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CHENNAI

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TITLE

Twitter Hate Speech and Offensive Language Detection

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Date:

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ACKNOWLEDGMENT

Primarily, we would like to thank the almighty for all the blessings he showered over us to complete this project without any flaws. The success and final outcome of this assignment required a lot of guidance and assistance from many people, and we are extremely fortunate to have gotthis all along with the completion of our project. Whatever we have doneis only due to such guidance and assistance from our faculty, Dr. Priyadarshini, to whom we are thankful for giving us an opportunity to do this project. Last but not least, we are grateful to all our fellow classmatesand our friends for the suggestions and support given to us throughout the completion of our project.

ABSTRACT

In this project, we aim to develop a hate speech detector to classify tweets on social media platform Twitter. The spread of hate speech online has become a major concern in recent years, and social media platforms such as Twitter have been identified as a major arena for the spread of such harmful content. The use of paralinguistic signals and poorly written text in social media posts makes the task of detecting hate speech more difficult. The proposed hate speech detector will be implemented using the Python programming language and will be trained to identify and classify tweets as hate speech or not. The goal of this project is to contribute to the efforts to combat the spread of hate speech online and help create a safer and more inclusive environment on social media platforms

INTRODUCTION

This project is focused on addressing the pressing issue of toxic and abusive language on social media, specifically on the widely used platform, Twitter. With a user base of over 372 million individuals worldwide, Twitter has become a significant arena for the spread of hate speech and offensive language. As the dependence on technology for communication continues to increase, the use of social media platforms such as Twitter is at an all-time high. However, the exponential growth in usage has also brought about a rise in the spread of toxic and abusive language. This not only harms individuals who become victims of such language but also disrupts the harmony of any community.

The aim of this project is to develop a robust method to classify tweets as toxic or non-toxic, using advanced techniques in natural language processing and machine learning. By providing a tool that can automatically identify and flag toxic language, this project aims to make social media a safer and more inclusive space for all users. The ultimate goal is to create a positive impact on society by reducing the spread of hate speech and offensive language on the internet.

ABOUT THE DATASET

For our project, we have used two datasets. They are:

- 1) Hate Speech and Offensive Language Dataset
- 2) Twitter Sentiment Analysis

Here's some brief information of the datasets:

Hate Speech and Offensive Language Dataset:

This dataset is based on tweets circulated among an organization named CrowdFlower where the tweets were tweeted by the employees belonging to that organization.

Here are the features of the dataset:

Index - Index

Count - Number of CrowdFlower (CF) employees who tweeted each tweet.

Hate_speech - Number of CF employees who judged a tweet to be hate speech.

Offensive_language - Number of CF employees who judged a tweet to be offensive.

Neither - Number of CF employees who judged a tweet to be neither offensive nor non-offensive

Class - Class label for majority of CF employees. 0 corresponds to hate speech, 1 corresponds to offensive language and 2 corresponds to neither.

Text Tweet – The text content of a tweet

Dataset Link: https://www.kaggle.com/datasets/mrmorj/hate-speech-and-offensive-language-dataset

Twitter Sentiment Analysis:

This dataset is regarding a set of tweets and their class labels whether they are racist/sexual or not.

Here are the features of the dataset:

Id – Id assigned to the tweet

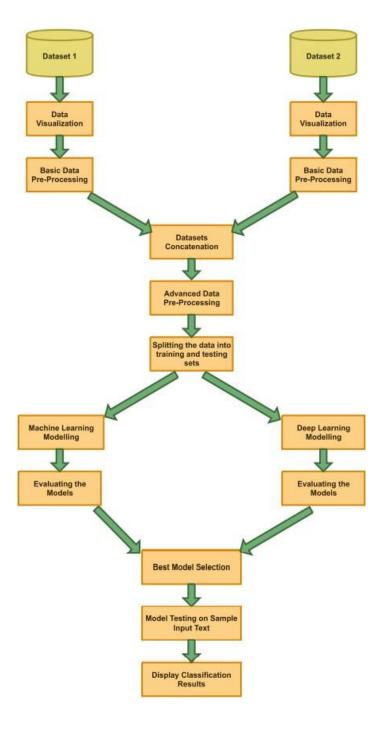
Label – Class label for the tweet

Tweet – The text content of the tweet

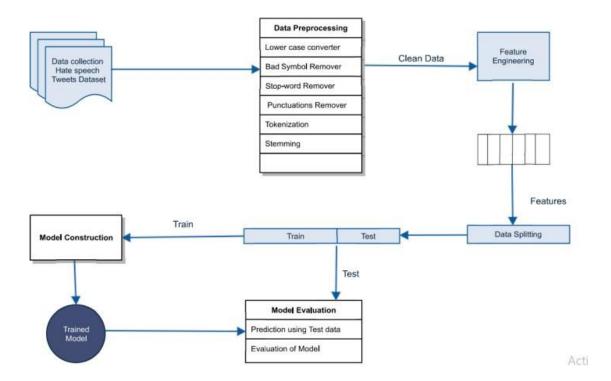
Dataset Link: https://www.kaggle.com/datasets/arkhoshghalb/twitter-sentiment-analysis-hatred-speech

DIAGRAMS CONCERNING THE PROJECT

Block Diagram:



Class Diagram:



WORKFLOW OF THE PROJECT

We take two different types of datasets and perform basic data visualization concerning the output labels and then concatenate them using basic data preprocessing techniques.

