Exploring Machine Learning Approaches for Sentiment Analysis: An Overview and Its Challenges

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Abstract: *Recent years have seen an increase in the number of researchers concerned with sentiment analysis, as textual data has proven useful for a variety of real-world applications and problems. Sentiment analysis is a technique of machine learning in which a machine is trained to evaluate the sentiments, emotions, etc. of multiple text statistics, such as movie reviews and product reviews. These reviews are steadily increasing in number, which necessitates the appearance of comments in character where reviews are required to be in the form of a transcript, yielding valuable data from the vast collection of reviews. It is extremely difficult to extract positive statistics from a lengthy article or to condense it. Text analysis determines the significance of syntaxes based on their grammatical properties. In this survey, we have endeavored to provide an overview of the current and historical research on sentiment analysis, as well as exemplary research questions and methodologies for future study.*

Keywords- NLP, opinion mining, Machine Learning, Sentiment Analysis.

Introduction

Nowadays surveys or remarks play an effect on clients getting by web based business sites. This sharing gives mentality, feeling, or response to clients. The remarks might be concerning products, or administrations, or several associated things. To settled on choices, on the accessibility of sentiment affluent and colossal amount of data (for instance remarks or reviews on Flipkart, Twitter, Amazon, Facebook, etc.). We require a canny framework for analyzing emotions. This investigation is recognized as Opinion Mining or Sentiment Analysis. It would be support the People, associations, and management to comprehend what the demeanor of general society as concerns their specific item or administration is [1]. Assessment mining is an errand that joins Natural Language Processing (NLP) and AI procedures to examine the content like true, false, or neutral. For instance," I had a Samsung M 20 cell phone for around one year. It efforts splendidly, solid, with dependable. Its presentation is delightful and the telephone is the quick and ultimate to carry into pocket", is a constructive conclusion. Assessments might be immediate and circumlocutory. The declaration of assessment on certain articles is alluded to as immediate Opinions. For example," OPPO F11 is an amazing cell phone with great front & rear Camera feature and fast processing", is a constructive sentiment for OOPO's Mobile phone. Aberrant assessments are contrasting at least two items and similitude and contrasts. For instance, "Nokia9 is extreme superior to iPhone. I take a gander at the specifications, ease, list of options, and processing speed and the whole thing". In the aforementioned model, the creator looks at the highlights of cell phones.

Subjectivity recognition is a procedure to decide assessment as an emotional or target articulation from a bit of content. For example, (1) DSLR Cameras are decent widget for capturing snaps. (2) The nature of the image on this DSLR camera is acceptable. Both the statements hold supposition behavior remarks well, in spite of the primary sentence is a target and truthful sentence (i.e., doesn't pass on any assumption) though the subsequent one portrays feeling as concerns that DSLR camera, which is an emotional statement. Slant categorization is to arrange the emotional statement as True, False, or neutral from the record, otherwise called extremity order. Conclusion Summarization gives notion rundown at angle stage.

The Opinion Mining can be used in Brand promotions, analyzing emotions with understanding the preferences, inclinations, and client designs by mining unstructured information from web journals and web-based life. Contender examination is likewise significant for associations to contrast with their companions and capable with know the quality and shortcomings of their items. In advertising knowledge, business associations gather input from clients via mail correspondence or online life and dissect which parts of the item or administration they are experiencing issues. This sort of examination is identified as grumbling investigation which recognizes original issues looked through the clients. In Video and Audio production, sentiment mining strategies are utilized like an information highlight for content to discourse amalgamation, and video streaming assessment. In the Commercial business, sentiment mining is utilized to foresee the securities exchange and to examine it. The legislature will make choices dependent on assessments of public sentiment gathered be social media websites to identify their quality and shortcoming.

