_of_vehicle	Service_year_of_vehicle	Defect_of_vehicle	\
0	Owner	Above 10yr	No defect	
1	Owner	5-10yrs	No defect	
2	Owner	NaN	No defect	
3	Governmental	NaN	No defect	
4	Owner	5-10yrs	No defect	

	Area_accident_occured	Lanes_or_Medians	\
0	Residential areas	NaN	
1	Office areas	Undivided Two way	
2	Recreational areas	other	
3	Office areas	other	
4	Industrial areas	other	

	Road_alignment	Types_of_Junction	\
0	Tangent road with flat terrain	No junction	
1	Tangent road with flat terrain	No junction	
2	NaN	No junction	
3	Tangent road with mild grade and flat terrain	Y Shape	
4	Tangent road with flat terrain	Y Shape	

	Road_surface_type	Road_surface_conditions	Light_conditions	\
0	Asphalt roads	Dry	Daylight	
1	Asphalt roads	Dry	Daylight	
2	Asphalt roads	Dry	Daylight	
3	Earth roads	Dry	Darkness - lights lit	
4	Asphalt roads	Dry	Darkness - lights lit	

	Weather_conditions	Type_of_collision	\
0	Normal	Collision with roadside-parked vehicles	
1	Normal	Vehicle with vehicle collision	
2	Normal	Collision with roadside objects	
3	Normal	Vehicle with vehicle collision	

4	Normal	Vehicle with vehicle collision		
---	--------	--------------------------------	--	--

	Number_of_vehicles_involved	Number_of_casualties	Vehicle_movement	\
0	2	2	Going straight	
1	2	2	Going straight	
2	2	2	Going straight	
3	2	2	Going straight	
4	2	2	Going straight	

	Casualty_class	Sex_of_casualty	Age_band_of_casualty	Casualty_severity	\
0	na	na	na	na	
1	na	na	na	na	
2	Driver or rider	Male	31-50	3	
3	Pedestrian	Female	18-30	3	
4	na	na	na	na	

	Work_of_casualty	Fitness_of_casualty	Pedestrian_movement	\
0	NaN	NaN	Not a Pedestrian	
1	NaN	NaN	Not a Pedestrian	
2	Driver	NaN	Not a Pedestrian	
3	Driver	Normal	Not a Pedestrian	
4	NaN	NaN	Not a Pedestrian	

	Cause_of_accident	Accident_severity
0	Moving Backward	Slight Injury
1	Overtaking	Slight Injury
2	Changing lane to the left	Serious Injury
3	Changing lane to the right	Slight Injury
4	Overtaking	Slight Injury

1.4 4: Data Cleaning

1.4.1 1) Remove Duplicate Values:

Removing duplicate values is an essential step of data cleaning for any data science project. It helps in reducing the bias where certain data points are represented multiple times. If the duplicate values are not removed, it can skew the results and therefore lead to incorrect conclusions

```
[227]: # Remove duplicates
cleaned_dataset = dataset.drop_duplicates()
```

1.4.2 2) Validation

This step of data cleaning is done to validate that the data in the dataset is useful for the problem we are solving

```
[228]:
```

```
# Remove entries with 'Number_of_vehicles_involved' = 0
cleaned_dataset =
↳ cleaned_dataset[cleaned_dataset['Number_of_vehicles_involved'] != 0]
```

1.4.3 3) Detection and Removal of Outliers

Outliers in the data can impact the decision making using the analytics from the data. We should detect and process the outliers

```
[229]: numerical_columns = ['Number_of_vehicles_involved', 'Number_of_casualties']
for column in numerical_columns:
    if not pd.api.types.is_numeric_dtype(cleaned_dataset[column]):
        print(f"Column '{column}' should be numeric but contains non-numeric_
↳ data.")

def detect_outliers(column):
    Q1 = cleaned_dataset[column].quantile(0.05)
    Q3 = cleaned_dataset[column].quantile(0.95)
    IQR = Q3 - Q1
    outliers = cleaned_dataset[(cleaned_dataset[column] < (Q1 - 1.5 * IQR)) |
↳ (cleaned_dataset[column] > (Q3 + 1.5 * IQR))]
    return outliers

for column in numerical_columns:
    outliers = detect_outliers(column)
    if not outliers.empty:
        print(f"Outliers detected in column '{column}':\n", outliers.shape)

def remove_outliers(df, column):
    Q1 = cleaned_dataset[column].quantile(0.05)
    Q3 = cleaned_dataset[column].quantile(0.95)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    return cleaned_dataset[(cleaned_dataset[column] >= lower_bound) &
↳ (cleaned_dataset[column] <= upper_bound)]

print("Shape before removing outliers:", cleaned_dataset.shape)
cleaned_dataset = remove_outliers(cleaned_dataset,
↳ 'Number_of_vehicles_involved')
cleaned_dataset = remove_outliers(cleaned_dataset, 'Number_of_casualties')

print("Shape after removing outliers:", cleaned_dataset.shape)
```

Outliers detected in column 'Number_of_vehicles_involved':

(7, 32)

Shape before removing outliers: (12316, 32)

Shape after removing outliers: (12309, 32)

1.4.4 4) Handling Missing Values:

In this step of Data Cleaning, we either remove or impute the missing values in the dataset

```
[230]: # Number of missing values
missing_value_count = cleaned_dataset.isnull().sum()
missing_value_count
```

```
[230]: Time                                0
      Day_of_week                        0
      Age_band_of_driver                 0
      Sex_of_driver                     0
      Educational_level                  741
      Vehicle_driver_relation            579
      Driving_experience                  829
      Type_of_vehicle                    950
      Owner_of_vehicle                   482
      Service_year_of_vehicle            3923
      Defect_of_vehicle                  4427
      Area_accident_occured              239
      Lanes_or_Medians                   385
      Road_allignment                    142
      Types_of_Junction                  887
      Road_surface_type                   172
      Road_surface_conditions             0
      Light_conditions                   0
      Weather_conditions                  0
      Type_of_collision                  155
      Number_of_vehicles_involved         0
      Number_of_casualties                0
      Vehicle_movement                   306
      Casualty_class                     0
      Sex_of_casualty                    0
      Age_band_of_casualty                0
      Casualty_severity                   0
      Work_of_casualty                   3197
      Fitness_of_casualty                 2634
      Pedestrian_movement                 0
      Cause_of_accident                   0
      Accident_severity                   0
      dtype: int64
```

```
[231]: dataset_columns = cleaned_dataset.columns.tolist()
      missing_values_columns = missing_value_count[missing_value_count > 0].index.
      ↪tolist()
      print(missing_values_columns)
```

```
['Educational_level', 'Vehicle_driver_relation', 'Driving_experience',
 'Type_of_vehicle', 'Owner_of_vehicle', 'Service_year_of_vehicle',
```

```
'Defect_of_vehicle', 'Area_accident_occured', 'Lanes_or_Medians',
'Road_alignment', 'Types_of_Junction', 'Road_surface_type',
'Type_of_collision', 'Vehicle_movement', 'Work_of_casualty',
'Fitness_of_casualty']
```

```
[232]: # Replace missing values
cleaned_dataset['Educational_level'].
    ↳fillna(cleaned_dataset['Educational_level'].mode()[0], inplace=True)
cleaned_dataset['Vehicle_driver_relation'].fillna('Unknown', inplace=True)
cleaned_dataset['Driving_experience'].
    ↳fillna(cleaned_dataset['Driving_experience'].mode()[0], inplace=True)
cleaned_dataset['Type_of_vehicle'].fillna('Unknown', inplace=True)
cleaned_dataset['Owner_of_vehicle'].fillna('Unknown', inplace=True)
cleaned_dataset['Service_year_of_vehicle'].fillna('Unknown', inplace=True)
cleaned_dataset['Defect_of_vehicle'].fillna('No defect', inplace=True)
cleaned_dataset['Area_accident_occured'].fillna('Unknown', inplace=True)
cleaned_dataset['Lanes_or_Medians'].fillna('Unknown', inplace=True)
cleaned_dataset['Road_alignment'].fillna('Unknown', inplace=True)
cleaned_dataset['Types_of_Junction'].fillna('Unknown', inplace=True)
cleaned_dataset['Road_surface_type'].fillna('Unknown', inplace=True)
cleaned_dataset['Type_of_collision'].fillna('Unknown', inplace=True)
cleaned_dataset['Vehicle_movement'].fillna('Unknown', inplace=True)
cleaned_dataset['Work_of_casualty'].fillna('Unknown', inplace=True)
cleaned_dataset['Fitness_of_casualty'].fillna('Unknown', inplace=True)
```

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:2
: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:3
: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:4  
: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:5  
: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:6  
: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:7  
: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:8  
: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:9  
: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:1
0: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:1
1: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:1
2: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:1
3: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:1  
4: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:1  
5: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:1  
6: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

```
/var/folders/75/vdppt_x106x0z977clxb5xh00000gn/T/ipykernel_46121/3289919421.py:17: FutureWarning:
```

A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.

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 inplace on the original object.

1.4.5 5) Correcting Errors:

In this data cleaning, we identify and fix the errors or inconsistencies present in the data

```
[233]: cleaned_dataset['Type_of_vehicle'] = cleaned_dataset['Type_of_vehicle'].
        ↪replace('Lorry (41?100Q)', 'Lorry (41 - 100 Q)')
cleaned_dataset['Type_of_vehicle'] = cleaned_dataset['Type_of_vehicle'].
        ↪replace('Lorry (11?40Q)', 'Lorry (11 - 40 Q)')
cleaned_dataset['Type_of_vehicle'] = cleaned_dataset['Type_of_vehicle'].
        ↪replace('Public (13?45 seats)', 'Public (13 - 45 seats)')
cleaned_dataset['Area_accident_occured'] = _
        ↪cleaned_dataset['Area_accident_occured'].replace(' Recreational areas', _
        ↪'Recreational areas')
cleaned_dataset['Area_accident_occured'] = _
        ↪cleaned_dataset['Area_accident_occured'].replace(' Market areas', 'Market_
        ↪areas')
cleaned_dataset['Area_accident_occured'] = _
        ↪cleaned_dataset['Area_accident_occured'].replace(' Church areas', 'Church_
        ↪areas')
```

```

cleaned_dataset['Area_accident_occured'] =
    ↪cleaned_dataset['Area_accident_occured'].replace(' Hospital areas',
    ↪'Hospital areas')
cleaned_dataset['Area_accident_occured'] =
    ↪cleaned_dataset['Area_accident_occured'].replace(' Industrial areas',
    ↪'Industrial areas')
cleaned_dataset['Area_accident_occured'] =
    ↪cleaned_dataset['Area_accident_occured'].replace(' Outside rural areas',
    ↪'Outside rural areas')
cleaned_dataset['Area_accident_occured'] =
    ↪cleaned_dataset['Area_accident_occured'].replace('Rural village areasOffice
    ↪areas', 'Rural Office areas')
cleaned_dataset['Road_allignment'] = cleaned_dataset['Road_allignment'].
    ↪replace('Tangent road with mountainous terrain and', 'Tangent road with
    ↪mountainous terrain')
cleaned_dataset['Fitness_of_casualty'] =
    ↪cleaned_dataset['Fitness_of_casualty'].replace('NormalNormal', 'Normal')
cleaned_dataset['Casualty_severity'] = cleaned_dataset['Casualty_severity'].
    ↪replace('na', 'Unknown')

