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ORIGINAL RESEARCH

The emergence of social media data and sentiment analysis in election prediction

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Abstract
This work presents and assesses the power of various volumetric, sentiment, and social network approaches to predict crucial decisions from online social media platforms. The views of individuals play a vital role in the discovery of some critical decisions. Social media has become a well-known platform for voicing the feelings of the general population around the globe for almost decades. Sentiment analysis or opinion mining is a method that is used to mine the general population's views or feelings. In this respect, the forecasting of election results is an application of sentiment analysis aimed at predicting the outcomes of an ongoing election by gauging the mood of the public through social media. This survey paper outlines the evaluation of sentiment analysis techniques and tries to edify the contribution of the researchers to predict election results through social media content. This paper also gives a review of studies that tried to infer the political stance of online users using social media platforms such as Facebook and Twitter. Besides, this paper highlights the research challenges associated with predicting election results and open issues related to sentiment analysis. Further, this paper also suggests some future directions in respective election prediction using social media content.

Keywords Sentiment analysis · Opinion mining · Election prediction · Social media · Twitter

1 Introduction

Social media platforms are mostly utilized these days for expressing the opinions or views about any product, topic, event, or any breaking news from anywhere at any time. Sentiment analysis or opinion mining is a field which predominantly revolves around the analysis of such opinions. Sentiment analysis is a sub-discipline of Natural Language Processing (NLP) which is used to discover the polarity of the textual data. Here, the polarity of textual data implies finding out whether the sentiments of given textual data are positive, negative, or neutral. Further, sentiment analysis can be done at five levels viz. *word-level*, *sentence-level*, *document-level*, *aspect-level* (Appel et al. 2015), and concept-level sentiment analysis. At *word-level*, *sentence level*, *and document level sentiment analysis*, the given text is analyzed to find out the polarity of the affective word, subjective sentence, and the whole document respectively. At *aspect-level sentiment analysis*, features or aspects of a product or any other entity which is being analyzed are selected as targets and attitude towards these targets is found. In *concept-level sentiment analysis*, words in opinionated texts having similar meanings are denoted and considered as the same concept. Further, concept-based sentiment analysis go beyond the word-level sentiment analysis of text and provide novel ways to perform the task of sentiment analysis and opinion mining (Cambria et al. 2010). Moreover, concept level methods classify text based on the semantics by using semantic networks such as ConceptNet.[1] E.g. "Flat rate was the best thing that happened this year, @UBER bring it back!!!". In this sentence, first of all, the algorithm will detect a category of a concept like "price" from the similar words network ("flat rate" in this case) and then sentiment classification of the above sentence will be done by considering "price" as a keyword. So, the above sentence gives a positive review of the "price" of Uber.

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1 http://conceptnet.io/ (Last accessed on: 13 March 2020).

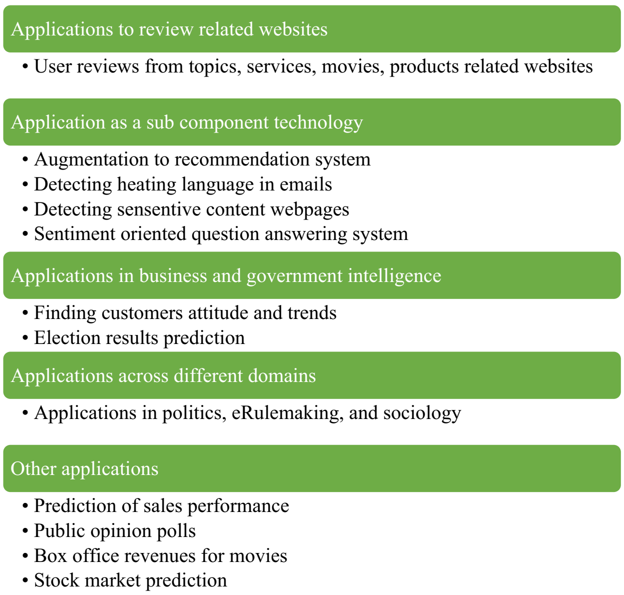


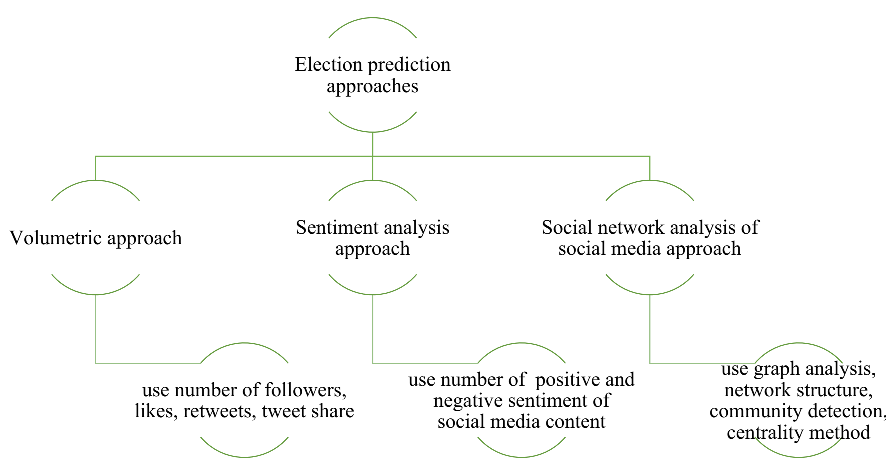
Fig. 1 Applications of sentiment analysis

In recent years, sentiment analysis has found its applications in various fields. Pang and Lee (2008) categorized the applications of sentiment analysis in four distinct areas as shown in Fig. 1. The first area of application is: *applications to review related websites* which includes summarizing the opinions of the user reviews from various topics, services, movies, and products related websites. The second area of application is: *applications as a sub-component technology* which includes augmentation to the recommendation system, detecting the heating language in emails, detecting webpages that contain sensitive content, and sentiment-oriented question answering systems. The third area of application is: *applications in business and government intelligence* which gives insights on finding customers' attitudes and trends from an unstructured text about an organization or company. The fourth area of application is *applications across different domains*, which include sentiment analysis applications in politics, eRulemaking, and sociology. Besides, (Liu 2012) mentioned some application-oriented papers which show the use of sentiment analysis in *prediction of sales performance*, *public opinion polls*, *election results*, *box office revenues for movies*, *and the stock market*. Further, predicting the election results is another emerging application of sentiment analysis. A Social media platform like Twitter, where people openly express their opinions about the electoral or any political party by mentioning them in the tweets can prove to be an acceptable data source for election prediction. Sentiments of the tweets can be analyzed as a function to aggregate the sentiments of all the tweets related to a topic, electoral, or an event. Various approaches like the volumetric approach, sentiment approach, and social network analysis approach can predict election results through social media as illustrated in Fig. 2 (Jaidka et al. 2018).

The *volumetric approach*, considers the volume of online followers, likes, and posts shared about an individual party or electoral for predicting election results. In the *sentiment analysis approach*, an aggregate of positive and negative sentiments of online posts about an electoral or political party is considered for election prediction. In the *social network analysis approach*, the networks of social media users who are supporting or discussing a couple of electoral or political parties are analyzed by measuring centrality method i.e. incoming, outgoing, or bidirectional links in a graph structure. This paper gives a detailed survey of thirty-eight (38) papers and the main objectives of this survey paper are to:

(i) provide a quick review of sentiment analysis: its introduction, techniques, applications, and some advancements in this field.

Fig. 2 Election prediction approaches



(ii) review and compare significant findings and outcomes related to the election results prediction using social media.
(iii) identify research gaps and findings in the prior associated studies.
(iv) address some future directions in election result prediction using social media.

The paper is organized as follows: Sect. 2 provides some facts which motivated authors for the present study. Then, Sect. 3 provides basic terminology and steps used in the overall sentiment analysis process. This section also gives a comprehensive discussion of some studies which have used deep learning methods for sentiment analysis. Section 4 gives a detailed explanation of the studies related to election prediction and political stance detection. Section 5 discusses some useful insights related to previous election prediction studies and points out some important findings. Further, Sect. 6 highlights the research gaps found in the related studies. After that, Sect. 7 aims to give some future directions in the field of election prediction. In the end, Sect. 8 concludes the paper.

2 The motivation of the study

Here are some essential factors which motivated authors of this manuscript to work on election prediction through social media data. In this section, all those crucial factors are discussed as given below:

Predicting the future is a great desire of human beings. To fulfill this kind of prediction desire, the significance of social media data has been correctly proven in many studies (Kim et al. 2017; Ni et al. 2017; Pagolu et al. 2017; Elshendy et al. 2018; Oikonomou and Tjortjis 2018). (Kalampokis et al. 2013; Schoen et al. 2013; Rousidis et al. 2019) have shown a vast variety of fields such as finance, marketing, and sociopolitical field which have used social media data for prediction. Reviewing the studies mentioned above in this section influenced us to work on social media prediction and mining human behavior. Thus, authors chose to work on election result prediction and it seems to be quite interested accordingly. Further, the challenges in the prediction of election results through social media data motivated authors to perform this study (Metaxas et al. 2011; Gayo-Avello 2012a, b, 2013).

Extracting the sentiments of social media data helps in identifying the public mood and drawing meaningful conclusions. Further, there is a considerable number of messages as tweets the collection of which is technically easy and straightforward. More than 500 million tweets are posted daily on Twitter, around 6 K tweets per second.[2],[3] Moreover, the Twiplomacy study,[4] the preeminent global study of world leaders on social media conducted by BCW,[5] showed that 97% of the 193 United Nations (UN) member states have an official Twitter account. Twiplomacy study also identified that a total of 951 government twitter accounts (372 personal and 579 institutional accounts) of 187 countries are there on Twitter. Moreover, according to a survey conducted by the Pew Research Centre[6] in 2018, 71% of Twitter users in the United States (US) found Twitter a relevant source for the news.[7] Twitter, therefore, seems to be an excellent source of data from where predictions can be made about the stance of the public towards political parties and their candidates.

Another reason to perform this study is that most of the political leaders, celebrities, actors as well as common users of all age groups above thirteen, genders and religions are there who express their sentiments as tweets on various topics. Thus, their sentiments can be discovered by interpreting the tweets, and this can assist in mining human behavior that can be helpful in the decision-making and prediction tasks.

