

Detecting Emotion from Natural Language Text Using Hybrid and NLP Pre-trained Models

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ABSTRACT

In current days emotion analysis has been attracting many users to continue their research towards detecting various emotions from natural text. Almost a lot of study is being done in the area of Artificial Intelligence (AI), which mainly focuses on identifying the human state rather than digging the inner reason behind those state or emotions, like why those states are not recognized properly. There were many failures in the primitive methods for emotion detection because of improper correlation among emotions. Hence this motivated me to design a new model, which can fill the gap between emotion recognition and emotion correlation mining through natural language text from text conversations. In this proposed model, we try to mine emotion correlation from emotion recognition through natural text by using various kinds of features and by applying machine learning and deep learning pre-trained models. The main features are anger, disgust, fear, guilt, joy, sadness, and shame. By conducting various experiments on proposed models by taking a sample dataset collected from the Kaggle website, we try to observe the performance metrics of each and every individual algorithm in order to detect the emotions very accurately from natural language text.

Key Words: Artificial Intelligence, Emotion Detection, Natural Language Text, Kaggle, Data Correlation, Machine Learning, Deep Learning, Pretrained Models.

INTRODUCTION

Emotion is one kind of response for specific contexts, and this may be complex, individual, and sometimes sensitive. Emotion mainly guides the human body to take action, decide, and continue the ongoing behaviour [1]. In general, emotions are subjective responses that mainly come from the interaction between several individuals on different aspects. Emotion recognition from the natural text is complex [2] because it is hidden within the text and requires a very clear understanding of that context. In current days this emotion detection is used in several applications, including human-computer interaction [4], data mining, big data, data filtering systems, e-commerce, online tutorials, and psychology. In general, there are six techniques to observe emotions from a natural language text.

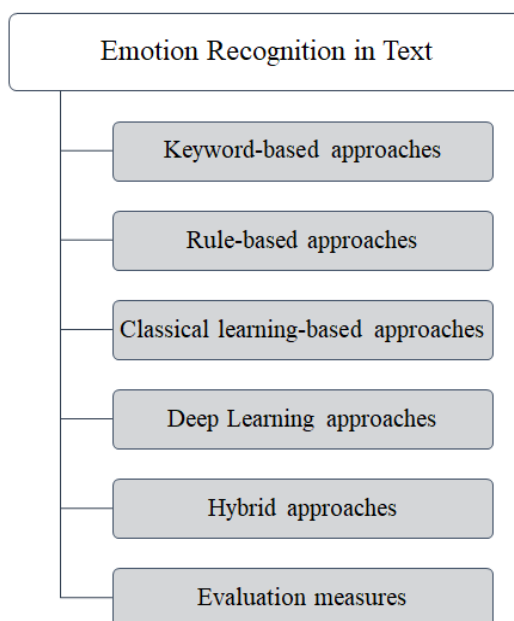


Figure 1. Main approaches for emotion detection from a natural text.

Sentiment analysis and Emotion analysis are two types of analysis that help in finding the expression and recognize the emotions from natural language text. There are 2 methods for identifying the emotions from any text corpus.

In sentiment analysis [3], only three feelings can be observed that are positive or negative or neutral. However, in the emotion analysis, we can detect the user's inner emotions such as happiness, sadness, anger, surprise, fear, and disgust from several users' input text in their conversations. In general emotion, analysis is a somewhat difficult task because emotion always changes instantly for a certain event. One user may feel one kind of feeling for certain text, and another user may feel a different kind of feeling for that same context. In this manner, emotion may differ among one another in its usage while extracting the most important features from the given input text. Hence this laid a path for the researchers to work on emotion detection from natural text using several machine learning and deep learning models.

Motivation to Design this Model

In general, detecting emotions from speech or facial expression is easy compared with detecting emotions from natural text. Detecting emotions from facial expression gives the best and most accurate result compared with context, that is due to text has a lot of diversions compared with one another. Hence this motivated me to design a model for detecting emotions from natural text using natural language processing. A lot of research is going on emotion detection from human speech, facial expression, and written context, and none of them proved accurately for identifying the emotion.

