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Collisions Seattle City**

**Khushboo Sawlani**

**25-09-2020**

**Background**

Seattle also known as the Emerald city is Washington state’s largest city and has many international people. Due to increasing population, number of vehicles in Seattle has increased causing often traffic jams. In addition, Seattle’s rainy weather is adding fire to the bad traffic conditions.

**Problem**

Road accidents have been a major cause for concern across Seattle City, claiming about thousand lives per year.

Next to this intolerably high number of lives lost, about millions are injured in road traffic crashes. As a result, our societies bear a huge cost. Road traffic injuries are the leading cause of death among young people in the region and are predicted to increase in countries with low or medium income as they become more highly motorized.

The fact that effective preventive strategies do exist makes this situation all the more unacceptable. The success of some other states in reducing the toll of deaths and injuries on their roads clearly demonstrates strong commitment. Much can be learned from these experiences and innovative approaches and be reapplied and adapted to various situations. With this project, our objective is to reduce road accident severity by analyzing certain known factors such as weather conditions, road conditions, speeding, etc.

**Data Understanding**

Road collisions data consist of information related to severity of the road collisions along with various factors that could cause road collisions. Injury Collision and Property Damage Collision are two the severe collisions recorded by Traffic management. Other major causes and details of collisions recorded includes Weather, Road condition, Light condition, junction information, speeding and so on.

Data set contains **194673 rows × 38 columns**. Data captures contains lot of empty fields, NAN (not a number) and other invalid values. These values won’t be considered for data modeling as it may result in incorrect information. Classification algorithm will be used for modeling as target variable SEVERITY is categorical with discrete value ‘Property damage’ and ‘Injury collision’.

**Data Cleaning**

Data cleaning starts with selecting only few relevant features. I have selected 13 features listed below for further analysis:

* SEVERITYCODE – This is target variable and corresponds to the severity of the collision:
* X - Longitude
* Y - Latitude
* ADDRTYPE - Collision address type (Alley, Block or Intersection).
* COLLISIONTYPE - Collision type.
* PERSONCOUNT - The total number of people involved in the collision.
* VEHCOUNT - The number of vehicles involved in the collision.
* UNDERINFL - Whether or not a driver involved was under the influence of drugs or alcohol.
* INATTENTIONIND - Whether or not collision was due to inattention.
* JUNCTIONTYPE - Category of junction at which collision took place.
* WEATHER - A description of the weather conditions during the time of the collision.
* ROADCOND - The condition of the road during the collision.
* LIGHTCOND - The light conditions during the collision.
* SPEEDING - Whether or not speeding was a factor in the collision.

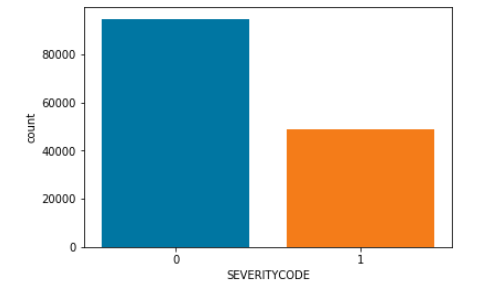
Next step is to find and remove missing data from the data set. We have removed the rows having value ‘Other’ and ‘Unknown’ from features WEATHER, ROADCOND, LIGHTCOND, JUNCTIONTYPE, COLLISIONTYPE.

LIGHTCOND feature having value “Dark - Unknown Lighting'” is also dropped as it is confusing value. Value ‘Dark - Street Lights Off’ is same as ‘Dark - No Street Lights’. Hence, both will be merged.

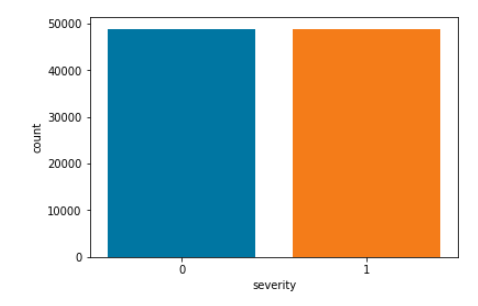
In order to standardize the data set value ‘Y’ and ‘N’/’nan’ is changed to ‘1’ and ‘0’ for UNDERINFL, SPEEDING and INATTENTIONIND. Severity code values is also changed to ‘1’ and ‘0’ from ‘2’ and ‘1’ respectively.

