Survey of Tools and Techniques for Sentiment Analysis of Social Networking Data

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Abstract—**Social media has rapidly expanded over a period of time and generated a huge repository of content. Sentiment analysis of this data has a vast scope in decision support and attracted many researchers to explore various possibilities for technique enhancement and accuracy improvement. Twitter is one of the social media platforms that are widely explored in the area of sentiment analysis. This paper presents a systematic survey related to Social Networking Sites Sentiment Analysis and mainly focus on Twitter sentiment analysis. The paper explores and identifies the techniques and tools used in a well-structured approach to find out the research gaps and identify future scope in this area of research. The techniques evolved over time to improve the efficiency of classification. Total 55 research papers are included in this survey. The result reflects that Twitter is the most explored social networking site for opinion mining. Naïve Bayes and SVM machine learning algorithms are implemented in maximum researches. As the latest advancements, Stack based ensemble, fuzzy based and neural network based classifiers are also implemented to enhance the efficiency of classification. WEKA, R Studio, Python are mostly used tools by research scholars for implementation. The overall evolution of the research goes through various changes in terms of technologies, tools, social media platforms and data corpus targeted.**

Keywords—Social networking sites sentiment analysis; twitter sentiment analysis; opinion mining; ensemble classifier; stack based ensemble

I. Introduction

The spread of information on social networking media like Facebook, Twitter, Instagram, Reddit, News forum etc. is comparatively faster than traditional social media platforms. Social media have become a rich resource of information for companies and research scholars that can be analyzed to get valuable information by using NLP (Natural Language Processing) and artificial intelligence techniques. The huge repository of information provided on social media platform is unprocessed and raw in nature, and over the time technologies are evolved to process the data and extract valuable information from that. This information can be analyzed and helpful in decision support and effective policy making in different areas related to business, politics, entertainment, medical and social uplifting.

Sentiment analysis of social media posts deals with finding out the opinion, sentiment or feelings related to these posts.

That can be mentioned at different levels of sentiments and mostly categorized as positive and negative. Several sentiment analyses and classification techniques like dictionary based, machine learning, ensemble based, neural network based, fuzzy based and hybrid are evolved over the period of time starting from the research in the area. Also, the targeted data size is increased and new tools are evolved for easy and effective evaluation of sentiment. Various research scholars have been doing research for more than a decade and research has gone through multiple phases with enhancement of technology and efficiency of outcomes.

Here in the present survey we have gone through a systematic literature survey and studied 55 finally selected research papers related to the area from 2009 to 2021. These 55 papers are selected after keen observation and following the criteria of inclusion and exclusion. We focus on Twitter sentiment analysis and provide the existing techniques used and scope of enhancement. There is abundance of research literature present in the field; we aim to find the relevant literature with respect to novelty of research, their applications domain and effectiveness.

Section I of the present survey paper gives the introduction of sentiment analysis for social networking sites. The research strategy used in the survey is mentioned in Section II. Research questions on the basis of which the survey is designed are mentioned in Section III. Section IV gives the details of related literature included in the survey. Survey outcomes of all the 55 research papers included are mentioned in Section V. Overall survey is concluded in Section VI.

II. Research Strategy Design

The survey related to 'Social networking sites sentiment analysis' was undertaken systematically by following the steps mentioned in Fig. 1. At the very first step, research questions are designed to give a proper direction to the survey. We continue by retrieving the related literature and then selecting the pertinent research papers from those that fulfill the requirement as per research questions. Finally, the findings and results as started by the author are analyzed and mentioned along with tools and technology used in the research.
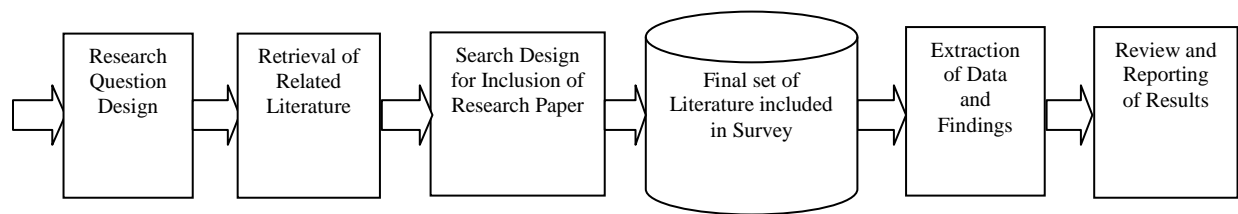
Fig. 1. Stepwise Strategy Design for Literature Review.

III. RESEARCH QUESTION

To design and conduct research, the following research questions (Q) are identified:

Q1: Which technique is used in the research?

Q2: Which framework, language or tools are used in research for implementation?

Q3: Which datasets are targeted in the research for implementation of mentioned models?

Q4: What are the main outcomes of the research literature?

IV. RELATED LITERATURE

Various researches performed in the area from 2009 to 2021 are mentioned below. Table I gives the summarization and key findings of the survey. The results, technologies, findings and tool used in the research are also elaborated in the section below:

Matthew et al. [1] in their research, implemented Bagging, Boosting and Random subspace method by using KNN, C4.5, SVM, MLP, RBF, LR as base classifiers. WEKA tool is used in the implementation of different classifiers. An enhanced performance is obtained with maximum accuracy of 90% over other approaches. Ensemble-based classifier performed better in all cases, particularly for noisy data, to enhance the overall accuracy of classification.

Kumar et al. [2] presented an article about the evolution of online social networks. The article investigates the dynamics of social cognitive theory and social networking. The research involved a photo sharing application (Flickr) and Yahoo 360 social network for analysis and implementation. Three different segments of networks are identified viz. singletons, isolated communities and giant component networks and detailed description of the evolution and structure of the three segments are researched on. The investigation of economical behavior of online social media networks is analyzed and user activity impact on incentives is examined.

