Empirical Study on Sentiment Analysis

M. Azhagiri, S. Divya Meena, A. Rajesh, M. Mangaleeswaran, M. Gowtham Sethupathi

Abstract: Sentiment analysis (SA), generally known as Opinion Mining (OM), is really the process of gathering and evaluating people's ideas, thoughts, feelings, beliefs, including views about various subjects, goods, as well as services. Individuals produce large amounts of comments and evaluations about products, services, and day-to-day tasks as Internet-based applications such as webpages, online sites, social networking sites, and blog posts continue to evolve at a rapid pace. Firms, government institutions medical researchers and scholars may use sentiment analysis to collect and evaluate mood of the people and perspectives, obtain business information, and make smarter and more informed choices. The approaches for sentiment analysis are thoroughly examined in this work, problems, trends and features in order to provide academics with a worldwide overview of sentiment analysis and topics of interest. The paper discusses the various uses of sentiment analysis as well as the general procedure for performing this assignment. The report subsequently examines, analyses, and analyses the various techniques in order to gain a comprehensive understanding of its benefits and downsides. Furthermore, to elucidate long term prospects, the constraints of sentiment analysis have been highlighted.

Keywords: Sentiment Analysis, Opinion Mining, Explicit and Implicit Feature, Natural Language Processing

I. INTRODUCTION

Sentiment analysis is a way of assessing client sentiment utilizing natural language processing, text analysis, and statistics. The best businesses understand their customers' feelings, including what they are saying, how they are saying it, and what they mean [1].

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Tweets, comments, reviews, and other sites where your brand is discussed may reveal customer sentiment. Sentiment Analysis is the field of employing software to analyze these feelings, and it's a must-have skill for today's engineers and executives [2]. Deep learning improvements have moved sentiment analysis to the forefront of cutting-edge algorithms, much like they have in many other fields. Natural language processing, statistics, and text analysis are increasingly used to extract and categorize words into positive, negative, and neutral categories. [3]. We were proposing a research based on sentiment analysis in comparison with previous researches and choose suitable challenges from each exploration, and clarify their consequences for feeling precision [4].

The relevance and consequences of sentiment analysis issues in sentiment evaluation are discussed in this overview, which is based on two correlations among 47 studies [5-42]. Sentiment audit frameworks and sentiment analysis issues are the focus of this investigation. As a result of this work, area reliance [43] is now a significant consideration in the interpretation of sentiment concerns. Also, the refutation challenge became well known in a wide range of audits organized simply contrasts in implicit and explicit significance. As a result, the results of this inquiry offer an office with information about how each emotional difficulty affects audit structure kinds.. The succeeding correlation is therefore determined by the feeling examination problems that apply to the precision rate. Their findings emphasize the significance of sentiment concerns in gauging feelings, as well as how to choose the optimal test to increase precision [44]. We discover a link between the extent to which sentiment approaches are used in hypothetical and specialized situations to deal with emotional challenges. This paper centres around the main difficulties in sentiment assessment stage that they have a huge impact in sentiment score and extremity location. This paper sums up keys of sentiment difficulties concerning the kind of review structure. It also divides problems into two types, making it easier to manage them and focusing on the level of critical importance. This investigation focuses on these emotional issues, as well as the factors that influence them and their relevance.

II. EMPIRICAL STUDY

In this sentiment analysis we were utilizing 2 sorts of examinations. In our first examination we were gathering difficulties from 37 exploration papers [45]. The goal of this correlation is to determine the relationship between sentiment challenges and audit construction, as well as the impact on sentiment results. To deal with this we need to consider three formulated sentiments like structured sentiments [37], semi-structured sentiments [43-52], and unstructured sentiments [54].

(i) Structured sentiment. Structured Sentiments are found in conventional opinion surveys, yet it focuses on the proper issues as books or examination. Since the authors are proficient and composing opinions or notification about the logical or reality issues [39]. Structured sentiment analysis endeavours to extricate full assessment tuples from a text, yet over the long run this undertaking has been partitioned into more modest and more modest sub-assignments.

(ii) Semi-Structured Sentiments are written in a free arrangement by the essayist, with next to no limitations. There could be no legitimate separation of positives and negatives and the substance may involve a couple of sentences, in which every sentence present more of features or conceivably speculations [47]. We can see from the model under those unstructured studies might perhaps give more plentiful and separated appraisal information than its accomplice

(iii) Unstructured Sentiments are a casual and free message design, that doesn't follow formal format, the author doesn't follow any limitations There could be no appropriate separation of positives and negative and the substance may involve a couple of sentences, in which every sentence contains features or possibly notions. We can see from the model under those unstructured reviews might perhaps give more abundant and ordered evaluation information than its accomplice.

- **Explicit feature**: In this on the off chance that an element shows up in fragment of audit sentences, this element is known as Explicit feature in an item. In this instance, the fragment image is brilliant, and image is unequivocal component.
- **Implicit feature**: In this on the off chance an element f doesn't show up in review, yet inferred, this is known as Implicit feature in an item.in this instance, the portion is pricey, and the cost was verifiable element, moreover costly was component marker. As for the significance of opinion examination, this study talks about the connection between the survey design and feeling investigation challenges. We analyse the feeling challenge that shows up additional kind of sentiment framework.

Table 1 represents examination in the middle of 41 review reports in sentiment investigation [5-37], the correlation's results articulate as there is a fundamental part significant and pertinent to audit structure. This component is space arranged, that needs holding a direction of theme area and its provisions to decide the test for the examination. This examination depends on connection middling the space and audit structure. The other outcome is invalidation, the main test which it has the best effect in many feelings investigation and assessment either organized, semi-organized, unstructured review. Be that as it may, the examination inadequacy requires updatable exploration continually to arrive at the reasonable difficulties effectively and rapidly. Second comparison clarifies the outline of opinion difficulties and how to work on the exactness of every one dependent on the past works. Its objective is distinguishing the main difficulties in feeling and how to further develop its outcomes applicable to the pre-owned methods. Table 1 recognizes the use of every strategy. The hypothetical moves utilize numerous methods to work on the outcomes with addressing the specific feeling difficulties. The most noteworthy procedure utilization in the hypothetical sort is parts-of-speech. Bag-of-words procedure is the subsequent method. Also, another factor is Maximum entropy technique. Be that as it may, the outcomes are diverse in technical sentimental challenge type, the most noteworthy utilization method is n-gram procedure, since it depends on expressions and articulations. Also, the least procedure utilization here is vocabulary-based method.