Another reason to analyze social media user's sentiments is that obtaining public opinion on social media platforms is a method that saves time and money compared to a field survey. For instance, if anyone wants to predict any election results, the survey is conducted by going through a restricted group of individuals and asking their views on different electoral and their respective political parties. Further results are evaluated on the grounds of their opinions, and prediction of election results is done. All this process of the offline survey cost so much while considering manpower, time, and money. It can, therefore, be safely concluded that election prediction from social media platforms covers a varied and extensive population, and save both time and men's efforts.

[2] https://blog.twitter.com/engineering/en_us/a/2013/new-tweets-per-second-record-and-how.html (Last accessed on: 20 Feb. 2020).

[3] https://blog.twitter.com/official/en_us/a/2014/the-2014-yearontwitter.html (Last accessed on: 20 Feb. 2020).

[4] https://twiplomacy.com/blog/twiplomacy-study-2018/ (Last accessed on: 17 Feb. 2020).

[5] https://bcw-global.com/ (Last accessed on: 17 Feb. 2020).

[6] "Pew Research Centre is a nonpartisan fact tank that informs the public about the issues, attitudes, and trends shaping the world. The research center conducts public opinion polling, demographic research, content analysis, and other data-driven social science research." https://www.pewresearch.org/about/ (Last accessed on 17 Feb. 2020).

[7] https://www.journalism.org/2018/09/10/news-use-across-social-media-platforms-2018/pj_2018-09-10_social-media-news_0-04/ (Last accessed on: 17 Feb. 2020).

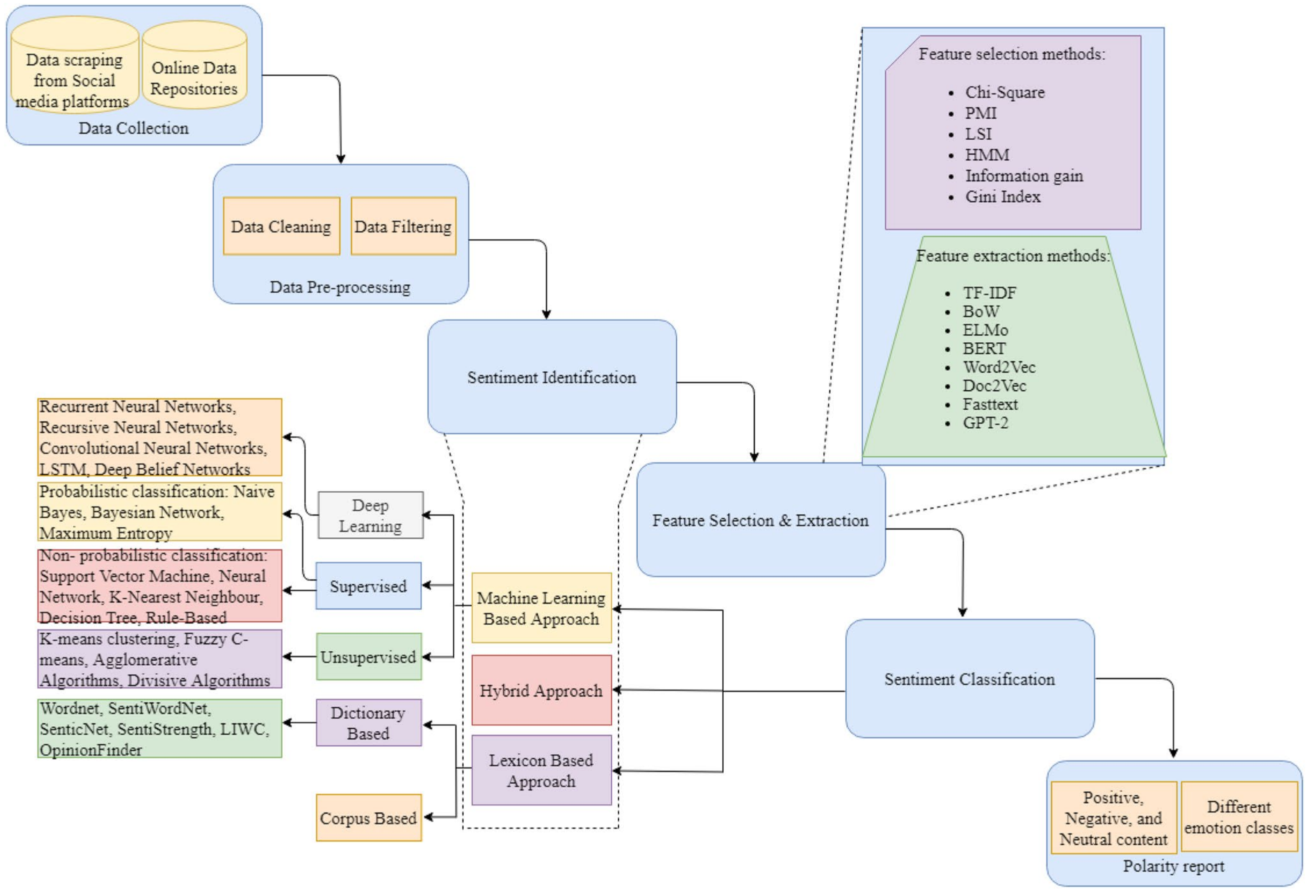


Fig. 3 Sentiment analysis process

3 Sentiment analysis process

Sentiment analysis can be viewed as a series of various data mining steps that make use of multiple disciplines such as information extraction, natural language processing, statistics, and machine learning. The step-wise step process of sentiment analysis is depicted in Fig. 3.

3.1 Data collection

Data collection is the first step in the sentiment analysis process. Data can be collected from a variety of sources such as internet blogs, online forums, chat history, online data repositories, and other social media websites like Facebook, Twitter, and many more (Kumar and Sebastian 2012; Vinodhini 2012). Habimana et al. (2020) summarized 20 most popular and real-world publicly available benchmarked datasets used in sentiment analysis literature.

While collecting data for election prediction from social media platforms, different data selection criteria such as @ mention of politician, hashtags, keywords can be used by a data collection team as mentioned by Jungherr (2016). The paper also mentioned different modes of Twitter data collection under two approaches. The first approach is a scripted approach developed by researchers to scrap data from twitter. For example, one can collect data from Twitter using the Application Programming Interface (API) that can be done in two ways: First is the *Representational State Transfer* (*REST*) API that is used to collect tweets once and second is the *streaming API* that is used when a consumer wants to do a continuous collection of real-time tweets for a specific period. Further, the second approach is collecting data using third-party software such as DataSift,[8] DiscoverText,[9] Topsy,[10] NodeXL.[11]

[8] https://datasift.com/ (Last accessed on: 13 March 2020).

[9] https://discovertext.com/solutions/ (Last accessed on: 13 March 2020).

[10] http://topsy.thisisthebrigade.com/ (Last accessed on: 13 March 2020).

[11] https://nodexl.com/ (Last accessed on: 13 March 2020).

3.2 Data pre-processing

Pre-processing involves cleaning and filtering of data, which can result in incorrect classification of the data if not done correctly. Data collected from Twitter or any other social media network platforms include much noisy information like misspelled words, slang words, user-generated abbreviations, and white spaces that can degrade the accuracy of a sentiment classifier approach. Consequently, the collected data is usually cleaned by correcting it. Further, data cleaning involves various tasks such as converting English language tweets to lower case letters only and stemming the textual data.

The filtering of data implies keeping only that portion of the data, which is usable and discarding unwanted or junk portion of the data so that classifiers can correctly classify the given data. For example, tweet's filtering involves removing hyperlinks, stop words, punctuations, retweets, and keeping tweets of any particular language (such as Hindi or English or Chinese) that a data collector wishes to keep in their dataset.

3.3 Sentiment identification

This step seeks to find out the opinionated words or phrases to discover sentiments among the given data. Sometimes, this step also classifies subjective and objective text to perform analysis of the subjective text only and discarding the objective text because subjective sentences are rich in opinions and sentiment related words. However, it should be noted that only subjective text is not enough for the sentiment analysis, there may be objective text also which implies opinions or sentiments. For example, the sentence "*We bought the car last month, and the windshield wiper has fallen off*" (Liu 2012) does not contain any sentiment-oriented word but has a negative opinion towards the car. Sentiment identification can be done using machine learning or lexicon-based techniques as shown in Fig. 3.

3.4 Feature selection and extraction

A feature in text plays a very important role in sentiment classification and if the feature is eliminated or ignored, the performance of the classification model degrades (Agarwal and Mittal 2016). Textual features can be classified into two categories named as *syntactic features and semantic features* (Giachanou and Crestani 2016). *Syntactic features* are the most frequently used features such as unigrams, bigrams, n-grams, term's frequencies (TF-IDF), Part of Speech (PoS) tags (nouns, verbs, adjective, adverbs, etc.), and dependency trees. *Semantic features* are features that reveal positive or negative sentiments of the text such as opinion or sentiment words/phrases, semantic concept, and negation.

Feature selection and feature extraction are both parts of the sentiment analysis pipeline however both of these steps are semantically different (Sebastiani 2002). Feature selection and extraction are done in two steps, first feature sets are selected and then the feature values are extracted from the text (Kumar et al. 2020). Selecting features (sometimes their combination) from the text play a very important role in detecting sentiments of the given text (Giachanou and Crestani 2016). Features of the given text are selected using various techniques such as Chi square, frequency-based, Latent Semantic Indexing (LSI), Mutual Information (MI), Hidden Markov Model (HMM), Latent Dirichlet Allocation (LDA), Weight by correlation, Information gain, and Gini index (Medhat et al. 2014; Tedmori and Awajan 2019).

Feature extraction is a very crucial and difficult step in sentiment analysis (Siqueira and Barros 2010). In this step, the given text is converted into a feature vector. This feature vector contains the most important features which are used for training as well as testing of the learning model. The vector representation of features is then used to classify the polarity of a text. Moreover, machine learning techniques comprehend only numerical data, therefore the collected raw data is transformed into numerical matrices using different feature extraction methods such as count vectorizer, Term Frequency-Inverse Document Frequency (TF-IDF) (Tripathy et al. 2016), Bag of Words (BOW) using n-grams, and Feature hashing (Kumar et al. 2020).

In recent years, deep learning models have changed the picture of sentiment analysis by outperforming better than the traditional machine learning techniques (Vateekul and Koomsubha 2016; Day and Teng 2017; Çano and Morisio 2018; Ciftci and Apaydin 2018; Sun et al. 2018; Rani and Kumar 2019). Deep learning models extract useful representations of the raw input data through each hidden neural layer. Deep learning models have built-in feature extraction capability to automatically extract features for the training using word embedding methods. Word embedding is a feature extraction method that transforms words in vocabulary to real number vector representation (Zhang et al. 2018). Recent word embedding methods follow the distribution hypothesis where words with the same context have similar meanings (Harris 1954). Some well-known word embedding methods are described below.