A. Agarwal et al. [3] proposed twitter sentiment analysis by using POS specific polarity features and explored tree kernels to prevent the need for tedious feature engineering. 11,875 manually labeled tweets publically available from commercial resources were used in implementation. The conjunction of new feature with the previously proposed features and tree kernels outperform the base line classifiers.

Bae Y. et al. [4] performed twitter sentiment analysis of twitter post related to famous personalities and news channels viz. Donald J. Trump, Barack Obama, Bill Gates, Ashton Kutcher, Lady Gaga, Larry King, Oprah Winfrey, Britney Spears, TechCrunch, Mashable, BBC Breaking News, CNN Breaking News, Dalai Lama.

Lima et al. [5] in their research implemented Naïve Bayes algorithm for tweets sentiment classification as positive and negative on real time tweets downloaded by using Twitter4J Library. Tweets are classified on the basis of emoticons, sentiment based words or a hybrid of both. The results show an enhanced accuracy in case of hybrid approach.

F. Neri et al. [6] implemented sentiment analysis on Facebook posts related to news post related to Rai1 and La7 news programs. Facebook posts are analyzed using 'iSyn Semantic Center'. Bayesian method and K-Means algorithm are used as supervised and unsupervised classification techniques. The research shows the importance of Facebook for online marketing.

H. Kang et al. [7] proposed an enhanced Naïve Bayes classification algorithm for sentiment classification of review documents of restaurants. The 70000 review documents are obtained from restaurant sites including star information. The proposed model shows the enhancement of accuracy and precision.

M. Ghiassi et al. [8] developed a new lexicon specifically for Twitter opinion mining using n-gram feature vector and supervised learning method. The 3440 tweets are manually collected and labeled on 'Justin Bieber' twitter account and the model proposed in research is tested using these tweets. The results show the improvement in accuracy for the proposed model over SVM with an accuracy of 95.1%.

Hassan et al. [9] implemented Bootstrap ensemble framework (BPEF). It works in two stages: expansion and contraction. In the expansion stage, large numbers of models are generated based on the dataset, features and classifier parameters. In contraction stage a subset of these models is selected by throwing redundant and less useful models. The experiment results show that BPEF gives a high value of recall as compared to other methods. SIMS module of BPEF extracted a model with higher performance.

E. Haddia et al. [10] show the role of preprocessing on sentiment analysis. Improvement is observed in the accuracies of TD-IDF matrix from 78.33 to 81.5, in Metric FF 76.33 to 83 and in FP matrix 82.33 to 83.

Patil et al. [11] in their research implemented SVM with and without feature extraction and show that SVM eliminated the need for feature selection due to the ability to generalize high dimension feature space.

Inoshika et al. [12] research on feature ranking and selection techniques for Twitter data opinion mining and

suggested to remove unrelated words from feature space to reduce dimensionality that further reduces the sparseness of the feature set. The research also proposed a new feature selection technique on the basis of information theory named as Ratio Method.

Bac Le et al. [13] proposed a model based on NB and SVM. Information Gain, Bigram, Object-oriented extraction methods are used for feature ranking and selection to select more appropriate features. As per reported results, the proposed model is highly efficient with high accuracy for predicting feelings.

B. S. Dattu [14] implemented twitter sentient analysis by using SVM and Naive Bayes on real time tweets downloaded between the time periods 12 September 2010 to 24 January 2011 with the keywords 'NFL teams'. They pointed out in their research that SVM proved to be better than Naive Bayes algorithm for text classification and categorization. For unbalanced data, Naïve Bayes is more appropriate as there are fewer variations in results for unbalanced data.

O. Kolchyna et al. [15] implemented two techniques viz. Lexicon based and machine learning for sentiment classification of twitter messages. This research uses the sentiment score extracted from Lexicon classifier as an additional feature in the feature vector and the results shows the improvement in accuracy for imbalanced data set. The research show that incorporating sentiment lexicons with abbreviations, emoticons and social media slang enhances the efficiency of lexicon-based classifier. Feature generation and selection also play a vital role for the enhancement of classification accuracy. SemEval-2013 competition, task 2-B standard twitter data set is used and the outcome of the research shows that SVM and NB machine learning methods perform better. A combination of lexicon and machine learning method further enhance the accuracy by 7 percent.

Prusa et al. [16] worked on bagging and boosting-based ensemble classifiers. These two are the most widely used ensemble techniques in machine learning. In the research, both techniques are tested with the use of seven diverse base learners. All the ensemble classifiers build are compared with all the seven base learners to observe the performance enhancement. Total 21 learning algorithms are trained and finally tested on two different datasets, one large-sized automatically class labeled lesser quality dataset and other small-sized manually class labeled superior quality dataset. The research proved to be better and ensemble classifier enhanced the accuracy, regardless of the quality of the data set used.

K. L. Devi et al. [17] compared ensemble classifiers viz. Boosting and Bagging with the machine learning classifiers like NB, SVM and maximum entropy classifier. Feature selection is performed by using MI and Chi-square methods and is proved to be better than previously used methods. SemEval 2013, Task 9 data sets are used for implementation.

Y. Wan et al. [18] in their research, implemented majority voting-based ensemble classification model on various classification techniques including SVM, Random Forest, Naive Bayes, Bayesian Network and C4.5 Decision Tree by

using 10 fold cross validation on a data set having 12864 tweets related to airline service Twitter dataset.

