FLIP ROBO

Malignant Comments Classifier Prediction Project

Submitted by:

Poonam Singh

ACKNOWLEDGMENT

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Separately, I would like to thank:

- FlipRobo Technologies team
- Data Trained Team

Research papers that helped me in this project was as follows:

- https://medium.com/@dobko_m/nlp-text-data-cleaning-and-preprocessing-ea3ffe0406c1
- https://towardsdatascience.com/your-guide-to-natural-language-processing-nlp-48ea2511f6e1

Articles that helped me in this project was as follows:

- TF-IDF Vectorizer scikit-learn. Deep understanding TfidfVectorizer by… | by Mukesh Chaudhary | Medium

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.
- 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.
- 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.

Conceptual Background of the Domain Problem

- In the past few years its 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 cyber bullying 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.

Motivation for the Problem Undertaken

The project was the first provided to me by FlipRobo as a part of the internship programme. 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 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.

Analytical Problem Framing

Data Sources and their formats

The data was provided by FlipRobo in CSV format. After loading the training dataset into Jupyter Notebook using Pandas and it can be seen that there are eight columns named as:
" id, comment_text, "malignant, highly_malignant, rude, threat, abuse, loathe"**.**

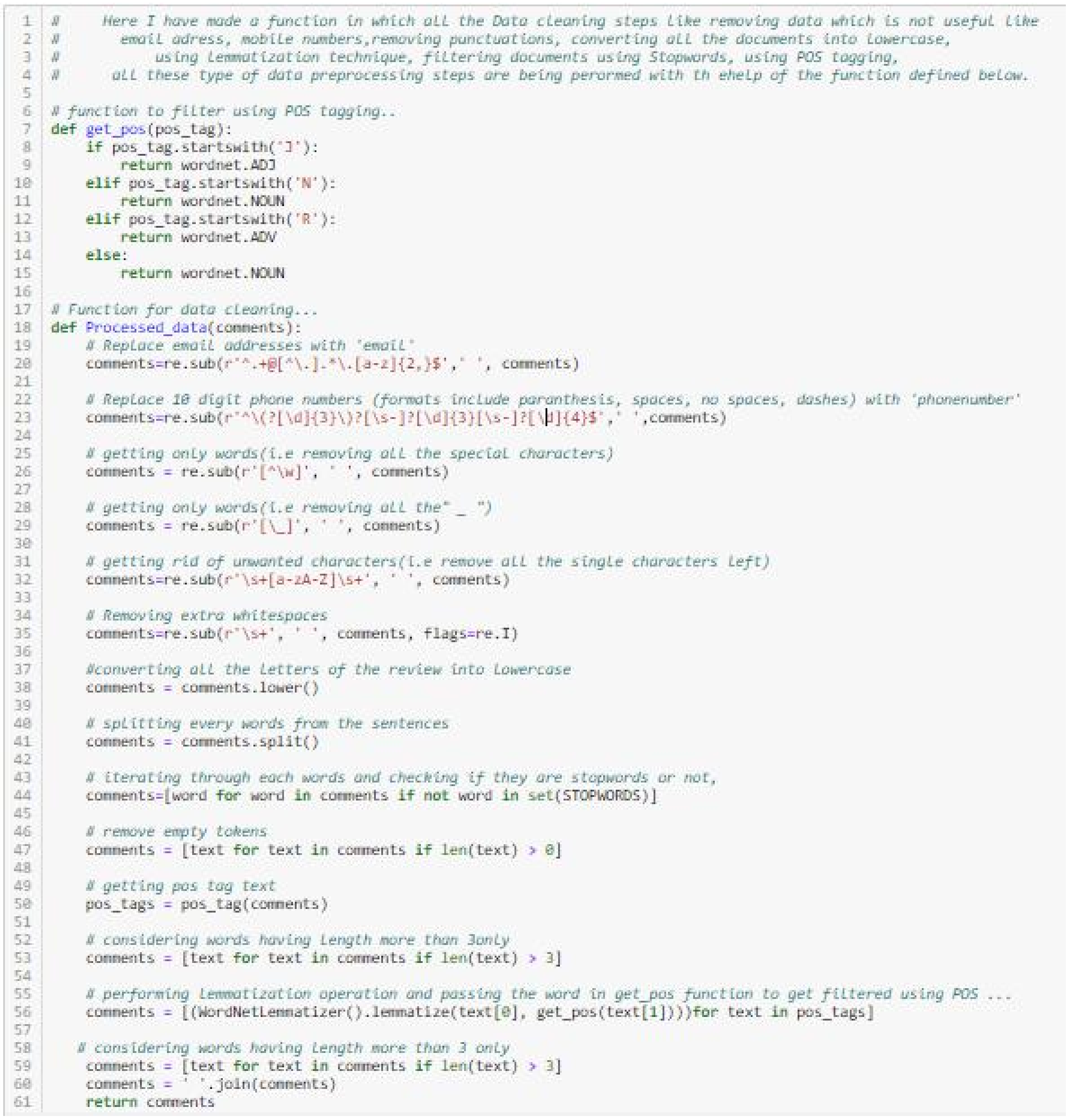
There are 8 columns in the dataset provided:
The description of each of the column is given below:

- **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.
- **ID:** It includes unique Ids associated with each comment text given.
- **Comment text:** This column contains the comments extracted from various social media platforms.

```
 Number of value_counts of malignant : 2
 0    144277
 1     15294
 Name: malignant, dtype: int64
 Number of value_counts of highly_malignant : 2
 0    157976
 1      1595
 Name: highly_malignant, dtype: int64
 Number of value_counts of rude : 2
 0    151122
 1      8449
 Name: rude, dtype: int64
 Number of value_counts of threat : 2
 0    159093
 1       478
 Name: threat, dtype: int64
 Number of value_counts of abuse : 2
 0    151694
 1      7877
 Name: abuse, dtype: int64
 Number of value_counts of loathe : 2
 0    158166
 1      1405
 Name: loathe, dtype: int64
```

```
Features Present in the Dataset:
 Index(['id', 'comment_text', 'malignant', 'highly_malignant', 'rude', 'threat',
       'abuse', 'loathe'],
      dtype='object')

Total Number of Rows :  159571
Total Number of Features :  8


Data Types of Features :
 id                  object
comment_text        object
malignant            int64
highly_malignant     int64
rude                 int64
threat               int64
abuse                int64
loathe               int64
dtype: object

Dataset contains any NaN/Empty cells :  False

Total number of empty rows in each feature:
 id                  0
comment_text        0
malignant           0
highly_malignant    0
rude                0
threat              0
abuse               0
loathe              0
dtype: int64


Total number of unique values in each feature:
Number of unique values of id : 159571
Number of unique values of comment_text : 159571
Number of unique values of malignant : 2
Number of unique values of highly_malignant : 2
Number of unique values of rude : 2
Number of unique values of threat : 2
Number of unique values of abuse : 2
Number of unique values of loathe : 2
```

