DIC_Project_Phase_1_prob2_50608504

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.

Question 1: What is the Impact of area, type of road cross-section, type of roads and road alignment on different types of Accidents

- This analysis will help us identify accident prone areas, common mistakes in road infrastructure, alignment and help us identify potential dark spots. It will help in future planning for Roads construction to avoid such road engineering mistakes like installing traffic signals, gradient of road, signboards, etc.
- Many a times slope of road, busy cross sections and other factors has influence on the accident, to identify and rectify these factors help in reduction of accidents.

Question 2: What is the impact of Environmental factors, Light(visibility) impact, Road surface, time of the day, etc. * This analysis will help us understand conditions/situations which forced human error, Most of time unavailability of light, less visibility, heavy rain can increase probability of accident. Appropriate changes in vehicle engineering and roads can help reduce casualties. * It is significant to identify conditions which affect driving experience.

1.2 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 downloading the data from the github repository directly to the dataframe

[30]:
```python
import pandas as pd
import numpy as np
import warnings

warnings.filterwarnings('ignore')
dataset = pd.read_csv('/content/RTA Dataset.csv')
#dataset = pd.read_csv('https://raw.githubusercontent.com/hmalpani/RTA-Dataset/
↪main/RTA_Dataset.csv')
```

[31]:
```python
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_casuality            9118 non-null   object
 28  Fitness_of_casuality         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
```

[32]:
```
dataset.head()
```

[32]:
```
       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 … Vehicle_movement  \
0            Owner              Above 10yr …   Going straight
1            Owner                 5-10yrs …   Going straight
2            Owner                     NaN …   Going straight
3     Governmental                     NaN …   Going straight
4            Owner                 5-10yrs …   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_casuality Fitness_of_casuality 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
```

```
[5 rows x 32 columns]
```

1.3 4: Data Cleaning

1.3.1 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

[33]:
```
# Remove duplicates
cleaned_dataset = dataset.drop_duplicates()
```

1.3.2 2) Validation

[34]:
```
# Remove entries with 'Number_of_vehicles_involved' = 0
cleaned_dataset =␣
↪cleaned_dataset[cleaned_dataset['Number_of_vehicles_involved'] != 0]
```

1.3.3 3) Detection and Removal of Outliers

[35]:
```
# code for outliers handling

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)
# Remove outliers from both columns
cleaned_dataset = remove_outliers(cleaned_dataset,␣
↪'Number_of_vehicles_involved')
cleaned_dataset = remove_outliers(cleaned_dataset, 'Number_of_casualties')

# Check the shape of the DataFrame after removal
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)
```

1.3.4 4) Handling Missing Values:

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

[36]:
```
# Find the number of missing values
missing_value_count = cleaned_dataset.isnull().sum()
missing_value_count
```

[36]:
```
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_casuality            3197
Fitness_of_casuality         2634
Pedestrian_movement             0
Cause_of_accident               0
Accident_severity               0
dtype: int64
```

[37]:
```
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_allignment', 'Types_of_Junction', 'Road_surface_type',
'Type_of_collision', 'Vehicle_movement', 'Work_of_casuality',
'Fitness_of_casuality']
```

[38]:
```
# 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_allignment'].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_casuality'].fillna('Unknown', inplace=True)
cleaned_dataset['Fitness_of_casuality'].fillna('Unknown', inplace=True)
```

1.3.5 5) Correcting Errors:

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

[39]:
```python
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_casuality'] =␣
    ↪cleaned_dataset['Fitness_of_casuality'].replace('NormalNormal', 'Normal')
cleaned_dataset['Casualty_severity'] = cleaned_dataset['Casualty_severity'].
    ↪replace('na', 'Unknown')
```

1.3.6 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

[40]:
```python
# 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')
```

1.3.7 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

[41]:
```
# Make all the characters to lowercase
cleaned_dataset = cleaned_dataset.map(lambda x: x.lower() if isinstance(x, str)␣
↪else x)
```

1.3.8 8) Feature Engineering

[42]:
```
print(cleaned_dataset['Time'].head())
cleaned_dataset['Hour'] = pd.to_datetime(cleaned_dataset['Time'], format='%H:%M:
↪%S').dt.hour
Time_of_dat = ['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:
```

[42]:

	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

9) Ordinal & One Hot Encoding

[43]:
```
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_casuality': 'one_hot',
    'Fitness_of_casuality': '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_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 == 'ordinal':
            # Apply ordinal encoding using a mapping dictionary
            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}")

        elif 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)

        else:
            print(f"Unknown encoding type: {encoding_type} for column:␣
↪{column}")
```

```
    return df

cleaned_dataset = apply_encoding(cleaned_dataset, encoding_dict,␣
↪ordinal_mappings)

cleaned_dataset.head()
```

[43]:

```
       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  …  \
0            owner              above 10yr  …
1            owner                 5-10yrs  …
2            owner                 unknown  …
3     governmental                 unknown  …
4            owner                 5-10yrs  …

  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

  Accident_severity_ordinal
0                       NaN
1                       NaN
2                       NaN
3                       NaN
4                       NaN

[5 rows x 184 columns]
```