Emotion detection and Sentiment analysis have been widely used in most the popular index named the happy planet index (HPI) of the particular country [5] to check the level of happiness calculated from a certain country. In general, the HPI will try to check the happiness and living style of that particular country among those people and compare the same factors with other country persons.

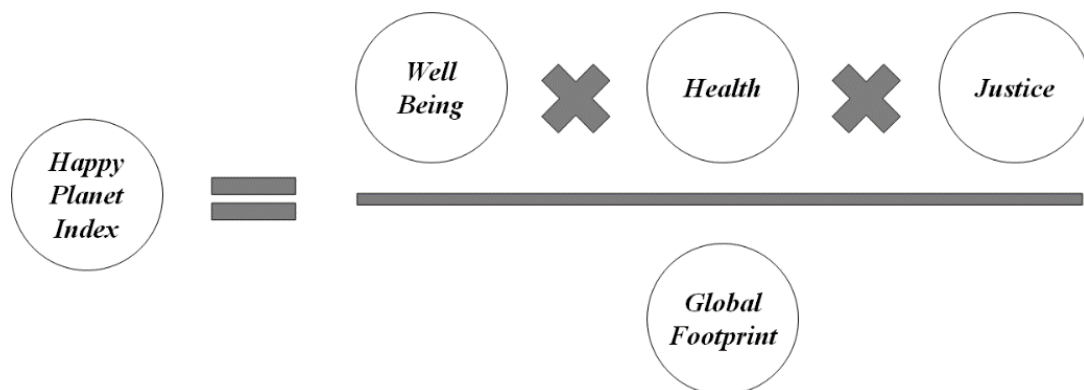


Figure 2. Represents the Factors for Deriving the Happy Planet Index

From the above Figure 2, we can see four main factors are required for calculating HPI for a certain country to check the rank of that country among several countries. The main factors are Well Being or Emotion, Life Expectancy or Health, Justice, and GlobalFootprint. Coming across all the four factors, the first factor plays the primary role in HPI, in which how well being or the emotion of that particular people of that country plays a main role in deciding the HPI. This factor is mainly collected from the reviews or comments given on products that they purchased and also collected from a conversation among personal blogs, online social network websites, etc. Hence, if the emotion detection is not properly detected, then there will be inaccurate results for measuring the HPI of any country.

LITERATURE REVIEW

This section mainly discusses the background work that is carried out in order to develop the proposed emotion detection from the natural text. Shiv Naresh and Saritha Khethawat et al. [6] proposed a paper on “Emotion Detection from Text”. In this paper, the authors discussed the importance of emotion detection from the natural text, and they mainly discussed several primitive methods for emotion identification, and they discussed some novel ways which are used to identify emotions from natural text. Some of the main techniques used in this

paper are keyword spotting technique, Learning-based Methods [16], and Hybrid Methods in a very detailed manner. Even though they defined more information about several methods for emotion detection since it is having a lot of limitations and all these limitations are left as future work. Shaheen and Shadi et al. [7] proposed a paper on Emotion Detection from Text which is based on Automatically Generated Rules". In this paper, the authors discussed the importance of emotion detection from the natural text, and firstly emotions are classified from given text messages in a grained mechanism. The authors discussed the semantic analysis technique for extracting the inner meaning of that word and try to classify the emotions based on meaning. In this proposed paper, the authors discussed two models like WordNet and ConceptNet, for covering all the emotions from given natural text. Experimental results clearly state that proposed models give the relation between words and helps in achieving high accuracy in classifying emotions from text corpus, but have some limitations in identifying the dimensions present in that text corpus. Mr. Dhruvi D. Gosai and Himangini J. Gohil et al. [8] proposed a paper related to emotion reorganization and text detection. In this paper, the authors discussed the importance of emotion detection from the natural text, and they mainly concentrated on emotions expressed using facial expression, voice, or text. The authors designed a novel model like the Ekman model, which includes emotions like happiness, joy, sadness, disgust, surprise, fear, and anger. Emotion Detection from text context. In this current paper, the authors mainly discussed emotion detection using the naive algorithm, and they want to increase the performance accuracy compared [17] with other classification algorithms. Ameeta Agarwal et al. [9] proposed a paper on detecting emotions from text using syntactic and semantic relations, which was unsupervised. In this paper, the author discussed about the importance of emotion detection from the natural text. They mainly concentrated on the context based approaches build using un-supervised models for detecting emotions from sentence level. The authors try to verify the emotion detection from several datasets and determine the accuracy of emotion detection varies from one dataset [15] to another. Ting-Hao Yang et al. [10] proposed a paper on detecting emotions from text which is a survey, and making possible improvements in it. In this paper, the authors discussed the importance of emotion detection from natural text, and they mainly concentrated on the possible improvements over current methods compared with primitive methods. In this paper, the authors designed ontology-based emotion detection to find the vocabularies present in that text and then try to match the sentence with multiple emotions present in that case study.

