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Reviewing Sentiment Analysis at the Microblog End

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ABSTRACT

The social media space has evolved into a large labyrinth of information exchange platform and due to the growth in the adoption of different social media platforms; there has been an increasing wave of interests in sentiment analysis as a paradigm for the mining and analysis of users' opinions and sentiments based on their posts. In this paper, we present a review of contextual sentiment analysis on social media entries with a specific focus on Twitter. The sentimental analysis consists of two broad approaches which are machine learning which uses classification techniques to classify text, and is further categorized into supervised learning and unsupervised learning; and the lexicon-based approach which uses a dictionary without using any test or training dataset, unlike the machine learning approach. The paper explores generic application areas including product/services analysis and security/terrorism investigations.

Keywords: Sentiment Analysis, Classification, Machine Learning, Twitter

1 Introduction

A microblog is a social media site to which a user makes short, frequent posts. Examples of microblogging platforms include social media channels like Twitter, Facebook, Instagram, Pinterest, and Tumblr. As a result of the instant messaging capabilities of microblogs, they enable users to create freeform contents that express their opinions and communicate their true emotions or feelings about anything ranging from personal sentiments to product/services reviews. The World Wide Web has become the main communication platform for public opinions, sentiments, comments, and reviews. It has grown to become a source for varied kinds of information. The number of active users and the size of their review created daily on online websites are huge. There are more than 2.4 billion active users, who read and write online around the world (Suman & Wenjun, 2015). Sentiment analysis (also known as emotion AI or opinion mining) is a method that is used to extract useful information from a piece of writing. It refers to the use of computational linguistic, text analysis, and natural language processing to extract individual information in source materials. In general, opinion mining tries to discover the sentiment of a writer about some definite aspect and also figure out the general contextual polarity of a document. The sentiment might be a mood, evaluation, or judgment of the writer (Osimo & Mureddu, 2010). A core approach in sentiment analysis is opinion classification, where a comment, text, or sentiment is classified to be positive, negative, or neutral.

There are two (2) main approaches to sentiment analysis: the machine learning-based approach and the lexicon-based approach. In the machine learning approach, classification techniques (which can either be supervised or unsupervised) are used to classify text. The lexicon-based approach on the other hand

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matches sentiment dictionary and opinion words with the data to determine polarity and sentiment scores which describes how negative, neutral, or positive the words contained in the dictionary are. In some extreme cases, the machine learning and lexicon-based approach can be combined to form a hybrid approach to sentiment analysis. This paper presents a systematic literature review of the existing sentiment analysis research that has been carried out in the microblog end. It also captures the summary, lapses, and future works in the research areas.

2 Review of Related Researches

Sentiment analysis is currently a very active research domain in Artificial Intelligence. There are over 2, 200, 000 research items available in the Google Scholar search engine with the keyword 'Sentiment Analysis'; and over 240, 000 research items with a more filtered search using 'Sentiment Analysis AND Twitter'. The systematic review provided in this section of this paper explored 50 most research items dealing with sentiment analysis on the Twitter dataset for product review channels and terrorism analysis.

2.1 Sentiment Analysis in Social Media (Tweets) Classification

There has been a lot of research on tweets classification. Apoorv *et al.* (2011) researched the sentiment analysis of Twitter data. They acquired 11,875 tweets manually from a commercial source. The tweets were classified as having a positive, negative, or neutral sentiment. They used the polarity of words features, counting, and presence of exclamation marks and capitalized text form which they called the senti-feature. The SVM classifier and unigram features were used to experiment and an accuracy of 71.36% was obtained. When they combined the unigram features with the senti-features, the result accuracy increased to 75.39%.

Paridhi and Dinesh (2018) did a study on Twitter sentiment classification. In their work, they calculated the polarity of tweets using the lazy learning method – K-nearest neighbor classifier. The bag-of-word model was used for classification and representation of text data. They experimented using 1.6million tweets and obtained an accuracy of 81.1% and specificity of 84.7% of the test dataset.

Rosenthal *et al.* (2014) also proposed an approach for Twitter sentiment analysis. Their system also relied on lexical features. The system introduced the concept of cost sensitive classification in the task of Twitter sentiment classification. They found the training data to be unbalanced, biasing the learner towards a neutral class. To account for this bias, the paper proposed to assign a higher penalty for misclassification of polar classes. This was reported to nullify the bias and increase overall accuracy.

