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Systematic Literature Review of Sentiment Analysis Techniques

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Abstract

Sentiment analysis has become an important research area that aims to understand people's opinions by analyzing a large size of information. There are two types of sentiment analysis methods: those based on the lexicon and those based on Machine Learning algorithms. Although there are many proposals related to sentiment analysis, there is still a great margin for improving results. The objective of this work is to identify the current state of the latest research related to the analysis of feelings, making use of a framework for the systematic review of the literature, in order to answer the following research questions: RQ1 What are the types of methods used for sentiment analysis? RQ2 What kind of data sources are used to perform sentiment analysis? A crossover analysis of the results was performed. One of the results showed that the most used classifier was Naïve Bayes. Besides, most of the works reviewed used texts extracted from microblogs, web pages, E-Commerce, and other data sources, to perform sentiment analysis.

Keywords: Natural Language Processing, Opinion Mining, Sentence Classification, Sentiment Analysis.

1. INTRODUCTION

With the great growth of texts generated by users on the web, discovering a method to extract and classify the opinions reflected in the texts automatically would be of great help for people, businesses, and even for the governments' intelligence when making decisions [1,4]. Sentiment analysis has become an important research area that aims to understand people's opinions by analyzing a large amount of information [3]. Twitter has become a social network where many people worldwide give their opinion or express their thoughts or feelings regarding a topic, a person, or different types of events, which is why Twitter is considered an important source of information to perform sentiment analysis [6]. Sentiment mining or sentiment analysis in Twitter platform tweets has many applications in different areas such as marketing, research, and brand analysis; companies use sentiment analysis of tweets to discover or analyze the opinions they have customers approach the products or services they offer, and from there, generate strategies for the brand [5]. There are two types of sentiment analysis methods: those based on the lexicon and those based on Machine Learning algorithms [4].

For these reasons, in recent years, different proposals have emerged that have contributed to analyzing feelings to determine people's opinions about a particular topic based on word processing. Therefore, in this article, a systematic review of the literature regarding the techniques for sentiment analysis has been carried out, considering the types of Methods (RQ1) and the types of Datasource (RQ2) proposed in the reviewed studies.

The work is organized in. Section II describes the research methodology used for the systematic review of the works' literature regarding sentiment analysis. Section III presents the analysis of the studies obtained in the systematic review of the literature. Section IV consists of the analysis of the results obtained. Finally, section V presents the conclusions obtained after conducting the systematic review of the literature.

2. RESEARCH METHODOLOGY

The research methodology used for the systematic review of the literature regarding the techniques for the analysis of feelings has been proposed considering the principles used by Kitchenham et al. [2], which consists of three phases: (1) Planning the review: in this phase, the research questions are elaborated, and the review protocol is defined. (2) Development of the review: in this phase, the primary studies are selected considering the selection and exclusion criteria. Moreover, (3) Results of the review: in this phase, the statistics and the analysis carried out on the previously selected studies are presented.

2.1. Planning the review

In planning the review, research questions were elaborated, and a research protocol was defined, which are mentioned below: RQ1 What are the types of methods used for sentiment analysis? RQ2 What kind of data sources are used to perform sentiment analysis?

The IEEE Xplore Digital Library database was selected to carry out the research; the date range was between 2015 and 2020. The keywords used for the search were: "Natural Language Processing", "Opinion Mining", "Sentence Classification", "Sentiment Analysis". After searching with the mentioned keywords, the selection and exclusion criteria detailed in Table I was applied.

TABLE I
SELECTION AND EXCLUSION CRITERIA

Selection Criteria	Exclusion Criteria
Different types of proposals: frameworks, methods, models, systems, and techniques to perform sentiment analysis.	The study language is not English.
Studies related to the motivation and state of the art.	Sentiment analysis but which are not oriented software engineering.
	Papers that were not published between 2015 and 2020.

2.2. Review process

After researching by applying the keywords in the IEEE Xplore Digital Library database, the studies that met the selection and exclusion criteria were selected (see Table I). Fig. 1 shows the review process applied, during which 21483 potentially eligible studies were obtained, of which, after applying the selection and exclusion criteria, 18 selected studies were obtained (see Table II).In the second classification of "Components for the development of chatbots", the most prominent article is by Ruan et al. [10]. They developed QuizBot, a dialogue-based agent that helps students learn science factual knowledge, safety, and English language vocabulary. Quizbot has three key components: (i) A dialogue system. (ii) A systematic similarity model. (iii) An adaptive system also included a Tensorflow package for a universal sentence encoder.