Table 1: Challenges in Sentiment Analysis

Domain Aligned	Challenge Type	SA Challenge	Review Structure
-	T	Dependence on a Domain	S and Objectives Expression
-	T	Spam and Fake Detection + negation	SS
-	T	Negation + huge lexicon	SS
N, online -collaborative media	Technical	Huge lexicon	S and US
Y, social media	Technical	Bi-polar words	US
N, online customer review	T	Spam and Fake Detection	US
-	T	NLP Overhead (Emotions)	US
N, Broader sense domain	T	Negation	SS NN/ADJ/VB/ and ADV-clauses and phrases
Y, online news review	T	World Knowledge	SS nouns, US
Y, social media	T	NLP Overhead (Emotions)	US
-	T	Negation	SS adjectives only
Y, scientific papers	Technical + T	Lexicon + feature extraction + negation +world knowledge	S
Y, products	Technical	Extracting features or keyword	SS
Y, facebook and twitter	T	NLP overheads (Short abbreviation)	US
Y, tweets	Technical	Huge lexicon	US
Y, with aspect level	Technical	Extracting features or keyword	SS

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Y, CNET, IMDB movie review	Technical	Huge lexicon	SS
Y	Technical + T	Negation + bipolar	SS, sentences or topic documents
-	T	NLP overheads (Ambiguity)	Structured adjective only
Y, tweets	Technical	Bipolar words	US
Yes, movie review	T	Negation	US
Yes	T	Dependence on a Domain	US conjunction with predefined taxonomy of emotional terms
Y, movie and product domains	Technical	Bi-polar words	US
Y, trip advisor	Technical	Extracting features or keyword	SS
Y	T	Dependence on a Domain	US, online customers reviews
Y, tweets NLP	T	overheads (Sarcasm) + negation	US
Y, ecommerce and online security	T	Spam and fake detection	SS
N mutli-domain	T	Dependence on a Domain	SS
-	T and Technical	Negation + entity features/keywords	S or SS
Y, tweets	T	NLP overheads (Sarcasm) + negation	US
Y, tweets	T	NLP overheads (Sarcasm)	US
Y	T	Dependence on a Domain	S, news articles
Y, tweets	T	NLP overheads (Short Abbreviations)	US
Y, product reviews	T	Spam and fake detection	US
N, online customer reviews	T	Spam and fake detection	US
Yes health/medical domain	T	Negation	SS
Yes movies	T	Negation + Dependence on a Domain	SS ADV, ADJ
-	T	Dependence on a Domain	US, emotion reviews
Yes movies	T	Negation + Dependence on a Domain	SS ADV, ADJ
Y, social media	T	Spam and fake detection	US
Y	T	Dependence on a Domain	US, Twitter

Where T-Theoretical, S-Structured, SS- Semi-Structured, US- Unstructured. NN-Noun, ADJ-Adjective, VB-Verb, and ADV-Adverb

Table 2 analyses a few boundaries applicable to sentiment analysis challenges. These boundaries are dictionary type, space situated, dataset, this strategy utilized the exactness consequences. This examination sums up impact of sentimental challenges arrangements in breaking down, assessing feeling investigation precisely. The pre-owned vocabulary has the opinion word and extremity. The extremity contrasts in opinion characterization extremity levelled. This grouping of extremity is isolated to a few class kind levels like two levels, three levels as in the progressive level, or four level, and more indicated order into five levels. The examination's qualities are;

- The ability to comprehend hot area research,
- Demonstrating the most significant difficulties to accuracy results,
- Evaluating the prevalence of each sentiment analysis approach
- Investigating the link between domain reliance, lexicon type, and accuracy outcomes. The consequences of examination were vital in picking appropriate method to tackle feeling difficulties to arrive at most elevated precision.

Table 2: Challenges in Sentiment Analysis based on Dataset

SA challenge	Technique Used	Domain Aligned	Lexicon type	Data set	Accuracy
Bi-polar words	Features (n-grams) and pre-processing techniques combined (unsupervised stemming and phonetic transcription).	aligned	English Facebook	10,000 Facebook postings are included in the sample.	69%
Negation + domain dependence	BOW term frequencies	aligned	Two wordlists	There have been 2000 movie reviews, 1000 positive and 1000 negative.	with a greater recall of 65% 83 percentage points
Spam/fake reviews	Similarities in POS tagging and the n-gram algorithm	online customer reviews	LIWC	800 opinions	Nearly 90%
Domain Dependence	SemEval-2013	Y	Tweets and MPQA English	2000 positive words and 4700 negative words, as well as the well-known MPQA	Improve accuracy and F-measurement by roughly 13% from

					the baseline to reach 69 percent.
NLP overheads (emotions)	(Naive Bayes, Maximum Entropy, and SVM)	N multi domain	Microblogging lexicon	Tweets containing emoticons, 1,600,000 training tweets, 800,000 tweets containing positive emoticons, and 800,000 tweets containing negative emoticons,	Naive Bayes accuracy increased from 81.3 percent to 82.7 percent, while MaxEnt accuracy increased from 81.3 percent to 82.7 percent (from 80.5 to 82.7). SVM, on the other hand, has declined (from 82.2 percent to 81.6 percent).
Domain Dependence	WordNet- lexicon based	Y	News reviews	Articles from newspapers (the set of 1292 quotes)	82% improve the base line 21%
Huge lexicon	Distinguishing between previous and contextual polarity.	N	Multiperspecti ve Question Answering (MPQA) Opinion Corpus1,	There are 15,991 subjective expressions in 425 documents (8,984 sentences)	75.9%,
Nlp overheads (Multilingual)	An integrated method that combines information retrieval, natural language processing, and machine learning.	Y	English, Dutch and French tex	Texts found on the World Wide Web in blogs, reviews, and forums	83% 70% and 68%
Domain Dependence	Dependency-SentimentLDA- Markov chain	Y	Hownet- Senti- wordnetMPQA	HowNet 2700 2009 English translation of positive/negative Chinese SentiWordNet 4800 2290 Words with a positive or negative score- MPQA 4152 2304 Subjectivity Lexicon of MPQA	70.7
NLP overheads (emotions)	Fine-grained emotions	Y	Chinese lexicon	35,000 tweets about Sichuan earthquake	80%,
Domain dependence	WEKA5 N Naive Bayes and support vector machines	multi domain	46English	The two datasets, movie review (MR) data and multi domain data,	90%
Domain Dependence	Deep sentiment analysis is a technique similar to machine translation.	N	Japanese	Polar clauses conveying goodness and badness in a specific domain	94% (25 to 33%)
Negation Domain Dependence	Part of speech (POS) Emotion Dependency Tuple (EDT- improved (BOW) TF-IDF and cross entropy, space vector model	40 different topics N	Open NLP Chinese	Dutch language COAE2014 dataset	71.23% for negation (Precision improves with 1.17%) 60%
Bi-polar words	n-gram (uni and bi-grams)	Y	HL and MPQA lexicon.	Data set of 1,600 Facebook messages	70%
Spam and fake reviews	Combine lexicon and use shallow dependency parser	N, online customers reviews	SentiWordNet and MPQA	Store#364,	85.7% for sentiment method but word counting approach 76.7%
Feature and grained	POS tagging with fine app applications	- N, 7	SentiStrength	7 apps from the Apple App Store and Google Play Store	91%

