Car Accident Severity Prediction

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1. Introduction:

1.1. Background

Accidents in traffic lead to associated fatalities and economic losses every year worldwide and thus is an area of primary concern to Society from loss prevention point of view. In Great Britain, recent statistics showing that there are nearly 3 deaths per 100,000 people, for all road users. Motorways are potential sites of fatal highway accidents in UK. The accident data analysis, visualization and better accident severity prediction models will be helpful in enhancing the safety performance of road traffic system. Traffic accidents are generally classified into fatal, serious and slight accidents based on their severity. Each accident severity has some pattern relation with accident related physical features such as accident location, weather conditions, light conditions, season, month, day, time, driver experience etc. Modelling accident severity prediction and improving the model are critical to the effective performance of road traffic systems for improved safety. In accident severity modelling, the input vectors are the characteristics of the accident, such as driver behaviour and attributes of vehicle, highway and environment characteristics while the output vector is the corresponding class of accident severity.

There are two main engineering approaches for dealing with traffic safety problems: the reactive approach and the proactive approach. The reactive approach, or retrofit approach, consists of making the necessary improvements to variable, for instance, taking necessary actions at identified hazardous sites in order to reduce collision frequency and severity at these sites. The proactive approach, on the other hand, includes a collision prevention approach, like, preventing a potential unsafe road conditions from occurring in the first place. We focus on proactive approach which involves prediction of accident severity and working backwards, the concerned entity implements appropriate preventive measures to improve road safety. By recognizing the key factors that influence accident severity, the solution may be of great utility to various Government Departments/Authorities like Police, R&B and Transport from public policy point of view. The results of analysis and modelling can be used by these Departments to take appropriate measures to reduce accident impact and thereby improve traffic safety. It is also useful to the Insurers in terms of reduced claims and better underwriting as well as rate making.

Seattle, also known as the Emerald city, is Washington State’s largest city, with home to a large tech industry with Microsoft and Amazon headquartered in its metropolitan area. As of 2020, it has a total metro area population of 3.4 million (www.macrotrends.net). The total number of personal vehicles in Seattle in the year 2016 hit a new high of nearly 444,000 vehicles. In one South Lake Union census tract, the car population has more than doubled since 2010 (www.seattletimes.com). The increase in car ownership rates can lead to higher numbers of accidents on the road because of a simple probability. Worldwide, approximately 1.35 million people die in road crashes each year, on average 3,700 people lose their lives every day on the roads and an additional 20-50 million suffer non-fatal injuries, often resulting in long-term disabilities.

1.2. Business Problem

The Washington State Department of Transportation Crash Data Portal provides crash information for accidents that occurred state-wide. According to the 2019 data, there were 45,524 accidents on all roads. Of those:

- 235 were fatal crashes
- 973 were suspected of serious injury accidents
- 2,798 were suspected of minor injury accidents
- 9,412 were possible injury crashes
- 32,106 were no apparent injury collisions

Our motivation is to use the weather, location and road condition data provided in the dataset, made available by the Seattle Department of Transportation Traffic Management Division, to arrive at a correlation to predict the severity of road accidents. This tool/data can then be made available to the public and the Seattle traffic authorities to possibly prevent/reduce severe or fatal accidents in the future by taking precautionary measures.

2. Data Collection and Understanding

2.1. Data Collection

The dataset used for this project is based on car accidents which have taken place within the city of Seattle, Washington from the year 2004 to 2020. This data is regarding car accidents the severity of each car accidents along with the time and conditions under which each accident occurred.

The dataset contains around 0.194 million records and 37 columns. We will do data cleaning and pre-processing. The data corresponding to slight severity is 84.84%, serious severity is 13.86% and for fatal severity is 1.30%. In addition to severity information, the data contains information regarding accident characteristics (accident occurrence time and accident location), vehicle characteristics (vehicle type involved and vehicle condition), environmental factors (weather condition and visibility distance), and road conditions (pavement condition, road geometrics and roadway surface condition, etc.). Previous studies indicated that the factors associated with accident severity mainly include road characteristics, accidents characteristics, vehicle characteristics, driver characteristics, and environmental factors. Several processing techniques as under sampling and oversampling will tried. Our main aim is to predict the serious and fatal severity with high precision and F1 score. Seven different classifiers will be tried on this dataset.