Severity of the property damage (value=0) accidents is almost as double as the one involving injuries (value=1). RandomUnderSampler resampling technique is used to balance the data set in order to improve the accuracy. Below you can see how data set is balanced:

**Before:**



**After:**



After Data cleaning, data is reduced to **143741 rows × 14 columns** from 194673 rows × 38 columns.

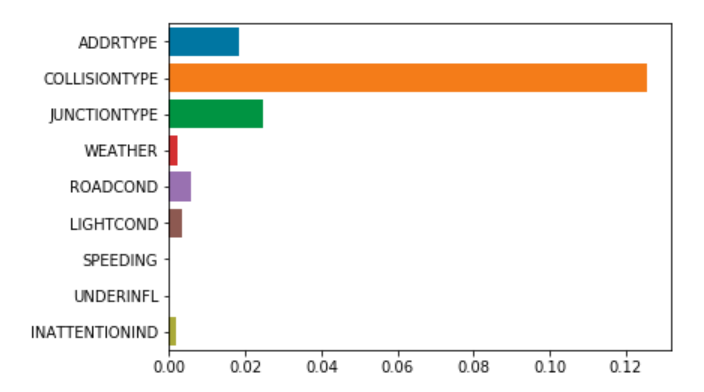
**Feature Selection**

Feature selection plays important role in predictive modeling. Correct feature selection will result in greater accuracy. Feature selection is performed using mutual information method of scikit learn library.

After analyzing the feature, it is observed that COLLISION TYPE feature affects the most in determining the collision severity (target variable). Severity of accidents depends on where was the collision occurred. However, COLLITION TYPE, ADDRTYPE and JUNCTION TYPE features can’t predict the severity beforehand. There features can only be known after the accident. Hence, COLLISION TYPE, ADDRTYPE and JUNCTION TYPE features will not be considered for modeling.

Four features WEATHER, ROADCONDITION, LIGHTCONDITION and INATTENTIONIND are used to for modeling.

Rest of the features doesn’t affect much on severity and won’t be considered for modeling.



Feature ADDRTYPE: 0.018286

Feature COLLISIONTYPE: 0.125731

Feature JUNCTIONTYPE: 0.024836

Feature WEATHER: 0.002015

Feature ROADCOND: 0.005881

Feature LIGHTCOND: 0.003328

Feature SPEEDING: 0.000000

Feature UNDERINFL: 0.000000

Feature INATTENTIONIND: 0.001673

**Exploratory Data Analysis**

Seaborn count plot is used for analyzing impact of individual feature over target variable severity.

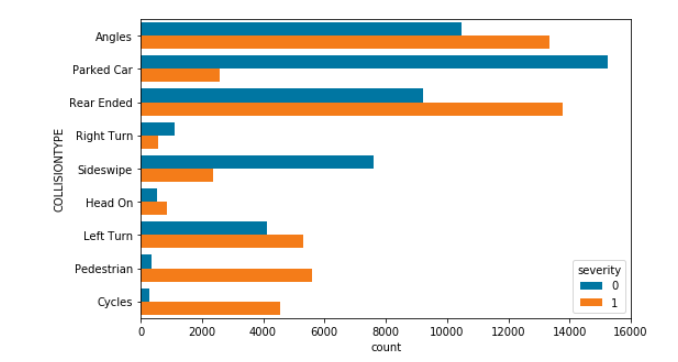
Severity values are:

0 - Property Damage Only Collision

1 - Injury Collision

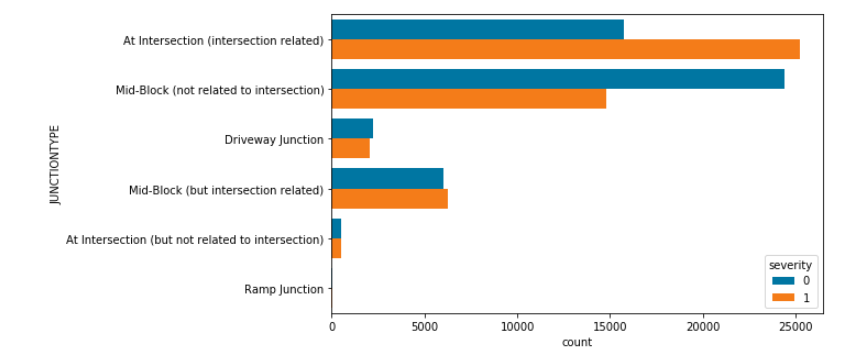
**Relationship between Severity and Collision**

