**Sentiment Strength Detection: An In-Depth Systematic Literature Review on Context-Based Lexicon Approaches**

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| ***Abstract****.*  *Sentiment strength detection is a critical aspect of sentiment analysis that involves evaluating the intensity of sentiments within textual content. This research conducts a comprehensive systematic literature review focusing on context-based lexicon approaches to sentiment strength detection. The study examines the evolution, challenges, and opportunities in this domain, offering insights into frameworks and methodologies proposed in the existing literature. Despite the considerable body of sentiment analysis research, investigations into sentiment strength detection utilizing context-based lexicons remain relatively limited.* *This research is a literature study that uses literacy published in 2020–2023. The purpose of this study is to provide an overview of the technology that is widely used in sentiment strength detection with context-based lexicons, either by methods, algorithms, datasets, or types of sentiment analysis. The stages carried out in this study include planning a review, implementing a review protocol, and submitting the results of the review. This research is expected to be able to help future research to develop new methods and techniques to provide more optimal results.*  ***Keywords:*** *Sentiment Strength Detection, Context-Based Lexicon Approaches, Sentiment Analysis, Systematic Literature Review.* |

**1. INTRODUCTION**

Sentiment is a key aspect in text analysis that plays an important role in understanding the opinions, responses, and attitudes of a text [1]. Sentiment analysis is not only limited to determining whether a text is positive, negative, or neutral, but also involves measuring the strength of the sentiment it contains [2]. In recent years, the research focus has increasingly shifted towards in-depth, paying further attention to sentiment strength detection to provide a more holistic picture of the views and feelings contained in a text [3].

Sentiment strength detection is possible by finding out the sentiment polarity of phrases [4]. The goal is not only to find out whether a text tends to be positive, negative, or neutral, but also to measure how strong the positive or negative sentiment is [5]. This polarity assessment has significant implications in various contexts, such as the evaluation of product reviews, the analysis of responses to news, and the understanding of overall public opinion [6]. Unfortunately, few studies have considered the strength of user sentiment [7]. For example, in the business domain, user sentiment is required to analyze the sentiment power of reviews to rank products and merchants [8]. This is because different reviews for the same product can have very different sentiment strengths, even though they express the same sentiment polarity [9]. Additionally, in the social domain, there is great merit to research geared towards understanding the role of emotions in online communication [10]. If there is a detection tool that is sensitive to the strength of sentiment expressed, then the strength of user sentiment becomes very important to research [11]. For example, the strength of user sentiment can be used to identify people who are depressed or at risk of suicide [12].

Sentiment analysis, particularly sentiment strength detection, utilizes various approaches [13]. One common method involves the use of lexicons, which are dictionaries containing words associated with sentiment scores [14]. Lexicons provide a foundation for assessing the strength of sentiment in a text by assigning numerical values to words based on their emotional impact [15]. Another approach is machine learning-based, where models are trained on labeled datasets to predict sentiment strength [16]. Supervised learning algorithms, such as Support Vector Machines (SVM) or neural networks, can be employed for this purpose [17]. Additionally, deep learning techniques, like Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks, have shown promise in capturing nuanced sentiment information due to their ability to consider contextual information in sequential data[18].

In the context of sentiment strength detection, the role of contextual information is crucial [19]. Words can exhibit different sentiment strengths based on their context within a sentence or paragraph [20]. For instance, phrases that include intensifiers or modifiers can significantly impact the perceived strength of sentiment [21]. Recognizing the importance of context, researchers have explored methods like n-grams and word embeddings to capture the relationships between words and their surrounding context, enhancing the accuracy of sentiment strength assessment [22].

Furthermore, sentiment strength detection is not only limited to textual content [23]. Multimodal sentiment analysis, which incorporates information from text, images, and videos, offers a more comprehensive understanding of sentiment expression [13]. Analyzing visual cues, such as facial expressions or emojis, alongside textual data contributes to a more nuanced assessment of sentiment strength [24].

Despite advancements, challenges persist in sentiment strength detection. Ambiguity in language, varying cultural expressions, and the dynamic nature of online communication pose difficulties in precisely gauging sentiment strength [25]. However, ongoing research endeavors continually refine techniques to address these challenges and enhance the effectiveness of sentiment strength detection methods [26].

