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Systematic review of methods, applications, and challenges of Sentimental Analysis

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ABSTRACT
The number of comments has increased significantly as a result of the widespread use of Internet-based apps, growing at an exponential rate. Analysing the sentiments and attitudes stated in comments provides governments, businesses, and academics with important support. However, it is difficult to correctly infer the user's emotion from the large number of comments. Sentiment analysis (SA) is a quick and efficient technique that reads and understands reviewers' opinions and sentiments automatically. However, the present reviews of the literature are narrowly focused, either on a small number of studies or devoted to a specific area of sentiment analysis research. This study carried out a thorough review of the body of literature on sentiment analysis approaches, uses, and problems. The goal of sentiment analysis is thoroughly analysed, technique comparisons are shown, the areas where sentiment analysis is used are examined, the difficulties and constraints faced by researchers are noted, suggestions for potential solutions are made, and future research directions are explored in this systematic literature review. The results of the study highlight how important artificial intelligence technologies are to automated text sentiment analysis and how important sentiment analysis is to people's daily lives and productivity. This study adds to the body of knowledge already available on sentiment analysis and helps practitioners and academics choose the best strategy and put sentiment analysis techniques into practice.
Keywords: Multiple language Models testing, Methods and Applications of Sentiment Analysis, Sentiment Analysis elements and Challenges.

1. Introduction

A significant number of online comments have been generated over the course of the past ten years as a result of the rapid expansion of the Internet. It is of considerable importance for social development and stability to conduct an analysis of the feelings expressed by internet users in their comments (Birjali et al., 2021). SA technology has arisen as a solution to this trend. Sentiment analysis (SA), commonly referred to as opinion analysis or opinion mining, is a significant field of study in natural language processing (NLP) (Chaturvedi et al., 2018;). It aims to automatically extract and analyses sentiments and viewpoints from text (Liu and Zhang, 2012). Sentiment analysis (SA) plays a key role in the advancement of artificial intelligence, as highlighted by Liu and Zhang in 2012.

Sentiments of positivity, neutrality, and negativity can all be categorised into separate and unique groups. Bose et al., (2020) suggest that these categories can be subdivided into further subcategories, including anticipation, fear, surprise, anger, trust, grief, disgust and delight etc.. There is a diverse selection of natural languages that can be utilised for sentiment analysis research. Among the languages included in the study are English (Rodriguez et al., 2023), Russian (Smetanin, 2020), German (Remus et al., 2010), Arabic (Oueslati et al., 2020) and Chinese (Peng et al., 2017) etc.

Through the analysis and comprehension of human emotional indicators, machines can generate intelligent responses that enhance their ability to aid humans. Eskandari et al., (2015) and Susnjak (2024) found that Human Machine Intelligence and ChatGPT, both derive significant advantages from sentiment analysis. In addition to this, Sentiment Analysis plays a crucial role in the advancement of digital payment platforms, government operations, banking services, foreign evaluations, health care systems, and Internet social platforms.The pervasive nature of individuals' online presence has led to a significant surge in the volume of online comments (Jain et al., 2021). To improve public opinion monitoring and decision-making in different industries, it is possible to automatically capture the psychological perceptions of commentators at a cheap cost and effectively evaluate tens of thousands of comments.The growing body of relevant research studies and publications has therefore resulted in a significant rise in the popularity of sentiment analysis (SA) within scientific communities. There has been a substantial rise in the number of research publications focused on the field of SA in the past decade, which suggests a growing academic interest in this domain. Figure 1 illustrates the temporal distribution of publications in Web of Science.The enormous amount of literature on sentiment analysis is a difficulty for academics attempting to conduct relevant and up-to-date investigations. Researchers have argued that doing a complete and systematic review of the existing literature is a trustworthy approach to addressing this issue. Mercha and Benbrahim (2023) compared SA tools such as Valence Aware Dictionary, and Sentiment Reasoner (VADER), Text Blob and Natural Language Toolkit (NLTK) to investigate lexicon-based approaches to SA and found that VADER outperformed among the other tools. Birjali et al., (2021) undertook a thorough investigation on the approaches, challenges, and patterns associated with SA. This study discussed the preprocessing stages and classified various sentiment analysis approaches. Several sentiment analysis evaluations have focused on deep learning (DL) techniques. Shaik et al., (2023) focuses on the challenges presented by SA and its importance in the realm of education. Hzunic et al., did a review in 2020 that focused on Sensitivity Analysis (SA) applications in health and Xu et al., (2022b) did a thorough examination and comparison of various sentiment analysis studies in the social media industry. They investigated the studies' complexity, as well as the datasets, languages, techniques, and evaluation measures used. There are two types of sentiment analysis: aspect-level sentiment analysis and document-level sentiment analysis, which look at distinct levels of text. Matrane et al., (2023) examined the development of pre-trained models and sequential transfer learning. They assessed the models' applicability and suggested prospective areas for future investigation. Literature revealed that large number of Arabic reviews are also available for SA. Alyami et al., (2022) provided a detailed survey of prompt-based sentiment analysis algorithms. They also discussed the use of large-scale language models in this setting. Furthermore, the study's future focus will be on multimodal sentiment analysis of technology and its accompanying issues (Das and Singh, 2023).

Prior sentiment analysis surveys were primarily focused on specific subfields and did not cover some of the most recent SA technologies. The surveys largely examined transformer learning, machine learning, and lexicon-based techniques. This work incorporates a variety of methodologies, setting it unique from previous work, despite the fact that these tasks were incorporated. Furthermore, the currently available surveys are generally concerned with SA, such as e-commerce. Behdenna et al., (2018) concentrated on aspect-level sentiment analysis and document-level sentiment respectively, whereas Huang et al., (2023) explored potential future opportunities in e-commerce industry to employ sentiment analysis. The review offered a succinct outline of the techniques and algorithms used in sentiment analysis for e-commerce.This survey distinguishes itself from prior research by offering a current viewpoint on the majority of applications and expansive language models. Moreover, the earlier evaluations were deficient in terms of the amount of research they included and provided insufficient descriptions of the difficulties and future prospects. In order to address this deficiency, our study encompasses a broader spectrum of literature, examining over 200 research papers. In addition, the survey made use of manual analysis in order to gain more profound insights.The system's main advantages are its extensive coverage of literature, its ability to perform manual analysis for more profound discoveries, and its current perspective on language models. The paper provides essential contributions by offering a thorough examination of sentiment analysis, covering all areas of the issue, including a broad range of technologies, state-of-the-art applications, and extensive problems. This article is quite helpful for movies and researchers alike because it provides them with the opportunity to get a wealth of information regarding the subject matter in a single study. The survey has made noteworthy contributions, which can be summarised as follows:

· A comprehensive array of studies was meticulously examined to provide scholars with profound insights for the development of approaches grounded in previous research.· An evaluation of existing sentiment analysis methods to aid researchers in choosing suitable ways for this purpose. A contemporary viewpoint on the utilisation of applications and extensive language models to stay abreast of the most recent advancements in research.

