A Literature Review On Sentiment Analysis Techniques Involving Social Media Platforms

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***Abstract*— Sentiment analysis refers to the active field of Natural language processing that extracts the attitude and emotion of a human being. With the growth of social media, more people are using online platforms such as Twitter, Facebook, YouTube, etc. to express their opinions. Twitter is considered to be the purest platform to express one's views. Mostly all personalities from diverse backgrounds use twitter. Therefore, it becomes a need of the hour to study public opinion. This provides us valuable information and helps organizations and governments to contemplate mass public opinion and take better decisions accordingly. In this review paper, an extensive and exhaustive guide to the subfield of Natural language processing (NLP), focusing precisely on sentiment analysis on twitter dataset, has been presented. It highlights three main approaches to analyze the sentiment. We have summarized and compared the approaches on different metrics opted by various researchers in the field of sentiment analysis using the twitter dataset. With so much active work in this field, this review paper would assist all future researchers.**

Keywords*— *Text classification, Sentiment Analysis, machine learning, Social media, Deep Learning, Natural Language Processing

I. Introduction

Artificial Intelligence right from its origination, has made a remarkable contribution in providing realistic and non-theoretical solutions to essential societal and human issues under a variety of different domains, including NLP, where computational and linguistics techniques are used in order to assist the computers to recognize and produce the desired results. Several noteworthy developments in the area of NLP cover sentiment analysis (SA), information retrieval (IR), emotion detection (ED), text summarization systems, and questions and answering (Q & A) systems. The Core intent of Sentiment analysis is to inspect the human language and extract significant patterns of information. It analyses the sentiments or the attitude of the user towards the subject of interest. This helps the organisation to consider public opinion and make decisions accordingly. It is used to classify sentiments as objective or subjective, positive or negative or neutral, summarizing opinions and detecting spams.

Micro blogging websites such as Twitter have emerged as a giant reservoir consisting of a vast variety of information. Users of these websites proactively participate in discussions on various current issues/topics and are freely able to express their concerns and opinions on them. According to a Forbes report, on an average 456000 tweets were made by different twitter users present all over the globe every minute in the year 2018 [1]. Hence this development of vast unstructured data available has provided data scientists and researchers with a huge opportunity of exploration in the field of sentiment analysis. According to statistics, Twitter presently has a huge 330 million active monthly user base and thereby is accessible through its website interface, SMS, and other mobile devices [2]. Twitter remains to be a better choice among researchers working in the field of sentiment analysis of text in comparison to its other popular existing counterparts. Though Facebook has a much higher user database as compared to Twitter, the user content available is mixed with photos, videos, etc, which is not of much use to researchers working in the field of sentiment text classification. Hence in this way, Twitter is viewed as the purest form of ideas and thoughts expression social media platform. Another probable reason for the widespread use of Twitter could be the regular updating of the twitter corpus with the required information only. [3]

This review paper compares and summarizes the recent work of researchers and data scientists working in the domain of SA, focusing on Twitter as a primary source of data. This paper comprises VII sections, while section II deals with the various levels of SA. Section III deals with the associated work done until now in the domain of SA in detail. Section IV briefly outlines each technique used in the research areas. Section V provides the general phases of sentiment analysis and contains the comparison table (Table-1). Finally, section VI discusses the various quality attributes used by researchers in the work, and section VII concludes the paper.

The literature search was performed for research papers published by different publishers in recent years (Fig. 1). The investigation focused on retrieving documents written in English and included a set of keywords involving the topic "Sentiment analysis on twitter dataset." Various approaches could be used to analyze the sentiment ranging from lexicon to deep-learning. With so much active research in this domain, our review paper could witness a valuable resource to future researchers.