Significant difficulties are tended to in different investigation studies [2]: Entity Identification is a significant errand in sentiment mining. A statement might include various elements; the supposition mining framework requires distinguishing on which element the conclusion is communicated. Sentiment container recognition is the errand of distinguishing supposition points and assessment holders. Evaluation categorization decides if the assessment of the statement is true, false, or neutral. Sentiment threat recognition is significant undertakings utilized to distinguish the counterfeit suppositions in surveys and discussions. Mockery distinguishing proof is a typical method that a statement might include verifiable supposition beyond the nearness of several assessment behavior statements, recognizing such a statement is a significant matter in conclusion mining. The target of this task gives philosophies and ongoing advancements of Sentiment Analysis (SA) that could be pertained in everyday exercises.

Rest of the paper is organized as: in section 2 brief explanation of sentiment analysis is given with its framework, in section 3 different challenges of sentiment analysis are explained, in section 4, the research work previously carried out by various researchers are given in section 4 as related work, in section 5 problem statement of domain is given, the research gap of current state of sentiment analysis is given in section 6, lastly we conclude our work in section 7 which is followed by references used.

2. Sentiment Analysis

The region of study that deciphers individuals' feelings, against a specific theme, as concerns any occasion, and so on in content mining it is known as assessment mining or conclusion examination. It creates a huge issue zone. There are likewise different names and having various undertakings, e.g., assumption examination, conclusion extraction, supposition mining, feeling mining, influence investigation, subjectivity examination, audit mining, and so on [24]

2.1 Sentiment Analysis Framework

This segment talks as concerns the essential Sentiment examination system which can be utilized to pass judgment on the feelings from the site. This system comprises of three fundamental advances. The initial step being information assortment, trailed by preprocessing of the information gathered. The last advance is the grouping which arranges the information prepared into either positive or negative. Fig. 1 gives a fundamental outline of the Sentiment examination structure.

A. Data Collection

Sentiment Analysis should be possible on any information. The information can either be gathered from any informational collection or can be removed from any site. The informational collection is accessible online with a huge number of surveys alongside the name of positive and negative. Then again, removing information from the web is an extensive errand however one can perform a Sentiment examination on the information voluntarily.

B. Pre-Processing

Information removed from the web contains a few syntactic highlights that may not be valuable and in this way information cleaning and sifting should be finished. So as to evacuate the natural information, this progression should be performed. It is basic to preprocess all the information to do advanced functionalities. The different pre-preparing steps included are given beneath:

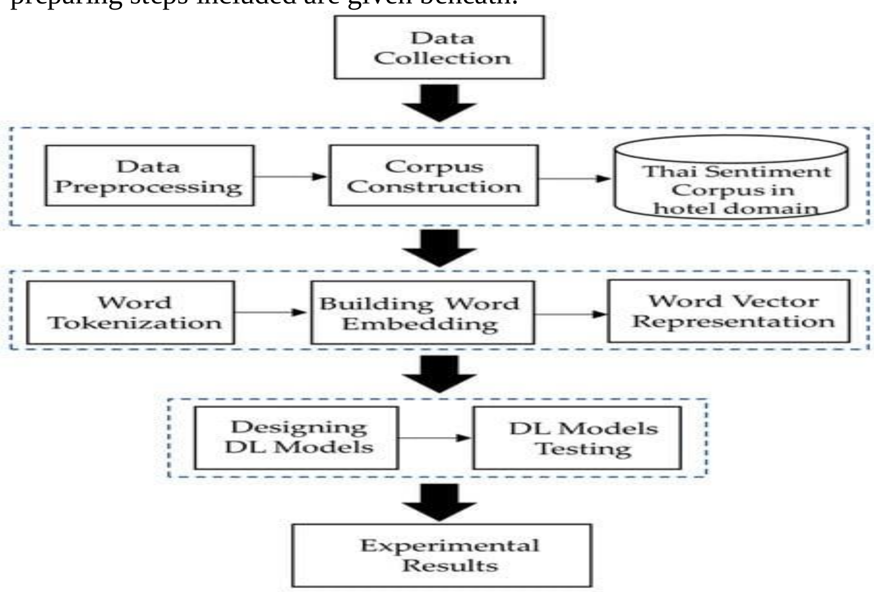

Fig. I: Sentiment Analysis Framework.

