# A Study on Sentiment Analysis Techniques of Twitter Data

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Project: Sentiment Analysis of social media data

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Abstract and Figures

The entire world is transforming quickly under the present innovations. The Internet has become a basic requirement for everybody with the Web being utilized in every field. With the rapid increase in social network applications, people are using these platforms to voice them their opinions with regard to daily issues. Gathering and analyzing peoples' reactions toward buying a product, public services, and so on are vital. Sentiment analysis (or opinion mining) is a common dialogue preparing task that aims to discover the sentiments behind opinions in texts on varying subjects. In recent years, researchers in the field of sentiment analysis have been concerned with analyzing opinions on different topics such as movies, commercial products, and daily societal issues. Twitter is an enormously popular microblog on which clients may voice their opinions. Opinion investigation of Twitter data is a field that has been given much attention over the last decade and involves dissecting "tweets" (comments) and the content of these expressions. As such, this paper explores the various sentiment analysis applied to Twitter data and their outcomes.

Example of Document-bas…

The Estimation Computation…

# A Study on Sentiment Analysis Techniques of T Data

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**Abstract—The entire world is transforming quickly under the present innovations. The Internet has become a basic requirement for everybody with the Web being utilized in every field. With the rapid increase in social network applications, people are using these platforms to voice them their opinions with regard to daily issues. Gathering and analyzing peoples' reactions toward buying a product, public services, and so on are vital. Sentiment analysis (or opinion mining) is a common dialogue preparing task that aims to discover the sentiments behind opinions in texts on varying subjects. In recent years, researchers in the field of sentiment analysis have been concerned with analyzing opinions on different topics such as movies, commercial products, and daily societal issues. Twitter is an enormously popular microblog on which clients may voice their opinions. Opinion investigation of Twitter data is a field that has been given much attention over the last decade and involves dissecting "tweets" (comments) and the content of these expressions. As such, this paper explores the various sentiment analysis applied to Twitter data and their outcomes.**

**Keywords—Twitter; sentiment; Web data; text mining; SVM; Bayesian algorithm; hybrid; ensembles**

## I. Introduction

Sentiment analysis is also known as "opinion mining" or "emotion Artificial Intelligence" and alludes to the utilization of natural language processing (NLP), text mining, computational linguistics, and bio measurements to methodically recognize, extricate, evaluate, and examine emotional states and subjective information. Sentiment analysis is generally concerned with the voice in client materials; for example, surveys and reviews on the Web and web-based social networks.

As a rule, sentiment analysis attempts to determine the disposition of a speaker, essayist, or other subjects in terms of theme via extreme emotional or passionate responses to an archive, communication, or occasion. The disposition might be a judgment or assessment, full of emotion (in other words, the passionate condition of the creator or speaker) or an expectation of enthusiastic responses (in other words, the impact intended by the creator or buyer). Vast numbers of client surveys or recommendations on all topics are available on the Web these days and audits may contain surveys on items such as on clients or fault-findings of films, and so on. Surveys are expanding rapidly, on the basis that individuals like to provide their views on the Web. Large quantities of surveys are accessible for solitary items which make it problematic for clients as they must peruse each one in order to Subsequently, mining this information, distir assessments and organizing them is a vit Sentiment mining is a task that takes advanta information extraction (IE) approaches to analy number of archives in order to gather the comments posed by different authors [1, 2] incorporates various strategies, including etymology and information retrieval (IR) [2]. T sentiment investigation is to detect the p documents or short sentences and classify premise. Sentiment polarity is categorized "negative" or "impartial" (neutral). It is import the fact that sentiment mining can be performed as follows [3]:

- Document-level sentiment classification document can be classified entirely "negative", or "neutral".
- Sentence-level sentiment classification each sentence is classified as "positive" unbiased.
- Aspect and feature level sentiment classi level, sentences/documents can be "positive", "negative" or "non-partisa certain aspects of sentences/archives known as "perspective-level assessment

The main objective of this paper is to stu sentiment analysis methods of Twitter dat theoretical comparisons of the state-of-art a paper is organized as follows: the first two subs comment on the definitions, motivations, an techniques used in sentiment analysis. A numb level sentiment analysis approaches and sentiment analysis approaches are also expl sentiment-analysis approaches used for Twitte including supervised, unsupervised, lexico approached. Finally, discussions and comparis are highlighted.

## II. Definition and Motivati

Sentiment analysis is a strategy for checking people or groups; for example, a portion of a br or an individual customer in correspondence w supports representative. With regard to a scor especially those associated with a business, product or service, or theme.

Sentiment analysis is a means of assessing written or spoken languages to decide whether articulation is positive, negative or neutral and to what degree. The current analysis tools in the market are able to deal with tremendous volumes of customer criticism reliably and precisely. In conjunction with contents investigation, sentiment analysis discovers customers' opinions on various topics, including the purchase of items, provision of services, or presentation of promotions.

Immense quantities of client-created web-based social networking communications are being persistently delivered in the forms of surveys, online journals, comments, discourses, pictures, and recordings. These correspondences offer significant opportunities to obtain and comprehend the points of view of clients on themes such as intrigue and provide data equipped for clarifying and anticipating business and social news, such as product offers [4], stock returns [5], and the results of political decisions [6]. Integral to these examinations is the assessment of the notions communicated between clients in their content interchanges.

"Notion examination" is a dynamic area of research designed to enhance computerized understanding of feelings communicated in content, with increases in implementation prompting more powerful utilization of the inferred data. Among the different web-based social networking platforms, Twitter has incited particularly far-reaching client appropriation and rapid development in terms of correspondence volume.