Word2Vec (Mikolov et al. 2013) is a word embedding method used for feature extraction in sentiment analysis and other text mining tasks. Word2Vec can create word embedding for the training of a deep neural network using its two variants called *Continuous Bag of Words* (*CBOW*) model which predict a target word from its context word and *Skip-gram* model which predict the context word from the given target word (Zhang et al. 2018).

Doc2Vec (Le and Mikolov 2014) is an enhancement of the Word2Vec embedding method in which another vector called paragraph vector is added. This paragraph vector learns fixed-length feature representations from sentences, paragraphs, and documents. As in Word2Vec, instead of predicting a word from its context words, Doc2Vec method represents each document by a dense vector that is trained to predict words in the document.

Global Vectors for Word Representation (*GloVe*) (Pennington et al. 2017) captures global as well as local statistics of a corpus to come up with the word vectors. The GloVe is a global log-bilinear regression model for the unsupervised learning of word representations.

FastText (Bojanowski et al. 2017) assist in finding the vector representation of rare words, means FastText can give the vector representations of the words not present in the dictionary. FastText is more superior than word2vec and GloVe because both of these word embedding methods are not able to provide any vector representations for the rare words not present in the dictionary.

Embeddings from Language Models (*ELMo*) (Peters et al. 2018) uses a deep, bi-directional Long Short Term Memory (LSTM) model to create word representations. Rather than a dictionary of words and their corresponding vectors, ELMo analyses words within the context that they are used.

Bidirectional Encoder Representations from Transformers (*BERT*) (Devlin et al. 2018) uses transformer which is an attention model that try to learn contextual relationship between words of a text. BERT is designed to pre-train deep bidirectional representations from the unlabeled text.

Generative Pre-trained Transformer-2 (*GPT-2*) (Radford et al. 2018) is trained to predict the next word based on 40 GB text. GPT-2 uses an unsupervised learning approach to train the language model. Unlike other models such as ELMo and BERT which need two stages for training i.e. pre-training and fine-tuning stage, there is no fine-tuning stage for GPT-2.

3.5 Sentiment classification

For the classification of sentiments, various sentiment analysis techniques can be used to analyze the positivity and negativity of a vast number of opinions of users. There are mainly three approaches to sentiment analysis that can be used to determine the sentiments of the text (Medhat et al. 2014; Chauhan and Singh 2017; Hemmatian and Sohrabi 2017). The first approach is the *machine learning approach*, using supervised and unsupervised learning techniques. Supervised techniques are further divided into probabilistic classification techniques and non-probabilistic classification techniques. Various probabilistic classification techniques for sentiment are Maximum Entropy (ME), Naïve Bayes (NB), and Bayesian Network (BN). Non-probabilistic classification techniques are Support Vector Machine (SVM), Decision Tree (DT), Neural Networks (NN), Rule-based, and K-Nearest Neighbor (K-NN). Some studies which used supervised machine learning techniques are (Asiaee et al. 2012; Hamdan et al. 2013; Mohammad et al. 2013). Further, unsupervised learning techniques used for sentiment analysis are cluster-based techniques such as Agglomerative algorithms, divisive algorithms, K-means, and Fuzzy C-means (Hemmatian and Sohrabi 2017; Kumar and Jaiswal 2017).

From the last decade, deep learning has evolved as a new and fast-growing solution for sentiment analysis of textual as well as visual data. Deep learning is a subfield or family of machine learning (Ay Karakuş et al. 2018; Yue et al. 2018; Zhang et al. 2018) and an application of Artificial Neural Network (ANN) which uses multiple or dense layered architectures for the training of a model. In the last few years deep learning in NLP has gained a lot of traction due to big improvements in model's prediction accuracy compared to standard machine learning models (Vateekul and Koomsubha 2016; Day and Teng 2017; Çano and Morisio 2018; Ciftci and Apaydin 2018; Sun et al. 2018; Rani and Kumar 2019). The improvement in the model's prediction accuracy is due to advanced word embedding methods used for feature extraction methods and usage of complex neural network architectures such as Convolution neural network (CNN), Long Short Term Memory (LSTM), Recurrent Neural Network (RecNN), Recursive neural network (RNN), and Deep Belief Network (DBN) (Tang et al. 2015; Zhang et al. 2018; Yadav and Vishwakarma 2019).

The second approach for sentiment analysis is *lexicon-based*. A lexicon-based approach is further categorized into two categories named as dictionary-based and corpus-based methods for sentiment classification (Liu 2011). A dictionary-based method has a predefined dictionary of positive and negative words along with their synonymous, anonymous, and their polarity score. The polarity score of positive and negative words in a sentence or document is added to give the total sentiment score of that sentence or document (Priyavrat and Sharma 2018). Dictionary can be manually created by users or some already available dictionaries used for sentiment analysis are Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al. 2012), WordNet (Miller 1995), SentiWordNet (Esuli et al. 2006), SenticNet,[12] SentiStrength,[13] and OpinionFinder (Wilson et al. 2005). The main disadvantage of the dictionary-based method is that it is domain and context-independent and it is hard to use the dictionary-based methods to find the domain or context-dependent orientations of sentiment words. A corpus-based method is a domain and context-specific. However, orientations of domain-specific sentiment words are useful, but

[12] https://sentic.net/ (Last accessed on: 13 March 2020).

[13] http://sentistrength.wlv.ac.uk/#About (Last accessed on: 13 March 2020).

sometimes it is not always correct because many words in the same domain can have different meanings in different contexts.

There are some benefits of deep learning approaches over traditional machine learning and lexicon-based approaches. The traditional machine learning and lexicon approaches for sentiment analysis are based on the frequency of nouns and noun phrases in the text and they work well only when the text contains a high frequency of terms but they fail when terms are infrequent. Further, lexicon-based approaches for sentiment analysis are very specific for particular domains whereas deep learning solutions for sentiment analysis are more generalized for multiple domains due to state-of-the-art word embedding methods and semantic mapping capability between words. Also, traditional lexicon-based approaches were able to capture only syntactic features of text and machine learning techniques required a high level of feature engineering methods to extract syntactic as well as semantic features of the textual data whereas this is not a case with deep learning models used for sentiment analysis. Deep learning models can capture both syntactic as well as semantically related features automatically without any need for high-level feature engineering methods. Deep learning models provide built-in methods (embedding methods) for automatic extraction of required features of explicit as well as implicit aspects during the learning phase (Perez Rosas et al. 2013).

For sentiment analysis various deep learning approaches are used such as unsupervised pre-trained networks, CNN, RecNN, RNN, deep reinforcement learning, and hybrid deep neural networks (Habimana et al. 2020). The state-of-the-art studies as mentioned in Ain et al. (2017) and Chen et al. (2019) show the heavy use of different deep learning models in sentiment analysis. The next paragraph discusses some studies which used deep learning models for sentiment analysis and also highlights some studies which prove that deep learning models have performed better than the traditional machine learning models.

Yadav and Vishwakarma (2019) gave a detailed review of deep learning models such as CNN, RecNN, RNN, LSTM, and DBN. The paper also presented a taxonomy of sentiment analysis including handcrafted feature extraction and machine-learned feature extraction methods. Further, the paper discussed some studies from 2011 to 2019 which used a deep learning approach for sentiment analysis. After analyzing various studies on sentiment analysis using deep learning models, the authors concluded that the LSTM model had given the best results as compared to others. Further, Tang et al. (2015), Rojas-Barahona (2016) and Habimana et al. (2020) discussed the state-of-the-art deep learning models used for many sentiment analysis tasks. The paper also layout some open challenges in the related field. Also, Hassan and Mahmood (2017) proposed a neural network architecture ConvLstm that employs CNN and LSTM for sentiment analysis of the IMBD movie review dataset and Stanford Sentiment Treebank (SSTb) dataset. The result of this paper had shown a better performance of their model as compared to other deep learning and traditional machine learning models. Çano and Morisio (2018) introduced a new deep learning architecture called ngramCNN for sentiment analysis of long text documents. The paper reported 91.2, 75.6, and 95.9% accuracy over IMDB reviews dataset, song lyrics dataset, and phone reviews dataset respectively. The performance of the new model was better than other baseline machine learning models they considered. Also, Goularas and Kamis (2019) compared ensembles and combinations of CNN and LSTM and empirically shown that CNN + LSTM perform better together than when used alone. Further, Ain et al. (2017) and Zhang et al. (2018) gave a review of various variants of CNN, RNN, and Deep neural network (DNN) models used for sentiment analysis text as well as images. Moreover, Li and Li (2018) explained some advanced deep learning architectures for sentiment analysis. This paper also found that short length reviews with high readability can achieve better performance than a combination of the levels of word counts and readability.

The following part of this section discusses some studies in which sentiment analysis of text written in different languages is done with deep learning models. This shows that deep learning models have also been used to perform sentiment analysis of different languages without affecting their performance.

Ciftci and Apaydin (2018) compared Naïve Bayes, Logistic Regression, and LSTM methods used for sentiment analysis of shopping and movie reviews in the Turkish language. The study found that the LSTM model outperformed the other two models. Sun et al. (2018) compared three machine learning models such as SVM, CNN, and a hybrid deep learning model (CNN-LSTM) for the sentiment analysis of Tibetan microblogs. The results showed a good performance using a hybrid deep learning model. Vateekul and Koomsubha (2016) classified sentiments of Thai Twitter data using LSTM, Dynamic CNN (DCNN), SVM, ME, Naïve Bayes. The result has shown that DCNN has better classification performance than other models. Further, Day and Teng (2017) proposed a deep learning approach for sentiment analysis on word of mouth of the smart bracelet in the Chinese language. They also constructed a sentiment dictionary called iTSBSD for their Chinese reviews related to smart bracelet on Taobao (a chinese online shopping website). The study found that the proposed LSTM model for sentiment analysis outperformed than NB and SVM techniques based on accuracy. Also, Rani and Kumar (2019) performed sentiment analysis of Hindi movie reviews collected from online newspapers and websites using CNN. The results have shown that the classification accuracy of the

CNN model is better than NB, k-NN, ME, and SVM models. Moreover, Ay Karakuş et al. (2018) evaluated seven variants of CNN and LSTM by changing their number of layers, tuning hyper-parameters, and ensembles of these models. The result shows that when combining CNN and LSTM, it performs better than other variants they considered.

