

BiLSTM and Multiple Linear Regression based Sentiment Analysis Model using Polarity and Subjectivity of a Text

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Abstract—Sentiment analysis has become more and more requested by companies to improve their services. However, the main contribution of this paper is to present the results of the study which consists in proposing a combined model of sentiment analysis that is able to find the binary polarity of the analyzed text. The proposed model is based on a Bidirectional-Long Short-Term Memory recurrent neural network and the TextBlob model which computes both the polarity and the subjectivity of the input text. These two models are combined in a classification model that implements each of the Logistic Regression, k-Nearest Neighbors, Random Forest, Support Vector Machine, K-means and Naive Bayes algorithms. The training and test data come from the Twitter Airlines Sentiment data set. Experimental results show that the proposed system gives better performance metrics (accuracy and F1 score) than those found with the BiLSTM and TextBlob models used separately. The obtained results well serve organizations, companies and brands to get useful information that helps them to understand a customer's opinion of a particular product or service.

Keywords—Sentiment analysis; textblob; long short term memory; logistic regression; k-nearest neighbors; random forest; support vector machine; k-means; naive bayes

I. INTRODUCTION

Sentiment analysis is a technique that focuses on the evaluation of emotions, attitudes and opinions. Today, organizations, companies and brands use this technique to obtain useful information that helps them to understand a customer's opinion of a particular product or service. For this purpose, several models of sentiment analysis, which is a field of artificial intelligence, in particular natural language processing, have emerged. In this sense, given the importance of texts coming from Twitter, several studies have been focused on this topic, among these studies, we can cite the analysis of subjectivity [1], the detection of events [2], the evaluation of online reputation [3], the identification of trends on social networks [4]. Sentiments are essentially labeled according to the polarity of the text, i.e., whether the message has a positive, negative or neutral connotation. The determination of polarity can be done at different levels, namely the document [5], the sentence [6], the word [7] or the attribute [8]. In a previous study, Chiny et al. [9] proposed a hybrid sentiment analysis model based on three input models; the LSTM model, the TF-IDF word weighting model and the pre-trained model based on the VADER lexicon. These three models are combined using a classifier that returns the binary

sentiment experienced in the input text. The proposed architecture is characterized by the small amount of data required for training. In addition, the model is characterized by its ability to transfer the knowledge already acquired to process a different dataset than the one that provided the training data. However, in a text, the semantics of a given word does not only depend on the words preceding it, but also on the following words. For this reason, we thought of implementing the BiLSTM model which evolves in both directions rather than the LSTM model which considers the current word and the previous words only as a temporal sequence. Therefore, the aim of this research paper is to propose a hybrid sentiment analysis system by combining two input modules. The first model is based on the use of BiLSTM networks. In the second model, a Textblob sentiment analyser is used to evaluate the subjectivity and polarity of texts. Subjectivity and polarity are features of a linear regression model that returns a single sentiment score. Both models were trained on the US Airlines Sentiments twitter dataset. Each model returns scores of positivity or negativity from the text to be analyzed. Then, these two (input) models are combined into a binary classification model in which the Logistic Regression, k-Nearest Neighbors, Random Forest, Support Vector Machine, K-means and Naive Bayes models are implemented.

After implementing the proposed architecture, we wish to have performance metrics (i.e., accuracy and F1 score) superior to the metrics calculated for the two modules (BiLSTM and TextBlob) separately. The main contribution of this paper is to have a more advantageous performance than the model proposed in the study by Chiny et al. [9]. This improvement will allow organizations, companies and brands to have more relevant and meaningful information that will help them to understand and analyze customer opinions about a product or service provided.

II. RELATED WORK

A. Bidirectional Long Short Term Memory

Processing sequential data and natural language (NLP) leads to several major problems related to the nature of the data. To solve these problems, the authors of [10] used recurrent neural networks (RNN), which are artificial neural networks that use hidden states to model the behavior of dynamic systems.

According to [11], a BiLSTM (Bidirectional Long Short-Term Memory) network is a recurrent neural network that processes data in two different ways. The use of this network is particularly requested in the field of natural language processing. Indeed, the meaning of a word in a sentence may depend on the preceding and following words. Therefore, in this kind of cases, it is desirable to go through the sentence in both directions to get the right meaning. The BiLSTM offers this particularity which makes it different from LSTM networks.

