Emotion Detection From Tweets

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***Abstract*—Human Emotions are subjective experiences that are often accompanied by physiological and behavioral changes. They can range from positive emotions such as joy, love and happiness to negative emotions such as anger and sadness. In In the 20th century, psychologist Paul Ekman identified six basic types of emotions: happiness, sadness, fear, anger, disgust, and surprise. Every human in this world express their though with this 6 emotions. Nowadays majority of people express their emotion via social media platform. They like to share their feelings as well as they want to know about what's going on all over the world. Social media platform will feed similar interested posts such as Twitter refer all tweets that belongs to person's past tweets and interests. But sometimes recommendation system fails to recommend appropriate tweets. An AI system cannot understand the feeling behind person tweet as a human can.**

I. Motivation

So, our motive is to build an algorithm that can detect various emotions from tweets. We can learn more about how people feel about a certain subject, object, or event by being able to recognise emotions in tweets. The system will learn about people feeling by recognising emotions via tweets. Recent system can be worse sometimes. For example, if someone is sad and he get similar types of posts which will make a person more depress. Similarly, if a person is angry and recommendation system suggest the reason of becoming angrier. help people who might be experiencing mental health issues like depression or anxiety. This might make early assistance and intervention easier.

II. Literature Review

[1] In this paper, dataset was built by hard and weak labels. On this dataset they apply classification model SVM and reach accuracy 0.84 then they use Bidirectional Encoder Representation for Transformers(BERT) for emotion recognition. From different types of BERTs BERTweet model gives more accuracy compared to rest i.e 0.89. Later they ensemble this two models and got the accuracy 0.91 which is highest among all the research till today.

[2] 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.

[3] 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.

[4] In this research paper paper the aim is to predict user's sentiment or attitude through their tweets. The paper classifies various tweets among multiple emottions. The techniques used here are Naive Bayes (NB), Support Vector Machine classifier (SVM), and K Nearest Neighbour (KNN). This can help us to detect the feeling expressed through tweets. This is done by mining the twitter data and then further preprocessing it and training models on it. the it is classified into cheerful, sad, depressing, enthusiastic, impartial, and no information are the six categories. SVM performed better than Naive bayes in terms of precision. 90% accuracy was found in classifying rage emotion

[5] WordNet-Affect and EmoSenticNet was used to find out emotion containing words to be used as features. This was done on 4000 samples(1000 samples from each dataset). The accuracy achieved from random forest was 90% on the anger

class, and using SVM classifier, the accuracy achieved was 89.28%. Logistic regression was used to find the features they needed, and random forest was used as their main classifier.

[6] This research paper describes a rule based approach to detect and classify the emotion of tweets,using k-fold cross validation over 1 million records, giving an accuracy of 85.1%. They include noise elimination, text normalization, tagging and knowledge based preparation to preprocess the text data from social media. Emotion detection system was evaluated based on Precision, Recall and F-measure score obtained. The system consists of four classes of emotions namely:- Happy-Active, Happy-Inactive, Unhappy-Active, and Unhappy-Inactive. This system can be used by healthcare professionals for early detection of psychological disorders such as anxiety or depression

III. Novelty

Emojis are a modern way to express your thought in tweet and nowadays most of people use emojis compare to plain text and use of emojis in tweets is a way to better understand the emotional content of the tweet because emojis can easily describe the whole sentence. For example, certain emojis may be more strongly associated with particular emotions than others and by incorporating this information into the analysis, the accuracy of the emotion detection could be improved.

Pre-trained language model such as BERT have shown promising results in natural language processing tasks. That will provide some extraordinary result to us but for accurate result we need to try all the possible way to fine-tuning so we do a Fine-tuning of this model on a large corpus of tweets that would improve the accuracy of emotion detection.

IV. Methodology

After the literature reviews we analyse that all the researcher either used classification Machine learning model like SVM, Decision tree or they choose NLP model like BERT. Maximum accuracy that will gave by any model is 91% so our main motive was to increase the accuracy of this model. But how? Paper which claims 91% accuracy in that researcher used uses ensemble model which build using various types of BERT (Vanilla BERT, BERTweet) and SVM model. It published in 2022. So now our target was to add some more Semantic features to identify emotion from given tweets. For extracting semantic features from tweets, we will use Part of Speech (POS) tags, Named entity recognition and Dependency Parsing tree techniques. That semantic feature would help model to understand language in a better way.

