NAME OF THE PROJECT

MALIGNANT COMMENTS CLASSIFICATION

Submitted by:

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ACKNOWLEDGMENT

I would like to express my deepest gratitude to my SME (Subject Matter Expert) Khushboo Garg as well as Flip Robo Technologies who gave me the opportunity to do this project on Malignant Comments Classification, which also helped me in doing lots of research where I came to know about so many new things especially the Natural Language Processing and Natural Language Toolkit parts.

Also, I have utilized a few external resources that helped me to complete this project. I ensured that I learn from the samples and modify things according to my project requirement. All the external resources that were used in creating this project are listed below:

1) https://www.google.com/

2) https://www.youtube.com/

3) https://scikit-learn.org/stable/user_guide.html

4) https://github.com/

5) https://www.kaggle.com/

6) https://medium.com/

7) https://towardsdatascience.com/

8) https://www.analyticsvidhya.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 influencers 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 be 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

Online platforms and social media become the place where people share the thoughts freely without any partiality and overcoming all the race people share their thoughts and ideas among the crowd.

Social media is a computer-based technology that facilitates the sharing of ideas, thoughts, and information through the building of virtual networks and communities. By design, social media is Internet-based and gives users quick electronic communication of content. Content includes personal information, documents, videos, and photos. Users engage with social media via a computer, tablet, or smartphone via web-based software or applications.

While social media is ubiquitous in America and Europe, Asian countries like India lead the list of social media usage. More than 3.8 billion people use social media.

In this huge online platform or an online community there are some people or some motivated mob wilfully bully others to make them not to share their thought in rightful way. They bully others in a foul language which among the civilized society is seen as ignominy. And

when innocent individuals are being bullied by these mob these individuals are going silent without speaking anything. So, ideally the motive of this disgraceful mob is achieved.

To solve this problem, we are now building a model that identifies all the foul language and foul words, using which the online platforms like social media principally stops these mob using the foul language in an online community or even block them or block them from using this foul language.

Review of Literature

The purpose of the literature review is to:

1. Identify the foul words or foul statements that are being used.

2. Stop the people from using these foul languages in online public forum. To solve this problem, we are now building a model using our machine language technique that identifies all the foul language and foul words, using which the online platforms like social media principally stops these mob using the foul language in an online community or even block them or block them from using this foul language.

I have used 9 different Classification algorithms and shortlisted the best on basis of the metrics of performance and I have chosen one algorithm and built a model in that algorithm.

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 cyberbullying.

Motivation for the Problem Undertaken

One of the first lessons we learn as children is that the louder you scream and the bigger of a tantrum you throw, the more you get your way. Part of growing up and maturing into an adult and functioning member of society is learning how to use language and reasoning skills to communicate our beliefs and respectfully disagree with others, using evidence and persuasiveness to try and bring them over to our way of thinking. Social media is reverting us back to those animalistic tantrums, schoolyard taunts and unfettered bullying that define youth, creating a dystopia where even renowned academics and dispassionate journalists transform from Dr. Jekyll into raving Mr. Hydes, raising the critical question of whether social media should simply enact a blanket ban on profanity and name calling? Actually, ban should be implemented on these profanities and taking that as a motivation I have started this project to identify the malignant comments in social media or in online public forums. With widespread usage of online social networks and its popularity, social networking platforms have given us incalculable opportunities than ever before, and its benefits are undeniable. Despite benefits, people may be humiliated, insulted, bullied, and harassed by anonymous users, strangers, or peers. In this study, we have proposed a cyberbullying detection framework to generate features from online content by leveraging a pointwise mutual information technique. Based on these features, we developed a supervised machine learning solution for cyberbullying detection and multi-class categorization of its severity. Results

from experiments with our proposed framework in a multi-class setting are promising both with respect to classifier accuracy and f-measure metrics. These results indicate that our proposed framework provides a feasible solution to detect cyberbullying behaviour and its severity in online social networks.

Analytical Problem Framing

 Mathematical/ Analytical Modelling of the Problem

The libraries/dependencies imported for this project are shown below:

```
import warnings
warnings.simplefilter("ignore")
warnings.filterwarnings("ignore")
import joblib

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

import missingno
import pandas_profiling
from scipy import interp
#import scikitplot as skplt
from itertools import cycle
import matplotlib.ticker as plticker

import nltk
nltk.download('stopwords', quiet=True)
nltk.download('punkt', quiet=True)
from wordcloud import WordCloud
from nltk.corpus import stopwords
from nltk.stem import SnowballStemmer
from nltk.tokenize import word_tokenize, regexp_tokenize

from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV, RandomizedSearchCV
from scipy.sparse import csr_matrix
```

```
import timeit, sys
from sklearn import metrics
import tqdm.notebook as tqdm
from skmultilearn.problem_transform import BinaryRelevance
from sklearn.svm import SVC, LinearSVC
from sklearn.multiclass import OneVsRestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import MultinomialNB, GaussianNB
from sklearn.ensemble import AdaBoostClassifier, BaggingClassifier, RandomForestClassifier
from sklearn.metrics import hamming_loss, log_loss, accuracy_score, classification_report, confusion_matrix
from sklearn.metrics import roc_curve, auc, roc_auc_score, multilabel_confusion_matrix
```

Here in this project, we have been provided with two datasets namely train and test CSV files. I will build a machine learning model by using NLP using train dataset. And using this model we will make predictions for our test dataset.

I will need to build multiple classification machine learning models. Before model building will need to perform all data pre-processing steps involving NLP. After trying different classification models with different hyper parameters then will select the best model out of it. Will need to follow the complete life cycle of data science that includes steps like -

1. Data Cleaning
2. Exploratory Data Analysis
3. Data Pre-processing
4. Model Building
5. Model Evaluation
6. Selecting the best model

Finally, we compared the results of proposed and baseline features with other machine learning algorithms. Findings of the comparison

indicate the significance of the proposed features in cyberbullying detection.

Data Sources and their format

The data set contains the training set, which has approximately 1,59,000 samples and the test set which contains nearly 1,53,000 samples. 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 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.

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.

