



## **Sentiment Analysis of Twitter for Electoral Process: A Systematic Literature Review**

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### **Abstract**

The pervasive use of social media made publicity of any political party so quick and inexpensive for real time election campaigning and prediction of results. Several political parties take the benefit from it with the help of sentiment analysis of social media platforms. However, our study will focus on the literature published on sentiment analysis done on twitter for election campaigning and results prediction. So, many researchers have worked on sentiment analysis of elections for social media platform, however, to best of our knowledge no one has worked on systematic literature review (SLR) for last five years. Thus, our study will review published studies on sentiment analysis of twitter forelections from January 2015 to October 2020. The review of studies will be done on four aspects as named, data collection technique, preprocessing, algorithms used in study and performance metrics. Thus, for review 7 studies are



selected from 3 high quality and reliable databases namely, PubMed, ACM and Science Direct. Lastly, we have observed few limitations in the studies and suggested future directions. So, this SLR will be very much beneficial to upcoming researchers engaged in sentiment analysis of twitter for elections.

**Keywords:** Sentiment analysis, twitter, elections, electoral process, predicting elections, analyzing elections

## **Introduction**

Twitter is extensively used social media platform for networking and communication between humans, where users can send tweets of 280 characters maximum for sharing their opinions (Ansari et al. 2020). It was also observed that twitter has more than 321 million users that are active per month in India as of 2018 (Ansari et al. 2020). Additionally, during US 2016 Presidential elections Twitter was the biggest source of information that means political leader success completely depends on how he communicate to the masses (Ansari et al. 2020). Thus, Twitter has become crucial part for election campaigning and prediction using sentiment analysis.

Sentiment analysis is process in which message is checked whether, it is positive or negative with the help counting positive and negative words used in message and if number of positive words are greater than negative words then message is considered positive on the other hand if negative words are greater than positive words then it is considered negative message which ultimately gives insights of sentiments of public opinions (Sharma and Ghose 2020). Sentiment analysis is done in three phases first of all we need data, which is



collected from twitter search API's, then that data is preprocessed and in preprocessing noise is removed from text such as white spaces, hashtags etc. at last machine learning algorithm is applied for classifying positive or negative message (Ansari et al. 2020).The studies which we are reviewing have used different algorithms for checking sentiment of twitter messages such as(Ansari et al. 2020) study has used support vector machine (SVM), Decision Tree Classifier, Logistic Regression, Long Short Term Memory and Random forest Classifier while study (Bansal and Srivastava 2018)and (Antonakaki et al. 2017)used Random Forest and SVM respectively. So, in the same way all studies used different algorithms for measuring sentiment score. At last each algorithm performance is measured with different performance metrics as discussed in Section **Table 5**.

The preceding review studies on sentiment analysis for elections has focused on overall process till 2015, however to the best of our knowledge no study focuses on this topic from 2015 to 2020 has published which completely reviews on topic sentiment analysis for elections on twitter. So, our study aims to review to published studies from January 2015 to October 2020 on the basis of four aspects namely, preprocessing techniques, data collection from twitter, ML algorithms used and performance measures used on selected studies.

## **Research Methodology**

We have divided methodology of SLR in five key phases, namely search strategy of primary studies, search results, selection of primary studies, quality assessment and data extraction, where in search strategy of primary studies our motive is to review objectives and



identifies problem statement along with finding keywords, making query and selection academic databases for finding primary studies (will be discussed in [Section 2.1](#)). Where as in search results phase, the query is executed on selected databases and in selection of primary studies phase studies are selected on the basis few rules as discussed in [Section 2.3](#) and in quality assessment papers quality is measured on the basis of QAC. Last but not the least data extraction phase shows what extraction strategy is applied on selected papers (will be discussed in [Section 3.0](#) in detail).

### Search Strategy of Primary Studies

This SLR focus is to review the published material on election campaigning on twitter using sentiment analysis. Thus, we have created various groups of keywords to retrieve literature from three high quality and reliable academic databases. namely, PubMed, ACM (Association for Computing Machinery) and Science Direct then we prepared list of keywords to find the literature on topic "Sentiment Analysis of election campaigning on twitter data" from selected databases. As **Table 1** clearly shows how keywords are selected and each group of keywords are placed in double quotations and separated by OR operator. Where as in between of groups AND operator is used to form query as shown in **Table 1** and last row of **Table 1**. Final query is applied on selected academic databases for title and abstract of relevant conference or Journal Papers written in English language and published between January 2015 to October 2020.



