Malignant Comment Classification Project

Submitted by:

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I also want to express my gratitude towards my friends and family who have patiently extended all sorts of help for accomplishing this.

I am grateful to one and all who are directly or indirectly involved in successful completion of this project.

Other reference websites used to complete this project are:
1. Data source provided by the client.
2. Wikipedia
3. Towardsdatascience.com
4. Datacamp.com

INTRODUCTION

In the past few years, the cases related to social media hatred have increased exponentially. Social media is turning into a venomous pit for people. In Social media people involved in such acts use filthy and aggressive language to offend and hurt the person on other side.

The proliferation of social media enables people to express their opinions online but, at the same time, this has resulted in the emergence of conflict and making online environments uninviting for users. Online hate is a major threat on social media platforms making it toxic. Although researchers have found that hate is a problem across multiple platforms, there is a lack of models for online hate detection.

There has been increase in cases of cyber bullying and trolls on various social media platforms. This can affect anyone 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.

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 cyber bullying. We have made use of Natural Language Processing techniques to build this classification model.

ANALYTICAL FRAMING

We have build a machine learning model here and before that we have done necessary pre-processing steps involved in NLP. We have build various models and selected the best one. Steps followed are:

1. Data Cleaning
2. Exploratory Data Analysis
3. Data Pre-Processing
4. Model Building
5. Model Evaluation

Data Set Description

The data set contains the training set, which has approximately 1,59,000 samples and the test set which contains nearly 1,53,000samples. All the data samples contain 8 fields which includes 'Id', 'Comments', 'Malignant', 'Highly malignant', 'Rude', 'Threat', 'Abuse' and 'Loathe'.

The label can be either 0 or 1, where 0denotes 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.

The data set includes:

- **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.

We have test and train dataset given. Test dataset consists of "**Comment text**" and "**id**". We will use train dataset to build the model and predict values in test dataset.

Train data Sample:

	id	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe
0	0000997932d777bf	Explanation\nWhy the edits made under my usern...	0	0	0	0	0	0
1	000103f0d9cfb60f	D'aww! He matches this background colour I'm s...	0	0	0	0	0	0
2	000113f07ec002fd	Hey man, I'm really not trying to edit war. It...	0	0	0	0	0	0
3	0001b41b1c6bb37e	"\nMore\nI can't make any real suggestions on ...	0	0	0	0	0	0
4	0001d958c54c6e35	You, sir, are my hero. Any chance you remember...	0	0	0	0	0	0

Test data Sample:

	id	comment_text
0	00001cee341fdb12	Yo bitch Ja Rule is more succesful then you'll...
1	0000247867823ef7	== From RfC == \n\n The title is fine as it is...
2	00013b17ad220c46	" \n\n == Sources == \n\n * Zawe Ashton on Lap...
3	00017563c3f7919a	:If you have a look back at the source, the in...
4	00017695ad8997eb	I don't anonymously edit articles at all.

Hardware and Software Requirements and Tools Used

- Laptop with stable internet connection (Project done in jupyter notebook)
- scikit-learn
- TfidVectorizer
- nltk
- matplotlib
- pandas
- numpy

Exploratory Data Analysis

This project involves extensive EDA to gain conclusion from dataset provided. We have first checked the count of label in each target variable