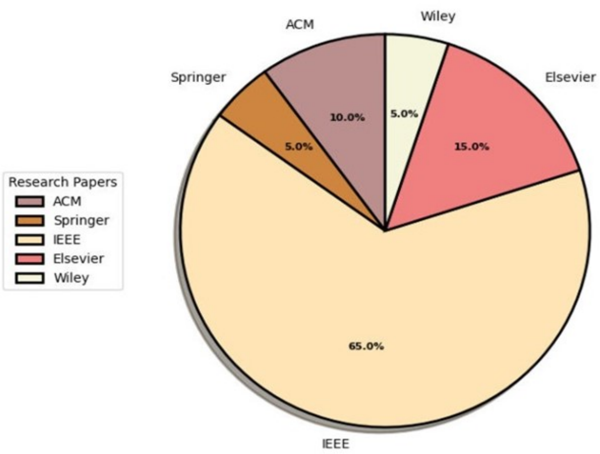

Fig. 1 Number of Published Papers in 2019-2020

II. Sentiment Analysis

Sentiment analysis is meant to inspect the emotions, attitude, and expression of a person and classify it accordingly into positive, negative, and neutral labels. Broadly speaking, sentiment analysis is subdivided into 3 main levels which are as follows:

1. Document Level Analysis: At this stage, the task is to analyze the documents sentiment as a whole. The sentiment of the whole document is then further classified as positive, negative, or neutral depending upon the text. Thus a comparative learning text can't be considered under this level.

2. Sentence Level Analysis: At this stage, the task is to analyze a particular sentence and then decide whether that sentence represents a negative, positive, or a neutral opinion. A sentence that does not show any opinion is classified as a neutral sentence.

3. Aspect Level Analysis: Both the above discussed levels are unable to evaluate one's likes and dislikes. Hence aspect level presents a throughout analysis. The fundamental key task of the entity level is identification. Earlier Aspect level was known as feature level.

III. Background

Research papers by different authors can be classified on the basis of approaches they have adopted.

Singh et al.,[4] analyzed the sentiments of people regarding the Motor Vehicle Act, 2019. The author analyzed polarity on the twitter data extracted using Twitter streaming API. The author recorded most tweets are positive even if the new rules are a burden for the public, they tend to tweet positive because of the betterment of the society [4]. This work would help the government to consider public opinion and make decisions accordingly.

On similar lines, Muntazar et al [5] correctly analyzed the tweets and predicted the opinion of the UK parliament and EU over Brexit. The author used Textblob to measure polarity[5].

V. Sindhu et al.,[6] successfully depicted the people's positive, negative and neutral remarks about a person, trend, or object using visualization techniques such as histogram, word cloud, and Pie chart. The author used Bag of Words for feature extraction and classification over manually extracted twitter data [6].

Olivier Kraaijeveld, Johannes De Smedt [7] used a cryptocurrency-specific lexicon-based sentiment analysis approach which was then integrated with bilateral Granger-causality testing to predict the price return of nine cryptocurrencies[7]. The VADER lexicon was accompanied by the addition of tokens which were obtained from the Loughran & McDonald financial corpus, 2016, which was then applied over a dataset having 24 million entries which were obtained using various twitter APIs and CoinMarketCap. Finally, a heuristic approach was used which led to the conclusion that about 1% to14% of the tweets obtained were posted on twitter by various Twitter ''bot" accounts. [7]

Ansari et al., [8] in their paper analyzed the sentiment for various national political parties of India with reference to the Lok Sabha elections(2019) using classical ML classifiers with feature extraction using the TF-IDF approach. The ML classifiers used were Random Forest, LSTM, Logistic Regression, SVM, and Decision Tree. According to them, their study revealed that LSTM and Random Forest performed better on various metrics while the overall analysis revealed that the performance of SVM was the poorest amongst all. [8]

Liang, Umarani Ganesh Babu, Thomas Thorne [9] in their approach used a new ML network called Gaussian Process Dynamic Bayesian Network that integrates Gaussian Process Regression to evaluate the sentiment in the previous period at a given point of time based upon the relevant domain. This paper also builds a Sequential Monte Carlo sampler which executes Bayesian inference on a Dynamic Bayesian Network model. This helps us to infer networks showing how opinion in a particular domain can lead to a change of opinion in the other domain.[9]

