# Literature Review on Sentiment Analysis in Social Media: Open Challenges toward Applications

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# Literature Review on Sentiment Analysis in Social Media: Open Challenges toward Applications

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***Abstract***

*In today's world, sentiment analysis stands as the prominent research topic in demand under the Natural Language Processing (NLP). The fundamental objective of this research topic is to spot out the emotions and opinions of the customers or users via a text basis. Even though numerous research works have been carried put in this field through diverse models, sentiment analysis is still considered a challenging problem with so many conflicts to be solved. Some of the existing challenges are due to the slang words, new accents, grammatical and spelling mistakes etc. This paper plans to make a literature review using different machine learning algorithms with various data. The current literature review temps to survey nearly 20 contributions, which covers different types of applications being used for sentimental analysis. At first, the analysis focuses on illustrating the contributions of each work and observes the type of machine learning algorithms used. Moreover, the analysis also concentrates on the identification of the type of data used. Further, the utilized environment and the performance measures covered in each work is evaluated, and concluded with proper research gaps and challenges, which helps to identify the non-saturated application for which the sentimental analysis is needed most in upcoming research.*

***Keywords****-Sentiment Analysis; Application-oriented Analysis; Machine Learning Algorithms; Performance Analysis; Research Gaps and Challenges*

Nomenclature

| **Abbreviations** | **Descriptions** |
|---|---|
| NLP | Natural Language Processing |
| SVR | Support Vector Regression |
| RF | Random Forest |
| DTs | Decision Trees |
| RNN | Recurrent Neural Networks |
| CNN | Convolutional Neural Networks |
| LSTM | Long Short-Term Memory |
| SVM | Support Vector Machine |
| KNN | K-Nearest Neighbour |
| ConVNet-SVMBoVW | Convolutional Neural Network-SVM Bag-of-Visual-Words |
| IG | Information Gain |
| MVO | Multi-Verse Optimizer |
| NB | Naive Bayes |
| SRH | Slum Rehabilitation Housing |
| MSE | Mean Square Error |
| MAE | Mean Absolute Error |
| RMSE | Root Mean Square Error |
| TPR | True Positive Rate |
| ARS | Average ROUGE Score |
| ME | Maximum Entropy |

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## 1. Introduction

There is a vigorous improvement in the micro blogging websites as well as social networks. One of the major web destinations to the users is micro blogging websites, which are helpful for expressing the user's attitudes, opinions, and thoughts regarding various contexts [21] [22]. The most used social networking services and the micro blogging platform is twitter, which provides more data. At present, for the sentiment analysis of the user's opinions on the product, event, or context, researchers make use of social data. Moreover, the other name for sentiment analysis is opinion mining, which is the significant NLP task. This sentiment analysis defines orientation of sentiments related to text as either neutral, positive, or negative [23] [24]. Moreover, sentiment analysis represents the text analytics, computational linguistics, and NLP implementations for recognizing and categorizing the opinions of the user. In general, the main intention of the sentiment analysis is to define the author's point of view concerning the similar context or the entire document's contextual polarity. The view can be either a user's judgment or assessment, affective state or the deliberated communication of emotion.

In general, the classification of text expressions in source materials into facts and opinions is done by the sentiment analysis. Facts are the objective expressions regarding the events and their attributes as well as entities. The opinions are the subjective expressions of sentiments, emotions, feelings, events and attributes, and attitudes. This must be specified that not all the objective sentences include no opinions and not all subjective sentences include opinions. Thus, for sentiment analysis, it is significant for recognizing and extracting the facts and opinions from source materials. However, this seems to be quite complex for attaining precisely. In recent times, important approaches are related to machine learning, rule-based, and the combination of both techniques. Machine learning models consist of conventional approaches like deep learning and conditional random field approaches, whereas the rule-based models consist of lexicon-based approach. Object detection [25] [26], network optimization [28], image recognition [27], system security [32],sensor networks[29] [30] [31], and transportation [33] are based on deep learning methods, which are mostly utilized in different fields. Several researchers have combined deep learning as well as machine learning algorithms into text sentiment analysis by sentiment lexicon formulation and best results are obtained [34].