The bi-directional nature of BiLSTM has given it great potential to be at the heart of many works related to natural language processing. For example, Zhou et al. [12] applied a two-way LSTM with 2D max pooling to the Stanford Sentiment Treebank (STS) database; each vector is represented by a 2D matrix. In addition, to find optimal performance, Shen et al. [13] proposed a new design combining the CNN and BiLSTM models. They found that this combination achieved an accuracy of 89.7%. This result is better than that of each of the models individually. In another study, Yoon et al. [14] proposed a CNN-BiLSTM architecture for document-level emotion prediction using multi-channel integration with CNN. The model worked on different datasets and achieved average performance from 51.97% to 70.08%.

Wu Xing et al. [15] used long-term memory (LSTM) to automatically generate poems based on the author's style. In [16], Felix et al. studied bidirectional long-term memory networks (BLSTMs) and i-vectors to model the author's speech. They also used i-vectors to model the longer term acoustic context. Also, in [17], Nowak et al. (2017) compared the LSTM model and the BLSTM model in the emotion classification of Amazon's book review dataset. The results obtained by the authors show that the BLSTM model is more accurate than the LSTM model in this task.

Seneewong Na Ayutthaya and Pasupa (2018) attempted to merge the BLSTM and CNN deep learning models to examine word sequences and discover local text characteristics [18]. The results showed that the combination of deep learning models improved the accuracy of sentiment analysis. Furthermore, deep bi-directional LSTMs (DBLSTMs) have recently been shown to provide performance for solving many problems, such as text analysis. These problems include sentiment classification [19], speech recognition [20], semantic labelling [21] and large-scale acoustic modeling [22]. BLSTM networks have proven useful in discovering character input patterns for processing a wide variety of natural languages.

In the literature, different deep learning algorithms have been applied to process different types of data. The researchers used complex neural networks (CNNs) to process computer vision subjects and analyze text to infer a local structure, while using long-term memory (LSTM) and bidirectional LSTM (BLSTM) for sequential data processing and different language models [23,24,25].

To analyze the sentiment trend of Chinese texts. Gan et al. [26] used a joint multi-channel dilated evolutionary architecture of a convolutional neural network and a

bidirectional long-term memory model (CNN-BiLSTM) with an attention mechanism.

In [27], Wang et al. used a bidirectional short-term memory network enhanced by emotion semantics (BiLSTM) with the multi-headed attention mechanism model (EBIL).

The work of Batbaatar et al. [28] aimed to propose a new neural network architecture, called SENN (Semantic-Emotion Neural Network), which can use both semantic/syntactic and emotional information by adopting pre-trained word representations.

B. Subjectivity and Polarity

Sentiment analysis, also known as opinion research, is aimed at understanding how a reader could interpret a person's subjectivity and translate it into an algorithm capable of performing this task automatically. According to the authors' studies [29, 30], the polarity of a sentiment is a quantified measure on the scale of values corresponding to a positive or negative assessment of emotional significance. From this quantification, we can test the polarity of the subjective text by the classification of sentiment. Indeed, if we have a review about a product, the sentiment analysis system must determine whether the emotion expressed in that review has a positive or negative connotation. In general, the polarity of the text can be positive, negative and sometimes neutral to identify a lack of feeling in a text.

According to [31], studies on polarity analysis are subdivided into two approaches: a lexical approach (also known as a knowledge-based approach) and a machine learning-based approach. The first approach uses dictionaries, such as LIWC (Language Inquiry and Word Count) [32] and Senti Word Net [33]. Generally, a dictionary consists of words and the corresponding classification value. Indeed, in a dictionary, we can find the word "pleasure" with a value +1 which signifies that this word has a positive polarity or, conversely, it can contain the word "hate" with the value -1 representing a negative polarity. According to the authors [32] and [33], adding the values of all the words in the text gives the resulting polarity. The result of the summation (positive or negative) determines the global polarity of the text. On the other hand, the second approach, is based on the use of classification algorithms, such as Naïve Bayes (NB), Maximum entropy (ME) and Support Vector Machines (SVM). These algorithms have been tested by the authors [34, 35, 36, 37] to perform text classification; the obtained results are promising. Polarity determination can be measured at the levels: document [48], sentence [39], word [40] or attribute [41]. The document level treats the whole document as the basic unit. The sentence level draws and determines the sentiment of each sentence in the text. At the word level, each word in the text is analyzed and classified. The attribute level identifies and extracts the attributes of an entity (e.g., product, person, company) in the text and determines the sentiment for each attribute [42].