Prusa J. et al. [19] researched on 10 different feature selection methods and four classifiers viz. 5-NN, C4.5, LR, MLP. All classifiers by using all feature ranking and selection techniques are implemented on 10 different sized feature subsets up to maximum 200 features. The results of research show that filter-based feature selection, Chi-Squared (CS) improved classification performance for small-size feature sets. After comparing all the combinations of classifiers and feature rankers, it was observed that LR performed best with 150 features selected by KS ranker. The models performed better with larger number of features and the best models have features 75 or more. Only the feature rankers MI, ROC, PRC, CS and KS shows enhanced efficiency as compared to no feature selection.

R. Mansour et al. [20] in their research used multiple sets of features for sentiment classification by using an ensemble classifier. The classification complexity comes out linear with the increase in feature set size. The ensemble is implemented on two features sets; one optimal set with 20000 features and other NRC data set with 4 million features. The feature set with selected 20000 features has shown relative 9.9% and 11.9% performance gain over 4 million feature set.

O. Abdelwahab et al. [21] in their research demonstrated the effect of training set size on accuracy of SVM and NB classifiers. The Python NLTK library is used for implementation of classifiers. The results show that there is a little increase in accuracy if training data increases from 20 to 90 to percent. So a moderate size data can be trained to get acceptable results.

S. Akter et al. [22] predicted the sentiment for the Facebook posts using a lexicon-based sentiment analysis technique. The data set used in the implementation is FOODBANK the Facebook group in Bangladesh. In the research a console is developed using C# and Graph API is used to collect data.

M. Bouazizi et al. [23] proposed a new model for detecting the sarcasm using sentiment analysis of twitter data as micro blogging social networking sites are very useful in detecting sarcastic statements. A pattern-based sarcasm detection approach is used for twitter. A feature set with four relevant features for identifying different kinds of sarcasm is used and tweets are classified as non-sarcastic and sarcastic two classes. The model achieved an accuracy of 83.1% with 91.1% precision. SVM classifier is used and WEKA tool is used in implementation.

Grandin and Adan et al. [24] proposed a model Piegas for the sentiment of Portugal tweets. The Naïve Bayes classifier is implemented by using JavaScript and Ruby on Rails are used for the development of the system. The main requirement of the model is to develop a system with good usability and high precision.

Nádia et al. [25] proposed a new semi-supervised approach to solve the problem of cost of getting supervised data for machine learning. Unsupervised information retrieved from the similarity matrix created from unlabeled data is used with

various classifiers in place of classified data. Similarity matrix can be used as a powerful knowledge extraction tool to get information from non-labeled data. The results of the proposed framework show the improved accuracy for Twitter sentiment classification by using unlabeled data.

A. Tripathy [26] implemented four machine learning classification algorithms SVM, NB, Maximum Entropy (ME) and Stochastic Gradient Descent (SGD) on IMDb data set for sentiment classification. These classification models are implemented on unigram, bigram and n-gram features and it is observed that if the value of n is increased in n-gram after 2 than accuracy is decreased rather than increasing. For unigram and bigram accuracy is good but for trigram, four-gram, five-gram accuracy is decreased. Also, the use of count vectorizer technique and TF- IDF for converting the text into a matrix of weights, enhance the accuracy of classification.

A. Krouska et al. [27] in their research show the effect of preprocessing on the classification accuracy. The research also shows a major enhancement in result when IG is used for attribute selection. The research uses Unigram, Bigram and 1-3 gram feature vector. Preprocessing and feature selection enhance the accuracy. Unigram and 1-3 gram performed best among all.

K. Ali et al. [28] proposed SAaaS (Sentiment Analysis as a Service) framework to abstract sentiments of various social media information services. Public health surveillance related to social media based is done by using spatial attributes of social media users to find the location of disease outbreak. A new quality model is introduced to remove noise from the social media content. The real-world datasets from Twitter, Instagram, Reddit, news forum are used in the research. Sentistrength and Alchemy API tools are used in research. The Sentistrength tool is used for the analysis of short and informal text while Alchemy API for long and formal text.

A. U. Hassan et al. [29] In this paper, presented the method to detect the depression level of a person by fetching emotions from the social media text by using NLP and machine learning techniques on social media Twitter dataset and 20 newsgroups.

M. R. Huq et al. [30] used two techniques for sentiment analysis: First technique is a sentiment classification algorithm (SCA) based on KNN and the second is based on SVM. The research shows the comparative analysis of both the methods on the basis of recall, precision, accuracy, F-Score, TPR and FPR for 1000 tweets.

M. Ahmad [31] implemented Support Vector Machine (SVM) on two twitter pre-classified data sets for textual polarity detection. Recall, Precision and F-Measure are used for comparative analysis. The result shows that performance of SVM depends on the dataset itself. So it can be an area of research that what kind of classification algorithm is good for which kind of data set and what is the reason for that.

J. Brandon et al. [32] implemented twitter sentiment analysis to find the opinion of people for candidates in 2016 US Presidential elections. Lexicon based classifier and NB Machine learning classifiers are used on two data sets. One data set is a manually labeled Twitter data set and the other is

an automatically labeled data set based on Hashtags and topic. A high correlation of 94 percent was found with polling data by using a moving average smoothing technique.

R. Wijayanti et al. [33] proposed an ensemble classifier based on a voting-based technique and used SVM, NB, LR (Logistic Regression) and Decision Tree classification algorithms for the implementation of proposed ensemble classifier. They used various feature representation techniques such as TF-IDF, sentiment lexicon score and term presence in their research. Ensemble classification results are proved to be better than individual machine learning classifiers, but ensemble accuracy highly depends on the selection of single classifiers used for creating the ensemble classifier.