Zhai Penghua, Zhang Dingyi [10], used various deep learning approaches to analyze the sentiment of the dataset obtained from SemEval-2014-Task2014 and twitter. They proposed a bidirectional GRU neural network model that embeds the attention mechanism to solve the task of aspect-level sentiment analysis. [10] The mentioned model extracted features using the GloVe technique and achieves good performance with different datasets. Authors compared the model with various state-of-the-art models such as GRU, CNN, and TC-LSTM. [10] The comparison between DL approaches could also be studied in the paper by Cheng, Song Tsai [11].

MSR Hitesh, Vedhosi, Y.J. Abhishek Kalki, Suraj Harshaand, Santoshi Kumari [2] compared various feature extraction techniques such as word2vec, TF-IDF, and Bag of words using Random Forest classifier. They found word2vec performs better than other embedding techniques [2].

The rest of all research papers are reviewed and mentioned in Table 1.

Table 1: The following table contains different techniques opted by researchers on Sentiment Analysis performed on various social media platforms

Year, Publication	Dataset used	Technique	Feature Represent-ation	Observations	Accuracy
2020,[10] (ACM)	SemEval-2014 Task2014, Twitter	GRU, CNN, TC-LSTM, ATAE-LSTM, ABAE-Bi-GRU	GloVe	• Used a bidirectional GRU neural network model that merged the attention mechanism to solve aspect-level sentiment analysis • GRU has a worst performance amongst all.	ATAE LSTM: 91% ABAE-LSTM:81.2%
2020,[1] (IEEE)	Sentiment140	Logistic Regression	LSA TF-IDF , word2vec, ELMo	• Showed that word2vec has the highest accuracy of 86.87% for feature extraction as compared to TF-IDF,ELMo, and LSA over RF classifier . • Showed the accuracy of ELMo is low when compared with Word2Vec, probably due to small dataset.	Word2vec: 77% ELMo: 73% LSA –TFIDF:71.0%
2020,[12] (Springer)	Live tweets from Twitter	SVM,KNN	N-gram	• Employed N-Gram modelling approach to design the feature extraction algorithm. • Observed that absolute competence is still not achieved.	KNN : 91.45 % SVM : 81.51%
2020,[13] (IEEE)	Twitter	Hadoop based deep RNN method		• Hadoop based deep RNN classifier model delivered maximal specificity, accuracy, sensitivity and of 0.9157, 0.9302, 0.9404 respectively.	93.02%
2020,[14] (IEEE)	Airline sentiment (Welkin10)	SVM,KNN, Random Forest (RF)		• Used K-fold cross-validation (K-10) for training and testing the available datasets. • Showed Random forest classifier as compared to other classifiers had more accuracy.	RF: 81% SVM: 74% KNN: 58%
2020,[15] (Elsevier)	Chilean Earthquake, 2010, Catalan Independence ,2017	TAN,NB, BF-TAN, SVM, Random forest	Bag of words	• Observed that SVM obtained the best performance in dataset 1 and RF in dataset 2.	SVM: 81.2% BFTAN: 76% NB: 74.2% RF: 72.5% TAN: 72.1%
2020,[16] (IEEE)	Github and kaggle (Demonetizati-on sentiment analysis)	SVM, Random Forest, Decision Tree	Bag of words	• Categorized every single feature extracted from the text data into morphological and Word N gram features. • Showed that Decision tree and random forest have more accuracy than SVM for sentiment analysis.	RF: 99.4% Decision Tree: 99.3% SVM: 91.6%
2020, [17] (IEEE)	Sentiment140 , Crowdflower Data	SentiWordNet, MNB, LR, SVM, RNN with LSTM, Ensemble models		• Investigated that Lexicon based approach were less accurate as compared to ML approach while RNN is observed to be most accurate	RNN With LSTM :82% SVM: 77.98% Ensemble 77.67% MNB: 76.52% LR: 76.44% SentiWordNet: 45%
2020,[18] (IEEE)	Live tweets: bitcoin tweets, First GOP debate, Imdb movies reviews	NB, MNB, Bernoulli classifier, LR, SGD, Linear SVC, NuSVC, LSTM, CNN		• Showed Deep learning techniques are more accurate than ML techniques or polarity based techniques	LSTM: 97% CNN LSTM : 95% MLclassifiers:82%
2020,[9] (IEEE)	9.72M manually annotated tweets	Gaussian Process Dynamic Bayesian Network		• Proposed Gaussian Process Dynamic Bayesian Network is 92% accurate to evaluate the sentiment in the previous period at a given point of time based upon the relevant domain.	92%
2020,[19] (Wiley)	Data collected from 100 twitter users with 10,275 entries.	SVM, Gaussian models: (SGM) & (MGM)		• Proposed a multivariate Gaussian to identify potential abnormal emotions of a user. • The user data was scored by joint probability density of multivariate Gaussian and was determined by a threshold. It was observed that abnormal emotion had a low joint probability density.	84.60%
2020,[20] (IEEE)	7368 manually annotated tweets & Airline-Sentiment	Feature ensemble method.		• Revealed that the proposed method based on feature ensemble and CNN models improved the performance in the sentiment analysis of tweets containing fuzzy sentiment.	F1-Score: 0.72