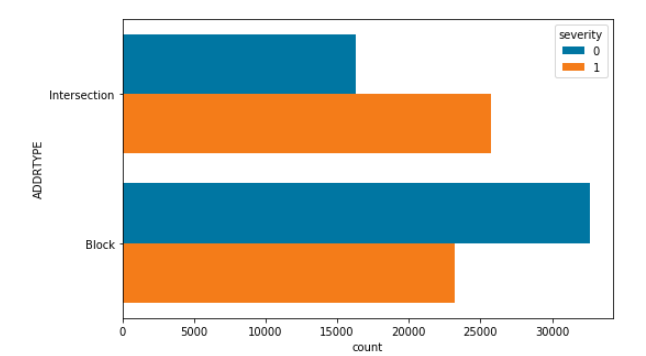
Below histogram shows most injury collision happens in Angles, Rear end and Left Turn. There is less risk of property damage by Pedestrian, Cycles and Head on collision. However, Pedestrian and Cycles can cause injury collision. It is also being notice Left turn is risker than Right turn. Parked cars can cause most property damage.



**Junction Type and Address Type**

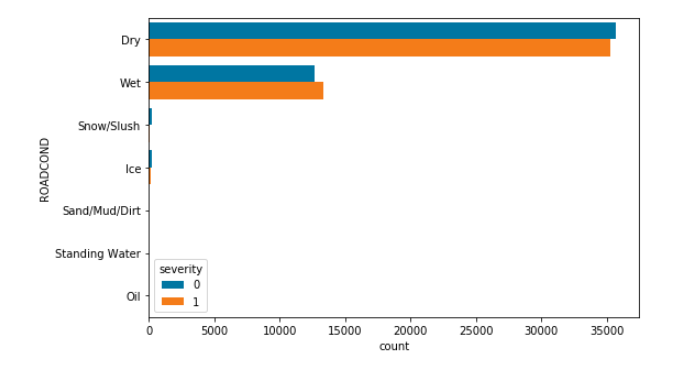
There are two types of Junctions Mid-Block and Intersection. Injury collision happens more at intersections. Mid-Block junction not related to intersection does more property damage than intersection. Similar results are observed in Address Type as shown below:





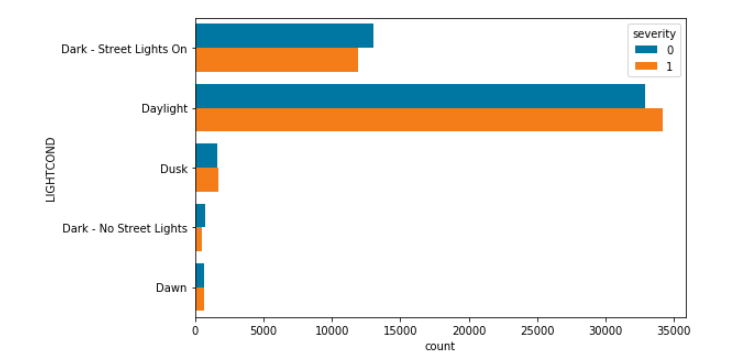
**Road condition**

Property damage and Injury collision both are higher in Dry Roads than Wet Roads.



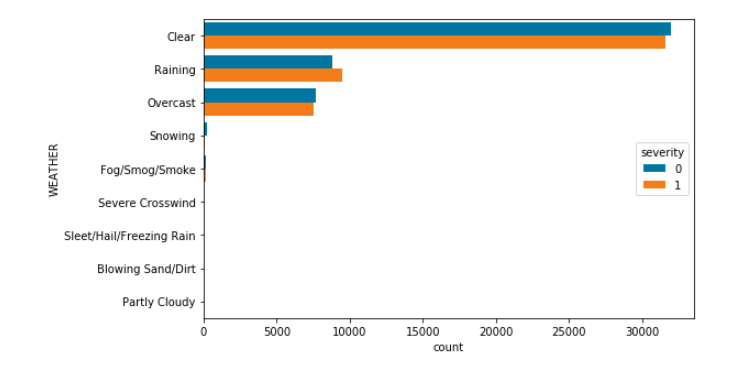
**Light condition**

More accidents occur during day Light than during night.