This project is more about exploration, feature engineering and classification that can be done on this data. Since the data set is huge and includes many categories of comments, we can do good amount of data exploration and derive some interesting features using the comments text column available. You need to build a model that can differentiate between comments and its categories.

Data Pre-processing Done

The following pre-processing pipeline is required to be performed before building the classification model prediction:

1. Load dataset
2. Remove null values

3. Drop column id
4. Convert comment text to lower case and replace '\n' with single space.
5. Keep only text data i.e., a-z' and remove other data from comment text.
6. Remove stop words and punctuations

7. Apply Stemming using SnowballStemmer

8. Convert text to vectors using TfidfVectorizer

9. Load saved or serialized model

10. Predict values for multi class label

Data Inputs- Logic- Output Relationships

I have analysed the input output logic with word cloud and I have word clouded the sentenced that are classified as foul language in every category. A tag/word cloud is a novelty visual representation of text data, typically used to depict keyword metadata on websites, or to visualize free form text. It's an image composed of words used in a particular text or subject, in which the size of each word indicates its frequency or importance.

Code

```
from wordcloud import WordCloud

# WordCloud: Getting sense of loud words in each of the output labels.

cols = 3
rows = len(output_labels)//cols
if len(output_labels) % cols != 0:
    rows += 1

fig = plt.figure(figsize=(16,rows*cols*1.8))
fig.subplots_adjust(top=0.8, hspace=0.3)

p=1
for i in output_labels:
    word_cloud = WordCloud(height=650, width=800,
                           background_color="white",max_words=80).generate(' '.join(df.comment_text[df[i]==1]))
    ax = fig.add_subplot(rows,cols,p)
    ax.imshow(word_cloud)
    ax.set_title(f"WordCloud for {i} column",fontsize=14)
    for spine in ax.spines.values():
        spine.set_edgecolor('r')

    ax.set_xticks([])
    ax.set_yticks([])
    p += 1

fig.suptitle("WordCloud: Representation of Loud words in BAD COMMENTS",fontsize=16)
fig.tight_layout(pad=2)
```

These are the comments that belongs to different type so with which the help of word cloud we can see if there is abuse comment which type of words it contains to other comments as well.

? State the set of assumptions (if any) related to the

problem under consideration

Cyberbullying has become a growing problem in countries around the world. Essentially, cyberbullying doesn’t differ much from the type of bullying that many children have unfortunately grown accustomed to in school. The only difference is that it takes place online.

Cyberbullying is a very serious issue affecting not just the young victims, but also the victims' families, the bully, and those who witness instances of cyberbullying. However, the effect of cyberbullying can be most detrimental to the victim, of course, as they may experience a number of emotional issues that affect their social and academic performance as well as their overall mental health.

Hardware and Software Requirements and Tools Used

Hardware technology being used.

RAM : 8.00 GB

CPU : Intel(R) Core(TM) i5-10300H CPU @ 2.50GHz

GPU : NVIDIA GeForce GTX 1650 Ti

Software technology being used.

Programming language : Python

Distribution : Anaconda Navigator

Browser based language shell : Jupyter Notebook

Libraries/Packages specifically being used.

Pandas, NumPy, matplotlib, seaborn, scikit-learn, pandas-profiling, missingno, NLTK

Model/s Development and Evaluation

Identification of possible problem-solving approaches

(methods)

I checked through the entire training dataset for any kind of missing values information and all these pre-processing steps were repeated on the testing dataset as well.

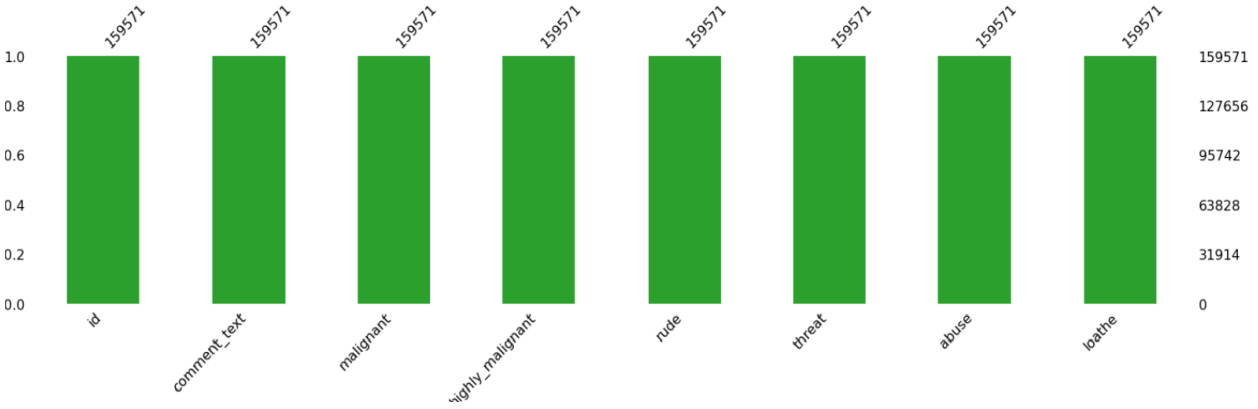
Code:

```
df_train.isna().sum() # checking for missing values
```

```
id                0
comment_text      0
malignant         0
highly_malignant  0
rude              0
threat            0
abuse             0
loathe            0
dtype: int64
```

```
missingno.bar(df_train, figsize = (25,5), color="tab:green")
```

```
<AxesSubplot:>
```



Then we went ahead and took a look at the dataset information. Using the info method, we are able to confirm the non-null count details as well as the datatype information. We have a total of 8 columns out of which 2 columns have object datatype while the remaining 6 columns are of integer datatype.

