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A Review: A Cross-media sentiment analysis of social multimedia contents and advances

[1] Richa Rawal, [2] Sandhya Sharma , [1] Srawan Nath
[1] Research Scholar, Computer Science and Engg., Suresh Gyan Vihar University Jaipur
[2] Assistant Professor, ECE., Suresh Gyan Vihar University Jaipur
Email: richarawal23@gmail.com

Abstract: - This paper presents a comprehensive review of cross-media sentiment analysis applied to social multimedia contents, exploring recent advancements and key developments in the field of cross-media sentiment analysis. The proliferation of social media platforms and by increasing use of multimedia content day by day, understanding sentiment across different media types has become crucial for various applications such as marketing, management, and public opinions. This review paper examines general methodologies, techniques, and algorithms used in cross-media sentiment analysis, including text, image, video, and audio data. It also discusses challenges and opportunities faces in the multimodal fusion, data heterogeneity, and scalability, along with future research directions. By reviewing existing literature and highlighting emerging trends, this review paper offers valuable insights for researchers and practitioners aiming to fulfil the purpose of sentiment analysis across different media sources in the context of social multimedia.

Keywords: Cross-media, social media, sentiment analysis, text, techniques, challenges

I. Introduction

Sentiment analysis is the use of natural language processing and machine learning strategies to differentiate attitudes and perceptions of text document writers against an entity, such as a commodity, service, individual, occurrence, brand or corporation. Sentiment research on social network content created by the consumer may provide an overall impression of the approval or disapproval of products or services [1]. The knowledge from a credible study should be utilised by both individuals and organisations' critical decisionmaking processes. Subjective knowledge retrieval from text is the core activity of emotion analysis [2]. In its primary type, emotional interpretation categorises records as good or destructive, based on their textual orientation. The availability of a wide variety of user generated content with views has enabled sentiment analysis to identify public opinion patterns in the social network with a range of purposes including politics, finance and marketing with the advent of Web 2.0 and related technologies [3]. The aim of this work is to outline the inspiration behind the research work on sentiment analysis and a description of the key areas of expertise involved in this document. The general and particular priorities that have driven the work are also presented.

In recent years, the proliferation of social media platforms and the exponential growth of multimedia content have transformed the landscape of sentiment analysis. Traditional sentiment analysis techniques have primarily focused on text-based data, overlooking the rich multimodal information present in social multimedia content. As users increasingly express their opinions through diverse mediums such as text, images, videos, and audio, there is a pressing need for advanced sentiment analysis methods capable of effectively analyzing cross-media content [4,5].

This paper presents a comprehensive review of the state-of-the-art in cross-media sentiment analysis of social multimedia contents. By integrating text, images, videos, and audio, cross-media sentiment analysis offers a holistic understanding of user sentiments across different modalities. We explore recent advancements in text analysis, image analysis, video analysis, and audio analysis techniques within the context of sentiment analysis. Additionally, we investigate multimodal fusion methods that combine information from multiple modalities to enhance sentiment analysis performance [6].

Correspondence to: Richa Rawal, Department of Computer Science and Information Technology, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: richarawal23@gmail.com

The challenges posed by the heterogeneity of multimedia data, scalability issues, and the dynamic nature of social media platforms are discussed. We highlight the importance of addressing these challenges to develop robust and scalable cross-media sentiment analysis systems. Furthermore, we identify emerging research directions and opportunities for future research in this rapidly evolving field [7].

Through this review, we aim to provide researchers and practitioners with a comprehensive understanding of the current state of cross-media sentiment analysis and inspire further advancements in this exciting area of research. The realm of sentiment analysis has witnessed a significant evolution with the advent of social multimedia platforms, where users generate a diverse range of content comprising text, images, videos, and audio [8]. Traditional sentiment analysis techniques have primarily focused on text-based data, often overlooking the valuable insights embedded in multimedia content. In response to this, the emerging field of cross-media sentiment analysis has emerged, aiming to extract sentiment from multiple modalities and provide a more comprehensive understanding of user opinions. This paper embarks on a novel exploration into the cross-media sentiment analysis of social multimedia contents, delving into recent advancements and cutting-edge methodologies [9]. Unlike conventional sentiment analysis methods, which predominantly analyse textual data, cross-media sentiment analysis integrates information from various modalities, including text, images, videos, and audio, to capture nuanced sentiment expressions across different media formats [10,11].