In another research, Kathy *et al*. (2011) present a Twitter trending topic which was classified into 18 general categories like technology, sports, politics, etc. They experimented with two approaches for the topic classification, i) Bag-of-words approach for text classification and ii) network-based classification. In the text-based classification method, they constructed word vectors with the trending topic definition and tweets, and the most commonly used tf-idf (term frequency-inverse document frequency) weights were used to classify the topics using the Naïve Bayes classifier. For the network-based classification method, they identify the top 5 similar topics based on the number of common influential users using a C5.0 decision tree learner. Their experiment was done on 768 randomly selected trending topics with over 18 classes and it gave an accuracy of 65% and 70% using the text-based and network-based classification models respectively.

Khan *et al.* (2011) used a rule-based domain-independent to conduct a sentence-level sentiment classification. Sentences were categorized first into subjective and objective sentences and the sentiment score was then calculated using SentiWord Net. After this, they considered the sentence structure, and the final sentiment score was calculated. An accuracy of 86.6% was achieved at the sentence level. This experiment is a lexicon-based approach.

Sayali *et al.* (2018) created a dataset by Twitter API and collected all tweets regarding the topic blue whale game. Their main aim was to perform analysis on sentimental tweets. They used the Naïve Bayes, SVM, Maximum entropy, and Ensemble classifier. SVM and Naïve Bayes classifiers were implemented using MATLAB built-in functions. Maximum Entropy classifier was implemented using MaxEntsoftware. Based on comparative results, Navies Bayes had better precision and slightly lower recall and accuracy of 89%, and other classifiers had a close accuracy level.

Brody and Diakopoulos (2011) in Using Word Lengthening to Detect Sentiment in Microblogs developed an unsupervised algorithm which automatically detects the stem of a user-defined lengthen word (such as niiiice or nicccce to nice in communicating their emotion) on the web, which by exploring the phenomenon lengthening words by repeating a single letter within the construct.

Mohammad et al. (2013) in their work utilized the hand-annotated datasets by workshop organizers and build a classifier that does Twitter sentiment analysis. Unlike previous work, this system made use of a POS tagger and tokenizer designed specifically for Twitter. The feature set included a large number of features with some focusing on the specific nature of tweets like the use of elongated words, emoticons, all caps words, URL links, etc. They also relied heavily on lexicons that assigned a sentiment to a token as a positive (if the word is positive) or negative real number. These features are called lexical features. It was reported that after the bag of words (that almost all research works have used), lexical features were most useful. They used the linear kernel SVM and the results are published using the metric provided by workshop organizers: the average F1 measure of positive and negative class. With all features included, the system received a score of 69.02.

Dos Santos and Gatti (2014) proposed a deep convolutional neural network that extracts character- to sentence-level information to perform sentiment analysis of short texts. In their work, they applied their approach for two corpora of two different domains: the Stanford Sentiment Treebank (SSTb) and the Stanford Twitter Sentiment corpus (STS). SSTb contained sentences from movie reviews while the STS contained Twitter messages. For the STS corpus, their approach obtained a sentiment prediction accuracy of 86.4% while for the SSTb corpus; they obtained a sentiment prediction in both binary positive/negative classifications with 85.7% accuracy, and fine-grained classification, with 48.3% accuracy.

Nafees *et al.* (2019) in a research sentiment analysis of Twitter accounts using natural language processing gathered data from Twitter using the Tweepy API and then used the natural language processing techniques to extract features. Then, the natural language processing was applied to the data to classify the sentiments as positive, negative, and neutral. Polarity and Partiality were calculated by the TextBlob dictionary, which consists of a semantic score of a tweet. From their experiment, it was observed that natural language processing is a good method for sentiment analysis as compared to traditional methods. One limitation of this research was that it could not eliminate feature vectors and their selections.

Kouloumpis *et al.* (2011) investigated the utility of linguistic features for detecting the sentiment of Twitter messages. For their data, three different corpora of Twitter messages were used for their

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experiment. For development and training, they used the hashtagged dataset (HASH) and the emoticon dataset (EMOT) and for evaluation, they used a manually annotated dataset. A variety of features was used for their classification experiments. For the baseline, they used the unigrams and bigrams features, they also included lexicon features, Part-of-speech features, and Micro-blogging features. A supervised approach was used to solve the problem, but leverage existing hashtags in the Twitter data for building training data.