In order to determine where future research efforts should be concentrated, a detailed overview of the difficulties faced by SA and potential solutions for reference purposes is required.

Figure 1: Articles published in WOS (Web of Science) from 2013 to 2023.

2. Systematic Review Methodology

SLR is a methodical approach to identifying, gathering, selecting, and analysing primary studies on a specific subject and offers an impartial, comprehensive, and expeditious summary of the latest research. This evaluation is conducted using the Preferred Reporting Items for the Systematic Review and Meta-Analysis (PRISMA) approach. The review method consists of four distinct steps: formulating research inquiries, conducting a comprehensive search of relevant literature, evaluating and selecting data, and analysing the collected data (Sarkis-Onofre et al., 2021).

Based on the several variables such as level of sentiment analysis, datasets, methods, applications and other aspects, the research questions have been established as follows:

RQ1: What techniques are employed to carry out sentiment analysis?

RQ2: What are the most efficient strategies for sentiment analysis?

RQ3: Which datasets and assessment measures are utilised in sentiment analysis?
RQ4: What are the predominant domains where SA is widely used?
RQ5: What are the obstacles and prospective areas of study for sentiment analysis?
The literature uses the PRISMA guidelines and figure 2 depicts the process of selecting literature. The review is initially identified then screened and finally only relevant papers were included for the current research work. The articles in reputed journals, conferences, scientific digital databases and academic search engines have been selected for the period of 2013 to 2023.
During the screening stage, only those papers which match specific standards were selected for further data analysis and other papers leads to exclusion. During the screening stage, those articles and their abstracts fail to present a definitive conclusion or were repetitive in nature, were directly excluded, hence 550 papers were excluded, and 112 publications were selected for final stage.

2.1. Data analysis

The articles published in databases cited are Springer Link, Elsevier Science Direct, Scopus, Web of Science, and Google Scholar etc are selected. This step entails the discussion of the data obtained from the primary research conducted during the inclusion phase. Each trial yields two separate categories of data. A data type encompasses information such as the author's particulars, publication years, and publishing entity. The second category of data relates to the research subjects of our Systematic Literature Review (SLR). Important factors to take into account when doing a Systematic Literature Review (SLR) are the methods and techniques used, the specific application domain, the availability of public datasets, the assessment metrics employed, and any current problems or challenges.

Fig. 2. The PRISMA flow diagram for literature selection.

The survey is categorised into three primary sections: methodology, applications, and difficulties, as depicted in Figure 3. At first, we have defined and created a methodical categorization for sentiment analysis methodologies. In addition, this study has analysed several scholarly articles to investigate the areas in which sentiment analysis can be utilised. A newly incorporated segment titled "Discussion and Challenges" has been introduced to scrutinize, evaluate, and appraise the assessed studies, while also highlighting forthcoming avenues and areas necessitating further investigation.

Table 1: Criteria adopted to include or exclude the articles

Criteria of Inclusion of articles	Criteria of Exclusion of articles
The must be published between 2013 to 2023.	The paper not relevant to Sentiment Analysis.
The language of paper must be English.	Paper in other language not considered
Paper must be in reputed journal, database, conferences.	The paper in the form of images should be excluded.

3. Sentiment analysis levels

Sentiment analysis divides the documents into phrases, and aspect levels dependent on the size of the text being examined and can be further recognized based on their language and types (Do et al., 2019). SA has been classified into various levels which are explained as:
Sentence-level sentiment analysis categories each sentence into either objective or subjective categories, which further breaks the sentences into positive or negative aspects based on the perception of customers. The study utilised a sequence model to categories the sentiment elements of remarks and segregates the different aspects based on the objectives. Su et al., (2023) presented a supervised method for analysing sentiment at the phrase level, employing advanced machine learning techniques. Document-level sentiment analysis entails evaluating the entire emotional essence of each document and treats it an individual object, assigning only one sentiment aspect to it, hence this task is classified as coarse-grained. Zhang et al., (2022a) proposed a theoretical SA model express similar thoughts which are more likely to submit similar assessments and to improve the precision of SA. The goal was accomplished by using the linguistic attributes of the Urdu language (Altaf et al., 2023).Aspect-level sentiment analysis specifically examines the relationship between the words, category, key terms, and sentiment elements. It consists of two primary stages such as extraction of aspect and opinion terms and determination of the sentiment elements. With regards to the assertion, "The steak served at this establishment is exceptionally delicious." The phrase "steak" is classified as a subcategory within the broader category of "food". The steak is described as "delicious," which is a subjective judgement. The expressed orientation of sentiment emotions linked with the steak is positive. Zhu et al., (2024) thoroughly examined the correlated deliberations and contextual phrases to assign different weights, thereby reducing errors and to enhance aspect-level sentiment analysis (Wen et al., 2020; Huang et al., 2022a).

4. Sentiment analysis techniques

Datasets are partitioned into training datasets using conventional machine learning methods. In contrast to textual content, the databases primarily consist of visual and auditory media, including images, audio files, and videos. Machine learning models may effectively utilise extensive past knowledge from training datasets to produce accurate predictions and classifications. Following the completion of training, test datasets are employed to assess the efficacy and influence of these models. The evaluation technique is crucial since it demonstrates the model's ability to generalize to unfamiliar and untested data. The successful utilisation of many conventional machine learning approaches has addressed the issues associated with sentiment categorization. In this particular setting, often employed approaches include support vector techniques, decision trees, and Naïve Bayes (Kang et al., 2012). Ahmad et al., (2017) have classified SA strategies into four categories named as traditional machine-learning, hybrid approaches, deep-learning, and lexicon-based (Thakkar and Patel, 2015), which are further depicted in figure 4. Naive Bayes classifiers, as an illustration, are probabilistic models that depend on Bayes' theorem. Due to their efficacy and straightforwardness, they are particularly beneficial for text categorization. The assumption is made that the presence of a characteristic in a class is not influenced by the presence of any other feature, which is known as conditional independence. Despite their simplistic assumption, Naive Bayes classifiers have demonstrated exceptional performance in various real-world applications, such as sentiment analysis. Decision trees are non-parametric models that use a graphical representation of decisions and their possible consequences, which looks like a tree. They are a widely favoured choice for numerous machine learning tasks due to their simplicity and intuitiveness. Decision trees are a valuable tool for managing both numerical and categorical data in sentiment categorization. The data is partitioned into branches that finally culminate in a determination of the sentiment of the input text.Support vector machines, often known as SVMs, are a powerful approach for sentiment analysis. Support Vector Machines (SVMs) operate by locating the hyperplane that effectively separates the data into the most distinguishable classes. They are widely recognised for their accuracy and durability and are particularly valuable in complex and multi-dimensional domains. SVMs, with the aid of kernel functions, have the capability to handle both linear and non-linear classification tasks, hence making them versatile for addressing a broad spectrum of sentiment analysis problems. Test datasets are crucial for evaluating the efficacy of machine learning models, which utilise the data from training datasets to perform sentiment classification. When dealing with these challenges, conventional methods like Naïve Bayes, decision trees, and SVMs provide robust frameworks, each with distinct advantages and applications. The continual deployment and enhancement of these models have significantly advanced sentiment analysis.
The lexicon-based approach strategy allocates scores to the tokens that have been collected and acknowledges the tone of a specific sentence, which can be fluctuated across various domains. For instance, let us examine the sentence that the movie has a long climax. In this case, the adjective "long" is associated with a negative connotation. In the another sentence, that the supporting hero has a longer appearance. The longer digit is considered more visually appealing. To resolve this issue, we can employ a mechanism called dictionary adaptation. Dictionary-based and corpus-based methods are the two primary categories into which lexicon-based approaches are frequently classified (Mitra, 2020). The advantages and disadvantages of lexicon-based techniques are summarised in Table 2.
The optimisation of class boundaries is facilitated by the SVM's capacity to differentiate between distinct hyperplanes (Khoshnevisan et al., 2015). Naive Bayes (NB) is a classification method that employs the Bayes theorem to determine the probability of an event occurring, while considering prior information. The objective of maximum entropy (ME) is to optimise the information entropy of the classification outcome while simultaneously guaranteeing adherence to the specified constraints (Mubarok et al., 2017). As described by Kingsford and Salzberg in 2008, the DT technique employs a collection of training examples to construct a tree for the purpose of analysing the sentiment of text. In their 2020 study, Daeli and Adiwijaya employed the K-nearest neighbours (KNN) algorithm to classify the test data and conduct comparisons with the neighbouring data points. Logistic regression (LR) is capable of generating approximate probability estimates and making predictions for various categories. Nevertheless, LR is susceptible to underfitting and exhibits a low level of classification accuracy. In algorithms such as Grid search and Randomised search cross-validation, the K value is a hyperparameter that can be selected. Table 3 offers a comprehensive overview of the advantages and disadvantages of the various methodologies employed to summarise evaluations of sentiment analysis technologies.

