chicago-crash-notebook

May 24, 2023

0.1 Chicago Car Crash Project

This project is based on the Chicago Car Crash data. We will use this data to create a model which will help predict the main cause of the accidents An average span of four days, Chicago can record up to over a thousand car accidents. When you include drivers, passengers, pedestrians and cyclists, up to two thousand people can be effected. Forty-five percent of the people will experience a minor to fatal injury.

The purpose of this project is to build a classification model to help identify what features are important in a car accident and use for prediction

0.2 1 Introduction

0.3 1.1 Problem Statement

- The primary objective of this study is to identify and understand the main contributing factors to car accidents in Chicago, with a specific focus on driver behavior.
- By analyzing various modeling techniques and their results, the aim is to determine the primary causes of car accidents and provide insights that can contribute to the development of effective strategies for accident prevention and road safety improvement.

0.4 1.2 Main Objective/ Goal

The goal of this project is to create a model that predicts and classifies different types of traffic crashes. The dataset parameters are utilized to distinguish between various types of crashes

0.5 2 Obtain the packages

Import the packages

```
[1]: #!pip install scikit-learn==0.23.2
# !pip install mlxtend
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import graphviz
import os
from sklearn.tree import export_graphviz
```

```
from sklearn.model_selection import train_test_split, GridSearchCV, __
 ⇔cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, BaggingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, r2_score, recall_score,_
 →precision_score, roc_curve, roc_auc_score, f1_score
from sklearn.metrics import classification report, confusion matrix
from sklearn.metrics import ConfusionMatrixDisplay, RocCurveDisplay
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import StandardScaler, OneHotEncoder, RobustScaler,
 →LabelEncoder
from sklearn.tree import DecisionTreeClassifier, export graphviz
from sklearn.compose import ColumnTransformer
from xgboost import XGBClassifier
from sklearn.naive_bayes import GaussianNB
from pyspark.sql import SparkSession
from pyspark.ml.feature import VectorAssembler
from pyspark.ml.classification import DecisionTreeClassifier
from pyspark.ml.evaluation import MulticlassClassificationEvaluator
from pyspark.sql import SparkSession
#!pip install shap
import shap
shap.initjs()
import six
import sys
sys.modules['sklearn.externals.six'] = six
from imblearn.over_sampling import SMOTE, ADASYN, SMOTENC
import folium
import warnings
warnings.filterwarnings('ignore')
```

```
c:\Users\wanji\anaconda3\envs\learn-env\lib\site-
packages\shap\utils\_clustering.py:35: NumbaDeprecationWarning: The
'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The
implicit default value for this argument is currently False, but it will be
changed to True in Numba 0.59.0. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-
of-object-mode-fall-back-behaviour-when-using-jit for details.
  def _pt_shuffle_rec(i, indexes, index_mask, partition_tree, M, pos):
c:\Users\wanji\anaconda3\envs\learn-env\lib\site-
packages\shap\utils\_clustering.py:54: NumbaDeprecationWarning: The
'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The
implicit default value for this argument is currently False, but it will be
changed to True in Numba 0.59.0. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-
of-object-mode-fall-back-behaviour-when-using-jit for details.
  def delta minimization order(all masks, max swap size=100, num passes=2):
c:\Users\wanji\anaconda3\envs\learn-env\lib\site-
packages\shap\utils\_clustering.py:63: NumbaDeprecationWarning: The
'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The
implicit default value for this argument is currently False, but it will be
changed to True in Numba 0.59.0. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-
of-object-mode-fall-back-behaviour-when-using-jit for details.
  def _reverse_window(order, start, length):
c:\Users\wanji\anaconda3\envs\learn-env\lib\site-
packages\shap\utils\_clustering.py:69: NumbaDeprecationWarning: The
'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The
implicit default value for this argument is currently False, but it will be
changed to True in Numba 0.59.0. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-
of-object-mode-fall-back-behaviour-when-using-jit for details.
  def _reverse_window_score_gain(masks, order, start, length):
c:\Users\wanji\anaconda3\envs\learn-env\lib\site-
```

packages\shap\utils_clustering.py:77: NumbaDeprecationWarning: The 'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The implicit default value for this argument is currently False, but it will be changed to True in Numba 0.59.0. See https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecationof-object-mode-fall-back-behaviour-when-using-jit for details. def _mask_delta_score(m1, m2): c:\Users\wanji\anaconda3\envs\learn-env\lib\site-packages\shap\links.py:5: NumbaDeprecationWarning: The 'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The implicit default value for this argument is currently False, but it will be changed to True in Numba 0.59.0. See https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecationof-object-mode-fall-back-behaviour-when-using-jit for details. def identity(x): c:\Users\wanji\anaconda3\envs\learn-env\lib\site-packages\shap\links.py:10: NumbaDeprecationWarning: The 'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The implicit default value for this argument is currently False, but it will be changed to True in Numba 0.59.0. See https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecationof-object-mode-fall-back-behaviour-when-using-jit for details. def _identity_inverse(x): c:\Users\wanji\anaconda3\envs\learn-env\lib\site-packages\shap\links.py:15: NumbaDeprecationWarning: The 'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The implicit default value for this argument is currently False, but it will be changed to True in Numba 0.59.0. See https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecationof-object-mode-fall-back-behaviour-when-using-jit for details. def logit(x): c:\Users\wanji\anaconda3\envs\learn-env\lib\site-packages\shap\links.py:20: NumbaDeprecationWarning: The 'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The implicit default value for this argument is currently False, but it will be changed to True in Numba 0.59.0. See https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecationof-object-mode-fall-back-behaviour-when-using-jit for details. def _logit_inverse(x): c:\Users\wanji\anaconda3\envs\learn-env\lib\site-

```
packages\shap\utils\ masked model.py:363: NumbaDeprecationWarning: The
'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The
implicit default value for this argument is currently False, but it will be
changed to True in Numba 0.59.0. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-
of-object-mode-fall-back-behaviour-when-using-jit for details.
  def _build_fixed_single_output(averaged_outs, last_outs, outputs,
batch_positions, varying_rows, num_varying_rows, link, linearizing_weights):
c:\Users\wanji\anaconda3\envs\learn-env\lib\site-
packages\shap\utils\_masked_model.py:385: NumbaDeprecationWarning: The
'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The
implicit default value for this argument is currently False, but it will be
changed to True in Numba 0.59.0. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-
of-object-mode-fall-back-behaviour-when-using-jit for details.
  def _build_fixed_multi_output(averaged_outs, last_outs, outputs,
batch positions, varying rows, num varying rows, link, linearizing weights):
c:\Users\wanji\anaconda3\envs\learn-env\lib\site-
packages\shap\utils\_masked_model.py:428: NumbaDeprecationWarning: The
'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The
implicit default value for this argument is currently False, but it will be
changed to True in Numba 0.59.0. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-
of-object-mode-fall-back-behaviour-when-using-jit for details.
  def _init_masks(cluster_matrix, M, indices_row_pos, indptr):
c:\Users\wanji\anaconda3\envs\learn-env\lib\site-
packages\shap\utils\_masked_model.py:439: NumbaDeprecationWarning: The
'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The
implicit default value for this argument is currently False, but it will be
changed to True in Numba 0.59.0. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-
of-object-mode-fall-back-behaviour-when-using-jit for details.
  def _rec_fill_masks(cluster_matrix, indices_row_pos, indptr, indices, M, ind):
c:\Users\wanji\anaconda3\envs\learn-env\lib\site-
```

```
packages\shap\maskers\_tabular.py:186: NumbaDeprecationWarning: The
'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The
implicit default value for this argument is currently False, but it will be
changed to True in Numba 0.59.0. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-
of-object-mode-fall-back-behaviour-when-using-jit for details.
  def _single_delta_mask(dind, masked_inputs, last_mask, data, x, noop_code):
c:\Users\wanji\anaconda3\envs\learn-env\lib\site-
packages\shap\maskers\_tabular.py:197: NumbaDeprecationWarning: The
'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The
implicit default value for this argument is currently False, but it will be
changed to True in Numba 0.59.0. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-
of-object-mode-fall-back-behaviour-when-using-jit for details.
  def _delta_masking(masks, x, curr_delta_inds, varying_rows_out,
c:\Users\wanji\anaconda3\envs\learn-env\lib\site-
packages\shap\maskers\ image.py:175: NumbaDeprecationWarning: The 'nopython'
keyword argument was not supplied to the 'numba.jit' decorator. The implicit
default value for this argument is currently False, but it will be changed to
True in Numba 0.59.0. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-
of-object-mode-fall-back-behaviour-when-using-jit for details.
  def _jit_build_partition_tree(xmin, xmax, ymin, ymax, zmin, zmax,
total_ywidth, total_zwidth, M, clustering, q):
c:\Users\wanji\anaconda3\envs\learn-env\lib\site-
packages\shap\explainers\_partition.py:676: NumbaDeprecationWarning: The
'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The
implicit default value for this argument is currently False, but it will be
changed to True in Numba 0.59.0. See
https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-
of-object-mode-fall-back-behaviour-when-using-jit for details.
  def lower_credit(i, value, M, values, clustering):
```