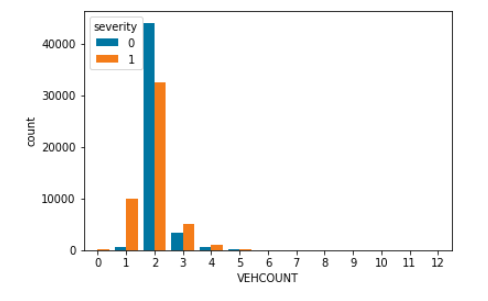
**Weather**

As shown in Road condition histogram, accidents are more frequent during clear weather than raining and overcast.



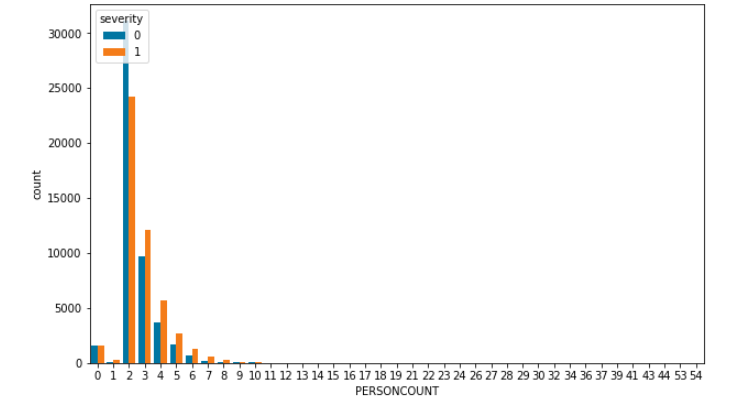
**Vehicle Count**

Vehicle count data will only be available after accident. Hence do not help in model prediction.



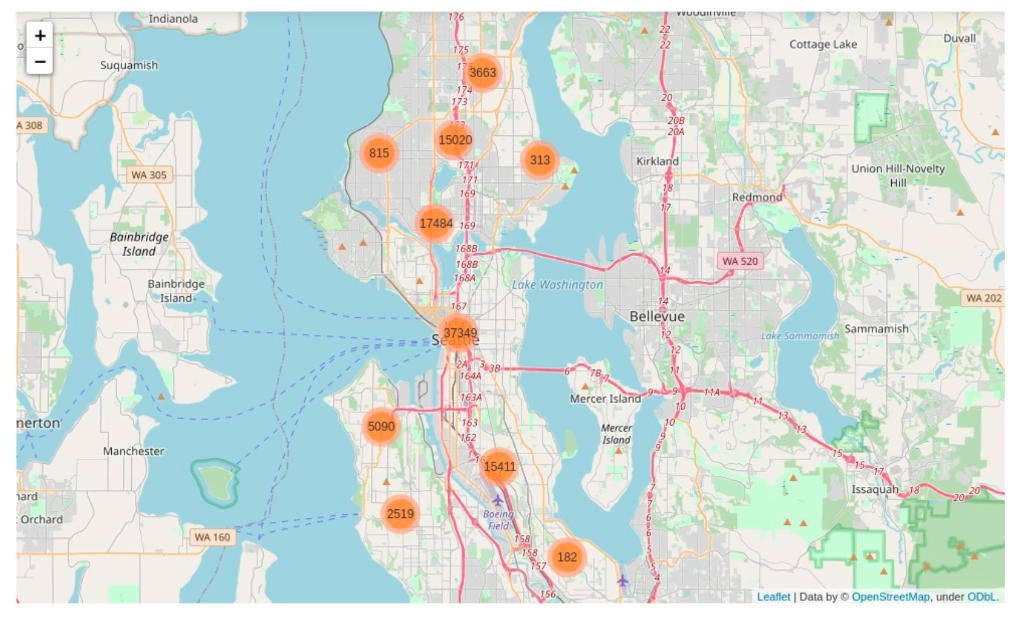
**Person Count**

Same goes for Person count, data will only be available after collision and doesn’t add any value to model prediction.