In conclusion, sentiment strength detection is a vital component of sentiment analysis, offering a deeper insight into the emotional nuances of text [27]. The integration of lexicons, machine learning, and deep learning approaches, coupled with a focus on contextual information and multimodal analysis, contributes to the evolving landscape of sentiment analysis research [28]. As technology advances, the ability to accurately measure sentiment strength becomes increasingly refined, unlocking new possibilities for applications in diverse domains [29].

Research in the field of sentiment analysis has been quite active [30]. In general, there are two main approaches in sentiment analysis, as well as detecting sentiment strength, namely lexicon-based approaches and machine learning-based approaches [31]. Lexicon-based approaches use sentiment lexicons, such as Opinion Lexicon and SentiWordNet [32]. Basically, a lexicon is a dictionary of sentiment words with context-dependent orientation and strength [33]. Slowly, various studies related to sentiment strength detection, especially using the lexicon approach, began to be carried out [34]. The research conducted also uses different methods and algorithms. A systematic literature review is conducted to identify and analyze research trends, such as years, journals, and keywords that produce the most similar research, methods used, data sets, and what algorithms are popularly used in sentiment strength detection using a context-based lexicon approach.

**II. THEORITICAL FOUNDATION**

* 1. Systematic Literature Review

Systematic literature review is the activity of identifying, evaluate, and interpret published published research articles that are relevant to the research question [35].

* 1. Sentiment Strength Detection

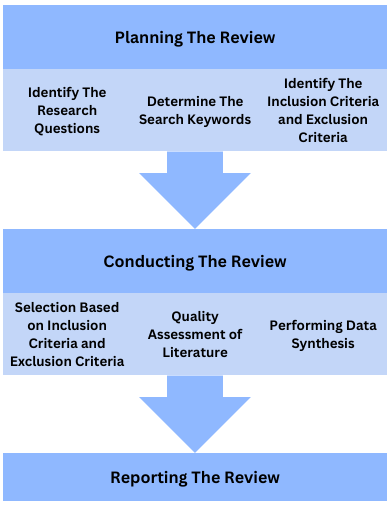
Sentiment strength detection aims to evaluate both the intensity of positive and negative sentiments in a text, assuming that the text may simultaneously express both types of feelings [36]. To address the sentiment strength detection task, one approach is to assign default strengths to sentiment terms, such as assigning a higher weight to "love" compared to "like" [32].

* 1. Context-Based Lexicon Approaches

The theoretical foundation of Context-Based Lexicon Approaches lies in the integration of contextual information into sentiment lexicons for more accurate sentiment analysis [37]. Unlike traditional lexicons that assign fixed sentiment scores to words, context-based lexicons consider the influence of surrounding words, phrases, or the overall context on the sentiment strength of a particular term [38]. This approach recognizes that the sentiment of a word can vary based on the context in which it is used, allowing for a more nuanced and contextually aware sentiment analysis [39]. By leveraging contextual information, context-based lexicon approaches aim to enhance the precision and reliability of sentiment detection across diverse textual contexts, including social media, product reviews, and news articles [40].

**III. METHODS**

This study is conducted to extract insights from research articles focusing on sentiment strength detection through context-driven lexicon approaches. The selected articles range from 2020 to 2023, aligning with the period when context-driven lexicon approaches gained prominence in sentiment analysis. The research involves an analysis aimed at understanding the variations in existing literature addressing sentiment strength detection. Furthermore, the study seeks to explore the diverse technologies utilized in the field of sentiment analysis employing context-driven lexicons. This research is carried out by implementing the stages outlined in the systematic literature review guidelines proposed by Kitchenham and Charters [41]. The stages conducted in this study can be observed in Figure 1.