Malignant: No: 144277
Yes: 15294

Highly-Malignant: No: 157976
Yes: 1595

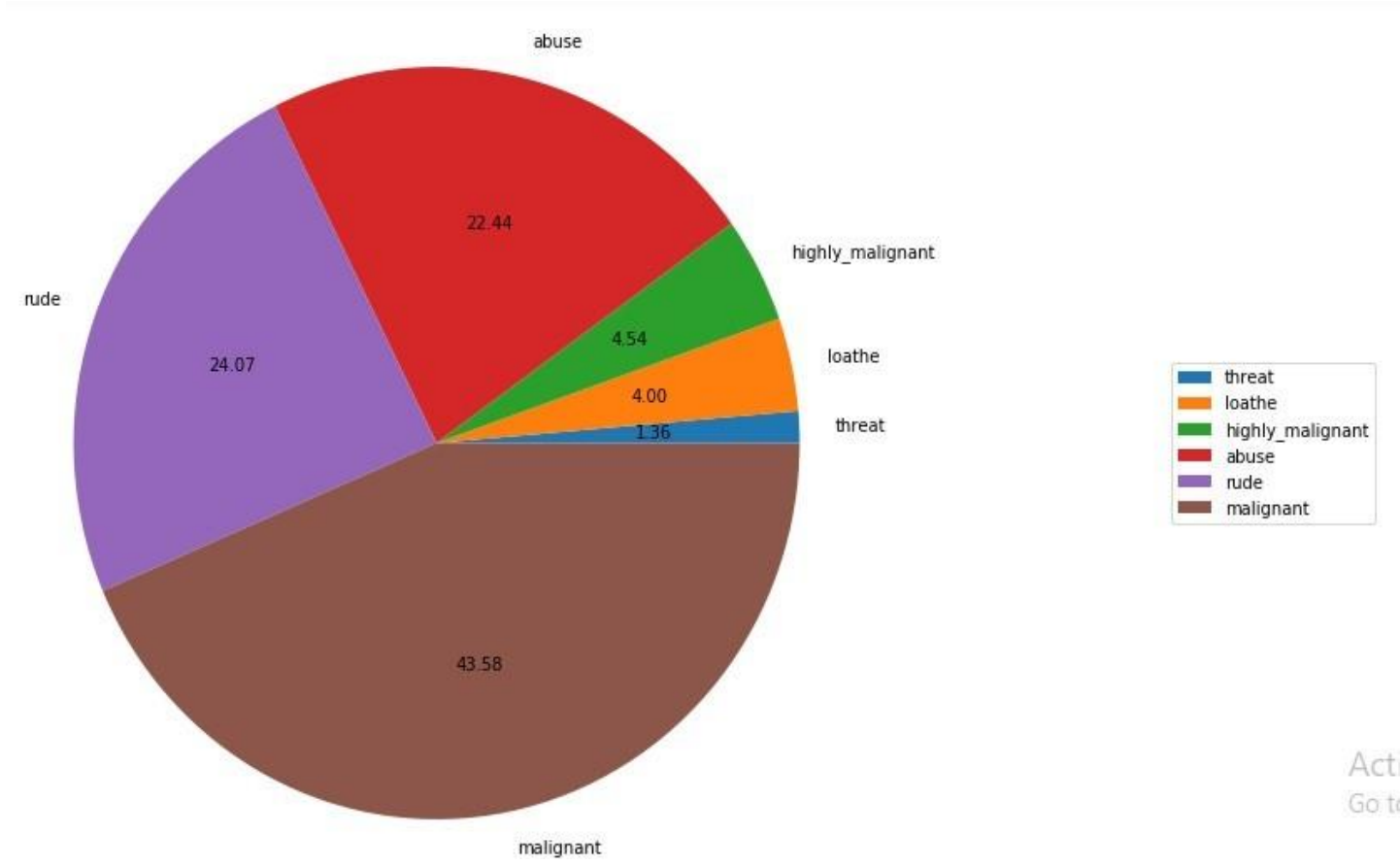
Threat: No: 159093
Yes: 478

Rude: No: 151122
Yes: 8449

Abuse: No: 151694
Yes: 7877

Loathe: No: 158166
Yes: 1405

<u>Label distribution over comments:</u>

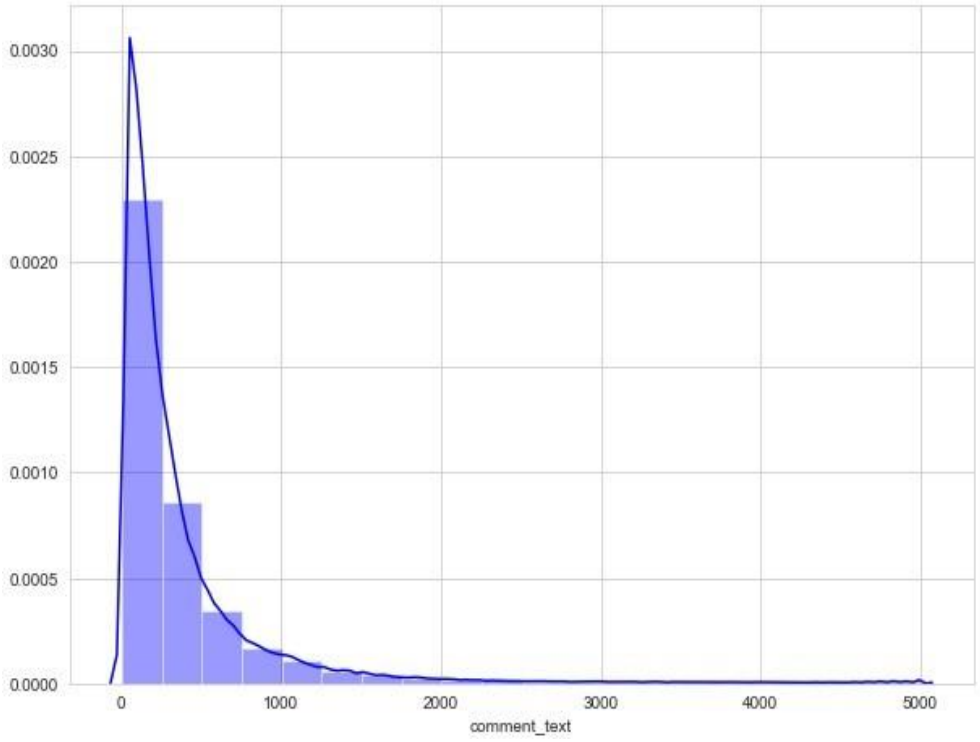


From the label counts and label distribution over comments we observe imbalanced data and among the negative comments least number of comments are classified as threat whereas, more number of comments are classified as malignant. We can further classify data as good/neutral and negative comments and below is the percent we obtain:

Percentage of good/neutral comments = 89.83211235124176
Percentage of negative comments = 10.167887648758239

Since there are 6 independent features whose value is to be predicted so we will introduce a new column in dataset as '**label**' which indicates '**1**' for good/neutral comments and '**0**' for negative comments.

Distribution of comments length

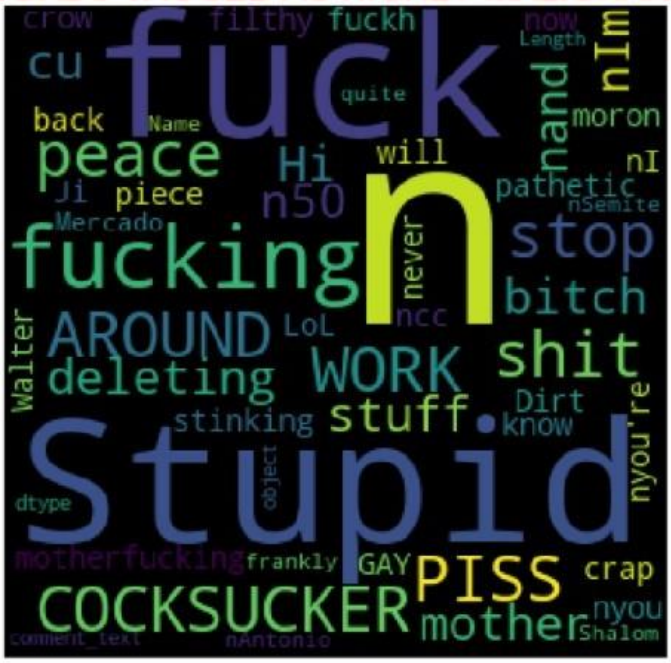


Next we have observed most frequent words in positive and negative comments through word-cloud

From the wordclouds, we can see that the large texts have more weightage in their respective type of comments whereas small texts have the lesser weightage.

