State-of-Art Methods Used in Sentiment Analysis: A Literature Review

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***Abstract*--Understanding human sentiments on social media is a hot topic. Due to its practical applications, many organizations across several domains are involved and invested in sentiment analysis. Marketers are interested in extracting the voice of customers to gain insights. The challenges to the gathering, decoding, and extracting actionable knowledge from the huge volume of data that is constantly generated has increased manifold. Even with newer technologies, increased computing capacity, crunching social data remains a challenge. This organized study is dedicated to understanding the general state of the art of sentiment analysis including common methods, approaches, and gaps. The contribution of this paper is significant because firstly it identifies the types and techniques of sentiment analysis, and secondly, this study adopts a systematic approach to identify, gather empirical evidence, interpret results, critically analyze, and integrate the findings of all relevant high-quality studies to address specific research questions about the defined research domain.**

I. Introduction

A large variety and volume of data are generated and consumed on social media, and it has become a one-stop-shop for information, entertainment, and e-commerce. Social media establishes an open communication channel between businesses and users. Businesses use social media to communicate about their products and users use it to provide their opinion and feedback about the product. With such an open communication established on social media, analysts from every domain are interested in mining actionable insights from these platforms. The social media platform is in-fact the best source of data to understand human sentiments and opinions because the data generated is open, raw, unadulterated and it comes directly from the engaging users.

Academic research and practical applications in the field of sentiment analysis have grown in the last 5 years and have contributed to the expansion of the web. Web has progressed from the being passive provider of content to an active socially aware distributor of collective intelligence [1]. This new collaborative Web (called Web 2.0) [2], encourages a wider range of expressive capability, facilitates more collaborative ways of working, enables community creation, and created dialogues for knowledge sharing [1]. Web 2.0 and the increasing usage and popularity of social platforms have given rise to social commerce (s-commerce) which is a subset of e-commerce. S-commerce takes advantage of online social capital and encourages users to share product information with their friends or sell products or services via social media [3]. S-commerce has expanded the scope of commercial activities by enabling the users to discuss, share, analyze, criticize, compare, appreciate and research about products, brands, services through social platforms like Voonik, Facebook, Twitter, etc. This pool of information can be explored for the mutual benefit of both the customer and the organization. With so many discussions taking place on social platforms, analysts use the comments, tweets, reviews, feedbacks to gain insights on their businesses which has given rise to sentiment analysis.

Several kinds of research that is been conducted on various social web platforms such as Quora, Facebook, Wikipedia, yelp, etc. Of all the social platforms, Twitter is the biggest source of data collection for sentiment analysis. Twitter is one of the most popular microblog platforms on which users can publish their thoughts and opinions [4]. As [5], [6] notes the importance of Twitter in mining public opining to capture the view of their products and their competitions.

This paper is organized as follows: Section 1 is the introduction, Section 2, covers a broad overview of sentiment analysis and its general framework. Section 3 elaborates on the literature review methodology. This paper uses a systematic literature review process (SLR) defined by Ketchenham and Charters for reviewing the literature. In section 3 the research questions, strategies, study selection, & data synthesis is explained in detail. Section 4 overviews the pertinent literature of the selected studies concisely. Section 5 provides the results to the research questions and discussion followed by the conclusion to the review.

II. Overview of Sentiment Analysis

Sentiment analysis also is known as opining mining is defined as a series of methods, techniques, and tools about detecting and extracting subjective information, such as opinion and attitudes, from language [7] in the hope of understanding a collective sentiment from a group of people engaging in certain conversation given a topic. In the past, sentiment analysis has been about opinion polarity, whether someone has a positive, neutral, or negative opinion towards a topic [8].

Mantyala and others [9] observed that the first academic studies measuring public opinions are during and after WWII and their motivation is highly political in nature [10]. The outbreak of modern sentiment analysis happened only in the mid-2000s, and it focused on the product reviews available on the Web [8]. Since then, the use of sentiment analysis has reached numerous other areas such as the prediction of financial markets [11], reactions to terrorist attacks [12], product sales

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[13], and stock returns [14]. The purpose of sentiment analysis is to automatically determine the expressive direction of user reviews [15]. The demand for sentiment analysis is raised due to the increasing requirement of analyzing and structured hidden information that comes from social media in the form of unstructured data [16]. Research overlapping sentiment analysis and natural language processing have addressed many problems that contribute to the applicability of sentiment analysis such as irony detection [17] and multi-lingual support [18]. Furthermore, concerning emotions, effort is advancing from simple polarity detection to more complex nuances of emotions and differentiating negative emotions such as anger and grief [19].

Sentiment analysis is a multidisciplinary field. It includes the study of various fields such as computational linguistics, information retrieval, semantics, natural language processing, artificial intelligence, and machine learning [20]. There are three approaches to sentiment analysis as conducted currently: 1. Machine learning based, 2. Lexicon-based and 3. Hybrid.