With the merged dataset in hand, we then perform advanced data preprocessing techniques in order to extract features from text i.e., splitting each and every word present in the text by removing certain unnecessary characters. We further use libraries like CountVectorizer and TfidfTransformer to enhance this process.

We then move to the modeling phase where we use machine learning models like Naïve Bayes and XG Boost on the data transformed by CountVectorizer and TfidfTransformer and compare the results of the models.

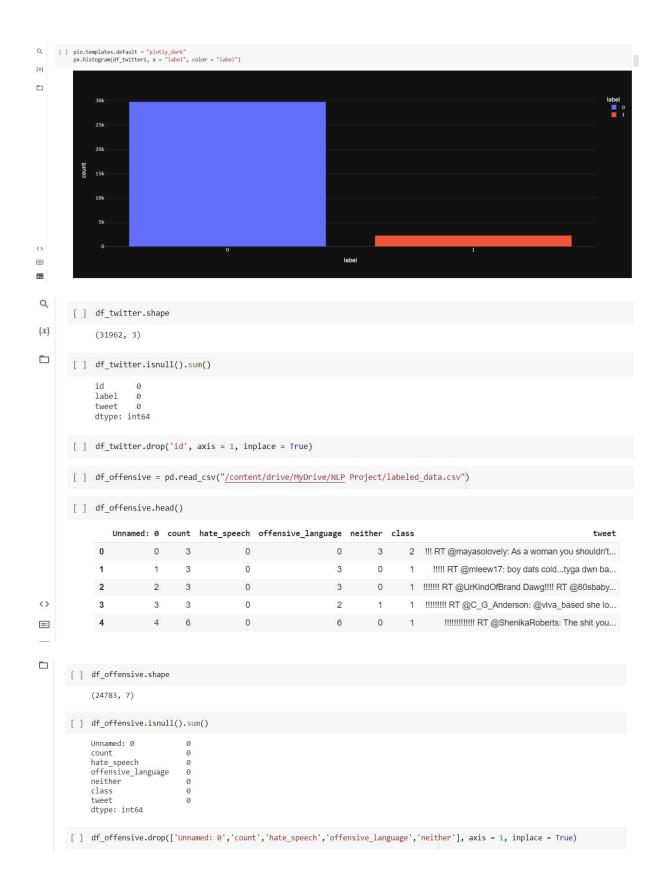
We then move on to the deep learning modeling phase where we use a LSTM model. In order to use the model, we first use a tokenizer that converts texts to sequences on the base training data as well as on the base testing data. We then run the model and then check the metrics of the model like accuracy score, confusion matrix etc.

On comparing the confusion matrices of the machine and deep learning models, we can come to know that the deep learning model performs well. So, we plan to save the model and use it for further testing purposes.

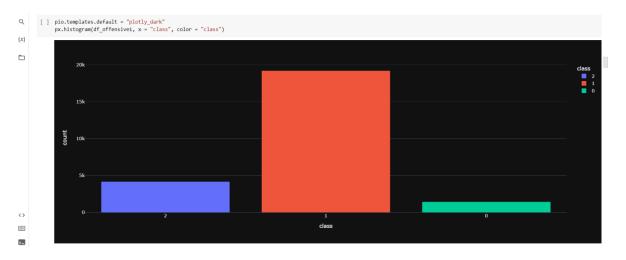
We then run the model with three separate test instances in order to classify whether they belong to the hate and offensive category ornot.