2020,[7] (Elsevier)	Cryptocurrency tweets, financial data from CoinMarketCap	Lexicon-based , bi-lateral Granger-causality testing.		• Predicted the price returns of Litecoin, Bitcoin Cash and Bitcoin by applying a crypto currency-specific lexicon-based approach and bi-variate Granger-causality tests. • Discovered that bots posted 1-14% crypto currency related tweets using a heuristic approach	The polarity scores are relatively constant Mean polarity= 0.33.
2019,[21] (IEEE)	Live tweets in English only	Bagging, Lexicon approach, SVM, MAXENT, DT, RF, Naive Bayes,		• Used the approach of 4-fold cross validation for training and testing. • For both the available data's of McDonalds and KFC, Testing data of several supervised algorithms proved that Maxent (Maximum entropy) had the highest accuracy.	F-score: Bagging: 0.70 SVM: 0.67 RF:0.62 Maxent: 0.58 DT:0.57 Naive Bayes: 0.51
2019,[8] (Elsevier)	3896 manually annotated tweets	LSTM, SVM, Decision Tree, LR, RF	TF-IDF	• Analyzed the sentiment for various national political parties of India with reference to the Lok Sabha elections, 2019. • Presented that Random Forest and LSTM performed better on various metrics while the performance of SVM was found to be the poorest of all.	F-score LSTM: 0.74 RF: 0.74 DT: 0.70 LR: 0.69 SVM: 0.39
2019,[11] (ACM)	YouTube, Face book	LSTM, Bi-LSTM, GRU	word2vec, GloVe	• Used a DL-based framework to handle slang and special social language.	Bi-LSTM: 87.17% LSTM: 80.83% GRU: 64.92%
2019,[2] (IEEE)	35,000 manually annotated tweets	Random forest	word2vec, Bag of words, TF-IDF	• Showed that word2vec provides the highest accuracy of 86.87% for feature extraction as compared to TF-IDF and BOW over RF classifier.	Word2Vec: 86.8% TF-IDF: 84.4% Bag-of-Words: 83.4%
2019,[3] (IEEE)	1.1M manually annotated tweets	SentiWordNet		• Observed a net negative sentiment using lexicon-based system on the 'US ban Huawei' topic i.e. against US ban huawei. • Visualized the data using geographic vision.	Negative sentiment score = - 1641
2019,[22] (IEEE)	Live tweets	Sentiment dictionary		• A model to anticipate the boom of Indian Major Telecom Companies in terms of subscriber addition was proposed. • Indicated that the overall public incorporates a relatively stronger positive opinion concerning Reliance Jio.	Sentiment score: Jio 7530 Vodafone 3752 Airtel 2841, Idea 1353

IV. Existing Methodology

This section calls attention to machine learning (ML), deep learning (DL), lexicon-based approaches, and other general approaches to detect sentiments from available texts.