Code:

```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 159571 entries, 0 to 159570
Data columns (total 8 columns):
 #   Column            Non-Null Count   Dtype 
---  ------            --------------   ----- 
 0   id                159571 non-null  object
 1   comment_text      159571 non-null  object
 2   malignant         159571 non-null  int64 
 3   highly_malignant  159571 non-null  int64 
 4   rude              159571 non-null  int64 
 5   threat            159571 non-null  int64 
 6   abuse             159571 non-null  int64 
 7   loathe            159571 non-null  int64 
dtypes: int64(6), object(2)
memory usage: 9.7+ MB
```

Then we went ahead and performed multiple data cleaning and data

transformation steps. I have added an additional column to store the original length of our comment_text column.

```
# checking the length of comments and storing it into another column 'original_length'
# copying df_train into another object df
df = df_train.copy()
df['original_length'] = df.comment_text.str.len()

# checking the first five and last five rows here
df
```

	id	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe	original_length
0	0000997932d777bf	Explanation\nWhy the edits made under my usern...	0	0	0	0	0	0	264
1	000103f0d9cfb60f	D'aww! He matches this background colour I'm s...	0	0	0	0	0	0	112
2	000113f07ec002fd	Hey man, I'm really not trying to edit war. It...	0	0	0	0	0	0	233
3	0001b41b1c6bb37e	"\nMore\nI can't make any real suggestions on ...	0	0	0	0	0	0	622
4	0001d958c54c6e35	You, sir, are my hero. Any chance you remember...	0	0	0	0	0	0	67
...	...	...	...	...	...	...	...	...	...
159566	ffe987279560d7ff	":::::And for the second time of asking, when ...	0	0	0	0	0	0	295
159567	ffea4adeee384e90	You should be ashamed of yourself \n\nThat is ...	0	0	0	0	0	0	99

```
# copying df_train into another object df
df = df_train.copy()
df['original_length'] = df.comment_text.str.len()

# checking the first five and last five rows here
df
```

```
# Data Cleansing

# as the feature 'id' has no relevance w.r.t. model training I am dropping this column
df.drop(columns=['id'],inplace=True)
# converting comment text to lowercase format
df['comment_text'] = df.comment_text.str.lower()
df.head()
```

	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe	original_length
0	explanation\nwhy the edits made under my usern...	0	0	0	0	0	0	264
1	d'aww! he matches this background colour i'm s...	0	0	0	0	0	0	112
2	hey man, i'm really not trying to edit war. it...	0	0	0	0	0	0	233
3	"\nmore\ni can't make any real suggestions on ...	0	0	0	0	0	0	622
4	you, sir, are my hero. any chance you remember...	0	0	0	0	0	0	67

```
# Removing and Replacing unwanted characters in the comment_text column

# Replacing '\n' with ' '
df.comment_text = df.comment_text.str.replace('\n',' ')

# Keeping only text with letters a to z, 0 to 9 and words like can't, don't, couldn't etc
df.comment_text = df.comment_text.apply(lambda x: ' '.join(regexp_tokenize(x,"[a-z']+")))

# Removing Stop Words and Punctuations

# Getting the list of stop words of english language as set
stop_words = set(stopwords.words('english'))

# Updating the stop_words set by adding letters from a to z
for ch in range(ord('a'),ord('z')+1):
    stop_words.update(chr(ch))

# Updating stop_words further by adding some custom words
custom_words = ("d'aww","mr","hmm","umm","also","maybe","that's","he's","she's","i'll","he'll","s
                "ok","there's","hey","heh","hi","oh","bbq","i'm","i've","nt","can't","could","ur"
                "rofl","lol","stfu","lmk","ily","yolo","smh","lmfao","nvm","ikr","ofc","omg","ilu
stop_words.update(custom_words)

# Checking the new list of stop words
print("New list of custom stop words are as follows:\n\n")
print(stop_words)
```

```
# Removing stop words
df.comment_text = df.comment_text.apply(lambda x: ' '.join(word for word in x.split() if word not in stop_words).strip())

# Removing punctuations
df.comment_text = df.comment_text.str.replace("[^\w\d\s]","")

# Checking any 10 random rows to see the applied changes
df.sample(10)
```

```
# Removing stop words
df.comment_text = df.comment_text.apply(lambda x: ' '.join(word for word in x.split() if word not in stop_words).strip())

# Removing punctuations
df.comment_text = df.comment_text.str.replace("[^\w\d\s]","")

# Checking any 10 random rows to see the applied changes
df.sample(10)
```

```
# Stemming words
snb_stem = SnowballStemmer('english')
df.comment_text = df.comment_text.apply(lambda x: ' '.join(snb_stem.stem(word) for word in word_tokenize(x)))

# Checking any 10 random rows to see the applied changes
df.sample(10)
```

```
# Checking the length of comment_text after cleaning and storing it in cleaned_length variable
df["cleaned_length"] = df.comment_text.str.len()

# Taking a loot at first 10 rows of data
df.head(10)
```

	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe	original_length	cleaned_length
0	explan edit made usernam hardcor metallica fan...	0	0	0	0	0	0	264	135
1	match background colour seem stuck thank talk ...	0	0	0	0	0	0	112	57
2	man realli tri edit war guy constant remov rel...	0	0	0	0	0	0	233	112
3	make real suggest improv wonder section statis...	0	0	0	0	0	0	622	310
4	sir hero chanc rememb page	0	0	0	0	0	0	67	26
5	congratul well use tool well talk	0	0	0	0	0	0	65	33
6	cocksuck piss around work	1	1	1	0	1	0	44	25
7	vandal matt shirvington articl revert pleas ban	0	0	0	0	0	0	115	47
8	sorri word nonsens offens anyway intend write ...	0	0	0	0	0	0	472	235
9	align subject contrari dulithgow	0	0	0	0	0	0	70	32

```
# Now checking the percentage of length cleaned
print(f"Total Original Length        : {df.original_length.sum()}")
print(f"Total Cleaned Length         : {df.cleaned_length.sum()}")
print(f"Percentage of Length Cleaned : {(df.original_length.sum()-df.cleaned_length.sum())*100/df.original_length.sum()}%")
```

```
Total Original Length        : 62893130
Total Cleaned Length         : 34297506
Percentage of Length Cleaned : 45.46700728680541%
```

Visualizations

I used the pandas profiling feature to generate an initial detailed report on my dataframe values. It gives us various information on the rendered dataset like the correlations, missing values, duplicate rows, variable types, memory size etc. This assists us in further detailed visualization separating each part one by one comparing and research for the impacts on the prediction of our target label from all the available feature columns.

```
: pandas_profiling.ProfileReport(df)
```

