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A Review on Twitter Sentiment Analysis Approaches

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***Abstract*—Sentiment analysis addresses the issue of interpreting the data presented in several contexts and realms in terms of feelings, interests, and opinions. It can be useful for industries that need an awareness of the views of people on any specific subject or case. Twitter is one of the most widely used micro blog sites where users can express their thoughts, views, and opinions, making it an excellent resource for analyzing sentiment. Several works from different years are studied and briefly described in this review article. The reviewed works are categorized according to their implemented classification algorithms. A contrastive analysis on various strategies and methods of sentiment analysis using Twitter data is carried out in this review paper. Additionally, performance analysis, research gaps, and future scope of Twitter sentiment analysis are addressed.**

***Index Terms*—Sentiment analysis, Social media, Twitter, Machine learning, Lexicon**

I. Introduction

Sentiment Analysis is the way toward extricating data from a given dataset. It joins Natural Language Processing with Artificial Intelligence and analysis of a text. The sentiment analysis approach is utilized to mine data and deciphers individuals' feelings, against a specific topic, about any function and others. The reason for performing sentiment analysis is to consequently decide the expressive course of the opinions of the user. As online media's data is not organized and structured, it increased the importance of sentiment analysis in the field.

Huge amounts of different user-created web- based media are ceaselessly delivered, including the reviews, remarks, blogs, conversations, pictures, and video-recordings. These correspondences offer important occasions to comprehend users' viewpoints on subjects of interest, and they contain data fit for clarifying and contemplating business and social marvels. Among the different web-based media stages, Twitter has encountered especially far and wideuser selection and rapid development in correspondence volume. Twitter is miniature writing for a blog stage where users' "tweets" reach their supporters or shipped off another user. Tweets regularly express a user's sentiment on a subject of interest, giving essential bits of insight on issues identified with society and business. Specialists have used data determined through Twitter sentiment analysis (TSA) to clarify individuals' assessment concerning any function and foresee deals and political, social, or financial developments. These and different utilization of data inferred through TSA are needy upon their fundamental ways to assess the notions communicated by users in their tweets. Thus, the researchers gave much exploration to create improved ways to deal with the TSA. Thinking about the prevalence of Twitter and ongoing investigations that have shown the estimation of data determined through TSA, we play out a survey of the bit by bit approach and the contrastive dissection of existing frame- works. There is a lack of publicly available datasets for twitter sentiment analysis. Sufficient data with proper labelling is not available. This problem causes uneven analysis of the works, as many of the works get dataset dependent. The reviewed works are performed to analyze different types of sentiments (General or event-based). In order to review and analyze the works equally, we have taken papers for general sentiment analysis.

II. Twitter Sentiment Analysis

A. Definition

Sentiment Analysis of Twitter is a particular region inside sentiment analysis, a prominent subject of exploration in computational semantics. Sentiment Analysis exercises incorporate order of assumption extremity communicated in a text (e.g., fair, negative, evenhanded), specific slant target/ subject, assessment holder ID, and recognizing sentiment for different parts of a point, item, or association.

B. Levels

Generally, sentiment analysis can be arranged into predominantly three unique levels:

- Document Level Analysis: It groups if the total archive shows positive feeling or negative feeling. The archive is on a single theme is thought of. In this way, messages which involve similar lore cannot be regarded under record level.
- Sentence Level Analysis: This level works sentence by sentence and chooses if the sentences show positive, negative, or unbiased sentiment. Unbiased, if a sentence does not offer any input implies it is impartial. It identifies sentence level reasoning with subjectivity order. That communicates factual data from sentences that offer emotional viewpoints and thoughts—for example, great- awful terms.