4.0.1. Classification of Deep learning methodologies

CNN is a type of neural network that utilises convolutional computing and pooling operations. In 2015, Chen conducted study on this feed-forward network, and in 2021b, Li et al., conducted research on it. CNN, first established in the realm of computer vision, has expanded its scope to encompass many fields, including natural language processing (NLP). In 2015, Chen presented a well recognised method for sentiment analysis called convolutional neural network (CNN). This method utilised word2vec for sentiment classification on a sentence level. This strategy demonstrated superior efficacy compared to previous ways. This study demonstrates the effectiveness of using pre-trained word embeddings in the context of deep learning.

Sentiment analysis (SA) commonly utilises the recurrent neural network (RNN) (Liu et al., 2016) due to its ability to effectively gather and store information from long sequences (Zaremba et al., 2014). One remarkable characteristic of RNN is its ability to leverage existing knowledge, enabling it to preserve and recall previous information. Hochreiter and Schmidhuber (1997) classified long short-term memory (LSTM) networks as a distinct subtype of recurrent neural networks (RNNs) that successfully address the problems of gradient explosion and vanishing. In addition, LSTM utilises a gating mechanism to address the issue of long-range dependency, which is a barrier that standard RNNs are unable to overcome. Xu et al., (2016) have shown that an LSTM with cache capabilities can effectively store information that is located far away from the present point in a sequence. The Tree-LSTM, created by Tai et al., (2015), demonstrated superior performance compared to existing LSTM baseline approaches. The performance of gated recurrent unit (GRU) networks and long short-term memory (LSTM) networks is nearly identical, and their topologies have characteristics. GRU offers a more streamlined model and faster convergence speed, making it advantageous. However, Long Short-Term Memory (LSTM) models demonstrate improved performance in scenarios with large amounts of data because to their much higher number of gates and parameters.

Fig. 3. Research contents.

4.1. Hybrid approach

Appel et al., (2016) found that hybrid sentiment strategy combines the few elements of lexicon approach, traditional machine learning approach and deep learning approaches and then based on the derived results, the new hybrid results are developed.

Fig. 4. Sentiment analysis Approaches.

For instance, Chang et al., (2020) employed support vector machine and relief techniques. The model is trained using a dataset containing a maximum of 6900 tweets. When 96 percent of the characteristics are incorporated, their model exceeds the performance of the majority of models. The results presented that by meticulously selecting the architecture and hyperparameters, hybrid models possess the capability to surpass all other models in terms of performance. Table 4 displays a variety of sentiment analysis methods and their corresponding comparisons.

4.1.1. Transformer-based models

Parmar et al., (2018) profound that transformer model is widely regarded as one of the most powerful and important deep learning models and has the tendency to solve the sequence-to-sequence problems through attention mechanism than LTSM, which results in enhanced performance and reduced computing complexity. The Transformer utilizes the self-attention technique for modelling. Due to its finite memory and computational limits, the Transformer theoretically has the capacity to encode text of any length. As a result of the large amount of attention that is being calculated, as well as the fact that both the complexity of the computation and the sequence length, the amount of memory and calculations performed are increasing at a rapid rate. Practically, the encoding process is constrained by limited memory and computer capabilities, typically allowing just a specific length to be encoded, such as 512. For the purpose of making other datasets better at long-range encoding In order to improve the modelling of long texts, particularly in document-level corpora, it is necessary to optimize the length of the Transformer encoding. When the length of the analysed text exceeds the maximum length, in the field of parallel computing, one common approach is sequence parallelism, as described by Li et al., in their 2021 paper.

Table 2 Different types of Lexicon Approach

Technique	Benefit	Shortcoming
Dictionary based	The utilisation of training data is not required.	Opinions are characterized by a particular content orientation.
Approach	It is important to provide positive results for certain domain vocabulary.	Opinion terms that are related with certain subject areas that have not yet been included in the dictionary are not able to be recognised by the dictionary.
Approach	Get definitions of words in the vocabulary in a short amount of time. The capacity to identify content-oriented opinion expressions that are distinct from one another. In situations where the domains are diverse, the results are superior.	The extensive diversity of the lexicon results in varying levels of performance. Despite the fact that it is challenging to generate whole texts that are capable of covering every text phrase, it is not viable to use it on an individual basis due to the complexity of doing so.