**Geographical Maps to show accident numbers**

Below map gives the good overview of total number of accidents in Seattle city. More you zoom into the map; area wise information will be revealed. Traffic management can use this map to identify accidents hot spots and provide more frequent warning to the traffic.



**Modeling**

Classification algorithm – KNN, Decision Tree, Logistic Regression, Random Forest and SVM models are used for predictive modeling. Target variable severity is a categorical variable with a discrete value ‘0’ property damage and ‘1’ injury collision. As explained in the feature selection section, WEATHER, ROAD CONDITION and LIGHT CONDITION features are chosen features for modeling.

Data Standardization is performed before predictive modeling using standard scalar preprocessing technique.

Next step is to perform Out of Sample Accuracy using Train/Test split approach. Out of Sample Accuracy is the percentage of correct predictions that the model makes on the data set that the model has NOT been trained on. Train/Test Split involves splitting the dataset into training and testing sets respectively, which are mutually exclusive. After which, data is trained with the training set and tested with the testing set.

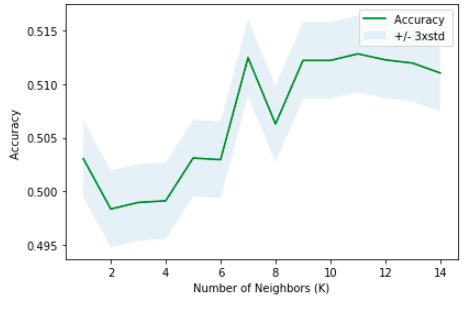
Model Accuracy will provide Precision, Recall and f1-score results.

* **Precision:** Precision refers to the percentage of results which are relevant, in simpler terms it can be seen as how many of the selected items from the model are relevant. Mathematically, it is calculated by dividing true positives by true positive and false positive
* **Recall:** Recall refers to the percentage of total relevant results correctly classified by the algorithm. In simpler terms, it tells how many relevant items were selected. It is calculated by dividing true positives by true positive and false negative
* **F1-Score:** f1-score is a measure of accuracy of the model, which is the harmonic mean of the model’s precision and recall. Perfect precision and recall is shown by the f1-score as 1, which is the highest value for the f1-score, whereas the lowest possible value is 0 which means that either precision or recall is 0

**KNN**

**K-Nearest Neighbors** is an algorithm for supervised learning. Where the data is 'trained' with data points corresponding to their classification. Once a point is to be predicted, it takes into account the 'K' nearest points to it to determine it's classification.

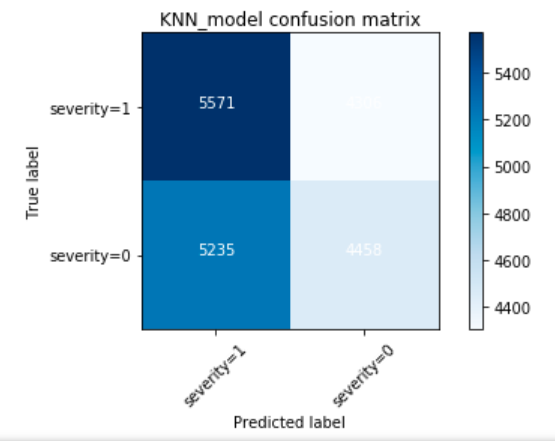
Below graph shows the best accuracy is when K is equal to 13. However, highest K values comes with risk of overfitting. Hence, we will choose K equal to 7.



