# MALIGNANT COMMENTS CLASSIFICATION

Submitted By: Ishmeet Kaur Sahota

## **ACKNOWLEDGMENT**

I want to express my sincere thanks to Flip Robo Techniques and my SME Khusboo Garg who helped me in every possible way that she could and guide me through new things. without whom I won't have been able to complete this project.

# INTRODUCTION

### • Business Problem Framing:-

The proliferation of social media enables people to express their opinions widely online. However, at the same time, this has resulted in the emergence of conflict and hate, making online environments uninviting for users. Although researchers have found that hate is a problem across multiple platforms, there is a lack of models for online hate detection. This can take a toll on anyone and affect them mentally leading to depression, mental illness, self-hatred, and suicidal thoughts.

### • Review of Literature:-

Our goal in this project is to build a prototype of online hate and abuse comment classifier which can be used to classify hate and offensive comments so that they can be controlled and restricted from spreading hatred and cyber bullying. These are some columns in our data 'Id', 'Comments', 'Malignant', 'Highly malignant', 'Rude', 'Threat', 'Abuse', and 'Loathe'.

## Motivation for the Problem Undertaken:-

There has been a remarkable increase in the cases of cyber bullying and trolls on various social media platforms. Many celebrities and influences are facing backlash from people and have to come across hateful and offensive comments. This can take a toll on anyone and affect them mentally leading to depression, mental illness, self-hatred, and suicidal thoughts.

## **Analytical Problem Framing**

### • Mathematical/ Analytical Modelling of the Problem :-

The Dataset contains 159571 rows and 8 columns. The columns contains both object data type and integer data type., i have seen the value of each columns by applying value\_count method. Then I have used describe method. Is Null. Sum for checking the Nan values and getting their sums. Applied some visualization techniques for better understanding of the data. Then check the skewness of the data. I have replaced some numbers with numbers and data containing addresses, email, etc with some meaningful data by applying replace method. I have Stored all the targets in one single column. Convert text into vectors then split the data using train test split and used 4 different classification models.

## • Data Sources and their formats :-

The Dataset contains 159571 rows and 8 columns respectively. containing all the necessary details.

These are some columns in our data 'Id', 'Comments', 'Malignant', 'Highly malignant', 'Rude', 'Threat', 'Abuse', and 'Loathe'.

## Data Preprocessing Done :-

The dataset contain some of object type data sol have replaced some numbers with numbers and data containing addresses, email, etc with some meaningful data by applying replace method. And Stored all the targets in one single column. Convert text into vectors and used all these methods for better model prediction.

# • State the set of assumptions (if any) related to the problem under consideration: -

In The dataset we have taken assumption as : In every columns : 0 = NO, 1 = YES

## Hardware and Software Requirements and Tools Used:-

Libraries have I have used for data cleaning, Visualization and model building.

import pandas as pd

import numpy as np

import seaborn as sns

import matplotlib.pyplot as plt

%matplotlib inline

import warnings

warnings.filterwarnings('ignore')

from sklearn.feature\_extraction.text import TfidfVectorizer

from sklearn.model\_selection import train\_test\_split

from sklearn.metrics import accuracy\_score,classification\_report,confusion\_matrix,f1\_score

from sklearn.metrics import roc\_curve,roc\_auc\_score,auc

from sklearn.metrics import plot\_roc\_curve

from sklearn.linear\_model import LogisticRegression

from sklearn.tree import DecisionTreeClassifier

from sklearn.metrics import roc\_curve, roc\_auc\_score

from sklearn.metrics import plot\_roc\_curve

from sklearn.ensemble import RandomForestClassifier

from sklearn.neighbors import KNeighborsClassifier

## **Model/s Development and Evaluation**

# • Identification of possible problem-solving approaches (methods):-

I have used these approaches

pandas, numpy, seaborn, matplotlib.pyplot, %matplotlib inline, import warnings, WordNetLemmatizer, stopwords, nltk, TfidfVectorizer.

## • Testing of Identified Approaches (Algorithms):-

from sklearn.feature extraction.text import TfidfVectorizer

from sklearn.model\_selection import train\_test\_split

from sklearn.metrics import accuracy\_score,classification\_report,confusion\_matrix,f1\_score