Summarize dataset: 100% 26/26 [00:23<00:00, 4.03it/s, Completed]

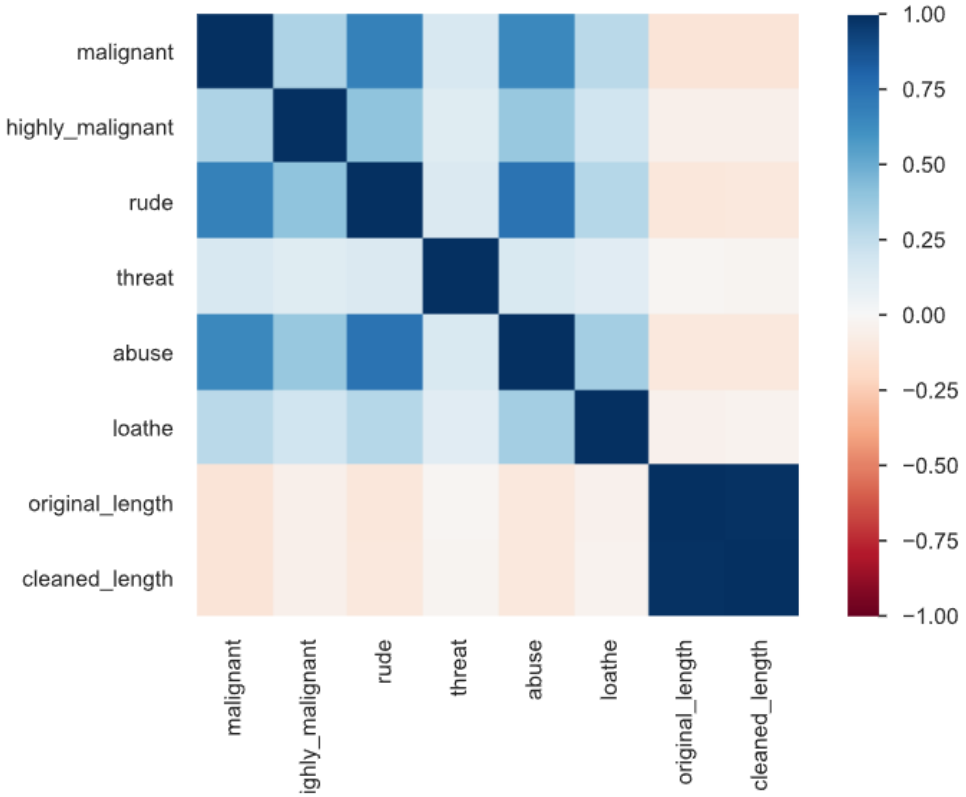
Generate report structure: 100% 1/1 [00:02<00:00, 2.53s/it]

Render HTML: 100% 1/1 [00:00<00:00, 1.92it/s]

Most frequently occurring

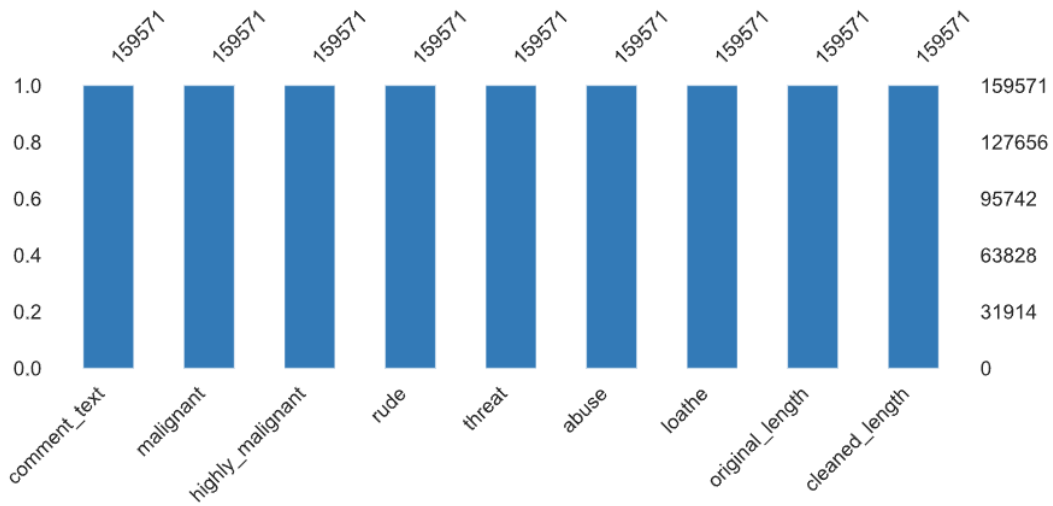
	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe	original_length
2		0	0	0	0	0	0	16
93	jun utc	0	0	0	0	0	0	24
104	mar utc	0	0	0	0	0	0	24
5		0	0	0	0	0	0	21
4		0	0	0	0	0	0	20
6		0	0	0	0	0	0	22
115	nov utc	0	0	0	0	0	0	24
12		0	0	0	0	0	0	28
62	feb utc	0	0	0	0	0	0	24
81	jan utc	0	0	0	0	0	0	24