Luiz *et al.* (2014) adopted an entirely different approach that combines the SVM classifier with a cluster classification to Twitter data. They proposed that the SVM classifier and cluster ensemble can offer better classification accuracies than a stand-alone SVM. In their research, they employed an algorithm named C^3E-SL, which is capable of combing classifiers and cluster ensembles. The proposed algorithm used could refine tweets classifications from additional information provided by clusters, assuming that similar instances from the same clusters are more likely to share the same class label. Their approach achieved an average accuracy of 81.84% which shows that the algorithm is promising for tweet sentiment analysis.

Kurnia *et al.* (2018) to obtain the best text classification method they conducted a comparison of the performance of different text classification methods that is, using the most three common classifiers namely Naïve Bayes, Decision Tree and Support Vector Machine in Business Intelligence Model to Analyse Social Media Information research work. But in this work, SVM was found to have a higher accuracy than the Naïve Bayes and Decision Tree algorithms used, with the accuracy 78.99%, while the later are 74.78%, and 57.66% therefore, SVM was chosen to build the text classification method.

Prerna *et al.* (2015) developed a sentiment analysis system by combining a rule-based classifier with supervised learning. The rule-based classification is based on rules that are dependent on the occurrence of emoticons and opinion words in tweets. After developing the rule-based classifier and training the SVM, they combined them to refine the SVM predictions. The SVM was trained on 9418 tweets and an accuracy of 71.5% was achieved but 72.3% accuracy was achieved when the rule-based classification was combined with SVM.

Neethu and Rajasree (2013) performed an analysis of tweets based on some specific domains using different machine learning techniques. They tried to focus on problems that are faced during the identification of emotional keywords from multiple keywords and difficulty in handling misspellings and slang words. A feature vector was created and its accuracy was tested using the Naïve Bayes, SVM, Maximum entropy, and Ensemble classifiers.

Pak and Paroubek (2010) used distance learning to acquire sentiment data.They collected two types of data to train the classifier to recognize positive and negative statements. subjective and objective. For objective data they collect the tweets ending with emoticons, and for the subjective data they crawl Twitter accounts of popular newspapers and magazines. For their feature extraction, they experimented with unigrams, bigrams, and trigrams. The Naïve Bayes classifier and SVM was used to build the sentiment classifier.

Ahmed and Qadoos (2018) did research on terrorism detection by tweet sentimental analysis. They gathered dataset and applied processing technique, they then trained that collected dataset with the multinomial Naïve Bayes classifier and Random Forest classifier. The sentiWordNet and textblob features

were also used. The Random Forest classifier gave an accuracy of 83% and the Naïve Bayes gave an accuracy of 80%.

An existing approach using terrorism-related tweets to predict support for ISIS groups was done in Walid (2015) where authors used Twitter data to study the antecedent of the ISIS support of users. They classify tweets and also predict future support for ISIS but it is still lacking the ability to interpret the true intentions of the Twitter account holder.

Barbosa and Feng (2010) developed an approach to automatically detect sentiments on Twitter messages(tweets). Their data was collected from three different websites; i) Twendz ii) Twitter Sentiment iii) TweetFeel. In their work, they implemented a 2-step sentiment detection framework. The first step targets on distinguishing subjective tweets from non-subjective tweets(subjectivity detection). The second step is the polarity classifier, it classifies the subjective tweets into positive and negative. They also used two sets of features: meta-features and tweet syntax features. They use polarity prediction of noisy labels gotten from the three websites to train a model and used 1000 manually labeled tweets for tuning and another 1000 tweets for testing. They propose the use of syntax features of tweets like a retweet, hashtags, links, exclamation marks, and punctuations. They also use features like prior polarity of words and POS.The tweet syntax features helped to increase accuracy.

Mittal and Goel (2011) analyzed the tweets of stock market data using the Self-organizing Fuzzy Neural Network(SOFNN). In their work, they used Twitter data to predict public mood and use the predicted mood and previous days' DJIA(Dow Jones Industrial Average) values to predict stock market movements. For result testing, they proposed new cross-validation methods for financial data and obtained an accuracy of 75.56%.

