TRAFFIC SEVERITY ANALYSIS

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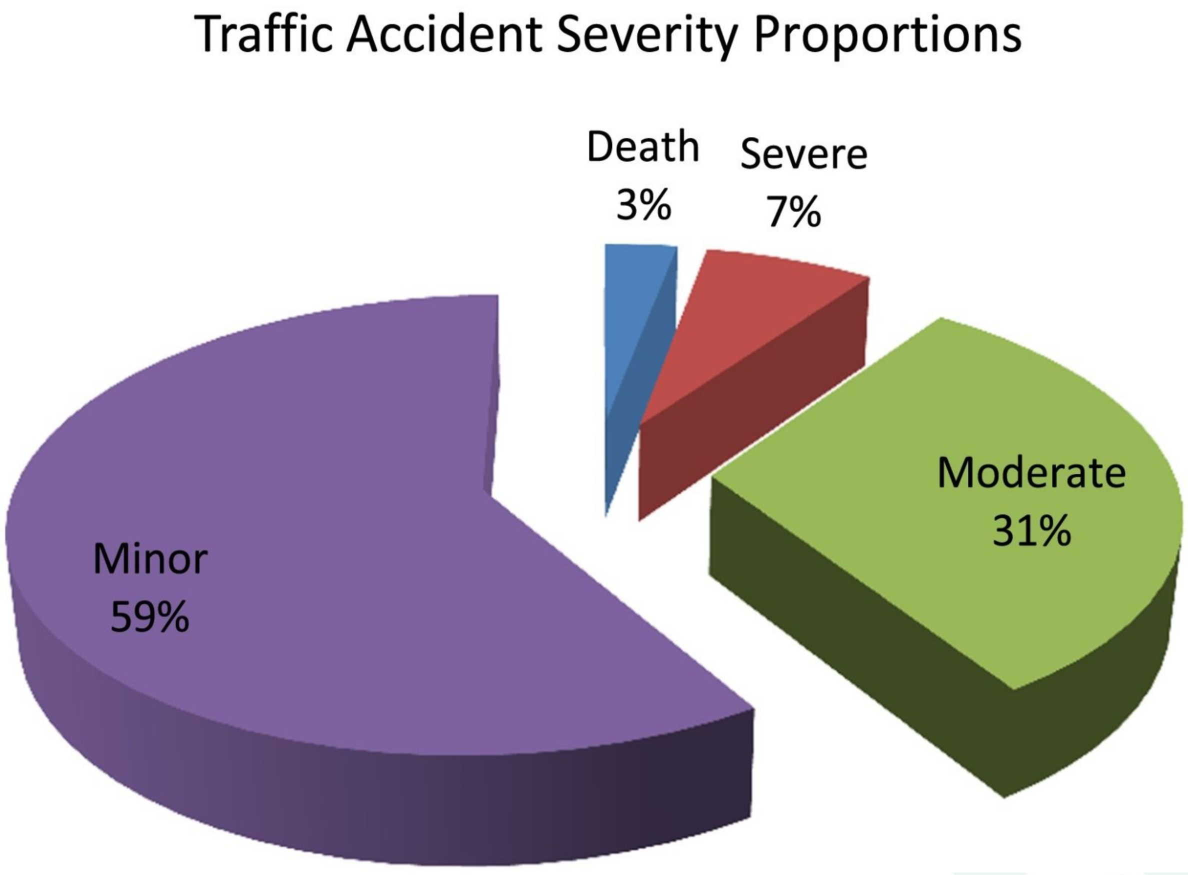
Motivation

Traffic Severity significantly impacts society through economic expenses, physical and mental health disorders, a loss of productivity and most importantly, the loss of many valuable lives.

Take the example of the USA, where the National Highway Traffic Safety Administration released its latest report estimating that there had been about 42,795 fatalities in 2022 due to motor vehicle crashes.

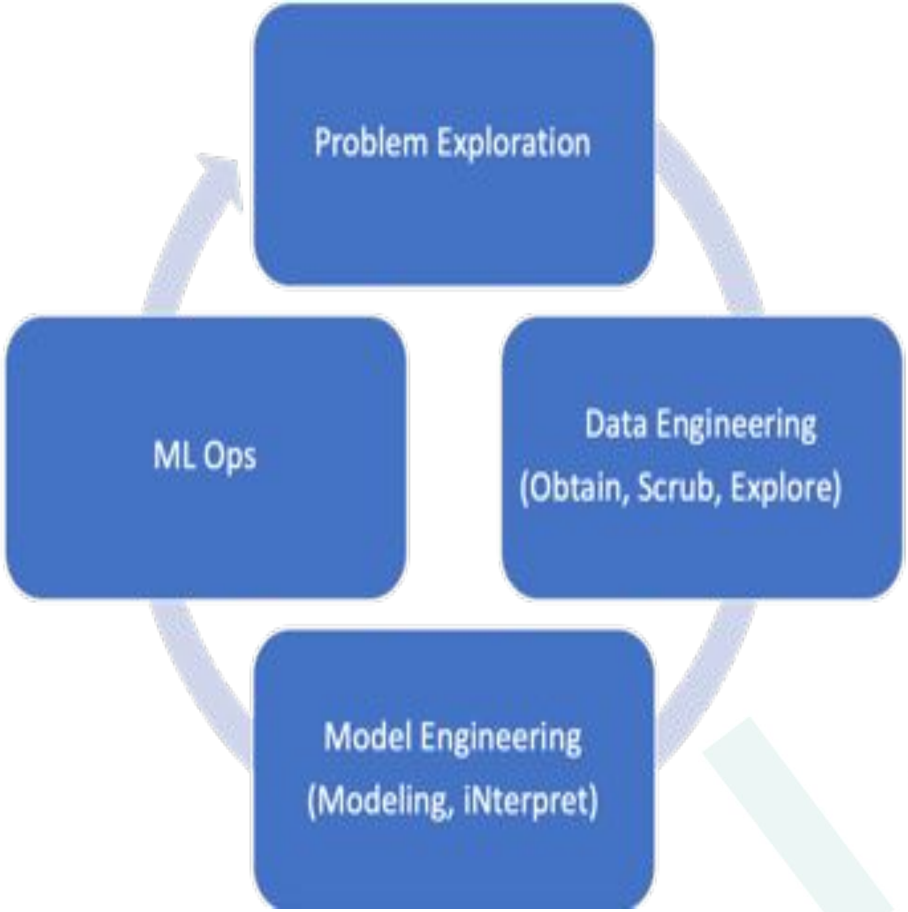


(*Source : ResearchGate*)

Motivation

In order to come up with effective approaches to prevent such accidents, it is critical that we perform Traffic Severity Analysis to identify frequent patterns and trends.

This involves carefully examining the dataset and identifying the key factors/variables that influence traffic severity, and then using these factors to create a model which can accurately predict the severity of any future traffic situations.