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World knowledge	Adding word polarity scores from sentiment lexicons	Y	Contextdependent lexicon	6500 answers on game reviews	Improve acc 60% to 80%
Negation	Parse Tree and dependency	Y	English, health/medical domain	Dataset that consists of 1000 sentences	Between 79.2% to 82% with different four methods
Domain dependence + NLP overheads (multilanguage)	Lexicon-based method depends on POS tagging	N	16 domain Lexicon-based tool for Arabic opinion mining.	Deal with emoticons, chat language, Arabizi,	93.9%
Huge lexicon	Lexicon based technique	Y	6,74,412 tweets	The polarities of the words in the dictionary are set according to a specific domain,	73.5%
Domaindependence	n-gram	N, 7 domains	Chinese reviews b	560 Chinese review	65%
Negation	POS (Part of Speech) (Word Sense Disambiguation, Sentiment analysis)	Y	WORDNET	There are 1000 positive and 1000 negative reviews for the English film 1000.	98:7%-
Lexicon + Feature extraction + Negation + world knowledge	Enhancement BOW model	Y, scientific papers	New lexicon	Three datasets (training set, test set and the verified set) 1000, 5000, and 10.000	83.5%
Domain Dependence + Extracting Features or Keywords	Instead of terms, use character n-grams.	Y	Hotel reviews in Germany .	A total of 1559 hotel reviews were gathered from the internet	83%
SVM with a large lexicon Bag-of-word11s.	SVM Bag-of-Words.	pSenti movie reviews from Y, CNET, and IMDB	pSenti	The first dataset is Software Reviews, while the second is Movie Reviews.	82.30%

These examination's decision in Table 2, where incorporates the connection in middle of the sentiment analysis and the significance of essence. Different outcomes in from the subsequent examination pronounce in pic. 2 level of Average of exactness upgrade identified with the thought about research papers. Although the negative is the most influenced in many attitude types, the results in association in Table 1 indicate that there is a significant number of examinations. That means that the research area with the bi-polar words has the lowest average accuracy. Then, at that point, area reliance and NLP overheads have the subsequent position. What's more, the negation challenge has third position. Nullification has the most elevated exactness rate that can uphold the consequence of the main examination on the grounds that investigates in sentiment don't have to comprehend the negative surveys whether express or certain [98]. Our recommendation is to build an investigation into the words 'minimal record' and 'accuracy' because they are bi-polar terms in research.

III. LEVELS OF SENTIMENT ANALYSIS

Sentiment analysis has been studied on a variety of levels. The easiest way to identify sentiments and opinions is to look at the text, phrase, or aspect level [32–34]. Figure 2 shows the various levels of sentiment analysis. The first two levels are both enjoyable and difficult. The third level, on the other hand, is more difficult due to the investigation's fine-grained nature [9]. Here's a quick breakdown of each level's responsibilities:

A. Sentiment Analysis at the Aspect Level

This level conducts fine-grained analysis to uncover sentiments about specific entity characteristics. Consider this: "The iPhone 11's photography is incredible." The review focuses on the "camera," a feature of the entity "iPhone 11," and the result is positive. As a result, work at this level assists in determining what individuals like and dislike [35]. Rather than the sentiment of paragraphs or words, it is concerned with the attributes of entities (e.g., product qualities). An implicit or explicit characteristic can be extracted from a text using sentiment analysis, according to [36]. A review of implicit aspect extraction approaches was proposed in this area by the authors.

Numerous real-world applications necessitate this level of detail investigation. For example, in order to develop a product, firms assess which components or features appeal to customers. Aspect-based Adaptive Mowlaei et al. [37] presented lexicons as a method for sentiment analysis based on aspects. The authors developed two strategies for creating two dynamic lexicons with the goal of providing aspect-based sentiment analysis: one statistical method and one genetic algorithm Section 4.2 delves deeper into lexicon-based techniques. Automatic updates are possible with a dynamic lexicon, which also allows for more accurate ratings of terms that are relevant to the current context. To categorise the aspects in reviews, the recommended lexicons were coupled with a collection of well-known static lexicons from literature.

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To boost performance, two or more levels of sentiment analysis could be combined instead of a single level of sentiment analysis being performed. Using a technique developed by Mai and Le [38], it was suggested that product comments on YouTube be analysed using sentiment analysis at the sentence and aspect levels. It has been hypothesised by the authors that sentiment polarity on the sentence level is dependent on and influences sentiment polarity on the aspect level, and that the combined method is capable of dealing with the issues associated with both levels of sentiment analysis. After pre-processing the comments, the author's emotional response was extracted at the sentence and aspect levels using a BERT-based model [39]. The outcomes of the analysis were then combined to provide statistics reports for the target product.

B. Sentence-Level Sentiment Analysis

Here, the overall meaning of the text is emphasised. Analysis of the sentence is the primary goal in identifying whether a statement indicates a favourable, unfavourable, or neutral attitude [40]. To do this, it is necessary to distinguish between objective phrases that convey factual information and subjective statements that convey thoughts and views. This level of study has been addressed in a number of ways. According to Chen et al. [41], Sentence-level sentiment analysis can be improved by grouping sentences into several categories. Based on the number of targets in the initial occurrence of a phrase, they were able to classify it into one of three categories: low, medium, or high (sentence with nontarget, one-target, or multi-target). For their classification, they employed a one-dimensional convolutional neural network, where each type of text was fed into the model individually. At both the sentence and the document level, sentiment analysis is critical. It does not create opinions on all elements of an object, however, since it does not specify precisely what individuals like or hate about an object, and because it does not describe precisely what individuals like or dislike about an object [21].