Deep learning approaches have shown excellent improvement in the performance of the sentiment analysis process. But still, there are some drawbacks to applying these approaches. Deep learning methods need a large amount of data and time to train a deep learning model. Also, Deep learning models behave like a "black box" to some researchers means they don't know what features are extracted for the prediction of a particular sentiment-oriented sentence method (Yadav and Vishwakarma 2019). Further, deep learning methods require tuning of parameters that have a high impact on the performance of a deep learning model and deciding these optimal parameter values is a very tedious and challenging task.

The third approach for sentiment analysis is *hybrid approach* that is a combination of techniques from machine learning and lexicon-based approaches (Zhang et al. 2011; Ghiassi et al. 2013; Khan et al. 2014). Many studies (Ghiassi et al. 2013; Khan et al. 2014; Appel et al. 2016a, b; Mumtaz and Ahuja 2018) have reported that hybrid approach for sentiment analysis is very useful in terms of accuracy and high performance as compared to machine learning or lexicon-based approaches. Hybrid approaches leverage the combined strength or properties (Yusof et al. 2015) of lexicon resources as well as the machine learning techniques. One advantage of the hybrid approach is that the results of this approach are mostly accurate. Second advantage of this approach is that it is more useful in a cross-style environment where training is done on one dataset and testing is done on different test datasets (Mudinas et al. 2012; Mumtaz and Ahuja 2018). The third advantage of the hybrid method is that it can detect and measure sentiments at concept level also (Mudinas et al. 2012). One drawback of using a hybrid approach is that for a complex sentence or when irrelevant words and noise occur frequently in the text, the hybrid method fails to detect any sentiment and assign those sentences a neutral score (D'Andrea et al. 2015).

3.6 Polarity report

Polarity report provide the outcomes of public opinions about a particular entity (electoral, event, topic, and product). Polarity report results in the number of positive, negative, and neutral tweets about a particular entity. Different graphs or charts represent outcomes for this purpose interactively. Moreover, results of the sentiment analysis of any content have been refined in many studies (Ahuja et al. 2017; Asghar et al. 2017; Sailunaz and Alhajj 2019) which include mining emotions from the content and analyzing sentiments more deeply in different emotion categories.

4 Related work

Many researchers, academicians, and social analysts around the globe have contributed to predicting election outcomes through social media data. This section provides a short overview of the work done by them and also summarizes the related studies in Table 1. Further, this section discusses some studies related to the detection of political stance from the social media data as depicted in Table 2.

4.1 Election prediction and social media

This sub-section gives a comprehensive review of the outcomes of the research work related to election result prediction using social media data.

For Germany federal election 2009, Tumasjan et al. (2010) concluded that "the sentiment profiles of politicians and parties reflect many nuances of the election campaign, and tweets data can reflect the election result." They also stated that a mere number of tweets can predict election results. In response to this, Jungherr et al. (2012) refuted their work of election prediction and also demonstrated that the results reported by Tumasjan and others are not valid for several reasons as mentioned in the paper. Skoric et al. (2012) analyzed the capability of twitter data by considering twitter share for the 2011 Dutch Senate election. The study concluded that some conditions and the number of tweets mentioning a party or candidate name can be used as a rough indicator to predict political sentiments. The study also found that there is a strong correlation between the share of votes and tweets at the national level but weaker at constituency level. Bermingham and Smeaton (2011) analyzed Irish general election 2011 and explained that sentiment-based and volume-based measures were more predictive as compared to other measures. Gayo-Avello (2011) analyzed US senate special election as well as congressional election 2010 and found that until a large majority of people do not become regular on social media, its users cannot be considered as a representative sample, and thus forecasting can be incorrect in many cases. For the United Kingdom (UK) general election 2010, Boutet et al. (2012) showed the visualization of the retweet graph showing a highly segregated party structure. They analyzed that party members are more likely to make references to their own party than others. Wang et al. (2012) proposed a model for real-time analysis of Twitter data before the 2012 US presidential election. The study found that the volume of tweets was largely driven by campaign events and public sentiment changes in response to emerging political events

Table 1 A preview of election prediction related work

References	Election detail	Number of political parties/candidates	Data source	Approach/es	Prediction method/s, (algorithms, techniques)	Performance evaluation metric/s	Actual prediction	Result
Tumasjan et al. (2010)	2009 Federal election (Germany)	6 parties + other parties, 9 candidates, and 5 coalitions	Twitter (104,003 tweets)	Volumetric Sentiment analysis	Share of Twitter traffic (no. of party mentions) LIWC 2007 dictionary	MAE = 1.65	After the announcement of actual election result	Positive
Gayo-Avello (2011)	2008 Presidential election (US)	2 candidates	Twitter (250,000 tweets) using Twitter search API	Volumetric Sentiment analysis	Counting number of appearances of a candidate name in user tweets Semantic orientation method Lexicon based method	MAE = 13.10	After the announcement of actual election result	Negative
Gayo-Avello et al. (2011)	2010 Senate special election in Massachusetts and US Congressional election (US)	2 candidates (Senate special election in Massachusetts) 12 candidates (Congressional election)	Twitter (234,697 tweets) (Masen10 dataset) Twitter (13,019 tweets) (USsen10 dataset) using streaming API	Volumetric Sentiment analysis	Vote share basis OpinionFinder lexicon	MAE = 17.1 (for vote share) MAE = 7.6 (for seat share)	After the announcement of actual election result	Negative
Livne et al. (2011)	2010 Midterm election (US)	3 parties	Twitter (460,038 tweets)	Social network analysis	Graphs (density and in-degree based Logistic regression	Accuracy = 88% (for the prediction of candidates' victory)	Before the announcement of actual election result	Positive
Chung and Mustafaraj (2011)	2010 Senate special election in Massachusetts (US)	2 parties	Twitter (234,697 tweets) using streaming API	Sentiment analysis	OpinionFinder SentiWordNet lexicons	Accuracy = 41.41% for OpinionFinder and 47.19% for SentiWordNet lexicon	After the announcement of actual election result	Negative
Bermingham and Smeaton (2011)	2011 General election (Ireland)	5 parties	Twitter (32,578 tweets)	Volumetric Sentiment analysis	Number of tweets mentioning a party 5 Machine learning classifiers Linear regression	MAE = 5.85 (for actual results) MAE = 3.67 (for poll results)	After the announcement of actual election result	Positive
Choy et al. (2011)	2011 Presidential election **(Singapore)**	4 candidates	Twitter (16,616 tweets) using Google API	Sentiment analysis	Corpus-based approach (developed their own corpus)	Not available (NA)	After the announcement of actual election result	Negative

Table 1 (continued)

References	Election detail	Number of political parties/candidates	Data source	Approach/es	Prediction method/s, (algorithms, techniques)	Performance evaluation metric/s	Actual prediction	Result
Jungherr et al. (2012)	2009 Federal election **(Germany)**	6 parties + other parties	Twitter	Volumetric	Share of Twitter traffic (number of party mentions)	MAE = 2.13	After the announcement of actual election result	Negative
Boutet et al. (2012)	2010 General election (UK)	3 parties	Twitter (1,150,000 tweets)	Sentiment analysis Social network analysis	Volume classifier Retweet classifier SVM classifier Bayesian volume classifier Graphical method	Accuracy = 86% (Bayesian volume classifier)	NA	Other (real time classification of twitter data)
Sang and Bos (2012)	2011 Dutch Senate election (The Netherlands)	12 parties	Twitter (64,395 tweets) using streaming API	Volumetric Sentiment analysis	Population weight Corpus-based Tweets counts Name of the party mentioned in tweets	Offset value compared with actual results 17.4% (vote prediction) 8% (seat prediction)	After the announcement of actual election result	Positive
Shi et al. (2012)	2011 American Republican Presidential election (US)	4 candidates	Twitter (300,000,000 tweets) using streaming API	Volumetric Sentiment analysis	Share of Twitter traffic Lexicon method (OpinionFinder)	NA	After the announcement of actual election result	Other (correlation between predicted results and RCP score)
Skoric et al. (2012)	2011 General election (Singapore)	7 parties and candidates	Twitter (110,815 tweets) using REST API	Volumetric	Number of tweets collected by each party	MAE = 5.23	After the announcement of actual election result	Positive
Wang et al. (2012)	2012 Presidential election (US)	4 candidates	Twitter (17,000 tweets)	Volumetric Sentiment analysis	NB Number of tweets mentioning candidate names	NA	NA	Other (proposed a model for Real-time analysis before the 2012 U.S. Presidential)
Dang-Xuan et al. (2013)	2011 Berlin parliament election (Germany)	6 parties	Twitter (17,788 tweets) using Twitter search API	Volumetric Sentiment analysis	SentiStrength lexicon Number of tweets and retweets mentioning a party or candidate name Regression Analysis	NA	Before the announcement of actual election result	Other (found some useful results from political emotional tweets)

Table 1 (continued)

References	Election detail	Number of political parties/candidates	Data source	Approach/es	Prediction method/s, (algorithms, techniques)	Performance evaluation metric/s	Actual prediction	Result
Song et al. (2014)	2012 Presidential election (Korea)	3 candidates	Twitter (1,737,969 tweets) using streaming API	Multinomial topic modeling Social network analysis	Dirichlet multinomial regression (DMR) Community detection method Term co-occurrence analysis	NA	After the announcement of actual election result	Other (community detection and investigation of important issues)
Anjaria and Guddeti (2014)	2012 Presidential election (US) 2013 Karnataka state assembly election (India)	4 candidates and 2 parties (US) 4 parties (India)	Twitter (150,000 tweets) Twitter (23,000 tweets) using Twitter API	Sentiment analysis Social network analysis	NN, SVM, NB, ME classifiers Retweet count	Accuracy = 88% (US) Accuracy = 68% (Karnataka, India)	After the announcement of actual election result	Positive
Unankard et al. (2014)	2013 Federal election (Australia) (2013)	2 candidates	Twitter (808,661 tweets) using Twitter search API	Sentiment analysis	WordNet lexicon Part of speech tagging	MAE = 4.43	After the announcement of actual election result	Positive
Ahmed and Skoric (2014)	2013 General election (Pakistan)	4 parties and 4 candidates	Twitter (10,140 tweets) using otter API	Volumetric Social network analysis	Number of followers of party and candidates Number of replies Klout Score	NA	After the announcement of actual election result	Positive
Ceron et al. (2015)	2012 Presidential election (US) 1st and 2nd round of primary election **(Italy)**	2 candidates (US) 5 candidates (Italy)	Twitter [50,000,000 (USA)] 500,000 for 1st round and 25,000 for 2nd round (Italy)	Sentiment analysis	Hopkins and Kings method with standard supervised machine learning classifiers	MAE = 0.02 (for 2012 US presidential election) MAE = 1.96 (for Italian primary election)	Before the announcement of actual election result	Positive
You et al. (2015)	2012 Presidential election (US) 2014 House race (USA)	2 candidates 2 parties	Flickr using Flickr API	Sentiment analysis	Competitive Vector Auto Regression (CVAR) model Sentiment140	NA	After the announcement of actual election result	Positive
Khatua et al. (2015)	2014 General election (India)	11 parties	Twitter (400,000 tweets) using streaming API	Volumetric Sentiment analysis	Number of tweets shared Opinion and AFFIN lexicon	MAE = 4.50 (volumetric) MAE = 5.99 (sentiment score)	After the announcement of actual election result	Positive
Singhal et al. (2015)	2014 General election of NCT Delhi (India)	1 party	Twitter (259 tweets)	Sentiment analysis	SentiWordNet lexicon and Semantic rule-based method	Error % = 6.11%	After the announcement of actual election result	Positive

