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Comprehensive Overview of Sentimental Analysis by Utilizing Machine Learning Techniques

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Abstract:

Objective: This Comprehensive review employs the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology to comprehensively examine the landscape of sentiment analysis techniques utilizing machine learning algorithms and artificial intelligence (AI) approaches.

Background: Sentiment analysis has emerged as a critical domain in natural language processing. It leverages advanced computational techniques to extract and interpret emotional nuances from textual data across diverse domains, including social media, customer feedback, market research, and political discourse.

Methodology: A comprehensive systematic review was conducted following the PRISMA 2020 guidelines. Multiple academic databases, including Web of Science, Scopus, IEEE Xplore, and ACM Digital Library, were systematically searched using predefined inclusion and exclusion criteria. The search strategy employed a combination of keywords: "sentiment analysis," "machine learning," "artificial intelligence," "natural language processing," and related terms.

Conclusion: The systematic review reveals significant advancements in sentiment analysis through machine learning and AI technologies. The emerging techniques demonstrate remarkable potential in understanding and interpreting human emotions across diverse textual landscapes, with continuous improvements in accuracy, interpretability, and domain adaptability.

Keywords: Sentiment Analysis, Machine Learning, Artificial Intelligence, Natural Language Processing, PRISMA Review, Emotion Detection

1. INTRODUCTION

Sentiment analysis, also known as opinion mining, involves using computational methods to analyze how people feel about various entities - from products and services to broader issues and events. This field helps track public sentiment to generate practical insights. Researchers can better understand and predict social trends and behaviors by studying opinions, emotions, and attitudes expressed online (Pozzi et al. 2017).

In the business context, sentiment analysis has become crucial as companies strive to understand their customers better in an increasingly customer-centric marketplace (Chagas et al. 2018). With the massive proliferation of online platforms like discussion forums, review sites, and social media, businesses face a challenge in processing the vast amount of customer feedback. However, this challenge also presents an opportunity by applying sentiment analysis to this wealth of digital content, companies can gain valuable insights into consumer attitudes (Lu, Q, Zhu, 2020). This helps marketers identify customers who might need additional attention, ultimately leading to improved customer satisfaction and business performance). (Vyas and Uma 2019).

Sentiment analysis represents a fascinating intersection of multiple academic disciplines, drawing from diverse fields such as psychology to understand human emotions, sociology to comprehend social contexts, natural language processing to interpret text, and machine learning to automate analysis at scale (Liu B (2020). The field has undergone a remarkable transformation in recent years, primarily driven by two key factors: the unprecedented explosion in available data and the dramatic increase in computational capabilities. This technological evolution has pushed machine learning to the forefront, making it the preferred methodology for conducting sentiment analysis in modern applications (Luo, J, Huang S, 2020).

The academic landscape surrounding sentiment analysis is particularly rich, featuring extensive research and numerous studies. What's especially noteworthy is the presence of secondary studies and specialized research efforts that analyze and synthesize findings from multiple primary research papers (Hung BT, 2020). These secondary studies serve a crucial role in the broader research ecosystem. In the context of software engineering, secondary studies gained prominence in 2004 with the introduction of "Evidence-based Software Engineering" (EBSE) by Kitchenham and colleagues (Hussain, A, Cambria, 2018). This marked a significant shift in how software Engineering research was conducted and evaluated. The concept, borrowed from medical research methodologies, has since become deeply embedded in software engineering research practices (Ji, C and Wu H, 2020). Today, these secondary studies serve as fundamental tools for researchers, helping them synthesize and make sense of the vast body of existing research systematically and methodically (Jia Z, et al, 2020). This structured approach to reviewing and analyzing existing research has become increasingly important as the volume of primary research continues to grow, helping researchers identify patterns, trends, and gaps in current knowledge while providing a solid foundation for future research directions (Jiang, T, et, al).

There are mainly two types of systematic secondary studies that are involved:

i. A Systematic Literature Review (SLR) is a comprehensive research method that involves three key steps: finding relevant original studies, gathering specific data related to the research questions, and analyzing this information to draw meaningful conclusions. What sets SLRs apart is their adherence to strict methodological guidelines, ensuring that the review process remains objective and can be replicated by other researchers.

ii. Systematic Mapping Study (SMS) takes a broader view by creating a landscape overview of a specific research field. Rather than diving deep into specific questions, an SMS organizes and classifies existing research according to various categories or dimensions. This approach helps researchers understand the overall structure and patterns within a research area by creating a high-level map of existing studies.

