Accident Report for Sanlam Insurance

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Overview

The goal for the report to enhance the underwriting process by leveraging data analytics to gain insights into the factors contributing to severe crashes. The focus is on predicting the likelihood of a crash resulting in "INJURY AND / OR TOW DUE TO CRASH" versus "NO INJURY / DRIVE AWAY." This prediction will enable Sanlam Insurance to more accurately assess risk and make informed decisions regarding insurance pricing, ultimately reducing claims costs and increasing profitability.

To achieve this, data from historical accident reports is analyzed, with a focus on features like weather conditions, lighting, road defects, and time factors such as the day of the week and month. By using various machine learning models, including Logistic Regression and Decision Tree Classifiers, the project evaluates the impact of different data preprocessing techniques, such as scaling and encoding, on model performance. The goal is to identify the best approach for predicting crash severity, thereby providing actionable insights that can improve risk assessment and policy pricing strategies.

Business Problem

Questions to consider:

- What are the business's pain points related to this project?
- How did you pick the data analysis question(s) that you did?
- Why are these questions important from a business perspective?
- What is the Success criteria

Sanlam Insurance faces significant challenges in accurately assessing the risk of accidents that result in injuries or severe vehicle damage, leading to higher claims costs. The traditional underwriting process may not fully account for the myriad factors that contribute to crash severity, potentially leading to suboptimal pricing strategies and increased financial risk.

To address this pain point, the project explores key questions related to the factors influencing crash outcomes. By understanding these factors through data analysis, Sanlam Insurance can refine its underwriting models, improve risk predictions, and ultimately reduce the frequency and cost of claims. These improvements are crucial for maintaining a competitive edge in the insurance market and ensuring long-term profitability.

The output shoud be able to draw the conclusion that, following the stipulated parameters for a accident to occur, the type of accident / crash should fall either injured or not injured, and a suitable critea can be selected by the company to state the renumuration from claims that are in those categories

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Data Understanding

Questions to consider:

- Where did the data come from, and how do they relate to the data analysis questions?
- What do the data represent? Who is in the sample and what variables are included?
- What is the target variable?
- What are the properties of the variables you intend to use?

- The **crashes.csv** that contains data from the electronic crash reporting system (E-Crash) at Chicago Police Department, excluding any personally identifiable information, will be our source found from the [Chicago Data Portal (https://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3if/about_data)](https://data.cityofchicago.org/Transportation/Traffic-Crashes-Crashes/85ca-t3if/about_data) for insight to our business problem.

In [81]:
```
# Import libraires here...
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import train_test_split
from sklearn.compose import make_column_transformer
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler, StandardScaler, RobustScaler, MaxAbsScaler
from sklearn.metrics import accuracy_score, precision_score, recall_score,f1_score, confusion_matrix, roc_auc_sc
from imblearn.under_sampling import RandomUnderSampler
from imblearn.pipeline import Pipeline as ImbPipeline
from scipy.stats import f_oneway
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
pd.set_option('max_columns',200)

#Import the data...
crashes = pd.read_csv('./data/Traffic_Crashes_-_Crashes_20240826.csv')
```

In [82]:
```
# Dataset head
crashes.head()
```

Out[82]:

	CRASH_RECORD_ID	CRASH_DATE_EST_I	CRASH_DATE	POSTED_SPEED_LIMIT	TRAFFIC_CONTROL_DEVICE	DEVICE_
0	6c1659069e9c6285a650e70d6f9b574ed5f64c12888479...	NaN	08/18/2023 12:50:00 PM	15	OTHER	FU
1	5f54a59fcb087b12ae5b1acff96a3caf4f2d37e79f8db4...	NaN	07/29/2023 02:45:00 PM	30	TRAFFIC SIGNAL	FU
2	61fcb8c1eb522a6469b460e2134df3d15f82e81fd93e9c...	NaN	08/18/2023 05:58:00 PM	30	NO CONTROLS	NC
3	004cd14d0303a9163aad69a2d7f341b7da2a8572b2ab33...	NaN	11/26/2019 08:38:00 AM	25	NO CONTROLS	NC
4	a1d5f0ea90897745365a4cbb06cc60329a120d89753fac...	NaN	08/18/2023 10:45:00 AM	20	NO CONTROLS	NC

In [83]:
```
# For more info...
crashes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 866411 entries, 0 to 866410
Data columns (total 48 columns):
 #   Column                         Non-Null Count   Dtype  
---  ------                         --------------   -----  
 0   CRASH_RECORD_ID                866411 non-null  object 
 1   CRASH_DATE_EST_I               64356 non-null   object 
 2   CRASH_DATE                     866411 non-null  object 
 3   POSTED_SPEED_LIMIT             866411 non-null  int64  
 4   TRAFFIC_CONTROL_DEVICE         866411 non-null  object 
 5   DEVICE_CONDITION               866411 non-null  object 
 6   WEATHER_CONDITION              866411 non-null  object 
 7   LIGHTING_CONDITION             866411 non-null  object 
 8   FIRST_CRASH_TYPE               866411 non-null  object 
 9   TRAFFICWAY_TYPE                866411 non-null  object 
 10  LANE_CNT                       199015 non-null  float64
 11  ALIGNMENT                      866411 non-null  object 
 12  ROADWAY_SURFACE_COND           866411 non-null  object 
 13  ROAD_DEFECT                    866411 non-null  object 
 14  REPORT_TYPE                    840008 non-null  object 
 15  CRASH_TYPE                     866411 non-null  object 
 16  INTERSECTION_RELATED_I         198603 non-null  object 
 17  NOT_RIGHT_OF_WAY_I             39667 non-null   object 
 18  HIT_AND_RUN_I                  271579 non-null  object 
 19  DAMAGE                         866411 non-null  object 
 20  DATE_POLICE_NOTIFIED           866411 non-null  object 
 21  PRIM_CONTRIBUTORY_CAUSE        866411 non-null  object 
 22  SEC_CONTRIBUTORY_CAUSE         866411 non-null  object 
 23  STREET_NO                      866411 non-null  int64  
 24  STREET_DIRECTION               866407 non-null  object 
 25  STREET_NAME                    866410 non-null  object 
 26  BEAT_OF_OCCURRENCE             866406 non-null  float64
 27  PHOTOS_TAKEN_I                 11675 non-null   object 
 28  STATEMENTS_TAKEN_I             19762 non-null   object 
 29  DOORING_I                      2719 non-null    object 
 30  WORK_ZONE_I                    4898 non-null    object 
 31  WORK_ZONE_TYPE                 3780 non-null    object 
 32  WORKERS_PRESENT_I              1255 non-null    object 
 33  NUM_UNITS                      866411 non-null  int64  
 34  MOST_SEVERE_INJURY             864495 non-null  object 
 35  INJURIES_TOTAL                 864508 non-null  float64
 36  INJURIES_FATAL                 864508 non-null  float64
 37  INJURIES_INCAPACITATING        864508 non-null  float64
 38  INJURIES_NON_INCAPACITATING    864508 non-null  float64
 39  INJURIES_REPORTED_NOT_EVIDENT  864508 non-null  float64
 40  INJURIES_NO_INDICATION         864508 non-null  float64
 41  INJURIES_UNKNOWN               864508 non-null  float64
 42  CRASH_HOUR                     866411 non-null  int64  
 43  CRASH_DAY_OF_WEEK              866411 non-null  int64  
 44  CRASH_MONTH                    866411 non-null  int64  
 45  LATITUDE                       860273 non-null  float64
 46  LONGITUDE                      860273 non-null  float64
 47  LOCATION                       860273 non-null  object 
dtypes: float64(11), int64(6), object(31)
memory usage: 317.3+ MB
```

In [84]:
```
# the feature are...
crashes.columns
```

Out[84]:
```
Index(['CRASH_RECORD_ID', 'CRASH_DATE_EST_I', 'CRASH_DATE',
       'POSTED_SPEED_LIMIT', 'TRAFFIC_CONTROL_DEVICE', 'DEVICE_CONDITION',
       'WEATHER_CONDITION', 'LIGHTING_CONDITION', 'FIRST_CRASH_TYPE',
       'TRAFFICWAY_TYPE', 'LANE_CNT', 'ALIGNMENT', 'ROADWAY_SURFACE_COND',
       'ROAD_DEFECT', 'REPORT_TYPE', 'CRASH_TYPE', 'INTERSECTION_RELATED_I',
       'NOT_RIGHT_OF_WAY_I', 'HIT_AND_RUN_I', 'DAMAGE', 'DATE_POLICE_NOTIFIED',
       'PRIM_CONTRIBUTORY_CAUSE', 'SEC_CONTRIBUTORY_CAUSE', 'STREET_NO',
       'STREET_DIRECTION', 'STREET_NAME', 'BEAT_OF_OCCURRENCE',
       'PHOTOS_TAKEN_I', 'STATEMENTS_TAKEN_I', 'DOORING_I', 'WORK_ZONE_I',
       'WORK_ZONE_TYPE', 'WORKERS_PRESENT_I', 'NUM_UNITS',
       'MOST_SEVERE_INJURY', 'INJURIES_TOTAL', 'INJURIES_FATAL',
       'INJURIES_INCAPACITATING', 'INJURIES_NON_INCAPACITATING',
       'INJURIES_REPORTED_NOT_EVIDENT', 'INJURIES_NO_INDICATION',
       'INJURIES_UNKNOWN', 'CRASH_HOUR', 'CRASH_DAY_OF_WEEK', 'CRASH_MONTH',
       'LATITUDE', 'LONGITUDE', 'LOCATION'],
      dtype='object')
```

In [85]:
```
# Check unique values in target variable
crashes['CRASH_TYPE'].unique()
```

Out[85]:
```
array(['INJURY AND / OR TOW DUE TO CRASH', 'NO INJURY / DRIVE AWAY'],
      dtype=object)
```

Data Preparation

Questions to consider:

- Were there variables you dropped or created?
- How did you address missing values or outliers?
- Why are these choices appropriate given the data and the business problem?

Steps taken

1. Label encode target feature
2. Split data into training and testing data
3. Independent Features selection
4. Exploratory data analysis (EDA)
5. Univariate Analysis
6. Bivariate Analysis

Label encode target feature

In [86]:
```
#Instatiate label encoder
encoder = LabelEncoder()
```

In [87]:
```
# Check unique values in target variable
crashes['CRASH_TYPE'].unique()
```

Out[87]:
```
array(['INJURY AND / OR TOW DUE TO CRASH', 'NO INJURY / DRIVE AWAY'],
      dtype=object)
```

In [88]:
```
# Check imbalance...
crashes['CRASH_TYPE'].value_counts()
```

Out[88]:
```
NO INJURY / DRIVE AWAY              633902
INJURY AND / OR TOW DUE TO CRASH    232509
Name: CRASH_TYPE, dtype: int64
```

In [89]:
```
# Fit and transform the CRASH_TYPE column
crashes['CRASH_TYPE_ENCODED'] = encoder.fit_transform(crashes['CRASH_TYPE'])

# To see the mapping between original labels and encoded values
label_mapping = dict(zip(encoder.classes_, encoder.transform(encoder.classes_)))

# Output the label mapping and the first few rows of the DataFrame
print("Label Mapping:", label_mapping)
print(crashes[['CRASH_TYPE', 'CRASH_TYPE_ENCODED']].head())
```

```
Label Mapping: {'INJURY AND / OR TOW DUE TO CRASH': 0, 'NO INJURY / DRIVE AWAY': 1}
                         CRASH_TYPE  CRASH_TYPE_ENCODED
0  INJURY AND / OR TOW DUE TO CRASH                   0
1            NO INJURY / DRIVE AWAY                   1
2  INJURY AND / OR TOW DUE TO CRASH                   0
3  INJURY AND / OR TOW DUE TO CRASH                   0
4            NO INJURY / DRIVE AWAY                   1
```

In [90]:
```
# New Target feature imbalance...
crashes['CRASH_TYPE_ENCODED'].value_counts()
```

Out[90]:
```
1    633902
0    232509
Name: CRASH_TYPE_ENCODED, dtype: int64
```

In [91]:
```
# New column CRASH_TYPE_ENCODED has been added which will be our Target column
crashes.columns
```

Out[91]:
```
Index(['CRASH_RECORD_ID', 'CRASH_DATE_EST_I', 'CRASH_DATE',
       'POSTED_SPEED_LIMIT', 'TRAFFIC_CONTROL_DEVICE', 'DEVICE_CONDITION',
       'WEATHER_CONDITION', 'LIGHTING_CONDITION', 'FIRST_CRASH_TYPE',
       'TRAFFICWAY_TYPE', 'LANE_CNT', 'ALIGNMENT', 'ROADWAY_SURFACE_COND',
       'ROAD_DEFECT', 'REPORT_TYPE', 'CRASH_TYPE', 'INTERSECTION_RELATED_I',
       'NOT_RIGHT_OF_WAY_I', 'HIT_AND_RUN_I', 'DAMAGE', 'DATE_POLICE_NOTIFIED',
       'PRIM_CONTRIBUTORY_CAUSE', 'SEC_CONTRIBUTORY_CAUSE', 'STREET_NO',
       'STREET_DIRECTION', 'STREET_NAME', 'BEAT_OF_OCCURRENCE',
       'PHOTOS_TAKEN_I', 'STATEMENTS_TAKEN_I', 'DOORING_I', 'WORK_ZONE_I',
       'WORK_ZONE_TYPE', 'WORKERS_PRESENT_I', 'NUM_UNITS',
       'MOST_SEVERE_INJURY', 'INJURIES_TOTAL', 'INJURIES_FATAL',
       'INJURIES_INCAPACITATING', 'INJURIES_NON_INCAPACITATING',
       'INJURIES_REPORTED_NOT_EVIDENT', 'INJURIES_NO_INDICATION',
       'INJURIES_UNKNOWN', 'CRASH_HOUR', 'CRASH_DAY_OF_WEEK', 'CRASH_MONTH',
       'LATITUDE', 'LONGITUDE', 'LOCATION', 'CRASH_TYPE_ENCODED'],
      dtype='object')
```

In [92]:
```
# New Target datatype and old target datatype
print ( "New Target datatye: " f'{crashes["CRASH_TYPE_ENCODED"].dtypes}')
print("Old Target datatye: " f'{crashes["CRASH_TYPE"].dtypes}')
```

```
New Target datatye: int64
Old Target datatye: object
```

Split the Data

In [93]:
```
# Define features and target
X = crashes.drop(columns=['CRASH_TYPE','CRASH_TYPE_ENCODED'])
y = crashes['CRASH_TYPE_ENCODED']

# Perform train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.2,
                                                    random_state=42)
```