Data Pre-Processing: Data pre-processing is an important stage for handling the data before using it in the data mining algorithms. This process involves various steps, including cleaning, normalization, feature selection, transformation.

Dataset Description:

1. Number of Vehicles - Number of Vehicles involved in an accident
2. Number of Casualties - Number of Casualties involved in an accident
3. Road Type 1: Roundabout 2: One-way street 3: Dual carriageway 4: Single carriageway 5: Slip
4. Road Speed limit - The Speed limitation of the road where the accident happened
5. Light Conditions 1: Daylight 2: Darkness - lights lit 3: Darkness - lights unlit 4: Darkness - no lighting 5: Darkness - lighting unknown
6. Road Surface Conditions 1: Dry 2: Wet or damp 3: Snow 4: Frost or ice 5: Flood over 3cm. deep 6: Oil or diesel 7: Mud 8: Data missing or out of range
7. Weather Conditions 1: Fine no high winds 2: Raining no high winds 3: Snowing no high winds 4: Fine and high winds 5: Raining and high winds 6: Snowing and high winds 7: Fog or mist 8: Other 9: Unknown
8. Urban or Rural Area 1: Urban 2: Rural

Accidents are classified into 2 categories: 1. Fatal 2. Slight

2.2. Data Understanding

There are a lot of problems with the data set keeping in mind that this is a machine learning project which uses classification to predict a categorical variable. The dataset has total observations of 194673 with variation in number of observations for every feature. First of all, the total dataset was high variation in the lengths of almost every column of the dataset. The dataset had a lot of empty columns which could have been beneficial had the data been present there. These columns included pedestrian granted way or not, segment lane key, cross walk key and hit parked car.

The models aim was to predict the severity of an accident, considering that, the variable of Severity Code was in the form of 1 (Property Damage Only) and 2 (Injury Collision) which were encoded to the form of 0 (Property Damage Only) and 1 (Injury Collision). Furthermore, the Y was given value of 1 whereas N and no value was given 0 for the variables Inattention, Speeding and Under the influence. For lighting condition, Light was given 0 along with Medium as 1 and Dark as 2. For Road Condition, Dry was assigned 0, Mushy was assigned 1 and Wet was given 2. As for Weather Condition, 0 is Clear, Overcast is 1, Windy is 2 and Rain and Snow was given 3. 0 was assigned to the element of each variable which can be the least probable cause of severe accident whereas a high number represented adverse condition which can lead to a higher accident severity. Whereas, there were unique values for every variable which were either ‘Other’ or ‘Unknown’, deleting those rows entirely would have led to a lot of loss of data which is not preferred.

We chose the unbalanced dataset provided by the Seattle Department of Transportation Traffic Management Division with 194673 rows (accidents) and 37 columns (features) where each accident is given a severity code. It covers accidents from January 2004 to May 2020. Some of the features in this dataset include and are not limited to Severity code, Location/Address of accident, Weather condition at the incident site, Driver state (whether under influence or not), collision type. Hence, we think it's a good generalized dataset which will help us in creating an accurate predictive model.