C. Document-Level Sentiment Analysis

The technique seeks to evaluate whether a work as a whole demonstrates a negative or positive attitude or outlook [42] by employing this degree of examination. All of the documents are classified according to the general feeling the opinion bearer has against a certain entity, as expressed in their words and actions directed towards that entity (e.g., single product). This type of classification is most successful when the document is generated by a single individual, and it is not suited for publications that evaluate or compare many things at the same time, as is the case with most research articles. There have been a number of different approaches to sentiment analysis at the document level presented. Zhao et al. [43] developed a Domain-Independent Framework for Document-Level Sentiment Analysis (DFDS), which was published in the Journal of Documentary Studies and included Rhetorical Structure Theory-based weighting criteria (RST).To compute the emotion ratings of the sentences in each of the texts, the authors parsed the articles into rhetorical structure trees, which they then compared to two well-known lexicons. When the researchers tallied up the scores of sentences based on weighting processes, they were able to establish the polarity of the document's overall mood. It is likely that the text may contain some conflicting sentiments that will have an impact on the final decision. In a wide variety of fields, the use of sentiment analysis is quite advantageous.

IV. RELATED FIELDS

Few subjects that fall within the subject of SA and have recently piqued the interest of scholars. Three of these subjects are discussed in greater depth in the next subsection.

A. Emotion Detection

According to neuroscientists, an opinion is a transitional phrase that conveys an attitude toward an entity - sentiment reveals feelings or emotions, whereas emotion reflects an attitude toward an entity. In natural language processing, sentiment analysis has been described as a job that identifies different points of view on an entity. Because the distinction between opinion, sentiment, and emotion is fuzzy, they described it as a combination of the three .Emotion Detection (ED) may be classified as a SA task. When it comes to describing positive or negative concepts, SA is more interested in doing so than ED, which is more concerned with distinguishing distinct emotions from text. ED can be implemented as a Sentiment Analysis job that uses either a Machine Learning technique or a Lexicon-based approach, depending on the situation. Happiness, grief, anger, fear, trust, disgust, surprise, and anticipation, according to Plutchik, are the eight essential emotions that serve as archetypal examples of human behaviour.

According to the probability distribution of common mutual actions between the subject and object of an event, it is called a probability distribution of mutual actions. Lu and Lin, who used text-mining technologies to analyse emotion in human language, were the first to suggest ED at the sentence level. lu and Lin an event emotion detection system was built with the use of web-based text mining and semantic role labelling approaches, as well as a number of reference entity pairs and hand-crafted algorithms. Neither large-scale lexical sources nor knowledge bases were used in their investigation. In their demonstration, they established that their method gave acceptable results for recognising joyful, negative, and neutral emotions. They revealed that the difficulty in detecting emotions is based on the setting.

As an example, Balahur and colleagues [45] presented a strategy that integrated machine learning with a Lexicon-based approach. They discussed an approach in their presentation that was based on common-sense facts contained in the emotion corpus knowledge repository (EmotiNet). According to them, emotions are not necessarily portrayed through the use of emotive words such as cheerful, but rather through the description of real-world situations that readers associate with a certain sensation. To achieve their aim, they employed the SVM and SVM-SO algorithms. They demonstrated that the EmotiNet-based technique is the best for detecting emotions in settings with no affect-related words.

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Techniques based on common sense can be used to identify emotions in texts such as those in the ISEAR emotion corpus, as demonstrated by the researchers (where little or no lexical signals of affect are present). They found that using Emoti Net outperformed other methods, such as supervised learning with a smaller training set or lexical knowledge.

Neviarouskaya et al. have developed an Affect Analysis Model (AAM), which stands for Affect Analysis Model. Affect Analysis (AA) is the process of recognising the emotions elicited by a specific semiotic modality and categorising them accordingly. Five steps comprise the AAM: the symbolic cue, syntactical structure, word-level, phrase level, and sentence-level analysis. The AAM is divided into five stages. AAMs such as these were used in a number of applications, which were detailed in Neviarouskaya's research. Another effort reported by Neviarouskaya et al. is sentence classification using fine-grained attitude categories. They created a method for attitude analysis based on the compositionality principle and a novel strategy for dealing with verb semantics. They examined 1000 sentences from the website experienceproject.com. This is a website on which individuals can share their personal narratives. Their study revealed that their method produced trustworthy findings in the textual attitude analysis task. Using a corpus-based method, affect emotion terms such as those proposed by Keshtkar and Inkpen could be employed. In their study, they presented a bootstrapping strategy for recognising paraphrases and extracting them from nonparallel corpora based on contextual and lexical criteria. They started with just a few seeds. It was through the use of their method that they uncovered patterns for six different sorts of emotions. They employed text to extract excerpts from annotated blogs and other data sources, which they then used to create their final product. For their effort, they drew on information from real-time journals and blogs, text effects, fairy tales, and annotations from blogs. Using their data set, they demonstrated that their technique worked effectively.

Aozora Bunko Japanese stories were used in the study by Ptaszynski et al. [50], who conducted text-based affect analysis (AA). The topic of person/character related affect recognition in stories was the subject of their investigation. They employed anaphoric expression analysis to extract the emotion subject from a phrase, and then they used the affect analysis technique to determine what type of emotional state each character was in for each segment of the narrative. Mohammad [49] pioneered the study of AA through mail and books. He examined the Enron email corpus and discovered significant disparities in how men and women utilise emotion terms in work-related emails. Annotations on the word's correlations with positive/negative and the eight major emotions were manually annotated utilising crowdsourcing to build an annotated lexicon. Analysing and monitoring emotional terms in books and communications, he employed this tool to do so. By reading books and fairy tales, he introduced the concept of emotional word density. Fairy stories featured a considerably broader range of emotional word density than books, according to him.

B. Building Resources

When constructing resources, the goal is to employ polarity to annotate opinion statements in dictionaries, corpora, and lexica. Although it may contribute in the improvement of SA and ED, creating resources is not a SA activity. The key obstacles that this category's study faced were word ambiguity, multilinguality, granularity, and disparities in viewpoint expression across textual media.

It was introduced by Tan and Wu [20]. While doing their research, they used a random walk technique to construct a sentiment lexicon for different domains at the same time. They used three different types of sentiment data in their study. Their findings revealed that using their proposed technique improved the efficiency of automated sentiment lexicon development for domains.