The review spans recent developments in text analysis, image analysis, video analysis, and audio analysis within the context of sentiment analysis [12]. We scrutinize multimodal fusion techniques designed to combine insights from disparate modalities, thereby enriching sentiment analysis outcomes. Moreover, we shed light on the challenges inherent in analysing heterogeneous multimedia data and propose innovative solutions to address scalability issues and adapt to the dynamic nature of social media platforms. Central to our discussion is the emphasis on novelty, as we uncover emerging research avenues and untapped potentials in the domain of cross-media sentiment analysis [13]. By synthesizing existing knowledge and envisioning future prospects, this paper aims to catalyse advancements in sentiment analysis methodologies and inspire novel approaches to unravel sentiment patterns in social multimedia contents. Through this exploration of novelty, we endeavour to propel the field of cross-media sentiment analysis towards greater innovation and efficacy in capturing the complexities of user sentiment across diverse media modalities.

II. Literature Review

We introduce a novel method to address Opinion List (OL) queries on social media platforms like Twitter, leveraging a classifier trained on task-specific features to identify relevant lists, extracting list answers from tweets using regex patterns, and presenting the items in a list format. It conducted a qualitative study on engineering students' social media conversations to understand their educational challenges, revealing issues like homework overload and lack of social engagement. We developed a methodology to mine insights from informal social media data, leading to the creation of a student problem detection system. Experimental results demonstrate the efficiency of our system and algorithms in handling real-time emotions expressed on platforms like Twitter [14].

Researchers have become increasingly interested in utilizing consumer-generated data on Twitter as a source of emotional insights. This article addresses the challenge of predicting users' views on issues they have not explicitly addressed using a social perspective process. Experimental results demonstrate that this framework outperforms existing collective filtering approaches, particularly when considering both social and topical contexts. Additionally, a novel non-query-based method incorporating association rules, generalized rules, and sentiment analysis is proposed to analyse sentiments on Twitter [15]. Unlike previous approaches, this method captures trends and sentiment patterns in microblogging texts comprehensively. Initial experiments conducted on a dataset of 1.7 million tweets demonstrate the effectiveness of the proposed approach, particularly in analysing emotions during the American pre-election campaign. Overall, the study confirms the potential of leveraging online opinion resources for gaining valuable insights into public opinion trends [16].

Twitter serves as a valuable database for research in various fields due to its concise format and user-generated content covering news, trends, emotions, and opinions. However, the inclusion of emojis complicates text mining and emotional interpretation. This paper proposes methodologies for mining user-equipped tweets, detecting incidents using geospatial emotional vectors, and identifying social media user divisions during election cycles. Experimental results demonstrate the effectiveness of these methods in accurately predicting user sentiments and polarizations [17]. The sentiment analysis on Twitter is essential for policymakers and businesses to understand public opinions. Methods like Milestones Rank and IOM-NN are introduced to identify opinion leaders and analyse user sentiments during election cycles, respectively. Furthermore, the Piegas method is developed to automatically assess tweet sentiments, while a methodology for selecting overview tweets from news stories is proposed to enhance consistency and discusses the challenges and opportunities in sentiment analysis, emphasizing the need to understand sentiment variations and their underlying reasons [18].

Correspondence to: Richa Rawal, Department of Computer Science and Information Technology, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: richarawal23@gmail.com

This study explores sentiment analysis on Twitter, examining statistical and temporal properties of sentiment dynamics across user groups. A novel visualization concept, "Whisper," is proposed to monitor knowledge distribution in real-time on social media. Additionally, a system to detect optimistic predictions in financial tweets is suggested, achieving high precision. Emotion Recognition in Communication (ERC) challenges and sports fan sentiment on Twitter are also discussed, emphasizing the importance of sentiment analysis in understanding public opinion and emotions [19].

This study proposes a hybrid sentiment analysis model using a Wrapper Approach and Genetic Algorithm to select prime features and reduce feature volume, improving accuracy without compromising performance. Another approach introduces a novel genetic algorithm-based feature reduction technique to enhance sentiment analysis scalability, achieving a 42% reduction in feature set size while maintaining precision [20]. Additionally, the extraction of live Twitter data for opinion mining is discussed, highlighting the value of sentiment analysis for industry researchers and consumers. Furthermore, a method for forecasting public opinion on Twitter using machine learning models is presented, demonstrating its efficacy in analysing current affairs and consumer behaviour. Lastly, a Bayesian approach combined with Emotional PageRank algorithms is suggested to determine the influence of Twitter users on the opinions of target users, leveraging retweet and favourite marks for estimation [21].

In today's digital age, social media platforms serve as a primary means for individuals to share opinions and feedback. Extracting sentiments from platforms like Twitter is crucial for market research and sentiment analysis. This article proposes various methods, including machine learning and natural language processing techniques, to analyse sentiment from Twitter data. By preprocessing and analysing tweets, sentiments are categorized into positive, negative, and neutral, aiding in understanding public opinion on various topics. The study demonstrates the effectiveness of different algorithms in sentiment analysis and emphasizes the importance of social media in knowledge exchange. Additionally, the paper explores techniques to target specific users on Twitter for marketing purposes by analysing their preferences and behaviours. Overall, the integration of data mining and sentiment analysis offers valuable insights for real-time information exploitation [22].