Twitter is a small-scale blogging stage where clients generate 'tweets' that are communicated to their devotees or to another client. At 2016, Twitter has more than 313 million dynamic clients inside a given month, including 100 million clients daily [7]. Client origins are widespread, with 77% situated outside of the US, producing more than 500 million tweets every day [8]. The Twitter site positioned twelfth universally for activity in 2017 [9] and reacted to more than 15 billion API calls every day [10]. Twitter content likewise shows up in more than one million outsider sites [8]. In accordance with this enormous development, Twitter has of late been the subject of much scrutiny, as Tweets frequently express client's sentiment on controversial issues. In the social media context, sentiment analysis and mining opinions are highly challenging tasks, and this is due to the enormous information generated by humans and machines [11].

## III. Importance and Background

Opinions are fundamental to every single human action since they are key influencers of our practices. At whatever point we have to settle on a choice, we need to know others' thoughts. In reality, organizations and associations dependably need to discover users' popular sentiments about their items and services. Clients use different types of online platforms for social engagement including web-based social networking sites; for example, Facebook and Twitter. Through these web-based social networks, buyer engagement happens

nationality, sexual orientation, race and class ut share encounters and impressions about virtual of their lives. Other than composing messag leaving remarks on corporate sites, a great m utilize informal organization destinations to express feelings and uncover insights about lives. Individuals compose correspondence on r including films, brands, or social exercise circulate throughout online groups and are vi where shoppers illuminate and impact others. T these logs provide profound snippets of insight behavioral inclinations and present a continuou find out about client emotions and recognitions without interruption or incitement. Be that as explosions in client-produced content on s introducing unique difficulties in capturing, translating printed content since informatio confused, and divided [12].

Opinion investigation is a method of info that can overcome these difficulties by methodi and dissecting web-based information without With conclusion examination, advertisers are a shoppers' emotions and states of mind continuo the difficulties of information structure anc enthusiasm in this study for utilizing sentimen instrument for promoting research instrument is

Sentiment analysis critically encourages c determine customers' likes and dislikes abou company image. In addition, it plays a vital rc data of industries and organizations to aid t business decisions.

## IV. Classification Techniqu

In the machine learning field, classificatio been developed, which use different strateg unlabeled data. Classifiers could possibly requi Examples of machine learning classifiers are Maximum Entropy and Support Vector Machir These are categorized as supervised-machine le as these require training data. It is important training a classifier effectively will make fu easier.

### A. Naïve Bayes

This is a classification method that re Theorem with strong (naive) independenc between the features. A Naive Bayes classifier closeness of a specific feature (element) disconnected to the closeness of some other instance, an organic fruit might be considered t its color is red, its shape is round an approximately three inches in breadth. Regard these features are dependent upon one anoth presence of other features, a Naïve Bayes c consider these properties independent due to the this natural fruit is an apple. Alongside eff Naive Bayes is known to out-perform ev



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$$p\left(\frac{a}{b}\right) = \left[p\left(\frac{b}{a}\right) * p(a)\right] / p(b) \quad (1)$$

Where $p\left(\frac{a}{b}\right)$ is the posterior probability of class a given predictor b and $p\left(\frac{b}{a}\right)$ is the likelihood that is the probability of predictor b given class a. The prior probability of class a is denoted as $p(a)$, and the prior probability of predictor p is denoted as $p(b)$.

The Naive Bayes is widely used in the task of classifying texts into multiple classes and was recently utilized for sentiment analysis classification.

B. Maximum Entropy

The Maximum Entropy (MaxEnt) classifier estimates the conditional distribution of a class marked a given a record b utilizing a type of exponential family with one weight for every constraint. The model with maximum entropy is the one in the parametric family $P_{MaxEnt}\left(\frac{a}{b}\right)$ that maximizes the likelihood. Numerical methods such as iterative scaling and quasi-Newton optimization are usually employed to solve the optimization problem. The model is represented by the following:

$$P_{MaxEnt}\left(\frac{a}{b}\right) = \frac{exp[\sum_i \alpha_i f_i(a,b)]}{\sum_a exp[\sum_i \alpha_i f_i(a,b)]} \quad (2)$$

Where a is the class, b is the predictor. The weight of vector is denoted as $\alpha_i$

C. Support Vector Machine

The support vector machine (SVM) is known to perform well in sentiment analysis [13]. SVM investigates information, characterizes choice limits and uses the components for the calculation, which are performed in the input space [18]. The vital information is presented in two arrangements of vectors, each of size m. At this point, each datum (expressed as a vector) is ordered into a class. Next, the machine identifies the boundary between the two classes that is far from any place in the training samples [19]. The separate characterizes the classification edge, expanding the edge lessens ambivalent choices. As demonstrated in [20], the SVM has been proven to perform more effectively than the Naïve Bayes classifier in various text classification problems.

## V. Document-Level Sentiment Analysis Approaches

Sharma et al. [2] proposed an unsupervised document-based sentiment analysis system able to determine the sentiment orientation of text documents based on their polarities. This system [2] categorizes documents as positive and negative [2, 3, 19] and extracts sentiment words from document collections, classifying them according to their polarities. Fig. 1 shows a case of document-based opinion mining. The unsupervised dictionary-based strategy is utilized as a part of this system, which additionally takes care of negation. WordNet is a lexicon adopted to define opinion vocabularies, their equivalent words, and antonyms [2]. In this particular study, movie reviews were collected to utilize as the summary report produced by the system makers. With this system, the sentiment p document is decided based on the major vocabularies that appear in documents.

Chunxu Wu [21] proposed a method for s semantic orientations of context-dependent cannot be determined using WordNet. The prop utilized to decide the sentiment of opinio semantic closeness measures. This approach measures to determine the orientation of review insufficient relevant information. The experi by Chunxu Wu [21] demonstrated that the prop was extremely effective.

Fig 1. Example of Document-based Opinion





Taboada et al. [22] utilized a lexicon-based technique to detect and classify documents based on their sentiments. To

[25] showed that the SVM classifier achiev accuracy score when combined with the TFIDF

movie reviews datasets.