### Search Results

When query is executed on selected academic databases then total 192 studies are the shown from databases where 4 studies are from PubMed, 10 are from ACM and 178 from Science Direct as **Table 2** shows detailed screening of studies. Furthermore, we also added all selected studies in citation manager tool Endnote for using automate references in this study.

### Selection of Primary Studies

As 192 papers are fetched after applying query on databases, but after screening of title only 16 studies are selected which matches to our topic as shown in **Table 2**. Furthermore, after screening of abstract, full text and inclusion and exclusion criteria (on **Table 3**) which helped us to filters from 192 studies to 7 studies and other studies are excluded on the basis of voting from authors by following inclusion exclusion criteria. There is important reason to exclude 185 studies, and that is, many studies are using sentiment analysis on twitter for other purposes were included but our purpose is to select those studies that were doing Sentiment analysis on twitter for election campaigning as mentioned in inclusion exclusion criteria on **Table 3**.

**Table 1: Selected Keywords and Groups.**

Group	Keywords
Group 1 – Keywords related to electoral process	Elections, Election, Electoral Process
Group 2 – Keywords related to social media platforms	Social Media, Twitter

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Group 3 – Keywords related to data interpretation	Sentiment Analysis
Group 4 – Publication years	January 2015 to October 2020
Group 5 - Document Types	Journal and Conferences
Group 5 – Languages	English
Final Search Query	(Group 1) AND (Group 2) AND (Group 3) AND (Group 4) AND (Group 5)

**Table 2: Results After Applying Queries on Academic Databases**

Database	Initial Search	After Title Screening	After Full-Text Screening	After Reference Scanning	After Quality Assessment
PubMed	4				
ScienceDirect	178				
ACM	10	16	7	7	7
total	192				

**Table 3: Inclusion and Exclusion Criteria**

S. No	Inclusion Criteria
1	The paper should have sentiment analysis of twitter data for the purpose of election as one of the main topics.
2	Data has been collected from twitter through twitter API.
3	The paper which do sentiment analysis of twitter data using
4	Machine Learning approaches.
5	The paper should be written in English.
6	Journals must be published between 2015 to 2020.



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Article is either conference proceeding or journal article.

## **S. No Exclusion Criteria**

1 Studies not primarily aimed to use sentiment analysis of  
2 twitter.

Studies not primarily aimed to use Machine Learning approaches are discarded.

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## **Quality Assessment**

We have created quality assessment criteria for assessment of selected 7 studies, and its purpose is to check whether the selected study is following our SLR objectives or not. So, for that purpose we created few checklist questions mentioned in Table 6. The Answer to questions can be in two cases either yes or no, where yes carry the 1 weight and no carry 0 weight, then task of checking papers is divided in authors and threshold is set for quality assessment that if paper having minimum 4 points from 7 will be selected for further review and result of that assessment is shown in Table 7.

## **Data Extraction**

We applied data extraction on selected studies on the basis of three aspects: (1) how data is collected from twitter, (2) How data is pre-processed (3) type of Machine learning algorithm applied and (4) what is performance metric is used (as discussed in detail in Section 3.0).

## **Review**

This review section is for analyzing the studies which has been selected on 3 different aspects, which are, how data is collected from twitter, type of Machine learning algorithm applied and what is performance metric is used in the studies.



