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A Deep Learning Model for Opinion mining in Twitter Combining Text and Emojis

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Abstract

Several approaches have been proposed to study opinions on Social Network Sites (SNS). Unfortunately, those works are not topic-sensitive and do not investigate the impact of emojis on text-based classification. In this paper, we propose a novel approach to predict the users' opinions expressed through textual tweets and emojis. Thus, we construct an emoji sentiment lexicon. Then, we extract opinions from the text before considering both the text and emojis to see how they enhance the expression of opinions in SNS discussions. We conduct a set of benchmarks using several well-known machine learning algorithms, leading to an accuracy of 83, 7%.

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1. Introduction

Online media and social networking sites (SNS) are growing in popularity as they allow people to express themselves through short texts on a range of topics. Those media consist of very unstructured data that includes words, emojis, photos, and videos to raise public awareness about a variety of concerns. In fact, on social networks like Twitter, the data is short and posted without much care for the language.

1.1. Background and Key Issues

In recent years, sentiment analysis has become an important research field. Companies use sentiment analysis to assess and forecast the popularity of their product performance based on consumer feedback. Various platforms, such

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as SNS, serve as data repositories and provide a database for user experience analysis. Unfortunately, it is difficult to search all user posts, especially for popular articles or topics with hundreds or even thousands of posts. Therefore, it is difficult for a potential user to read them and make an informed decision about whether to accept the ideas.

Opinion mining is the detection and classification of opinions in a text. The polarity of sentiment is usually classified into three categories: positive, negative, and neutral [13]. Our opinion mining approach is based on the words in the tweet, the topic of the tweet, and the emoji polarities. We chose Twitter as a microblogging website where users can express their opinions. Many companies conduct surveys for various purposes, such as product development, competing products and market research, brand equity research, customer service research, new product adoption and demand research, and customer company and product enhancements. However, those works do not incrementally study the impact of emojis on the polarity of tweets.

1.2. Motivation

The use of emojis has become ubiquitous on social media platforms such as Twitter. They can assist in compensating for textual features for opinion mining [1]. Emojis have been standardized only in recent years and they have entered common usage in the past few years [29]. However, as their use has spread, researchers have begun to focus on the problem of opinion mining using emojis in social networks [3], [5], [10], [20], [21], [24], [1], [12]. The proposed approaches are also not topic-sensitive. They do not extract opinions from the text before considering both text and emojis to see how they enhance the expression of opinions in social media discussions. This motivated us to propose an approach to solve the problems raised.

1.3. Goals and Contributions

The main objective of this work is to identify users' opinions on a given topic on online social networks. We use natural language processing and machine learning to analyze tweets and determine their polarity. Our main contributions can be summarized as follows:

- We construct an emoji sentiment lexicon using an existing lexicon and definitions provided by emoji creators in Emojipedia.
- We propose a joint topic-opinion mining approach.
- We propose a new Deep Learning architecture based on Convolution Neural Networks (CNN) and Long Short-Term Memory (LSTM). These architectures integrate sequential and non-sequential features in opinion mining.
- We analyze in depth how the use of emojis can improve the expression of opinions on SNS.

1.4. Organization

The rest of this article is organized as follows. Section 2 discusses related work. Section 3 details our proposed CNN and LSTM architectures and their individual components. Section 4 outlines our experimental results, while the last section summarizes our work and gives an outlook on future research directions.

2. Related work

In the last decade, there has been an increasing interest in research activities on opinion mining on social networking sites (SNS). The latter enjoys great popularity worldwide as a means through which people socialize and interact with like-minded people. Driven by Web 2.0, these SNS are explicitly participatory, dialogic, and user-supplied with content. Opinion research activities fall into three categories. The first category uses supervised machine learning, where algorithms classify previously labeled data to classify new unlabeled data. The second category is based on unsupervised machine learning models, where opinion polarity computation is based on some predefined syntactic patterns and rules used to express opinions. The third category is concept-based and uses ontologies to capture the semantic connection between concepts and relations.

2.1. Supervised Approaches

Several supervised approaches have been proposed to address the opinion challenge. In this section, we present some of these approaches.

