Emotion Detection From Tweet

Mid Term Project Review

Kapuriya Janak (MT22032)
Kirtirajsinh Mahida (MT22104)
Mansi Patel (MT22109)
Tanay (2020140)
Vijay (2020582)
Abhisek (2020014)

➢ Updated Problem Formulation

Social media platforms will feed similar exciting posts, such as Instagram suggest reels, YouTube recommends videos, and Twitter refers to all tweets that belong to a person’s past tweets and interests. But sometimes recommendation system fails to recommend appropriate tweets. An AI system cannot understand the feeling behind a person's tweet as a human can. So, we aim to build an algorithm that can detect various emotions from tweets. Our project is Engineering based project.

➢ Literature Review

[1] In this research paper, the authors have built a model by fine-tuning BERT(BERT Base) model on tweet datasets for both uncased and cased parts. The architecture is 12 encoders with eight layers each (4 multi-head self-attention layers and four multi feed-forward layers). This architecture was used for emotion and sentiment analysis with an extended softmax layer in emotion classifiers(the number of classes and neurons are equal). The data was split in 8:1:1. Undersampling was used to balance the imbalance dataset. Meaningless tweets(had only non-ASCII characters) or concise tweets were removed. In emotion detection, Along with the label, the classification also had the intensity parameter(ranging 0-1) which shows the intensity of the tweet. The model was trained for the epochs ranging from 1 to 6 to avoid overfitting of data. For the uncased BERT, the validation loss increased after only 2 epochs and hence the optimal training was at two epochs. Accuracy and F1 score for uncased BERT: 0.89 and 0.89, respectively, Accuracy for cased BERT was 0.90.

[2] In this research paper, a system called "EmoDet2" was studied. It uses DL architectures to detect emotions and sentiment in an English text and classify it into Happy, sad, angry, and other. The dataset used for the same was public data they collected, and it has five columns: ID, Turn 1, Turn 2, Turn 3, and Label. Further emoji were converted to text, and no stemming and removing stopwords were performed on the data, which means that for the BERT model, no preprocessing was done to the raw data. TweetToLexiconFeatureVectorAttribute was used for feature extraction. EmoDet2 was built by ensembling models like EmoDense, EmoDet-BiLSTM-submodel1, EmoDet-BiLSTM-submodel2 and EmoDet-BERT-BiLSTM (uncased). So, these models alone gave low F1 scores. When a model ensembling them was made without using BERT embeddings, i.e., the baseline model of EmoDet2, it gave the F1-score 0.57, and when the BERT embeddings were used, the system performance was F1-Score 0.75(best performance). Apart from all these, they also used word embedding models with feature vectors extracted from AffectiveTweets. So, the final result showed EmoDet2(F1 score = 0.75) has higher proficiency in detecting emotions in a conversational text and surpasses the F1-score of baseline model performance.

➢ Updated Baseline Results

Previous Baseline Result : f1 score - 88%
Updated Baseline Result : f1 score - 90%

Run summary:

eval/accuracy	0.90415
eval/f1	0.90391
eval/loss	0.79939
eval/precision	0.90406
eval/recall	0.90415
eval/runtime	10.2883
eval/samples_per_second	150.074
eval/steps_per_second	18.759
train/epoch	9.0
train/global_step	6948
train/learning_rate	0.0
train/loss	0.0085
train/total_flos	2854651914532800.0
train/train_loss	0.22395
train/train_runtime	1396.9512

