CAR EVALUATION DATABASE

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1. ABSTRACT.

Cars are essentially part of our regular day to day life. There are various kind of cars produced by different manufacturers; subsequently the buyers has a decision to make. When as an individual consider of buying a car, there are numerous aspects that could influence his/her choice on which kind of car he/she is keen on. The choice buyer or drivers have generally relies upon the price, safety, and how luxurious and how spacious the car is.
Car evaluation database is significant structure information that everyone should take a look at for the car features and useful in decision making. This dataset are labeled according to the specification of PRICE, COMFORT and SAFETY. The dataset utilized in this assignment can be access https://archive.ics.uci.edu/ml/datasets/Car+Evaluation

The objective of this report is especially to determine the decision making, identifying the car variables like car price value with other various variable to decide between a good acceptable cars from the unaccepted values from the target value.

Keywords: Classification, Car Evaluation.

2. INTRODUCTION.

Understanding the idea in making a decision on a choice in getting a car is basic to everybody particularly the first time buyer or anyone who are inexperienced in how the car business functions. Generally we need a car as a methods for transportation however as we include fun into it and we tend to forget that we shouldn't underestimate.
In present times it is continuously the car sales representative who encourages us to purchase this car or not and from the conclusion of our family and companions who had past experienced with vehicle inconveniences. It would have been better to have a device that can check car features and tell that it's an X car or a Y car. If there is such device there should be no worries in purchasing a car. We may or probably won't know it consciously however we are basically ignoring the factors that would help us financially, comfortably, and safety in a long run.
In this assignment we process the data, exploring the variables relationship between the attributes and we model the data from different classification models, those are K nearest neighbor and Decision trees in terms of their best set of parameter for each case and performance on car evaluation data set.

2.1 Dataset Attributes

The data set that we accessed from the UCI repository which is collection of observation of the specified attributes of a car, it was donated by Marco Bohanec in 1997.
The Car Evaluation dataset contains following concept structure:
CAR- car acceptability.
PRICE- overall price of a car
buying -buying price of a car
maint -price of the maintenance
TECH- technical characteristics of a car
COMFORT- comfort in a car
doors -number of doors in a car
persons- capacity in terms of persons to carry in a car
lug_boot- the size of luggage boot in a car
safety- estimated safety of the car

2.1. A. Do we need all the Variables?

Getting rid of unnecessary variables is a good initial step when managing with any data set, since dropping attributes diminishes complexity nature and can make calculation on the data set quicker. Regardless of whether we should dispose an attributes or not will rely upon size of the data set and the goal of our investigation however in any case be useful to drop variables that will only distract from the aim and goal of the assignment.

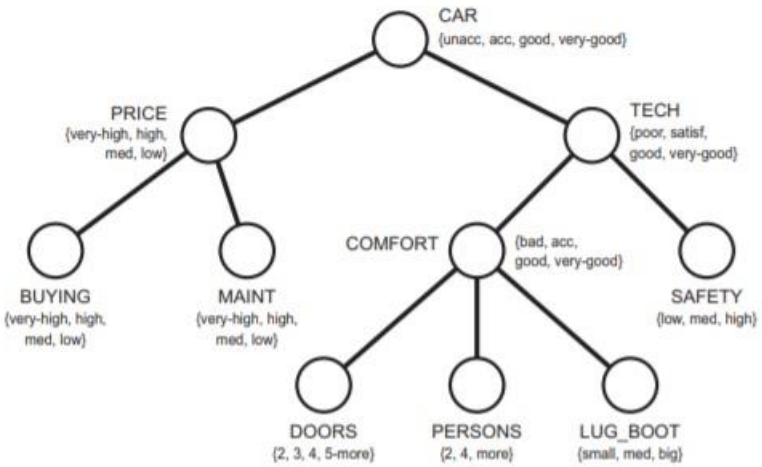


Diagram1: Dataset attributes

The car directly relay on six attributes: 'buying','maint','doors','persons','lug_boot','safety','classes'. The dataset contains 1727 instances and possible values each attribute along with the data type are below.