Data Pre-processing Done



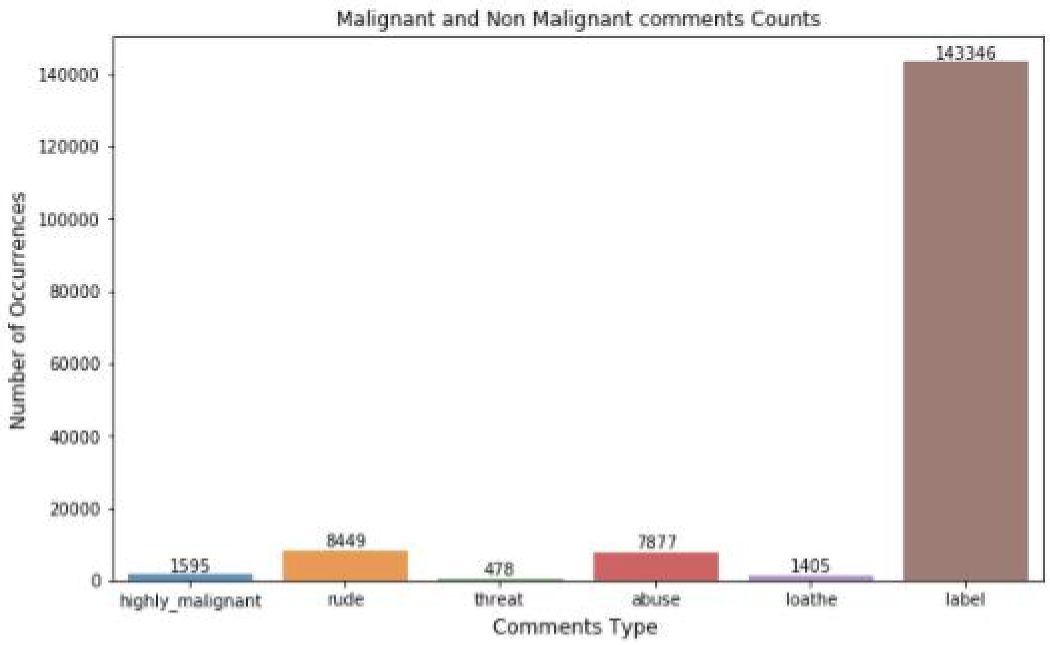
```python
#     Here I have made a function in which all the Data cleaning steps like removing data which is not useful like
#       email adress, mobile numbers,removing punctuations, converting all the documents into lowercase,
#           using lemmatization technique, filtering documents using Stopwords, using POS tagging,
#      all these type of data preprocessing steps are being perormed with th ehelp of the function defined below.

# function to filter using POS tagging..
def get_pos(pos_tag):
    if pos_tag.startswith('J'):
        return wordnet.ADJ
    elif pos_tag.startswith('N'):
        return wordnet.NOUN
    elif pos_tag.startswith('R'):
        return wordnet.ADV
    else:
        return wordnet.NOUN

# Function for data cleaning...
def Processed_data(comments):
    # Replace email addresses with 'email'
    comments=re.sub(r'^.+@[^\.].*\.[a-z]{2,}$',' ', comments)

    # Replace 10 digit phone numbers (formats include paranthesis, spaces, no spaces, dashes) with 'phonenumber'
    comments=re.sub(r'^\(?[\d]{3}\)?[\s-]?[\d]{3}[\s-]?[\d]{4}$',' ',comments)

    # getting only words(i.e removing all the special characters)
    comments = re.sub(r'[^\w]', ' ', comments)

    # getting only words(i.e removing all the" _ ")
    comments = re.sub(r'[\_]', ' ', comments)

    # getting rid of unwanted characters(i.e remove all the single characters left)
    comments=re.sub(r'\s+[a-zA-Z]\s+', ' ', comments)

    # Removing extra whitespaces
    comments=re.sub(r'\s+', ' ', comments, flags=re.I)

    #converting all the letters of the review into lowercase
    comments = comments.lower()

    # splitting every words from the sentences
    comments = comments.split()

    # iterating through each words and checking if they are stopwords or not,
    comments=[word for word in comments if not word in set(STOPWORDS)]

    # remove empty tokens
    comments = [text for text in comments if len(text) > 0]

    # getting pos tag text
    pos_tags = pos_tag(comments)

    # considering words having length more than 3only
    comments = [text for text in comments if len(text) > 3]

    # performing lemmatization operation and passing the word in get_pos function to get filtered using POS ...
    comments = [(WordNetLemmatizer().lemmatize(text[0], get_pos(text[1])))for text in pos_tags]

   # considering words having length more than 3 only
    comments = [text for text in comments if len(text) > 3]
    comments = ' '.join(comments)
    return comments
```

For Data pre-processing we did some data cleaning, where we used wordNet lemmatizer to clean the words and removed special characters using Regexp Tokenizer and filter the words by removing stop words and then used lemmatizers and joined and return the filtered words.

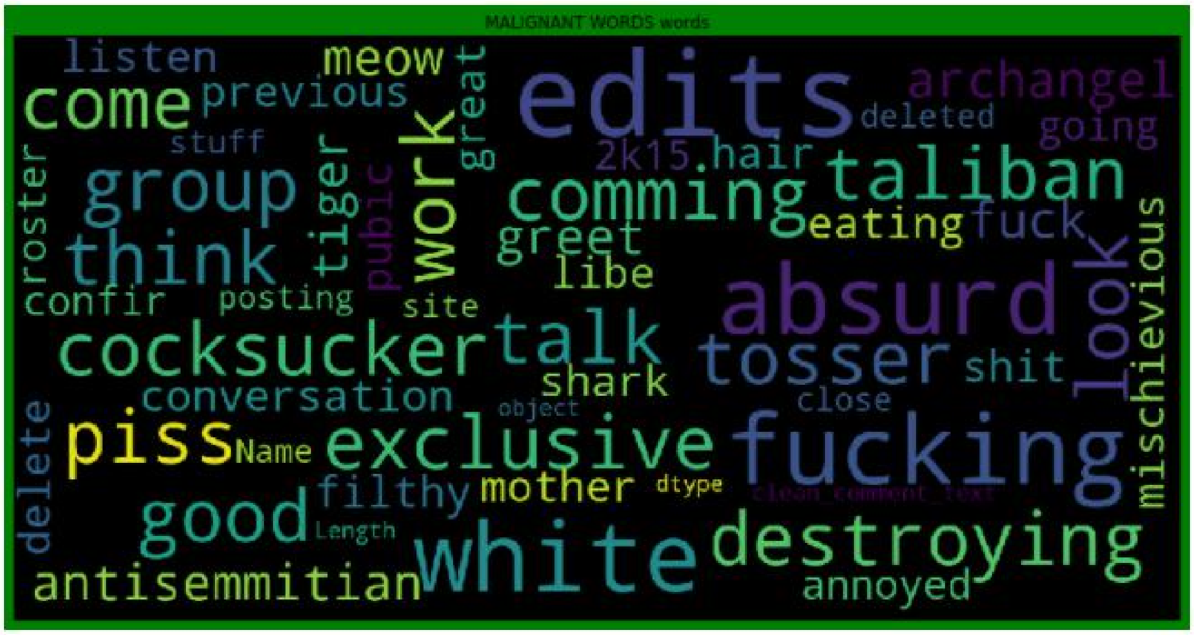
Used TFIDF vectorizer to convert those text into vectors, and split the data and into test and train and trained various Machine learning algorithms.