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TABLE I: Machine Learning Approaches

Referencing Works	**Technology**	**Datasets**	**Accuracy**
Asdrubal et al. [1] ´	Naive Bayes, SVM Decision Tree	Publicly available	For anger: 91.4%, joy: 78.8%, surprise: 81.3%, disgust: 89.7%, sadness: 76.8%, fear: 66.1%, ambiguous: 50.3%
Kalaivani et al. [2]	BPNN, SVM	Publicly available	69.24%, 66.85%
Anupama et al. [3]	Naive Bayes	Self constructed	83%
Ranganathan et al. [4]	SVM, LibLinear Model	Self constructed	98%
Xiong et al. [5]	SGD, SVM, NB-SVM, CNN	SemEval	85% with CNN and MAF
Wazery et al. [6]	SVM, Naive Bayes, KNN, Decision Tree, RNN, LSTM	IMDB, Amazon, and Airlines' twitter dataset	88%, 87%, 93% (LSTM)
Gupta et al. [7]	Naïve Bayes, SVM, Maximum entropy	Self- constructed	86.4% 73.5% 88.97%
Amolik et al. [8]	Naive Bayes, SVM	Self constructed	75%
Ficamos et al. [9]	SVM	Self constructed	74%
Gautam et al. [10]	Naive Bayes, SVM, Maximum Entropy, WordNet	Twitter Dataset	WordNet: 89.9%
Montejo-Ráez et al. [11]	SVM	Self constructed	SVM yielded Precision 64% (approx.)
Neethu et al. [12]	Naive Bayes, SVM, Maximum Entropy	Self constructed	90%
Bahrainian et al. [13]	Naïve Bayes, SVM, Maximum Entropy	Self constructed	89%
Po-Wei et al. [14]	Naïve Bayes	Twitter Dataset	76.8%

- Aspect/ Entity Level Analysis: The aforementioned levels do not discover people groups like and aversions. Aspect/Entity level gives all through examination. Aspect/Entity level was prior known as the feature level. The root busi- ness of this level is to distinguishing proof.

C. Approaches

Sentiment analysis can be performed in subsequent approaches:

- Keyword Spotting: This strategy orders the content dependent on the presence of genuinely exact words in it. Hence, the words or watchwords present in the content have signif- icance regarding sentiment analysis.
- Lexical affinity: Lexical affinity doles out self-assertive words a probabilistic similitude for a specific feeling.
- Statistical methods: It measures the demeanor or focus of full of feeling watchwords and word coincident frequencies on the base of an enormous preparing corpus.

D. Features

Features Twitter Sentiment highlights are as per the following:

- Sentiment features (SENF): Extracts the positive and negative sentiment from words and emotions.
- Syntax-based features (SYNF): This shows question, exclamation, parentheses and quotation marks and the total count of existence in the sentence.
- Semantic features (SEMF): Deals with the logic form of the sentences.
- Unigram-based features (UGF): As seed words for a user-defined input, this includes hypernyms (i.e. more general) and hyponyms (i.e. more specific) features.
- N-gram features (NGF): To specify a feature, N number of sequential words are extracted as a group.
- Top words features (TWF): This extracts the words which are highly occurring in a sentence.
- Pattern-based features (PTF): Use Part-of-Speech tags (for example, positive and negative tags) to derive trends in sentiments, names, positive and negative verbs, positive and negative adjectives, pronouns, etc.)

E. Steps for Twitter Sentiment Analysis

Fig. 1: Twitter Sentiment Analysis Workflow

1) Data Collection: First beginning by picking a subject, then tweets with watchword are gathered and implemented for sentiment analysis. Tweets can be an organized, semi-organized, and unstructured sort. Tweets can be gathered utilizing distinctive programming dialects (i.e. R, Python). Figure 1 shows the Twitter sentiment analysis workflow.

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TABLE II: Deep Learning Approaches

Referencing Works	Technology	Datasets	Accuracy
Ge et al. [15]	LSTM, Spark	Sentiment 140, Twitter dataset	Positive: 82.1% Negative: 79.9%
Jianqiang et al. [16]	SVM, CNN	STS-Test, STS-Gold, SS-Twitter, SE-twitter.	87.62%
Dhar et al. [17]	CNN	Product Data Review, Twitter Dataset	74.15%, 64.69%
Vateekul et al. [18]	LSTM, DCNN Naive Bayes, SVM	Twitter Dataset	LSTM: 75.30% DCNN: 75.30%

TABLE III: Lexicon-based approach

Referencing Works	Technology	Datasets	Accuracy
Arslan et al. [19]	Lexicon based approaches	STS, Self-constructed	Dynamic: 80% Static: 92.64%
Feng et al. [20]	Lexicon based approaches	SemEval 2007, Sentiment Twitter	75.2%, 76.8%
Hu et al. [21]	Lexicon based approaches	Stanford Twitter Sentiment, Obama-McCain Debate	STS: 96.11% OMD: 88.84%
Subhabrata et al. [22]	TwiSent	Self-constructed	71%
Saif et al. [23]	SentiCircles	OMD, HCR, STS-Gold	72.39%

2) Preprocessing: Data preprocessing is only sifting the information to eliminate the deficient boisterous and conflicting information. Removal of Retweets, Removing URLs, Punctuation, Numbers, and other special characters, Stopwords removal, Stemming, Tokenizatioing are associated with pre-handling task.