The concept of creating corpus was proposed by Robaldo and Di Caro [34]. They introduced Opinion Mining-ML, a new XML-based approach for labelling textual expressions conveying viewpoints on current events deemed important. Along with Emotion-ML and WordNet, it is a new standard. There were two elements to their effort. First, they developed a standardised approach for annotating emotional claims in text that was completely independent of any application domain. Second, they investigated domain-specific adaptation, which was based on the usage of a domain-specific ontology of support. They began with a data set of food blogs and extracted them using a query-oriented technique. They assessed their idea using a fine-grained examination of conflict among different authors. Their findings suggested that their idea constituted an efficient technique capable of covering considerable complexity while maintaining good accord among different individuals.

This fine-grained annotation technique was developed by Boldrini et al. [41] for categorising subjectivity in unconventional literary genres. This research focused on document, phrase, and element-level annotations. EmotiBlog, a collection of 270,000 blog posts published in three languages: Spanish, English, and Italian, was also displayed. Natural language processing challenges were used to verify the model's sturdiness and applicability. They used ISEAR to test their model on a variety of corpora. Their research yielded positive outcomes. EmotiBlog was used to classify sentiment polarity and identify emotions. These researchers proved that the resources they used improved the performance of systems built just for this task.

Steinberger et al. [43] presented about the Building Dictionary. They developed a semi-automated method for constructing emotion dictionaries in a variety of languages in their research. After constructing emotion dictionaries of the highest calibre in two languages, they mechanically translated each dictionary into a third language. In order to get the most out of your target language vocabulary, you should look for words that appear on both lists. Morphological inflection and the subjective nature of human annotation and judgement were the main topics of their investigation. Gathering information from the news was their responsibility. Triangulated lists were compared to non-Triangulated Machine Translation Word Lists to verify their process.

C. Transfer Learning

It is the technique of using knowledge from an auxiliary domain to enhance learning in the target domain. Moving information from a Wikipedia page to a tweet or an English search to an Arabic search is only one example. There are many aspects of cross-domain learning that can be covered by transfer learning. Text classification , sentiment analysis, named entity identification, part-of-speech tagging, and other text mining tasks can all benefit from it. This can be done by transferring sentiment categorizations from one area to another or by establishing a bridge between two different fields of study. To discover high frequency domain-specific (HFDS) characteristics, Tan and Wang [21] developed an Entropy-based technique and a weighting model that considered both the aspects and occurrences. Lower weights were assigned to HFDS characteristics and events that had the same label with the appropriate pivot feature.. A Chinese data collection was utilised to compile appraisals of education, equities, and computers. In a study, they found that their proposed model could alleviate some of the harmful impacts of having HFDS. There is a good chance that their model is a better option for SA applications that require a lot more classification than the training data available. An approach proposed by Wu and Tan [22] for sentiment categorization in various domains is a two-stage process. An initial linkage between source and target domains was set up so that they could access the most reliable tagged content in their target domain. In the second stage, they applied the intrinsic structure of the labelled documents to the target-domain data in order to tag it. They worked on reviews of books, hotels, and notebooks from a certain domain based on data from China. They demonstrated that their proposed scheme has the potential to increase sentiment categorization accuracy across a variety of different areas.

The Stochastic Agreement Regularization method is used to classify cross-domain polarity. It's a probabilistic agreement approach that works by reducing the Bhattacharyya distance between trained models with two distinct perspectives. It generalises the models out of each point of view by limiting the amount of disagreement they may have on unlabeled cases from a scientific approach. Lambova et al. [23] reported work on the challenge of cross-domain text subjectivity categorization, which employed the Stochastic Agreement Regularization technique as a foundation. Using the agreement-constrained co-training method and multiple views of a problem, they came up with three new algorithms. Three well-known data sets were utilised to analyse movie reviews and questions. They demonstrated that their suggested approach outperforms the Stochastic Agreement Regularization technique. For combined modelling of several data sources, diversity among distinct data sources is an issue. Gupta et al. [32] attempted to overcome this challenge since joint modelling is vital for transfer learning. Their paper proposes a regularised shared subspace learning framework that may take advantage of the mutual strengths of linked data sources while avoiding the consequences of each source's changeability. For their effort, they drew on data from well-known social media and news sites including Blogspot, Flickr, and YouTube. They were able to show that their strategy was superior to others.

V. APPLICATIONS OF SENTIMENT ANALYSIS

Sentiment analysis may help with everything from detecting client opinions to assessing individual mental wellbeing [44,45] through social platforms .As a result of technological breakthroughs such as Big Data [47,48], Cloud Computing [50], and Blockchain [50], sentiment analysis may now be used in virtually any business.. The following subsections, for example, cover the most typical sentiment analysis applications.

A. Intelligence for Business

There are numerous advantages of using sentiment analysis in the world of business intelligence. Organizations may apply sentiment analysis data to improve goods, study customer comments, or create a new marketing strategy [51]. For example. in the realm of business intelligence, the most common use of sentiment analysis is to examine consumer perceptions of products or services. Buyers may utilise this research to evaluate products and make well educated selections, not only product manufacturers. Bose et al. [45] studied Amazon evaluations of local cuisine over eight years. Using the NRC emotion vocabulary, customers' reviews were divided into eight emotional responses (rage, fright, faith, eagerness, grief, astonishment, disgust, and joy) and two sentiments (positive and negative). Their research discovered that sentiment analysis may be useful in detecting consumer attitudes and mitigating risks in order to keep customers delighted. Market and forex fluctuations were also predicted using sentiment research. Rognone and colleagues [52] investigated the impact of news emotion on Bitcoin and traditional currency returns, volume, and fluctuation. Ravenpack News Analytics 4.01 was used to look at high-frequency intra-day data (15 minutes) across a seven-year period (2012–2018) to see how unscheduled news about Bitcoin and six other currencies affected mood. According to the authors, traditional currencies react swiftly and dramatically to business news wire transfers. The results of the Bitcoin experiment were different from those of the Forex experiment, demonstrating that Bitcoin does not react to information in the same manner that conventional currencies do. Bitcoin and digital currencies (also known as cryptocurrencies) are terms for a new technology known as Blockchain, which is a fully decentralised ledger that allows peer-to-peer assets (such as digital money) to be transferred effectively and securely without the use of third-party intermediaries such as banks and legal teams [50]. Participants in the blockchain network use peer-to-peer general agreement procedures to validate transactions in real time. A small number of studies have used sentiment analysis to estimate the value of digital currencies, but Kraaijeveld and De Smedt's[53] research is an exception. Cryptocurrency experts employed a specific cryptocurrency terminology to do sentiment analysis on Twitter to estimate the price returns of several well-known digital currencies. Jing and Murugesan [54] developed a theoretical framework for automatically recognising fake news on social media using blockchain technology principles and methodologies.