Data Inputs- Logic- Output Relationships

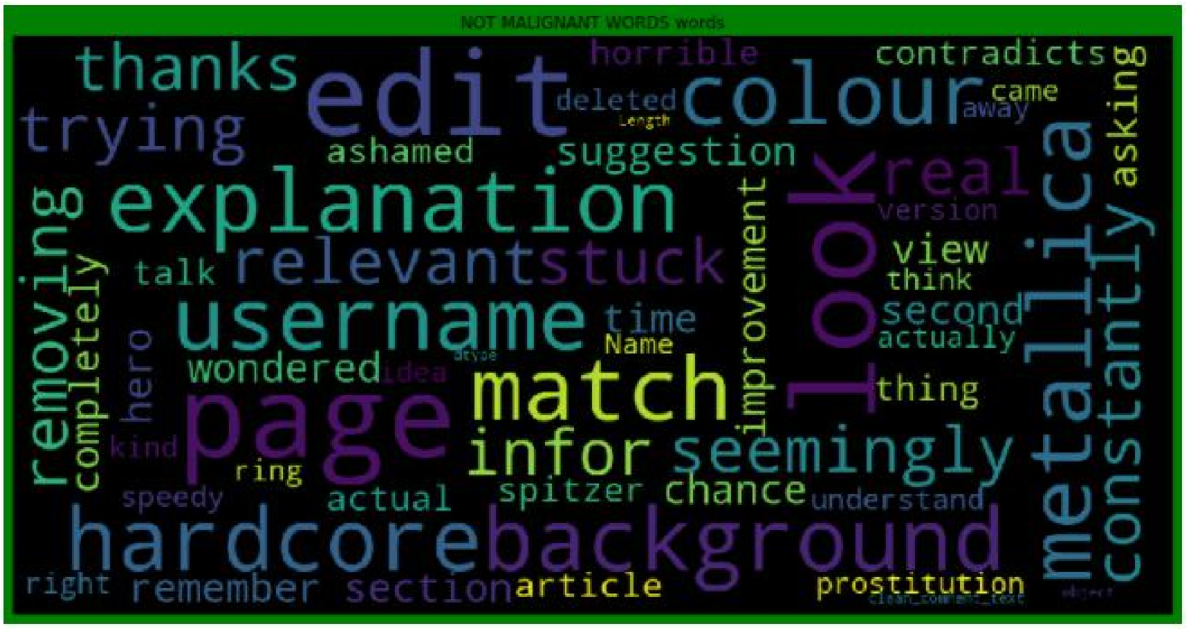
Comments categories counts:



Malignant Words:



Not Malignant Words:

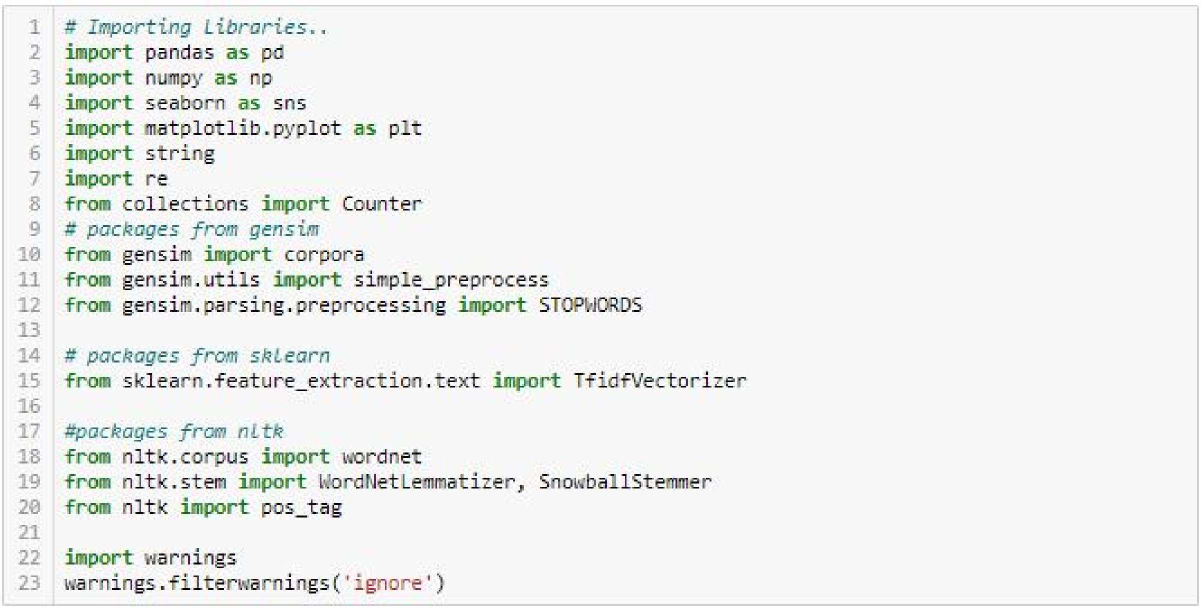


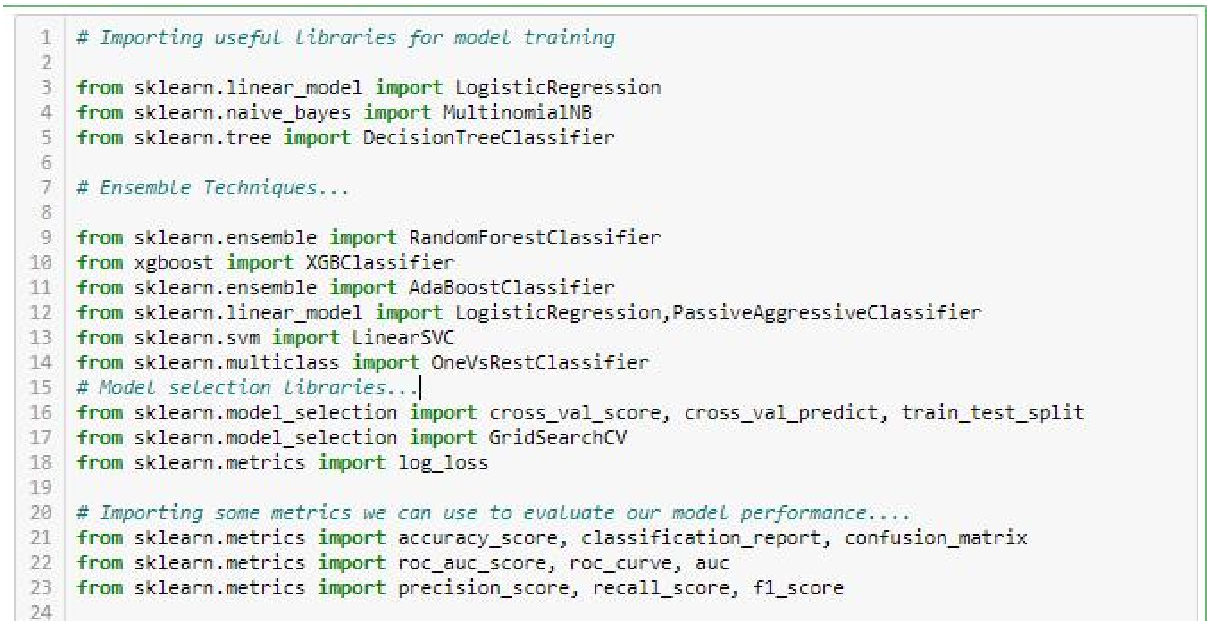
From the above we can see that most frequent words for both Malignant and Non Malignant category.

Hardware and Software Requirements and Tools Used

- Hardware: 8GB RAM, 64-bit, 9th gen i7 processor.
- Software: MS-Excel, Jupyter Notebook, python 3.6.

Libraries used:-

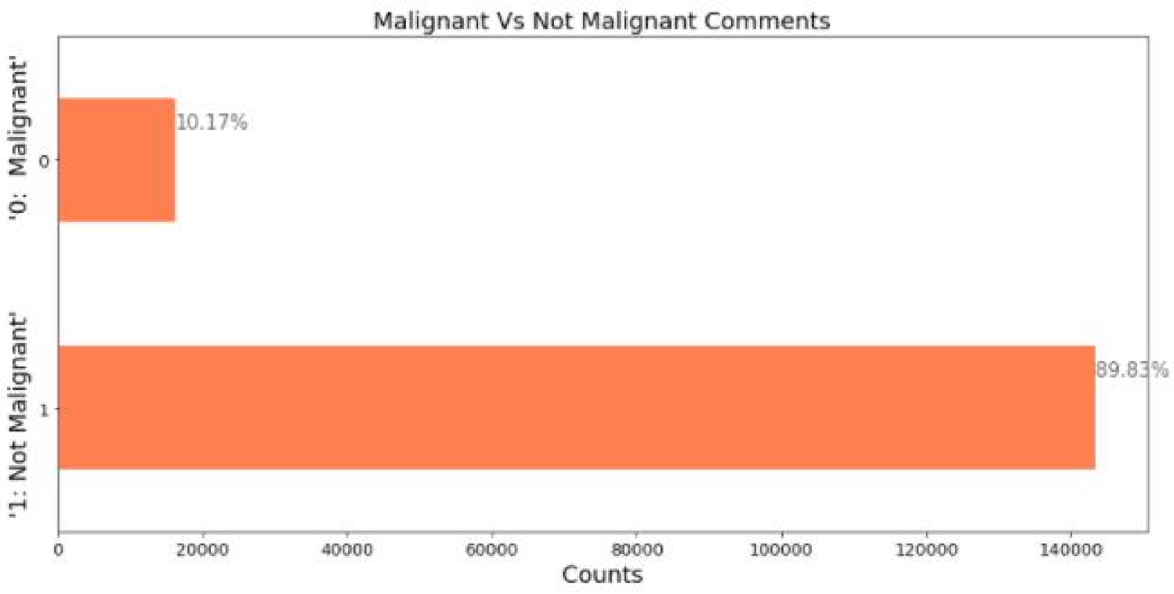

```
# Importing Libraries..
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import string
import re
from collections import Counter
# packages from gensim
from gensim import corpora
from gensim.utils import simple_preprocess
from gensim.parsing.preprocessing import STOPWORDS

# packages from sklearn
from sklearn.feature_extraction.text import TfidfVectorizer

#packages from nltk
from nltk.corpus import wordnet
from nltk.stem import WordNetLemmatizer, SnowballStemmer
from nltk import pos_tag

import warnings
warnings.filterwarnings('ignore')
```



```python
# Importing useful libraries for model training

from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier

# Ensemble Techniques...

from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.linear_model import LogisticRegression,PassiveAggressiveClassifier
from sklearn.svm import LinearSVC
from sklearn.multiclass import OneVsRestClassifier
# Model selection libraries...
from sklearn.model_selection import cross_val_score, cross_val_predict, train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import log_loss

# Importing some metrics we can use to evaluate our model performance....
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
from sklearn.metrics import roc_auc_score, roc_curve, auc
from sklearn.metrics import precision_score, recall_score, f1_score

```

Model/s Development and Evaluation

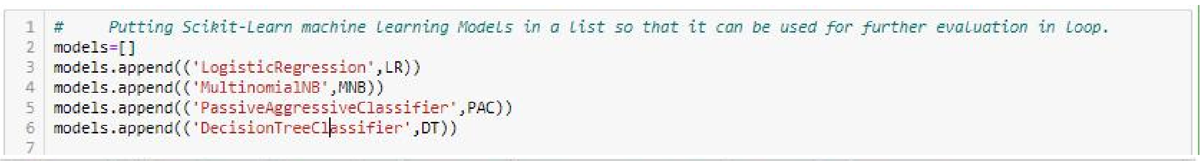
Identification of possible problem-solving approaches (methods).