```

1.4.6 6) Standardize the Data

- a) Convert all the entries in Time column to a consistent format.
- b) Convert Over 51 to 51 and Over in the Age_band_of_driver column

```

[234]: # Standardize the 'Time' column
cleaned_dataset['Time'] = pd.to_datetime(cleaned_dataset['Time'], format='%H:%M:
    ↪%S').dt.time
# Make 'Over 51' to '51 and Over' for Driver Age band
cleaned_dataset['Age_band_of_driver'] = cleaned_dataset['Age_band_of_driver'].
    ↪replace('Over 51', '51 and Over')

```

1.4.7 7) Parsing the data

Convert all the text in the dataset to lowercase to ensure consistency. This helps in avoiding the situations where same words with different cases are considered different

```

[235]: # Make all the characters to lowercase
cleaned_dataset = cleaned_dataset.map(lambda x: x.lower() if isinstance(x, str)
    ↪else x)

```

1.4.8 8) Feature Engineering

Using the existing columns, we create new features which helps in finding new patterns in the data

```

[236]: print(cleaned_dataset['Time'].head())
cleaned_dataset['Hour'] = pd.to_datetime(cleaned_dataset['Time'], format='%H:%M:
    ↪%S').dt.hour

```

```

Time_of_day = ['Night', 'Morning', 'Noon', 'Evening']

def categorize_time_of_day(hour):
    if 5 <= hour < 12:
        return 2
    elif 12 <= hour < 17:
        return 3
    elif 17 <= hour < 21:
        return 4
    else:
        return 1

cleaned_dataset['Time_of_day'] = cleaned_dataset['Hour'].
    ↪ apply(categorize_time_of_day)

print("Data head after categorizing and encoding Time_of_day:\n")
cleaned_dataset[['Time', 'Hour', 'Time_of_day']].head()

```

```

0    17:02:00
1    17:02:00
2    17:02:00
3    01:06:00
4    01:06:00
Name: Time, dtype: object
Data head after categorizing and encoding Time_of_day:

```

```

[236]:
      Time  Hour  Time_of_day
0  17:02:00   17           4
1  17:02:00   17           4
2  17:02:00   17           4
3  01:06:00    1           1
4  01:06:00    1           1

```

1.4.9 9) Ordinal Encoding

Categorical data should be converted so that they can be fed to the algorithms that are used on the data

```

[237]: from sklearn.preprocessing import OneHotEncoder

encoding_dict = {
    'Day_of_week': 'ordinal',
    'Age_band_of_driver': 'ordinal',
    'Sex_of_driver': 'one_hot',
    'Educational_level': 'ordinal',
    'Vehicle_driver_relation': 'one_hot',

```

```

'Driving_experience': 'ordinal',
'Type_of_vehicle': 'one_hot',
'Owner_of_vehicle': 'one_hot',
'Service_year_of_vehicle': 'ordinal',
'Defect_of_vehicle': 'one_hot',
'Area_accident_occured': 'one_hot',
'Lanes_or_Medians': 'one_hot',
'Road_allignment': 'one_hot',
'Types_of_Junction': 'one_hot',
'Road_surface_type': 'one_hot',
'Road_surface_conditions': 'ordinal',
'Light_conditions': 'one_hot',
'Weather_conditions': 'one_hot',
'Type_of_collision': 'one_hot',
'Vehicle_movement': 'one_hot',
'Casualty_class': 'one_hot',
'Sex_of_casualty': 'one_hot',
'Age_band_of_casualty': 'ordinal',
'Casualty_severity': 'ordinal',
'Work_of_casualty': 'one_hot',
'Fitness_of_casualty': 'one_hot',
'Pedestrian_movement': 'one_hot',
'Cause_of_accident': 'one_hot',
'Accident_severity': 'ordinal'
}

ordinal_mappings = {
    'Day_of_week': {
        'Monday': 0, 'Tuesday': 1, 'Wednesday': 2, 'Thursday': 3,
        'Friday': 4, 'Saturday': 5, 'Sunday': 6, 'Unknown': -1
    },
    'Age_band_of_driver': {
        'Under 18': 0, '18-30': 1, '31-50': 2, 'Over 51': 3, 'Unknown': -1
    },
    'Educational_level': {
        'Illiterate': 0, 'Writing & reading': 1, 'Elementary school': 2,
        'Junior high school': 3, 'High school': 4, 'Above high school': 5,
        'Unknown': -1
    },
    'Driving_experience': {
        'No Licence': 0, 'Below 1yr': 1, '1-2yr': 2, '2-5yr': 3, '5-10yr': 4,
        'Above 10yr': 5, 'unknown': -1
    },
    'Service_year_of_vehicle': {
        'Below 1yr': 0, '1-2yr': 1, '2-5yrs': 2, '5-10yrs': 3,
        'Above 10yr': 4, 'Unknown': -1
    },

```

```

        'Road_surface_conditions': {
            'Dry': 0, 'Wet or damp': 1, 'Snow': 2, 'Flood over 3cm. deep': 3,
            ↪ 'Unknown': -1
        },
        'Age_band_of_casualty': {
            'Under 18': 0, '18-30': 1, '31-50': 2, 'Over 51': 3, '5': 4, 'na': -1,
            ↪ 'Unknown': -1
        },
        'Casualty_severity': {
            '3': 0, '2': 1, '1': 2, 'na': -1, 'Unknown': -1
        },
        'Accident_severity': {
            'Slight Injury': 0, 'Serious Injury': 1, 'Fatal injury': 2, 'Unknown':
            ↪ -1
        }
    }

def apply_ordinal_encoding(df, encoding_dict, ordinal_mappings):
    for column, encoding_type in encoding_dict.items():
        if encoding_type == 'ordinal':
            if column in ordinal_mappings:
                df[f"{column}_ordinal"] = df[column].
                ↪ map(ordinal_mappings[column])
            else:
                print(f"No ordinal mapping provided for column: {column}")
    return df

cleaned_dataset = apply_ordinal_encoding(cleaned_dataset, encoding_dict,
    ↪ ordinal_mappings)

cleaned_dataset.head()

```

```

[237]:      Time Day_of_week Age_band_of_driver Sex_of_driver Educational_level \
0  17:02:00    monday      18-30      male  above high school
1  17:02:00    monday      31-50      male  junior high school
2  17:02:00    monday      18-30      male  junior high school
3  01:06:00    sunday      18-30      male  junior high school
4  01:06:00    sunday      18-30      male  junior high school

      Vehicle_driver_relation Driving_experience      Type_of_vehicle \
0      employee      1-2yr      automobile
1      employee  above 10yr  public (> 45 seats)
2      employee      1-2yr  lorry (41 - 100 q)
3      employee      5-10yr  public (> 45 seats)
4      employee      2-5yr      unknown

      Owner_of_vehicle Service_year_of_vehicle Defect_of_vehicle \

```


0	owner	above 10yr	no defect
1	owner	5-10yrs	no defect
2	owner	unknown	no defect
3	governmental	unknown	no defect
4	owner	5-10yrs	no defect

	Area_accident_occured	Lanes_or_Medians	\
0	residential areas	unknown	
1	office areas	undivided two way	
2	recreational areas	other	
3	office areas	other	
4	industrial areas	other	

	Road_alignment	Types_of_Junction	\
0	tangent road with flat terrain	no junction	
1	tangent road with flat terrain	no junction	
2	unknown	no junction	
3	tangent road with mild grade and flat terrain	y shape	
4	tangent road with flat terrain	y shape	

	Road_surface_type	Road_surface_conditions	Light_conditions	\
0	asphalt roads	dry	daylight	
1	asphalt roads	dry	daylight	
2	asphalt roads	dry	daylight	
3	earth roads	dry	darkness - lights lit	
4	asphalt roads	dry	darkness - lights lit	

	Weather_conditions	Type_of_collision	\
0	normal	collision with roadside-parked vehicles	
1	normal	vehicle with vehicle collision	
2	normal	collision with roadside objects	
3	normal	vehicle with vehicle collision	
4	normal	vehicle with vehicle collision	

	Number_of_vehicles_involved	Number_of_casualties	Vehicle_movement	\
0	2	2	going straight	
1	2	2	going straight	
2	2	2	going straight	
3	2	2	going straight	
4	2	2	going straight	

	Casualty_class	Sex_of_casualty	Age_band_of_casualty	Casualty_severity	\
0	na	na	na	unknown	
1	na	na	na	unknown	
2	driver or rider	male	31-50	3	
3	pedestrian	female	18-30	3	
4	na	na	na	unknown	

	Work_of_casualty	Fitness_of_casualty	Pedestrian_movement	\
0	unknown	unknown	not a pedestrian	
1	unknown	unknown	not a pedestrian	
2	driver	unknown	not a pedestrian	
3	driver	normal	not a pedestrian	
4	unknown	unknown	not a pedestrian	

	Cause_of_accident	Accident_severity	Hour	Time_of_day	\
0	moving backward	slight injury	17	4	
1	overtaking	slight injury	17	4	
2	changing lane to the left	serious injury	17	4	
3	changing lane to the right	slight injury	1	1	
4	overtaking	slight injury	1	1	

	Day_of_week_ordinal	Age_band_of_driver_ordinal	Educational_level_ordinal	\
0	NaN	1.0	NaN	
1	NaN	2.0	NaN	
2	NaN	1.0	NaN	
3	NaN	1.0	NaN	
4	NaN	1.0	NaN	

	Driving_experience_ordinal	Service_year_of_vehicle_ordinal	\
0	2.0	NaN	
1	NaN	3.0	
2	2.0	NaN	
3	4.0	NaN	
4	3.0	3.0	

	Road_surface_conditions_ordinal	Age_band_of_casualty_ordinal	\
0	NaN	-1.0	
1	NaN	-1.0	
2	NaN	2.0	
3	NaN	1.0	
4	NaN	-1.0	

	Casualty_severity_ordinal	Accident_severity_ordinal
0	NaN	NaN
1	NaN	NaN
2	0.0	NaN
3	0.0	NaN
4	NaN	NaN

1.4.10 10) One Hot Encoding

Categorical data should be converted so that they can be fed to the algorithms that are used on the data

```
[238]: def apply_onehot_encoding(df, encoding_dict, ordinal_mappings):
        one_hot_encoder = OneHotEncoder(sparse_output=False, drop='first')

        for column, encoding_type in encoding_dict.items():
            if encoding_type == 'one_hot':
                one_hot_encoded_df = pd.get_dummies(df[column], prefix=column,
↳drop_first=True)
                df = pd.concat([df, one_hot_encoded_df], axis=1)
        return df

cleaned_dataset = apply_onehot_encoding(cleaned_dataset, encoding_dict,
↳ordinal_mappings)

cleaned_dataset.head()
```

```
[238]:      Time Day_of_week Age_band_of_driver Sex_of_driver Educational_level \
0  17:02:00    monday      18-30      male  above high school
1  17:02:00    monday      31-50      male  junior high school
2  17:02:00    monday      18-30      male  junior high school
3  01:06:00    sunday      18-30      male  junior high school
4  01:06:00    sunday      18-30      male  junior high school

      Vehicle_driver_relation Driving_experience      Type_of_vehicle \
0      employee      1-2yr      automobile
1      employee  above 10yr  public (> 45 seats)
2      employee      1-2yr  lorry (41 - 100 q)
3      employee      5-10yr  public (> 45 seats)
4      employee      2-5yr      unknown

      Owner_of_vehicle Service_year_of_vehicle Defect_of_vehicle \
0      owner      above 10yr      no defect
1      owner      5-10yrs      no defect
2      owner      unknown      no defect
3  governmental      unknown      no defect
4      owner      5-10yrs      no defect

      Area_accident_occured Lanes_or_Medians \
0      residential areas      unknown
1      office areas  undivided two way
2      recreational areas      other
3      office areas      other
4      industrial areas      other

      Road_alignment Types_of_Junction \
0      tangent road with flat terrain      no junction
1      tangent road with flat terrain      no junction
2      unknown      no junction
```