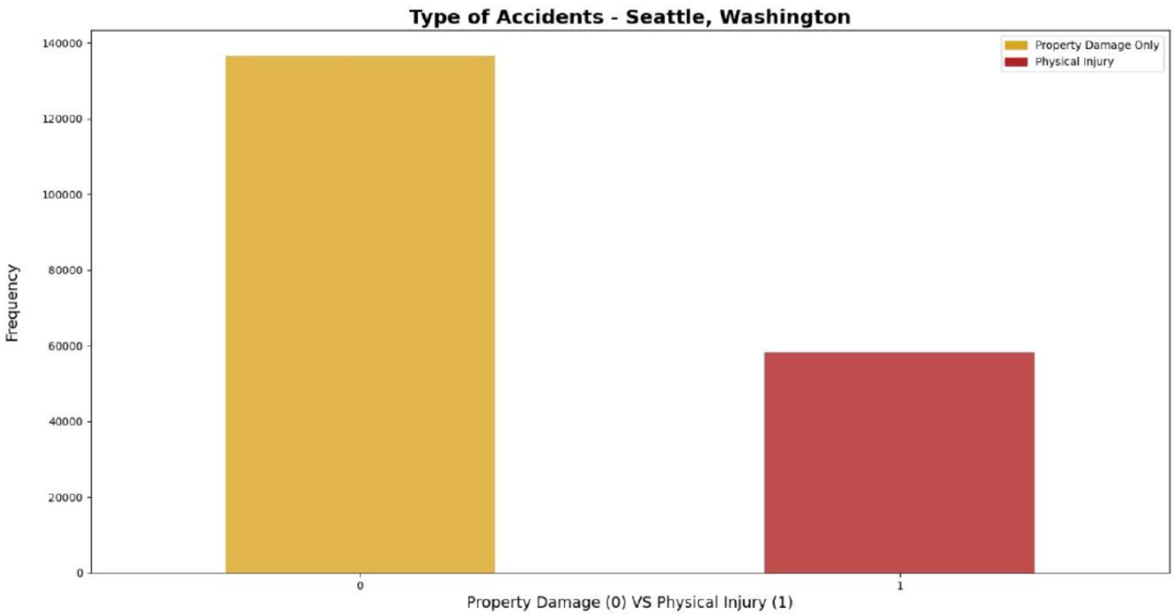
The unbalance with respect to the severity code in the dataset is as follows.

SEVERITY CODE	Count
1	136485
2	58188

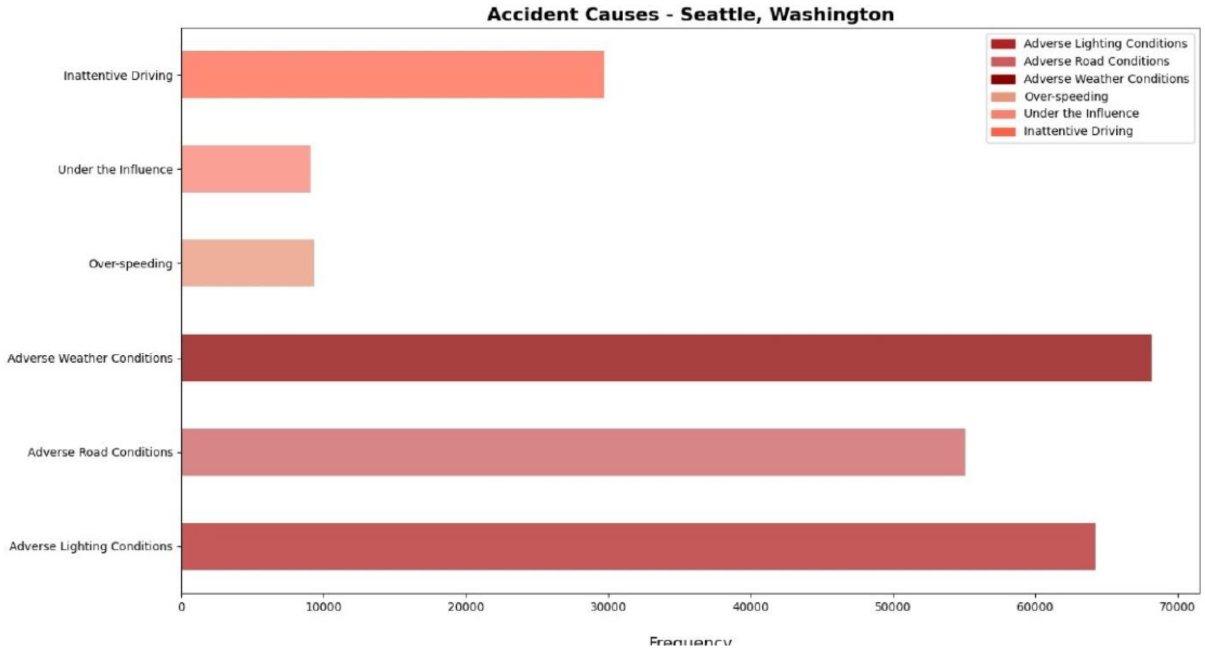
3. Methodology

3.1. Exploratory Data Analysis

Considering that the feature set and the target variable are categorical variables with the likes of weather, road condition and light condition being an above level 2 categorical variables whose values are limited and usually based on a particular finite group whose correlation might depict a different image then what it actually is. Generally, considering the effect of these variables in car accidents are important hence these variables were selected. A few pictorial depictions of the dataset were made in order to better understand the data.