In [94]:
```
# Target training data rows
y_train.shape
```

Out[94]:
```
(693128,)
```

In [95]:
```
# Target Testing Data rows
y_test.shape
```

Out[95]:
```
(173283,)
```

In [96]:
```
# Independent training data rows
X_train.shape
```

Out[96]:
```
(693128, 47)
```

In [97]:
```
# Independent Testing data rows
X_test.shape
```

Out[97]:
```
(173283, 47)
```

Independent Features selection

In [98]:
```
# Independent Training dataset column index
X_train.columns
```

Out[98]:
```
Index(['CRASH_RECORD_ID', 'CRASH_DATE_EST_I', 'CRASH_DATE',
       'POSTED_SPEED_LIMIT', 'TRAFFIC_CONTROL_DEVICE', 'DEVICE_CONDITION',
       'WEATHER_CONDITION', 'LIGHTING_CONDITION', 'FIRST_CRASH_TYPE',
       'TRAFFICWAY_TYPE', 'LANE_CNT', 'ALIGNMENT', 'ROADWAY_SURFACE_COND',
       'ROAD_DEFECT', 'REPORT_TYPE', 'INTERSECTION_RELATED_I',
       'NOT_RIGHT_OF_WAY_I', 'HIT_AND_RUN_I', 'DAMAGE', 'DATE_POLICE_NOTIFIED',
       'PRIM_CONTRIBUTORY_CAUSE', 'SEC_CONTRIBUTORY_CAUSE', 'STREET_NO',
       'STREET_DIRECTION', 'STREET_NAME', 'BEAT_OF_OCCURRENCE',
       'PHOTOS_TAKEN_I', 'STATEMENTS_TAKEN_I', 'DOORING_I', 'WORK_ZONE_I',
       'WORK_ZONE_TYPE', 'WORKERS_PRESENT_I', 'NUM_UNITS',
       'MOST_SEVERE_INJURY', 'INJURIES_TOTAL', 'INJURIES_FATAL',
       'INJURIES_INCAPACITATING', 'INJURIES_NON_INCAPACITATING',
       'INJURIES_REPORTED_NOT_EVIDENT', 'INJURIES_NO_INDICATION',
       'INJURIES_UNKNOWN', 'CRASH_HOUR', 'CRASH_DAY_OF_WEEK', 'CRASH_MONTH',
       'LATITUDE', 'LONGITUDE', 'LOCATION'],
      dtype='object')
```

In [99]:
```python
# 13 features selected for analysis in our modeling

X_train_selected= X_train[[ #'CRASH_RECORD_ID', 'CRASH_DATE_EST_I', 'CRASH_DATE',
       # 'POSTED_SPEED_LIMIT', 'TRAFFIC_CONTROL_DEVICE', 'DEVICE_CONDITION',
       'WEATHER_CONDITION', 'LIGHTING_CONDITION',
       #'FIRST_CRASH_TYPE','TRAFFICWAY_TYPE', 'LANE_CNT',
       'ALIGNMENT', 'ROADWAY_SURFACE_COND','ROAD_DEFECT', #'REPORT_TYPE',
       # 'INTERSECTION_RELATED_I','NOT_RIGHT_OF_WAY_I', 'HIT_AND_RUN_I',
       'DAMAGE',
       # 'DATE_POLICE_NOTIFIED','PRIM_CONTRIBUTORY_CAUSE', 'SEC_CONTRIBUTORY_CAUSE',
       'STREET_NO',
       #'STREET_DIRECTION',
       'STREET_NAME',
       #'BEAT_OF_OCCURRENCE','PHOTOS_TAKEN_I', 'STATEMENTS_TAKEN_I', 'DOORING_I', 'WORK_ZONE_I',
       #'WORK_ZONE_TYPE', 'WORKERS_PRESENT_I',
       'NUM_UNITS',
       #'MOST_SEVERE_INJURY', 'INJURIES_TOTAL', 'INJURIES_FATAL',
       #'INJURIES_INCAPACITATING', 'INJURIES_NON_INCAPACITATING',
       #'INJURIES_REPORTED_NOT_EVIDENT', 'INJURIES_NO_INDICATION','INJURIES_UNKNOWN',
       'CRASH_HOUR', 'CRASH_DAY_OF_WEEK', 'CRASH_MONTH',
       #'LATITUDE', 'LONGITUDE', 'LOCATION'
       ]].copy()

X_test_selected = X_test[[ #'CRASH_RECORD_ID', 'CRASH_DATE_EST_I', 'CRASH_DATE',
       # 'POSTED_SPEED_LIMIT', 'TRAFFIC_CONTROL_DEVICE', 'DEVICE_CONDITION',
       'WEATHER_CONDITION', 'LIGHTING_CONDITION',
       #'FIRST_CRASH_TYPE','TRAFFICWAY_TYPE', 'LANE_CNT',
       'ALIGNMENT', 'ROADWAY_SURFACE_COND','ROAD_DEFECT', #'REPORT_TYPE',
       # 'INTERSECTION_RELATED_I','NOT_RIGHT_OF_WAY_I', 'HIT_AND_RUN_I',
       'DAMAGE',
       # 'DATE_POLICE_NOTIFIED','PRIM_CONTRIBUTORY_CAUSE', 'SEC_CONTRIBUTORY_CAUSE',
       'STREET_NO',
       #'STREET_DIRECTION',
       'STREET_NAME',
       #'BEAT_OF_OCCURRENCE','PHOTOS_TAKEN_I', 'STATEMENTS_TAKEN_I', 'DOORING_I', 'WORK_ZONE_I',
       #'WORK_ZONE_TYPE', 'WORKERS_PRESENT_I',
       'NUM_UNITS',
       #'MOST_SEVERE_INJURY', 'INJURIES_TOTAL', 'INJURIES_FATAL',
       #'INJURIES_INCAPACITATING', 'INJURIES_NON_INCAPACITATING',
       #'INJURIES_REPORTED_NOT_EVIDENT', 'INJURIES_NO_INDICATION','INJURIES_UNKNOWN',
       'CRASH_HOUR', 'CRASH_DAY_OF_WEEK', 'CRASH_MONTH',
       #'LATITUDE', 'LONGITUDE', 'LOCATION'
       ]].copy()
```

In [100]:
```python
# Show selected Independent Training dataset columns
X_train_selected.columns
```

Out[100]:
```
Index(['WEATHER_CONDITION', 'LIGHTING_CONDITION', 'ALIGNMENT',
       'ROADWAY_SURFACE_COND', 'ROAD_DEFECT', 'DAMAGE', 'STREET_NO',
       'STREET_NAME', 'NUM_UNITS', 'CRASH_HOUR', 'CRASH_DAY_OF_WEEK',
       'CRASH_MONTH'],
      dtype='object')
```

In [101]:
```python
# Show selected Independent Testing dataset columns
X_test_selected.columns
```

Out[101]:
```
Index(['WEATHER_CONDITION', 'LIGHTING_CONDITION', 'ALIGNMENT',
       'ROADWAY_SURFACE_COND', 'ROAD_DEFECT', 'DAMAGE', 'STREET_NO',
       'STREET_NAME', 'NUM_UNITS', 'CRASH_HOUR', 'CRASH_DAY_OF_WEEK',
       'CRASH_MONTH'],
      dtype='object')
```

- The dataset had the extensive information with over 40 features to selct from. As most features are categorical, the number of units were selected with the consideration most common known causes of accidents i.e speeding,road conditions, visibity due to time of day, weather condtions or other obstrustions, intoxication e.t.c, and the features available that can predict accident type.
- if results using the selected features are unsubstancial, other features can be included and note if performance improves

Exploratory data analysis (EDA)

In [102]:
```
# Check missing values in Predictor training variables
X_train_selected.isna().sum()
```

Out[102]:
```
WEATHER_CONDITION       0
LIGHTING_CONDITION      0
ALIGNMENT               0
ROADWAY_SURFACE_COND    0
ROAD_DEFECT             0
DAMAGE                  0
STREET_NO               0
STREET_NAME             1
NUM_UNITS               0
CRASH_HOUR              0
CRASH_DAY_OF_WEEK       0
CRASH_MONTH             0
dtype: int64
```

> one missing a value in the STREET_NAME column in the training columns

In [103]:
```
# Check missing values in Predictor testing variables
X_test_selected.isna().sum()
```

Out[103]:
```
WEATHER_CONDITION       0
LIGHTING_CONDITION      0
ALIGNMENT               0
ROADWAY_SURFACE_COND    0
ROAD_DEFECT             0
DAMAGE                  0
STREET_NO               0
STREET_NAME             0
NUM_UNITS               0
CRASH_HOUR              0
CRASH_DAY_OF_WEEK       0
CRASH_MONTH             0
dtype: int64
```

In [104]:
```
# Check missing values in Target training variables
y_train.isna().sum()
```

Out[104]:
```
0
```

In [105]:
```
# Check missing values in Target testing variables
y_test.isna().sum()
```

Out[105]:
```
0
```

In [106]:
```
#Check cardinality in missing value feature
X_train_selected['STREET_NAME'].unique()
```

Out[106]:
```
array(['ABERDEEN ST', 'CICERO AVE', 'HOLLYWOOD AVE', ..., 'CLARK',
       'I57 EXPY OB', 'STONE ST'], dtype=object)
```

> it is noted that this feature, 'STREET_NAME', has high cadinality

Handling Missing value

In [107]:
```
# lets fill the missing value in the Street name column with the mode.
X_train_selected['STREET_NAME'] = X_train_selected['STREET_NAME'].fillna(X_train_selected['STREET_NAME'].mode()[
```

In [108]:
```
#check for missing values
X_train_selected.isnull().sum()
```

Out[108]:
```
WEATHER_CONDITION       0
LIGHTING_CONDITION      0
ALIGNMENT               0
ROADWAY_SURFACE_COND    0
ROAD_DEFECT             0
DAMAGE                  0
STREET_NO               0
STREET_NAME             0
NUM_UNITS               0
CRASH_HOUR              0
CRASH_DAY_OF_WEEK       0
CRASH_MONTH             0
dtype: int64
```

No null values found

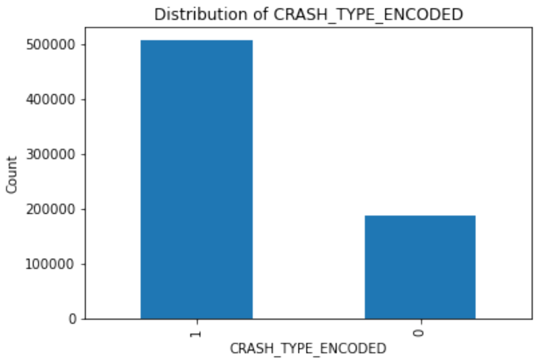
Univariate Analysis

Target Variable Analysis

In [109]:
```
# Check imbalance in target training dataset
y_train.value_counts()
```

Out[109]:
```
1    506983
0    186145
Name: CRASH_TYPE_ENCODED, dtype: int64
```

In [110]:
```
# Visualize the distribution of the target variable.
y_train.value_counts().plot(kind='bar', title='Distribution of CRASH_TYPE_ENCODED')
plt.xlabel('CRASH_TYPE_ENCODED')
plt.ylabel('Count')
plt.show()
```



In [111]:
```
# Check target class imbalance by the ratio.
imbalance_ratio = y_train.value_counts(normalize=True)
print(imbalance_ratio)
```

```
1    0.731442
0    0.268558
Name: CRASH_TYPE_ENCODED, dtype: float64
```

The Target dataset has high imbalance which can have a complex implications in our dataset.

Independent Variable Analysis

In [112]:
```
# Check independent training dataset
X_train_selected
```

Out[112]:

	WEATHER_CONDITION	LIGHTING_CONDITION	ALIGNMENT	ROADWAY_SURFACE_COND	ROAD_DEFECT	DAMAGE	STREET_NO	STREET_NAME
212995	CLEAR	DAWN	STRAIGHT AND LEVEL	DRY	NO DEFECTS	OVER $1,500	8700	ABERDEEN ST
407508	CLEAR	DUSK	STRAIGHT AND LEVEL	WET	NO DEFECTS	OVER $1,500	1200	CICERO AVE
38450	CLEAR	DAYLIGHT	STRAIGHT AND LEVEL	SNOW OR SLUSH	NO DEFECTS	OVER $1,500	1216	HOLLYWOOD AVE
104223	CLEAR	DAYLIGHT	STRAIGHT AND LEVEL	DRY	NO DEFECTS	OVER $1,500	1800	HASTINGS ST
442570	CLEAR	DAYLIGHT	STRAIGHT AND LEVEL	DRY	UNKNOWN	$500 OR LESS	4701	KEDZIE AVE
...	...	...	...	...	...	...	...	...
259178	CLEAR	DAYLIGHT	STRAIGHT AND LEVEL	DRY	NO DEFECTS	$500 OR LESS	8900	JEFFERY BLVD
365838	CLEAR	DARKNESS, LIGHTED ROAD	STRAIGHT AND LEVEL	WET	NO DEFECTS	501 – 1,500	2007	71ST ST
131932	CLEAR	DAYLIGHT	STRAIGHT AND LEVEL	DRY	NO DEFECTS	501 – 1,500	800	BLACKHAWK ST
671155	CLEAR	DAYLIGHT	STRAIGHT AND LEVEL	DRY	NO DEFECTS	OVER $1,500	735	STATE ST
121958	CLEAR	DAYLIGHT	STRAIGHT AND LEVEL	DRY	NO DEFECTS	501 – 1,500	400	WACKER DR

693128 rows × 12 columns

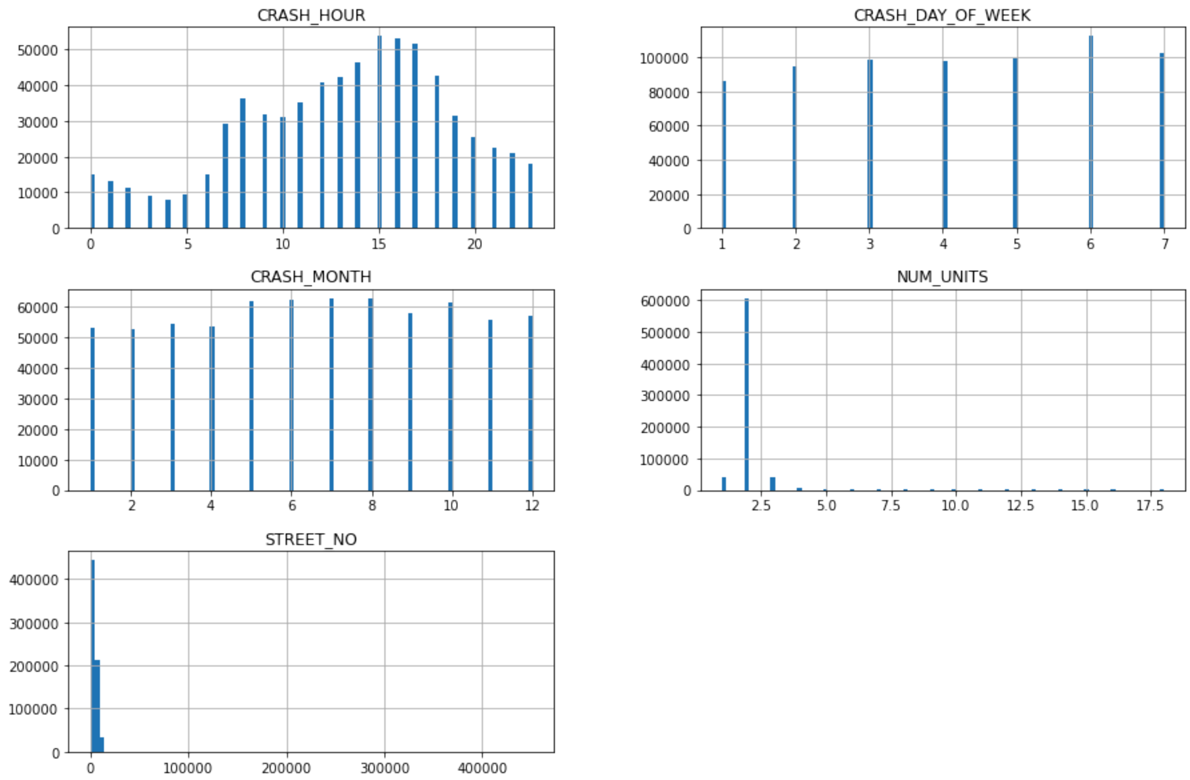
In [113]:
```
# Determine the mode and count of unique values
for col in X_train_selected:
    mode = X_train_selected[col].mode()[0]
    unique_vals = X_train_selected[col].nunique()
    print(f'{col}: Mode = {mode}, Unique Values = {unique_vals}')
```

```
WEATHER_CONDITION: Mode = CLEAR, Unique Values = 12
LIGHTING_CONDITION: Mode = DAYLIGHT, Unique Values = 6
ALIGNMENT: Mode = STRAIGHT AND LEVEL, Unique Values = 6
ROADWAY_SURFACE_COND: Mode = DRY, Unique Values = 7
ROAD_DEFECT: Mode = NO DEFECTS, Unique Values = 7
DAMAGE: Mode = OVER $1,500, Unique Values = 3
STREET_NO: Mode = 1600, Unique Values = 11559
STREET_NAME: Mode = WESTERN AVE, Unique Values = 1617
NUM_UNITS: Mode = 2, Unique Values = 17
CRASH_HOUR: Mode = 15, Unique Values = 24
CRASH_DAY_OF_WEEK: Mode = 6, Unique Values = 7
CRASH_MONTH: Mode = 7, Unique Values = 12
```