The main aim of the sentiment lexicon-based model is to develop a sentiment lexicon, which is done by choosing suitable negative words, sentimental words, and degree adverbs. For the constructed sentiment lexicon, sentimental polarity and intensity are marked. Once the text is given as input, the words are matched with the sentiment words present in the sentiment lexicon, and those words are weighted and added for acquiring the input text's sentiment value, thus the determination of sentimental polarity is done as per the sentiment value. However, there are few approaches for acquiring the features of word vector related to the text like Glove, Word2Vec, and FastText automatically. However, the conventional machine learning models still require the emotional feature extraction of the structured information from the input text by text vectorization, human intervention, and later that algorithms are utilized for categorizing the sentiment of the text features [35].

The main contributions of this paper are portrayed as follows.

- To undergo a critical review of sentiment analysis under different applications.
- To carry out the detailed review of various sentiment analysis models based on the machine learning algorithms, types of data, tools, and different performance measures.
- To formulate the valuable research gaps and challenges based on the existing contributions under sentiment analysis.

The review on sentiment analysis classification is designed in the following manner: Section II specifies the literature review on conventional sentimental analysis in social media. Section III describes various machine learning algorithms for sentiment analysis along with performance measures. The analysis on different types of data used and tools for sentiment analysis is given in Section IV. The research gaps and challenges of sentiment analysis using machine learning algorithms are shown in Section V. Section VI specifies the conclusion of the entire paper.

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## 2. Literature Review

### *A. Related Works*

In 2019, Saad and Yang [1] have aimed for giving a complete tweet sentiment analysis on the basis of ordinal regression with machine learning algorithms. The suggested model included pre-processing tweets as first step and with the feature extraction model, an effective feature was generated. The methods such as SVR, RF, Multinomial logistic regression (SoftMax), and DTs were employed for classifying the sentiment analysis. Moreover, twitter dataset was used for experimenting the suggested model. The test results have shown that the suggested model has attained the best accuracy, and also DTs were performed well when compared over other methods. In 2018, Fang *et al*. [2] have suggested multi-strategy sentiment analysis models using the semantic fuzziness for resolving the issues. The outcomes have demonstrated that the proposed model has attained high efficiency.

In 2019, Afzaal *et al.* [3] have recommended a novel approach of aspect-based sentiment classification, which recognized the features in a precise manner and attained the best classification accuracy. Moreover, the scheme was developed as a mobile application, which assisted the tourists in identifying the best hotel in the town, and the proposed model was analyzed using the real-world data sets. The results have shown that the presented model was effective in both recognition as well as classification.

In 2019, Feizollah *et al*. [4] have concentrated on tweets related to two halal products such as halal cosmetics and halal tourism. By utilizing Twitter search function, Twitter information was extracted, and a new model was employed for data filtering. Later, with the help of deep learning models, a test was performed for computing and evaluating the tweets. Moreover, for enhancing the accuracy and building prediction methods, RNN, CNN, and LSTM were employed. From the outcomes, it was seemed that the combination of LSTM and CNN attained the best accuracy.

In 2018, Mukhtar *et al*. [5] have performed the sentiment analysis to the Urdu blogs attained from several domain with Supervised Machine learning and Lexicon-based models. In Lexicon-based models, a well-performing Urdu sentiment analyzer and an Urdu Sentiment Lexicons were employed, whereas, in Supervised Machine learning algorithm, DT, KNN, and SVM were employed. The data were combined from the two soruces for performing the best sentiment analysis. Based on the tests conducted, the outcomes were shown that the Lexicon-based model was superior to the supervised machine learning algorithm.

In 2020, Kumar *et al*. [6] have presented a hybrid deep learning approach named ConVNet-SVMBoVW that dealt with the real-time data for predicting the fine-grained sentiment. In order to measure the hybrid polarity, an aggregation model was developed. Moreover, SVM was used for training the BoVW to forecast the sentiment of visual content. Finally, it was concluded that the suggested ConvNet-SVMBoVW was outperformed by the conventional models.

