MALIGNANT COMMENTS CLASSIFIER PROJECT

MADE BY:

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ACKNOWLEDGMENT

I have taken efforts in this project by referring from below websites,

- WWW.GOOGLE.COM
- WWW.ANALYTICSVIDHYA.COM
- WWW.MEDIUM.COM
- https://stackoverflow.com/

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

REVIEW OF LITERATURE

In the past few years it’s 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 2 threat on online social media platforms. These kinds of activities must be checked for a better future.

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 and loathe**.**
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.

```
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
```

DATA PREPROCESSING

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.

```python
# 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
```

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

    # Replacing 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()
```

```python
    # 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
```

```python
df["clean_comment_text"] = df["comment_text"].apply(lambda x: Processed_data(x))
```

```python
df["clean_comment_text"]
```

```
0         explanation edits username hardcore metallica ...
1         match background colour seemingly stuck thanks...
2         trying edit constantly removing relevant infor...
3         real suggestion improvement wondered section s...
4                                 hero chance remember page
                               ...
159566    second time asking view completely contradicts...
159567                      ashamed horrible thing talk page
159568    spitzer there actual article prostitution ring...
159569       look like actually speedy version deleted look
159570    think understand came idea right away kind com...
Name: clean_comment_text, Length: 159571, dtype: object
```

HARDWARE AND SOFTWARE REQUIREMENTS AND TOOLS USED

For doing this project, the hardware used is a laptop with high end specification and a stable internet connection. While coming to software part, I had used anaconda navigator and in that I have used **Jupyter notebook** to do my python programming and analysis.
For using a CSV file, Microsoft excel is needed. In Jupyter notebook, I had used lots of python libraries to carry out this project and I have mentioned below with proper justification:

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import string
import re
import nltk
from collections import Counter
!pip install -U gensim
from gensim import corpora
from gensim.utils import simple_preprocess
from gensim.parsing.preprocessing import STOPWORDS
from sklearn.feature_extraction.text import TfidfVectorizer
from nltk.corpus import wordnet
from nltk.stem import WordNetLemmatizer, SnowballStemmer
from nltk import pos_tag

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

```
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression,PassiveAggressiveClassifier
from sklearn.model_selection import cross_val_score, cross_val_predict, train_test_split
from sklearn.model_selection import GridSearchCV
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
from sklearn.metrics import log_loss

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

```
models=[]
models.append(('LogisticRegression',LR))
models.append(('MultinomialNB',MNB))
models.append(('PassiveAggressiveClassifier',PAC))
models.append(('DecisionTreeClassifier',DT))
```

MODEL'S DEVELOPMENT AND EVALUATION

IDENTIFICATION OF POSSIBLE PROBLEM-SOLVING APPROACHES

```
data=[]
from nltk.tokenize import word_tokenize
for j,i in enumerate(df['clean_comment_text']):
    a=word_tokenize(i,'english')
    data.append(a)
```