Human and Shikha (2016) did a sentiment analysis on the movie dataset by downloading the tweets from a Twitter API. Thye used the Hadoop framework for processing the dataset. The classification was done using the Naïve Bayes algorithm and the performance was increased by pre-processing the tweets. The final result showed the classification of text in their required classes with accurate performance.

Bac and Huy (2015) built a model to analyze sentiment on Twitter using machine learning techniques by applying effective feature set to enhance the accuracy i.e., bigram, unigram, and object-oriented features. The classification of tweets was done using two algorithms which are the Naive Bayes and SVM classifier. The accuracy of the classifiers was tested by calculating precision, recall, and f1-score.

Davidov *et al.* (2010) proposed an approach to utilize Twitter user-defined hashtags in tweets as a classification of sentiment type using punctuation, single words, n-grams, and patterns as different feature types, which are then combined into a single feature vector for sentiment classification. They made use of the K-Nearest Neighbour classifier to assign sentiment labels by constructing a feature vector for each example in the training and test set.

Wei *et al.* (2014) used Twitter API to collect Twitter data. Their training data falls in three different categories (camera, movie, mobile). The data was labeled as positive, negative, and non-opinions. Tweets containing opinions were filtered, unigram feature was used and the Naive Bayes model was implemented. The Naive Bayes simplifying independence assumption was employed and they also eliminated useless features by using the Mutual Information and Chi-square feature extraction method. Finally, the orientation of a tweet is predicted, i.e. positive or negative.

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Pablo *et al.* (2014) presented variations of Naive Bayes classifiers for detecting the polarity of English tweets. Two different variants of Naive Bayes classifiers were built namely Baseline (trained to classify tweets as positive, negative and neutral), and Binary (makes use of a polarity lexicon and classifies as positive and negative. Neutral tweets neglected). The features considered by classifiers were Lemmas (nouns, verbs, adjectives, and adverbs), Polarity Lexicons, and Multiword from different sources and Valence Shifters.

Xia *et al.* (2011) used an ensemble framework for Sentiment Classification which is obtained by combining various feature sets and classification techniques. In their work, they used two types of feature sets (Part-of-speech information and Word relations) and three base classifiers (Naive Bayes, Maximum Entropy, and Support Vector Machines). They applied ensemble approaches like the fixed combination, weighted combination, and Meta-classifier combination for sentiment classification and obtained better accuracy.

2.2 Sentiment Analysis in Product/Services Reviews

In Classification of Sentimental Reviews Using Machine Learning Techniques, Tripathy *et al.* (2015) used the Naïve Bayes and Support Vector Machine classifiers to classify movie reviews' dataset into positive and negative and comparing the accuracy of those classifiers. With 1000 positive and 1000 negative reviews for cross-validation, the accuracy of the Naïve Bayes was 0.895 while SVM gave an accuracy of 0.940. It is observed that SVM classifier outperforms the Naïve Bayes classifier in predicting the sentiment of a review. However, the number of the corpus greatly affects the accuracy of classifiers, we discover that few numbers of reviews were used i.e. but positive and negative comments are 2000 which is considered to have been the reason Naïve Bayes did not outperform the SVM.

Anuja and Padma (2016) proposed a method for performing sentiment analysis on a dataset from Apple, Bank, and BSNL of size ranging from 200-4000. ¾ of the dataset was taken as training and the remaining ¼ was used for testing. The Multinomial Naïve Bayes classifier and Decision tree classifier techniques were used. Pre-processing of tweets was done using feature extraction. They also used Apache Spark framework which is scalable and gives faster accurate results. Finally, the decision tree classifier gave a 100% accuracy, precision, recall, and f1 score.

In another research by Dey *et al.* (2016), two sets of the dataset were collected; movie review and hotel review. They used the Naïve Bayes and K-NN classifiers. They aimed to check which classifier gives better results on both datasets. The experimental results showed that the Naive Bayes classifier gives better performance in the case of the movie reviews dataset and on considering the hotel reviews dataset, both classifiers showed approximate results. They finally concluded that the Naïve Bayes classifier is better for movie review classification.

Mejova (2019) discussed the overview of sentiment analysis i.e., he gave a brief description of the word sentiment analysis and novelty methods that are used to perform analysis on emoticon character text by covering all the challenges that are faced during the analysis of product or text.