In 2018, Abdi *et al*. [7] have proffered a machine learning technique for summarizing the opinions of the users mentioned in reviews. The suggested method merged multiple kinds of features into a unique feature set for modelling accurate classification model. Therefore, a performance investigation was done for four best feature selection models for attaining the best performance and seven classifiers for choosing the relevant feature set and recognized an effective machine learning algorithm. The suggested method was implemented in various datasets. The outcomes have demonstrated that the combination of IG as the feature selection approach and SVM-based classification approach enhanced the performance.

In 2019, Ray and Chakrabarti [8] have introduced a deep learning algorithm for extracting the features from text and the user's sentiment analysis with respect to the feature. In opinionated sentences, a seven layer Deep CNN was employed for tagging the features. In order to enhance the performance of sentiment scoring and feature extraction models, the authors merged the deep learning methods using a set of rule-based models. Finally, it was seen that the suggested method achieved the best accuracy. In 2019, Zhao *et al*. [9] have offered a novel image-text consistency driven multi-modal sentiment evaluation model, which explored the correlation among the text and image. Later, a multi-modal adaptive sentiment analysis model was implemented. By using the traditional SentiBank model, the mid-level visual features were extracted and those were employed for representing the visual theories by integrating the different characteristics like social, textual, and visual features for introducing a machine learning model. The suggested model has attained best performance when compared over traditional models.

In 2019, Park *et al*. [10] have developed a semi-supervised sentiment-discriminative objective for resolving the issue by documents partial sentiment data. The suggested model not only reflected the partial data, but also secured the local structures obtained from real data. The suggested model was evaluated on real time datasets. The results have shown that the suggested model was performing well. In 2019, Vashishtha and Susan [11] have calculated the sentiment related to social media posts by a new set of fuzzy rules consisting of many datasets and lexicons. The developed model combined Word Sense Disambiguation and NLP models with a new unsupervised fuzzy rule-based model for categorizing the comments into negative, neutral, and positive sentiment class. The experiments were performed on 3 sentiment lexicons, four existing models, and nine freely available twitter datasets. The outcomes have shown that the introduced method was attaining the best results.

In 2019, Yousif *et al*. [12] have presented a multi-task learning method on the basis of CNN and RNN. The structure of the suggested method was helpful for denoting the citation context and feature extraction was done in an automatic way. By considering two freely accessible datasets, the suggested technique was analyzed. The outcomes have shown that the proposed model was improved than conventional models. In 2020, Hassonah *et al*. [13] have recommended hybrid machine learning algorithm for improving the sentiment analysis, because a classification approach was built on the basis of "Positive, Negative, and Neutral" classes with SVM classifier, at the same time two feature selection methods were merged by the MVO and Relief models. Moreover, Twitter data was employed for evaluating the proposed model. The experimental results indicated that the suggested technique was performing well than conventional techniques.

In 2020, Xu *et al*. [14] have introduced a NB method for multi-domain and large-scale E-commerce platform product review classification of sentiment. Consequently, the parameter evaluation method was extended in NB for continuous learning fashion. Later, for fine-tuning the learned distribution on the basis of three types of assumptions, many ways were introduced for acquiring the best performance. The results have shown that the suggested model has high accuracy in Amazon product and movie review sentiment datasets.

In 2018, Smadi *et al*. [15] have proposed existing models on the basis of supervised machine learning algorithms for specifying the defects of feature-based sentiment analysis of Arabic hotel's review. Moreover, SVM and Deep RNN were developed and trained with word, lexical, morphological, semantic, and syntactic features. The reference dataset of Arabic hotel's review dataset was used for evaluating the proposed model. The outcomes have shown that SVM was performing well when compared over RNN model. In 2020, Maqsood *et al*. [16] have explored the impact of various events happened in the year 2012-2016 on stock markets. Here, Twitter dataset was employed for computing the sentiment analysis to each of these events. The dataset included millions of tweets, which were employed for defining the event sentiment.