[44]:
```
cleaned_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 12309 entries, 0 to 12315
Columns: 184 entries, Time to Accident_severity_ordinal
dtypes: bool(141), float64(9), int32(1), int64(3), object(30)
memory usage: 5.7+ MB
```

[45]:
```
def categorize_time_of_dayby3(hour):
    if 3<= hour < 6:
        return 'Early Morning'
    elif 6 <= hour < 9:
        return 'Morning'
    elif 9 <= hour < 12:
        return 'Pre-Noon'
    elif 12 <= hour < 15:
        return 'Post-Noon'
    elif 15 <= hour < 18:
        return 'Evening'
    elif 18 <= hour < 21:
        return 'Night'
    elif 21 <= hour < 24:
```

```
        return 'Late-Night'
    else:
        return 'Midnight'

df_new=cleaned_dataset
df_new['Time_of_day_3hr'] = df_new['Hour'].apply(categorize_time_of_dayby3)
```

Question 2:

Analysis of impact of Environmental factors, Light(visibility) impact, Road surface, time of the day, etc on driving skills

Algorithm 2 : Support Vector Machine (SVM)

- It is a supervised machine learning algorithm used for classification and regression.It finds the hyper-plane which divides the points belonging to different groups in a high dimensional space.
- Data Points which are inseparable in lower dimensions can be separated in higher dimensions using kernel transformations.
- formula for optimization of SVM with soft margin :

lecture notes Intro to ML,Mingchen Gao

Why SVM

- Selected sum model because it is easy to separate complex data in SVM with help of kernel functions by projecting the Data into Higher dimensions.
- RBF : Radial Bias Function is used to project data to infinite dimension.
- SVM provides soft margin for some data points to be misclassified but still separating then using slack variables.
- We has multi-class outputs for SVM works well it compares and separates each class with each other

[46]:
```
cleaned_df = pd.DataFrame(df_new)
dfc= cleaned_df.groupby('Accident_severity').size()
dfc.head(10)
```

[46]:
```
Accident_severity
fatal injury        158
serious injury     1743
slight injury     10408
dtype: int64
```

[47]:
```
cleaned_df['Number_of_casualties'].value_counts()
```

[47]:
```
Number_of_casualties
1    8390
2    2290
```

```
3     909
4     394
5     207
6      89
7      22
8       8
Name: count, dtype: int64
```

Selecting Columns from Dataset relevant to our analysis of accidents subject to environmental, road and light conditions

[48]:
```
dfsvm=␣
↪cleaned_df[['Time_of_day_3hr','Area_accident_occured','Road_surface_type','Road_surface_con
dfsvm.head(10)
```

[48]:
```
  Time_of_day_3hr Area_accident_occured Road_surface_type  \
0         Evening     residential areas     asphalt roads
1         Evening          office areas     asphalt roads
2         Evening    recreational areas     asphalt roads
3        Midnight          office areas       earth roads
4        Midnight      industrial areas     asphalt roads
5       Post-Noon               unknown           unknown
6         Evening     residential areas           unknown
7         Evening     residential areas     asphalt roads
8         Evening      industrial areas       earth roads
9         Evening     residential areas     asphalt roads

  Road_surface_conditions       Light_conditions Weather_conditions  \
0                     dry               daylight             normal
1                     dry               daylight             normal
2                     dry               daylight             normal
3                     dry  darkness - lights lit             normal
4                     dry  darkness - lights lit             normal
5                     dry               daylight             normal
6                     dry               daylight             normal
7                     dry               daylight             normal
8                     dry               daylight             normal
9                     dry               daylight             normal

  Vehicle_movement                        Type_of_collision  \
0   going straight  collision with roadside-parked vehicles
1   going straight           vehicle with vehicle collision
2   going straight          collision with roadside objects
3   going straight           vehicle with vehicle collision
4   going straight           vehicle with vehicle collision
5           u-turn           vehicle with vehicle collision
6  moving backward           vehicle with vehicle collision
7           u-turn           vehicle with vehicle collision
```

```
8   going straight  collision with roadside-parked vehicles
9           u-turn  collision with roadside-parked vehicles

            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
5                 overloading     slight injury
6                       other     slight injury
7      no priority to vehicle     slight injury
8  changing lane to the right     slight injury
9             moving backward    serious injury
```

[49]:

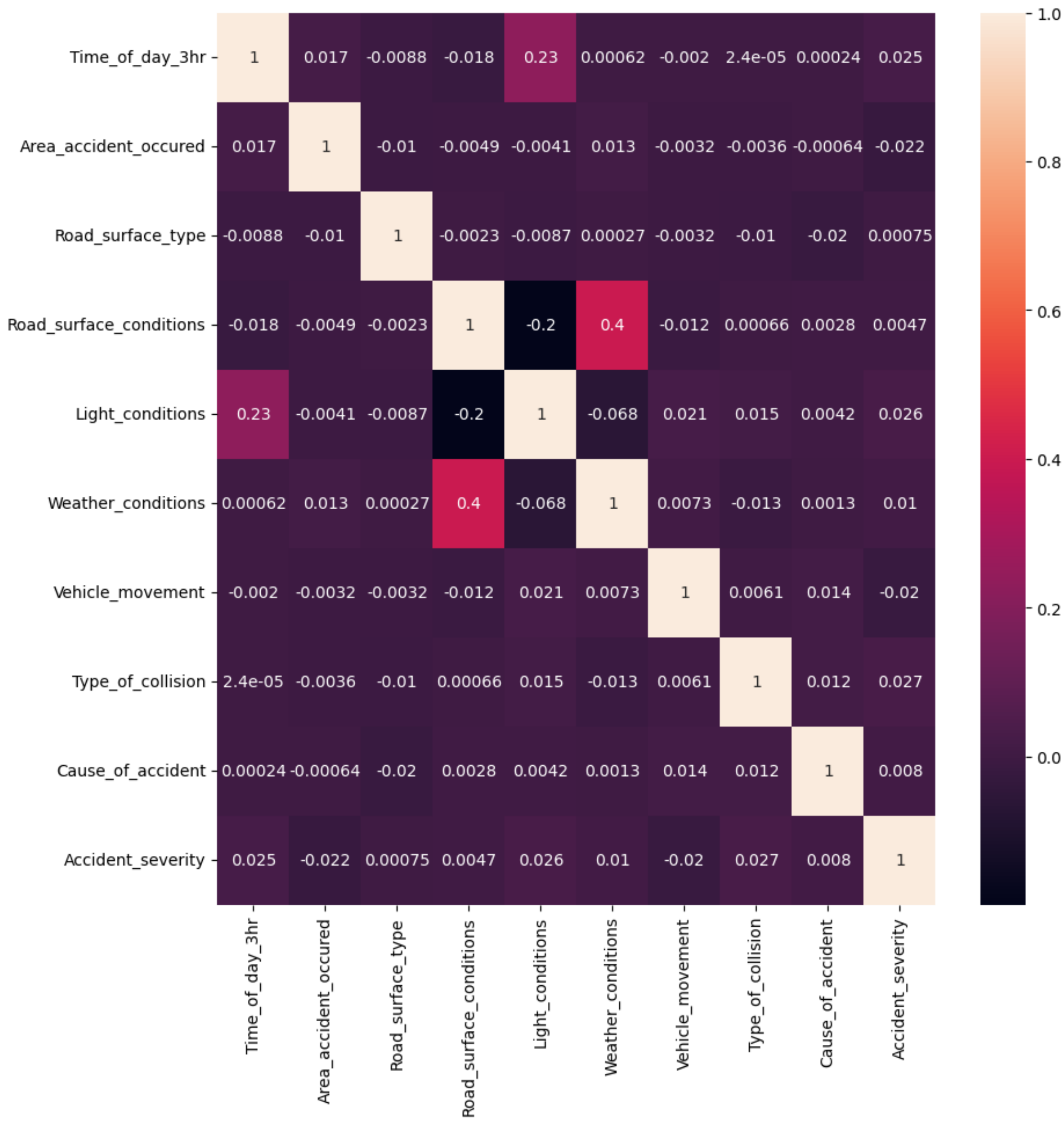
```
from sklearn.preprocessing import LabelEncoder
LE = LabelEncoder()
dfsvmLE=dfsvm.apply(LE.fit_transform)
```

Heat map to show the correlation between the columns

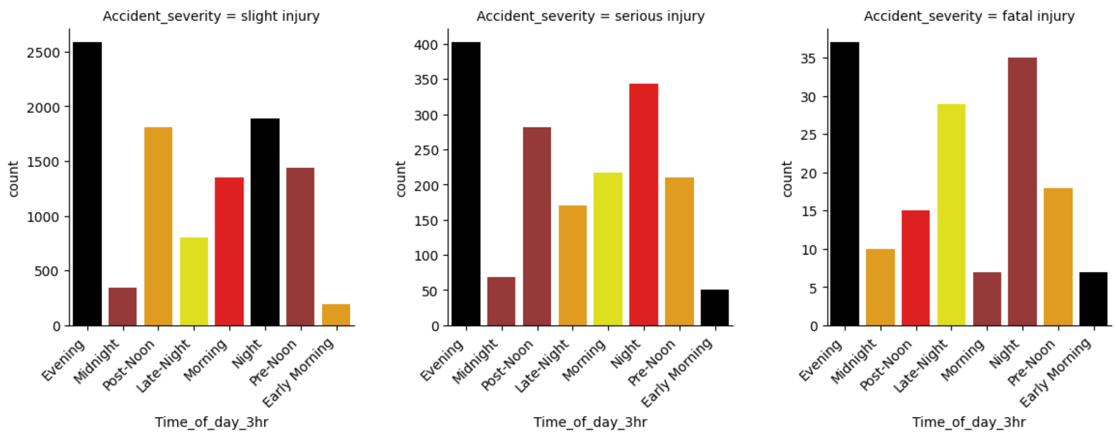
[50]:

```
import matplotlib.pyplot as plt
import seaborn as sns
plt.figure(figsize=[10,10])
sns.heatmap(dfsvmLE.corr(),annot=True)
```