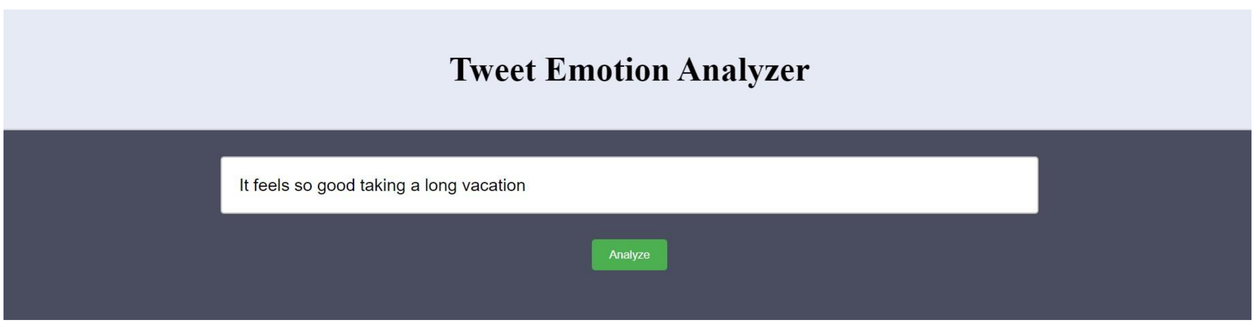
➢ Dataset Details

During model training and test we have used 80:20 split. Where 80% of original was used as trainset and 20% of dataset as test set.

➢ Prototype Result

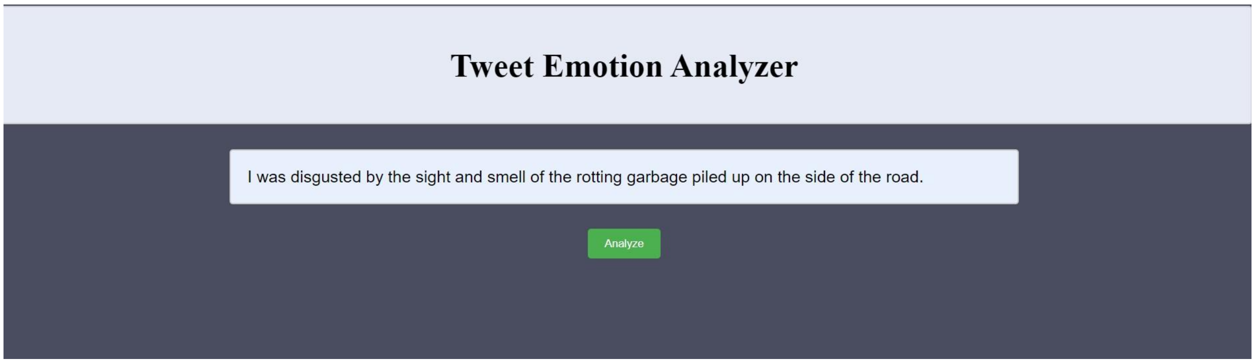
Here we have given two example of out implemented system with UI.

Example 1 (Prompt)



Example 1 (Result)

Example 2 (Prompt)



Example 2 (Result)

➢ Proposed Method

In our implementation we will use semantic features such as POS tags, Named Entity and Dependency pairs of twitter text with original twitter text. This semantic features helps model to learn the semantic meaning of each word in text.

We have implemented POS tag feature with current implementation. We will implement two other semantic feature as part of our final project submission.

We have Use BERT Tokenizer for text to token conversion of our feature which are concatination of original tweet with POS tag sentence . On top of that tokens we applied

BERT base Cased model for classification of tweet text which will give us the one of six emotions which are Happy, Sad, Fear, Disgust, Surprice and Angry.

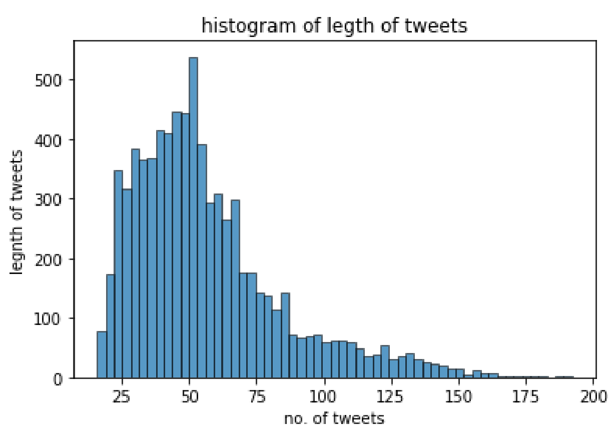
Model was trained on batch size of 8 and run with 9 epochs. Total train loss we observed after training was 0.0085.