Lexicon based sentiment analysis can be further classified into Dictionary-based and Corpus-based. Machine learning can be classified into Linear classifiers, Decision tree classifiers, and Probabilistic classifiers [21]. Saida. A [21] and others summarize the ML, lexicon and hybrid methods as follows

A. Machine Learning Approach:

Machine Learning algorithms train the classifier from manually labeled data. This type of technique is implemented by extracting the sentences and words [93]. The quality and coverage of training data have a high influence on the performance of the classifier [21]. The feature set consist of Parts of Speech (POS) tags, n-grams, bi-grams, uni-grams, and bag-of-words. Machine learning contains three flavors: Naive Bayes, Support Vector Machine (SVM), and Maximum Entropy [93]. . These techniques are based on decision trees such as k-Nearest Neighbors (k-NN), Conditional Random Field (CRF), Hidden Markov Model (HMM), Single Dimensional Classification (SDC) and Sequential Minimal Optimization (SMO), related to methodologies of sentiment classification [93]. The machine learning approach has higher accuracy then lexicon-based algorithms that uses either a per defined dictionary of the is based on the corpus of texts [21] [93].

B. Lexicon-Based or corpus bases Approach:

This approach utilizes a sentiment dictionary to describe the divergence (positive, negative, and neutral) of textual content. This approach is more comprehensible and can be easily implemented in contrast to machine learning-based algorithms. But the drawback is that it requires the involvement of human beings in the process of text analysis [21]. Lexicon based approach can further be divided into two categories: Dictionary-based approach (based on dictionary words i.e. WordNet or other entries) and Corpus-based approach (using corpus data, can further be divided into Statistical and Semantic approaches).

C. Hybrid Approach:

This approach is the amalgamation of both machine learning and lexicon-based methods. This overview can be valuable for newcomer scientists in this field as it includes a survey of different work on lexicon-based sentiment analysis.

The generic framework of sentiment analysis is as shown in figure 1. Once the sentiment topic and the social platform in narrowed down, data is collected using keyword searches. The collected data that is in the form of text is then preprocessed by removing symbols, numbers, duplicates, and punctuations. There are fundamentally two methods that can be applied for sentiment analysis. Lexicon and Machine Learning (ML). Based on the chosen method, sentiment detection and classification are generated. Some studies especially the one that uses machine learning methods conduct an additional step to validate the results. The final step is reading and interpreting the data through visualization for gaining insights on the overall sentiments.

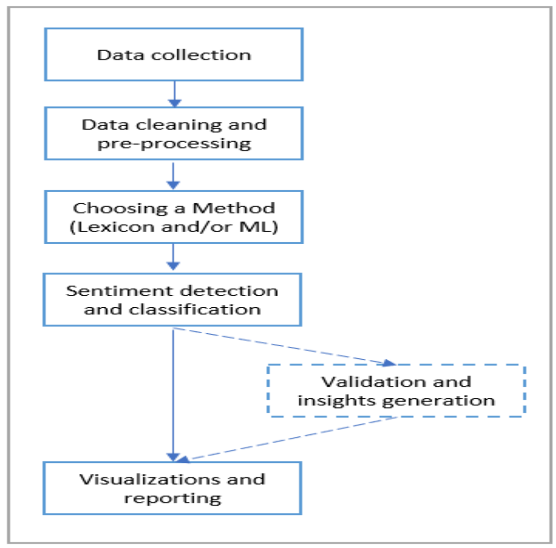

Fig. 1. Generic Framework of Sentiment Analysis

III. Literature Review Process

This review follows the format of Systematic literature review (SLR) defined by Ketchenham and Charters [22]. Many academics have used SLR for literature review [23]–[27]. This review process is divided into 2 stages: Research synthesis and planning and research review and results. In the first stage, the research questions are formulated, and search & selection criteria are defined. In the next stage, data extraction and result reporting are performed. The goal of the first stage is to ascertain and formulate the research question by defining the boundaries and scope of work. Search strategies were formulated to ascertain how the databased would be identified and the search would be conducted. This stage aims to identify relevant and useful research questions. The scope of the study was narrowed down by defining the selection and exclusion criteria. Based on the first stage, the data was extracted to answer the research questions to finally critically analyses and report out the findings. The summary includes critiques on identified studies, implications, practical application, identifying gaps, identifying inconsistencies, and providing directions for future research.

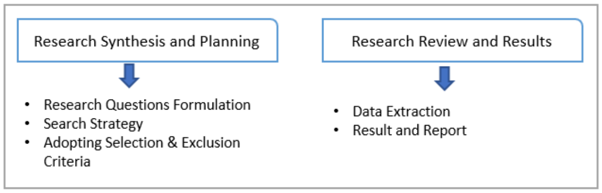

Fig. 2. Systematic Literature Review used in this study

IV. Research Synthesis and Planning

A. Research Questions Formulation

The research questions identified are as follows

RQ1: What is the best social platform to gather data for sentiment analysis?
RQ2: Which are the most distinguished journals to study sentiment analysis?
RQ3: What are the most used methods and techniques in sentiment analysis?
RQ4: What are the primary reasons for conducting sentiment analysis?
RQ5: What are the most common challenges faced in sentiment analysis?