Subjectivity aims at determining whether a text is subjective (opinion, emotions, evaluations, beliefs or speculations) or simply a fact, while the classification of feelings aims at determining the proper value of this

subjectivity [43]. Subjectivity detection prevents sentiment ranking from considering only texts that are relevant or potentially misleading. In addition, it reduces the size of the set of labels that can be assigned to a text, i.e., it must first be checked whether the text is objective or subjective, and those that are considered as such are subjected to a new classification process that will determine the polarity. In addition, sentiment analysis may involve identifying the target entity, i.e., the subject of the text to which the sentiment is addressed, and identifying the person or organization expressing the opinion [44]. There are texts in which the polarity is not as noticeable, as in mixed experiences, i.e. when there are both positive and negative remarks, which is different from a neutral text that is purely factual.

Among the most commonly used feedback mechanisms in Twitter data analysis is sentiment analysis, which provides insight into the sentiment expressed in messages [45]. This feeling is essentially labelled according to the polarity of the text, i.e. whether the message has a positive, negative or neutral connotation. For companies, this measure provides insight into the public's and market's opinion of themselves.

In [46], the authors found that machine learning techniques applied to sentiment analysis perform better than those obtained by random selection (50%) or by human classification (between 58% and 64%). To generate a classification model, this approach needs a dataset for training.

Pak et al. [47] discuss ways to collect tweets to exploit them in sentiment analysis. They employ a specific lexicon of emotions to reduce the manual tagging of tweets for the classification of feelings. Emotions are classified into two types, happy representing a positive sample and sad for a negative sample.

Among the works that used learning techniques for the classification of feelings, Pang et al. [48] employed Naïve Bayes algorithms, logistic regression and the support vector machine. In this work, the authors used film reviews to classify the polarity of sentiments. But, opinions are considered neutral when there is no opinion in the text or the opinion falls between the two polarities.

III. PROPOSED SENTIMENT ANALYSIS ARCHITECTURE MODEL

The purpose of this research is to propose and test the validity of a new model of sentiment analysis (Fig. 1) composed of two input models. In the first model we used the BiLSTM algorithm, the validation of this model is tested on a corpus of US Airlines twitter sentiments. In the second model, we have exploited the TextBlob sentiment analyzer in the goal to evaluate the subjectivity and polarity of natural language texts. The subjectivity analysis attempts to estimate how subjective or objective the text is, while the polarity analysis determines whether the feeling in the text is positive or negative. The two outputs of the TextBlob model that represent the subjectivity and polarity scores are coupled with a multiple regression model to estimate the weights associated with each of these two features in the category of texts in our

study (short microblogging texts such as those from Twitter). After, the binary sentiment of the input text will be provided by a classifier that uses the scores already calculated by the BiLSTM and TextBlob models.

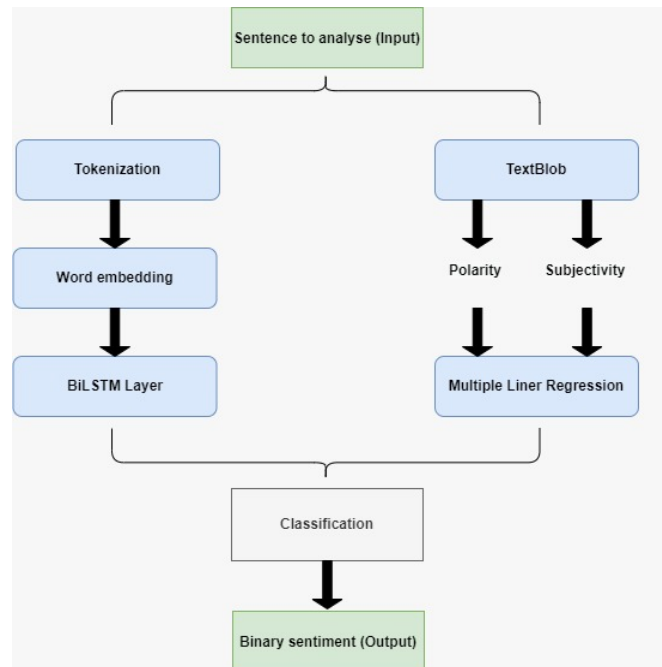


Fig. 1. Proposed BiLSTM and TextBlob based Combined Sentiment Analysis Model.