3	tangent road with mild grade and flat terrain	y shape
4	tangent road with flat terrain	y shape

	Road_surface_type	Road_surface_conditions	Light_conditions	\
0	asphalt roads	dry	daylight	
1	asphalt roads	dry	daylight	
2	asphalt roads	dry	daylight	
3	earth roads	dry	darkness - lights lit	
4	asphalt roads	dry	darkness - lights lit	

	Weather_conditions	Type_of_collision	\
0	normal	collision with roadside-parked vehicles	
1	normal	vehicle with vehicle collision	
2	normal	collision with roadside objects	
3	normal	vehicle with vehicle collision	
4	normal	vehicle with vehicle collision	

	Number_of_vehicles_involved	Number_of_casualties	Vehicle_movement	\
0	2	2	going straight	
1	2	2	going straight	
2	2	2	going straight	
3	2	2	going straight	
4	2	2	going straight	

	Casualty_class	Sex_of_casualty	Age_band_of_casualty	Casualty_severity	\
0	na	na	na	unknown	
1	na	na	na	unknown	
2	driver or rider	male	31-50	3	
3	pedestrian	female	18-30	3	
4	na	na	na	unknown	

	Work_of_casualty	Fitness_of_casualty	Pedestrian_movement	\
0	unknown	unknown	not a pedestrian	
1	unknown	unknown	not a pedestrian	
2	driver	unknown	not a pedestrian	
3	driver	normal	not a pedestrian	
4	unknown	unknown	not a pedestrian	

	Cause_of_accident	Accident_severity	Hour	Time_of_day	\
0	moving backward	slight injury	17	4	
1	overtaking	slight injury	17	4	
2	changing lane to the left	serious injury	17	4	
3	changing lane to the right	slight injury	1	1	
4	overtaking	slight injury	1	1	

	Day_of_week_ordinal	Age_band_of_driver_ordinal	Educational_level_ordinal	\
0	NaN	1.0	NaN	

1	NaN	2.0	NaN
2	NaN	1.0	NaN
3	NaN	1.0	NaN
4	NaN	1.0	NaN

	Driving_experience_ordinal	Service_year_of_vehicle_ordinal	\
0	2.0	NaN	
1	NaN	3.0	
2	2.0	NaN	
3	4.0	NaN	
4	3.0	3.0	

	Road_surface_conditions_ordinal	Age_band_of_casualty_ordinal	\
0	NaN	-1.0	
1	NaN	-1.0	
2	NaN	2.0	
3	NaN	1.0	
4	NaN	-1.0	

	Casualty_severity_ordinal	Accident_severity_ordinal	Sex_of_driver_male	\
0	NaN	NaN	True	
1	NaN	NaN	True	
2	0.0	NaN	True	
3	0.0	NaN	True	
4	NaN	NaN	True	

	Sex_of_driver_unknown	Vehicle_driver_relation_other	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	

	Vehicle_driver_relation_owner	Vehicle_driver_relation_unknown	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	

	Type_of_vehicle_bajaj	Type_of_vehicle_bicycle	Type_of_vehicle_long lorry	\
0	False	False	False	
1	False	False	False	
2	False	False	False	
3	False	False	False	
4	False	False	False	

	Type_of_vehicle_lorry (11 - 40 q)	Type_of_vehicle_lorry (41 - 100 q)	\
0	False	False	
1	False	False	
2	False	True	
3	False	False	
4	False	False	

	Type_of_vehicle_motorcycle	Type_of_vehicle_other	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	

	Type_of_vehicle_pick up upto 10q	Type_of_vehicle_public (12 seats)	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	

	Type_of_vehicle_public (13 - 45 seats)	\
0	False	
1	False	
2	False	
3	False	
4	False	

	Type_of_vehicle_public (> 45 seats)	Type_of_vehicle_ridden horse	\
0	False	False	
1	True	False	
2	False	False	
3	True	False	
4	False	False	

	Type_of_vehicle_special vehicle	Type_of_vehicle_stationwagen	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	

	Type_of_vehicle_taxi	Type_of_vehicle_turbo	Type_of_vehicle_unknown	\
0	False	False	False	
1	False	False	False	
2	False	False	False	
3	False	False	False	

4	False	False	True
---	-------	-------	------

	Owner_of_vehicle_organization	Owner_of_vehicle_other \
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

	Owner_of_vehicle_owner	Owner_of_vehicle_unknown	Defect_of_vehicle_7 \
0	True	False	False
1	True	False	False
2	True	False	False
3	False	False	False
4	True	False	False

	Defect_of_vehicle_no defect	Area_accident_occured_hospital areas \
0	True	False
1	True	False
2	True	False
3	True	False
4	True	False

	Area_accident_occured_industrial areas	Area_accident_occured_market areas \
0	False	False
1	False	False
2	False	False
3	False	False
4	True	False

	Area_accident_occured_office areas	Area_accident_occured_other \
0	False	False
1	True	False
2	False	False
3	True	False
4	False	False

	Area_accident_occured_outside rural areas \
0	False
1	False
2	False
3	False
4	False

	Area_accident_occured_recreational areas \
0	False
1	False

2	True
3	False
4	False

Area_accident_occured_residential areas \	
0	True
1	False
2	False
3	False
4	False

Area_accident_occured_rural office areas \	
0	False
1	False
2	False
3	False
4	False

Area_accident_occured_rural village areas \	
0	False
1	False
2	False
3	False
4	False

Area_accident_occured_school areas		Area_accident_occured_unknown \	
0	False		False
1	False		False
2	False		False
3	False		False
4	False		False

Lanes_or_Medians_one way		Lanes_or_Medians_other \	
0	False		False
1	False		False
2	False		True
3	False		True
4	False		True

Lanes_or_Medians_two-way (divided with broken lines road marking) \	
0	False
1	False
2	False
3	False
4	False

Lanes_or_Medians_two-way (divided with solid lines road marking) \	
--	--

0		False
1		False
2		False
3		False
4		False

	Lanes_or_Medians_undivided two way	Lanes_or_Medians_unknown \
0	False	True
1	True	False
2	False	False
3	False	False
4	False	False

	Road_allignment_gentle horizontal curve \
0	False
1	False
2	False
3	False
4	False

	Road_allignment_sharp reverse curve \
0	False
1	False
2	False
3	False
4	False

	Road_allignment_steep grade downward with mountainous terrain \
0	False
1	False
2	False
3	False
4	False

	Road_allignment_steep grade upward with mountainous terrain \
0	False
1	False
2	False
3	False
4	False

	Road_allignment_tangent road with flat terrain \
0	True
1	True
2	False
3	False
4	True

	Road_allignment_tangent road with mild grade and flat terrain \	
0	False	
1	False	
2	False	
3	True	
4	False	

	Road_allignment_tangent road with mountainous terrain \	
0	False	
1	False	
2	False	
3	False	
4	False	

	Road_allignment_tangent road with rolling terrain	Road_allignment_unknown \
0	False	False
1	False	False
2	False	True
3	False	False
4	False	False

	Types_of_Junction_no junction	Types_of_Junction_o shape \
0	True	False
1	True	False
2	True	False
3	False	False
4	False	False

	Types_of_Junction_other	Types_of_Junction_t shape \
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

	Types_of_Junction_unknown	Types_of_Junction_x shape \
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

	Types_of_Junction_y shape \
0	False
1	False
2	False

3	True
4	True

	Road_surface_type_asphalt roads with some distress \
0	False
1	False
2	False
3	False
4	False

	Road_surface_type_earth roads	Road_surface_type_gravel roads \
0	False	False
1	False	False
2	False	False
3	True	False
4	False	False

	Road_surface_type_other	Road_surface_type_unknown \
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

	Light_conditions_darkness - lights unlit \
0	False
1	False
2	False
3	False
4	False

	Light_conditions_darkness - no lighting	Light_conditions_daylight \
0	False	True
1	False	True
2	False	True
3	False	False
4	False	False

	Weather_conditions_fog or mist	Weather_conditions_normal \
0	False	True
1	False	True
2	False	True
3	False	True
4	False	True

	Weather_conditions_other	Weather_conditions_raining \
0	False	False

1	False	False
2	False	False
3	False	False
4	False	False

	Weather_conditions_raining and windy	Weather_conditions_snow \
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

	Weather_conditions_unknown	Weather_conditions_windy \
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

	Type_of_collision_collision with pedestrians \
0	False
1	False
2	False
3	False
4	False

	Type_of_collision_collision with roadside objects \
0	False
1	False
2	True
3	False
4	False

	Type_of_collision_collision with roadside-parked vehicles \
0	True
1	False
2	False
3	False
4	False

	Type_of_collision_fall from vehicles	Type_of_collision_other \
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

	Type_of_collision_rollover	Type_of_collision_unknown \
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

	Type_of_collision_vehicle with vehicle collision \
0	False
1	True
2	False
3	True
4	True

	Type_of_collision_with train	Vehicle_movement_getting off \
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

	Vehicle_movement_going straight	Vehicle_movement_moving backward \
0	True	False
1	True	False
2	True	False
3	True	False
4	True	False

	Vehicle_movement_other	Vehicle_movement_overtaking \
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

	Vehicle_movement_parked	Vehicle_movement_reversing \
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

	Vehicle_movement_stopping	Vehicle_movement_turnover \
0	False	False
1	False	False
2	False	False
3	False	False

4	False	False
---	-------	-------

	Vehicle_movement_u-turn	Vehicle_movement_unknown	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	

	Vehicle_movement_waiting to go	Casualty_class_na	\
0	False	True	
1	False	True	
2	False	False	
3	False	False	
4	False	True	

	Casualty_class_passenger	Casualty_class_pedestrian	Sex_of_casualty_male	\
0	False	False	False	
1	False	False	False	
2	False	False	True	
3	False	True	False	
4	False	False	False	

	Sex_of_casualty_na	Work_of_casualty_employee	Work_of_casualty_other	\
0	True	False	False	
1	True	False	False	
2	False	False	False	
3	False	False	False	
4	True	False	False	

	Work_of_casualty_self-employed	Work_of_casualty_student	\
0	False	False	
1	False	False	
2	False	False	
3	False	False	
4	False	False	

	Work_of_casualty_unemployed	Work_of_casualty_unknown	\
0	False	True	
1	False	True	
2	False	False	
3	False	False	
4	False	True	