B. Search Strategy

Google scholar, Portland state university library website, and EBSCOhost were the primary source of the search for this literature review. The keyword search terms identified were sentiment analysis, opinion mining, machine learning, lexicon, emotions, emotion mining, social media, social network, etc. were explored in titles with both and/or criteria. Abstracts were studies to extract all the related primary research studies from journals of high repute and highest relevance to the topic of study, available within five prominent digital libraries (publishers), namely, ACM, IEEE, Elsevier, Wiley, and Springer. Previously conducted literature reviews on sentiment analysis were also considered to identify and fill the gaps in this research. Boolean expressions and data criteria or the last ten years were selected. The reference section of relevant papers was examined to extract cross citations. With this step, I was able to weed out all the irrelevant and redundant papers from the search.

C. Study selection

In this phase, the inclusion and exclusion criteria for the research were established. The inclusion and exclusion criteria are as follows

Inclusion criteria

- Studies published in journals, books and chapters
- Studies specific to sentiment analysis on social media
- Studies that use public data and the data source is available
- Studies related to sentiment analysis that uses only ML, Lexicon and hybrid methods
- Studies that are performed in the English language
- Studies that used the English language to identify sentiments
- Studied conducted in between 2011 and 2020

Exclusion criteria

- Irrelevant studies
- Studies without proper statistical and empirical analysis
- Studied that are performed on nonsocial platforms such as websites, document corpus from textbook, example and simulated texts
- Studies with only textual data were considered and non-textual or other multimedia sentiment analysis was not included
- Quality assessment: To meet the quality of work reviewed, only the published and/or peer-reviewed work has been considered. Most of the work used in this literature review has more than 1 citations. Also, the top 5 digital libraries considered hold high quality and high influence published papers.

V. Research Review and results

A. Data extraction

A large amount of data was extracted for this literature survey. Details about the author, publication, the year of study, the dataset used, the platform of data source, tools, approaches, and methods, the domain in which the study was conducted along with limitations and gaps were systematically recorded to answer the research questions. Previously conducted literature surveys and its references are studied, and an attempt is made to fill the missing gaps.

B. Data synthesis

Table 1 shows the number count of documents used in this literature review. From the top 5 databases, 930 research papers were yielded by using the keywords: Emotion mining, Opining mining, Sentiment analysis, Social media, social platform, and Twitter. Applying the inclusion and exclusion criteria listed above, 65 papers were of value to this research.

TABLE 1: DATA SYNTHESIS

	Initial Extracted Documents with Keywords	Documents fitting Exclusion and Inclusion criteria	Total Relevant Document used in this study
ACM	52	47	5
Elsevier	508	479	29
IEEE	80	70	10
Springer	92	76	16
Wiley	198	193	5
Total	930	865	65

VI. LITERATURE SURVEY

This section briefs the learnings and observations made from 65 papers taken from the top 5 publications. Table 2 details the name of the author, year of publication, technique, dataset, toolset and approaches employed, the domain in which the research was conducted, polarity, and the list of emotions studied in sentiment analysis. Appendix 1 gives the furthermore details used to conduct this review.

Machine learning and lexicon-based sentiment analysis are fundamentally different. Machine learning is a subfield of computer science that studies algorithms that can learn from data to make predictions [94]. Machine learning algorithms that are commonly used in sentiment analysis are Support vector machines (SVM), Naïve Bayes (NB), Neural Network (NN), Deep Neural Network (DNN), Conditional Random Fields (CRF), Decision tree (DT), K Nearest Neighbor (kNN), Linear Regression (LR), Logistic Regression (LogR), Multiple Regression (MR), Fuzzy Logic, Evolutionary Computing (EC), Ensemble Methods (EM), Random Forest (RF), Bootstrap (BS) and Stochastic Gradient (SGD). The table below gives the number of times an algorithm is used. SVM, NB, and LR are the most used algorithms in sentiment analysis. Lexicon based uses an external dictionary for word classification. The common dictionary is AFFIN, BING, and NCR.

