road-acc-encoded

March 31, 2023

1 Problem statement

"To develop a predictive model to identify the factors that contribute to the severity of a vehicle accident based on various features such as the number of vehicles involved, engine capacity, age of vehicle, weather conditions, road surface conditions, urban or rural area, propulsion code, vehicle maneuver, towing and articulation, skidding and overturning, and the first point of impact."

The objective of this problem statement is to develop a machine learning model that can accurately predict the severity of an accident based on the given features. The model can be used to identify the contributing factors to the severity of accidents and help in developing strategies to reduce the frequency and severity of accidents.

The data for this problem is given in a special encoded format.

[84]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

unzipping data

[85]:
```
!unzip -q "/content/drive/MyDrive/Freelance/Sri/road_acc_binary/Data.zip"
```

```
replace Data/testing_set.csv? [y]es, [n]o, [A]ll, [N]one, [r]ename: A
```

Importing required libraries

[86]:
```
# Libraries to help with reading and manipulating data
import pandas as pd
import numpy as np

# Libaries to help with data visualization
import matplotlib.pyplot as plt
import seaborn as sns

# To tune model, get different metric scores, and split data
from sklearn.metrics import (
    f1_score,
    accuracy_score,
```

```python
    recall_score,
    precision_score,
    confusion_matrix,
    roc_auc_score
)
from sklearn.model_selection import train_test_split, StratifiedKFold,␣
↪cross_val_score

# To be used for data scaling and one hot encoding
from sklearn.preprocessing import StandardScaler, MinMaxScaler, OneHotEncoder
from sklearn import metrics

# To impute missing values
from sklearn.impute import SimpleImputer

# To oversample and undersample data
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler

# To do hyperparameter tuning
from sklearn.model_selection import RandomizedSearchCV

# To be used for creating pipelines and personalizing them
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer

# To define maximum number of columns to be displayed in a dataframe
pd.set_option("display.max_columns", None)

# To supress scientific notations for a dataframe
pd.set_option("display.float_format", lambda x: "%.3f" % x)

# To help with model building
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import (
    AdaBoostClassifier,
    GradientBoostingClassifier,
    RandomForestClassifier,
    BaggingClassifier,
)
from xgboost import XGBClassifier

# To suppress scientific notations
pd.set_option("display.float_format", lambda x: "%.3f" % x)

# To supress warnings
```

```python
import warnings

warnings.filterwarnings("ignore")
```

[87]:
```python
train_df = pd.read_csv("/content/Data/training_set.csv")
test_df = pd.read_csv("/content/Data/testing_set.csv")
```

[88]:
```python
train_df.head()
```

[88]:
```
   Unnamed: 0  accident_severity  number_of_vehicles  engine_capacity_cc  \
0      972755                  3                   2                1242
1      956023                  3                   2                 998
2      939829                  3                   2                 999
3      928714                  2                   1                1560
4      733228                  3                   2                1388

   age_of_vehicle  weather_conditions_2  weather_conditions_3  \
0              10                     0                     0
1               5                     0                     0
2               0                     0                     0
3              10                     0                     0
4              15                     0                     0

   weather_conditions_4  weather_conditions_5  weather_conditions_6  \
0                     0                     0                     0
1                     0                     0                     0
2                     0                     0                     0
3                     0                     0                     0
4                     0                     0                     0

   weather_conditions_7  weather_conditions_8  weather_conditions_9  \
0                     0                     0                     0
1                     0                     0                     0
2                     0                     0                     0
3                     0                     0                     0
4                     0                     0                     0

   road_surface_conditions_2  road_surface_conditions_3  \
0                          1                          0
1                          1                          0
2                          0                          0
3                          0                          0
4                          0                          0

   road_surface_conditions_4  road_surface_conditions_5  \
0                          0                          0
1                          0                          0
```

```
2                          0                          0
3                          0                          0
4                          0                          0

   road_surface_conditions_9  urban_or_rural_area_2  accident_year_2021  \
0                          0                      0                   1
1                          0                      1                   1
2                          0                      0                   1
3                          0                      1                   1
4                          0                      0                   0

   propulsion_code_2  propulsion_code_7  vehicle_manoeuvre_2  \
0                  0                  0                    0
1                  0                  0                    1
2                  0                  0                    0
3                  1                  0                    0
4                  0                  0                    0

   vehicle_manoeuvre_3  vehicle_manoeuvre_4  vehicle_manoeuvre_5  \
0                    0                    0                    0
1                    0                    0                    0
2                    0                    0                    0
3                    0                    0                    0
4                    0                    0                    0

   vehicle_manoeuvre_6  vehicle_manoeuvre_7  vehicle_manoeuvre_8  \
0                    0                    0                    0
1                    0                    0                    0
2                    0                    0                    0
3                    0                    0                    0
4                    0                    0                    0

   vehicle_manoeuvre_9  vehicle_manoeuvre_10  vehicle_manoeuvre_11  \
0                    1                     0                     0
1                    0                     0                     0
2                    0                     0                     0
3                    0                     0                     0
4                    0                     0                     0

   vehicle_manoeuvre_12  vehicle_manoeuvre_13  vehicle_manoeuvre_14  \
0                     0                     0                     0
1                     0                     0                     0
2                     0                     0                     0
3                     0                     0                     0
4                     0                     0                     0

   vehicle_manoeuvre_15  vehicle_manoeuvre_16  vehicle_manoeuvre_17  \
```

```
0                      0                      0                      0
1                      0                      0                      0
2                      0                      0                      0
3                      0                      0                      0
4                      0                      0                      0

   vehicle_manoeuvre_18  vehicle_manoeuvre_99  vehicle_type_19  \
0                     0                     0                0
1                     0                     0                0
2                     1                     0                0
3                     1                     0                0
4                     1                     0                0

   towing_and_articulation_2  towing_and_articulation_3  \
0                          0                          0
1                          0                          0
2                          0                          0
3                          0                          0
4                          0                          0

   towing_and_articulation_4  towing_and_articulation_5  \
0                          0                          0
1                          0                          0
2                          0                          0
3                          0                          0
4                          0                          0

   towing_and_articulation_9  skidding_and_overturning_1  \
0                          0                           0
1                          0                           0
2                          0                           0
3                          0                           0
4                          0                           0

   skidding_and_overturning_2  skidding_and_overturning_3  \
0                           0                           0
1                           0                           0
2                           0                           0
3                           0                           0
4                           0                           0

   skidding_and_overturning_5  skidding_and_overturning_9  \
0                           0                           0
1                           0                           0
2                           0                           0
3                           0                           0
4                           0                           0
```

```
   first_point_of_impact_1  first_point_of_impact_2  first_point_of_impact_3  \
0                        0                        0                        0
1                        0                        1                        0
2                        0                        0                        0
3                        1                        0                        0
4                        0                        1                        0

   first_point_of_impact_4  first_point_of_impact_9
0                        1                        0
1                        0                        0
2                        1                        0
3                        0                        0
4                        0                        0
```

[89]:
```
test_df.head()
```

[89]:
```
   Unnamed: 0  accident_severity  number_of_vehicles  engine_capacity_cc  \
0      692319                  3                   3                1242
1      726673                  2                   2                1242
2      894444                  3                   2                1084
3      998488                  3                   1                1399
4      917152                  3                   2                 998

   age_of_vehicle  weather_conditions_2  weather_conditions_3  \
0               6                     0                     0
1              14                     0                     0
2               3                     0                     0
3              11                     0                     0
4               3                     0                     0

   weather_conditions_4  weather_conditions_5  weather_conditions_6  \
0                     0                     0                     0
1                     0                     0                     0
2                     0                     0                     0
3                     0                     0                     0
4                     0                     0                     0

   weather_conditions_7  weather_conditions_8  weather_conditions_9  \
0                     0                     0                     0
1                     0                     0                     0
2                     0                     0                     1
3                     0                     0                     0
4                     0                     0                     0

   road_surface_conditions_2  road_surface_conditions_3  \
0                          0                          0
```

```
1                          0                          0
2                          0                          0
3                          0                          0
4                          0                          0

   road_surface_conditions_4  road_surface_conditions_5  \
0                          0                          0
1                          0                          0
2                          0                          0
3                          0                          0
4                          0                          0

   road_surface_conditions_9  urban_or_rural_area_2  accident_year_2021  \
0                          0                      0                   0
1                          0                      0                   0
2                          0                      1                   1
3                          0                      1                   1
4                          0                      0                   1

   propulsion_code_2  propulsion_code_7  vehicle_manoeuvre_2  \
0                  0                  0                    1
1                  0                  0                    0
2                  0                  0                    0
3                  1                  0                    0
4                  0                  0                    0

   vehicle_manoeuvre_3  vehicle_manoeuvre_4  vehicle_manoeuvre_5  \
0                    0                    0                    0
1                    0                    0                    0
2                    0                    0                    0
3                    0                    0                    0
4                    0                    0                    0

   vehicle_manoeuvre_6  vehicle_manoeuvre_7  vehicle_manoeuvre_8  \
0                    0                    0                    0
1                    0                    0                    0
2                    0                    0                    0
3                    0                    0                    0
4                    0                    0                    0

   vehicle_manoeuvre_9  vehicle_manoeuvre_10  vehicle_manoeuvre_11  \
0                    0                     0                     0
1                    0                     0                     0
2                    0                     0                     0
3                    0                     0                     1
4                    0                     0                     0
```

```
   vehicle_manoeuvre_12  vehicle_manoeuvre_13  vehicle_manoeuvre_14  \
0                     0                     0                     0
1                     0                     0                     0
2                     0                     0                     0
3                     0                     0                     0
4                     0                     0                     0

   vehicle_manoeuvre_15  vehicle_manoeuvre_16  vehicle_manoeuvre_17  \
0                     0                     0                     0
1                     0                     0                     0
2                     0                     0                     0
3                     0                     0                     0
4                     0                     0                     0

   vehicle_manoeuvre_18  vehicle_manoeuvre_99  vehicle_type_19  \
0                     0                     0                0
1                     1                     0                0
2                     1                     0                0
3                     0                     0                0
4                     1                     0                0

   towing_and_articulation_2  towing_and_articulation_3  \
0                          0                          0
1                          0                          0
2                          0                          0
3                          0                          0
4                          0                          0

   towing_and_articulation_4  towing_and_articulation_5  \
0                          0                          0
1                          0                          0
2                          0                          0
3                          0                          0
4                          0                          0

   towing_and_articulation_9  skidding_and_overturning_1  \
0                          0                           0
1                          0                           0
2                          0                           0
3                          0                           1
4                          0                           0

   skidding_and_overturning_2  skidding_and_overturning_3  \
0                           0                           0
1                           0                           0
2                           0                           0
3                           0                           0
```

```
4                         0                          0

   skidding_and_overturning_5  skidding_and_overturning_9  \
0                           0                           0
1                           0                           0
2                           0                           0
3                           0                           0
4                           0                           0

   first_point_of_impact_1  first_point_of_impact_2  first_point_of_impact_3  \
0                        1                        0                        0
1                        1                        0                        0
2                        1                        0                        0
3                        0                        0                        0
4                        1                        0                        0

   first_point_of_impact_4  first_point_of_impact_9
0                        0                        0
1                        0                        0
2                        0                        0
3                        1                        0
4                        0                        0
```