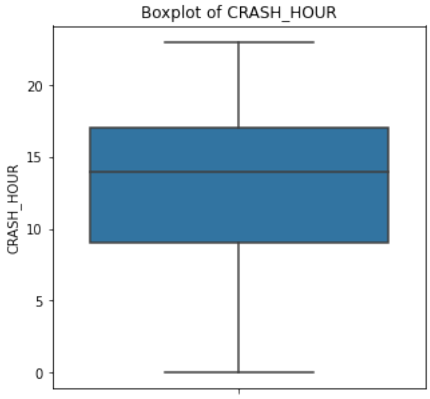
As Noted all categorical features identified by object and numerical identified by int64. analysis was done for numerical and categorical features to identify distribution, correlation and outliers for numerical and how each feature can be encoded to get optimal model output

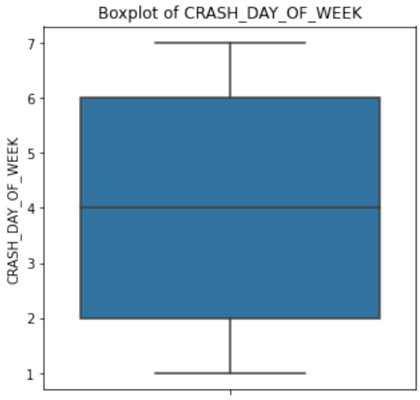
Numerical Features

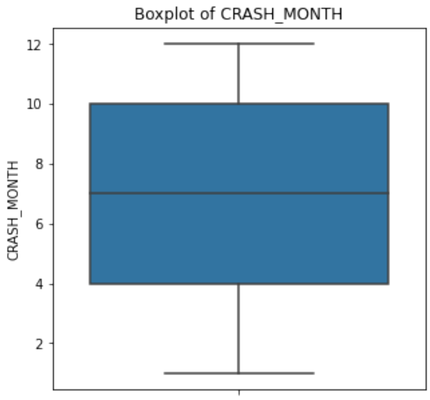
In [114]:
```
# Identify the distribution
numerical_columns = [ 'CRASH_HOUR', 'CRASH_DAY_OF_WEEK', 'CRASH_MONTH', 'NUM_UNITS','STREET_NO']

X_train_selected[numerical_columns].hist(bins=100, figsize=(15, 10))
plt.show()
```

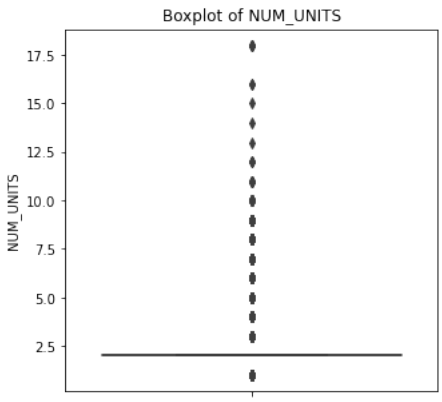


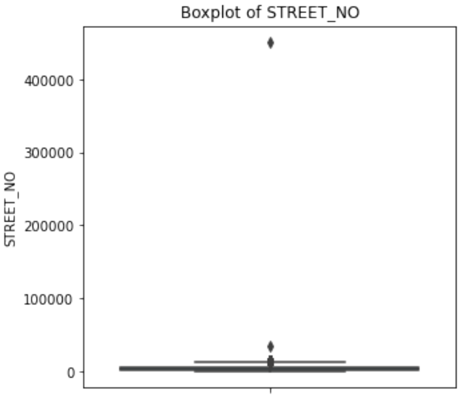
In [115]:
```
# Identify the outliers
for col in numerical_columns:
    plt.figure(figsize=(5, 5))
    sns.boxplot(y=X_train_selected[col])
    plt.title(f'Boxplot of {col}')
    plt.show()
```











Ouliers identified in NUM_STREETS AND STREET_NO due to the high cardinalty in these columns

In [116]:
```
# Identify percentage distribution of each unique values
for col in numerical_columns:
    print(X_train_selected[col].value_counts(normalize=True) * 100)
```

```
15    7.754845
16    7.649958
17    7.436289
14    6.677122
18    6.132634
13    6.080984
12    5.878279
8     5.249247
11    5.070203
9     4.596265
19    4.544904
10    4.509412
7     4.190568
20    3.659353
21    3.273133
22    3.032485
23    2.610052
0     2.175933
6     2.164102
1     1.874690
2     1.607784
5     1.371464
3     1.303367
4     1.156929
Name: CRASH_HOUR, dtype: float64
6    16.227306
7    14.851514
5    14.343527
3    14.220029
4    14.181363
2    13.730509
1    12.445753
Name: CRASH_DAY_OF_WEEK, dtype: float64
7     9.035272
8     9.019402
6     8.969628
5     8.914804
10    8.853920
9     8.345933
12    8.184491
11    8.008189
3     7.820345
4     7.670733
1     7.623700
2     7.553583
Name: CRASH_MONTH, dtype: float64
2     87.542705
3      5.514277
1      5.497542
4      1.061997
5      0.261279
6      0.074878
7      0.026691
8      0.011109
9      0.004761
10     0.002020
11     0.000866
18     0.000721
12     0.000433
16     0.000289
13     0.000144
14     0.000144
15     0.000144
Name: NUM_UNITS, dtype: float64
1600     0.637833
100      0.596571
800      0.580557
200      0.560647
2400     0.493560
           ...
6896     0.000144
8897     0.000144
11169    0.000144
13507    0.000144
5188     0.000144
Name: STREET_NO, Length: 11559, dtype: float64
```

In [117]:
```
# Identify occurrences in unique values
for col in numerical_columns:
    print(X_train_selected[col].value_counts())

# features with high cardinalty could be viewed easily by creating a csv file with the column
# We can create a csv file to view the columns with high cardinality
# X_train_selected['STREET_NO'].value_counts().to_csv('street_no_train_counts.csv')
```

```
15    53751
16    53024
17    51543
14    46281
18    42507
13    42149
12    40744
8     36384
11    35143
9     31858
19    31502
10    31256
7     29046
20    25364
21    22687
22    21019
23    18091
0     15082
6     15000
1     12994
2     11144
5      9506
3      9034
4      8019
Name: CRASH_HOUR, dtype: int64
6    112476
7    102940
5     99419
3     98563
4     98295
2     95170
1     86265
Name: CRASH_DAY_OF_WEEK, dtype: int64
7     62626
8     62516
6     62171
5     61791
10    61369
9     57848
12    56729
11    55507
3     54205
4     53168
1     52842
2     52356
Name: CRASH_MONTH, dtype: int64
2     606783
3      38221
1      38105
4       7361
5       1811
6        519
7        185
8         77
9         33
10        14
11         6
18         5
12         3
16         2
13         1
14         1
15         1
Name: NUM_UNITS, dtype: int64
1600     4421
100      4135
800      4024
200      3886
2400     3421
         ...
6896        1
8897        1
11169       1
13507       1
5188        1
Name: STREET_NO, Length: 11559, dtype: int64
```

Steps taken for numerical data

STREET_NO

- This column has high cardinalty with outliers and over 11000 unique values. We will work with our models as is for this column and see how it will affect our model and how we can adjust feature for optimal output

NUM_UNITS

- this column contains number of units in a crash. As I believe to impact the predictive nature of our models, though it contains outliers
- use the values as is for the baseline Logistic Regression Model and initial decision tree and Gradient Descent Models
- `Binning` : This will be used in the 1st iterations of Logistic regression, Decision Tree and Gradient Descent.For the Bin we will use `1,2,3, and >3` as for our analysis since the data is left skewed

CRASH_HOUR

- for this is hour itself represents numerical values it can remain as is for all iterations.

CRASH_DAY_OF_WEEK & **CRASH_MONTH**

- As the format is interger we can use `maping` in model representation to explore results of modelling, but like the hour column we will use as is for analysis

Encoding Numerical features

In [118]:
```
# Independent training dataset data types
X_train_selected.dtypes
```

Out[118]:
```
WEATHER_CONDITION       object
LIGHTING_CONDITION      object
ALIGNMENT               object
ROADWAY_SURFACE_COND    object
ROAD_DEFECT             object
DAMAGE                  object
STREET_NO                int64
STREET_NAME             object
NUM_UNITS                int64
CRASH_HOUR               int64
CRASH_DAY_OF_WEEK        int64
CRASH_MONTH              int64
dtype: object
```

In [119]:
```
# Identify missing values in numerical features
print(X_train_selected['CRASH_HOUR'].isnull().sum())
print(X_train_selected['CRASH_DAY_OF_WEEK'].isnull().sum())
print(X_train_selected['CRASH_MONTH'].isnull().sum())
print(X_train_selected['NUM_UNITS'].isnull().sum())
print(X_train_selected['STREET_NO'].isnull().sum())
```

```
0
0
0
0
0
```

In [120]:
```
# Identify unique values in numerical features
print(X_train_selected['CRASH_HOUR'].unique())
print(X_train_selected['CRASH_DAY_OF_WEEK'].unique())
print(X_train_selected['CRASH_MONTH'].unique())
print(X_train_selected['NUM_UNITS'].unique())
print(X_train_selected['STREET_NO'].unique())
```

```
[ 6  3 14 13 18 16 20 15  5 19 17  8 11  7  1 10 23 21  9 12 22  2  4  0]
[7 1 3 2 6 4 5]
[ 9  1  3  6 10  4  8 11  7  5  2 12]
[ 2  3  4  1  5  6  7 18  9 10 12  8 13 11 16 14 15]
[ 8700  1200  1216 ... 12546  8394 12920]
```

In [121]:
```
# Let's make a copy of the the data for encoding and binning
X_train_encoded = X_train_selected.copy()
X_test_encoded = X_test_selected.copy()

month_mapping = {1:'January', 2:'February', 3:'March',
                 4:'April', 5:'May', 6:'June',
                 7:'July', 8:'August', 9:'September',
                 10:'October', 11:'November', 12:'December'}

day_mapping = {1:'Sunday',
               2:'Monday',
               3:'Tuesday',
               4:'Wednesday',
               5:'Thursday',
               6:'Friday',
               7:'Saturday'}

# encode the training dataset
X_train_encoded['CRASH_MONTH'] = X_train_encoded['CRASH_MONTH'].map(month_mapping)
X_train_encoded['CRASH_DAY_OF_WEEK'] = X_train_encoded['CRASH_DAY_OF_WEEK'].map(day_mapping)

# encode the testing dataset
X_test_encoded['CRASH_MONTH'] = X_test_encoded['CRASH_MONTH'].map(month_mapping)
X_test_encoded['CRASH_DAY_OF_WEEK'] = X_test_encoded['CRASH_DAY_OF_WEEK'].map(day_mapping)

bins = [0,1, 2, 3, X_train_selected['NUM_UNITS'].max()]
labels = ['Single Unit', 'Two Units', 'Three Units','Multiple Units']
X_train_encoded['NUM_UNITS_BINNED'] = pd.cut(X_train_encoded['NUM_UNITS'], bins=bins, labels=labels, include_low
X_test_encoded['NUM_UNITS_BINNED'] = pd.cut(X_test_encoded['NUM_UNITS'], bins=bins, labels=labels, include_lowes

# Check the results
print(X_train_encoded.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 693128 entries, 212995 to 121958
Data columns (total 13 columns):
 #   Column                Non-Null Count   Dtype   
---  ------                --------------   -----   
 0   WEATHER_CONDITION     693128 non-null  object  
 1   LIGHTING_CONDITION    693128 non-null  object  
 2   ALIGNMENT             693128 non-null  object  
 3   ROADWAY_SURFACE_COND  693128 non-null  object  
 4   ROAD_DEFECT           693128 non-null  object  
 5   DAMAGE                693128 non-null  object  
 6   STREET_NO             693128 non-null  int64   
 7   STREET_NAME           693128 non-null  object  
 8   NUM_UNITS             693128 non-null  int64   
 9   CRASH_HOUR            693128 non-null  int64   
 10  CRASH_DAY_OF_WEEK     693128 non-null  object  
 11  CRASH_MONTH           693128 non-null  object  
 12  NUM_UNITS_BINNED      693128 non-null  category
dtypes: category(1), int64(3), object(9)
memory usage: 69.4+ MB
None
```

In [122]:
```
# Encoded training data first 5...
X_train_encoded.head()
```

Out[122]:

	WEATHER_CONDITION	LIGHTING_CONDITION	ALIGNMENT	ROADWAY_SURFACE_COND	ROAD_DEFECT	DAMAGE	STREET_NO	STREET_NAME
212995	CLEAR	DAWN	STRAIGHT AND LEVEL	DRY	NO DEFECTS	OVER $1,500	8700	ABERDEEN ST
407508	CLEAR	DUSK	STRAIGHT AND LEVEL	WET	NO DEFECTS	OVER $1,500	1200	CICERO AVE
38450	CLEAR	DAYLIGHT	STRAIGHT AND LEVEL	SNOW OR SLUSH	NO DEFECTS	OVER $1,500	1216	HOLLYWOOD AVE
104223	CLEAR	DAYLIGHT	STRAIGHT AND LEVEL	DRY	NO DEFECTS	OVER $1,500	1800	HASTINGS ST
442570	CLEAR	DAYLIGHT	STRAIGHT AND LEVEL	DRY	UNKNOWN	$500 OR LESS	4701	KEDZIE AVE

In [123]:
```
# Check missing values in Encoded training data
X_train_encoded.isnull().sum()
```

Out[123]:
```
WEATHER_CONDITION       0
LIGHTING_CONDITION      0
ALIGNMENT               0
ROADWAY_SURFACE_COND    0
ROAD_DEFECT             0
DAMAGE                  0
STREET_NO               0
STREET_NAME             0
NUM_UNITS               0
CRASH_HOUR              0
CRASH_DAY_OF_WEEK       0
CRASH_MONTH             0
NUM_UNITS_BINNED        0
dtype: int64
```

In [124]:
```
# Encoded training data columns first 5
print(X_train_encoded['CRASH_DAY_OF_WEEK'].head())
print(X_train_encoded['CRASH_MONTH'].head())
print(X_train_encoded['NUM_UNITS_BINNED'].head())
```

```
212995    Saturday
407508    Saturday
38450       Sunday
104223     Tuesday
442570    Saturday
Name: CRASH_DAY_OF_WEEK, dtype: object
212995    September
407508      January
38450       January
104223    September
442570        March
Name: CRASH_MONTH, dtype: object
212995    Two Units
407508    Two Units
38450     Two Units
104223    Two Units
442570    Two Units
Name: NUM_UNITS_BINNED, dtype: category
Categories (4, object): ['Single Unit' < 'Two Units' < 'Three Units' < 'Multiple Units']
```