### Data Collection from Twitter

The data from twitter is collected using Twitter Search API Table 4. All studies have used specific keywords. Antonakaki et al. (2017) has used hashtags #dimopsifisma and #greferendom. These tweets are collected through the period of Greek referendum. The referendum period was from 25<sup>th</sup> June 2015 to 5<sup>th</sup> July 2015. Bansal and Srivastava (2018) Used keywords, hashtags and twitter handlers of all stake holders in Indian Legislative election. This study has focused on quality of topics to obtain comparative tweets of different parties on India. (Ansari et al. 2020) used the hashtags such as #LokSabhaElections, #ElectionsInIndia etc. The mining of data from twitter was conducted from Jan to March 2019. Khatua, Khatua, and Cambria (2020) used twitter search API and hashtags #AAPPositive, #MyVoteForCongress, #WeWantModi and the keywords related to political parties of India between the period of 15<sup>th</sup> March 2014 until 12<sup>th</sup> May 2104. (Kušen and Strembeck 2018) used twitter search API to collect tweets about Austrian 2016 presidential election. This study included tweets in both English and German languages and the retweets, tweets posted by two presidential candidates i.e. Alexander Van der Bellen (@vanderbellen) and Norbert Hofer (@norbertghofer). The hashtags used were #vdb, #vdb16, #VanDerBellen, #MehrDennJe, #Nor. Sharma and Ghose (2020) harvested tweets using twitter search API and R language. The keywords corresponded to the general election of India. Kulshrestha, Shah, and Lu (2017) Collected tweets from twitter handlers of political actors by using keywords related to politicians and political commentators.





### Preprocessing Techniques

All studies have processed the tweets obtained from the twitter according to its analysis methodologies. The preprocessing in all studies included certain steps. Step1; filtration of lexical token such as mentions, hashtags, emotions. Step2; elimination of duplicate tweets, re-tweets, stop words, URL and noise. (Antonakaki et al. 2017) has classified the tweets according to number of unique entries number of variants per entity. (Bansal and Srivastava 2018) has divided the tweets in five different topics based on the comparison of re-tweets and likes ratio. Topics are defined using BTM( biterm topic model) and LDA ( latent Dirichlet allocation). (Ansari et al. 2020) transformed the tweets with respect to opinion and speculation annotations. Each annotation category consisted of eight classes. Khatua, Khatua, and Cambria (2020) classified tweets in topics i.e. mix tweets and final category. (Kušen and Strembeck 2018) has assigned scoring to tweets as negative and positive context. Lexicons of sentiment words, a list of idioms and a list of emotions are used in SentiStrength for the data set created. (Sharma and Ghose 2020) has used sentiment scores, tweet polarity and tweetsubjectivity. Rapid miner's alyien extension and TwitterR were used for dataset. (Kulshrestha, Shah, and Lu 2017) used the data corpus consisted of Users, Tweets and sentiments.

### Machine learning Algorithms Applied

Table 4. shows machine learning algorithms used in experiments, along with the key algorithm that has generated the best classifying results. All the studies which were selected use any or some of the machine learning algorithms which helps systems to acquire and



enhance knowledge automatically without specific programming. (Antonakaki et al. 2017) has used senti-strength and support vector machine (SVM) algorithm for classification of positive, negative or neutral tweets. The study (Bansal) used the RF and Sentiwordnet for classifying tweets. For classifying tweets (Ansari et al. 2020) used the support vector machine, Decision Tree classification, Linear regression and Random Forest classification. The study (Khatua, Khatua, and Cambria 2020) uses three different algorithms for classification of tweets namely MNL regression, RNN, LSTM, Bi-LSTM. (Kušen and Strembeck 2018) also use 3 different algorithms which are Binomial Regression Model, Ego-Network and SentiStrength. Whereas the study (Sharma and Ghose 2020) uses K means clustering, sentidff and Aylien tool of a rapid miner for sentiment extraction. Lastly the study (Kulshrestha, Shah, and Lu 2017) created his own model called contagion Augmented contagion model having complexity of  $O(n)$  for classification of tweets.

**Table 4: Data Collection and Algorithm Used**

Study	Data collection	Purpose	Number of tweets obtained.	Algorithm
(Antonakaki et al. 2017)	Twitter Search API	Greek referendum and Legislative Elections (2015)	301,000	Senti-Strength and SVM



(Bansal and Srivastava 2018)	Twitter Search API,	India Uttar Pradesh Legislative election	300,000	RF and Sentiwordnet
(Ansari et al. 2020)	Twitter Search API	General Election of India in 2019	3,896	SVM, DTC, LR, and RFC
(Khatua, Khatua, and Cambria 2020)	Twitter Search API	General Election of India in 2014	2,400,000	MNL Regression, RNN, LSTM, Bi-LSTM
(Kušen and Strembeck 2018)	Twitter Search API	2016 Austrian Presidential Election	343,766	Binomial Regression Model, Ego-Network, SentiStrength
(Sharma and Ghose 2020)	Twitter Search API with TwitterR package	2019 general election of India	987,788	K-means clustering, sentidiff, Aylien
(Kulshrestha, Shah, and Lu 2017)	Twitter Search API	General Election of India in 2014	10,600,000	Augmented contagion model