[90]:
```
train_df.columns
```

[90]:
```
Index(['Unnamed: 0', 'accident_severity', 'number_of_vehicles',
       'engine_capacity_cc', 'age_of_vehicle', 'weather_conditions_2',
       'weather_conditions_3', 'weather_conditions_4', 'weather_conditions_5',
       'weather_conditions_6', 'weather_conditions_7', 'weather_conditions_8',
       'weather_conditions_9', 'road_surface_conditions_2',
       'road_surface_conditions_3', 'road_surface_conditions_4',
       'road_surface_conditions_5', 'road_surface_conditions_9',
       'urban_or_rural_area_2', 'accident_year_2021', 'propulsion_code_2',
       'propulsion_code_7', 'vehicle_manoeuvre_2', 'vehicle_manoeuvre_3',
       'vehicle_manoeuvre_4', 'vehicle_manoeuvre_5', 'vehicle_manoeuvre_6',
       'vehicle_manoeuvre_7', 'vehicle_manoeuvre_8', 'vehicle_manoeuvre_9',
       'vehicle_manoeuvre_10', 'vehicle_manoeuvre_11', 'vehicle_manoeuvre_12',
       'vehicle_manoeuvre_13', 'vehicle_manoeuvre_14', 'vehicle_manoeuvre_15',
       'vehicle_manoeuvre_16', 'vehicle_manoeuvre_17', 'vehicle_manoeuvre_18',
       'vehicle_manoeuvre_99', 'vehicle_type_19', 'towing_and_articulation_2',
       'towing_and_articulation_3', 'towing_and_articulation_4',
       'towing_and_articulation_5', 'towing_and_articulation_9',
       'skidding_and_overturning_1', 'skidding_and_overturning_2',
       'skidding_and_overturning_3', 'skidding_and_overturning_5',
       'skidding_and_overturning_9', 'first_point_of_impact_1',
       'first_point_of_impact_2', 'first_point_of_impact_3',
       'first_point_of_impact_4', 'first_point_of_impact_9'],
```

```
      dtype='object')
```

[91]:
```
train_df = train_df.drop('Unnamed: 0', axis =1)
test_df = test_df.drop('Unnamed: 0', axis =1)
```

- Let us only keep the test_Data for testing the model

[92]:
```
train_df.shape
```

[92]:
```
(7403, 55)
```

[93]:
```
# let's check the data types of the columns in the dataset
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7403 entries, 0 to 7402
Data columns (total 55 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   accident_severity            7403 non-null   int64
 1   number_of_vehicles           7403 non-null   int64
 2   engine_capacity_cc           7403 non-null   int64
 3   age_of_vehicle               7403 non-null   int64
 4   weather_conditions_2         7403 non-null   int64
 5   weather_conditions_3         7403 non-null   int64
 6   weather_conditions_4         7403 non-null   int64
 7   weather_conditions_5         7403 non-null   int64
 8   weather_conditions_6         7403 non-null   int64
 9   weather_conditions_7         7403 non-null   int64
 10  weather_conditions_8         7403 non-null   int64
 11  weather_conditions_9         7403 non-null   int64
 12  road_surface_conditions_2    7403 non-null   int64
 13  road_surface_conditions_3    7403 non-null   int64
 14  road_surface_conditions_4    7403 non-null   int64
 15  road_surface_conditions_5    7403 non-null   int64
 16  road_surface_conditions_9    7403 non-null   int64
 17  urban_or_rural_area_2        7403 non-null   int64
 18  accident_year_2021           7403 non-null   int64
 19  propulsion_code_2            7403 non-null   int64
 20  propulsion_code_7            7403 non-null   int64
 21  vehicle_manoeuvre_2          7403 non-null   int64
 22  vehicle_manoeuvre_3          7403 non-null   int64
 23  vehicle_manoeuvre_4          7403 non-null   int64
 24  vehicle_manoeuvre_5          7403 non-null   int64
 25  vehicle_manoeuvre_6          7403 non-null   int64
 26  vehicle_manoeuvre_7          7403 non-null   int64
 27  vehicle_manoeuvre_8          7403 non-null   int64
 28  vehicle_manoeuvre_9          7403 non-null   int64
```

```
 29  vehicle_manoeuvre_10        7403 non-null   int64
 30  vehicle_manoeuvre_11        7403 non-null   int64
 31  vehicle_manoeuvre_12        7403 non-null   int64
 32  vehicle_manoeuvre_13        7403 non-null   int64
 33  vehicle_manoeuvre_14        7403 non-null   int64
 34  vehicle_manoeuvre_15        7403 non-null   int64
 35  vehicle_manoeuvre_16        7403 non-null   int64
 36  vehicle_manoeuvre_17        7403 non-null   int64
 37  vehicle_manoeuvre_18        7403 non-null   int64
 38  vehicle_manoeuvre_99        7403 non-null   int64
 39  vehicle_type_19             7403 non-null   int64
 40  towing_and_articulation_2   7403 non-null   int64
 41  towing_and_articulation_3   7403 non-null   int64
 42  towing_and_articulation_4   7403 non-null   int64
 43  towing_and_articulation_5   7403 non-null   int64
 44  towing_and_articulation_9   7403 non-null   int64
 45  skidding_and_overturning_1  7403 non-null   int64
 46  skidding_and_overturning_2  7403 non-null   int64
 47  skidding_and_overturning_3  7403 non-null   int64
 48  skidding_and_overturning_5  7403 non-null   int64
 49  skidding_and_overturning_9  7403 non-null   int64
 50  first_point_of_impact_1     7403 non-null   int64
 51  first_point_of_impact_2     7403 non-null   int64
 52  first_point_of_impact_3     7403 non-null   int64
 53  first_point_of_impact_4     7403 non-null   int64
 54  first_point_of_impact_9     7403 non-null   int64
dtypes: int64(55)
memory usage: 3.1 MB
```

[94]:
```
# let's check for duplicate values in the data
train_df.duplicated().sum()
```

[94]:
```
1007
```

[95]:
```
train_df = train_df.drop_duplicates()
```

[96]:
```
# let's check for missing values in the data
round(train_df.isnull().sum() / train_df.isnull().count() * 100, 2)
```

[96]:
```
accident_severity             0.000
number_of_vehicles            0.000
engine_capacity_cc            0.000
age_of_vehicle                0.000
weather_conditions_2          0.000
weather_conditions_3          0.000
weather_conditions_4          0.000
weather_conditions_5          0.000
```

weather_conditions_6	0.000
weather_conditions_7	0.000
weather_conditions_8	0.000
weather_conditions_9	0.000
road_surface_conditions_2	0.000
road_surface_conditions_3	0.000
road_surface_conditions_4	0.000
road_surface_conditions_5	0.000
road_surface_conditions_9	0.000
urban_or_rural_area_2	0.000
accident_year_2021	0.000
propulsion_code_2	0.000
propulsion_code_7	0.000
vehicle_manoeuvre_2	0.000
vehicle_manoeuvre_3	0.000
vehicle_manoeuvre_4	0.000
vehicle_manoeuvre_5	0.000
vehicle_manoeuvre_6	0.000
vehicle_manoeuvre_7	0.000
vehicle_manoeuvre_8	0.000
vehicle_manoeuvre_9	0.000
vehicle_manoeuvre_10	0.000
vehicle_manoeuvre_11	0.000
vehicle_manoeuvre_12	0.000
vehicle_manoeuvre_13	0.000
vehicle_manoeuvre_14	0.000
vehicle_manoeuvre_15	0.000
vehicle_manoeuvre_16	0.000
vehicle_manoeuvre_17	0.000
vehicle_manoeuvre_18	0.000
vehicle_manoeuvre_99	0.000
vehicle_type_19	0.000
towing_and_articulation_2	0.000
towing_and_articulation_3	0.000
towing_and_articulation_4	0.000
towing_and_articulation_5	0.000
towing_and_articulation_9	0.000
skidding_and_overturning_1	0.000
skidding_and_overturning_2	0.000
skidding_and_overturning_3	0.000
skidding_and_overturning_5	0.000
skidding_and_overturning_9	0.000
first_point_of_impact_1	0.000
first_point_of_impact_2	0.000
first_point_of_impact_3	0.000
first_point_of_impact_4	0.000
first_point_of_impact_9	0.000

```
dtype: float64
```

[97]:
```
# let's view the statistical summary of the numerical columns in the data
train_df.describe().T
```

[97]:
```
                           count     mean     std     min      25%  \
accident_severity       6396.000    2.769   0.454   1.000    3.000
number_of_vehicles      6396.000    2.097   0.897   1.000    2.000
engine_capacity_cc      6396.000 1280.523 206.324 998.000 1084.000
age_of_vehicle          6396.000    9.260   5.036   0.000    5.000
weather_conditions_2    6396.000    0.134   0.341   0.000    0.000
weather_conditions_3    6396.000    0.006   0.078   0.000    0.000
weather_conditions_4    6396.000    0.015   0.120   0.000    0.000
weather_conditions_5    6396.000    0.018   0.134   0.000    0.000
weather_conditions_6    6396.000    0.001   0.035   0.000    0.000
weather_conditions_7    6396.000    0.008   0.089   0.000    0.000
weather_conditions_8    6396.000    0.039   0.195   0.000    0.000
weather_conditions_9    6396.000    0.023   0.149   0.000    0.000
road_surface_conditions_2 6396.000  0.318   0.466   0.000    0.000
road_surface_conditions_3 6396.000  0.005   0.069   0.000    0.000
road_surface_conditions_4 6396.000  0.015   0.122   0.000    0.000
road_surface_conditions_5 6396.000  0.002   0.047   0.000    0.000
road_surface_conditions_9 6396.000  0.005   0.073   0.000    0.000
urban_or_rural_area_2   6396.000    0.403   0.490   0.000    0.000
accident_year_2021      6396.000    0.487   0.500   0.000    0.000
propulsion_code_2       6396.000    0.161   0.367   0.000    0.000
propulsion_code_7       6396.000    0.000   0.013   0.000    0.000
vehicle_manoeuvre_2     6396.000    0.054   0.226   0.000    0.000
vehicle_manoeuvre_3     6396.000    0.047   0.211   0.000    0.000
vehicle_manoeuvre_4     6396.000    0.063   0.244   0.000    0.000
vehicle_manoeuvre_5     6396.000    0.048   0.213   0.000    0.000
vehicle_manoeuvre_6     6396.000    0.008   0.090   0.000    0.000
vehicle_manoeuvre_7     6396.000    0.039   0.194   0.000    0.000
vehicle_manoeuvre_8     6396.000    0.006   0.077   0.000    0.000
vehicle_manoeuvre_9     6396.000    0.109   0.312   0.000    0.000
vehicle_manoeuvre_10    6396.000    0.020   0.140   0.000    0.000
vehicle_manoeuvre_11    6396.000    0.006   0.077   0.000    0.000
vehicle_manoeuvre_12    6396.000    0.008   0.087   0.000    0.000
vehicle_manoeuvre_13    6396.000    0.014   0.118   0.000    0.000
vehicle_manoeuvre_14    6396.000    0.008   0.087   0.000    0.000
vehicle_manoeuvre_15    6396.000    0.005   0.071   0.000    0.000
vehicle_manoeuvre_16    6396.000    0.045   0.207   0.000    0.000
vehicle_manoeuvre_17    6396.000    0.051   0.221   0.000    0.000
vehicle_manoeuvre_18    6396.000    0.416   0.493   0.000    0.000
vehicle_manoeuvre_99    6396.000    0.041   0.199   0.000    0.000
vehicle_type_19         6396.000    0.003   0.050   0.000    0.000
towing_and_articulation_2 6396.000  0.000   0.013   0.000    0.000
```

towing_and_articulation_3	6396.000	0.000	0.013	0.000	0.000
towing_and_articulation_4	6396.000	0.000	0.018	0.000	0.000
towing_and_articulation_5	6396.000	0.001	0.028	0.000	0.000
towing_and_articulation_9	6396.000	0.005	0.069	0.000	0.000
skidding_and_overturning_1	6396.000	0.086	0.281	0.000	0.000
skidding_and_overturning_2	6396.000	0.025	0.157	0.000	0.000
skidding_and_overturning_3	6396.000	0.000	0.013	0.000	0.000
skidding_and_overturning_5	6396.000	0.031	0.174	0.000	0.000
skidding_and_overturning_9	6396.000	0.041	0.197	0.000	0.000
first_point_of_impact_1	6396.000	0.504	0.500	0.000	0.000
first_point_of_impact_2	6396.000	0.181	0.385	0.000	0.000
first_point_of_impact_3	6396.000	0.145	0.352	0.000	0.000
first_point_of_impact_4	6396.000	0.130	0.336	0.000	0.000
first_point_of_impact_9	6396.000	0.016	0.125	0.000	0.000