**Fig. 1.** Stages of Systematic Literature Review Research [42]

* 1. Planning The Review
     1. Identify The Research Questions

The first stage undertaken in identifying the research problem is defining the research questions. A Systematic Literature Review identifies the research problem, which is a crucial aspect [43]. This is done to provide boundaries in the discussion, enabling more focused research. To facilitate and concentrate the study, research questions are formulated as follows:

1. Research Question 1: What year was the research related to sentiment strength detection with context-based lexicons carried out?
2. Research Question 2: What journals have published articles that discuss sentiment strength detection with context-driven lexicon approaches?
3. Research Question 3: What keywords are there in sentiment strength detection with context-based lexicons?
4. Research Question 4: What type of sentiment analysis is performed in sentiment strength detection with context-based lexicons research?
5. Research Question 5: What algorithms or optimization are applied in sentiment strength detection with context-based lexicons?
6. Research Question 6: What methods and technologies are applied in sentiment strength detection with context-based lexicons research?
7. Research Question 7: What data platforms are used in sentiment strength detection with context-based lexicons research?

Based on the list of research questions above, the next step involves determining the search keywords for the subsequent stage.

* + 1. Determine The Search Keywords

Keywords play a crucial role in research exploration. The use of precise keywords is essential to obtain articles relevant to the discussed research topic. To achieve a comprehensive search string, this study identifies terms from the research questions, employs basic and affixed terms aligned with the research theme, and utilizes AND and OR operators as needed. The research reviews articles indexed in Scopus, all composed in English. Thus, the keywords are also formulated in English. Based on the keyword development, the following search string is derived.

(("sentiment") AND ("strength" OR "power" OR "intensity" OR "detection") AND ("context" OR "lexicon" OR "sentistrength" OR "vader" OR "sss-lex" OR "affin" OR "wordnet") AND ("machine learning" OR "deep learning" OR "text mining" OR “data mining” OR "natural language processing" OR "NLP" OR "feature extraction" OR "feature selection" OR "dimensionality reduction" OR "cross-validation" OR "hyperparameter tuning" OR "ensemble methods" OR "transfer learning" OR "sequence-to-sequence" OR "attention mechanisms" OR "word embeddings" OR "sentiment lexicons" OR "feature engineering" OR "time series analysis" OR "Regression Analysis") AND ("regression models" OR "logistic regression" OR "Naïve Bayes" OR "Random Forest" OR "Neural Networks" OR "Support Vector Machines" OR "Convolutional Neural Networks" OR "BERT" OR "LSTM" OR "CNN" OR "convolutional neural network" OR "GRU" OR "word2vec" OR "GloVe" OR "Naïve Bayes"))

The above search string is employed as the search keywords for articles to be used in this research. The article search is conducted using Harzing’s Publish or Perish application, and only articles indexed in Scopus are filtered. Through the use of several string combinations in the search, a total of 498 articles most relevant to the research topic within the Quartile 1 to Quartile 4 range are obtained. Based on these 493 articles 89 articles were in Quartile 1, 60 articles in Quartile 2, 36 articles in Quartile 3, and 64 articles in Quartile 4. Distribution chart number of articles based on Scopus Quartile Rank Quartile Scopus is shown in Figure 2.

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Description automatically generated

**Fig. 2.** Distribution Chart of the Number of Publications of Sentiment Strength Detection with Context-Based Lexicons in The World by Scopus Quartile

* + 1. Identify The Inclusion Criteria and Exclusion Criteria

In acquiring literature pertinent to the research topic, it becomes imperative to establish specific criteria, comprising both inclusion and exclusion criteria. Inclusion criteria serve as the parameters guiding the selection of literature, delineating the characteristics essential for inclusion in the study. Conversely, exclusion criteria are delineated factors that are not considered in the literature selection process. These criteria collectively contribute to a refined and methodical approach, ensuring the retrieval of the most pertinent and contextually relevant articles for the research endeavor.