In 2019, Abdi *et al*. [17] have suggested a deep-learning-based technique for categorizing the opinion of the user mentioned in reviews. Moreover, a deep learning model was a unified feature set that was representative of sentiment shifter rules, word embedding, sentiment knowledge, linguistic and statistical knowledge has not been continuously explored for a sentiment analysis. Moreover, the suggested model used RNN that consisted of LSTM for considering the benefit of sequential processing and conquered many issues in conventional algorithms. In 2020, Park *et al*. [18] have designed a deep learning approach for improving performance. In order to improve the performance, two questions have come into picture. The content attention was required for being sophisticated for merging many attention results non-linearly and assumes the whole context for mentioning the complex sentences. The test results have shown that the proposed model was attained as the best performance.

In 2019, Bardhan *et al*. [19] have explored a quasi-qualitative model for understanding the underlying the affects of gender mainstreaming in SRH management. In order to explore the stakeholder concerns, verbal narratives froms semi-structured intervies and concentrated on group discussions. For decoding the emotions over the stakeholders, sentiment analysis with machine learning algorithm of NLP is employed. In 2017, Araque *et al*. [20] have introduced a deep learning model for enhancing the performance by incorporating the existing surface models with deep learning models on the basis of manually extracted features. With the help of linear machine learning and word embeddings methods, a deep learning-based sentiment classifier was introduced. Here, 7 datasets were used for verifying the efficiency of the suggested model. The results have confirmed that the presented method was effective when compared with traditional methods.

## 3. VARIOUS MACHINE LEARNING ALGORITHM FOR SENTIMENT ANALYSIS ALONG WITH PERFORMANCE MEASURES

### A. *Categorization of Machine Learning Algorithms*

The classification of machine learning algorithms for sentiment analysis is shown in Fig.1. For different contributions of sentiment analysis, the techniques like SVM, DT, NB, CNN, KNN, ConvNet-SVMBoVW, fuzzy rule-based classifier, RCNN, SVR, RNN, and Ensemble classifier are used.

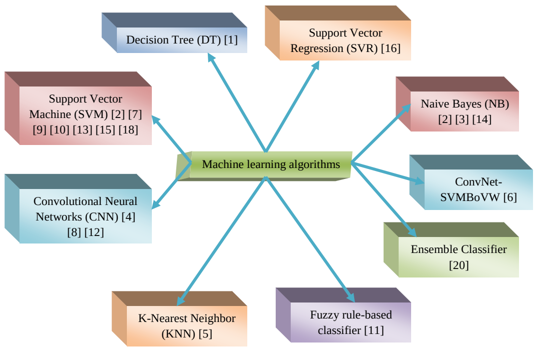


Fig. 1. Taxonomy of Machine Learning Algorithms adopted for sentiment analysis

### B. *Performance Measures*

Table I shows the analysis on evaluation metrics concerning sentiment analysis using machine learning models. In this, the measures like "accuracy, precision, recall, and F-Measure" are taken into consideration in many of the earlier contributions. The rarely employed performance metrics are specified in miscellaneous. From Table I, the accuracy measure is considered in 80% of earlier contributions. Similarly, the precision is taken in 60% of the past works. Moreover, the recall and f-measure are considered in 60% and 55% of the previous contributions, respectively. At last, it is concluded that the accuracy is taken into consideration in many of the earlier contributions, and the other metrics are considered infrequently.

TABLE I. PERFORMANCE MEASURES CONCERNED FOR SENTIMENT ANALYSIS UNDER DIFFERENT APPLICATIONS

| Citations | Accuracy | Precision | Recall | F-Measure | Miscellaneous |
|---|---|---|---|---|---|
| [1] | ✓ | ✓ | ✓ | ✓ | support, MSE, and MAE |
| [2] | ✓ | ✓ | - | - | MAE, and RMSE |
| [3] | ✓ | ✓ | ✓ | ✓ | TPR |
| [4] | ✓ | ✓ | ✓ | ✓ | - |
| [5] | ✓ | ✓ | ✓ | ✓ | - |
| [6] | ✓ | ✓ | ✓ | - | - |
| [7] | - | - | - | - | ROUGE-N metric, and ARS |
| [8] | ✓ | ✓ | ✓ | - | - |
| [9] | ✓ | ✓ | ✓ | ✓ | - |
| [10] | ✓ | - | - | - | - |
| [11] | ✓ | ✓ | ✓ | ✓ | - |
| [12] | - | ✓ | ✓ | ✓ | - |
| [13] | ✓ | ✓ | ✓ | ✓ | - |