(*Source : DataScience.org*)

Literature Survey

1. Improved naive Bayes classification algorithm for traffic risk management *by*

Hong Chen , Songhua Hu , Rui Hua and Xiuju Zhao

- Paper highlights Naive Bayes' advantages of minimal parameter estimation from limited training data.
- However, simple Naive Bayes faces some obvious shortcomings. So, it introduces an "Improved Naive Bayes Classifier" with feature weighting for enhanced feature importance.
- Further addresses accuracy issues in small sample, large attribute scenarios using Laplace calibration.
- Offers promising potential for more accurate traffic risk prediction.

Feature-weighted naive Bayes classification algorithm

$$N(A_j = x_j)$$

w_j represents the proportion of the number of samples in the total number of samples when attribute A_j is x_j.

$$P(C_i|X) = \alpha \prod_{j=1}^{k} w_j \frac{N(C = C_i, A_j = x_j)}{N(C_i)} \cdot \frac{N(C_i)}{N(D)}$$

$$= \alpha \prod_{j=1}^{k} \frac{N(A_j = x_j)}{N(D)} \cdot \frac{N(C = C_i, A_j = x_j)}{N(C_i)} \cdot \frac{N(C_i)}{N(D)}$$

Laplace calibration

$$P(C_i|X) = \alpha \frac{N(C_i)}{N(D)} \prod_{j=1}^{k} \frac{N(A_j = x_j) + 1}{N(D) + q_j} \cdot \frac{N(C = C_i, A_j = x_j) + 1}{N(C_i) + q_j}$$

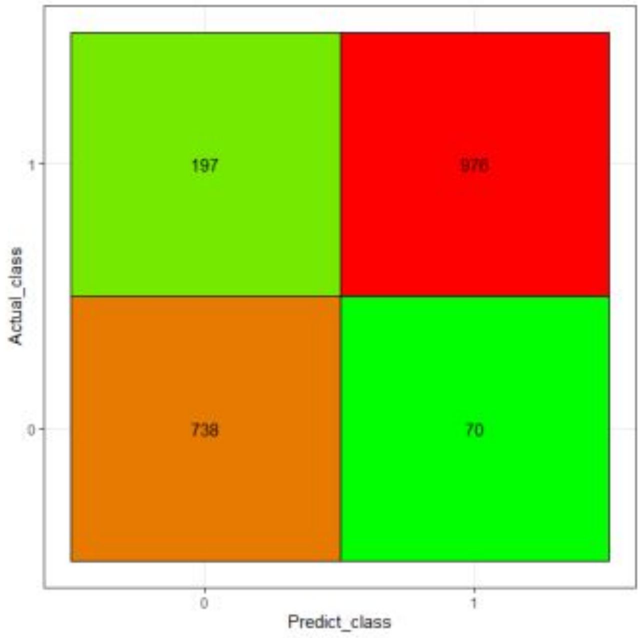
q_j represents the number of possible values of attribute A_j.

Literature Survey

2. [Traffic Accidents Severity Prediction using Support Vector Machine Models](#) *by*

Zeinab Farhat, Ali Karouni, Bassam Daya, Pierre Chauvet, Nizar Hmadeh

- Paper explores SVM models for predicting accident fatality rates, comparing radial basis function (RBF) and linear kernels.
- Dataset from Lebanon in 2016-2017 underwent preprocessing with normalization and outlier removal.
- SVM seeks to maximize hyperplane margin for optimal class separation. This model employs a binary SVM.
- Paper employs SVM kernels (linear, RBF) for data prediction model.
- Model achieved 91% accuracy on the testing set with RBF kernel and 84.6% with the linear kernel.



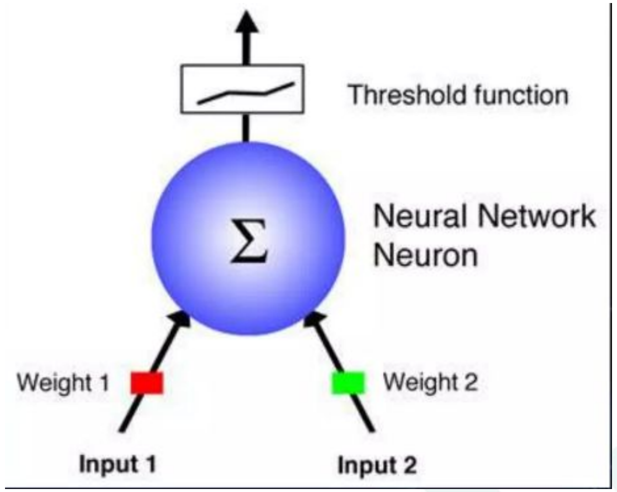
Testing confusion matrix

Literature Survey

4. Traffic Accident Analysis Using Decision Trees and Neural Networks

by Victor Akinbola Olutayo and Adekunle Eludire

- The paper employs Decision Trees and Neural Network techniques to perform traffic accident analysis which is used to identify variables that are correlated to the severity level, standard errors, varying importance of different features, and their effects on the target variable
- The data set used Nigeria Road Safety Corps, covering a 24-month period from January 2002 to December 2003 as their dataset
- The results observed were Decision Tree better than RBF neural network which was better than MLP



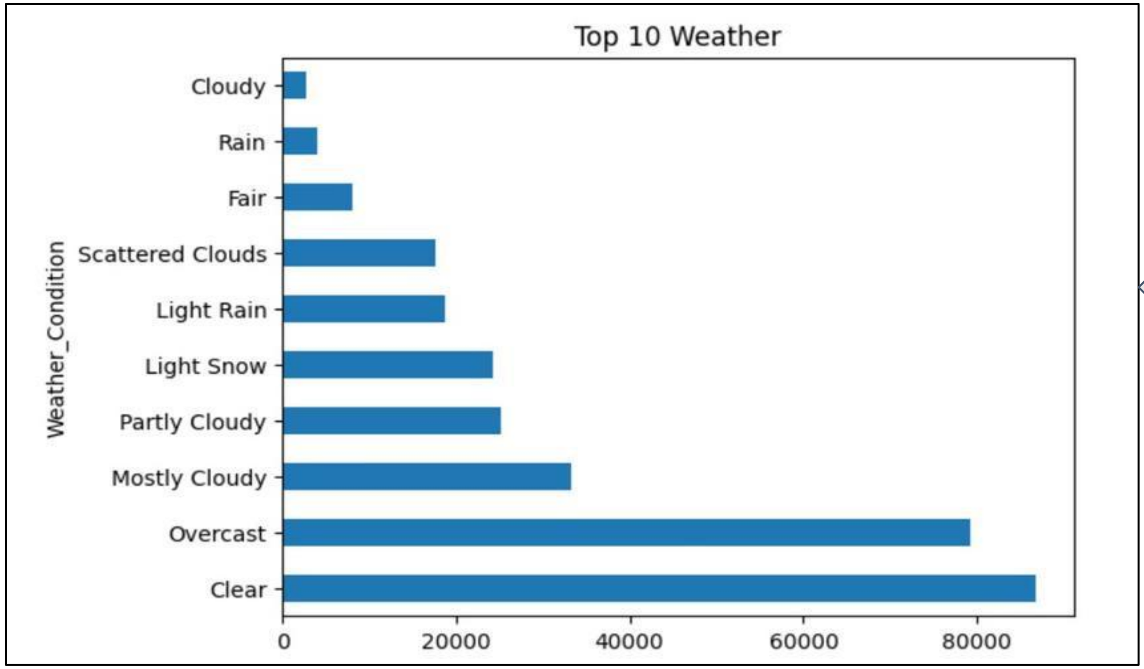
DATASET DESCRIPTION

The dataset includes traffic severity information covering 49 states of the US from the years 2016 - 2018. There are a total of 314285 rows and 18 features in the dataset to begin with. On the basis of these attributes, an accident is classified as having a severity between 1 - 4 (inclusive).