2.3 Sentiment Analysis in Security and Terrorism Analysis

Ferrara *et al.* (2016) applied machine learning to social media content to detect the interactions of terrorists. They experimented on more than 20,000 tweets gotten from Twitter accounts which were later

suspended by Twitter. Their experiment was in two dimensions which were time-independent and real-time prediction tasks. They obtained an accuracy of about 93% concerning terrorism detection.

Hartung *et al.* (2017) also proposed a machine learning technique for detecting terrorism post in German Twitter accounts. They used several features such as emotions, linguistic patterns, and textual clues. The system yielded an improved result.

Shakeel *et al.* (2019) developed a model for the detection and classification of social media-based extremist affiliations using sentiment analysis techniques. Their work proposed a terrorism-related content analysis framework with the focus on classifying tweets into extremist and non-extremist classes. They developed a tweet classification system using deep learning-based sentiment analysis techniques. They used the LSTM + CNN machine learning and deep learning was used for the experiment. The CNN model was applied for feature extraction and the LSTM model receives input from the output of the CNN model and retains the sequential correlation by taking into account the previous data for capturing the global dependencies of a sentence in the document concerning tweet classification into extremist and non-extremist.

Sofea and Izzatdin (2017) did a comparative study on sentiment analysis for terrorism detection. Data was gotten from Twitter using a Twitter API, and the sentence was categorized into positive, negative, and neutral categories. They experimented with the Naïve Bayes approach and added user behavioral analysis to increase the accuracy. The user behavioral analytics focused on the retrieval of tweets history from a particular user based on specific keywords related to terrorism issues. The lastest and previous tweets of a particular user's sentiment score will be compared, then a new class of sentiment (positive, negative, and neutral) is being used based on the comparison of the lastest and previous tweets.

Wei *et al.* (2016) proposed a machine learning-based classification system for identifying extremist-related conversations on Twitter. Different features were investigated for identifying extremist behavior on Twitter based on public tweets by applying the KNN classifier.

Pooja and Bhatia (2016) developed an approach where radical tweets are classified under the categories of war, terrorism, operations, extremism, jihads, country, and Al-Qaeda. They used security dictionaries of enriched themes categorized by semantically related words. In their work, they built dictionaries by selecting tweets with hashtags like Al-Qaeda, Jihad, terrorism, and extremism; they also collected other words relevant for their purpose. They went further and vectorized a document based on the presence of security-related keywords. For instance, if the categories in which the message should be classified are Terrorism, Country, and Jihad, then for each category that the message contains such related words, 1 will be assigned to it otherwise 0. The presence of one or more words relevant to the category was used to deduce the final category. An accuracy of 90% was obtained which shows that keywords play an important role in tweet sentiment classification.

Ashcroft *et al.* (2015) researched on detecting Jihadist messages on Twitter. They experimented using three different class features: stylometric features, time-based features, and sentiment-based features. The stylometric features contained most frequent words in the database; the time-based features contain information about when the tweets were posted while the sentiment-based feature determines the attitude of text in the dataset. These experiments were conducted using a machine learning tool called Weka on about 4000-7500 tweets with three classification algorithms; SVM, Naïve Bayes, and Adaboost. The accuracy obtained was 98.5%, 96.8%, and 99.5% respectively.

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Chen *et al.* (2011) explored lexical-semantic features in predicting offensiveness in users' conversation histories during research work, Poster FBI: Detecting Offensive Language in Social Networks for Protection of Youth Online Safety. They demonstrated an approach to provide high accuracy and precise performance.

Ellman and Chalothorn (2012) proposed a sentiment analysis model to analyze online radical posts using different lexical sources like the SentiWordNet, WordNet, and NLTK toolkit. Textual data were acquired from different web forums such as Montad and Qawem, then they performed the pre-processing task. After this, different feature-driven measures were applied to detect and manipulate religious and terrorism content. Experimental results showed that the Montada forum has a more positive post than the Qawem forum. From their work, they concluded that the Qawen forum has more radical postings.

Kaati *et al.* (2015) trained a machine learning model to detect Twitter accounts that support jihadist groups and disseminate propaganda content. To train the model, they used data-dependent features such as most common hashtags, word bigrams, and most frequent words, as well as data-independent features such as frequency of word length, letters, digits, and emotion words. They showed that their model has significant accuracy for English tweets while for Arabic tweets the performance was worse.