### Performance Metrics Used

By using different performance metrics, the performance of the classification model can be measured which are accuracy, precision, recall, F-measure, specificity, sensitivity and their values can be computed by the help of TP, TN, FP, FN. To measure the performance of a model the selected studies uses precision, recall, f1 measure, confusion matrix, and human raters.

#### Precision

The ratio of correctly classifying the tweets to the total positively predicted tweets, also called positive predictive value (PPV). formally written as

$$\text{Precision} = \frac{TP}{TP + FP}$$

#### Recall

It is the ratio of correctly classifying the tweets to the all tweets in actual positive class, also called positive rate (TPR) or sensitivity. Formally written as

$$\text{Recall} = \frac{TP}{TP + FN}$$

#### F-Measure

The weighted average of precision and recall, formally written as:

$$F\text{-measure} = \frac{2 \times (\text{precision} \times \text{recall})}{(\text{precision} + \text{recall})}$$

#### Accuracy

This performance metric is widely used. The ratio of correctly classifying the tweets to the total tweets. Formally written as:

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + FN + TN)}$$



Table 5: Performance Metrics

Study	Precision	Recall	F1 score	Accuracy	Loss	Correctness	Human raters	Confidence Level Measure
(Antonakaki et al. 2017)	.70	.71	.70	x	x	x	x	x
(Bansal and Srivastava 2018)	.78	.8	.79	x	x	x	x	x
(Ansari et al. 2020)	.72	.39	.5	x	x	x	x	x
(Khatua, Khatua, and Cambria 2020)	x	x	x	.87	.46	x	x	x
(Kušen and Strembeck 2018)	.67	.53	.67	x	x	x	x	x
(Sharma and Ghose 2020)	x	x	x	.68	x	x	x	.75
(Kulshrestha, Shah, and Lu 2017)	.67	.75	.78	x	x	x	x	x



## Discussion and Limitations

Our review of all seven journal articles shows that sentiment analysis is used to predict and analyze the result of electoral process. Twitter's tweets are processed on the basis of sentiment tokens and corpus'. And then frequency of these tokens over the period of election campaigns is fed to different models of machine learning. These models then rationalized the effective agents. The data set created was then analyzed further to give positive or negative scoring to token corpus'. In prediction, the highest positive scoring parties or politicians have high chances to win the election. In analysis, the key agents defining results are listed. The data set obtained from twitter was noisy so different researches used different methods to filter the data. The limitation in processing the tweets was the presence of fake news and non-political tweets. A few researches tend to use the imbalance data set which caused the analysis to be more complicated. (Antonakaki et al. 2017) has used hashtags #dimopsifisma and #greferendom. These tweets are collected through the period of Greek referendum. The referendum period was from 25<sup>th</sup> June 2015 to 5<sup>th</sup> July 2015. (Bansal and Srivastava 2018) used keywords, hashtags and twitter handlers of all stake holders in Indian Legislative election. This study has focused on quality of topics to obtain comparative tweets of different parties on India. The senti-strength tool is used to classify the lexicons and corpus'. And then SVM is used to predict. The limitation of SVM is that it is not compatible for large data set. SVM also under performs if the number of features increased than the training data . (Ansari et al. 2020) used the



hashtags such as #LokSabhaElections, #ElectionsInIndia etc. The mining of data from twitter was conducted from Jan to March 2019. For opinion mining sentiwordnet was used. For classification, random forest RF is used for labelled lexicons. The limitations in using random forest is that large number of trees makes it difficult to fast result. Hence making it difficult for real-time predictions. Khatua, Khatua, and Cambria (2020) used twitter search API and hashtags #AAPPositive, #MyVoteForCongress, #WeWantModi and the keywords related to political parties of India between the period of 15<sup>th</sup> March 2014 until 12<sup>th</sup> May 2104. This study has used SVM (support vector machine) and random forest (RF). Both classifiers are limited to large sets of data. They perform slow for large number of features. Making it hard for predicting and analyzing the results.