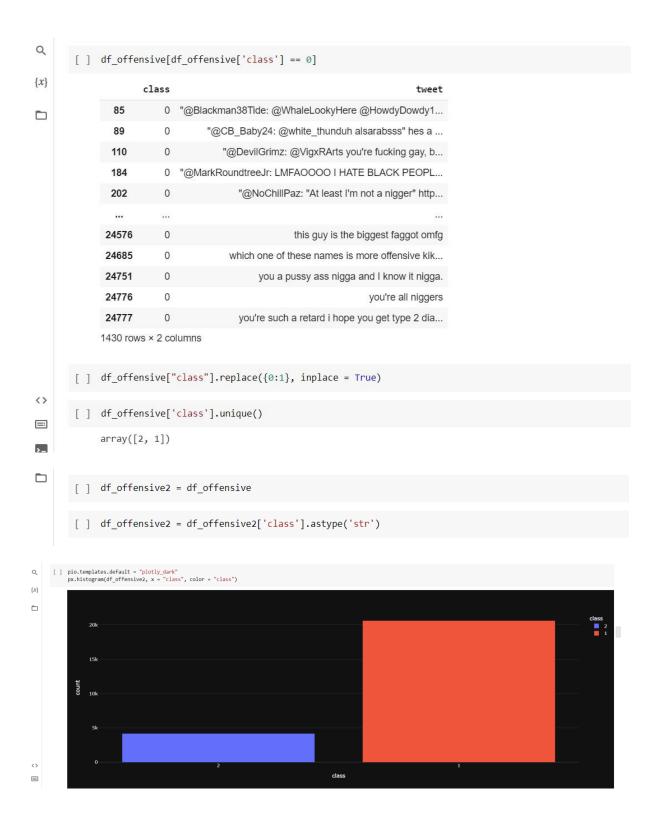
CODE SCREENSHOTS

```
[ ] # Importing Required Libraries
Q
       [ ] import numpy as np
{x}
            import pandas as pd
            import seaborn as sns
import re
            import nltk
            from nltk.corpus import stopwords
            import string
            from wordcloud import WordCloud, STOPWORDS
            import matplotlib.pyplot as plt
            from sklearn.model_selection import train_test_split
            from sklearn.feature_extraction.text import CountVectorizer
            from sklearn.feature_extraction.text import TfidfTransformer
            from sklearn.naive_bayes import MultinomialNB
            from sklearn.metrics import classification report
            from sklearn.metrics import confusion_matrix
            import xgboost as xgb
            from keras.models import Model
            from keras.layers import LSTM, Activation, Dense, Dropout, Input, Embedding, SpatialDropout1D
             from tensorflow.keras.optimizers import RMSprop
            from keras.preprocessing.text import Tokenizer
            from keras.preprocessing import sequence
            from tensorflow.keras.utils import to_categorical
            from keras.callbacks import EarlyStopping
             from keras.models import Sequential
            from keras.callbacks import EarlyStopping,ModelCheckpoint
<>
            import keras
=:
            import plotly.express as px
             import plotly.io as pio
>_
            import pickle
       [ ] # Reading the first dataset
\{x\}
       [ ] df_twitter = pd.read_csv("/content/drive/MyDrive/NLP Project/train.csv")
[ ] df_twitter.head()
                id label
                                                             tweet
                       0 @user when a father is dysfunctional and is s...
                        0 @user @user thanks for #lyft credit i can't us...
                                                 bihday your majesty
                4
                        0
                              #model i love u take with u all the time in ...
                       0
                                    factsguide: society now #motivation
       [ ] df_twitter1 = df_twitter
       [ ] df_twitter1 = df_twitter1["label"].astype('str')
```



```
[ ] df_offensive.head(10)
Q
                  class
                                                                   tweet
{x}
              0
                      2 !!! RT @mayasolovely: As a woman you shouldn't...
                            !!!!! RT @mleew17: boy dats cold...tyga dwn ba...
              1
!!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...
              2
              3
                          !!!!!!!!! RT @C_G_Anderson: @viva_based she lo...
                               !!!!!!!!!!! RT @ShenikaRoberts: The shit you...
                                 !!!!!!!!!!!"@T_Madison_x: The shit just...
              5
                               !!!!!!"@__BrighterDays: I can not just sit up ...
              6
              7
                             !!!!"@selfiequeenbri: cause I'm tired of...
              8
                            " & you might not get ya bitch back & ...
                            " @rhythmixx_ :hobbies include: fighting Maria...
        [ ] df_offensive['class'].unique()
             array([2, 1, 0])
        [ ] df_offensive1 = df_offensive
<>
        [ ] df_offensive1 = df_offensive1['class'].astype('str')
==:
```





```
[ ] df_offensive[df_offensive['class'] == 0]
                      class tweet
           [ ] df_offensive["class"].replace({2:0}, inplace = True)
           [ ] df_offensive3 = df_offensive
           [ ] df_offensive3 = df_offensive3['class'].astype('str')
Q
     [ ] pio.templates.default = "plotly_dark"
px.histogram(df_offensive3, x = "class", color = "class")
\{x\}
15k
\equiv
>_
      [ ] df_offensive.rename(columns = {'class':'label'}, inplace = True)
{x}
[ ] df_offensive.head()
              label
            0 0 !!! RT @mayasolovely: As a woman you shouldn't...
                  1 !!!!! RT @mleew17: boy dats cold...tyga dwn ba...
           2 1 !!!!!!! RT @UrKindOfBrand Dawg!!!! RT @80sbaby...
                  1 !!!!!!!!! RT @C_G_Anderson: @viva_based she lo...
            4 1 !!!!!!!!!!! RT @ShenikaRoberts: The shit you...
      [ ] df_offensive.iloc[0]['tweet']
           '!!! RT @mayasolovely: As a woman you shouldn't complain about cleaning up your house. & as a man you should always take the trash out...'
      [ ] df_offensive.iloc[5]['tweet']
           "!!!!!!!!!!!!!"@T_Madison_x: The shit just blows me..claim you so faithful and down for somebody but still fucking with hoes! 😂😂😂
      [ ] frame = [df_twitter,df_offensive]
df = pd.concat(frame)
```

```
[ ] df.head()
                    label
                                                                    tweet
                0
                         0 @user when a father is dysfunctional and is s...
                             @user @user thanks for #lyft credit i can't us...
                1
                         0
                2
                         0
                                                      bihday your majesty
                3
                         0
                                #model i love u take with u all the time in ...
                         0
                                        factsguide: society now #motivation
          [ ] df1 = df
          [ ] df1 = df1['label'].astype('str')
    [ ] pio.templates.default = "plotly_dark"
    px.histogram(df1, x = "label", color = "label")
30k
             25k
             15k
             10k
<>
\equiv
>--
 Q
         [ ] df.shape
               (56745, 2)
\{x\}
         [ ] nltk.download('stopwords')
    stemmer = nltk.SnowballStemmer("english")
 stopword = set(stopwords.words('english'))
               [nltk_data] Downloading package stopwords to /root/nltk_data...
               [nltk_data] Package stopwords is already up-to-date!
         [ ] def make_wordcloud(df):
                    comment_words="
                    for val in df.tweet:
                        val = str(val).lower()
comment_words += " ".join(val)+" "
                    print(comment_words[0:100])