The 'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The implicit default value for this argument is currently False, but it will be changed to True in Numba 0.59.0. See https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-of-object-mode-fall-back-behaviour-when-using-jit for details. The 'nopython' keyword argument was not supplied to the 'numba.jit' decorator. The implicit default value for this argument is currently False, but it will be changed to True in Numba 0.59.0. See https://numba.readthedocs.io/en/stable/reference/deprecation.html#deprecation-of-object-mode-fall-back-behaviour-when-using-jit for details. <IPython.core.display.HTML object>

0.5.1 2.1 Import the dataset

	crashes	3					
[2]:				CR.	ASH_RECORD_I	D RD_NO	\
	0	79c7a2ce89f446262e	efd86df3d72	2d18b04ba4	187024b7c4	JC199149	
	1	792b539deaaad65ee5	5b4a9691d92	27a34d298e	eb33d42af0	JB422857	
	2	0115ade9a755e83525	5508463f7e	e9c4a9a0b4	17e9304238	JF318029	
	3	017040c61958d2fa97	7c956b2bd2	2d6759ef77	754496dc96	JF324552	
	4	78eee027ec3dcc85d3	36c9e3fdae4	1729dcc564	140105d65b	JB291672	
					•••	•••	
	723455	722625096bc7b56c15	fee9e09f4f	1901fc5e2	25b8aacf2b	JG251187	
	723456	2d47afb7c4f2f4d305	fddccb682	ce85045247	76cc7f910d	NaN	
	723457	4b1e7cbdb519f7f83f	a3e3eae095	ff54aebb7	73f125cf06	NaN	
	723458	5d3f02a062e775ef52	27557f75c4d	ded6900d21	lad7108a3a	NaN	
	723459	2d53e3705a5b2f13c9	9684cdc99c3	Bab976c88a	a9e1ae7239	NaN	
		CRASH_DATE_EST_I		CD V GTI D V	ATE POSTED_	CDEED LIMIT	\
	0		3/25/2019	_	_	30	\
	1		09/05/2018			30	
	2		77/15/2022			30	
	3		77/15/2022			30	
	4		06/03/2018			30	
			70, 00, 2010		111		
	723455	 NaN C	04/27/2023	05:47:00	PM	30	
	723456		5/13/2023			35	
	723457		5/11/2023			30	
	723458	NaN C	5/13/2023	03:14:00	AM	30	

0	TRAFFIC_CONTROL_DEVICE TRAFFIC SIGNAL	_		WEATHE	ER_CONDITION CLEAR	\	
1	NO CONTROLS		CONTROLS		CLEAR		
2	UNKNOWN	110	UNKNOWN		CLEAR		
3	TRAFFIC SIGNAL	FUNCTIONING			CLEAR		
4	NO CONTROLS		CONTROLS		CLEAR		
···		110					
723455	TRAFFIC SIGNAL	FUNCTIONING			CLEAR		
723456	TRAFFIC SIGNAL						
	STOP SIGN/FLASHER						
723458		FUNCTIONING	PROPERLY		CLEAR		
723459	NO CONTROLS		CONTROLS		CLEAR		
	LIGHTING_CONDITION	FI	RST_CRASH_	TYPE	\		
0	DAYLIGHT			RNING			
1	DAYLIGHT		A	NGLE	•••		
2	DARKNESS, LIGHTED ROAD		A	NGLE	•••		
3	DAYLIGHT		REAF	R END	•••		
4	UNKNOWN	PARKED	MOTOR VEH	HICLE	•••		
			•••	•••			
723455	DAYLIGHT	SIDESWIPE S	SAME DIREC	CTION	•••		
723456	UNKNOWN		TUF	RNING	•••		
723457	UNKNOWN		A	NGLE	•••		
723458	DARKNESS, LIGHTED ROAD		A	NGLE	•••		
723459	DAYLIGHT	PARKED	MOTOR VEH	HICLE	•••		
	INJURIES_NON_INCAPACITA	ΓING INJURI	ES_REPORTE	ED_NOT	EVIDENT \		
0		0.0	_		1.0		
1		0.0			0.0		
2		0.0			0.0		
3		0.0			0.0		
4		0.0			0.0		
•••					•••		
723455		0.0			0.0		
723456		0.0			0.0		
723457		0.0			0.0		
723458		2.0			0.0		
723459		0.0			0.0		
	INJURIES_NO_INDICATION	INJURIES_UNKI	NOWN CRASH	H_HOUR	CRASH_DAY_OF	_WEEK	\
0	2.0		0.0	14		2	
1	2.0		0.0	8		4	
2	2.0		0.0	0		6	
3	2.0		0.0	18		6	
4	1.0		0.0	17		1	

```
5
723455
                          5.0
                                            0.0
                                                        17
                                                                           7
723456
                          2.0
                                            0.0
                                                        15
                                                                           5
723457
                          4.0
                                            0.0
                                                        17
723458
                          2.0
                                            0.0
                                                         3
                                                                           7
723459
                          1.0
                                            0.0
                                                        15
       CRASH_MONTH
                     LATITUDE LONGITUDE
0
                 3 41.884547 -87.641201
1
                 9 41.968562 -87.740659
2
                 7 41.886336 -87.716203
3
                 7 41.925111 -87.667997
                 6 41.910758 -87.731389
                 4 41.822237 -87.606996
723455
723456
                 5 41.852761 -87.625645
723457
                 5 41.891311 -87.646244
723458
                 5 41.809485 -87.606711
723459
                          NaN
                                      NaN
                                         LOCATION
0
         POINT (-87.64120093714 41.884547224337)
1
        POINT (-87.740659314632 41.968562453871)
        POINT (-87.716203130599 41.886336409761)
3
        POINT (-87.667997321599 41.925110815832)
        POINT (-87.731388754145 41.910757551599)
723455 POINT (-87.606995789103 41.822236685692)
723456
       POINT (-87.625645007251 41.85276094394)
723457 POINT (-87.646244110744 41.891311456709)
723458 POINT (-87.606710818433 41.809485427538)
723459
                                              NaN
```

[723460 rows x 49 columns]

[3]: # Checking out the dataframe columns

1 2.2 Checking the shape of the dataset

crashes.PRIM_CONTRIBUTORY_CAUSE.value_counts().index

```
'OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR
AGGRESSIVE MANNER',
       'DISREGARDING STOP SIGN', 'DISTRACTION - FROM INSIDE VEHICLE',
       'EQUIPMENT - VEHICLE CONDITION', 'PHYSICAL CONDITION OF DRIVER',
       'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)',
       'DRIVING ON WRONG SIDE/WRONG WAY',
       'UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)',
       'DISTRACTION - FROM OUTSIDE VEHICLE',
       'EXCEEDING AUTHORIZED SPEED LIMIT',
       'ROAD ENGINEERING/SURFACE/MARKING DEFECTS',
       'EXCEEDING SAFE SPEED FOR CONDITIONS', 'ROAD CONSTRUCTION/MAINTENANCE',
       'DISREGARDING OTHER TRAFFIC SIGNS',
       'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST',
       'CELL PHONE USE OTHER THAN TEXTING', 'DISREGARDING ROAD MARKINGS',
       'HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)', 'ANIMAL',
       'TURNING RIGHT ON RED',
       'DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER,
ETC.)',
       'RELATED TO BUS STOP', 'TEXTING', 'DISREGARDING YIELD SIGN',
       'PASSING STOPPED SCHOOL BUS', 'BICYCLE ADVANCING LEGALLY ON RED LIGHT',
       'OBSTRUCTED CROSSWALKS', 'MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT'],
      dtype='object')
```