Z. Jianqiang et al. [34] monitored the effect of six preprocessing techniques by using four classification algorithms (NB, SVM, RF, LR) and two feature selection methods. The result shows that accuracy is improved after using preprocessing techniques on the dataset. But removal of URL's, numbers and stop words hardly affects the accuracy, so they can be removed. Random deletion of words reduces the accuracy as the deleted word might be important in sentiment detection. NB and RF are more sensitive to the use of different pre-processing techniques.

Rahman et al.[35] analyzed the reliable decision making for a friend request to be accepted in Online Social Networks. Here, a quantitative study for analyzing the friend request has been carried out and the information regarding the social media websites were explained and information misuse of the other users and friends due to being deficient in trustworthy Friend Request Acceptance. In the research, a method is proposed for reliable friend request acceptance in Online Social Networks by finding out more details of the person who has sent the friend request.

Jianqiang et al. [36] proposed a method for opinion mining using deep convolution neural networks. Unsupervised learning is used for obtaining word embeddings by using a large set of Twitter data. The n-grams features combined with the word embeddings and polarity score extracted from sentiment lexicon are used for Twitter sentiment analysis. Sentiment classification labels were predicted after training the feature set with deep convolution network. GloVe-DCNN on the STSTd dataset performed best with accuracy 87.62%.

K. Tago et al. [37] performed an analysis based on Twitter data using user relationships and analysis of emotional behaviors. Here, two dictionaries of emotional words are analyzed using the machine learning classifiers and keyword matching is used for calculating emotion scores. Moreover, with different settings, three experiments were designed and these are the user's average emotion scores that were calculated. Using all the emotional tweets, the average of emotion score is calculated after user of few emotional tweets was excluded. Brunner–Munzel test was used to evaluate emotional behaviors to user relationships. As per results, positive users participate more than negative users in building a relationship in some particular conditions.

In Ikoro, Victoria, et al. [38], sentiment analysis of UK energy consumers is done by using messages posted on

Twitter. Big Six and three new entrant energy providers companies are compared on the basis of tweet sentiments. Two sentiment lexicons are used to maximize accuracy. As per results, consumers are more positive towards new companies and the use of multiple lexicons helps to improve the accuracy of sentiment analysis.

C. Troussas et al. [39] implemented four different ensemble techniques: bagging, Boosting, Voting and Stack based ensemble on three different data sets. Stack-based ensemble model is implemented by using NB, SVM, KNN and C4.5 as base classifiers and LR as a Meta classifier. The result shows that stack-based model surpasses the efficiency of other classifiers. Three datasets are used viz. OMD, HCR, STS-Gold. Stack based ensemble classifier performed best with an accuracy of 89.02% on STS-Gold dataset.

M. M. Fouad et al. [40] focused their research on the efficient classification of twitter data by combining NLP and data mining techniques. They implemented majority voting-based ensemble classification technique by using SVM, LR, NB classifiers and Information Gain (IG) feature selection technique. IG technique enhances the efficiency of classifier by selecting more appropriate features. The ensemble classifier also improves the accuracy, but if any one of the participant algorithms in ensemble does not suit the data set, then accuracy is decremented. Feature subset further enhanced with the use of emoticons does not enhance the efficiency of classification.

Y. Emre Isik et al. [41] also used stack-based ensemble classification techniques for sentiment classification of text. The ensemble is performed at two levels, one at feature selection level and other at classifier level; as a less accurate feature selection can lead to poor classification, so two techniques are used at feature selection level to reduce error and for enhanced feature selection. Two classification methods are used as an ensemble to enhance classification accuracy. The technique shows good results as compared to other machine learning classifiers.

F. T. Giuntini et al. [42] in their research perform the sentiment analysis on Facebook post. The aim of the research is to find the relevancy of emoticons used in the Facebook posts whether the emoticons match with the actual sentiment present in the post at six basic emotion levels. The paper proposed a 'Expectation Maximization algorithm' that finds correlation between the emoticons used in the tweet and the emotion class of the post. As per research, the use of emoticons as attribute enhances the result of classification of Twitter posts.

S. E. Saad et al. [43] used ordinal regression for twitter data sentiment analysis for twitter dataset provided by the NLTK. The algorithms used for opinion mining in the proposed model framework are SoftMax (Multinomial logistic regression), SVR (Support Vector Regression), DTs (Decision Trees), and RF (Random Forest). As per research, proposed framework can detect ordinal regression and decision tree proved to be the best from the above mentioned algorithms.

S. Vashishtha at al. [44] performed opinion mining of tweets by using three different lexicons and nine pubic twitter

data sets, for classifying tweets at two and three levels of sentiments. The research proposed a fusion of multiple lexicons with fuzzy classification approach for enhanced classification. The nine datasets used in implementation are viz. The dataset used are Sanders Twitter Dataset, Nuclear Twitter Dataset, Apple Twitter Dataset, (STS-Test), Sentiment140, SemEval 2017, SemEval 2015 and Data used by Gilbert & Hutto, 2014, SemEval 2016.

K. Elshakankery et al. [45] proposed a new hybrid approach named HILATSA by combining lexicon and machine learning approach. The proposed approach performed with an accuracy of 73.67 % for three class classification and 83.73 % for two class classification problem. Six different data sets used in the implementation are ASTD, Mini Arabic Tweets Sentiment Dataset, ArSAS, Arabic Gold Standard Twitter Data set, Syrian Tweets Corpus and Twitter dataset for Arabic Sentiment Analysis.

Martin-Domingo et al. [46] used machine learning classification for airport service quality analysis on London Heathrow airport's Twitter account dataset by using machine learning sentiment analysis technique. They used Theysay and Twinword tools for implementation. Theysay performed better than Twinword with 78.7 percent accuracy as compared to 69.6% of Theysay. The purpose of research is to generate a list of service attributes that reflect the ASQ and results reflect that additional attribute does not reflect more accurate ASQ prediction.

