NAME OF THE PROJECT

Malignant-Comments-Classifier

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ACKNOWLEDGMENT

I would like to express my special gratitude to “Flip Robo” team, who has given me this opportunity to deal with a beautiful dataset and it has helped me to improve my analyzationskills. And I want to express my huge gratitude to Ms.Gulshana Chaudhary (SME Flip Robo), she is the person who has helped me to get out of all the difficulties I faced while doing the project.

A huge thanks to “Data trained” who are the reason behind my Internship at Fliprobo.

Last but not least my parents who have been my backbone in every step of my life.

- References use in this project:

- SCIKIT Learn Library Documentation
-
- Blogs from towardsdatascience, Analytics Vidya, Medium Andrew Ng Notes on Machine Learning (GitHub)
- Data Science Projects with Python Second Edition by Packt
-
- Hands on Machine learning with scikit learn and tensor flow by Aurelien Geron
- Stackoverflow.com to resolve some project related queries.
- Predicting Credit Default among Micro Borrowers in Ghana Kwame Simpe Ofori, Eli FianuPredicting Microfinance Credit Default: A Study of Nsoatreman Rural Bank, Ghana Ernest Yeboah Boateng.

A Machine Learning Approach for Micro-Credit Scoring ApostolosAmpountolas And also thank you for many other persons who has helped me directly or indirectly to complete the project.

INTRODUCTION

Malignant Commentes Classifier - Multi Label Classification Project using NLP

- 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 behavior.
- 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.

Problem Statement

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.

Multi –Label Classification Problem

- Difference between multi-class classification & multi-label classification is that in multi-class problems the classes are mutually exclusive, whereas for multi-label problems each label represents a different classification task, but the tasks are somehow related.
- For example, multi-class classification makes the assumption that each sample is assigned to one and only one label: a fruit can be either an apple or a pear but not both at the same time. Whereas, an instance of multi-label classification can be that a text might be about any of religion, politics, finance or education at the same time or none of these.

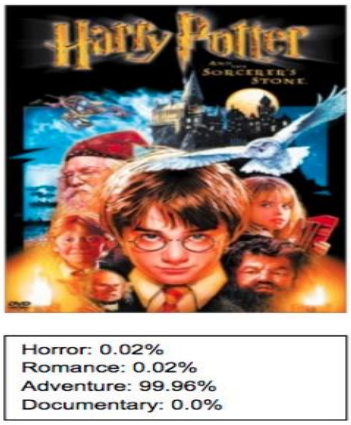
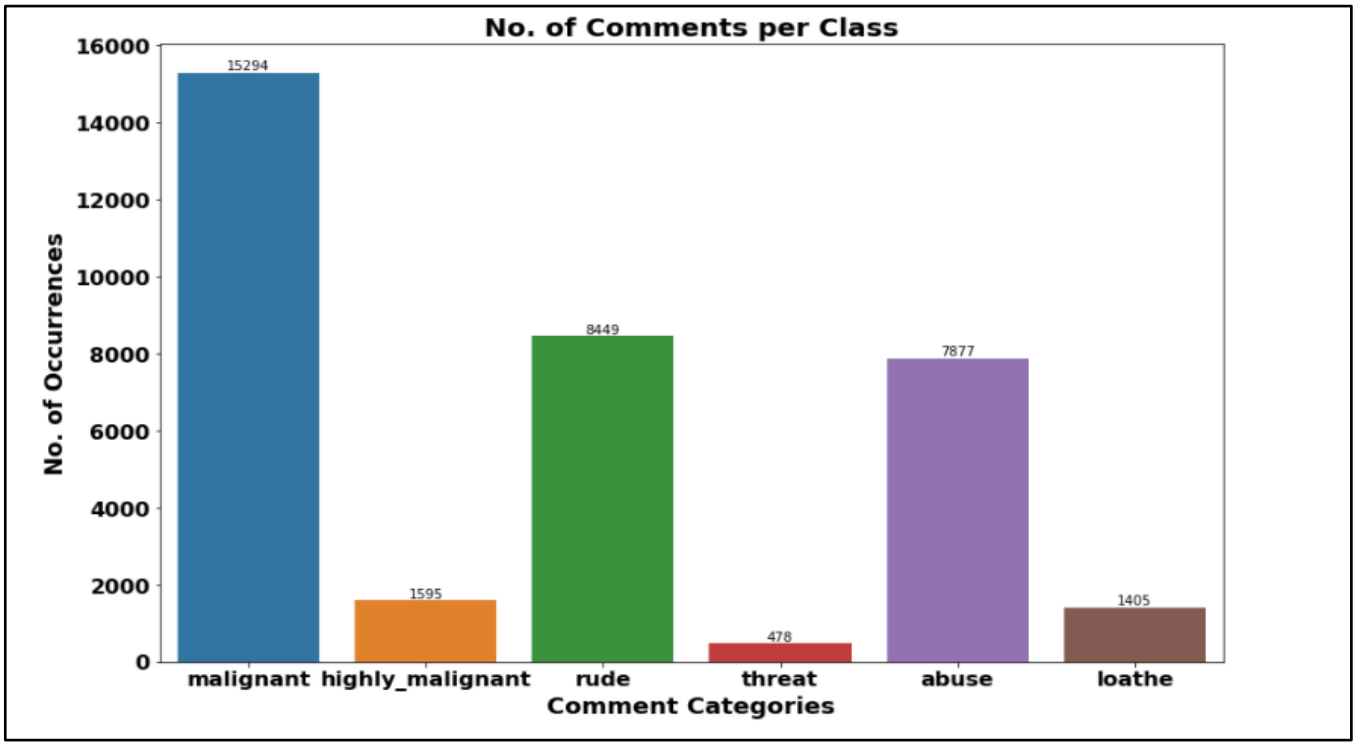