Harb et al. [18] proposed a document-level sentiment extraction approach concentrating on three stages. In the first stage, a dataset consists of documents containing opinions which have been automatically extracted from the Internet. Secondly, positive and negative adjective sets are extracted from this learning dataset. In the third stage, new document test sets are classified based on adjective lists collected in the second stage. Numerous experiments were conducted on real data and the approach proposed by Harb et al. [18] accomplished an F1 score of 0.717 for identifying positive documents and an F1 score of 0.622 for recognizing negative records.

Zagibalov et al. [23] addressed the issue of sentiment classification of reviews about products written in Chinese. Their approach relied on unsupervised classification able to teach itself by increasing the vocabulary seed. It initially included a single word (good) that was tagged as positive. The initial seed was iteratively retrained for sentiment classification. The opinion density criterion was then utilized to compute the ratio of sentiments for a document. The experiments showed that the trained classifier attained an F-score of 87% for sentiment polarity detection after 20 iterations.

Tripathy et al. [24] attempted to classify reviews according to their polarity using supervised learning algorithms such as the Naïve Bayes, the SVM, random forest, and linear discriminant analysis. To achieve this, the proposed approach included four steps. First, the preprocessing step was carried out to remove stop words, numeric and special characters. Second, text reviews were converted into a numeric matrix. Third, the generated vectors were used as inputs for four different classifiers. The results were subsequently obtained by classification of two datasets. After that, various metrics, such as precision, recall, f-measure, and classification accuracy, were computed to assess the performance of the proposed approach. For the polarity and IMDb datasets, the random forest classifier outperformed other classifiers.

Saleh et al. [25] applied the SVM to three different datasets in order to classify document reviews. Several n-grams schemes were employed to evaluate the impact of the SVM in classifying documents. The researchers utilized three weighting approaches to generate feature vectors: namely, Term Frequency Inverse Document Frequency (TFIDF), Binary Occurrence (BO) and Term Occurrence (TO). Numerous experiments were then conducted to measure the possible combinations of various n-grams and weighting approaches. For the Taboada dataset, the best accuracy result was obtained using a combination of the SVM with the TFIDF and trigram. For the Pang corpus, the best results were obtained using the BO and trigram. As regards the SINAI corpus, Saleh et al.

negative, or neutral. Twitter sentiment analysis example of sentence-level sentiment analysis. T explores Twitter sentiment analysis approa learning approaches utilize classification meth text into various categories. There are mainl machine learning strategies: supervised learning

There are four basic Twitter sentiment anal including supervised machine learning-ba methods, lexicon-based, and hybrid. These four described are as follows:

A. Twitter Sentiment Analysis using Supervised Learning Approaches

It depends on labelled datasets that are gi learning models during the training process. datasets are utilized to train these mode significant outputs. In machine learning system are required: training set and test set. Ma approaches such as classifiers can be utilize sentiment of Twitter. The performance of Tw classifiers is principally relying upon the num data and the features sets are extractors. Tw analysis strategies that rely on machine-learni more popular, especially SVM and NB cla illustrates the procedure of supervised ma approaches for Twitter sentiment analysis.

The Twitter sentiment analysis process co steps. First, the classifier is trained using data positive, negative, and unbiased tweets. Exam are shown below:

- The following tweets are examples of po

1) PM@narendramodi and the President o Akufo-Addo had a wonderful meeting. Their discussions on energy, climate change and trade

2) Billy D. Williams @Msdebramaye Fo they mark, and the children, they know The p sidewalk ends.

3) @abdullah "Staying positive is all i #PositiveTweets

- Unbiased tweets

1) (@Nisha38871234): "#WorldBloodDo Donation is the best donation in the world. Sav night #Twitter and #TheLegionoftheFallen. awfully early!

2) (@imunbiased). Be excellent to each o holler..or in NoVA

3) Today several crucial MoUs were si boost India-France friendship.





- Negative tweets

1) Any negative polls are fake news, just like the CNN, #DonaldTrump

classifiers and, using a hybrid feature selectio accuracy of 88%. The experiment attempt principal component analysis (PCA) along classifier to reduce feature dimensionality unigram, bigram, hybrid (unigram and bi

(@teenagesleuth)

3) Sasha and Malia Obama, daughters have some selfie fun during the Inaugural Parade for their father President Obama on ... Follow @JessicaDurando

From the examples above, it is clear that tweets can contain valuable information expressing opinions on any topic. However, they may also include specific characters that are not helpful in detecting sentiment polarity; hence, it makes sense to preprocess tweets. This second step consists of converting all tweet texts to lower case. In addition, tweets should be cleaned by removing URLs, hashtag characters (such as #Trump) or user mentions (such as @Trump) as Twitter sentiment-analysis methods are not concerned with these characters. The preprocessing step includes filtering out stop words that are considered unusual discriminant features [11].

After preprocessing, predictions are performed. In this phase, various prediction algorithms, such as the SVM, Bayesian classifier, and Entropy Classifier, can be used to decide the sentiment polarity of tweets. For example, Vishal et al. [17] reviewed current procedures for opinion mining such as machine learning and vocabulary-based methodologies. Utilizing different machine learning algorithms like NB, Max Entropy, and SVM, Vishal et al. [17] additionally described general difficulties and utilizations of Twitter sentiment analysis.

Go and L.Huang [26] proposed an answer for conclusion examination for Twitter information by utilizing far off supervision, in which their preparation information comprised of tweets with emojis which filled in as uproarious names. Go et al [26] introduced a method to classify the sentiment of tweets. The idea behind it was to aggregate feedback automatically. The sentiment problem was treated as a binary classification, in which tweets were classified into positive and negative. Training data containing tweets with emoticons were collected based on supervision approach that was proposed by Read [27]. To achieve this, Go et al [26] utilized the Twitter API to extract tweets that included emoticons. These were used to identify tweets as either negative or positive. Retweeted posts and repeated tweets were removed. In addition, tweets containing positive and negative emotions were filtered out. Various classifiers such as the NB, MaxEnt, and SVM were employed to classify tweets. Different features were extracted such as unigrams, bigrams, unigrams with bigrams, and unigrams with POS. The best results were obtained by the MaxEnt classifier in conjunction with unigram and bigram features, which achieved an accuracy of 83% compared to the NB with a classification accuracy of 82.7%.