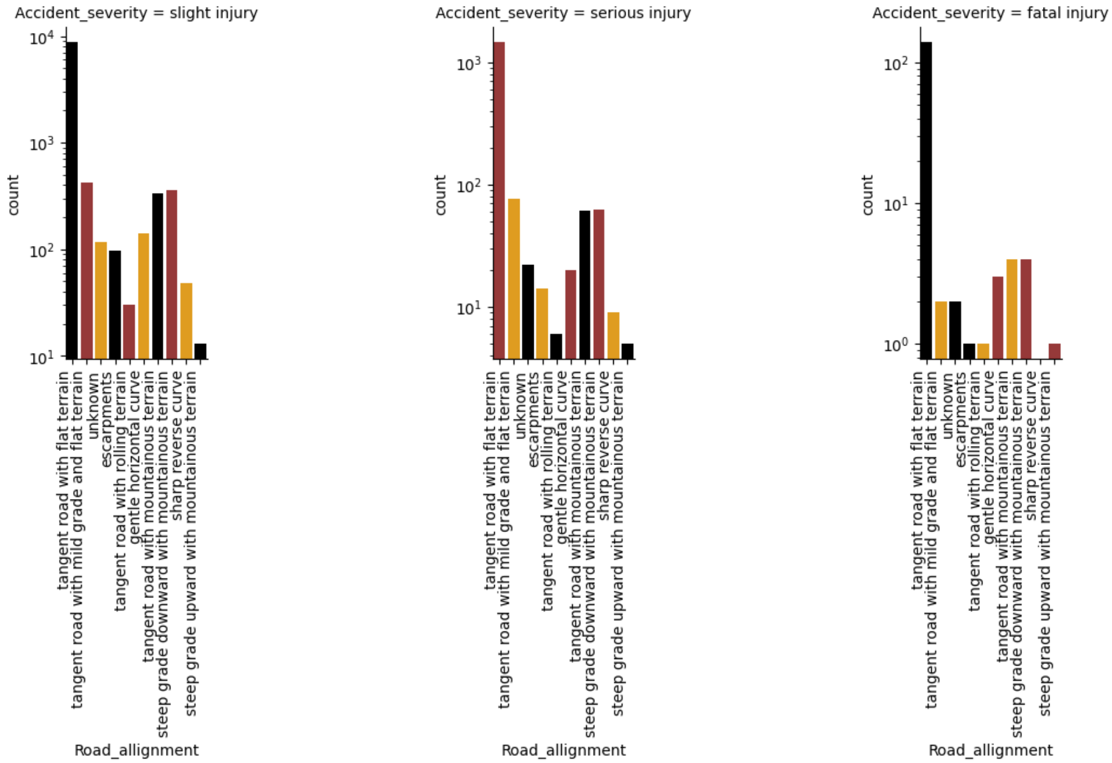
[50]: <Axes: >

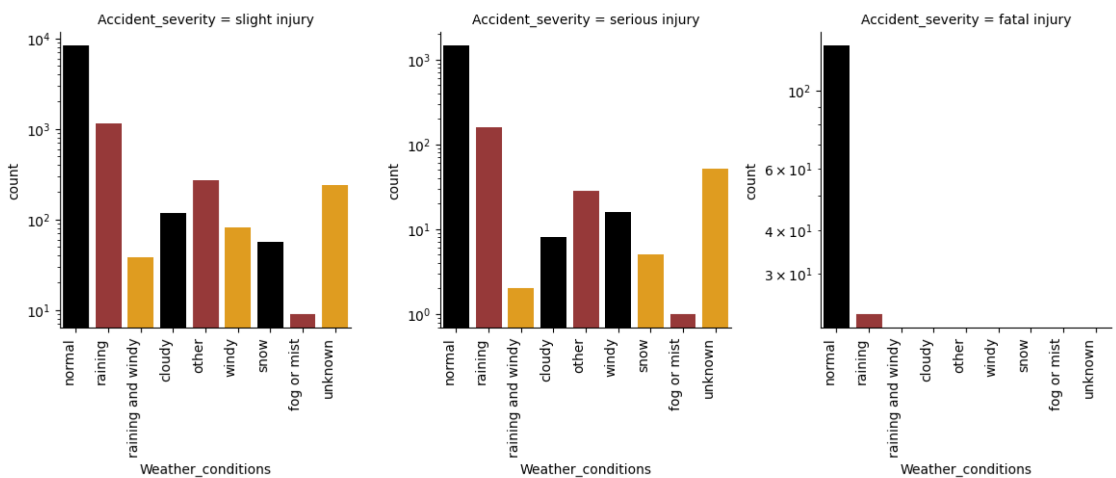


[51]:
```python
grid = sns.FacetGrid(data=cleaned_df, col='Accident_severity', height=4, aspect=1, sharey=False)
grid.map(sns.countplot, 'Time_of_day_3hr', palette=['black', 'brown', 'orange','yellow','red'])
for x in grid.axes.flat:
    for label in x.get_xticklabels():
        label.set_rotation(45)
        label.set_ha('right')
plt.show()
```