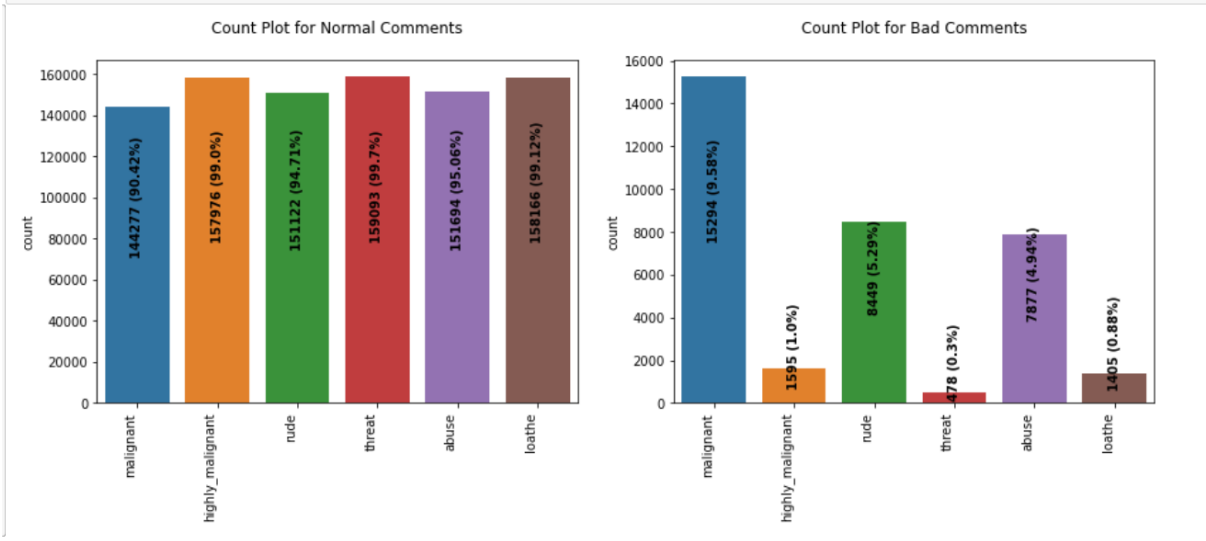
Correlations



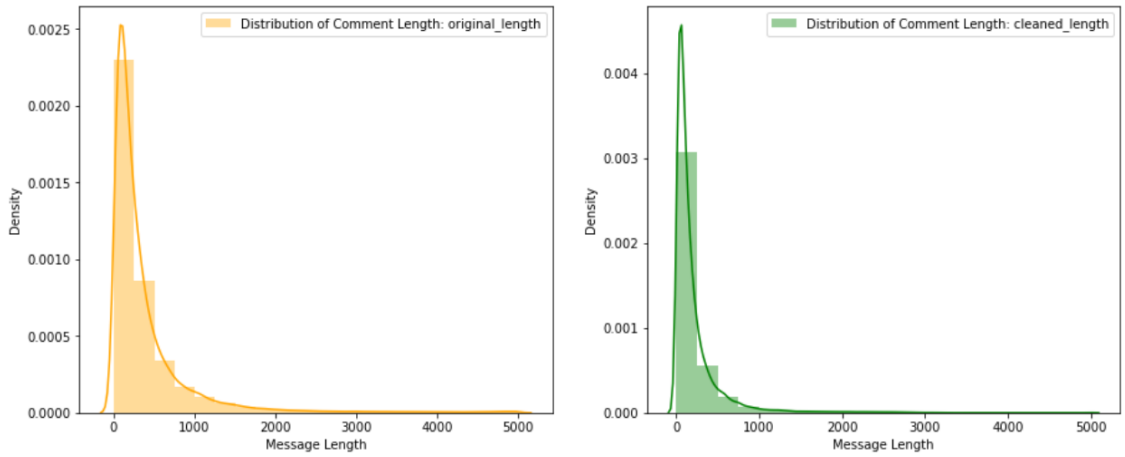
Missing values

Count | Matrix



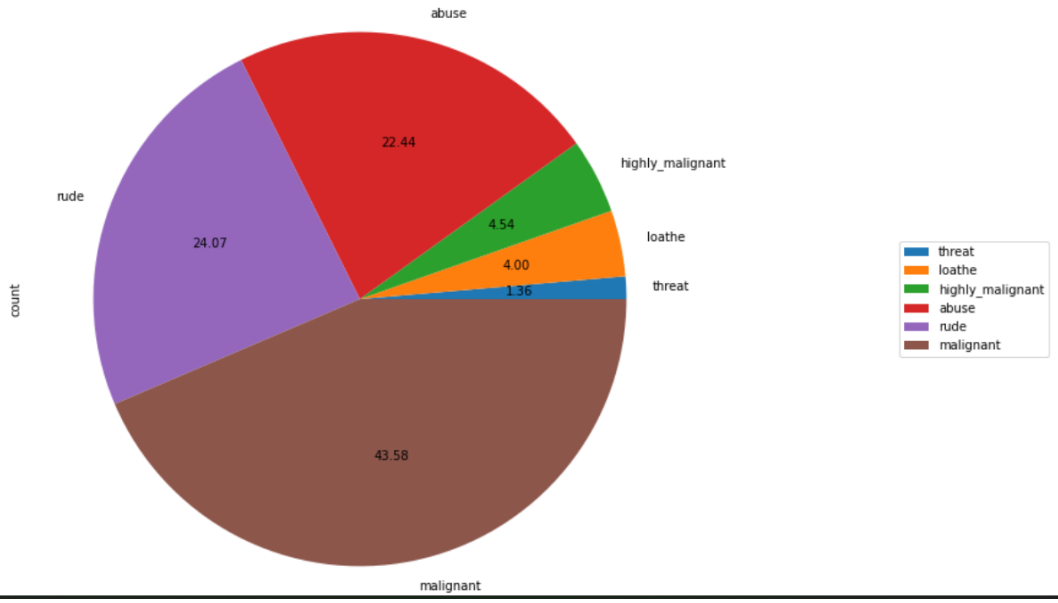



```
# Comparing the comment text length distribution before cleaning and after cleaning

fig, ax = plt.subplots(1,2,figsize=(15,6))
j=0
colors = ['orange','green']
for i in df.columns[-2:]:
    label_text = f"Distribution of Comment Length: {i}"
    sns.distplot(df[i],ax=ax[j],bins=20,color=colors[j],label=label_text)
    ax[j].set_xlabel("Message Length")
    ax[j].legend()
    j += 1

plt.show()
```