	50%	75%	max
accident_severity	3.000	3.000	3.000
number_of_vehicles	2.000	2.000	12.000
engine_capacity_cc	1242.000	1399.000	1999.000
age_of_vehicle	9.000	13.000	39.000
weather_conditions_2	0.000	0.000	1.000
weather_conditions_3	0.000	0.000	1.000
weather_conditions_4	0.000	0.000	1.000
weather_conditions_5	0.000	0.000	1.000
weather_conditions_6	0.000	0.000	1.000
weather_conditions_7	0.000	0.000	1.000
weather_conditions_8	0.000	0.000	1.000
weather_conditions_9	0.000	0.000	1.000
road_surface_conditions_2	0.000	1.000	1.000
road_surface_conditions_3	0.000	0.000	1.000
road_surface_conditions_4	0.000	0.000	1.000
road_surface_conditions_5	0.000	0.000	1.000
road_surface_conditions_9	0.000	0.000	1.000
urban_or_rural_area_2	0.000	1.000	1.000
accident_year_2021	0.000	1.000	1.000
propulsion_code_2	0.000	0.000	1.000
propulsion_code_7	0.000	0.000	1.000
vehicle_manoeuvre_2	0.000	0.000	1.000
vehicle_manoeuvre_3	0.000	0.000	1.000
vehicle_manoeuvre_4	0.000	0.000	1.000
vehicle_manoeuvre_5	0.000	0.000	1.000
vehicle_manoeuvre_6	0.000	0.000	1.000
vehicle_manoeuvre_7	0.000	0.000	1.000
vehicle_manoeuvre_8	0.000	0.000	1.000
vehicle_manoeuvre_9	0.000	0.000	1.000
vehicle_manoeuvre_10	0.000	0.000	1.000
vehicle_manoeuvre_11	0.000	0.000	1.000

```
vehicle_manoeuvre_12         0.000    0.000    1.000
vehicle_manoeuvre_13         0.000    0.000    1.000
vehicle_manoeuvre_14         0.000    0.000    1.000
vehicle_manoeuvre_15         0.000    0.000    1.000
vehicle_manoeuvre_16         0.000    0.000    1.000
vehicle_manoeuvre_17         0.000    0.000    1.000
vehicle_manoeuvre_18         0.000    1.000    1.000
vehicle_manoeuvre_99         0.000    0.000    1.000
vehicle_type_19              0.000    0.000    1.000
towing_and_articulation_2    0.000    0.000    1.000
towing_and_articulation_3    0.000    0.000    1.000
towing_and_articulation_4    0.000    0.000    1.000
towing_and_articulation_5    0.000    0.000    1.000
towing_and_articulation_9    0.000    0.000    1.000
skidding_and_overturning_1   0.000    0.000    1.000
skidding_and_overturning_2   0.000    0.000    1.000
skidding_and_overturning_3   0.000    0.000    1.000
skidding_and_overturning_5   0.000    0.000    1.000
skidding_and_overturning_9   0.000    0.000    1.000
first_point_of_impact_1      1.000    1.000    1.000
first_point_of_impact_2      0.000    0.000    1.000
first_point_of_impact_3      0.000    0.000    1.000
first_point_of_impact_4      0.000    0.000    1.000
first_point_of_impact_9      0.000    0.000    1.000
```

- The accident severity variable ranges from 1 to 3, with 1 being the least severe and 3 being the most severe. The mean accident severity is 2.769, with a standard deviation of 0.454.
- The number of vehicles involved variable ranges from 1 to 12, with a mean of 2.097 and a standard deviation of 0.897.
- Finally, the engine capacity variable ranges from 998 cc to 1999 cc, with a mean of 1280.523 cc and a standard deviation of 206.324 cc. The quartiles suggest that most of the accidents involve cars with engine capacities between 998 cc and 1399 cc.

[97]:

```

```

[98]:

```python
# checking for value_counts in each nominal feature
columns = ['accident_severity', 'number_of_vehicles','engine_capacity_cc',␣
 ↪'age_of_vehicle']
for i in columns:
    print("Unique values in", i, "are :")
    print(train_df[i].value_counts())
    print("*" * 50)
```

```
Unique values in accident_severity are :
3    5012
2    1292
1      92
```

```
Name: accident_severity, dtype: int64
**************************************************
Unique values in number_of_vehicles are :
2     3882
1     1256
3      867
4      261
5       82
6       26
7       10
8        5
9        3
10       2
12       1
11       1
Name: number_of_vehicles, dtype: int64
**************************************************
Unique values in engine_capacity_cc are :
1242    2010
998     1376
1388     998
1596     522
1399     472
1560     328
1499     227
999      129
1084     124
1299      90
1999      68
1496      31
1117       5
1118       3
1250       2
1200       2
1796       1
1300       1
1400       1
1995       1
1396       1
1597       1
1600       1
1392       1
1119       1
Name: engine_capacity_cc, dtype: int64
**************************************************
Unique values in age_of_vehicle are :
12    474
6     445
```

```
11    429
5     426
7     410
13    409
10    398
8     393
4     373
9     372
14    363
3     322
15    285
2     256
1     240
16    214
17    192
18    128
0      87
19     73
20     32
21     25
23     16
22     14
24      6
29      4
31      3
39      2
28      1
34      1
27      1
30      1
25      1
Name: age_of_vehicle, dtype: int64
**************************************************
```

- The variable accident_severity has three unique values with code 1, 2, and 3, where 3 has the highest count of 5012. The variable number_of_vehicles has 12 unique values with code ranging from 1 to 12, where 2 has the highest count of 3882.
- The variable engine_capacity_cc has 26 unique values ranging from 998 to 1999, where 1242 has the highest count of 2010. The variable age_of_vehicle has 34 unique values ranging from 0 to 39, where 12 has the highest count of 474. These values can provide insights into the distribution and characteristics of the data for further analysis.

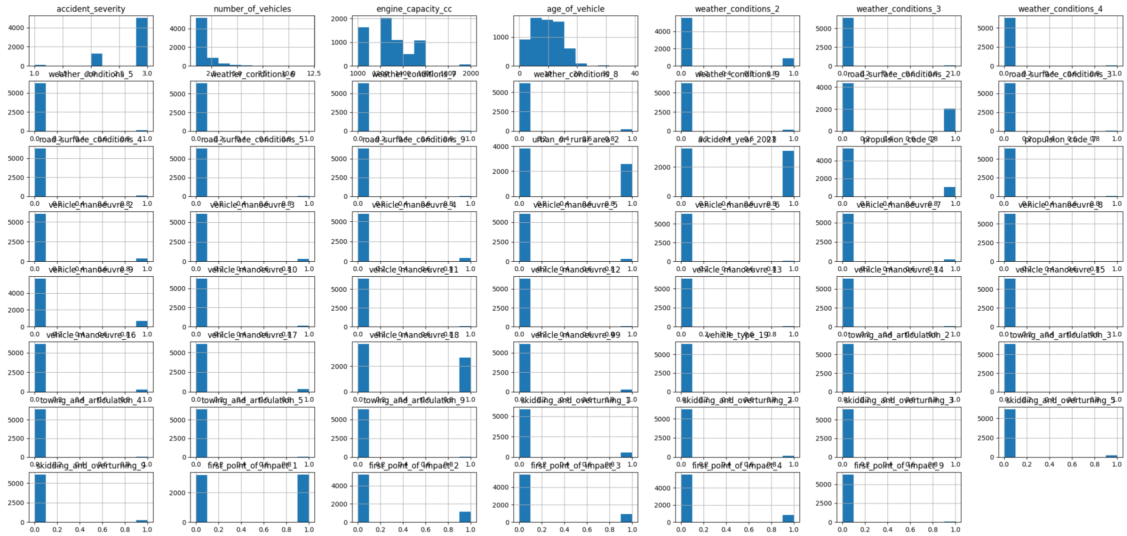
1.0.1 EDA

[99]:
```python
### Function to plot distributions


def distribution_plot_wrt_target(data, predictor, target):
```

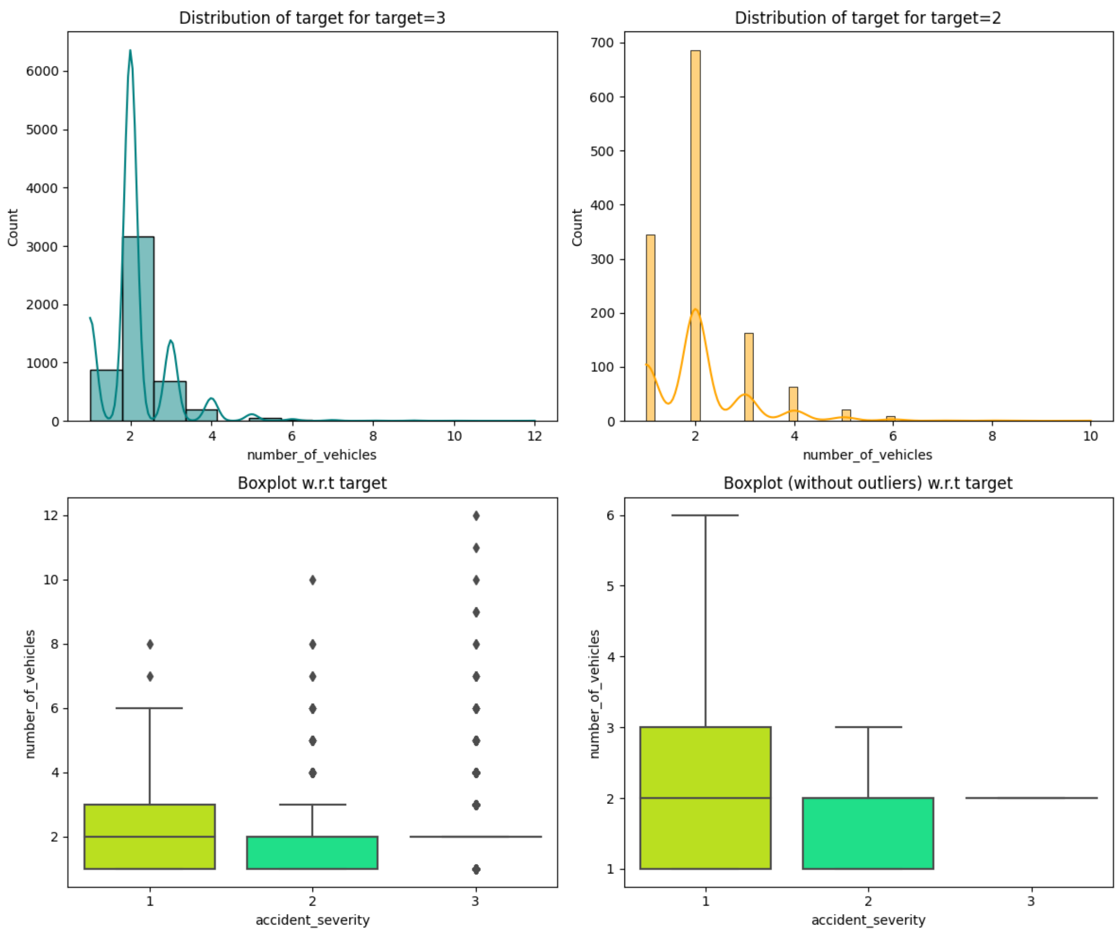
```
    fig, axs = plt.subplots(2, 2, figsize=(12, 10))

    target_uniq = data[target].unique()

    axs[0, 0].set_title("Distribution of target for target=" +␣
↪str(target_uniq[0]))
    sns.histplot(
        data=data[data[target] == target_uniq[0]],
        x=predictor,
        kde=True,
        ax=axs[0, 0],
        color="teal",
    )

    axs[0, 1].set_title("Distribution of target for target=" +␣
↪str(target_uniq[1]))
    sns.histplot(
        data=data[data[target] == target_uniq[1]],
        x=predictor,
        kde=True,
        ax=axs[0, 1],
        color="orange",
    )

    axs[1, 0].set_title("Boxplot w.r.t target")
    sns.boxplot(data=data, x=target, y=predictor, ax=axs[1, 0],␣
↪palette="gist_rainbow")

    axs[1, 1].set_title("Boxplot (without outliers) w.r.t target")
    sns.boxplot(
        data=data,
        x=target,
        y=predictor,
        ax=axs[1, 1],
        showfliers=False,
        palette="gist_rainbow",
    )

    plt.tight_layout()
    plt.show()
```

