Project report on Malignant Comments Classifier

Submitted By

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Internship-29

ACKNOWLEDGMENT

I would like to express my sincere thanks of gratitude to present this report on "Malignant Comments Classification" project. Working on this project was a good experience that has given me a basic knowledge about Machine Learning Model with NLP. This project also helped me in doing lots of research wherein I came to know about so many new things.

At the commencement of this project report, I would like to evince my deepest sense of gratitude to SME Mr Shwetank Mishra . Without his guidance, insightful decision, valuable comments and corrections it would not have possible to reach up to this mark.

I would like to draw my gratitude to Flip Robo Technologies and Data Trained for providing me a suitable environment and guidance to complete my work. Finally, I would like to thank my family and friends who have helped me with their valuable suggestions and guidance and have been very helpful in various stages of project completion. Last but not the least thanks to the brilliant authors from where I have got the idea to carry out the project.

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1.INTRODUCTION

Over the years, social media and social networking use have been increasing exponentially due to an upsurge in the use of the internet. Flood of information arises from online conversation in a daily basis as people are able discuss, express themselves and air their opinion via these platforms.
Every day, we get a tremendous amount of short content data from the blast of online correspondence, web-based business and the utilization of advanced gadgets. This volume of data requires text mining apparatuses to carry out the various report tasks in an opportune and suitable way. Detecting and controlling verbal abuse in an automated fashion is inherently an NLP task (Natural Language Processing). Text Classification is a great point for NLP.
Nowadays, every social media site and applications use machine learning approach. Machine Learning has simplified the task that may take long duration to complete without it. Most of the approaches require text analysis and classification techniques. Classification of the comments is necessary before posting on online platforms. This paper discusses different methodologies like logistic regression, support vector machine, multinomial naïve bayes etc. for comment classification into 6 different categories viz. malignant, highly malignant, rude, threat, abuse and loathe.

1.1 Business Problem Framing

Social media has given a lot of people which beyond imagination. In this era of technology, it has become the hub of information. The numbers of contents on social media are vast and rich and everything has found a place on social media that may be anything. It has given wings to its users to fly high and express their feelings. It has become a boon for the mankind but we all know that if there is good there must be bad. Likewise, social media has also got the dark side.

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. Online hate, described as abusive language, aggression, cyberbullying, hatefulness and many others has been identified as a major threat on online social media platforms. Social media platforms are the most prominent grounds for such toxic behaviour.
There has been a remarkable increase in the cases of cyberbullying and trolls on various social media platforms. Many celebrities and influences are facing backlashes 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.

Internet comments are bastions of hatred and vitriol. While online anonymity has provided a new outlet for aggression and hate speech, machine learning can be used to fight it. The problem we sought to solve was the tagging of internet comments that are aggressive towards other users. This means that insults to third parties such as celebrities will be tagged as unoffensive, but “u are an idiot” is clearly offensive.

1.2 Conceptual Background of the Domain Problem

In the past few years, it is seen that the cases related to social media hatred have increased exponentially. The social media is turning into a dark venomous pit for people now a days. Online hate is the result of difference in opinion, race, religion, occupation, nationality etc. In social media the people spreading or involved in such kind of activities uses filthy languages, aggression, images etc. to offend and gravely hurt the person on the other side. This is one of the major concerns now.

The result of such activities can be dangerous. It gives mental trauma to the victims making their lives miserable. People who are not well aware of mental health online hate or cyberbullying become life threatening for them. Such cases are also at rise. It is also taking its toll on religions. Each and every day we can see an incident of fighting between people of different communities or religions due to offensive social media posts.

Online hate, described as abusive language, aggression, cyberbullying, hatefulness, insults, personal attacks, provocation, racism, sexism, threats, or toxicity has been identified as a major threat on online social media platforms. These kinds of activities must be checked for a better future.

1.3 Review of Literature

Aggression by text is a complex phenomenon, and different knowledge fields try to study and tackle this problem. In this study, several related literatures are used to express different types of aggression. Some of those are hate, cyberbullying, abusive language, malignant, flaming, threating, extremism, radicalization and hate speech. This research found a few dedicated works that addresses the effect of incorporating different text transformations on the model accuracy for sentiment classification. In this work, we performed a systematic review of the state-of-the-art in malignant comment classification using machine learning methods with NLP text processing. In our analysis of every primary study, we investigated data set used, evaluation metric, used machine learning methods, classes of malignant and non-malignant, and comment language.

1.4 Motivation for the Problem Undertaken

The main objective of this study is to investigate which method from a chosen set of machine learning techniques performs the best. So far, we have a range of publicly available models served through the Perspective API, including toxicity/malignant comments. But the current models still make errors, and they don’t allow users to select which type of toxicity they are interested in finding.

The project which is given by Flip ROBO as a part of the internship programme which gives an insight to identify major factors that lead to cyberbullying and online abusive comments. The exposure to real world data and the opportunity to deploy my skillset in solving a real time problem has been the primary objective. However, the motivation for taking this project was that it is relatively a new field of research. Here we have many options but less concrete solutions. The main motivation was to classify the news in order to bring awareness and reduce unwanted chaos and make a good model which will help us to know such kind of miscreants. Our goal is to build a prototype of online hate and abuse comment classifier which can used to classify hate and offensive comments so that it can be controlled and restricted from spreading hatred and cyberbullying.

2. ANALYTICAL PROBLEM FRAMING

2.1 Mathematical/ Analytical Modelling of the Problem:

We are provided with two different datasets. One for training and another one to test the efficiency of the model created using the training dataset. The training data provided here has both dependent and independent variables. As it is a multiclass problem it has 6 independent/target variables. Here the target variables named “malignant”, “highly malignant”, “rude”, “threat”, “abuse” and “loathe”. The label can be either 0 or 1, where 0 denotes a NO while 1 denotes a YES. There are various comments which have multiple labels. The first attribute is a unique ID associated with each comment.

Clearly it is a binary classification problem as the target columns giving binary outputs and all independent variables has text so it is clear that it is a supervised machine learning problem where we can use the techniques of NLP and classification-based algorithms of Machine Learning. Here we will use NLP techniques like word tokenization, lemmatization, stemming and tfidf vectorizer then those processed data will be used to create best model using various classification based supervised ML algorithms like Logistic Regression, Multinomial NB, LGBM Classifier, XGB Classifier, Gradient Boosting Classifier, LinearSVC, Decision Tree Classifier and Adaboost Classifier.

2.2 Data Sources and their formats

Data set provided by Flip Robo was in the format of CSV (Comma Separated Values). The data set contains the training set, which has approximately 159571 samples and the test set which contains nearly 153164 samples. All the data samples contain 8 fields which includes ‘Id’, ‘Comments’, ‘Malignant’, ‘Highly malignant’, ‘Rude’, ‘Threat’, ‘Abuse’ and ‘Loathe’. In the particular dataset all the columns are of object data type. The attribution information is as follows:

Variables	Defination
id	It includes unique Ids associated with each comment text given
comment_text	The comments extracted from various social media platforms
malignant	It denotes the comments are 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

2.3 Data Pre-processing Done

Data pre-processing is the process of converting raw data into a well-readable format to be used by Machine Learning model. Data pre-processing is an integral step in Machine Learning as the quality of data and the useful information that can be derived from it directly affects the ability of our model to learn; therefore, it is extremely important that we pre-process our data before feeding it into our model. I have used following pre-processing steps:

- Importing necessary libraries and loading dataset as a data frame.

- Checked some statistical information like shape, number of unique values present, info, null values, value counts, duplicated values etc.

- Checked for null values and did not find any null values. And removed Id.

- Done feature engineering and created new columns viz label: which contain both good and bad comments which is the sum of all the labels, comment_length: which contains the length of comment text.

- Visualized each feature using seaborn and matplotlib libraries by plotting categorical plots like pie plot, count plot, distribution plot and wordcloud for each label.

- Done text pre-processing techniques like Removing Punctuations and other special characters, Splitting the comments into individual words, Removing Stop Words, Stemming and Lemmatization.

- Then created new column as clean_length after cleaning the data. All these steps were done on both train and test datasets. Checked correlation using heatmap.

- After getting a cleaned data used TF-IDF vectorizer. It'll help to transform the text data to feature vector which can be used as input in our modelling. It is a common algorithm to transform text into numbers. It measures the originality of a word by comparing the frequency of appearance of a word in a document with the number of documents the words appear in.

  Mathematically,
  TF-IDF = TF(t*d)*IDF(t,d)

- Balanced the data using Randomoversampler method.

2.4 Data Inputs- Logic- Output Relationships

The train dataset consists of multiple labels and features. The features are independent and label is dependent as the values of our independent variables changes as our label varies.

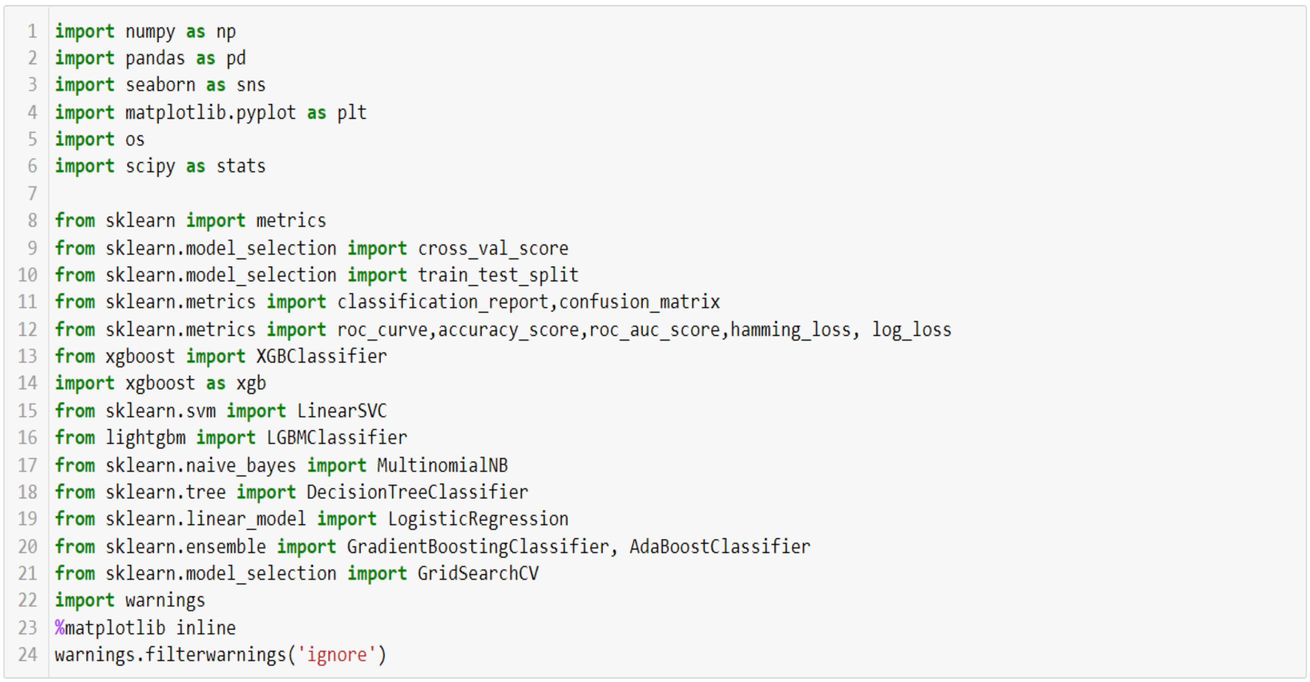
- I checked the distribution of skewness using dist plots and used count plots to check the counts available in each column .
- Got to know sense of loud words in every label using wordcloud which gives the words frequented in the labels.
- I have checked the correlation between the label and features using heat map.

2.5 Hardware & Software Requirements & Tools Used

To build the machine learning projects it is important to have the following hardware and software requirements and tools.

Hardware	Processor: core i5 RAM: 12 GB ROM/SSD: 512 GB
Software	Distribution: Anaconda Navigator Programming language: Python Browser based language shell: Jupyter Notebook

Libraries required:



```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import os
import scipy as stats

from sklearn import metrics
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report,confusion_matrix
from sklearn.metrics import roc_curve,accuracy_score,roc_auc_score,hamming_loss, log_loss
from xgboost import XGBClassifier
import xgboost as xgb
from sklearn.svm import LinearSVC
from lightgbm import LGBMClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import GradientBoostingClassifier, AdaBoostClassifier
from sklearn.model_selection import GridSearchCV
import warnings
%matplotlib inline
warnings.filterwarnings('ignore')
```

- **import numpy as np:** It is defined as a Python package used for performing the various numerical computations and processing of the multidimensional and single dimensional array elements. The calculations using Numpy arrays are faster than the normal Python array.

- **import pandas as pd:** Pandas is a Python library that is used for faster data analysis, data cleaning and data pre-processing. The data-frame term is coming from Pandas only.

- **import matplotlib.pyplot as plt:** Matplotlib and Seaborn acts as the backbone of data visualization through Python.

- **Matplotlib**: It is a Python library used for plotting graphs with the help of other libraries like Numpy and Pandas. It is a powerful tool for visualizing data in Python. It is used for creating statistical interferences and plotting 2D graphs of arrays.

- **import seaborn as sns: Seaborn** is also a Python library used for plotting graphs with the help of Matplotlib, Pandas, and Numpy. It is built on the roof of Matplotlib and is considered as a superset of the Matplotlib library. It helps in visualization of data.

With the above sufficient libraries, we can perform pre-processing and data cleaning and model building.