Attributes	Possible Values	Attributes Types
buying	vhigh, high, med,low	nominal
maint	Vhigh,high, med, low	nominal
doors	2, 3, 4, 5more	nominal
persons	2, 4, more	nominal
lug_boot	Small, med, big	nominal
safety	Low, med, high	nominal

Table 1: attributes values

2.1. B. Target Attribute- classes:

The data analysis is done on this dataset to identify some patterns and also attributes range with their Percentages (frequency).

The target variable classes indicates whether each car is unacc, acc, good, vgood , since predicting analysis is our goal.

classes	Number of observation per class	Percentage
unacc	1209	70.023
acc	384	22.222%
good	69	3.993%
vgood	65	3.762%

Table 2: Class Distribution

Attribute Characteristics: Categorical.
Associated Tasks: Classification task to acquire the knowledge from the data set.
Based on the distribution, from the table it looks like more no of instances are in unacc classes which means its skewed data, so it means we have chosen right task (classification) to analyse this distribution.

3. METHOLODOGY

3.1 Data collection:

The Car Evaluation Dataset is selected from UCI Machine learning repository for this assignment. This dataset contains 1727 instance and 6 attributes. We are importing necessary pandas modules to the read the car evaluation data set from our system drive.

3.2 Data preprocessing:

The dataset from UCI repository has be cleaned and it is standard quality before the module analysis is proceed. Data set often contains missing values and extreme values called outliers and this values can effect out test and even sometimes it even can cause classifier to fail. It better to remove all outliers and fill the missing values with near values. In our dataset, we don't have any missing values in given table below Table 3.

Attributes	Missing Values
buying	0
Maint	0
doors	0
persons	0
lug_boot	0
safety	0
classes	0

Table 3: Missing values In Car Evaluation Dataset.

Detecting the missing values is easy task more over it is difficult to decide how to handle missing values, missing values in categorical data set are not troubling because we can treat them as NA on the other hand missing vales in numerical variables will cause troublesome to our analysis.
Before starting up the analysis it's a good idea to start off by checking the dimension of our dataset by checking the description of the variables.

- **Exploring the attributes and variables**

The initial step in data exploratory analysis is reading the data information and then exploring the attributes factors. It is essential to get a sense of how many variables and cases are, and there attributes datatypes, the possible range of values that attributes take on.

- **Transforming the Variables (Data transformation)**
  When we first load the dataset , few variables may be encoded as datatypes and they doesn't fit well in our dataset for example Classes variable(Target variable) that indicates the Unacceptable, acceptable, good and very good that only takes the values like 1, 2, 3 and 4.

Most of the variables are encoded as object type and in this data analysis all the variable holding a categorical variables and the variables are in string format, to go further operation we need to change the String type to integer type, more over this models requires the variables to be in integers and we have converted by giving specified number to each variable (encoding).

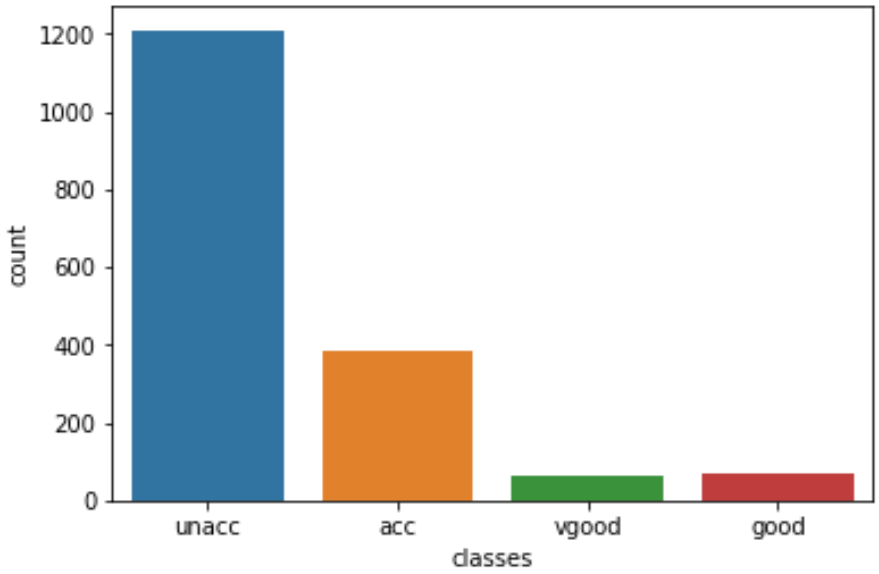
3.3 Data exploration

Data exploration is a technique similar to data analysis where data is summarized in visual exploration and the characteristics of data.
The data exploration includes following

- Univariate
  Exploration and analyze of each variable.
- Bivariate
  Exploration and analyze pair of variables and their relationship.
- Multivariate
  Exploration of multiple variables in the data set.