[100]:

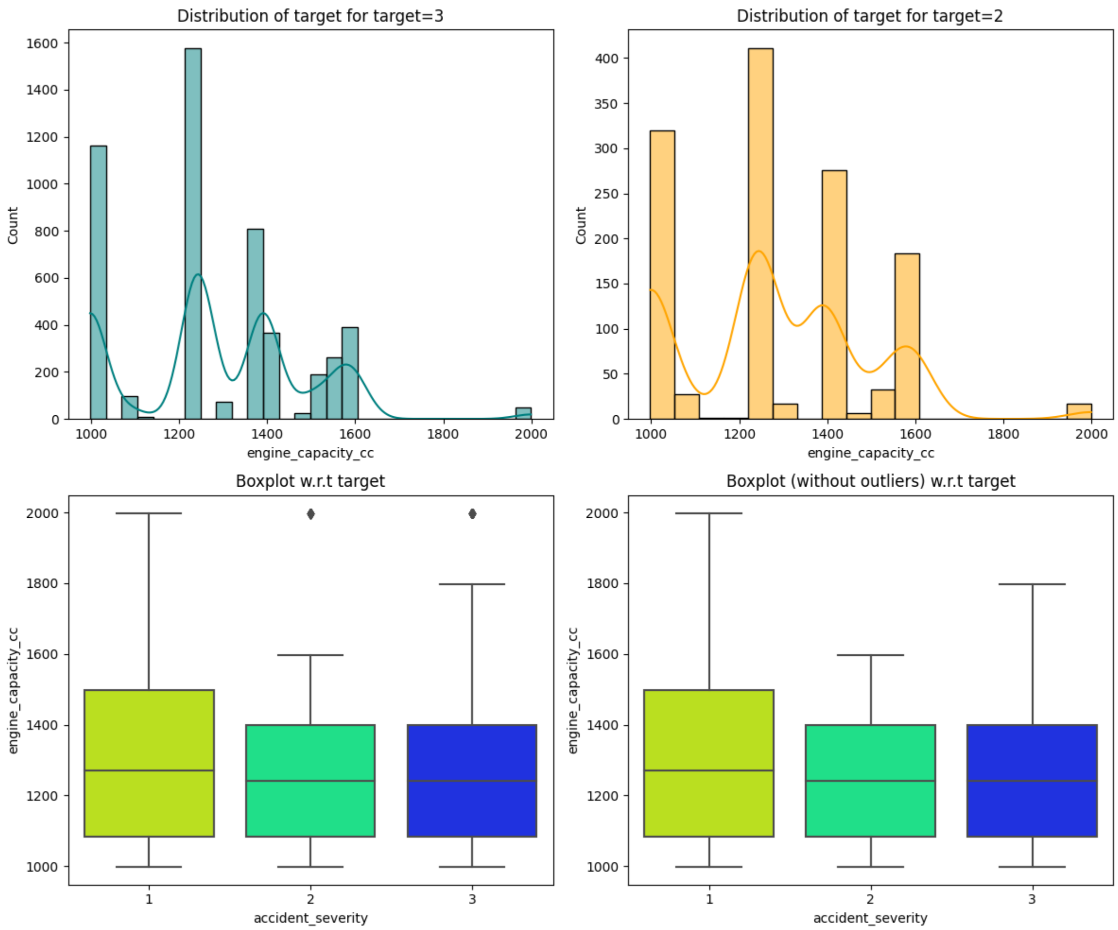
```
# creating histograms
train_df.hist(figsize=(30, 14))
plt.show()
```



[101]:
```
distribution_plot_wrt_target(train_df, "number_of_vehicles",␣
    ↪"accident_severity")
```

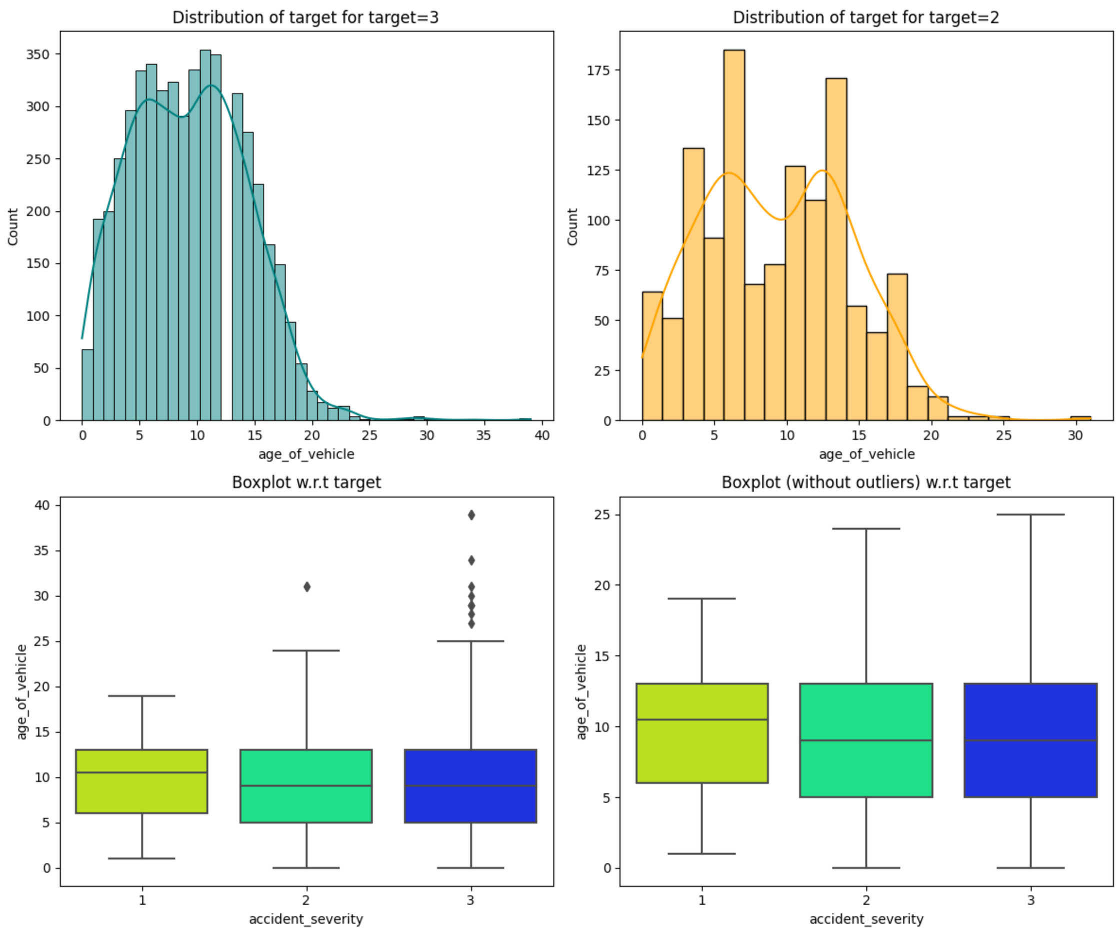


[102]:
```
distribution_plot_wrt_target(train_df, "engine_capacity_cc",␣
↪"accident_severity")
```



- We can observe that most of the data is normally distributed and they are already one hot encoded vectors so it is easy to use them for modeling without further encoding

[103]:
```
distribution_plot_wrt_target(train_df, "age_of_vehicle", "accident_severity")
```



[104]:
```
train_df.head()
```

[104]:

	accident_severity	number_of_vehicles	engine_capacity_cc	age_of_vehicle	\
0	3	2	1242	10	
1	3	2	998	5	
2	3	2	999	0	
3	2	1	1560	10	
4	3	2	1388	15	

	weather_conditions_2	weather_conditions_3	weather_conditions_4	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	weather_conditions_5	weather_conditions_6	weather_conditions_7	\
0	0	0	0	