Table. 1. Inclusion Criteria and Exclusion Criteria

|  |  |  |
| --- | --- | --- |
| No. | Inclusion Criteria | Exclusion Criteria |
| 1 | Research journals published between 2020 - 2023 | Research journals published before 2020 |
| 2 | Research journals in English | Research journals not in English English |
| 3 | Research journals Scopus indexed | Research journals not indexed by Scopus |
| 4 | Research journals addressing sentiment strength detection utilizing a context-based lexicon approach. | Research journals addressing sentiment strength detection utilizing approach besides a context-based lexicon. |
| 5 | Research journals that have complete information | Duplicated rsearch journals |

* 1. Conducting The Review
     1. Selection Based on Inclusion Criteria and Exclusion Criteria

In the planning stage of the review, the identification of inclusion and exclusion criteria was conducted, resulting in 5 inclusion criteria and 5 exclusion criteria. Subsequently, the identified inclusion and exclusion criteria were used to screen articles. Based on the selection results using the inclusion and exclusion criteria from the initial pool of 493 articles, 165 articles that were most relevant were obtained.

* + 1. Quality Assessment of Literature

To maintain the quality in the systematic literature review process and achieve a more robust review outcome, an assessment of the research article quality is conducted based on specific parameters. The parameters used in this study include:

1. The articles are reputable and indexed in Scopus.
2. Only journal articles are included in the study.
3. Each stage of this systematic literature review is conducted in accordance with the predefined steps.
   * 1. Performing Data Synthesis

Data synthesis is conducted to gather evidence from the selected literature. During the data synthesis process, papers are analyzed, synthesized, compared, and summarized to obtain the most relevant information for addressing the research questions. The results of data synthesis are compiled in tabular format. The data is visualized through line charts, pie charts, and bar charts to facilitate the presentation of information on the distribution of articles related to the sentiment strength detection utilizing context-driven lexicon approaches.

* 1. Reporting The Review

The presentation of the review results is the concluding part of this systematic literature review research stage. The review results are further discussed in the results and discussion chapter.

**IV. RESULT AND DISCUSSION**

* 1. Literacy Review Result

In the past 4 years, many researchers have conducted research on sentiment strength detection with context-based lexicons around the world.

In 2020 to 2021, there is an increasing trend. Many researchers adopted the topic of sentiment strength detection with context-based lexicons in the world. The same is true in 2022 to 2023, where the increase in trends related to this topic increases more drastically than 2021.

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**Fig. 3.** Distribution Chart of the Number of Publications of Sentiment Strength Detection with Context-Based Lexicons per Year by Scopus Quartile

* 1. Research Articles by Publisher

With the rise of research related to sentiment strength detection with context-based lexicons in the world, many journals have published these articles. This research reviews journals published by different publishers. Overall, this study used journals published by 112 publishers. IEEE Access is the publisher that publishes the most articles on sentiment strength detection. Based on these 112 publishers, the 25 publishers that published the most articles discussing sentiment strength detection with context-based lexicons are shown in Figure 4.

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**Fig. 4.** Graph of Journals Publishing Articles on Sentiment Strength Detection with Context-Based Lexicons by Scopus Quartile

* 1. Keywords

Sentiment Strength Detection is a widely researched study nowadays. By applying various keywords to facilitate the search. Based on the literacy used in this research, the most used keywords in sentiment strength detection are sentiment analysis, deep learning, machine learning, and bert.

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**Fig. 5.** Research Distribution Chart Based on Keyword Usage

* 1. Sentiment Analysis Type

Figure 6 shows that sentiment analysis is the most widely used type of sentiment analysis in research.

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**Fig. 6.** Research Distribution Chart by Sentiment Analysis Type and Quartile

* 1. Algorithms

Algorithms is a very important part of sentiment strength detection research. By knowing the right algorithm, an optimal model will be produced. Figure 7 shows the algorithms that are widely used in sentiment strength detection with context-based lexicons. From Figure 7, it can be seen that bert is the most chosen algorithm, followed by transformers and neural networks.

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**Fig. 7.** Research Distribution Chart Based on Algorithms or Optimizations Used and Quartile

* 1. Methods or Techniques

Methods or techniques are often used for data-related research to achieve optimal results. Figure 8 shows the methods or techniques that are widely used in sentiment strength detection with context-based lexicons. From Figure 8, deep learning is the most chosen method or technique, followed by machine learning.

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**Fig. 8.** Research Distribution Chart Based on Methods or Techniques Used and Quartile

* 1. Datasets

Figure 9 shows that twitter is the most widely used datasets in research.