[7] use The Stanford SNAP data, which contains more than 400 million English and non-English tweets. Their work examines the ”token level. The authors propose an opinion mining system that first automatically extracts opinion tokens from tweets and then uses a graph propagation algorithm to label the polarities of the tokens by considering the most frequently occurring emotion tokens in tweets. Therefore, matches between words act as links in the construction of a graph, and finally, a multilingual sentiment analysis algorithm is implemented. Emotion tokens include emotion symbols, which include all possible combinations of symbols, alphabets, and numbers. It is a more extensive version of traditional emoticons. They also include repeating punctuation and repeating letters.

[16] rely on a Twitter dataset containing the words ”cell phone”, ”Nokia”, and 500 reviews. The model of [16] is based on extracting features from the products, and their polarity degrees are converted into fuzzy sets. Opinion words are extracted and a document term matrix is built using stemming and Parts of Speech (POS) tagging. The evaluation shows promising results (Fscore = 0.33 compared to SVM’s FSCore = 0.36). Otherwise, SVM has high accuracy compared to the proposed MAXENT algorithm.

[22] use the bidirectional LSTM. A human- annotated corpus of 20000 Spanish tweets, split into 16000 for training and 4000 for testing to evaluate their model. The subset used as training set contains 5865 funny tweets and 10135 tweets classified as non-humorous. The proposed approach achieved an accuracy of 0.85, which is slightly higher than the initial score obtained by the INGEOTEC Team.

Although these approaches have produced promising results compared with other families, the need for labeled data is a major limitation. It is worth noting that most of the datasets used are reviews. Opinion mining in social media has not been thoroughly investigated, as opinionated texts tend to be short and noisy compared to reviews. The datasets used are small, which is a significant drawback. On a small dataset, the machine learning model seems to train effectively as it predicts significant accuracy on the original dataset. However, on a new dataset, the accuracy might plummet. The data augmentation approach can be used in the preprocessing phase to partially alleviate this problem [18].

2.2. Unsupervised Approaches

Several unsupervised approaches addressed the opinion mining problem. [14] and [8] propose unsupervised approaches for opinion mining at the document level. Both works are applied to opinion mining on Twitter.

[14] evaluate their proposed OMLMl approach for opinion mining based on lexicon and machine learning using two datasets obtained from a social Twitter network between 2008 and 2013. The approach includes three different features: the sum of the computed Term Frequency-Inverse Document Frequency (TF-IDF) weights of words in the opinion, the number of positive emotions obtained from the opinions corresponding to the sum of positive emotional weights of all their words, and the number of negative emotions obtained from the opinions corresponding to the sum of negative emotional weights of all their words. This approach consists of two parts: First, the polarity of opinions about a target word is determined using an approach based on the textual properties of the words and the lexicon. Second, the opinions are explored and categorized using a better neural technique that maps the feature space into a 3-D vector. [8] propose an approach that entails first creating a dynamic dictionary of word polarity based on a set of hashtags relating to a specific topic, and then categorizing tweets into different classes by introducing new features to fine-tune the polarity degree of a post.

The authors evaluate their approach, authors selected English tweets about US Elections in 2016. In a first stage, they focus on two candidates Hillary and Trump. The obtained data contains 120,000 tweets (divided into 30,000 tweets for positive and negative classes). This classification is provided based on positive and negative Hashtags. In the second stage, they collect all Twitter messages that contains a total of 3600000 tweets for both Trump and Hillary. Finally, they combines the result of processed data in the second stage as well as tweets’ information.

Unsupervised approaches overcome the drawbacks associated with supervised approaches because they do not require a training corpus. However, compared to supervised approaches, they still provide less accurate results.

2.3. Concept-based Approaches

The concept-based approach is a new category of opinion research. It is also known as the ontology-based approach. In OSPM (Ontology-Supported Polarity Mining) [32], integrated ontologies in Opinion Mining (OM) are used with both supervised and unsupervised techniques to extract the polarity of text segments. Raw data was selected in the proposed architecture. The authors chose a movie review as an example from a dataset of 180 movie reviews.