A. LSTM Bidirectional

The bidirectional LSTM algorithm (BiLSTM) is a recurrent neural network. This algorithm finds its major application in natural language processing. It has the advantage that the input flows in both directions: forward and reverse direction. BiLSTM is a very efficient algorithm for modeling sequential dependencies between words and sentences in both directions of the sequence.

To use the BiLSTM algorithm in the text to be analyzed, we need to do cleaning and filtering, followed by tokenization and then word embedding.

B. TextBlob

The TextBlob sentiment analyzer is a Python library for processing text data. It makes it possible to recognize the subjectivity and polarity expressed in natural language texts. Polarity analysis determines whether a subjective text is positive or negative in a range between [-1, 1], -1 indicating negative feelings and +1 positive feelings.

C. Cleaning and Filtering

To analyze the tweets reliably and correctly by our proposed system, we performed preprocessing on the dataset. The purpose of this preprocessing is to ensure that the tweets will be prepared in a formal language format that will be interpreted by the machine. Subsequently, we chose a dataset of 14,427 unique texts for the training and testing of our model.

D. Tokenisation

Tokenization is a technique used to transform text into single words (unigram) (individual tokens) or combinations of successive words (n-gram). In our model, we have divided the texts into a series of individual tokens in order to use the Glove model. We have defined the sequence length that is equal to the number of time steps for the BiLSTM layer.

E. Word Embedding

Word embedding is a technique based on the linguistic theory founded by Zelling Harris. It is in great demand in the classification of documents [49] because it uses machine learning algorithms to represent textual data (words or sentences of a text) by vectors of real numbers. In our research, this representation facilitates and improves the performance of automatic language processing methods (or Natural Language Processing) and more particularly it simplifies the processing of Sentiment Analysis.

To describe the words of our text by a numerical vector, there are several algorithms including Word2Vec and GloVe. We used the algorithm GloVe (Global Vectors for Word Representation) [50]. This choice is dictated by the nature of our proposed system. We used the calculated 100-dimensional GloVe integrations of 400,000 words.

F. BiLSTMLayer

When defining the BiLSTM layer, we tested several parameters and kept the ones that gave good results. The number of hidden units is set at 256 and the rmsprop optimizer is used, which compares favorably with other adaptive learning algorithms. The Table I summarizes all the hyper parameters of the chosen model.

G. Training and Evaluation of the Model {BiLSTM, TextBlob}

To train and evaluate our proposed system, we chose to use the US Airlines Twitter dataset [51]. This database is exemplary on the binary classification of text. It contains 14449 unique texts. We have selected 7000 reviews in the train and 2000 in the test series of our BiLSTM and TextBlob models.

The TextBlob model allows the calculation of polarity and subjectivity scores separately. We therefore used these two scores as features of a linear regression model to calculate an overall sentiment score. The two input models (BiLSTM, TextBlob) are then combined into a binary classification model.

H. Model de Classification

To improve and increase the performance of predictions on the sentiment conveyed by the input text, we propose a hybrid system consisting of two sentiment analysis models with a classification model. For this, we chose the BiLSTM model in the first place. This model is characterized by its ability to adapt to sequential data processing. In the second step, and to recognize the subjectivity and polarity expressed in the texts, we worked with the TextBlob sentiment analyzer.

TABLE I. HYPER-PARAMETERS OF THE BiLSTM MODEL

Hyper-parameter	value
Bath_size	128
Epochs	2
Outout embedding dimension	100
BiLstm layer internalunits	256
Optimizer	Rmsprop
Loss	Categorical_crossentropy

With this proposal, we aim to have a good accuracy and a good F1 score that will be provided by our system compared to the BiLSM and TextBlob models applied separately on the same data.

To have a general binary prediction (positive or negative) of the sentiment of the input text, the two inputs of our classifier (Fig. 1) are linked directly to the outputs of the BiLSTM and TextBlob models. It should be mentioned that the values of the entries of the classifier are continuous in an interval of [0,1].