M. Naz at al. [47] in their research implemented an ensemble classification model by using two classifiers K-Nearest Neighbor and Naïve Bayes. They used two feature selection techniques: Forest Optimization algorithm (FOA) and minimum redundancy and maximum relevance (mRMR). FOA is used for feature selection and mRMR for the removal of irrelevant features. As per the results of the research, ensemble classifier combined with feature selection technique performed comparatively better than the individual machine learning algorithms. Results are further improved by using an ensemble of KNN, NB and SVM. It is also evident from the research that the hybrid of FOAKNN and FOA-NB has outperformed single KNN and NB classifiers. Accuracy is increased when FOA and nRMR feature selection techniques are applied. The Blitzer's dataset, retrieved from the UCI repository related to the reviews of electronic products, is used for the implementation of various classifiers in the research.

J. J. Bird et al. [48] proposed multiclass sentiment classification for five different levels of sentiments in a range from1-5 representing negative to positive score. Various single classifiers viz. OneR, MLP, NB, NBM, RT, J48, SMO SVM and ensemble classifiers named RF, AdaBoost (RT), Vote (RT, NBM, MLP), Vote (RF, MLP, NBM), AdaBoost (RF) are implemented. The research shows that the majority voting-based ensemble of NBM, RF, MLP performed best with 91.02 % accuracy. In individual classifiers, RT (Random Tree) performed best with accuracy of 78.6%. All ensemble methods outperformed single classifier.

M. Khader et al. [49] in their research show the effect of preprocessing techniques such as using tokenization, PoS tagging, removing stop words, URL, other users' mention,

numbers and hashtags and lemmatization on Naïve Bayes machine learning classifier. Mapreduce of Hadoop is used for the implementation on Stanford twitter Sentiment data set. The proposed technique reflects an increase of 5% accuracy yielding to 73% for NB classifier.

R. Ahujaa et al. [50] implemented six classifiers viz. Decision Tree, SVM, KNN RF, LR TF-IDF, NB by using two feature selection techniques N-gram and TF-IDF on 'SS-Tweets' data set. The results show that TF-IDF feature selection show 3-4 % increase in performance as compared to N-gram feature.

M. bibi et al. [51] in their research proposed a new feature selection technique CAARIA "class association and attribute relevancy based imputation algorithm" that is proved to be better than IG and PC with an AUC (F-measure) value of 0.79. The research is performed on three twitter data sets HCR, SS-Tweet and FleTweetsPak on two machine learning classifiers SVM and NB by using WEKA tool. The newly proposed technique reduces feature dimension space by selecting tweets that have same class and carry useful information.

M. Bibi et al. [52] used hierarchical based clustering techniques named SL (single linkage), AL (average linkage) and CL (complete linkage) for the sentiment mining of twitter data. A combined framework architecture is built by using these three clustering techniques to select the best possible cluster with the help of using majority voting. The hierarchical clustering techniques proposed in the research are compared with k-means, SVM and NB classifiers. The outcome of research indicates that majority voting-based cooperative clustering is better in terms of quality of clusters but poor in term of time efficiency.

Z. Kermani et al. [53] used IDF, Term Frequency, sentiment scoring using lexicon dictionary SentiWordNet, semantic similarity for representing each feature weight of tweet in the feature vector. The percentage of contribution in the weight by each method is optimized and solved by genetic algorithm. The weight of feature obtained from all the four techniques are merged by using Einstein sum. SVM and multinomial NB classification methods are used on this weighted enhanced feature vector to classify tweets. Four Twitter data sets used for the implementation are Stanford testing dataset, Strict Obama McCain Debate dataset, STS-Gold and Obama-McCain Debate dataset.

Esraa A. Afify et al. [54] in their research aim to classify the Facebook account as fake or genuine, on the basis of content generated and finding the correlation between user generated content. Credibility of an account is decided at two levels. First binary classification is applied to classify account as fake or genuine. After that, credibility score of the genuine class is calculated by using Analytical Hierarchical Process. On the basis of that score account credibility is decided. The research used machine learning and deep learning techniques for the identification of Facebook profile credibility by using Scikit-learn and Keras with TensorFlow. Scikit-learn is used for the implementation of machine learning techniques and Keras with TensorFlow for implementing deep learning.

George S.R. et al. [55] proposed a framework for opinion prediction for a product or brand name in Facebook during social distancing by using machine learning algorithms and netnography. The study actually proposes a conceptual framework and suggested various tools used by different researchers for opinion mining of Facebook viz. netnography, Google analytics, tweetstats, brandwatch, Facebook insights, sematrica's lexalytics, Google alerts and people browser.

Most of the work aim to find out the sentiment related to service or product by using dictionary-based, Machine learning based or hybrid classifiers. The overall purpose is to enhance accuracy and efficiency of classification models. Different researches are performed on different data corpus. Different tools are used by researchers to observe the variations in the outcome. Table I summarizes the tool, technology, data corpus used and final outcome of all the papers included in the survey.