Malhar and Ram [28] proposed the supervised method to categorize Twitter data. The results of this experiment demonstrated that the SVM performed better than other

results obtained a classification accuracy of 92%

Anton and Andrey [29] developed a m sentiment polarity from Twitter data. The fea were words containing n-grams and e experiment carried out demonstrated that the S better than the Naïve Bayes. The best ove method was the SVM in combination with u extraction, achieving a precision accuracy of 8 accuracy of 74%.

Po-Wei Liang et al. [30] designed a frame "opinion miner" that automatically investigate the sentiments of social media messages. A were combined for the undertaking of the anal framework, messages which contained feelings (non-opinion tweets were removed) and determined (i.e. positive or negative). To ac experimenters [30] classified the tweets into "non-opinion" using the NB classifier with a likewise disposed of irrelevant features by utili Information and chi-square extraction experimental outcomes confirmed the ade framework for sentiment analysis in genuine applications.

a) Training

Labels

Tweets

Feature Extraction

Features

b) Testing

Tweets

Feature Extraction

Features

Fig 2. Sentiment Analysis using Supervised Machine Le





Pak and Paroubek [31] used Twitter API and emoticons to collect negative and positive sentiments, in the same way as Go et al. [26]. Sentiment analysis was treated as multi-label, with tweets classified as positive, negative, or neutral. The statistical-linguistic analysis was performed on the collected training data based on determining the frequency distribution of words. The collected training datasets were used to build a

and the polarities of these tweets. The exper that adding adjectives, SentiWordNet and DBpe to minor improvements in the accuracy of bot NB. The ratios of these slight impro approximately 2% with the SVM and 4% with t

Akba et al. [35] employed feature sele

methods. The MNB with part of speech tags and n-gram features was the technique that produced the best performance in the experiments.

Kouloumpis et al. [32] explored the usefulness of various linguistic features for mining the sentiments of Twitter data. The hash-tagged (HASH) and emoticon (EMOT) datasets were utilized to train the classifiers and the iSieve dataset was used for the evaluation. In this study, various feature sets were introduced using unigrams, bigrams, lexicons, micro-blogging and part-of-speech elements. The AdaBoost classifier was trained using these selected features in different combinations. The results showed that part-of-speech features were poor for sentiment analysis of Twitter data whilst micro-blogging features were the most useful. The best results were achieved when n-gram features were employed alongside lexicon and micro-blogging features. An F-score of 0.68 was obtained with HASH datasets and an F-score of 0.65 with HASH and EMOT datasets combined.

Saif et al. [33] introduced the idea of merging semantic with unigram and part of speech features. Semantic features are concepts that encapsulate entities mined from Twitter data. The extracted features were used to compute the correlation of entity groups augmented by their sentiment polarities. It is worth noting that incorporating semantic features into the analysis can help in detecting the sentiment of tweets that include entities. Saif et al. [33] used three datasets collected from Twitter to evaluate the impact of adding semantic features. In the conducted experiment, the Naïve Bayes classifier was used alongside the extracted semantic features. The findings demonstrated that semantic features led to improvements in detecting sentiments compared to the unigram and part-of-speech features. Nevertheless, for the HCR and OMD datasets, the sentiment-topic approach tended to perform better than the semantic approach. For the HCR, the former achieved an F1 score of 68.15 compared to an F1 score of 66.10 obtained by the semantic approach. For the OMD dataset, an F1 score of 78.20 was reached using the sentiment-topic approach compared to an F1 score of 77.85 achieved by the semantic approach.

Hamdan et al. [34] extracted different types of features with the intention of enhancing the accuracy of sentiment classification. Unigram features were introduced as a baseline whereas words were considered independent features. Domain-specific features were also included, such as the number of re-tweets. DBpedia was utilized to mine the concepts contained in tweets; these will be termed DBpedia features. WordNet was used to identify the synonyms of nouns, verbs, adverbs, and adjectives. SentiWordNet was employed to compute the frequency of positive and negative words appearing in tweets

led to improvements over previous studies. In a
al. [36] investigated the impact of information g
selection criterion in order to rank unigrams
features. They concluded that the performance
can be acceptable even when selecting 
sentiment-topic features using information gain.

B. Twitter Sentiment Analysis using Ensemble

The basic principle of ensemble methods
multiple classifiers with a view to obtaining m
accurate predictions. Ensemble methods are 
text classification purposes and in the fi
sentiment analysis, such methods may be ac
improving the classification accuracy of Twitter

Xia et al. [1] investigated the effectiven
ensemble learners for sentiment classification
intention was to efficiently mix diverse feature
classification algorithms to create a more pow
They utilized a gathering system for sentime
which was acquired by combining different
arrangement procedures. Traditional text
approaches are not suited to sentiment classific
of words (BOW) misses-out some word infor
study, two feature types (POS and Word-relat
classifiers (NB, MaxEnt and SVM) were utiliz
of ensemble classifiers were proposed and eva
weighted grouping, fixed grouping, and
grouping. The results showed that the ensemble
clear improvements compared to the indivi
Moreover, the outcomes proved that the ens
various classifiers with different feature sets
significant improvements.

Lin and Kolcz [37] proposed incorpo
classifiers into large-scale twitter data. They at
logistic regression (LR) classifiers from the has
features. The training dataset varied from one to
examples with ensembles of 3 to 41 classifiers.
showed that the accuracy of sentiment analysis
using multiple classifiers was greater than
classifier. The drawback of the ensemble meth
running time increased as n classifiers requ
predictions. The best performance was obta
number of classifiers was 21 and the number o
100 million, achieving a classification accuracy

da Silva et al. [38] suggested an ensembl
consisted of four base classifiers: the SVM,
forest, and logistic regression. Two approache
represent the features: BOW and feature hash



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gathered illustrated that the ensemble classifier with a combination of BOW and lexicon features led to improvements in the classification accuracy [38]. The ensemble method proposed in [38] attained accuracy scores of 76.99, 81.06, 84.89, and 76.81 for HCR, STS, Sanders, and OMD datasets, respectively.