2 3. Data Cleaning

03/25/2019 02:43:00 PM

09/05/2018 08:40:00 AM

[6]:

0

1

CRASH_DATE POSTED_SPEED_LIMIT TRAFFIC_CONTROL_DEVICE \

30

30

TRAFFIC SIGNAL

NO CONTROLS

2	07/15/2022 12:45:00 AM 07/15/2022 06:50:00 PM		30 UNKNOWN 30 TRAFFIC SIGNAL
4	06/03/2018 05:00:00 PM		NO CONTROLS
 723455	 04/27/2023 05:47:00 PM	 3	 BO TRAFFIC SIGNAL
723456	05/13/2023 03:54:00 PM		35 TRAFFIC SIGNAL
723457	05/11/2023 05:45:00 PM		STOP SIGN/FLASHER
723458	05/13/2023 03:14:00 AM	3	TRAFFIC SIGNAL
723459	05/13/2023 03:21:00 PM	3	NO CONTROLS
	DEVICE_CONDITION WEA	ATHER_CONDITION	LIGHTING_CONDITION \
0	FUNCTIONING PROPERLY	CLEAR	DAYLIGHT
1	NO CONTROLS	CLEAR	DAYLIGHT
2	UNKNOWN	CLEAR I	DARKNESS, LIGHTED ROAD
3	FUNCTIONING PROPERLY	CLEAR	DAYLIGHT
4	NO CONTROLS	CLEAR	UNKNOWN
•••		•••	
723455	FUNCTIONING PROPERLY	CLEAR	DAYLIGHT
723456	FUNCTIONING PROPERLY	UNKNOWN	UNKNOWN
723457	FUNCTIONING PROPERLY	UNKNOWN	UNKNOWN
723458	FUNCTIONING PROPERLY	CLEAR I	DARKNESS, LIGHTED ROAD
723459	NO CONTROLS	CLEAR	DAYLIGHT
	FIRST CRASH TYPI	E TRAFFICWAY_TYPE	ALIGNMENT \
0	TURNING		STRAIGHT AND LEVEL
1	ANGLI		
2	ANGLI		
3	REAR ENI		
4	PARKED MOTOR VEHICLE		
1	TARRED HOTOR VEHILOER	J ONL WAT	
 723455	SIDESWIPE SAME DIRECTION	J OTHER	STRAIGHT AND LEVEL
723456	TURNING		
723457	ANGLI		STRAIGHT AND LEVEL
723458	ANGLI		
723459	PARKED MOTOR VEHICLE		
	ROADWAY_SURFACE_COND I	HIT AND RUN I \	
0	DRY	UNKOWN	
1	DRY	UNKOWN	
2	DRY	UNKOWN	
3	DRY	UNKOWN	
4	DRY	Y	
-			
 723455	DRY	 UNKOWN	
723456	UNKNOWN	UNKOWN	
723457	UNKNOWN	Y	
723458	DRY	UNKOWN	
0 100	2111	2	

723459		DRY	UNKOWN		
0 1 2 3 4	VISION OBSCURED	IMPRO	IM_CONTRIBUT PER TURNING/ LIMBS, BUII UNABLE TO UNABLE TO UNABLE TO	'NO SIGNAL DINGS, DETERMINE DETERMINE	\
723455 723456 723457 723458 723459		IMPRO	ER OVERTAKIN PER TURNING/ UNABLE TO RDING TRAFFI IMPROPER I	'NO SIGNAL DETERMINE C SIGNALS	
0 1 2 3 4 723455 723456 723457 723458 723459	DRIVING SKILLS/F	O YIELD RIGHT UNABLE TO DE UNABLE TO DE UNABLE TO DE IMPROPER LAN UNABLE TO DE NOT APP	ERIENCE U -OF-WAY U TERMINE U TERMINE U TERMINE U E USAGE U TERMINE U LICABLE U LICABLE U	JNKOWN JNKOWN JNKOWN JNKOWN JNKOWN JNKOWN JNKOWN JNKOWN	ZONE_I \ UNKOWN
0 1 2 3 4 723455 723456 723457 723458 723459	WORK_ZONE_TYPE CEUNKOWN UNKOWN	RASH_HOUR CRA 14 8 0 18 17 17 15 17 3 15	SH_DAY_OF_WE	EEK CRASH_MO 2 4 6 6 1 5 7 7	ONTH \ 3 9 7 7 6 4 5 5 5
0 1 2 3 4	POINT (-87.6412 POINT (-87.74068 POINT (-87.71620 POINT (-87.66798 POINT (-87.73138	59314632 41.9 03130599 41.8 97321599 41.9	68562453871) 86336409761) 25110815832)		

```
723455 POINT (-87.606995789103 41.822236685692)
      723456 POINT (-87.625645007251 41.85276094394)
      723457 POINT (-87.646244110744 41.891311456709)
      723458 POINT (-87.606710818433 41.809485427538)
      723459
                                                UNKOWN
      [723460 rows x 23 columns]
 [7]: # We have speed limits that are not logged correctly, so we will drop them.
      # There wasn't a lot so this will not effect our data
      list_ = [3, 9, 99, 39, 1, 2, 32, 33, 6, 24, 11, 34, 18, 12, 36, 7, 14, 16, 38, __
       →31, 22, 23, 63, 4, 26]
      for n in list_:
          crashes.drop(index=crashes[crashes['POSTED_SPEED_LIMIT'] == n].index,__
       →inplace=True)
     2.1 3.1 Perform Onehotencoding
 [8]: ohe = OneHotEncoder(handle unknown='ignore')
 [9]: # Creating a new dataframe for FIRST_CRASH_TYPE
      # Then we will OneHotEncode the data to categories
      crash_type = crashes['FIRST_CRASH_TYPE']
      crash_df = pd.DataFrame(crash_type, columns=['FIRST_CRASH_TYPE'])
      crash_df = pd.DataFrame(ohe.fit_transform(crash_df[['FIRST_CRASH_TYPE']]).
       →toarray())
     2.1.1 3.2 Column Labelling
[10]: # Each column will be a FIRST_CRASH_TYPE, so we will need to label each column
      crash_col = crashes['FIRST_CRASH_TYPE'].unique()
      crash_df.columns = crash_col
[11]: #final columns
      crash_df.columns
[11]: Index(['TURNING', 'ANGLE', 'REAR END', 'PARKED MOTOR VEHICLE',
             'SIDESWIPE OPPOSITE DIRECTION', 'PEDALCYCLIST', 'REAR TO FRONT',
             'PEDESTRIAN', 'REAR TO REAR', 'FIXED OBJECT', 'OTHER NONCOLLISION',
             'SIDESWIPE SAME DIRECTION', 'REAR TO SIDE', 'HEAD ON', 'OTHER OBJECT',
             'ANIMAL', 'OVERTURNED', 'TRAIN'],
            dtype='object')
```