	Fitness_of_casualty_deaf	Fitness_of_casualty_normal	\
0	False	False	
1	False	False	

2	False	False
3	False	True
4	False	False

	Fitness_of_casualty_other	Fitness_of_casualty_unknown	\
0	False	True	
1	False	True	
2	False	True	
3	False	False	
4	False	True	

Pedestrian_movement_crossing from nearside - masked by parked or stationot a pedestrianry vehicle \

0	False
1	False
2	False
3	False
4	False

Pedestrian_movement_crossing from offside - masked by parked or stationot a pedestrianry vehicle \

0	False
1	False
2	False
3	False
4	False

Pedestrian_movement_in carriageway, stationot a pedestrianry - not crossing (standing or playing) \

0	False
1	False
2	False
3	False
4	False

Pedestrian_movement_in carriageway, stationot a pedestrianry - not crossing (standing or playing) - masked by parked or stationot a pedestrianry vehicle \

0	False
1	False
2	False
3	False
4	False

	Pedestrian_movement_not a pedestrian	Pedestrian_movement_unknown or other	\
0	True	False	
1	True	False	
2	True	False	

3	True	False
4	True	False

	Pedestrian_movement_walking along in carriageway, back to traffic \
0	False
1	False
2	False
3	False
4	False

	Pedestrian_movement_walking along in carriageway, facing traffic \
0	False
1	False
2	False
3	False
4	False

	Cause_of_accident_changing lane to the right \
0	False
1	False
2	False
3	True
4	False

	Cause_of_accident_driving at high speed \
0	False
1	False
2	False
3	False
4	False

	Cause_of_accident_driving carelessly \
0	False
1	False
2	False
3	False
4	False

	Cause_of_accident_driving to the left \
0	False
1	False
2	False
3	False
4	False

	Cause_of_accident_driving under the influence of drugs \
0	False

1	False
2	False
3	False
4	False

Cause_of_accident_drunk driving \	
0	False
1	False
2	False
3	False
4	False

Cause_of_accident_getting off the vehicle improperly \	
0	False
1	False
2	False
3	False
4	False

Cause_of_accident_improper parking		Cause_of_accident_moving backward \	
0	False		True
1	False		False
2	False		False
3	False		False
4	False		False

Cause_of_accident_no distancing \	
0	False
1	False
2	False
3	False
4	False

Cause_of_accident_no priority to pedestrian \	
0	False
1	False
2	False
3	False
4	False

Cause_of_accident_no priority to vehicle		Cause_of_accident_other \	
0	False		False
1	False		False
2	False		False
3	False		False
4	False		False

	Cause_of_accident_overloading	Cause_of_accident_overspeed \
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

	Cause_of_accident_overtaking	Cause_of_accident_overturning \
0	False	False
1	True	False
2	False	False
3	False	False
4	True	False

	Cause_of_accident_turnover	Cause_of_accident_unknown
0	False	False
1	False	False
2	False	False
3	False	False
4	False	False

1.5 5: Exploratory Data Analysis (EDA)

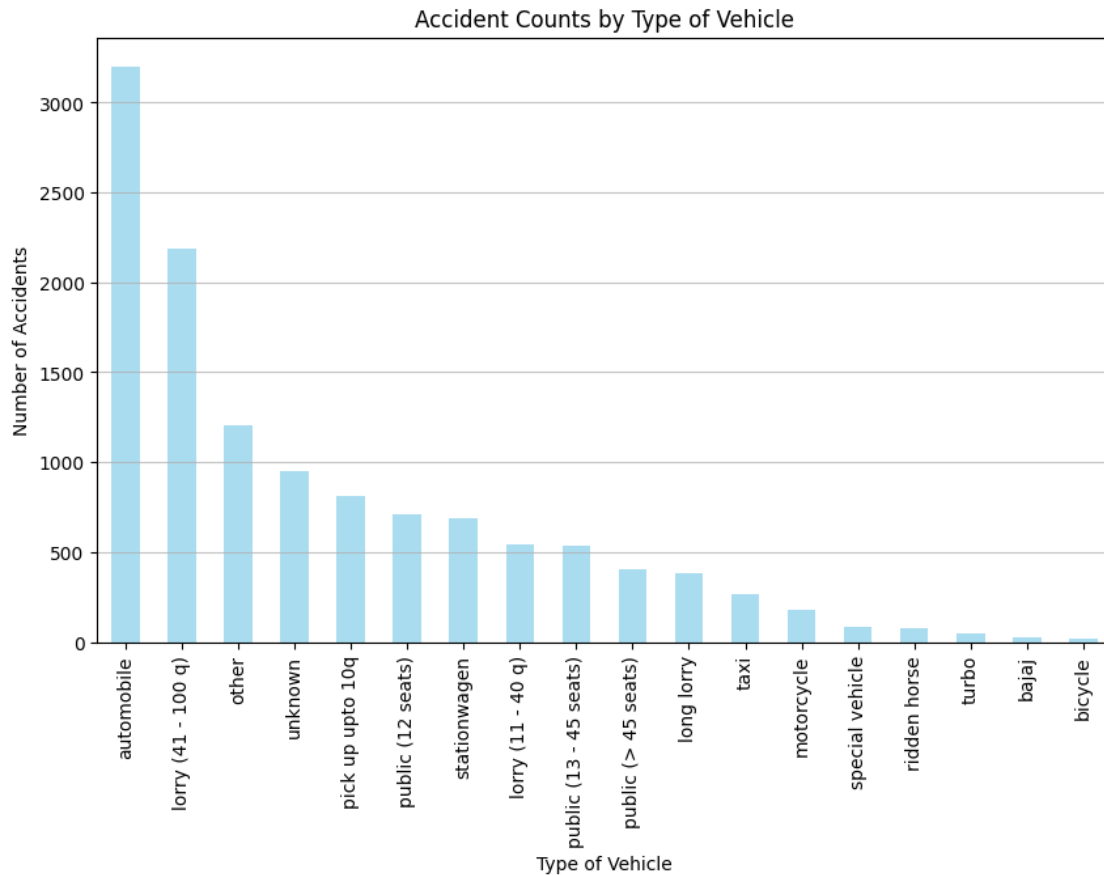
1.5.1 Harshit Malpani: 50608809

Question 1: What vehicles should the authorities focus more on to reduce the cases of road accidents and the severity of road accidents

Hypothesis 1: Not all vehicles are involved in road accidents equally. Some vehicles have higher tendency to be involved in any road accident

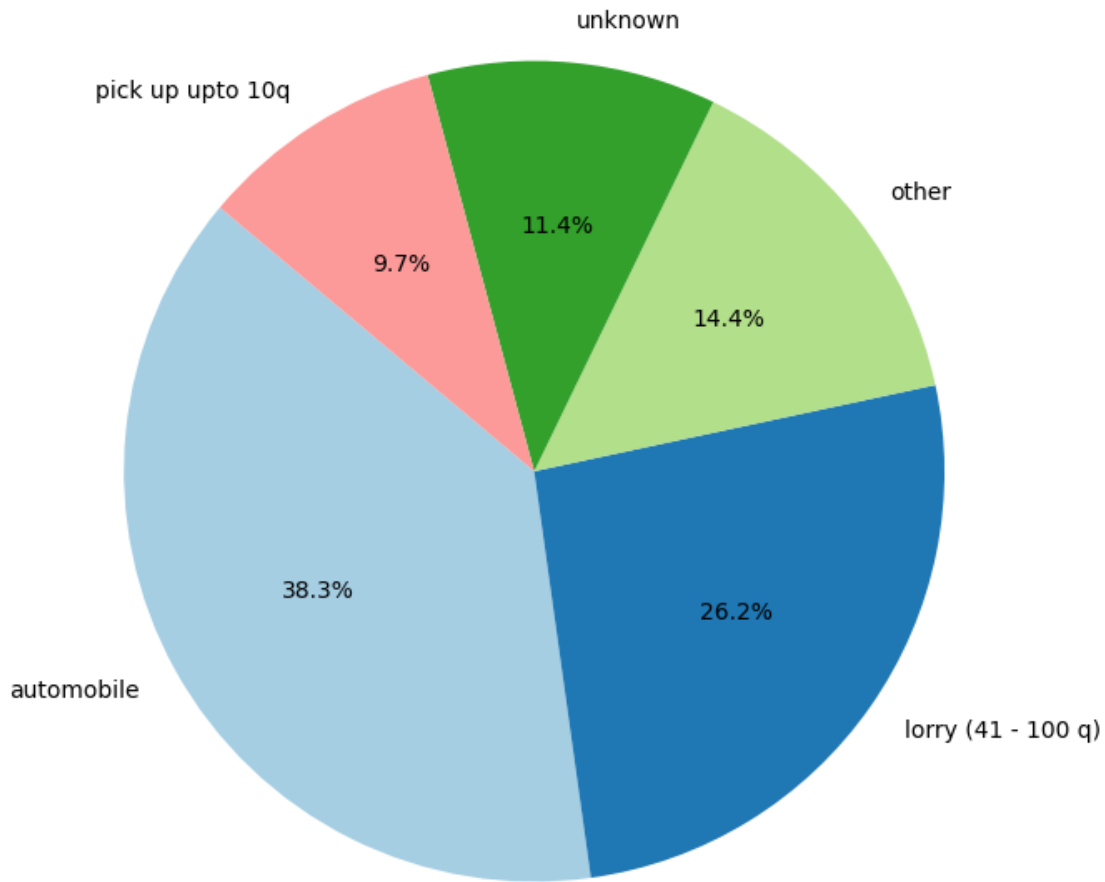
```
[239]: import matplotlib.pyplot as plt
import seaborn as sns
```

```
[240]: vehicle_counts = cleaned_dataset['Type_of_vehicle'].value_counts()
plt.figure(figsize=(10, 6))
vehicle_counts.plot(kind='bar', color='skyblue', alpha=0.7)
plt.title('Accident Counts by Type of Vehicle')
plt.xlabel('Type of Vehicle')
plt.ylabel('Number of Accidents')
plt.xticks(rotation=90)
plt.grid(axis='y', alpha=0.75)
plt.show()
```