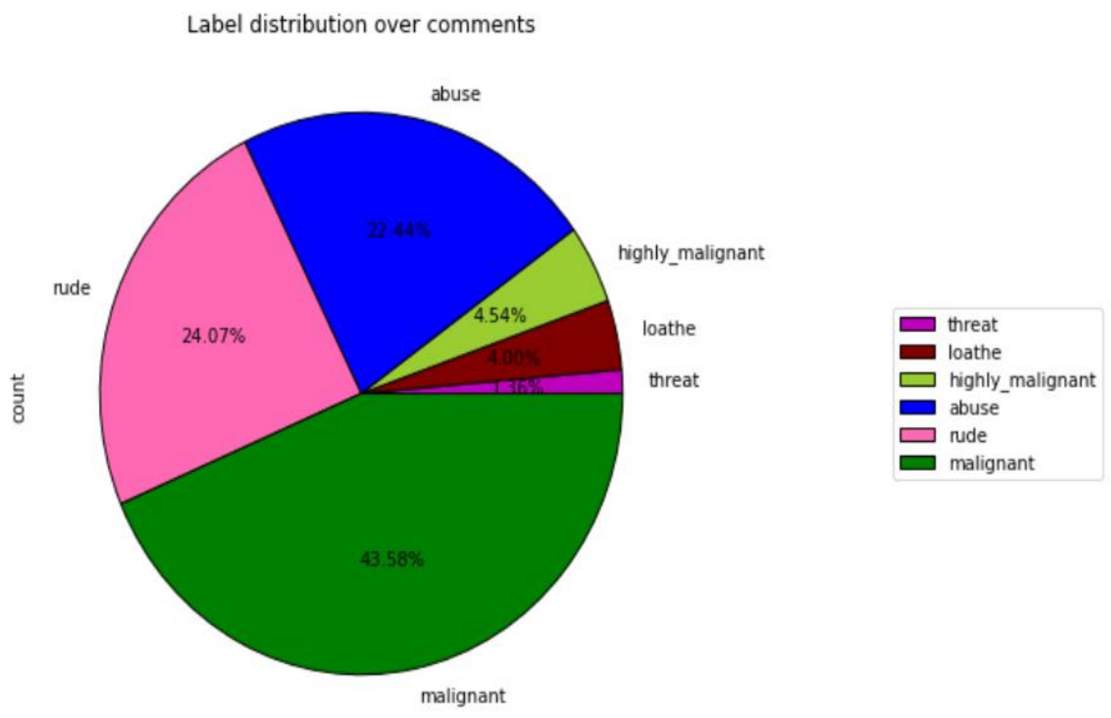
3. MODEL/S DEVELOPMENT AND EVALUATION

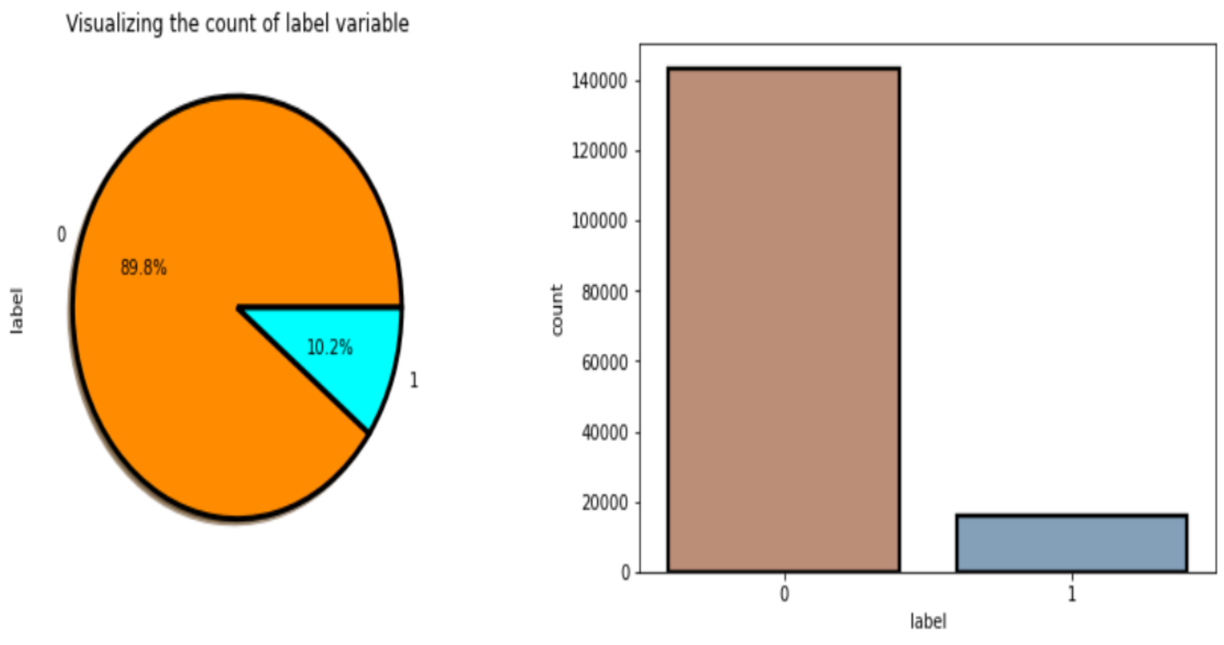
3.1 Identification of possible Problem-solving approaches (Methods):

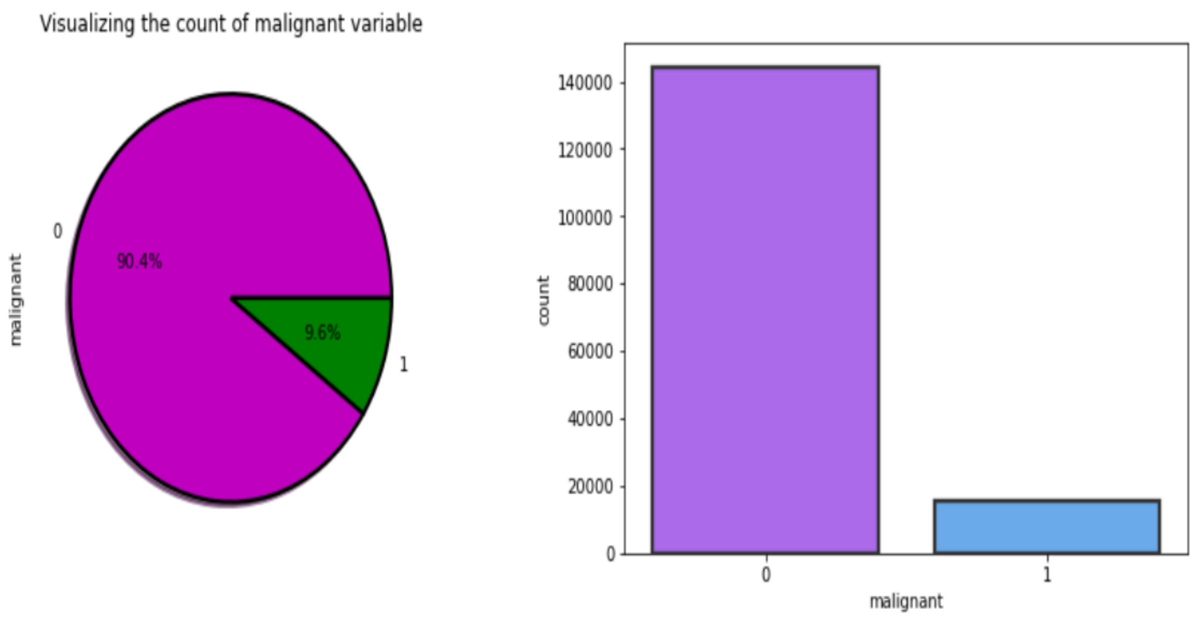
In this project there were 6 features which defines the type of comment like malignant, hate, abuse, threat, loathe but we created another feature named as “label” which is combined of all the above features and contains the labelled data into the format of 0 and 1 where 0 represents “NO” and 1 represents “Yes”. In this NLP based project we need to predict the multiple labels which are binary. I have converted text into feature vectors using TF-IDF vectorizer and separated our feature and labels. Also, before building the model, I made sure that the input data is cleaned and scaled before it was fed into the machine learning models.

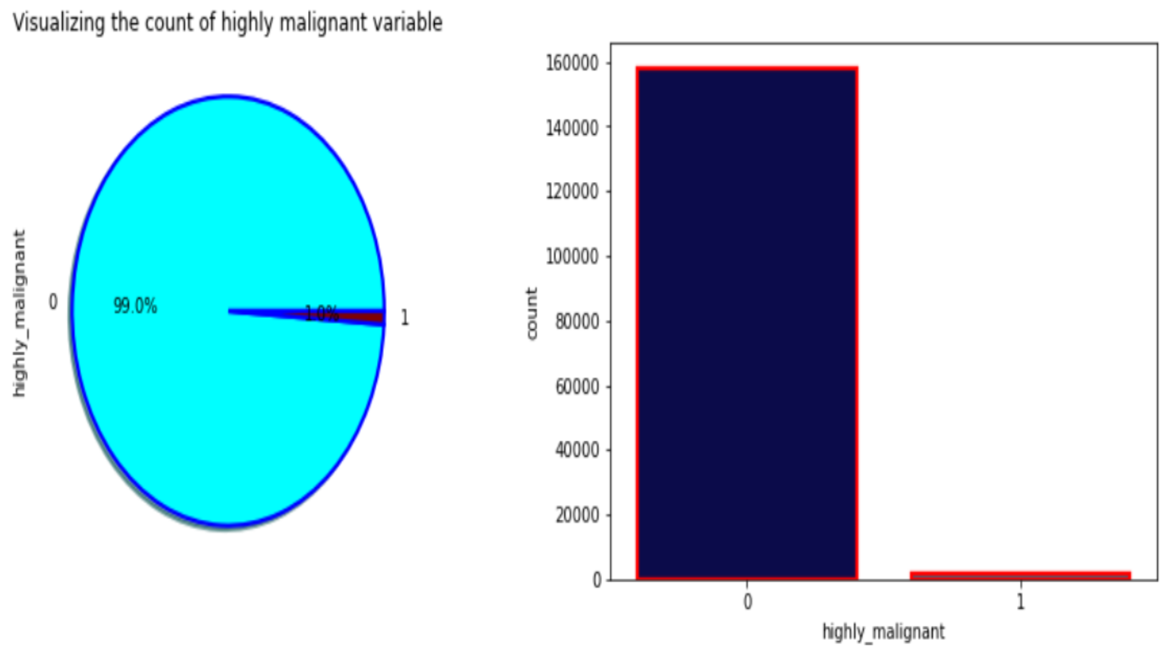
3.2 Visualizations

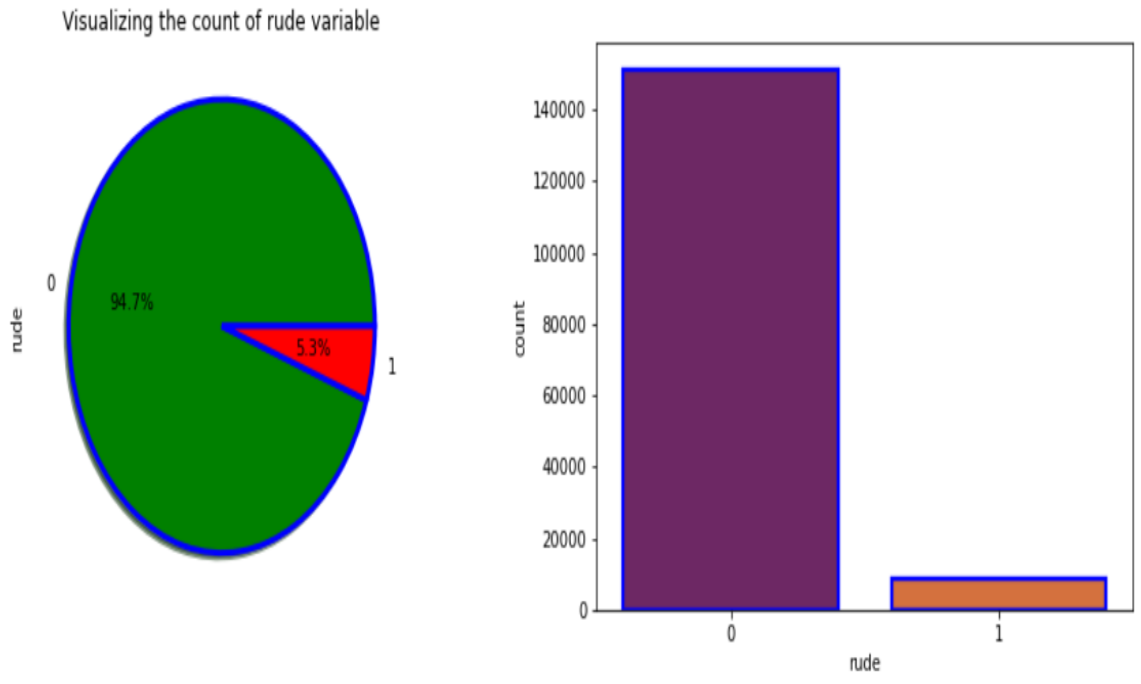
I used pandas profiling to get the over viewed visualization on the pre-processed data. Pandas is an open-source Python module with which we can do an exploratory data analysis to get detailed description of the features and it helps in visualizing and understanding the distribution of each variable. I have used wordcloud to get the sense of loud words in the labels.