1) Removing URLs

Uniform Resource Locators (URLs) are of not helpful while executing the analysis of sentiment and could for few moments initiate bogus investigation. For instance "user browsed in to www.Mchine.eduasI·ybored. This statement is unconstructive but due to there is single constructive statement in the URL, it turns into impartial thus principal to a mistaken forecast. To evade the probabilities of bogus forecast, such URLs have to be eliminated.

2) Filtering

Rehashed letters in words like "thankuuuuu" are regularly used to show the profundity of articulation. Be that as it may, these words are missing in the word reference subsequently the additional letters in the word should be wiped out. This is done based on a standard that a letter can't rehash itself multiple occasions and if there is such a letter, that will be dispensed with.

3) Questions

Words similar to "what", "which", "how" etc., doesn't supply to division and thus such words must be detached in order to decrease the difficulty.

4) Removing special characters

So as to expel disparities during the Sentiment Analysis process, unique characters like '[] {} 0/' ought to be evacuated. For instance "it's acceptable:" If these characters are not disposed of before performing slant investigation, they will get joined with the words, and those words won't be perceived. To maintain a strategic distance from the circumstance, the expulsion of such characters is significant.

5) Removing Stop words and emoticons

Stop words will be words that ought to be barred so as to continue with the SA procedure. Stop words don't convey as much significance, for example, determiners and relational words (in, to, from, and so on.) and in this way should be separated. More often than not, while composing an audit, individuals will in general use emojis so as to communicate their sentiments better. Despite the fact that these emojis help in a superior comprehension of the feelings while performing Sentiment examination, this can misdirect and foresee wrong.

6) Lemmatization or stemming

Lemmatization and stemming mean to diminish inflectional and related types of a word to a typical base structure. Stemming accomplishes its objective effectively more often than not by evacuating the parts of the bargains. Though, lemmatization does likewise process appropriately with the utilization of jargon and morphological investigation of words.

7) Tokenization

Tokenization alludes to parting the statement into its ideal constituent parts. It is a significant advance in all NLP errands.

2.2 Classes of Sentiment Analysis

Estimations can be ordered into three classes' .for example positive, negative, and unbiased assumptions.

a) **Positive Sentiments:** These are the acceptable words as concerns the objective in thought. In the event that the positive assessments are expanded, it is eluded to be acceptable. In the event of item audits, if the positive surveys as concerns the item are more, it is purchased by numerous clients.

b) **Negative Sentiments:** These are the awful words as concerns the objective in thought. In the event that the negative assessments are expanded, it is disposed of from the inclination list. If there should be an occurrence of item audits, if the negative surveys as concerns the item are more, nobody means to get it.

c) **Neutral Sentiments:** These are neither acceptable nor awful words as concerns the objective. Consequently, it is neither favored nor disregarded.

2.3 Levels of Sentiment classification:

There are three unique degrees of slant arrangement. for example word level, express level, and report level slant characterization.

a) **Word Level Classification:** this arrangement is done based on the words which demonstrate the notion as concerns the objective occasion. The word might be a thing, converter, or qualifier. This sort of grouping gives exact ordered assessments.

b) **Phrase Level Classification:** This sort falls in great just as an awful class. The expression meaning the assessment is discovered from the statement and the order is finished. In any case, it now and again gives wrong outcomes if a refutation word is included in front of the expression. The expression alludes to a blend of at least two words that are firmly identified with one another.

c) **Document Level Classification:** In this degree of characterization, a solitary report is considered as concerns the obstinate content. A solitary survey as concerns the single theme from this report is thought of. Be that as it may, now and again it isn't advantageous if there should arise an occurrence of websites and discussions as clients may contrast one item and the other which has comparative attributes. Again the archive may comprise of insignificant statements that don't look like supposition as concerns the occasion.

3. Challenges in Sentiment Analysis

Sentiment analysis (SA) could be reflection of as a substance order task since it arranges messages as True, False, or Neutral. Be that as it may, sentiment analysis is trying as contrasted and regular substance portrayal, in spite of the fact that it has just three divisions due to the accompanying variables [3].