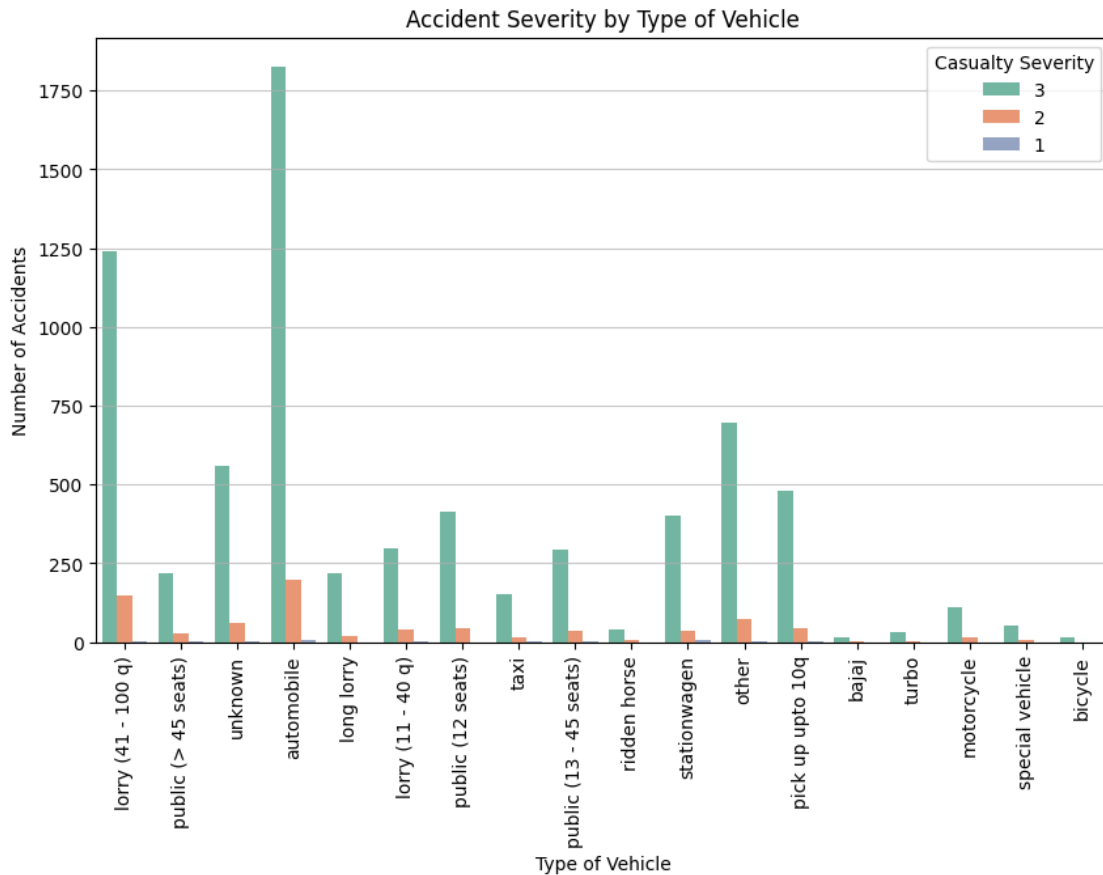


```
[241]: accidents_per_vehicle = cleaned_dataset['Type_of_vehicle'].value_counts()
accidents_per_vehicle = accidents_per_vehicle[:5]
plt.figure(figsize=(10, 8))
plt.pie(accidents_per_vehicle, labels=accidents_per_vehicle.index, autopct='%1.
↳1f%', startangle=140, colors=plt.cm.Paired.colors)
plt.title('Top 5 vehicle types with most accidents')
plt.show()
```

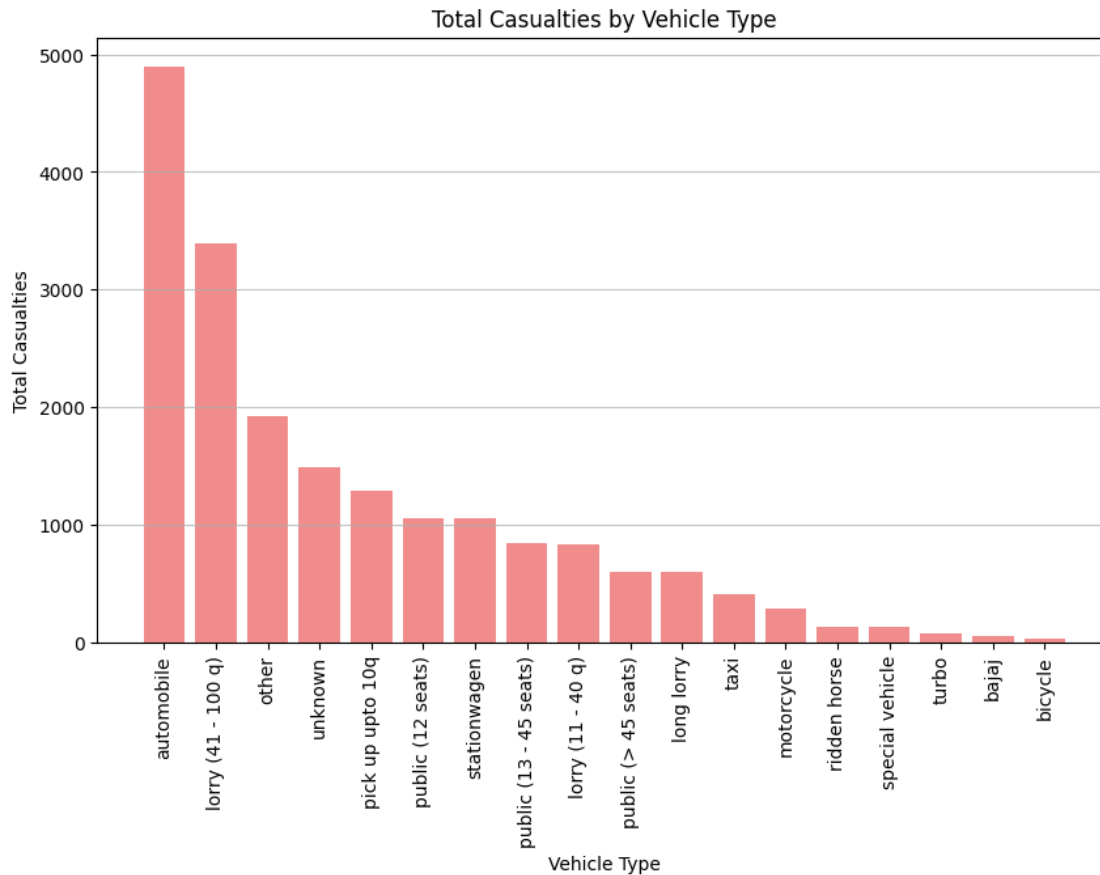
Top 5 vehicle types with most accidents



```
[242]: # Without unknown severity
without_unknown_casualty = cleaned_dataset[cleaned_dataset['Casualty_severity'] != 'unknown']
plt.figure(figsize=(10, 6))
sns.countplot(data=without_unknown_casualty, x='Type_of_vehicle', hue='Casualty_severity', palette='Set2')
plt.title('Accident Severity by Type of Vehicle')
plt.xlabel('Type of Vehicle')
plt.ylabel('Number of Accidents')
plt.legend(title='Casualty Severity')
plt.xticks(rotation=90)
plt.grid(axis='y', alpha=0.7)
plt.show()
```



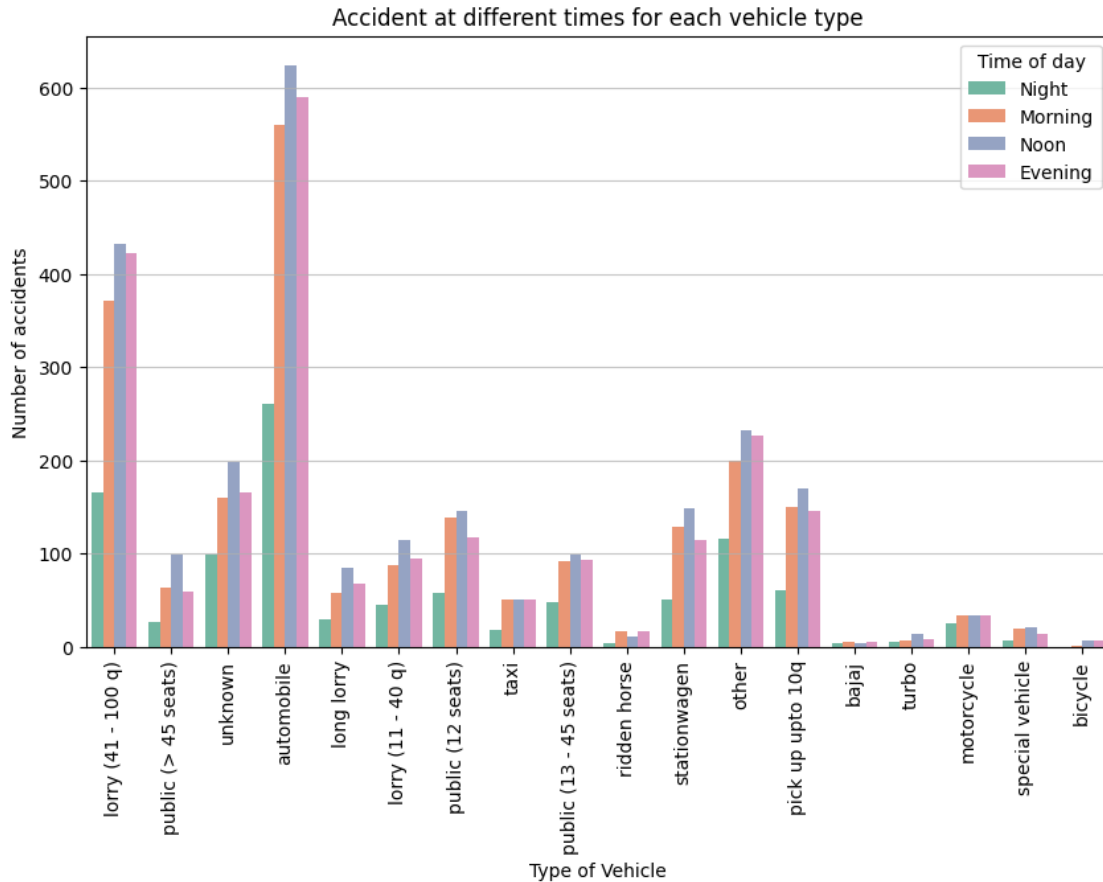
```
[243]: total_casualties_by_vehicle = cleaned_dataset.
        ↳groupby('Type_of_vehicle')['Number_of_casualties'].sum().reset_index()
total_casualties_by_vehicle = total_casualties_by_vehicle.
        ↳sort_values(by='Number_of_casualties', ascending=False)
plt.figure(figsize=(10, 6))
plt.bar(total_casualties_by_vehicle['Type_of_vehicle'],
        ↳total_casualties_by_vehicle['Number_of_casualties'], color='lightcoral',
        ↳alpha=0.9)
plt.title('Total Casualties by Vehicle Type')
plt.xlabel('Vehicle Type')
plt.ylabel('Total Casualties')
plt.xticks(rotation=90)
plt.grid(axis='y', alpha=0.75)
plt.show()
```



From the above plots, we can clearly notice that Automobile and Lorry(41 - 100 q) are more probable to be involved in road accidents. More focus should be on these types of vehicles as fixing the reasons why they involve in accidents more will help reduce the road accidents which also reduces the casualties.