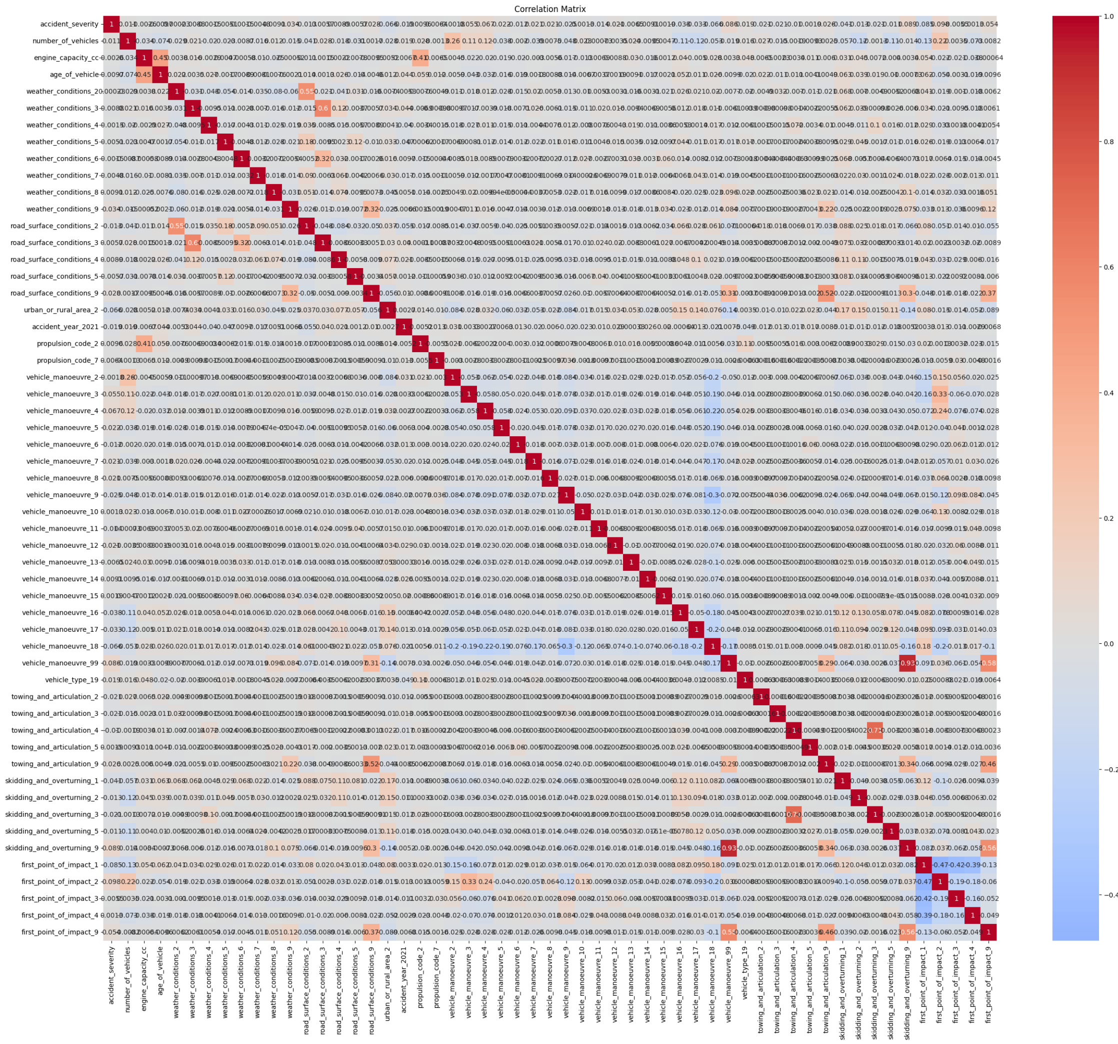
```
1                      0                      0                      0
2                      0                      0                      0
3                      0                      0                      0
4                      0                      0                      0

   weather_conditions_8  weather_conditions_9  road_surface_conditions_2  \
0                     0                     0                          1
1                     0                     0                          1
2                     0                     0                          0
3                     0                     0                          0
4                     0                     0                          0

   road_surface_conditions_3  road_surface_conditions_4  \
0                          0                          0
1                          0                          0
2                          0                          0
3                          0                          0
4                          0                          0

   road_surface_conditions_5  road_surface_conditions_9  \
0                          0                          0
1                          0                          0
2                          0                          0
3                          0                          0
4                          0                          0

   urban_or_rural_area_2  accident_year_2021  propulsion_code_2  \
0                      0                   1                  0
1                      1                   1                  0
2                      0                   1                  0
3                      1                   1                  1
4                      0                   0                  0

   propulsion_code_7  vehicle_manoeuvre_2  vehicle_manoeuvre_3  \
0                  0                    0                    0
1                  0                    1                    0
2                  0                    0                    0
3                  0                    0                    0
4                  0                    0                    0

   vehicle_manoeuvre_4  vehicle_manoeuvre_5  vehicle_manoeuvre_6  \
0                    0                    0                    0
1                    0                    0                    0
2                    0                    0                    0
3                    0                    0                    0
4                    0                    0                    0
```

```
   vehicle_manoeuvre_7  vehicle_manoeuvre_8  vehicle_manoeuvre_9  \
0                    0                    0                    1
1                    0                    0                    0
2                    0                    0                    0
3                    0                    0                    0
4                    0                    0                    0

   vehicle_manoeuvre_10  vehicle_manoeuvre_11  vehicle_manoeuvre_12  \
0                     0                     0                     0
1                     0                     0                     0
2                     0                     0                     0
3                     0                     0                     0
4                     0                     0                     0

   vehicle_manoeuvre_13  vehicle_manoeuvre_14  vehicle_manoeuvre_15  \
0                     0                     0                     0
1                     0                     0                     0
2                     0                     0                     0
3                     0                     0                     0
4                     0                     0                     0

   vehicle_manoeuvre_16  vehicle_manoeuvre_17  vehicle_manoeuvre_18  \
0                     0                     0                     0
1                     0                     0                     0
2                     0                     0                     1
3                     0                     0                     1
4                     0                     0                     1

   vehicle_manoeuvre_99  vehicle_type_19  towing_and_articulation_2  \
0                     0                0                          0
1                     0                0                          0
2                     0                0                          0
3                     0                0                          0
4                     0                0                          0

   towing_and_articulation_3  towing_and_articulation_4  \
0                          0                          0
1                          0                          0
2                          0                          0
3                          0                          0
4                          0                          0

   towing_and_articulation_5  towing_and_articulation_9  \
0                          0                          0
1                          0                          0
2                          0                          0
3                          0                          0
```

```
4                          0                           0

   skidding_and_overturning_1  skidding_and_overturning_2  \
0                           0                           0
1                           0                           0
2                           0                           0
3                           0                           0
4                           0                           0

   skidding_and_overturning_3  skidding_and_overturning_5  \
0                           0                           0
1                           0                           0
2                           0                           0
3                           0                           0
4                           0                           0

   skidding_and_overturning_9  first_point_of_impact_1  \
0                           0                        0
1                           0                        0
2                           0                        0
3                           0                        1
4                           0                        0

   first_point_of_impact_2  first_point_of_impact_3  first_point_of_impact_4  \
0                        0                        0                        1
1                        1                        0                        0
2                        0                        0                        1
3                        0                        0                        0
4                        1                        0                        0

   first_point_of_impact_9
0                        0
1                        0
2                        0
3                        0
4                        0
```

[105]:

```
corr_matrix = train_df.corr()

# Set the figure size
plt.figure(figsize=(30, 25))
# plot correlation matrix as heatmap
sns.heatmap(corr_matrix, cmap='coolwarm', center=0, annot=True)
plt.title('Correlation Matrix')
plt.show()
```



- it seems most of the columns are not highly correlated and they are in the encoded format

Making data ready for modeling

[106]:
```python
X = train_df.drop(["accident_severity"], axis=1)
y = train_df["accident_severity"]
```

[107]:
```python
# As we already have test data so we will just split data into train and vaidation

X_train, X_val, y_train, y_val = train_test_split(
    X, y, test_size=0.2, random_state=1, stratify=y
)

X_test = test_df.drop(["accident_severity"], axis=1)
y_test = test_df["accident_severity"]
```

```python
print(X_train.shape, X_val.shape, X_test.shape)
```

```
(5116, 54) (1280, 54) (1851, 54)
```

[108]:
```python
# Checking that no column has missing values in train or test sets
print(X_train.isna().sum())
print("-" * 30)
print(X_val.isna().sum())
print("-" * 30)
print(X_test.isna().sum())
```

```
number_of_vehicles              0
engine_capacity_cc              0
age_of_vehicle                  0
weather_conditions_2            0
weather_conditions_3            0
weather_conditions_4            0
weather_conditions_5            0
weather_conditions_6            0
weather_conditions_7            0
weather_conditions_8            0
weather_conditions_9            0
road_surface_conditions_2       0
road_surface_conditions_3       0
road_surface_conditions_4       0
road_surface_conditions_5       0
road_surface_conditions_9       0
urban_or_rural_area_2           0
accident_year_2021              0
propulsion_code_2               0
propulsion_code_7               0
vehicle_manoeuvre_2             0
vehicle_manoeuvre_3             0
vehicle_manoeuvre_4             0
vehicle_manoeuvre_5             0
vehicle_manoeuvre_6             0
vehicle_manoeuvre_7             0
vehicle_manoeuvre_8             0
vehicle_manoeuvre_9             0
vehicle_manoeuvre_10            0
vehicle_manoeuvre_11            0
vehicle_manoeuvre_12            0
vehicle_manoeuvre_13            0
vehicle_manoeuvre_14            0
vehicle_manoeuvre_15            0
vehicle_manoeuvre_16            0
vehicle_manoeuvre_17            0
vehicle_manoeuvre_18            0
```

```
vehicle_manoeuvre_99          0
vehicle_type_19               0
towing_and_articulation_2     0
towing_and_articulation_3     0
towing_and_articulation_4     0
towing_and_articulation_5     0
towing_and_articulation_9     0
skidding_and_overturning_1    0
skidding_and_overturning_2    0
skidding_and_overturning_3    0
skidding_and_overturning_5    0
skidding_and_overturning_9    0
first_point_of_impact_1       0
first_point_of_impact_2       0
first_point_of_impact_3       0
first_point_of_impact_4       0
first_point_of_impact_9       0
dtype: int64
------------------------------
number_of_vehicles            0
engine_capacity_cc            0
age_of_vehicle                0
weather_conditions_2          0
weather_conditions_3          0
weather_conditions_4          0
weather_conditions_5          0
weather_conditions_6          0
weather_conditions_7          0
weather_conditions_8          0
weather_conditions_9          0
road_surface_conditions_2     0
road_surface_conditions_3     0
road_surface_conditions_4     0
road_surface_conditions_5     0
road_surface_conditions_9     0
urban_or_rural_area_2         0
accident_year_2021            0
propulsion_code_2             0
propulsion_code_7             0
vehicle_manoeuvre_2           0
vehicle_manoeuvre_3           0
vehicle_manoeuvre_4           0
vehicle_manoeuvre_5           0
vehicle_manoeuvre_6           0
vehicle_manoeuvre_7           0
vehicle_manoeuvre_8           0
vehicle_manoeuvre_9           0
vehicle_manoeuvre_10          0
```

```
vehicle_manoeuvre_11          0
vehicle_manoeuvre_12          0
vehicle_manoeuvre_13          0
vehicle_manoeuvre_14          0
vehicle_manoeuvre_15          0
vehicle_manoeuvre_16          0
vehicle_manoeuvre_17          0
vehicle_manoeuvre_18          0
vehicle_manoeuvre_99          0
vehicle_type_19               0
towing_and_articulation_2     0
towing_and_articulation_3     0
towing_and_articulation_4     0
towing_and_articulation_5     0
towing_and_articulation_9     0
skidding_and_overturning_1    0
skidding_and_overturning_2    0
skidding_and_overturning_3    0
skidding_and_overturning_5    0
skidding_and_overturning_9    0
first_point_of_impact_1       0
first_point_of_impact_2       0
first_point_of_impact_3       0
first_point_of_impact_4       0
first_point_of_impact_9       0
dtype: int64
------------------------------
number_of_vehicles            0
engine_capacity_cc            0
age_of_vehicle                0
weather_conditions_2          0
weather_conditions_3          0
weather_conditions_4          0
weather_conditions_5          0
weather_conditions_6          0
weather_conditions_7          0
weather_conditions_8          0
weather_conditions_9          0
road_surface_conditions_2     0
road_surface_conditions_3     0
road_surface_conditions_4     0
road_surface_conditions_5     0
road_surface_conditions_9     0
urban_or_rural_area_2         0
accident_year_2021            0
propulsion_code_2             0
propulsion_code_7             0
vehicle_manoeuvre_2           0
```

```
vehicle_manoeuvre_3          0
vehicle_manoeuvre_4          0
vehicle_manoeuvre_5          0
vehicle_manoeuvre_6          0
vehicle_manoeuvre_7          0
vehicle_manoeuvre_8          0
vehicle_manoeuvre_9          0
vehicle_manoeuvre_10         0
vehicle_manoeuvre_11         0
vehicle_manoeuvre_12         0
vehicle_manoeuvre_13         0
vehicle_manoeuvre_14         0
vehicle_manoeuvre_15         0
vehicle_manoeuvre_16         0
vehicle_manoeuvre_17         0
vehicle_manoeuvre_18         0
vehicle_manoeuvre_99         0
vehicle_type_19              0
towing_and_articulation_2    0
towing_and_articulation_3    0
towing_and_articulation_4    0
towing_and_articulation_5    0
towing_and_articulation_9    0
skidding_and_overturning_1   0
skidding_and_overturning_2   0
skidding_and_overturning_3   0
skidding_and_overturning_5   0
skidding_and_overturning_9   0
first_point_of_impact_1      0
first_point_of_impact_2      0
first_point_of_impact_3      0
first_point_of_impact_4      0
first_point_of_impact_9      0
dtype: int64
```

1.0.2 Building Models

[109]:
```
# Both the functions taken from google for reference as it is easy to plot␣
 ↪using these functions
# defining a function to compute different metrics to check performance of a␣
 ↪classification model built using sklearn
def model_performance_classification_sklearn(model, predictors, target):
    """
    Function to compute different metrics to check classification model␣
 ↪performance

    model: classifier
```

```
    predictors: independent variables
    target: dependent variable
    """

    # predicting using the independent variables
    pred = model.predict(predictors)

    acc = accuracy_score(target, pred)  # to compute Accuracy
    recall = recall_score(target, pred, average = "weighted")  # to compute␣
↪Recall
    precision = precision_score(target, pred, average = 'weighted')  # to␣
↪compute Precision
    f1 = f1_score(target, pred, average = 'weighted')  # to compute F1-score

    # creating a dataframe of metrics
    df_perf = pd.DataFrame(
        {"Accuracy": acc, "Recall": recall, "Precision": precision, "F1": f1,},
        index=[0],
    )

    return df_perf

def confusion_matrix_sklearn(model, predictors, target):
    """
    To plot the confusion_matrix with percentages

    model: classifier
    predictors: independent variables
    target: dependent variable
    """
    y_pred = model.predict(predictors)
    cm = confusion_matrix(target, y_pred)
    labels = np.asarray(
        [
            ["{0:0.0f}".format(item) + "\n{0:.2%}".format(item / cm.flatten().
↪sum())]
            for item in cm.flatten()
        ]
    ).reshape(3,3)

    plt.figure(figsize=(8, 6))
    sns.heatmap(cm, annot=labels, fmt="")
    plt.ylabel("True label")
    plt.xlabel("Predicted label")
```