Before cleaning comment_text column most of the comment's length lies between 0 to 1100 while after cleaning it has been reduced between 0 to 900.

```
: # Visualizing the label distribution of comments using pie chart

  comments_labels = ['malignant', 'highly_malignant', 'rude', 'threat', 'abuse', 'loathe']
  df_distribution = df_train[comments_labels].sum()\
                              .to_frame()\
                              .rename(columns={0: 'count'})\
                              .sort_values('count')

  df_distribution.plot.pie(y = 'count', title = 'Label distribution over comments', autopct='%.2f', figsize = (15, 10))\
                              .legend(loc='center left', bbox_to_anchor=(1.3, 0.5))
```




```
# Preparing the list of models for classification purpose
models = {"GaussianNB": {"name": GaussianNB()},
          "MultinomialNB": {"name": MultinomialNB()},
          "Logistic Regression": {"name": LogisticRegression()},
          "Random Forest Classifier": {"name": RandomForestClassifier()},
          "Support Vector Classifier": {"name": LinearSVC(max_iter = 3000)},
          "Ada Boost Classifier": {"name": AdaBoostClassifier()},
          "K Nearest Neighbors Classifier": {"name": KNeighborsClassifier()},
          "Decision Tree Classifier": {"name": DecisionTreeClassifier()},
          "Bagging Classifier": {"name": BaggingClassifier(base_estimator=LinearSVC())},
         }

# Taking one forth of the total data for training and testing purpose
half = len(df)//4
trained_models = build_models(models,X[:half,:],Y[:half,:])
```

Hyperparameter Tuning

```
# Choosing Linear Support Vector Classifier model

fmod_param = {'estimator__penalty' : ['l1', 'l2'],
              'estimator__loss' : ['hinge', 'squared_hinge'],
              'estimator__multi_class' : ['ovr', 'crammer_singer'],
              'estimator__random_state' : [42, 72, 111]
             }
SVC = OneVsRestClassifier(LinearSVC())
GSCV = GridSearchCV(SVC, fmod_param, cv=3)
x_train,x_test,y_train,y_test = train_test_split(X[:half,:], Y[:half,:], test_size=0.30, random_state=42)
GSCV.fit(x_train,y_train)
GSCV.best_params_
```

```
{'estimator__loss': 'hinge',
 'estimator__multi_class': 'ovr',
 'estimator__penalty': 'l2',
 'estimator__random_state': 42}
```

```
Final_Model = OneVsRestClassifier(LinearSVC(loss='hinge', multi_class='ovr', penalty='l2', random_state=42))
Classifier = Final_Model.fit(x_train, y_train)
fmod_pred = Final_Model.predict(x_test)
fmod_acc = (accuracy_score(y_test, fmod_pred))*100
print("Accuracy score for the Best Model is:", fmod_acc)
h_loss = hamming_loss(y_test,fmod_pred)*100
print("Hamming loss for the Best Model is:", h_loss)
```

```
Final_Model = OneVsRestClassifier(LinearSVC(loss='hinge', multi_class='ovr', penalty='l2', random_state=42))
Classifier = Final_Model.fit(x_train, y_train)
fmod_pred = Final_Model.predict(x_test)
fmod_acc = (accuracy_score(y_test, fmod_pred))*100
print("Accuracy score for the Best Model is:", fmod_acc)
h_loss = hamming_loss(y_test,fmod_pred)*100
print("Hamming loss for the Best Model is:", h_loss)
```

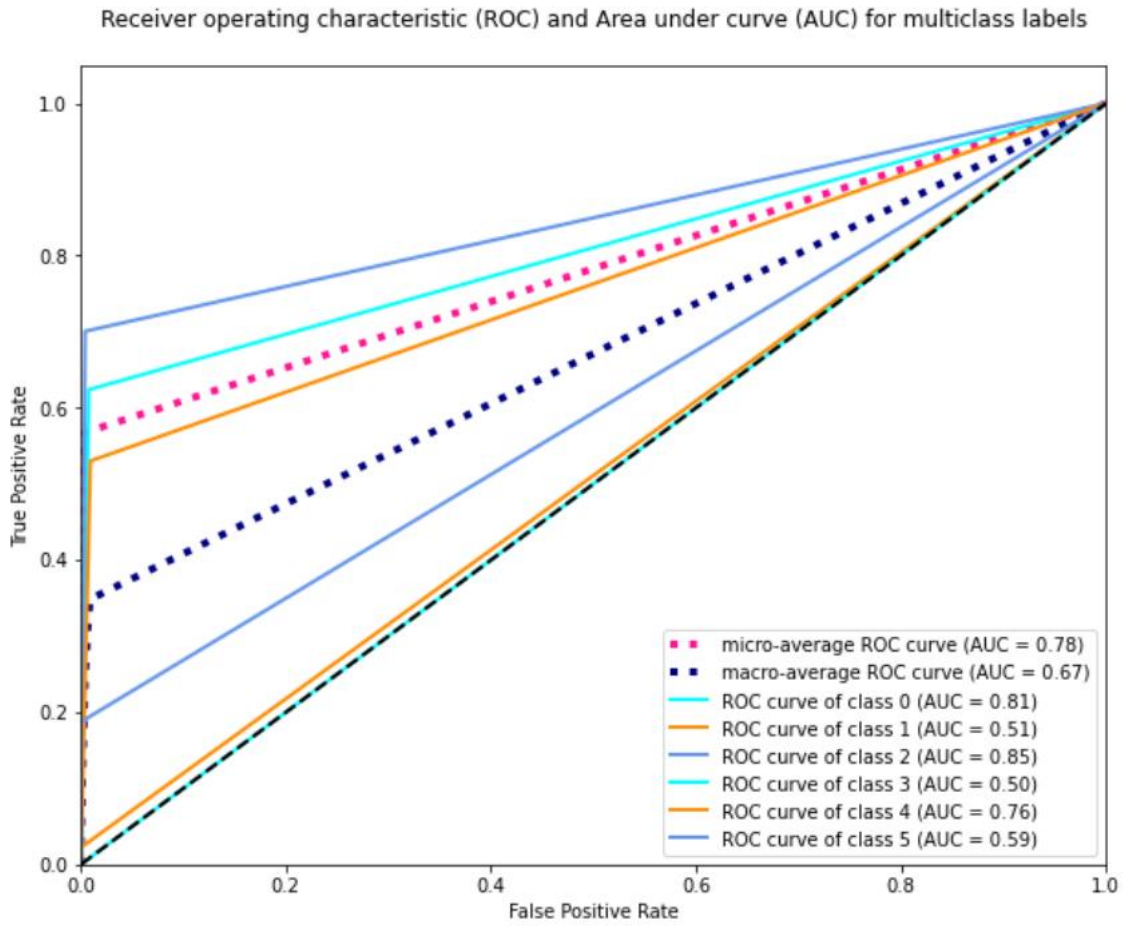
```
Accuracy score for the Best Model is: 91.51069518716578
Hamming loss for the Best Model is: 1.9593917112299464
```