Hypothesis 2: Accidents are more likely to happen in Evening

```
[244]: plt.figure(figsize=(10, 6))
sns.countplot(data=without_unknown_casualty, x='Type_of_vehicle',
             hue='Time_of_day', palette='Set2')
plt.title('Accident at different times for each vehicle type')
plt.xlabel('Type of Vehicle')
plt.ylabel('Number of accidents')
plt.legend(title='Time of day', labels=Time_of_day)
plt.xticks(rotation=90)
plt.grid(axis='y', alpha=0.7)
plt.show()
```



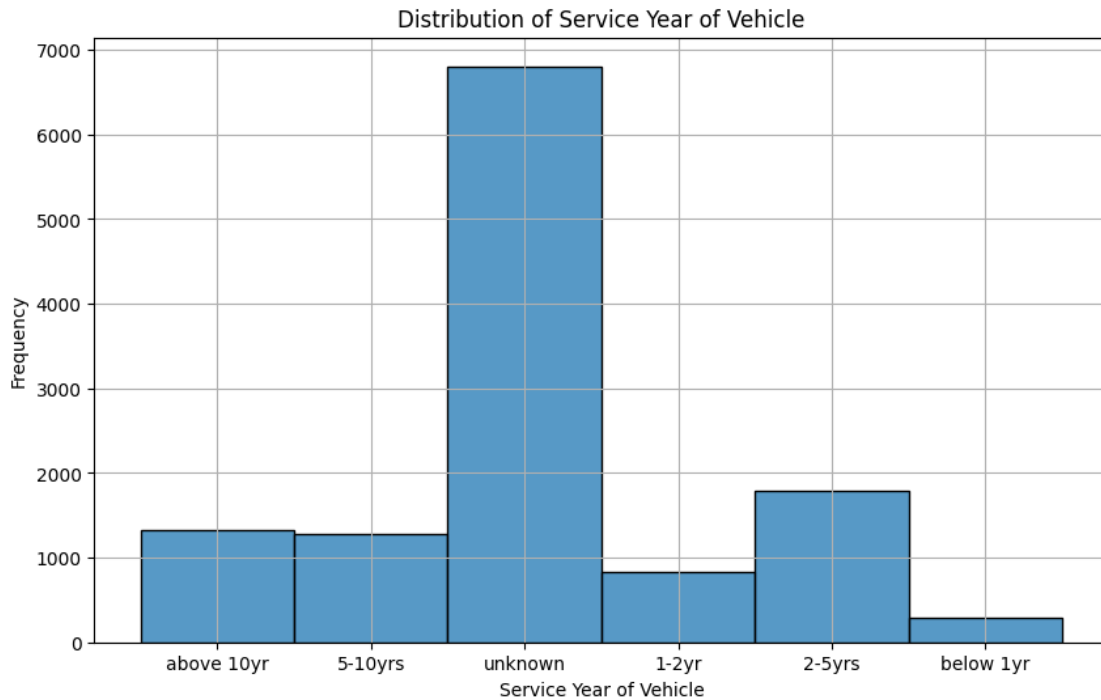
The hypothesis is wrong. From the above plot, we can see that most vehicle types are involved in a road accident during noon. Although one might think that most accidents should occur in the evening or night due to low visibility or sleepiness, but most accidents happen in the noon. This opens up the possibility of finding other factors like road type and vehicle faults, which might contribute to the accidents, and then fixing them.

Question 2: Does the service period of the vehicle and ownership of the vehicle have any correlation with the accidents? The state of vehicle and the person driving it plays an important role in road safety. We need to find out how the state of the vehicle and the ownership of the vehicle affect the possibility of a vehicle to be involved in an accident. This study will help in making policies and rules to reduce road accidents and related casualties.

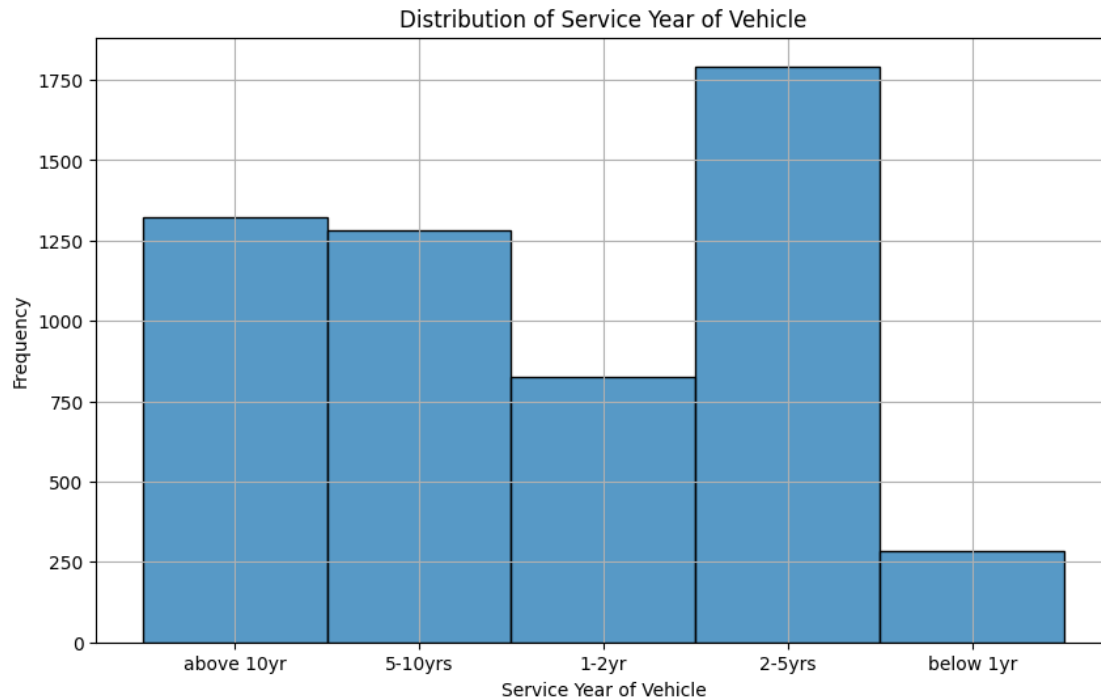
Hypothesis 1: The vehicles which are serviced regularly have less chances of getting involved in accidents as they are less prone to machine malfunction

```
[245]: plt.figure(figsize=(10, 6))
sns.histplot(cleaned_dataset['Service_year_of_vehicle'].astype(str), bins=30,
             kde=False)
plt.title('Distribution of Service Year of Vehicle')
plt.xlabel('Service Year of Vehicle')
```

```
plt.ylabel('Frequency')
plt.grid()
plt.show()
```



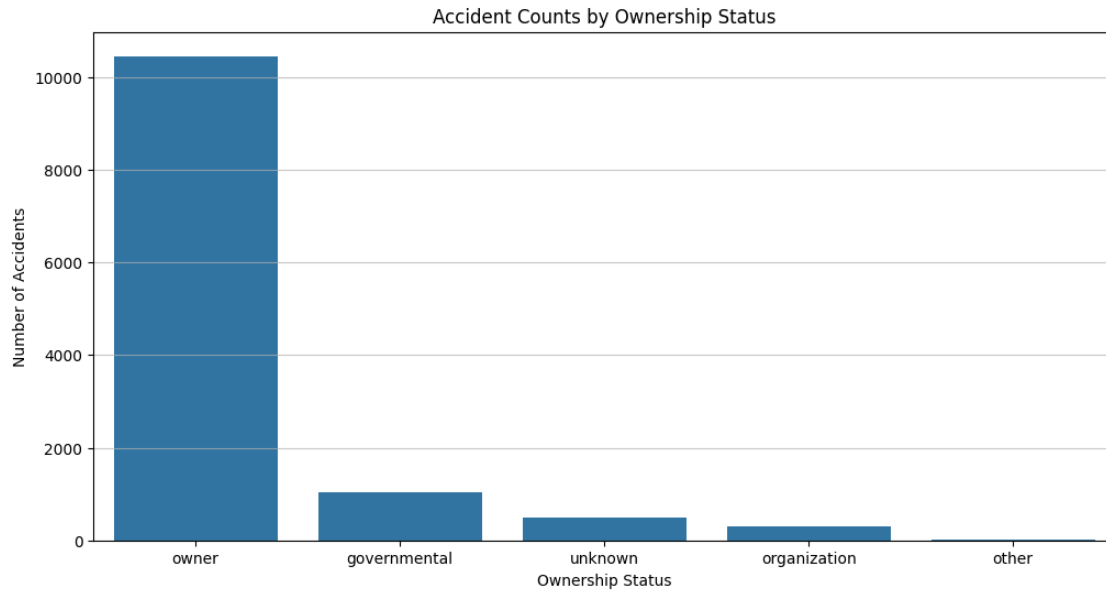
```
[246]: # remove data entries with 'unknown' service period
without_unknown_service =
    cleaned_dataset[cleaned_dataset['Service_year_of_vehicle'] != 'unknown']
plt.figure(figsize=(10, 6))
sns.histplot(without_unknown_service['Service_year_of_vehicle'].astype(str),
    bins=30, kde=False)
plt.title('Distribution of Service Year of Vehicle')
plt.xlabel('Service Year of Vehicle')
plt.ylabel('Frequency')
plt.grid()
plt.show()
```

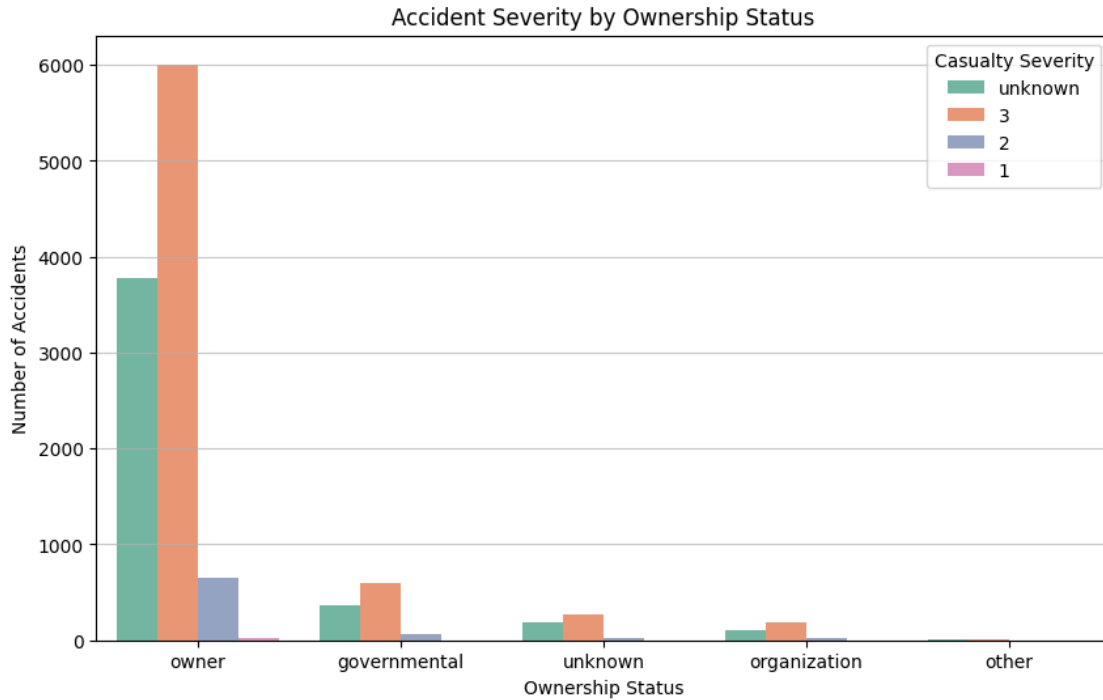
The hypothesis is correct. From the above bar graph, we can see that the vehicles with last service data less than a year ago are involved in much fewer accidents when compared to the vehicles that had last service done more than a year ago. This data is useful in implementing stricter policies in regards to the regular servicing of the vehicles.