A. Rule construction approach[23]*:*

The rule construction approach circumscribes lexical affinity methods, and keyword recognition (KR)[23]. These methods deal with the constructive use of sentiment dictionaries or lexicons. There are many Keyword recognition dictionaries, namely the WordNet, SentiWordNet dictionaries, EmoSenticNet, the National Research Council of Canada (NRC) lexicon, and DepecheMood. The main aim is to find the occurrences of sentiment based search words in a sentence. Once such lexicon is identified in the sentence, polarity and a label are designated to that sentence. Examples of this approach are [17], [21], [7], [3] and [22] respectively.

B. Machine Learning approach:

It solves the analysis problem by categorizing the texts into various labels through ML classifiers' implementation.

- *Naive Bayes (NB):* Belongs to a family of "probabilistic classifiers" supported by applying the Bayes theorem. This is used in seen in, e.g., [15].
- *Support Vector machines (SVM):* It uses a hyper-plane in N-D space that clearly classifies the data points. Here N is the number of features. This model is used in [12], [14], [15], [16], and many more.
- *Logistic regression (LR):* Provides a method for reducing and classifying words existing in the document and special features in the same instance. E.g., in [18], [1].
- *Random Forest (RF) and Decision Trees (DT):* Both are non-linear classical supervised ML classification algorithms based upon iteratively asking partition data questions. This approach was observed in [8], [16], etc.
- *K nearest neighbour (KNN):* This algorithm is based on finding the nearest k neighbor of a decision. It is used for non-linear classification. This could be witnessed in [12], [14], respectively.
- *Maximum Entropy (Maxent):* A probabilistic classifier which depends upon the Principle of Maximum Entropy. It chooses the dataset having the largest entropy amongst all the models that fits our training data. [21]

Other approaches could also be seen in ML such as Tree augmented Naïve Bayes (TAN) [15] , Bayes Factor-TAN (BF-TAN) [15], Multinomial Naïve Bayes (MNB) [17][24], bagging [21], Bernoulli classifier, Stochastic gradient descent (SDG) , Linear SVC, NuSVC[18], Gaussian models [19], and Bayesian network [9].

C. Deep-Learning approaches:

Deep learning is another refined derivative of machine learning, which is based upon multilayer ANN (artificial Neural network) to mimic the given tasks. The Neuron is the smallest and information processing unit of the neural network, It learns to perform numerous jobs by updating the weights between two neurons, just as working of a living brain. Deep learning models are mainly of two types: CNN [25] and RNN [13]. CNN is presented in [10], [18].There are two more refined models of RNN: (GRU)Gated Recurrent Unit [11], (BI-LSTM) Bidirectional long short-term memory [11], and (LSTM) Long Short-Term Memory [26]. Cheng et al. [11] used all the sophisticated approaches of RNN.

D. Other Techniques:

TextBlob and NLTK are Python in-built libraries for processing the data in the textual form. Textblob provides a simple Application programming interface for doing common NLP tasks such as noun phrase extraction, POS tagging, sentiment analysis, translation, classification, etc. Many authors such as Cheng et al. [11], Muntazar et al. [5], Singh et al. [4], and Sahu et al.[27], used these techniques

V. Phases Of Sentiment Analysis

The sentiment analysis includes five stages: data extraction, data pre-processing, feature extraction, sentiment classification, and finally, analysis of output.

A. *Data extraction:* In this initial step, various approaches to data collection can be showcased as extracting real-time tweets using twitter APIs, datasets available at multiple sources, or collected by multiple authors. Tweets extracted from Twitter may be unstructured, semi-structured, or structured type.