3) Sentiment identification: Sentiment word recognizable proof is significant work in numerous uses of feeling examination and sentiment mining, for example, tweets mining, supposition holder finding, and tweet order. Sentiment words can be characterized as Positive words, Negative words, and indifferent words.

TABLE IV: Hybrid Approaches

Referencing Works	Technology	Datasets	Accuracy
Shehu et al. [24]	Hybrid of SVM and Random Forest	Self-constructed	86.40%
Kumar et al. [25]	SentiBank, SentiStrength	Publicly available	91.32%
Mittal et al. [26]	SentiWordNet, Probability-based method	Publicly available	72.56%
Zhang et al. [27]	ML, Lexicon	Self-constructed	85.40%

4) Classification: There are two fundamental strategies for sentiment analysis:
ML-based and lexicon-based. New exploration considers we have utilized a blend of these two techniques for better execution.

- ML approach: The Machine Learning (ML) approach utilizes a "directed learning" strat- egy for sentiment analysis. Support Vector Machines (SVM), Naive Bayes (NB), Maximum Entropy (ME) are some common Machine Learning approaches.
- Lexicon based methodology: The lexicon- based procedures to sentiment analysis are unaided learning as it does not need earlier preparation to arrange the information. K Nearest Neighbors (KNN), Hidden Markov Model (HMM) are some of the lexicon-based strategies.
- Hybrid approach: Few examination methods having a blend of both the ML and the lexicon- based methodologies used to improve sentiment analysis execution.

5) Analysis: The essential idea of sentiment analysis is to convert raw data into valuable information. After the analysis, the outcomes are shown on diagrams or graphs to show the exactness of the planned model. Quintessential comparisons with conversations are given if necessary.
This section is dedicated to analyzing the cur- rent works on Twitter sentiment analysis and comparison among their performances.

III. Literature Survey

A. Comparative Analysis of Techniques of Twitter Sentiment Analysis

The approaches most used in sentiment anal- ysis for Twitter data are: Machine learning based and Lexicon based approaches. The combination of Lexicon-based and Machine learning-based methods- the "Hybrid method" is also used in some cases. The deep learning method, which is a part of machine learning, is also being used individually as the technology advances. Therefore, we can categorize the existing Twitter sentiment analysis techniques as:
- Machine learning approaches
- Deep learning approaches

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- Lexicon based approaches
- Hybrid approaches

The analysis of the current work will be based on the methods mentioned above.

1) Machine Learning Approaches: A machine learning classifier trained on different characteristics of tweets is used by most of the proposed methods dealing with TSA. Some of the Machine Learning based Twitter sentiment analysis works are listed in the table I.

2) Deep Learning Approaches: Deep learning is one of machine learning's fastest-growing fields, used to solve problems like image recognition and natural language comprehension.The techniques of deep learning are also studied in the Twitter sentiment analysis industry and related works are listed in the table II.

3) Lexicon Based Approaches: The lexicon-based approach uses a previously constructed list of positive and negative words to extract the message's polarity or the person under investigation. Some of the Lexicon based Twitter sentiment analysis works are listed in the table III.

4) Hybrid Approaches: To achieve better efficiency, approaches that adopt the hybrid approach combines machine learning and lexicon-based techniques. Some of the Hybrid method based Twitter sentiment analysis works are listed in the table IV.