The above figure illustrates, after data cleaning has taken place, the distribution of the target variables between Physical Injury and Property Damage Only. As it can be seen that the dataset is supervised but an unbalanced dataset where the distribution of the target variable is in almost 1:2 ratio in favor of property damage. It is very important to have a balanced dataset when using machine learning algorithms. Hence, SMOTE was used from imblearn library in order to balance the target variable in equal proportions in order to have an unbiased classification model which is trained on equal instances of both the elements under severity of accidents.



As mentioned earlier, a number '0' as an element of an independent variable is supposed to depict the least probable cause of a severe accident. The graph above is supposed to depict all the non-zero values within each independent variable of the model and can be seen as the frequency of adverse conditions under which accidents took place. The factor which had most number of accidents under adverse conditions was adverse weather conditions while adverse lighting condition had the second most number of accidents caused by it. The factors which contributed the least to an instance of an accident are over-speeding and the driver being under the influence.

3.2. Data Pre-processing

An unbalanced dataset is used, provided by the Seattle Department of Transportation Traffic Management Division with 194673 rows (accidents) and 37 columns (features) where each accident is given a severity code. The steps taken in pre-processing the dataset are as follows.

3.2.1. Removal of irrelevant columns or features

Columns containing descriptions and identification numbers that would not help in the classification are dropped from the dataset to reduce the complexity and dimensionality of the dataset. 'OBJECTID', 'INCKEY', 'COLDETKEY', 'REPORTNO', 'STATUS', 'INTKEY', 'EXCEPTRSNCODE' and more belong to this category. Certain other categorical features were removed as they had a large number of distinct values, example: 'LOCATION'.

After performing this step, the dimensionality dropped from 37 to 18.

```
Data columns (total 37 columns):
```

V

```
Data columns (total 15 columns):
```

3.2.2. Identification and handling missing values

To identify columns and rows with missing values is the next step. Empty boxes, ‘Unknown’ and ‘Other’ were values considered as missing values. These were replaced with NA to make the dataset uniform.

```
df.replace(r'^\s*$', np.nan, regex=True)
df.replace("Unknown", np.nan, inplace = True)
df.replace("Other", np.nan, inplace = True)
```

Columns ("INATTENTIONIND","PEDROWNOTGRNT","SPEEDING") which had more than 20% of its values missing were noted down and were dropped. For columns ("X","Y","COLLISIONTYPE","JUNCTIONTYPE"….) which had less than 20% of its values missing, the respective rows were removed since most of the columns in this dataset are categorical type, goal was to not impute the non-numerical columns; hence it did not make sense to replace the values.

Once the above two strategies were performed, the dataset reduced from having 194673 rows and 15 columns to having 143747 rows and 15 columns.

```
Int64Index: 143747 entries, 0 to 194672
Data columns (total 15 columns):
```

3.2.3. Balancing the dataset

With the above two pre-processing steps complete, a dataset (143747 rows) with 94821 rows for severity code 1 and 48926 rows for severity code 2 is obtained. Training an algorithm on an unbalanced dataset w.r.t the target category will result in a biased model. The model will have learnt more about one the category that has more data. In order to prevent this, a new balanced dataset (97852 rows) is created by randomly sampling out 48926 rows with severity code 2 and then concatenating it with 48926 rows with severity code 1. The dataset is then shuffled to randomize the rows.

```
Int64Index: 97852 entries, 139054 to 72625
Data columns (total 15 columns):
```

3.2.4. Encoding of data

The dataset is split into two datasets, X and Y, where Y contains the target feature (SEVERITYCODE) and X contains all the independent features/variables.