B. *Data Pre-processing:* They can be collected using different programming languages such as R or python. The input data set is transformed into a structure that is suitable for feature representation using various NLP tools. Tasks involved in the pre-processing study are:

- Removing the twitter handles (for twitter dataset)
- Removal of Punctuations, URLs, Stop words, Special characters.
- Stemming and Tokenization of dataset.

C. *Feature Representation:* At this stage, features are extracted to define the polarity of tweets. As observed, the authors used various techniques such as TF-IDF, N-grams, Bag of words, word2vec, and Glove.

D. *Sentiment Classification:* The fundamental task of sentiment analysis is to segregate the tweets depending upon their polarity. The polarity of a text may be neutral, negative or, positive. Classifiers are used to extract the sentiment of tweets.

E. *Analysis of output:* Evaluation of the obtained result using different metrics helps to take decisions regarding the model. It also paves the way for comparing other techniques. The result is expressed using pie charts, bar-graphs, and measured parameters.

VI. Discussion And Result Analysis

Analysis of the result is mostly used to test the accuracy of each model and verify. It also helps us to depict the results. This includes accuracy, F-score, recall and Precision, hence collectively called key performance indicators (KPIs). [14].

A. *Accuracy:* Is defined as the percentage of correctly classified instances.

$$Accuracy = \frac{True\ Positive + True\ Negitive}{All\ Samples} \quad -(1)$$

B. *F-score:* Is defined as the harmonic mean of recall and precision.

$$F - Score = 2\left(\frac{Precision\ X\ Recall}{Precision + Recall}\right) \quad -(2)$$

C. *Precision:* Defines the percentage of the relevancy of the obtained results.

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad -(3)$$

D. *Recall:* Defines the percentage of total relevant results correctly classified.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negitives} \quad -(4)$$

Other ways is to visualise the results using bar-graph analysis, histograms, pie-charts, heat maps and creative approaches such as word cloud as in Qing Lim [1], geographic visualisation, e.g., [3].

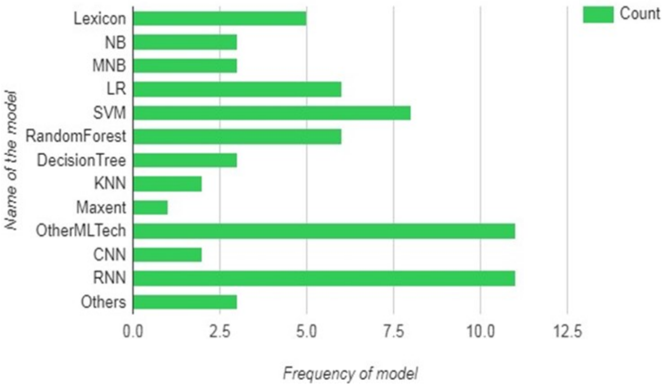

Fig.3 Model Frequency Distribution

VII. Conclusion

This paper introduces the concept of sentiment analysis, 3 main available approaches, highlights some important datasets available for opinion mining. This paper discusses the current available state-of-the-art approaches compared to the various available metrics. It is observed that the most commonly used techniques for sentiment analysis are ML techniques, specifically SVM classifier and Naive Bayes. While RNN and its derived models are most opted classifier in deep-learning *(Fig.3)*. However, amongst the various techniques, deep-learning techniques outperform machine learning techniques and lexicon based approach [17]. Chandra et al. [18] showed that the best machine-learning classifier has an accuracy of 82%, while deep-learning approaches like LSTM and CNN witnessed 97% and 95% respectively. Lexicon based technique performance is the poorest amongst all especially when large dataset is available[17]. Highest accuracy observed is 99.4% using Random Forest as a classifier presented in [16]. The performance of each approach heavily depends upon size and type of dataset. Future work includes areas such as crime detection i.e., mitigation by interpreting messages of victims so as to identify the menacing words, analysis of patient messages to determine his level of depression, etc. Finally, the cultural bonding of a person greatly influences his sentiment towards any scenario. Our survey paper highly relies on English literature resources. However, research on sentiment analysis in other languages can also be worked upon.

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