AUC ROC Curve for Final Model

]:
```
n_classes = y_test.shape[1]

# Compute ROC curve and ROC area for each class
fpr = dict()
tpr = dict()
roc_auc = dict()
for i in range(n_classes):
    fpr[i], tpr[i], _ = roc_curve(y_test[:, i], fmod_pred[:, i])
    roc_auc[i] = auc(fpr[i], tpr[i])

# Compute micro-average ROC curve and ROC area
fpr["micro"], tpr["micro"], _ = roc_curve(y_test.ravel(), fmod_pred.ravel())
roc_auc["micro"] = auc(fpr["micro"], tpr["micro"])

plt.rcParams["figure.figsize"] = (10,8) # used to change the output figure size

# First aggregate all false positive rates
all_fpr = np.unique(np.concatenate([fpr[i] for i in range(n_classes)]))

# Then interpolate all ROC curves at this points
mean_tpr = np.zeros_like(all_fpr)
for i in range(n_classes):
    mean_tpr += interp(all_fpr, fpr[i], tpr[i])

# Finally average it and compute AUC
mean_tpr /= n_classes
```

```
fpr["macro"] = all_fpr
tpr["macro"] = mean_tpr
roc_auc["macro"] = auc(fpr["macro"], tpr["macro"])

# Plot all ROC curves
plt.figure()
plt.plot(
    fpr["micro"],
    tpr["micro"],
    label="micro-average ROC curve (AUC = {0:0.2f})".format(roc_auc["micro"]),
    color="deeppink",
    linestyle=":",
    linewidth=4,
)

plt.plot(
    fpr["macro"],
    tpr["macro"],
    label="macro-average ROC curve (AUC = {0:0.2f})".format(roc_auc["macro"]),
    color="navy",
    linestyle=":",
    linewidth=4,
)

colors = cycle(["aqua", "darkorange", "cornflowerblue"])
for i, color in zip(range(n_classes), colors):
    plt.plot(
        fpr[i],
        tpr[i],
        color=color,
```

```
        label="ROC curve of class {0} (AUC = {1:0.2f})".format(i, roc_auc[i]),
    )

plt.plot([0, 1], [0, 1], "k--", lw=2)
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Receiver operating characteristic (ROC) and Area under curve (AUC) for multiclass labels\n")
plt.legend(loc="lower right")
plt.show()
```