EmotiNet [2] construct an ontology for representing and storing effective responses to real-world contexts. They use several existing dictionaries and corpora such as SentiWordNet, ConceptNet, VerbOcean, and ISEAR, to extract emotion-triggering words. They evaluate the proposed ontology on three datasets of different sizes, created with ISEAR and obtain promising results. In the future, EmotiNet could be improved by adding more affective properties to the concepts.

[4]is a sentence-level approach. The authors propose a neurosymbolic Artificial Intelligence (AI) system based on commonsense. They build symbolic representations to convert natural language to a protolanguage to better understand the sentiment in the sentence. They evaluate the proposed framework against 20 popular English lexica for sentiment analysis on 10 benchmark datasets. The results of the proposed approach on the different datasets vary between 77.04% and 90.08%.

The review of all existing machine learning models for opinion mining in social networks is beyond the scope of this paper, and the interested reader is referred to the specialized literature– see for example [15], [9], [18] and [28].

2.4. Approaches that Use Emojis

In conclusion, one can note that regardless of the category of approach used, most of them use a text to determine the opinion (positive, negative or neutral). There were a few approaches that used emojis [3], [5], [10], [20], [21], [24], [1], [12]. For example, [21] and [10] used the absence or presence of a positive or negative emoticon as a feature to classify collected tweets, including emoticons. They extracted the maximum entropy and SVM classifiers in combination with various features such as unigrams, bigrams, negations, and POS. [24] used the total number of positive, negative and neutral emojis. Based on the Emo15 dictionary, the total number of words, the number of positive exclamations (wow!), the number of negative exclamations, the total number of positive, negative, and neutral emojis in tweets, negation (number of negative words), the number of neutral words, and the number of intense words based on psy2015 are used to classify opinion. Hybrid clustering with K-means and cuckoo search (CSK) is then used to classify the data. In the next section, we will explain our proposal that uses both text and emoji for opinion classification. [1] extracts features from emojis using a variety of approaches, including emoji frequency, lexicon-based features, emoji embedding-based features, and word embedding-based features. The authors use different approaches to extract textual features such as structural features, TF-IDF feature extraction, Latent Semantic Analysis feature extraction, and word-embedding-based features. In order to integrate both emojis and text, the authors distinguish three types of fusion: feature level, score level, and decision level. They later build models to detect the tweets' polarity using different feature extraction approaches and different fusion levels. Support Vector Machines (SVM) and Linear Regression (LR) are adopted in the experiments. However, the proposed approaches are built exclusively for the Arabic language. They are not context-sensitive. [12] use a specific hashtag (#iphone) to extract data from Twitter. They have extracted only tweets with emojis. The authors used machine learning and deep learning approaches. For the machine learning techniques they used the Linear regression, linear discriminant Analysis, k-nearest neighbor, classification and regression trees, naive Bayes and support vector machines. They use two different deep learning approaches namely the artificial neural network and the convolutional neutral network and a basic search classifier. The proposed approach does not consider the impact of emojis on only text classification since they consider only tweets that have emojis.

Using both text and emojis for opinion mining and taking into account the topics in an incremental way is an open issue. The fusion using different classifiers was proposed in [1]. This significantly increases the complexity. Our purpose is to include all the features considering the complexity of the system as a constraint.

3. Our Opinion Mining Model

Machine learning is a growing field of computational algorithms that aim to mimic human intelligence by learning from their environment. Pattern recognition, computer vision, space technology, finance, entertainment, and computational biology, as well as biological and medical applications, have all benefited from machine learning techniques. A widely accepted definition of machine learning states that a program learns to perform a T task by improving its P performance through E experience.

Supervised approaches have shown promising results compared to other families, despite the main drawback of the need for labeled data. First, we need to solve the problem of how to decide which machine learning algorithm to use. Choosing the right algorithm can seem like a tedious process: There are dozens of supervised machine learning algorithms, and each approach learns differently way. There is no one best or only approach. Part of determining the right algorithm to use is a matter of trial and error. Even the most experienced data scientists can't predict how well an algorithm will perform without performing certain tests. The choice of an algorithm also depends on the nature of the data and its volume, the information you want to extract from it, and what you want to do with it.