In [125]:
```
# Encoded testing Dataset data types
X_test_encoded.dtypes
```

Out[125]:
```
WEATHER_CONDITION         object
LIGHTING_CONDITION        object
ALIGNMENT                 object
ROADWAY_SURFACE_COND      object
ROAD_DEFECT               object
DAMAGE                    object
STREET_NO                  int64
STREET_NAME               object
NUM_UNITS                  int64
CRASH_HOUR                 int64
CRASH_DAY_OF_WEEK         object
CRASH_MONTH               object
NUM_UNITS_BINNED        category
dtype: object
```

In [126]:
```
# Encoded testing Dataset data first 5
X_test_encoded.head()
```

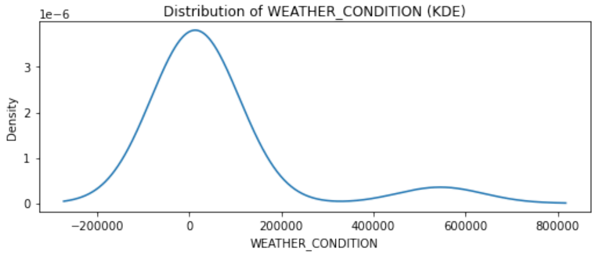
Out[126]:

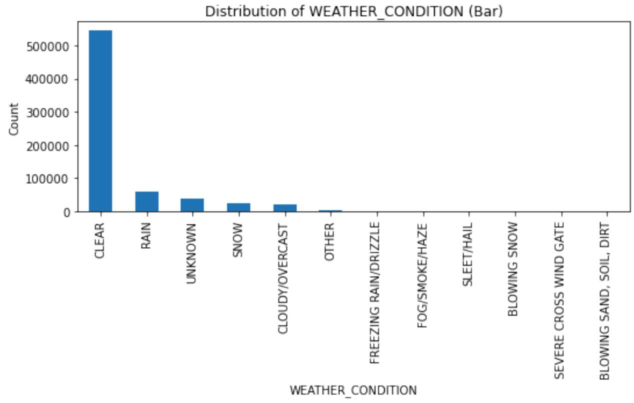
	WEATHER_CONDITION	LIGHTING_CONDITION	ALIGNMENT	ROADWAY_SURFACE_COND	ROAD_DEFECT	DAMAGE	STREET_NO	STREET_NAME
618541	CLEAR	DARKNESS	STRAIGHT AND LEVEL	DRY	NO DEFECTS	OVER $1,500	2932	FOSTER AVE
562247	CLEAR	DAYLIGHT	STRAIGHT AND LEVEL	DRY	NO DEFECTS	OVER $1,500	1900	LUMBER ST
224406	CLEAR	DUSK	STRAIGHT AND LEVEL	DRY	NO DEFECTS	501 – 1,500	5636	TROY ST
814994	CLEAR	DAYLIGHT	STRAIGHT AND LEVEL	DRY	UNKNOWN	501 – 1,500	10900	WENTWORTH AVE
500910	SNOW	DAYLIGHT	STRAIGHT AND LEVEL	SNOW OR SLUSH	NO DEFECTS	501 – 1,500	2217	KEDZIE AVE

The new X_train_encoded and X_test encoded were created for reference after modelling, we will keep the original selected columns for modelling.

Categorical Features

In [127]:
```
# Analyze and visualize the distribution of categorical features using bar plots
categorical_columns = ['WEATHER_CONDITION', 'LIGHTING_CONDITION', 'ALIGNMENT', 'ROADWAY_SURFACE_COND', 'ROAD_DEF

for col in categorical_columns:
  # Create a figure with two subplots
  fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(15, 5))

  # Plot KDE on the first subplot
  X_train_selected[col].value_counts().plot(kind='kde', ax=ax1)
  ax1.set_title(f'Distribution of {col} (KDE)')
  ax1.set_xlabel(col)
  ax1.set_ylabel('Density')

  # Plot bar chart on the second subplot
  X_train_selected[col].value_counts().plot(kind='bar', ax=ax2)
  ax2.set_title(f'Distribution of {col} (Bar)')
  ax2.set_xlabel(col)
  ax2.set_ylabel('Count')

  # Adjust layout and spacing
  plt.tight_layout()
  plt.show()
```





Distribution of LIGHTING_CONDITION (KDE) Distribution of LIGHTING_CONDITION (Bar)

In [128]:
```
# Examine the frequency percentage of each category within categorical features.
for col in categorical_columns:
    print(X_train_selected[col].value_counts(normalize=True) * 100)
```

```
CLEAR                        78.595296
RAIN                          8.721189
UNKNOWN                       5.616856
SNOW                          3.291167
CLOUDY/OVERCAST               2.926155
OTHER                         0.309755
FREEZING RAIN/DRIZZLE         0.197366
FOG/SMOKE/HAZE                0.156681
SLEET/HAIL                    0.117294
BLOWING SNOW                  0.049774
SEVERE CROSS WIND GATE        0.017601
BLOWING SAND, SOIL, DIRT      0.000866
Name: WEATHER_CONDITION, dtype: float64
DAYLIGHT                   64.309478
DARKNESS, LIGHTED ROAD     21.831033
DARKNESS                    4.701440
UNKNOWN                     4.634065
DUSK                        2.850123
DAWN                        1.673861
Name: LIGHTING_CONDITION, dtype: float64
STRAIGHT AND LEVEL       97.611697
STRAIGHT ON GRADE         1.229499
CURVE, LEVEL              0.709104
STRAIGHT ON HILLCREST     0.254354
CURVE ON GRADE            0.151487
CURVE ON HILLCREST        0.043859
Name: ALIGNMENT, dtype: float64
DRY                73.898328
WET                13.196264
UNKNOWN             8.704164
SNOW OR SLUSH       3.266785
ICE                 0.646778
OTHER               0.250026
SAND, MUD, DIRT     0.037655
Name: ROADWAY_SURFACE_COND, dtype: float64
NO DEFECTS           80.008166
UNKNOWN              18.068813
RUT, HOLES            0.716462
OTHER                 0.545065
WORN SURFACE          0.408438
SHOULDER DEFECT       0.178322
DEBRIS ON ROADWAY     0.074734
Name: ROAD_DEFECT, dtype: float64
OVER $1,500      62.610225
$501 - $1,500    26.081186
$500 OR LESS     11.308589
Name: DAMAGE, dtype: float64
WESTERN AVE              2.732973
PULASKI RD               2.421775
CICERO AVE               2.235085
ASHLAND AVE              2.165257
HALSTED ST               1.939180
                           ...
UNKNOWN                  0.000144
THOMPSON DR              0.000144
STAGING AREA E ST        0.000144
NAPOLEON AVE             0.000144
LOWER WACKER RAMP DR     0.000144
Name: STREET_NAME, Length: 1617, dtype: float64
```

In [129]:
```
# Independent training dataset data types
X_train_selected.dtypes
```

Out[129]:
```
WEATHER_CONDITION       object
LIGHTING_CONDITION      object
ALIGNMENT               object
ROADWAY_SURFACE_COND    object
ROAD_DEFECT             object
DAMAGE                  object
STREET_NO                int64
STREET_NAME             object
NUM_UNITS                int64
CRASH_HOUR               int64
CRASH_DAY_OF_WEEK        int64
CRASH_MONTH              int64
dtype: object
```

In [130]:
```
# Value count for categorical columns in selected training datset
for col in categorical_columns:
    print(X_train_selected[col].value_counts())

# features with high cardinalty could be viewed easily by creating a csv file with the column
# We can create a csv file to view the columns with high cardinality
# X_train_selected['STREET_NAME'].value_counts().to_csv('street_name_train_counts.csv')
```

```
CLEAR                         544766
RAIN                           60449
UNKNOWN                        38932
SNOW                           22812
CLOUDY/OVERCAST                20282
OTHER                           2147
FREEZING RAIN/DRIZZLE           1368
FOG/SMOKE/HAZE                  1086
SLEET/HAIL                       813
BLOWING SNOW                     345
SEVERE CROSS WIND GATE           122
BLOWING SAND, SOIL, DIRT           6
Name: WEATHER_CONDITION, dtype: int64
DAYLIGHT                  445747
DARKNESS, LIGHTED ROAD    151317
DARKNESS                   32587
UNKNOWN                    32120
DUSK                       19755
DAWN                       11602
Name: LIGHTING_CONDITION, dtype: int64
STRAIGHT AND LEVEL       676574
STRAIGHT ON GRADE          8522
CURVE, LEVEL               4915
STRAIGHT ON HILLCREST      1763
CURVE ON GRADE             1050
CURVE ON HILLCREST          304
Name: ALIGNMENT, dtype: int64
DRY                512210
WET                 91467
UNKNOWN             60331
SNOW OR SLUSH       22643
ICE                  4483
OTHER                1733
SAND, MUD, DIRT       261
Name: ROADWAY_SURFACE_COND, dtype: int64
NO DEFECTS           554559
UNKNOWN              125240
RUT, HOLES             4966
OTHER                  3778
WORN SURFACE           2831
SHOULDER DEFECT        1236
DEBRIS ON ROADWAY       518
Name: ROAD_DEFECT, dtype: int64
OVER $1,500      433969
$501 - $1,500    180776
$500 OR LESS      78383
Name: DAMAGE, dtype: int64
WESTERN AVE             18943
PULASKI RD              16786
CICERO AVE              15492
ASHLAND AVE             15008
HALSTED ST              13441
                        ...
UNKNOWN                     1
THOMPSON DR                 1
STAGING AREA E ST           1
NAPOLEON AVE                1
LOWER WACKER RAMP DR        1
Name: STREET_NAME, Length: 1617, dtype: int64
```

Steps taken for categorical data

STREET_NAME

- This column has high cardinality with the large number of street name identified with accidents, and is skewed to the left. `Frequency encoding` seems to be feasible for this analysis.
- *DAMAGE**
- Since DAMAGE is ordinal, `ordinal encoding` would be appropriate to maintain the natural order.

ROAD_DEFECT

- for this column `one hot encoding` will be the most feasible option with this column as well. The data seems skewed with No Defects and unknown taking the most counts followed few rare categories
- For our alternate iteration we will group into 3 rare groups `No Defects, Unknown and Other defects` , for model improvement

ROADWAY_SURFACE_COND

- This feature has no inherent order with dry being a dominate value in the column, with wet also shows having some significant impact compared to snow or lush and unknown. `one hot encoding` seems to be the most feasable option

- For our second iteration we could group into 4 rare categories; `Dry, Wet, Unknown and other` , and see the impact on our models
- *ALIGNMENT**
- Highly imbalaced feature that clould lead to model bias if not addressed.
- For this column, first, we will `one hot encode` and see how the distribution affects the model.
- Secondly, we will group into 2 rare categories; `straight and curve` , and check on the 1st iteration of our models.

LIGHTING_CONDITION

- For this feature we will use `one hot encoding` for the model instace to view the impact.
- For the iteration we will also group into 5 categories; `DAYLIGHT,DARKNESS, LIGHTED ROAD DARKNESS, UNKNOWN and Other.`

WEATHER_CONDITION

- For this feature we will use `one hot encoding` for the model instace to view the impact.
- For the iteration we will also group into 6 categories; `CLEAR,RAIN,UNKNOWN,SNOW,OVERCAST and OTHER`

- > Most Features will use `one hot encoding` for analysis, only *STREET NAME* will use `frequency encoding` , while we will use `ordinal` encoding for the *DAMAGES* column

- > Most columns have unknown values that has been considered as a category.

Encoding categorical features

In [131]:
```python
# create a dataset to  encode
X_train_cat_encoded= X_train_selected.copy()
X_test_cat_encoded = X_test_selected.copy()

# One Hot Encoding for Categorical Features
categorical_ohe_columns = ['WEATHER_CONDITION', 'LIGHTING_CONDITION', 'ALIGNMENT',
                       'ROADWAY_SURFACE_COND', 'ROAD_DEFECT',]

# Initialize OneHotEncoder
encoder = OneHotEncoder(handle_unknown='ignore',sparse=False)

# Fit the data
X_train_encoded = encoder.fit(X_train_cat_encoded[categorical_ohe_columns])

# Transform the test data
X_train_encoded = encoder.transform(X_train_cat_encoded[categorical_ohe_columns])
X_test_encoded = encoder.transform(X_test_cat_encoded[categorical_ohe_columns])

# Take column names to use in encoded data
feature_names = []
for col in categorical_ohe_columns:
    feature_names.extend([f"{col}_{val}" for val in encoder.categories_[categorical_ohe_columns.index(col)]])

# Convert to DataFrame
X_train_encoded_df = pd.DataFrame(X_train_encoded, columns=feature_names, index=X_train_cat_encoded.index)
X_test_encoded_df = pd.DataFrame(X_test_encoded, columns=feature_names, index=X_test_cat_encoded.index)


# Concatenate the encoded columns with the original dataframe (excluding the original categorical columns)
X_train_cat_encoded = pd.concat([X_train_cat_encoded.drop(columns=categorical_ohe_columns),
                                  X_train_encoded_df], axis=1)
X_test_cat_encoded = pd.concat([X_test_cat_encoded.drop(columns=categorical_ohe_columns),
                                 X_test_encoded_df], axis=1)

# Frequency Encoding for 'STREET_NAME'
street_freq = X_train_selected['STREET_NAME'].value_counts(normalize=True)

# Map frequencies to the train and test sets
X_train_cat_encoded['STREET_NAME_FREQ'] = X_train_selected['STREET_NAME'].map(street_freq)
X_test_cat_encoded['STREET_NAME_FREQ'] = X_test_selected['STREET_NAME'].map(street_freq)

# Handle unknown categories by filling NaN with a default value (e.g., 0)
X_train_cat_encoded['STREET_NAME_FREQ'].fillna(0, inplace=True)
X_test_cat_encoded['STREET_NAME_FREQ'].fillna(0, inplace=True)

# Drop the original 'STREET_NAME' column after encoding
X_train_cat_encoded = X_train_cat_encoded.drop(columns=['STREET_NAME'])
X_test_cat_encoded = X_test_cat_encoded.drop(columns=['STREET_NAME'])

# lets also map the damages column
damage_mapping = {'$500 OR LESS': 1, '$501 - $1,500': 2, 'OVER $1,500': 3}
X_train_cat_encoded['DAMAGE'] = X_train_cat_encoded['DAMAGE'].map(damage_mapping)
X_test_cat_encoded['DAMAGE'] = X_test_cat_encoded['DAMAGE'].map(damage_mapping)

# Checking for missing values
print(X_train_cat_encoded.isnull().sum())
```

```
DAMAGE                                      0
STREET_NO                                   0
NUM_UNITS                                   0
CRASH_HOUR                                  0
CRASH_DAY_OF_WEEK                           0
CRASH_MONTH                                 0
WEATHER_CONDITION_BLOWING SAND, SOIL, DIRT  0
WEATHER_CONDITION_BLOWING SNOW              0
WEATHER_CONDITION_CLEAR                     0
WEATHER_CONDITION_CLOUDY/OVERCAST           0
WEATHER_CONDITION_FOG/SMOKE/HAZE            0
WEATHER_CONDITION_FREEZING RAIN/DRIZZLE     0
WEATHER_CONDITION_OTHER                     0
WEATHER_CONDITION_RAIN                      0
WEATHER_CONDITION_SEVERE CROSS WIND GATE    0
WEATHER_CONDITION_SLEET/HAIL                0
WEATHER_CONDITION_SNOW                      0
WEATHER_CONDITION_UNKNOWN                   0
LIGHTING_CONDITION_DARKNESS                 0
LIGHTING_CONDITION_DARKNESS, LIGHTED ROAD   0
LIGHTING_CONDITION_DAWN                     0
LIGHTING_CONDITION_DAYLIGHT                 0
LIGHTING_CONDITION_DUSK                     0
LIGHTING_CONDITION_UNKNOWN                  0
ALIGNMENT_CURVE ON GRADE                    0
ALIGNMENT_CURVE ON HILLCREST                0
ALIGNMENT_CURVE, LEVEL                      0
ALIGNMENT_STRAIGHT AND LEVEL                0
ALIGNMENT_STRAIGHT ON GRADE                 0
ALIGNMENT_STRAIGHT ON HILLCREST             0
ROADWAY_SURFACE_COND_DRY                    0
ROADWAY_SURFACE_COND_ICE                    0
ROADWAY_SURFACE_COND_OTHER                  0
ROADWAY_SURFACE_COND_SAND, MUD, DIRT        0
ROADWAY_SURFACE_COND_SNOW OR SLUSH          0
ROADWAY_SURFACE_COND_UNKNOWN                0
ROADWAY_SURFACE_COND_WET                    0
ROAD_DEFECT_DEBRIS ON ROADWAY               0
ROAD_DEFECT_NO DEFECTS                      0
ROAD_DEFECT_OTHER                           0
ROAD_DEFECT_RUT, HOLES                      0
ROAD_DEFECT_SHOULDER DEFECT                 0
ROAD_DEFECT_UNKNOWN                         0
ROAD_DEFECT_WORN SURFACE                    0
STREET_NAME_FREQ                            0
dtype: int64
```