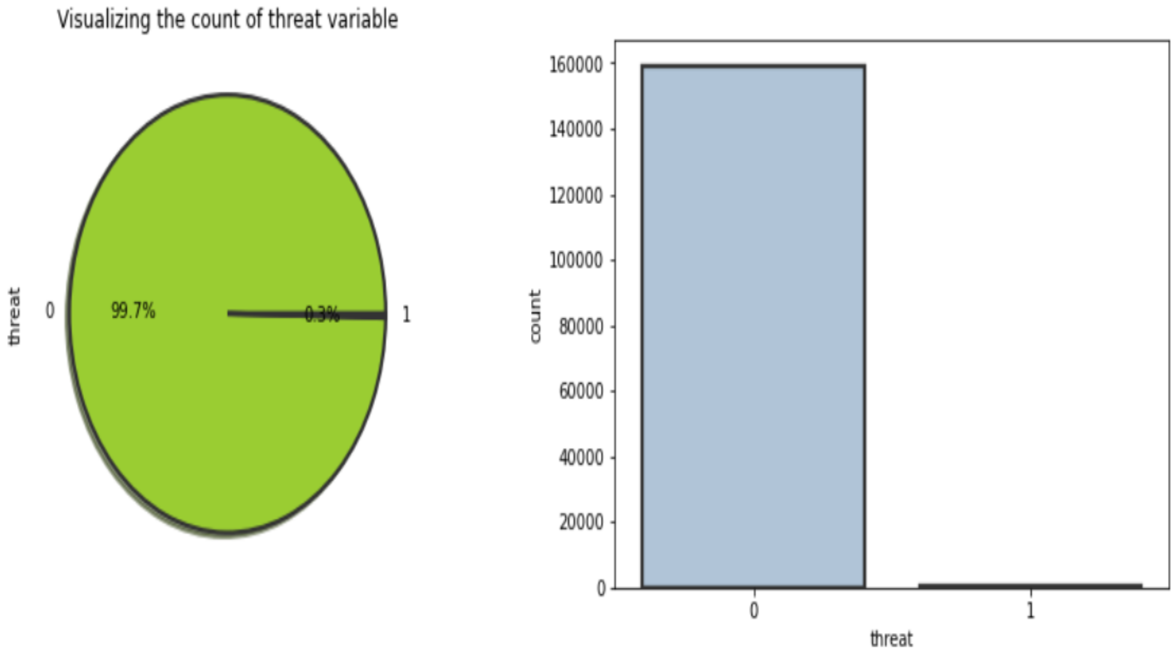

Label distribution over comments
abuse
22.44%
highly_malignant
4.54%
rude
24.07%
loathe
4.00%
threat
1.36%
count
43.58%
malignant
threat
loathe
highly_malignant
abuse
rude
malignant

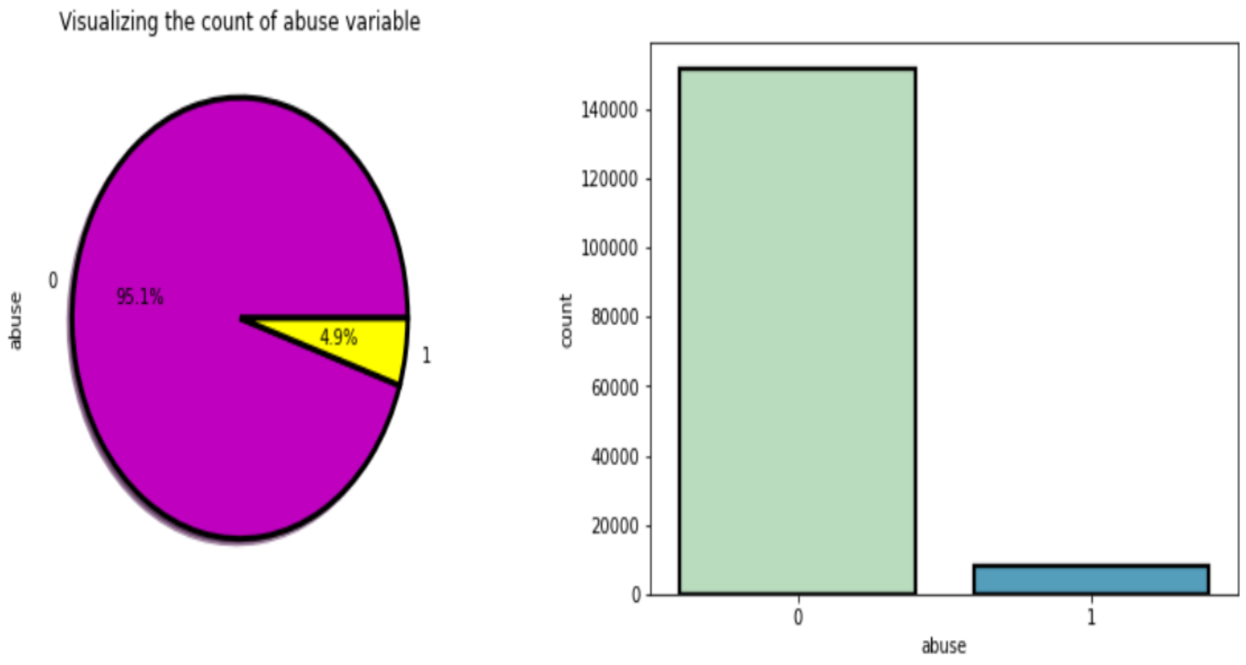

Visualizing the count of label variable
0
89.8%
label
10.2%
1
140000
120000
100000
80000
60000
40000
20000
0
count
0
1
label

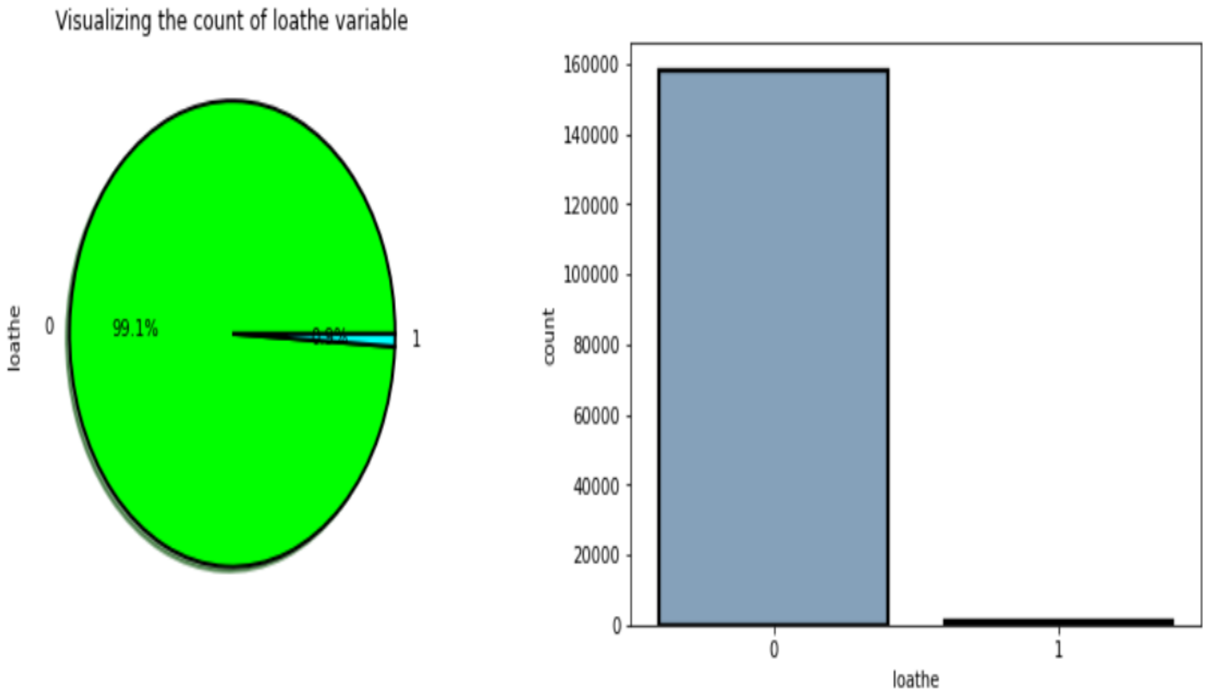

Visualizing the count of malignant variable
malignant
0
90.4%
9.6%
1
count
140000
120000
100000
80000
60000
40000
20000
0
0
1
malignant


Visualizing the count of highly malignant variable
highly_malignant
0
99.0%
1.0%
1
count
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
highly_malignant


Visualizing the count of rude variable
rude
0
94.7%
5.3%
1
count
140000
120000
100000
80000
60000
40000
20000
0
0
1
rude


Visualizing the count of threat variable
threat
0
99.7%
0.3%
1
count
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
threat


Visualizing the count of abuse variable
abuse
0
95.1%
4.9%
1
count
140000
120000
100000
80000
60000
40000
20000
0
0
1
abuse


Visualizing the count of loathe variable
loathe
0
99.1%
0.9%
1
count
160000
140000
120000
100000
80000
60000
40000
20000
0
0
1
loathe

Observations from the count plots and Pie plots

- From the pie chart we can notice approximately 43% of the comments are malignant, 24% of the comments are rude and 22% are abuse. The count of malignant comments are high compared to other type of comments and the count of threat comments are very less.

- From the above plots we can observe the count of negative comments are high compared to the non negative comments. Here around 90% of the comments are turned out to be a negative comments and only 10% of them are considered to be positive or neutral comments. We can also observe the data imbalance issue here, we need to balance the data.

- From the above plots we can observe the count of malignant comments are high compared to non malignant comments. That is around 90% of the comments are malignant and only 9.6% of the comments are good.

- From the plot we can observe the count of highly malignant comments are very high which is about 99% and only 1% of the comments are normal.

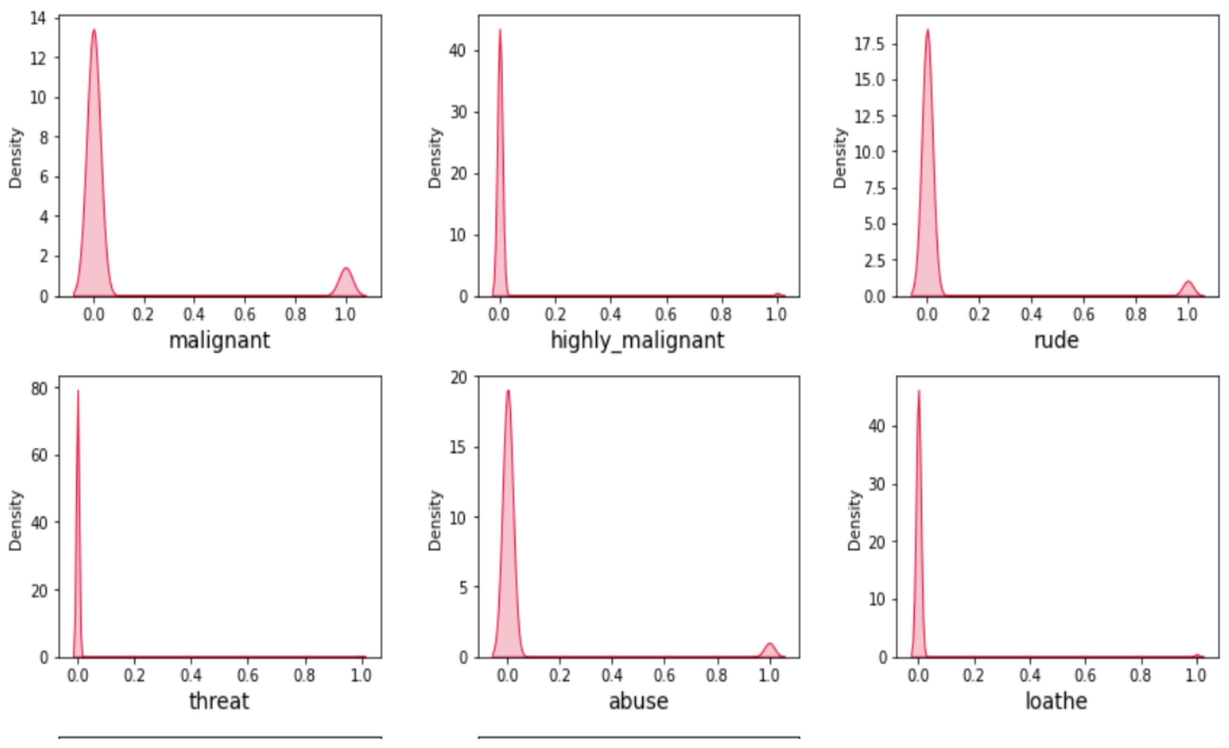
- The count of rude comments are high compared to normal comments. Around 94% of the comments are falls down into rude and remaining considered to be normal comments.

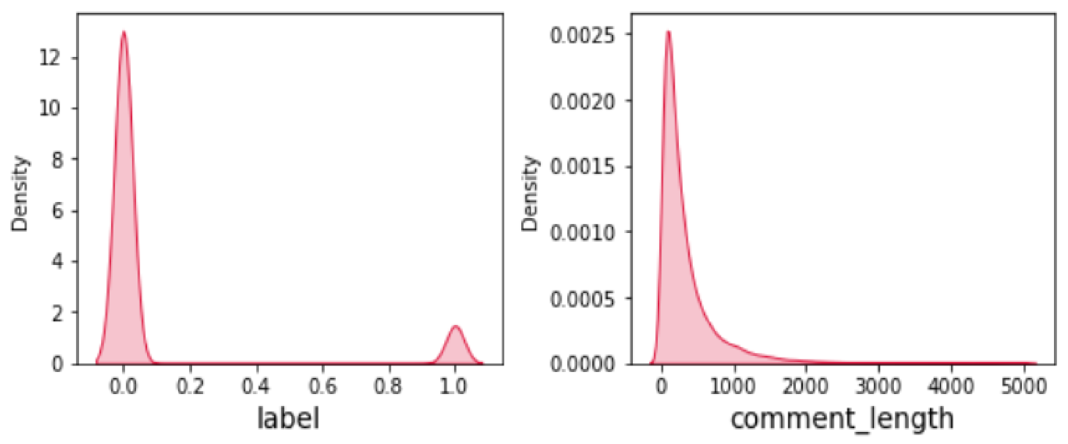
- Here also 99.7% of the comments are threat and only 0.3% of the comments are look normal.

- The count of abusing type comments are high which has 95.1% and only 4.9% of the comments are normal.

- The count of loathe is high compared to normal text comments.