The features have been divided into 4 types of attributes depending upon the kind of information that they provide.

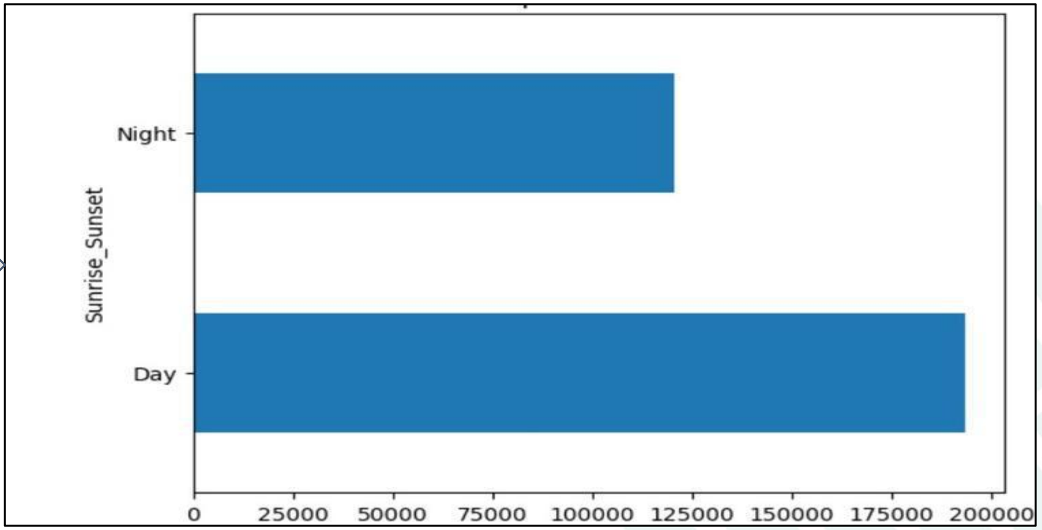
Traffic Attributes	Severity, Distance, Traffic Signal, Time Difference
Location Attributes	Start Latitude, Start Longitude, Street, City, County, State, Airport Code
Weather Attributes	Temperature, Wind Chill, Visibility, Wind Direction, Weather Condition
Time Attributes	Year, Sunrise_Sunset

DATA INFERENCES

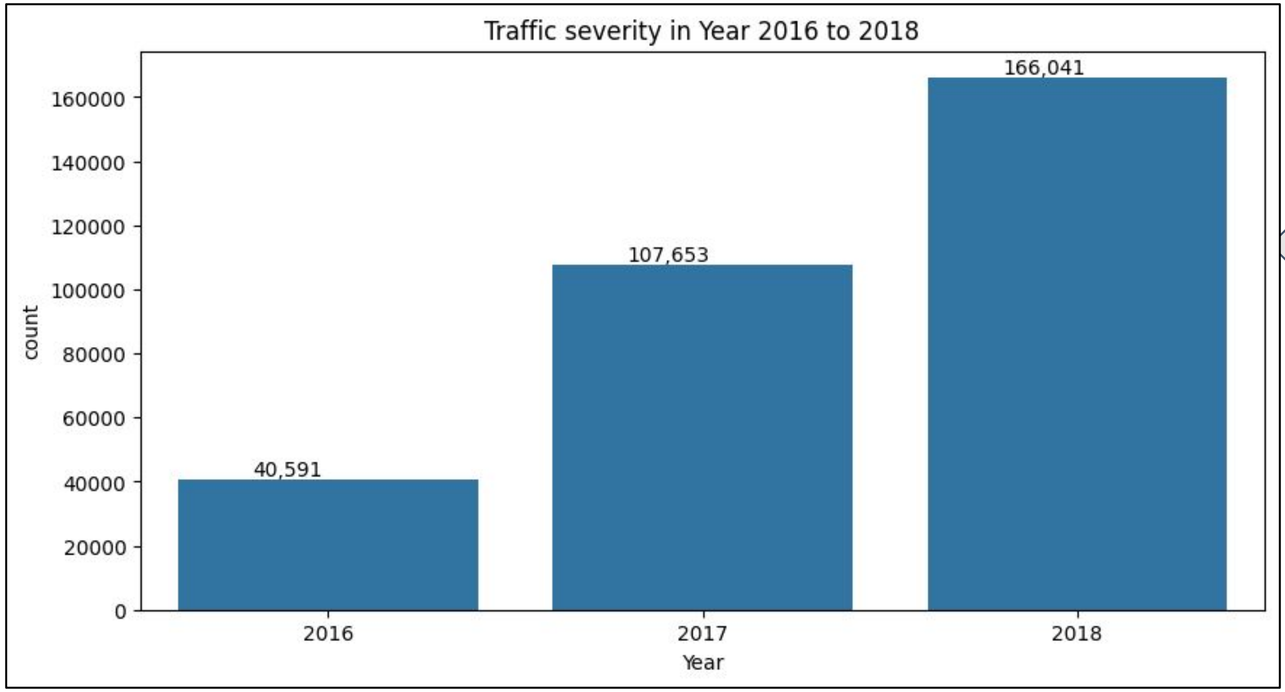


The bar graph representing weather conditions reveals that the majority of accidents occur during clear or overcast weather conditions.

The bar graph depicting sunrise and sunset times indicates that the majority of accidents occur during daylight hours.