(Kušen and Strembeck 2018) used twitter search API to collect tweets about Austrian 2016 presidential election. This study included tweets in both English and German languages and the retweets, tweets posted by two presidential candidates i.e. Alexander Van der Bellen (@vanderbellen) and Norbert Hofer (@norbertghofer). The hashtags used were #vdb, #vdb16, #VanDerBellen, #MehrDennJe, #Nor. It is using recurrent neural network (RNN). RNN is not optimal for processing long sequences. It is also using multi nominal logit (MNL) regression model. The limitation is that it shows linear boundaries on measure independencies.(Sharma and Ghose 2020)harvested tweets using twitter search API and TwitterR language. The keywords corresponded to the general election of India. It has used K-mean clustering. It is hard to select k value and the clusters



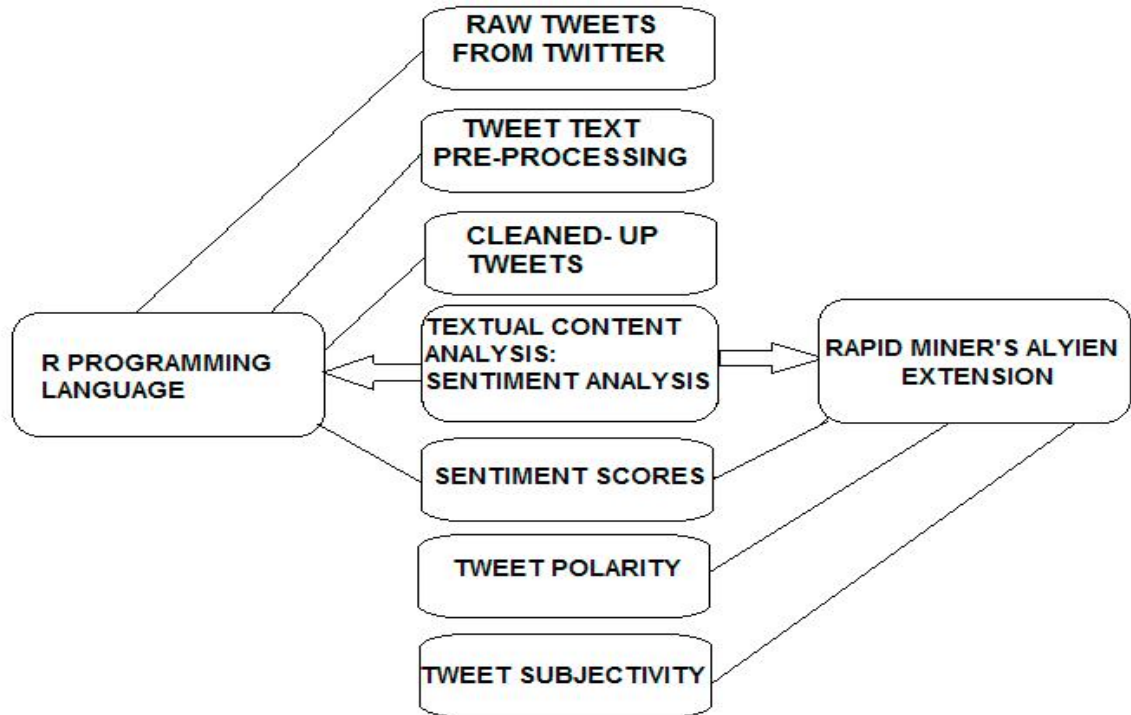
completely dependent on initial values. K-means can only handles numeric data.(Kulshrestha, Shah, and Lu 2017) collected tweets from twitter handlers of political actors by using keywords related to politicians and political commentators. The study (Kulshrestha, Shah, and Lu 2017) study uses their own created algorithm called Augmented contagion model though its complexity is very low as  $O(n)$ .These are referred in Table 4.In the conclusion of(Antonakaki et al. 2017), the finding of the study were described properly. But the accuracy of testing set is not mentioned clearly. And the results of the classifier is not explained in the conclusion. (Bansal and Srivastava 2018). (Ansari et al. 2020) transformed the tweets with respect to opinion and speculation annotations. Each annotation category consisted of eight classes. Khatua, Khatua, and Cambria (2020) classified tweets in topics i.e. mix tweets and final category. (Kušen and Strembeck 2018) has assigned scoring to tweets as negative and positive context. Lexicons of sentiment words, a list of idioms and a list of emotions are used in SentiStrength for the data set created. (Sharma and Ghose 2020) has used sentiment scores, tweet polarity and tweet subjectivity. Rapid miner's alyien extension and TwitterR were used for dataset. (Kulshrestha, Shah, and Lu 2017) used the data corpus consisted of Users, Tweets and sentiments are classified using Augmented contagion model. It only specifies the frequency of sentiments scores. It is mathematical model with only restricted classification of data set.