<u>Visualization of the type of distribution for each feature</u>

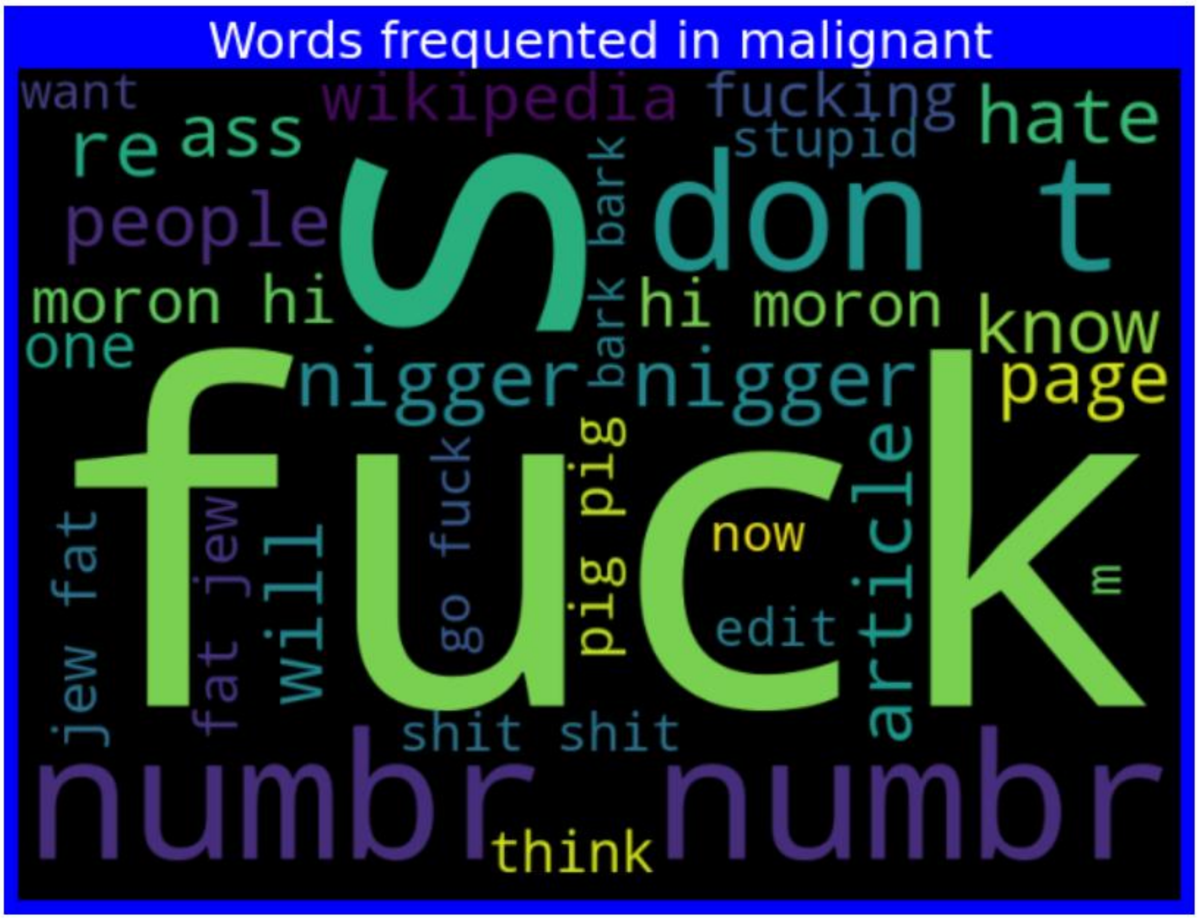


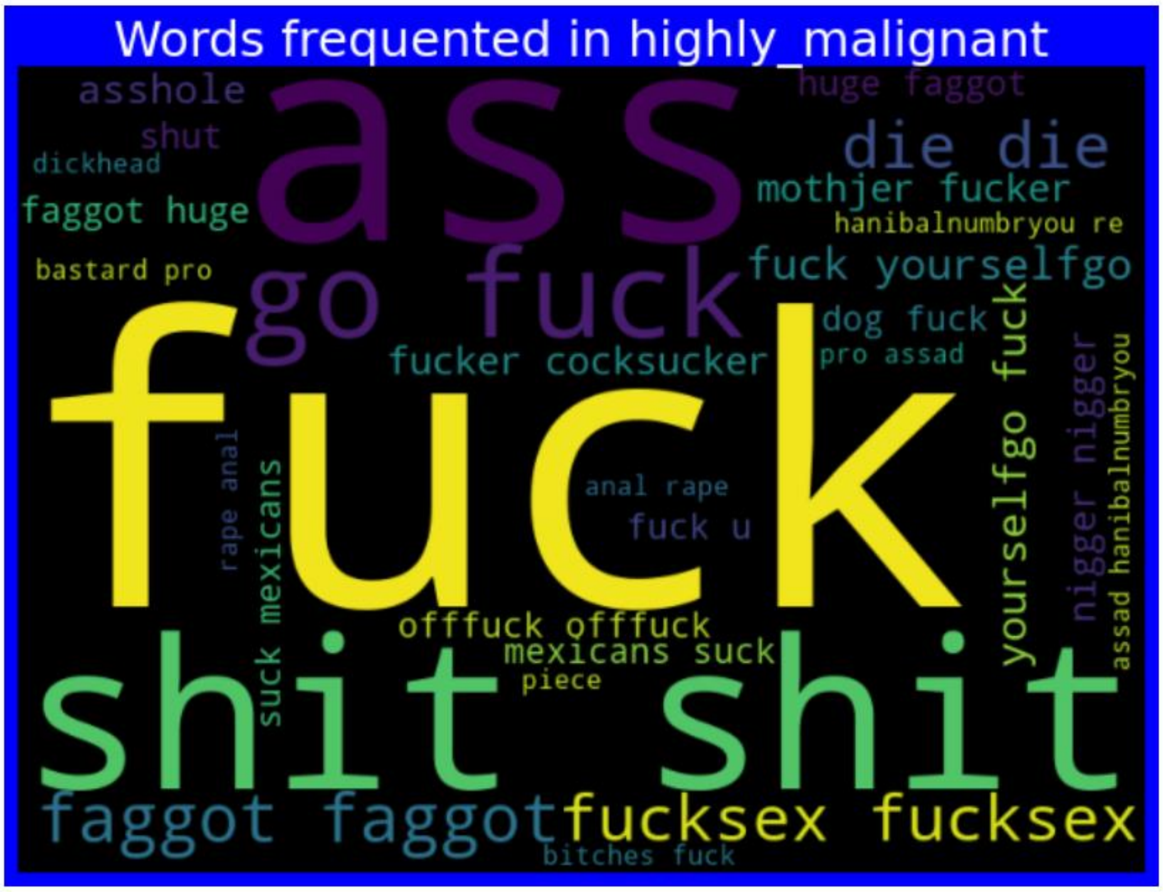


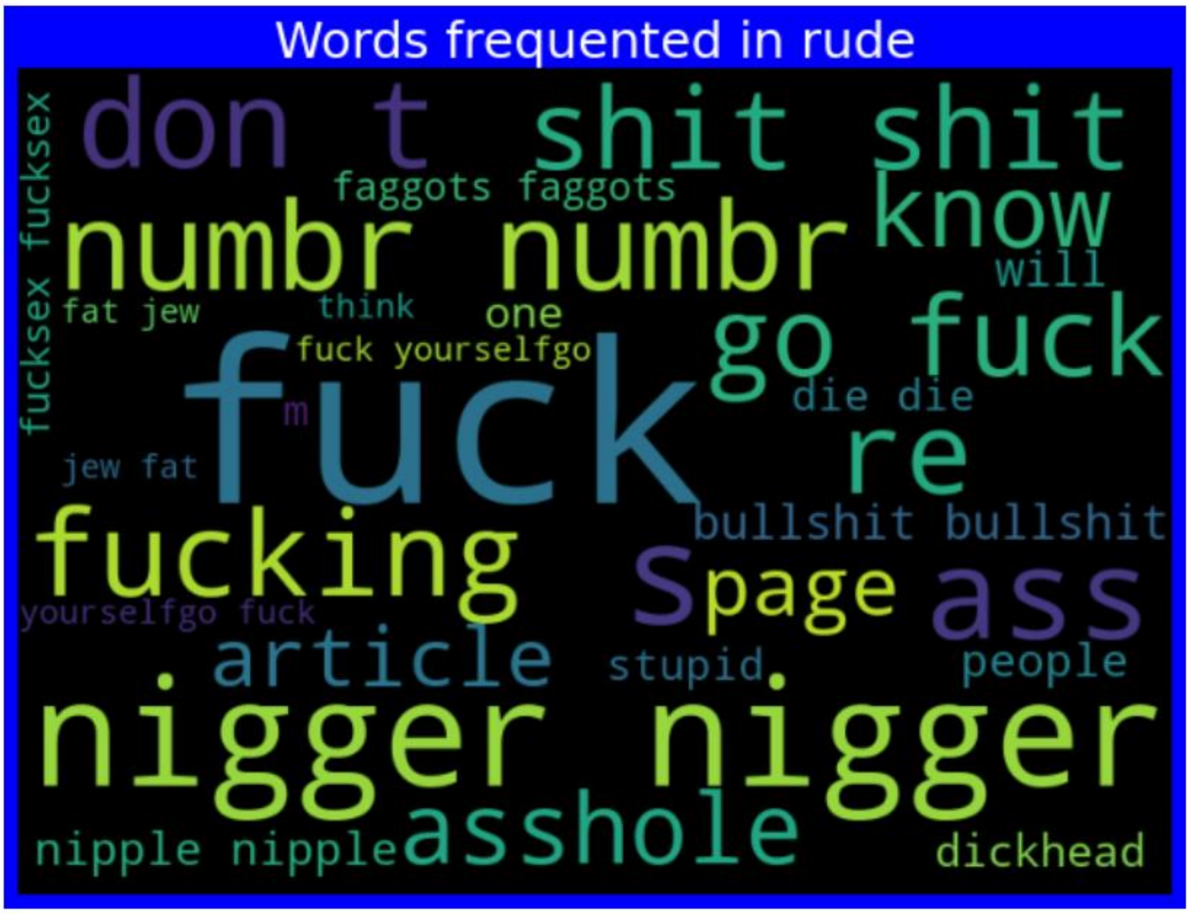
Observations from the dist plots

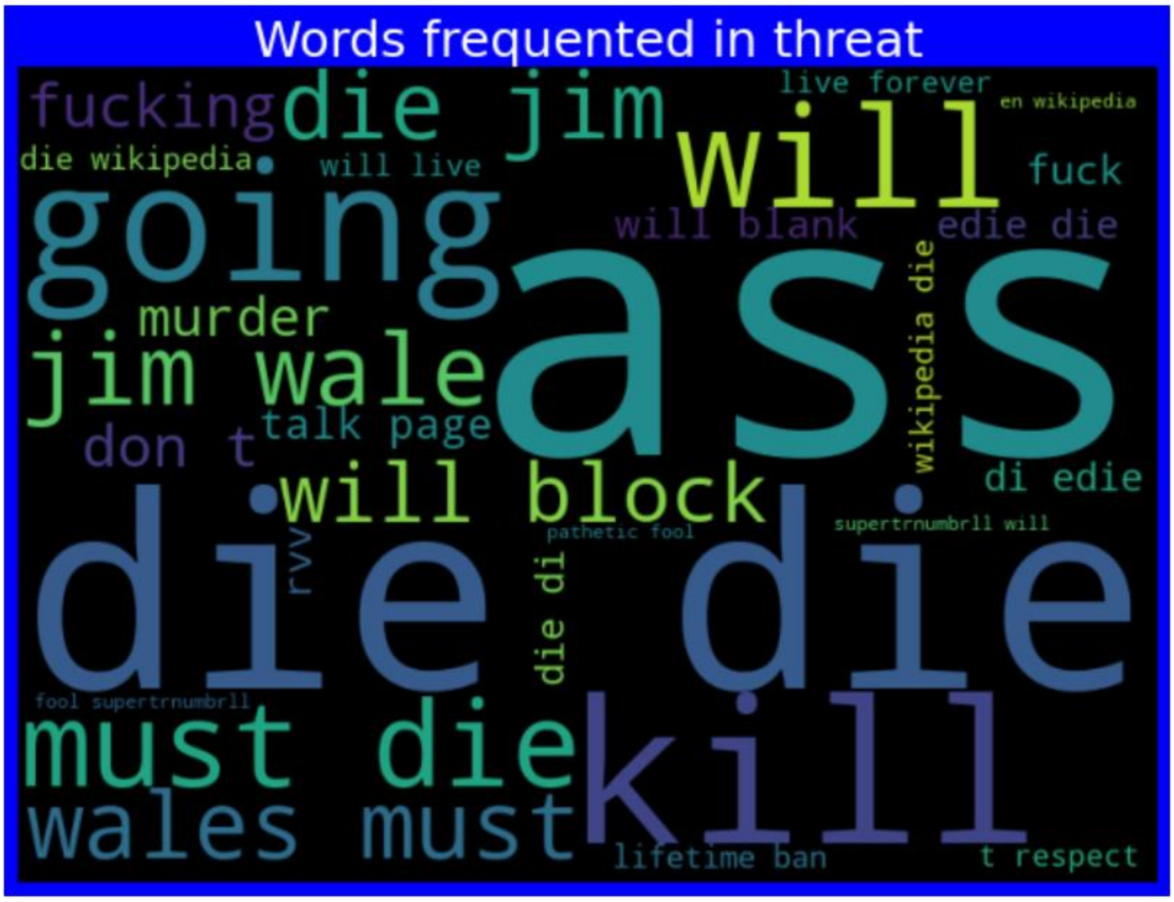
- From the distribution plots we can notice that all the columns are skewned to right except comment_label column. Since all the columns are categorical in nature there is no need to remove skewness and outliers in any of the columns.

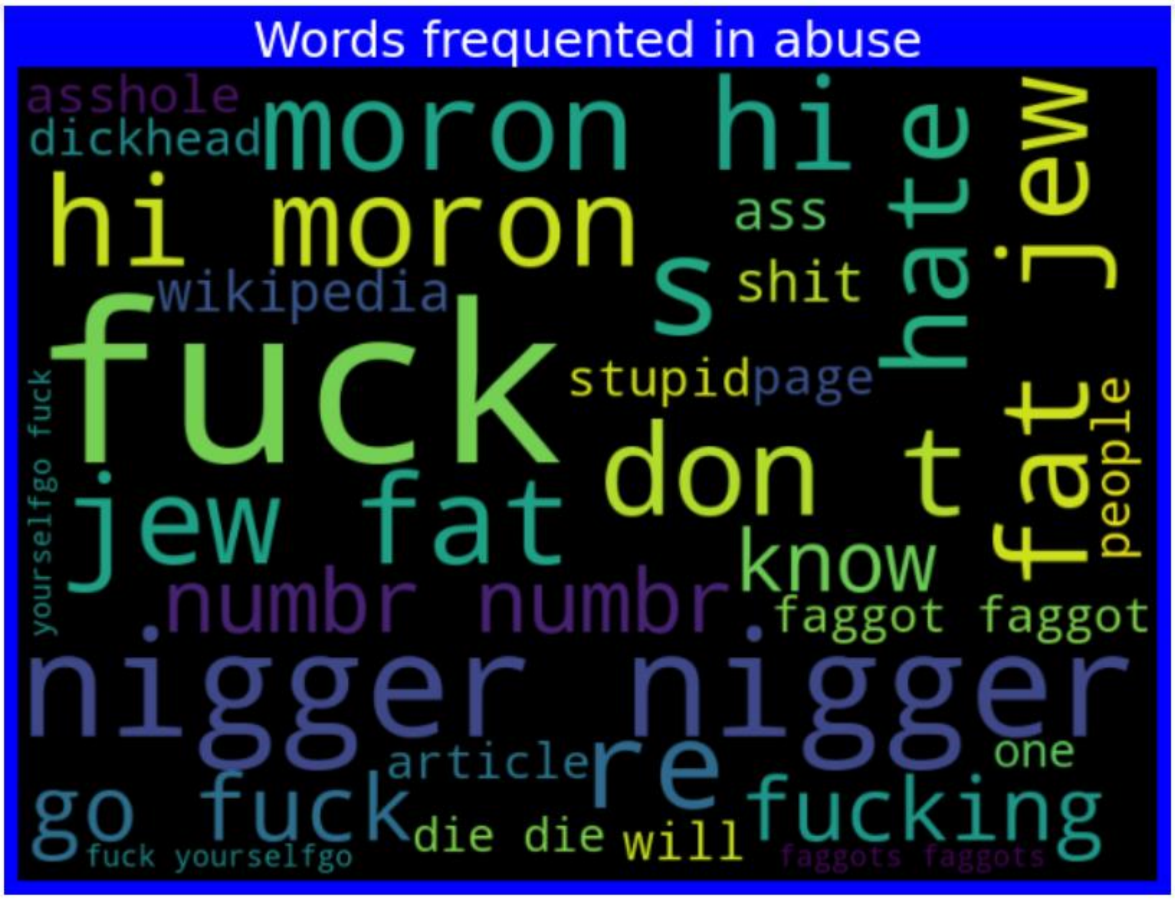
<u>Plotting WordCloud for each label</u>