WORDS TAGGED AS MALIGNANT

WORDS TAGGED AS HIGHLY-MALIGNANT



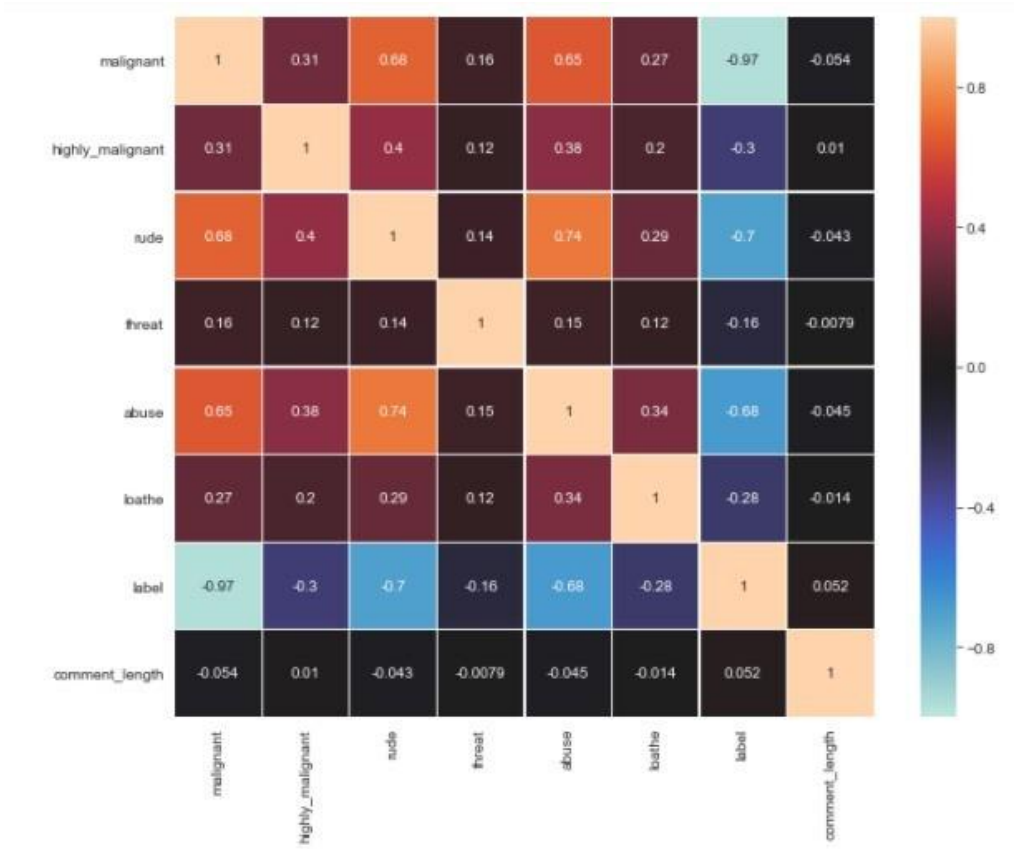
WORDS TAGGED AS RUDE

WORDS TAGGED AS ABUSE

WORDS TAGGED AS LOATHE

WORDS TAGGED AS THREAT

Finding relations with help of correlation



Above is the heatmap showing correlation between features. We make following conclusions:

- Highest correlation is observed between ‘rude’ and ‘abuse’.
- Correlation observed here is both positive and negative

Data Pre-Processing

We have used data cleaning steps involved in NLP and modified data which is not in proper format.

- First step is to remove unnecessary features like ’id’.
- Next we have made a function to filter using POS tagging.
- Created another function named “Clean_data” which involves:
  1. Removing ‘\n’ or extra lines.
  2. Removing numbers, HTML tags, websites, unwanted white spaces, etc.
  3. Transforming text into lower case.
  4. Removing remaining small and irrelevant tokens.

5. Lemmatizing words using WordsNetLemmatizer().

The code for given steps is mentioned below:

```
: #Creating a 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 Clean_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()

    # 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
```

After performing these steps we have added a new_comment_length variable.

Preparing Data for Model

We have first separated data and then converted it to number features using TfidVectorizer. Further split our data into train and test part.

```
def Tf_idf_train(text):
    tfid = TfidfVectorizer(min_df=3,smooth_idf=False)
    return tfid.fit_transform(text)
x=Tf_idf_train(train['clean_comment_text'])

print("Shape of x: ",x.shape)

y = train['label'].values
print("Shape of y: ",y.shape)
```

```
Shape of x:  (159571, 43141)
Shape of y:  (159571,)
```

```
#Splitting the training and testing data
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.30, random_state=42, stratify=y)
```

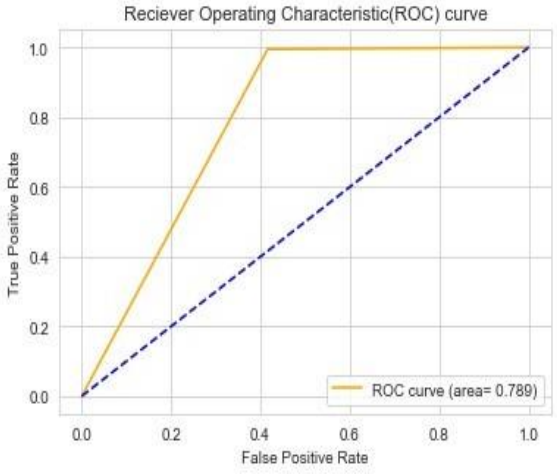
MODEL BUILDING AND EVALUATION

Algorithms used are:

- Logistic Regression
- Decision Tree Classifier
- KNeighbors Classifier
- Random Forest Classifier
- Gradient Boosting Classifier
- AdaBoostClassifier

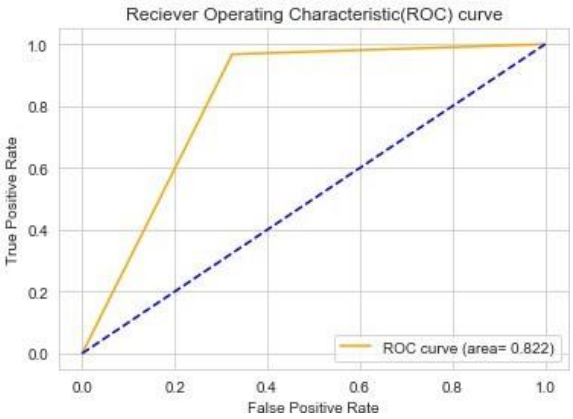
Logistic Regression

```
*** Logistic Regression ***

accuracy_score:  0.9529578877005348

cross_val_score:  0.9537823308256245

roc_auc_score:  0.7892786644906702

Classification report:

              precision    recall  f1-score   support

           0       0.93      0.58      0.72      4868
           1       0.95      0.99      0.97     43004

    accuracy                           0.95     47872
   macro avg       0.94      0.79      0.85     47872
weighted avg       0.95      0.95      0.95     47872


Confusion matrix:

[[ 2842  2026]
 [  226 42778]]
```



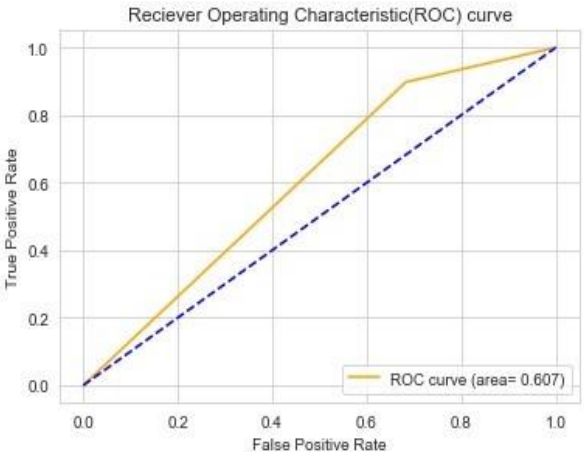
DecisionTree

```
*** DecisionTreeClassifier ***

accuracy_score:  0.937917780748663

cross_val_score:  0.9380213133700785

roc_auc_score:  0.8217133228782982

Classification report:

              precision    recall  f1-score   support

           0       0.70      0.68      0.69      4868
           1       0.96      0.97      0.97     43004

    accuracy                           0.94     47872
   macro avg       0.83      0.82      0.83     47872
weighted avg       0.94      0.94      0.94     47872


Confusion matrix:

[[ 3290  1578]
 [ 1394 41610]]
```



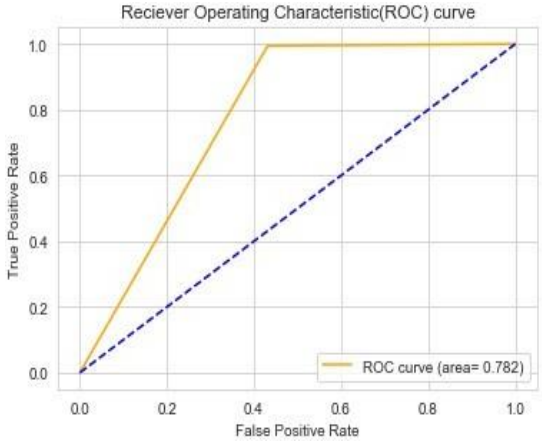
KNeighbors

```
*** KNeighborsClassifier ***

accuracy_score:  0.8386112967914439

cross_val_score:  0.8471464524877395

roc_auc_score:  0.6074964878771094

Classification report:

              precision    recall  f1-score   support

           0       0.26      0.32      0.29      4868
           1       0.92      0.90      0.91     43004

    accuracy                           0.84     47872
   macro avg       0.59      0.61      0.60     47872
weighted avg       0.85      0.84      0.85     47872


Confusion matrix:

[[ 1545  3323]
 [ 4403 38601]]
```