Here we will check each feature with the classes with the distribution.

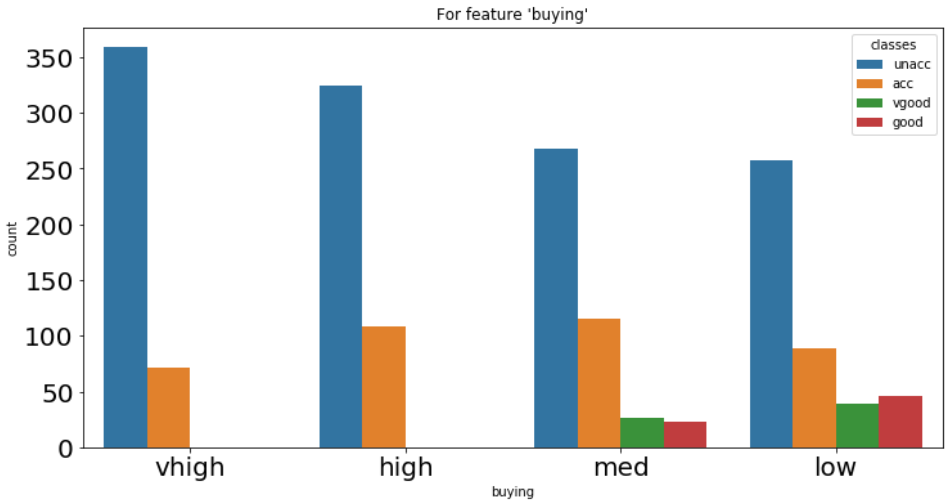
Classes



Classes distribution which give the number of count (unique values in the column) vs the classes.
From the give graph result almost 70% of cars are in classes unacceptable (unacc), which means it skewed distribution.

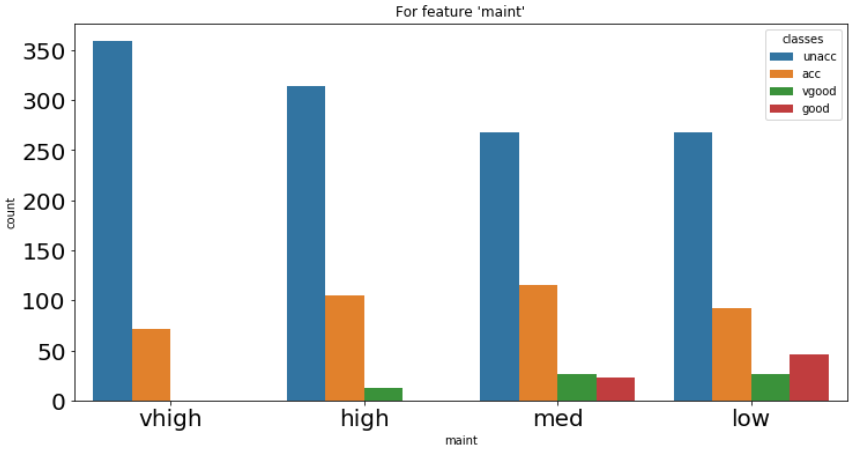
In the above graph, from the out of total 1727 instances of car in the dataset 1209(70%) were unacceptable, 384(22%) were acceptable, 69(3.9%) were in good and 65(3.7%) are in very good.

buying.