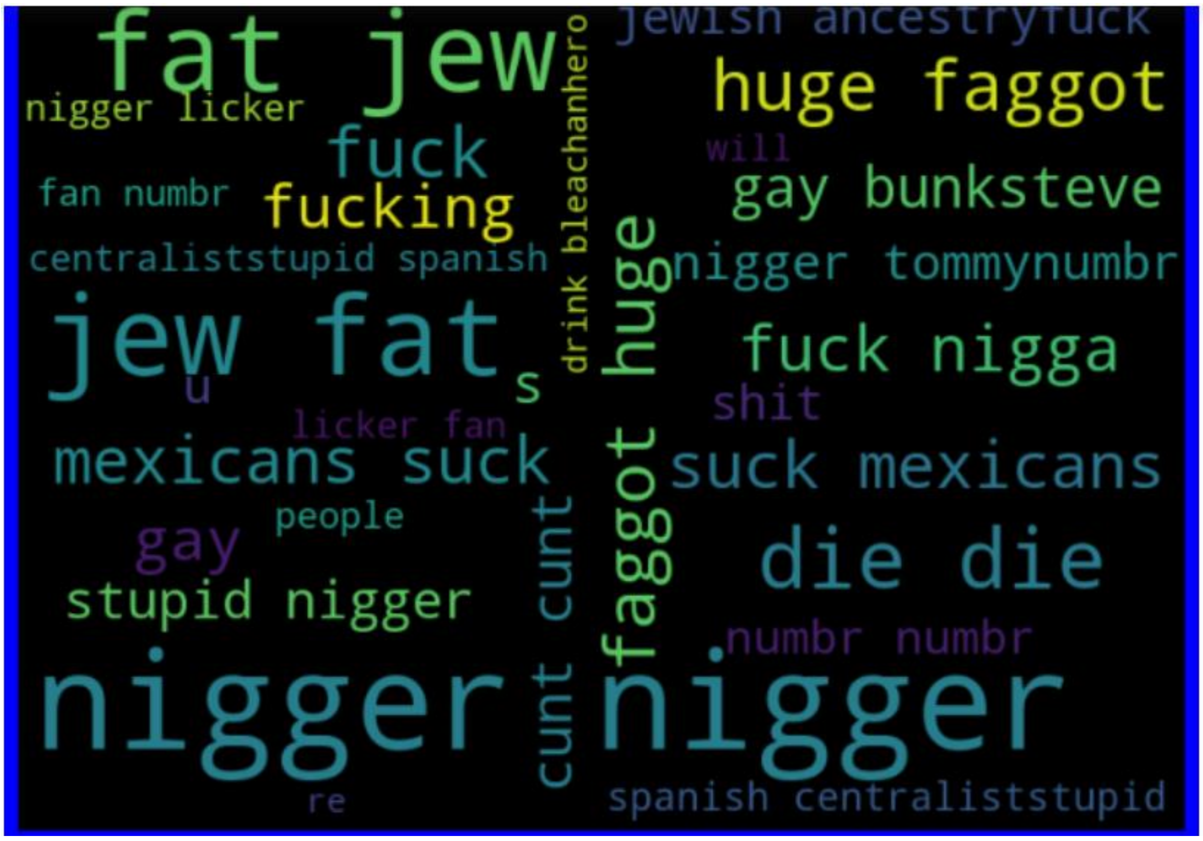



Words frequented in highly_malignant
fuck
ass
shit shit
go fuck
faggot faggot
fucksex fucksex
die die
asshole
huge faggot
shut
dickhead
faggot huge
mothjer fucker
hanibalnumbryou re
bastard pro
fuck yourselfgo
dog fuck
fucker cocksucker
pro assad
yourselfgo fuck
nigger nigger
assad hanibalnumbryou
rape anal
suck mexicans
anal rape
fuck u
offfuck offfuck
mexicans suck
piece
bitches fuck


Words frequented in rude
fucksex fucksex
don t
shit shit
faggots faggots
numbr numbr
know
will
fat jew
think
one
fuck yourselfgo
go fuck
fuck
m
die die
re
jew fat
bullshit bullshit
fucking
Spage
ass
yourselfgo fuck
article
stupid
people
nigger nigger
asshole
nipple nipple
dickhead


Words frequented in threat
ass
die die
kill
will
going
die jim
fucking
jim wale
must die
wales must
will block
murder
don t
talk page
die wikipedia
will live
live forever
en wikipedia
fuck
will blank
edie die
wikipedia die
di edie
supertrnumbrll will
pathetic fool
rvv
die di
fool supertrnumbrll
lifetime ban
t respect

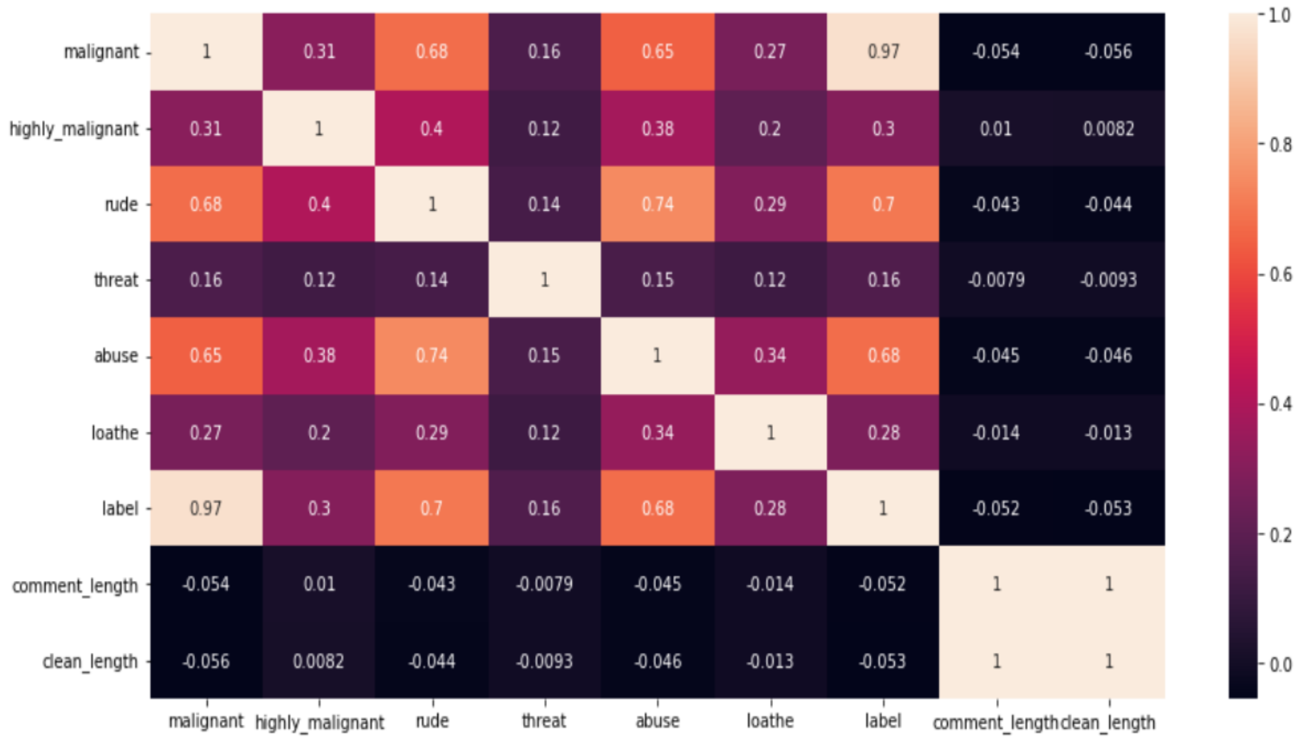

Words frequented in abuse
fuck
nigger nigger
moron hi
hi moron
jew fat
fat jew
hate
don t
s
asshole
dickhead
ass
shit
wikipedia
stupid
page
know
people
numbr numbr
faggot faggot
yourselfgo fuck
article
re
one
go fuck
fucking
die die
will
fuck yourselfgo
faggots faggots



Observations from the word cloud

- From the above plots we can clearly see the toxic words which are indication of malignant, highly malignant, rude, threat, abuse and loathe words.
- Here most frequent words used for each label is displayed in the word cloud based on different label and also when all the values are present.

<u>Plotting heatmap plot to find out the correlation among the features and label and multi-corlinearity</u>



Observations from the Heatmap Plot

- From the heat map we can observe the features have some strong relation with each other. We can also observe multicorllinearity problem.

3.3 Testing of Identified Approaches (Algorithms)

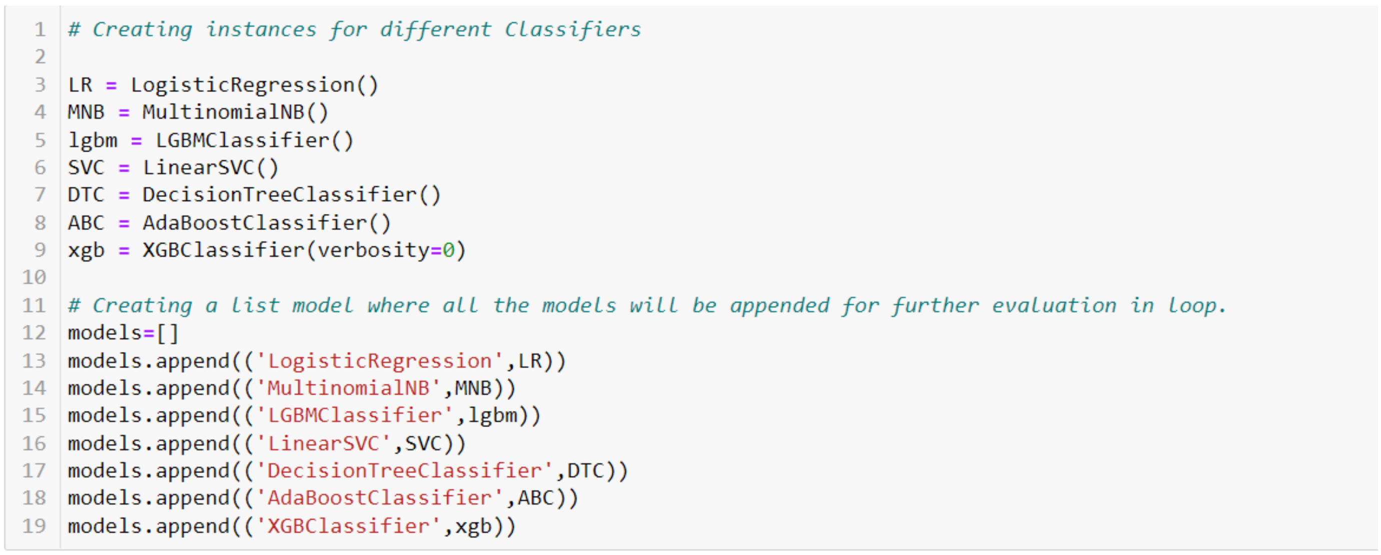
Since the target variable is categorical in nature, from this I can conclude that it is a classification type problem hence I have used following classification algorithms. After the pre-processing and data cleaning I left with 10 columns including targets. The algorithms used on training the data are as follows:

- Logistic Regression
- MultinomialNB
- LightGBM Classifier
- LinearSVC
- Decision Tree Classifier

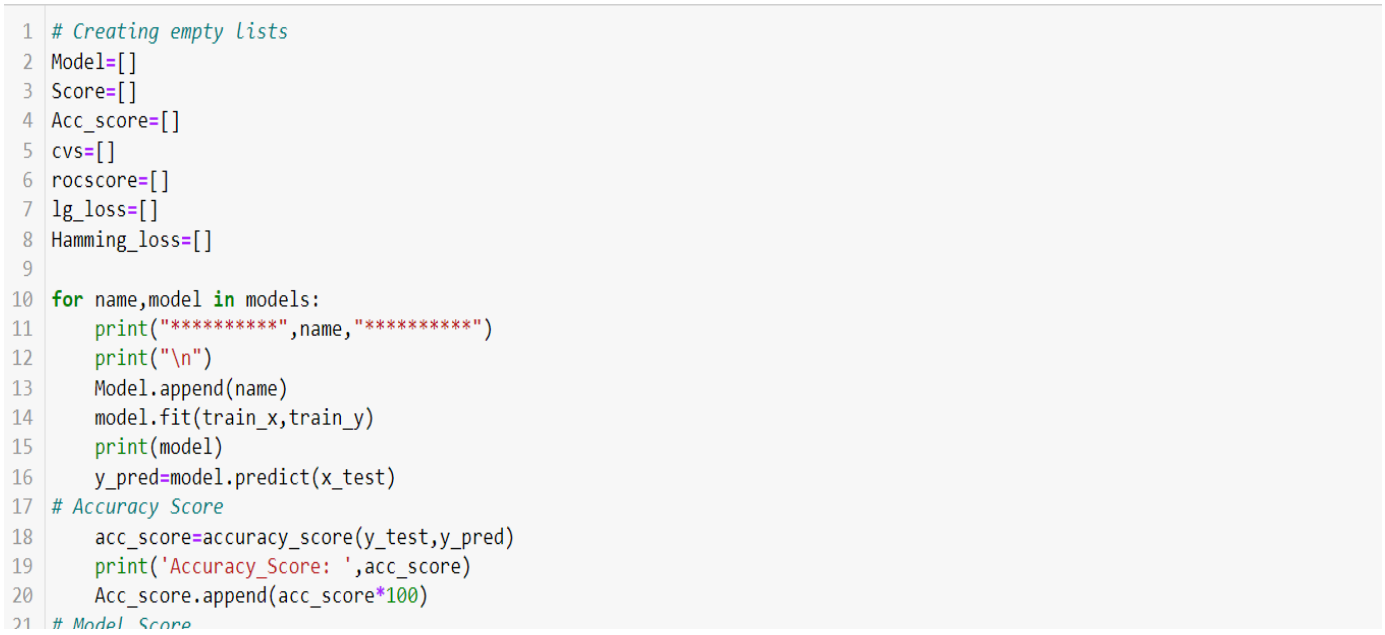
- Extreme Gradient Boosting Classifier (XGB)
- AdaBoost Classifier