**Classification Report:**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Precision** | **Recall** | **F1-Score** | **Support** |
| **Property Damage** | **0.51** | **0.46** | **0.48** | **9693** |
| **Personal Injury** | **0.52** | **0.56** | **0.54** | **9877** |
| **Accuracy** |  |  | **0.51** | **19570** |
| **Macro avg** | **0.51** | **0.51** | **0.51** | **19570** |
| **Weighted avg** | **0.51** | **0.51** | **0.51** | **19570** |

**Confusion Matrix:**



**Decision Tree**

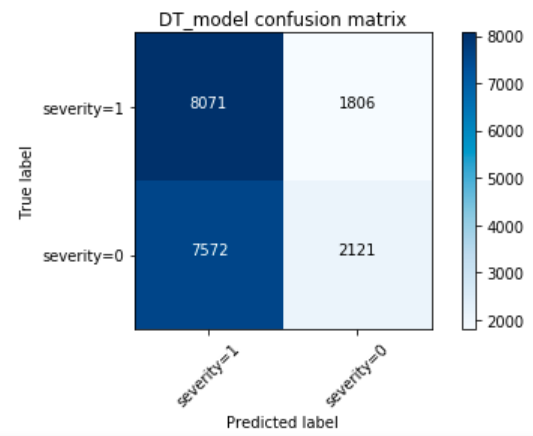
Decision trees are built by splitting the training set into distinct nodes, where one node contains all or most of one category of the data. Instance of the decision tree classifier is created. Entropy Criterion is selected inside the classifier to see the information gain.

Below is the classification report and confusion matrix:

**Classification Report**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Precision** | **Recall** | **F1-Score** | **Support** |
| **Property Damage** | **0.54** | **0.22** | **0.31** | **9693** |
| **Personal Injury** | **0.52** | **0.82** | **0.63** | **9877** |
| **Accuracy** |  |  | **0.52** | **19570** |
| **Macro avg** | **0.53** | **0.52** | **0.47** | **19570** |
| **Weighted avg** | **0.53** | **0.52** | **0.47** | **19570** |

**Confusion Matrix:**



**SVM**

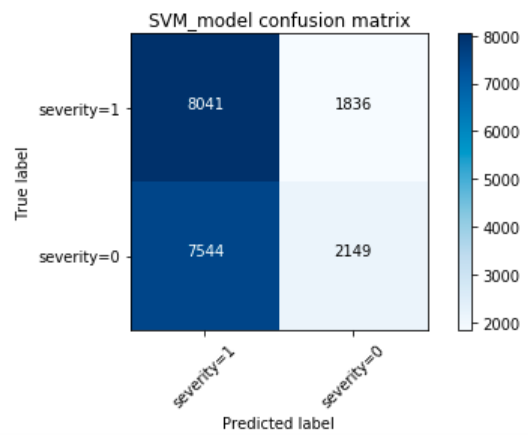
SVM works by mapping data to a high-dimensional feature space so that data points can be categorized, even when the data are not otherwise linearly separable. A separator between the categories is found, then the data is transformed in such a way that the separator could be drawn as a hyperplane. Following this, characteristics of new data can be used to predict the group to which a new record should belong.

The SVM algorithm offers a choice of kernel functions for performing its processing. Basically, mapping data into a higher dimensional space is called kernelling. The mathematical function used for the transformation is known as the kernel function. We have used Radial basis function (RBF).

**Classification Report:**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Precision** | **Recall** | **F1-Score** | **Support** |
| **Property Damage** | **0.54** | **0.22** | **0.31** | **9693** |
| **Personal Injury** | **0.52** | **0.81** | **0.63** | **9877** |
| **Accuracy** |  |  | **0.52** | **19570** |
| **Macro avg** | **0.53** | **0.52** | **0.47** | **19570** |
| **Weighted avg** | **0.53** | **0.52** | **0.47** | **19570** |

**Confusion Matrix:**



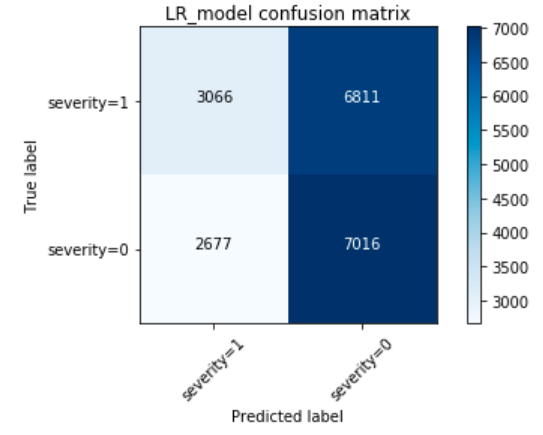
**Logistic Regression:**

Logistic Regression is a variation of Linear Regression, useful when the observed dependent variable, **y**, is categorical. It produces a formula that predicts the probability of the class label as a function of the independent variables. We have used the inverse of regularization strength in C = 0.1 for model prediction.