Mei and Frank (2015) developed a model that combined sentiment analysis and a web-crawler with a decision tree to differentiate pro-extremist webpages from anti-extremism. The goal of their approach was to create a tool that made predictions about the content found on the sites it downloaded. Their technique classified extremist text at a high rate of accuracy of 92%.

Yang *et al.* (2011) used a machine learning and sematic-oriented approach to identify terrorist opinions in hate groups. Four different types of text features were used for the experiment. They are: syntactic, stylistic, content-specific, and lexicon features. They also made use of three classification techniques (SVM, Naïve Bayes, and AdaBoost) which gave different accuracy.

Walid *et al.* (2015) used ISIS-related tweets to predict future support for the ISIS groups. In this work, Twitter data was used to study the antecedents of the ISIS supporters. They used the bag-of-words features which included individual terms, hashtags, and user mention. They trained the SVM classifier and at the end of the experiment, the trained model was able to predict future support and opposition of an ISIS user with an accuracy of 70%.

In another research by CCINT (2018), the experiment was done on the Twitter platform, and data was collected using the Twitter streaming API, tweets were filtered based on keywords that represent the top terrorist groups. At the end of the collection process, their dataset consists of about 700k tweets. Heterogeneous features like textual, social, and psychological were combined to detect radical contents. Using an unsupervised machine learning method, messages were clustered into radical/ non-radical. The addition of the heterogeneous feature improved detection accuracy.

3 Summary of Reviews

The various publications and research work reviewed in the above section has essentially described various works that apply machine learning algorithms, sentiment analysis and its techniques to solve problems of sentiment analysis. They had shown clearly that sentiment analysis is a classification task used to extract data from social media, saving the data, comparing it with a given set of keywords, and

categorizing it into some classes. The works had shown sufficient applications of sentimental analysis in the two broad approaches which are the machine learning approach and the lexicon-based approach. Table 1 contains a summary of findings for all the reviewed articles.

Table 1: Summary of Findings

Study	Data	Settings/Method	Key Findings
Apoorv *et al.* (2011)	11,875 tweets acquired manually from a commercial source	SVM classifier, unigram features	The researchers used the SVM classifier to build a sentiment analysis model (*using the polarity of word features, presence of capitalized text and exclamation marks*) on tweets obtained from a commercial source. The model had an accuracy of 75.39%
Paridhi and Dinesh (2018)	1.6 million tweets	K-nearest neighbor classifier	The researchers built a Twitter sentiment analysis model for calculating the polarity of tweets. The model had an accuracy of 81.1% and specificity of 84.7%
Rosenthal *et al.* (2014)	Not stated	Sentiment analysis using lexical features	The authors introduced the concept of sentiment analysis by assigning a higher penalty for the misclassification of polar classes. The model had a higher accuracy.
Kathy *et al.* (2011)	768 randomly selected trending topic with over 18 classes	Naïve Bayes classifier, C5.0 decision tree learner	The authors employed two approaches to topic classification: network-based approach and bag-of-word approach. The former model had an accuracy of 70% while the latter had an accuracy of 65% on the test set
Khan *et al.* (2011)	Not stated	Using SentiWordNet to classify sentences	The authors built a sentiment classification model that generates sentiment scores for sentences using the lexicon-based approach. The model had an accuracy of 86.6%
Sayali *et al.* (2018)	They extracted the data from Twitter using Twitter API	Naïve Bayes, SVM, Maximum entropy and Ensemble classifier	The Naïve Bayes classifier outperformed other algorithms- it had better precision, recall, and accuracy
Brody and Diakopoulos (2011)	Not stated	Unsupervised algorithm	The authors used word lengthening to detect the stem of a user-defined lengthen words like nicccce
Mohammad et al. (2013)	Hand annotated datasets by workshop organizers	Linear Kernel SVM	The researchers used POS tagger, tokenizer, and lexicons to analyze the sentiments of tweets from a workshop. The model built had an F1 score of 69.02%
Dos Santos and Gatti (2014)	Movie reviews, Twitter messages	Stanford Sentiment Treebank (SSTb), Stanford Twitter Sentiment corpus (STS)	The researchers used a deep learning neural network to analyze short texts on SSTb and STS. They had an accuracy of 86.4% on the STS corpus and an accuracy of 85.7% on the SSTb corpus
Nafees *et al.* (2019)	Tweets from Twitter using the Tweepy API	Calculating polarity and partiality using TextBlob dictionary	Natural language processing outperforms other traditional sentiment analysis techniques. Though, the authors weren't able to eliminate feature vectors and their selections
Kouloumpis *et al.* (2011)	Hashtagged dataset, emoticon dataset, and a manually annotated data set	Supervised approach	The authors used unigrams and bigrams features, lexicon features, Part-of-speech features and Micro-blogging features to detect the sentiment of Twitter messages