B. Recommender System

An algorithm that attempts to present users with appropriate material (movies, music, or product recommendations) is known as a recommender system. [55]. A good recommender system can bring in a lot of money in some industries. As a result, using sentiment analysis to these systems [56-58] can aid in the generation of more accurate recommendations.

The Sentiment Based Matrix Factorization with Reliability (SBMF+R) approach is a novel approach for utilising reviews for trustworthy suggestions.1) they built a sentiment lexicon and utilised it to translate reviews into sentiment ratings. 2) In the second step, user dependability metrics were produced, which included user consistency and comments on reviews. 3) a probabilistic matrix factorization of the rating, reviews, and feedback. Using social networks as a model of responsive e-learning, the authors showed that the use of large data sets and sentiment analysis has the potential to completely transform the e-learning landscape. Using the proposed sentiment analysis, we can identify social aspects impacting learners that are important in the establishment of an effective learning rhythm.

C. Government-Provided Intelligence

In addition to products and services, people comment on a wide range of topics, including politics, religious beliefs, social issues, and even products and services themselves, as researchers found out by analysing Twitter posts for sentiment on Brexit outcomes and other similar topics. monitoring public reaction to the effective execution of specific measures is immensely valuable, examined local government tweets in the United States to see whether emotion (tone) affects citizen engagement with government via social media platforms. Sentiment Political Compass (SPC) was used to measure newspapers' attitudes on political parties. The goal of this study is to determine how political preferences expressed in newspapers affect the evolution of voter opinion. More than 740,000 political entities were extracted from 180,000 newspaper articles over an 18-month period during the German Federal Elections by crawling the data from twenty-five newspapers. These data are used to study the link between newspapers and political parties. In some instances, sentiment analysis should be conducted in real time to monitor the public mood. The use of additional technological solutions, such as Big Data, in real-time sentiment analysis, on the other hand, is required. There is no need to employ sentiment analysis and Big Data in tandem for real-time analysis. [48] The term "Big Data" refers to an enormous amount of complex data that is currently being handled ineptly. By utilised Big Data techniques, an adaptive system that analyses social media posts in real time to extract user opinions was developed. This method is divided into three stages: creating word embedding dictionaries for each item, categorising postings, and adjusting sentiment weights before running a prediction algorithm. They compared their method to various sentiment analysis tools after evaluating the post-classification performance of the analysed tweets in terms of whether or not they were viewed as positive or negative.

D. Medical and Healthcare Domain

A lot of attention has been paid recently to the application of sentiment analysis in the medical area. In order to provide better treatment, this programme assists healthcare providers in collecting and analysing data concerning diseases, poor medication responses, epidemics, and patient emotions. The sentiment analysis is challenging to utilise in this sector due to a number of issues, including terminology Clark et al. It uses tweets about patient experiences as an unique public health surveillance method and found and studied them. Twitter's public streaming API was used to collect over 5.3 million breast cancer-related tweets. Researchers have used sentiment analysis to analyse breast cancer patients' tweets. They found that good experiences with patient care, mobilising support, and increasing awareness were shared. The study shows that social media might be a useful tool for patients to communicate their wants and concerns.

As previously stated, additional technologies may be used with sentiment analysis to assist its adoption in a range of industries by addressing some of the challenges that sentiment analysis encounters, such as data imbalance and the requirement for processing resources. For example, cloud computing technology may be utilised to do sentiment analysis using computationally expensive approaches, as well as for a variety of other tasks. On-demand network access to computing services (hardware and software) can be provided by leveraging mutually and dynamically scalable resources that can be delivered and released with little involvement from the service provider. [49]. It was developed to be compatible with a health monitoring system that recognises emotions. On a wearable computer, physiological data is collected and tracked. The gathered data is analysed and assessed using machine learning algorithms in order to foresee participants' physiological or psychological circumstances.

VI. CONCLUSION AND FUTURE WORK

According to this survey, sentiment analysis issues have a significant impact on sentiment appraisal. Using data from 47 research, two comparisons were made. The key contrast is between the structure of sentiment reviews and the associated difficulties. The result demonstrates domain dependence, which is a key factor to consider while attempting to comprehend sentiment issues. Furthermore, the negation challenge has grown in popularity in all sorts of evaluations, with the only difference being the implied or unequivocal significance. This comparative result makes it easier to see how each sentiment issue affects the different types of review structure. We find that the appropriate difficulties for the evaluation sentiment reviews are determined by the issue type and review format. The other comparison is based on sentiment analysis difficulties related to the accuracy rate. Their findings provide light on the importance of sentiment challenges in analysing feelings, as well as how to select the ideal test to maximise the level of accuracy. We analyse the correlation between the ratio of sentiment strategies used to address sentiment issues in conceptual and practical categories.

Another finding explains why conceptual type sentiment problems are a major topic of investigation. The more study done, the lower the average accuracy rate in a sentiment challenge. The average of exactness rates decreases as the number of tests in an emotion challenge increase. The long-term effort will consist of continually expanding the comparison circle with fresh findings.