Hypothesis 2: Ownership of the vehicle doesn't have any relation to the accidents. The person driving a vehicle is equally likely to be involved in an accident regardless of the ownership of the vehicle he/she drives

```
[247]: plt.figure(figsize=(12, 6))
sns.countplot(data=cleaned_dataset, x='Owner_of_vehicle',
              order=cleaned_dataset['Owner_of_vehicle'].value_counts().index)
plt.title('Accident Counts by Ownership Status')
plt.xlabel('Ownership Status')
plt.ylabel('Number of Accidents')
plt.grid(axis='y', alpha=0.7)
plt.show()
```



```
[248]: plt.figure(figsize=(10, 6))
sns.countplot(data=cleaned_dataset, x='Owner_of_vehicle',
             hue='Casualty_severity', palette='Set2')
plt.title('Accident Severity by Ownership Status')
plt.xlabel('Ownership Status')
plt.ylabel('Number of Accidents')
plt.legend(title='Casualty Severity')
plt.grid(axis='y', alpha=0.7)
plt.show()
```



The hypothesis that ownership of vehicle doesn't play role in accidents is incorrect. From the above two plots, we can see that a person is more likely to be involved in a accident if they own the vehicle.

[]:

2 Phase 2

What vehicles should the authorities focus more on to reduce the cases of road accidents and the severity of road accidents

- 1) Not all vehicles are involved in road accidents equally. Some vehicles have a higher tendency to be involved in any road accident

Using the Naive Bayes Classifier for classifying the accident's severity given the type of vehicle and other attributes related to the accident. Naive Bayes can be very useful for multiclass classification (in this case, the accident severity) based on the input features. Naive Bayes being a probabilistic classifier, predicts the probability of accident severity.

```
[258]: from sklearn.model_selection import train_test_split
X = cleaned_dataset.drop(columns=["Time", "Day_of_week", "Age_band_of_driver",
↳ "Sex_of_driver", "Educational_level",
↳ "Vehicle_driver_relation", "Driving_experience",
↳ "Type_of_vehicle", "Owner_of_vehicle",
↳ "Service_year_of_vehicle", "Defect_of_vehicle",
↳ "Area_accident_occured", "Lanes_or_Medians",
```

```

        "Road_alignment", "Types_of_Junction",
        ↪ "Road_surface_type", "Road_surface_conditions",
        "Light_conditions", "Weather_conditions",
        ↪ "Type_of_collision", "Number_of_vehicles_involved",
        "Number_of_casualties", "Vehicle_movement",
        ↪ "Casualty_class", "Sex_of_casualty",
        "Age_band_of_casualty", "Work_of_casualty",
        ↪ "Fitness_of_casualty", "Pedestrian_movement",
        "Cause_of_accident", "Road_surface_conditions_ordinal",
        ↪ "Day_of_week_ordinal",
        "Accident_severity_ordinal",
        ↪ "Educational_level_ordinal", "Service_year_of_vehicle_ordinal",
        "Casualty_severity_ordinal",
        ↪ "Age_band_of_driver_ordinal", "Driving_experience_ordinal",
        "Age_band_of_casualty_ordinal", "Casualty_severity"])

y = X["Accident_severity"]
X = X.drop(columns=["Accident_severity"])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
        ↪ random_state=42)

```

The code below splits the dataset into train and test dataset. This is useful for training the model. Naive Bayes Classifier has a hyperparameter: α . Tuning this hyperparameter can help in getting the best classifier. To tune the hyperparameter, we can train the model for different values of α and then select the classifier that performs the best. The code below trains the model for different values of alpha ranging from 0.01 to 2 with step of 0.01

```

[259]: import numpy as np
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.naive_bayes import CategoricalNB
from sklearn.metrics import accuracy_score, classification_report
from imblearn.over_sampling import SMOTE
from sklearn.preprocessing import OrdinalEncoder, LabelEncoder

smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X, y)
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled,
        ↪ test_size=0.3, random_state=42)

model = CategoricalNB()
param_grid = {
    'alpha': np.arange(0.01, 2, 0.01)
}

grid_search = GridSearchCV(estimator=model, param_grid=param_grid,
        ↪ scoring='accuracy', cv=3)

```

```

grid_search.fit(X_train, y_train)
best_model = grid_search.best_estimator_
y_pred = best_model.predict(X_test)

print("Best parameters found: ", grid_search.best_params_)
print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))

```

Best parameters found: {'alpha': np.float64(0.12)}

Accuracy: 0.7409265584970111

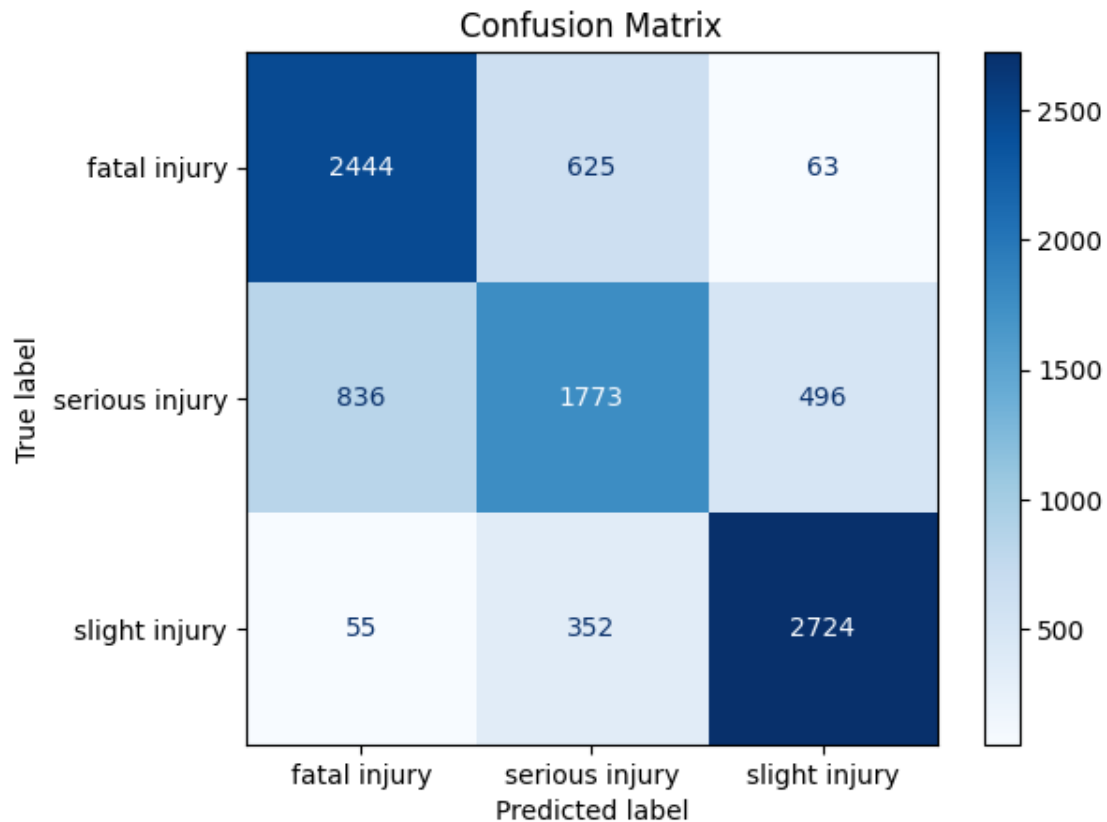
	precision	recall	f1-score	support
fatal injury	0.73	0.78	0.76	3132
serious injury	0.64	0.57	0.61	3105
slight injury	0.83	0.87	0.85	3131
accuracy			0.74	9368
macro avg	0.74	0.74	0.74	9368
weighted avg	0.74	0.74	0.74	9368

```

[260]: from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=grid_search.
    ↪best_estimator_.classes_)
disp.plot(cmap=plt.cm.Blues)
plt.title("Confusion Matrix")
plt.show()

```



The above plot shows the confusion matrix for the model. The accuracy of the model is close to 74%

This accuracy can be improved by: - Adding more data to the dataset - Adding data that is equally distributed across various classes. In the case above, the dataset has very few entries for slight injury. For this, I used SMOTE technique to address the class imbalance. However, this may not always give accurate results as the technique creates synthetic cases for minority classes. Having actual cases in the dataset will help in making the model more robust.

```
[261]: from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize

model.fit(X_train, y_train)
y_pred_proba = model.predict_proba(X_test)

y_test_bin = label_binarize(y_test, classes=['fatal injury', 'serious injury', 'slight injury'])
n_classes = y_test_bin.shape[1]
fpr = dict()
tpr = dict()
roc_auc = dict()
```

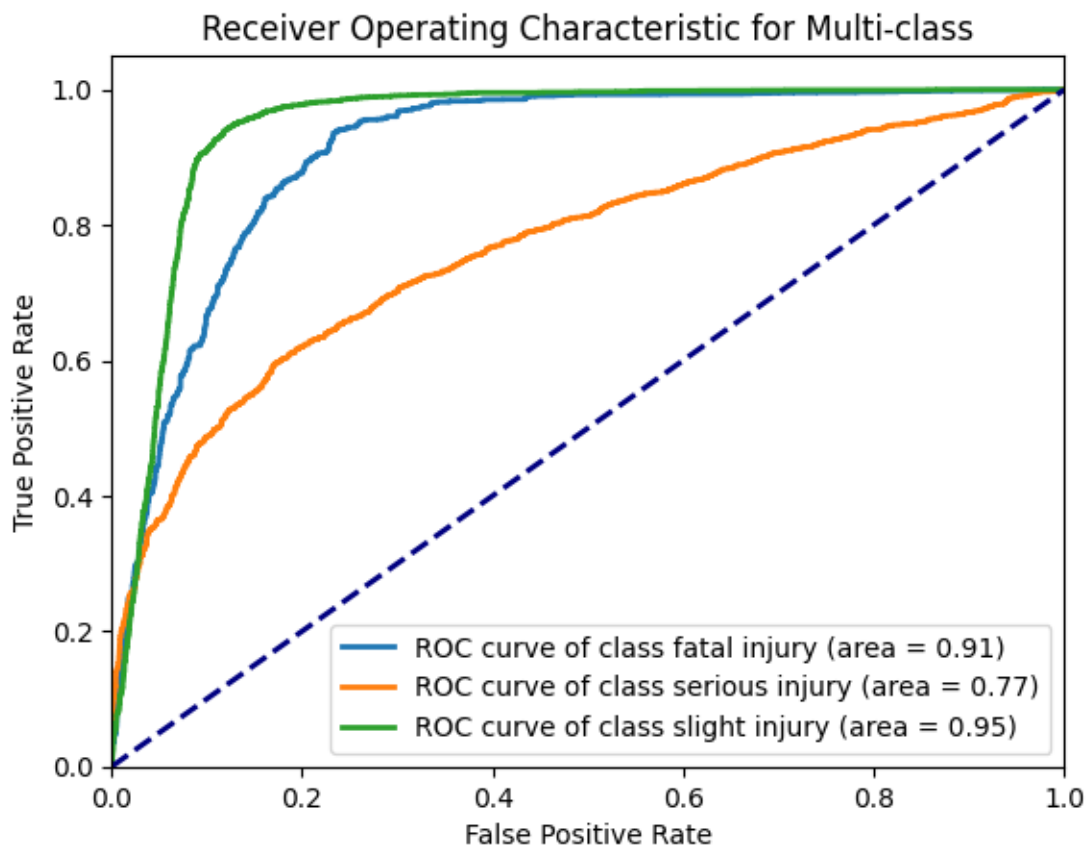
```

for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test_bin[:, i], y_pred_proba[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

plt.figure()
for i in range(n_classes):
    plt.plot(fpr[i], tpr[i], lw=2, label='ROC curve of class {0} (area = {1:0.
    ↪2f})'
                                ''.format(['fatal injury', 'serious_
    ↪injury', 'slight injury'][i], roc_auc[i]))

plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic for Multi-class')
plt.legend(loc="lower right")
plt.show()