Hagen, Matthias et al. [39] reproduced and combined four Twitter sentiment classifiers to create an ensemble model

improvements in the classification accuracies
The ratio of improvement was around 15% c
results further showed that the proposed
ensemble classifier achieved an accuracy s
compared to a score of 92.71 achieved by the S
datasets. In addition, the majority-voting ens
achieved an accuracy score of 78.70 comp
obtained by the SVM for the Stanford-1K da
for the HCR dataset, the NB achieved an ac

classifiers, Hagen, Matthias et al. [39] introduced a confidence score for the four classifiers in order to obtain the final predictions. In their work, they computed the confidence scores for each individual classifier and each class. The classification decisions were made based on the highest scores on average. The Webis classifier was used as a strong baseline because it was the winner in the SemEval-2015 Task 10. The ensemble method produced an F-score of 64.84 for subtask B.

Martınez-Cámara, Eugenio et al. [40] employed an ensemble classifier that used various Twitter sentiment approaches to enhance the performance and efficiency of classifying the polarity of tweets. Their model was a combination of a ranking algorithm and skip-gram scorer, Word2Vec, and a linguistic resources-based approach [40]. It is important to highlight that their proposed ensemble method relied upon voting strategies. For evaluating the proposed approach, the training data of the TASS competition were chosen. The results of the experiments showed that a slight improvement was obtained with the ensemble method compared to the ranking algorithm and skip gram methods. The Macro-F1 score achieved by the former was 62.98% compared to a macro F1 score of 61.60% obtained by the latter combination.

Chalothorn and Ellman [41] demonstrated that the ensemble model could produce superior accuracy of emotion classification compared to a single classifier. They [41] combined BOW and lexicon features in the context of ensemble classification and conducted experiments showing that when the extracted features were used in combination with these features, the accuracy of classification increased. The mixture of the SVM, SentiStrength and stacking methods using majority voting produced an F-score of 86.05%; this was considered the highest score.

Fouad et al. [42] proposed a system of classifying tweets based on the majority voting of three classifiers: the SVM, NB, and LR. The collected tweets were split into two sets: training and testing. Individual classifiers received the same training set to record their decisions. The ensemble method produced a final decision based on the majority votes collected from the classifiers. The most interesting aspect of their study [42] was that information gain was utilized to reduce the dimensionality of feature vectors. In their work [42], experiments were carried out to examine the impact of information gain on the accuracy of the classifier and the results demonstrated improvements in classification accuracy after feature vector dimensionality was reduced using information gain. Information gain showed clear

Approaches (Unsupervised Methods)

Normally, lexicon-based methodologies analysis depend on the understanding that the p sample can be acquired on the grounds of the words which comprise it. However, because of of natural languages, such a basic approach inadequate since numerous aspects of the lan nearness of the negation) are not taken into con result, Musto [43] proposed a lexicon-base identify the sentiment of any given tweet T, breaking down the tweet into a number of sma such as $m_1 \ldots m_n$ as indicated by the part sig the content. Punctuations, adverbs and conjunct the part signal and, at whatever point a part sig the text, another micro-phrase is constructed.

The sentiment of a tweet was determined polarity of each smaller micro-phrase after the At this point, the score was standardized acro the entire Tweet. In this situation, the micr simply exploited to reverse the polarity when found in the content.

The polarity of a micro-blog post depended of the micro phrases which united it:

$\mathrm{pol(Tweet)} = \sum_{i=1}^{k} \mathrm{pol}(m_i)$ and Tweet = $-- - m_k$

The polarity of a micro-phrase (m) de polarity of the terms which composed it:

$$\mathrm{pol}(m_i) = \sum_{j=1}^{n} \mathrm{score}(t_j)$$

The score of each micro-phrase was norma to its length

$$\mathrm{pol}(m_i) = \sum_{j=1}^{n} \mathrm{score}(t_j) / m_i$$

Specific POS categories were provided wit categories including adverbs, verbs, adjectiv shifters (intensifiers and down-toners). Severa evaluated as follows:

- Emphasized version

$$\mathrm{pol}(m_i) = \sum_{j=1}^{n} \mathrm{score}(t_j) * w_j$$

- Normalized-Emphasized version

$$\mathrm{pol}(m_i) = \sum_{j=1}^{n} \left(\frac{\mathrm{score}(t_j)}{m_i}\right) * w_j$$

Fig 3. The Estimation Computation Procedure [44].

Lexicon and external lexical resources are SentiWordNet, MPQA and WordNet-Affect, SenticNet are required to compute the $\mathrm{score}(t_j)$. The procedure for the estimation computation is schematically shown in Fig. 3 and can be depicted with the accompanying advances: Lexicon based strategies like the ones we are examining locate the total sentiment of a bit(piece) of content by including the individual sentiment scores for each word in the text [43]. SentiWordNet and MPQA [11] are the most utilized dictionaries that are widely utilized for detecting the sentiment of the given tweets.

According to Xia et al. [45], it was an easy task to gather a vast number of unlabeled data from social networks; however, detecting the sentiment labels of these data was very costly. Thus, it was necessary to use unsupervised sentiment analysis approaches. Moreover, unsupervised learning methods are increasingly considered vital as the volume of unlabeled information in social media increases.