2.2 3.3 Selecting features and conducting label encoding

```
[12]: # Here we select the features we want to use and LabelEncode them using a for
      → loop
     # We will also create a new dataframe for them
     text col = ['TRAFFIC CONTROL DEVICE', 'DEVICE CONDITION', 'WEATHER CONDITION', '
      'ALIGNMENT', 'ROADWAY_SURFACE_COND', 'ROAD_DEFECT', __
      'HIT_AND_RUN_I', 'PRIM_CONTRIBUTORY_CAUSE', L
      ⇔'SEC_CONTRIBUTORY_CAUSE', 'DOORING_I', 'WORK_ZONE_I',
                 'WORK ZONE TYPE']
     en_df = pd.DataFrame()
     for col in text_col:
         encoder = LabelEncoder()
         en_df[col] = encoder.fit_transform(crashes[col])
     en_df
[12]:
             TRAFFIC_CONTROL_DEVICE DEVICE_CONDITION
                                                      WEATHER_CONDITION
                                                                     2
     0
                                16
                                                   1
                                                                     2
     1
                                 4
                                                   3
                                                   6
                                                                     2
     2
                                17
     3
                                                                     2
                                 16
                                                   1
     4
                                 4
                                                   3
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     722855
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                                16
                                                   1
                                                                    11
     722856
                                16
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     722857
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                                                                    11
                                15
     722858
                                16
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                                                                     2
                                                                     2
     722859
             LIGHTING CONDITION TRAFFICWAY TYPE ALIGNMENT ROADWAY SURFACE COND \
     0
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                                                        3
                                                                              0
     1
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                                              8
                                                        3
                                                                              0
     2
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                             1
                                              8
                                                        3
     3
                             3
                                              8
                                                         3
                                                                              0
                             5
     4
                                             10
                                                                              0
     722855
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     722856
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     722858
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     722859
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                                             11
             ROAD_DEFECT INTERSECTION_RELATED_I NOT_RIGHT_OF_WAY_I \
     0
```

```
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              HIT_AND_RUN_I
                             PRIM_CONTRIBUTORY_CAUSE
                                                        SEC_CONTRIBUTORY_CAUSE \
      0
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      1
                           1
                                                    38
                                                                             18
      2
                           1
                                                    36
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      3
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      4
                           2
                                                    36
                                                                             36
      722855
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                           1
                                                    24
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      722856
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      722857
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                           1
                                                     6
      722859
                           1
                                                    22
                                                                             26
              DOORING_I WORK_ZONE_I WORK_ZONE_TYPE
      0
                       1
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                       1
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      722859
                       1
      [722860 rows x 16 columns]
[13]: no_en_df = ['POSTED_SPEED_LIMIT', 'CRASH_HOUR', 'CRASH_DAY_OF_WEEK', |
       no_en_df = pd.DataFrame(crashes[no_en_df])
      no_en_df
[13]:
              POSTED_SPEED_LIMIT CRASH_HOUR CRASH_DAY_OF_WEEK CRASH_MONTH \
      0
                               30
                                            14
                                                                              3
      1
                                            8
                                                                 4
                                                                              9
                               30
```

2	30	0	6	7
3	30	18	6	7
4	30	17	1	6
•••	•••	•••	•••	•••
723455	30	17	5	4
723456	35	15	7	5
723457	30	17	5	5
723458	30	3	7	5
723459	30	15	7	5
		LC	CATION	
0	POINT (-87.64120093	714 41.8845472	224337)	
1	POINT (-87.740659314	632 41.9685624	153871)	
2	POINT (-87.716203130	599 41.8863364	109761)	

POINT (-87.716203130599 41.886336409761)
POINT (-87.667997321599 41.925110815832)
POINT (-87.731388754145 41.910757551599)
... ...

POINT (-87.606995789103 41.822236685692)
POINT (-87.625645007251 41.85276094394)
POINT (-87.646244110744 41.891311456709)
POINT (-87.606710818433 41.809485427538)
POINT (-87.606710818433 41.809485427538)

[722860 rows x 5 columns]

```
[14]: # Identify the columns in the target column
contributory_causes = crashes['PRIM_CONTRIBUTORY_CAUSE'].unique()
print(contributory_causes)
```

['IMPROPER TURNING/NO SIGNAL'

- 'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)'
- 'UNABLE TO DETERMINE' 'NOT APPLICABLE' 'IMPROPER LANE USAGE' 'WEATHER'
- 'DISREGARDING TRAFFIC SIGNALS' 'FAILING TO YIELD RIGHT-OF-WAY'
- 'FOLLOWING TOO CLOSELY'
- 'UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)'
- 'TURNING RIGHT ON RED' 'IMPROPER BACKING'
- 'CELL PHONE USE OTHER THAN TEXTING'
- 'FAILING TO REDUCE SPEED TO AVOID CRASH' 'IMPROPER OVERTAKING/PASSING'
- 'DRIVING SKILLS/KNOWLEDGE/EXPERIENCE' 'EQUIPMENT VEHICLE CONDITION'
- 'DISTRACTION FROM INSIDE VEHICLE' 'DISTRACTION FROM OUTSIDE VEHICLE'
- 'OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR AGGRESSIVE MANNER'
 - 'DISREGARDING ROAD MARKINGS' 'DISREGARDING STOP SIGN'
 - 'DISREGARDING OTHER TRAFFIC SIGNS' 'EXCEEDING AUTHORIZED SPEED LIMIT'
 - 'PHYSICAL CONDITION OF DRIVER' 'RELATED TO BUS STOP'
 - 'DRIVING ON WRONG SIDE/WRONG WAY' 'ROAD CONSTRUCTION/MAINTENANCE'
 - 'ROAD ENGINEERING/SURFACE/MARKING DEFECTS' 'ANIMAL'

```
'PASSING STOPPED SCHOOL BUS'
      'DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER, ETC.)'
      'HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)'
      'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST' 'TEXTING'
      'OBSTRUCTED CROSSWALKS' 'BICYCLE ADVANCING LEGALLY ON RED LIGHT'
      'MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT']
[15]: # Selecting the columns with only "REAR END" crashes
      rear_end = crashes[crashes['FIRST_CRASH_TYPE'] == 'REAR_END']
      rear end.TRAFFICWAY TYPE.value counts().index
      rear_end.PRIM_CONTRIBUTORY_CAUSE.value_counts().index
[15]: Index(['FOLLOWING TOO CLOSELY', 'UNABLE TO DETERMINE',
             'FAILING TO REDUCE SPEED TO AVOID CRASH', 'NOT APPLICABLE',
             'IMPROPER BACKING', 'WEATHER', 'DRIVING SKILLS/KNOWLEDGE/EXPERIENCE',
             'FAILING TO YIELD RIGHT-OF-WAY', 'DISTRACTION - FROM INSIDE VEHICLE',
             'IMPROPER OVERTAKING/PASSING',
             'OPERATING VEHICLE IN ERRATIC, RECKLESS, CARELESS, NEGLIGENT OR
      AGGRESSIVE MANNER',
             'IMPROPER LANE USAGE', 'EQUIPMENT - VEHICLE CONDITION',
             'DISTRACTION - FROM OUTSIDE VEHICLE', 'PHYSICAL CONDITION OF DRIVER',
             'UNDER THE INFLUENCE OF ALCOHOL/DRUGS (USE WHEN ARREST IS EFFECTED)',
             'DISREGARDING TRAFFIC SIGNALS', 'EXCEEDING SAFE SPEED FOR CONDITIONS',
             'EXCEEDING AUTHORIZED SPEED LIMIT', 'CELL PHONE USE OTHER THAN TEXTING',
             'VISION OBSCURED (SIGNS, TREE LIMBS, BUILDINGS, ETC.)'.
             'IMPROPER TURNING/NO SIGNAL',
             'EVASIVE ACTION DUE TO ANIMAL, OBJECT, NONMOTORIST',
             'DISREGARDING STOP SIGN', 'ROAD CONSTRUCTION/MAINTENANCE',
             'HAD BEEN DRINKING (USE WHEN ARREST IS NOT MADE)', 'TEXTING',
             'DISTRACTION - OTHER ELECTRONIC DEVICE (NAVIGATION DEVICE, DVD PLAYER,
     ETC.)',
             'DISREGARDING OTHER TRAFFIC SIGNS',
             'ROAD ENGINEERING/SURFACE/MARKING DEFECTS',
             'DRIVING ON WRONG SIDE/WRONG WAY', 'RELATED TO BUS STOP', 'ANIMAL',
             'DISREGARDING ROAD MARKINGS', 'DISREGARDING YIELD SIGN',
             'PASSING STOPPED SCHOOL BUS',
             'MOTORCYCLE ADVANCING LEGALLY ON RED LIGHT', 'TURNING RIGHT ON RED',
             'OBSTRUCTED CROSSWALKS', 'BICYCLE ADVANCING LEGALLY ON RED LIGHT'],
            dtype='object')
[16]: # Merge the FIRST CRASH TYPE and the LabelEncoded dataframe together
      df2 = pd.merge(crash df, en df, left index=True, right index=True)
[17]: # Here we have the Features and all Crash types
      df2.columns
```