In [132]:
```
# Checking for missing values in encoded testing data
print(X_test_cat_encoded.isnull().sum())
```

```
DAMAGE                                      0
STREET_NO                                   0
NUM_UNITS                                   0
CRASH_HOUR                                  0
CRASH_DAY_OF_WEEK                           0
CRASH_MONTH                                 0
WEATHER_CONDITION_BLOWING SAND, SOIL, DIRT    0
WEATHER_CONDITION_BLOWING SNOW              0
WEATHER_CONDITION_CLEAR                     0
WEATHER_CONDITION_CLOUDY/OVERCAST           0
WEATHER_CONDITION_FOG/SMOKE/HAZE            0
WEATHER_CONDITION_FREEZING RAIN/DRIZZLE     0
WEATHER_CONDITION_OTHER                     0
WEATHER_CONDITION_RAIN                      0
WEATHER_CONDITION_SEVERE CROSS WIND GATE    0
WEATHER_CONDITION_SLEET/HAIL                0
WEATHER_CONDITION_SNOW                      0
WEATHER_CONDITION_UNKNOWN                   0
LIGHTING_CONDITION_DARKNESS                 0
LIGHTING_CONDITION_DARKNESS, LIGHTED ROAD    0
LIGHTING_CONDITION_DAWN                     0
LIGHTING_CONDITION_DAYLIGHT                 0
LIGHTING_CONDITION_DUSK                     0
LIGHTING_CONDITION_UNKNOWN                  0
ALIGNMENT_CURVE ON GRADE                    0
ALIGNMENT_CURVE ON HILLCREST                0
ALIGNMENT_CURVE, LEVEL                      0
ALIGNMENT_STRAIGHT AND LEVEL                0
ALIGNMENT_STRAIGHT ON GRADE                 0
ALIGNMENT_STRAIGHT ON HILLCREST             0
ROADWAY_SURFACE_COND_DRY                    0
ROADWAY_SURFACE_COND_ICE                    0
ROADWAY_SURFACE_COND_OTHER                  0
ROADWAY_SURFACE_COND_SAND, MUD, DIRT        0
ROADWAY_SURFACE_COND_SNOW OR SLUSH          0
ROADWAY_SURFACE_COND_UNKNOWN                0
ROADWAY_SURFACE_COND_WET                    0
ROAD_DEFECT_DEBRIS ON ROADWAY               0
ROAD_DEFECT_NO DEFECTS                      0
ROAD_DEFECT_OTHER                           0
ROAD_DEFECT_RUT, HOLES                      0
ROAD_DEFECT_SHOULDER DEFECT                 0
ROAD_DEFECT_UNKNOWN                         0
ROAD_DEFECT_WORN SURFACE                    0
STREET_NAME_FREQ                            0
dtype: int64
```

In [133]:
```
# Checking datatype in encoded training data
X_train_cat_encoded.dtypes
```

Out[133]:
```
DAMAGE                                         int64
STREET_NO                                      int64
NUM_UNITS                                      int64
CRASH_HOUR                                     int64
CRASH_DAY_OF_WEEK                              int64
CRASH_MONTH                                    int64
WEATHER_CONDITION_BLOWING SAND, SOIL, DIRT    float64
WEATHER_CONDITION_BLOWING SNOW                float64
WEATHER_CONDITION_CLEAR                       float64
WEATHER_CONDITION_CLOUDY/OVERCAST             float64
WEATHER_CONDITION_FOG/SMOKE/HAZE              float64
WEATHER_CONDITION_FREEZING RAIN/DRIZZLE       float64
WEATHER_CONDITION_OTHER                       float64
WEATHER_CONDITION_RAIN                        float64
WEATHER_CONDITION_SEVERE CROSS WIND GATE      float64
WEATHER_CONDITION_SLEET/HAIL                  float64
WEATHER_CONDITION_SNOW                        float64
WEATHER_CONDITION_UNKNOWN                     float64
LIGHTING_CONDITION_DARKNESS                   float64
LIGHTING_CONDITION_DARKNESS, LIGHTED ROAD     float64
LIGHTING_CONDITION_DAWN                       float64
LIGHTING_CONDITION_DAYLIGHT                   float64
LIGHTING_CONDITION_DUSK                       float64
LIGHTING_CONDITION_UNKNOWN                    float64
ALIGNMENT_CURVE ON GRADE                      float64
ALIGNMENT_CURVE ON HILLCREST                  float64
ALIGNMENT_CURVE, LEVEL                        float64
ALIGNMENT_STRAIGHT AND LEVEL                  float64
ALIGNMENT_STRAIGHT ON GRADE                   float64
ALIGNMENT_STRAIGHT ON HILLCREST               float64
ROADWAY_SURFACE_COND_DRY                      float64
ROADWAY_SURFACE_COND_ICE                      float64
ROADWAY_SURFACE_COND_OTHER                    float64
ROADWAY_SURFACE_COND_SAND, MUD, DIRT          float64
ROADWAY_SURFACE_COND_SNOW OR SLUSH            float64
ROADWAY_SURFACE_COND_UNKNOWN                  float64
ROADWAY_SURFACE_COND_WET                      float64
ROAD_DEFECT_DEBRIS ON ROADWAY                 float64
ROAD_DEFECT_NO DEFECTS                        float64
ROAD_DEFECT_OTHER                             float64
ROAD_DEFECT_RUT, HOLES                        float64
ROAD_DEFECT_SHOULDER DEFECT                   float64
ROAD_DEFECT_UNKNOWN                           float64
ROAD_DEFECT_WORN SURFACE                      float64
STREET_NAME_FREQ                              float64
dtype: object
```

In [134]:
```
# Checking datatype in encoded testing data
X_test_cat_encoded.dtypes
```

Out[134]:
```
DAMAGE                                        int64
STREET_NO                                     int64
NUM_UNITS                                     int64
CRASH_HOUR                                    int64
CRASH_DAY_OF_WEEK                             int64
CRASH_MONTH                                   int64
WEATHER_CONDITION_BLOWING SAND, SOIL, DIRT  float64
WEATHER_CONDITION_BLOWING SNOW              float64
WEATHER_CONDITION_CLEAR                     float64
WEATHER_CONDITION_CLOUDY/OVERCAST           float64
WEATHER_CONDITION_FOG/SMOKE/HAZE            float64
WEATHER_CONDITION_FREEZING RAIN/DRIZZLE     float64
WEATHER_CONDITION_OTHER                     float64
WEATHER_CONDITION_RAIN                      float64
WEATHER_CONDITION_SEVERE CROSS WIND GATE    float64
WEATHER_CONDITION_SLEET/HAIL                float64
WEATHER_CONDITION_SNOW                      float64
WEATHER_CONDITION_UNKNOWN                   float64
LIGHTING_CONDITION_DARKNESS                 float64
LIGHTING_CONDITION_DARKNESS, LIGHTED ROAD   float64
LIGHTING_CONDITION_DAWN                     float64
LIGHTING_CONDITION_DAYLIGHT                 float64
LIGHTING_CONDITION_DUSK                     float64
LIGHTING_CONDITION_UNKNOWN                  float64
ALIGNMENT_CURVE ON GRADE                    float64
ALIGNMENT_CURVE ON HILLCREST                float64
ALIGNMENT_CURVE, LEVEL                      float64
ALIGNMENT_STRAIGHT AND LEVEL                float64
ALIGNMENT_STRAIGHT ON GRADE                 float64
ALIGNMENT_STRAIGHT ON HILLCREST             float64
ROADWAY_SURFACE_COND_DRY                    float64
ROADWAY_SURFACE_COND_ICE                    float64
ROADWAY_SURFACE_COND_OTHER                  float64
ROADWAY_SURFACE_COND_SAND, MUD, DIRT        float64
ROADWAY_SURFACE_COND_SNOW OR SLUSH          float64
ROADWAY_SURFACE_COND_UNKNOWN                float64
ROADWAY_SURFACE_COND_WET                    float64
ROAD_DEFECT_DEBRIS ON ROADWAY               float64
ROAD_DEFECT_NO DEFECTS                      float64
ROAD_DEFECT_OTHER                           float64
ROAD_DEFECT_RUT, HOLES                      float64
ROAD_DEFECT_SHOULDER DEFECT                 float64
ROAD_DEFECT_UNKNOWN                         float64
ROAD_DEFECT_WORN SURFACE                    float64
STREET_NAME_FREQ                            float64
dtype: object
```

Bivariate Analysis

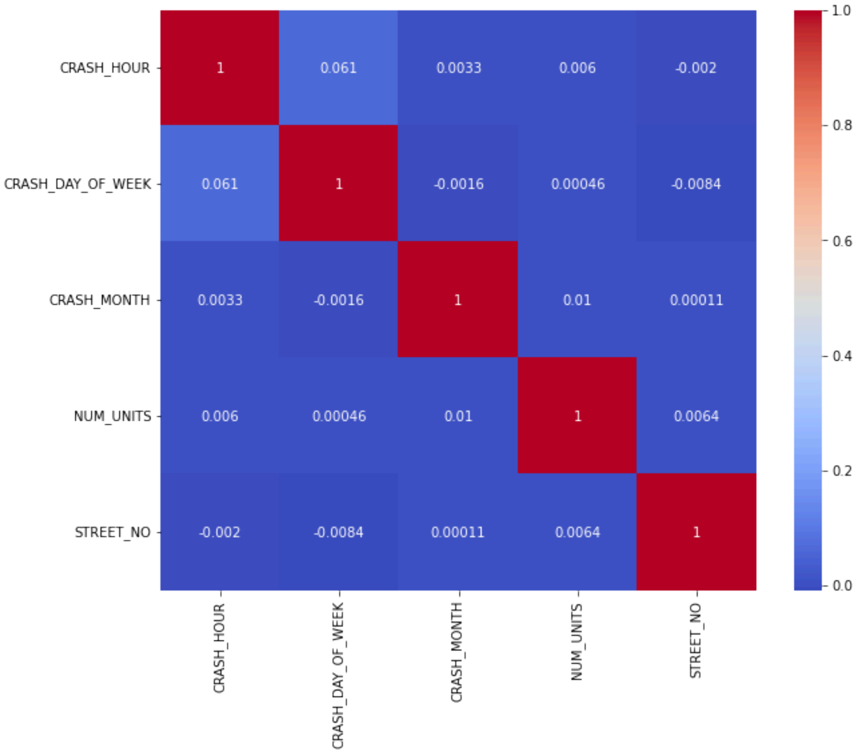
- We will use the categorical encoded dataset for this analysis. to compare the the analysis i.e X_train_cat_encoded and X_test_cat_encoded
- As the Independent univariate feature analysis, we will group the columns to numerical and categorical

In [135]:
```
# Add y_train to X_train_encoded for correlation analysis
# lets create a copy of the encoded X_Train
X_train_cat_encodedv1= X_train_cat_encoded.copy()

X_train_cat_encodedv1['target'] = y_train
print(X_train_cat_encodedv1.columns)
```

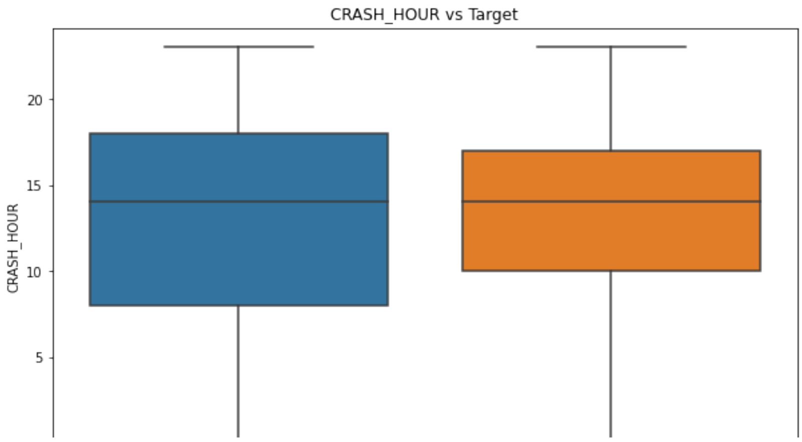
```
Index(['DAMAGE', 'STREET_NO', 'NUM_UNITS', 'CRASH_HOUR', 'CRASH_DAY_OF_WEEK',
       'CRASH_MONTH', 'WEATHER_CONDITION_BLOWING SAND, SOIL, DIRT',
       'WEATHER_CONDITION_BLOWING SNOW', 'WEATHER_CONDITION_CLEAR',
       'WEATHER_CONDITION_CLOUDY/OVERCAST', 'WEATHER_CONDITION_FOG/SMOKE/HAZE',
       'WEATHER_CONDITION_FREEZING RAIN/DRIZZLE', 'WEATHER_CONDITION_OTHER',
       'WEATHER_CONDITION_RAIN', 'WEATHER_CONDITION_SEVERE CROSS WIND GATE',
       'WEATHER_CONDITION_SLEET/HAIL', 'WEATHER_CONDITION_SNOW',
       'WEATHER_CONDITION_UNKNOWN', 'LIGHTING_CONDITION_DARKNESS',
       'LIGHTING_CONDITION_DARKNESS, LIGHTED ROAD', 'LIGHTING_CONDITION_DAWN',
       'LIGHTING_CONDITION_DAYLIGHT', 'LIGHTING_CONDITION_DUSK',
       'LIGHTING_CONDITION_UNKNOWN', 'ALIGNMENT_CURVE ON GRADE',
       'ALIGNMENT_CURVE ON HILLCREST', 'ALIGNMENT_CURVE, LEVEL',
       'ALIGNMENT_STRAIGHT AND LEVEL', 'ALIGNMENT_STRAIGHT ON GRADE',
       'ALIGNMENT_STRAIGHT ON HILLCREST', 'ROADWAY_SURFACE_COND_DRY',
       'ROADWAY_SURFACE_COND_ICE', 'ROADWAY_SURFACE_COND_OTHER',
       'ROADWAY_SURFACE_COND_SAND, MUD, DIRT',
       'ROADWAY_SURFACE_COND_SNOW OR SLUSH', 'ROADWAY_SURFACE_COND_UNKNOWN',
       'ROADWAY_SURFACE_COND_WET', 'ROAD_DEFECT_DEBRIS ON ROADWAY',
       'ROAD_DEFECT_NO DEFECTS', 'ROAD_DEFECT_OTHER', 'ROAD_DEFECT_RUT, HOLES',
       'ROAD_DEFECT_SHOULDER DEFECT', 'ROAD_DEFECT_UNKNOWN',
       'ROAD_DEFECT_WORN SURFACE', 'STREET_NAME_FREQ', 'target'],
      dtype='object')
```