Most work based on machine learning has conducted several comparative studies to find the best machine learning approach for opinion classification, as in [25] and [26]. For our concern, we will use the following models: Long-Short Term Memory (LSTM), Convolutional Neural Network (CNN). We implement these models in Python language and use Keras module to implement CNN, LSTM and SKLearn module for CRF, Word2vec and Natural Language Toolkit (NLTK) module for Natural Language Processing (NLP). Hereafter, we will detail the architecture of our Deep Learning models.

3.1. LSTM for Opinion Mining

LSTM is effective at dealing with sequential data because it allows for long-term dependencies to remain throughout the network. That explains their broad use in text mining applications. LSTM suppose a relation between data items in sequence. Our objective is to examine the impact of emojis and topics as non-sequential data on the performance of LSTM for opinion polarity. We propose an LSTM architecture in which two input layers are concatenated using a concatenation layer. The first input to the LSTM layer consists of two sequential features, namely the polarity of words and the Part Of Speech tag of each word. The second input includes the non-sequential features such as the associated topic and emojis. The architecture of the proposed LSTM is depicted in Figure 1.

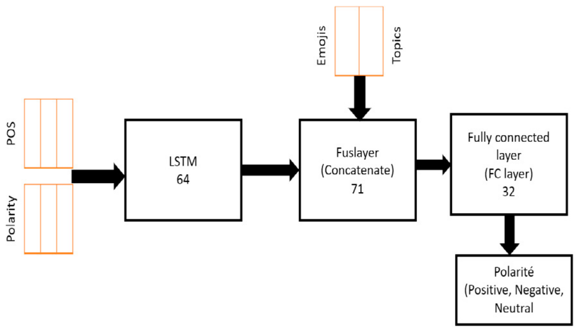

Fig. 1. The architecture of the LSTM model

3.2. CNN for Opinion Mining

CNN is extensively used in image processing and image recognition [31]. It is also known for handling challenges related to NLP tasks such as sentiment analysis. In the CNN architecture, the convolutional layers are made up of neurons that search for patterns in their input. Pooling layers are frequently added after convolutional layers, primarily to minimize the dimensionality of the feature map. We propose a CNN architecture where two input layers are concatenated using a concatenation layer. The first input for the CNN layer includes two sequential features: the polarity of words and the Part Of Speech tag of each word. Then, a pooling layer is used to minimize the size of the feature map by selecting the most important features. The second input includes the non-sequential features like the associated topic and emojis. We employ a fully - connected layer to flatten the data into a one-dimensional array to get the polarity finally. The architecture of the proposed CNN is represented in Figure 2.

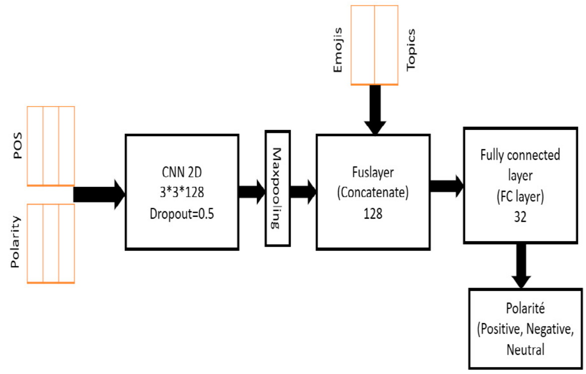

Fig. 2. The architecture of the CNN model

In the next section, we will conduct an extensive experimentation of the proposed architectures as well as analyze the obtained results regarding the use of emoji.

4. Experiments

The main purpose of these experiments is to analyze the performance of the proposed architectures with respect to the use of emoji in opinion mining. To do this, we must first describe the process by which the data used was acquired and preprocessed from Twitter.