PROPOSED METHODOLOGY

In the proposed system, pre-trained models were implemented in ML and Deep learning to extract the main features from general text and classify the emotions from the given input text. In general, the Multinomial Naive Bayes Algorithm [11] (MNB), Bi-LSTM Model, and Hybrid Model were implemented for detecting emotion from text data. For this, Natural Language Processing Tool Kit is used for extracting the features which are present in the given input text corpus and train the input dataset by using all these models. To check the performance of each and every model, the dataset from the Kaggle website [12] is downloaded and then check the performance of each and every model in detail. In general, the steps to find out the emotion detection from the natural text are as follows:

Load the Dataset and libraries:

Initially, the input dataset is loaded, which is collected from Kaggle Website [14]. This input dataset contains nearly 14407 distinct text messages collected from Online Social Networks communication [13]. The dataset collected is in the form of a document with a .csv extension. Initially the emotion_text.csv file is uploaded as input, and the file contains nearly 14407 rows contained with textual messages i.e., 14,407 records, and 3 distinct columns. The text column represents the text messages which have been taken as input from dataset, the label column represents the emotion of the particular text message, whether it could be joy, fear, anger, sadness, disgust, guilt and shame, the label_encoded column represents numbers which are given according to the alphabetical order of the labels.

Sl. No.	text	label	label_encoded
0	[On days when I feel close to my partner and ...	joy	4
1	Every time I imagine that someone I love or I ...	fear	2
2	When I had been obviously unjustly treated and ...	anger	0
3	When I think about the short time that we live...	sadness	5
4	At a gathering I found my self involuntarily...	disgust	1

Table 1. Report of few records in the given dataset.

Data Pre-processing:

Data cleaning techniques were applied to the input dataset, which helps to extract all the unique features which are present in the whole text dataset and try to tokenize each and every feature with individual tokens, and we try to count the number of attributes that are present in that input dataset. CountVectorizer and regular expression tokenizer methods were imported. The regular expression tokenizer method is for identifying the most useful words which are present in that dataset. For this, we try to apply logic to check token which contains only alphabets and numbers in both upper & lower case. Once the tokens are identified, we apply CountVectorizer to convert text messages to 0's and 1's, which promotes creating a sparse matrix and removes the stop words from that tokens and try to send only useful words which are having proper meaning. Once the feature extraction is done, the whole dataset is divided into 20: 80 percent. Here for testing purposes, we assign 20 percent of data present from that input dataset and the remaining 80 percent of data we apply for training purposes.

a) Applying Multinomial Naive Bayes Model

Initially, the Multinomial Naive Bayes classification method is executed to find out how many messages are having which type of emotions from the given input dataset. We can also determine the accuracy of the NB classification technique on the input dataset by importing the MNB module from the naive_bayes algorithm package, and we apply the given input dataset under text and train methods.