3.1 Conditional and Sarcasm Sentences

On the off chance that a client is utilizing a constructive sentence as concerns an item however his/her goals are harmful. As it were, we could state that the significance is the exact inverse. These sorts of sentences belong to the group of sarcasm. It is extremely hard for a framework to recognize the sarcastic sentence. Various clients utilize sarcasm in an alternate way. How this diverse goal could be grasped by the framework? It's a difficult assignment. For instance, 'this movie is adequate to squander currency' is a sarcastic sentence [3].

To grasp the conditional sentences is additionally an ordinary activity for a framework. For instance, 'the movie would be great if the fairy-tale is attractive'. A few endeavors have been built to recognize Sarcasm. Twitter has been a pivotal wellspring of preparing for such proto-types. Utilizing '#' in Twitter's Tweet is the highest quality level, for instance, '#sarcasm'. Another significant asset is item audits from Amazon.

Lexical characteristics are utilized to characterize the sarcastic and non- sarcastic tweets dependent on the word reference based labels. The last order was performed by the SVM classifier and logistic regression classifier method [4]. The AI approach with linguistic characteristics was utilized to recognize sarcasm in tweets which were '#'. A decent fan was actualized, and the outcome was good [5]. A standard based methodology with #-based emotion was additionally utilized for the Twitter dataset. Within this, they not just believe the scope of sarcastic converters to watch the significance of tweets yet in addition sentiment extremity [6]. Once more, a standard based methodology is applied with lexical, certain disjointedness, unequivocal incoherency, and down to earth highlights for Twitter information and conversation discussion [7].

3.2 Detection of Spam

There are such a significant number of clients who attempt to present negative surveys on spoil other's fame. In the present situation, it is a moving assignment to recognize spam among the numerous surveys. In this way, it is basic need to grow such a framework that can distinguish spam and could evacuate it [3]. Three methodologies, for example, genre identification text, psycho-grammatical deception recognition, and text categorization, were utilized for finding deluding reviews. A device called LIWC—Linguistic Enquiry and Word Count— is utilized by a subsequent methodology called Psycholinguistics deception recognition [8]. A hierarchical structure was utilized for spam recognition utilizing a singleton audit [9]. They discover a connection between's the volume of single survey and score in light of the fact that as the audit builds, the rating diminishes or increments drastically. Various groupings of AI calculations, for example, SVM, DT, ADABoost, RNN, and KNN were actualized on two genuine and enormous open datasets. By utilizing these methodologies, the best by and large outcomes were accomplished by the sacking of the choice tree in this situation in which they didn't consolidate highlights. Boosting (AdaBoost) accomplished the best with the mix of highlights Survey of Challenges in Sentiment Analysis vectors. The assessed procedures indicated the best outcome for adjusted classes [10].

A shallow reliance parsing strategy is utilized to register the sentiment rating. A connection between spam reviews and sentiment rating was specified by them. Spam inspection identification was joined with a sentiment analysis. Moreover, by utilizing the discriminative standards, the spam audits can be additionally distinguished from the strange time frame. The contextual investigation and the examination indicated the viability of these strategies [11]. As opposed to before work, they saw misleading surveys don't communicate the feelings as unequivocally as the certified audits do. They utilized a standard based technique for beguiling spam datasets. They utilized profound linguistic highlights to assemble a superior beguiling spam identification model. The conclusive outcome of this methodology gave an improvement in execution by 1.1% [12].

3.3 Anaphora Resolution

Throughout the sentiment analysis, pronouns are disregarded by the majority of the specialists. It is hard for a framework to recognize what a pronoun or thing alludes to in the sentence. Much of the time, pronouns likewise assume a significant job to think as concerns the clients' recognition. For instance, 'The film is great. It contains numerous great activities just as feelings'. In this model the word 'it' alludes to the film. We can't allude 'great' to 'film' without knowing its reference [3]. The issue of source co-reference goals was proposed by [13]. In any case, they utilized somewhat directed bunching as opposed to utilizing basically supervised learning calculations. An administered AI approach with two semantic highlights was utilized to improve the co-reference goals precision [14].