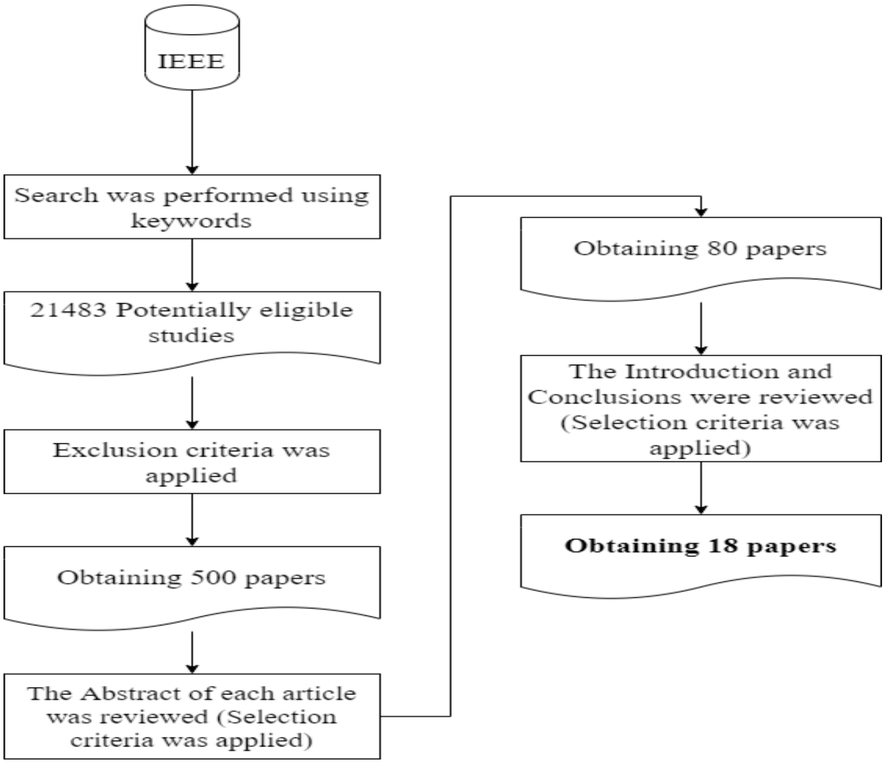

Fig. 1. Systematic literature review process. Shows the steps of the review process

2.3. Review results

The studies selected during the development of the systematic review contained information regarding different techniques used for sentiment analysis. Table II presents the number of potentially eligible studies in the IEEE Xplore Digital Library database and the number of selected studies.

TABLE II:
POTENTIALLY ELIGIBLE STUDIES AND SELECTED STUDIES

Source	Potentially eligible studies	Selected studies
IEEE Xplore Digital Library	21483	18

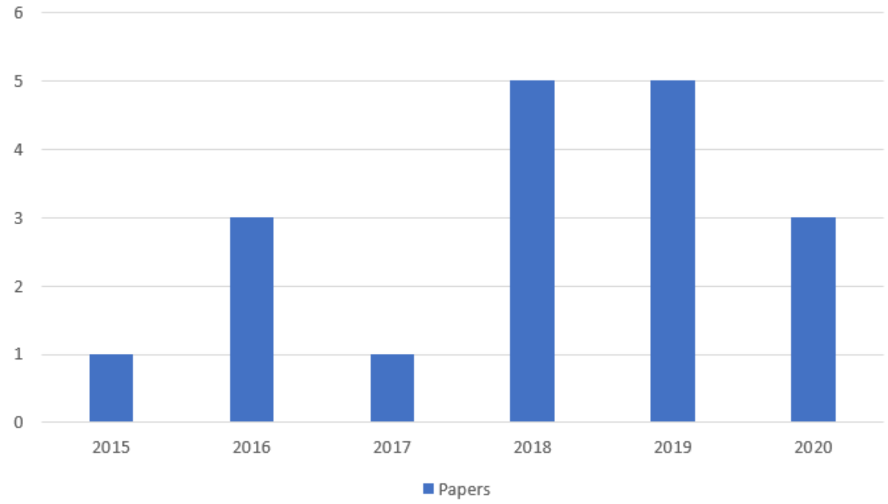

Fig. 2: Number of papers per year. Presents the number of studies selected per year between 2015 and 2020, where it is observed that, in recent years, the number of studies regarding techniques for sentiment analysis has been increasing; in 2018 and 2019 5 studies were found per year, and in 2020 3 studies were found.