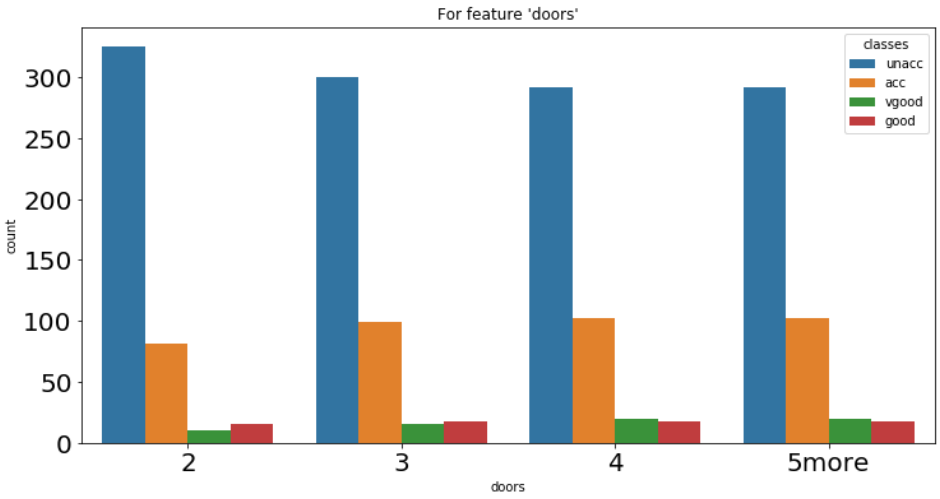
Buying histogram- the distribution of the classes(values) trend to be uniformly distributed, while very high and high buying cost of a car will probably made a car be in unaccepted.

maint (Maintenance).



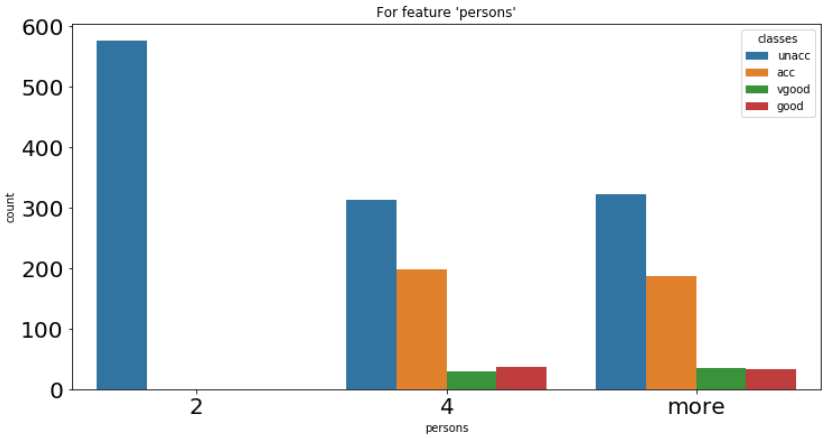
From the maintenance distribution with the very high and high maintenance price will probably made a car be to unaccepted

doors.



Here, distribution of each classes tend to be uniformly distributed of the classes values whereas 2 doors will effect a car to be in unaccepted classes.

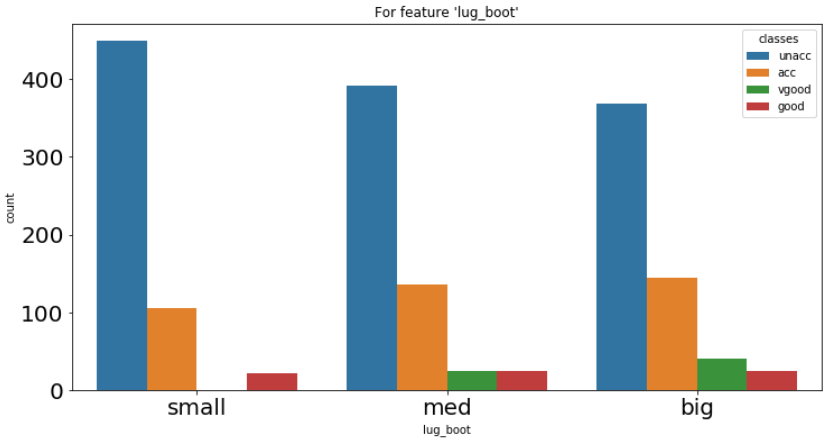
persons.



In this persons distribution of the classes, with 2 persons capacity of the car it will be unaccepted.