Xia et al. [45] exploited emotional signals to detect sentiments appearing in social media data. These emotional signals were defined as any information that correlated or was associated with sentiment polarities. Xia et al. [45] proposed a framework: Emotional Signals for unsupervised Sentiment Analysis (ESSA). They then proposed modelling emotional indicator to detect the sentiment polarity of posts and to bring this closer to the emotional indictors within the post. Moreover, they proposed modelling word-level emotional indicators to detect the polarity of posts and to bring the polarity of the words closer to the word-level emotional indicators. Stanford Twitter sentiment (STS) and OMD were used as datasets for the conducted experiments. The ESSA framework obtained classification accuracies of 0.726 for the STS and 0.692 for the OMD datasets. The results demonstrated the usefulness of the ESSA framework compared to other techniques.

Azzouza, Noureddine et al. [46] presen
architecture to detect opinions in Twitter data
relied on an unsupervised machine learnin
explore tweets and detect their polarity. Thi
technique used a dictionary-based approach
polarity of tweeted opinions and their ar
consisted of multiple modules. Tweets were co
tweet-acquisition module that was connected w
API to retrieve tweets using queries posed. Tex
using a separate module. Then, lexical co
standardization, and syntactic correctness were
in the tweet-processing module. The researcher
opinion-analysis module to compute the opi
emoticons, words, and the average of opini
experiments were conducted based on the Sem
measure the quality of the real-time archite
SemEval-2013 dataset, the proposed syste
accuracy score of 0.559 compared to 0.50 o
SSA-UO system proposed by Ortega et al. [47
the architecture proposed in [46] achieved an ac
compared to 0.539 obtained by the GTI researc
SemEval-2016 dataset.

Paltoglou and Thelwall [48] employed a
approach to estimate the level of emotional in
predictions. This approach was appropriate f
subjective texts expressing opinion and for sen
classification to decide whether the given text
negative. The proposed lexicon-based metho
scores of 76.2, 80.6, and 86.5 for the Digg,
Twitter datasets outperforming all supervised cl

Masud et al. [49] applied a vocabulary-ba
sentiment classification, which characterized tw
negative, or unbiased. This system [49] dis





scored slang utilized in tweets. The experimental outcomes demonstrated that the proposed framework outperformed existing frameworks, accomplishing 92% precision in double characterization and 87% in multi-class grouping. The framework needed to enhance accuracy in negative cases and to review in nonpartisan cases.

Asghar et al. [50] proposed an improved lexicon-based sentiment classification that incorporated a rule-based classifier. It aimed to reduce data sparseness and to improve the accuracy of sentiment classification. Classifiers, such as those using emoticons or modifier-negation, or those which were SWN-based or domain-specific, were incorporated

used aspect-based sentiment classification. H
STC datasets were used to evaluate the perf
proposed hybrid model. This model incorpor
mining them with feature extraction methods. S
word aspects were identified based on a rule-m
with heuristic combination in POS patterns.
Stanford dependency parser (SDP) was u
dependencies between aspects and opini
component analysis (PCA), latent semantic a
and random projection (RP) feature selection
also adopted in the experiments. The new
combining the ABSA framework, SentiWo
PCA, and the SVM classifier outperforme

D. Twitter Sentiment Analysis using Hybrid Methods

Balage Filho and Pardo [51] introduced a hybrid system for detecting the sentiments present in tweets. Moreover, their system combined three classification methods: machine learning, rule-based, and lexicon-based. Balage Filho and Pardo [51] used the SentiStrength lexicon and the SVM classifier as a machine learning method. The results obtained from the experiments showed that a hybrid system outperformed the individual classifiers, achieving an F-measure of 0.56 compared to 0.14, 0.448, and 0.49 obtained by the rule-based, lexicon-based, and SVM classifiers respectively.

Another hybrid method was proposed by Ghiassi et al. [52] who utilized Twitter API to collect tweets. They attempted to combine n-gram features with a developed dynamic artificial neural network (DAN2) sentiment analysis method. Unigram, bigram, and trigram features were identified. Ghiassi et al. [52] developed a reduced Twitter lexicon that was used alongside sentiment classification methods. DAN2 and SVM classification models were trained to detect the sentiment of tweets. The collected results showed that the DAN2 learning method performed slightly better than the SVM classifier even when incorporating the same Twitter-specific lexicon. For the negative class, the DAN2 achieved an accuracy of 92.5 on average compared to the SVM, which achieved an accuracy of 91.45. For the positive class, the DAN2 obtained a classification accuracy of 68.2 on average compared to the SVM, which achieved an accuracy of 67.6.

Khan et al. [53] proposed a Twitter opinion mining (TOM) framework for tweets sentiment classification. The proposed hybrid scheme in [53] consisted of SentiWordNet analysis, emoticon analysis, and an enhanced polarity classifier. The proposed classifier mitigated the sparsity problems by employing various pre-processing and multiple sentiment methods. The experiments were conducted using six datasets demonstrated that the proposed algorithm achieved an average harmonic mean of 83.3%.

Recently, Zainuddin et al. [54] proposed an aspect-based sentiment analysis (ABSA) framework, which contained two principal tasks. The first task used aspect-based feature extraction to identify aspects of entities and the second task

Asghar et al. [55] proposed a hybrid Tw system that incorporated four classifiers: a (SC), an emoticon classifier (EC), a general pu classifier (GPSC), and an improved domain sp (IDSC). Their technique was inspired by the p by Khan et al. [53] and Asghar et al. [50], w tweets using multiple supervised and classification models. The proposed framewor sentiment of tweets after detecting the presen emoticons. The results showed that computin score of slang expressions lead to an improved sentiment classification of tweets. In terms o impact of SC, the framework proposed by As achieved an F-score of 0.92 compared to 0. Masud et al. [49]. The results also showed that emoticons in Twitter sentiment increased accuracy from 79% to 85%.

VII. DISCUSSION AND FINDING

In this section of the study, an attempte compare the different techniques and outcome performance. Table 1 summarizes various supe learning approaches for Twitter sentiment important to mention that the unigram-based S considered a benchmark against which the pro are measured and compared [11]. From Table 1 integrating multiple features led to im classification accuracy, especially combining bigrams as demonstrated in Go et al. [26] and M [28]. In contrast, Anton and Andrey [29] demon SVM classifier when combined with un outperformed hybrid features. According to Sai results showed that incorporating semantic features produced better performance than the selection.