TABLE 2: LITERATURE REVIEW DETAILS

SL N	Name of paper	Author	Database	Year	Method	Dataset	Tools	Approach	Domain	Topics and Domain	Polarity	Emotions
1	Learning to predict reciprocity and triadic closure in social networks [28]	Lou et al	ACM	2013	_	35746336 Tweets	SVM-light	ML	Elite users	Celebrity	None	None
2	Forecasting with Twitter data [29]	Arias et al	ACM	2013	_	Tweets from specific	Weka	ML	Stock Market, movies,	Banking & Finance	None	None
3	Feature selection using principal component analysis for massive retweet detection [30]	Morchid et al	ACM	2014	SVM, NB	6M tweets	Weka	ML	General	Multiple topics	_	None
4	Irony detection in Twitter: the role of affective content [31]	Farias et al	ACM	2016	NB, DT, SVM	30000tweets	Weka	ML	Education, news, politics,	Politics	_	None
5	Dystemo: distant supervision method formulti-category emotion recognition in tweets [32]	Sintsova and Pu	ACM	2016	NB, LogR, DT	52218 tweets	Weka, LibLINEAR	ML	Sports	Sports	_	None
6	Quality-aware similarity assessment for entity matching in Web data [33]	Yerva et al	Elsevier	2012	NB	WePS-3	Matlab, open Calais alchemy API	ML	US census data	Politics	None	None
7	An ensemble heterogeneous classification methodology for discovering health-related knowledge in social media messages [34]	Tuarob et at	Elsevier	2014	NB	700M tweets	LibSVM, Weka	ML	Health	Healthcare	_	None
8	Ranked WordNet graph for sentiment polarity classification in Twitter [35]	Montejo-Raez at al	Elsevier	2014	SVM	376296 tweets	SVM-light	ML	General	Multiple topics	_	None
9	Stream-based active learning for sentiment analysis in the financial domain [36]	Smailovic et al	Elsevier	2014	SVM, kNN	1600000tweets	1pegasos SVM	ML	Stock Market	Banking & Finance	_	None
10	Active learning for sentiment analysis on data streams: methodology and workflow implementation in the ClowdFlows platform [37]	Kranjc et al	Elsevier	2015	SVM	1600000 tweetss from Stanford	SVMperf, ClowdFlows, Django	ML	General	Multiple topics	_	None
11	Estimating reputation polarity on microblog posts. [38]	Peetz at al	Elsevier	2016	DT	RepLab 2012-2013	Weka	ML	Automotive, Banking, Education,	Multiple topics	_	None
12	Figurative messages and affect in Twitter: differences between #irony, #sarcasm and #not [39]	Sulis et al	Elsevier	2016	DT, RF, SVM, NB, LogR	12532 tweets	Weka	ML	Comedians etc.	Comedy	_	None
13	Microblog sentiment classification with heterogeneous sentiment knowledge [40]	Wu at al	Elsevier	2016	SVM, NB, LogR	Sander	MatLab	ML	High tech companies	High-Tech Companies	_	None
14	Ranking of high-value social audiences on Twitter [41]	Lo et al	Elsevier	2016	FL, LR, Hybrid of (SVM + BS), Hybrid of (SVM +	124462 tweets	OpenCalais, LibSVM	ML	Various catagories	Multiple topics	_	None
15	Social media research: the application of supervised machine learning in organizational communication research [42]	van Zoonen and Toni	Elsevier	2016	SVM, NB, LogR	578803 tweets	Scikit-learn, python	ML	Various catagories	Multiple topics	_	None
16	In the mood for sharing contents: emotions, personality and interaction styles in the diffusion of news [43]	Celli et al	Elsevier	2016	LogR, RF	Gold Standard	_	ML	News	News, Trending	_	None

SL N	Name of paper	Author	Database	Year	Method	Dataset	Tools	Approach	Domain	Topics and Domain	Polarity	Emotions
17	Account classification in online social networks with LBCA and wavelets [44]	Igawa et al	Elsevier	2016	RF, NN	FIFA Dataset	_	ML	Sports	Sports	_	None
18	The impact of microblogging data for stock market prediction: using Twitter to predict returns, volatility, tradingvvolume and survey sentiment indices [45]	Oliveira et al	Elsevier	2016	MR, NN, SVM, RF	31M tweets	R	ML	Stock market	Finance and Banking	_	None
19	Recognizing emotions in text using ensemble of classifiers [46]	Perikos and Hatzilgeroudis	Elsevier	2016	NB	250tweets	Python	ML	News	News, Trending	_	None
20	Applying spark based machine learning model on streaming big data for health status prediction [47]	Nair et al	Elsevier	2017	DT	data from Heart disease data	Apache Spark ML	ML	Health	Healthcare	_	None
21	Using ensembles forproblemswith characterizable changes in data distribution: a case study on quantification [48]	Perez-Gallego et al	Elsevier	2017	NB, LogR, SVM	16M tweets	LibLINEAR	ML	General	Multiple topics	_	None
22	Weighted argumentation for analysis of discussions in Twitter [49]	Alsine et al	Elsevier	2017	SVM	Tweets from specific	NLTK	ML	Tax, politics, Campaign	Politics	_	None
23	Effective surveillance and predictive mapping of mosquito-borne diseases using social media [50]	Jain and Kumar	Elsevier	2017	SVM, NB, LogR	Tweets from specific period	LibLINEAR	ML	Health	Healthcare	_	None
24	ALGA: adaptive lexicon learning using genetic algorithm for sentiment analysis of microblogs. [51]	Keshavarz and Abadeh	Elsevier	2017	GA	sEMeVAL 2013	_	ML	hightech companies	High-Tech Companies	_	None
25	Towards Twitter sentiment classification by multi-level sentiment-enriched word embeddings [52]	Xiong et al	Elsevier	2017	SGD, SVM, NB-SVM	sEMeVAL 2013	Sentistrength	ML			_	None
26	Sentiment analysis during Hurricane Sandy in emergency response [53]	Neppalli et al	Elsevier	2017	SVM, NB	74708 TWEETS	_	ML	Environmental crisis	Environment	_	None
27	Social media data analytics to improve supply chain management in food industries [54]	Singh et al	Elsevier	2017	SVM, NB	10664 tweets	_	ML	food	Food	_	None
28	Microblog sentiment analysis with weak dependency connections [55]	Xiaomei et al	Elsevier	2017	SVM, NB	HCR	_	ML	random	Multiple topics	_	None
29	Discovering public sentiment in social media for predicting stock movement of publicly listed companies [56]	Li et al	Elsevier	2017	NB, DT	196370 tweets	Mongo DB	ML	Stock Market	Banking & Finance	_	None
30	A domain transferable lexicon set for Twitter sentiment analysis using a supervised machine learning approach [57]	Ghiassi & Lee	Elsevier	2018	NN, SVM	40000	WEKA, JAVA, MSSQL	ML	Products	Products	_	None
31	A comparative evaluation of pre-processing techniques and their interactions for Twitter sentiment analysis [58]	Symeonidis et al	Elsevier	2018	NB, SVM, logR, CNN	SS-Twitter	NLTK, Sklearn	ML	random	Multiple topics	_	None
32	A sentiment reporting framework for major city events: Case study on the China-United States trade war [59]	Manar et al	Elsevier	2020	Ranking, Neural network, SVM, CNN	70,000 users to detect tweets: 100000 tweets	_	ML	politics, economics, and education	Politics	Strong support, Support, Dissent, Stong Dissent	Calm, Happy, Exicted, Proud, Sad, Surprised, Depressed, Worried.