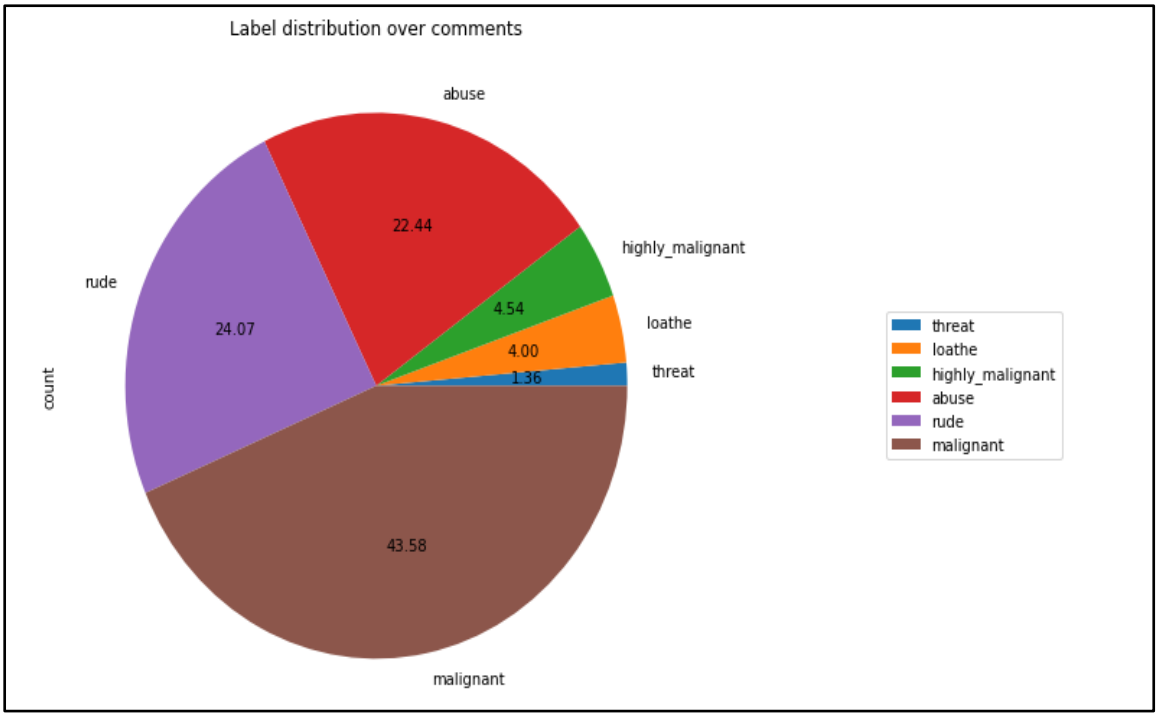
Fig-2: Multi-label classification to find genres based on movie posters.