3.4 Run and Evaluate Selected Models

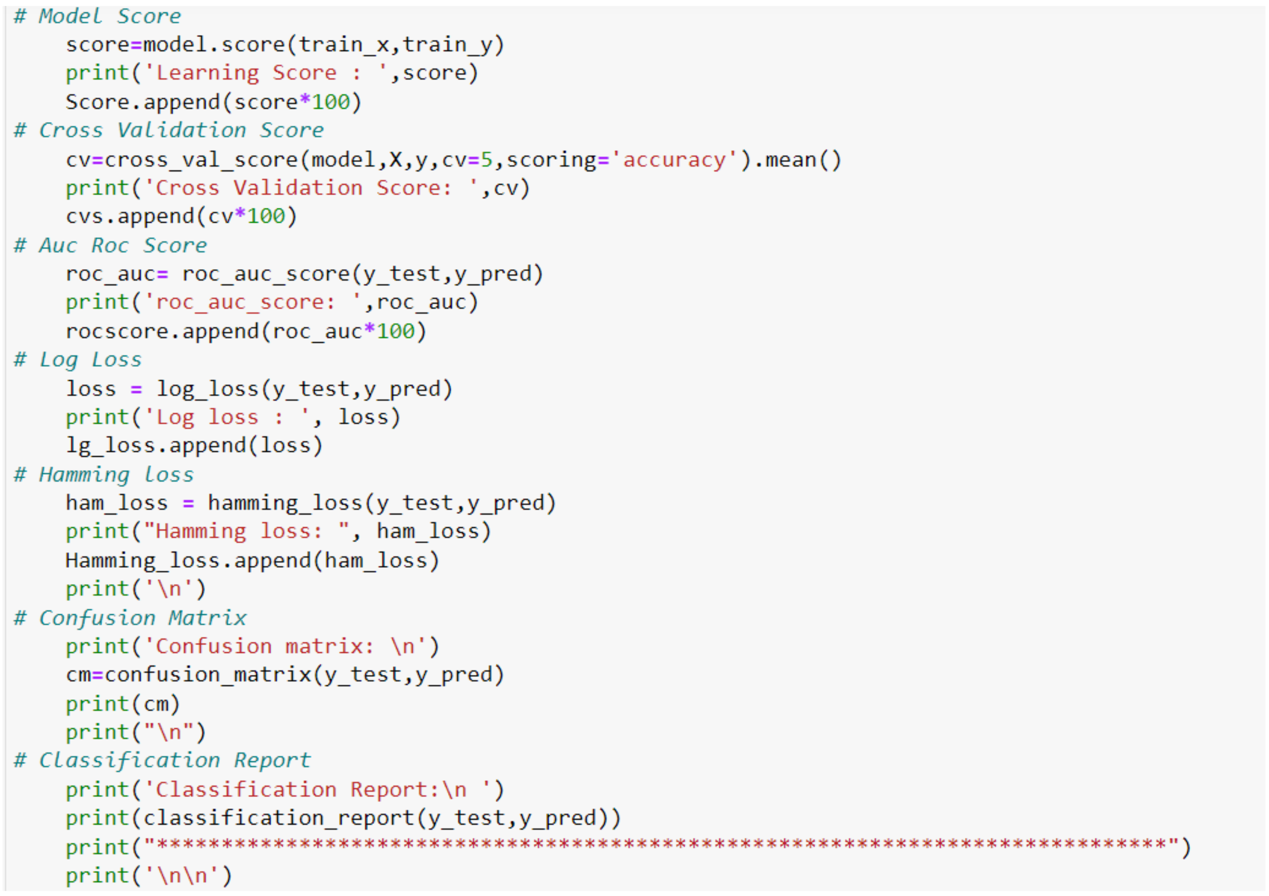
I have used 7 classification algorithms. First, I have created 7 different classification algorithms and are appended in the variable models. Then, ran a for loop which contained the accuracy of the models along with different evaluation metrics.



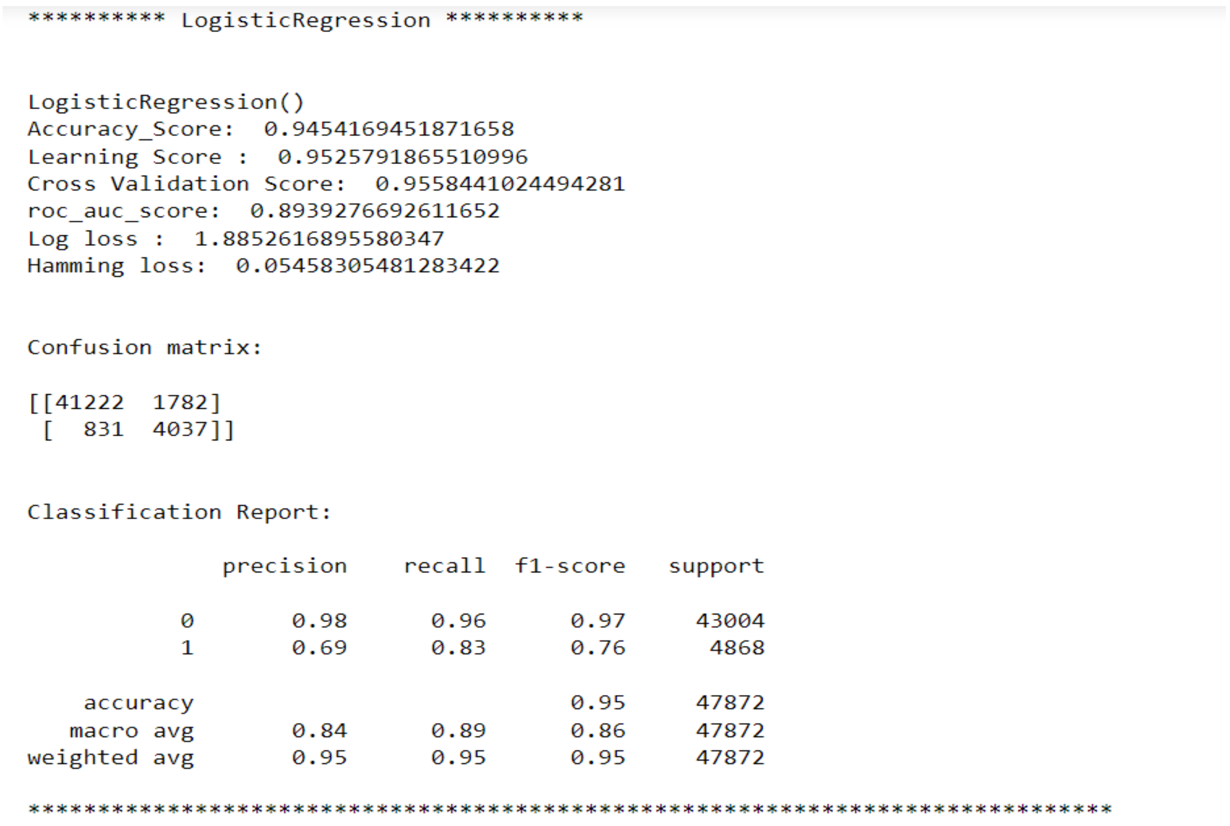
```python
# Creating instances for different Classifiers

LR = LogisticRegression()
MNB = MultinomialNB()
lgbm = LGBMClassifier()
SVC = LinearSVC()
DTC = DecisionTreeClassifier()
ABC = AdaBoostClassifier()
xgb = XGBClassifier(verbosity=0)

# Creating a list model where all the models will be appended for further evaluation in loop.
models=[]
models.append(('LogisticRegression',LR))
models.append(('MultinomialNB',MNB))
models.append(('LGBMClassifier',lgbm))
models.append(('LinearSVC',SVC))
models.append(('DecisionTreeClassifier',DTC))
models.append(('AdaBoostClassifier',ABC))
models.append(('XGBClassifier',xgb))
```



```python
# Creating empty lists
Model=[]
Score=[]
Acc_score=[]
cvs=[]
rocscore=[]
lg_loss=[]
Hamming_loss=[]

for name,model in models:
    print("**********",name,"**********")
    print("\n")
    Model.append(name)
    model.fit(train_x,train_y)
    print(model)
    y_pred=model.predict(x_test)
# Accuracy Score
    acc_score=accuracy_score(y_test,y_pred)
    print('Accuracy_Score: ',acc_score)
    Acc_score.append(acc_score*100)
# Model Score
```



```
# Model Score
    score=model.score(train_x,train_y)
    print('Learning Score : ',score)
    Score.append(score*100)
# Cross Validation Score
    cv=cross_val_score(model,X,y,cv=5,scoring='accuracy').mean()
    print('Cross Validation Score: ',cv)
    cvs.append(cv*100)
# Auc Roc Score
    roc_auc= roc_auc_score(y_test,y_pred)
    print('roc_auc_score: ',roc_auc)
    rocscore.append(roc_auc*100)
# Log Loss
    loss = log_loss(y_test,y_pred)
    print('Log loss : ', loss)
    lg_loss.append(loss)
# Hamming loss
    ham_loss = hamming_loss(y_test,y_pred)
    print("Hamming loss: ", ham_loss)
    Hamming_loss.append(ham_loss)
    print('\n')
# Confusion Matrix
    print('Confusion matrix: \n')
    cm=confusion_matrix(y_test,y_pred)
    print(cm)
    print("\n")
# Classification Report
    print('Classification Report:\n ')
    print(classification_report(y_test,y_pred))
    print("******************************************************************************")
    print('\n\n')
```



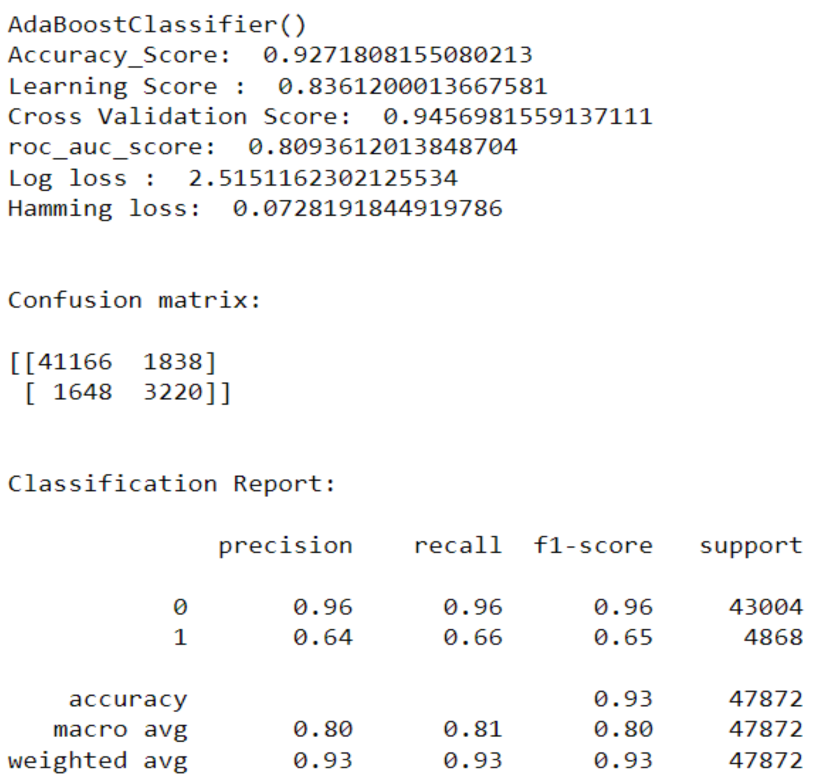
```
********** LogisticRegression **********


LogisticRegression()
Accuracy_Score:  0.9454169451871658
Learning Score :  0.9525791865510996
Cross Validation Score:  0.9558441024494281
roc_auc_score:  0.8939276692611652
Log loss :  1.8852616895580347
Hamming loss:  0.05458305481283422


Confusion matrix:

[[41222  1782]
 [  831  4037]]


Classification Report:

              precision    recall  f1-score   support

           0       0.98      0.96      0.97     43004
           1       0.69      0.83      0.76      4868

    accuracy                           0.95     47872
   macro avg       0.84      0.89      0.86     47872
weighted avg       0.95      0.95      0.95     47872

******************************************************************************
```

```
********** MultinomialNB **********


MultinomialNB()
Accuracy_Score:  0.9109918114973262
Learning Score :  0.9134215651658902
Cross Validation Score:  0.946982848930392
roc_auc_score:  0.8867898493629645
Log loss :  3.074293415457069
Hamming loss:  0.0890081885026738


Confusion matrix:

[[39442  3562]
 [  699  4169]]


Classification Report:

              precision    recall  f1-score   support

           0       0.98      0.92      0.95     43004
           1       0.54      0.86      0.66      4868

    accuracy                           0.91     47872
   macro avg       0.76      0.89      0.81     47872
weighted avg       0.94      0.91      0.92     47872
```

```
********** LGBMClassifier **********


LGBMClassifier()
Accuracy_Score:  0.9472969585561497
Learning Score :  0.9051811524049249
Cross Validation Score:  0.9554054262487964
roc_auc_score:  0.8648250278375053
Log loss :  1.8203212962997612
Hamming loss:  0.05270304144385027


Confusion matrix:

[[41643  1361]
 [ 1162  3706]]


Classification Report:

              precision    recall  f1-score   support

           0       0.97      0.97      0.97     43004
           1       0.73      0.76      0.75      4868

    accuracy                           0.95     47872
   macro avg       0.85      0.86      0.86     47872
weighted avg       0.95      0.95      0.95     47872
```