4.1. Data Acquisition and Preprocessing

We used the dataset collected from Twitter in [19]. The dataset contains various data related to the tweets and the user's profile, while maintaining the structure of a connected network. This data includes the ID of the tweet, the ID of the user, the name of the user, the content of the tweet, the language of the tweet, the number of likes, the number of replies, the number of retweets, the origin of the retweet, the time, the followers, the followers, the link, the source of the video, the cover of the video, and the images. The data was crawled between July and August 2020. However, the tweets may be earlier than that since we extracted an average of 1000 tweet per user. The details of the dataset can be found in Table 1.

Table 1. Data description

Total number of tweets	11 695 015
Number of tweets with text	11 695 015
Number of tweets with text and images	1 143 190
Number of users	1245474
Number of edges	12 388 966
Number of images	1 335 898

From this dataset, we select 395 562 tweets so that we balance classes (positive, negative, neutral). Stated otherwise, we select 131 854 tweets for each class. Having these tweets at hand, we proceed to the manual annotation of a sample

3 000 tweets containing emojis. The sample is class balanced and containing 1 000 tweets for each class. Each tweet was annotated by five experts, and the majority label is taken as the class of the tweet.

After being manually labeled, we proceed to the preprocessing of these tweets. This step includes: tokenization, punctuation removal, link removal, emoticon cleanup, hashtag cleanup, and mention cleanup. We tokenize with a regular expression that we have defined regular expressions for currency (actually $ and £) and for dates like: dd-mm-yyyy and yyyy-mm-dd. After the preprocessing, we will extract opinions from the text. We should go through natural language processing to extract useful information and features. We're going to take an incremental approach, so we're going to limit ourselves to text first and then add emojis as a feature. We generated the feature vectors for the text version as follows:

- 1 if the word is an adjective, verb, adverb (POS), 0 otherwise
- 1 if the word is negative (dict), 0 otherwise
- 1 if the word is positive (dict), 0 otherwise
- 1 if the word is neutral (dict), 0 otherwise
- A value between 0 and 1: Similarity with the context (corresponding topic in our case) according to word2vec

The polarity of a word is determined on the basis of [11] which is the most widely used lexicon in the literature.
For the emojis we did the mapping based on [27] and [30].

- 1 if the word is an adjective, verb, adverb (POS), 0 otherwise
- 1 if the word is negative (dict), 0 otherwise
- 1 if the word is positive (dict), 0 otherwise
- 1 if the word is neutral (dict), 0 otherwise
- A value between 0 and 1: Similarity with the context (corresponding topic in our case) according to word2vec
- a vector of 3 attributes where each attribute receives 0 or 1 to indicate the presence of a negative, neutral or positive emoji.

In the next subsection, we will outline simulation results.

4.2. Simulation Results

In our experiments, we have used the following parameters for the used learning architectures:

- $N-FEAT = 11$ presents the number of features.
- $N-TRAIN = 3 * 131854$ presents the number of tweets (training set).
- $N-WORDS = 30$presents the number of words that we consider.
- $N-CLASS = 3$ presents the number of classes (positive, negative, and neutral).
- $Epochs = 30$ presents the number of epochs(number of complete passes through the training dataset).
- $BATCH = 128$ number of training samples to work through before the model's internal parameters are updated.
- $CELLS = [64, 128]$ number of layers.

In Table 2 we present a clearer description of the proposed LSTM:

Table 2. LSTM proposed architecture

Layer (type)	Output Shape	Param #	Connected to
input-1 (InputLayer)	(None, 30, 4)	0	——
$lstm_1$ (LSTM)	(None, 64)	17664	$input_1[0][0]$
$input_2$ (InputLayer)	(None, 7)	0	——
$concatenate_1$ (Concatenate)	(None, 71)	0	$lstm_1[0][0]$ $input_2[0][0]$
$dense-1(Dense)$	(None, 32)	2304	$concatenate_1[0][0]$
$dense-2(Dense)$	(None, 3)	99	$dense_1[0][0]$

In Table 3 we present a clearer description of the proposed CNN:

Table 3. CNN proposed architecture

Layer (type)	Output Shape	Param #	Connected to
input-1 (InputLayer)	(None, 30, 4)	0	—–
$lstm_1$ (LSTM)	(None, 64)	17664	$input_1$[0][0]
$reshape_1(Reshape)$	(None, 30, 4, 1)	0	$input_1$[0][0]
$conv2d_1(Conv2D)$	(None, 28, 2, 128)	1280	$reshape_1$[0][0]
$dropout_1(Dropout)$	(None, 28, 2, 128)	0	$conv2d_1$[0][0]
$max_pooling2d_1(MaxPooling2D)$	(None, 14, 1, 128)	0	$dropout_1$[0][0]
$flatten_1(Flatten)$	(None, 1792)	0	$max_pooling2d_1$[0][0]
$input_2(InputLayer)$	(None, 7)	0	—-
$concatenate_1(Concatenate)$	(None, 1799)	0	$flatten_1$[0][0]$input_2$[0][0]
$dense_1(Dense)$	(None, 32)	57600	$concatenate_1$[0][0]
$dense_2(Dense)$	(None, 3)	99	$dense_1$[0][0]

In order to assess their effectiveness, we compare the proposed LSTM and CNN to Conditional Random Fields (CRF) [17] and to Gated recurrent units (GRUs) [6]. We divide the data into training and test data. As we mentioned earlier, we use 3000 tweets for test data and the rest of the dataset for training. As for evaluation, we use standard evaluation criteria: accuracy, precision, recall and F1-score [23]. Simulation results are outlined in Tables 4 and 5. Table 4 presents the results obtained using text only, while Table 5 presents the results using text and emojis.

Table 4. Evaluation metrics with the use of text only

Algorithm	Accuracy	Precision	Recall	F1-score
LSTM	0.784	0.794	0.791	0.785
CNN	0.782	0.790	0.7873	0.783
CRF	0.832	0.824	0.832	0.827
GRU	0.788	0.794	0.786	0.786

Table 5. Evaluation metrics with the use of text and emojis

Algorithm	Accuracy	Precision	Recall	F1-score
LSTM	0.837	0.836	0.842	0.837
CNN	0.790	0.798	0.798	0.791
CRF	0.827	0.634	0.614	0.621
GRU	0.821	0.826	0.828	0.820

As a first remark, we can notice from these tables that CRF gives the best results when using text only, whereas LSTM gives the best results when combing text and emojis. Also, we can notice that for the majority of the models, the use of emoji enhances the computation of opinions. For example, regarding LSTM we have enhanced the F1-score from 0.785 to 0.837, that is an increase of about 6.6%. The confusion matrices reported in Tables 6 and 9 (for LSTM and CNN) give us better insight of the obtained results.

Table 6. LSTM confusion matrix without emojis

Predicted True	Negative	Neutral	Positive
Negative	749	69	29
Neutral	255	821	37
Positive	76	183	781

Table 7. LSTM confusion matrix with emojis

Predicted True	Negative	Neutral	Positive
Negative	759	56	32
Neutral	160	870	83
Positive	73	86	881

Table 8. CNN confusion matrix without emojis

Predicted True	Negative	Neutral	Positive
Negative	751	68	28
Neutral	261	806	46
Positive	84	144	812

Table 9. CNN confusion matrix with emojis

Predicted True	Negative	Neutral	Positive
Negative	759	56	32
Neutral	160	870	83
Positive	73	86	881

As a summary of these experiments, one easily notices that the results are better when using emoji. This can be explained by the fact that emojis provide information about the tweet's class. There was clear evidence of exceeding LSTM in terms of accuracy and F1-score compared to other machine learning approaches. This can also be seen referring to the confusion matrix where the model classifies 759 true negative, 870 true positive, and 881 true neutral for the with emojis version compared to 751, 806, and 812 for the proposed CNN model. The single most striking observation to emerge from the obtained results was that CNN performed better in the neutral class than LSTM. Both models performed better compared to the without-emojis version.

This result was expected because LSTM has the advantage over alternative RNNs, hidden Markov models, and other sequence learning approaches due to its relative insensitivity to space length. The other algorithms had results that were close to each other. For CRF, the addition of emojis did not lead to an improvement in the result, on the contrary we notice a deterioration in the results. This can be explained by the fact that the features used cannot lead to an appropriate fit and to biased performance estimates in the CRF case.