SL N	Name of paper	Author	Database	Year	Method	Dataset	Tools	Approach	Domain	Topics and Domain	Polarity	Emotions
32	A sentiment reporting framework for major city events: Case study on the China-United States trade war [59]	Manar et al	Elsevier	2020	Ranking, Neural network, SVM, CNN	70,000 users to detect tweets: 100000 tweets	_	ML	politics, economics, and education	Politics	Strong support, Support, Dissent, Stong Dissent	Calm, Happy, Exicted, Proud, Sad, Surprised, Depressed, Worried,
33	Sensing climate change and energy issues: Sentiment and emotion analysis with social media in the U.K. and Spain [60]	Maria et al	Elsevier	2020	NLP, NCR,	1.7 million tweets	python	Lexicon, ML	Energy	Energy	Positive, Negative	Anger, Fear, Anticipation, Trust, Surprise, Sadness, Joy, and
34	Beyond negative and positive: Exploring the effects of emotions in social media during the stock market crash [61]	Yidi Ge et al	Elsevier	2020	Hidden Markov Model (HMM) for market cognition mining, and uses ordered logistic	_	_	ML	_	_	Positive, egative Arousal high, low	Fear, Disgust
35	Sentence-based sentiment analysis for expressive text-to-speech [62]	Trialla and Alias	IEEE	2013	NB	Semeval 2007	Weka, EmoLib	ML	News	News, Trending	Positive, Negative, Neutral	None
36	Mining social media data for understanding students' learning experiences [63]	Chen et al	IEEE	2014	NB, SVM	19799 tweets	LibSVM, lemur toolkit	ML	Engineering	Science	_	None
37	TASC: topic-adaptive sentiment classification on dynamic tweets [64]	Liu et al	IEEE	2015	SVM, DT, RF	9413 tweets about taco bell &3238 tweets about Presidential Debate	Weka	ML	General companies	High-Tech Companies	_	None
38	Managing diverse sentiments at large scale [65]	Tsytsarau and	IEEE	2016	SVM	7M tweets	LK	ML	General	Multiple topics	_	None
39	Highlighting relationships of a smartphone's social ecosystem in potentially large investigations [66]	Andriotis et al	IEEE	2016	SVM, NB	Sentiment 140 dataset	Weka	ML	SmartPhones	Product	_	None
40	Sentiment embeddings with applications to sentiment analysis [67]	Tang et al	IEEE	2016	kNN, SVM, NN	Tweets from specific	LibLINEAR	ML	General	Multiple topics	_	None
41	A pattern-based approach for sarcasm detection on Twitter [68]	Bouazizi and Ohtsuki	IEEE	2016	SVM, kNN, RF	7628 tweets	Apache openNLP, Weka, LibSVM	ML	General	Multiple topics	_	None
42	Comparison research on text pre-processing methods on Twitter sentiment analysis [69]	Jianqiang and Xiaolin	IEEE	2017	SVM, NB, LogR, RF	_	scikit-learn	ML	_	_	_	None
43	A pattern-based approach for multi-class sentiment analysis in Twitter [70]	Bouazizi and Ohtsuki	IEEE	2017	RF	21000 tweets	SENTA	ML	General	Multiple topics	_	None
44	Deep convolution neural networks for Twitter sentiment analysis [71]	Jianqiang et al	IEEE	2018	SVM, CNN	STS	GloVe	ML	Random	Multiple topics	_	None
45	Learning to discover political activism in the Twitterverse [72]	Finn and Musatafaraj	Springer	2012	NB	15,000 Political tweets and 50,000 non-	Weka	ML	Politics	Politics	None	None
46	Learning from syntax generalizations for automatic semantic annotation [73]	Boella et al	Springer	2014	SVM	1M tweets	Weka	ML	General	Multiple topics	_	None
47	Emotion classification of social media posts for estimating people's reactions to communicated alert messages during crises [74]	Brybielsson at al	Springer	2014	SVM, NB	2.3 Tweets	Weka	ML	Natural crisis	Environment	_	None