                    wordcloud = WordCloud(width = 800, height = 800,
                                  background_color ='white',
                                  stopwords = stopwords,min_font_size = 10).generate(comment_words)
                    plt.figure(figsize = (8, 8), facecolor = None)
                    plt.imshow(wordcloud)
                    plt.axis("off")
                    plt.tight_layout(pad = 0)
                    plt.show()
 <>
```

```
\{x\}
        [ ] def clean_text(text):
                  text = str(text).lower()
                  text = re.sub('\[.*?\]', '', text)
text = re.sub('https?://\S+|www\.\S+', '', text)
                  text = re.sub('<.*?>+', '', text)
                  text = re.sub('[%s]' % re.escape(string.punctuation), '', text)
text = re.sub('\n', '', text)
                  text = re.sub('\w*\d\w*', '', text)
                  text = [word for word in text.split(' ') if word not in stopword]
                  text = " ".join(text)
                  text = [stemmer.stem(word) for word in text.split(' ')]
text = " ".join(text)
                  return text
        [ ] df['tweet'] = df['tweet'].apply(clean_text)
        [ ] df.head()
                  label
                                                                       tweet
                       0
               0
                                  user father dysfunct selfish drag kid dysfunc...
                       0
                                 user user thank lyft credit cant use caus dont...
()
               2
                      0
                                                               bihday majesti
\equiv
                       0 model love u take u time ur\delta \Box \Box \pm \delta \Box \Box \Box \delta \Box \Box \Box \delta \Box \Box \Box ...
>_
                                                        factsguid societi motiv
        [ ] x = df['tweet']
{x}
             y = df['label']
[ ] x_train, x_test, y_train, y_test = train_test_split(x, y, random_state = 42)
             print(len(x_train), len(y_train))
             print(len(x_test), len(y_test))
             42558 42558
             14187 14187
        [ ] count = CountVectorizer(stop_words = 'english', ngram_range = (1,5))
             x_train_vectorizer = count.fit_transform(x_train)
        [ ] x_test_vectorizer = count.transform(x_test)
```

```
\{x\}
        [ ] count.vocabulary_
'got hoe': 264878,
              'boy ryanbowersob got': 87737,
              'ryanbowersob got hoe': 573407,
              'boy ryanbowersob got hoe': 87738,
              'hate': 286834,
              'aliv': 11793,
'hater': 288324,
              'orlandounit': 480071,
              'hate aliv': 286847,
              'aliv hater': 11819,
              'hater orlandounit': 288353,
              'hate aliv hater': 286848,
              'aliv hater orlandounit': 11820,
              'hate aliv hater orlandounit': 286849,
              'book': 83638,
'endur': 192647,
              'convict': 131799,
              'fred': 231715,
              'korematsu': 359709,
              'amp': 17807,
'quest': 523179,
'justic': 348074,
              'humanright': 313763,
              'htâ': 312750,
<>
              'book endur': 83763,
              'endur convict': 192648,
              'convict fred': 131800,
==
              'fred korematsu': 231716,
              'korematsu amp': 359710,
        [ ] tfidf = TfidfTransformer()
{x}
            x_train_tfidf = tfidf.fit_transform(x_train_vectorizer)
            x_test_tfidf = tfidf.transform(x_test_vectorizer)
[ ] model_vectorizer = MultinomialNB().fit(x_train_vectorizer, y_train)
            prediction_vectorizer = model_vectorizer.predict(x_test_vectorizer)
            print(confusion_matrix(y_test,prediction_vectorizer))
            print(classification_report(y_test, prediction_vectorizer))
            [[7878 575]
              [ 458 5276]]
                           precision
                                         recall f1-score support
                                0.95
                                           0.93
                                                      0.94
                                                                8453
                                0.90
                                           0.92
                                                      0.91
                                                                5734
                        1
                 accuracy
                                                      0.93
                                                               14187
               macro avg
                                0.92
                                           0.93
                                                      0.92
                                                               14187
            weighted avg
                                0.93
                                           0.93
                                                      0.93
                                                               14187
```

```
[ ] model_tfidf = MultinomialNB().fit(x_train_tfidf, y_train)
{x}
            prediction tfidf = model tfidf.predict(x test tfidf)
            print(confusion_matrix(y_test,prediction_tfidf))
print(classification_report(y_test, prediction_tfidf))
            [[8213 240]
             [ 860 4874]]
                          precision
                                       recall f1-score
                                                           support
                               0.91
                                          0.97
                                                    0.94
                                                              8453
                       0
                               0.95
                                          0.85
                                                    0.90
                                                              5734
                                                    0.92
                                                             14187
                accuracy
                               0.93
                                          0.91
               macro avg