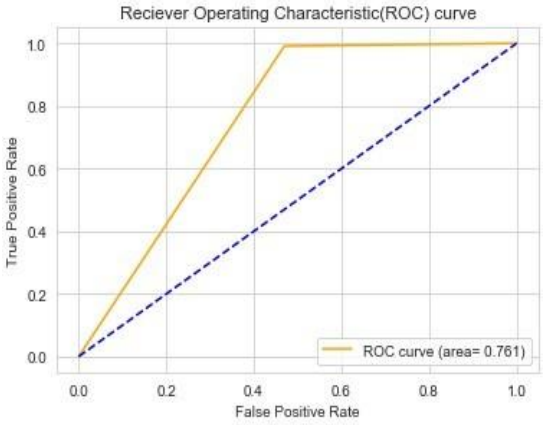
Random Forest

```
*** RandomForestClassifier ***

accuracy_score:  0.9510987633689839

cross_val_score:  0.9515137516440152

roc_auc_score:  0.7815036047553467

Classification report:

              precision    recall  f1-score   support

           0       0.92      0.57      0.70      4868
           1       0.95      0.99      0.97     43004

    accuracy                           0.95     47872
   macro avg       0.94      0.78      0.84     47872
weighted avg       0.95      0.95      0.95     47872


Confusion matrix:

[[ 2768  2100]
 [  241 42763]]
```



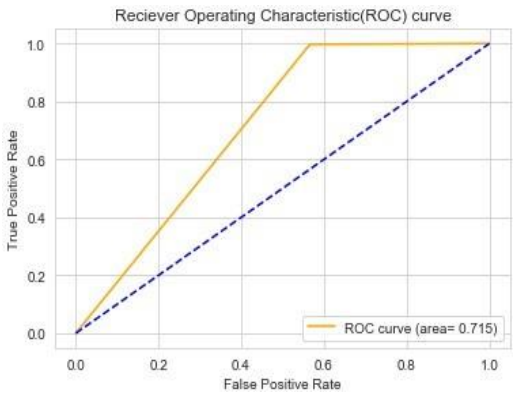
AdaBoost

```
*** AdaBoostClassifier ***

accuracy_score:  0.9444351604278075

cross_val_score:  0.9457796177925338

roc_auc_score:  0.7607617972439092

Classification report:

              precision    recall  f1-score   support

           0       0.87      0.53      0.66      4868
           1       0.95      0.99      0.97     43004

    accuracy                           0.94     47872
   macro avg       0.91      0.76      0.81     47872
weighted avg       0.94      0.94      0.94     47872


Confusion matrix:

[[ 2581  2287]
 [  373 42631]]
```



Gradient Boosting

```
*** GradientBoostingClassifier ***

accuracy_score:  0.9396933489304813

cross_val_score:  0.9407536437789279

roc_auc_score:  0.7154037552219445

Classification report:

              precision    recall  f1-score   support

           0       0.94      0.43      0.59      4868
           1       0.94      1.00      0.97     43004

    accuracy                           0.94     47872
   macro avg       0.94      0.72      0.78     47872
weighted avg       0.94      0.94      0.93     47872


Confusion matrix:

[[ 2112  2756]
 [  131 42873]]
```



Choosing Best Model

After running the loop we get a dataframe showing each model and scores obtained from it.

	Model	Accuracy_score	Cross_val_score	ROC_Score
0	Logistic Regression	95.295789	95.378233	78.927866
1	DecisionTreeClassifier	93.791778	93.802131	82.171332
2	KNeighborsClassifier	83.861130	84.714645	60.749649
3	RandomForestClassifier	95.109876	95.151375	78.150360
4	AdaBoostClassifier	94.443516	94.577962	76.076180
5	GradientBoostingClassifier	93.969335	94.075364	71.540376

Looking the various metrics we conclude "**Decision Tree Model**" as our best model.

We will now finalize it by saving our model using pickle.