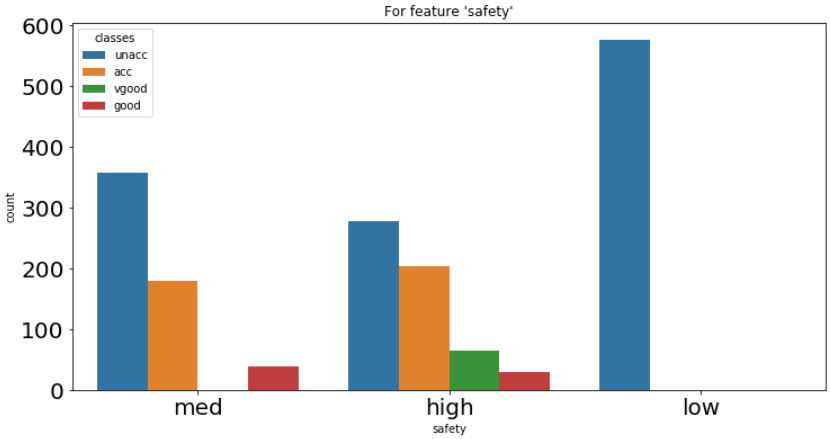
Car seating capacity is an important factor for the customers in accepting or rejecting a car.

lug_boot(Luggage boot space).



In this luggage boot space in the car distribution, where small luggage boot is causing the car to be in unaccepted.

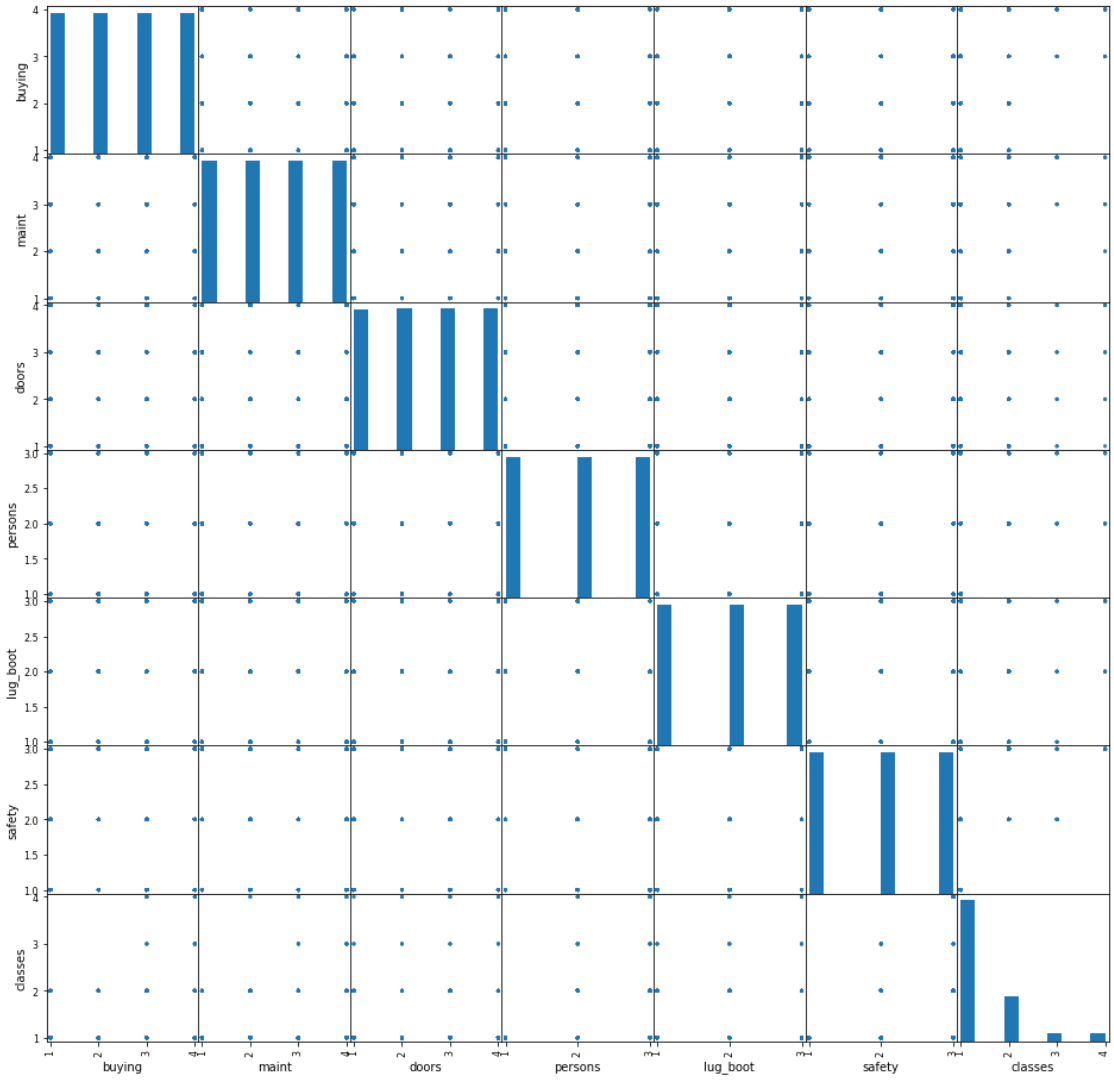
Safety.