                                                    0.92
                                                             14187
                               0.92
                                          0.92
                                                    0.92
                                                             14187
            weighted avg
       [ ] import xgboost as xgb
            xgb_model = xgb.XGBClassifier(
                    learning_rate = 0.1,
                    max_depth = 7,
                    n_estimators = 80,
                    use_label_encoder = False,
                    eval metric = 'auc' )
Q
       [ ] xgb_model_vectorizer = xgb_model.fit(x_train_vectorizer, y_train)
            xgb_predictions_vectorizer = xgb_model_vectorizer.predict(x_test_vectorizer)
{x}
            print(confusion_matrix(y_test,xgb_predictions_vectorizer))
            print(classification_report(y_test, xgb_predictions_vectorizer))
[[8367
             [ 923 4811]]
                          precision
                                       recall f1-score
                                                          support
                               0.90
                                         0.99
                                                   0.94
                                                             8453
                       0
                       1
                               0.98
                                         0.84
                                                   0.91
                                                             5734
                accuracy
                                                   0.93
                                                            14187
                                         0.91
               macro avg
                               0.94
                                                   0.92
                                                            14187
            weighted avg
                               0.93
                                         0.93
                                                   0.93
                                                            14187
       [ ] xgb_model = xgb_model.fit(x_train_tfidf, y_train)
            xgb_predictions = xgb_model.predict(x_test_tfidf)
            print(confusion_matrix(y_test,xgb_predictions))
            print(classification_report(y_test, xgb_predictions))
            [[8358
                    95]
             [ 939 4795]]
                          precision
                                       recall f1-score
                                                          support
                               0.90
                                         0.99
                                                   0.94
                                                             8453
<>
                               0.98
                                         0.84
                                                   0.90
                                                             5734
                       1
\equiv
                                                   0.93
                                                            14187
                accuracy
               macro avg
                               0.94
                                         0.91
                                                   0.92
                                                            14187
>_
            weighted avg
                               0.93
                                         0.93
                                                   0.93
                                                            14187
```

```
[ ] max_words = 50000
Q
       max_len = 300
       tokenizer = Tokenizer(num_words=max_words)
       tokenizer.fit_on_texts(x_train)
\{x\}
        sequences = tokenizer.texts_to_sequences(x_train)
       sequences_matrix = sequence.pad_sequences(sequences,maxlen = max_len)
[ ] model = Sequential()
       model.add(Embedding(max words, 100, input length = max len))
       model.add(SpatialDropout1D(0.2))
       model.add(LSTM(100, dropout = 0.2, recurrent_dropout = 0.2))
model.add(Dense(1, activation = 'sigmoid'))
       model.summary()
       model.compile(loss = 'binary crossentropy', optimizer = RMSprop(), metrics = ['accuracy'])
       WARNING:tensorflow:Layer lstm will not use cuDNN kernels since it doesn't meet the criteria. It will use a generic GPU kernel as fallback when running on GPU. Model: "sequential"
       Layer (type)
                          Output Shape
                                          Param #
        embedding (Embedding)
                          (None, 300, 100)
                                           5000000
        spatial_dropout1d (SpatialD (None, 300, 100)
        ropout1D)
        1stm (LSTM)
                          (None, 100)
                                          80400
        dense (Dense)
                          (None, 1)
                                           101
<>
Total params: 5,080,501
       Trainable params: 5,080,501
>_
       Non-trainable params: 0
       [ ] stop = EarlyStopping(
               monitor = 'val_accuracy',
               mode = 'max',
                patience = 5
            checkpoint = ModelCheckpoint(
               filepath ='./',
                save weights only = True,
               monitor ='val accuracy',
               mode ='max',
                save_best_only = True)
[ ] history = model.fit(sequences_matrix, y_train, batch_size = 1024, epochs = 15,
                validation_split = 0.2, callbacks=[stop,checkpoint])
         Epoch 1/15
                     34/34 [====
         Epoch 2/15
         Epoch 3/15
                          :========] - 45s 1s/step - loss: 0.1471 - accuracy: 0.9488 - val_loss: 0.1643 - val_accuracy: 0.9409
         34/34 [====
         Fnoch 4/15
         34/34 [====
                         ========] - 44s 1s/step - loss: 0.1110 - accuracy: 0.9620 - val_loss: 0.1657 - val_accuracy: 0.9394
         Epoch 5/15
                     34/34 [=====
         Epoch 6/15
         34/34 [====
                          Epoch 7/15
                     34/34 [=====
         Epoch 8/15
                  34/34 [====