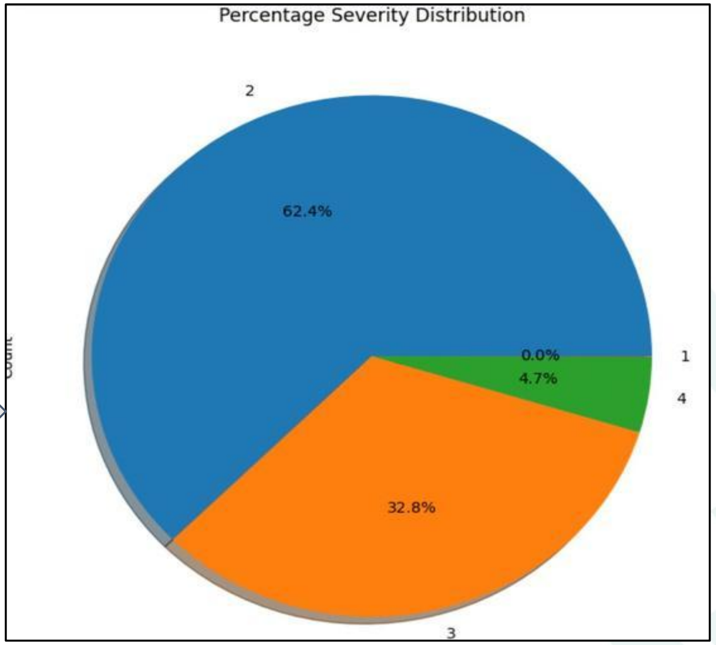


DATA INFERENCES

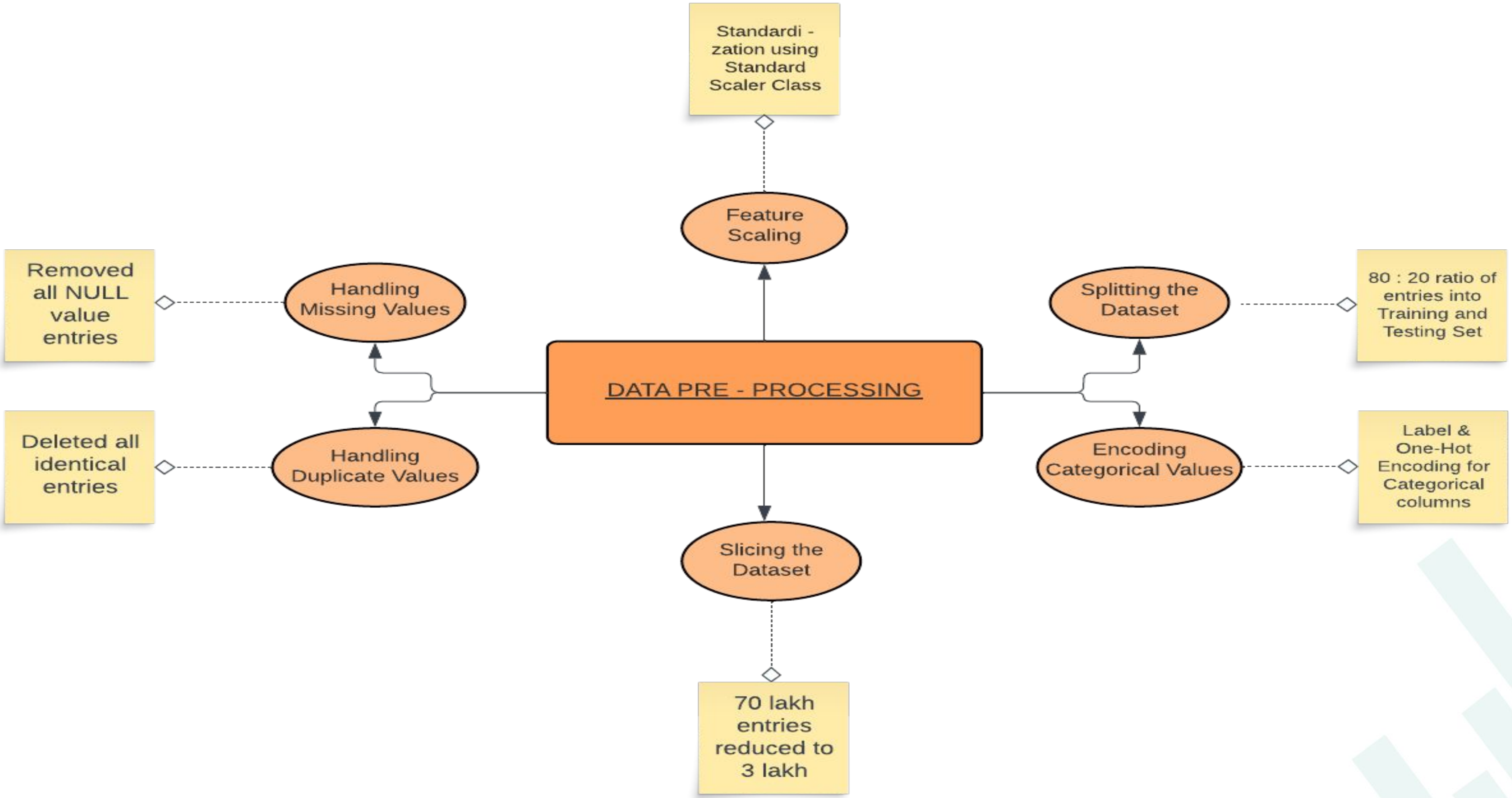


The bar graph of the year wise traffic distribution shows that the traffic severity has kept on increasing over the years, with the 2018 count being about 4 times the 2016 count.

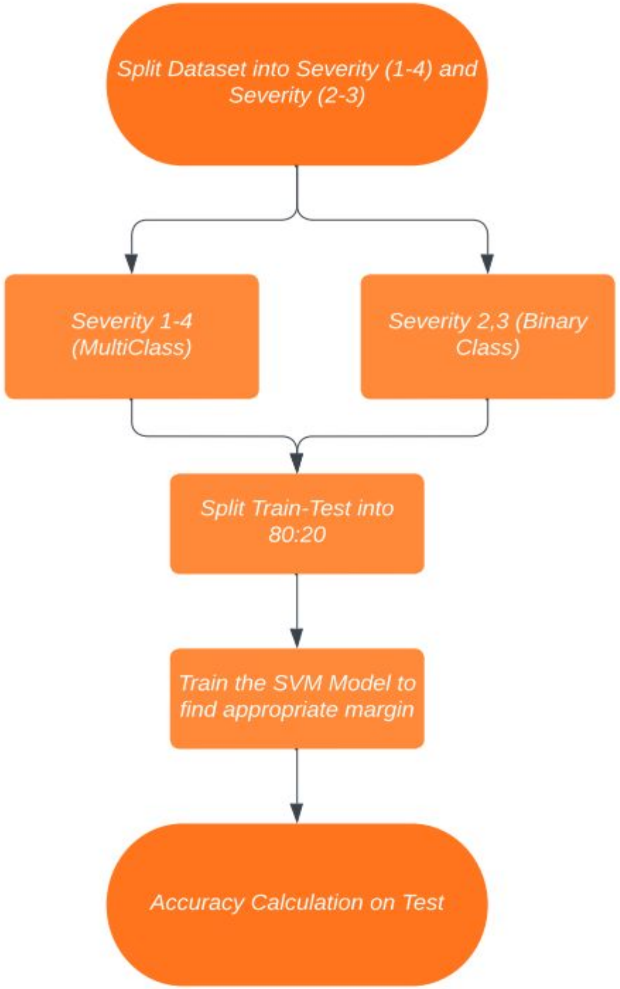
The pie-chart of the percentage severity distribution tells us that most of the traffic observed on the roads is of severity level 2 (62.4%) and severity level 3 (32.8%). Traffic severity levels of 1 and 4 are rarely observed.