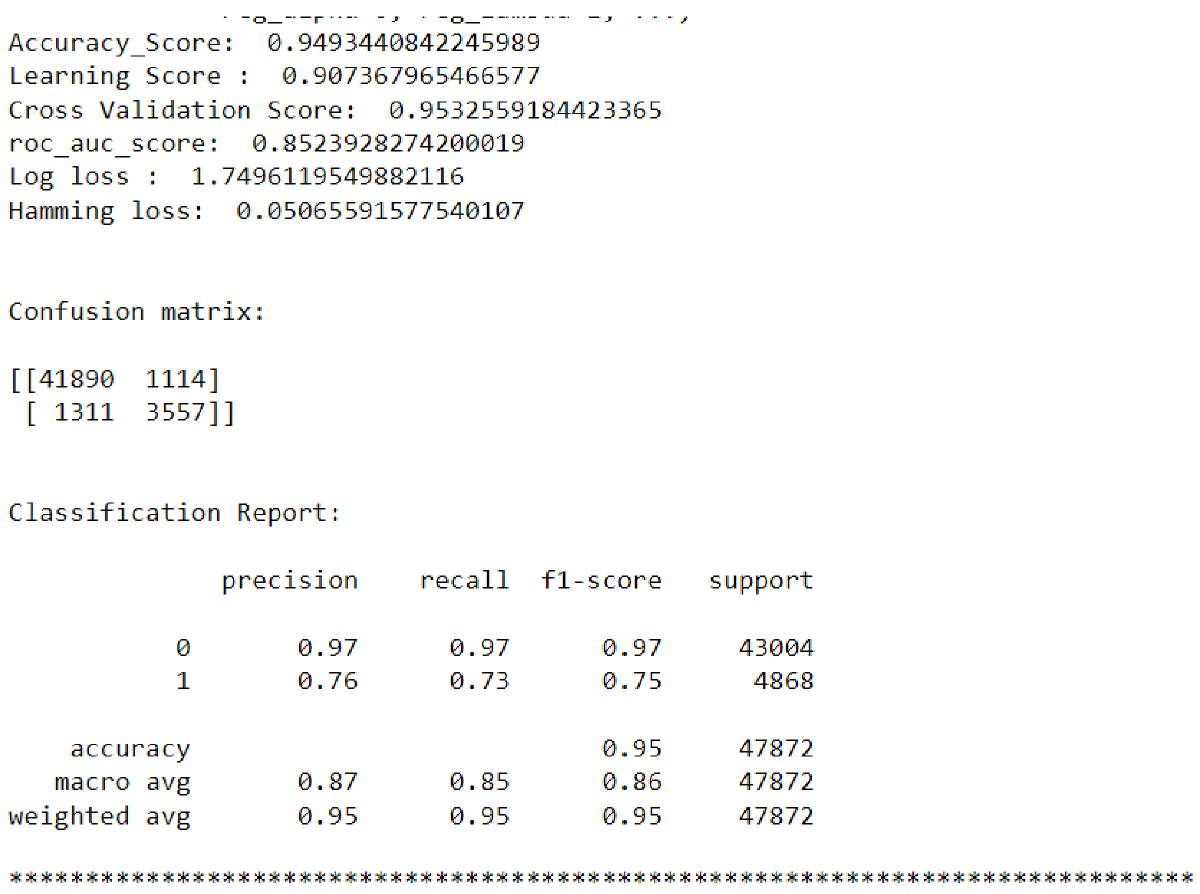
```
********** LinearSVC **********


LinearSVC()
Accuracy_Score:  0.9396724598930482
Learning Score :  0.9729552728390984
Cross Validation Score:  0.959547784553488
roc_auc_score:  0.8859027999688474
Log loss :  2.0836728906616018
Hamming loss:  0.06032754010695187


Confusion matrix:

[[41000  2004]
 [  884  3984]]


Classification Report:

              precision    recall  f1-score   support

           0       0.98      0.95      0.97     43004
           1       0.67      0.82      0.73      4868

    accuracy                           0.94     47872
   macro avg       0.82      0.89      0.85     47872
weighted avg       0.95      0.94      0.94     47872
```

```
DecisionTreeClassifier()
Accuracy_Score:  0.9287266042780749
Learning Score :  0.9983997539835305
Cross Validation Score:  0.9419004741229836
roc_auc_score:  0.8386400317273806
Log loss :  2.461730552801227
Hamming loss:  0.07127339572192513


Confusion matrix:

[[40928  2076]
 [ 1336  3532]]


Classification Report:

              precision    recall  f1-score   support

           0       0.97      0.95      0.96     43004
           1       0.63      0.73      0.67      4868

    accuracy                           0.93     47872
   macro avg       0.80      0.84      0.82     47872
weighted avg       0.93      0.93      0.93     47872

****************************************************************************
```



```
AdaBoostClassifier()
Accuracy_Score:  0.9271808155080213
Learning Score :  0.8361200013667581
Cross Validation Score:  0.9456981559137111
roc_auc_score:  0.8093612013848704
Log loss :  2.5151162302125534
Hamming loss:  0.0728191844919786


Confusion matrix:

[[41166  1838]
 [ 1648  3220]]


Classification Report:

              precision    recall  f1-score   support

           0       0.96      0.96      0.96     43004
           1       0.64      0.66      0.65      4868

    accuracy                           0.93     47872
   macro avg       0.80      0.81      0.80     47872
weighted avg       0.93      0.93      0.93     47872
```

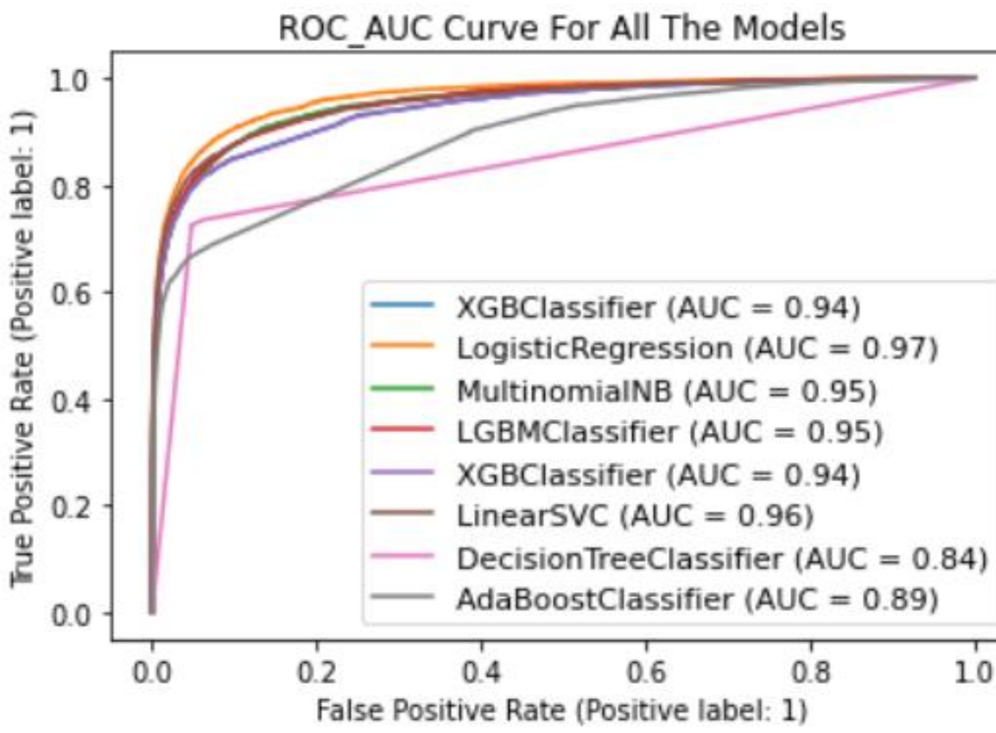
XGB Classifier



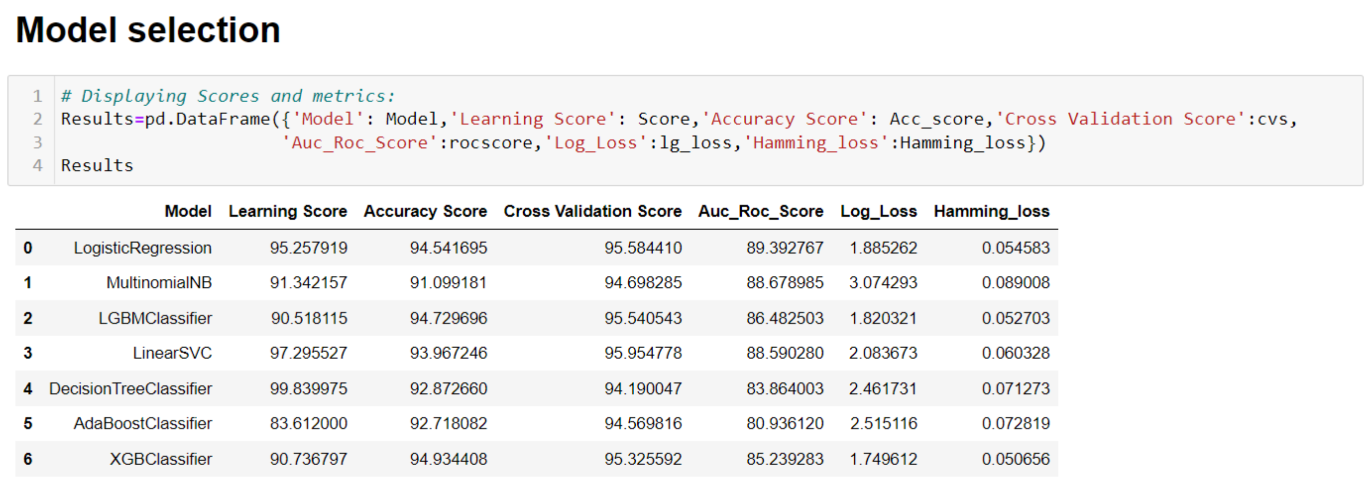
```
Accuracy_Score:  0.9493440842245989
Learning Score :  0.907367965466577
Cross Validation Score:  0.9532559184423365
roc_auc_score:  0.8523928274200019
Log loss :  1.7496119549882116
Hamming loss:  0.05065591577540107


Confusion matrix:

[[41890  1114]
 [ 1311  3557]]


Classification Report:

              precision    recall  f1-score   support

           0       0.97      0.97      0.97     43004
           1       0.76      0.73      0.75      4868

    accuracy                           0.95     47872
   macro avg       0.87      0.85      0.86     47872
weighted avg       0.95      0.95      0.95     47872

*****************************************************************************
```

Plotting ROC and compare AUC for all the models used

```python
# Plotting for all the models used here
from sklearn import datasets
from sklearn import metrics
from sklearn import model_selection
from sklearn.metrics import plot_roc_curve

disp = plot_roc_curve(xgb,x_test,y_test)     # ax_=Axes with confusion matrix
plot_roc_curve(LR, x_test, y_test, ax=disp.ax_)
plot_roc_curve(MNB, x_test, y_test, ax=disp.ax_)
plot_roc_curve(lgbm, x_test, y_test, ax=disp.ax_)
plot_roc_curve(xgb, x_test, y_test, ax=disp.ax_)
plot_roc_curve(SVC, x_test, y_test, ax=disp.ax_)
plot_roc_curve(DTC, x_test, y_test, ax=disp.ax_)
plot_roc_curve(ABC, x_test, y_test, ax=disp.ax_)
plt.title("ROC_AUC Curve For All The Models")
plt.legend(prop={'size':11}, loc='lower right')
plt.show()
```



Model Selection:



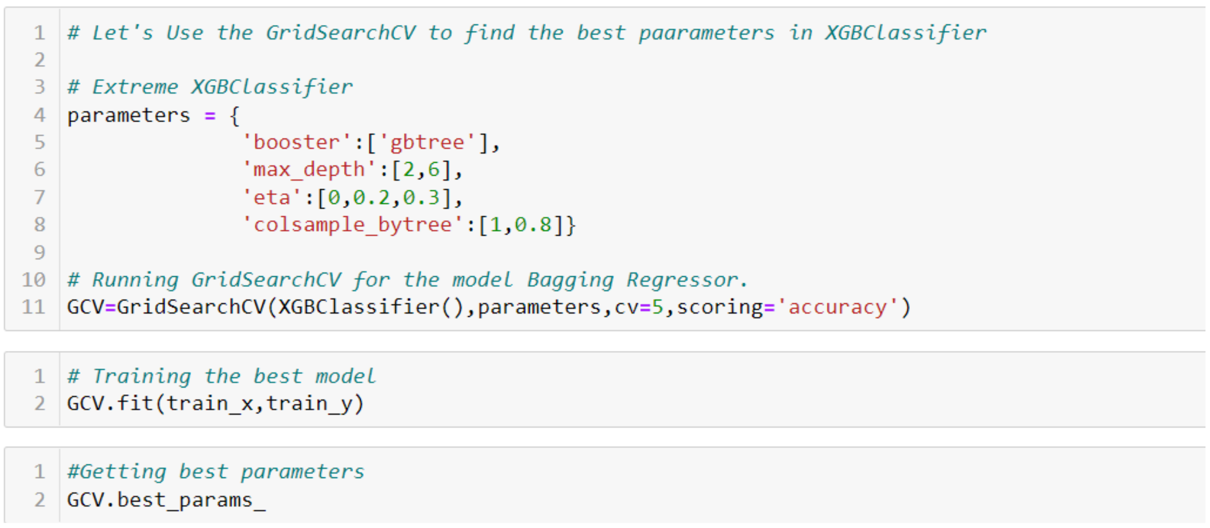
Model selection

```
# Displaying Scores and metrics:
Results=pd.DataFrame({'Model': Model,'Learning Score': Score,'Accuracy Score': Acc_score,'Cross Validation Score':cvs,
                      'Auc_Roc_Score':rocscore,'Log_Loss':lg_loss,'Hamming_loss':Hamming_loss})
Results
```

	Model	Learning Score	Accuracy Score	Cross Validation Score	Auc_Roc_Score	Log_Loss	Hamming_loss
0	LogisticRegression	95.257919	94.541695	95.584410	89.392767	1.885262	0.054583
1	MultinomialNB	91.342157	91.099181	94.698285	88.678985	3.074293	0.089008
2	LGBMClassifier	90.518115	94.729696	95.540543	86.482503	1.820321	0.052703
3	LinearSVC	97.295527	93.967246	95.954778	88.590280	2.083673	0.060328
4	DecisionTreeClassifier	99.839975	92.872660	94.190047	83.864003	2.461731	0.071273
5	AdaBoostClassifier	83.612000	92.718082	94.569816	80.936120	2.515116	0.072819
6	XGBClassifier	90.736797	94.934408	95.325592	85.239283	1.749612	0.050656

- After creating and training different classification algorithms, we can see that the difference between accuracy and cross validation score is less for "Extreme Gradient Boosting Classifier (XGBClassifier)" and Gradient Boosting Classifier. But, XGBClassifier giving less loss values, auc roc score and high accuracy score compared to Gradient Boosting Classifier. On this basis I can conclude that "XGBClassifier" as the best fitting model. Now, we will try Hyperparameter Tuning to find out the best parameters and using them to improve the scores and metrics values.