First step toward any model building is Data Pre-processing. In real world data is not in formal or clean form it's noisy and not suitable for model training so our main task is to clean the data and remove some unnecessary stuff or tokens. And this process known as data cleaning. This step performed operations likes Lower casing the data, removing unwanted columns, removing all the URLs present in the tweet, removing punctuations, removing numbers and emoji's, removing stop words, and finally, applied lemmatization to the tweets that makes data more understandable by extract the meaning from the verbs or adverbs. Pre-processed data have a tweets in form of string but for training a model we need to convert this data into vector form in which every word is a element of a vector and known as a token. "Word2vec" is the library which is used to convert all the string data into vector of words. This method used the context of similar words to make word embedding that will help model to learn semantic of word in the better way. now we have a proper data which can easily feed to the model for training purpose. So we applied this data on various Machine Learning model and mark the accuracy of the all model and result are shown below the table.

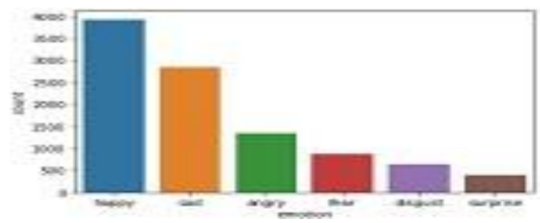
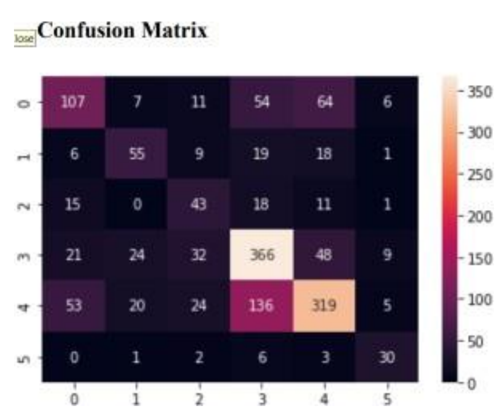


Fig. 1. Example of a figure caption.

So we classify out data with these 4 model and the result that shown in above table is achieved by all these models after result confusion matrices of all models also created which shows the true positive , true negative , false positive and false negative value based on the testing of the data. And that are also mentioned below.

So , after comparing all the results and the metrices we got highest accuracy and F1-score in Decision tree 88% but that is not sufficient and also only classification is not a good approach when we deal with real world data so we need to apply some NLP model that will understand the meaning of a sentence and then perform any classification task. Before training of our data with BERT model data compression task must required because 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. And the images shown below is histogram of the length of tweets.

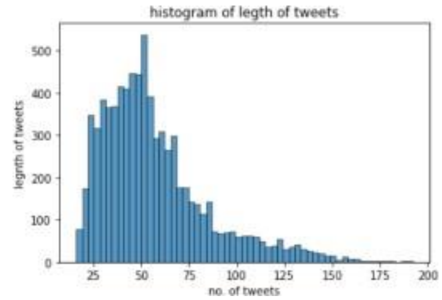


Analysis part is done and now it's time to train our model. We'll employ semantic features like POS tags, Named Entities, Confusion Matrix

and Dependency Pairs of Twitter Text with Original Twitter Text in our solution. This semantic information aids in teaching the model the semantic significance of each word in the text. With the current implementation, we have incorporated the POS tag feature. To complete and submit our project, we will also include two additional semantic features. We use BERT Tokenizer to convert text to tokens for our feature that combine the original tweet with the POS tag sentence. Additionally, we used the BERT case Cased model to classify the text of tweets into one of six emotions: happy, sad, fearful, disgusting, surprised, and angry.

The model was run with 9 epochs and trained on batches of size 8. Following training, we noticed a total train loss of 0.0085. After training, we saved the model, and we utilized the preserved model to predict the sentiment of a new tweet during inference. We used the Flask API to deploy the model

Confusion Matrix



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

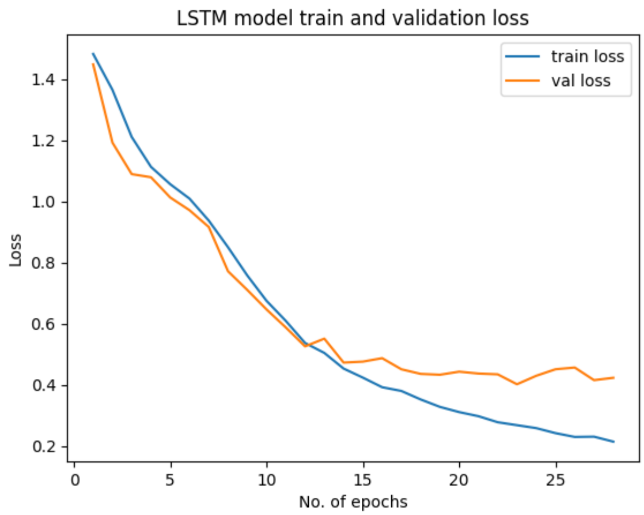
on a local server. By doing this we achieved 90% accuracy which is greater than the previous one and rest of the matrices are shown below which are achieved during the model training mode.