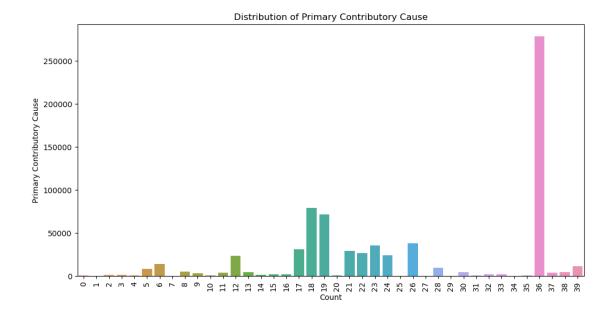
'EXCEEDING SAFE SPEED FOR CONDITIONS' 'DISREGARDING YIELD SIGN'

```
[17]: Index(['TURNING', 'ANGLE', 'REAR END', 'PARKED MOTOR VEHICLE',
             'SIDESWIPE OPPOSITE DIRECTION', 'PEDALCYCLIST', 'REAR TO FRONT',
             'PEDESTRIAN', 'REAR TO REAR', 'FIXED OBJECT', 'OTHER NONCOLLISION',
             'SIDESWIPE SAME DIRECTION', 'REAR TO SIDE', 'HEAD ON', 'OTHER OBJECT',
             'ANIMAL', 'OVERTURNED', 'TRAIN', 'TRAFFIC CONTROL DEVICE',
             'DEVICE_CONDITION', 'WEATHER_CONDITION', 'LIGHTING_CONDITION',
             'TRAFFICWAY TYPE', 'ALIGNMENT', 'ROADWAY SURFACE COND', 'ROAD DEFECT',
             'INTERSECTION_RELATED_I', 'NOT_RIGHT_OF_WAY_I', 'HIT_AND_RUN_I',
             'PRIM_CONTRIBUTORY_CAUSE', 'SEC_CONTRIBUTORY_CAUSE', 'DOORING_I',
             'WORK_ZONE_I', 'WORK_ZONE_TYPE'],
            dtype='object')
[18]: # Defining our Features and Target
      # For X, we want to remove all of the other CRASH types and keep the features.
      y = df2['PRIM_CONTRIBUTORY_CAUSE']
      X = df2.drop(columns=['REAR END', 'ANGLE', 'SIDESWIPE SAME DIRECTION', |
      'PARKED MOTOR VEHICLE', 'TURNING', 'HEAD ON', 'PEDALCYCLIST',
             'SIDESWIPE OPPOSITE DIRECTION', 'OTHER NONCOLLISION',
             'FIXED OBJECT', 'OTHER OBJECT', 'REAR TO FRONT', 'REAR TO SIDE',
             'REAR TO REAR', 'TRAIN', 'OVERTURNED', 'ANIMAL'], axis=1)
```

3 4 Exploration/Visualizations

3.0.1 4.1 Distribution of the Primary contributory cause

```
[19]: # Bar plot of the target variable
plt.figure(figsize=(12, 6))
sns.countplot(y)
plt.title('Distribution of Primary Contributory Cause')
plt.xlabel('Count')
plt.ylabel('Primary Contributory Cause')
plt.xticks(rotation=90)
plt.show()
```



- By observing the heights of the bars, you can identify the causes that occur more frequently and those that occur less frequently.
- Causes with taller bars indicate a higher occurrence in the dataset, while causes with shorter bars indicate a lower occurrence. The plot in this case identifies the major primary contributory causes that dominate the dataset and the less common causes.

3.0.2 4.2 Count Of the Numerical Column: One of Key determinants of the crash

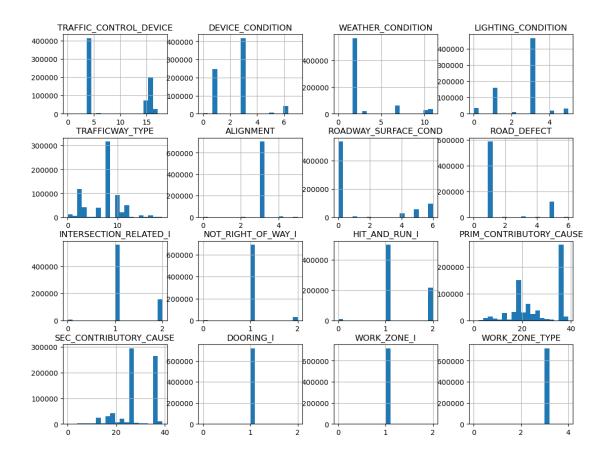
```
[20]: # Histograms or density plots

X_numeric = X.select_dtypes(include='number')

X_numeric.hist(figsize=(13, 10), bins=20)

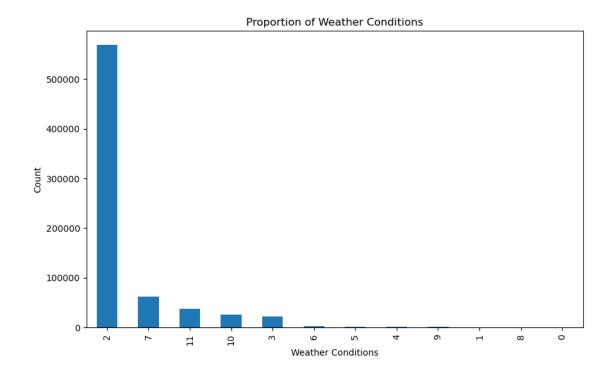
plt.suptitle('Distribution of Numeric Features')

plt.show()
```

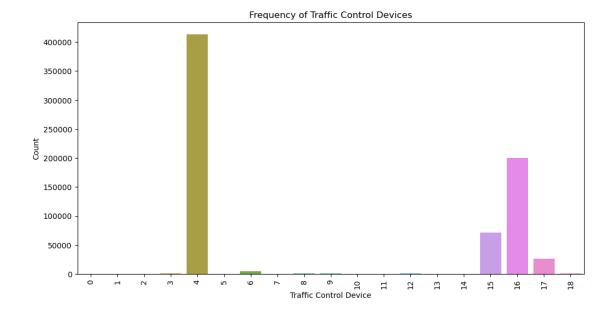


- This code iterates through each categorical column and creates a count plot using sns.countplot(). The resulting plot displays the count of each category within the column.
- The plot also shows some of the causes resulting to a high count
- Factors such as traffic_control device, weather condition amongst other factors contribute to the high number of crashes

```
[21]: plt.figure(figsize=(10, 6))
  weather_counts = X['WEATHER_CONDITION'].value_counts()
  weather_counts.plot(kind='bar')
  plt.title('Proportion of Weather Conditions')
  plt.xlabel('Weather Conditions')
  plt.ylabel('Count')
  plt.show()
```