3. Analysis of studies

To carry out the analysis of the studies selected in the systematic review of the literature regarding the techniques for the analysis of feelings, a taxonomy was defined (see Fig. 3) according to the research questions posed in the planning phase of the Review: "Methods" (RQ1) and "Datasource" (RQ2). The "Methods" classification is related to investigations that applied different algorithms, methods, and models to analyze feelings. In the “Datasource” classification, the studies used different data sources to perform sentiment analysis.

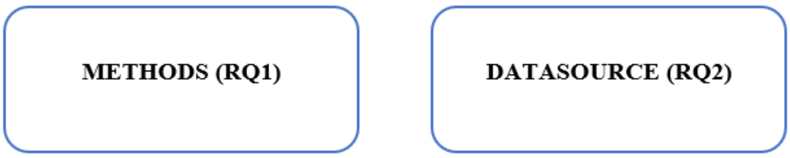

Fig. 3. Proposed taxonomy for the literature review

In summary, Table III presents the studies selected in the systematic review of the literature according to the proposed taxonomy (Fig. 3.).

TABLE III
PAPERS CLASSIFICATION

Classification	**References**	**Total**
Methods	[3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20]	18
Datasource	[3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20]	17

The following is an analysis of the studies selected according to the classification to which they belong.

3.1. Methods (RQ1)

Table IV shows the two (02) types of proposed methods in the selected studies for sentiment analysis. Each study consists of different algorithms, methods, and models for pre-processing and classification to perform sentiment analysis.

TABLE IV
APPLIED METHODS TO PERFORM SENTIMENT ANALYSIS

ID	Methods	References
M01	Machine Learning	[3, 4, 5, 6, 8, 10, 11, 12, 13, 15, 16, 17, 18, 19, 20]
M02	Lexicon based	[3, 4, 6, 7, 9, 12, 14, 17, 19]

Salinca [3] proposed a method for the analysis of user opinions regarding businesses such as restaurants and service providers; in the preprocessing, he eliminated the scores, converted the uppercase to lowercase to reduce redundancy in the selection of characteristics, applied Four classifiers: Multinomial Naïve Bayes, Linear Support Vector Classification, Logistic Regression, and Stochastic Gradient Descent Classifier, the classifier that obtained the best results was Stochastic Gradient Descent with an accuracy of 92.6%. Woldemariam [4] evaluated the available technologies for sentiment analysis in order to compare them considering the accuracy and in this way discover which has the best performance; one of the methods that he evaluated was a Recurrent Neural Tensor Network (RNTN), For which, he used a previously trained model of feelings. The steps to follow were: 1) Tokenize the sentences in individual words, 2) Lemmatize each word to its base form, 3) Assign tags to the words, 4) Parse the sentences in sub sentences and build a syntactic tree, 5) Make the tree binary, 6) Classify the sentences, and 7) Apply softmax to calculate the results, with this method he obtained an accuracy of 48.34% and a precision of 82%. Li et al. [5] proposed a simple, effective, and easy-to-implement solution to improve performance in the classification of feelings through the combination of SSWE and WTFM; they trained the SSWE model and used the WTFM model to generate features of four types: negation, and three features corresponding to the similarity with the three types of polarity (negative, positive and neutral), when combining SSWE and WTFM, the resulting features were: the representation of each text based on SSWE and the features obtained by the WTFM model, they tested different classification algorithms, of which the LibLinear algorithm obtained the best results with an accuracy of 68.3%. Jose et al. [6] introduced a sentiment classifier by combining machine learning classifiers with a classifier based on the lexicon; in the preprocessing of the data, they only considered the texts in English and also eliminated the special characters; besides, they applied a simple algorithm to The handling of negation, for the classification they applied Naïve Bayes and the Hidden Markov model, to determine the final result regarding the feeling of a text, they compared the results of the classifiers and selected the result that had the majority, with their proposal they achieved a 71.48% accuracy.

Maia et al. [8] proposed a classifier called FSSL for sentiment analysis in finance texts, whose classes were positive, neutral, and negative; first, they simplified large and compound sentences to shorter and independent sentences by decoupling clauses and phrases, then classified distant supervision, using the Long Short-Term Memory (LSTM) neural network, finally applied a model for the classification of feelings in sentences, for the implementation of the model they used the NLTK library and the modules and models of Twitie POS, achieved an average accuracy of 90.9%.