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Tripathy *et al.* (2015)	Movie reviews' dataset (1000 positive and 1000 negative)	Naïve Bayes and Support Vector Machine classifiers	The support vector machine classifier outperformed the Naïve Bayes classifier - it had an accuracy of 94.0%. The authors suggested that it's because the number of reviews used was a few
Luiz *et al.* (2014)	Twitter data	SVM classifier and cluster ensemble (C^3E-SL)	The combination of SVM classifier and cluster ensemble yielded better accuracy (81.84%) than a stand-alone SVM
Kurnia *et al.* (2018)	Not stated	Naïve Bayes, Decision Tree and Support Vector Machine	The authors compared three common classifiers for text classification and the SVM classifier (accuracy of 78.99%) outperformed Decision Tree (74.78% accuracy) and Naïve Bayes (57.66%) classifiers
Prerna *et al.* (2015)	A dataset of 9418 tweets	Supervised learnings	The model was built using a combination of rule-based classifiers and SVM. It had an accuracy of 72.3%.
Chen *et al.* (2011)	Not stated	Not stated	The authors developed a model that detects offensive languages in social networks for the protection of youth online safety. The model had high accuracy and precision.
Neethu and Rajasree (2013)	Not stated	Naïve Bayes, SVM, Maximum entropy and Ensemble classifiers	The research deals with the analysis of tweets by addressing problems like handling slang words, misspellings, identifying emotional keywords from multiple keywords.
Pak and Paroubek (2010)	Subjective and objective sentiment data	Distant learning, Naïve Bayes classifier and SVM	The subjective data was crawled from Twitter accounts of famous magazines and newspapers while the objective data were tweets ending with emoticons.
Ahmed and Qadoos (2018)	Twitter data	Multinomial Naïve bayes classifier and Random Forest classsifier	The Random forest classifier gave an accuracy of 83% and the Naïve Bayes gave an accuracy of 80%.
Barbosa and Feng (2010)	The data was collected from Twendz, Twitter Sentiment, and TweetFeel	The polarity of words and POS	The researchers implemented a 2-step sentiment detection framework. The first framework distinguishes subjective tweets from non-subjective tweets while the second classifies the subjective tweets into positive and negative
Mittal and Goel (2011)	Twitter data	Self-organizing Fuzzy Neural Network(SOFNN)	The researchers built a model that predicts stock market movement. It had an accuracy of 75.56%.
Human and Shikha (2016)	Twitter data got through Twitter API	Hadoop framework, Naïve Bayes algorithm	The sentiment analysis model can predict the class a movie belongs to.
Bac and Huy (2015)	Twitter data got through Twitter API	Naive Bayes and SVM classifier	The researchers used bigram, unigram and object-oriented features to enhance the accuracy of the sentiment analysis model.
Mejova (2019)	Not stated	Not stated	The researcher gave a summary of sentiment analysis and the methods used for analyzing emotion character text.
Dadhe *et al.* (2018)	Extracted data from Twitter	Density-Based Algorithm (DBA)	The authors built a sentiment analyzer that classifies tweets and also predicts future support for ISIS. Though, the model is unable to interpret the true intentions of the Twitter account holder.