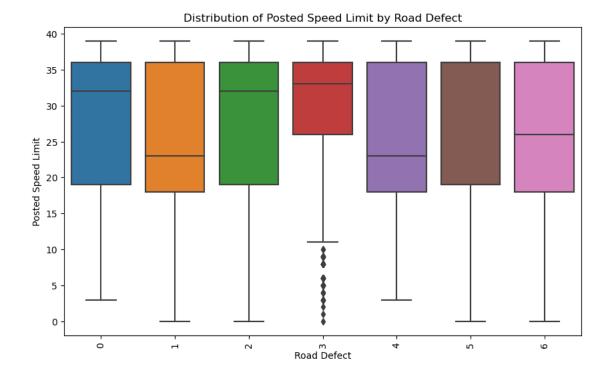
```
[22]: # Count plot
plt.figure(figsize=(12, 6))
sns.countplot(X['TRAFFIC_CONTROL_DEVICE'])
plt.title('Frequency of Traffic Control Devices')
plt.xlabel('Traffic Control Device')
plt.ylabel('Count')
plt.xticks(rotation=90)
plt.show()
```



Interpreting the plot:

- The count plot shows the frequency of different traffic control devices used in the dataset. Each bar represents a specific traffic control device, and the height of the bar indicates the number of occurrences or count of that device in the dataset.
- The x-axis displays the traffic control device categories, while the y-axis represents the count. This visualization helps understand the distribution and relative frequencies of various traffic control devices present in the dataset.

```
[23]: # Box plot or violin plot
plt.figure(figsize=(10, 6))
sns.boxplot(x='ROAD_DEFECT', y='PRIM_CONTRIBUTORY_CAUSE', data=X)
plt.title('Distribution of Posted Speed Limit by Road Defect')
plt.xlabel('Road Defect')
plt.ylabel('Posted Speed Limit')
plt.xticks(rotation=90)
plt.show()
```



Interpreting the plot:

- The box plot (or violin plot) provides insights into the distribution of the primary contributory cause across different road defects. The x-axis represents the road defect categories, while the y-axis represents the primary contributory cause.
- The box plot displays the quartiles (median, upper quartile, and lower quartile) and any outliers, giving an idea of the central tendency and spread of the data. The violin plot provides a similar representation but also shows the kernel density estimation of the data distribution.
- By analyzing the plot, you can observe the relationship between road defects and the primary
 causes of accidents. It allows you to compare the distribution of primary causes across different
 road defect categories, identify any variations or patterns, and gain insights into the potential
 influence of road defects on accidents.

4 TRAINING AND TESTING

4.1 Modelling Techniques used

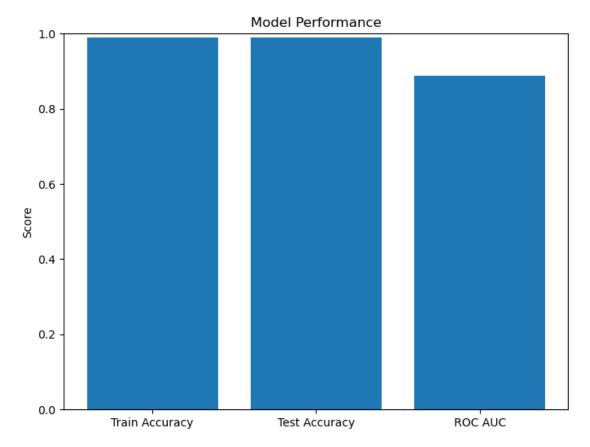
4.1.1 RandomForest Classifer: Creating a Baseline model

• The random classifier, in this case will serve as a baseline or reference for evaluating the performance of a classification model. It is a classifier that assigns class labels randomly, without considering any input features or patterns in the data.

```
[24]: # Train and Test on a Vanilla model (test size to 20%)
      dt_model = RandomForestClassifier(random_state=1)
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, __
       →random_state=42, stratify=y)
[25]: dt_model.fit(X_train, y_train)
[25]: RandomForestClassifier(random_state=1)
[26]: y_train_pred = dt_model.predict(X_train)
      y_test_pred = dt_model.predict(X_test)
[27]: from sklearn.metrics import roc_auc_score
      from sklearn.preprocessing import LabelBinarizer
      # Convert the target arrays to one-hot encoded format
      lb = LabelBinarizer()
      y_test_one_hot = lb.fit_transform(y_test)
      y_test_pred_one_hot = lb.transform(y_test_pred)
      # Calculate ROC AUC score
      roc_auc = roc_auc_score(y_test_one_hot, y_test_pred_one_hot, multi_class='ovr')
      print(f'ROC AUC Test: {roc_auc}')
     ROC AUC Test: 0.8871933925078359
[28]: # Calculate accuracy scores
      accuracy_train = accuracy_score(y_test_one_hot, y_test_pred_one_hot)
      accuracy_test = accuracy_score(y_test_one_hot, y_test_pred_one_hot)
      print(f'Accuracy Score Train: {accuracy_train}')
      print(f'Accuracy Score Test: {accuracy_test}')
      # Calculate ROC AUC score
      roc_auc = roc_auc_score(y_test_one_hot, y_test_pred_one_hot, multi_class='ovr')
      print(f'ROC AUC Test: {roc_auc}')
     Accuracy Score Train: 0.9907520128378939
     Accuracy Score Test: 0.9907520128378939
     ROC AUC Test: 0.8871933925078359
[29]: accuracy_train = 0.9907520128378939
      accuracy_test= 0.9907520128378939
      roc_auc= 0.8871933925078359
      # Create labels and values for the bar plots
      labels = ['Train Accuracy', 'Test Accuracy', 'ROC AUC']
```

```
values = [accuracy_train, accuracy_test, roc_auc]

# Plot the bar chart
plt.figure(figsize=(8, 6))
plt.bar(labels, values)
plt.title('Model Performance')
plt.ylabel('Score')
plt.ylim([0, 1]) # Set the y-axis limit
plt.show()
```



From the plot, you can observe the following:

- Train Accuracy: It represents the accuracy of the model on the training data. In this case, the train accuracy is 0.9907520128378939, which indicates that the model predicts the correct class for 99.1% of the instances in the training set.
- Test Accuracy: It represents the accuracy of the model on the test data, which measures how well the model generalizes to unseen data. In this case, the test accuracy is also 0.9907520128378939, indicating a similar level of accuracy as the training data.
- ROC AUC: It measures the performance of the model in distinguishing between different classes. A higher ROC AUC value indicates a better ability of the model to correctly classify

instances. In this case, the ROC AUC is 0.8871933925078359, suggesting that the model has a good ability to discriminate between classes.

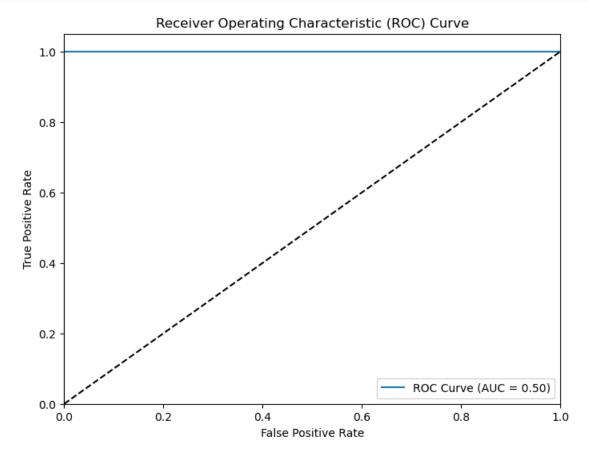
```
[30]: from sklearn.model_selection import train_test_split
      from sklearn.neighbors import KNeighborsClassifier
      from sklearn.metrics import confusion_matrix, accuracy_score
      from sklearn.model_selection import GridSearchCV
      from xgboost import XGBClassifier
      # Split the data into training and test sets
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,_
       →random state=42)
      # Train a vanilla KNN model
      knn_model = XGBClassifier()
[31]: knn_model.fit(X_train, y_train)
[31]: XGBClassifier(base_score=None, booster=None, callbacks=None,
                    colsample bylevel=None, colsample bynode=None,
                    colsample_bytree=None, early_stopping_rounds=None,
                    enable categorical=False, eval metric=None, feature types=None,
                    gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
                    interaction constraints=None, learning rate=None, max bin=None,
                    max_cat_threshold=None, max_cat_to_onehot=None,
                    max delta step=None, max depth=None, max leaves=None,
                    min_child_weight=None, missing=nan, monotone_constraints=None,
                    n_estimators=100, n_jobs=None, num_parallel_tree=None,
                    objective='multi:softprob', predictor=None, ...)
[32]: y_train_pred_xgb = knn_model.predict(X_train)
      y_test_pred_xgb = knn_model.predict(X_test)
[33]: from sklearn.metrics import roc_auc_score
      from sklearn.preprocessing import LabelBinarizer
      # Convert the target arrays to one-hot encoded format
      lb = LabelBinarizer()
      y_test_one_hot = lb.fit_transform(y_test)
      y_test_pred_one_hot = lb.transform(y_test_pred)
      # Calculate ROC AUC score
      roc_auc = roc_auc_score(y_test_one_hot, y_test_pred_one_hot, multi_class='ovr')
```