```



The plot above shows ROC curve for the NB classifier.

```
[262]: import ipywidgets as widgets
from IPython.display import display

alpha_slider = widgets.FloatSlider(value=1.0, min=0.01, max=2.0, step=0.01,
    ↪description='Alpha:')

def update_model(alpha):
    model = CategoricalNB(alpha=alpha)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    print("Accuracy:", accuracy_score(y_test, y_pred))

widgets.interactive(update_model, alpha=alpha_slider)
```

```
[262]: interactive(children=(FloatSlider(value=1.0, description='Alpha:', max=2.0,
min=0.01, step=0.01), Output()), _...
```

The slider above shows the accuracy for various values of α for Naive Bayes Classifier

Does the service period of the vehicle and ownership of the vehicle have any correlation with the accidents The code below implements Random Forest Classifier. A Random Forest Classifier is a machine-learning algorithm that uses multiple decision trees to classify data and produce a single result. This

```
[284]: import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import classification_report, confusion_matrix
from imblearn.ensemble import EasyEnsembleClassifier
from imblearn.over_sampling import SMOTE

data = cleaned_dataset[["Owner_of_vehicle",
                        "Service_year_of_vehicle",
                        "Number_of_casualties",
    ↪"Service_year_of_vehicle_ordinal",
                        "Casualty_severity", "Number_of_vehicles_involved",
    ↪"Number_of_casualties"]]
data = data[data['Service_year_of_vehicle'] != 'unknown']
data["Service_year_of_vehicle_ordinal"] = data["Service_year_of_vehicle"].
    ↪map(ord_mapping)
data = data.drop("Service_year_of_vehicle", axis=1)
```



```

owner_ord_mapping = {'owner':0, 'governmental':1, 'unknown':2, 'organization':
    ↳3, 'other':4}

data["Owner_of_vehicle_ordinal"] = data["Owner_of_vehicle"].
    ↳map(owner_ord_mapping)
data = data.drop("Owner_of_vehicle", axis=1)
data = data[data["Casualty_severity"] != "unknown"]
X = data.drop('Casualty_severity', axis=1)
X = X.drop('Number_of_casualties', axis=1)

severity_ord_mapping = {'1':0, '2':1, '3':2}
y = data['Casualty_severity'].map(severity_ord_mapping)

smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X, y)

X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled,
    ↳test_size=0.2, random_state=31)

rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)

print("Accuracy Random Forest with class weights:", accuracy_score(y_test,
    ↳y_pred_rf))
print("Random Forest (with class weights) Classification Report:\n",
    ↳classification_report(y_test, y_pred_rf, zero_division=0))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_rf))

import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_pred_rf)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Fatal Injury',
    ↳'Serious Injury', 'Slight Injury'], yticklabels=['Fatal Injury', 'Serious
    ↳Injury', 'Slight Injury'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

```

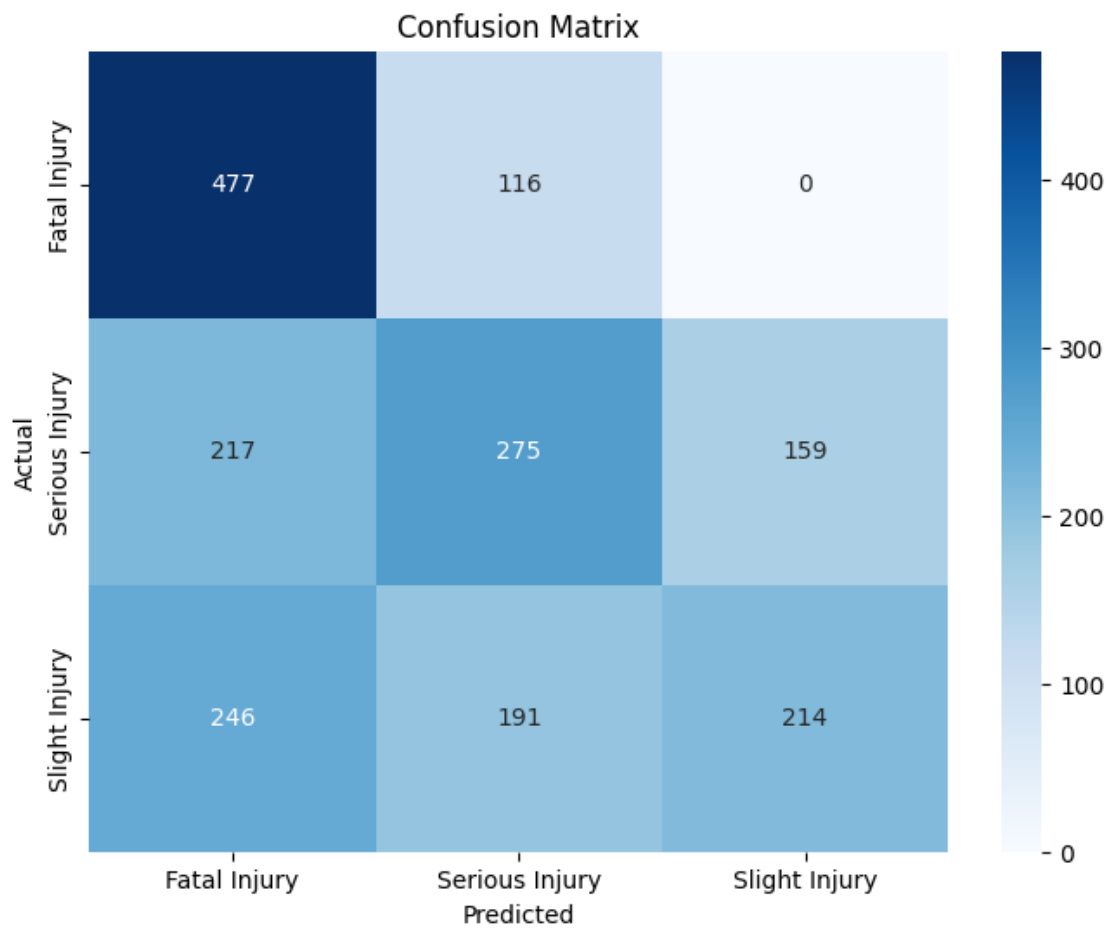
Accuracy Random Forest with class weights: 0.5097625329815303

Random Forest (with class weights) Classification Report:

	precision	recall	f1-score	support
0	0.51	0.80	0.62	593
1	0.47	0.42	0.45	651
2	0.57	0.33	0.42	651
accuracy			0.51	1895
macro avg	0.52	0.52	0.50	1895
weighted avg	0.52	0.51	0.49	1895

Confusion Matrix:

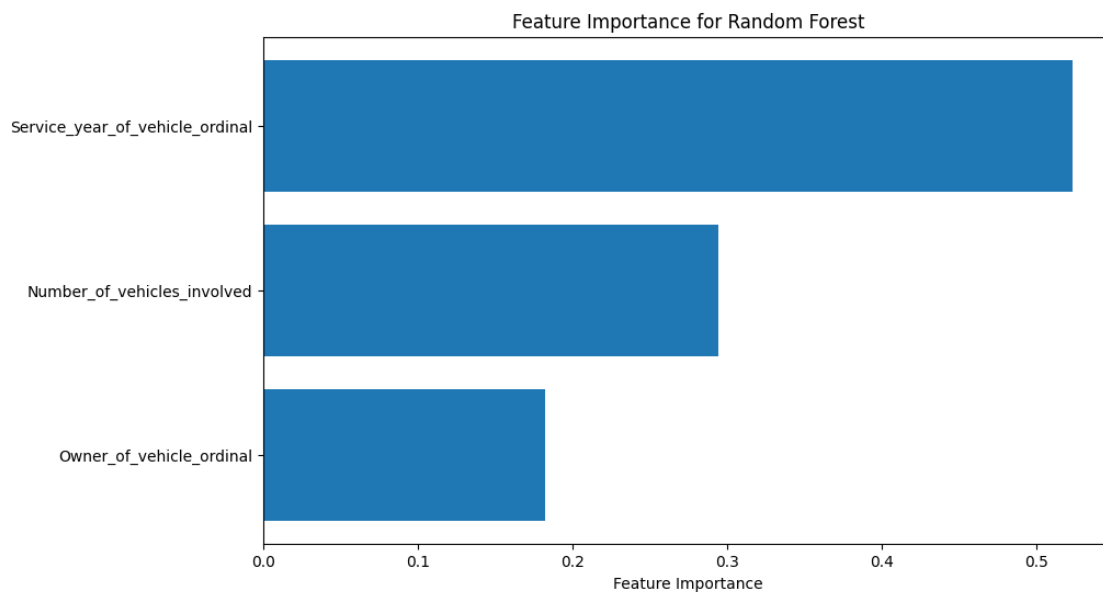
```
[[477 116  0]
 [217 275 159]
 [246 191 214]]
```



This Random Forest Classifier doesn't work well on the synthesised dataset. Using SMOTE doesn't help to address the class imbalance.

```
[283]: import numpy as np

feature_importance = rf_model.feature_importances_
indices = np.argsort(feature_importance)
plt.figure(figsize=(10, 6))
plt.barh(range(len(indices)), feature_importance[indices], align='center')
plt.yticks(range(len(indices)), [X.columns[i] for i in indices])
plt.xlabel('Feature Importance')
plt.title('Feature Importance for Random Forest')
plt.show()
```



```
[282]: import plotly.graph_objs as go
import pandas as pd

a = X["Service_year_of_vehicle_ordinal"]
b = X["Owner_of_vehicle_ordinal"]

fig = go.Figure(data=[go.Scatter3d(x=a, y=b, z=y, mode='markers', marker=dict(
    size=5,
    color=y,
    colorscale='Viridis',
    opacity=0.8
))])

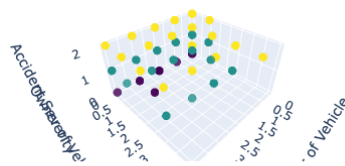
fig.update_layout(
```

```

    title='3D Scatter Plot of Service Year, Vehicle Ownership, and Accident_
↪Severity',
    scene=dict(
        xaxis_title='Service Year of Vehicle',
        yaxis_title='Owner of Vehicle (Ordinal)',
        zaxis_title='Accident Severity'
    ),
)
fig.show()

```

3D Scatter Plot of Service Year, Vehicle Ownership, and Accident Severity



In the above trial to create a Random Forest Classifier to find the accident severity based on ownership and service history of the vehicle didn't perform well on the given dataset. Using more attributes from the dataset and then creating the model might help in improving the effectiveness of the model.