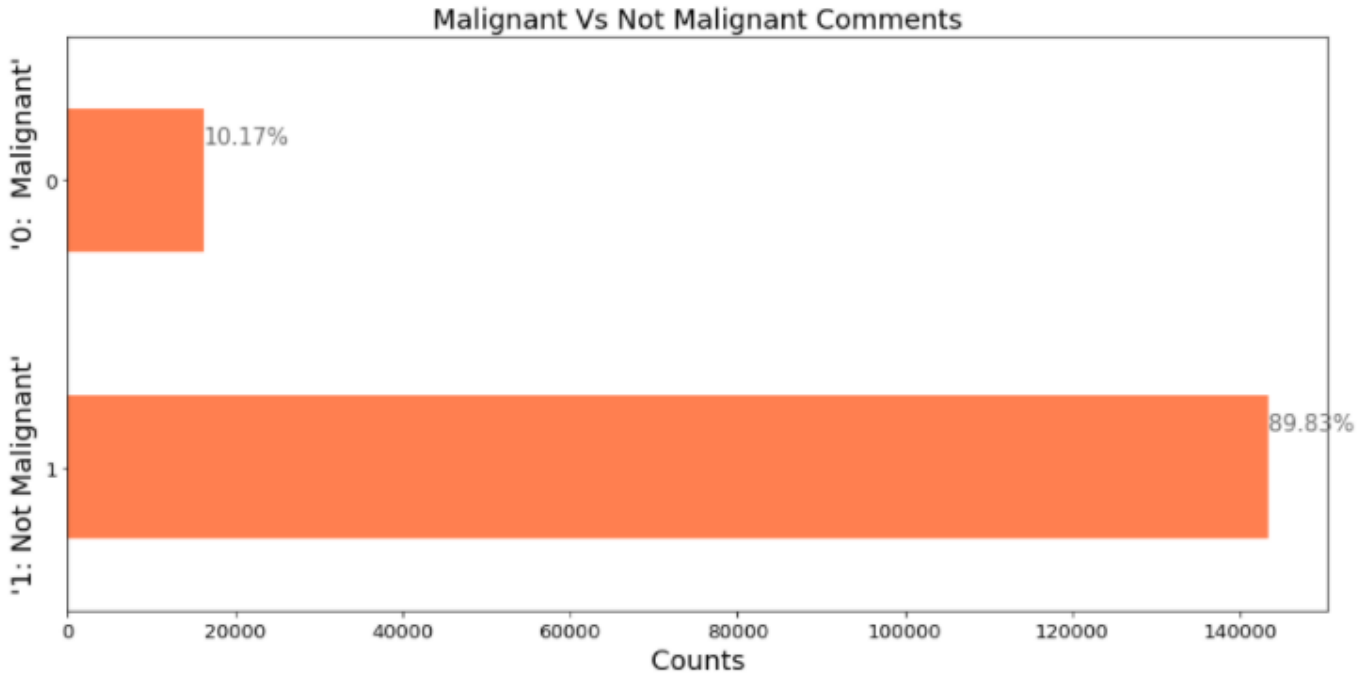
```
dictionary = corpora.Dictionary(data)
print(dictionary)
```

```
Dictionary(167144 unique tokens: ['closure', 'doll', 'edits', 'explanation', 'hardcore']...)
```

```
ax = df['label'].value_counts().plot(kind='barh', figsize=(15,7),color="coral", fontsize=13)
ax.set_alpha(0.8)
ax.set_title("Malignant Vs Not Malignant Comments", fontsize=18)
ax.set_xlabel("Counts",  fontsize=18)
ax.set_ylabel("'1: Not Malignant'            '0:  Malignant'", fontsize=18)
totals = []
for i in ax.patches:
    totals.append(i.get_width())

total = sum(totals)

for i in ax.patches:
    ax.text(i.get_width()+.3, i.get_y()+.38, str(round((i.get_width()/total)*100, 2))+'%', fontsize=15,color='dimgrey')
```



The algorithms we used for the training and testing are as follows:

- Logistic Regression
- Decision Tree Classifier
- Multinomial NB
- Passive Aggressive Classifier

Model Building

```
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression,PassiveAggressiveClassifier
from sklearn.model_selection import cross_val_score, cross_val_predict, train_test_split
from sklearn.model_selection import GridSearchCV
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
from sklearn.metrics import log_loss

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

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models=[]
models.append(('LogisticRegression',LR))
models.append(('MultinomialNB',MNB))
models.append(('PassiveAggressiveClassifier',PAC))
models.append(('DecisionTreeClassifier',DT))
```

```
def max_acc_score(clf,x,y):
    max_acc_score=0
    final_r_state=0
    for r_state in range(42,100):
        x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=.30,random_state=r_state,stratify=y)
        clf.fit(x_train,y_train)
        y_pred=clf.predict(x_test)
        acc_score=accuracy_score(y_test,y_pred)
        if acc_score > max_acc_score:
            max_acc_score=acc_score
            final_r_state=r_state
    print('Max Accuracy Score corresponding to Random State ', final_r_state, 'is:', max_acc_score)
    print('\n')
    return final_r_state
```

```
Model=[]
Score=[]
Acc_score=[]
cvs=[]
rocscore=[]
lg_loss=[]

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

    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')
```

********** LogisticRegression **********

LogisticRegression()

Max Accuracy Score corresponding to Random State 44 is: 0.9543574532085561

Learning Score : 0.9570721313530112
Accuracy Score : 0.9543574532085561
Cross Val Score : 0.9647437145554436
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]]

```
************************** 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]]
```

```
PassiveAggressiveClassifier()


Max Accuracy Score corresponding to Random State  58 is: 0.947735628342246


Learning Score :  0.9897313315249018
Accuracy Score :  0.9460018382352942
Cross Val Score :  0.9359602149598304
roc auc score :  0.8312225661376249


Log loss :  1.8650558733232439


Classification Report:
               precision    recall  f1-score   support

           0       0.76      0.69      0.72      4868
           1       0.96      0.98      0.97     43004

    accuracy                           0.95     47872
   macro avg       0.86      0.83      0.85     47872
weighted avg       0.94      0.95      0.94     47872



Confusion Matrix:
 [[ 3345  1523]
 [ 1062 41942]]
```