In this safety distribution of the each classes it is seen that normal distribution and low safety will most likely caused a car being unaccepted.

Safety is an important factor in terms of accepting or rejecting a car for customers.
Whereas low safety cars are not accepted by the customers. Where in measurement view of normal distribution is a nature in practical real-world cases, then we can decide safety is the most important features in our module analysis

Data exploration -Multivariate analysis.



As we encoded the string data (categorical data) to integer type, and our dataset doesn't contain continuous values. As our data set contains only 3 to 4 possible values for each variables in the dataset. Hence diagram looks similar for all cases in our dataset.

3.4 Splitting of dataset and randomization.

Training and Testing:

In this assignment, we have divided the dataset into training set and testing set and the 3 splits pairs used in this assignment on each classifier are show in the table 4.

Training and Testing % split
50% 50%
60% 40%
80% 20%

Table 4: Training and Testing Split

3.5 Data modeling (classification)

The experiment is carried on using the classifiers models, those are K-nearest neighbors and Decision trees. This experiment is to determine which classifier best suits for our data set in terms of classifying the trained and tested set and also making prediction module obtained during the training process. The detailed procedure of the experiment is below.

I. K-nearest neighbors

K-NN is a classifier which just finds the classes of the k-nearest neighbors (based on a distance metric the shortest distance between the samples which is known as Euclidean) and then find the classes in the larger part and assign that class to the test pattern. Knn module is a technique of learning where a particular instance is mapped against many labels. Here we are pre-specifying the labels to train our module.

power parameter, p=1 or 2.

- **Manhattan distance.**
  For p = 1
  if x=(a, b)x=(a, b) and y=(c, d)y=(c, d), the Manhattan distance between xx and yy is
  |a−c|+|b−d||a−c|+|b−d|.
- **Euclidean distance**
  For p = 2.
  if x=(a, b)x=(a, b) and y=(c, d)y=(c, d), the Euclidean distance between xx and yy is

$$d(A,B) = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

i. For 50% training set and 50% testing set

The data set has been divided into 50% train and 50% test set with instances of 863 and 864 respectively.

ii. For 60% training set and 40% testing set

The data set has been divided into 60% train and 40% test set with instances of 1036 and 691 respectively.

iii. **For 80% training set and 20% testing set**

The data set has been divided into 80% train and 20% test set with instances of 1381 and 346 respectively.

The accuracy achieved for different dataset spilt are presented in the table 5.

Splitting Percentage (Training % and Testing %)	50% 50%	60% 40%	80% 20%
n_neighbors	5	5	7
Power variable (p)	2	1	2
Testing accuracy	91.20%	92.61%	93.641%

Classification error rate	8.79%	7.38%	6.35%
Confusion Matrix	[[577 6 3 0] [46 167 3 3] [4 3 21 1] [1 2 4 23]]	[[459 4 2 0] [28 148 3 0] [3 5 15 0] [1 5 0 18]]	[[231 2 1 0] [14 73 0 0] [1 1 10 0] [0 2 1 10]]
precision	0.846	0.899	0.927
recall	0.809	0.804	0.857
f1 score:	0.824	0.845	0.887

Table 5: Accuracy test for K nearest neighbor

From the output for KNN classifier, we can say that the split 80% 20% train and test dataset gives us the best accuracy when compared to other splitting ratio.