In 2019, Liu et al. undertook a study that resulted in the creation of a unique Transformer model called Bidirectional Encoder Representations from Transformers (BERT). BERT, developed by Google Research in early 2018, is a breakthrough in the field of natural language processing (NLP). The model utilizes word and positional encoding to optimize the performance of the Transformer Encoder layers, which are the core components of BERT. The embedding layer of BERT analyses input reviews and utilizes contextual information to generate token-level representations. By incorporating sentiment contextual information into language representation models, BERT enhances its ability to integrate auxiliary sentiment knowledge, leading to a more nuanced and comprehensive understanding of language.The BERT framework consists of two distinct stages: pre-training and fine-tuning. During the pre-training phase, the model utilizes a significant quantity of unlabeled data to obtain a fundamental model through self-supervised learning. This step enables BERT to acquire a profound comprehension of language structures and semantics through the prediction of missing words inside phrases and the comprehension of sentence links. During the fine-tuning phase, annotated data is employed to customize the pre-trained model for specific tasks, resulting in the refinement and optimization of the model for subsequent applications. BERT's performance in a range of NLP tasks, including as sentiment analysis, question answering, and text classification, is **notably excellent due to this technique.**

Table 3 Types of Sentiment Analysis Method

Technique	Benefit	Shortcoming
SVM	The most well-known SA's algorithm. Accomplish a high level of accuracy for a large dataset.	The process of fine-tuning a model is both time-consuming and subject to change.For large datasets, a significant amount of training time is required.
NB	It is easy to put into work. It is necessary to have fewer training data. When compared to other approaches, this one requires significantly less data and training time.	Assuming that the traits are independent of one another. Possibly encountering a problem with zero frequency. Disparities in the data categories are a limitation.
ME	Make use of a probabilistic strategy in your operations. There is a reduced requirement for training data.	It is not possible to use the model with another database because it is domain-oriented.
DT	It is easy to construct. Less time spent on training. Extensive datasets are not necessary for training purposes.	It is more likely that models will exhibit over-fitting.
	Less time spent on training. There is the possibility of constructing non-linear decision boundaries.	There will be construction of the domain-oriented model.
KNN	It is possible for data to be continuously contributed throughout the course of time, even in the absence of explicit training.	The more datasets and dimensions that are included, the more complicated the predictions will be.
		Each and every characteristic is of equal importance.
LR	To do categorization tasks, simple models are used.	In addition to being linear, boundaries are incapable of dealing with complex nonlinear situations.
CNN	The precision is higher. A more rapid training.	It is necessary to have a significant volume of train datasets and train time.
LSTM	Contrary to the Long-term dependencies are able to be captured by RNN.	

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GRU	It is less complicated than LSTM. It is quicker than LSTM.	Evaluate in comparison to other models exercise at a slower pace. Complicated and expensive in terms of the computing involved.
Transformer	For the purpose of determining dependencies, self-attention models are utilized. The focus is solely on the most important aspects of the statement.	Extremely complicated model with a lengthy training course. Computing in parallel is not possible.
ABSA	Analysis of sentiment attributes with a finer grain quality.	The absence of a substantial annotated database
Learning	Enhance the performance of the baseline. Saving time on the development of models	Convergence of the model parameters is not an easy task. There is a tendency for models to be over-fitted.
Multi-Modal Sentiment Analysis	When there are more sources of knowledge, the model is able to make more informed decisions. A representation of the features that is more thorough.	Expenses are incurred when labeling data. Cross-domain problems should be modeled.
Multi-Task Learning	The number of models should be reduced. Improve the usage of the data. Better performance in terms of generalization.	The performance of some subtasks may be satisfactory, while the performance of others may be subpar.There is considerable variation in the rate at which several tasks converge.
RNN	Make it possible to remember long-distance associations between consecutive data with a large degree of dependability.	Pooling layers may cause the feature to lose its position or order, depending on the circumstances.

Zhao and Yu (2021) emphasized the substantial progress in feature representation accomplished by BERT, where additional output layer was incorporated to the pre-trained BERT model so that cutting-edge models suitable for different situations may be developed. These models utilise the extensive and impartial representations obtained from unannotated assessments during the pre-training phase.

Zhou and Srikumar (2021) conducted a study on the BERT family by employing probing techniques to investigate the influence of fine-tuning on the underlying embedding space. Their research, in addition to the creation of multiple other iterations of pre-trained models, has played a role in improving other facets of BERT. The improvements have strengthened BERT's status as a favored approach for processing input statements and acquiring a more profound comprehension of contextual information.

BERT's two-step process of pre-training and fine-tuning, together with its capacity to incorporate contextual sentiment information, has significantly transformed the field of Natural Language Processing (NLP). The ongoing enhancements and modifications of BERT models have significantly enhanced feature representation, establishing BERT as a fundamental component of contemporary NLP research and applications.

· Decrease the quantity of models. • Enhance data utilisation.
· Enhanced ability to generalize and perform well on a wide range of tasks.
· Annotating data incurs significant costs.
· Address cross-domain concerns.
· Increased access to additional sources of information enhances the model's ability to make more informed decisions.
· The rate at which several tasks converge is variable.

Table 4 Comparative analysis of Sentiment Analysis Algorithms

Method	Benefit	Shortcoming
Lexicon- Based Approach	Straightforward and simple to comprehend.	The accuracy of the judgment of the sentiment conveyed by the text is not very highly regarded. In addition to a considerable amount of labor, it was necessary to make use of the emotional dictionary.
Conventional Machine Learning Approach	The capability to categorize the feelings conveyed by text based on the selection of sentiment features and the different emotional classifiers.	The performance of the individual cannot be improved by raising the size of the training set to a specific amount. Inability to make full use of the knowledge that has been contextualized when it is presented. A significant quantity of data support is required to fulfill this need.
Deep Learning Approach	Competent enough to actively learn information that is contextualized Within the context of improving the performance of sentiment analysis, it can gain the semantic information.	In most cases, the amount of time required for training that algorithms require is quite substantial.
	It is possible to boost performance by increasing the size of the training sets.	A rather low level of interpretability exists about the fundamental structure of deep networks as well as the theoretical understanding of these networks.

4.1.2. Aspect-based sentiment analysis (ABSA)

ABSA is a focused expression of emotion on a particular aspect of an entity. ABSA primarily focuses on identifying sentiment aspects across several levels and is to extract and predict many sentiment features that are contained inside the text. The comprehensive analysis of ABSA tasks and the subsequent text can be accomplished by employing different components of ABSA. For instance, the Aspect-Opinion Pair Extraction (AOPE) job is designed to analyse the aspects, opinions, perceptions, sentiments, words, and predictions from the relationship between the two. Furthermore, a classifier is utilised to discern the accurate anticipated aspects and viewpoints in order to form output triplets. The determination of sentiment polarity is accomplished by locating the correlation that exists between the factors of interest and the manifestations of opinion (Chen et al., 2022b).

Target Aspect Sentiment Detection is the process of identifying the aspect phrases and categories, and predicting sentiment analysis. Ke et al., (2023) introduced a data augmentation method based on contrastive prompts, which is capable of generating high-quality textual representations.