This research aims to comprehensively analyze the field of sentiment analysis by examining and synthesizing findings from existing systematic literature reviews (SLR) and systematic mapping studies (SMS). This work represents a tertiary study - a systematic review of systematic reviews - which helps identify promising areas for future research. The study maps out various aspects of sentiment analysis, including models, tasks, features, datasets, and approaches, while also highlighting challenges and unresolved issues in the field. While tertiary studies have been conducted in other areas like software engineering and testing, this represents the first tertiary study focused specifically on sentiment analysis.

The paper makes three primary contributions:

i. It presents the first-ever tertiary study on sentiment analysis.
ii. It systematically identifies and synthesizes existing systematic reviews in sentiment analysis.
iii. It incorporates recent survey papers focusing on deep-learning approaches to sentiment analysis and discusses important lexicons in the field.

The paper's structure follows the sections covering background information, methodology, detailed results, discussion, and conclusions.

1.1. Research Questions

RQ1: What are the various approaches that should be considered in Sentiment Analysis?
RQ2: What Domains have been addressed in the Adopted Datasets?

2. BACKGROUND AND RELATED WORK

Sentiment analysis and opinion mining are terms that are often used interchangeably. Some researchers point out a subtle distinction between the two, suggesting that sentiments refer to feelings, while opinions represent more concrete thoughts (Pozzi et al. 2017). Despite this nuance, sentiments and opinions are closely related concepts, and when discussing one, the other is generally implied. Therefore, this research uses sentiment analysis as an overarching term to encompass both sentiment analysis and opinion mining.

Sentiment analysis encompasses various tasks, approaches, and analysis types, which are outlined in this section. Additionally, Fig. 1 offers an overview of sentiment analysis, adapted from Hemmatian and Sohrabi (2017), Kumar and Jaiswal (2020), Mite-Baidal et al. (2018), Pozzi et al. (2017), and Ravi and Ravi (2015). According to Cambria et al. (2017), a holistic approach to sentiment analysis is necessary, as simple categorization or classification is insufficient. They describe the problem using a three-layer structure that covers 15 Natural Language Processing (NLP) challenges, as follows:

- **Syntactics layer:** Micro text normalization, sentence boundary disambiguation, POS tagging, text chunking, and lemmatization.
- **Semantics layer:** Word sense disambiguation, concept extraction, named entity recognition, anaphora resolution, and subjectivity detection.

According to (Jin, N, et al, 2020) sentiment analysis and affective computing methodologies can be categorized into three main groups: (1) techniques based on knowledge systems, (2) approaches rooted in statistical analysis (including machine learning and deep learning), and (3) hybrid methods that integrate both knowledge-based and statistical approaches. When developing sentiment analysis models, researchers can employ different preliminary processing techniques and feature selection methods (Joasiassen, A., et, al). The preliminary processing phase involves normalizing text data through various steps, such as eliminating articles and implementing either stemming or lemmatization techniques to standardize word forms. Feature selection, on the other hand, focuses on identifying which specific characteristics of the text will serve as input data for the analysis (Kabra, A Shrawani, 2020).

This explanation provides a foundational framework for understanding how sentiment analysis systems are constructed and the different methodological approaches that can be employed in their development.

2.1. Key Aspects of Sentiment Analysis

2.1.1. Sentiment Classification

It represents one of the most fundamental and extensively studied areas within sentiment analysis. While often confused with the entire field, polarity determination is actually just one component that focuses on categorizing text as positive or negative, with some research including a neutral category(Kamal N, et al, 2006). Two specialized areas have emerged: cross-domain classification, which transfers insights from data-rich areas to those with limited data, and cross-language classification, which applies similar principles across different languages. Researchers like (Xia et al. (2015) have shown that understanding context at the opinion level helps resolve ambiguous sentiment words, while Vechtomova (2017) demonstrated that information retrieval methods can be effective alternatives to machine learning for clarifying word polarity.

2.1.2. Subjectivity Classification

Subjectivity classification serves as a preliminary step in sentiment analysis, focusing on identifying whether text contains subjective elements. As explained by Kasmuri and Basiron (2017), this process involves detecting "subjective clues" - words that convey emotions or personal judgments like "expensive," "easy," or "better." The primary purpose is to filter out objective content before proceeding with deeper analysis, making the overall process more efficient and focused on relevant emotional content (Kansara, et al, 2020).