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REFERENCE

1. B. Pang, L. Lee, Opinion mining and sentiment analysis, Found. Trends Inform. Retrieval 2 (2008) 1–135. https://doi.org/10.1561/1500000011
2. A. Balahur, Methods and Resources for Sentiment Analysis in Multilingual Documents of Different Text Types, PhD Thesis, University of Alicante, Spain, 2011, 273p.
3. I. Niles, A. Pease, Linking lexicons and ontologies :mapping WordNet to the suggested upper merged ontology, in: Proceedings of the 2003 International Conference on Information and Knowledge Engineering (IKE 03), Las Vegas, 2003, pp. 23–26.
4. C. Strapparava, A. Valitutti, WordNet-Affect: an affective extension of WordNet, in: Proceedings of LREC, vol. 4, 2004, pp. 1083–1086.
5. A. Esuli, F. Sebastiani, SENTIWORDNET: a publicly available lexical resource for opinion mining, in: Proceedings of the 5th Conference on Language Resources and Evaluation LREC-06, Genoa, Italy, 2006, pp. 417–422 (See also: http://sentiwordnet.isti.cnr.it/).
6. S. Baccianella, A. Esuli, F. Sebastiani, SENTIWORDNET 3.0: an enhanced lexical resource for sentiment analysis and opinion mining, in: Proceedings of LREC- 10, Malta, 2010, pp. 2200–2204.
7. J. Yi, T. Nasukawa, R. Bunescu, W. Niblack, Sentiment analyzer: extracting sentiments about a given topic using natural language processing techniques, in: Proceedings of the Third IEEE International Conference on Data Mining, 2003, pp. 427–434.
8. S.K. Li, Z. Guan, L.Y. Tang, et al., Exploiting consumer reviews for product feature ranking, J. Comput. Sci. Technol. 27 (3) (2012) 635–649, http:// dx.doi.org/10.1007/s11390-012-1250-z. https://doi.org/10.1007/s11390-012-1250-z
9. J. Kamps, M. Marx, Words with attitude, in: Proceedings of the 1st International WordNet Conference, Mysore, India, 2002, pp. 332–341.
10. K. Crammer, Y. Singer, Ultraconservative online algorithms for multiclass problems, JMLR (2003).
11. J.C.B. Rabelo, R.B.C. Prudêncio, F.A. Barros, Using link structure to infer vopinions in social networks, IEEE International Conference on Systems, Man, and Cybernetics (SMC 2012), IEEE, 2012. https://doi.org/10.1109/ICSMC.2012.6377805
12. T. Wilson, J. Wiebe, P. Hoffmann, Recognizing contextual polarity in phrase- level sentiment analysis, in: Proceedings of HLT/EMNLP-05, Vancouver, Canada, 2005. https://doi.org/10.3115/1220575.1220619
13. A. Moreo, M. Romero, J.L. Castro, J.M. Zurita, Lexicon-based comments- oriented news sentiment analyzer system, Expert Syst. Appl. 39 (2012) 9166– 9180. https://doi.org/10.1016/j.eswa.2012.02.057
14. R. Feldman, Techniques and applications for sentiment analysis, Commun.ACM 56 (4) (2013) 82–89 (Review Articles). https://doi.org/10.1145/2436256.2436274
15. E. Cambria, B. Schuller, Y.-Q. Xia, New avenues in opinion mining and sentiment analysis (extended abstract), in: Proceedings of IJCAI, Buenos Aires 2015.
16. H. Tang, S. Tan, X. Cheng, A survey on sentiment detection of reviews, Expert Syst. Appl. 36 (2009) 10760–10773. https://doi.org/10.1016/j.eswa.2008.01.047
17. H. Chen, D. Zimbra, AI and opinion mining, IEEE Intell. Syst. 25 (2010) 74–80. https://doi.org/10.1109/MIS.2010.75
18. J. Bollen, H. Mao, X. Zeng, Twitter mood predicts the stock market, J. Comput.Sci. 2 (2012) 1–8. https://doi.org/10.1016/j.jocs.2010.12.007
19. S. Kumar, F. Morstatter, H. Liu, Twitter Data Analytics, Springer, 2013 (August 19) https://doi.org/10.1007/978-1-4614-9372-3
20. R. McDonald, K. Crammer, F. Pereira, Online large-margin training of dependency parsers, in: Proc. ACL, 2005. https://doi.org/10.3115/1219840.1219852
21. A.C.-R. Tsai, C.-E. Wu, R.T.-H. Tsai, J.Y.-J. Hsu, Building a concept-level sentiment dictionary based on commonsense knowledge, IEEE Intell. Syst. 2 (2013) 22–30. https://doi.org/10.1109/MIS.2013.25
22. C. Bosco, V. Patti, A. Bolioli, Developing corpora for sentiment analysis: The case of irony and senti-tut, IEEE Intell. Syst. 2 (2013) 55–63. https://doi.org/10.1109/MIS.2013.28
23. S. Poria, A. Gelbukh, A. Hussain, N. Howard, D. Das, S. Bandyopadhyay, Enhanced SenticNet with affective labels for concept-based opinion mining, IEEE Intell. Syst. 2 (2013) 31–38. https://doi.org/10.1109/MIS.2013.4
24. I. Maks, P. Vossen, A lexicon model for deep sentiment analysis and opinion mining applications, Decis. Support Syst. 53 (2012) 680–688. https://doi.org/10.1016/j.dss.2012.05.025
25. Q. Miao, Q. Li, R. Dai, AMAZING: a sentiment mining and retrieval system, Expert Syst. Appl. 36 (2009) 7192–7198. https://doi.org/10.1016/j.eswa.2008.09.035
26. M.R. Saleh, M.T. Martín-Valdivia, A. Montejo-Ráez, L.A. Ureña-López, Experiments with SVM to classify opinions in different domains, Expert Syst. Appl. 38 (2011) 14799–14804. https://doi.org/10.1016/j.eswa.2011.05.070
27. P. Sobkowicz, M. Kaschesky, G. Bouchard, Opinion mining in social media: modeling, simulating, and forecasting political opinions in the web, Gov. Inform. Quart. 29 (2012) 470–479. https://doi.org/10.1016/j.giq.2012.06.005
28. J. Pennebaker, R. Booth, M. Francias, Linguistic Inquiry and Word Count. LIWC 2007, 2007.
29. R. Narayanan, B. Liu, A. Choudhary, Sentiment analysis of conditional sentences, Proceedings of the 2009 Conference on Empirical Methods in Natural Language Processing, vol. 1, Association for Computational Linguistics, 2009, pp. 180–189. https://doi.org/10.3115/1699510.1699534
30. A. Balahur, Jesu's M. Hermida, Andre's Montoyo, Building and exploiting EmotiNet, a knowledge base for emotion detection based on the appraisal theory model, IEEE Trans. Affect. Comput. 3 (1) (2012). https://doi.org/10.1109/T-AFFC.2011.33
31. V. Hatzivassiloglou, J. Wiebe, Effects of adjective orientation and gradability on sentence subjectivity, Proceedings of the 18th Conference on Computational Linguistics, vol. 1, Association for Computational Linguistics, 2000, pp. 299–305. https://doi.org/10.3115/990820.990864
32. P. Turney, Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews, in: Proceedings of the 40th Annual Meeting on Association for Computational Linguistics ACL'02, Association for Computational Linguistics, Stroudsburg, PA, USA, 2002, pp. 417–424. https://doi.org/10.3115/1073083.1073153
33. B. Pang, L. Lee, S. Vaithyanathan, Thumbs up? Sentiment classification using machine learning techniques, Proceedings of the ACL-02 Conference on Empirical Methods in Natural Language Processing, vol. 10, Association for Computational Linguistics, 2002, pp. 79–86. https://doi.org/10.3115/1118693.1118704
34. T. Wilson, P. Hoffmann, S. Somasundaran, J. Kessler, J. Wiebe, Y. Choi, C. Cardie, E. Riloff, S. Patwardhan, Opinion Finder: a system for subjectivity analysis, in: Proceedings of HLT/EMNLP on Interactive Demonstrations, Association for Computational Linguistics, 2005, pp. 34–35. https://doi.org/10.3115/1225733.1225751
35. I. Peñalver-Martinez et al., Feature-based opinion mining through ontologies, Expert Syst. Appl. (2014), http://dx.doi.org/10.1016/j.eswa.2014.03.022.
36. H. Cho et al., Data-driven integration of multiple sentiment dictionaries for lexicon-based sentiment classification of product reviews, Knowl.-Based Syst.71 (2014) 61–71. https://doi.org/10.1016/j.knosys.2014.06.001
37. L. Chen, L. Qi, F. Wang, Comparison of feature-level learning methods for mining online consumer reviews, Expert Syst. Appl. 39