Table 1 (continued)

References	Election detail	Number of political parties/candidates	Data source	Approach/es	Prediction method/s, (algorithms, techniques)	Performance evaluation metric/s	Actual prediction	Result
Tsakalidis et al. (2015)	2014 European Union elections (Germany, The Netherlands, and Greece)	6 parties (Germany) 10 parties (The Netherlands) 8 parties (Greece)	Twitter (361,713 tweets) (Germany) Twitter (452,348 tweets) (The Netherlands) Twitter (263,465 tweets) (Greece) using Streaming API	Volumetric Sentiment analysis	Lexicons: SentiWordNet, opinion, and subjectivity lexicon Linear regression Gaussian process Sequential minimal optimization for regression Support vector regression Number of times party name mentioned in tweets	Germany (MAE = 0.64, MSE = 0.71, Kendall Tau = 0.90) The Netherlands (MAE = 1.94, MSE = 5.19, Kendall Tau = 0.78) Greece (MAE = 1.35, MSE = 3.75, Kendall Tau = 0.89)	Before the announcement of actual election result	Positive
Jose and Chooralil (2015)	2015 Delhi assembly election (India)	2 candidates	Twitter using streaming API	Sentiment analysis	Lexicon methods (SentiWordNet and WordNet)	Accuracy = 78.6% (for the method used)	Before the announcement of actual election result	Positive
Elghazaly et al. (2016)	2012 Presidential election (Egypt)	6 candidates	Twitter (18,278 tweets)	Sentiment analysis	Naïve Bayes and SVM classifiers	NA	After the announcement of actual election result	Other (compared NB and SVM classifiers for the Arabic political tweets)
Burnap et al. (2016)	2015 General election (UK)	11 candidates, and 9 parties	Twitter (13,899,073 tweets) using streaming API	Volumetric Sentiment analysis	Tweets mentioning a party name SentiStrength lexicon	NA	Before the announcement of actual election result	Positive
Jose and Chooralil (2016)	2015 Delhi assembly election (India)	2 candidates	Twitter using streaming API	Sentiment analysis	Ensemble method Lexicon (SentiWordNet) NB and hidden Markov model classifier	Accuracy = 71.48% (ensemble method)	Before the announcement of actual election result	Positive
Sharma and Moh (2016)	2016 General states election (India)	5 parties	Twitter (42,235 tweets)	Sentiment analysis	Dictionary-based (SentiWordNet) NB and SVM classifier	Accuracy = 34% (dictionary based) 62.1% (NB) 78.4% (SVM)	After the announcement of actual election result	Positive

Table 1 (continued)

References	Election detail	Number of political parties/candidates	Data source	Approach/es	Prediction method/s, (algorithms, techniques)	Performance evaluation metric/s	Actual prediction	Result
Singh et al. (2017)	2016 Presidential election (US)	2 candidates	Twitter (327,127 tweets) using Tweetinvi library in c#	Sentiment analysis	SVM	NA	Before the announcement of actual election result	Positive
Wang and Gan (2017)	2017 French election	2 candidates	Twitter	Sentiment analysis	The popularity of the candidate using the lexicon method	Error % = 2%	After the announcement of actual election result	Positive
Jaidka et al. (2018)	2013 General election (Malaysia and Pakistan) 2014 General election (India)	14 parties (Malaysia) 11 parties (Pakistan) 15 parties (India)	Twitter (3,400,000 tweets) using streaming API	Volumetric Sentiment analysis Social network analysis	Frequency of mentions, retweets, supporters and likes NB SentiStrength lexicon Centrality method	MAE Root mean square error (RMSE) Normalized Kendall's tau rank distance	After the announcement of actual election result	Positive for India and Pakistan Negative for Malaysia
Heredia et al. (2018)	2016 Presidential election (US)	2 candidates	Twitter (1,600,000 tweets)	Volumetric method Sentiment analysis	Number of tweets mentioning candidates CNN Event study	NA	After the announcement of actual election result	Positive at national level and negative at the state level
Budiharto and Meiliana (2018)	2018 Presidential election (Indonesia)	2 candidates	Twitter (250 tweets)	Volumetric Sentiment analysis	Calculated sentiment score Number of likes, tweets, and retweets shared	NA	Before the announcement of actual election results	Positive
Xie et al. (2018)	2016 General election (Taiwan)	3 candidates	Facebook, Twitter, and Google (Google API)	Volumetric	Number of Facebook likes Number of tweets shared Kalman filter	Prediction error < 5.87% (for all 3 candidates)	After the announcement of actual election result	Positive
Brito et al. (2019)	2018 Presidential election (Brazil)	13 candidates	Facebook, Twitter, and Instagram (44,263 posts)	Volumetric	Number of followers, retweets, likes, and comments Number of interactions	Relative absolute error and root relative square error	After the announcement of actual election result	Positive correlation between no. of followers and votes received Negative correlation between no. of posts, messages and votes received

Table 1 (continued)

References	Election detail	Number of political parties/candidates	Data source	Approach/es	Prediction method/s, (algorithms, techniques)	Performance evaluation metric/s	Actual prediction	Result
Bose et al. (2019)	2017 Gujarat state legislative assembly election (India)	2 candidates	Twitter (1000 tweets) using streaming API	Sentiment analysis	NRC lexicon Parallel dot API	NA	After the announcement of actual election result	Positive
Awais et al. (2019)	2018 General election (Pakistan)	4 parties	Multisource data such as "the result of the past four elections", "public poll data of the last two years", and "tweets"	Volumetric method Sentiment analysis	Retweet count Polarity score Bayesian optimization	Accuracy = 83%	After the announcement of actual election result	Positive
Bilal et al. (2018)	2018 General election (Pakistan)	5 parties	Twitter using Twitter API	Sentiment analysis	Recurrent neural network	Accuracy = 85%	After the announcement of actual election result	Positive

and news they unfold. For American republican presidential election 2011, Shi et al. (2012) found a correlation between predicted results and Real Clear Politics[14] (RCP) score, and the experimental results were feasible to predict the election result. Ahmed and Skoric (2014) applied volumetric and social network analysis methods to mine the various political campaigns during the 2013 Pakistan general election. The study advocated that it is possible to use Twitter for election campaign updates by interacting with the public, especially youths, and mobilizing them to vote. The research work done by Song et al. (2014) is useful in finding dynamic social trends in the Twitter data. Using network structure analysis of the data, Song investigated 2012 presidential election and found some interesting trends and topics from the data. They also detected communities and the rising issues during the election period. Khatua et al. (2015) used Twitter data to test if it can predict the Indian 2014 general election. The study endorses that a combination of volumetric and sentiment scores of social media content can predict changes in the vote score. Tsakalidis et al. (2015) predicted election results of three countries of EU (European Union) parliament. The study analyzed tweets of users related to more than 24 parties of 3 countries The Netherlands, Greece, and Germany. The positive results of the study conveyed an indicative evidence on using social media data for the election prediction task. Jaidka et al. (2018) used volumetric, sentiment, and social network analysis approach for the prediction of general election outcome of Malaysia (2013), Pakistan (2013), and India (2014). The study predicted the correct election outcome for India and Pakistan but incorrect for Malaysia. The study also recommended that recent twitter posts are more relevant for election prediction, and a combination of several approaches is more accurate than independent ones. Xie et al. (2018) used data from various online sources (Facebook, Twitter, and Google) to predict Taiwan general election 2016. The study used an approach combining Kalman filter and event study methods for the prediction task. The study suggested that "the Kalman filter with the event detection model could be packaged as a fundamental kit for political vote analytics". The study also found that events happening during election time also have an impact on election results. Further, this study found that Twitter is an influential tool in political communication, and also showed that emotional appraisals on tweets by the candidates are correlated with a large number of retweets. Heredia et al. (2018) investigated the effectiveness of Twitter data to predict the 2016 US presidential election results. In this study, text, date, username, and location fields of the tweets related to two front-runner candidates (Donald Trump and

[14] "Real Clear Politics is website that calculate poll results." https://www.realclearpolitics.com/ (Last accessed on 15 March 2020).

Table 2 Overview of political stance detection studies

References	Event	Social media platform	Approach	Highest accuracy achieved
Rao et al. (2010)	2012 US President election	Twitter	SVM classification using ngram features	82.84%
Pennacchiotti and Popescu (2011)	2012 US President election	Twitter	Hybrid approach: machine learning (gradient boosted decision tree algorithm) and graph model)	88.90%
Al Zamal et al. (2012)	2012 US President election	Twitter	SVM classification	93.20%
Volkova et al. (2014)	2012 US President election	Twitter	Dynamic Bayesian update classification using user neighbor feature	99%
Makazhanov et al. (2014)	2012 Albertan and 2013 Pakistan general elections	Twitter	Multiple classifiers such as Naïve Bayes, J48, SentiStrength, logistic regression	68% (for Albert election) 87% (for Pakistan election)
Fang et al. (2015)	Scottish referendum	Twitter	Topic-based Naïve Bayes classification	90.4%
Preotiuc-Pietro et al. (2017)	2012 US President election	Twitter	Graph regularization approach	27.6%
Tsakalidis et al. (2018)	Greek referendum	Twitter	Multiple convolution kernel learning using text and social network features	88.31%
Zubiaga et al. (2019)	Different independence movements of three territories (Catalonia, The Basque, and Scotland)	Twitter	Maximum entropy using the user's network feature	97.2% (for Catalonia), 90.3% (for The Basque), and 84.9% (for Scotland)
Idan and Feigenbaum (2019)	2016 US Presidential election	Facebook	EM algorithm (a semi Supervised approach)	82.5%

Hilary Clinton) for the presidential election were utilized. To predict election results, tweet volume and positive sentiment of both of the candidates were used as metrics. The study used CNN to analyze sentiments of the public towards both of the candidates. Also, the study found that at the national level the volumetric method is not a good predictor of the election outcome, but the sentiment method is very close to the polls whereas at the state level neither volumetric nor sentiment method predicted positive result. For the Gujarat state assembly election 2017 (India), Bose et al. (2019) analyzed that Vijay Rupani, the elected candidate of Bharatiya Janata Party (BJP) a national political party of India, had a strong possibility of winning the election. In addition, some researchers also worked on analyzing and improving accuracy of techniques used for sentiment analysis in election prediction as discussed below.