In a similar way, Hamdan et al. [34] show more features such as DBpedia, WordNet and led to improvements in sentiment classific According to Vishal et al. [17], mac methodologies like NB, Max Entropy, and S slightly better with bigram features compared models such as unigrams or trigrams.





TABLE I. THE SUPERVISED MACHINE LEARNING APPROACH FOR TWITTER SENTIMENT ANALYSIS

| Study | Methods | Algorithms | Features | Datasets | Outcomes |
|---|---|---|---|---|---|
| Go et al [26] | Supervised ML | NB, MaxEnt, and SVM classifiers. | Unigrams, bigrams, POS | Tweets collected using Twitter API | The MaxEnt with bot bigrams achieved an compared to the NB 82.7%. |
| Malhar and Ram [28] | Supervised ML | NB, SVM, MaxEnt, and ANN classifiers. | Unigrams, bigrams, hybrids (unigrams+ bigrams) | Tweets collected using Twitter API | The SVM using the h selection achieved an In addition, the SVM achieved an accuracy |
| | | | | Tweets | |

| | | | | | |
|---|---|---|---|---|---|
| Pak and Paroubek [31] | Supervised ML | Multinomial NB and SVM classifiers | Unigrams, bigrams, trigrams | Tweets collected using Twitter API | Multinomial NB with a better performance unigrams and trigram |
| Kouloumpis et al. [32] | Supervised ML | AdaBoost classifier. | Unigrams, bigrams, lexicon, POS features, and micro-blogging features | The hash-tagged (HASH) and emoticon (EMOT) as training datasets. | An F-measure of 0.68 HASH. In addition, a 0.65 was obtained by HASH and EMOT da combination of n-gra microblogging featur |
| Saif et al. [33] | Supervised ML | NB | Unigrams, POS features, sentiment-topic features semantic features | STS, HCR and OMD datasets | Semantic features ou unigrams and POS. H sentiment-topic appro marginally better tha approach in the case OMD datasets. |
| Hamdan et al. [34] | Supervised ML | NB, SVM | Unigrams, DBpedia wordNet, and SentiWordNet | SemEval- 2013 datasets | Experiments showed features such as DBp SentiWordNet led to the F-measure accura these slight improver with the SVM and 4% |

Table 2 illustrates various ensemble approaches for Twitter sentiment analysis. For the HCR dataset, the ensemble methods proposed by da Silva et al. [38] that incorporated LR, RF, SVM, and MNB alongside BOW and lexicon features achieved the F1 score of 76.99. In comparison, Fouad et al. [42] showed that the majority voting ensemble method with information-gain feature selection method achieved an accuracy of 84.75. This demonstrates that the ensemble methods proposed by Fouad et al. [42] outperformed the ensemble method proposed by da Silva et al. [38]. This was due to incorporating the information gain as a feature selection method.

Saif et al. [33] showed that the NB classifier achieved an F1 score of 68.15 for the HCR dataset. In comparison to the ensemble methods proposed by da Silva et al. [38] which incorporated LR, RF, the SVM, and the MNB score of 63.75 for the HCR dataset. Furthermor [38] obtained a slight improvement using the BOW and lexicon features, producing an F1 compared to 68.15 obtained by the NB classifi Saif et al. [33].

According to Fouad et al. [42], the perfo ensemble method was marginally better t classifier for the Sanders dataset, as shown in was attributed to the majority voting idea that w determine the final sentiments of tweets. Ho HCR dataset, NB with an information gain f achieved the highest accuracy score of 85.09 co the ensemble method proposed by Fouad et al. method proposed by da Silva et al. [38] produ 76.99.





TABLE II. ENSEMBLE APPROACHES FOR TWITTER SENTIMENT ANALYSIS

| Study | Methods | Algorithms | Features | Datasets | Outcomes |
|---|---|---|---|---|---|
| Lin and Kolcz [37] | Ensemble | Logistic regression classifier | Hashed byte 4-grams | Large-scale datasets | For 100 million instan methods achieved an a 0.81 when the number 21. |
| da Silva et al.[38] | Ensemble | MNB, RF, SVM, and LR | BOW, lexicon, and feature hashing | Stanford (STS), Sanders, OMD, and HCR datasets | An ensemble classifier accuracies when both features were utilized. method achieved accu 76.99, 81.06, 84.89 , a HCR, STS, Sanders, |

| | | | | | |
|---|---|---|---|---|---|
| Hagen, Matthias, et al. [39] | Ensemble | NRC, GU-MLT-LT, KLUE, and TeamX | dictionaries, punctuation marks, emoticons, word lengthening, clustering, negation, stems | SemEval-2013 training | The ensemble method score of 64.84 for subt SemEval-2015 Compe |
| Martınez-Cámara, Eugenio, et al.[40] | Ensemble | The ranking algorithm and skip-gram scorer, Word2Vec, and linguistic resources-based approach | The ranking algorithm and skip-gram scorer | General Corpus of the TASS competition | The ensemble method F1-score of 62.98%. H ranking algorithm and obtained a macro F1 s |
| Chalothorn and Ellman [41] | Ensemble | The majority vote, SVM, NB, SentiStrength and Stacking. | Sentiment lexicons and BOW features | SemEval-2013 | The ensemble classifie score of 86.05% for ta |
| Fouad et al. [42] | Ensemble | SVM, NB, and LR | Various combinations of BOW, lexicon-based features, emotion-based and POS features. | Stanford (STS), Sanders, and HCR | For the Sanders datase (majority voting) class accuracy score of 93.9 92.71 achieved by the -1K dataset, the major classifier achieved an 78.70 to 78.10 obtaine the HCR, the NB achi score of 85.09 compa majority vote ensembl obtained a score of 84 |

Table 3 summarizes various lexicon-based algorithm investigated in this paper. Xia et. al [45] showed that their lexicon-based sentiment method achieved a classification accuracy of 0.692 for the OMD dataset compared to a classification accuracy score of 76.81 that attained by the ensemble method proposed by da Silva et al. [38]. This may attribute to the utilization of the majority voting ensemble classifier and combining lexicons with BOW features.