         Epoch 9/15
         34/34 [===
                         Epoch 10/15
         34/34 [====================] - 45s 1s/step - loss: 0.0457 - accuracy: 0.9850 - val_loss: 0.1996 - val_accuracy: 0.9326
```

```
Q
        [ ] test_sequences = tokenizer.texts_to_sequences(x_test)
              test_sequences_matrix = sequence.pad_sequences(test_sequences, maxlen = max_len)
\{x\}
        [ ] accr = model.evaluate(test_sequences_matrix, y_test)
444/444 [============ ] - 37s 82ms/step - loss: 0.2226 - accuracy: 0.9281
        [ ] lstm_prediction = model.predict(test_sequences_matrix)
        [ ] res = []
              for prediction in lstm_prediction:
                   if prediction[0] < 0.5:
                        res.append(0)
                   else:
                        res.append(1)
        [ ] print(confusion_matrix(y_test, res))
              [[7871 582]
                [ 438 5296]]
        [ ] with open('tokenizer.pickle', 'wb') as handle:
                   pickle.dump(tokenizer, handle, protocol = pickle.HIGHEST_PROTOCOL)
<>
\equiv
        [ ] model.save("hate&abusive model.h5")
    [ ] load_model = keras.models.load_model("./hate&abusive_model.h5") with open('tokenizer.pickle', 'rb') as handle:
        with open('tokenizer.pickle', 'rb') as ha
load_tokenizer = pickle.load(handle)
        WARNING:tensorflow:Layer lstm will not use cuDNN kernels since it doesn't meet the criteria. It will use a generic GPU kernel as fallback when running on GPU.
        [ ] test = 'I love NLP!!!'
Q
              def clean_text(text):
                  print(text)
\{x\}
                  text = str(text).lower()
                  text = re.sub('\[.*?\]', '', text)
text = re.sub('https?://\S+|www\.\S+', '', text)
text = re.sub('<.*?>+', '', text)
                  text = re.sub('[%s]' % re.escape(string.punctuation), '', text)
text = re.sub('\n', '', text)
text = re.sub('\w*\d\w*', '', text)
                  print(text)
                  text = [word for word in text.split(' ') if word not in stopword]
text=" ".join(text)
                  text = [stemmer.stem(word) for word in text.split(' ')]
                  text=" ".join(text)
                  return text
              test = [clean_text(test)]
              seq = load tokenizer.texts to sequences(test)
              padded = sequence.pad_sequences(seq, maxlen=300)
              pred = load_model.predict(padded)
              print("pred", pred)
              if pred < 0.5:
                  print("no hate")
              else:
                  print("hate and offensive")
              T love NIPIII
<>
              i love nlp
              pred [[0.19120216]]
\equiv
              no hate
```

```
Q
       [ ] test1 = 'I hate you'
            def clean_text(text):
                 print(text)
\{x\}
                 text = str(text).lower()
                 text = re.sub('\[.*?\]', '', text)
text = re.sub('https?://\S+|www\.\S+', '', text)
                 text = re.sub('<.*?>+', '', text)
                 text = re.sub('\w*\d\w*', '', text)
                 print(text)
                 text = [word for word in text.split(' ') if word not in stopword]
text=" ".join(text)
                 text = [stemmer.stem(word) for word in text.split(' ')]
                 text=" ".join(text)
                return text
            test1 = [clean_text(test1)]
             seq = load_tokenizer.texts_to_sequences(test1)
            padded = sequence.pad_sequences(seq, maxlen=300)
            pred = load_model.predict(padded)
            print("pred", pred)
             if pred < 0.5:
                print("no hate")
             else:
                 print("hate and offensive")
            I hate you
<>
            i hate you
            pred [[0.6952494]]
==
            hate and offensive
Q
       [ ] test2 = 'You are a bloody bitch!!!'
            def clean_text(text):
{x}
                print(text)
                text = str(text).lower()
                text = re.sub('\[.*?\]', '', text)
text = re.sub('https?://\S+|www\.\S+', '', text)
                text = re.sub('<.*?>+', '', text)
                text = re.sub('[%s]' % re.escape(string.punctuation), '', text)
text = re.sub('\n', '', text)
text = re.sub('\w*\d\w*', '', text)
                print(text)
                text = [word for word in text.split(' ') if word not in stopword]
text=" ".join(text)
                text = [stemmer.stem(word) for word in text.split(' ')]
                text=" ".join(text)
                return text
            test2 = [clean_text(test2)]
            seq = load_tokenizer.texts_to_sequences(test2)
            padded = sequence.pad_sequences(seq, maxlen=300)
            pred = load_model.predict(padded)
            print("pred", pred)
            if pred < 0.5:
                print("no hate")
            else:
                print("hate and abusive")
<>
            You are a bloody bitch!!!
            you are a bloody bitch
            pred [[0.99358785]]
=:
            hate and abusive
>_
```

```
[ ] test3 = 'I hate people who are dumb'
\{x\}
            def clean_text(text):
                print(text)
                text = str(text).lower()
text = re.sub('\[.*?\]', '', text)
                text = re.sub('https?://\S+|www\.\S+', '', text)
                text = re.sub('<.*?>+', '', text)
                text = re.sub('[%s]' % re.escape(string.punctuation), '', text)
text = re.sub('\n', '', text)
                text = re.sub('\w*\d\w*', '', text)
                print(text)
                text = [word for word in text.split(' ') if word not in stopword]
                text=" ".join(text)
                text = [stemmer.stem(word) for word in text.split(' ')]
                text=" ".join(text)
                return text
            test3 = [clean_text(test3)]
             seq = load_tokenizer.texts_to_sequences(test3)
             padded = sequence.pad_sequences(seq, maxlen=300)
             pred = load_model.predict(padded)
             print("pred", pred)
             if pred < 0.5:
                print("no hate")
             else:
                print("hate and abusive")
<>
            I hate people who are dumb
==
            i hate people who are dumb
            pred [[0.9158933]]
>_
            hate and abusive
```