Models with the Org. Data

[110]:
```python
models = []  # Empty list to store all the models

# Appending models into the list
models.append(("Logistic regression", LogisticRegression(random_state=1)))
models.append(("Bagging", BaggingClassifier(random_state=1)))
models.append(("Random forest", RandomForestClassifier(random_state=1)))
models.append(("GBM", GradientBoostingClassifier(random_state=1)))
models.append(("Adaboost", AdaBoostClassifier(random_state=1)))
models.append(("dtree", DecisionTreeClassifier(random_state=1)))


print("\n" "Training Performance:" "\n")
for name, model in models:
    model.fit(X_train, y_train)
    scores = recall_score(y_train, model.predict(X_train), average = "weighted")
    print("{}: {}".format(name, scores))

print("\n" "Validation Performance:" "\n")

for name, model in models:
    model.fit(X_train, y_train)
    scores_val = recall_score(y_val, model.predict(X_val), average = "weighted")
    print("{}: {}".format(name, scores_val))
```

```
Training Performance:

Logistic regression: 0.7836200156372166
Bagging: 0.9552384675527756
Random forest: 0.9648162627052385
GBM: 0.790852228303362
Adaboost: 0.7832290852228303
dtree: 0.9648162627052385

Validation Performance:

Logistic regression: 0.78359375
Bagging: 0.67578125
Random forest: 0.72421875
GBM: 0.7796875
Adaboost: 0.78359375
dtree: 0.63125
```

- Logistic Regression: This is a linear model that uses a logistic function to predict the probability of an outcome. It is commonly used for binary classification problems.
- Bagging: This is an ensemble method that combines multiple models (usually decision trees) to make a prediction. It does this by training each model on a random subset of the training

data, and then averaging the predictions.

- Random Forest: This is another ensemble method that uses decision trees, but each tree is trained on a random subset of the features, as well as a random subset of the training data. This helps to reduce overfitting and improve the generalization of the model.
- Gradient Boosting Machine (GBM): This is a boosting algorithm that combines weak learners (usually decision trees) into a strong learner. It does this by iteratively training new trees to correct the mistakes of the previous trees, with a focus on difficult examples.
- Adaboost: This is another boosting algorithm that combines weak learners into a strong learner. It works by assigning higher weights to misclassified examples, and then training new weak learners to focus on these examples.
- Decision Tree: This is a simple non-parametric model that uses a tree structure to make a prediction. Each internal node of the tree represents a decision based on a feature, and each leaf node represents a class label.

Models with oversampled data

[111]:
```
print("Before Oversampling, counts of label '1': {}".format(sum(y_train == 1)))
print("Before Oversampling, counts of label '2': {} \n".format(sum(y_train ==␣
↪2)))
print("Before Oversampling, counts of label '3': {} \n".format(sum(y_train ==␣
↪3)))

sm = SMOTE(
    sampling_strategy="auto", k_neighbors=5, random_state=1
)  # Synthetic Minority Over Sampling Technique
X_train_over, y_train_over = sm.fit_resample(X_train, y_train)


print("Before Oversampling, counts of label '1': {}".format(sum(y_train_over ==␣
↪1)))
print("Before Oversampling, counts of label '2': {} \n".format(sum(y_train_over␣
↪== 2)))
print("Before Oversampling, counts of label '3': {} \n".format(sum(y_train_over␣
↪== 3)))

print("After Oversampling, the shape of train_X: {}".format(X_train_over.shape))
print("After Oversampling, the shape of train_y: {} \n".format(y_train_over.
↪shape))
```

```
Before Oversampling, counts of label '1': 74
Before Oversampling, counts of label '2': 1033

Before Oversampling, counts of label '3': 4009

Before Oversampling, counts of label '1': 4009
Before Oversampling, counts of label '2': 4009
```

```
Before Oversampling, counts of label '3': 4009

After Oversampling, the shape of train_X: (12027, 54)
After Oversampling, the shape of train_y: (12027,)
```

- **SMOTE** stands for Synthetic Minority Over Sampling Technique, which is a data augmentation method commonly used in imbalanced classification problems. It generates new synthetic samples of the minority class by interpolating between existing minority samples. This helps to balance the class distribution and improve the performance of the classifier.
- The code you above uses the SMOTE class from the imblearn library to oversample the minority class in the training data. The sampling_strategy parameter is set to "auto", which means that SMOTE will automatically determine the appropriate sampling ratio to balance the class distribution. The k_neighbors parameter is set to 5, which specifies the number of nearest neighbors to use for generating synthetic samples. Finally, the random_state parameter is set to 1 for reproducibility.
- The fit_resample() method of the SMOTE class is then called on X_train and y_train to generate new synthetic samples of the minority class. The resulting oversampled data is then assigned to new variables X_train_over and y_train_over. These new variables can be used to train a classifier that is less biased towards the majority class, and hopefully improves the overall classification performance.

Training all models on the oversampled data

[112]:
```
models = []  # Empty list to store all the models

# Appending models into the list
models.append(("Logistic regression", LogisticRegression(random_state=1)))
models.append(("Bagging", BaggingClassifier(random_state=1)))
models.append(("Random forest", RandomForestClassifier(random_state=1)))
models.append(("GBM", GradientBoostingClassifier(random_state=1)))
models.append(("Adaboost", AdaBoostClassifier(random_state=1)))
models.append(("dtree", DecisionTreeClassifier(random_state=1)))


print("\n" "Training Performance:" "\n")
for name, model in models:
    model.fit(X_train_over, y_train_over)
    scores = recall_score(y_train_over, model.predict(X_train_over), average =␣
 ↪"weighted")
    print("{}: {}".format(name, scores))

print("\n" "Validation Performance:" "\n")

for name, model in models:
    model.fit(X_train_over, y_train_over)
```

```
    scores = recall_score(y_val, model.predict(X_val), average = "weighted")
    print("{}: {}".format(name, scores))
```

```
Training Performance:

Logistic regression: 0.529974224661179
Bagging: 0.9512762950029101
Random forest: 0.9604223829716472
GBM: 0.7080735012887669
Adaboost: 0.5965743743244367
dtree: 0.9604223829716472

Validation Performance:

Logistic regression: 0.48828125
Bagging: 0.59765625
Random forest: 0.64765625
GBM: 0.6125
Adaboost: 0.4640625
dtree: 0.575
```

1.0.3 Models with undersampling of data

[113]:
```
rus = RandomUnderSampler(random_state=1)
X_train_un, y_train_un = rus.fit_resample(X_train, y_train)
```

- RandomUnderSampler is a technique used for handling imbalanced datasets in machine learning. It is used to randomly remove examples from the majority class in order to balance the dataset. This helps to prevent the model from being biased towards the majority class and can improve the performance of the model.
- In the code above, the RandomUnderSampler is initialized with a random_state of 1, which ensures that the sampling is reproducible. Then, the fit_resample method is called with the training data X_train and y_train as input. This method returns a new set of training data X_train_un and labels y_train_un, where the majority class has been undersampled to balance the classes. The new dataset can then be used to train a machine learning model that is less prone to bias towards the majority class.

[114]:
```
print("Before Under Sampling, counts of label 'Yes': {}".format(sum(y_train ==␣
 ↪1)))
print("Before Under Sampling, counts of label 'No': {} \n".format(sum(y_train␣
 ↪== 2)))
print("Before Under Sampling, counts of label 'No': {} \n".format(sum(y_train␣
 ↪== 3)))

print("After Under Sampling, counts of label 'Yes': {}".format(sum(y_train_un␣
 ↪== 1)))
```

```
print("After Under Sampling, counts of label 'No': {} \n".format(sum(y_train_un␣
↪== 2)))
print("After Under Sampling, counts of label 'No': {} \n".format(sum(y_train_un␣
↪== 3)))

print("After Under Sampling, the shape of train_X: {}".format(X_train_un.shape))
print("After Under Sampling, the shape of train_y: {} \n".format(y_train_un.
↪shape))
```

```
Before Under Sampling, counts of label 'Yes': 74
Before Under Sampling, counts of label 'No': 1033

Before Under Sampling, counts of label 'No': 4009

After Under Sampling, counts of label 'Yes': 74
After Under Sampling, counts of label 'No': 74

After Under Sampling, counts of label 'No': 74

After Under Sampling, the shape of train_X: (222, 54)
After Under Sampling, the shape of train_y: (222,)
```

MOdels with undersampled data

[115]:
```
models = []  # Empty list to store all the models

# Appending models into the list
models.append(("Logistic regression", LogisticRegression(random_state=1)))
models.append(("Bagging", BaggingClassifier(random_state=1)))
models.append(("Random forest", RandomForestClassifier(random_state=1)))
models.append(("GBM", GradientBoostingClassifier(random_state=1)))
models.append(("Adaboost", AdaBoostClassifier(random_state=1)))
models.append(("dtree", DecisionTreeClassifier(random_state=1)))


print("\n" "Training Performance:" "\n")
for name, model in models:
    model.fit(X_train_un, y_train_un)
    scores = recall_score(y_train_un, model.predict(X_train_un), average =␣
↪"weighted")
    print("{}: {}".format(name, scores))

print("\n" "Validation Performance:" "\n")

for name, model in models:
    model.fit(X_train_un, y_train_un)
    scores = recall_score(y_val, model.predict(X_val), average = "weighted")
```

```
    print("{}: {}".format(name, scores))
```

```
Training Performance:

Logistic regression: 0.5045045045045045
Bagging: 0.990990990990991
Random forest: 1.0
GBM: 0.8918918918918919
Adaboost: 0.545045045045045
dtree: 1.0

Validation Performance:

Logistic regression: 0.3953125
Bagging: 0.38515625
Random forest: 0.4171875
GBM: 0.45078125
Adaboost: 0.425
dtree: 0.3796875
```

- Looking at the training performance, it appears that the Bagging, Random Forest, and Decision Tree classifiers were able to achieve a recall score of 1.0, meaning that they correctly identified all positive examples in the undersampled training set. The GBM and Adaboost classifiers performed moderately well, achieving a recall score of 0.8919 and 0.5450, respectively.
- For the validation performance, we see that the Random Forest classifier achieved the highest recall score of 0.4172, while the GBM classifier was a close second with a score of 0.4508. The Bagging and Adaboost classifiers had similar recall scores of 0.3852 and 0.4250, respectively. The Logistic Regression and Decision Tree classifiers performed the worst on the validation set, with recall scores of 0.3953 and 0.3797, respectively.
- Overall, the Adaboost and GBM classifiers appear to be the good performing models on the dataset based on their recall scores on the validation set.