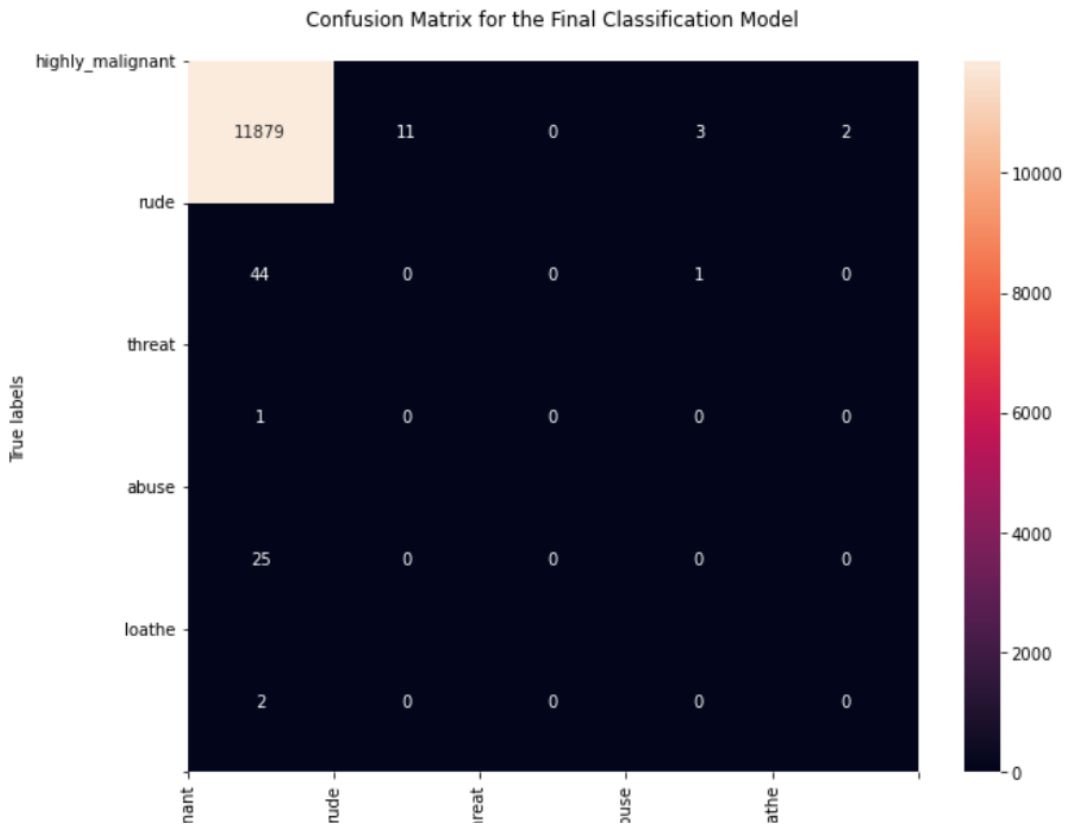


Confusion Matrix for Final Model

```
: print("Confusion matrix:\n\n", multilabel_confusion_matrix(y_test, fmod_pred))
```

```
Confusion matrix:

 [[[10710    83]
  [  442   733]]

 [[11832     1]
  [  132     3]]

 [[11263    47]
  [  197   461]]

 [[11930     0]
  [   38     0]]

 [[11266   106]
  [  280   316]]

 [[11869     3]
  [   78    18]]]
```

```
plt.rcParams["figure.figsize"] = (10,8) # used to change the output figure size
ax= plt.subplot()
cm = confusion_matrix(np.asarray(y_test).argmax(axis=1), np.asarray(fmod_pred).argmax(axis=1))
sns.heatmap(cm, annot=True, fmt='g', ax=ax);  # annot=True to annotate cells, ftm='g' to disable scientific notation

# title, labels and ticks
ax.set_title('Confusion Matrix for the Final Classification Model\n');
ax.set_xlabel('Predicted labels'); ax.set_ylabel('True labels');
loc = plticker.MultipleLocator()
ax.xaxis.set_major_locator(loc); ax.yaxis.set_major_locator(loc);
ax.set_xticklabels(comments_labels); ax.set_yticklabels(comments_labels);
plt.xticks(rotation=90); plt.yticks(rotation=0);
plt.show()
```



Model Saving or Serialization

```
# selecting the best model
best_model = trained_models['Support Vector Classifier']['trained']

# saving the best classification model
joblib.dump(best_model,open('Malignant_comments_classifier.pkl','wb'))
```

Preprocessing Pipeline for test dataframe

The following preprocessing pipeline is required to perform model prediction:

```
Use the test dataset
Remove null values if any
Drop column id
Convert comment text to lower case and replace '\n' with single space
Keep only text data ie. a-z' and remove other data from comment text
Remove stop words and punctuations
Apply Stemming using SnowballStemmer
Convert text to vectors using TfidfVectorizer
Load saved or serialized best model
Predict values and create a new CSV file
```

```
# Remove null values
if df_test.isnull().sum()[1] != 0:
    df_test.dropna(inplace=True)

# Drop coulmn id
df_test.drop(columns=['id'],inplace=True)

# Convert comment text to lower case and replace '\n' with single space
df_test["comment_text"] = df_test.comment_text.str.lower()
df_test["comment_text"] = df_test.comment_text.str.replace('\n',' ')

# Keep only text data i.e., a-z' and remove other data from comment text.
df_test.comment_text = df_test.comment_text.apply(lambda x: ' '.join(regexp_tokenize(x,"[a-z']+")))

# Remove stopwords
df_test.comment_text = df_test.comment_text.apply(lambda x: ' '.join(word for word in x.split() if word not in stop_words).strip

# Remove punctuations
df_test.comment_text = df_test.comment_text.str.replace("[^\w\d\s]","")

# Apply Stemming using SnowballStemmer
df_test.comment_text = df_test.comment_text.apply(lambda x: ' '.join(snb_stem.stem(word) for word in word_tokenize(x)))

print(df_test.info(memory_usage="deep"))

# Convert text to vectors using TfidfVectorizer
tfidf = TfidfVectorizer(analyzer = 'word', max_features=4000)
test_features = tfidf.fit_transform(df_test.comment_text).toarray()
# Load saved or serialized model and predict
model_loaded = joblib.load('Malignant comments classifier.pkl')
```

```
# Make predictions and view the results
predict_test = model_loaded.predict(test_features)

# Saving predicted values into a CSV file
pd.DataFrame(predict_test.toarray()).to_csv('Predicted_test_output.csv')
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 153164 entries, 0 to 153163
Data columns (total 1 columns):
 #   Column        Non-Null Count   Dtype 
---  ------        --------------   ----- 
 0   comment_text  153164 non-null  object
dtypes: object(1)
memory usage: 37.2 MB
None
```

```
df1 = pd.read_csv('Predicted_test_output.csv')
df1.drop("Unnamed: 0", axis=1, inplace=True)
df1.rename({'0':'malignant', '1':'highly_malignant', '2':'rude', '3':'threat', '4':'abuse', '5':'loathe'},
           axis='columns', inplace=True)
df2=df_test.copy()
df = pd.concat([df2, df1], axis=1)
df
```

	comment_text	malignant	highly_malignant	rude	threat	abuse	loathe
0	yo bitch ja rule succes ever what hate sad mof...	0	0	0	0	0	0
1	rfc titl fine imo	0	0	0	0	0	0
2	sourc zaw ashton lapland	0	0	0	0	0	0
3	look back sourc inform updat correct form gues...	0	0	0	0	0	0
4	anonym edit articl	0	0	0	0	0	0
...	...	...	...	...	...	...	...
153159	total agre stuff noth long crap	0	0	0	0	0	0
153160	throw field home plate get faster throw cut ma...	0	0	0	0	0	0
153161	okinotorishima categori see chang agre correct...	0	0	0	0	0	0
153162	one found nation eu germani law return quit si...	0	0	0	0	0	0
153163	stop alreadi bullshit welcom fool think kind e...	0	0	0	0	0	0

153164 rows × 7 columns

```
df.to_csv('Malignant_Comments_Classifier_test_dataset_predictions.csv', index=False)
```

Inference

Starting with univariate analysis, with the help of count plot it was found that dataset is imbalanced with having higher number of records for normal comments than bad comments (including malignant, highly malignant, rude, threat, abuse and loathe). Also, with the help of distribution plot for comments length it was found that after cleaning most of comments length decreases from range 0-1100 to 0-900. Moving further with wordcloud it was found that malignant comments consists of words like fuck, nigger, moron, hate, suck etc. highly_malignant comments consists of words like ass, fuck, bitch, shit, die, suck, faggot etc. rude comments consists of words like nigger, ass, fuck, suck, bullshit, bitch etc. threat comments consists of words like die, must die, kill, murder etc. abuse comments consists of words like moron, nigger, fat, jew, bitch etc. and loathe comments consists of words like nigga, stupid, nigger, die, gay, cunt etc.

Problems faced while working in this project:

More computational power was required as it took more time for processing the huge dataset. Imbalanced dataset and bad comment texts. Better parameters could not be obtained using hyperparameter tuning as more time was consumed.