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


DecisionTreeClassifier()


Max Accuracy Score corresponding to Random State  87 is: 0.941949364973262


Learning Score :  0.9982721420961692
Accuracy Score :  0.9420120320855615
Cross Val Score :  0.8346283576844614
roc auc score :  0.8343758433508737


Log loss :  2.0028579103214796


Classification Report:
              precision    recall  f1-score   support

           0       0.72      0.70      0.71      4868
           1       0.97      0.97      0.97     43004

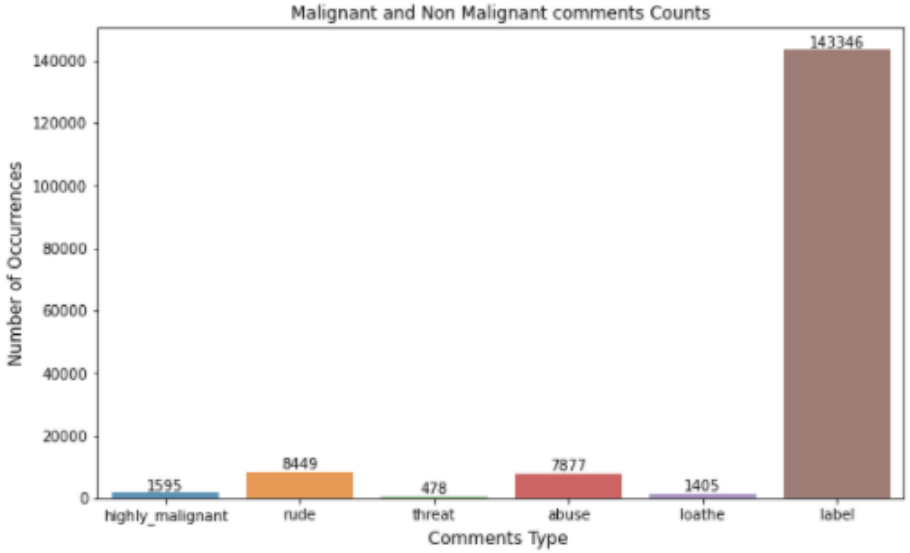
    accuracy                           0.94     47872
   macro avg       0.84      0.83      0.84     47872
weighted avg       0.94      0.94      0.94     47872