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**Fig. 9.** Research Distribution Chart Based on Datasets Used and Quartile

Based on the 165 literacies used in this study, then after conducting quality assessment and data synthesis, the authors selected 10 papers that can represent literacy as a whole shown in Table 2.

Table. 2. State of The Art Sentiment Strength Detection with Context-Based Lexicons

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| No. | Ref. | Author | Dataset | Approach | Lexicon | Evaluation |
| 1 | [37] | Minghui Huanga, Haoran Xie b, Yanghui Raoa, Jingrong Fenga, Fu Lee Wangc | Youtube, Twitter, BBC, Digg, MySpace, RunnersWorld | Context-dependent Lexicon-based CNN | SSS-LEX | MAE, |
| 2 | [44] | Kian Long Tan, Chin Poo Lee, Kalaiarasi Sonai Muthu Anbananthen, Kian Ming Lim | IMDb, Twitter US Airline Sentiment, Sentiment140 | RoBERTa-LSTM | - | Accuracy, Precision, Recall, F1-Score |
| 3 | [36] | Azizkhan F Pathan, Chetana Prakash | SemEval 2014 | Bi-LSTM | Lexicon based | Accuracy, Precision, Recall, F1-Score, MCC |
| 4 | [45] | Liang-Chih Yu, Member, IEEE, Jin Wang, K. Robert Lai, and Xuejie Zhang | SemEval 2016 | Polanyi and Zaenen, Kennedy and Inkpen, SentiStrength, SoCal, Liu and Seneff, Carillo-de-Albornoz and Plaza, Vader method being used | Vader, SoCal, SentiStrength | Lexicon Coverage, Kendall’s t, Improvement, Spearman’s p, Improvement |
| 5 | [8] | Adrien Boukobza, Anita Burgun, Bertrand Roudier, Rosy Tsopra | Tweets: “coronavirus” or “COVID” | CNN + lexicon | AFINN, BING, NRC | Accuracy, Precision, Recall, F1-Score |
| 6 | [46] | Wenhao Pan, Yingying Han, Jinjin Li, Emily Zhang & Bikai He | Weibo | Weibo fine grained sentiment | Fine-grained sentiment lexicon | F & P |
| 7 | [47] | Yu-Chih Deng, Sin-Horng Chen, Lung-Hao Lee | CVAS & CVAT from Chinese EmoBank Corpus | BERT | Lexicon based | MAE & PCC |
| 8 | [48] | Christopher SG Khoo, Sathik Basha JohnKhan | Amazon product review scopus | SVM & Naïve Bayes | WKWSCI, SoCal, General Inquirer, MPQA, NRC and Hu & Liu | Accuracy, Precision, Recall, F1-Score |
| 9 | [49] | Clemente Rubio Manzano, Christian Vidal-Castro, Claudia Martinez-Araneda, Alejandra Segura Navarrete | Twitter | SVM | EmoLex | Accuracy |
| 10 | [50] | Leveraging Lexicon-Based and Sentiment Analysis Techniques for Online Reputation Generation | 4 Twitter datasets: movie, phone product, hotel, restaurant | BERT, RNN, LSTM, CNN, Bi-LSTM | Polarity Lexicon | F1-Score, Accuracy |

**V. CONCLUSION**

This research reviews research journals that discuss sentiment strength detection with context-based lexicons in the world with the aim of knowing search keywords, types of sentiment analysis, algorithms or optimization, methods or techniques, and datasets that are trending and widely used in research related to sentiment strength detection with context-based lexicons in journals published between 2020 - 2023.

Based on the results of the review conducted using the systematic literature review method, it is known that sentiment analysis is a type of sentiment analysis that is still widely used, followed by sentiment polarity, and sentiment intensity. The algorithm chosen by many researchers is the BERT (Bidirectional Encoder Representations from Transformers) algorithm, followed by transformers, and neural networks. Then, the methods or techniques that are often used in research are deep learning and machine learning. As for datasets, twitter is still the main choice of researchers, followed by semeval datasets. Finally, for keywords, sentiment analysis, deep learning, machine learning, and bert are still the choice of many researchers in performing sentiment strength detection.

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