B. Performance analysis

We have visualized the examined works based on their implemented datasets and accuracy. Figure 2 depicts the im-

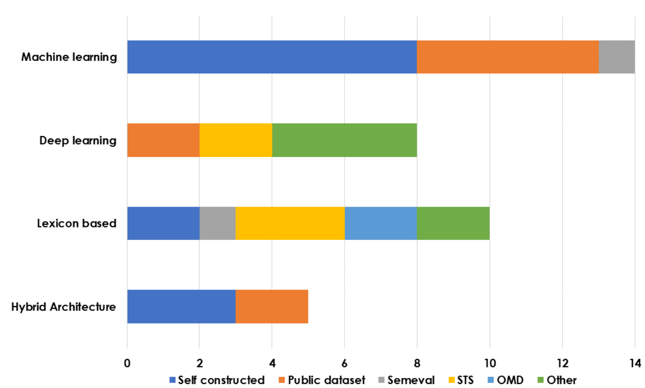

Fig. 2: Implemented Datasets for Twitter Sentiment Analysis

plemented datasets for the research works. For visualizing the datasets implemented, we have generalized all implemented datasets into more common dataset categories. For Machine learning-based works, most researchers have implemented self-developed datasets, collecting tweets using mostly Twitter API. Publicly available datasets were implemented in some of the proposed works. For Deep learning- based papers, publicly available datasets, STS were seen to be implemented. Most

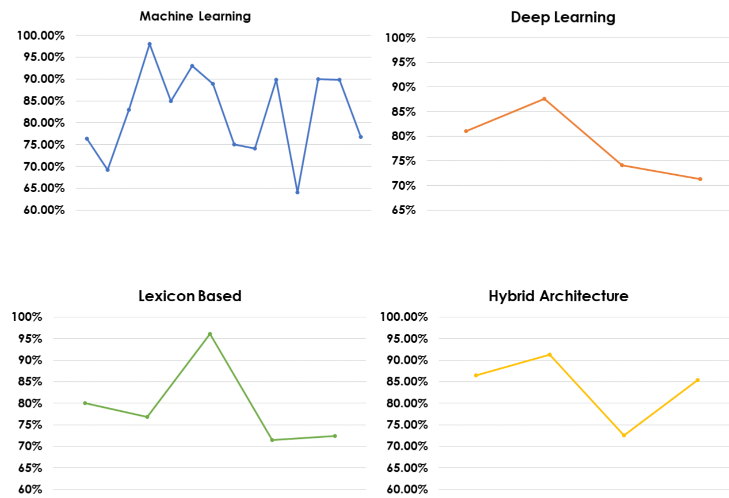

Fig. 3: Performance Analysis of the existing works

of the deep learning-based works have implemented other datasets.

For Lexicon based works, a variety of datasets were found to be implemented, including STS, OMD, Semeval, Self-constructed, and publicly available datasets.

Works based on hybrid technology are found to implement Self-constructed and Publicly available datasets for sentiment analysis purposes.

The accuracy of the studied works is shown in the Figure 3.

From the performance graph, Machine learning based works are found to show a large variation in accuracy. It also shows the highest accuracy (98%), among all the works studied. Deep learning-based and Lexicon based works are found to achieve satisfactory achievement, with a highest of 87.62% and 96.11% respectively. The works based on hybrid technology have shown improved accuracy rate than Machine learning and Lexicon based works. Although, many of the studied works performed sentiment analysis with the self-constructed dataset, which may show data dependency, resulting in a lower accuracy rate than the provided classification rate.

IV. Conclusion

16 Twitter is a significant web-based media stage that has encountered enormous development in correspondence volume and user participation worldwide. Many analysts and firms have perceived that significant experiences on business and society issues might be accomplished by breaking down the suppositions communicated in tweets' plenitude. This paper characterized the idea of supposition examination, discussed about different methods, approaches of conclusion investigation on Twitter datasets, and demonstrated a similar presentation examination by these methodologies. We have reviewed several sentiment analysis techniques, providing analysis on recent papers. The papers were analyzed based on their classification algorithms, datasets and accuracy to provide an overall

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review of twitter sentiment analysis. After breaking down many existing works, a few disadvantages and research gaps were discovered, inspiring this field's future exploration work. We have focused on the English language based datasets. Multi-language twitter sentiment analysis works are not used for this review paper. Our approach was mostly focused on general sentiment analysis. Event based or emotion specific works were not selected for this paper. Researchers need to explore new computational methods for improving the opinion order exactness on the social Web, making this field of study a conceivably dynamic for the experts.

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