**Classification Report:**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Precision** | **Recall** | **F1-Score** | **Support** |
| **Property Damage** | **0.51** | **0.72** | **0.60** | **9693** |
| **Personal Injury** | **0.53** | **0.31** | **0.39** | **9877** |
| **Accuracy** |  |  | **0.52** | **19570** |
| **Macro avg** | **0.52** | **0.52** | **0.49** | **19570** |
| **Weighted avg** | **0.52** | **0.52** | **0.49** | **19570** |

**Confusion Matrix:**



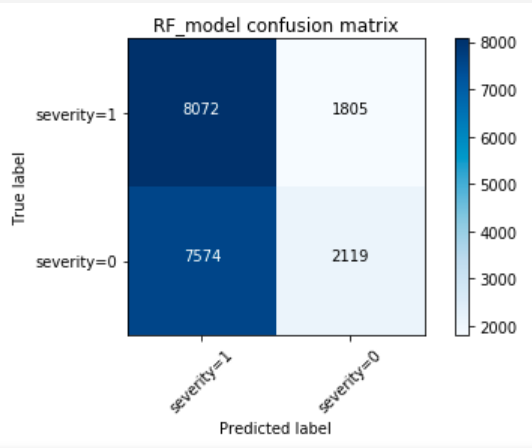
**Random Forest**

Random forest builds multiple decision trees and merges them together to get a more accurate and stable prediction. Random forest adds additional randomness to the model, while growing the trees. Instead of searching for the most important feature while splitting a node, it searches for the best feature among a random subset of features. This results in a wide diversity that generally results in a better model.

**Classification Report:**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Precision** | **Recall** | **F1-Score** | **Support** |
| **Property Damage** | **0.54** | **0.22** | **0.31** | **9693** |
| **Personal Injury** | **0.52** | **0.82** | **0.63** | **9877** |
| **Accuracy** |  |  | **0.52** | **19570** |
| **Macro avg** | **0.53** | **0.52** | **0.47** | **19570** |
| **Weighted avg** | **0.53** | **0.52** | **0.47** | **19570** |

**Confusion Matrix:**



**Optimization Results**

Optimization is performed to calculate best performing model. Based on optimization results, Random forest is the best predictive model to use for car collision data analysis. Optimization results shows max 12 features and 81 estimators.

Below table shows different model accuracy, jaccard index and f1-score results:

|  |  |  |  |
| --- | --- | --- | --- |
| **Model** | **Accuracy** | **Jaccard** | **f1** |
| **KNN** | **0.51** | **0.37** | **0.51** |
| **Decision Tree** | **0.52** | **0.46** | **0.47** |
| **SVM** | **0.52** | **0.46** | **0.47** |
| **Logistic Regression** | **0.52** | **0.24** | **0.49** |
| **Random Forest** | **0.52** | **0.46** | **0.47** |

**Discussions**

Based on different model results, it is being observed that all the models had similar results. Accuracy of all the models are around 50 %. More analysis is needed to improve the accuracy.

**Conclusion**

In order to build road accidents possibilities model, we have first cleaned the data provided by Seattle traffic management system. Data is also balanced on severity level using resampling technique. Feature selection using mutual information classifier is performed which resulted in selecting four features Weather, Road condition, Light condition and Inattention id. We have used KNN, Decision Tree, SVM, Logistic Regression and Random Forest algorithm for predictive modeling. Accuracy of all the models are around 50 percent which won’t be enough for prediction. Further analysis is needed to improve the accuracy.

We also found about relation between accident severity and other features. Below points should be considered by traffic management before warning traffic.

* Angles, Rear end and Left turn causes more injury collisions.
* Parked cars are more prone towards property damage.
* Left turn is riskier than right turn.
* Injury occurred more for pedestrian and cyclist than the property damage.
* Most of the road accidents happens in clear weather. However, caution should be taken during bad weather condition.
* Most of the road accidents happens during day light.