Table 5 Interpreting ABSA types with examples

Task	input	Example input	Output	Example Output
Aspect sentiment Triplet Extraction (ASTE)	X	Sentence	p,q,r	Salads, Fantastic, Point of Sale, Server
End-to-End ABSA(E2E-ABSA)	X	Sentence	p,s	Salads, Point of Sale
Aspect Category Detection (ACD)	X	Sentence	s	Food, Service
Aspect sentiment	x, a1	Sentence	r1	Point of Sale
Classification (ASC)	x, a2	Salads, sentence, server	r2	Neg
Aspect Term Etraction (ATE)	*X*	Sentence	p	Salads, Server
Opinion Term Extraction (OTE)	X	Sentence	q	Fantastic, Unfriendly
Aspect-Opinion Pair Extraction (AOPE)	X	Sentence	p,q	Salads, Fantastic, Server, Unfriendly
Aspect Category sentiment Analysis (ACSA)	X	sentence	p,s	Salads, Food, Server, Service
Sentiment (ACOS)Quadruple Extraction	X	sentence	p,s,r	Salads, Fantastic, Food, Point of Sale

Ke et al., (2022) incorporated the influence of long-distance relationships between triplets and the uneven distribution of labels by combining Prior-BERT with multi-task learning for the purpose of conducting TASD tasks. Extraction of quadruples consisting of aspect, category, opinion, and sentiment in the ACOS framework. The objective of this challenge is to identify and extract quadruples (a,c, o, p) from the provided phrase. The ACOS quadruple extraction task is the most comprehensive ABSA task compared to others, as it extracts all available information. The ACOS tasks play a crucial role in implicit sentiment analysis (Peper and Wang, 2022).

Fig. 5. The ABSA tasks.

4.1.3. Transfer learning

Transfer learning, an advanced artificial intelligence technique, enables the utilisation of previously acquired information and its corresponding opinion words in pairs. The aspect opinion pair extraction (AOPE) analysis can utilise the pipeline technique to get results by combining the outputs of two subtasks, specifically ATE and OTE. The task of Aspect Category Sentiment Analysis (ACSA) focuses on identifying aspect phrases and predicting the corresponding sentiment polarities. The pipeline method is the predominant approach for handling ABSA. This approach entails initially identifying the aspect categories and subsequently forecasting the emotional polarity associated with those aspect categories (Liu et al., 2023). End-to-End ABSA (E2E-ABSA) identify and comprehend aspect phrases, while also predicting the sentiment polarity associated with those aspect terms. Tian et al., (2021) utilise domain-specific embedding in their methodology for conducting E2E-ABSA. Liang et al., (2021) created a prototype of an interactive architecture. This model was enhanced for E2E-ABSA and relied on knowledge of dependent syntactic structures. This model demonstrates the efficient utilisation of dependency links and multi-task learning.

Aspect Sentiment Triplet Extraction (ASTE) is a method used to extract triplets from a given text. These triplets comprise an aspect, a sentiment, and a target. The ASTE challenges aim to achieve the tasks of identifying aspect phrases, associated opinion terms, and forecasting the polarity of sentiment. Regarding ASTE, there is a plethora of exceptional works. Peng et al. (2020) partitioned the Aspect Sentiment Triplet Extraction (ASTE) process into two distinct stages during their analysis. At first, they acquired novel knowledge about a preexisting model and implemented it in a new model. Transfer learning involves the transfer of knowledge from an old model to a new model, allowing the new model to utilise the data and patterns that the old model has already recognised. This approach offers the advantage of significantly minimising the need for extra training data, a task that often demands a substantial investment of time and resources.

Peng and colleagues circumvented the need to begin from the beginning by leveraging a pre-existing technique for training the new model. This technique is highly advantageous for practical applications as it enhances efficiency and time-saving. In this scenario, transfer learning is employed to demonstrate how the modification of pre-existing models can expedite the development and deployment of novel models, particularly in demanding tasks such as ASTE, where obtaining substantial volumes of labelled data is not always readily attainable. Celik et al.,'s 2020 study demonstrates that the discussed approach facilitates the transfer of knowledge across different domains, leading to enhanced levels of accuracy and outcomes (Liang et al., 2020). Chen et al., (2020) created a synchronous double channel RNN to investigate the difficulty of evaluating and forecasting events in the field of operations and events (AOPE). Furthermore, to identify aspect-opinion pairs, multiple researchers develop a unified learning framework that incorporates both semantic and grammatical perspectives, this framework is regarded as a collaborative learning framework. An alternative approach entails initially extracting the aspect terms, often known as the ATE problem, and subsequently identifying the opinion words linked to each term.

5. Evaluated Measured through different datasets

5.1. Datasets

Table 6 displays a diverse range of datasets commonly utilised by academics to evaluate the efficacy of mood analysis models for example SemEval, Yelp, IMBD and Stanford Sentiment Treebank (SST) etc. The SemEval and SST databases are distinctive due to their extensive coverage of several topics. Each iteration of the datasets corresponds to a distinct scenario. SemEval is renowned for its well-organized initiatives and benchmarks in the field of semantic evaluation. Additionally, it offers a wide range of diverse datasets suitable for various types of sentiment analysis tasks. However, SST provides you with precise sentiment labels at the sentence or phrase level, facilitating the classification and analysis of sentiment with a high level of precision. The Yelp databases contain extensive information pertaining to several domains, including restaurants, retail, hotels, travel, and other related subjects. These databases are valuable for doing research on individuals' sentiments towards various firms and services, making them a versatile tool for mood analysis research. The platform provides a plethora of user-generated content, including authentic reviews and opinions, which greatly enhances the practicality and effectiveness of the models (Verma et al., 2017).

IMDB is a widely used dataset that is renowned for its extensive compilation of movie reviews. This dataset has a mixture of positive and negative reviews, making it ideal for tasks that require classifying sentiment into two categories. Due to its frequent usage in academia, it serves as a benchmark for evaluating the performance of models in sentiment analysis of entertainment content. These datasets, each possessing distinct characteristics that are valuable for various aspects of sentiment analysis, form a robust foundation for evaluating sentiment analysis models. These datasets enable researchers to construct and evaluate algorithms that accurately comprehend and classify emotions across many scenarios and domains. The ISEAR datasets provide data on individuals displaying seven distinct emotions in various situations. These databases contain writings gathered from several internet channels, such as social media, review websites, forums, and e-commerce platforms. The researchers have methodically classified these datasets based on various mental states. Nevertheless, the data frequently lacks organisation and requires preprocessing prior to further study (Moghaddam and Ester, 2010). There are many methods available for assessing the effectiveness and efficiency of suggested models. In misclassification circumstances, one of the metrics used is True Negative (TN), which represents the accurate categorization of negative data by the classifier. In addition, to enable thorough study of outcomes, supplementary metrics have been utilised to evaluate sentiment analysis. Statistical measures including Mean Square Error, Ranking Loss, Receiver Operator Characteristic, Area Under the Curve, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) (Krupinski, 2017).