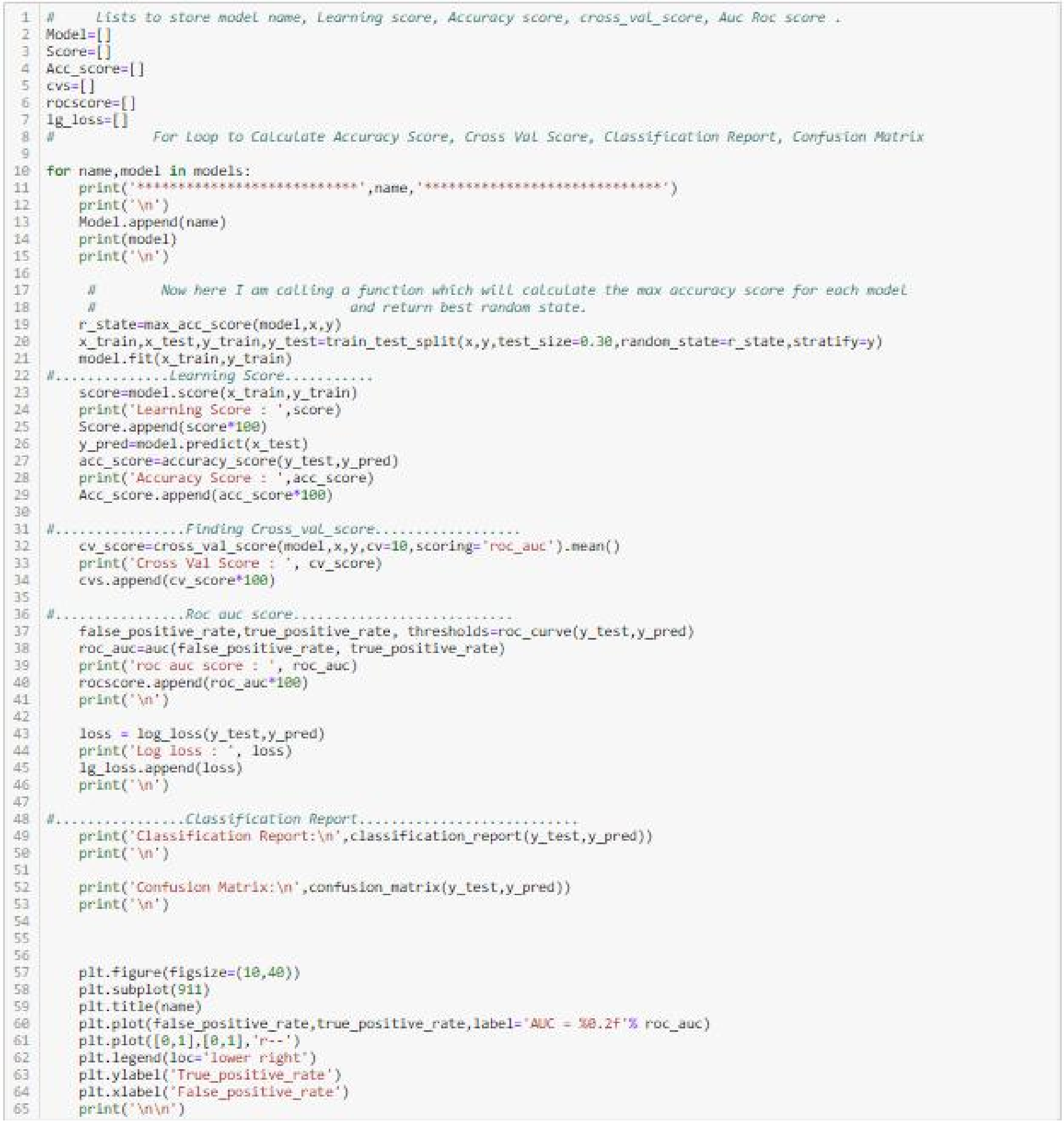
Testing of Identified Approaches (Algorithms)

- LR=LogisticRegression()
- MNB=MultinomialNB()
- PAC=PassiveAggressiveClassifier()
- DT=DecisionTreeClassifier()

Run and Evaluated selected models

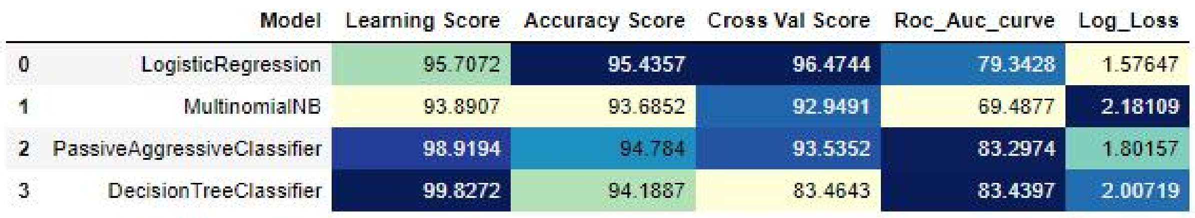


```
#     Putting Scikit-Learn machine Learning Models in a list so that it can be used for further evaluation in loop.
models=[]
models.append(('LogisticRegression',LR))
models.append(('MultinomialNB',MNB))
models.append(('PassiveAggressiveClassifier',PAC))
models.append(('DecisionTreeClassifier',DT))

```



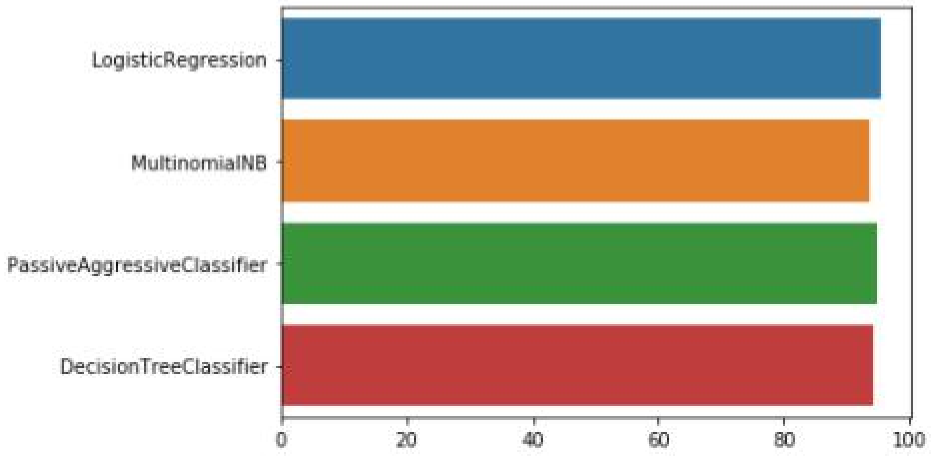
```
#     Lists to store model name, Learning score, Accuracy score, cross_val_score, Auc Roc score .
Model=[]
Score=[]
Acc_score=[]
cvs=[]
rocscore=[]
lg_loss=[]
#           For Loop to Calculate Accuracy Score, Cross Val Score, Classification Report, Confusion Matrix

for name,model in models:
    print('****************************',name,'******************************')
    print('\n')
    Model.append(name)
    print(model)
    print('\n')

     #        Now here I am calling a function which will calculate the max accuracy score for each model
     #                              and return best random state.
    r_state=max_acc_score(model,x,y)
    x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.30,random_state=r_state,stratify=y)
    model.fit(x_train,y_train)
#.............Learning Score..........
    score=model.score(x_train,y_train)
    print('Learning Score : ',score)
    Score.append(score*100)
    y_pred=model.predict(x_test)
    acc_score=accuracy_score(y_test,y_pred)
    print('Accuracy Score : ',acc_score)
    Acc_score.append(acc_score*100)

#................Finding Cross_val_score..................
    cv_score=cross_val_score(model,x,y,cv=10,scoring='roc_auc').mean()
    print('Cross Val Score : ', cv_score)
    cvs.append(cv_score*100)

#................Roc auc score............................
    false_positive_rate,true_positive_rate, thresholds=roc_curve(y_test,y_pred)
    roc_auc=auc(false_positive_rate, true_positive_rate)
    print('roc auc score : ', roc_auc)
    rocscore.append(roc_auc*100)
    print('\n')

    loss = log_loss(y_test,y_pred)
    print('Log loss : ', loss)
    lg_loss.append(loss)
    print('\n')

#................Classification Report...........................
    print('Classification Report:\n',classification_report(y_test,y_pred))
    print('\n')

    print('Confusion Matrix:\n',confusion_matrix(y_test,y_pred))
    print('\n')



    plt.figure(figsize=(10,40))
    plt.subplot(911)
    plt.title(name)
    plt.plot(false_positive_rate,true_positive_rate,label='AUC = %0.2f'% roc_auc)
    plt.plot([0,1],[0,1],'r--')
    plt.legend(loc='lower right')
    plt.ylabel('True_positive_rate')
    plt.xlabel('False_positive_rate')
    print('\n\n')
```