TABLE I.   SUMMARY OF REVIEWED LITERATURE

Author (Year)	Technique/ Approach	Tool Used	Data Corpus / Context	Results / Outcomes
M Whitehead et al. [1] (2009)	Ensemble classifiers: Bagging and AdaBoost-r (KNN, C4.5,SVM, MLP, RBF, LR)	WEKA	Twitter	Ensemble classifier performed better, for noisy data also.
Kumar et al. [2] (2010)	Evolution and analysis of Social Networks in three different size networks by Graph Theory.	Representation and analysis of social network as timegraph.	Yahoo!s 360 social network and Flickr photo sharing application.	Mention the evolution of social network components of different sizes and shows "star" as most prevailing structure of social network.
A Agarwal et al. [3] (2011)	Tree kernels with POS specific polarity features	Python	11,875 manually labeled tweets	Maximum tweets are classified in neutral class.
Bae Y. et al. [4] (2011)	Dictionary based classification using LIWC2007	Twitter API, LIWC2007	Twitter	Sentiment analysis of twitter data related to famous personalities as negative or positive.
ACES Lima et al. [5] (2012)	Naïve Bayes	Twitter4J Library , JAVA	Twitter Dataset: Real Time Tweets.	Sentiment classification on the basis of emoticons, sentiment based words or hybrid. Hybrid approach enhances accuracy.
F Neri et al. [6] (2012)	Bayesian method and K-Means algorithm	iSyn Semantic Center	Facebook about newscasts (La7 and Rai1 news programs)	Show importance of Facebook for online marketing.

H Kang et al. [7] (2012)	Naïve Bayes, SVM	WEKA	70000 review documents from restaurant sites	Proposed enhanced NB algorithm. Enhancement in precision and accuracy in proposed algorithm.
M Ghiassi et al. [8] (2013)	Supervised learning technique using n-gram statistical analysis	SVM and DAN2	Real time collected for keyword 'Justin Bieber'	Proposed model performed better than SVM with an accuracy of 95.1%.
Hassan et al. [9] (2013)	Bootstrap ensemble framework (BPEF).	FRN, Viralheat, Popular Tool, Light side, Lymbix, Sentistrength, Sentiment 140	Twitter dataset: Telco, Tech, Pharma	SIMS module of BPEF was able to extract models with higher efficiency.
E Haddia et al. [10] (2013)	*Preprocessing Methods*. Classifier SVM . Feature wt. using TD-IDF, FF, FP.	'e1071' in R Tool	movie reviews, DAT-1400, Dat-2000	Improvement observed in accuracies of TD-IDF matrix from 78.33 to 81.5, in Metric FF 76.33 to 83 and in FP matrix 82.33 to 83.
G Patil et. al [11] (2014)	ANN, SVM And TF-IDF	----	Twitter	SVM Performed better than ANN. SVM use few irrelevant feature and High dim. Feature space.
Inoshika et al. [12] (2014)	**Machine Learning:** SVM, Decision Tree, RF, J48, CART. **Feature Selection:** feed forward and feedback selection, IG , Chi square	----	Twitter Data set: Data by Ada Derana, News First, Ceylon Today, Lanka Breaking News, ITN.	Proposed a new information theory based feature ranker named Ratio Method that result in improved efficiency.
Bac Le et al. [13] (2015)	Machine Learning :SVM and NB IG, Bigram, Object-oriented extraction for feature selection	AlchemyAPI, Scikit-Learn tool	Twitter : AlchemyAPI, Zemanta, OpenCalais	Accuracy enhanced.
BS Dattu et al. [14] (2015)	SVM , NB	TwitterSentiment and SentiStrength	Real Time Twitter Data related to 'NFL teams'	SVM performed better than NB and NB is insensitive to unbalanced data.
O Kolchyna et al. [15], (2015)	Lexicon-based and machine learning (SVM, NB)	WEKA	SemEval-2013 competition, task 2-B	Combining lexicon with SVM and NB enhance accuracy.
J Prusa et al. [16] (2015)	Ensemble Technique : Bagging and Boosting using 7 base learners (5NN, C4.5D, C4.5N, MLP, LR, SVM, RBF).	WEKA	Sentiment140 (S_3000, S_359)	Ensemble Classifier enhances accuracy. Enhancement in result is less uniform for smaller size data set.
K.L Devi et al. [17] (2015)	Ensemble classifiers: Bagging and Boosting (SVM, NB, ME) Feature Selection using MI and Chi-square	----	Twitter dataset: SemEval 2013, Task 9	Ensemble based learners produce improve accuracy than base learners.
Y Wan et al. [18] (2015)	Majority voting ensemble(NB, SVM, Bayesian Network, RF and C4.5) and IG Feature selection	WEKA	12864 tweets related to airline service Twitter dataset.	Ensemble outperformed with an accuracy of 91.7%. RF learner was best in machine learners with accuracy 90.8%.
J Prusa et al. [19] (2015)	Four classifiers(5-NN, C4.5, LR, MLP) 10 feature selection methods: CS, GI, KS, MI, PR, PRC, ROC, S2N, SAM, WRS.	WEKA	Twitter Dataset: Sentiment140	**Best feature selection methods** - CS and MI. **Best feature set size -** 100 to 200. CS, MI, PRC, KS and ROC resulted in performance enhancement in comparison to using no feature selection
R Mansour et al. [20] (2015)	Ensemble Classification. Feature selection. NCR Feature set, LLR Feature selection.	Natural Language Toolkit (NLTK)	Twitter Dataset: SemEval and CrowdScale	Performance gain of 9.9% on CrowdScale and 11.9% on SemEval.
O Abdelwahab et al. [21] (2015)	SVM and NB	Python NLTK library	SEMEVAL 2014	SVM is more Robust than NB but NB is faster comparatively. Increase in training set size after 20 % have very little effect on accuracy enhancement.
S Akter et al. [22] (2016)	Lexicon Based Approach / Dictionary Based Approach.	Graph API, C#	FOODBANK: Facebook group in Bangladesh	Identified sentiment behind a status post of Facebook by using lexicon based approach.
M Bouazizi et al. [23] (2016)	SVM	WEKA and OpenNLP, Gate Twitter partof-speech tagger,	Twitter	Sarcasm Detection: Accuracy of 83.1% with to 91.1% precision.
P Grandin et al. [24] (2016)	NB	JavaScript and Ruby on Rails	Twitter	Sentiment classification of Portugal tweets, Good Accuracy with improved classification time.
Nádia et al. [25] (2016)	Hybrid (Classification and Clustering Ensembles) : Semi-supervised approach (Labeled and Unlabeled data), SVM, Lexicon Based	----	SMS2013, Twitter2014, Twitter Sarcasm 2014, LiveJournal, Twitter2013.	Proposed framework shows the improved accuracy (80%).