Applications of sentiment analysis

Business analysis in South Africa offers numerous benefits, for example, sentiment analysis can collect customer input and enhance market strategies to enhance their products and services. Moreover, consumers can employ the study to compare items and make more informed decisions. As a result, it is not restricted to companies that manufacture products. Wang and Zheng (2016) analysed Chinese internet evaluations to determine the potential influence of a model on its success. Accuracy, F1-score, precision, and recall are the primary evaluation metrics for sentiment analysis. A brief description of these measures may be found in Table 7. The term False Positive (FP) refers to the quantity of negative samples that a classifier mistakenly counts as positive whereas True Positive (TP) is a metric that quantifies the number of positive samples correctly classified by the classifier as positive. Various domains are analysed in the context of sentiment categorization to uncover parameters influencing accuracy. A decade's worth of customer meal reviews from Amazon.com were gathered for a thorough analysis by Bose et al. (2020). The NRC emotion vocabulary was used by the study to group reviews into eight different emotions: surprise, trust, anticipation, anger, fear, sadness, disgust, and joy. Stock price forecasting and financial market behaviour prediction have also been done using sentiment analysis. Future changes in the price of stocks can be predicted by examining market news. To obtain pertinent datasets, a variety of data sources can be used, such as Weibo, blogs, Twitter, and news sources. News is a major factor in stock price trend prediction, according to Xing et al. (2018). Upward stock trends are correlated with positive news, while downward trends are correlated with negative news.

5.2. Government intelligence

The emergence of online social media has led to the proliferation of diverse opinions and discussions on politics, life, and current social concerns. Utilizing sentiment analysis to uncover opinions on social issues or policies might assist the government in monitoring potential public responses. The government should implement appropriate measures or develop applicable policies, which would be advantageous. Zavattaro et al. (2015) analysed tweets from municipal governments in the United States to investigate how emotional content affects public involvement with government entities through social media. Real-time sentiment analysis is advisable in specific situations to efficiently monitor the current public sentiment. Falck et al. (2020) utilised the Emotional Political Compass (SPC) to evaluate the correspondence between newspapers and political parties, with the objective of investigating the influence of media political biases on voters' convictions (Alaoui et al., 2018).

5.3. Healthcare domain

Sentiment analysis (SA) has been widely utilised in the healthcare and medical sectors in recent times. In order to improve the standard of medical care, healthcare professionals can utilise this technology to gather and evaluate data on illnesses, negative drug responses, outbreaks, and patient sentiments. This methodology facilitates a more nuanced comprehension of patient experiences and has the potential to enhance therapeutic decision-making. Chintalapudi et al., (2021) introduces the integration of sentiment analysis and health information in text mining apps specifically designed for sailors. Medical practitioners and health organisations greatly benefit from the visualisation of patient symptoms. It enhances patients' understanding of their conditions, monitors their medical data, and assesses their input. Baker et al. (2022) employed three advanced deep learning techniques, namely Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Convolutional Neural Networks (CNN), to analyses and represent assessments and data gathered from individuals diagnosed with colon cancer. This research endeavors to forecast the future incidence of colon cancer by scrutinizing datasets related to the disease. The ultimate goal is to enhance early detection and treatment approaches, leading to more efficient outcomes.

ChatGPT is a highly sophisticated language model created by OpenAI (Thorp, 2023). According to Shen et al., (2023), it demonstrates a strong proficiency in understanding and generating human language with a high degree of fluency and accuracy. ChatGPT is an optimal tool for doing sentiment analysis due to its comprehension of the intricacies and nuances of human language. ChatGPT may acquire the semantic understanding of text and the inherent connections between different texts when a user provides input. The integration of sentiment analysis with ChatGPT provides numerous advantages for both companies and customers. Several advantages of this technology include immediate feedback, automated analysis, customer-centric approach, cost-efficiency, and a competitive edge. In their work, Sudirjo et al., (2023) investigated the application of ChatGPT in analysing consumer sentiment in the commercial context. This study shown that

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ChatGPT can enhance comprehension and fulfilment of consumer requirements, preferences, and contentment. Furthermore, it revealed that ChatGPT offers advantages to commercial organisations. In 2023, Wang et al. performed an assessment of ChatGPT's aptitude in comprehending opinions and moods expressed through written language. The study demonstrated that ChatGPT excels in sentiment analysis in several evaluation circumstances, exhibiting performance on par with BERT and other cutting-edge models.

The objective **of** scientometric analysis is to analyses the feelings of authors expressed in scientific citations. The potential of this field for utilizing sentiment analysis in different contexts is vast. However, there has been a scarcity of scientific studies undertaken on citations in South Africa. Wang et al., (2023) conducted a comprehensive examination of sentiment analysis in scientific citations. The authors presented several methodologies and deliberated on the primary obstacles. Furthermore, the authors also discussed pertinent domains that have recently garnered significant interest, such as the classification of citation functions and the suggestion of citations.

6. Discussion

SLR's main discoveries, problems and limits, as well as potential future study directions, are described in this section of the analysis.

6.1. Significant findings

When conducting sentiment analysis tasks, the researchers prioritized the utilisation of universal sentiment lexicons over domain-specific sentiment lexicons. Shaukat et al.,'s 2020 study suggests that the complexity of constructing extensive sentiment lexicons is likely lowered. In addition, the majority of sentiment lexicons utilised in primary research are universally essential. Nevertheless, the use of sentiment lexicons has intrinsic difficulties, such as the requirement for frequent updates to correspond with the changing characteristics of society. Furthermore, lexicon-based systems need to efficiently address negative words, spelling mistakes, synonyms, and slang, necessitating accurate alignment between textual expressions and the terms present in the lexicon. Precision is crucial for the effectiveness of lexicon-based approaches.

Conventional machine learning and deep learning techniques have been adopted worldwide to overcome the constraints of previous lexicon-based methods. This is done to bypass the deficiencies of these approaches. Sentiment Analysis (SA) applications heavily rely on the Support Vector Machine (SVM), which consistently achieves high accuracy on a diverse range of publicly available datasets. One potential explanation for this phenomena is the capacity of the support vector machine (SVM) to effectively handle text features over a high-dimensional space. However, a disadvantage of support vector machines (SVM) is that the training time rises linearly with the size of the training datasets.

The predominant deep learning architecture used in primary research for sentiment analysis applications is the Bi-LSTM architecture. One potential rationale is that Bi LSTM possesses the capability to detect and comprehend long-term dependencies, making it highly advantageous for tasks involving continuous input, such as text analysis. Another factor to be taken into account is the optimal duration of training for the Bi-LSTM method when dealing with large datasets.

Zhou and Srikumar (2021) have shown that transformer-based pre-trained language models like BERT have achieved remarkable results and are extensively used in sentiment analysis applications. Initially, the BERT model undergoes training using extensive quantities of textual data, followed by a subsequent fine-tuning process for specific applications. Consequently, there has been a substantial decrease in both the duration of training and the quantity of data needed. It is possible that using BERT for certain jobs may not necessitate a large amount of new datasets. In addition, BERT effectively distinguishes between words with similar spellings but distinct meanings due to its utilisation of a bidirectional Transformer encoder design. This results in improved accuracy of sentiment analysis tasks because to its enhanced contextual awareness, allowing it to effectively capture the interdependencies across different contexts. As a result, the precision of sentiment analysis jobs is enhanced. (Devlin et al., 2018). Sentiment analysis tasks are differentiated from other natural language processing tasks due to their distinct characteristics, which need a greater amount of semantic tokens and contextual information. Therefore, it is essential to recognise important tokens that have a big impact on the overall sentiment in a specific context. The process of selecting these tokens is frequently regarded as time-consuming. By making suitable adjustments to the output layer of the BERT model, it becomes possible to extract the meaning and context from text, enabling the retrieval of contextual information. Although there have been tremendous breakthroughs, research efforts in this sector can be limited at times because to the substantial computational or resource requirements.