We randomly chose 7000 reviews from our dataset. These data are different from the training set and test set data used for the BiLSTM and TextBlob models. To have the predictions calculated by the BiLSTM and TextBlob models, we provided this data as input to our global system. Subsequently, the output of the results are divided into two datasets, 75% for the train set and 25% for the test set of our binary classification model. In this work, we used six classifier algorithms namely: Logistic Regression (LR), k Nearest Neighbors (k-NN), Random Forest (RF), Support Vector Machine (SVM), K-Means and Naive Bayes (NB).

Table II summarizes the chosen hyper parameters that were subsequently applied to our classification models. These hyper parameters are experimentally retained; we have taken those that have given the best possible evaluations for our dataset.

TABLE II. HYPERMETERS APPLIED TO ALGORITHMS IMPLEMENTED IN CLASSIFICATION MODELS

Algorithme	hyperparameter	Value
Logistic Regression	Inverse of regularization	1
K Nearest Neighbors	strength Number of neighbors	13
Random Forest	-Number of in the forest	18
	-Maximum depth of the tree	2
Support vector Machine	Kernel type	rbf
Naïve Bayes	Function	Gaussian
K-Means	n_clusters	3

IV. RESULTS

A. Evaluation of our Proposed Model

To demonstrate the performance improvement brought by the proposed architecture, we trained the whole model with the same set of tests that allowed us to evaluate separately the BiLSTM and TextBlob. Fig. 2 shows the implementation of six different algorithms in the Classifier model.

TABLE III. PERFORMANCE METRICS DISPLAYED BY THE TWO INPUT MODELS ON THE TWITTER US AIRLINES SENTIMENTS

Model	Recal	F1	Accuracy
Bilstm	0.37	0.49	0.85
TextBlob	0.36	0.37	0.87

Table III shows that after training the BiLSTM model, its evaluation on the test data gave an accuracy score of 0.85 and an F1 score of 0.49 and with TextBlob we obtained an accuracy score of 0.87 and an F1 score of 0.34.

Table IV summarizes the performance obtained. These results are obtained after training and evaluating our model which consists of six classification algorithms.

TABLE IV. THE PERFORMANCE MEASURES OF OUR MODULE OBTAINED BY THE IMPLEMENTATION OF THE SIX CLASSIFICATION ALGORITHMS

Algorithme	Recal	F1	Accuracy
Logistic Regression	0.75	0.72	0.89
K Nearest Neighbors	0.80	0.68	0.87
K-Means	0.84	0.73	0.89
Random Forest	0.71	0.71	0.89
Naïve Bayes	0.88	0.64	0.82
Support vector Machine	0.72	0.71	0.89

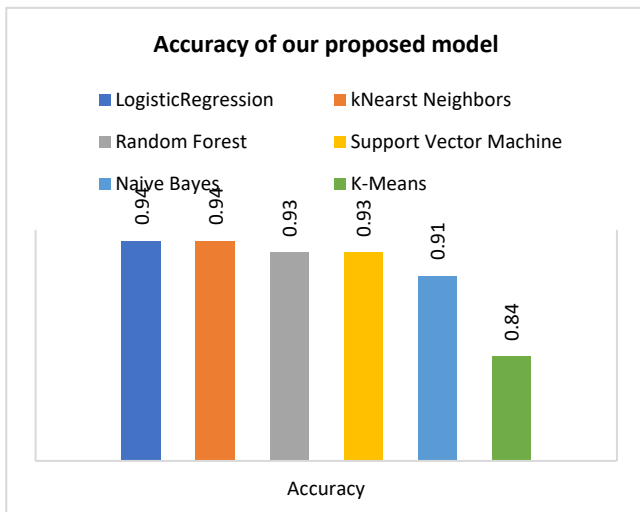


Fig. 2. Accuracy of our Proposed Model.