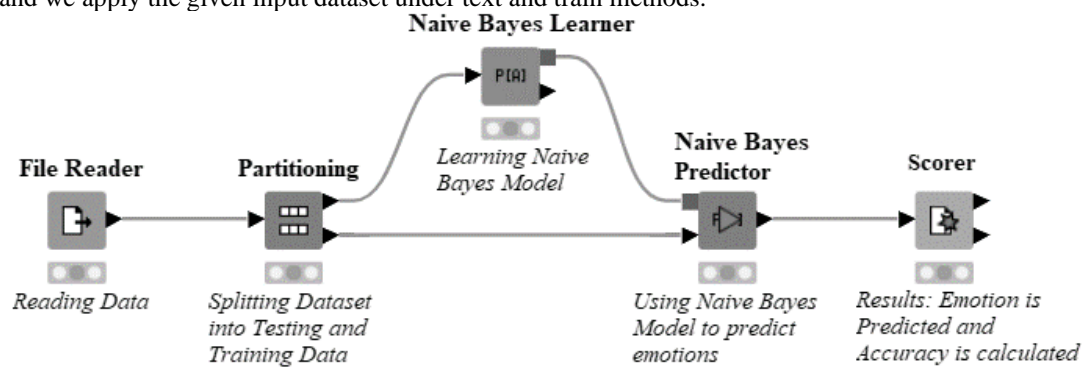


Figure 3. Represents the Flow of Naive Bayes Model for Emotion Detection

We can see that we initially try to import the text dataset from our local repository into our system. Once the dataset is loaded, we now try to divide the data into two parts: the testing part and the training part. Once the dataset is partitioned, we try to apply the naïve bayes learner model in order to predict the outcome. Here the learner model will check each and every feature present in the dataset and try to match those inputs with train data. Now we come to the predictor model where the dataset is finally evaluated for emotion prediction. In the end, we finally get the outcome as emotion detected, and we can also check the accuracy for the given model. Applying the MNB classification technique, it is also possible to extract and classify all the several messages present in that input dataset. In general, we have seven types of emotions, and based on the appropriate type of emotion, our algorithm separated all the messages into these seven categories, and we can see the count of each and every emotion. Here we import the MNB module from the naïve_bayes algorithm package to check the accuracy. In this method, we got nearly 64 percent of accuracy for the emotion detection input dataset.

Emotions	Number of messages with relevant emotions
<i>Fear</i>	3235
<i>Anger</i>	2711
<i>Joy</i>	2629
<i>Sadness</i>	2553
<i>Disgust</i>	1094
<i>Shame</i>	1094
<i>Guilt</i>	1091

Table 2. Represents emotions and the total number of messages corresponding to that relevant emotion.

b) Applying Bi-Directional LSTM Model

Bi-Directional LSTM Model is an extension of primitive LSTM, which is used for text classification. To increase the performance of our model, this BI-LSTM is designed for text classification. For a normal LSTM, only one input sequence is collected as input from one direction, i.e., either from Left or from Right. But coming to this BI-LSTM, at a time, we can execute two input sequences for text classification. One from Left and another from Right. Here we have a merge mode, which can allow the input to read from the recurrent layer, and this can be either from a forward or backward direction. Here few of the well-known models were imported from a natural language tool kit like word_tokenizer, which splits a sentence into words and tokenizes. WordNetLemmatizer converts into root word format BeautifulSoup module helps in removing hyperlinks from the given text message. Initially, the input dataset is categorized into a set of words. Each and every word is labelled as W_1, W_2, \dots, W_n . Here the 'n' indicates n-words present in the dataset. Now all these words are embedded into the Bi-LSTM model in both directions to get more accuracy for the model. The two output parameters are concatenated, and finally, the words are aggregated to apply the classifier.