In order to address these concerns, the experiment was conducted by removing various components from the originally proposed architecture. Moreover, removing the alternating layers of BERT yielded more advantageous outcomes, even when the model was minimized to its minimum size. Fields such as finance and medical, which lack access to specialised data, have greatly benefited from the advantages provided by BERT pre-trained language models. The BERT model was employed to do sentiment analysis in multiple languages such as English, Russian, Chinese, French, and Arabic etc. languages, yielding impeccable results.

ABSA is a research discipline that concentrates on evaluating opinions at a deeper level. ABSA has achieved substantial advancements in performance in recent years. However, there remain several unresolved difficulties. The application of the ABSA model to a domain that is distinct from its training datasets sometimes results in a decrease in performance for conventional methodologies and is a well-known obstacle referred to as the domain adaptation problem. In order to address this issue, it is crucial to have a substantial collection of data for each specific task domain. This data will be used to train a model that is capable of accurately capturing the relevant contextual elements. Roughly 50% of the ABSA research have employed benchmark datasets that are openly available through SemEval. These studies have primarily concentrated on two particular domains: restaurants and laptops. Nevertheless, the ABSA models that are most effective utilise domain-specific tagged data in order to enhance performance and precision.

Chauhan et al., (2023) have noted that different fields may interpret sentiment phrases in different ways. Consequently, ABSA models that have been trained in specific domains may sometimes exhibit subpar performance when applied to datasets from different domains. Moreover, conventional methods lack the capability to efficiently connect several aspect terms derived from diverse remark phrases, leading to the extraction of aspect keywords that are unrelated to the current subject. Poria et al. (2016) demonstrated that the lack of precision in aspect extraction can greatly hinder the overall efficacy of ABSA. It is possible to determine the specific meanings of aspect words and opinion terms by gathering information on the correlations between phrases and taking into consideration the intricacies of the context with which they are used. Moreover, the utilisation of BERT representations and models that rely on supervised hierarchical attention is expected to improve aspect extraction. Incorporating sentence co-reference resolution techniques into the preprocessing phase, which should be finished before deploying the ABSA method, is a possible option that can be considered before executing ABSA.

6.2. Challenges faced during the work

The study's findings emphasise the urgent requirement to create extensive datasets in several languages, which should be thoroughly annotated and carefully evaluated. hese datasets are crucial for progressing research in sentiment analysis and guaranteeing that models can proficiently comprehend and handle sentiment in various linguistic and cultural contexts. Through the process of labelling data with sentiment indicators, aspect terms, and contextual nuances, it is possible to create multilingual datasets that have thorough annotations. This offers a solid foundation for training and assessing models that perform sentiment analysis. Precise grading guarantees that the datasets adequately reflect the nuances of sentiment, allowing models to detect minor fluctuations in sentiment and perform with more accuracy in practical scenarios. The primary concern is to address the co-reference resolution problem, whereas the identification of concealed emotions, irony, and sarcasm remains an unresolved scientific inquiry in sentiment analysis. There are a number of challenges that are encountered when extracting features in SA. These challenges include context dependency, high dimensionality, redundancy, and slang terms. Furthermore, current areas of research in sentiment analysis encompass the management of multilingual data, enhancing accuracy across different domains, analysing sentiment across several datasets, and inferring implicit sentiment based on contextual information. Specifically, there are numerous obstacles and limits associated with two prominent study topics, ABSA and BERT. Below are stated some of the challenges.

Irony and mockery: Research in the subject of SA has been struggling for a long time with the difficult task of determining whether or not a piece of text contains sarcasm or ridicule. Emotions that are not explicitly stated in the text are referred to as implicit emotions. Individuals detect these emotions by means of two cues: vocal communication and written context. Through the use of many modes of communication, such as verbal and nonverbal cues, multimodal sentiment analysis can accurately identify implicit emotions by considering the surrounding context. The accuracy of SA can be improved through the use of multi-modal SA, which integrates two or three different sources of input, including text, voice, and visuals. One potential future study strategy is integrating many sensory inputs and contextual information to detect implicit indications of sentiment in text.

Context dependency is the idea that the significance or understanding of a word or phrase is affected by the surrounding circumstances or surroundings. Some words have inherent objectivity but can become subjective in certain contexts, therefore acquiring emotional significance (Denecke and Deng, 2015). The term "long" does not inherently evoke any particular emotion, but its connotation can vary significantly depending on the context in which it is employed. In certain contexts, the term "extended" can have a positive connotation, as shown in phrases like "extended battery duration." However, it can also carry a negative connotation, as exemplified by words like "prolonged waiting time in a queue." Oftentimes, words that are not adjacent but rather distant inside a sentence can significantly alter the meaning of a word. In order to accurately represent these distant relationships, word vectors and parse tree models collaborate to identify intricate sub-structures. This facilitates a more comprehensive understanding of how meaning varies based on the surrounding circumstances. The significance of employing sophisticated modelling techniques in mood analysis is shown by the level of complexity exhibited.

The issue of high dimensionality is frequently encountered in this field. This occurs when there is a high degree of variability or complexity in the data or problems being considered. Utilising effective feature selection techniques is crucial for managing and enhancing high-dimensional data due to the potential slowdown of computer systems caused by a large number of feature sets (Wilson et al., 2005). Ensuring proper management of high dimensionality is crucial for maintaining the effectiveness and accuracy of mood analysis models.

An effective strategy for handling multilingual data involves creating tailored language models specifically designed for code-mixed data. Utilising this approach significantly enhances the precision of mood analysis, particularly in multilingual scenarios. In addition, machine translation is emerging as a potent method for addressing challenges in multilingual sentiment analysis. By including sentiment-related cues into the translation process, machine translation systems can enhance their ability to accurately convey the emotional tone of the original text. Saadany and Orasan (2020) highlight that sentiment information in machine translation coding preserves negation, antonyms, and colloquial idioms. In order to advance sentiment analysis, it is imperative that we address the challenges posed by context dependence, high dimensionality, and multilingual data. This necessitates the use of intricate models and procedures that enhance both the precision and usability across many language contexts.

Colloquialisms and acronyms: The usage of slang and acronyms in messages is common among people who use the internet (Wu et al., 2018). As per the information provided by Wikipedia in 2014, slang refers to a form of language that consists of non-standard terms and idioms such as GR8, SMH, YYDS, and XOXO. The primary rationale behind the utilisation of slang is its convenience, frequent comprehensibility, and time-saving nature. Many slang terms with positive or bad connotations are used in WeChat, Twitter, and Facebook chat (Asghar et al., 2014). It is now essential to detect, evaluate, and identify the polarity of slang in order to determine the semantic orientation (SO) of a review. According to Kundi et al. (2014), the research provides a system that is referred to as Detecting and Scoring Internet Slang (DSIS). This system utilises SentiWordNet in conjunction with other lexical resources in order to recognise and assess Internet slang. This novel method utilises the preexisting SentiWordNet architecture, which gives sentiment scores to words based on their semantic meanings, and expands its capabilities to include the subtle expressions present in Internet slang. By integrating additional lexical resources, DSIS improves its capacity to precisely recognise and assess the attitude expressed by Internet slang phrases.