2.1.3. Opinion Spam Detection

Opinion Spam Detection has become increasingly critical with the rise of e-commerce and review platforms. This area focuses on identifying deliberately crafted false reviews that aim to either boost or damage a product's reputation. The analysis typically examines three key aspects: the actual content of reviews (using machine learning), metadata (such as user information and ratings), and real-world context (like unexpected patterns in product ratings). For instance, a sudden surge of positive reviews for a historically low-rated product might trigger suspicion of spam activity, though access to complete metadata for analysis isn't always available (Karimpour J, et al, 2012).

These three components work together to create a comprehensive framework for understanding and analyzing sentiment in text, each addressing different challenges in the field of sentiment analysis.

2.1.4. Implicit Language Detection

It deals with the complex challenge of identifying subtle forms of expression like humor, sarcasm, and irony in text. These forms of communication are particularly challenging because they can completely reverse the apparent meaning of a statement. For example, in the phrase "I love pain," the conflict between the positive word "love" and the negative concept of "pain" likely indicates sarcasm. Traditional detection methods look for specific indicators such as emoticons, laughter expressions, or excessive punctuation, as noted by (Filatova, 2012). This detection is crucial because missing implicit meaning can lead to completely misinterpreting the true sentiment of a statement.

2.1.5. Aspect Extraction

It focuses on identifying specific features or components being discussed within the text, particularly important for detailed sentiment analysis. According to Liu, N, Shen, 2020), this could involve extracting information about products, people, events, or organizations. The process employs several methods:

A. Frequency-Based Analysis

This traditional approach identifies aspects by looking for frequently occurring nouns or compound nouns (Lou Y, 2020). The general rule suggests that if a noun appears in at least 1% of sentences, it likely represents an important aspect. While Schouten and Frasincar (2016) note this method's effectiveness, they also point out its limitations, as not all frequently used nouns necessarily indicate relevant aspects.

B. Syntax-Based Methods

This more sophisticated approach identifies aspects through their syntactic relationships in text, such as when they're modified by sentiment-carrying adjectives. While this method can identify less frequently mentioned aspects, it requires extensive knowledge of sentiment words. (Qiu et al. , 2009) developed an innovative algorithm that works bi-directionally - using known aspects to identify sentiment words and vice versa, creating a more comprehensive analysis system.