Zvarevashe et al. [10] proposed a framework for the analysis of the opinions of hotel clients through sentiment analysis (SPBM); they tagged the texts based on the polarity of the sentiment using an algorithm; the result of this showed if a comment was negative, positive or neutral, then they converted the text that was labeled to vectors by using filters; finally, they selected a classification algorithm between multinomial Naïve Bayes (NBM), Sequential minimal optimization (SMO), Compliment Naïve Bayes (CNB) and Composite hypercubes on iterated random projections (CHIRP) for training and testing. This algorithm obtained the best results was multinomial Naïve Bayes with an accuracy of 80.9%. Sun et al. [11] designed a multi-network model to analyze the sentiment of the texts obtained from microblogs in the Tibetan language, used three convolutional layers and two LSTM layers, applied Word2Vec to construct vectors from the words, then used a fusion of CNN-LSTM, since this mixed Deep Learning model allowed them to obtain deeper semantic information from the texts, the convolutional neural network focused on global measurement and the RNN was responsible for the reconstruction of each adjacent information, they applied the optimizer Adam and the activation function Tanh for the prediction of the tags, achieved an accuracy of 86.21%. Bandana [12] proposed a system for analyzing feelings about people's opinions regarding movies by using the combination of Machine Learning methods and lexicon-based methods. For the implementation of his proposal, he used Python 3.4 in The classification applied the Naïve Bayes and Linear Support Vector Machine classifiers obtained the best results with the Naïve Bayes classifier with an accuracy of 89%.

Wongkar et al. [13] aimed to analyze the community's sentiment towards Indonesia's presidential candidates in 2019 from the tweets of the Twitter platform by using a data crawler to obtain the texts and the Naïve Bayes classifier. Once they had the texts applied Text Analysis and Tokenization, they converted the sentences to simple words and took the words that had a value; finally, they carried out the text mining using Naïve Bayes, they achieved an accuracy of 80.90%. Lee et al. [15] with their proposal they sought to perform sentiment analysis using Deep Learning to determine if the information is positive or negative; in the preprocessing, they applied the GB 18030 coding, they translated all the characters to simplified Chinese, they removed the special characters and the empty words They also tokenized the texts using Jieba. They converted the words into vectors using Count Vector; the classification model they proposed was based on Gated Recurrent Unit (GRU), which was a variation of LSTM; for the implementation, they used Keras, when they trained the model with 50% positive data and 50% negative data achieved an accuracy of 87.66%.

When they trained the model with unbalanced data (82% positive and 18% negative), they achieved an accuracy of 87.2%, demonstrating the effectiveness and robustness of its model. Cheng et al. [16] proposed a framework based on Deep Learning for the analysis of feelings in texts from social networks; they preprocessed the texts they collected since they contained special characters and words such as emoticons, to which placed their meaning, then analyzed the feelings of the texts obtained by using NLTK Textblob and the Google Cloud Natural Language API, then used word2vec and GloVe to obtain representations of each word; finally, they used three Deep Learning models to perform the classification of the texts, which were LSTM, BiLSTM, and GRU, the model that obtained the best results was BiLSTM with an accuracy of 87.17%. Rumelli et al. [17] proposed a model for the analysis of sentiments in Turkish texts, by integrating methods based on the lexicon and machine learning algorithms, for the extraction of characteristics, taking into account unigrams, boosted words, and bigrams, for the text classification, they applied four Machine Learning methods, which are: Naïve Bayesian (NB), Random Forest (RF), Support Vector Machine (SVM) and k-Nearest Neighbor (kNN), they achieved the best accuracy with kNN with a value of 73.8%. Poornima et al. [18] compared the performance of three classifiers in the task of analyzing the sentiment of the data obtained from Twitter, applied stemming, lemmatization, stop words removal to clean the data, then applied Term Frequency (TF) to determine the number of times that a word is repeated in a document, in the extraction of characteristics they used bigrams, to perform the classification of the sentences, they applied three classifiers: Logistic Regression Algorithm, Support Vector Machine and Multinomial Naïve Bayes, they analyzed the accuracy of the three classifiers, where Logistic Regression was the best with 86.23%, SVM with 85.69% and Multinomial Naïve Bayes with 83.54%. Yang et al. [19] proposed the SLCABG model, which was based on the advantages of the lexicon of feelings and Deep Learning techniques; they used a convolutional neural network CNN to extract the characteristics of the matrix in order to generate a vector, then they used the BiGRU model to extract the contextual characteristics of the text, then they applied an attention mechanism to give different weights to different words in a sentence; finally, they classified the extracted characteristics through the sigmoid activation function, they achieved an accuracy of 93.5%.