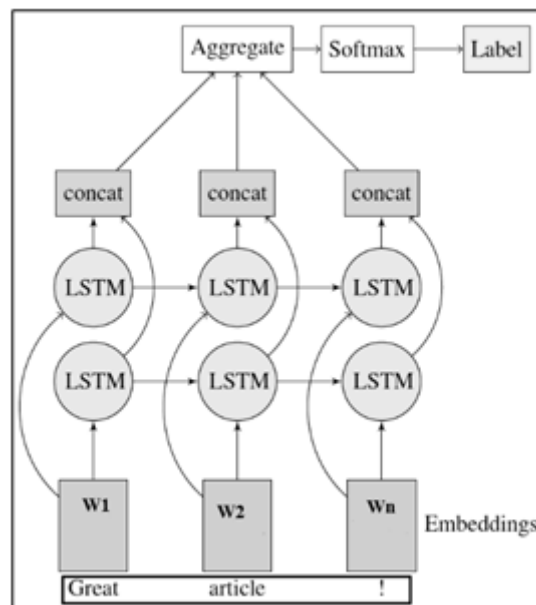


Figure 4. Represents the Flow of BI-LSTM Model for Emotion Detection

Here we applied softmax classifier in which is used to classify the emotions. Softmax classifiers exist in the network's final layer, i.e., input layer, hidden layers, softmax, and then the output layer. This softmax is considered as a classifier that yields our actual probability value for each class. Once the input word is matched with some softmax classifier, the emotion is automatically label for that appropriate input sentence. By applying the Bi-Directional LSTM model, we can classify the emotions based on the features and achieve an accuracy of 61 percent from the given input dataset.

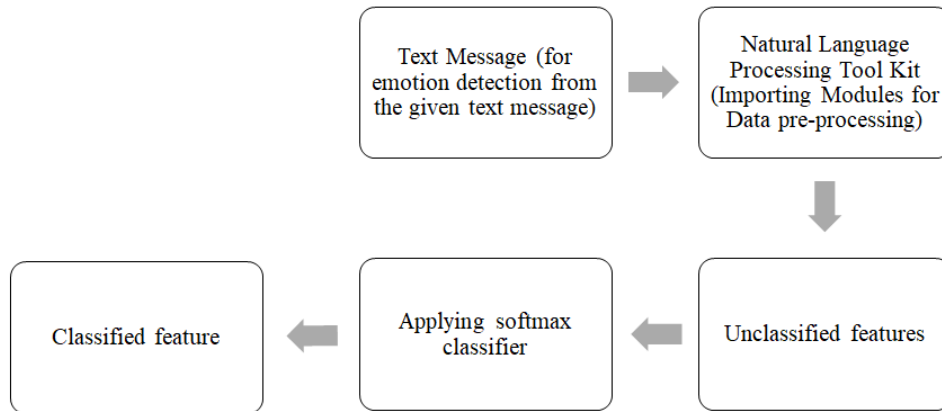


Figure 5. Application of softmax classifier

c) Applying Hybrid Model for emotion detection from text data

In this model, a hybrid model is designed based on the existing BERT model and a rule-based model. By combining BERT's existing features and applying some rule-based mechanism, we try to construct a hybrid model that can increase our proposed application's accuracy for emotion detection.