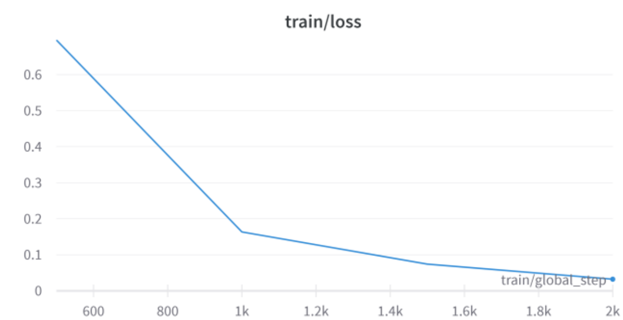
Till now we have not achieved the maximum accuracy that find in [1] so that's not a desirable result for us. Again we analyse the results and some previous work on this problem we found out that.

Bert is transformer based deep learning model which is used for multiclass classification. BERT model learns bidirectional semantics. It read sentence from both side and apply multi-head self-attention on that to learn semantics of sentence. We have fine-tuned BERT based case model on our dataset dataset2. BERT model trained with 8 Epoch and batch size of 64 samples and BERT gave us 0.9326 F1 score on test set which is the highest accuracy among the all models we have tried.

LSTM is variant of recurrent neural network which learn the long-term dependency in the sentence and learn semantic meaning of sentence and based on that it classified the sentence. We have used 256 units in LSTM layer and used different drop-out rate in different layer to avoid overfitting. We have trained LSTM model on dataset2 with 30 epochs with batch size of 512 samples. we have used cross entropy loss function as loss function and ADAM optimizer. Model performance on test set was 0.89 f1 score.

Graphs of losses and accuracy:





V. Database

Collected the dataset from Kaggle and split the data into 80:20 ratio for training or testing purpose also dataset distribute in various class and that graph is shown in image no. 1 dataset1 size = 10017 samples containing tweet text and label. dataset2 size = 22408 samples containing tweet text and label.

VI. Code

https://github.com/janak11111/IR_Project_2023

VII. Evaluation

	Accuracy	Precision	Recall	f1score
Naive bayes	0.5958	0.6095	0.5998	0.5972
Neural Network	0.8465	0.8493	0.8465	0.8447
SVM	0.8788	0.8791	0.9788	0.8782
Decision Tree	0.8814	0.8830	0.8814	0.8806
BERT-Dataset-1	0.9041	0.9040	0.9041	0.9039
LSTM-Dataset-2	0.8974	0.8973	0.8964	0.8973
BERT-Dataset-2	0.9326	0.9336	0.9326	0.9327

TABLE I
QUANTITATIVE EVALUATION OF DIFFERENT MODEL

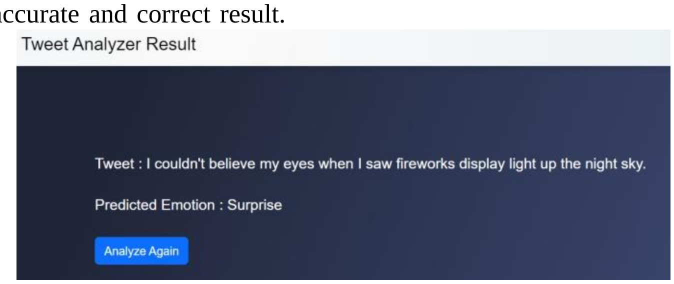
Based on the above table we can say that Bert on Dataset-2 outperform compare to all other models.

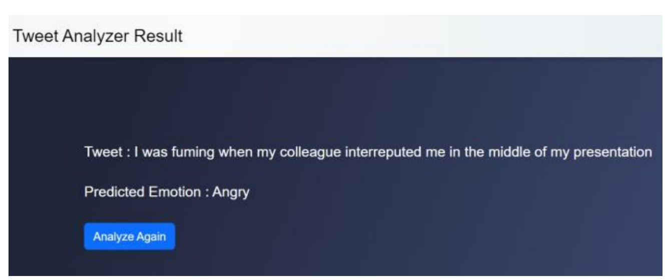
A. *Qualitative Results*

1) *Before Improvement:* image So, this tweet describe the surprise emotion but out mid-term model suggest it as a happywhich is not accurate. Result is shown below

So, this tweet describe the angry emotion but out mid-term model suggest it as a sad which is not accurate. Result is shown below

So these are some examples which predicted wrong by our earlier model so we improved our model and that suggest accurate and correct result.





VIII. Contribution

All the team memebers are contributed equally.Janak , Mansi and Kirtirajsinh worked on the model preparation and Project Report and Tanay , Abhishek and Vijay worked on model UI , PPT , Data preprocessing and model Deployment.

IX. References

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