II. Decision trees

Decision tree is a module that uses a tree-like-graph or module of condition of decisions and their possible consequences. It is one approach to display an algorithm that contains only conditional control statements.

It follows a flowchart like structure in each internal node that is condition on each attribute, each branch represents the outcome of the condition, and each leaf node represents a class table. The top down approach from the root to the leaf represents classification rule.

Root Node: This Node represents the total population (instances) and furthers breakdown into branches class sub-nodes based the conditions.

Decision node: When a sub node gets divided into further sub nodes then its called decision node.

Leaf node: When node cannot spilt further into sub nodes.

i. **For 50% training set and 50% testing set**

The data set has been divided into 50% train and 50% test set with instances of 863 and 864 respectively.

i. For 60% training set and 40% testing set

The data set has been divided into 60% train and 40% test set with instances of 1036 and 691 respectively.

ii. For 80% training set and 20% testing set

The data set has been divided into 80% train and 20% test set with instances of 1381 and 346 respectively.

The accuracy achieved for different dataset spilt are presented in the table 6.

Decision tree max_depth=6			
Splitting Percentage (Training % and Testing %)	**50% 50%**	**60% 40%**	**80% 20%**
Testing accuracy	92.24%	93.19%	93.641%
Classification error rate	7.75%	6.80%	6.35%
Confusion Matrix	[[568 16 2 0] [16 179 21 3] [0 0 24 5] [0 4 0 26]]	[[449 14 2 0] [2 156 18 3] [0 0 19 4] [0 4 0 20]]	[[224 9 1 0] [1 78 7 1] [0 0 11 1] [0 2 0 11]]
precision	0.786	0.780	0.824
recall	0.870	0.874	0.904
f1 score	0.817	0.815	0.854

Table 6: Accuracy test for decision tree

From the output for Decision tree classifier, we can say that the split 80% 20% train and test dataset gives us the best accuracy when compared to other splitting ratio.

4. RESULTS

The presentation of the results is based on following model analysis. To get better understand of the module we also used another measurement precision, recall, f1 score. In this analysis our splitting ration of k nearest neighbor 80% 20% seems good enough at its performance.

For 80% 20%

n_neighbour= 7 , p= 2

Testing accuracy	**Classification error rate**	**Confusion Matrix**	**precision**	**recall**	**f1 score:**
93.641%	6.35%	[[231 2 1 0] [14 73 0 0] [1 1 10 0] [0 2 1 10]]	0.927	0.857	**0.887**

Table 5.a: Accuracy results for K nearest neighbor

For 80% and 20%

Max_depth= 6

Testing accuracy	**Classification error rate**	**Confusion Matrix**	**precision**	**recall**	**f1 score:**
93.641%	6.35%	[[224 9 1 0] [1 78 7 1] [0 0 11 1] [0 2 0 11]]	0.824	0.904	**0.854**

Table 6.a: Accuracy results for K nearest neighbor

5. DISCUSSION

- Safety and person's capacity are main factors in rejecting the car classes as unacceptable.
- The splitting of data set from the two comparison shows that K nearest neighbor and decision tree have exactly same accuracy(93.64%) across the data split ratio (80:20).
- F1 score is combination of precision and recall then we can say that f1 score is used to measure our model performance.
- Also, it is seen that decision trees has less f1 score even though k nearest neighbor and decision tree have same accuracy.
- Here with the data split with 80-20 both the modules k-nearest neighbor and decision tree have same accuracy but accuracy can't be the fair criteria to determine unbalanced classification so let's check with f1 score and k-nearest neighbor with 80-20 have highest 0.88 when compared to decision tree f1 of 0.85.
- To provide a distinction between two classifiers and their performance, comparing the results of two classifiers are show in the table 5.a and table 6.a, table under the result.

6. CONLUSION

The comparison analysis for the classifiers used in this assignment show that K nearest neighbor and Decision tree have same performance in terms of accuracy. However, in terms of f1 score k nearest neighbor seems to be best compared to decision tree.

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