Confusion Matrix:
 [[ 3404  1464]
 [ 1312 41692]]
```

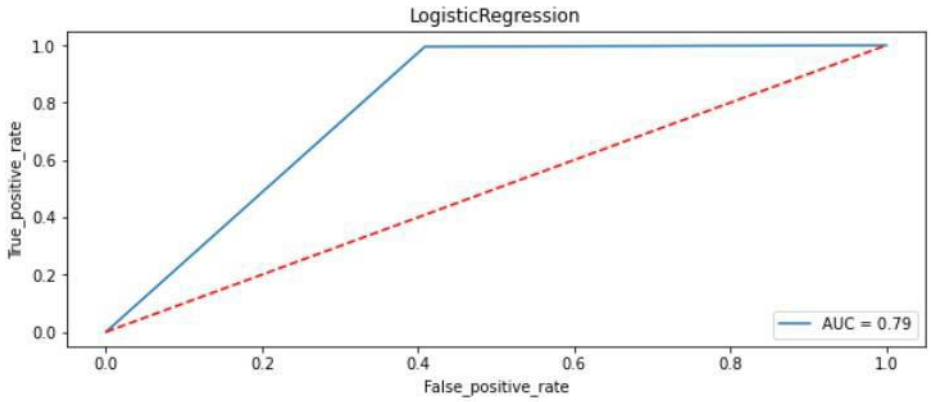
VISUALIZATION

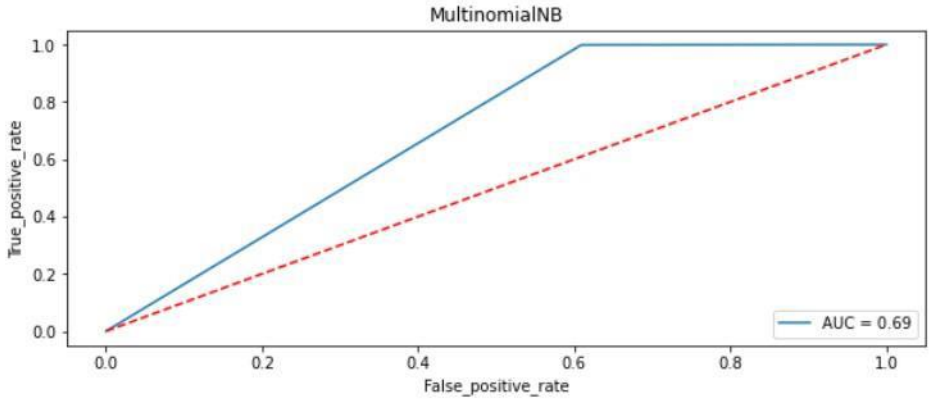
```
x=df.iloc[:,2:8].sum()
plt.figure(figsize=(10,6))
ax= sns.barplot(x.index, x.values, alpha=0.8)
plt.title("Malignant and Non Malignant comments Counts")
plt.ylabel('Number of Occurrences', fontsize=12)
plt.xlabel('Comments Type ', fontsize=12)
rects = ax.patches
labels = x.values
for rect, label in zip(rects, labels):
    height = rect.get_height()
    ax.text(rect.get_x() + rect.get_width()/2, height + 5, label, ha='center', va='bottom')
```

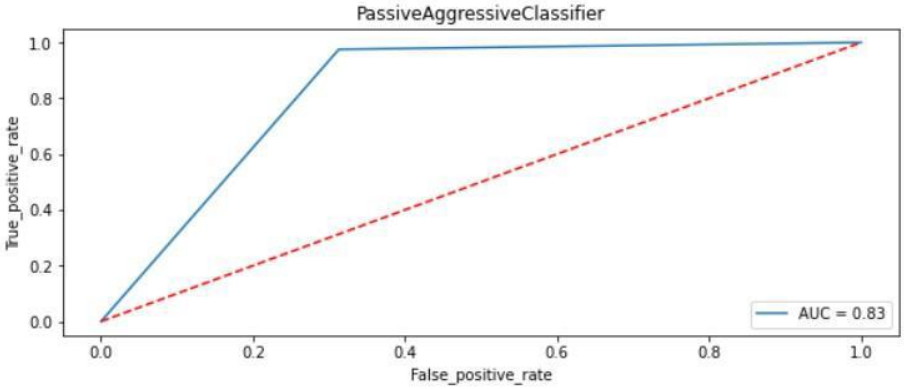


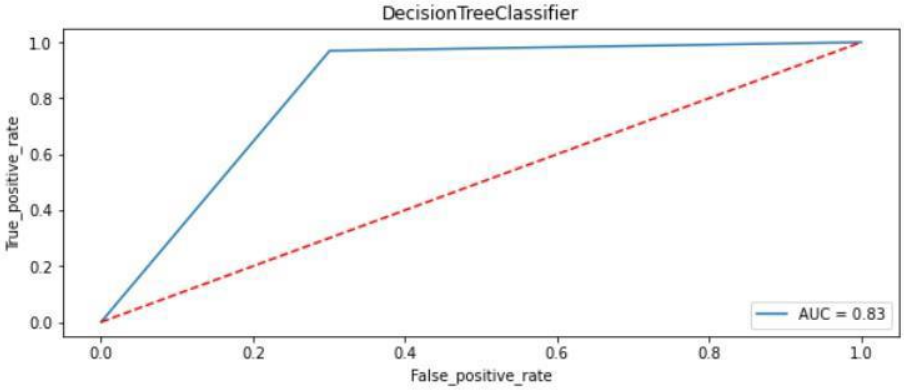

```
Display_wordcloud(df['clean_comment_text'][df['label']==1],"NOT MALIGNANT WORDS")
```

```
Display_wordcloud(df['clean_comment_text'][df['label']==0],"MALIGNANT WORDS")
```






PassiveAggressiveClassifier
True_positive_rate
False_positive_rate
AUC = 0.83
0.0
0.2
0.4
0.6
0.8
1.0


DecisionTreeClassifier
True_positive_rate
False_positive_rate
AUC = 0.83
0.0
0.2
0.4
0.6
0.8
1.0

OBSERVATION

From the above visualization and matrices found that the Passive Aggressive Classifier performed the best AUC_ROC_SCORE.

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.

THANKYOU.