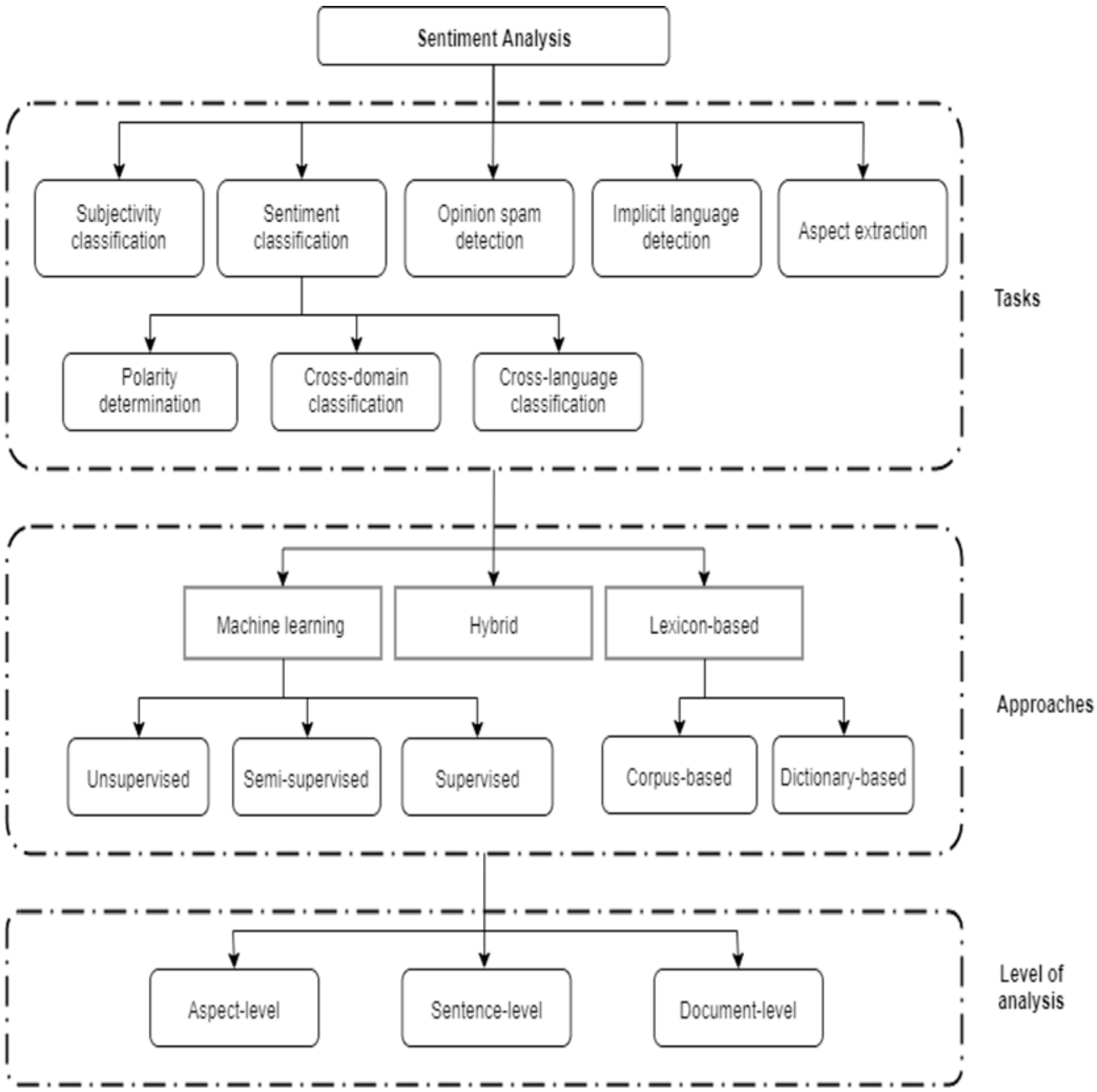

Fig. 1: Sentiment analysis Concept Overview (Ligthart, A., et al, 2021)

3. APPROACHES OF MACHINE LEARNING

3.1. Machine Learning Methods

Machine learning methods in sentiment analysis can be categorized into three main approaches: unsupervised, semi-supervised, and supervised learning techniques.

Unsupervised learning techniques work by automatically organizing unlabeled data into similar groupings or clusters. Features such as shared words or word combinations within documents can determine the similarity between data points, as noted by (Li and Liu ,2014). Semi-supervised learning combines both labeled and unlabeled data during model training. This approach involves using a limited set of labeled examples alongside a larger collection of unlabeled data to develop a classifier. (As da Silva et al., 2016) demonstrated, this method offers a good balance between accuracy and required human annotation effort compared to fully supervised approaches. Semi-supervised learning has proven particularly effective in cross-domain and cross-language classification tasks, where it helps extract domain-independent or language-independent features using unlabeled data while using labeled target data for classifier refinement (Peng et al. 2018).

Twitter sentiment analysis frequently employs semi-supervised learning due to the abundance of unlabeled tweets. Recent research has advanced this field significantly: Hussain and Cambria (2018) analyzed various semi-supervised methods' computational efficiency and introduced new models based on biased SVM and RLS. Wu et al. (2019) introduced a dimensional sentiment analysis model using variational autoencoders, while Xu and Tan (2019) developed TSSGM for target-oriented sentiment analysis. Han et al. (2019) created a multi-classifier model with dynamic thresholding that showed superior performance on movie reviews. Additionally, Duan et al. (2020) demonstrated success with their GEM-CW model for stock message sentiment classification, while Gupta et al. (2018) showed how semi-supervised approaches can improve performance in low-resource scenarios compared to supervised methods.

3.2. Deep Learning Methods

Deep learning, a specialized subdomain of machine learning characterized by the implementation of deep neural networks, has demonstrated significant applicability in sentiment analysis applications. This section examines two distinct categories of literature: (1) comprehensive reviews and comparative analyses of deep learning applications in sentiment analysis, excluding systematic literature reviews (SLRs) and systematic mapping studies (SMS), and (2) specific deep learning architectures deployed in sentiment analysis research (Seo, S, et al, 2020).