DATA PRE-PROCESSING



Methodology–Support Vector Machine



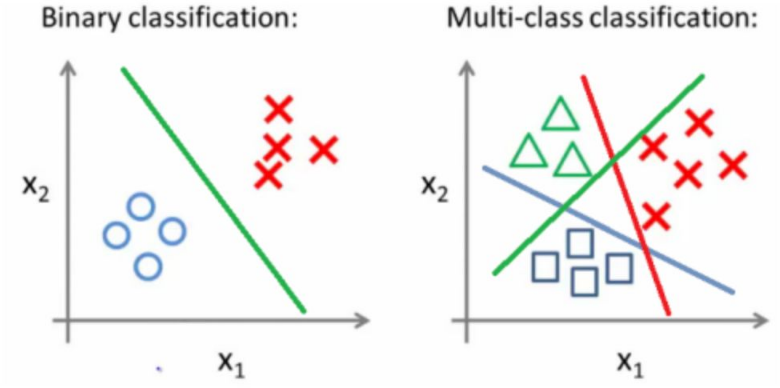
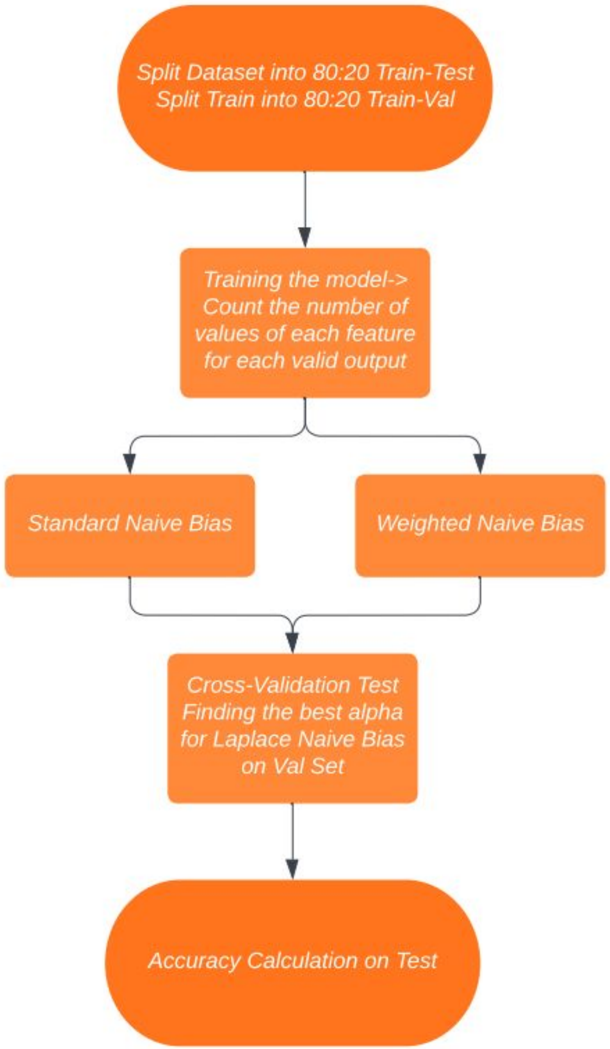


Fig : Multiclass breaks into many binary classes problems (*Source: Medium*)

	TrainSet	TestSet	SVM type
Severity(1-4)Outliers	0.6775	0.681	linear
Severity(1-4) w/o Outliers	0.689	0.657	linear
Severity (2,3)	71.43	0.669	linear

Methodology–Mixed Naive Bayes



Naive Bayesian classification

$$P(C_i|X) = \alpha \prod_{j=1}^{k} \frac{N(C = C_i, A_j = x_j)}{N(C_i)} \cdot \frac{N(C_i)}{N(D)}$$

Feature-weighted
Naive Bayesian classification

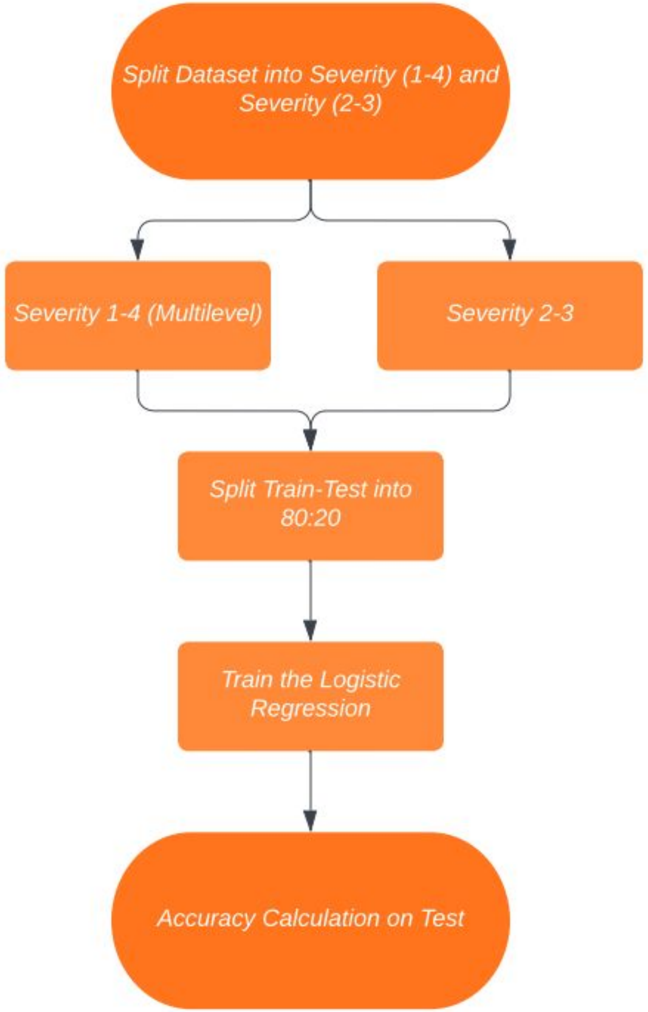
$$P(C_i|X) = \alpha \prod_{j=1}^{k} w_j \frac{N(C = C_i, A_j = x_j)}{N(C_i)} \cdot \frac{N(C_i)}{N(D)}$$