Key Metrics for success in solving problem under consideration



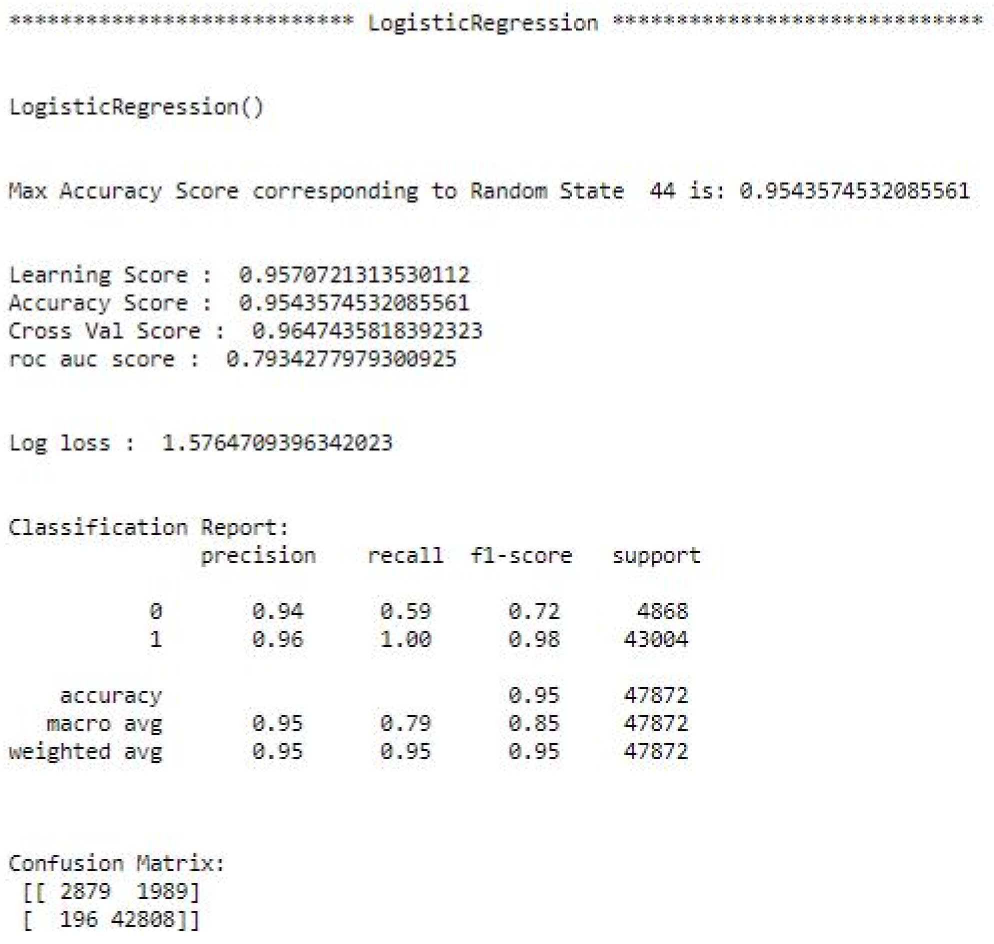
	Model	Learning Score	Accuracy Score	Cross Val Score	Roc_Auc_curve	Log_Loss
0	LogisticRegression	95.7072	95.4357	96.4744	79.3428	1.57647
1	MultinomialNB	93.8907	93.6852	92.9491	69.4877	2.18109
2	PassiveAggressiveClassifier	98.9194	94.784	93.5352	83.2974	1.80157
3	DecisionTreeClassifier	99.8272	94.1887	83.4643	83.4397	2.00719

Key Metrices used were the Accuracy Score, Crossvalidation Score and AUC & ROC Curve as this was binary classification. From the above we can see that there are various models out of which we few gave good accuracy score as more than 90%,

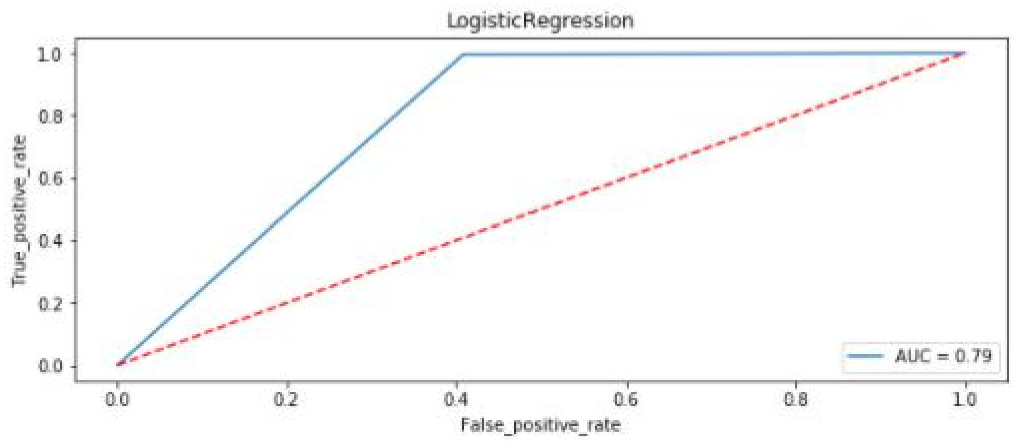


Visualizations:

Logistic regression:

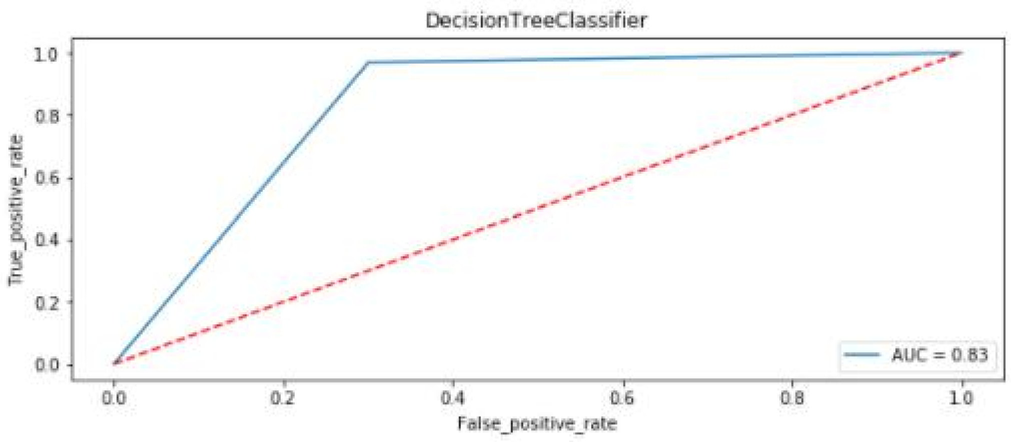


```
*************************** LogisticRegression *****************************


LogisticRegression()


Max Accuracy Score corresponding to Random State  44 is: 0.9543574532085561


Learning Score :  0.9570721313530112
Accuracy Score :  0.9543574532085561
Cross Val Score :  0.9647435818392323
roc auc score :  0.7934277979300925


Log loss :  1.5764709396342023


Classification Report:
               precision    recall  f1-score   support

           0       0.94      0.59      0.72      4868
           1       0.96      1.00      0.98     43004

    accuracy                           0.95     47872
   macro avg       0.95      0.79      0.85     47872
weighted avg       0.95      0.95      0.95     47872



Confusion Matrix:
 [[ 2879  1989]
 [  196 42808]]
```



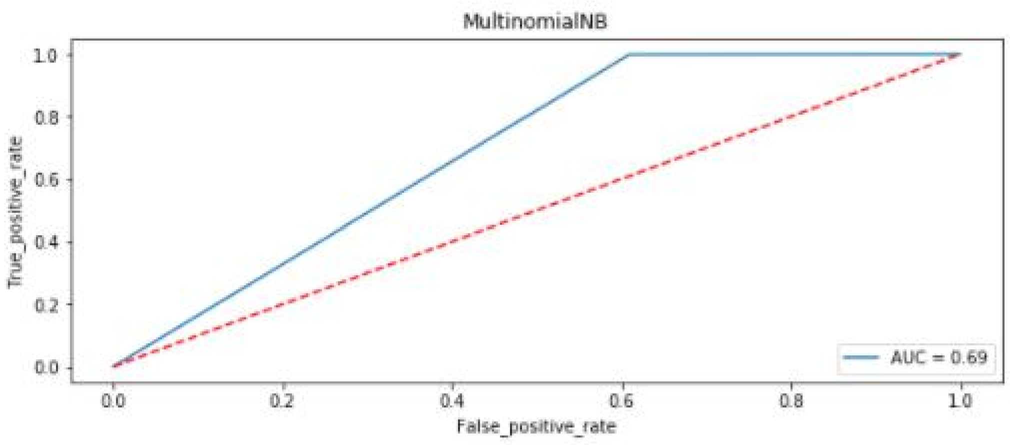
Decision Tree Classifier:

```
*************************** DecisionTreeClassifier *****************************


DecisionTreeClassifier()


Max Accuracy Score corresponding to Random State  87 is: 0.942617814171123


Learning Score :  0.9982721420961692
Accuracy Score :  0.9418866978609626
Cross Val Score :  0.8346433157361837
roc auc score :  0.8343971671588594


Log loss :  2.0071867843767115


Classification Report:
               precision    recall  f1-score   support

           0       0.72      0.70      0.71      4868
           1       0.97      0.97      0.97     43004

    accuracy                           0.94     47872
   macro avg       0.84      0.83      0.84     47872
weighted avg       0.94      0.94      0.94     47872


Confusion Matrix:
 [[ 3405  1463]
 [ 1319 41685]]
```



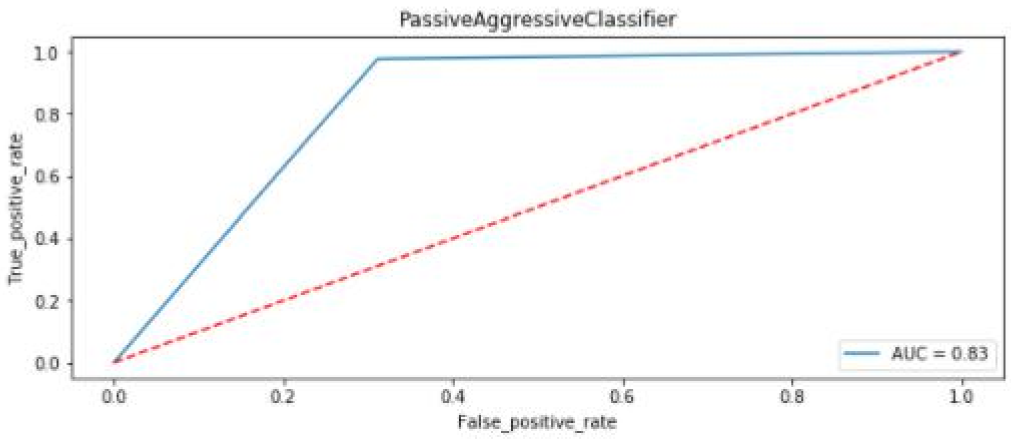
MultiNomial NB:

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


MultinomialNB()


Max Accuracy Score corresponding to Random State  54 is: 0.9368524398395722


Learning Score :  0.9389072417837223
Accuracy Score :  0.9368524398395722
Cross Val Score :  0.9294912255583274
roc auc score :  0.6948768767912668


Log loss :  2.1810889674255955


Classification Report:
               precision    recall  f1-score   support

           0       0.97      0.39      0.56      4868
           1       0.94      1.00      0.97     43004

    accuracy                           0.94     47872
   macro avg       0.95      0.69      0.76     47872
weighted avg       0.94      0.94      0.92     47872