1.0.4 Tuning Adaboost and Gradient Boosting

Tuning with undersampling of data

[116]:
```
%%time

# defining model
Model = AdaBoostClassifier(random_state=1)

# Parameter grid to pass in RandomSearchCV
param_grid = {
    "n_estimators": np.arange(10, 110, 10),
    "learning_rate": [0.1, 0.01, 0.2, 0.05, 1],
```

```
    "base_estimator": [
        DecisionTreeClassifier(max_depth=1, random_state=1),
        DecisionTreeClassifier(max_depth=2, random_state=1),
        DecisionTreeClassifier(max_depth=3, random_state=1),
    ],
}

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model,␣
 ↪param_distributions=param_grid, n_jobs = -1, n_iter=50, scoring=scorer,␣
 ↪cv=5, random_state=1)

#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train_un,y_train_un)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.
 ↪best_params_,randomized_cv.best_score_))
```

```
Best parameters are {'n_estimators': 50, 'learning_rate': 0.01,
'base_estimator': DecisionTreeClassifier(max_depth=1, random_state=1)} with CV
score=nan:
CPU times: user 1.01 s, sys: 105 ms, total: 1.11 s
Wall time: 52.8 s
```

[117]:
```
tuned_adb1 = AdaBoostClassifier(
    random_state=1,
    n_estimators=50,
    learning_rate=0.01,
    base_estimator=DecisionTreeClassifier(max_depth=1, random_state=1),
)
tuned_adb1.fit(X_train_un, y_train_un)
```

[117]:
```
AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=1,
                                                         random_state=1),
                   learning_rate=0.01, random_state=1)
```

[118]:
```
# Checking model's performance on training set
adb1_train = model_performance_classification_sklearn(
    tuned_adb1, X_train_un, y_train_un
)
adb1_train
```

[118]:

	Accuracy	Recall	Precision	F1
0	0.437	0.437	0.411	0.410

[119]:
```
# Checking model's performance on validation set
adb1_val = model_performance_classification_sklearn(tuned_adb1, X_val, y_val)
adb1_val
```

[119]:

	Accuracy	Recall	Precision	F1
0	0.505	0.505	0.659	0.570

Tuning with Original data

[120]:
```
%%time

# defining model
Model = AdaBoostClassifier(random_state=1)

# Parameter grid to pass in RandomSearchCV
param_grid = {
    "n_estimators": np.arange(10, 110, 10),
    "learning_rate": [0.1, 0.01, 0.2, 0.05, 1],
    "base_estimator": [
        DecisionTreeClassifier(max_depth=1, random_state=1),
        DecisionTreeClassifier(max_depth=2, random_state=1),
        DecisionTreeClassifier(max_depth=3, random_state=1),
    ],
}

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model,␣
 ↪param_distributions=param_grid, n_jobs = -1, n_iter=50, scoring=scorer,␣
 ↪cv=5, random_state=1)

#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train,y_train)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.
 ↪best_params_,randomized_cv.best_score_))
```

```
Best parameters are {'n_estimators': 50, 'learning_rate': 0.01,
'base_estimator': DecisionTreeClassifier(max_depth=1, random_state=1)} with CV
score=nan:
CPU times: user 1.93 s, sys: 137 ms, total: 2.07 s
Wall time: 2min 20s
```

[121]:
```
tuned_adb2 = AdaBoostClassifier(
    random_state=1,
```

```
    n_estimators=50,
    learning_rate=0.01,
    base_estimator=DecisionTreeClassifier(max_depth=1, random_state=1),
)
tuned_adb2.fit(X_train, y_train)
```

[121]:
```
AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=1,
                                                         random_state=1),
                   learning_rate=0.01, random_state=1)
```

[122]:
```
# Checking model's performance on training set
adb2_train = model_performance_classification_sklearn(tuned_adb2, X_train,␣
 ↪y_train)
adb2_train
```

[122]:

	Accuracy	Recall	Precision	F1
0	0.784	0.784	0.614	0.689

[123]:
```
# Checking model's performance on validation set
adb2_val = model_performance_classification_sklearn(tuned_adb2, X_val, y_val)
adb2_val
```

[123]:

	Accuracy	Recall	Precision	F1
0	0.784	0.784	0.614	0.689

1.0.5 Tuning Gradient Boosting classifier

Tuning with undersampled data

[124]:
```
%%time

#Creating pipeline
Model = GradientBoostingClassifier(random_state=1)

#Parameter grid to pass in RandomSearchCV
param_grid = {
    "init":␣
 ↪[AdaBoostClassifier(random_state=1),DecisionTreeClassifier(random_state=1)],
    "n_estimators": np.arange(75,150,25),
    "learning_rate": [0.1, 0.01, 0.2, 0.05, 1],
    "subsample":[0.5,0.7,1],
    "max_features":[0.5,0.7,1],
}

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)
```

```
#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model,␣
 ↪param_distributions=param_grid, n_iter=50, scoring=scorer, cv=5,␣
 ↪random_state=1, n_jobs = -1)

#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train_un,y_train_un)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.
 ↪best_params_,randomized_cv.best_score_))
```

```
Best parameters are {'subsample': 0.5, 'n_estimators': 100, 'max_features': 0.7,
'learning_rate': 0.1, 'init': AdaBoostClassifier(random_state=1)} with CV
score=nan:
CPU times: user 1.62 s, sys: 108 ms, total: 1.73 s
Wall time: 1min 27s
```

[125]:
```
tuned_gbm1 = GradientBoostingClassifier(
    random_state=1,
    subsample=0.5,
    n_estimators=100,
    max_features=0.7,
    learning_rate=0.1,
    init=AdaBoostClassifier(random_state=1),
)
tuned_gbm1.fit(X_train_un, y_train_un)
```

[125]:
```
GradientBoostingClassifier(init=AdaBoostClassifier(random_state=1),
                           max_features=0.7, random_state=1, subsample=0.5)
```

[126]:
```
# Checking model's performance on training set
gbm1_train = model_performance_classification_sklearn(
    tuned_gbm1, X_train_un, y_train_un
)
gbm1_train
```

[126]:

	Accuracy	Recall	Precision	F1
0	0.905	0.905	0.905	0.905

[127]:
```
# Checking model's performance on validation set
gbm1_val = model_performance_classification_sklearn(tuned_gbm1, X_val, y_val)
gbm1_val
```

[127]:

	Accuracy	Recall	Precision	F1
0	0.454	0.454	0.683	0.529

Tuning with Original Data

[128]:
```
%%time

#defining model
Model = GradientBoostingClassifier(random_state=1)

#Parameter grid to pass in RandomSearchCV
param_grid = {
    "init":␣
 ↪[AdaBoostClassifier(random_state=1),DecisionTreeClassifier(random_state=1)],
    "n_estimators": np.arange(75,150,25),
    "learning_rate": [0.1, 0.01, 0.2, 0.05, 1],
    "subsample":[0.5,0.7,1],
    "max_features":[0.5,0.7,1],
}

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model,␣
 ↪param_distributions=param_grid, n_iter=50, scoring=scorer, cv=5,␣
 ↪random_state=1, n_jobs = -1)

#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train,y_train)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.
 ↪best_params_,randomized_cv.best_score_))
```

```
Best parameters are {'subsample': 0.5, 'n_estimators': 100, 'max_features': 0.7,
'learning_rate': 0.1, 'init': AdaBoostClassifier(random_state=1)} with CV
score=nan:
CPU times: user 4.32 s, sys: 250 ms, total: 4.57 s
Wall time: 5min 11s
```

[129]:
```
tuned_gbm2 = GradientBoostingClassifier(
    random_state=1,
    subsample=0.5,
    n_estimators=100,
    max_features=0.7,
    learning_rate=0.1,
    init=AdaBoostClassifier(random_state=1),
)
tuned_gbm2.fit(X_train, y_train)
```

[129]:
```
GradientBoostingClassifier(init=AdaBoostClassifier(random_state=1),
                           max_features=0.7, random_state=1, subsample=0.5)
```

[130]:
```
# Checking model's performance on training set
gbm2_train = model_performance_classification_sklearn(tuned_gbm1, X_train,␣
 ↪y_train)
gbm2_train
```

[130]:

	Accuracy	Recall	Precision	F1
0	0.453	0.453	0.699	0.522

[131]:
```
# Checking model's performance on validation set
gbm2_val = model_performance_classification_sklearn(tuned_gbm1, X_val, y_val)
gbm2_val
```

[131]:

	Accuracy	Recall	Precision	F1
0	0.454	0.454	0.683	0.529

It seems that Adaboost performs well so lets try to tune it on oversampled data

[132]:
```
%%time

# defining model
Model = AdaBoostClassifier(random_state=1)

# Parameter grid to pass in RandomSearchCV
param_grid = {
    "n_estimators": np.arange(10, 110, 10),
    "learning_rate": [0.1, 0.01, 0.2, 0.05, 1],
    "base_estimator": [
        DecisionTreeClassifier(max_depth=1, random_state=1),
        DecisionTreeClassifier(max_depth=2, random_state=1),
        DecisionTreeClassifier(max_depth=3, random_state=1),
    ],
}

# Type of scoring used to compare parameter combinations
scorer = metrics.make_scorer(metrics.recall_score)

#Calling RandomizedSearchCV
randomized_cv = RandomizedSearchCV(estimator=Model,␣
 ↪param_distributions=param_grid, n_jobs = -1, n_iter=50, scoring=scorer,␣
 ↪cv=5, random_state=1)

#Fitting parameters in RandomizedSearchCV
randomized_cv.fit(X_train_over,y_train_over)

print("Best parameters are {} with CV score={}:" .format(randomized_cv.
 ↪best_params_,randomized_cv.best_score_))
```

```
Best parameters are {'n_estimators': 50, 'learning_rate': 0.01,
```

```
'base_estimator': DecisionTreeClassifier(max_depth=1, random_state=1)} with CV
score=nan:
CPU times: user 2.28 s, sys: 153 ms, total: 2.43 s
Wall time: 3min 2s
```

[133]:
```
tuned_adb3 = AdaBoostClassifier(
    random_state=1,
    n_estimators=50,
    learning_rate=0.01,
    base_estimator=DecisionTreeClassifier(max_depth=1, random_state=1),
)
tuned_adb3.fit(X_train_over, y_train_over)
```

[133]:
```
AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_depth=1,
                                                         random_state=1),
                   learning_rate=0.01, random_state=1)
```

[134]:
```
# Checking model's performance on training set
adb3_train = model_performance_classification_sklearn(tuned_adb3, X_train_over,␣
 ↪y_train_over)
adb3_train
```

[134]:

	Accuracy	Recall	Precision	F1
0	0.471	0.471	0.521	0.477

[150]:
```
# Checking model's performance on validation set
adb3_val = model_performance_classification_sklearn(tuned_adb3, X_val, y_val)
adb3_val
```

[150]:

	Accuracy	Recall	Precision	F1
0	0.408	0.408	0.679	0.470

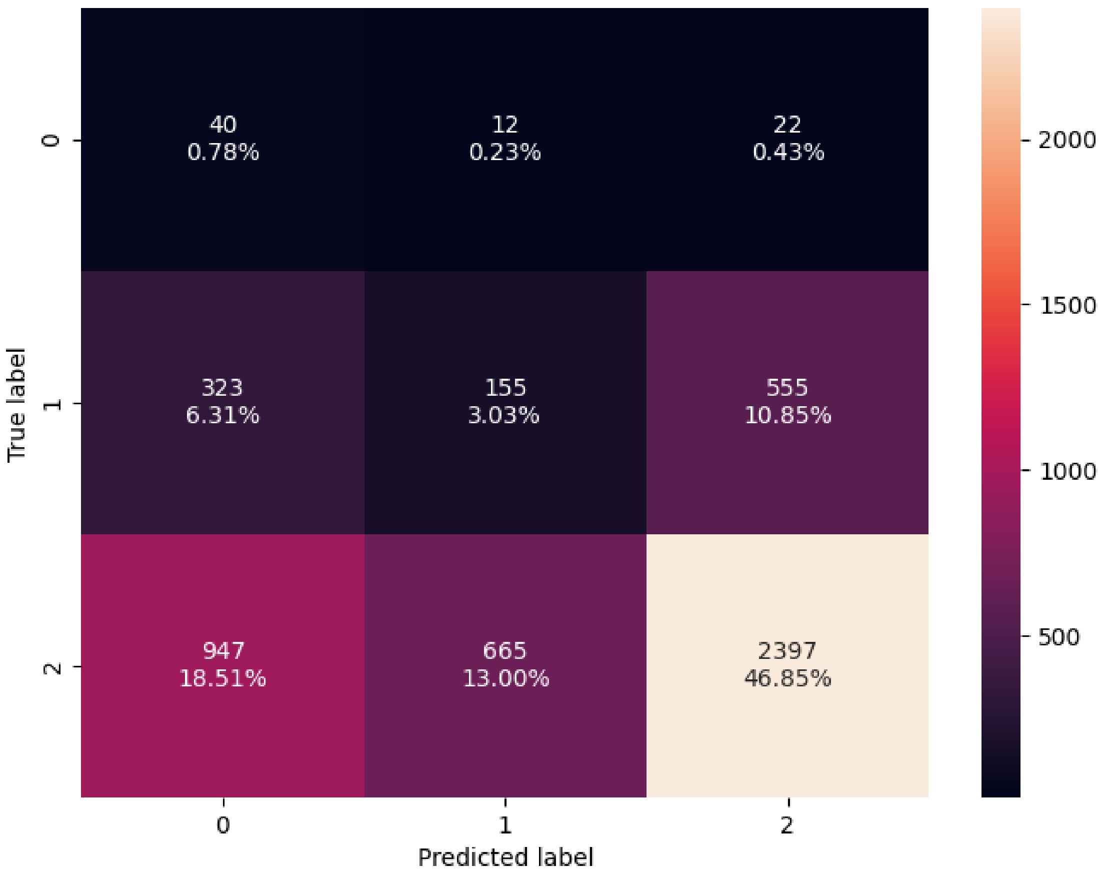
Predicting with the best model on test data