A Tripathy et al. [26] (2016)	SVM, NB, Maximum Entropy and Stochastic Gradient Descent. Features: unigram, bigram, Trigram and n-gram features.	----	Twitter IMDb data set	Up to bigram feature set accuracy enhances, After that for tri, four or five gram accuracy of decreases. A combination of Bi gram, Tri gram with POS also worked well. Unigram + Bigram (ME) - 88.42 Uni + Bi + Trigram (ME) - 83.36 Uni + Bigram (SVM) - 88.884 Uni+Bi +Trigram (SVM) - 88.944 Bigram (SGD) – 95
A Krouska et al. [27] (2016)	*Preprocessing Methods*. IG Feature Selection. Uni, Bi and 1-3 gram features. Machine Learners – NB, KNN, SVM, C4.5.	Snowball stemmer library, Rainbow list	Twitter OMD HCR STS-GOLD	Feature extraction improve accuracy. unigram and 1-to-3-grams perform better.
K Ali et al. [28] (2017)	SAaaS Model using spatio-temporal properties and Lexicon classifier	Sentistrength and Alchemy API . .Net framework by using ASP.Net/C#	Real world datasets from twitter, Instagram, Reddit, news forum	Identified sentiment and location of disease outbreak.
AU Hassan et al. [29](2017)	Machine Learning classifiers(SVM, NB, Maximum Entropy) Binary and Multiclass classification, Voting	----	twitter dataset and 20newsgroups	Detect the depression level of users. SVM performed better than NB. SVM - 91%, NB – 83%, ME – 80%.
MR Huq et al. [30] (2017)	k-nearest neighbor, SVM	Java language	Twitter	KNN with normalization and keyword base(5 features) performed good.
M Ahmad et al. [31] (2017)	SVM	WEKA	Twitter Dataset related to self-driving cars and apple products	Performance of SVM highly depends on Dataset.
J Brandon et al. [32] (2017)	Lexicon-based and machine learning	National Language Toolkit (NLTK)	Twitter	High correlation of 94 percent was found with polling data.
R Wijayanti et al. [33] (2017)	Voting based ensemble technique (NB, SVM, decision tree, LR) and feature selection using TF-IDF, sentiment lexicon score and term presence	----	Twitter: Indonesian Twitter messages, Indonesian online marketplaces	Ensemble classifier enhance efficiency (accuracy - 91.59% and F1-score - 91.59%) but highly depend on base classifiers.
Z Jianqiang et al. [34] (2017)	Six Preprocessing Methods. Machine Learning Classifiers – NB, LR, SVM, RF.	GridSearch to find optimal parameters. scikit-learn for classifier.	Twitter Dataset: STS-Gold, SE-Twitter, SemEval2014, SS-Twitter, STS-test.	Removal of URL's, stop words and numbers hardly affects the accuracy. Random deletion of word reduces the accuracy. NB and RF are more sensitive to use of different pre processing techniques.
Rahman et al. [35] (2018)	Tree based algorithm, Depth search based algorithms.	T-Test	Facebook Accounts of UMP students	Detect reliable friend request.
Jianqiang et al. [36] (2018)	Deep convolution neural networks. BoW-SVM and BoW-LR	----	Twitter Data Sets: STSTd, SemEval2014 Task9, STSGd, SED, SSTd	GloVe-DCNN on the STSTd dataset performed best with accuracy 87.62%.
K Tago et al. [37] (2018)	Machine learning	T Test, Brunner–Munzel test	Twitter: Five thousand twitter accounts by using Twitter API.	As per results positive user participate more than negative users in building relationship in some particular conditions.
V Ikoro, et al. [38] (2018)	Lexicon Based	----	Twitter : Tweets of UK energy consumers	Consumers are more positive towards new companies and Multiple lexicon help to improve accuracy of sentiment analysis.
C Troussas et al. [39] (2018)	Voting base ensemble, Bagging and Boosting, Stack base ensemble (NB, SVM, KNN and C4.5) LR as Meta classifier	WEKA	Twitter OMD, HCR, STS-Gold	Stack base ensemble performed best with accuracy 89.02% in case of STS-Gold dataset.
MM Fouad et al. [40] (2018)	Majority voting based ensemble technique using SVM, LR, NB classifiers. IG feature selection	Java (Stanford Core NLP library) for feature extraction RapidMiner	Stanford-1K, Stanford-3K, Sanders, HCR	Ensemble classifier enhances efficiency but highly depend on base classifiers. IG selection boosted accuracy.