Confusion Matrix:
 [[ 1904  2964]
 [   59 42945]]
```



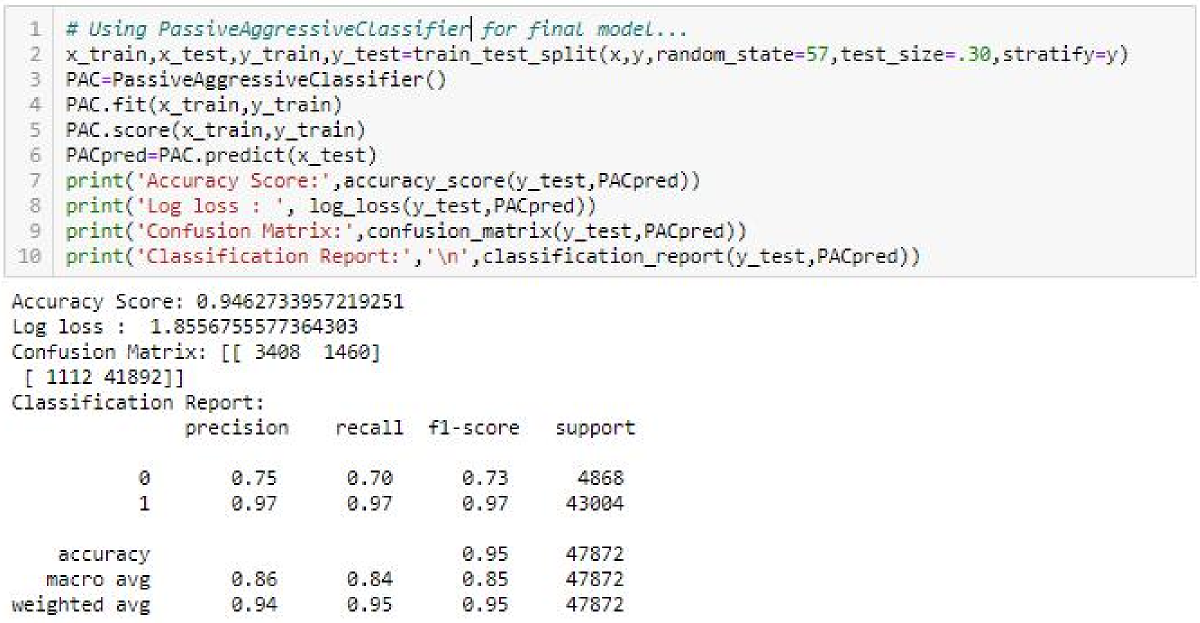
Passive Aggressive Classifier:

```
*************************** PassiveAggressiveClassifier *****************************


PassiveAggressiveClassifier()


Max Accuracy Score corresponding to Random State  57 is: 0.9477774064171123


Learning Score :  0.9891941736273377
Accuracy Score :  0.9478400735294118
Cross Val Score :  0.9353523827705535
roc auc score :  0.8329744048574871


Log loss :  1.8015653419159163


Classification Report:
               precision    recall  f1-score   support

           0       0.77      0.69      0.73      4868
           1       0.97      0.98      0.97     43004

    accuracy                           0.95     47872
   macro avg       0.87      0.83      0.85     47872
weighted avg       0.95      0.95      0.95     47872



Confusion Matrix:
 [[ 3353  1515]
 [  982 42022]]
```



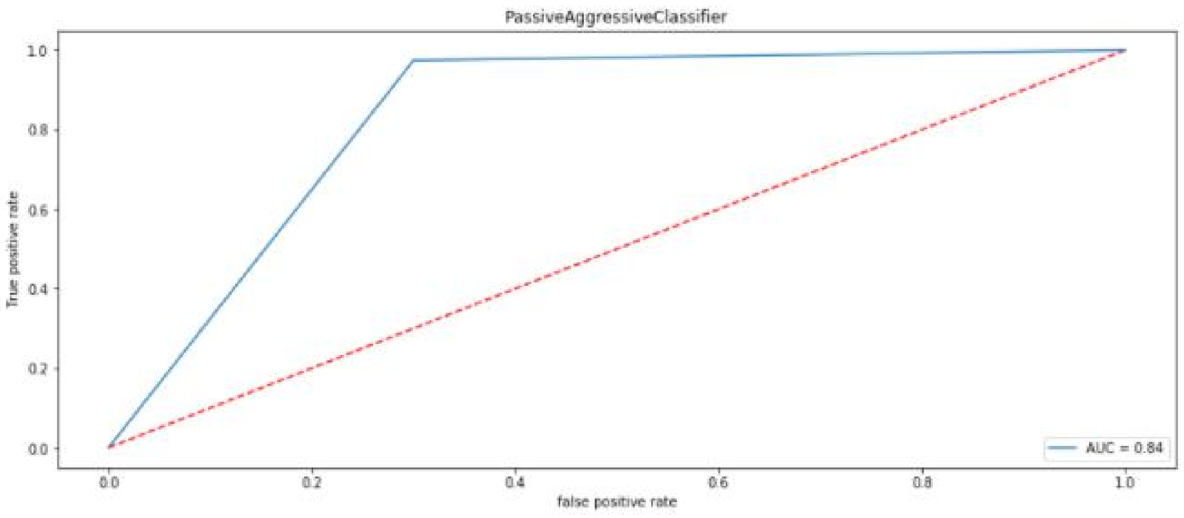
After all this process conclusion is that Passive Aggressive Classifier is giving accuracy of 94.78%. So, now I am making a final model using Passive Aggressive Classifier.

Final Model:



```python
# Using PassiveAggressiveClassifier for final model...
x_train,x_test,y_train,y_test=train_test_split(x,y,random_state=57,test_size=.30,stratify=y)
PAC=PassiveAggressiveClassifier()
PAC.fit(x_train,y_train)
PAC.score(x_train,y_train)
PACpred=PAC.predict(x_test)
print('Accuracy Score:',accuracy_score(y_test,PACpred))
print('Log loss : ', log_loss(y_test,PACpred))
print('Confusion Matrix:',confusion_matrix(y_test,PACpred))
print('Classification Report:','\n',classification_report(y_test,PACpred))
```

```
Accuracy Score: 0.9462733957219251
Log loss :  1.8556755577364303
Confusion Matrix: [[ 3408  1460]
 [ 1112 41892]]
Classification Report:
               precision    recall  f1-score   support

           0       0.75      0.70      0.73      4868
           1       0.97      0.97      0.97     43004

    accuracy                           0.95     47872
   macro avg       0.86      0.84      0.85     47872
weighted avg       0.94      0.95      0.95     47872
```



After all this process conclusion is that Passive Aggressive Classifier is giving accuracy of 94.78%, and with AUC_ROC score 0f 84%. So, now I am making a final model using Passive Aggressive Classifier.

Interpretation of the Results

- From the above visualization and matrices found that the Passive Aggressive Classifier performed the best AUC_ROC_SCORE **i.e. 94.78%.**

CONCLUSION

Key Findings and Conclusions of the Study

- 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.
- 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.

Learning Outcomes of the Study in respect of Data Science

It is possible to classify the comments content into the required categories of Malignant and Non Malignant. However, using this kind of project an awareness can be created to know what is good and bad. It will help to stop spreading hatred among people.

Limitations of this work and Scope for Future Work

- Machine Learning Algorithms like Decision Tree Classifier took enormous amount of time to build the model and Ensemble techniques were taking a lot more time thus I have not included Ensemble models.
- Using Hyper-parameter tuning would have resulted in some more accuracy.
- 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. Comment detection is an emerging research area with few public datasets. So, a lot of works need to be done on this field.