Machine Learning models are trained only on numerical data; hence all categorical features in the dataset have to be encoded so that the algorithms can be trained on those features. The ‘get_dummies’ method from pandas library is used to convert/encode each and every categorical feature. After application, number of features in dataset X increased from 14 to 50.

```
Int64Index: 97852 entries, 139054 to 72625
Data columns (total 50 columns):
 #   Column                                   Non-Null Count  Dtype
---  ------                                   --------------  -----
 0   X                                        97852 non-null  float64
 1   Y                                        97852 non-null  float64
 2   PERSONCOUNT                              97852 non-null  int64
 3   PEDCOUNT                                 97852 non-null  int64
 4   PEDCYLCOUNT                              97852 non-null  int64
 5   VEHCOUNT                                 97852 non-null  int64
 6   ADDRTYPE_Block                           97852 non-null  uint8
 7   ADDRTYPE_Intersection                    97852 non-null  uint8
 8   COLLISIONTYPE_Angles                     97852 non-null  uint8
 9   COLLISIONTYPE_Cycles                     97852 non-null  uint8
 10  COLLISIONTYPE_Head On                    97852 non-null  uint8
 11  COLLISIONTYPE_Left Turn                  97852 non-null  uint8
 12  COLLISIONTYPE_Parked Car                 97852 non-null  uint8
 13  COLLISIONTYPE_Pedestrian                 97852 non-null  uint8
```

3.2.5. Splitting into training and testing datasets

The datasets X and Y are split into X_train, Y_train, X_test,and Y_test. The first two will be used for training purposes and the last two will be used for testing purposes. The split ratio is 0.8, 80% of data is used for training and 20% of is used for testing.

```
X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size=0.2,random_state=0)
```

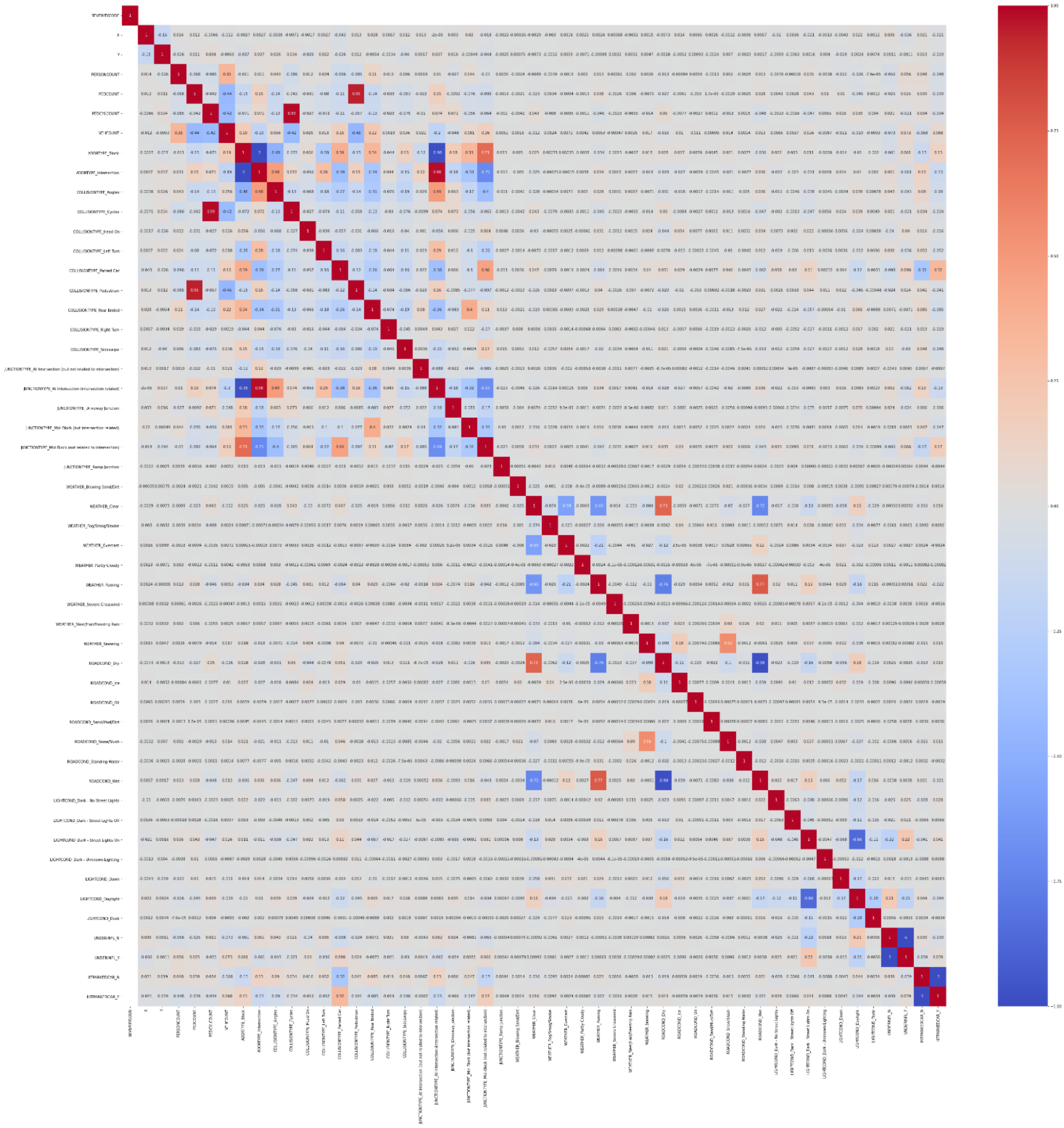
3.2.6. Normalizing/ Feature scaling of data