5. Conclusion

In this paper, we applied different machine learning algorithms to opinion mining: CNN, LSTM, CRF, and GRU. Those algorithms were first built and validated on data taken from Twitter. We then carried out several experiments to compare those algorithms' performance on text first then on text and emojis. Regarding CRF, the obtained results on text only were better than the results with the emoji. Regarding the CNN and LSTM algorithms, we opted for modified architectures that integrate sequential and non-sequential features. In our case, the sequential features represent the polarity according to a dictionary and the POS tag of the word. The non-sequential features are the topics and the emojis present in the post.

In our simulation, we considered a text-only version where we did not take into consideration emojis. Then, we added the emojis to measure their impact on the post polarity. Experimental results are very encouraging in terms of accuracy, precision, recall, and F-score and should stimulate further investigations. So, we moved to a deeper level of result analysis by considering the confusion matrix. We notice that the number of true positives is significant for all the studied algorithms. Future work will entail applying our generic approach to other data and problems.

References

[1] Al-Azani, S., El-Alfy, E.S.M., 2021. Early and late fusion of emojis and text to enhance opinion mining. IEEE Access 9, 121031–121045.

[2] Balahur, A., Hermida, J.M., Montoyo, A., 2011. Building and exploiting emotinet, a knowledge base for emotion detection based on the appraisal theory model. IEEE transactions on affective computing 3, 88–101.
[3] Barbosa, L., Feng, J., 2010. Robust sentiment detection on twitter from biased and noisy data, in: Coling 2010: Posters, pp. 36–44.
[4] Cambria, E., Liu, Q., Decherchi, S., Xing, F., Kwok, K., 2022. Senticnet 7: A commonsense-based neurosymbolic ai framework for explainable sentiment analysis, LREC.
[5] Chen, Y., Yuan, J., You, Q., Luo, J., 2018. Twitter sentiment analysis via bi-sense emoji embedding and attention-based lstm, in: Proceedings of the 26th ACM international conference on Multimedia, pp. 117–125.
[6] Cho, K., Van Merriënboer, B., Bahdanau, D., Bengio, Y., 2014. On the properties of neural machine translation: Encoder-decoder approaches. arXiv preprint arXiv:1409.1259 .
[7] Cui, A., Zhang, M., Liu, Y., Ma, S., 2011. Emotion tokens: Bridging the gap among multilingual twitter sentiment analysis, in: Asia information retrieval symposium, Springer. pp. 238–249.
[8] El Alaoui, I., Gahi, Y., Messoussi, R., Chaabi, Y., Todoskoff, A., Kobi, A., 2018. A novel adaptable approach for sentiment analysis on big social data. Journal of Big Data 5, 1–18.
[9] Gamal, D., Alfonse, M., M. El-Horbaty, E.S., M. Salem, A.B., 2019. Analysis of machine learning algorithms for opinion mining in different domains. Machine Learning and Knowledge Extraction 1, 224–234. URL: https://www.mdpi.com/2504-4990/1/1/14.
[10] Go, A., Bhayani, R., Huang, L., 2009. Twitter sentiment classification using distant supervision. CS224N project report, Stanford 1, 2009.
[11] Hu, M., Liu, B., 2004. Mining and summarizing customer reviews, in: Proceedings of the tenth ACM SIGKDD international conference on Knowledge discovery and data mining, pp. 168–177.
[12] Karthik, V., Nair, D., Anuradha, J., 2018. Opinion mining on emojis using deep learning techniques. Procedia computer science 132, 167–173.
[13] Kaur, A., Gupta, V., 2013. A survey on sentiment analysis and opinion mining techniques. Journal of Emerging Technologies in Web Intelligence 5, 367–371.