Numerical Features

In [136]:
```
# let's check the correlation of these numerical features
plt.figure(figsize=(10, 8))
sns.heatmap(X_train_cat_encodedv1[numerical_columns].corr(), annot=True, cmap='coolwarm')
plt.show()
```



In [137]:
```
# Boxplots to compare with target features
for col in numerical_columns:
    plt.figure(figsize=(10, 6))
    sns.boxplot(data=X_train_cat_encodedv1, x='target', y=col)
    plt.title(f'{col} vs Target')
    plt.show()
```



In [138]:
```
# ANOVA test for each numerical feature
for col in numerical_columns:
    groups = [X_train_cat_encodedv1[X_train_cat_encodedv1['target'] == i]
              [col] for i in X_train_cat_encodedv1['target'].unique()]
    f_stat, p_value = f_oneway(*groups)

    print(f'ANOVA test for {col}: p-value = {p_value}')
```

```
ANOVA test for CRASH_HOUR: p-value = 0.0
ANOVA test for CRASH_DAY_OF_WEEK: p-value = 2.1576939558625066e-18
ANOVA test for CRASH_MONTH: p-value = 1.0752844601163475e-24
ANOVA test for NUM_UNITS: p-value = 0.0
ANOVA test for STREET_NO: p-value = 7.029069156186773e-76
```

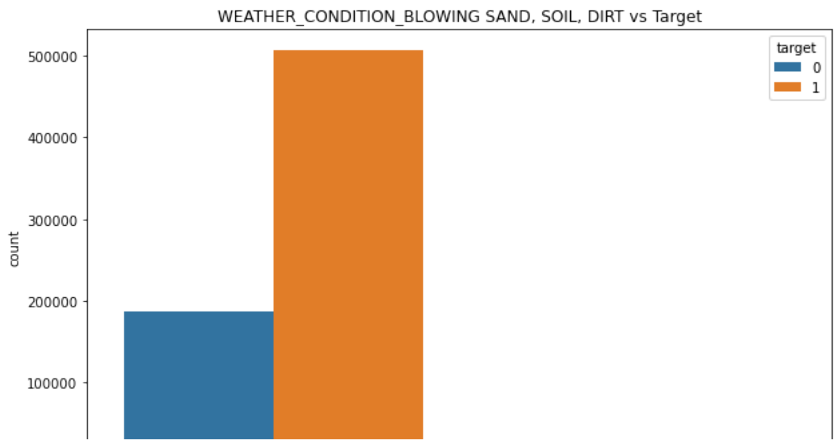
Categorical Features

In [139]:
```
# Lets define the features in our encoded dataframe
ohe_columns = [
       'WEATHER_CONDITION_BLOWING SAND, SOIL, DIRT',
       'WEATHER_CONDITION_BLOWING SNOW', 'WEATHER_CONDITION_CLEAR',
       'WEATHER_CONDITION_CLOUDY/OVERCAST', 'WEATHER_CONDITION_FOG/SMOKE/HAZE',
       'WEATHER_CONDITION_FREEZING RAIN/DRIZZLE', 'WEATHER_CONDITION_OTHER',
       'WEATHER_CONDITION_RAIN', 'WEATHER_CONDITION_SEVERE CROSS WIND GATE',
       'WEATHER_CONDITION_SLEET/HAIL', 'WEATHER_CONDITION_SNOW',
       'WEATHER_CONDITION_UNKNOWN', 'LIGHTING_CONDITION_DARKNESS',
       'LIGHTING_CONDITION_DARKNESS, LIGHTED ROAD', 'LIGHTING_CONDITION_DAWN',
       'LIGHTING_CONDITION_DAYLIGHT', 'LIGHTING_CONDITION_DUSK',
       'LIGHTING_CONDITION_UNKNOWN', 'ALIGNMENT_CURVE ON GRADE',
       'ALIGNMENT_CURVE ON HILLCREST', 'ALIGNMENT_CURVE, LEVEL',
       'ALIGNMENT_STRAIGHT AND LEVEL', 'ALIGNMENT_STRAIGHT ON GRADE',
       'ALIGNMENT_STRAIGHT ON HILLCREST', 'ROADWAY_SURFACE_COND_DRY',
       'ROADWAY_SURFACE_COND_ICE', 'ROADWAY_SURFACE_COND_OTHER',
       'ROADWAY_SURFACE_COND_SAND, MUD, DIRT',
       'ROADWAY_SURFACE_COND_SNOW OR SLUSH', 'ROADWAY_SURFACE_COND_UNKNOWN',
       'ROADWAY_SURFACE_COND_WET', 'ROAD_DEFECT_DEBRIS ON ROADWAY',
       'ROAD_DEFECT_NO DEFECTS', 'ROAD_DEFECT_OTHER', 'ROAD_DEFECT_RUT, HOLES',
       'ROAD_DEFECT_SHOULDER DEFECT', 'ROAD_DEFECT_UNKNOWN',
       'ROAD_DEFECT_WORN SURFACE','target']
```

In [140]:
```
# Calculate mean of target variable for each category
for col in ohe_columns:
    print(f'\nMean of target by {col}:')
    print(X_train_cat_encodedv1.groupby(col)['target'].mean())
```

```
Mean of target by WEATHER_CONDITION_BLOWING SAND, SOIL, DIRT:
WEATHER_CONDITION_BLOWING SAND, SOIL, DIRT
0.0    0.731441
1.0    0.833333
Name: target, dtype: float64

Mean of target by WEATHER_CONDITION_BLOWING SNOW:
WEATHER_CONDITION_BLOWING SNOW
0.0    0.731500
1.0    0.614493
Name: target, dtype: float64

Mean of target by WEATHER_CONDITION_CLEAR:
WEATHER_CONDITION_CLEAR
0.0    0.732849
1.0    0.731059
Name: target, dtype: float64

Mean of target by WEATHER_CONDITION_CLOUDY/OVERCAST:
```

In [141]:
```
# Plot target distribution for categorical features
for col in ohe_columns:
    plt.figure(figsize=(10, 6))
    sns.countplot(data=X_train_cat_encodedv1, x=col, hue='target')
    plt.title(f'{col} vs Target')
    plt.xticks(rotation=45)
    plt.show()
```



In [142]:
```
# Final training dataset for initial modeling
X_train_cat_encoded
```

Out[142]:

	DAMAGE	STREET_NO	NUM_UNITS	CRASH_HOUR	CRASH_DAY_OF_WEEK	CRASH_MONTH	WEATHER_CONDITION_BLOWING SAND, SOIL, DIRT	WEATHER_COND
212995	3	8700	2	6	7	9	0.0	
407508	3	1200	2	3	7	1	0.0	
38450	3	1216	2	14	1	1	0.0	
104223	3	1800	2	13	3	9	0.0	
442570	1	4701	2	18	7	3	0.0	
...	...	...	...	...	...	...	...	
259178	1	8900	2	15	4	9	0.0	
365838	2	2007	1	3	2	4	0.0	
131932	2	800	2	8	3	5	0.0	
671155	3	735	3	19	7	12	0.0	
121958	2	400	2	11	4	6	0.0	

693128 rows × 45 columns

In [143]:
```
# Final Testing data for modeling
X_test_cat_encoded
```

Out[143]:

	DAMAGE	STREET_NO	NUM_UNITS	CRASH_HOUR	CRASH_DAY_OF_WEEK	CRASH_MONTH	WEATHER_CONDITION_BLOWING SAND, SOIL, DIRT	WEATHER_COND
618541	3	2932	2	4	7	10	0.0	
562247	3	1900	2	16	3	10	0.0	
224406	2	5636	2	2	2	8	0.0	
814994	2	10900	2	17	6	3	0.0	
500910	2	2217	2	14	1	2	0.0	
...	...	...	...	...	...	...	...	
549773	3	1600	3	22	5	8	0.0	
125999	3	5500	2	16	5	4	0.0	
68850	3	5510	3	11	2	8	0.0	
87286	3	2256	1	17	3	12	0.0	
459903	1	7150	2	12	6	3	0.0	

173283 rows × 45 columns

Data Modeling

Questions to consider:

- How did you analyze or model the data?
- How did you iterate on your initial approach to make it better?
- Why are these choices appropriate given the data and the business problem?

Steps taken

1. define a pipeline
2. instatiate scaler for numerical values i.e int64
3. identify features to scale
4. Handle target imbalance
5. Initialize models
6. Results

- we will use a pipeline to hanle the steps suggested above.
- for the baseline model, `Logistic regression` with `random_state` and Standard scaler to be used
- The second iteration, will run the model with each remaining scaler and check the performance
- For the final iteration in this model will use parameter `(fit_intercept=False, C=1e12, solver='liblinear')` for anlysis with all scaler and compare the perfomance

Pipeline

In [144]:

```
 # Define the function to create a pipeline
def create_pipeline(scaler_name, model):
    # Choose the scaler
    scaler = {
        'MinMaxScaler': MinMaxScaler(),
        'StandardScaler': StandardScaler(),
        'RobustScaler': RobustScaler(),
        'MaxAbsScaler': MaxAbsScaler()
    }[scaler_name]

    # List of scaled features
    scaled_features=['DAMAGE', 'STREET_NO',
                    'NUM_UNITS', 'CRASH_HOUR',
                    'CRASH_DAY_OF_WEEK', 'CRASH_MONTH']


    # Define the transformers
    preprocessor = make_column_transformer(
        (scaler, scaled_features),
        remainder='passthrough'
    )

    # RandomUnderSampler to handle class imbalance
    undersampler = RandomUnderSampler(random_state=42)

    # Create pipeline using ImbPipeline from imblearn
    pipeline = ImbPipeline(steps=[
        ('undersampler', undersampler),
        ('preprocessor', preprocessor),
        ('classifier', model)
    ])

    return pipeline
```

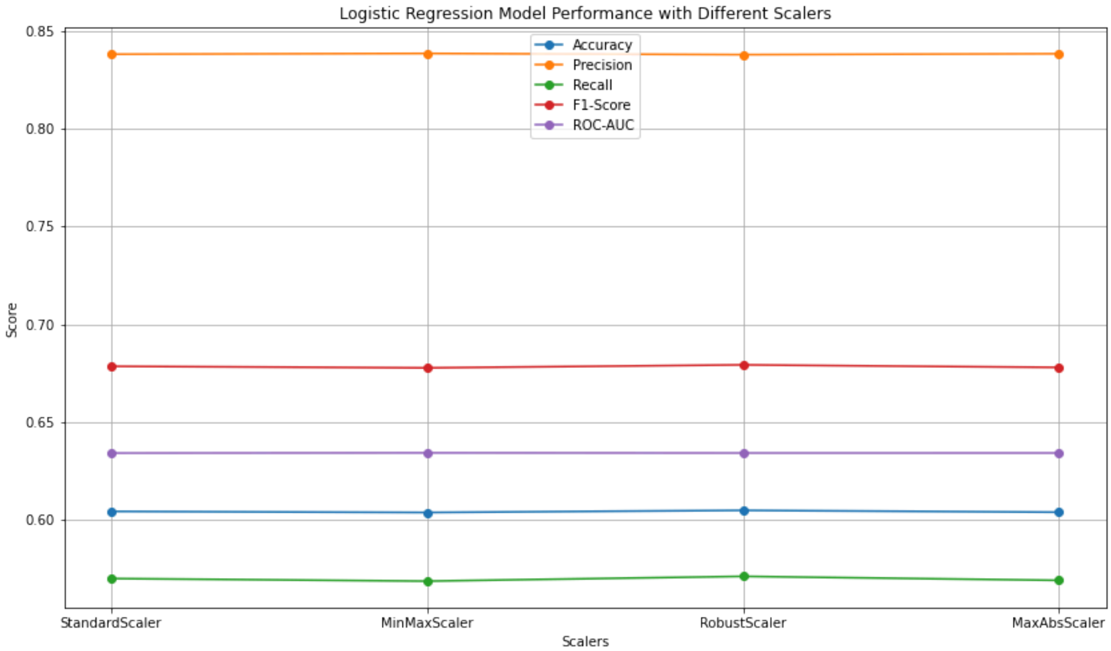
BaseLine Model - Logistic Regression

In [145]:

```
# Instantiate a Logistic Regression model
baseline_model = LogisticRegression(random_state=42)

# List of scalers to test
scalers = ['StandardScaler', 'MinMaxScaler', 'RobustScaler', 'MaxAbsScaler']

# Initialize lists to store metrics
scaler_names = []
accuracies = []
precisions = []
recalls = []
f1_scores = []
roc_aucs = []

# Iterate through each scaler
for scaler_name in scalers:
    # Create pipeline with the current scaler
    pipeline = create_pipeline(scaler_name, baseline_model)

    # Fit the pipeline on the training data
    pipeline.fit(X_train_cat_encoded, y_train)

    # Predict on the test set
    predictions = pipeline.predict(X_test_cat_encoded)

    # Evaluate the model with the current scaler
    accuracy = accuracy_score(y_test, predictions)
    precision = precision_score(y_test, predictions)
    recall = recall_score(y_test, predictions)
    f1 = f1_score(y_test, predictions)
    roc_auc = roc_auc_score(y_test, predictions)

    # Store metrics
    scaler_names.append(scaler_name)
    accuracies.append(accuracy)
    precisions.append(precision)
    recalls.append(recall)
    f1_scores.append(f1)
    roc_aucs.append(roc_auc)
```

Visualize results

In [146]:
```
# Visualize the results
plt.figure(figsize=(14, 8))
plt.plot(scaler_names, accuracies, marker='o', label='Accuracy')
plt.plot(scaler_names, precisions, marker='o', label='Precision')
plt.plot(scaler_names, recalls, marker='o', label='Recall')
plt.plot(scaler_names, f1_scores, marker='o', label='F1-Score')
plt.plot(scaler_names, roc_aucs, marker='o', label='ROC-AUC')
plt.xlabel('Scalers')
plt.ylabel('Score')
plt.title('Logistic Regression Model Performance with Different Scalers')
plt.legend(loc='best')
plt.grid(True)
plt.show()
```