3.4 Negation Handling

Negation handling with sentiment analysis assumes a significant job in modifying the extremity of the related descriptive word and subsequently the extremity of the content. Nullification words incorporate not, not one or the other, nor, and so forth, for instance, 'The film is acceptable' ought to be named positive. 'The film isn't acceptable' ought to be named negative. This sort of sentence can be taken care of by turning around the extremity of the descriptor happening after a negative word. In any case, this arrangement neglects to engage the cases like 'No big surprise the film is acceptable' and 'Not just the story was fascinating, the melodies were additionally engaging'. Invalidation has not been handled totally with the utilization of scientific models and language preparation methods.

In the French setting of sentiment analysis [15], they separated various kinds of negative administrators, negative quantifiers, and lexical refutations by utilizing syntactic highlights. Tree part based extension identification utilizes the parse data which is grammatically organized. Added to this, a method of choosing characteristics that are good with various PoS, as highlights have a proficiency which is imbalanced for 232 S. Singhal et al. characterizing degree, which is influenced by PoS was investigated by them [16]. A programmed framework was created to distinguish refutation and hypothesis signals by utilizing an AI approach. It is the primary framework that is prepared and tried on the SFU Review corpus clarified with theoretical and negative data. The outcomes revealed—92.37% in F1 and 89.64% for nullification—are empowering. In scope recognition task, the outcomes—F1, 84.07% in refutation, 78.88% in hypothesis, G-mean, 90.42% for nullification and 87.14% for theory, and PCRS, 71.43% in theory and 80.26% in invalidation, are promising [17].

3.5 Word Sense Disambiguation

Word sense disambiguation is distinguishing which feeling of a word is utilized in a sentence as the single word has numerous implications. It is constrained by the feeling of the word in that specific situation, for instance, 'Little'. On the off chance that we relate little with TV, it sounds negative sense. Be that as it may, in the event that you talk as concerns a cell phone, it tends to be certain. It relies upon the client, what he loves, or not. So it is hard to decide this for a framework.

A few specialists including [18–20] start by making vocabulary word references where words are related to the earlier extremity outside of any relevant connection to the issue at hand. The relevant extremity of a word present in expression may contrast from the word's earlier extremity in light of the fact that a word may show up in various faculties. Also, it is hard to characterize the earlier extremity for a few words, for example, long, short, think, profoundly, totally, little, feel, for all intents and purposes, and so forth since they don't convey explicit extremity without anyone else. Syntactic highlights were utilized to decide the extremity of the polar proviso [21]. These syntactic highlights incorporate adjustments highlights, structure highlights, and sentence highlights. Rather than disambiguating the word sense, the impact of enhancers, refutation, and converters is resolved to utilize the word setting.

The discourse design coordinating technique was utilized to determine the disambiguation of words at the sentence level [22]. So as to decide the extremity of the sentence, grammatical forms designs are removed and contrasted with WordNet glossaries all together with recognizing the proper sense in SentiWordNet. Be that as it may, results accomplished through grammatical forms design coordinating are not acceptable in light of the fact that a word utilized in similar grammatical features example might not have a similar sense. So as to distinguish the disambiguate feeling of the word; four errands were proposed [23].

a) Exact limits of the content are resolved where supposition as concerns a component is enunciated.
b) The setting of the word is recognized in a sentence utilizing a fitting strategy.
c) A setting coordinating component is given so as to get the extremity of the comparing setting from the dictionary.
d) Lexicon word reference is constructed which not just contains the faculties of words in a specific space yet additionally underpins a setting coordinating system.

The outcomes show that these strategies impressively improve the general execution of highlight level estimation examination.

4. Related Work

There are different content mining methods utilized to extract the information.