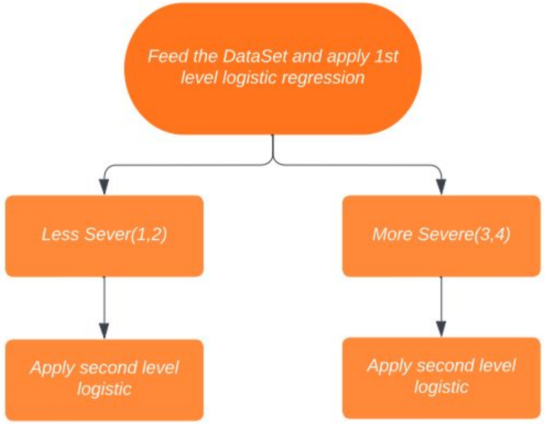
Laplace calibration
Naive Bayesian classification

$$P(C_i|X) = \alpha \frac{N(C_i)}{N(D)} \prod_{j=1}^{k} \frac{N(A_j = x_j) + 1}{N(D) + q_j} \cdot \frac{N(C = C_i, A_j = x_j) + 1}{N(C_i) + q_j} , i$$

	TestTrain	ValTrain	TestSet	Alpha
With Outliers	0.67	0.645	0.623	1.5
Without Outlier	0.687	0.676	0.679	1
Improved NBC	0.728	0.683	0.672	1

Methodology-Logistic Regression

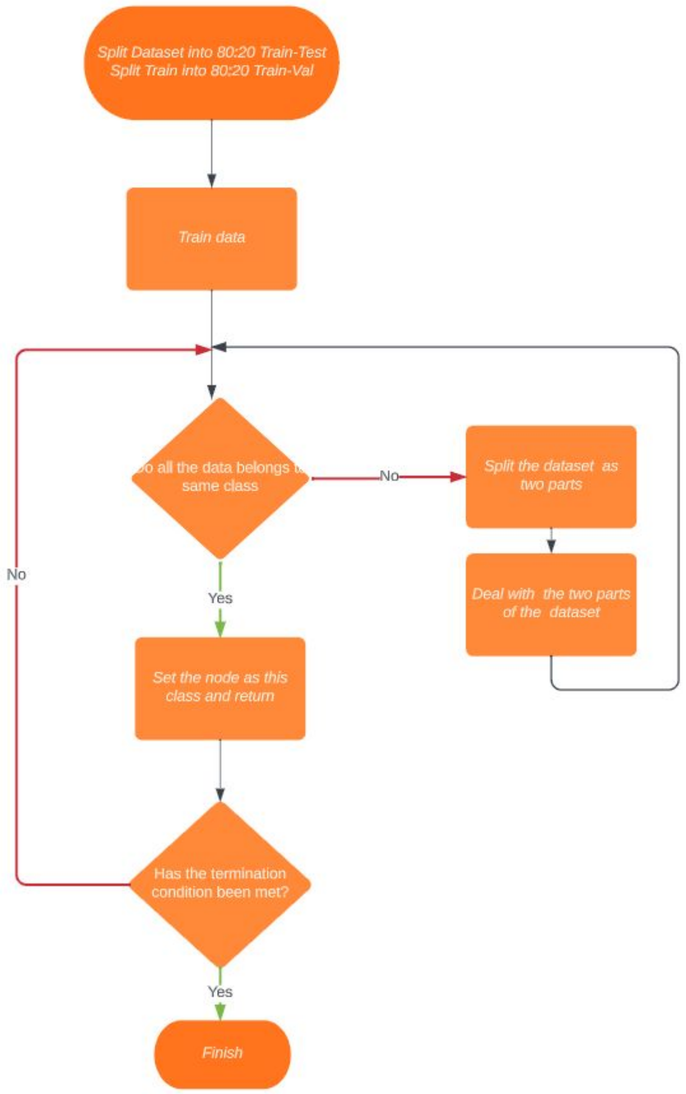




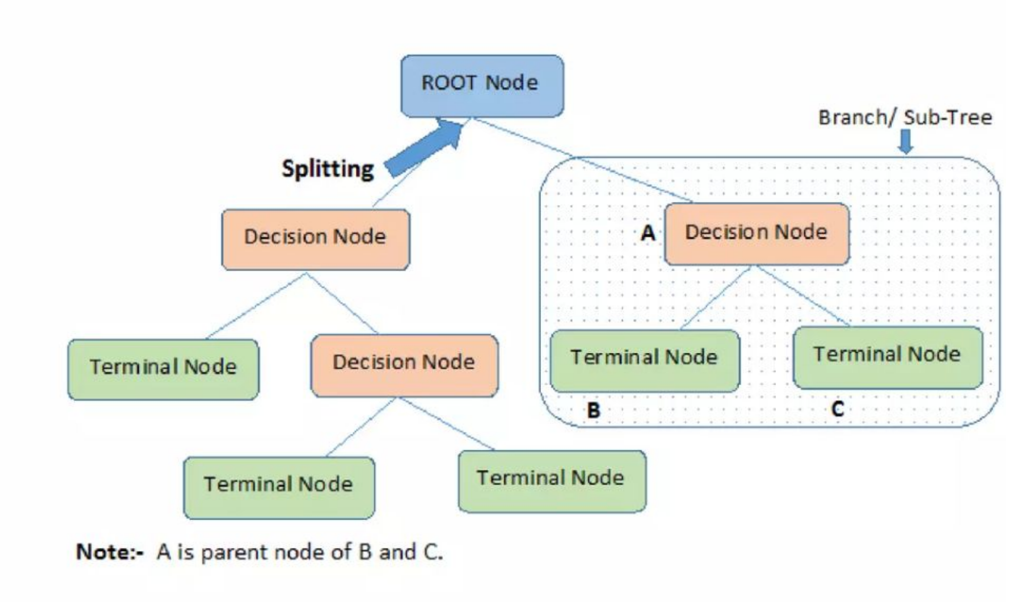
Multilevel Logistic Regression procedure

	TrainSet	TestSet
Basic With Outliers	0.65	0.603
Basic Without Outliers	0.67	0.62
Multilevel	0.57	0.53