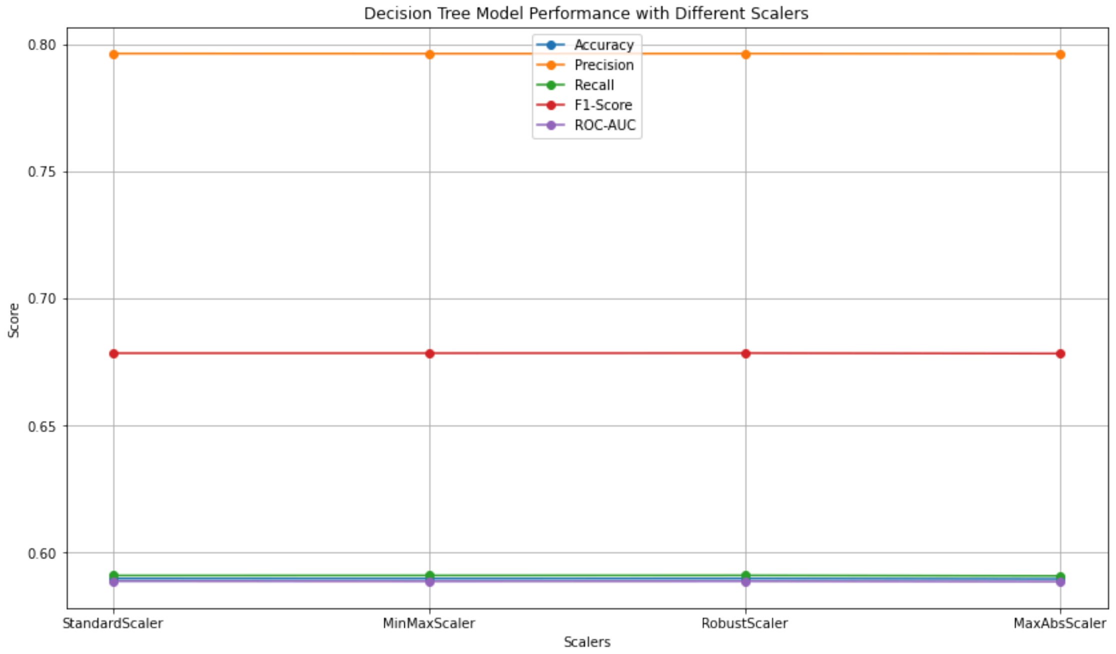


Decision Tree Model

In [147]:
```
# Instantiate a Decision Tree Classifier model
dt_model = DecisionTreeClassifier(random_state=42)

# Initialize lists to store metrics
dt_accuracies = []
dt_precisions = []
dt_recalls = []
dt_f1_scores = []
dt_roc_aucs = []

# Iterate through each scaler
for scaler_name in scalers:
    # Create pipeline with the current scaler
    pipeline = create_pipeline(scaler_name, dt_model)

    # Fit the pipeline on the training data
    pipeline.fit(X_train_cat_encoded, y_train)

    # Predict on the test set
    predictions = pipeline.predict(X_test_cat_encoded)

    # Evaluate the model with the current scaler
    accuracy = accuracy_score(y_test, predictions)
    precision = precision_score(y_test, predictions)
    recall = recall_score(y_test, predictions)
    f1 = f1_score(y_test, predictions)
    roc_auc = roc_auc_score(y_test, predictions)

    # Store metrics
    dt_accuracies.append(accuracy)
    dt_precisions.append(precision)
    dt_recalls.append(recall)
    dt_f1_scores.append(f1)
    dt_roc_aucs.append(roc_auc)
```

Visualize results

In [148]:
```
# Visualize the results
plt.figure(figsize=(14, 8))
plt.plot(scaler_names, dt_accuracies, marker='o', label='Accuracy')
plt.plot(scaler_names, dt_precisions, marker='o', label='Precision')
plt.plot(scaler_names, dt_recalls, marker='o', label='Recall')
plt.plot(scaler_names, dt_f1_scores, marker='o', label='F1-Score')
plt.plot(scaler_names, dt_roc_aucs, marker='o', label='ROC-AUC')
plt.xlabel('Scalers')
plt.ylabel('Score')
plt.title('Decision Tree Model Performance with Different Scalers')
plt.legend(loc='best')
plt.grid(True)
plt.show()
```



Evaluation

Questions to consider:

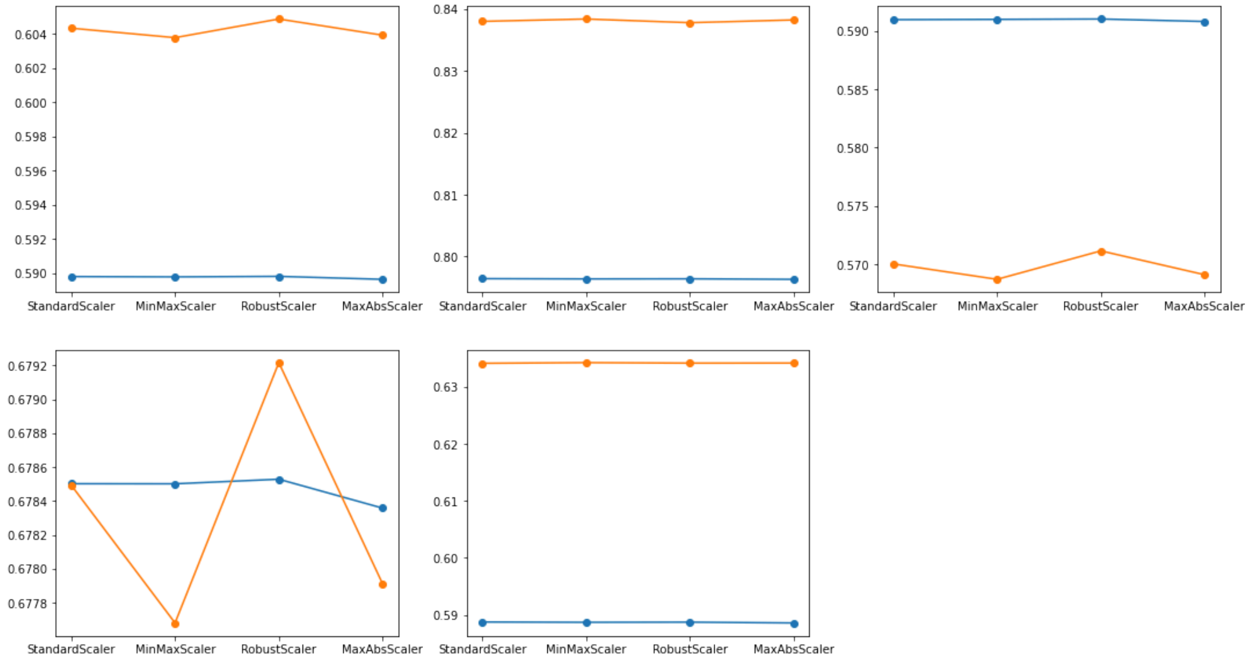
- How do you interpret the results?
- How well does your model fit your data? How much better is this than your baseline model?
- How confident are you that your results would generalize beyond the data you have?
- How confident are you that this model would benefit the business if put into use?

Visualize Results

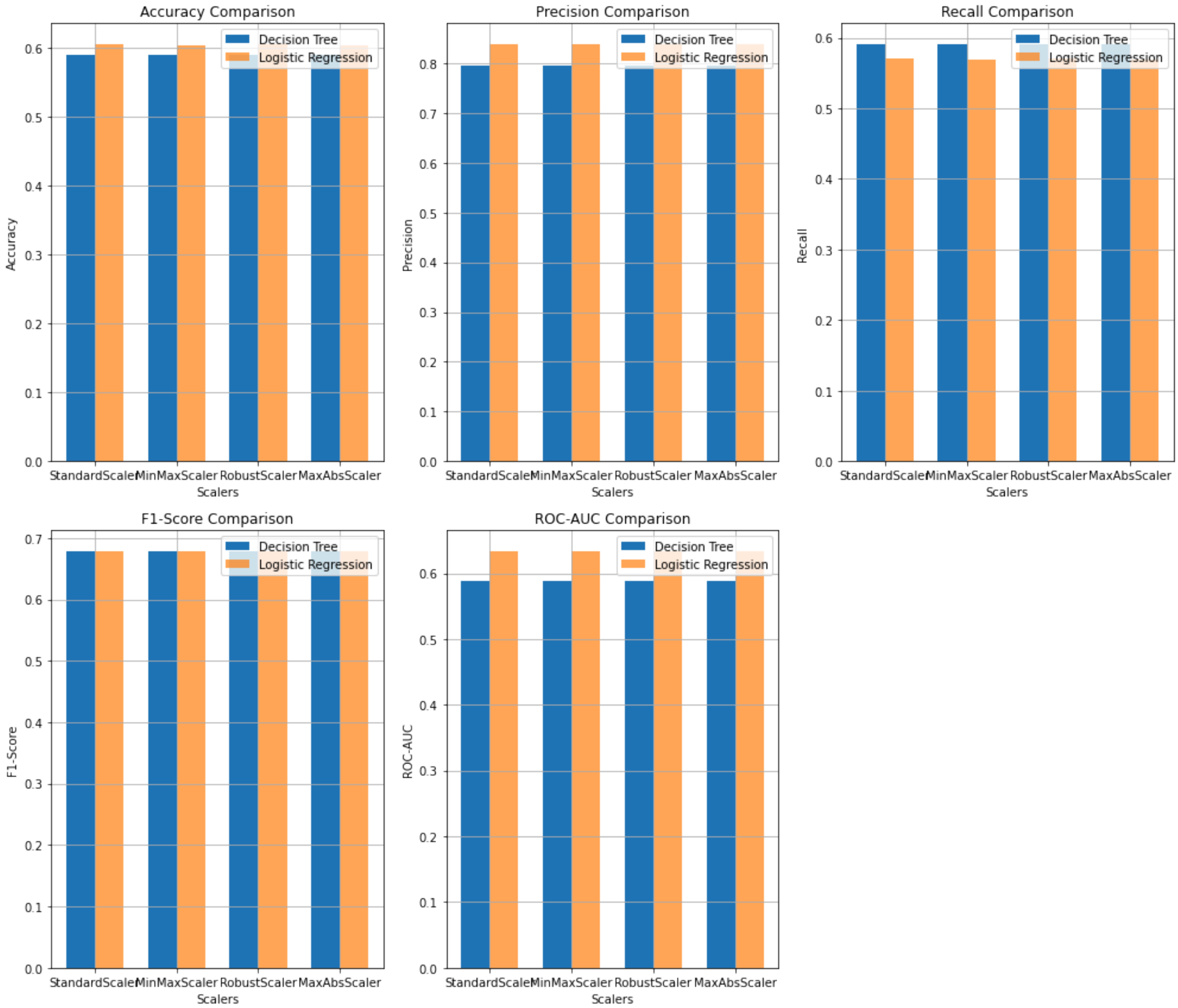
In [149]:
```
# Define the function to print comparison metrics
def print_metrics_comparison(scaler_name, dt_metrics, lr_metrics):
    dt_accuracy, dt_precision, dt_recall, dt_f1, dt_roc_auc = dt_metrics
    lr_accuracy, lr_precision, lr_recall, lr_f1, lr_roc_auc = lr_metrics

    print(f"\nScaler: {scaler_name}")
    print(f"{'Metric':<12} {'Decision Tree':<18} {'Logistic Regression':<18}")
    print(f"Accuracy    : {dt_accuracy:.4f}              {lr_accuracy:.4f}")
    print(f"Precision   : {dt_precision:.4f}              {lr_precision:.4f}")
    print(f"Recall      : {dt_recall:.4f}              {lr_recall:.4f}")
    print(f"F1-Score    : {dt_f1:.4f}              {lr_f1:.4f}")
    print(f"ROC-AUC     : {dt_roc_auc:.4f}              {lr_roc_auc:.4f}")

# Assuming metrics for Decision Tree and Logistic Regression are already calculated
for i, scaler_name in enumerate(scaler_names):
    dt_metrics = (dt_accuracies[i], dt_precisions[i], dt_recalls[i], dt_f1_scores[i], dt_roc_aucs[i])
    lr_metrics = (accuracies[i], precisions[i], recalls[i], f1_scores[i], roc_aucs[i])
    print_metrics_comparison(scaler_name, dt_metrics, lr_metrics)
```

```
Scaler: StandardScaler
Metric       Decision Tree      Logistic Regression
Accuracy    : 0.5898              0.6043
Precision   : 0.7964              0.8380
Recall      : 0.5910              0.5700
F1-Score    : 0.6785              0.6785
ROC-AUC     : 0.5888              0.6341

Scaler: MinMaxScaler
Metric       Decision Tree      Logistic Regression
Accuracy    : 0.5898              0.6038
Precision   : 0.7964              0.8383
Recall      : 0.5910              0.5687
F1-Score    : 0.6785              0.6777
ROC-AUC     : 0.5887              0.6343

Scaler: RobustScaler
Metric       Decision Tree      Logistic Regression
Accuracy    : 0.5898              0.6049
Precision   : 0.7964              0.8378
Recall      : 0.5910              0.5711
F1-Score    : 0.6785              0.6792
ROC-AUC     : 0.5887              0.6342

Scaler: MaxAbsScaler
Metric       Decision Tree      Logistic Regression
Accuracy    : 0.5896              0.6039
Precision   : 0.7963              0.8382
Recall      : 0.5908              0.5691
F1-Score    : 0.6784              0.6779
ROC-AUC     : 0.5886              0.6342
```

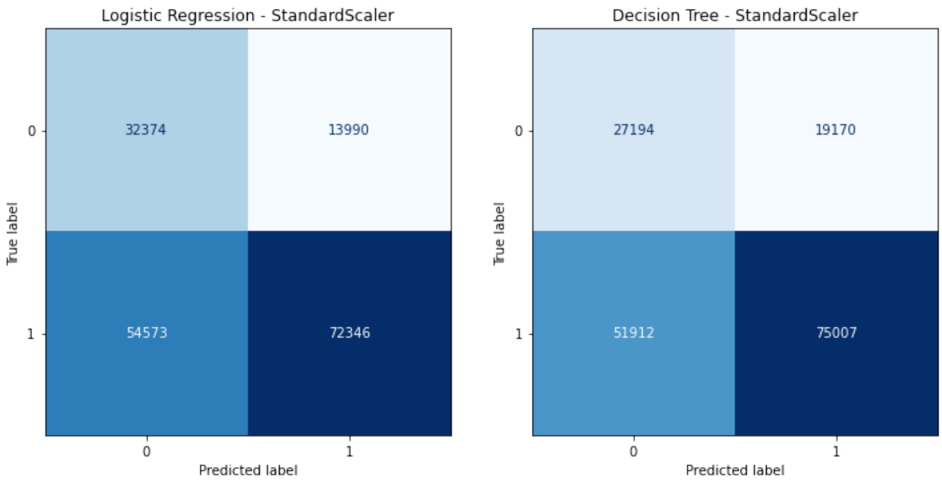
In [150]:
```
# Initialize the plot
plt.figure(figsize=(18, 10))

# Plot metrics for both models
metrics = ['Accuracy', 'Precision', 'Recall', 'F1-Score', 'ROC-AUC']
dt_metrics_list = [dt_accuracies, dt_precisions, dt_recalls, dt_f1_scores, dt_roc_aucs]
lr_metrics_list = [accuracies, precisions, recalls, f1_scores, roc_aucs]

for i, metric in enumerate(metrics):
    plt.subplot(2, 3, i+1)
    plt.plot(scaler_names, dt_metrics_list[i], marker='o', label='Decision Tree')
    plt.plot(scaler_names, lr_metrics_list[i], marker='o', label='Logistic Regression')
```