AlSalman [20] proposed an approach for the analysis of sentiments of text in the Arabic language using a Discriminative Multinomial Naïve Bayes (DMNB); his proposal consisted of two main steps: the preprocessing and normalization of the tweets, and the classification of the tweets, he used WEKA for the implementation of his solution, in the preprocessing and normalization, the words were tokenized using the 4 gram technique, then he used Khoja-stemmer to remove the stopwords, and finally, he applied term frequency with inverse document frequency (TF-IDF), in the classification, applied Discriminative Multinomial Naïve Bayes (DMNB) to classify the tweets as positive or negative, it achieved an accuracy of 87.5%.

Salinca [3], in the extraction of characteristics, implemented two approaches; the first consisted of building a dictionary from the training data, for which he applied Natural Language Toolkit (NLTK) methods, and finally managed to tokenize each word, and The second consisted of carrying out a lexical analysis of the opinions, for which he carried out the previous steps and also tokenized each sentence using POS, he also applied an algorithm for word meaning disambiguation (WSD). Woldemariam [4] also used a method based on the lexicon for the classification of feelings, for which he applied preprocessing, which consisted of uploading the texts to a Hadoop Distributed File System (HDFS), and then transformed them so that they can be analyzed, then applied the algorithm based on the lexicon, which consisted of 1) Tokenize the sentences in individual words, 2) Assign a polarity to each word (positive, negative, neutral) using a sentiment dictionary, 3) Calculate the sum of the polarities of each sentence, 4) Compare the results with 0 to determine if it is "positive", "negative" or "neutral", and 5) Assign the value of the feeling to the complete sentence (2 for positive, 1 for neutral and 0 for negative), with this method he obtained an accuracy of 38.45% and a precision of 63%. Jose et al. [6] also used SentiWordNet to classify feelings, a classifier based on the lexicon; using only this classifier, they obtained an accuracy of 21.05%. Li et al. [7] proposed a method for the analysis of sentiments of small texts extracted from microblogs, defined a set of rules to calculate the sentiment structure of a sentence, for which they used the Language Technology Platform (LTP), in order to After analyzing the dependency syntax between words, the microblogging texts did not exceed 140 words, which was on average three sentences, and to calculate the sentiment value of a text, they calculated the polarity of their sentences, to calculate the value of the sentiment of a sentence, they calculated the value of the sentiment from their sentiment structure, they achieved an average precision of 73.77% and an average recall of 74.01%.

Alshari et al. [9] proposed a model called Senti2Vec to enlarge the intersection of the SentiWordNet model (which is a model based on the lexicon to determine the polarity of texts) and the general vocabulary, with the aim of improving the effectiveness in the analysis of feelings , the first step of the model they proposed was to learn the representation of the terms based on the Word2Vec model, this allowed them to discover the semantic relationship between the terms of the general vocabulary, the second step was the Synset unification, which consisted of creating a dictionary of feelings from SentiWordNet where the terms in common would be represented by a single term with the positive or negative scores, finally, the third step was to learn the polarity of the sentiment of those words that do not express opinion, based on the polarity of the terms closest in SentiWordNet, achieved an accuracy of 85.4% in the classification of positive texts and an ex 83.9% attitude in the classification of negative texts. Bandana [12], for implementing her proposal, also used Natural Language Processing Toolkit (NLTK); in the preprocessing, she applied the methods: Remove HTML Markup Tags, Tokenization, Remove Stop Words, and Lemmatization, for the extraction of characteristics she applied SentiWordNet.

Rabeya et al. [14] proposed a lexicon-based backtracking algorithm in order to perform sentiment analysis on a YouTube channel in the Bengali language; they generated expressions from the texts for which they used three types of words: positive, negative, and denial, and also introduced positive and negative words to make the analysis more effective, besides, they used a list of phrases because some sentences did not contain keywords that represent feelings, but had a strong positive or negative meaning, then applied a backtracking algorithm in order to determine sentiment, for which they trained the algorithm with 288 unique expressions, they achieved an accuracy of 71.23%. Rumelli et al. [17] used the SentiTurkNet dictionary, which contained 15,000 Turkish terms, and each of these contained the level of the polarity of the word (positive, negative, or neutral); also, they used Zemberek, which is a tool for processing of Turkish natural language, which has the functions of tokenization, normalization, and normalization of text noise. Yang et al. [19] constructed a feeling lexicon based on the emotions vocabulary from Dalian University of Technology to improve feelings in the data, then applied the BERT model to train the words' vectors in order to obtain a weighted matrix of vector words.