Methodology-Decision Tree



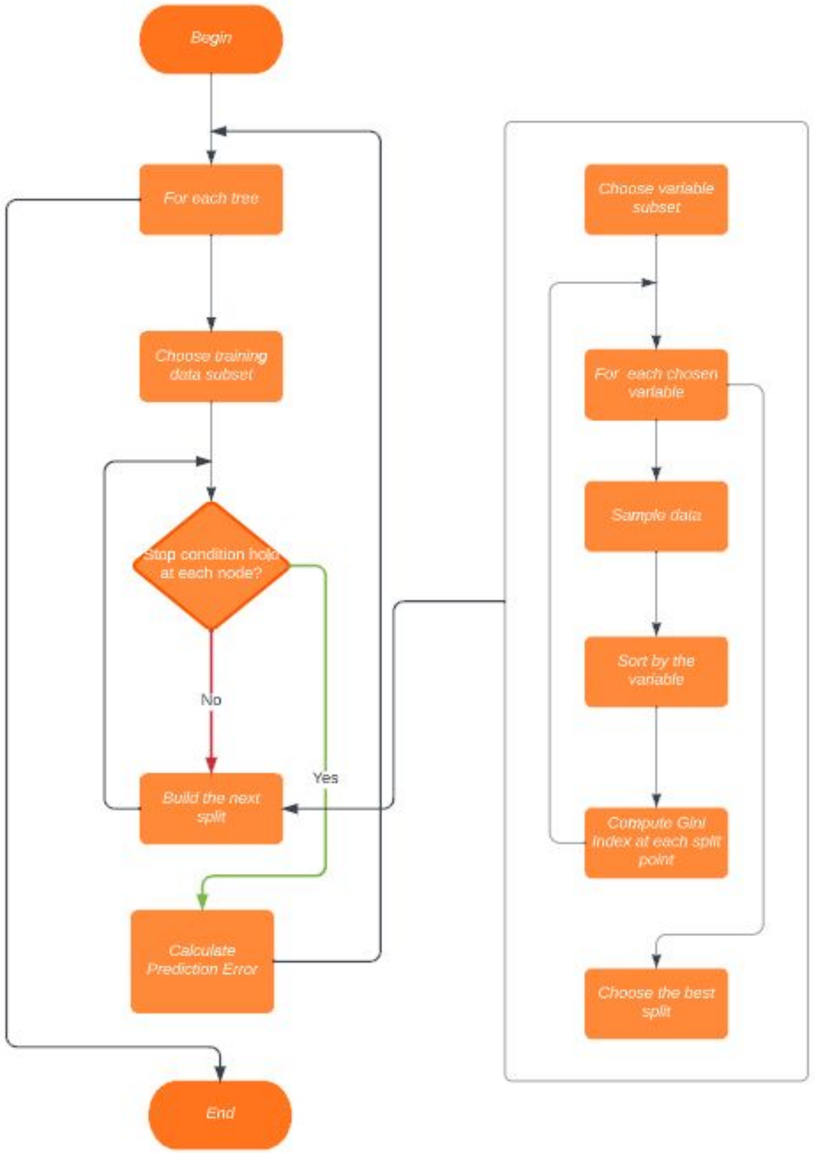
Decision Tree Procedure



	TrainSet	TestSet
Entropy	0.999	0.82032
Gini	0.999	0.82244
Grid Search CV	0.999	0.83

Accuracy Score

Methodology-Random Forest



No overfitting

Use of multiple trees reduce the risk of overfitting

Training time is less

High accuracy

Runs efficiently on large database

For large data, it produces highly accurate predictions

Estimates missing data

Random Forest can maintain accuracy when a large proportion of data is missing

Accuracy Score

	TrainSet	TestSet
Entropy	0.99	0.885
Gini	0.99	0.884
Grid Search CV	0.999	0.893

Methodology–Boosting Algorithm

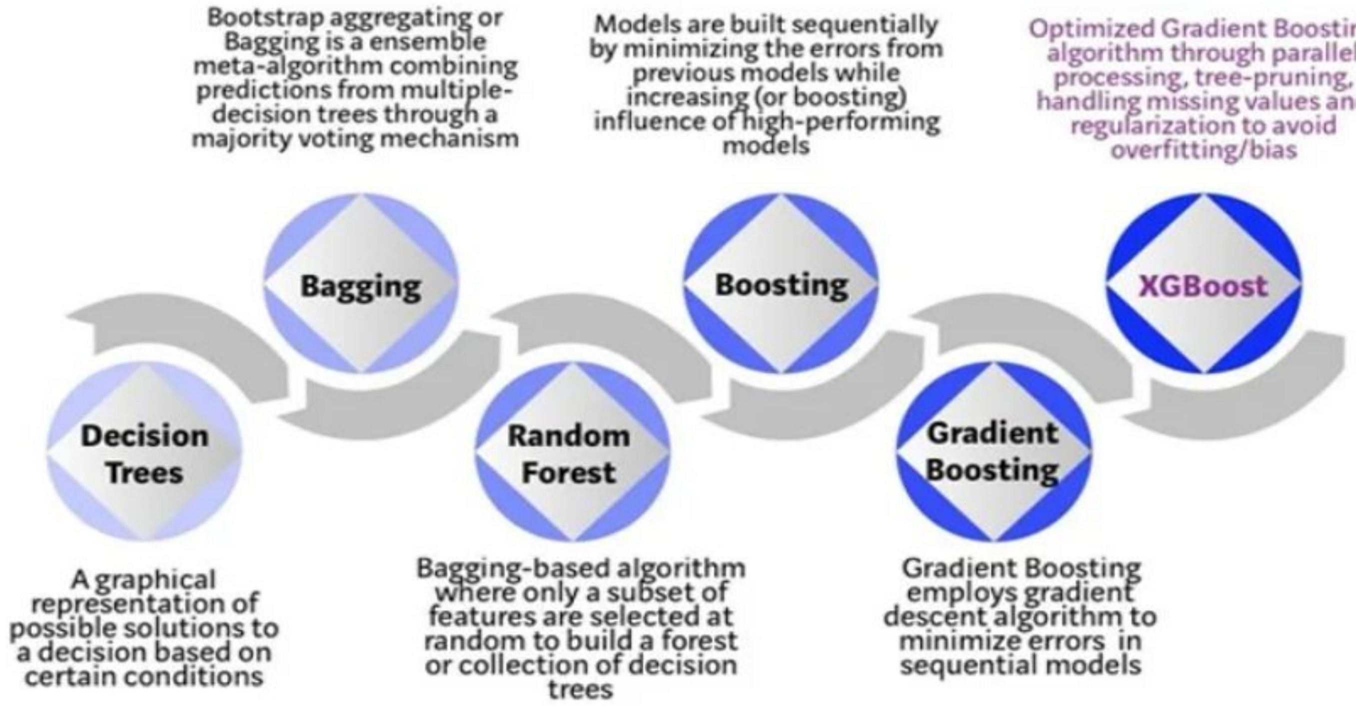
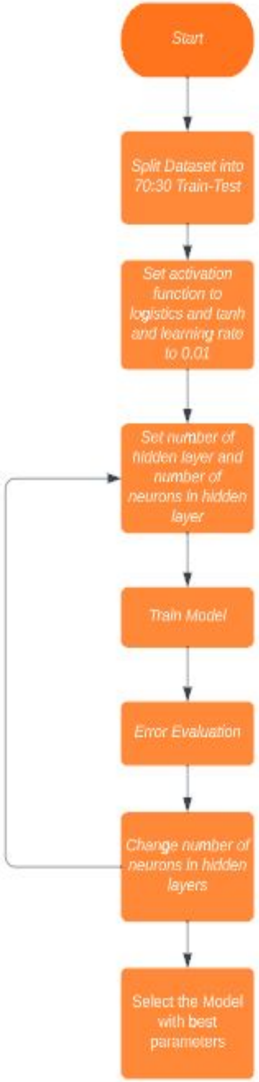