Anuja and Padma (2016)	200 – 4000 data from Apple, Bank, and BSNL	Multinomial Naïve Bayes classifier and Decision tree classifier	The sentiment analysis model built with the Decision trees classifier gave a 100% accuracy, precision, recall, and f1 score.
Dey *et al.* (2016)	Movie review and hotel review dataset	Naïve Bayes and KNN classifiers	The researchers reviewed the performance of two algorithms on the data collected. The Naïve Bayes classifier performed best for movie reviews classification.
Davidov *et al.* (2010)	Extracted tweets from Twitter	K-Nearest Neighbour classifier	The researchers used a KNN classifier for sentiment analysis on Twitter.
Wei *et al.* (2014)	Extracted tweets from Twitter with Twitter API	Naive Bayes classifier, Mutual Information, and Chi-square feature extraction method	The Naïve Bayes model predicts a tweet to either be positive or negative.
Pablo *et al.* (2014)	English tweets extracted from Twitter	Naive Bayes	The researchers compared two different variants of the Naïve Bayes classifiers considering features like Lemmas, Polarity Lexicons, and Multiword from different sources and Valence Shifters.
Xia *et al.* (2011)	Extracted English tweets from Twitter	Naive Bayes, Maximum Entropy and Support Vector Machines	The researchers applied the ensemble approach for sentiment classification and they obtained better accuracy.
Ferrara *et al.* (2016)	Extracted over 20,000 tweets from suspended Twitter accounts	Time-independent and real-time prediction	The terrorism detection model had an accuracy of 93%. It experimented in two dimensions: time-independent and real-time prediction tasks.
Hartung *et al.* (2017)	Not stated	Not stated	The machine learning model was built using several features like emotions, linguistic patterns, and textual clues.
Shakeel *et al.* (2019)	Extracted tweets from Twitter	LSTM + CNN machine learning and deep learning	The researchers proposed a terrorism-related content analysis framework for classifying tweets into extremist and non-extremist classes.
Sofea and Izzatdin (2017)	Extracted tweets from Twitter using an API	Naïve Bayes classifier, user behavioral analysis	The researchers carried out a comparative study on sentiment analysis for terrorism detection by categorizing sentences into positive, negative, and neutral categories.
Wei *et al.* (2016)	Extracted tweets from Twitter	KNN classifier	The researchers investigated different features for identifying extremist behavior on Twitter based on public tweets.
Pooja and Bhatia (2016)	Tweets with hashtags Al-Qaeda, Jihad, terrorism, extremism,	Sentiment classification.	The sentiment classification model returns 1 if it contains any of the radical hashtags and 0 otherwise. The model had an accuracy of 90%.
Ashcroft *et al.* (2015)	Extracted 4000 – 7500 tweets from Twitter	Weka, SVM, Naïve Bayes, Adaboost	The authors experimented using 3 different class features: stylometric features, time-based features, and sentiment-based features. The AdaBoost classifier gave the best accuracy of 99.5%.
Ellman and Chalothorn (2012)	Extracted textual data from different web forums such as Montad and Qawem	SentiWordNet, WordNet, NLTK toolkit	The Montada forum had a more positive post than the Qawem forum. Hence, the Qawen forum had more radical postings.
Kaati *et al.* (2015)	Tweets from Twitter	word, bigrams, hashtags; and	The model performed well on English tweets and poorly on Arabic tweets.

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		digits, emotion, words	
Mei and Frank (2015)	Not stated	Web crawling, sentiment analysis	The tool combines sentiment analysis, a web-crawler alongside a decision tree to differentiate pro-extremist webpages from anti-extremism. It had an accuracy of 92%.
Yang *et al.* (2011)	Not stated	SVM, Naïve Bayes and AdaBoost	The researchers used four different types of text features (syntactic, stylistic, content-specific, and lexicon features) for the experiment.
Walid *et al.* (2015)	Extracted tweets from Twitter	The use of bag-of-words features, an SVM classifier	The model was able to predict future support and opposition of an ISIS user with 79% accuracy.
CCINT (2018)	Extracted data from Twitter via the Twitter streaming API	The unsupervised machine learning method	The author combined heterogeneous features like textual, social, and psychological were combined to detect radical contents. 700k tweets were used for modeling

4 Conclusion

In this systematic literature review, we were able to explore and analyze the top relevant 50 existing work on sentiment analysis both for the lexicon-based approach and the machine learning approach. We gave a comprehensive review as well as a summary that contains relevant details like the author(s), the dataset used for the study, the settings/methodology, and the key findings. Some of the researchers made use of machine learning techniques for sentiment analysis. Others even made use of ensemble methods. This is a clear indication that common supervised learning algorithms (like Naïve Bayes and SVM) as well as unsupervised machine learning algorithms are leading the trails in the field of sentiment analysis. In unsupervised learning, there are no categories involved, and the targets are not provided. Hence, clustering was considered to be an essential factor there. In supervised learning, the labeled dataset extracted was used for modeling. Generally, we found that sentiment analysis can be very useful in goods/services reviews and terrorism analysis.

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