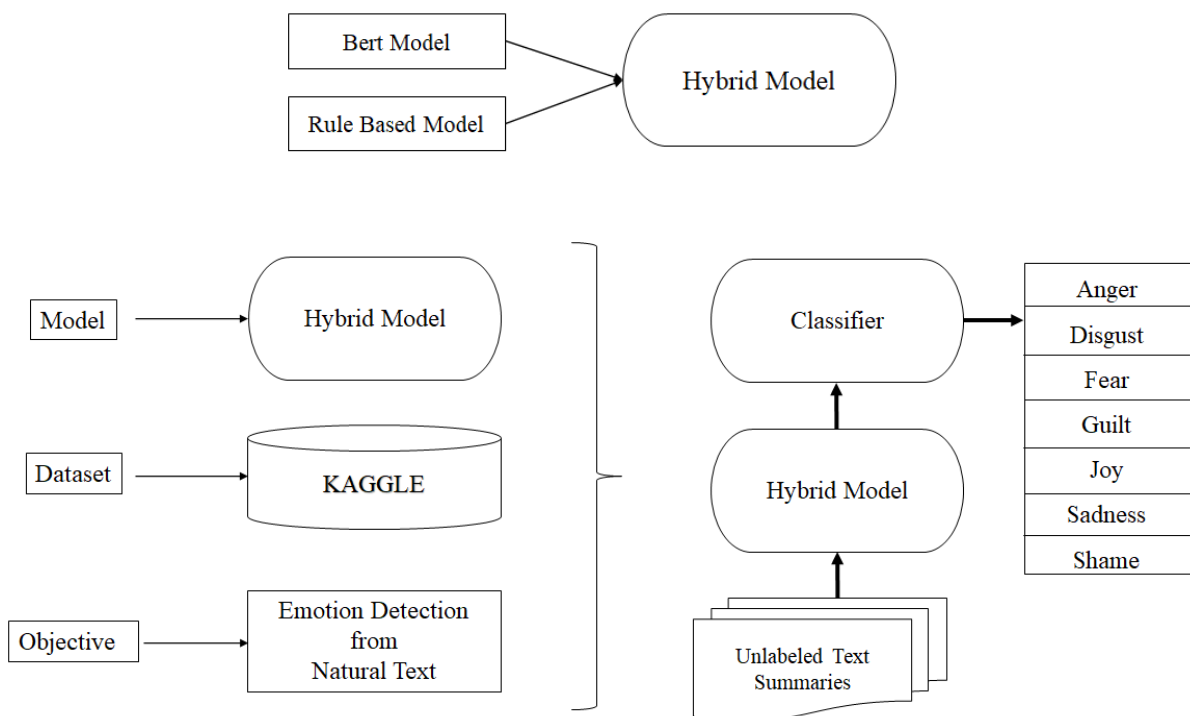


Figure 6. Represents the Flow of Hybrid Model for Emotion Detection

In general, the primitive BERT model has a problem like Overfitting, which is nothing, but BERT contains a huge number of parameters ranging from 200 to 300 million; implementing a small dataset on the BERT will result in an overfitting problem, and hence a lot of parameters are kept in an un-used state. Hence in this proposed article, we kept a rule on primitive G-BERT in which either small or large datasets can be taken as input for classification. In general, for the classification of text data on Google BERT, we need to train the entire architecture, and hence this may become a problem for the end-users based on the type of dataset which they select for the implementation. Hence in our current hybrid model, we try to use a rule like “freeze” which freezes the entire BERT architecture and uses only a few layers which are helpful for training the current model. During this process, we will freeze all the layers present in BERT and try to consider only a few neural network layers, and then train the given model

on our current application. Here the corresponding weights are updated based on the layers which we use for the application, and those layers are only updated during the model training, and other layers are not updated during the training period.

Procedure

The dataset for emotion detection is stacked from any repository, and all the necessary libraries were imported that are required for the Hybrid model. Data cleaning and Data pre-processing techniques were implemented, and then we declare the Hybrid Tokenizer Method so that tokens are assigned for the extracted main features. Here the stop words or duplicate words are removed from the input dataset, and only those which are useful are kept in the tokenizer variable. A hybrid model is constructed with a number of attributes based on the current requirement. The optimizer method is declared in which all the nodes are freeze and only useful nodes are kept to process the task in less time to increase the accuracy. From this proposed hybrid model, the accuracy we achieved is 76 percent for emotion detection from natural text.

PERFORMANCE ANALYSIS

In this section, we try to test a proposed application's performance on all the three models like Multinomial Naive Bayes Classification, Bi-Directional LSTM, and HYBRID Models, and we tested the performance of all three models on the sample dataset collected from the Kaggle Web site. The performance results clearly state that the Hybrid model has more accuracy and efficiency than other algorithms to detect the emotion from a text corpus. The training accuracy is achieved by testing the model with the trained data set whereas the validation accuracy is achieved by testing the model with a new/different data set.