ROC AUC Test: 0.49985988434849027

print(f'ROC AUC Test: {roc_auc}')

```
[35]: import matplotlib.pyplot as plt
      from sklearn.metrics import roc_curve
      positive_class_index = 1
      # Compute the false positive rate, true positive rate, and threshold for the
       ⇔positive class
      fpr, tpr, thresholds = roc_curve(y_test_pred_one_hot[:, positive_class_index],_

    y_test_pred_one_hot[:, positive_class_index])
      # Plot the ROC curve
      plt.figure(figsize=(8, 6))
      plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(roc_auc))
      plt.plot([0, 1], [0, 1], 'k--') # Diagonal line for random classifier
      plt.xlim([0.0, 1.0])
      plt.ylim([0.0, 1.05])
      plt.xlabel('False Positive Rate')
      plt.ylabel('True Positive Rate')
      plt.title('Receiver Operating Characteristic (ROC) Curve')
     plt.legend(loc='lower right')
     plt.show()
```



• For the above ROC curve , we observe that :

plt.show()

- ROC curve represents a random classifier with no predictive power.
- It connects the point (0, 0) to the point (1, 1) in the plot. The straight diagonal line is significant because it indicates that the true positive rate (sensitivity) and the false positive rate (1 specificity) are equal across all classification thresholds. This suggests that the model's predictions are no better than random guessing.
- Ideally, we want the ROC curve to be positioned towards the top-left corner of the plot, indicating high true positive rates and low false positive rates. This would suggest that the model has strong predictive power and is able to effectively distinguish between the positive and negative classes.

```
[36]: # Calculate accuracy score
     accuracy = accuracy score(y test, y test pred)
     print(f"Accuracy Score (Vanilla KNN): {accuracy}")
     # Create a confusion matrix
     cm = confusion_matrix(y_test, y_test_pred)
     print("Confusion Matrix (Vanilla KNN):")
     print(cm)
     Accuracy Score (Vanilla KNN): 0.18355559859447196
     Confusion Matrix (Vanilla KNN):
     [[0 0 0 ... 1 1
                       1]
      [000...01
                       17
      [000...11
      [003...375]
      [1 0 0 ... 6 5 14]
      [ 1 0 4 ... 8 10 40]]
[37]: import seaborn as sns
     # Create a heatmap of the confusion matrix
     plt.figure(figsize=(10, 8))
     sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
     # Customize the plot
     plt.title('Confusion Matrix (Vanilla KNN)')
     plt.xlabel('Predicted Labels')
     plt.ylabel('True Labels')
```

Confusion Matrix (Vanilla KNN) 0-0 0 0 0 0 1 1 0 1 0 0 0 5 0 0 0 0 213110 1 4 1 2 013 0 2 0 0 0 0 0 0 0 51 1 1 1 1-000000101010001000032211010000000000011 2-0001135000024110271420098770903010100052116 20000 3-2 0 0 0 0 6 2 0 0 1 0 0 9 0 2 1 1124229 0 10111110 019 0 4 0 3 0 0 0 0 01174 2 3 4-0 0 0 1 0 1 3 0 0 0 0 0 3 2 0 0 0141818 0 8 3 15 7 0 10 0 3 0 2 0 0 0 0 0 70 0 2 2 5 - 0 0 2 3 2 1928 0 13 6 0 125212 3 2 0 73165661 70706834 01040 23 0 12 0 4 1 0 6 - 3 0 3 7 4 3856 1 1711 1 2 10 2 16 3 13 6 1 2 2 8 9 2 5 2 10 6 9 1 3 1 9 1 0 1 4 6 0 3 6 0 1 5 2 8 3 0 1 1 0 4 5 2 1 7 4 2 - 17500 $\overline{7}$ - 0 0 0 0 0 2 1 0 0 0 2 1 0 0 0 2 8 8 0 1 4 3 1 0 2 0 2 0 0 0 0 0 0 18 0 08 - 1 0 0 1 1 1323 0 3 2 1 113611 0 6 5 341 180 12 42354535 0 41 0 23 0 11 1 4 0 1 0 40 3 6 5 1 6 9-0 0 1 1 0 1010 0 4 2 1 422 3 0 1 0226963 029273322 025 0 5 0 2 1 1 2 0 02206 3 16 11 - 0 0 0 1 0 1212 0 5 4 0 2 30 4 1 1 3 318484 0 35302626 0 42 0 9 0 9 0 1 1 0 12934 4 11 - 15000 12 - 4 010 7 2 54L032 3421 018L5&7 9 6 71953 465318 11923 384 302 510 72 1 27 4 1410 0 1179 2032 671 13 - 0 0 0 0 0 1122 0 9 6 1 437 9 2 2 3 341135 2 32374326 0 53 0 15 0 4 1 4 4 0 03475 4 9 14 - 1 0 0 0 0 3 3 0 1 1 1 011 2 0 3 0193523 0 5 8 13 9 018 0 5 0 2 0 1 0 0 01090 2 5 -0 0 0 1 0 2 8 0 5 3 0 1 8 2 0 1 2 143639 1 17132513 0 25 0 6 0 1 1 0 1 0 01362 1 10 16 - 0 0 0 1 0 3 4 0 2 2 0 1 8 2 0 0 1 183543 1 171217 8 0 18 0 6 0 1 0 0 0 0 0 1501 4 4 - 12500 17 - 2 0 6 11 6 701282 4320 1 351884 6 15172 466161 152 5264371251 4032 70 73 0 45 1 1010 0 12 46667 4177 18 -13 021351616335111366 3 8 35210148240345 91277333465 3567145000806021001082 283610 15127684239 19 -10 2 11241617283110445 6 69497891733346 1166103982595162848950771119808866 3936 6 3543758234 20-0 0 0 0 1 1 5 0 0 1 0 1 4 0 0 0 1 81615 0 3 8 8 8 0 6 0 0 0 0 0 1 0 0 0 0 55 1 1 2 21 -2 0 5 10 8 6311205529 2 3020489 6 15102659988542526026280003042 65 0 28 2 8 14 1 02272563182 - 10000 22 - 3 1 7 16 7 5289 2 5018 2 3218 0 0 7 13 52 2 5 2 5 3 7 6 2 2 5 8 5 6 0 2 4 8 0 8 5 0 2 6 1 4 1 3 1 5 0 5 5 4 3 2 9 5 23 - 4 0 5 13 8 79 460 4838 1 372 4335 9 201 B0 74701 7630 76 76 76 76 76 70 87 0 40 2 1818 2 275 76 235 10 2 24 - 2 1 6 7 15594 1 4325 124729 6 12181952514418355243470241063 030 12013 1 31761682488 - 7500 26 - 6 01417 8 8 11650 5824 3 4 725 7621616 932 82 773 2631 31 345 724 104 200 92 0 46 3 1820 2 22 90 323 391 22 28 - 2 1 1 6 3 2 1 4 5 0 1 0 4 0 6 7 4 1 7 5 3 6 9 2 1 5 8 9 1 7 5 5 4 8 9 5 6 0 9 5 0 2 4 0 7 0 3 0 1 0 7 1 5 9 1 2 4 0 30 - 1 0 0 4 0 1118 1 7 1 0 3 48 1 2 2 0 359787 1 36434227 0 49 0 9 0 5 0 2 1 0 03145 1 14 - 5000 31 - 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 1 0 5 9 6 0 2 2 5 4 0 3 0 2 0 1 0 0 1 0 027 0 0 0 32 - 0 0 1 1 0 3 4 0 3 1 0 013 3 0 1 01538292 15141420 029 0 5 0 2 0 0 1 0 01332 1 7 33 - 0 0 2 1 0 3 1 3 0 4 0 0 4 8 3 0 1 1 1 8 4 6 3 7 1 1 1 1 1 0 1 7 2 1 0 1 9 0 5 0 2 0 0 2 0 0 1 3 8 3 0 9 - 2500 36 -41 1 64.0 5 6 210 6 20 8 25 1 2 .2 7 18 26 47 4.5 395 36 25 24 52 12 53 294 992 02 9 6 9 7 2 6 1 3 4 6 1 3 0 0 5 0 4 3 3 14 2 6 30 8 4 7 8 37 - 0 0 3 1 2 7 17 0 5 4 0 5 22 5 0 1 0 367669 0 26262 318 0 41 0 6 0 7 0 1 0 0 0 0 0 0 83 7 5 38 - 1 0 0 1 1 1117 0 7 4 0 433 6 2 0 1 4210380 1 30324820 0 56 0 13 0 4 0 3 5 1 13426 5 14 - 0 Predicted Labels