Feature scaling of data is done to normalize the data in a dataset to a specific range. It also helps improve the performance of the ML algorithms. Standard Scaler metric is used to scale/normalize all the numerical data for both, the X_train and X_test datasets. This completes the pre-processing stage, we can move on to training our models.

3.2.7. Understanding Correlation in Dataset

Correlation is a statistical technique that can show whether and how strongly pairs of variables are related. Finding the correlation among the features of the dataset helps understand the data better. For example, in the below figure (correlation plot using matplotlib), it can be observed that some features have a strong positive/negative correlation while most of them have weak/ no correlation.

Examples, There is a strong positive correlation between ‘PEDCYLCOUNT’ and ‘COLLISIONTYPE_Cycles’. This means that if the collision involves cycles, at-least one cyclist is involved in the accident. There is a strong negative correlation between ‘ROADCOND_Wet’ and ‘ROADCOND_Dry’, meaning that if the road is wet it cannot be dry. This is how we can get a deeper understanding of the data using correlation plots.



4. Machine Learning Model Selection

Total of six ML algorithms were trained on the pre-processed dataset and their accuracies were compared. A brief explanation on how each of them works along with their results in shown below.

4.1. Logistic Regression Classifier

Logistic Regression is a classifier that estimates discrete values (binary values like 0/1, yes/no, true/false) based on a given set of an independent variables. It basically predicts the probability of occurrence of an event by fitting data to a logistic function**.** Hence it is also known as logistic regression. The values obtained would always lie within 0 and 1 since it predicts the probability.

The chosen dataset has only two target categories in terms of the accident severity code assigned; hence it was possible to apply this model to the same. The results, confusion matrix, classification report and accuracy, are:

```
[[5348 4499]
 [1502 8222]]

              precision    recall  f1-score   support

           1       0.78      0.54      0.64      9847
           2       0.65      0.85      0.73      9724

    accuracy                           0.69     19571
   macro avg       0.71      0.69      0.69     19571
weighted avg       0.71      0.69      0.69     19571

0.6933728475806039
```

4.2. K Nearest Neighbours Classifier

K nearest neighbours algorithm used for both classification and regression problems. It basically stores all available cases to classify the new cases by a majority vote of its k neighbours. The case assigned to the class is most common amongst its K nearest neighbours measured by a distance function (Euclidean, Manhattan, Minkowski, and Hamming).

In order to arrive at the optimum values for nearest neighbours (k) and the distance metric (Euclidean and Manhattan), a hyper parameter KNN was used. The best accuracy was obtained for 7 nearest neighbours with Euclidean being the distance metric when applied for the problem in question.