Barakat AlBadani, Ronghua Shi, et al. [24], created a model using deep learning by combining SVM and fine- tuning. They used their model on three datasets and detected the accuracy. They got accuracy as 99.78%, 99.71%, and 95.78% for Twitter US Airlines, IMDB, and GOP debate respectively. In their work, they considered document-level sentiment analysis but didn't consider aspect-level analysis.

A. Pasumpon Pandian et al. [25], in their research used 6 datasets and they represent models which use combinations of automation extraction and hand-crafted separation of features. In the future, they are going to extend their work and test it by using different languages. Kanhav Gupta, Dr. Munish Mehta, et al. [26], in their paper for sentiment analysis a brief idea about lexicon- based and machine learning analysis. According to their research lexicon-based analysis works best for fewer amounts of data as it does not require any testing, training, and multiple processes for preprocessing but for a abundant data machine learning approach is needed. They used SVM, Naïve Bayes, and logistic regression and got an acquire and accuracy of 90.85%, 85.6%, and 89.4% respectively.

Shanshan Yi, Xiaofang Liu, et al. [27], analyze customers review and determine the sentiment of customers towards a product. Created a hybrid recommendation system using a machine learning regression model. The performance of the model was analysed using three matrices namely MAE (mean absolute error), MSE (mean squared error), and MAPE (mean absolute percentage error). In the future, they are going to extend their work on customer interest across different geographical locations.

Peng Cen, Kexin Zhang, and Desheng Zheng et al. [28] used RNN, LSTM, and CNN for analyzing the sentiment of movie reviews from the IMDB dataset. CNN provides more accuracy than RNN and LSTM. The accuracy of CNN, RNN, and LSTM are 88.22%, 68.64%, and 85.32%, respectively.

Ayushi Mitra et al. [29], used a lexicon-based approach for sentiment analysis results were not that efficient when the size of the lexicon increased? To overcome this deficiency, they are going to use machine learning classifiers.

Nirag T. Bhatt, Asst. Prof. Saket J. Swarn deep et al. [30], in their paper they demon straight about sentiment analysis, levels of sentiment analysis, advantages and disadvantages of sentiment analysis and its application. Their main focus is on different feature extraction techniques and how they perform different machine learning approaches.

Alpna Patel and Arvind Kumar Tiwari et al. [31], in their paper the three methods for sentiment analysis are lexicon-basedapproach and deep learning approach. They analyzed the sentiment of the IMDB movie review data set by using the CNN and RNN methods. According to their result, RNN gives more accuracy than CNN. The accuracy level of RNN is 87.42%.
Hassan Raza, M. Faizan, Ahsan Hamza, et al. [32], in their research work, consider a scientific text for sentiment analysis where they use different machine learning classifiers like NB, SVM, LR, KNN, RF, and three different feature extraction techniques like unigram, bi-gram, and trigram.
Brian Keith Norambuena, Exequiel Fuentes Lettura, et al. [33], in their study of sentiment analysis, used three approaches supervised, unsupervised and hybrid approaches. NB, SVM is used as a supervised method, the scoring algorithm is used as an unsupervised method and HS-SVM is used as a hybrid model.
Mr. Kundan Reddy Mand et al. [34], in their research, analyze sentiment from Twitter data by using machine learning algorithms like Naïve Bayes, XGBoost and Random Forest, and CNN-LSTM. They come to an end that CNN-LSTM gives satisfactory results in anticipating the accuracy of sentiment.
Gurshobit Singh Brar, Asst. Prof. Ankit Sharma et al. [35], created a web-based API that determines whether sentiment is positive or negative. They tested this on 50 plus different reviews. They got average accuracy of 81.22%. In the future, they are going to extend the model and test it using a large- size dataset.
Wahyu Calvin Frans Mariel, Siti Mariyah, and Setia Pramana, et al. [36], combined different classification techniques and feature extraction techniques. They found that deep learning neural network gives better results than SVM and Naïve Bayes. According to their analysis, the Deep learning neural network along with Bigram provides the best result.
Dr. M. Sujithra et al. [37], in their paper, discussed data pre- processing, feature extraction, and different methods of machine learning. Predict the emotion of twitter data by using machine learning algorithms. In the future existing models can be further improved by increasing semantic knowledge.
Dipak R. Kawade, Dr.Kavita S. Oza et al. [38], collected twitter data about the Uri attack which was held on 18-sep- 2016, and analyze the sentiment of people by using preprocessing and machine learning classifiers. In the future, they are going to use big data analysis techniques to classify the emotions of large amounts of data.
Jaspreet Singh, Gurvinder Singh, and Rajinder Singh et al. [39] considered four machine learning classifiers for detecting emotions of three different datasets. According to their results Owner provides more accuracy than others. Whereas Naïve Bayes is faster among all. In the future, they are going to proceed with the same research using CNN and RNN.
Ms. Bhumika Gupta et al. [40], in their paper, examine the correctness of the model by putting the trained data in a machine learning model which is going to be used in the future to predict the result or to analyze the sentiment of the different dataset. In the future, different topics can be taken into consideration to check the accuracy of the model.
Table 1 provides a concise summary of the approaches, datasets, accuracy results, and future plans mentioned in each research paper.