Livne et al. (2011) studied the usage pattern of Twitter by candidates in the 2010 US midterm elections. This study has done a detailed analysis of the Twitter content and network structure of three parties in the election. The proposed model showed that the graph structure and content produced by users can improve the accuracy of the election prediction. The model was able to determine that whether a candidate will win or not. The study illustrated a significant relationship between content, graph structure, and election results. Chung and Mustafaraj (2011) tried to examine the election prediction methods (lexicon-based) used in two different studies Tumasjan et al. (2010) and O'Connor et al. (2010). The paper applied both of the methods to a new dataset which contain tweets of the users related to the 2010 US Senate special election. When Tumasjan's method was applied to the new dataset, results were very different and it reflected that the share of mentions a candidate receives is not enough for election forecasting. Thus, Chung followed the lexicon method introduced by O'Connor which used to detect correlations between the "key" words as mentioned in the paper. In this way they got 41.41% of accuracy which was very low. To improve the results, Chung used SentiWordNet lexicon on the same dataset and achieved accuracy of 47.19% which was also not so satisfactory. Apparently, it was found that there are various shortcomings in both of the methods and also reflect very low accuracy. The paper reported that simple word polarity methods are not enough for getting sentiments of the users. This study also suggested that preprocessing techniques and non-lexicon features might be necessary to improve the accuracy of sentiment analysis task. Anjaria and Guddeti (2014) compared five supervised machine learning classifiers that were used to classify sentiments of the Twitter users for the 2012 US presidential election and 2013 Karnataka state assembly election (India). The study reported that for both of the elections, SVM outperformed than all other classifiers by obtaining the highest accuracy rate. Ceron et al. (2015) monitored two election campaigns (2012 US presidential election and 2012 Italian Centre-Left Coalition election) on Twitter using sentiment analysis. The study adopted the Hopkins and King (HK) method, Hopkins and King (2010) a supervised statistical method to analyze the voting preference of Twitter users. Instead of estimating the opinion of the individual tweet, HK method analyzes all the word vectors of the test dataset together to estimate the aggregate distribution of opinions directly. The paper showed a better interpretation of textual data and predicted more accurate and reliable results. Singhal et al. (2015) proposed a semantic and context-based approach to detect opinion of Twitter users for predicting National Capital Territory (NCT) Delhi elections 2014. The study proposed a contextual rule based and dictionary-based hybrid model whose results were more accurate than the other existing methods used in various studies. Also, the proposed model was able to predict the positive result and handle sarcasm, conjunctions, implicit and explicit negations. You et al. (2015) showed how the Competitive Vector Auto Regression (CVAR) model can combine image data with textual data to predict the outcome of the 2012 US presidential election and the 2014 US house of representative elections (house race). The proposed model effectively predicted the results of both of the elections at national as well as state levels. Sharma and Moh (2016) used tweets in the Hindi language referencing to five national political parties to predict Indian general state elections 2016. The study compared SVM, NB, and dictionary-based methods and found that SVM has the best result with an accuracy of 78.4%. Elghazaly et al. (2016) used SVM and NB classifiers to get sentiments of the public towards the 2012 presidential election of Egypt from Twitter posts in the Arabic language. The tweets were classified into six classes, each class representing a candidate for the presidential seat. The study found that for Arabic text classification, NB is fast and accurate than SVM. Jose and Chooralil (2016) designed a real-time Twitter sentiment analyzer that gave a successful prediction of the 2015 Delhi assembly election using ensemble technique which combined one lexicon and two machine learning classifiers. The study also used negation handling and word sense disambiguation to improve the accuracy of the analyzer. Awais et al. (2019) utilized different data sources such as tweets, past four election results, and public poll data of the last 2 years to predict the 2018 general election of Pakistan. The predicting model employed the Bayesian optimization technique to find the winning probability of each candidate for every constituency of the country. The forecasting model effectively predicted most of the winning candidates for each constituency and displayed demographically successful results with 83% accuracy. Also, the study showed the effectiveness of WordNet lexicon and part of speech (POS) tagging in election result prediction.

Likewise, Table 1 gives a comprehensive overview of thirty-eight (38) studies that contributed to election result prediction worldwide. The *Reference* field gives reference to the paper which was studied. *Election detail* field informs about election details such as year, election name, and country in which elections were held. The next field gives number of several parties or electoral contested in the elections. *Data Source* field gives the name of the social media platform from where data was collected and also the volume of data. This field also gives the name of the API used for scraping data from the web sources in each referenced paper. The APIs used in the referenced papers are Streaming, Otter, REST, Twitter API, Google API, Twitter search API, and Tweetinvi C# library. *Approach/es* field implies the approaches authors have adopted in the respective referenced paper. Various approaches used in referenced papers are volumetric, sentiment analysis, social network analysis as described in Sect. 1 of this paper. *Prediction Method/s* field implies what algorithms, technique or method has applied to find out the election results. There are many methods from different approaches such as the volumetric approach uses the number of likes, followers, tweets, retweets, and several shares. Likewise, the sentiment analysis approach use machine leaning, lexicon-based, and hybrid methods and the social network analysis approach to use the centrality method, graphical method, community detection method, and Klout score. *Performance Evaluation Metric* field is an assessment of the work that specifies whether or not the work done in the respective referenced paper for election prediction was sufficiently precise. A maximum number of the researchers evaluated their election prediction performance based on Mean Absolute Error (MAE). MAE is the inaccuracy measure of the election prediction by finding out the average difference between the predicted results and the real outcomes. An accurate prediction has zero (0) percent MAE while an inaccurate prediction has 100 percent MAE (Martyn 2015). Some researchers have not used any metric and have done a general analysis of the data such as analyzing trends in the collected data, detecting communities in the social media content and comparing machine learning classifiers over political posts or messages. Also, some studies proposed a real-time data classification model. Another performance evaluator is the Klout score as used by Ahmed and Skoric (2014). Klout score is the measure of user's online social influencing activities. The *actual prediction* field implies whether the prediction was made before or after the actual announcement of election results. *The result* field conveys that predicted results in each paper were positive or negative following the actual results. Six studies (Boutet et al. 2012; Shi et al. 2012; Wang et al. 2012; Dang-Xuan et al. 2013; Song et al. 2014; Elghazaly et al. 2016) under "*other*" category signifies that these studies did not predict any election result but have done some other related tasks as given in Table 1.

4.2 Political stance detection

Besides election prediction, this subsection describe the work focusing on the detection of political stance or voting preference of the social media users. Political stance detection is a task to classify the users based on their voting preferences from messages, and posts they share on the social media platforms and over online political debates (Fang et al. 2015). Political stance detection informs the individual's voting intentions i.e. whether they are in favor or not in favor of the target topic, party, or an electoral. Table 2 gives an overview of approaches and accuracy achieved for political stance detection and prediction in various studies.

Al Zamal et al. (2012) and Volkova et al. (2014) inferred the real-time political preference of Twitter users. Both papers leverage content, retweets, and user mention of the neighbor users to predict a latent user's political preference. Volkova et al. (2014) found that neighborhood content is very useful and gives a substantial signal for the political preference classification than user self-authored content.

Also, Rao et al. (2010) classified political preference, and other attributes like age, gender from user's Twitter content. Further, Pennacchiotti and Popescu (2011) classified twitter users as democrats or republicans using a hybrid approach assuming that users from a class tend to reply and message of the users from the same class. Also, Fang et al. (2015) classified Twitter user's voting intention which were sharing their views on the Scottish Independence Referendum. They were able to classify the stance of the Twitter users whether they were in favor of independence or they opposed it. Moreover, Preotiuc-Pietro et al. (2017) examined political ideology to identify a politically moderate and neutral user group. They categories the political groups in very conservative v/s very liberals, moderate conservative v/s moderate liberals and moderate v/s extremists. Also, Tsakalidis et al. (2018) forecast the voting intentions of Twitter users by doing a time-sensitive classification of tweets at different time points during the pre-electoral period of 2015 Greek bailout referendum. Further, Zubiaga et al. (2019) classified Twitter users discussing independent country movements of three territories Catalonia, The Basque, and Scotland. The classification of users is done in two categories whether they support the independent national movement or oppose it. This work compared NB, SVM, Random Forest (RF), and Maximum Entropy (ME) classifiers along with the user's features like timeline content of the users, interactions, favorites, and network features. The study found that network structure of the users play an important role and also the most significative feature for determining the stance of the Twitter users.

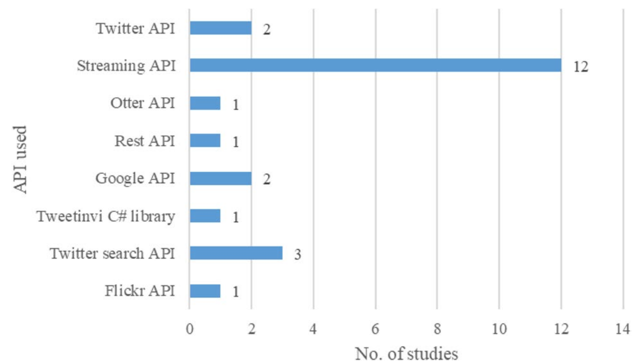


Fig. 4 APIs used

5 Discussion and findings

The study has analyzed some trends followed by the researchers in predicting election results. A graphical representation of the summarized evaluation of 38 papers mentioned in Table 1 is presented here in the form of charts as Figs. 4, 5, 6, 7 and 8. This section also highlights some major findings while reviewing the literature.