3.2. Datasource (RQ2)

The second classification corresponds to studies that used different types of data sources to perform sentiment analysis. Table V shows the types of data sources found in the systematic review of the literature.

TABLE V
TYPES OF DATASOURCE THAT WERE USED TO PERFORM SENTIMENT ANALYSIS

ID	Datasource	References
D01	Twitter	[5, 6, 13, 18, 20]
D02	Others	[3, 4, 7, 9, 10, 11, 12, 14, 15, 16, 17, 19]

Li et al. [5] trained the SSWE model that they used with 10 million tweets from the Twitter platform, of which 5 million contained positive emoticons and 5 million contained negative emoticons. Jose et al. [6] acquired their Twitter dataset using the Twitter Streaming API, where they extracted 12,000 tweets about the elections in Delhi. Wongkar et al. [13] obtained the texts using a data crawler method from Twitter; they obtained data related to the Indonesian presidential campaign from January to May 2019. Poornima et al. [18] obtained the data from Twitter (1.6 million pieces of data), which contained misspelled words and incorrectly placed punctuation marks. AlSalman [20] obtained 2000 texts in Arabic language (tweets and comments), of which 50% were positive, and 50% were negative.

Salinca [3] used the dataset corresponding to Yelp Challenge, which consisted of 1.6 million opinions from 366,000 users concerning 61,000 businesses, from which it built a training dataset with 1,346,545 opinions, which 80% was for training and 20% for testing. Woldemariam [4] used a dataset corresponding to the Snapshots Serengeti project (http://www.snapshotserengeti.org), where people wrote their opinions on the classification of animals and also on images of these.

Li et al. [7] In order to validate their proposed method, they used 2740 microblogging texts. Alshari et al. [9] In order to test the model they proposed, they used the ACLIMDB, which was a movie review dataset, and consisted of 100,000 reviews of which 50,000 were tagged. Zvarevashe et al. [10] used the OpinRank dataset and also obtained different user comments about the hotels. Sun et al. [11] used the Tibetan sentiment vocabulary built by Qinghai University, which had 27,361 words in total, including negative, positive, neutral words, they also used the Tibetan tagged microblogging dataset. Bandana [12] built a dataset using sources such as IMDB, Rotten Tomatoes, Netflix, from which he obtained the opinions of users regarding the films, obtained 2 subdatasets, the first of 250 texts and the second of 300 texts. Rabeya et al. [14] used the comments of a YouTube channel, among which were positive and negative texts. Lee et al. [15] obtained 32 558 reviews from Chinese E-Commerce, which were divided into 60 830 sentences, the sentences were labeled positive (30 876) and negative (29 954), additionally, they created a dataset containing various expressions (happiness, disappointment, denial, etc.), in order to maintain a high degree of neutrality, they used 80% for training and 20% for validation. Cheng et al. [16] applied a Python-based Web crawler to obtain data from social networks such as Facebook and YouTube; they collected 3000 positive and 3000 negative sentences from YouTube to validate the model they proposed. Rumelli et al. [17] built a dataset using E-Commerce, from which they obtained 272,218 data. Yang et al. [19] used a dataset that corresponds to Dangdang, a well-known E-Commerce in China; they obtained 100,000 reviews, 50,000 positive and 50,000 negatives.

4. ANALYSIS OF RESULTS

4.1. Methods (RQ1)

According to the results obtained in the systematic analysis of the literature regarding analyzing feelings, most of the reviewed papers used Machine Learning methods, with 15 studies, which represents 83% of the total papers reviewed (Table IV). The most widely used classifier was Naïve Bayes [3, 6, 10, 12, 13, 17, 18, 20], which obtained good results with an accuracy of 89% [12].

4.2. Datasource (RQ2)

According to the results obtained in the systematic analysis of the literature regarding the techniques for the analysis of feelings, 12 works used texts extracted from microblogs, web pages, E-Commerce, and other sources, to perform the sentiment analysis [3, 4, 7, 9, 10, 11, 12, 14, 15, 16, 17, 19], which represent 67% of the total of works reviewed (see Table V). All the works that used the tweets obtained from the Twitter platform to perform sentiment analysis applied preprocessing techniques to improve the text's quality, eliminate meaningless words, and perform the extraction of characteristics [5, 6, 13, 18, 20,21,22].