[52]:
```
grid = sns.FacetGrid(data=cleaned_df, col='Accident_severity', height=4,␣
 ↪aspect=1, sharey=False)
grid.map(sns.countplot, 'Road_allignment', palette=['black', 'brown', 'orange'])
for x in grid.axes.flat:
    x.set_yscale('log')
    for label in x.get_xticklabels():
        label.set_rotation(90)
        label.set_ha('right')
plt.show()
grid = sns.FacetGrid(data=cleaned_df, col='Accident_severity', height=4,␣
 ↪aspect=1, sharey=False)
grid.map(sns.countplot, 'Weather_conditions', palette=['black', 'brown',␣
 ↪'orange'])
for x in grid.axes.flat:
    x.set_yscale('log')
    for label in x.get_xticklabels():
        label.set_rotation(90)
        label.set_ha('right')
plt.show()
```





Training SVM Model

Important parameters for tuning of SVM

- **Kernel** : Defines what kind of transformation is to be applied to transform the data. examples : rbf, linear, sigmoid, poly

Lecture notes Intro to ML, Mingchen Gao * **C : Regularization Parameter** : It is used to incorporate slack variables in the classification of data points. It is a trade-off between maximizing the margin and minimizing classification errors.

- **Gamma** : It shows the impact of data points on decision boundary. Higher value means more complex boundary.

Tuning of parameters.

- Selection of Kernel: out of the three kernel viz, sigmoid , rbf and linear, we checked the performance of model over our data and we could see that ref had higher classification accuracy as compared to other 2.
- Selecting C: we checked different values of C and selected the best value at the after trial and error
- Selecting gamma: we checked different values of gamma and selected the best value at the after trial and error

From the above training and testing of our model we see that we get highest accuracy for model with X Kernel, with C = , Gamma= .

[59]:
```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.metrics import confusion_matrix


def svm_model(X_train,X_test,y_train,y_test):
  param_grid = {
        'C': [0.1,1,10],
        'kernel': ['rbf','linear'],#['linear','rbf','sigmoid'],
        'gamma': [1,'scale',10]#[10]#['scale', 'auto',0.1,1,5,10]
    }

  results = []

  for C in param_grid['C']:
      for kernel in param_grid['kernel']:
          for gamma in param_grid['gamma']:
              pipeline = Pipeline([
                  ('svm', SVC(C=C, kernel=kernel, gamma=gamma))
              ])
              pipeline.fit(X_train, y_train)

              y_pred = pipeline.predict(X_test)

              accuracy = accuracy_score(y_test, y_pred)

              results.append({
```

```
                'C': C,
                'kernel': kernel,
                'gamma': gamma,
                'accuracy': accuracy
            })
            print(f"Params: C={C}, kernel={kernel}, gamma={gamma} -> Accuracy:
↪ {accuracy:.4f}")

  best_result = max(results, key=lambda x: x['accuracy'])
  print("\nBest Parameters:")
  print(f"C={best_result['C']}, kernel={best_result['kernel']},␣
↪gamma={best_result['gamma']} -> Accuracy: {best_result['accuracy']:.4f}")
  return best_result['accuracy']
```

Implementing the best suitable model and analysing the performance of model over test data .

[55]:
```
def best_model(x1,y1,c,kernel,g):
  X_train,X_test,y_train,y_test=train_test_split(x1,y1,test_size=0.
↪2,random_state=42)
  results = []
  pipeline = Pipeline([
      ('svm', SVC(C=c, kernel=kernel, gamma=g))
  ])

  pipeline.fit(X_train, y_train)

  y_pred = pipeline.predict(X_test)

  accuracy = accuracy_score(y_test, y_pred)
  cm=confusion_matrix(y_test,y_pred)
  plt.figure(figsize=[10,10])
  sns.heatmap(cm,annot=True)
  results.append({
      'C': c,
      'kernel': kernel,
      'gamma': g,
      'accuracy': accuracy
  })
  print(f"Params: C={c}, kernel={kernel}, gamma={g} -> Accuracy: {accuracy:.
↪4f}")
```

Model 1 : Predicting the Accident severity based on Environmental,Light and road conditions.