from sklearn.metrics import roc\_curve,roc\_auc\_score,auc

from sklearn.metrics import plot\_roc\_curve

from sklearn.linear\_model import LogisticRegression

from sklearn.tree import DecisionTreeClassifier

from sklearn.metrics import roc\_curve, roc\_auc\_score

from sklearn.metrics import plot\_roc\_curve

from sklearn.ensemble import RandomForestClassifier

from sklearn.neighbors import KNeighborsClassifier

#### Run and Evaluate selected models :-

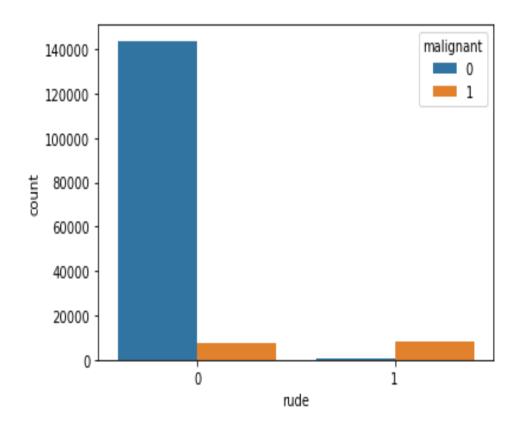
#### # KNeighbors Classifier

#### # Logistic Regression

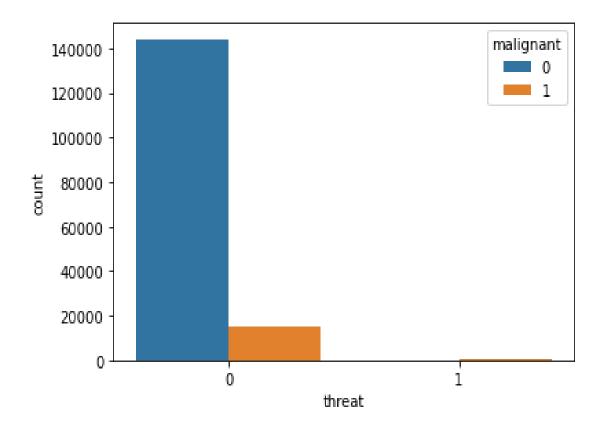
Training accuracy		9598138747		*****	*****	*****	****
****							
Test accuracy		9561961460					
*****	*****	*****	*****	*****	*****	******	****
confusion matrix [ 1246		28458 15	-	* * * * * * * * * * * *	. * * * * * * * * * * * *	*****	****
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Classification Re	eport :		precision	recall	f1-score	support	
0	0.96	0.99	0.98	28610			
1	0.93	0.62	0.75	3305			
accuracy			0.96	31915			
macro avg	0.94	0.81	0.86	31915			
weighted avg	0.96	0.96	0.95	31915			
# DecisionTr	eeClass	ifier					
Training accuracy				*****	*****	*******	****
****							
Test accuracy	: 0.	9181262729	124237				
	*****	*****	*****	*****	*****	*****	****
****							
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****** Classification Re			precision		f1-score	support	
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Classification Re	eport :		precision	recall			
Classification Re	eport : 0.92	1.00	precision 0.96 0.38	recall 28610 3305			
Classification Re 0 1 accuracy	0.92 0.87	1.00 0.25	precision 0.96 0.38 0.92	recall 28610 3305 31915			
Classification Re 0 1 accuracy macro avg	0.92 0.87	1.00 0.25	precision 0.96 0.38 0.92 0.67	recall 28610 3305 31915 31915			
Classification Re 0 1 accuracy	0.92 0.87	1.00 0.25	precision 0.96 0.38 0.92	recall 28610 3305 31915			
Classification Re 0 1 accuracy macro avg	0.92 0.87 0.90 0.91	1.00 0.25	precision 0.96 0.38 0.92 0.67	recall 28610 3305 31915 31915			
Classification Re  0 1 accuracy macro avg weighted avg  # RandomForestC	0.92 0.87 0.90 0.91	1.00 0.25 0.62 0.92	precision 0.96 0.38 0.92 0.67 0.90	recall 28610 3305 31915 31915			
Classification Re  0 1 accuracy macro avg weighted avg  # RandomForestC  Training accuracy	0.92 0.87 0.90 0.91 Classifier	1.00 0.25 0.62 0.92	precision 0.96 0.38 0.92 0.67 0.90	recall 28610 3305 31915 31915 31915	fl-score	support	
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Classification Re  0 1  accuracy macro avg weighted avg  # RandomForestC  Training accuracy ************************************	0.92 0.87 0.90 0.91 Classifier	1.00 0.25 0.62 0.92	precision  0.96 0.38  0.92 0.67 0.90	recall 28610 3305 31915 31915 31915	fl-score	support	
Classification Re  0 1  accuracy macro avg weighted avg  # RandomForestC  Training accuracy ************************************	0.92 0.87 0.90 0.91 Classifier 7 : 0.	1.00 0.25 0.62 0.92 9987074638 *********	precision  0.96 0.38  0.92 0.67 0.90  8089867 ************************************	recall 28610 3305 31915 31915 31915	f1-score	support	***
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Classification Re  0 1 accuracy macro avg weighted avg  # RandomForestC  Training accuracy ******* Test accuracy ******** confusion matrix [ 1028 2277]]	0.92 0.87 0.90 0.91 Classifier 7 : 0.	1.00 0.25 0.62 0.92 9987074638 ************************************	precision 0.96 0.38 0.92 0.67 0.90  8089867 ************************************	recall  28610 3305  31915 31915 31915  **********************************	f1-score	support	****
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As we can see both Logistic regression and ) RandomForestClassifier has the best accuracy score (0.96).