4.3. Cross analysis

Table VI presents the cross analysis performed between the types "Methods" and the types of "Datasource" found in the literature regarding the techniques for analyzing sentiments. As we can see, the texts extracted from Twitter (D01) and also the texts extracted from other data sources such as microblogs, web pages, YouTube, E-Commerce (D02) were used by the works that presented Machine Learning methods for the analysis of feelings (M01), and also for those works that presented methods based on the lexicon (M02).

TABLE VI

CROSS-TAB ANALYSIS

Datasource	D01	D02
Methods		
M01	√	√
M02	√	√

5. CONCLUSIONS

This article presented a systematic review of the literature of 21,483 potentially eligible articles related to sentiment analysis, of which the abstracts of 500 studies were reviewed, obtaining a total of 18 articles relevant to this study (see Fig. 1). The articles were analyzed based on the taxonomy proposed in Fig. 3; this work's conclusions are related to the 2 research questions posed in the planning phase of the review (see section II) and the cross-sectional analysis carried out Table VI. Table IV shows that most of the selected works, with a total of 15 studies, proposed machine learning methods for sentiment analysis, the most widely used method being the Naïve Bayes classifier. Besides, most of the selected works, with a total of 12 studies, used texts extracted from microblogs, web pages, E-Commerce, YouTube, and other data sources, to perform sentiment analysis; also, they applied techniques for the pre-processing of texts in order to improve the quality of the data and thus improve the results in the analysis of feelings.

References

[1] Bustamante, J.C., Rodriguez, C., Esenarro, D. (2019). Real time facial expression recognition system based on deep learning. International Journal of Recent Technology and Engineering, 2019, 8(2 Special Issue 11), pp. 4047-4051. doi: 10.35940/ijrte.B1591.0982S1119

[2] B. A. Kitchenham and S. Charters. (2007). Guidelines for performing systematic literature reviews in software engineering version 2.3. Retrieved January 9, 2014, from http://www.elsevier.com/__data/promis_misc/525444systematicreviewsguide.pdf.

[3] A. Salinca, "Business Reviews Classification Using Sentiment Analysis," 2015 17th International Symposium on Symbolic and Numeric Algorithms for Scientific Computing (SYNASC), Timisoara, 2015, pp. 247-250, doi: 10.1109/SYNASC.2015.46.

[4] Y. Woldemariam, "Sentiment analysis in a cross-media analysis framework," 2016 IEEE International Conference on Big Data Analysis (ICBDA), Hangzhou, 2016, pp. 1-5, doi: 10.1109/ICBDA.2016.7509790.

[5] Q. Li, S. Shah, R. Fang, A. Nourbakhsh and X. Liu, "Tweet Sentiment Analysis by Incorporating Sentiment-Specific Word Embedding and Weighted Text Features," 2016 IEEE/WIC/ACM International Conference on Web Intelligence (WI), Omaha, NE, 2016, pp. 568-571, doi: 10.1109/WI.2016.0097.

[6] R. Jose and V. S. Chooralil, "Prediction of election result by enhanced sentiment analysis on twitter data using classifier ensemble Approach," 2016 International Conference on Data Mining and Advanced Computing (SAPIENCE), Ernakulam, 2016, pp. 64-67, doi: 10.1109/SAPIENCE.2016.7684133.

[7] J. Li and L. Qiu, "A Sentiment Analysis Method of Short Texts in Microblog," 2017 IEEE International Conference on Computational Science and Engineering (CSE) and IEEE International Conference on Embedded and Ubiquitous Computing (EUC), Guangzhou, 2017, pp. 776-779, doi: 10.1109/CSE-EUC.2017.153.

[8] M. Maia, A. Freitas, and S. Handschuh, "FinSSLx: A Sentiment Analysis Model for the Financial Domain Using Text Simplification," 2018 IEEE 12th International Conference on Semantic Computing (ICSC), Laguna Hills, CA, 2018, pp. 318-319, doi: 10.1109/ICSC.2018.00065.

[9] E. M. Alshari, A. Azman, S. Doraisamy, N. Mustapha and M. Alkeshr, "Effective Method for Sentiment Lexical Dictionary Enrichment Based on Word2Vec for Sentiment Analysis," 2018 Fourth International Conference on Information Retrieval and Knowledge Management (CAMP), Kota Kinabalu, 2018, pp. 1-5, doi: 10.1109/INFRKM.2018.8464775.