- Multi-label classification of textual data is an important problem. Examples range from news articles to emails.
- **For instance, this can be employed to find the genres that a movie belongs to, based on the summary of its plot.**

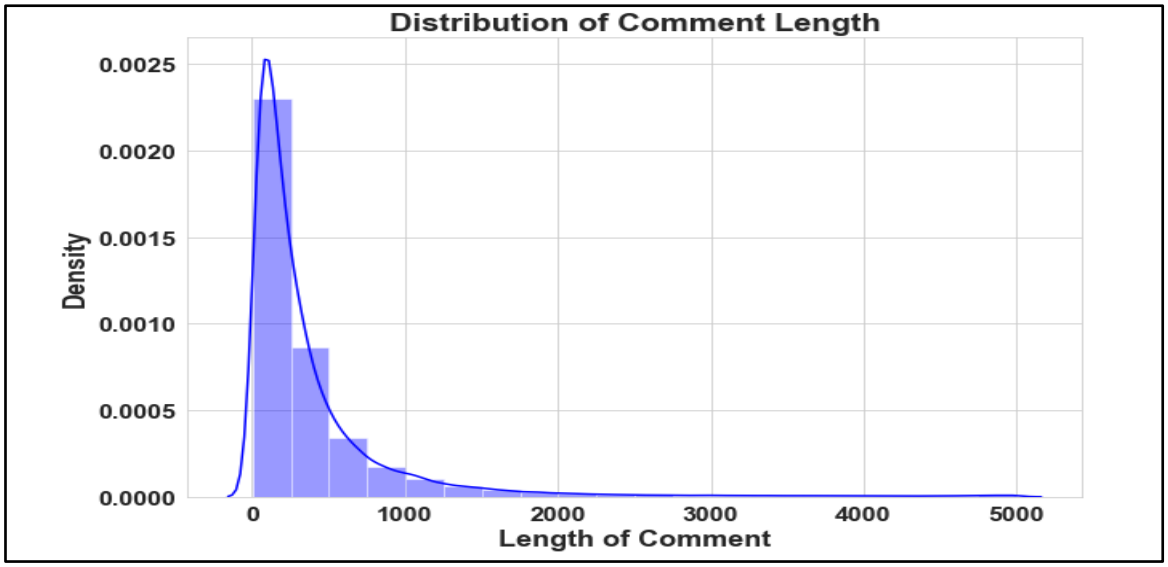
Exploration of Target Variable Ratings



- Out of total Negative comments the maximum negative comments come with Malignant in nature followed by rude categories.
- Around 90% comments are Good/Neutral in nature while rest 10% comments are Negative in nature.
- Very few comments come with threatening nature.



- Out of total negative comments around 43.58% are malignant in nature followed by 24.07% are rude comments



- Above is a plot showing the comment length frequency. As noticed, most of the comments are short with only a few comments longer than 1000 words.
- Majority of the comments are of length 500, where maximum length is 5000 and minimum length is 5. Median length being 250.

Data Pre Processing

- Convert the text to lowercase .
- Remove the punctuations, digits and special characters .
- Tokenize the text, filter out the adjectives used in the review and create a new .column in data frame .
- Remove the stop words.
- Stemming and Lemmatising.
- Applying Text Vectorization to convert text into numeric.

Multi-Label Classification Techniques

- One Vs Rest
- Binary Relevance
- Classifier Chains
- Label Powerset
- Adapted Algorithm

Word Cloud for getting word sense

- Word Cloud is a visualization technique for text data wherein each word is picturized with its importance in the context or its frequency.
- The more commonly the term appears within the text being analysed, the larger the word appears in the image generated.
- The enlarged texts are the greatest number of words used there and small texts are the smaller number of words used.