To predict values in test dataset we will first apply "Clean_data" function to clean text and then use TfidVectorizer to convert it into numeric form.

```
]: def Tf_idf_test(text):
       tfid=TfidfVectorizer(max_features=43141,smooth_idf=False)
       return tfid.fit_transform(text)
   x_test=Tf_idf_test(test['clean_comment_text'])
   x_test.shape
```

```
]: (153164, 43141)
```

Next, we will predict value using the model build.

In [59]:
```
Predict=lr.predict(x_test)
test['Predicted Label']=Predict
test
```

Out[59]:

	comment_text	comment_length	clean_comment_text	clean_comment_length	Predicted Label
0	Yo bitch Ja Rule is more succesful then you'll...	387	bitch rule more succesful then ever whats with...	227	1
1	== From RfC == \n\n The title is fine as it is...	50	from title fine	15	1
2	" \n\n == Sources == \n\n * Zawe Ashton on Lap...	54	source zawe ashton lapland	26	1
3	:If you have a look back at the source, the in...	205	have look back source information updated corr...	140	1
4	I don't anonymously edit articles at all.	41	anonymously edit article	24	1
5	Thank you for understanding. I think very high...	96	thank understanding think very highly would re...	69	1
6	Please do not add nonsense to Wikipedia. Such ...	176	please nonsense wikipedia such edits considere...	123	1
7	:Dear god this site is horrible.	32	dear this site horrible	23	1
8	" \n Only a fool can believe in such numbers. ...	556	only fool believe such number correct number b...	356	1
9	== Double Redirects == \n\n When fixing double...	224	double redirects when fixing double redirects ...	144	1
10	I think its crap that the link to roggenbier i...	119	think crap that link roggenbier this article s...	83	1
11	":: Somebody will invariably try to add Relig...	448	somebody will invariably religion really mean ...	293	1
12	, 25 February 2010 (UTC) \n\n :::Looking it ov...	293	february 2010 looking over clear that banned s...	198	1
13	" \n\n It says it right there that it IS a typ...	501	right there that type type institution needed ...	349	1
14	" \n\n == Before adding a new product to the l...	334	before adding product list make sure relevant ...	229	1
15	==Current Position== \n Anyone have confirmati...	113	current position anyone have confirmation that...	81	1
16	this other one from 1897	24	this other from 1897	20	1
17	== Reason for banning throwing == \n\n This ar...	159	reason banning throwing this article need sect...	101	1
18	:: Wallamoose was changing the cited material ...	336	wallamoose changing cited material thing origi...	199	1
19	|blocked]] from editing Wikipedia.	38	blocked from editing wikipedia	30	1
20	==Indefinitely blocked== \n I have indefinitel...	68	indefinitely blocked have indefinitely blocked...	59	0
21	== Arabs are committing genocide in Iraq, but ...	104	arab committing genocide iraq protest europe e...	66	1

After predicting we will save this file in csv format.

CONCLUSION

KEY FINDINGS AND CONCLUSIONS OF THE STUDY

We have first loaded both test and train dataset and looked into it to check for null values, data types, dropping unnecessary columns etc,

Exploratory Data Analysis is performed using visualizations to gain insights. We observe more of comments classified as malignant comments.

We have used NLP to pre-process and clean data. Since we had 6 labels to be predicted we introduced a new column 'label' which shows '1' for good/neutral comments and '0' for negative comments.

We have used Vectorizer to convert comment tokens to numeric form.

After considering the mentioned algorithms we concluded Decision Tree Classifier to be best model which gave an accuracy of 95.2%.

We further used the model selected to predict 'label' for test dataset and saved it in csv file.

LEARNING OUTCOMES OF THE STUDY IN RESPECT OF DATA SCIENCE

After the completion of this project, we got an insight of how to preprocess the data and analyzing the data using Natural Language Processing techniques. We have used various NLP techniques to clean our data like Lemmatization, POS tagging, etc.

We were also able to learn to convert strings into vectors through vectorizer.

LIMITATIONS OF THIS WORK AND SCOPE FOR FUTURE WORK

Since the data keeps changing, we cannot fully rely on this project in the distant future we need to update it with updating in data.

Due to lack of high computational power, it took a lot of time to predict scores for each algorithm.

The Dataset here is imbalanced which may have caused a problem in scores obtained.

This project is done with limited resources and can be made more efficient in future.