RESULTS AND CONCLUSION

After the modeling phase in our project, we implemented four test cases where the selected best model evaluated every case accurately. So, the model can be associated even with the real time use cases.

Here are the test cases and the predictions:

```
[ ] test = 'I love NLP!!!'
Q
              def clean_text(text):
                  print(text)
{x}
                  text = str(text).lower()
                  text = re.sub('\[.*?\]', '', text)
text = re.sub('https?://\S+|www\.\S+', '', text)
text = re.sub('<.*?>+', '', text)
                  text = re.sub('[%s]' % re.escape(string.punctuation), '', text)
text = re.sub('\n', '', text)
text = re.sub('\w*\d\w*', '', text)
                  print(text)
                  text = [word for word in text.split(' ') if word not in stopword]
                  text=" ".join(text)
                  text = [stemmer.stem(word) for word in text.split(' ')]
                  text=" ".join(text)
                  return text
              test = [clean text(test)]
              seq = load_tokenizer.texts_to_sequences(test)
              padded = sequence.pad_sequences(seq, maxlen=300)
              pred = load_model.predict(padded)
              print("pred", pred)
              if pred < 0.5:
                  print("no hate")
                  print("hate and offensive")
             I love NLP!!!
<>
              pred [[0.19120216]]
=
              no hate
```

```
Q
       [ ] test1 = 'I hate you'
            def clean_text(text):
                 print(text)
\{x\}
                 text = str(text).lower()
                 text = re.sub('\[.*?\]', '', text)
text = re.sub('https?://\S+|www\.\S+', '', text)
                 text = re.sub('<.*?>+', '', text)
                 text = re.sub('\w*\d\w*', '', text)
                 print(text)
                 text = [word for word in text.split(' ') if word not in stopword]
text=" ".join(text)
                 text = [stemmer.stem(word) for word in text.split(' ')]
                 text=" ".join(text)
                return text
            test1 = [clean_text(test1)]
             seq = load_tokenizer.texts_to_sequences(test1)
            padded = sequence.pad_sequences(seq, maxlen=300)
            pred = load_model.predict(padded)
            print("pred", pred)
             if pred < 0.5:
                print("no hate")
             else:
                 print("hate and offensive")
            I hate you
<>
            i hate you
            pred [[0.6952494]]
==
            hate and offensive
Q
       [ ] test2 = 'You are a bloody bitch!!!'
            def clean_text(text):
{x}
                print(text)
                text = str(text).lower()
                text = re.sub('\[.*?\]', '', text)
text = re.sub('https?://\S+|www\.\S+', '', text)
                text = re.sub('<.*?>+', '', text)
                text = re.sub('[%s]' % re.escape(string.punctuation), '', text)
text = re.sub('\n', '', text)
text = re.sub('\w*\d\w*', '', text)
                print(text)
                text = [word for word in text.split(' ') if word not in stopword]
text=" ".join(text)
                text = [stemmer.stem(word) for word in text.split(' ')]
                text=" ".join(text)
                return text
            test2 = [clean_text(test2)]
            seq = load_tokenizer.texts_to_sequences(test2)
            padded = sequence.pad_sequences(seq, maxlen=300)
            pred = load_model.predict(padded)
            print("pred", pred)
            if pred < 0.5:
                print("no hate")
            else:
                print("hate and abusive")
<>
            You are a bloody bitch!!!
            you are a bloody bitch
            pred [[0.99358785]]
=:
            hate and abusive
>_
```

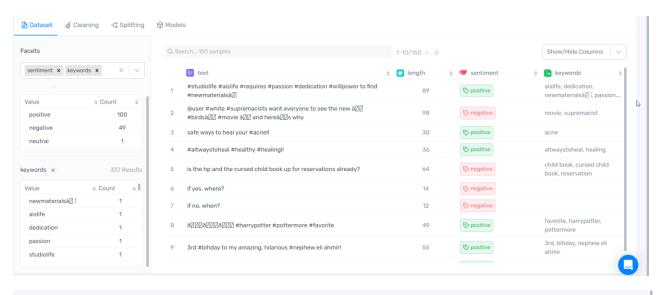
```
[ ] test3 = 'I hate people who are dumb'
{x}
            def clean text(text):
                print(text)
                text = str(text).lower()
text = re.sub('\[.*?\]', '', text)
                text = re.sub('https?://\S+|www\.\S+', '', text)
                text = re.sub('<.*?>+', '', text)
                text = re.sub('[%s]' % re.escape(string.punctuation), '', text)
                text = re.sub('\n', '', text)
                text = re.sub('\w*\d\w*', '', text)
                print(text)
                text = [word for word in text.split(' ') if word not in stopword]
                text=" ".join(text)
                text = [stemmer.stem(word) for word in text.split(' ')]
                text=" ".join(text)
                return text
            test3 = [clean_text(test3)]
            seq = load_tokenizer.texts_to_sequences(test3)
            padded = sequence.pad_sequences(seq, maxlen=300)
            pred = load_model.predict(padded)
            print("pred", pred)
            if pred < 0.5:
               print("no hate")
                print("hate and abusive")
<>
            I hate people who are dumb
==:
            i hate people who are dumb
            pred [[0.9158933]]
>_
            hate and abusive
```

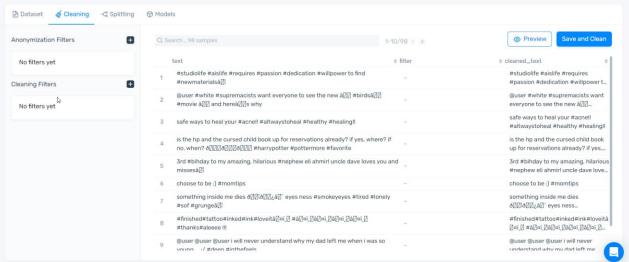
So, we conclude our project by creating a **Hate and Offensive Tweets Classifier** which can be relied on for classifying tweets in real time.