[ ]:
```
from sklearn.utils import resample

majority_class = dfsvmLE[dfsvmLE.Accident_severity == 2]
minority_class = dfsvmLE[dfsvmLE.Accident_severity == 0]
```

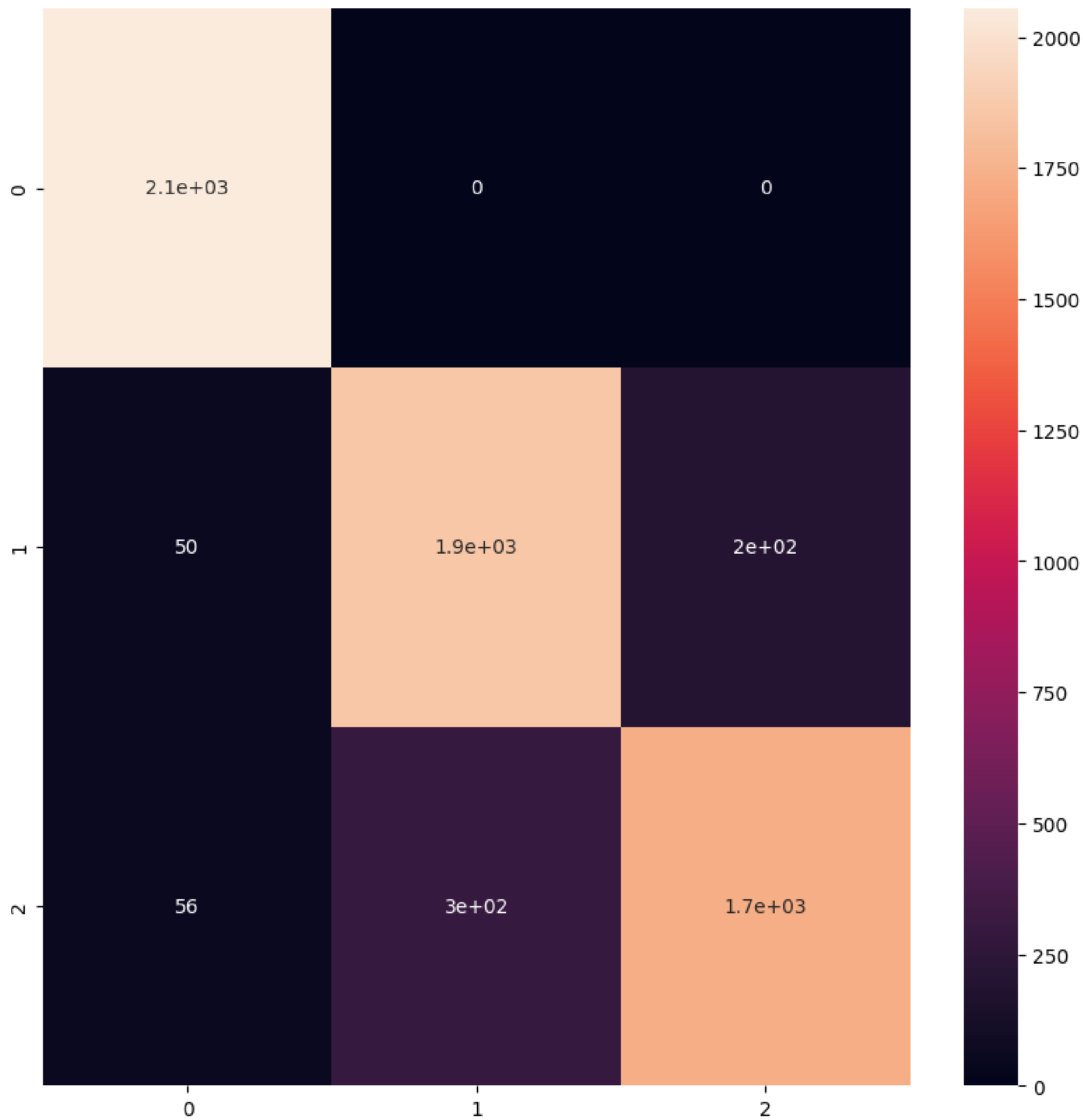
```
minority_class1 = dfsvmLE[dfsvmLE.Accident_severity == 1]

minority_upsampled =␣
↪resample(minority_class,replace=True,n_samples=len(majority_class),random_state=42)
minority_upsampled1 = resample(minority_class1,replace=True,␣
↪n_samples=len(majority_class), random_state=42)

upsampled_data = pd.concat([majority_class, minority_upsampled,␣
↪minority_upsampled1])

x1 = upsampled_data.drop('Accident_severity', axis=1)
y1 = upsampled_data['Accident_severity']

xtrain, xtest, ytrain, ytest = train_test_split(x1, y1, test_size=0.25,␣
↪random_state=42)
print(xtrain.shape, xtest.shape, ytrain.shape, ytest.shape)

acc=svm_model(xtrain,xtest,ytrain,ytest)
```

```
(23418, 9) (7806, 9) (23418,) (7806,)
Params: C=0.1, kernel=rbf, gamma=1 -> Accuracy: 0.8590
Params: C=0.1, kernel=rbf, gamma=scale -> Accuracy: 0.4673
Params: C=0.1, kernel=rbf, gamma=10 -> Accuracy: 0.8572
Params: C=0.1, kernel=linear, gamma=1 -> Accuracy: 0.3851
Params: C=0.1, kernel=linear, gamma=scale -> Accuracy: 0.3851
Params: C=0.1, kernel=linear, gamma=10 -> Accuracy: 0.3851
Params: C=1, kernel=rbf, gamma=1 -> Accuracy: 0.8919
Params: C=1, kernel=rbf, gamma=scale -> Accuracy: 0.5301
Params: C=1, kernel=rbf, gamma=10 -> Accuracy: 0.9023
Params: C=1, kernel=linear, gamma=1 -> Accuracy: 0.3853
Params: C=1, kernel=linear, gamma=scale -> Accuracy: 0.3853
Params: C=1, kernel=linear, gamma=10 -> Accuracy: 0.3853
Params: C=10, kernel=rbf, gamma=1 -> Accuracy: 0.8947
Params: C=10, kernel=rbf, gamma=scale -> Accuracy: 0.6024
Params: C=10, kernel=rbf, gamma=10 -> Accuracy: 0.9023
Params: C=10, kernel=linear, gamma=1 -> Accuracy: 0.3853
```