The assessment of survey papers analyzing deep learning-based sentiment analysis implementations is systematically documented in Table 1, which quantifies the volume of papers evaluated in each survey. (Dang et al.,2020) conducted an analytical review of 32 papers implementing deep learning architectures for sentiment analysis, with particular emphasis on the comparative performance evaluation of three primary neural architectures: Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) across eight distinct datasets (Sharma, SS and Dutta G, 2018). Their selection criteria for these architectures were based on implementation frequency within their corpus. The study implemented dual feature extraction methodologies - word embeddings and TF-IDF (Term Frequency-Inverse Document Frequency) - for neural network input preprocessing (Shayaa, S. et al, 2018) Their empirical analysis demonstrated superior performance metrics for RNN architectures utilizing word embeddings, albeit with computational overhead approximately ten times greater than CNN implementations. Their review identified multiple neural architectures in the literature, including CNN, various LSTM variants (tree-LSTM, discourse-LSTM, attention-LSTM, bi-LSTM), GRU, RNN, Coattention-MemNet, LRNN, SRN, and RNTN.

Yadav and Vishwakarma (2019) executed a more extensive review encompassing 130 research papers focused on deep learning applications in sentiment analysis. Their taxonomy of implemented architectures included: CNN, RecNN, RNN variants (LSTM and GRU), DBN, Attention-based Network, Bi-RNN, and Capsule Network. While their findings indicated superior performance characteristics for LSTM architectures and overall promising results for deep learning implementations, they identified two critical constraints: substantial data requirements and limited availability of training datasets.

Table 1. Survey Articles that utilized Deep Learning for Sentiment Analysis

Source	Reference	Title	No of Papers	Year
MDPI	Dang et al. (2020)	Sentiment analysis based on deep learning: A comparative study	40	2023
Springer	Yadav and Vishwakarma (2019)	Sentiment analysis using deep learning architectures: a review	131	2021
Wiley	Zhang et al. (2018)	Deep learning for sentiment analysis: A survey	62*	2018
Wiley	Rojas-Barahona (2016)	Deep learning for sentiment analysis. Language and Linguistics Compass	8	2016
Springer	Habimana et al. (2020a)	Sentiment analysis using deep learning approaches: an overview	54*	2020
Science Direct	Do et al. (2019)	Deep learning for aspect-based sentiment analysis: a comparative review	40	2019
Arxiv.org	Minaee et al. (2020)	Deep learning-based text classification: A comprehensive review	22	2020

Zhang et al. (2018) published a comprehensive survey examining the application of deep learning methods in sentiment analysis across three distinct classification levels: document, sentence, and aspect-level sentiment classification. At the document level, they identified a diverse range of implemented architectures including Artificial Neural Networks (ANN), Stacked Denoising Autoencoder (DSA), Denoising Autoencoder, CNN, LSTM, GRU, Memory Networks, and GRU-based Encoder. For sentence-level sentiment classification, they documented the use of several neural network architectures: CNN, RNN, Semi-supervised Recursive Autoencoders Network (RAE), Recursive Neural Network, and Recursive Neural Tensor Network. This comprehensive breakdown illustrates how different deep learning approaches are tailored to specific granularities of sentiment analysis tasks.