After training we have saved the model and during inference we have used saved model for predict emotion of new tweet.

We have deployed model on local host using Flask API.

➢ Features And Data Analysis

We have set sentence length to 150 because as most of tweet fall into range of 10 to 150. For smaller length sentence we have padded them and for sentence with longer than length 150 we have truncated. This will make sure the consistency throughout the training.



Wordcloud for various emotions

A word cloud is a visualization tool that shows the importance of words in a given text. Also, the size of word in the word cloud depends on how frequent that word is in the dataset. In the context of emotion detection word clouds are often used to visualize the most frequent words associated with certain emotions. For our dataset, we created word cloud for each emotion, such as happy, sad, angry, fear, surprised, and disgusted.

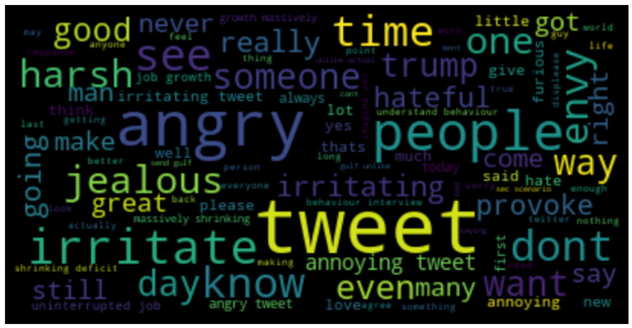
Word Cloud of Emotion Happy

Words associated with happy sentiment are present in this cloud like, thank, love, best, happy, hope, etc.

Word Cloud of Emotion Sad

Words associated with sad sentiment are present in this cloud like, unhappy, depressed, bad, regret, painful, etc.

Word Cloud of Emotion Angry

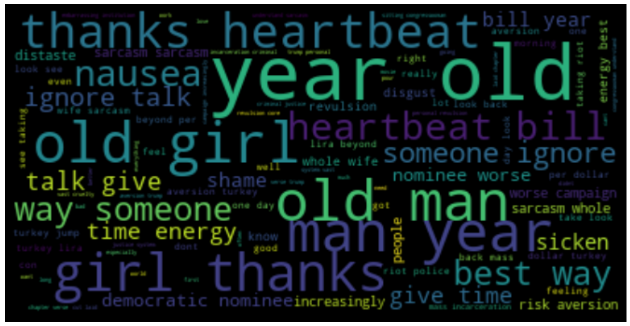


Words associated with angry sentiment are present in this cloud like, irritate, angry, envy and regret, etc.

Word Cloud of Emotion Fear

Words associated with fear sentiment are present in this cloud like, horror, fear, dread, terror, etc.

Word Cloud of Emotion Disgust



Words associated with disgust sentiment are present in this cloud like, old, sicken, ignore, etc.

Word Cloud of Emotion Surprise

Words associated with surprise sentiment are present in this cloud like, shock, gratify, astonish, surprise, etc.

➢ References

[1] Chiorrini, Andrea & Diamantini, Claudia & Mircoli, Alex & Potena, Domenico. (2021). Emotion and sentiment analysis of tweets using BERT.

[2] H. Al-Omari, M. A. Abdullah and S. Shaikh, "EmoDet2: Emotion Detection in English Textual Dialogue using BERT and BiLSTM Models," 2020 11th International Conference on Information and Communication Systems (ICICS), Irbid, Jordan, 2020, pp. 226-232, doi: 10.1109/ICICS49469.2020.239539.fgdfg