Table 4 shows the hybrid algorithms ex survey. The method proposed by Zainuddin et a an accuracy score of 76.55 % for the ST outperformed the lexicon-based methods propo [45] which achieved an accuracy score of 72.6 data set. In addition, the majority-voting en proposed by Fouad et al. [42] achieved a score best results were attained by da Silva et al ensemble methods scored an accuracy of 81.0 dataset.





TABLE III. LEXICON-BASED METHODS FOR TWITTER SENTIMENT ANALYSIS

| Study | Methods | Algorithms | Features | Datasets | Outcomes |
|---|---|---|---|---|---|
| Xia et. al [45] | Unsupervised method (lexicon-based) | Exploring slang sentiment words in Sentiment analysis (ESSA) | Unigrams | STS and OMD datasets | Classification accuracies of 0.72 dataset and 0.692 for the OMD d achieved. |
| Azzouza, Noureddine, et al. [46] | Unsupervised method | | POS features | SemEval-2013, SemEval-2014, SemEval-2015, SemEval-2016 | For the SemEval-2013 dataset, t obtained an accuracy score of 0.5 0.50 obtained by the SSA-UO. For the SemEval-2016 dataset, t achieved an accuracy score of 0. 0.539 obtained by the GTI. |
| Paltoglou and Thelwall [48] | Unsupervised method (lexicon-based) | Emotional lexicon | Unigrams | Digg, MySpace, and Twitter datasets | The proposed lexicon method ac 76.2, 80.6, and 86.5 for Digg, M datasets, respectively. |

| | | | | | |
|---|---|---|---|---|---|
| Asghar et al. [50] | Lexicon-enhanced-Rule-based | Rule-based classifier | Emoticon-handling features and an enhanced feature weighting scheme | Three review datasets | For the second dataset, the propo achieved an F1-measure of 0.79 achieved an F-score of 0.76. For the third dataset, the propose an F-score of 0.855 compared to obtained in [56]. |

TABLE IV. HYBRID METHODS FOR TWITTER SENTIMENT ANALYSIS

| Study | Methods | Algorithms | Features | Datasets | Outcomes |
|---|---|---|---|---|---|
| Balage Filho and Pardo [51] | Hybrid | The SVM as the machine learning classifier, and the SentiStrength as the lexicon-based classifier, and the rule-based classifier | BOW | SemEval-2013 Task datasets | The hybrid model achieve 0.563 compared to 0.499 o SVM. |
| Ghiassi et al.[52] | Hybrid | The Twitter-specific lexicon and DAN2 classifier | Trigrams and bigrams | Own datasets | For the negative class, the accuracy of 92.5 on averag 91.45 obtained by the SVM For the positive class, the accuracy of 68.2 on averag accuracy of 67.6 achieved |
| Khan et al. [53] | Hybrid | The Enhanced Emoticon Classifier (EEC), Improved Polarity Classifier (IPC), and SentiWordNet Classifier (SWNC) | SentiWordNet Emoticons, sentiment words | Own datasets | An accuracy of 85.7%, pre and recall of 82.2 recall we |
| Zainuddin et al.[54] | Hybrid | Principal component analysis (PCA) and the SVM classifier. | Association rule mining (ARM), POS and Stanford dependency parser (SDP) methods. | STS, HCTS, and STC datasets | The proposed hybrid mode other classifiers for the ST datasets with accuracies of 74.24%,respectively. |
| Asghar et al. [55] | Hybrid | SC, EC, (SentiWordNet), and IDSC classifier. | - | Own datasets | The proposed hybrid classi score of 0.88 compared to [49]. |





## VIII. CONCLUSION

In this article, diverse techniques for Twitter sentiment analysis methods were discussed, including machine learning, ensemble approaches and dictionary (lexicon) based approaches. In addition, hybrid and ensemble Twitter sentiment analysis techniques were explored. Research outcomes demonstrated that machine learning techniques; for example, the SVM and MNB produced the greatest precision, especially when multiple features were included. SVM classifiers may be viewed as standard learning strategies, while dictionary (lexicon) based techniques are extremely viable at times, requiring little efforts in the human-marked archive. Machine learning algorithms, such as The Naive Bayes, Maximum Entropy, and SVM, achieved an accuracy of approximately 80% when n-gram and bigram model were utilized. Ensemble and hybrid-based Twitter sentiment analysis algorithms tended to perform better than supervised machine learning techniques, as they were able to achieve a classification accuracy of approximately 85%.

In general, it was expected that ensemble Twitter

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However, hybrid methods also performed well and obtained reasonable classification accuracy scores, since they were able to take advantage of both machine learning classifiers and lexicon-based Twitter sentiment-analysis approaches.

One of the greatest difficulties encountered was in determining the best approach for detecting sentiments in Twitter data because comparing various approaches is a highly challenging task when there is a lack of agreed benchmarks. This difficulty with an absence of well-defined benchmarks was thus addressed in [10] and was found to be mitigated by relying on data sets that had been used for evaluating various algorithms in microblogging sentiment competitions such as SemEval'13 datasets.

Interesting area for future study includes the fluctuations in the performance of sentiment analysis algorithms in cases where multiple features are considered. In other words, combining various features was found to lead to improve the performance in most cases, but substandard performance in others. Thus, an exploration into the causes of these performance instabilities would be an intriguing direction for future works. Another might be to investigate the data sparsity issue using both ensemble and hybrid approaches. The intention behind this is to measure the robustness of various Twitter sentiment approaches the data sparsity. A further area of study might be the utilization of active learning techniques to detect Twitter sentiments and to increase the confidence of decision makers.

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