The results, confusion matrix, classification report and accuracy, are:

```
Best Hyperparameter KNN :  {'n_neighbors': 7, 'p': 1}
[[6478 3369]
 [3104 6620]]

              precision    recall  f1-score   support

           1       0.68      0.66      0.67      9847
           2       0.66      0.68      0.67      9724

    accuracy                           0.67     19571
   macro avg       0.67      0.67      0.67     19571
weighted avg       0.67      0.67      0.67     19571


0.6692555311430177
```

4.3. Naïve Bayes Classifier

Naive Bayes classifies objects based on Bayes' Theorem with an assumption that the predictors (features) are independent of each other. Bayes theorem is a way to calculate posterior probability P(c|x) from the P(c), P(x), P(x|c). Naive Bayes is naive because it assumes the presence of a particular feature is completely unrelated to the presence of another, and each of them contributes to the posterior probability independently.

The results, confusion matrix, classification report and accuracy, when Naïve Bayes was applied to the pre-processed accident severity dataset are:

```
[[9473  374]
 [7161 2563]]

              precision    recall  f1-score   support

           1       0.57      0.96      0.72      9847
           2       0.87      0.26      0.40      9724

    accuracy                           0.61     19571
   macro avg       0.72      0.61      0.56     19571
weighted avg       0.72      0.61      0.56     19571


0.6149915691584488
```

4.4. Decision Tree Classifier

Decision Tree makes decision with tree-like model. It splits the sample into two or more homogenous sets (leaves) based on the most significant differentiators in the input variables. To choose a differentiator (predictor), the algorithm considers all features and does a binary split on them (for categorical data, split by category; for continuous, pick a cut-off threshold). It will then choose the one with the least cost (i.e. highest accuracy), and repeats recursively, until it successfully splits the data in all leaves (or reaches the maximum depth).

Information gain for a decision tree classifier can be calculated either using the Gini Index measure or the Entropy measure, whichever gives a greater gain. A hyper parameter Decision Tree Classifier was used to decide which tree to use, DTC using entropy had greater information gain; hence it was used for this classification problem.

The results, confusion matrix, classification report and accuracy, are:

```
Best Hyperparameter DTC :  {'criterion': 'entropy', 'random_state': 0}
[[6296 3551]
 [3783 5941]]
              precision    recall  f1-score   support

           1       0.62      0.64      0.63      9847
           2       0.63      0.61      0.62      9724

    accuracy                           0.63     19571
   macro avg       0.63      0.63      0.63     19571
weighted avg       0.63      0.63      0.63     19571

0.6252618670481835
```

4.5. Random Forest Tree Classifier

Random Forest Classifier is an ensemble (algorithms which combines more than one algorithms of same or different kind for classifying objects) tree-based learning algorithm. RFC is a set of decision trees from randomly selected subset of training set. It aggregates the votes from different decision trees to decide the final class of the test object. Used for both classification and regression.

Similar to DTC, RFT requires an input that specifies a measure that is to be used for classification, along with that a value for the number of estimators (number of decision trees) is required. A hyper parameter RFT was used to determine the best choices for the above mentioned parameters. RFT with 75 DT's using entropy as the measure gave the best accuracy when trained and tested on pre-processed accident severity dataset.

The results, confusion matrix, classification report and accuracy, are:

```
Best Hyperparameter RFT :  {'criterion': 'entropy', 'n_estimators': 75, 'random_state': 0}
[[6401 3446]
 [3126 6598]]
              precision    recall  f1-score   support

           1       0.67      0.65      0.66      9847
           2       0.66      0.68      0.67      9724

    accuracy                           0.66     19571
   macro avg       0.66      0.66      0.66     19571
weighted avg       0.66      0.66      0.66     19571

0.6641970262122529
```

4.6. Support Vector Machine Classifier

Support Vector Machine is an algorithm which can be used for both classification and regression challenges. However, it is mostly used in classification problems. In the SVM algorithm, each data item is plotted as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, classification is performed by finding the hyper-plane that differentiates the two classes.