[153]:
```
# Checking model's performance on validation set
adb_test = model_performance_classification_sklearn(tuned_adb2, X_test, y_test)
adb_test
```

[153]:

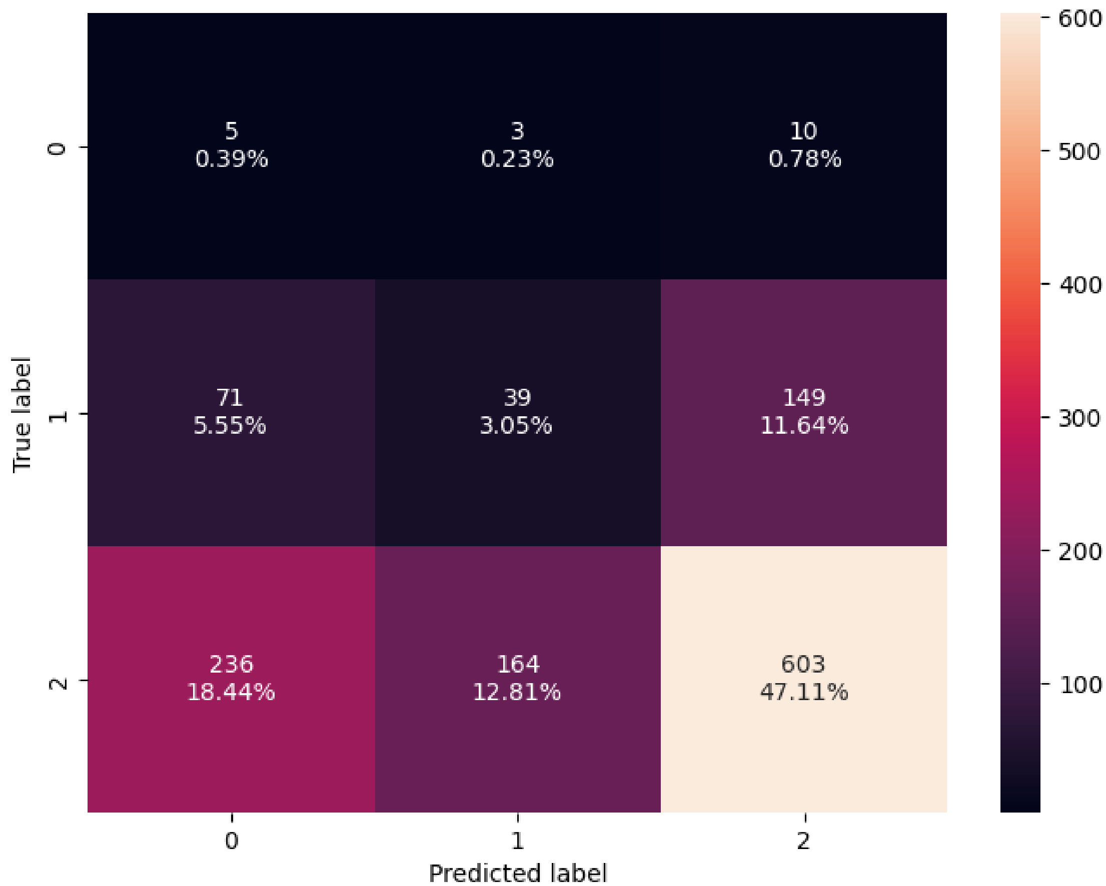
	Accuracy	Recall	Precision	F1
0	0.810	0.810	0.657	0.725

[154]:
```
confusion_matrix_sklearn(tuned_adb1, X_train, y_train)
```

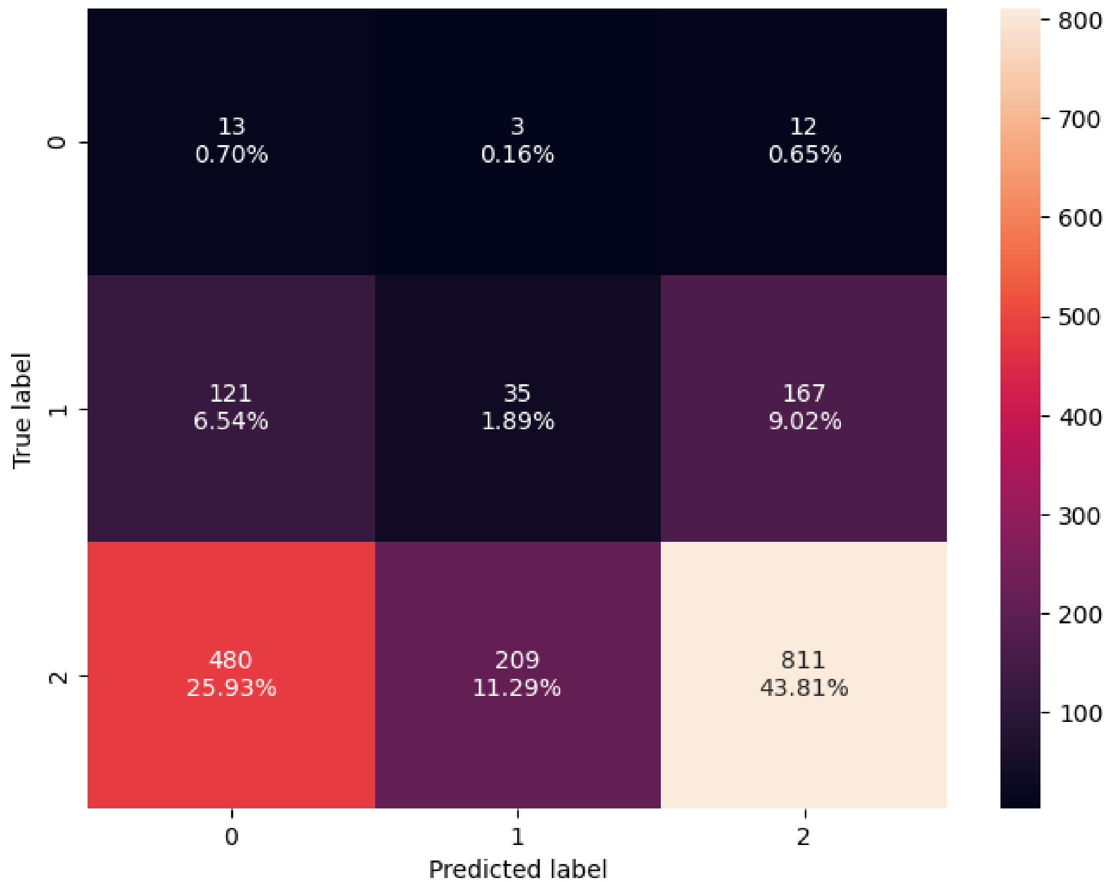


[155]:

```
confusion_matrix_sklearn(tuned_adb1, X_val, y_val)
```



[156]:
```
confusion_matrix_sklearn(tuned_adb1, X_test, y_test)
```



1.0.6 Model Performances comparison

[136]:
```
# training performance comparison

models_train_comp_df = pd.concat(
    [
        gbm1_train.T,
        gbm2_train.T,
        adb1_train.T,
        adb2_train.T,
        adb3_train.T
    ],
    axis=1,
)
models_train_comp_df.columns = [
    "Gradient boosting trained with Undersampled data",
    "Gradient boosting trained with Original data",
    "AdaBoost trained with Undersampled data",
    "AdaBoost trained with Original data",
```

```
    "Adaboost trained on Oversampled data"
]
print("Training performance comparison:")
models_train_comp_df
```

```
Training performance comparison:
```

[136]:

```
           Gradient boosting trained with Undersampled data  \
Accuracy                                              0.905
Recall                                                0.905
Precision                                             0.905
F1                                                    0.905

           Gradient boosting trained with Original data  \
Accuracy                                          0.453
Recall                                            0.453
Precision                                         0.699
F1                                                0.522

           AdaBoost trained with Undersampled data  \
Accuracy                                     0.437
Recall                                       0.437
Precision                                    0.411
F1                                           0.410

           AdaBoost trained with Original data  \
Accuracy                                 0.784
Recall                                   0.784
Precision                                0.614
F1                                       0.689

           Adaboost trained on Oversampled data
Accuracy                                  0.471
Recall                                    0.471
Precision                                 0.521
F1                                        0.477
```

[137]:

```
# Validation performance comparison

models_train_comp_df = pd.concat(
    [gbm1_val.T, gbm2_val.T, adb1_val.T, adb2_val.T,adb3_val.T], axis=1,
)
models_train_comp_df.columns = [

    "Gradient boosting trained with Undersampled data",
    "Gradient boosting trained with Original data",
    "AdaBoost trained with Undersampled data",
```

```
    "AdaBoost trained with Original data",
    "Adaboost trained on Oversampled data"
]
print("Validation performance comparison:")
models_train_comp_df
```

```
Validation performance comparison:
```

[137]:

```
           Gradient boosting trained with Undersampled data  \
Accuracy                                              0.454
Recall                                                0.454
Precision                                             0.683
F1                                                    0.529

           Gradient boosting trained with Original data  \
Accuracy                                          0.454
Recall                                            0.454
Precision                                         0.683
F1                                                0.529

           AdaBoost trained with Undersampled data  \
Accuracy                                     0.505
Recall                                       0.505
Precision                                    0.659
F1                                           0.570

           AdaBoost trained with Original data  \
Accuracy                                 0.784
Recall                                   0.784
Precision                                0.614
F1                                       0.689

           Adaboost trained on Oversampled data
Accuracy                                  0.408
Recall                                    0.408
Precision                                 0.679
F1                                        0.470
```

Conclusion

- The accuracy and recall of both gradient boosting and AdaBoost models trained with undersampled data are the same, indicating that undersampling did not have a significant impact on the model's ability to correctly classify samples.
- The accuracy and recall of both gradient boosting and AdaBoost models trained with original data are also the same, but they are lower than the corresponding values for the models trained with undersampled data. This suggests that oversampling may not always lead to better performance and can sometimes lead to overfitting.
- The AdaBoost model trained with original data has the highest accuracy and recall, indicating

that using the original data may lead to better results than undersampling or oversampling.

- The precision of the gradient boosting model trained with undersampled data is higher than that of the model trained with original data, indicating that undersampling may be beneficial for certain metrics.
- The precision of the AdaBoost model trained with original data is lower than that of the model trained with undersampled data, indicating that using undersampled data may be better for this metric.
- The F1 score of the AdaBoost model trained with original data is the highest among all models, indicating that it may be the best overall performer. The F1 score of the gradient boosting model trained with undersampled data is also relatively high.

Based on the given data and model performance, it appears that the classification models are performing moderately well. The highest accuracy and recall are achieved by AdaBoost trained with Original data, but even this model has an accuracy of only 0.784 and a recall of 0.784.

The precision scores are not very high for any of the models, indicating that they are not able to effectively distinguish between the different classes in the dataset.

The F1 score, which is a combination of precision and recall, is highest for AdaBoost trained with Original data, but again, it is not very high at 0.689.

Overall, it seems that the given data may be difficult to accurately classify with the models that were trained. So it would be further recommended to analyse, Further analysis may be necessary to determine if additional features or a different approach to modeling could improve performance in a better way.