# Visualization

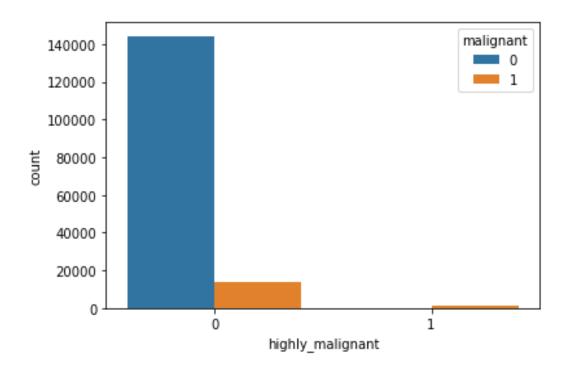


Used countplot for comparing 'rude' and 'malignant' columns.

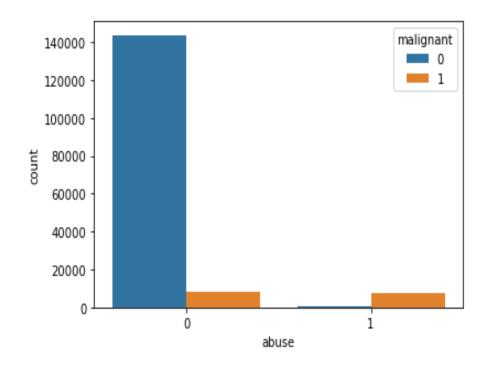


Compared 'threat' and 'malignant'

## Compared 'Highly malignant' and 'malignant'

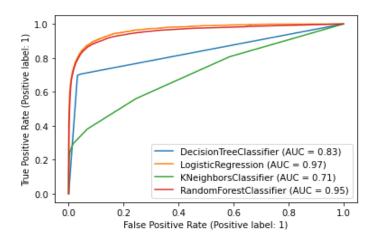


## Compared 'Abuse' and 'malignant'

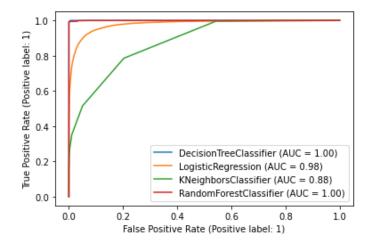


# Comparing the score of different models on training data that which model fit best

## • Training data



## • Testing data



Checking the score of different models on testing data that which model fit best Logistic Regression fits best among all other models As Logistic Regression is given: 0.97 score while testing 0.98 score while training.

## • Interpretation of the Results:-

After visualizing the data I have concluded that under all these columns: -

- Malignant: It is the Label column, which includes values 0 and 1, denoting if the comment is malignant or not.
- Highly Malignant: It denotes comments that are highly malignant and hurtful. Rude: It denotes comments that are very rude and offensive.
- Threat: It contains indication of the comments that are giving any threat to someone. Abuse: It is for comments that are abusive in nature.
- •Loathe: It describes the comments which are hateful and loathing in nature.

As value of 0 as No are more than value of 1 as Yes in these columns. Majority of these texts 0 that is are Not malignant. Logistic Regression fits best among all other models As Logistic Regression is given: 0.97 score while testing 0.98 score while training.

# CONCLUSION

## • Key Findings and Conclusions of the Study :-

As value of 0 as No are more the n value of 1 as Yes in these columns. Majority of these texts 0 that is are Not malignant. Logistic Regress ion fits best among all other models As Logistic Regression is given: 0.97 score while testing 0.98 score while training.

## Learning Outcomes of the Study in respect of Data Science:-

As data contain some object type data with the help of replace method, I have replaced some data containing addresses, e mail, etc with meaningful data. And replaced numbers with numbers. Store all the targets in one single column. Convert text into vectors and used all these methods for better model prediction. As value of 0 as No are more than value of 1 as Yes in these columns. Majority of these texts 0 that is are Not malignant. Logistic Regression fits best among all other models As Logistic Regression is given: 0.97 score while testing 0.98 score while training.