SL N	Name of paper	Author	Database	Year	Method	Dataset	Tools	Approach	Domain	Topics and Domain	Polarity	Emotions
48	Tweeting the terror: modelling the social media reaction to the Woolwich terrorist attack [75]	Burnap et al	Springer	2014	DT, Hybrid: NB+LogR= BLR	427330tweets	R software	ML	Terrorism	Terrorism	_	None
49	Predicting political preference of Twitter users [76]	Makazhanov et al	Springer	2014	NB, LogR, DT	181972 tweets	Weka	ML	Politics	Politics	_	None
50	Modeling individual topic-specific behavior and influence backbone networks in social media [77]	Bogdanov et al	Springer	2014	NB	467M posts	_	ML	Business, celebrity, politics,	Multiple topics	_	None
51	The ripple of fear, sympathy and solidarity during the Boston bombings [78]	Lin and Margolin	Springer	2014	LR, BS	Tweets from specific period	_	ML	Terrorism	Terrorism	_	None
52	Study of collective user behaviour in Twitter: a fuzzy approach [79]	Fu and Shen	Springer	2014	FL	1242522 tweets	_	ML	General	Multiple topics	_	None
53	Sentiment leaning of influential communities in social networks [80]	Sluban et al	Springer	2015	SVM	1600000 tweetss from Stanford	SVMperf, LATINO	ML	General	Multiple topics	_	None
54	Bridging social media via distant supervision [81]	Magdy et al	Springer	2015	NB, SVM, kNN	19.5M tweets	Weka, SVM-Light	ML	Politics, science, sports	Politics	_	None
55	A hybrid model of sentimental entity recognition on mobile social media [82]	Wang et al	Springer	2016	SVM, kNN, LogR, NB	Tweets from specific	Scikit-learn, python	ML	News	News, Trending	_	None
56	Multi-source models for civil unrest forecasting [83]	Korkmaz et al	Springer	2016	LogR, RF	500M Tweets	_	ML	Social and political	Politics	_	None
57	Us and them: identifying cyber hate on Twitter across multiple protected characteristics [84]	Burnap and Williams	Springer	2016	SVM, RF	1803 tewwts	_	ML	Cyber hate	Hate	_	None
58	CDS: collaborative distant supervision for Twitter account classification [85]	Cui et al	Springer	2017	SVM	132.6M tweets & 23.2M accounts	LibSVM	ML	NGO's, Charities, events, Journalists/bloggers, celebrities, politicians.	Sports	_	None
59	SNA. An efficient framework for real-time tweet classification [86]	Khan et al	Springer	2017	NB	20000tweets	Python	ML	Politics	Politics	_	None
60	A Hybrid Multilingual Fuzzy-Based Approach to the Sentiment Analysis Problem Using SentiWordNet [87]	Youness et al	Springer	2020	fuzzy logic		HDFS, Hadoop MapReduce	Lexicon WordNet			Positive, Negative, Neutral	
61	Adding Twitter-specific features to stylistic features for classifying tweets by user type and number of retweets [88]	Arakawa at al	Wiley	2014	RF	40 accounts, 28,765 tweets	MECab	ML	High engagement users	Celebrity	_	
62	Cyber hate speech on Twitter: an application of machine classification and statistical modeling for policy and decision making [89]	Burnap et al	Wiley	2015	RFDT, SVM, Hybrid	450000 tweets	CrowdFlower, Stanford Lexical Parser, Weka	ML	Hate speech, Murder of Drummer Lee Rigby	Significant Event	_	
63	Real-time classification of Twitter trends [90]	Zubiaga et al	Wiley	2015	SVM	567452 tweets	SVM-Light	ML	News, trending topic, memes, events	News, Trending	_	
64	Authorship verification using deep belief network systems [91]	Brocardo et al	Wiley	2016	SVM	3194 tweets	Weka	ML	General	Multiple topics	_	
65	Sentiment mining in a collaborative learning environment: capitalising on big data [92]	R.K Jena	Wiley	2019	ML	_	_	Lexicon WordNet	Education	Education	Positive, Negative, Neutral	

The table below shows the number of times the ML algorithms that were used in the previous researches. SVM, NB, and LR are the most common algorithms. Many studies also use more than one type of algorithm to compare the results for accuracy. Other studies use ensemble methods to collate the results.

TABLE 3: ALGORITHMS USED IN SENTIMENT ANALYSIS

Name of Algorithms	# used in research	References
Support vector machines	45	[29],[30],[31],[33],[34],[35],[36],[37],[39], [40],[41],[42],[45],[48],[49],[50],[52],[53], [54],[55],[57],[58],[59],[62],[63],[64],[65], [66],[67,[68],[69],[71],[72],[73],[74], [80], [81], [82], [84], [85], [89], [90], [91],[92]
Naïve Bayes	30	[30],[31],[32],[33],[34],[39],[40],[42],[48], [50],[52],[53],[54],[55],[56],[58],[62],[63], [66],[69],[72],[74],[75],[76],[77],[81],[82],[86],[92]
Logistic Regression	16	[32],[39],[40],[41],[42],[40],[48],[50],[58] ,[61],[62],[75],[76],[82],[83]
Random Forest	13	[34],[39],[43],[44],[45],[64],[68],[69], [70],[83],[84],[88],[89]
Decision Tree	11	[29,][31],[32],[38],[39],[47],[56],[64],[75],[76],[89]
K Nearest Neighbor	6	[36],[67],[68],[72],[81],[82]
Neural Network	6	[26],[43],[45],[57],[59],[97]
Convolutional Neural Network	3	[58],[59],[71]
Fuzzy Logic	3	[41],[79],[87]
Bootstrap	2	[41],[78]
Linear Regression	2	[29],[78]
Natural Language Processing	1	[59]
Genetic Algorithm	1	[51]
Multiple Regression	1	[45]