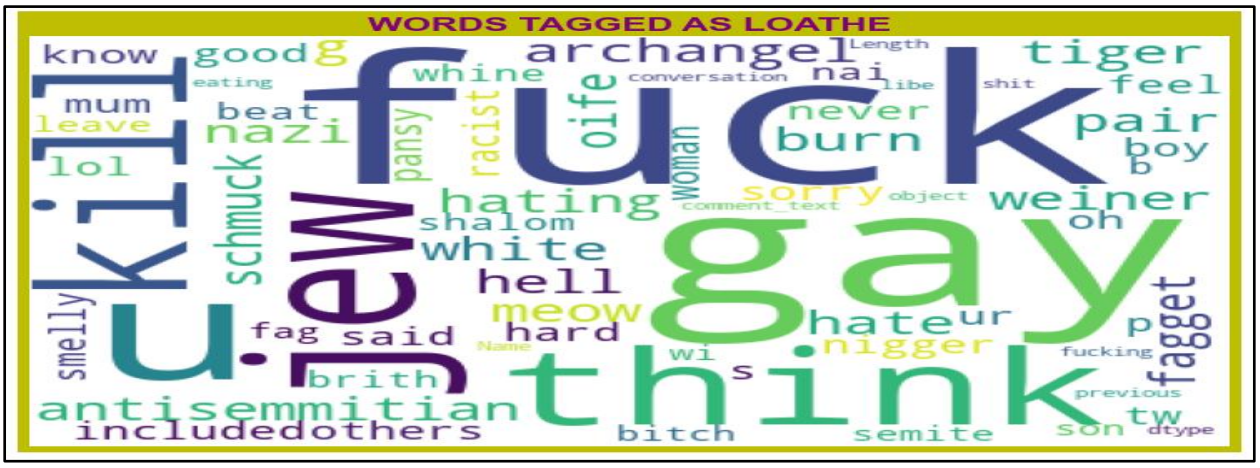
- **From word cloud of malignant comments, it is clear that it mostly consists of words like edits, hey, white, fucking, gay, cocksucker, work, think, Taliban etc**

- **From word cloud of Highly malignant comments, it is clear that it mostly consists of words like fuck, stupid, fucking, bitch, crow, shit, cocksucker etc.**

- **From word cloud of Rude comments, it is clear that it mostly consists of words like fucking, shit, white, piece, edits, stuff, absurd etc.**

- **From word cloud of Threat comments, it is clear that it mostly consists of words like fuck, suck, Bitch, die, stupid, etc.**

- **From word cloud of Abuse comments, it is clear that it mostly consists of words like edits, white, shit, stuff, fuck, piss, fucking etc.**



- **From word cloud of Loathe comments, it is clear that it mostly consists of words like fuck, gay, kill, think, jew, u etc.**

Visualization & Data Wrangling Library used

```
#Importing warning library to avoid any warnings
import pandas as pd # for data wrangling purpose
import numpy as np # Basic computation library
import seaborn as sns # For Visualization
import matplotlib.pyplot as plt # ploting package
%matplotlib inline
import warnings # Filtering warnings
warnings.filterwarnings('ignore')
```

Text Mining Library used

```
#Importing required libraries
import re
import string
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import SnowballStemmer, WordNetLemmatizer
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from wordcloud import WordCloud
```

Machine Learning Model Building Library used

```
#Importing Machine learning Model library
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
from skmultilearn.problem_transform import BinaryRelevance
from sklearn.svm import SVC, LinearSVC
from sklearn.multiclass import OneVsRestClassifier
from sklearn.model_selection import train_test_split,cross_val_score
from sklearn.metrics import confusion_matrix,classification_report,accuracy_score
from sklearn.metrics import roc_auc_score, roc_curve, auc
from sklearn.metrics import hamming_loss, log_loss
```

Machine Learning Model Building

The different classification algorithm used in this project to build ML model are as below:

- Random Forest classifier
- Support Vector Classifier
- Logistics Regression
- AdaBoost Classifier

Machine Learning Evaluation Matrix

- Support Vector Classifier gives maximum Accuracy Score: 91.1508 % and Hamming Loss: 2.0953% than the other classification models.
- Hyper parameter Tuning is perform over this best model using best param shown below :

```
Out[69]: {'estimator__loss': 'hinge',
          'estimator__multi_class': 'ovr',
          'estimator__penalty': 'l2',
          'estimator__random_state': 42}
```