Interdisciplinary: A significant obstacle encountered by SA is its limited capacity to excel in other fields due to a lack of adequate labelled data and subject expertise. The training datasets used in current sentiment analysis methods are consistently specific to a certain domain. This model has limited capacity for generalization and subpar performance when applied to novel domains. Furthermore, it is not feasible to utilise datasets from all fields for training models. Domain adaptation can address the issues by acquiring knowledge on the characteristics of imperceptible domains. Recently, researchers have been using word embedding methods like BERT and GloVe more often to address domain adaption difficulties. The word embeddings, which have been trained on datasets from several domains, naturally contain a significant amount of information that is not exclusive to any particular area. Therefore, the resolution of the current Domain Adaptation problem is highly dependent on the advancements made in open domain corpora, which in turn gives rise to difficulties regarding interpretability.

Primary obstacles faced by ABSA: The majority of ABSA datasets currently available are obtained from SemEval. A possible explanation for ABSA's underperformance in multi-lingual settings is the lack of review datasets in languages other than those used in SemEval serial datasets, such as Chinese and Arabic. Nevertheless, the limited quantity of data poses a difficulty in training high-performing models, such as PLM-based models. Hence, there is a need for more demanding datasets that encompass several domains and languages.

Furthermore, incorporating contextual information into various sections of reviews poses a significant difficulty. Identifying essential element words within a certain subject becomes tough without proper context and domain experience. Present technological constraints render it unfeasible to identify certain essential aspect terms or precisely record long-lasting connections between noun phrases. While deep learning algorithms are capable of identifying important n-grams, they currently lack the ability to comprehend sentence relationships, which is crucial for accurately extracting numerous aspect terms. Consequently, this limitation also hampers the extraction of aspect-opinion categories. Extracting effective and multi-aspect terms from a lengthy review text is challenging due to the need to build linkages between various terms and the contexts of distinct phrases. Furthermore, the findings presented by Lo et al., (2017) indicate that the process of extracting aspects in multilingual contexts encounters substantial obstacles, including lexical ambiguity, language-specific sentence patterns, and difficulties in translation. The efficacy of models may produce the different level of effectiveness, when examined in multiple languages. Hence, a substantial amount of effort is necessary to manage Aspect-Based Sentiment Analysis (ABSA) in jobs involving many languages. ABSA is currently in its early stages of development. As research progresses, individuals will eventually address those problems.

Limitations of BERT: At present, BERT is a model based on the Transformer architecture that has superior performance in sentiment analysis tasks. Nevertheless, training and utilising BERT demands substantial computational resources and time because to its considerable size, consisting of hundreds of millions of parameters. Despite being pre-trained on extensive corpora, the BERT model may experience inadequate learning in specific tasks, resulting in a decline in performance. The aptitude for acquiring knowledge of negative compound phrases is deficient. This limitation can potentially impact its effectiveness when applied to other languages. This article proposes utilising several integration approaches to incorporate numerous BERT versions, which offer ways to solve the limitations of BERT. The aim is to generate universal and diversified outputs.

6.3. Recommendations and future scope of current work

This research identifies many notable gaps in the field of Sentiment Analysis (SA) that necessitate additional exploration and resolution. It serves as a comprehensive resource for researchers from many perspectives, offering significant insights that may be utilised as a reference for future investigations.

The study highlights the significance of having high-quality and easily accessible datasets for sentiment analysis. The text highlights the importance of datasets that contain integrated dictionaries, fuzzy polarity, multiple emotion categories, domain adaption, and automated annotation. These datasets are essential for training and evaluating sentiment analysis models in many settings and domains, enabling researchers to assess the reliability and applicability of their approaches.

Furthermore, the inquiry identifies challenges in the domain of Aspect-Based Sentiment Analysis (ABSA), emphasising the need for a cohesive model that can proficiently address a range of ABSA-related activities. Moreover, there is a want to examine cross-domain transfer learning methods and employ larger and more intricate datasets to enhance the effectiveness of ABSA models.

The research highlights the ongoing challenges related to the identification of stop words, labelling of sarcasm, recognition of negation, and handling of emoticons in the context of feature extraction. These responsibilities are crucial for accurately capturing subtle variations in sentiment in textual data and highlight places where more improvement is needed.

The study examines various methods for sentiment analysis, including pragmatic analysis, generic cross-domain sentiment classifiers, and hybrid models for multilingual data, from a methodological standpoint. The need for continuous research in the advancement and improvement of sentiment analysis approaches is emphasised by the distinct benefits and difficulties that each strategy entails.

The report proposes several prospective domains for future investigation in South Africa. These involve creating benchmark datasets that cover a wide range of areas and languages. This enables researchers to evaluate the effectiveness of sentiment analysis models in different situations. Moreover, it is suggested to explore cross-task transfer learning strategies to utilise the information acquired from low-level ABSA tasks for higher-level tasks.

Furthermore, the inquiry advocates for the development of domain-specific sentiment lexicons using self-supervised algorithms. This approach has the potential to enhance the accuracy and applicability of sentiment analysis methods across different domains. Finally, the study advocates for the exploration of sentiment analysis applications in sectors that have received less attention in earlier research, such as healthcare, education, social media, aviation, tourism, and transportation services. These overlooked industries have promising prospects for leveraging sentiment analysis to make well-informed decisions and acquire valuable insights.

Additional work is being conducted in order to compare a number of different extended language models. An example of this would be conducting comparisons of GPT, Baidu ERNIE Bot, and PaLM over a range of granularity levels for all of the tasks that fall under the category of sentiment analysis.

The development of individualised dialectical grammar analyzers with the purpose of addressing ambiguity in particular words and taking into consideration compound words, such as terms that negate and intensify sentences.

Due to the fact that it is difficult to determine feelings based on the expressions that are implicit in text, it is essential to study possible solutions to this problem.

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This paper offers an exhaustive review of the previous research that has been conducted about text sentiment analysis. An overview of the many levels of sentiment analysis, such as the document-level, the sentence-level, and the aspect-level, was presented in the introduction. Additionally, this paper categorised several different approaches to sentiment analysis and evaluated the advantages and disadvantages of each of these approaches. Following that, we talked about the many different applications of sentiment analysis, such as its use in the commercial world, in government intelligence applications, in healthcare, and in recommendation systems. Additionally, advanced large language models like ChatGPT, ERNIE Bot, and PaLM are explored in this article. In conclusion, we had a comprehensive discussion on the existing issues that are encountered by sentiment analysis. We brought attention to the fact that there are still a great deal of unresolved issues that call for additional research.

Conflict of Interest

We have no conflicts of interest to disclose.

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