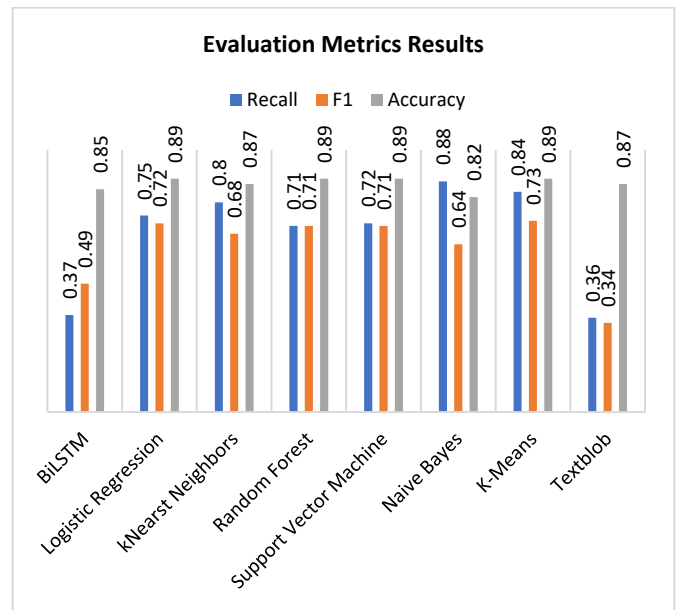


Fig. 3. Evaluation Metrics Results.

Fig. 3 shows the evaluation scores obtained with our model. We obtained six scores which depend on the classification algorithm used. The experimental results showed that the scores of our system are better than those obtained with the two models BiLSTM and TextBlob used separately. We note that the accuracy obtained with the BiLSTM (0.85) and TextBlob (0.87) models perform slightly better than the naive base algorithm (0.82).

Remarkably, it can be seen that the other classifiers Support Vector Mchine, Logistic Regression, Random Forest and K-Means gave a significantly higher accuracy (0.89) compared to the accuracy obtained with the two BiLSTM and TextBlob models. It can also be seen that the logistic regression model also provides a better F1 score (0.72) which is 23% higher than the BiLSTM F1 score (0.49) and 38% higher than the TextBlob F1 score (0.34).

With the exception of the results obtained by the Naive Bayes algorithm, it can be stated that our proposal improves the accuracy and F1 score results provided by the BiLSTM and TextBlob models used individually.

V. DISCUSSION

The experimental results obtained validate the usefulness of our proposed system. They also show the new performances in terms of accuracy and F1 score. Our proposed system, allowed us to have a 4% higher accuracy score and a 24% higher F1 score using the k-Means algorithm. It can be said that the use of BiLSTM and TextBlob input models will be effective in studies interested in sentiment analysis provided that they are hybridized with regression algorithms.

Moreover, most of the proposed models obtained better performances in terms of accuracy and F1 score (K-means, Logistic Regression, svm, Random Forest, K-nn respectively), except for the Naive-Baise model which obtained a slightly lower score in terms of accuracy (0.82) compared to the BiLSTM and Text Blob input models which have an accuracy

score of 0.85 and 0.87 respectively. The main reason could be that the Naive Bayes Classifier algorithm assumes the independence of the variables: This is a strong assumption and is violated in most real cases. Harry Zhang's publication [52] provides an explanation for this counter intuitive performance.

VI. CONCLUSION

Sentiment analysis of tweets remains an important technique to take advantage of the opinions and trends of the public around several events, in order to classify them according to polarity. However, categorizing the polarity of Twitter messages remains a difficult task for a number of reasons, including the speed at which messages are generated, the large number of messages generated on a particular topic, the short duration of those messages, and the familiarity of messages. To overcome these problems, this paper introduced a hybrid sentiment analysis model based on a BiTSM network and TextBlob. The TextBlob model allows the polarity and subjectivity scores to be calculated separately. We therefore used these two scores as features of a linear regression model to calculate an overall sentiment score. The two input models (BiLstm,TextBlob) are then combined into a binary classification model. For the attainment of this, we have implemented the following algorithms: Logistic Regression, k-Nearest Neighbors, Random Forest, Support Vector Machine, K-means and Naive Bayes. Then, both models were trained on a limited amount of data from the twitter US airlines data set.

The results of our experiments showed that the proposed hybrid system shows better performance in terms of accuracy and F1 score, compared to the input models considered in this study (BiLstm and TextBlob). This is mainly due to the different mechanisms implemented in each model. The mutualization of these mechanisms via our hybrid architecture was able to increase the performance demonstrated by the calculated metrics.

It should be noted that due to its bidirectional nature, the implementation of BiLSTM neural networks generates an overhead in terms of computational power and consequently, on the processing time, in this case with respect to long texts. For this reason, we recommend the use of the model proposed in this study to capture feelings in short texts such as tweets.

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