4. PRISMA APPROACH OF SYSTEMATIC REVIEW

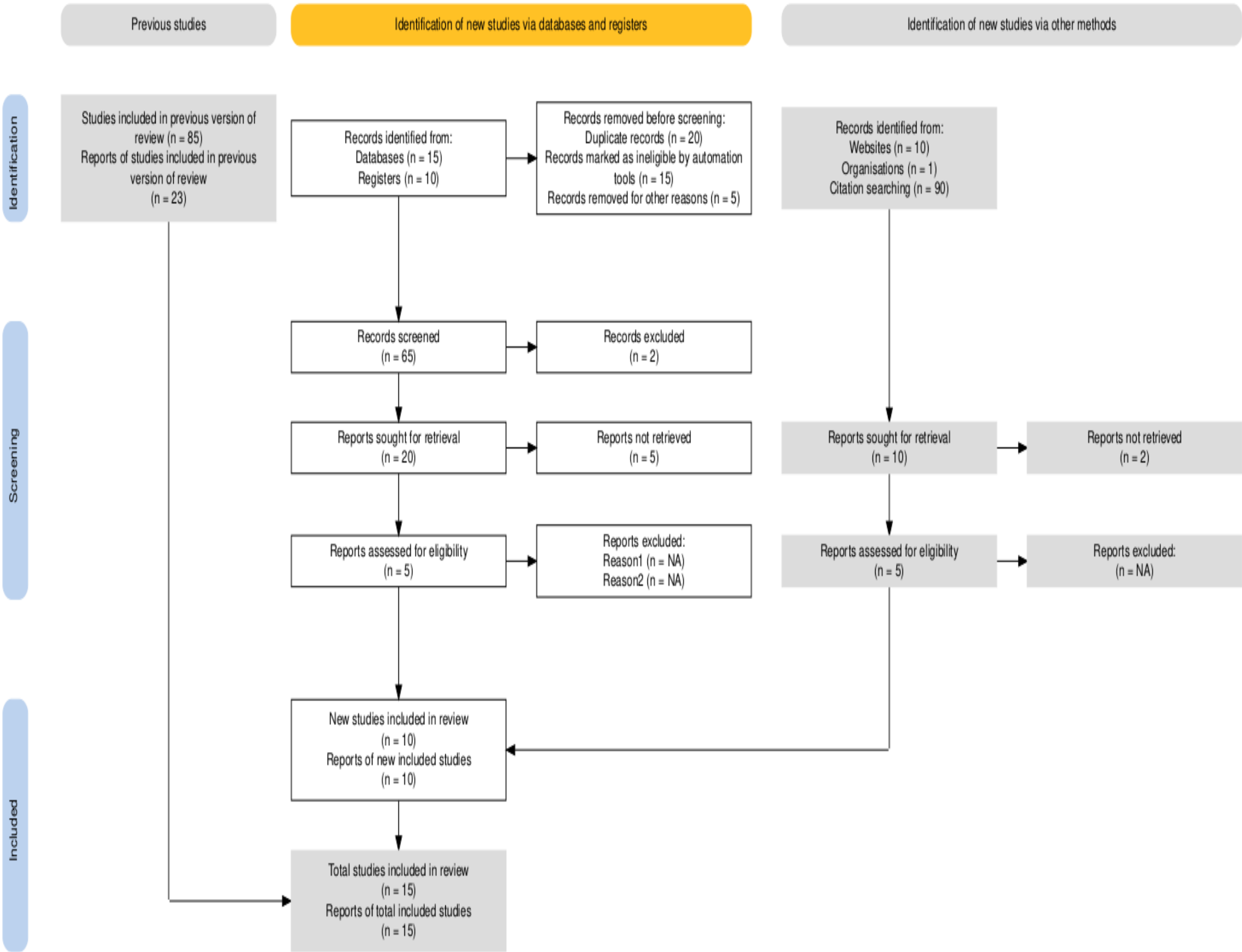

Fig. 2: Prisma Flow Diagram for Review of Sentiment Analysis

The PRISMA flow diagram presented illustrates the systematic review process for research papers focused on sentiment analysis. Beginning with a foundation of 85 previous studies documented in 23 reports, the review expanded through two main identification channels. The first channel involved searching databases and registers, which yielded 15 and 10 records respectively. These underwent a rigorous screening process where 20 duplicate records, 15 automated ineligibility removals, and 5 other removals were processed. From the remaining 65 records, 2 were excluded during screening, leaving 20 reports for retrieval. After 5 of these couldn't be retrieved, the remaining underwent eligibility assessment. The second identification channel explored alternative sources, finding 10 records from websites, 1 from organizations, and 90 through citation searching. This pathway led to 10 reports being sought, though 2 couldn't be retrieved, and 5 underwent eligibility assessment. The process culminated in the inclusion of 10 new sentiment analysis studies with their corresponding reports. When combined with the previous research, this resulted in a final collection of 15 studies and their associated reports, creating a comprehensive foundation for the systematic review of sentiment analysis research.

Table 2. Distribution of Machine Learning and Deep Learning Techniques from Year 2020-2024

S. No.	Technique used	No. of Papers involved	Accuracy achieved
1	LSTM	81	35.53
2	CNN	76	33.33
3	GRU	20	8.77
4	RNN	18	7.89
5	Bidirectional Encoder Representations from Transformers (BERT)	7	3.07
6	DNN	4	1.75
7	ReNN	4	1.75
8	Graph Convolutional Neural Network (GCN)	3	1.32
9	Capsule Network (CapsN)	2	0.88
10	Recurrent Convolutional Neural Network (RCNN)	2	0.88
11	Distillation Network (DN)	2	0.88
12	Generative Adversarial Network (GAN)	1	0.44
13	Gated Alternate Neural Network (GANN)	1	0.44
14	Category Attention Network (CAN)	1	0.44
15	Recurrent Memory Neural Network (ReMemNN)	1	0.44
16	Interactive Rule Attention Network (IRAN)	1	0.44
17	Self-Attention based Hierarchical Dilated Convolutional Neural	1	0.44

	Network (SA-HDCNN)		
18	Fusion-Extraction Network (FENet)	1	0.44
19	Deep Q-Network	1	0.44
20	Autoencoder	1	0.44

5. EXPLANATION OF RESEARCH QUESTIONS

RQ1: What are the various approaches that should be considered in Sentiment Analysis?