Confusion Matrix

[57]:
```
best_model1=best_model(x1,y1,1,'rbf',10)
```

```
Params: C=1, kernel=rbf, gamma=10 -> Accuracy: 0.9041
```



We reached accuracy of almost 90% while predicting the accident severity based on environmental, loght and other conditions. The parameters involved in training of SVM for the above model are C= 1 using RBF Kernel Function.

Model 2 : Predicting the Type of Collision based on Environmental,Light and road conditions.

[28]:
```
from sklearn.utils import resample

majority_class = dfsvmLE[dfsvmLE.Type_of_collision == 8]
minority_class = dfsvmLE[dfsvmLE.Type_of_collision == 0]
```

```
minority_upsampled = resample(minority_class,replace=True,␣
↪n_samples=len(majority_class), random_state=42)

minority_class1 = dfsvmLE[dfsvmLE.Type_of_collision == 3]
minority_upsampled1 = resample(minority_class1,replace=True,␣
↪n_samples=int(len(majority_class)/2), random_state=42)
minority_class2 = dfsvmLE[dfsvmLE.Type_of_collision == 4]
minority_upsampled2 = resample(minority_class2,replace=True, ␣
↪n_samples=int(len(majority_class)/2), random_state=42)
minority_class3 = dfsvmLE[dfsvmLE.Type_of_collision == 5]
minority_upsampled3 = resample(minority_class3,replace=True,  ␣
↪n_samples=int(len(majority_class)/2),random_state=42)
minority_class4 = dfsvmLE[dfsvmLE.Type_of_collision == 6]
minority_upsampled4 = resample(minority_class4,replace=True,␣
↪n_samples=int(len(majority_class)/2),  random_state=42)
minority_class5 = dfsvmLE[dfsvmLE.Type_of_collision == 1]
minority_upsampled5 = resample(minority_class5,replace=True,  ␣
↪n_samples=int(len(majority_class)/2), random_state=42)
minority_class6 = dfsvmLE[dfsvmLE.Type_of_collision == 7]
minority_upsampled6 = resample(minority_class6,replace=True,␣
↪n_samples=int(len(majority_class)/2),random_state=42)
minority_class7 = dfsvmLE[dfsvmLE.Type_of_collision == 2]
minority_upsampled7 = resample(minority_class7,replace=True,␣
↪n_samples=int(len(majority_class)/2), random_state=42)
minority_class8 = dfsvmLE[dfsvmLE.Type_of_collision == 9]
minority_upsampled8 = resample(minority_class8,replace=True,␣
↪n_samples=int(len(majority_class)/2), random_state=42)

print(majority_class.shape)
print(minority_class.shape)
print(minority_class1.shape)
print(minority_class2.shape)
print(minority_class3.shape)
print(minority_class4.shape)
print(minority_class5.shape)
print(minority_class6.shape)
print(minority_class7.shape)
print(minority_class8.shape)
upsampled_data = pd.concat([majority_class, minority_upsampled,␣
↪minority_upsampled1,minority_upsampled2,minority_upsampled3,minority_upsampled4,minority_up
x1 = upsampled_data.drop('Type_of_collision', axis=1)
y1 = upsampled_data['Type_of_collision']

xtrain, xtest, ytrain, ytest = train_test_split(x1, y1, test_size=0.2,␣
↪random_state=42)
print(xtrain.shape, xtest.shape, ytrain.shape, ytest.shape)
```