This literature review also studies the key tools used by researchers in the field of sentiment analysis. Weka is the most common tool which is used in 14 studies. Weka is an open-source data mining software for machine learning that can be accessed through GUI (Graphical User Interface), standard terminal, or Application Programming Interfaces (APIs). Weka is predominantly used in academia and industrial application from which the programming language such as Python and R can be accessed. Python is also an open-source programing language which is commonly used in the fields of data science and statistical analysis. SVM Light is a C program by Thorsten Joachims that implements a support vector machine and this library can be used both in Python and R programming languages. The table below shows the complete list of tools used in 65 relevant research papers. Open source tools and software is the most used tools in sentiment analysis.

TABLE 4: TOOLS USED IN SENTIMENT ANALYSIS

Tools	# used in Research	References
Count of Weka	14	[29],[30],[34],[38],[39],[62],[64],[66],[72],[73],[74],[76],[81],[89]
Count of Python	5	[41],[42],[63],[67],[82]
Count of SVM-Light	5	[28],[34],[35],[81],[90]
Count of SVMperf	2	[37],[80]
Count of Matlab	1	[40]
Count of ClowdFlows	1	[37]
Count of Django	1	[37]
Count of Pegasos SVM	1	[36]
Count of R-Software	1	[75]
Count of MECab	1	[88]
Count of API	1	[33]
Count of EmoLib	1	[62]

Sentiment analysis was conducted on various domains and the list is shown in the table below. Many studies use multiple topics to classify sentiments. 19 papers used more than 3 topics or general topics to study sentiments. In the year 2016, almost 5 papers research sentiments on Politics. As most of the researchers use twitter for sentiment analysis, new and trending topics are researched predominantly.

The graph below shows how sentiment analysis and its associated algorithms are studied over the years. From 2014 to 2017, there was a significant study on sentiment analysis which gradually came down in 2018 and 2019. (note: the year 2020 is not complete data, research papers were gathered until July'2020).

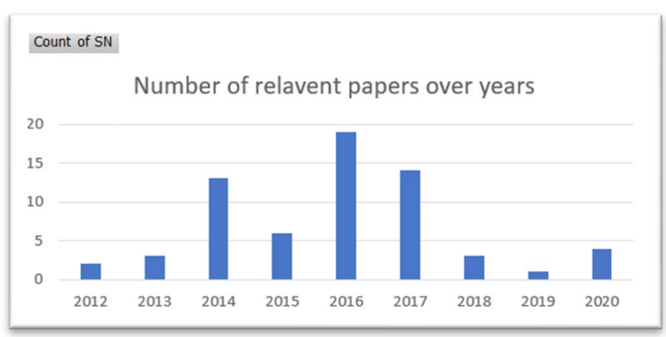

Fig. 3. Published papers over years

TABLE 5: DOMAINS AND TOPICS USED FOR SENTIMENT ANALYSIS

Domains Researched	# used in Research	References
Multiple topics	19	[30],[35],[37],[38],[41],[42],[48],[55],[58],[65],[67],[68],[70],[71],[73],[77],[79],[80],[91]
Politics	9	[31],[33],[49],[59],[72],[76],[81],[83],[86]
News, Trending	5	[43],[46],[62],[82],[90]
Unidentified/General	4	[52],[61],[69],[87]
Banking & Finance	3	[29],[36],[56]
Healthcare	3	[34],[47],[50]
High-Tech Companies	3	[40],[51],[64]
Sports	3	[32],[44],[85]
Celebrity	2	[28],[88]
Environment	2	[53],[74]
Terrorism	2	[75],[78]
Comedy	1	[36]
Education	1	[92]
Energy	1	[60]
Finance and Banking	1	[45]
Food	1	[54]
Hate	1	[84]
Products	2	[57],[66]
Science	1	[63]
Significant Event	1	[89]

VII. RESULTS

This study collected and reviewed many relevant research papers and performed SLR on methods used in Sentiment analysis from 2011 until Aug 2020. Below are the 5 research questions that were intended to answer through this survey.

RQ1: What is the best social platform to gather data for sentiment analysis?

Twitter is the most preferred platform for social media sentiment analysis. I believe that this is because Twitter provides APIs that are well structured and there are plenty of libraries available both in R and Python that makes data gathering easy. Facebook, on the other hand, restricts data imports making it very hard to gather comments, messages, and user engagement data.

RQ2: Which are the most distinguished journals to study sentiment analysis?