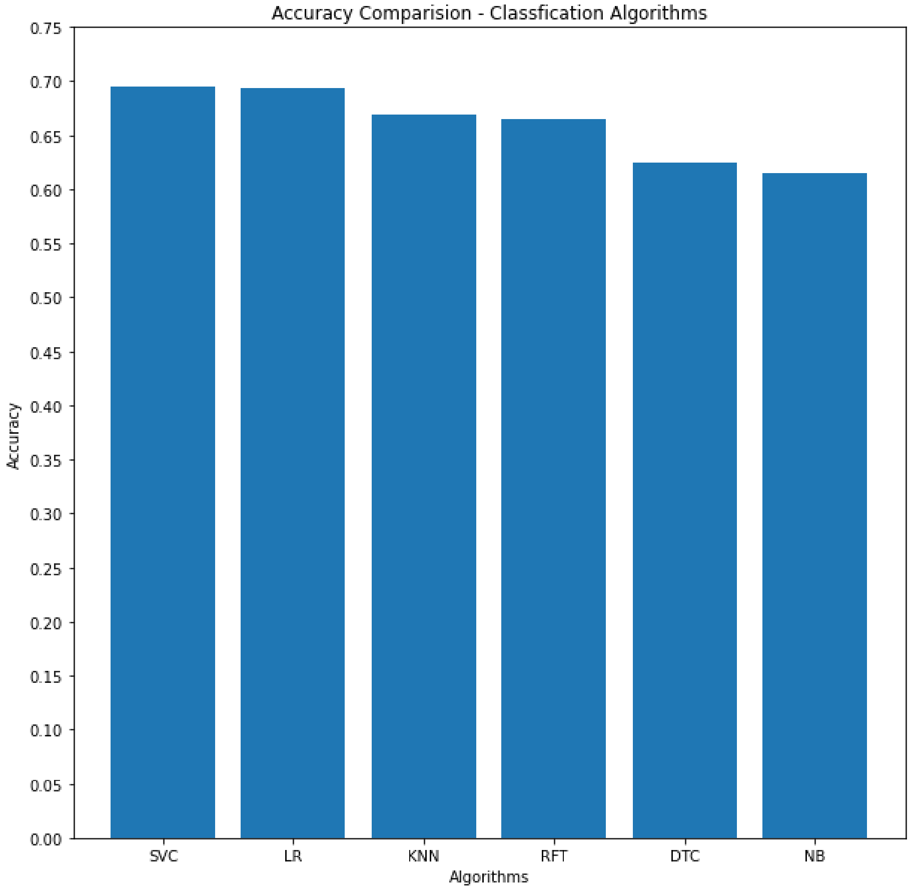
Hyper parameter SVC was used to choose between Linear SVC and a Kernel SVC and the latter arrived on top with a greater accuracy when applied on the dataset in question. It used the 'radial basis function' kernel for performing the classification.

The results, confusion matrix, classification report and accuracy, are:

```
Best Hyperparameter SVM :  {'kernel': 'rbf', 'random_state': 0}
[[5206 4641]
 [1334 8390]]

              precision    recall  f1-score   support

           1       0.80      0.53      0.64      9847
           2       0.64      0.86      0.74      9724

    accuracy                           0.69     19571
   macro avg       0.72      0.70      0.69     19571
weighted avg       0.72      0.69      0.69     19571


0.6947013438250472
```

5. Results

None of the algorithms implemented above gave an accuracy score equal to or greater than 0.7, they all ranged from 0.6 to 0.7. Meaning, these models can predict the severity code of an accident with an accuracy equalling 60-70%. A bar plot is plotted below with the bars representing the accuracy of each model in descending order respectively.



Clearly, Kernel Support Vector Machine is the best classifier for this classification problem based on accuracy, followed by the Logistic Regression model.

6. Conclusion

The accuracy of the classifiers is not great, highest being 69%. This usually means that the model is under fitted i.e. it needs to be trained on more data. Though the dataset has a lot of variety in terms of scenarios, more volume of the data for such scenarios has to be collected.

Certain features with missing values were removed, this reduced the dimensionality of the dataset, these features could have been correlated to other important features but they had to be removed. A better effort has to be made to collect data to reduce the number of missing values.

7. Future Work

As mentioned above, the amount of data available to train the above-mentioned models in not sufficient and it does not seem to have enough data of all varieties. Hence, integrating Cross Validation methods with hyper parameter model would help in training and possibly increase the accuracy of every classification model.