[14] Keyvanpour, M., Zandian, Z.K., Heidarypanah, M., 2020. Omlml: a helpful opinion mining method based on lexicon and machine learning in social networks. Social Network Analysis and Mining 10, 1–17.
[15] Kim Phung, T., An Te, N., Thi Thu Ha, T., 2021. A machine learning approach for opinion mining online customer reviews, in: 2021 21st ACIS International Winter Conference on Software Engineering, Artificial Intelligence, Networking and Parallel/Distributed Computing (SNPD-Winter), pp. 243–246. doi:10.1109/SNPDWinter52325.2021.00059.
[16] Krishna, B.V., Pandey, A.K., Kumar, A.S., 2018. Feature based opinion mining and sentiment analysis using fuzzy logic, in: Cognitive science and artificial intelligence. Springer, pp. 79–89.
[17] Lafferty, J., McCallum, A., Pereira, F.C., 2001. Conditional random fields: Probabilistic models for segmenting and labeling sequence data .
[18] Messaoudi, C., Guessoum, Z., Ben Romdhane, L., 2022. Opinion mining in online social media: A Survey. International Journal of Social Network Analysis and Mining (SNAM) 12, 5. doi:10.1007/s13278-021-00855-8.
[19] Messaoudi, C., Guessoum, Z., Romdhane, L.B., 2021. Topic extraction in social network, in: International Conference on Applied Data Science and Intelligence.
[20] Mohammad, S.M., Kiritchenko, S., Zhu, X., 2013. Nrc-canada: Building the state-of-the-art in sentiment analysis of tweets. arXiv preprint arXiv:1308.6242 .
[21] Mohammad, S.M., Zhu, X., Kiritchenko, S., Martin, J., 2015. Sentiment, emotion, purpose, and style in electoral tweets. Information Processing & Management 51, 480–499.
[22] Ortega-Bueno, R., Muniz-Cuza, C.E., Pagola, J.E.M., Rosso, P., 2018. Uo upv: Deep linguistic humor detection in spanish social media, in: Proceedings of the Third Workshop on Evaluation of Human Language Technologies for Iberian Languages (IberEval 2018) co-located with 34th Conference of the Spanish Society for Natural Language Processing (SEPLN 2018), pp. 204–213.
[23] Padmaja, S., Fatima, S.S., 2013. Opinion mining and sentiment analysis-an assessment of peoples' belief: A survey. International Journal of Ad hoc, Sensor & Ubiquitous Computing 4, 21.
[24] Pandey, A.C., Rajpoot, D.S., Saraswat, M., 2017. Twitter sentiment analysis using hybrid cuckoo search method. Information Processing & Management 53, 764–779.
[25] Pang, B., Lee, L., Vaithyanathan, S., 2002. Thumbs up? sentiment classification using machine learning techniques. arXiv preprint cs/0205070 .
[26] Poria, S., Cambria, E., Gelbukh, A., 2016. Aspect extraction for opinion mining with a deep convolutional neural network. Knowledge-Based Systems 108, 42–49.
[27] sifei, 2014. Dictionary-for-sentiment-analysis. https://github.com/sifei/Dictionary-for-Sentiment-Analysis.
[28] Soong, H.C., Jalil, N.B.A., Ayyasamy, R.K., Akbar, R., 2019. The essential of sentiment analysis and opinion mining in social media: Introduction and survey of the recent approaches and techniques, in: 2019 IEEE 9th symposium on computer applications & industrial electronics (ISCAIE), IEEE. pp. 272–277.
[29] Tomihira, T., Otsuka, A., Yamashita, A., Satoh, T., 2020. Multilingual emoji prediction using bert for sentiment analysis. International Journal of Web Information Systems .
[30] Wikipedia, 2021. List of emoticons — Wikipedia, the free encyclopedia. http://en.wikipedia.org/w/index.php?title=List%20of%20emoticons&oldid=1036483841. [Online; accessed 02-October-2021].
[31] Zhang, J., Shao, K., Luo, X., 2018. Small sample image recognition using improved convolutional neural network. Journal of Visual Communication and Image Representation 55, 640–647.
[32] Zhou, L., Chaovalit, P., 2008. Ontology-supported polarity mining. Journal of the American Society for Information Science and technology 59, 98–110.