| | | | | | |
|---|---|---|---|---|---|
| [14] | ✓ | - | - | - | - |
| [15] | - | - | - | - | Speed up rate and Execution time |
| [16] | - | - | - | - | MAE and RMSE |
| [17] | ✓ | ✓ | ✓ | ✓ | - |
| [18] | ✓ | - | - | ✓ | - |
| [19] | ✓ | - | - | - | - |
| [20] | ✓ | ✓ | ✓ | ✓ | - |

## 4. ANALYSIS ON DIFFERENT TYPES OF DATA USED AND TOOLS FOR SENTIMENT ANALYSIS

### *C. Data Types*

In Table II, the analysis on different data types using machine learning algorithms employed for sentiment analysis is tabulated. The twitter data is considered in [1] [4] [11] [13]. In [2] [3] [15], the data related to hotel is taken into consideration for evaluating the efficiency of the model. Urdu blogs are used in [5]. The textual and visual semiotic modalities of social data are employed in [6]. The movie review data is taken into consideration for experimentation in [7] [14] [17] [20]. The data related to camera and laptop is assumed in [8]. The social media information is taken in [9]. In [10] [14], the Amazon review data is considered for evaluating the machine learning algorithms. The citation sentiment and citation purpose data is employed in [12]. In [16], the stock market review data is considered for analysis. The text data collected from corpus is taken in [19] for assessing the performance of machine learning algorithms.

TABLE II. ANALYSIS ON DIFFERENT DATA TYPES USED FOR SENTIMENT ANALYSIS UNDER DIFFERENT CONTRIBUTIONS

| **Author and Citation** | **Data Type** |
|---|---|
| Saad and Yang [1] | Twitter data |
| Fang *et al*. [2] | Review of consumer products and services on hotel |
| Afzaal *et al*. [3] | Restaurant and hotel data |
| Feizollah *et al*. [4] | Twitter keywords related to halal tourism and halal cosmetics |
| Mukhtar *et al*. [5] | Urdu blogs in multiple domains |
| Kumar *et al*. [6] | Textual and visual semiotic modalities of social data |
| Abdi *et al*. [7] | DUC 2002, and Movie Review Data |
| Ray and Chakrabarti [8] | Nikon Camera Data, and laptop domain data |
| Zhao *et al*. [9] | Social Media data |
| Park *et al*. [10] | Amazon reviews and Yelp reviews |
| Vashishtha and Susan [11] | multiple public twitter data |
| Yousif *et al*. [12] | Citation sentiment, and Citation purpose |
| Hassonah *et al*. [13] | Twitter Social Network data |
| Xu *et al*. [14] | Amazon product and Movie review data |
| Smadi *et al*. [15] | Arabic hotel's review |
| Maqsood *et al*. [16] | stock markets review |
| Abdi *et al*. [17] | Movie Review |
| Park *et al*. [18] | laptop and restaurant reviews from SemEval 2014 |
| Bardhan *et al*. [19] | Text data from corpous |
| Araque *et al*. [20] | microblogging and movie reviews domain |

### *D.* Execution Tool

The execution software employed for various kinds of sentiment analysis with machine learning algorithms are diagrammatically shown in Fig. 2. In the earlier contributions, the tools such as MATLAB, Python, Java, R studio, and Mobile App are utilized. In most of the research works, Python software is adopted for sentiment analysis. Therefore, it is concluded that Python is the best tool used for sentiment analysis with machine learning algorithms and still has the possibilities of new models to be analyzed.