All the studies have used only the twitter search API and twitterR but the validation of tweets and the fake news is not filtered out in most





of the studies Table 4. Figure 1 shows the general flow of assigning scores which is well discussed in (Sharma and Ghose 2020).



**Figure 1. Methodology**

## Conclusion and Future Directions

A critical review of the field of sentiment analysis of twitter for electoral process was provided in this systematic literature review, integrating the various research activities to help researchers in this field, thus increasing their knowledge of current relevant technologies. Articles on sentiment analysis of twitter for elections published in 2015-2020 were reviewed. A total of 7 primary studies were selected for review from 3 high quality and reliable databases namely, PubMed, ACM and ScienceDirect. The review of studies will be done on four



aspects as named, data collection technique, preprocessing, algorithms used in study and performance metrics. The studies fully described their objectives. Mostly in every study data is collected from twitter through twitter search API. Data selected at first typically require preprocessing which is done in most of the paper except (Khatua, Khatua, and Cambria 2020). (Kulshrestha, Shah, and Lu 2017) to remove the noisy or irrelevant terms from the data set like URLs, punctuation, quotations. Some of the studies fully described the performance measure as in Table 7 except some (Kulshrestha, Shah, and Lu 2017) (Khatua, Khatua, and Cambria 2020; Sharma and Ghose 2020). Most of the studies uses SVM, senti-strength, sentidiff, K-means clustering and more and are described fully except (Bansal and Srivastava 2018; Kušen and Strembeck 2018; Sharma and Ghose 2020). In the conclusion of paper almost all have provided their results and interpretation. Our analysis found many study holes. In this section, many potential research directions need to be stressed in order to enhance the efficiency of sentiment analysis of twitter for elections. The below are the study recommendations. In regard to future directions quality of the data set can be enhanced by filtering out fake tweets, by analyzing pictorial data, videos data, audio data and data can also be selected from others platform like YouTube, Facebook, different social media platform snapchat etc. Neural networks can train to analyze the trends in the elections period in order to explore the marketing area for more sophisticated recommendations. Unsupervised clustering and reinforcement learning approaches can be followed.



**Table 6: Quality Check Questions**

S. No	Questions
1	Does study clearly mention its objectives?
2	Is methodology clearly defined for study?
3	Is the number of training and testing data clarified?
4	Are the preprocessing techniques are well described?
5	Are the classifiers are clearly described?
6	Were the performance measures fully defined?
7	Are the conclusions in synchronization with the findings?

**Table 7: Applied Criteria on Selected Studies**

Papers	Qno 1	Qno 2	Qno 3	Qno 4	Qno 5	Qno 6	Qno 7	Score
Ansari et al. 2020)	Yes	Yes	No	Yes	Yes	Yes	Yes	6
Bansal and Srivastava 2018)	Yes	Yes	Yes	Yes	No	Yes	Yes	6
Khatua, Khatua, and Cambria 2020)	Yes	Yes	No	No	Yes	No	Yes	4
(Kušen and Strembeck 2018)	Yes	Yes	No	Yes	No	Yes	Yes	5



Sharma and Ghose (2020)	Yes	No	No	Yes	No	No	Yes	3
Sharma and Ghose (2020)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	7
Kulshrestha , Shah, and Lu (2017)	Yes	Yes	No	No	Yes	No	Yes	4

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