[10] K. Zvarevashe and O. O. Olugbara, "A framework for sentiment analysis with opinion mining of hotel reviews," 2018 Conference on Information Communications Technology and Society (ICTAS), Durban, 2018, pp. 1-4, doi: 10.1109/ICTAS.2018.8368746.

[11] B. Sun, F. Tian and L. Liang, "Tibetan Micro-Blog Sentiment Analysis Based on Mixed Deep Learning," 2018 International Conference on Audio, Language, and Image Processing (ICALIP), Shanghai, 2018, pp. 109-112, doi: 10.1109/ICALIP.2018.8455328.

[12] R. Bandana, "Sentiment Analysis of Movie Reviews Using Heterogeneous Features," 2018 2nd International Conference on Electronics, Materials Engineering & Nano-Technology (IEMENTech), Kolkata, 2018, pp. 1-4, doi: 10.1109/IEMENTECH.2018.8465346.

[13] M. Wongkar and A. Angdresey, "Sentiment Analysis Using Naive Bayes Algorithm Of The Data Crawler: Twitter," 2019 Fourth International Conference on Informatics and Computing (ICIC), Semarang, Indonesia, 2019, pp. 1-5, doi: 10.1109/ICIC47613.2019.8985884.

[14] T. Rabeya, N. R. Chakraborty, S. Ferdous, M. Dash, and A. Al Marouf, "Sentiment Analysis of Bangla Song Review- A Lexicon Based Backtracking Approach," 2019 IEEE International Conference on Electrical, Computer and Communication Technologies (ICECCT), Coimbatore, India, 2019, pp. 1-7, doi: 10.1109/ICECCT.2019.8869290.

[15] J. S. Lee, D. Zuba and Y. Pang, "Sentiment Analysis of Chinese Product Reviews using Gated Recurrent Unit," 2019 IEEE Fifth International Conference on Big Data Computing Service and Applications (BigDataService), Newark, CA, USA, 2019, pp. 173-181, doi: 10.1109/BigDataService.2019.00030.

[16] L. Cheng and S. Tsai, "Deep Learning for Automated Sentiment Analysis of Social Media," 2019 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), Vancouver, BC, Canada, 2019, pp. 1001-1004, doi: 10.1145/3341161.3344821.

[17] M. Rumelli, D. Akkuş, Ö. Kart and Z. Isik, "Sentiment Analysis in Turkish Text with Machine Learning Algorithms," 2019 Innovations in Intelligent Systems and Applications Conference (ASYU), Izmir, Turkey, 2019, pp. 1-5, doi: 10.1109/ASYU48272.2019.8946436.

[18] A. Poornima and K. S. Priya, "A Comparative Sentiment Analysis Of Sentence Embedding Using Machine Learning Techniques," 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2020, pp. 493-496, doi: 10.1109/ICACCS48705.2020.9074312.

[19] L. Yang, Y. Li, J. Wang and R. S. Sherratt, "Sentiment Analysis for E-Commerce Product Reviews in Chinese Based on Sentiment Lexicon and Deep Learning," in IEEE Access, vol. 8, pp. 23522-23530, 2020, doi: 10.1109/ACCESS.2020.2969854.

[20] H. AlSalman, "An Improved Approach for Sentiment Analysis of Arabic Tweets in Twitter Social Media," 2020 3rd International Conference on Computer Applications & Information Security (ICCAIS), Riyadh, Saudi Arabia, 2020, pp. 1-4, doi: 10.1109/ICCAIS48893.2020.9096850.

[21] Huapaya, H. D., Rodriguez, C., y Esenarro, D. (2020). Comparative analysis of supervised machine learning algorithms for heart disease detection. 3C Tecnología. Glosas de innovación aplicadas a la pyme. Edición Especial, Abril 2020, 233-247. http://doi.org/10.17993/3ctecno.2020. specialissue5.233-247

[22] Rodriguez C., Angeles, D., Chafloque R., Kaseng F. and Pandey B., "Deep Learning Audio Spectrograms Processing to the Early COVID-19 Detection," **2020** 12th International Conference on Computational Intelligence and Communication Networks (CICN), Bhimtal, India, 2020, pp. 429-434, doi: 10.1109/CICN49253.2020.9242583.