(2012) 9588–9601. https://doi.org/10.1016/j.eswa.2012.07.005
38. M. Hu, B. Liu, Mining and summarizing customer reviews, in: Proceedings of Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ACM, 2004, pp. 168–177.
39. A.L. Maas, R.E. Daly, P.T. Pham, Dan. Huang, A.Y. Ng, C. Potts, Learning word vectors for sentiment analysis, in: Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics (ACL 2011) Portland, Oregon, USA, 2011, pp. 142–150.
40. Taddy, Measuring Political Sentiment on Twitter: Factor Optimal Design for Multinomial Inverse Regression, Technometrics, 2013, http://dx.doi.org/10.1080/00401706.2013.778791.
41. S.-T. Li, F.-C. Tsai, A fuzzy conceptualization model for text mining with application in opinion polarity classification, Knowl.-Based Syst. 39 (2013) 23–33. https://doi.org/10.1016/j.knosys.2012.10.005
42. F. Figueiredo, L. Rocha, T. Couto, T. Salles, M.A. Goncalves, W. Meira Jr., Word co-occurrence features for text classification, Inform. Syst. 36 (2011) 843– 858. https://doi.org/10.1016/j.is.2011.02.002
43. Y.-M. Li, Y.-L. Shiu, A diffusion mechanism for social advertising over microblogs, Decis. Support Syst. 54 (2012) 9–22. https://doi.org/10.1016/j.dss.2012.02.012
44. S. Wang, D. Li, X. Song, Y. Wei, H. Li, A feature selection method based on improved Fisher's discriminant ratio for text sentiment classification, Expert Syst. Appl. 38 (2011) 8696–8702. https://doi.org/10.1016/j.eswa.2011.03.057
45. Y. Dang, Y. Zhang, H. Chen, A lexicon-enhanced method for sentiment classification: an experiment on online product reviews, IEEE Intell. Syst. 25 (4) (2010) 46–53. https://doi.org/10.1109/MIS.2009.105
46. E. Boiy, M.-F. Moens, A machine learning approach to sentiment analysis in multilingual Web texts, Inform. Retrieval 12 (2009) 526–558, http:// dx.doi.org/10.1007/s10791-008-9070-z. https://doi.org/10.1007/s10791-008-9070-z
47. E.J. Fortuny, T.D. Smedt, D. Martens, W. Daelemans, Media coverage in times of political crisis: a text mining approach, Expert Syst. Appl. 39 (2012) 11616–11622. https://doi.org/10.1016/j.eswa.2012.04.013
48. L.-S. Chen, C.-H. Liu, H.-J. Chiu, A neural network based approach for sentiment classification in the blogosphere, J. Informet. 5 (2011) 313–322. https://doi.org/10.1016/j.joi.2011.01.003
49. H. Bao, Q. Li, S.S. Liao, S. Song, H. Gao, A new temporal and social PMF-based method to predict users' interests in micro-blogging, Decis. Support Syst. 55 (2013) 698–709. https://doi.org/10.1016/j.dss.2013.02.007
50. R. Moraes, J.F. Valiati, W.P. Gaviao Neto, Document-level sentiment classification: an empirical comparison between SVM and ANN, Expert Syst. Appl. 40 (2013) 621–633. https://doi.org/10.1016/j.eswa.2012.07.059
51. J. Du et al., Box office prediction based on microblog, Expert Syst. Appl. (2013), http://dx.doi.org/10.1016/j.eswa.2013.08.065.
52. E. Cambria, P. Gastaldo, F. Bisio, R. Zunino, An ELM-based model for affective analogical reasoning, Neurocomputing 149 (2015) 443–455. https://doi.org/10.1016/j.neucom.2014.01.064
53. T. Geva, J. Zahavi, Empirical evaluation of an automated intraday stock recommendation system incorporating both market data and textual news, Decis. Support Syst. (2013),http://dx.doi.org/10.1016 /j.dss.2013.09.013.
54. R. Xia, C. Zong, S. Li, Ensemble of feature sets and classification algorithms for sentiment classification, Inform. Sci. 181 (2011) 1138–1152. https://doi.org/10.1016/j.ins.2010.11.023
55. F.Å. Nielsen, A New ANEW: Evaluation of a Word List for Sentiment Analysis in Microblogs, 2011. Available from: <arXiv:1103.2903>.
56. Z. Zhai, Product feature grouping for opinion mining, IEEE Intell. Syst. 4 (2012) 37–44. https://doi.org/10.1109/MIS.2011.38
57. M. Ghiassi, J. Skinner, D. Zimbra, Twitter brand sentiment analysis: a hybrid system using n-gram analysis and dynamic artificial neural network, Expert Syst. Appl. 40 (2013) 6266–6282. https://doi.org/10.1016/j.eswa.2013.05.057
58. B. Desmet, V. Hoste, Emotion detection in suicide notes, Expert Syst. Appl. 40 (2013) 6351–6358. https://doi.org/10.1016/j.eswa.2013.05.050
59. Jyothirmayee, S., Kumar, V. D., Rao, Ch. S., & Shankar, R. S. (2019). Predicting Stock Exchange using Supervised Learning Algorithms. In International Journal of Innovative Technology and Exploring Engineering (Vol. 9, Issue 1, pp. 4081–4090). https://doi.org/10.35940/ijitee.a4144.11911 9
60. Rana, R. (2022). Entry of Indian Millennials into Stock Market Post Pandemic: A Boon or Bane. In Indian Journal of Economics and Finance (Vol. 2, Issue 2, pp. 12–20). https://doi.org/10.54105/ijef.d2519.111422

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