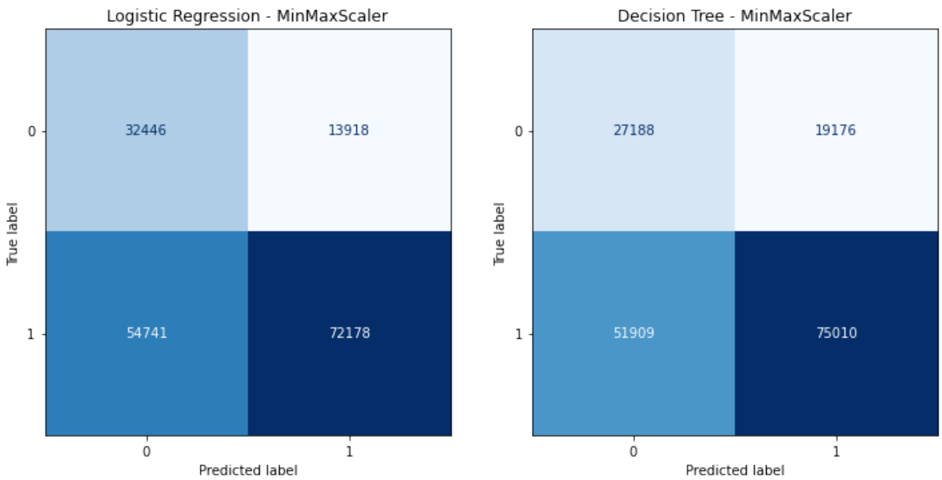


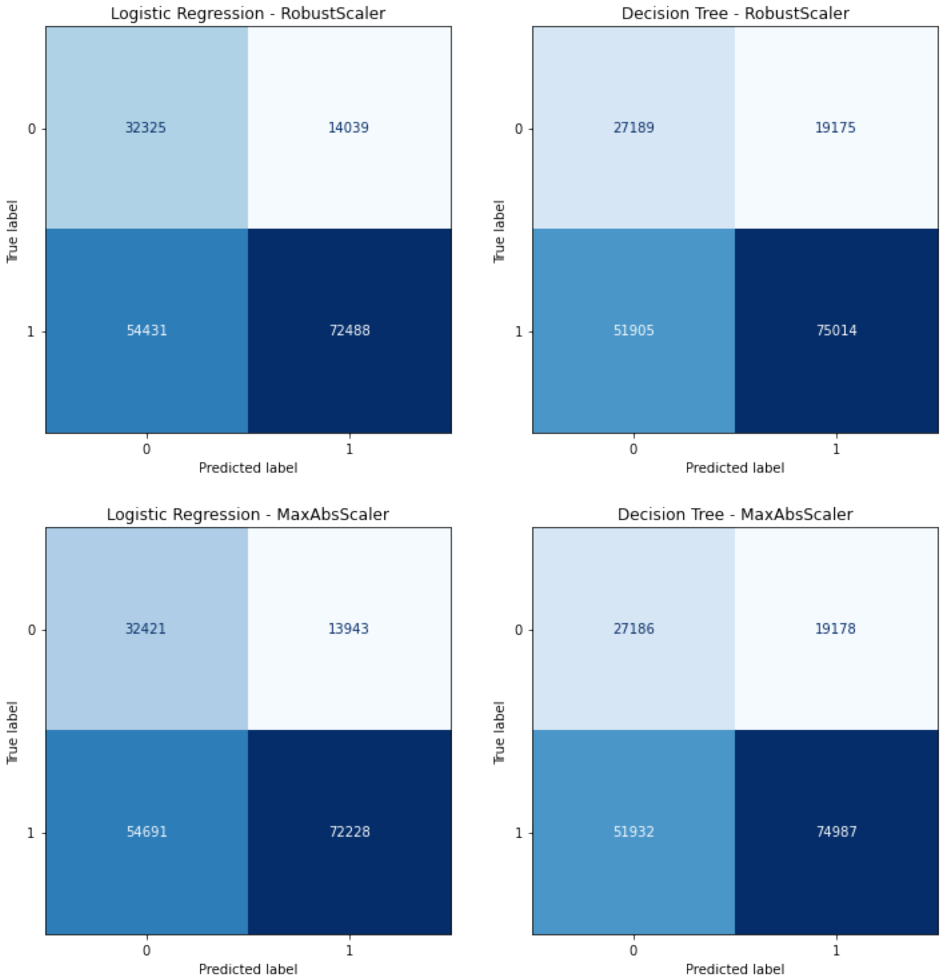
In [151]:
```
#  Metrics collected for each scaler for both models
metrics = {
    'Accuracy': (dt_accuracies, accuracies),
    'Precision': (dt_precisions, precisions),
    'Recall': (dt_recalls, recalls),
    'F1-Score': (dt_f1_scores, f1_scores),
    'ROC-AUC': (dt_roc_aucs, roc_aucs)
}

# Number of scalers and metrics
n_scalers = len(scaler_names)
n_metrics = len(metrics)  # Calculate the number of metrics

# Set a reasonable default layout (2 rows for 5 metrics or less)
rows = min(2, n_metrics)  # Ensure at most 2 rows
cols = int(np.ceil(n_metrics / rows))  # Adjust columns based on rows

# Set the bar width and the positions
bar_width = 0.35
index = np.arange(n_scalers)

# Create subplots for each metric
fig, axes = plt.subplots(nrows=rows, ncols=cols, figsize=(14, 12))
axes = axes.flatten()

for i, (metric_name, (dt_values, lr_values)) in enumerate(metrics.items()):
    ax = axes[i]

    # Plot bars for Decision Tree and Logistic Regression
    ax.bar(index, dt_values, bar_width, label='Decision Tree')
    ax.bar(index + bar_width, lr_values, bar_width, label='Logistic Regression', alpha=0.7)

    # Set the labels and title
    ax.set_xlabel('Scalers')
    ax.set_ylabel(metric_name)
    ax.set_title(f'{metric_name} Comparison')
    ax.set_xticks(index + bar_width / 2)
    ax.set_xticklabels(scaler_names)
    ax.legend(loc='upper right')
    ax.grid(True)

# Hide the extra subplot
axes[-1].axis('off')  # Turn off ticks and labels

# Adjust layout to prevent overlap
plt.tight_layout()
plt.show()
```


Accuracy Comparison
Precision Comparison
Recall Comparison
F1-Score Comparison
ROC-AUC Comparison
Decision Tree
Logistic Regression
Accuracy
Precision
Recall
F1-Score
ROC-AUC
StandardScaler
MinMaxScaler
RobustScaler
MaxAbsScaler
Scalers

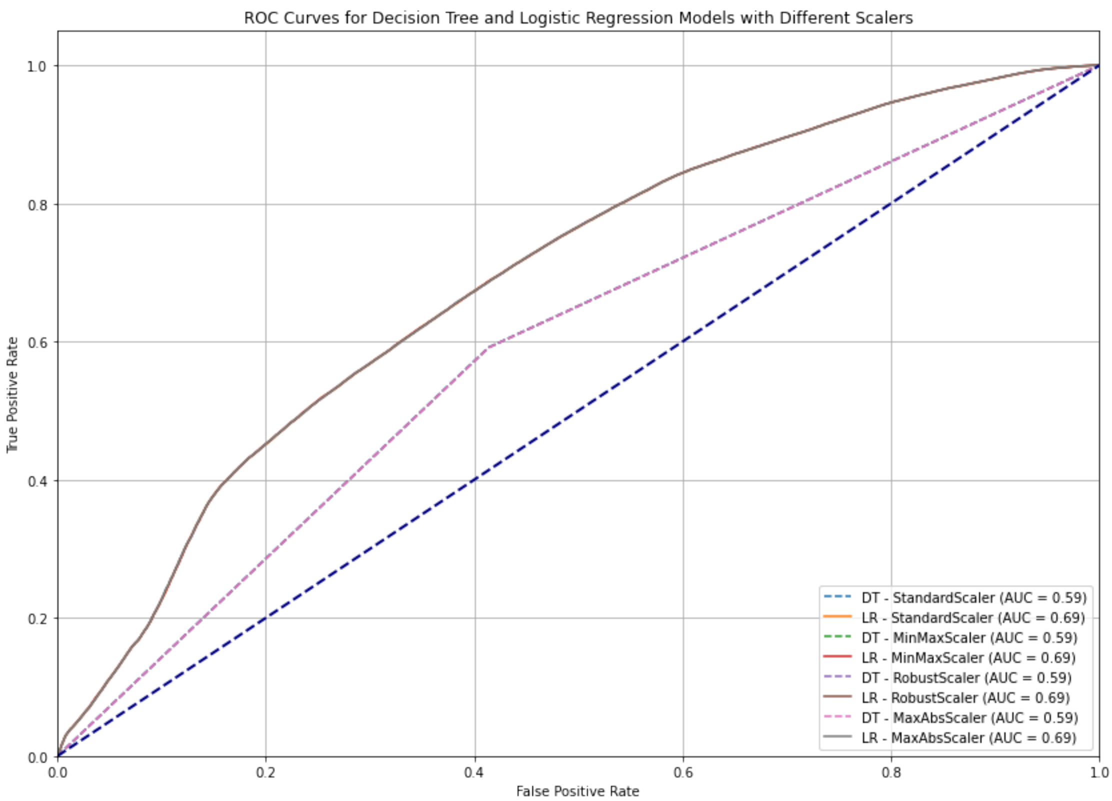
In [152]:
```
# Define the function to plot confusion matrices side by side
def plot_confusion_matrices_side_by_side(model1_name, model2_name, scaler_name, y_true, y_pred1, y_pred2):
    fig, ax = plt.subplots(1, 2, figsize=(12, 6))

    # Confusion Matrix for Model 1
    cm1 = confusion_matrix(y_true, y_pred1)
    disp1 = ConfusionMatrixDisplay(confusion_matrix=cm1)
    disp1.plot(cmap=plt.cm.Blues, ax=ax[0], colorbar=False)
    ax[0].set_title(f'{model1_name} - {scaler_name}')

    # Confusion Matrix for Model 2
    cm2 = confusion_matrix(y_true, y_pred2)
    disp2 = ConfusionMatrixDisplay(confusion_matrix=cm2)
    disp2.plot(cmap=plt.cm.Blues, ax=ax[1], colorbar=False)
    ax[1].set_title(f'{model2_name} - {scaler_name}')

    plt.show()

# Iterate through each scaler
for scaler_name in scalers:
    # Logistic Regression
    pipeline_lr = create_pipeline(scaler_name, baseline_model)
    pipeline_lr.fit(X_train_cat_encoded, y_train)
    predictions_lr = pipeline_lr.predict(X_test_cat_encoded)

    # Decision Tree
    pipeline_dt = create_pipeline(scaler_name, dt_model)
    pipeline_dt.fit(X_train_cat_encoded, y_train)
    predictions_dt = pipeline_dt.predict(X_test_cat_encoded)

    # Plot confusion matrices side by side
    plot_confusion_matrices_side_by_side('Logistic Regression', 'Decision Tree', scaler_name, y_test, prediction
```






Logistic Regression - RobustScaler
32325
14039
54431
72488
True label
Predicted label
Decision Tree - RobustScaler
27189
19175
51905
75014
True label
Predicted label
Logistic Regression - MaxAbsScaler
32421
13943
54691
72228
True label
Predicted label
Decision Tree - MaxAbsScaler
27186
19178
51932
74987
True label
Predicted label

In [153]:
```
# Initialize the plot
plt.figure(figsize=(14, 10))

# Iterate through each scaler to calculate and plot ROC curves
for i, scaler_name in enumerate(scaler_names):
    # Decision Tree Model
    pipeline_dt = create_pipeline(scaler_name, dt_model)
    pipeline_dt.fit(X_train_cat_encoded, y_train)
    y_score_dt = pipeline_dt.predict_proba(X_test_cat_encoded)[:, 1]
    fpr_dt, tpr_dt, _ = roc_curve(y_test, y_score_dt)
    roc_auc_dt = auc(fpr_dt, tpr_dt)

    # Logistic Regression Model
    pipeline_lr = create_pipeline(scaler_name, baseline_model)
    pipeline_lr.fit(X_train_cat_encoded, y_train)
    y_score_lr = pipeline_lr.predict_proba(X_test_cat_encoded)[:, 1]
    fpr_lr, tpr_lr, _ = roc_curve(y_test, y_score_lr)
    roc_auc_lr = auc(fpr_lr, tpr_lr)

    # Plot Decision Tree ROC curve
    plt.plot(fpr_dt, tpr_dt, label=f'DT - {scaler_name} (AUC = {roc_auc_dt:.2f})', linestyle='--')

    # Plot Logistic Regression ROC curve
    plt.plot(fpr_lr, tpr_lr, label=f'LR - {scaler_name} (AUC = {roc_auc_lr:.2f})')

# Plot the diagonal line (no-skill classifier)
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')

# Customize the plot
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curves for Decision Tree and Logistic Regression Models with Different Scalers')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```



Logistic Regression Evaluation

- The model correctly predicted the outcome for over 60% of the instances in the test set using the different scalers to evaluate.
- Of all the instances that the model had a precision for the positive class (1: 'INJURY AND / OR TOW DUE TO CRASH'), above 80% using the various scalers.
- Low recall as model correctly identified at about 56% of all actual positive instances. This indicates that the model misses about 44% of the true positive cases,
- 67% is the trade-off between precision and recall in all model instances
- the model has a modest score of 63.42% for the ROC-AUC, which indicates low discriminative power
- High number of false negatives over 54000, meaning it is missing many positive cases. This contributes to the lower recall value.

Decision Tree Evaluation

- The model correctly predicted the outcome for below 60% of the instances in the test set using the different scalers to evaluate.
- Of all the instances that the model had a precision for the positive class (1: 'INJURY AND / OR TOW DUE TO CRASH'), below 80% using the various scalers.
- Low recall as model correctly identified at about 59% of all actual positive instances. This indicates that the model misses about 41% of the true positive cases, higher than logistic regression
- 67% is the trade-off between precision and recall in all model instances similar to logistic regression model
- the model like logistic has a lower modest score approximatly 58.87% for the ROC-AUC, which indicates low discriminative power
- High number of false negatives over 51000, though lower than logistc regression model, means it is missing many positive cases. This contributes to the lower recall value.

Conclusions

Questions to consider:

- What would you recommend the business do as a result of this work?
- What are some reasons why your analysis might not fully solve the business problem?
- What else could you do in the future to improve this project?

Overall Model Performance:

```
`Logistic Regression` slightly outperformed the `Decision Tree` in terms of accuracy, precision, and ROC
-AUC. However, both models have relatively low recall, which indicates they miss a significant number of
true positive cases (i.e., severe crashes).
The Decision Tree model has a lower overall performance compared to the Logistic Regression, especially
in terms of precision and ROC-AUC. However, it had fewer false negatives than Logistic Regression, indic
ating it might slightly better capture severe crashes, although this comes at the cost of overall predic
tive accuracy.
```

Trade-off Between Precision and Recall:

```
Both models have similar F1-scores (~0.67), suggesting a balance between precision and recall. However,
the recall is notably low for both models, which is concerning given the context of the problem (i.e., i
dentifying severe crashes is crucial for insurance underwriting).

The models' ability to correctly classify severe crashes is inadequate, as reflected by the high number
of false negatives. This means that in many cases where a crash is severe, the models fail to predict it
correctly, which could result in underestimating the risk for certain claims.
```

Model Discriminative Power:

```
The ROC-AUC scores for both models (Logistic Regression: ~63.42%, Decision Tree: ~58.87%) suggest that n
either model is particularly strong at distinguishing between severe and non-severe crashes. The discrim
inative power of the models is relatively modest, indicating that more sophisticated models or additiona
l data/features might be needed to improve prediction performance
```

Recomendations

Feature Engineering: Explore creating new features or transforming existing ones to capture more relevant information.

Hyperparameter Tuning: Fine-tune the hyperparameters of both models to optimize their performance.

Ensemble Methods: Combine multiple models (e.g., using random forests or gradient boosting) to potentially improve overall performance and reduce overfitting.

Consider Other Models: Experiment with other machine learning algorithms that might be better suited to your specific problem.

Domain Expertise: Leverage insights from insurance experts to identify additional factors that might influence crash severity.

Cross-Validation:Use cross-validation techniques to ensure that the model performance observed is generalizable and not due to specificities in the train-test split. This will give a better estimate of model performance across different data subsets.

Next Steps

Data Quality: Ensure the quality and completeness of your data to avoid biases in your analysis. Using other datasets analyze features that would increase model efficiency

Cost-Sensitive Learning:Given the high cost of missing severe crashes, explore cost-sensitive learning approaches where the model penalizes false negatives more heavily. This could help improve the recall for severe crashes, which is critical for the business problem.

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