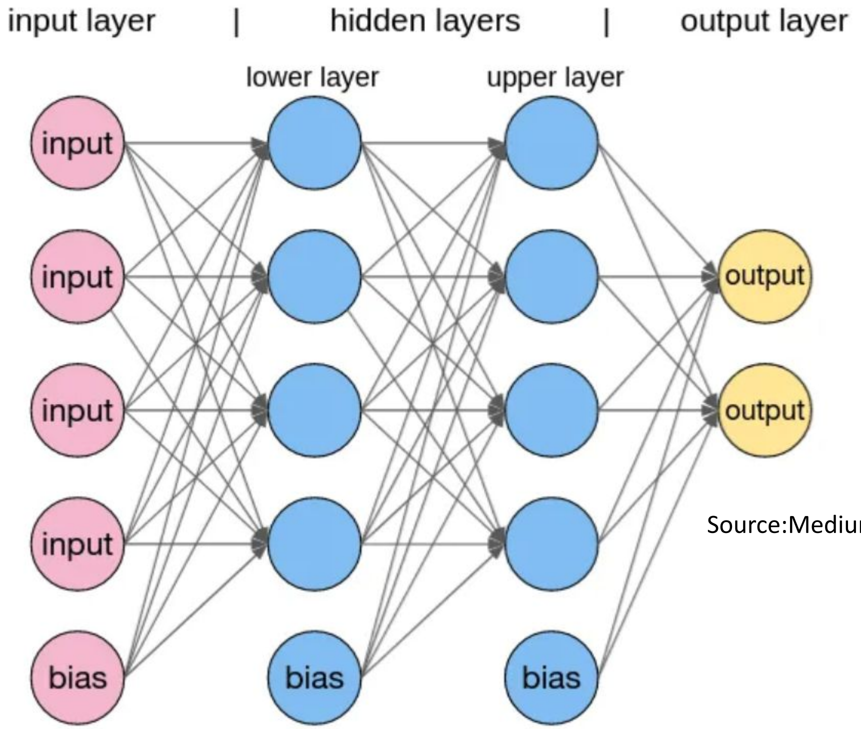
Fig from Madras Research

Accuracy Score

	TrainSet	TestSet
XG Boosting	0.999	0.913
Gradient Boosting	0.944	0.858
Ada Boosting	0.6533	0.6538

Methodology-MultiLayer Perceptron





Source:Medium

Basic structure of the MLP

	TrainSet	TestSet
Multi Layer Precepton	0.707	0.709

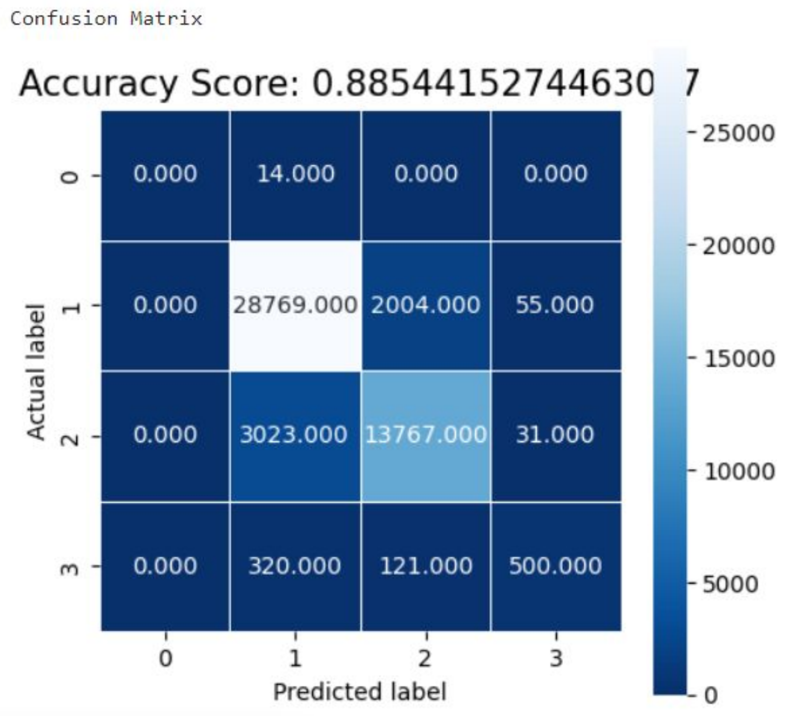
Accuracy Score

Results & Analysis

- Data Preprocessing is crucial since a significant improvement in accuracy is observed before and after removal of outliers.
- We here deal with a classification problem with discrete outputs so linear regression can't be used and hence is avoided.
- We have employed the models of SVM, Naive Bayes and Logistic Regression till now.
- It is observed that upon the use of weighted Naive Bayes and Laplace calibration, bias decreases by about 5%.
- For all SVM models, linear kernel is the best fit out of linear, polynomial and rbf kernels.
- Multilevel logistic regression is not an idealistic method for multiclass classification

Results & Analysis

- Our best model is XGBoost trained upon Dataset without outliers, while Random Forest and Gradient Boosting also gave high accuracy.
- KNN and K - Means didn't work on our data set since the data is not clusterable
- MLP performs quite well and doesn't really differ on adding more layers/neurons
- Boosting algorithms performed quite well and reduces variance as expected.



Results & Analysis

Technique	Train Score	Test Score
XGBoost	**0.999**	**0.913**
Random Forest	0.999	0.885
Gradient Boosting	0.944	0.858
Decision Tree	0.999	0.830
Multilayer Perceptron	0.707	0.709
Mixed Naive Bayes	0.665	0.660
Support Vector Machine	0.643	0.681
Adaptive Boosting	0.6533	0.6538
Logistic Regression	0.645	0.646

Timeline

Till Mid Evaluation		
Week Number	**Topic Covered**	**Status**
1-2	Data Collection & Cleaning	Completed
3-4	Pre-processing & Visualization	Completed
5	Feature Extraction, Analysis & Correlation	Completed
6-7	Logistic Regression, Naive Bayes & Support Vector Machines	Completed
After Mid Evaluation		
8	Random Forest & Decision Trees	Completed
9-10	Boosting Algorithms, Neural Network & kNN	Completed
11	Overfitting, Underfitting & Analysis	Completed
12	Final Report	Completed

Individual Contributions

- Data Collection - Chaitanya, Deepanshu, Rudra, Arpan
- Data Preprocessing & Cleaning - Arpan, Rudra
- Data Visualization - Chaitanya, Deepanshu
- Naive Bayes - Chaitanya
- Support Vector Machine - Deepanshu
- Logistic Regression - Arpan, Rudra
- XGBoost, kNN - Chaitanya Garg
- Decision Tree, Random Forest - Rudra
- Gradient Boosting, Adaptive Boosting - Deepanshu
- MLP, k-Means - Arpan
- Multilevel Logistic Regression - Chaitanya, Rudra
- Report - Chaitanya, Deepanshu, Rudra, Arpan
- Presentation - Chaitanya, Deepanshu, Rudra, Arpan