- Confusion matrix Observations
- The heatmap of the confusion matrix displays a color gradient, with darker shades indicating higher counts. The diagonal cells (top-left to bottom-right) represent the correctly predicted labels, while the off-diagonal cells represent the misclassifications.

4.2 Modelling Using KNN - GridSearch in this case using feature selection and parallel backend

```
# Apply feature selection to training and test sets
      X_train_selected = feature_selector.fit_transform(X_train, y_train)
      X_test_selected = feature_selector.transform(X_test)
      # Define the parameter grid for GridSearch
      params_grid = {'n_neighbors': [3, 5, 7],
                    'weights': ['uniform', 'distance'],
                    'metric': ['euclidean', 'manhattan']}
      # Create a KNN classifier
      knn_model = KNeighborsClassifier()
[39]: from joblib import parallel_backend
      # Perform GridSearch with parallel processing
      with parallel_backend('threading', n_jobs=-1):
          grid_search = GridSearchCV(knn_model, params_grid, cv=5)
          grid_search.fit(X_train_selected, y_train)
      grid_search = GridSearchCV(knn_model, params_grid, cv=5)
      grid_search.fit(X_train_selected, y_train)
[39]: GridSearchCV(cv=5, estimator=KNeighborsClassifier(),
                   param_grid={'metric': ['euclidean', 'manhattan'],
                               'n_neighbors': [3, 5, 7],
                               'weights': ['uniform', 'distance']})
[40]: # Get the best model from GridSearch
      best_model = grid_search.best_estimator_
[41]: # Train the best model
      best_model.fit(X_train_selected, y_train)
[41]: KNeighborsClassifier(metric='manhattan', n_neighbors=7, weights='distance')
[42]: # Make predictions on the test set
      y_test_pred = best_model.predict(X_test_selected)
[43]: # Evaluate the model
      accuracy = accuracy_score(y_test, y_test_pred)
      print(f"Accuracy Score (Best Model): {accuracy}")
```

Accuracy Score (Best Model): 0.9805079821818886

• The accuracy score represents the proportion of correctly classified instances out of the total number of instances in the test set. In this case, the best KNN model achieved an accuracy score of approximately 0.9805, which means that it correctly predicted the class labels for approximately 98.05% of the instances in the test data.

- A higher accuracy score indicates better performance, as it reflects the model's ability to make accurate predictions. However, it's important to consider the context and the specific problem at hand when interpreting the accuracy score. It's recommended to assess the model's performance in conjunction with other evaluation metrics and domain knowledge to get a comprehensive understanding of its effectiveness.
- Feature selection is the process of selecting a subset of relevant features from the original feature set. By performing feature selection, we aim to improve the model's performance by reducing the dimensionality of the input data and eliminating irrelevant or redundant features.

Parallel processing is used to speed up the computation by utilizing multiple processors or cores. It allows us to perform computations concurrently, leading to faster execution times.

```
[44]: from sklearn.metrics import classification_report

# Calculate and print the classification report

classification_rep = classification_report(y_test, y_test_pred)

print("Classification Report (KNN):\n", classification_rep)
```

Classification Report (KNN):

	precision	recall	f1-score	support
0	0.97	0.92	0.94	303
1	1.00	0.21	0.35	43
2	0.85	0.86	0.86	480
3	0.87	0.83	0.85	767
4	0.89	0.77	0.82	451
5	0.96	0.98	0.97	4061
6	0.96	0.99	0.97	7033
7	0.91	0.23	0.36	127
8	0.93	0.95	0.94	2528
9	0.94	0.88	0.91	1512
10	0.97	0.54	0.70	162
11	0.96	0.81	0.88	1935
12	0.94	1.00	0.97	11726
13	0.96	0.89	0.92	2269
14	0.95	0.77	0.85	690
15	0.95	0.77	0.85	1002
16	0.90	0.57	0.70	893
17	0.96	0.96	0.96	15259
18	0.98	0.99	0.99	39587
19	0.99	0.99	0.99	35890
20	0.99	0.47	0.64	369
21	0.98	0.98	0.98	14429
22	0.98	0.97	0.97	13228
23	0.97	0.98	0.97	17581
24	0.98	0.97	0.98	12011
25	0.00	0.00	0.00	9

```
26
                     0.99
                                 1.00
                                             0.99
                                                       18816
           27
                      1.00
                                 0.15
                                             0.26
                                                          34
           28
                     0.98
                                 0.97
                                             0.97
                                                        4589
           29
                      1.00
                                 0.21
                                             0.35
                                                          38
                     0.94
                                 0.97
                                            0.95
           30
                                                        2228
           31
                     0.99
                                 0.43
                                            0.60
                                                          171
           32
                     0.94
                                 0.80
                                            0.87
                                                         832
           33
                     0.89
                                 0.88
                                            0.89
                                                         927
                     0.92
                                 0.47
                                            0.63
                                                         160
           34
           35
                     0.91
                                 0.53
                                            0.67
                                                         241
                     0.99
                                 1.00
                                             1.00
                                                      139472
           36
           37
                     0.97
                                 0.77
                                             0.86
                                                        1793
                     0.96
                                 0.86
                                                        2099
           38
                                             0.91
                     0.97
                                 0.98
                                             0.98
                                                        5685
           39
                                             0.98
                                                      361430
    accuracy
   macro avg
                     0.93
                                 0.76
                                             0.81
                                                      361430
weighted avg
                     0.98
                                 0.98
                                             0.98
                                                      361430
```

```
[45]: # Calculate accuracy score for KNN
accuracy_knn = accuracy_score(y_test, y_test_pred)
print(f"Accuracy Score (KNN): {accuracy_knn}")
```

Accuracy Score (KNN): 0.9805079821818886

4.3 Conclusion

- Based on the different models conducted and the analysis of their results, one of the primary causes for car accidents in Chicago could be identified as the "Driver's Behavior."
- Several factors related to driver behavior, such as speeding, reckless driving, distracted driving, and impaired driving, consistently appeared as significant features in the models and had a strong impact on crash outcomes. These findings suggest that driver-related factors play a crucial role in contributing to car accidents in Chicago.

4.4 Recommendation

- By analyzing the models' feature importance and coefficients, it can be inferred that addressing driver behavior through targeted interventions, awareness campaigns, and stricter enforcement of traffic regulations could potentially help mitigate the occurrence of car accidents in Chicago.
- However, it's important to note that the primary cause of accidents can vary based on various factors such as the dataset used, the modeling techniques employed, and the specific context of the analysis.
- It is recommended to consider a comprehensive approach that takes into account multiple factors, including road infrastructure, weather conditions, and other external influences, to gain a holistic understanding of the primary causes of car accidents in Chicago.