5. Problem Statement

This study addresses the problem of sentiments stacked in enormous amount. Machine learning is used to evaluate the multi-dimensional and multi-variety statement in smart environments. As we have one preferably term interpretation. That it results is further a masterpiece challenge. That required demonstrating the efficiency of machine learning algorithms. One vital limitation of machine learning is its sensitivity to errors. As we have seen that in approximate cases machine learning fails. Thus, it requires several ideas of the problem at hand to set the right algorithm. In various controversies, machine learning takes lead, especially if you have restrictive computing power. Handling immense volumes of a word and one after the other computer models take it a chance of computing capability, which can potentially be far costly. So, earlier turning to machine learning, it's significant to clear whether you can invest the amount of time and/or money required to develop the technology to a relate where it will be useful. The undeniable amount of time involved will contradict dramatically tentative the statement source, the expression of the word and how it's as utilized.

6. Research Gap

Machine learning algorithms have been widely used for sentiment analysis, with significant success in many applications. However, there are still several areas where research is needed to improve the performance and reliability of these algorithms.

One challenge is handling complex and nuanced sentiment, such as sarcasm, irony, and ambiguity. Existing algorithms often struggle to identify these types of sentiment, because they rely on simple features such as word counts and sentiment lexicons. These features cannot capture the full richness of human language, which is often used to express complex and nuanced sentiment.

Another challenge is dealing with domain-specific sentiment. For example, the way that sentiment is expressed in financial news articles is different from the way that it is expressed in social media posts. Algorithms trained on general-purpose data may not be effective for sentiment analysis in specific domains, because they do not capture the unique features of that domain.

Machine learning algorithms have traditionally been used to analyze sentiment in text data. However, sentiment can also be expressed in other types of data, such as images, videos, and audio. There is a need for machine learning algorithms that can effectively analyze sentiment in multimodal data.

Finally, it is important to develop machine learning algorithms for sentiment analysis that are explainable. This means that we need to be able to understand how the algorithms make their predictions, and to identify and correct any biases that they may have. Explainable algorithms are more reliable and trustworthy, and they are also easier to use in practice.

In addition to these general challenges, there are also specific areas where research is needed to improve the performance of different machine learning algorithms for sentiment analysis. For example, deep learning algorithms have been shown to be effective for sentiment analysis, but they can be computationally expensive to train and deploy. There is a need for more efficient and scalable deep learning algorithms for sentiment analysis.

By addressing these research gaps, we can improve the performance and reliability of machine learning algorithms for sentiment analysis, and make them more applicable to a wider range of real-world problems.