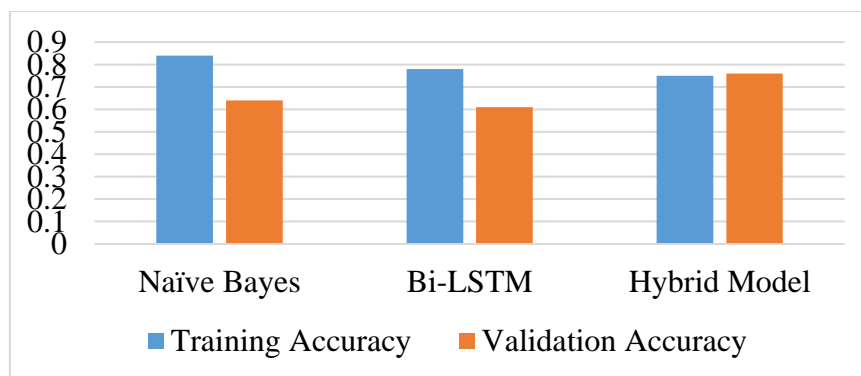


Figure 7: The training and validation accuracies of three models

The accuracies of the three models are as follows:

Models	Training Accuracy	Validation Accuracy
<i>Naive Bayes</i>	0.84	0.64
<i>Bi-LSTM</i>	0.78	0.61
<i>Hybrid Model</i>	0.75	0.76

Table 3. Models and their accuracies.

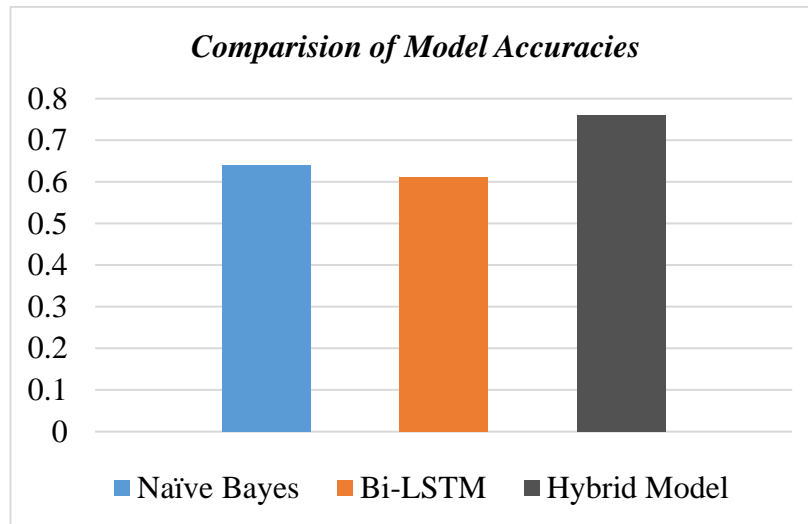


Figure 8. Comparison of three models.

From the above graph, we can conclude HYBRID model is very efficient in detecting a text corpus's emotions. In the future, we want to add some more factors to increase the accuracy percentage for this Hybrid model.

CONCLUSION

In this proposed model, we, for the first time, developed a comparative analysis of several pre-trained models which are required for emotion or state identification from the natural language text. In general a lot of study and research work is being done in the field of Artificial Intelligence, which mainly focuses on identifying the state rather than digging the inner reason behind those emotions. There were many failures in the primitive methods for emotion detection because of improper correlation among emotions. In this proposed research, we try to mine various types of emotion from the natural text by using various features and applying well-known pre-trained models like Naive Bayes, LSTM, and Hybrid models. By applying these models to the sample dataset, we try to mine the seven main emotions from natural text like sadness, disgust, fear, anger, guilt, shame and joy. By conducting various experiments on proposed models by taking a sample dataset collected from the Kaggle website, we try to observe the performance metrics of each and every individual algorithm in order to detect the emotions very accurately from natural language text. Our comparative reports clearly state that the Hybrid model is having more accurate and efficient when compared with the other two models, which we applied in this current application for emotion detection from natural language text. In the future, we want to extend some more new models which can increase the accuracy rate for emotion detection and emotion analysis on text datasets.

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