Final ML Model

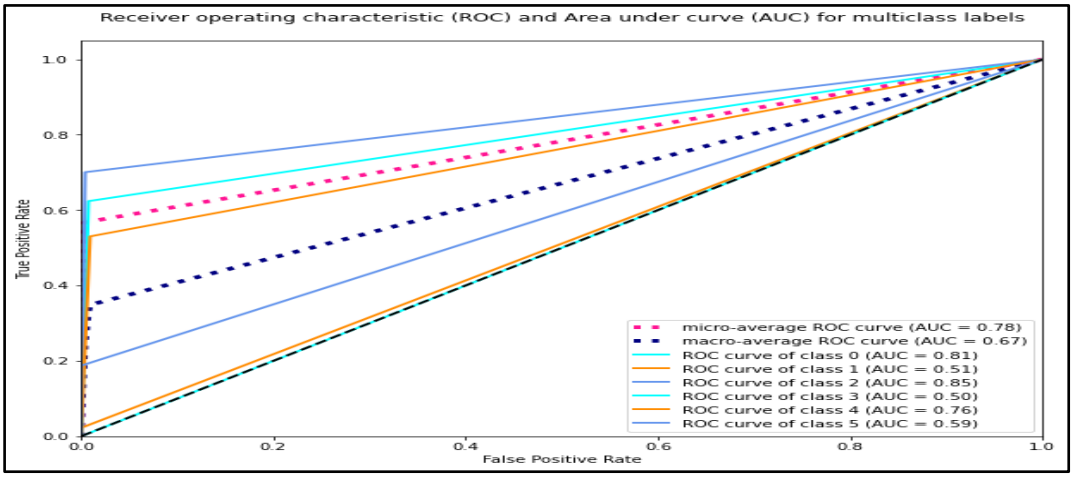
Final Model

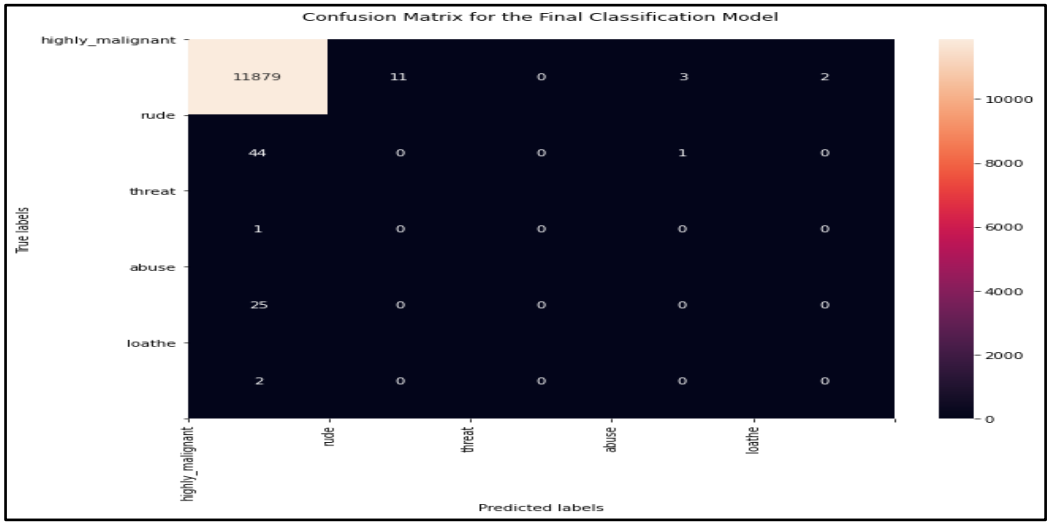
```
Final_Model = OneVsRestClassifier(LinearSVC(loss='hinge',
            multi_class='ovr', penalty='l2', random_state=42))

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: 91.26002673796792
Hamming loss for the Best Model is: 2.0819407308377897
```

- Final Model is giving us Accuracy score of 91.26% which is slightly improved compare to earlier Accuracy score of 91.15%.

AOC-ROC Curve & Confusion Matrix





Machine Learning Evaluation Matrix

Algorithm	Accuracy Score	Recall (Micro)	Precision (Micro)	F1 Score (Micro)	Humming Loss
Logistics Regression	0.9123	0.89	0.94	0.61	0.02206
Random Forest Classifier (RFC)	0.9074	0.56	0.79	0.66	0.02191
Support Vector Classifier	0.9115	0.56	0.82	0.67	0.02952
Ada Boost Classifier	0.9057	0.50	0.80	0.61	0.9057

CONCLUSION

- Linear Support Vector Classifier performs better with Accuracy Score: 91.15077857956704 % and Hamming Loss: 2.0952019242942144 % than the other classification models.
- Final Model (Hyperparameter Tuning) is giving us Accuracy score of 91.26% which is slightly improved compare to earlier Accuracy score of 91.15%.
- SVM classifier is fastest algorithm compare to others.

Limitations of this work and Scope for Future Work

- The Maximum feature used while vectorization is 2000. Employing more feature in vectorization lead to more accurate model which I not able to employed due computational resources.
- Data is imbalanced in nature but due to computational limitation we have not employed balancing techniques here.
- Deep learning CNN, ANN can be employed to create more accurate model.