7. Conclusion

As a result of information's progressive expansion, obtaining all statistics is impractical, but feasible measures can be taken to extract the vast majority of its valuable data. This is possible through SA (sentiment analysis), which provides the emotions, intelligence, or other reviews or product rankings. There are a number of areas in the SA domain that have yet to be defiled, and a great deal of progress could be made in terms of accessible methodologies with a more accurate understanding. Similarly, it is impractical to interpret the entire corpus of literal data in order to extract useful information for an individual due to the volume of such data. The purpose of this survey of prior work on reviews and text sentiment analysis (SA) is to identify original research areas by analyzing the strengths and weaknesses of existing methods and techniques.

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Table 1: Summary of sentiment analysis using various approaches.

Authors and Reference	Approach/Model	Datasets Used	Accuracy	Future Plans
Barakat AlBadani et al. [24]	Deep Learning (SVM + Fine-tuning)	Twitter US Airlines, IMDB, GOP debate	99.78%, 99.71%, 95.78%	Consideration of aspect-level analysis
A. Pasumpon Pandian et al. [25]	Combination of Automated Extraction and Hand-Crafted Features	6 datasets	Not specified	Extension of work to test with different languages
Kanhav Gupta et al. [26]	Lexicon-based and Machine Learning Analysis	Not specified	90.85%, 85.6%, 89.4%	Emphasis on lexicon-based analysis for smaller datasets, machine learning for abundant data
Shanshan Yi et al. [27]	Hybrid Recommendation System using ML Regression Model	Not specified	Not specified	Extension of work on customer interest across different geographical locations
Peng Cen et al. [28]	RNN, LSTM, CNN	IMDB dataset	88.22%, 68.64%, 85.32%	CNN provides more accuracy than RNN and LSTM
Ayushi Mitra et al. [29]	Lexicon-based Approach	Not specified	Not specified	Adoption of machine learning classifiers to overcome efficiency issues with increasing lexicon size

Nirag T. Bhatt et al. [30]	Feature Extraction Techniques, Various ML Approaches	Not specified	Not specified	Focus on different feature extraction techniques and their performance in sentiment analysis
Alpna Patel and Arvind Kumar Tiwari et al. [31]	Lexicon-based Approach, CNN, RNN	IMDB movie review dataset	RNN - 87.42%	Comparison of lexicon-based, CNN, and RNN methods for sentiment analysis
Hassan Raza et al. [32]	Various ML Classifiers, Different Feature Extraction Techniques	Not specified	Not specified	Exploration of scientific text for sentiment analysis, use of different classifiers and feature extraction methods
Brian Keith Norambuena et al. [33]	Supervised, Unsupervised, and Hybrid Approaches	NB, SVM, Scoring Algorithm, HS-SVM	Not specified	Exploration of different sentiment analysis approaches: supervised, unsupervised, and hybrid
Mr. Kundan Reddy Mand et al. [34]	Machine Learning Algorithms (Naïve Bayes, XGBoost, Random Forest, CNN-LSTM)	Twitter data	Not specified	CNN-LSTM found to give satisfactory results in predicting sentiment accuracy
Gurshobit Singh Brar et al. [35]	Web-based API for Sentiment Analysis	Tested on 50+ different reviews	Average accuracy of 81.22%	Extension and testing on large-size datasets
Wahyu Calvin Frans Mariel et al. [36]	Combination of Classification and Feature Extraction Techniques	Not specified	Deep Learning Neural Network with Bigram provides the	Preference for deep learning neural networks over SVM and Naïve Bayes

			best result	
Dr. M. Sujithra et al. [37]	Machine Learning Algorithms	Twitter data	Not specified	Focus on data preprocessing, feature extraction, and improving existing models through increased semantic knowledge
Dipak R. Kawade et al. [38]	Machine Learning Classifiers, Big Data Analysis Techniques	Twitter data about Uri attack	Not specified	Future use of big data analysis techniques for emotion classification in large datasets
Jaspreet Singh et al. [39]	Four Machine Learning Classifiers	Three different datasets	Not specified	Ongoing research using CNN and RNN for emotion detection
Ms. Bhumika Gupta et al. [40]	Model Correctness Examination using Trained Data	Not specified	Not specified	Future plans to predict results and analyze sentiment on different datasets