Reviewing over 500 research papers, and selecting 65 research studies, it was found that Elsevier has a higher percentage of research papers that study methods of sentiment analysis followed by Springer and IEEE.

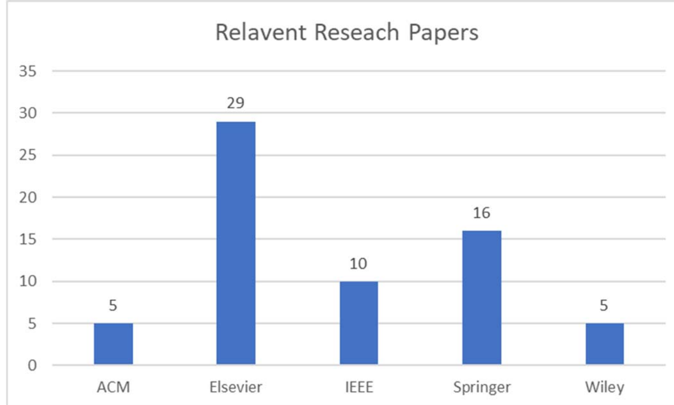

Fig. 4. Relevant papers from top databases

RQ3: What are the most used alogrithms in sentiment analysis?

When looking at studies conducting sentiment analysis that use machine learning methods, SVM (Support Vector Machine) is the most common algorithm preferred followed by Naïve Bayes(NB). Its also observed that many studies use more than one algorithm to compare accuracy levels. When it comes to studies that use lexicon methods, BING is the most commonly used dictionary.

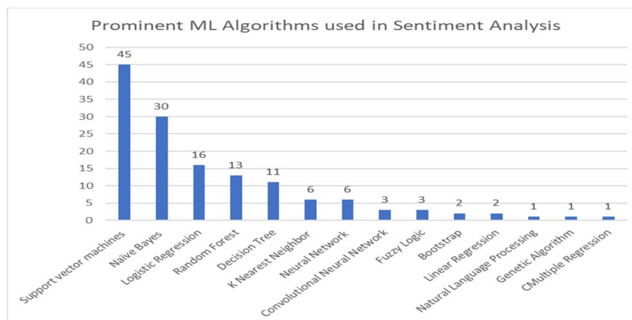

Fig. 5. Algorithms commonly used in Sentiment Analysis

RQ4: What are the primary reasons for conducting sentiment analysis?

Most of the ML based studies were conducted to compare and suggest algorithms to improve the classification accuracy. Some studies conducted analysis to gain insights to user sentiment regarding a topic or an event.

RQ5: What are the most common challenges faced in sentiment analysis?

The common challenges to effective and efficient sentiment classification can be classified into 2 board categories:

- Data gathering & validation challenges
- Algorithm & text classification challenges.

The primary problem to data gathering for sentiment analysis is the unwillingness of social media platforms to open their data for public use. The very reason that 80% of sentiment analysis happens on tweets is because Twitter is the only platform that has open API's for larger data gathering. With the massive data produced on social media, mining, analyzing and classifying the data effectively is computationally hard.

Even though sentiment analysis seems like a text classification problem, a deep dive shows that the quality of data cannot be achieved when user engage in non-formal communication. Especially of a platform such as Twitter, users engage in expressing sentiment and emotions through emojis, sarcasm, memes and trolling. These forms of communication are harder when they are co-expresses with textual tweets. Linguistic rules to classify text into various sentiments and emotions might not apply to tweets that carry emojis and sarcasm. Users using negation words to express (not, no etc.) is hard to classify using linguistic rules than uses formal language rules for sentiment classification. ML bases studies show the use of various algorithms, but we are still behind in accurately classifying the texts to detect sentiments.

VIII. Conclusion

Sentiment analysis and opining mining refers to understanding and acquiring actionable knowledge through subjective text generated on the social platform. Sentiment analysis is a rapidly growing topic both in academia and real-life practice and its application is enormous. This literature review studied 65 published papers on sentiment analysis intending to answer 5 research questions listed in section 3. This review contributes to knowledge on the state of art methods used in sentiment analysis by looking at researches conducted in the decade. This review adds value to both academic knowledge and practitioners by exploring all the methods used on sentiment classification in the last decade. This studied identifies challenges, gaps, and suggestions in the previous sections. According to the studies, sentiment analysis is broadly conducted used ML or/and Lexicon methods. Machine learning papers focused on experimenting and suggesting novel algorithms to improve the efficiency of sentiment classification whereas lexicon-based papers focused on using a pre-existing dictionary to classify the sentiments from tweets to draw actionable insights. The lexicon method is the simplest compared to ML but has its shortcomings. ML algorithms are used to predict the sentiment of the user by mimicking the human mind. Though both methods are adding value to sentiment analysis, ML contributes towards computational sciences and the Lexicon contributes towards business and insights mining. There are several limitations to this review, the articles considered were all in the English language and the explores only the published work. This study restricted itself to exploring sentiment analysis for management insights. The keyword selection is limited to “Sentiment analysis”, “Emotions mining”, “Social Media”, and “Twitter”. There may be articles that might relate to my research topic that might be found with other keywords in a different database.

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