Y Emre Isik et al. [41] (2018)	Stack base ensemble classification, Ensemble at feature selection level.	----	Twitter	Enhanced accuracy than machine learners.
FT Giuntini et al. [42] (2019)	Expectation Maximization algorithm	Lime Survey tool,	Facebook	Relevancy of emoticons used in the Facebook posts
SE Saad et al. [43] (2019)	SoftMax (Multinomial logistic regression), SVR(Support Vector Regression), DTs(Decision Trees), and RF (Random Forest)	Python software	Twitter dataset provided by the NLTK	Decision tree proved to be the best.
S Vashishtha at al. [44] (2019)	Unsupervised Fuzzy Classification, SVM. Lexicon: SentiWordNet, AFINN, AFINN	Python	Twitter Dataset : Sanders Twitter Dataset, Nuclear Twitter Dataset, Apple Twitter Dataset, (STS-Test), Sentiment140, SemEval 2017, SemEval 2015 and Data used by Gilbert & Hutto, 2014, SemEval 2016.	The method based on Fuzzy Rule performed better than SVM. VADER and AFINN lexicon outperformed as compared to SentiWordNet.
K Elshakankery et al. [45] (2019)	HILATSA as Combination of lexicon based approach and machine learning classifiers (SVM, L2 Logistic Regression, RNN)	JAVA Libraries- LIBSVM, DL4J and LIBLINEAR	ASTD, Mini Arabic Sentiment Tweets Dataset, ArSAS, Arabic Gold Standard Twitter Data set, Syrian Tweets Corpus and Twitter dataset	The proposed approach with accuracy: 73.67% - 3-class classification 83.73% - 2-class classification
Martin-Domingo et al. [46] (2019)	Machine learning	Twitter Archive, Theysay and Twinword	Twitter : London Heathrow airport's Twitter account dataset	Theysay performed better than Twinword with 78.7 percent
M Naz at al. [47] et al. (2019)	Ensemble Technique using K-Nearest neighbor NB and SVM. FOA and mRMR feature selection algorithm.	MATLAB	Twitter : Blitzer's dataset, retrieved from UCI repository	Ensemble of KNN, NB, SVM with feature selection enhances accuracy.
JJ Bird et al. [48] (2019)	OneR, MLP, NB, NBM, RT, J48, SMO SVM, Ensemble classifiers: RF, Vote (RF, MLP, NBM), AdaBoost (RT), AdaBoost (RF), Vote (RT, NBM, MLP).	JAVA	Twitter : London based restaurant tweets from TripAdvisor	Vote (RF, NBM, MLP) performed best with 91.02 % accuracy.
M Khader et al. [49] (2019)	*Machine Learning Classifier: Naïve Bayes* PoS Tagging, lemmatization, weighting terms.	Apache OpenNLP of MapReduce (Hadoop).	Stanford Twitter Sentiment data set	5% increase in accuracy for Stanford Sentiment data set.
R Ahujaa et al. [50] (2019)	*Machine Learning Classifier:* Decision Tree, SVM, KNN RF, LR TF-IDF, NB. Feature selection: N-gram TF-IDF	----	Twitter Dataset: SS-Tweets	TF-IDF performance is 3-4 % higher than N-gram feature.
M bibi et al. [51] (2019)	**Machine Learning:** SVM, NB *Feature Selection : IG and PC*	WEKA	Twitter Dataset: HCR, SS-Tweet, FleTweetsPak	CAARIA: Proposed feature selection technique. CAARIA proved to be better than IG and PC with AUC (F-measure) value 0.79.
M Bibi et al. [52] (2020)	Clustering and classification technique using majority voting, k-means, SVM and NB classifiers	WEKA	Twitter Data Sets : **HCR** - Health Care Reform, **SS-Tweet** - Sentiment Strength Twitter Dataset **STS-Test** - Stanford Twitter Sentiment Test Set	Majority voting based cooperative clustering is better in terms of quality
Z Kermani et al. [53] (2020)	Machine Learning-based approach and genetic algorithm for calculating feature weight.	NLTK, Scikit packages of Python software	Twitter Data Sets : Stanford test data corpus, STS-Gold, Strict Obama McCain Debate, Obama McCain Debate Datasets.	Efficiency of proposed method TSA is improved but time complexity is poor, specially for big twitter data sets.
EA Afify et al. [54] (2020)	Machine Learning, Deep Learning.	Machine Learning-Scikit-learn, Deep Learning-Keras with TensorFlow	Facebook	Evaluate Facebook profile credibility. Identify fake and genuine users.
SR George et al. [55] (2021)	Machine Learning Classifier.	Netnography	Facebook	Proposed conceptual framework for Facebook opinion mining

V. SURVEY OUTCOMES

In the present survey paper we have conducted a systematic survey of literature related to social networking site's sentiment analysis or opinion mining. From 2009 to 2021 several researches have been conducted and technology evolved from simple dictionary-based sentiment prediction to ensemble, fuzzy, deep learning and neural based sentiment analysis. Detailed outcomes of researches are mentioned in Table I with tools and technologies used. Various advancements occur in the area of attribute selection, preprocessing and classifiers used. Data becomes big and technology changed as per data need. From the detailed survey of included literature, it has been observed that Naïve Bayes and SVM are the most explored machine learning classifiers. Lots of work has been conducted in the area of ensemble classification technique. The most of the researchers are attracted by Twitter opinion mining and Facebook is the second most explored social media platform. Sentiment 140 is quite a frequently used data corpus. WEKA, RStudio, Python and NLTK are used in several research implementations. Facebook and Twitter are relatively less unstructured and sentiment analysis does not include image, audio or video. As media content can be in any one of these forms also, so sentiment extraction from these resources can be quite interesting and important but challenging too. So lots of work has been done on text sentiment analysis and most of them target to improve efficiency of classification.

VI. CONCLUSION

The manuscript presents a survey conducted on 55 different research papers related to social networking site's sentiment analysis. The survey reflected the evolution and enhancement of tools and technologies from 2009 to 2021 for sentiment analysis. Twitter is the maximum explored social networking site in the area of sentiment analysis. WEKA, RStudio and NLTK are most popular tools used by researchers. The area of text sentiment classification has been widely explored with the use of advanced classification techniques, big data technology, better simulation tools and most of them target to improve efficiency of sentiment classification. A new scope can be sentiment analysis from images, audio and video content as this area is comparatively untouched and huge repository of audio and video content is available on social media.

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