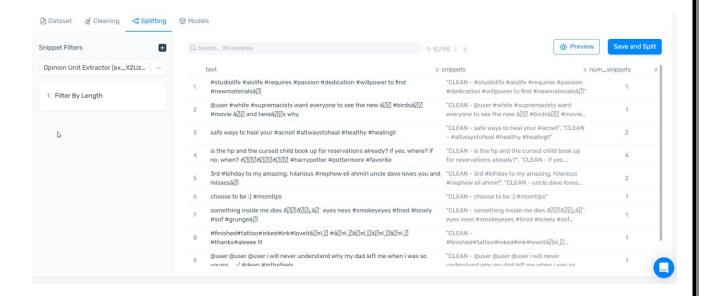
Analytics using Social media tool

Tool used: Monkey Learn

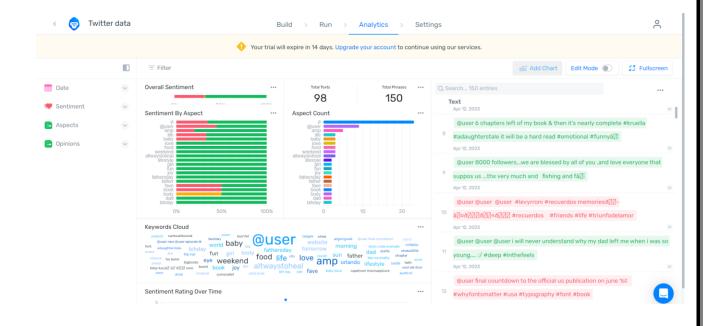
[Dataset, Cleaning, Splitting]







Analytics



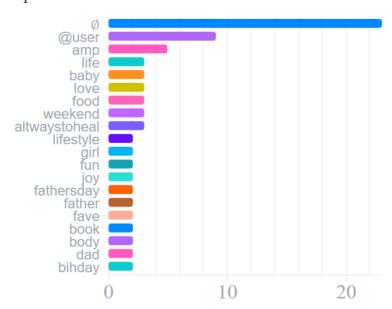
Overall Sentiment



Sentiment by Aspect



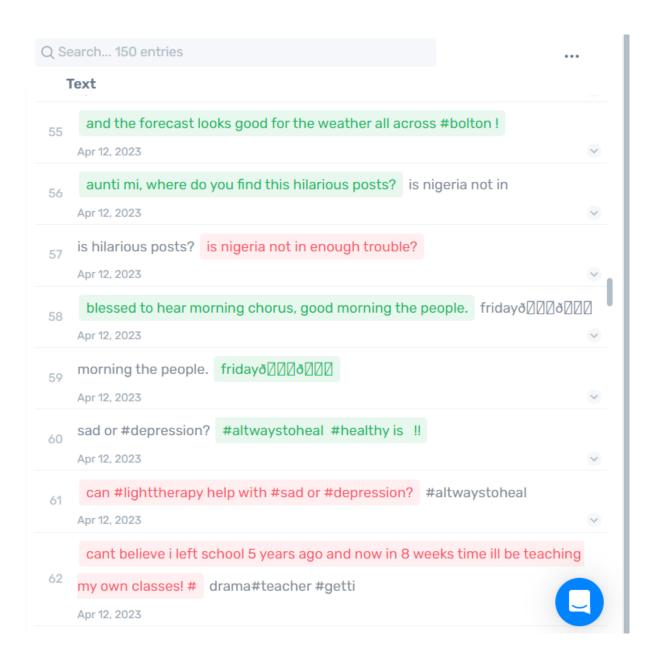
Aspect Count

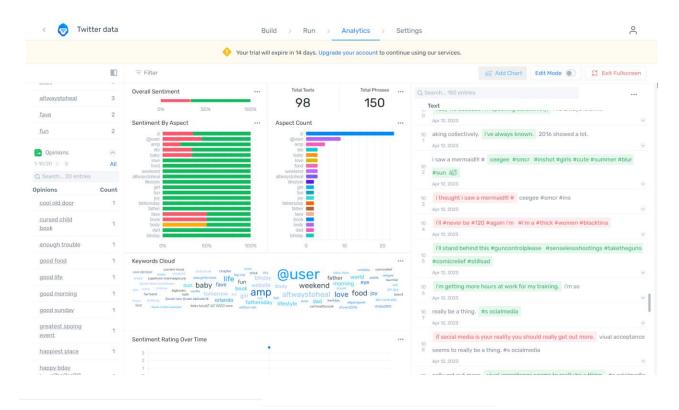


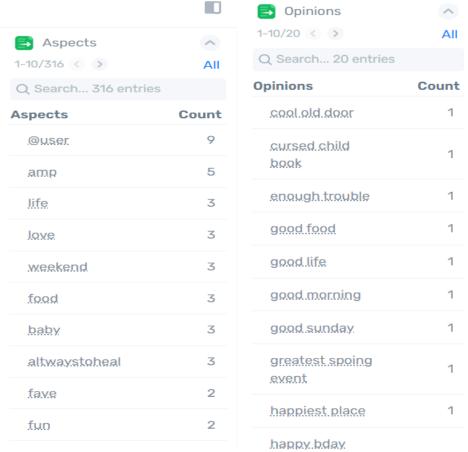


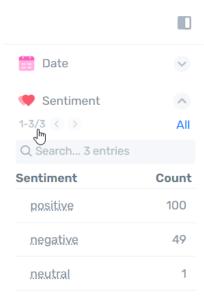
Sentiment Rating over time











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