Figure 4 illustrates the number of different APIs used for crawling data from social media platforms. Here, the results show that out of thirty-eight (38) studies, twenty-three (23) studies mentioned about the API they have used and most of the time, streaming API has been used to collect tweets among the studies. Figure 5 illustrates the trending approaches used for election prediction. Various approaches used in election prediction are volumetric, sentiment analysis, and social network analysis approach, as discussed in the introduction section. Some researches (Bermingham and Smeaton 2011; Skoric et al. 2012; Bose et al. 2019) have found that a combination of two or more approaches is more effective in predicting election results than using a single approach. Figure 5 also show heavy use of sentiment analysis and volumetric approaches for election prediction in most of the studies.

Further, Fig. 6 illustrates the different methods of sentiment analysis approaches used in the election result prediction papers. Also, it is found that thirty-one (31) studies have used sentiment analysis approaches along with the combination of other approaches and among them, sixteen (16) researchers used lexicon method, twelve (12) used machine learning method and three (3) used hybrid methods. Figure 7 illustrates the outcomes of election results analyzed in thirty-eight papers that have been studied. As the results show,

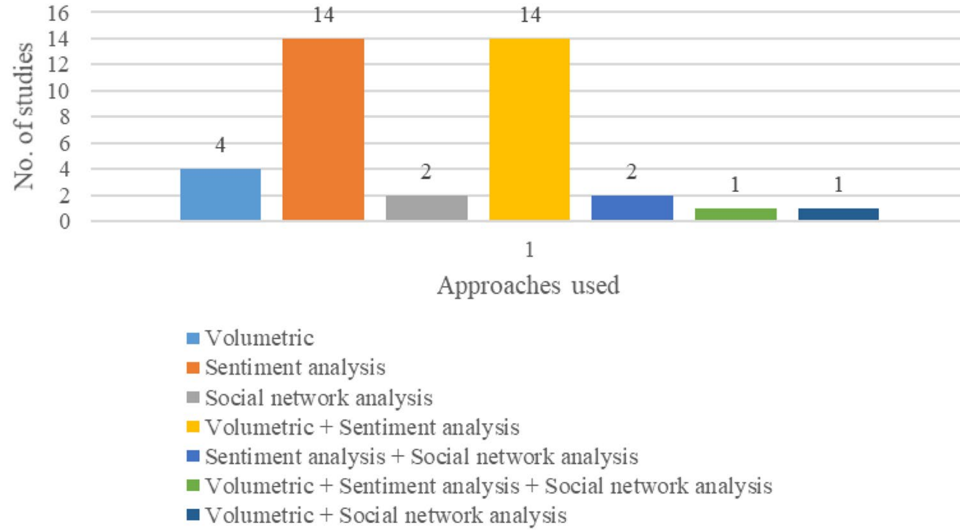


Fig. 5 Trending approaches

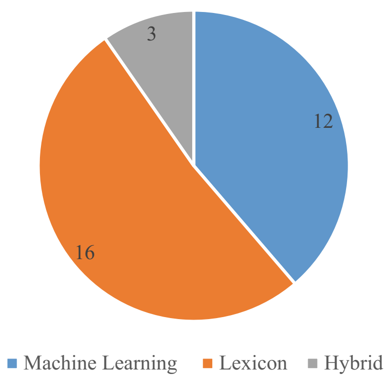


Fig. 6 Trending sentiment analysis approaches

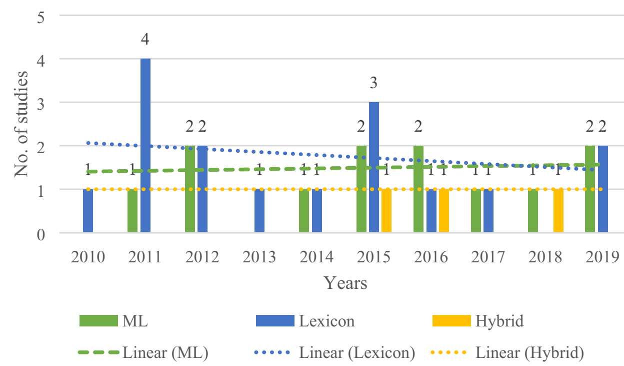


Fig. 8 Trendlines of sentiment analysis approaches for election prediction

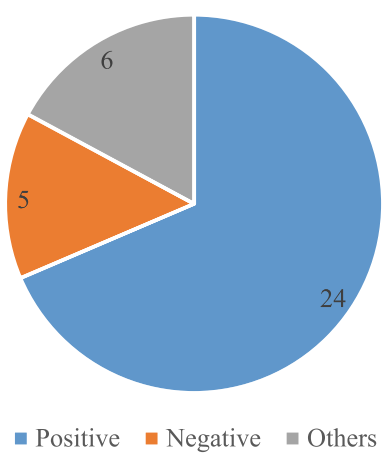


Fig. 7 Prediction results

there are five (5) number of studies where election prediction went negative, twenty-four (24) were positive and six (6) were other studies which didn't predict anything but did some other task as mentioned in Table 1. Also, there were three (3) studies (Heredia et al. 2018; Jaidka et al. 2018; Brito et al. 2019) which have positive as well as negative predictions about election results while considering different criteria. Figure 8 depicts the linear trendline about the sentiment analysis approaches over time based on studies mentioned in Table 1. On the basis of the studies reviewed in this paper, it has been seen that all the studies related to election prediction were done after 2010 and most of the time lexicon approaches were used. Further, it can be depicted that till now machine learning-based approaches like deep learning have not used so much in the field of election prediction. Moreover, the trendlines for machine learning approach is growing over time whereas trendline for lexicon based approach going down overtime. Also, hybrid approach has been used in some studies after 2015.

5.1 Major Findings

- It has been seen that most of the studies have used twitter as a corpus to predict election results.
- For the collection of data, Streaming APIs are mostly used in the studies.
- It has been seen that most of the time researchers have analyzed sentiments-oriented content from social media to predict election results and to analyze the stance of political campaigns.
- Most of the studies have used traditional lexicon-based approaches in election prediction while machine learning approaches are emerging in this field especially deep learning techniques which are used only in three studies (Heredia et al. 2018; Bilal et al. 2018; Bose et al. 2019).
- Recent studies show that research community is also getting attracted towards detecting political stance on social media and classifying users.
- Most of the studies have predicted successful positive election results in their research work and this shows the emerging power of social media data and intelligent computational approaches to make such complex predictions.

6 Research challenges

From the literature study, it can be observed that there is a lot more work to do for election result prediction as there is not a valid, acceptable predictive model for this field. After reviewing 38 papers, few gaps in the election result prediction have been found and this section highlights all those crucial challenges as depicted in Fig. 9. Also, this section discusses the open research gaps in the field of sentiment analysis and data preprocessing.

6.1 Multilingual and geo-located content

Social media platforms provide many language options for the comfort of its users and there is hardly any multilingual model available that can analyze sentiments written in multi-languages. Analyzing sentiments of multi-language texts is still a challenging problem. Also, the location of a user plays a vital role in the election prediction because there may be a scenario when a user sitting somewhere in any part of the world and tweeting about any country's politics. This scenario may be irrelevant. But, most of the time, users keep their location field hidden and it is not possible to know that from which location they are posting or messaging on their social media accounts. In this respect, Shi et al. (2012) proposed a model to predict the 2012 American Republican Presidential election which also used the geographic location of twitter users. The geolocation location of the users was obtained from the "location" field of collected twitter data. In this study, tweets of only matching locations were considered for the sentiment analysis while other (non-matching or blank) tweets were discarded. Also, the results of the study revealed that it is possible to predict the American republican presidential election from the Twitter data. Likewise Skoric et al. (2012) also used the geographic location of Twitter data in the 2011 Singapore General Election.

6.2 Embedded URL links

Some tweets also contain Uniform Resource Locator (URL) links to any webpages which contain, text, images, audio and video information which can explore some more hidden sentiments of the users. But, generally these links are removed prior to analysis of text during text pre-processing step and in this way some valuable information is lost that convey sentiments of the users more precisely.

6.3 Accuracy

Accuracy of the election prediction model is also the main challenge. Prediction with a high level of accuracy is the primary goal of any prediction system. Since raw data collected from different sources contain noise which can result in the wrong prediction. Therefore, more research is needed against the flaws of simple sentiment analysis approaches such as machine learning and lexicon-based methods.

6.4 Irrelevant, junk, fake, spam data and bot accounts

Over social media, there are some individual or groups or sometimes bot accounts (programs) which try to spread misinformation, disinformation, spams about any entity. Identifying and classifying these groups is also a challenging problem. Further, irrelevant and junk tweets also lead to the development of a robust predicting model.

6.5 Topic monitoring

During the election, many political topics are in the hot news. The common topic modeling techniques like LDA are not suitable for topic extractions in short texts (Curiskis et al. 2019). Therefore, robust topic modeling techniques are required to extract hot topics and to correlate the categories of the events.

6.6 Swing voters

It is obvious that with time the mood of the users changes. Thus monitoring stance of the public for electoral and political parties is a very hard and challenging task.