Hyper Parameter Tuning Using GridSearchCV

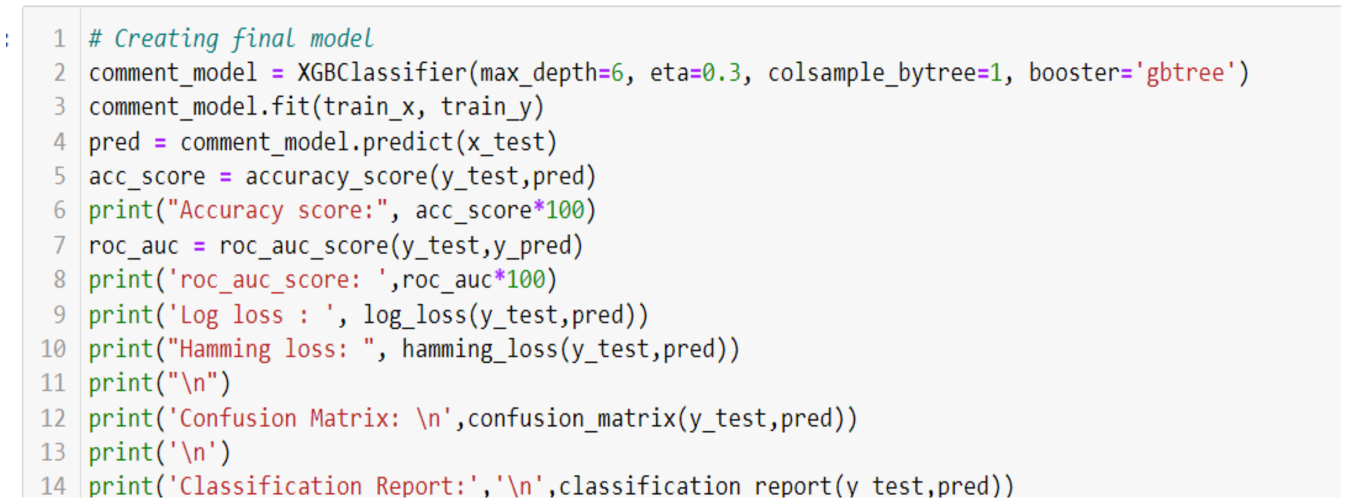


```
# Let's Use the GridSearchCV to find the best paarameters in XGBClassifier

# Extreme XGBClassifier
parameters = {
              'booster':['gbtree'],
              'max_depth':[2,6],
              'eta':[0,0.2,0.3],
              'colsample_bytree':[1,0.8]}

# Running GridSearchCV for the model Bagging Regressor.
GCV=GridSearchCV(XGBClassifier(),parameters,cv=5,scoring='accuracy')
```

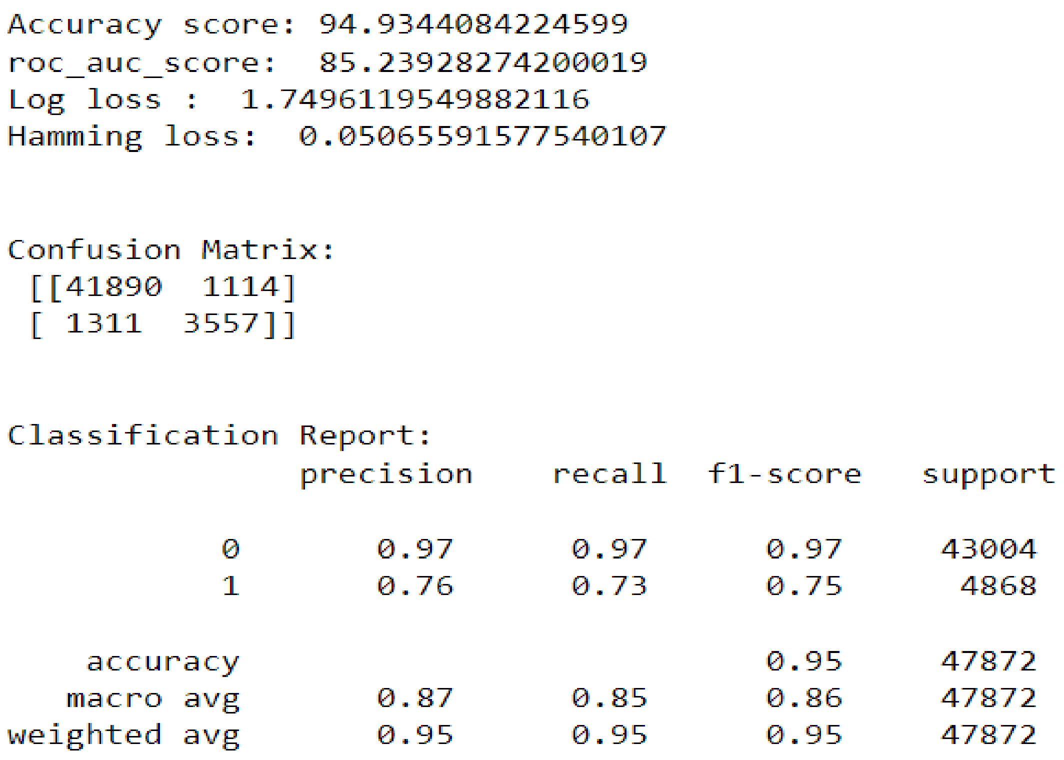
```
# Training the best model
GCV.fit(train_x,train_y)
```

```
#Getting best parameters
GCV.best_params_
```

Creating Final Model:



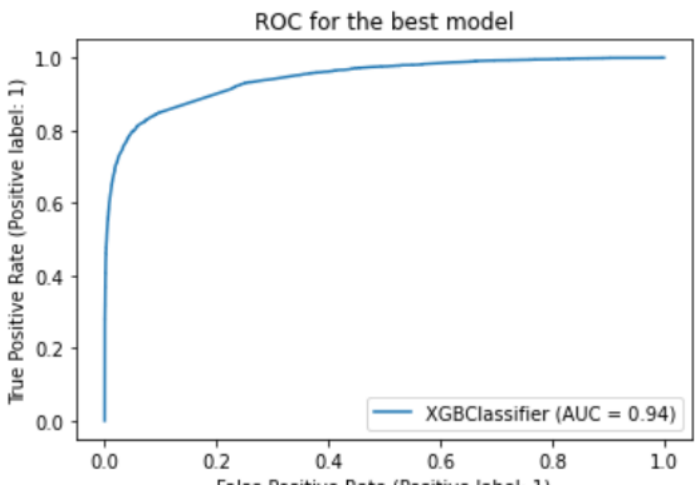
```python
# Creating final model
comment_model = XGBClassifier(max_depth=6, eta=0.3, colsample_bytree=1, booster='gbtree')
comment_model.fit(train_x, train_y)
pred = comment_model.predict(x_test)
acc_score = accuracy_score(y_test,pred)
print("Accuracy score:", acc_score*100)
roc_auc = roc_auc_score(y_test,y_pred)
print('roc_auc_score: ',roc_auc*100)
print('Log loss : ', log_loss(y_test,pred))
print("Hamming loss: ", hamming_loss(y_test,pred))
print("\n")
print('Confusion Matrix: \n',confusion_matrix(y_test,pred))
print('\n')
print('Classification Report:','\n',classification_report(y_test,pred))
```



```
Accuracy score: 94.9344084224599
roc_auc_score:  85.23928274200019
Log loss :  1.7496119549882116
Hamming loss:  0.05065591577540107


Confusion Matrix:
 [[41890  1114]
 [ 1311  3557]]


Classification Report:
               precision    recall  f1-score   support

           0       0.97      0.97      0.97     43004
           1       0.76      0.73      0.75      4868

    accuracy                           0.95     47872
   macro avg       0.87      0.85      0.86     47872
weighted avg       0.95      0.95      0.95     47872
```

Plotting ROC and Compare AUC for the Final model

```

plot_roc_curve(comment_model, x_test, y_test)
plt.title("ROC for the best model")
plt.show()
```



Saving the model

```
# Saving the model using .pkl
import joblib
joblib.dump(comment_model,"Malignant_Comments_Classification.pkl")
```

```
['Malignant_Comments_Classification.pkl']
```

```
# Predicting the trained final model
comment_model.predict(X)
```

```
array([0, 0, 0, ..., 0, 0, 0])
```

```

# loading the final model
model = joblib.load('Malignant_Comments_Classification.pkl')
```

```
# Lets load the test data set
test
```

Prediction using the saved model

```
# Predicting the values for test data after loading trained model
Predictions = model.predict(x)
Predictions
```

```
array([0, 0, 0, ..., 0, 0, 0])
```

```
# Adding the predicted values to test dataframe
test['Predicted_Values']=Predictions
test
```

3.5 Key Metrics for success in solving problem under consideration

In order to evaluate the performance of each algorithm, several metrics are defined accordingly, and are discussed briefly below.

Accuracy score: This metric measures how many of the comments are labelled correctly. However, in our dataset, where most of comments are not toxic, regardless of performance of model, a high accuracy was achieved. Accuracy is the ratio of number of correct predictions into number of predictions. In binary classification problem, accuracy can be calculated as below,
Where TP = True Positive, TN = True Negative, FP = False Positive,
FN =False Negative.

Precision and Recall: Precision and recall were designed to measure the model performance in its ability to correctly classify the malignant comments. Precision explains what fraction of malignant classified comments are truly malignant, and Recall measures what fraction of malignant comments are labelled correctly.

F1 Score is used to express the performance of the machine learning model (or classifier). It gives the combined information about the precision and recall of a model. This means a high F1-score indicates a high value for both recall and precision.

Confusion Matrix is one of the evaluation metrics for machine learning classification problems, where a trained model is being evaluated for accuracy and other performance measures. And this matrix is called the confusion matrix since it results in an output that shows how the system is confused between the two classes.

Cross Validation Score is a technique in which we train our model using the subset of the data-set and then evaluate using the complementary subset of the data-set. It is used to protect against overfitting in a predictive model, particularly in a case where the amount of data may be limited. In cross-validation, you make a fixed number of folds (or partitions) of the data, run the analysis on each fold, and then average the overall error estimate. It is used to estimate the performance of ML models.

Roc Auc Score: The **Receiver Operator Characteristic (ROC)** curve is an evaluation metric for binary classification problems. It is a probability curve that plots the **TPR** against **FPR** at various threshold values.
The **Area Under Curve (AUC)** is the measure of the ability of a classifier to distinguish between classes and is used as a summary of the ROC curve.

Log Loss is the most important classification metric based on probabilities. Log Loss is the negative average of the log of corrected predicted probabilities for each instance.

Hamming Loss is the fraction of wrong labels to the total number of labels. In multi-class classification, hamming loss is calculated as the hamming distance between y_true and y_pred. In multi-label classification, hamming loss penalizes only the individual labels.

3.6 Interpretation of the Results

Visualizations: I have used distribution plot to visualize how the data has been distributed. Used count plots and pie charts to check the count of particular category for each feature. The heat map helped me to understand the correlation between dependent and independent features. Also, heat map helped to detect the multicollinearity problem and feature importance. With the help of WordClouds I would able to sense the loud words in each label. AUC-ROC curve helped to select the best model.

Pre-processing: The dataset should be cleaned and scaled to build the ML models to get good predictions. I have performed few NLP text processing steps which I have already mentioned in the pre-processing steps where all the important features are present in the dataset and ready for model building.

Model building: After cleaning and processing data, I performed train test split to build the model. I have built multiple classification models to get the accurate accuracy score, and evaluation metrics like precision, recall, confusion matrix, f1 score, log loss, hamming loss. I got Extreme Gradient Boosting Classifier (XGB Classifier) as the best model which gives 94.96% accuracy score. I checked the cross-validation score ensuring there will be no overfitting. After tuning the best model XGB Classifier, I got 95.47% accuracy score and also got increment in AUC-ROC curve. Finally, I saved my final model and got the good predictions results for test dataset.

4.CONCLUSION

4.1 Key Findings and Conclusions of the Study

From the above analysis the below mentioned results were achieved which depicts the chances and conditions of a comment being a hateful comment or a normal comment;

With the increasing popularity of social media more and more people consume feeds from social media and due differences they spread hate comments to instead of love and harmony. It has strong negative impacts on individual users and broader society.

The conclusion for our study:

- In training dataset, we have only 10% of data which is spreading hate on social media.
- In this 10% data most of the comments are malignant, rude or abuse.
- After using the wordcloud we find that there are so many abusive words present in the negative comments. While in positive comments there is no use of such comments.
- Some of the comments are very long while some are very short

4.2 Learning Outcomes of the Study in respect of Data Science

While working on this project we learned many things and gains new techniques and ways to deal with uncleaned text data. Found how to deal with multiple target features. Tools used for visualizations gives a better understanding of dataset. We have used a lot of algorithms and find that in the classification problem where we have only two labels, XGB Classifier gives better results compared to others.

It is possible to classify the comments content into the required categories of authentic and however, using this kind of project an awareness can be created to know what is fake and authentic.

4.3 Limitations of this work and scope for future work

Limitations: This project was amazing to work on, it creates new ideas to think about but there were some limitations in this project like unbalanced dataset. Every effort has been put on it for perfection but nothing is perfect and this project is of no exception. There are certain areas which can be enhanced.

Future work: In future work, we can focus on performance and error analysis of the model as lots of comments are misclassified into the hate category. Previous work has achieved success using various algorithms on data in English language but in future, we can consider having data in regional languages. We can also work on after work of the detection of the malignant comments like automatic blocking of the user, auto-deletion of harmful comments on social media platforms. Comment detection is an emerging research area with few public datasets. So, a lot of works need to be done on this field.