A review of selected papers indicates that sentiment analysis implementations typically fall into three main categories: machine learning-based approaches (encompassing deep learning, unsupervised learning, and ensemble methods), lexicon-based approaches, and hybrid methodologies that combine multiple techniques. The presence of checkmarks in the literature signifies that these approaches were explicitly examined and discussed within the corresponding research papers.

Ensemble classification represents a methodology where multiple learning algorithms are combined to achieve enhanced performance metrics, as documented by Behera et al. (2016). The approach encompasses three primary ensemble methodologies: bagging (bootstrap aggregating), boosting, and stacking. In bagging implementations, homogeneous algorithms are trained independently using randomly sampled training data points, followed by a deterministic averaging procedure. Conversely, boosting employs a sequential and adaptive learning process for homogeneous algorithms before implementing an averaging mechanism.

RQ2: What Domains have been addressed in the Adopted Datasets?

Sentiment analysis datasets are predominantly composed of user-generated textual content, with significant variations in linguistic patterns and characteristics across different domains and platforms. The textual content exhibits distinct properties depending on its source: social media data typically contains subjective content and informal language, while news articles maintain objectivity and formal writing structures. Platform-specific constraints further differentiate the content - Twitter posts are restricted by character limits and include platform-specific elements like hashtags and references, whereas product review platforms facilitate detailed, product-focused descriptions. A critical challenge in this field is that Machine Learning models trained on one domain typically demonstrate poor performance when applied to different domains, as each domain employs unique language patterns and requires specialized analytical approaches. This domain dependency underscores the necessity for tailored methodological approaches in sentiment analysis across different content types.

6. DISCUSSION

This study presents a comprehensive overview of machine learning models' current applications and challenges in sentiment analysis. The research methodology follows the systematic literature review guidelines established by Kitchenham and Charters (2007), critically analyzing selected secondary studies and extracting relevant data based on predefined research questions. Initially, 16 secondary studies were selected, though this number was reduced to 14 following a quality assessment phase. The methodology was deliberately designed to be transparent and reproducible by other researchers, though like any secondary study, it acknowledges certain limitations. The systematic literature reviews (SLRs) included in this study each maintain their specific research focus within sentiment analysis. Despite similarities in methodological approaches across the 14 secondary studies, there were significant variations in how techniques and methods were documented. Furthermore, the comprehensiveness of the SLR papers varied considerably, with some providing more detailed analysis than others. These inconsistencies in documentation and depth made the data extraction process more challenging and potentially susceptible to errors.

7. CONCLUSION AND FUTURE SCOPE

This tertiary study examines sentiment analysis methods, focusing on identifying adopted features (input/output), approaches, datasets, and associated challenges. The findings were derived from a comprehensive analysis of secondary studies. The research revealed varying numbers of input and output features, with some features appearing consistently across all secondary studies while others were specific to particular studies. A notable finding was the prevalence of sentiment analysis applications in social media compared to other domains, with evidence suggesting that different domains require distinct analytical techniques.

The research identified an emerging trend toward deep learning techniques, which excel at detecting complex patterns in text and perform particularly well with larger datasets. In specific applications, such as advertising, even minor performance improvements achieved through deep learning can have a significant impact. However, traditional machine learning models maintain their relevance due to their lower computational requirements and satisfactory performance in sentiment analysis tasks. These conventional approaches continue to receive widespread recognition for their efficiency and effectiveness. The study highlights domain and language dependency as the most significant challenges in sentiment analysis. Different domains and languages require specific text corpora for effective analysis. While attempts have been made to develop cross-domain and multi-lingual sentiment analysis models, this remains a challenging area requiring further research. Additional prominent challenges include opinion spam detection and the implementation of deep learning in sentiment analysis tasks. The findings emphasize that sentiment analysis remains a crucial and timely research area.

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