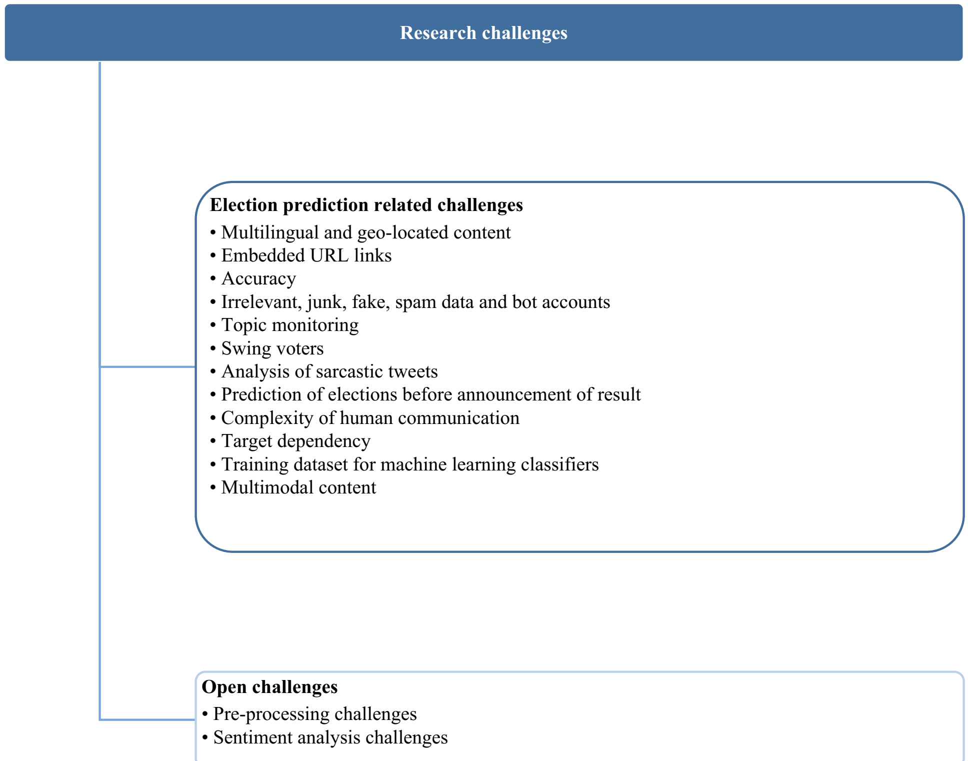


Fig. 9 Research challenges

6.7 Analysis of sarcastic tweets

Sarcasm is a new trend where somebody hurt others feeling by saying something that seems to be positive. Identifying sarcastic messages or tweets is a very hard nut to crack.

6.8 Prediction of elections before the announcement of the result

Predicting the future has become a dominant need in this fast-growing competitive world and it helps in decision making. The main challenge in election prediction lies in predicting the election results before the announcement of election results. Table 1 shows most of the studies who have predicted election results after the announcement of actual results and this may show a kind of bias towards predicted results (Gayo-Avello 2016).

6.9 The complexity of human communication

There is a problem of analyzing the political sentiments of the people from social content because of the complex style of communication between users. Sometimes users share their own created abbreviations, slangs, and double meaning sentences which are very hard to interpret.

6.10 Target dependency

Some tweets or social media messages contain names of more than one entity or target. For example, "I don't really want Hillary to win but I want Trump to lose can we just do the election over". Most of the sentiment analyzer works in a target-independent manner and fail to identify correct sentiments for multiple candidates in the same sentence (Cambria et al. 2017).

6.11 The training dataset for machine learning classifiers

While using standard machine learning approaches in sentiment analysis for the election prediction task, the unavailability of the training dataset for the election result prediction of a particular country or state is also a big research challenge.

6.12 Multimodal content

During election periods, people don't limit themselves to share only textual data over the social media platform, they are highly involved in sharing images, audio, emojis, emoticons, gifs, and video information over social network platforms. Extracting, analyzing, combining, and getting sentiments of this heterogonous type of data is a very difficult task.

Table 3 Open research challenges

Research challenge category	Research challenge	Description	Example
Pre-processing challenges	Spelling mistakes by users	Sometimes, messages or tweets may contain wrongly spelled words which can create difficulties. A strong lexicon that can handle wrongly typed spellings has to be introduced	"This is amazing powerful and beautiful fon from honor best camera, battery, design, display, sound quality, processor" *fon is a misspelled word here*
	Whether to keep emoticons and special symbols or not?	Keeping emoticons during the processing of text may be ambiguous sometimes	"I am happy :(". *This is a positive sentence with a negative smile*
	Use of slang words	Slang words are shortcut words created by the user. Slang words could have sentiment-oriented words. So, identifying the real meaning of these slang words is also a major problem	syl (See you later), whtsgingon? (What is going on?), gbu (God bless you), r u thr? (are you there?)
	Any language is written in another language format	Other languages written in English or any other language format is also a big problem	"Aaj ka khana aunty ne kaafi swaad bnaya tha, dil khush ho gya". *This is a positive Hindi sentence written in English language format*
Sentiment analysis challenges (Sharma and Dey 2012)	Domain-specific	Sentiments are domain-specific. Meaning of the words that a user use depends upon the context in which they have used it	"Go listen to music". *It would be a favorable statement for a new music album released but in the context of a movie review, it may suggest that songs are preferred over the movie*
	Multiple opinions in sentence	A single sentence may contain multiple (more than one) opinions i.e. a sentence can have positive as well as negative opinions	"The picture quality of this camera is amazing, but the battery life is not favorable"
	Negation handling	Negation words are also called as polarity reversers. Handling negation is a very tricky task in sentiment analysis	"I like this guy" and "I don't like this guy." differs from each other by only one word "not" and thus belongs to the different and opposite classes
	Sarcasm	Sarcasm and irony are quite difficult to identify	"The movie was so good that I felt slept!"
	Opinion spam	Opinion spams are fake reviews or opinions which try to mislead other readers. This is done by assigning undeserving positive opinions to some target objects or a product to promote it and/or by giving malicious negative opinions to some other object to damage their reputations	NA
	Thwarted expectations	Sometimes, the user or reviewer makes a positive context in the starting of the sentence and refutes it in the end	"Excellent camera, very good speakers, stunning design, all in vain because of the low quality of processor used in the mobile phone"
	Pragmatics	The pragmatics of the user needs to be identified	"it was good to see India destroy Australia in the final. The match destroyed my interest in sports"
	World knowledge	Sometimes the knowledge of an entity which is used in the sentence is required to identify the sentiment	"He is a good person as Dracula." *The system should have detailed knowledge about the characteristics of Dracula to understand the correct sentiment behind this sentence*

In this manuscript, some other research problems are classified into two categories, the first one is *pre-processing problems*, and the second one is *sentiment analysis problems* as depicted in Table 3. *Pre-processing problems* are the problems related to pre-processing of texts or tweets before doing their sentiment analysis while *sentiment analysis problems* are the problems that are being faced to get more accurate results while analyzing the sentiment of the tweets.

7 Future directions

This section gives some suggestions for the researchers and practitioners while thinking of predicting election results through sentiment analysis and social media data. As per our knowledge, there is hardly any model that can predict election results holding in some groups of continents or countries. Metaxas et al. (2011) suggested that the method of election result prediction should be an algorithm and it should clearly describe the following mentioned points before the elections to avoid any kind of bias: What data has to collect and from where it has to be collected? duration of data collection, preprocessing steps for data cleaning, analysis method to be used, and the semantics under which election results have to interpret. Also predicting election results before the announcement of results will reflect the true meaning of election prediction task as suggested by Gayo-Avello (2012b). Further, people are not limited to share only textual data over the social media platform. They are highly involved in sharing images, emojis, emoticons, gifs, and also videos. Therefore, along with text, this multimodal data may also be examined. Also, try to consider the tweets of eligible users only and these eligible users can be found by collecting filtered geo-located and age-restricted tweets. Moreover, to avoid age and location bias as discussed in the research challenge section, Burnap et al. (2016), Jaidka et al. (2018) and Bose et al. (2019) suggested that more work has to be done on geo-located tweets. Burnap et al. (2016), Jaidka et al. (2018) and Bose et al. (2019) also suggested that analysis of multilingual tweets may be very helpful during election prediction. Further, practitioners and researchers must use only valid data in election prediction to interpret true results and this valid data can be obtained by the detection and removal of the bot accounts, spam messages, sarcastic tweets/messages. In this context, Heredia et al. (2018) suggested that work has to be done to deal with spam and bot accounts. Moreover, new practices like deep learning, soft computing methods can enhance election prediction performance.

Table 1 shows that there are only three number of studies which have made use of deep learning model while deep learning has shown more precise results in other research fields also as discussed in Sect. 3.5. Along with the election prediction, political stance or voting preference of the social media users may also be considered. However, most of the studies in Oikonomou and Tjortjis (2018), Tumasjan et al. (2010), Monti et al. (2013), Ahmed and Skoric (2014) and Jaidka et al. (2018) have indicated the potential of Twitter in the field of election prediction. Still it is suggested that data from other social media platforms such as Facebook, Instagram, etc. may also be analyzed in a combined form to achieve better prediction performance. Sometimes social media users share URL links among their network to convey some information that may carry some sentiment values also. Therefore, Tumasjan et al. (2011) suggested that Embedded URL links and replies in the messages or tweets should also be used during the analysis process. Further, a proper topic modeling technique may be included to correlate the categories of the events happening during the election duration. In this context, Bose et al. (2019) suggested that topic modeling techniques can be used to correlate topics with different categories of the event. Further, Choy et al. (2011) and Song et al. (2014) suggested that there should be a modification to the election prediction model by calibrating the swing voters and handling their psychology.

Moreover, predicting the accuracy of a sentiment classifier may be improved by using pre-processing techniques and going beyond methods that depend upon words polarity alone as suggest by Chung and Mustafaraj (2011), Tumasjan et al. (2011) and Awais et al. (2019). Also, Tumasjan et al. (2010), Chung and Mustafaraj (2011), Gayo-Avello et al. (2011), Shi et al. (2012), Martyn (2015), Tsakalidis et al. (2015), Elghazaly et al. (2016), Sharma and Moh (2016) and Heredia et al. (2018) suggested that more research is needed against the flaws of simple sentiment analysis methods such as machine learning and lexicon-based methods. Skoric et al. (2012) concluded that “focus should be on robust data collection methods and rigorous analytical approaches.”

8 Conclusion

Predicting elections is a very old field and many traditional methods have been tried to perform this task. Nowadays technology has changed a lot of things around us and people can predict, analyze and quantify a lot of crucial and difficult tasks in seconds because of the immense amount of data available from different sources. Sentiment analysis of public views from social media has evolved many research opportunities. In this survey paper, an overview of sentiment analysis and its techniques is given. The paper also highlighted some state-of-the-art studies related to sentiment analysis using deep learning and word embedding methods. Further, this paper analyzed the past work done on the prediction of election results in some countries and states where the prediction sometimes met success and sometimes a miss. Moreover, it tried to explore some critical research gaps in this field, which needs quick attention by the research communities so that prediction can be made more accurate. Further, a detailed analysis of the trending approaches, methods, and number of positive and negative predictions is explained in the discussion section. After that research challenges in election prediction and sentiment analysis fields were highlighted. This paper also gave some future directions in the related field. This paper concludes that election prediction is a long and critical task and as per our knowledge, researchers have not developed any election prediction system which has been recognized worldwide. There are many flaws in this field as discussed in the research challenges section. Also, it has been seen that most of the studies have applied standard machine learning models for the election prediction task and there are only a few studies that have implemented deep learning models for this task. So, the election result prediction seems to be an unexplored area and needs more improvement for correct prediction.

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