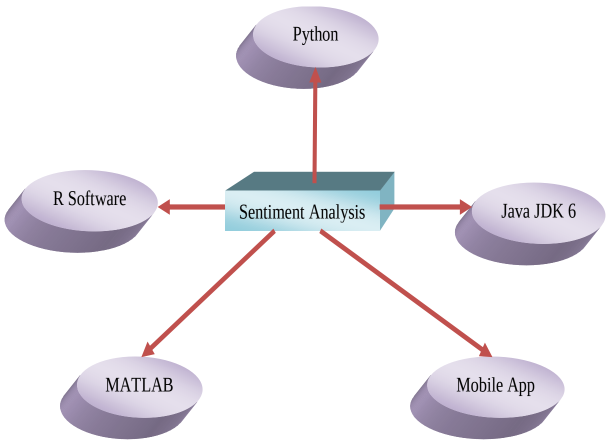


Fig. 2. Various tools used for executing sentiment analysis

## 5. Research Gaps and Challenges

The machine learning algorithm uses linguistic features by an objective of system's performance optimization with the example data. The big data models like Pentaho and Mahout consists of plug-ins and library related to the machine learning algorithm that is evaluated for performing the classification of sentiment. In evaluation of big data, the user must define the method type, which should be given to the data and that method has been performed using big data analytics tools in order to solve the certain problem like predictive analytics. In most of the cases, two document sets are needed for performing the machine learning-based categorization. These sets are considered as the training as well as testing sets. In order to learn the features of the document, the training set has been given to the machine learning algorithm, and for evaluating the performance of the classifier, testing set is employed.

By using the machine learning algorithms, the text classification models are split into unsupervised as well as supervised learning algorithms. The unsupervised learning models are employed in finding the training documents, which are quite complex. The supervised learning models employ more amounts of labelled training documents. Moreover, these supervised algorithms attain satisfactory efficiency but those are generally language dependent and domain specific. Moreover, these algorithms need labelled information that is frequently labour intensive. In the mean time, the unsupervised algorithms have more demand as the freely accessible information is frequently unlabelled and therefore best solutions are required. At that time, semi-supervised learning algorithm is developed and produces best results in classifying the sentiments. In order to construct best learning methods in unsupervised learning algorithms, it requires more amount of labelled as well as unlabelled data.

In sentiment analysis, many machine learning algorithms have been employed for classification. The famous machine learning algorithms, which have attained more successful in classifying the text are NB, ME, and SVM. The remaining machine learning algorithms in NLP are ID3, centroid classifier, N-gram model, K-Nearest Neighbour, C5, and winnow classifier. Many of the conventional models are associated with the public-related sentiments from social network, and text applications. However, there is less amount of work, in which the ontology and semantics are seemed to be more important research works in sentiment analysis. Now-a-days, the conventional research models are experimented using the public review datasets. However, this kind of review has not been evaluated keenly by concerning the sentiments. By categorizing the sentiments as positive or negative, it will not provide the original and the concealed information beyond the actual concepts of sentiments. In addition, there are some specific sentences that are quite complicating and accurate classification cannot be performed. There have been many constraints such as assessment of sentiment during the review, and document exploration using many subjects. Moreover, traditional models concentrated on major problems rather than minor ones, in which the accuracy is not seemed to be optimized. It is observed that there are few research methodologies, which have been recognized as standard models. There is only little number of researches other than standard models, whose results are seemed to be less efficiency over a suitable approach. The evaluation of less dimension text might utilize less number of resources. However, the collection of sentiments from the collaborative environment will utilize more amounts of resources. It is unfortunate that in the conventional researches, the authors didn’t found several confirmations related to the computational expenses of efficient techniques for performing huge data sentiment analysis.

## 6. Conclusion

The present paper has developed the review of earlier contributions with various machine learning models using discrete information. The present review has explored 20 research works that covered various implementations employed for sentiment analysis. Initially, the assessment has concentrated on clarifying the contribution of every task and observed the type of machine learning algorithm utilized. The evaluation also focused in recognizing the type of data employed. Later, the environment utilized and the performance metrics covered in each contribution was analyzed. Finally, the research gaps and challenges were mentioned that were useful for recognizing the non-saturated implementation for which the sentiment analysis was required in further researches.

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