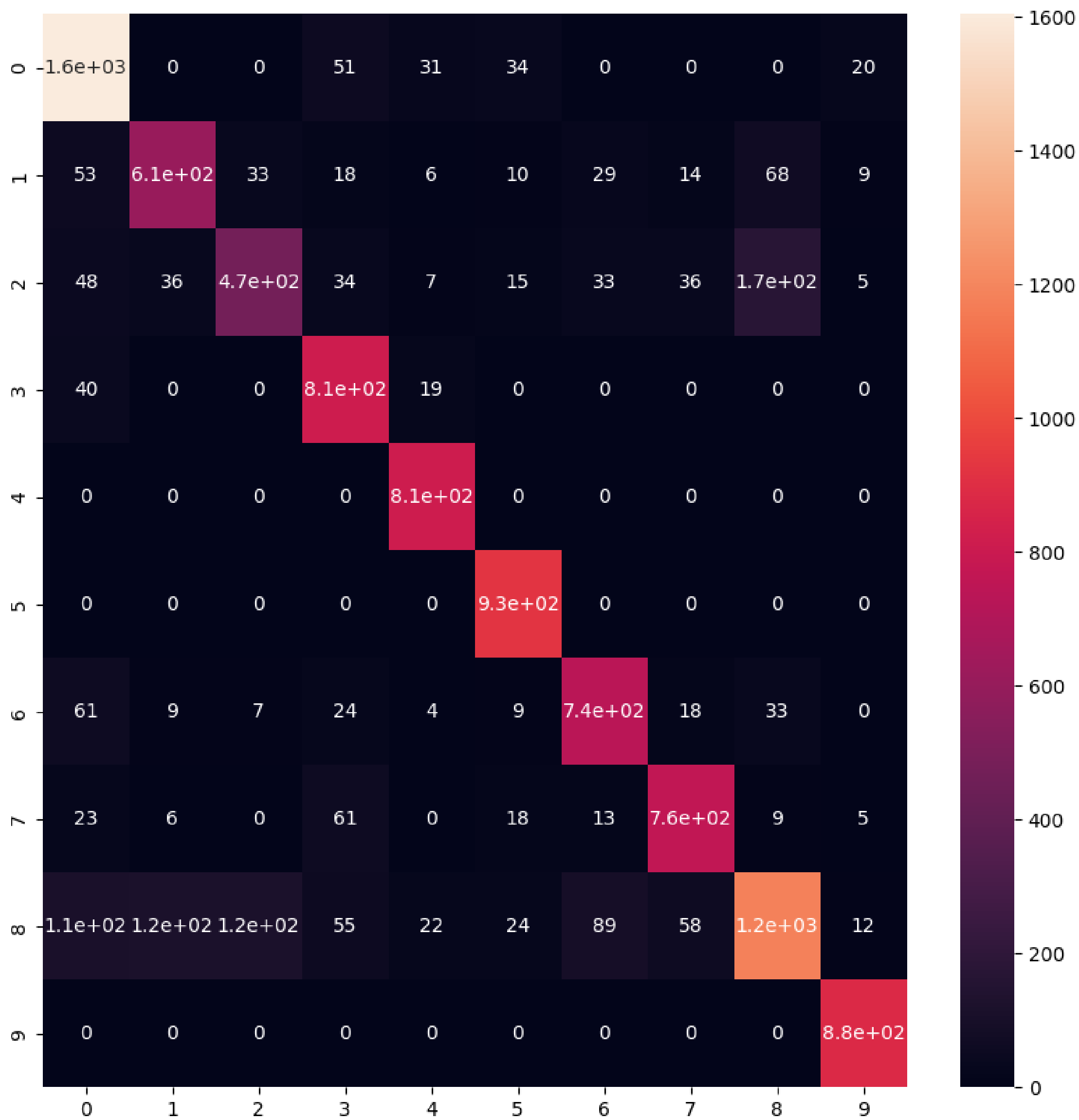
```
acc=svm_model(xtrain,xtest,ytrain,ytest)
```

```
(8769, 10)
(171, 10)
(54, 10)
(34, 10)
(26, 10)
(396, 10)
(896, 10)
(169, 10)
(1785, 10)
(9, 10)
(42088, 9) (10522, 9) (42088,) (10522,)
Params: C=10, kernel=rbf, gamma=1 -> Accuracy: 0.8390
Params: C=10, kernel=rbf, gamma=10 -> Accuracy: 0.8429

Best Parameters:
C=10, kernel=rbf, gamma=10 -> Accuracy: 0.8429
```

Confusion Matrix

[29]:
```
best_model2=best_model(x1,y1,10,'rbf',10)
```

```
Params: C=10, kernel=rbf, gamma=10 -> Accuracy: 0.8360
```



Training SVM model over data to predict the type of collision gives accuracy of about 84% with parameters , C=10, RBF kernel function and gamma =10 and the above confusion matrix shows the classification of predictions

Key Takeaway
* In this problem we are identifying the impact of time of day, weather, light condition, road surface conditions, type of collisions etc on the severity of accident. We are learning from the available data about the severity of accidents under certain conditions and predicting how much severe of accidents are more likely to happen. Also predicting what kind of collision can happen given the surrounding conditions.

- By understanding these factors and predicting results in advance can help drivers to understand vulnerable conditions to take care of while driving under similar situations and be cautious to avoid collisions. It helps authorities to devise plans to tackle the environmental conditions and spread awareness about dangerous road sections, low visibility regions, appropriate road signs to warn drivers, take measures to improve lighting conditions, frequently cleaning snow on road etc.

- Analysis of accident severity based on weather conditions, light, time of day can help health infrastructure to be alert and responsive when combination of these parameters are present. It will help in reduction of severe injury and lower casualties as proper medical help is provided on time