Real-time Twitter research is invaluable for understanding public sentiments and viewpoints. By analysing tweets, sentiment analysis models can determine whether opinions are positive, negative, or neutral, aiding in monitoring user views and gaining insights into societal trends. This study proposes sentiment analysis models focused on various countries, leveraging Hadoop Ecosystem for processing large volumes of data. Additionally, sentiment analysis techniques are applied to diverse topics, such as tourism in Oman and opinions on plastic bans in India, to gauge public sentiment and inform decision-making. The use of machine learning algorithms, such as Naïve Bayes and SVM, enables accurate sentiment classification, providing valuable insights for businesses and policymakers. Furthermore, sentiment analysis on social media platforms like Twitter offers insights into political sentiments, such as during the Indonesian presidential elections, and consumer opinions on services like airline companies. Overall, sentiment analysis on social media data facilitates understanding public perceptions and behaviours, aiding in decision-making across various domains [23,24].

The goal is to develop automated systems for classifying tweets based on whether they express human inference. Integrating natural language processing (NLP) and text mining, the approach utilizes Named Entity Recognition (NER) for neutral and non-neutral labelling [25]. The system addresses challenges such as scarcity of labeled data and model updates by combining semi-supervised learning and multiple classification systems. Testing on 14 Twitter stream datasets demonstrates superiority over traditional ensemble methods like Bagging and AdaBoost. Additionally, a new method for classifying text from Twitter into seven levels of emotion is proposed, achieving up to 60.2% precision in multi-class classification, and high accuracy in binary and ternary classification tasks [26].

Table 1: Comparison of various models and their performances

Ref.	Description	Model	Data Source	Efficiency
[27]	Use of binary data to classify (Thumb up / Thumb down). They look for two words POS patterns.	Unsupervised/Statistic (PMI)	Reviews (Cars, banks, movies, destinies)	66-84%
[28]	Use of overall rating of movies as training data. Word counting to classify Reviews	NB, SVM, ME, BoW	Reviews (Movies)	77-82.9%
[29]	Thumb up / Thumb down to train algorithm and classify semantic	Semisupervised	Reviews (products) Cnet and Amazon	85.3%

Correspondence to: Richa Rawal, Department of Computer Science and Information Technology, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: richarawal23@gmail.com

	orientation of reviews			
[30]	Subjectivity evaluation of sentences by similarity of every word with respect of seed words (+/-).	Statistic	News (News wire)	68-90%
[31]	Document-level analysis by considering just subjective information in sentences. 5000 sentences were tagged for training.	NB, SVM	Reviews (Movies)	86.4-87.2
[32]	Turney's PMI plus extended anchor words from 2 to 10 (5 positives and 5 negative). Combination of PMI results with Naive Bayes	Statistic (PMI) / NB	Reviews (Movies)	65.8
[33]	Scalar rating of 1-4 as training data. NLP Linguistic approach.	SVM	Reviews (products)	77.5-85.47
[34]	Use of text with emoticons as training dataset of algorithms.	NB, SVM	News (Finance, M&A) and Reviews (Movies) UseNet	70%
[35]	Classify sentiment in a 3 and 4 scale points in Reviews.	SVM + metric labeling SVM + PSP	Reviews (Movies)	75%
[36]	Phrase-level analysis. They classify sentence as subjective-objective. NLP Linguistic approach.	Lexicon Extended from inquirer	Text documents	63-82%
[37]	Identify mood. Find most frequent vocabulary for every single mood.	SVM	Comments Blogs (LiveJournal)	49 to 65.75
[38]	To detect 8 sentiments in fairytales and determine semantic orientation	Heuristic linear classification	Fairytales	64%
[39]	They used tagged data and untagged by the use of similarity measures. They used PSP (Positive Sentence Percentage). Predict numeric ratings (stars 0-3).	Semisupervised graph based. / SVM	Reviews (Movies)	49.8-59.2
[40]	Classification focus on specific domain: Food and beverage	Statistic similarity of phrases	Reviews (Food)	87.4
[41]	Classify news articles in multiple languages and compare efficiency against other classifier	SentiWordNet	News Reviews (Movies) Reviews in German	55-89%

III. Methodology

This study employs a comprehensive research methodology to investigate the cross-media sentiment analysis of social multimedia contents. The methodology comprises several key steps as shown on figure 1.

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Corresponding author. E-mail addresses: richarawal23@gmail.com

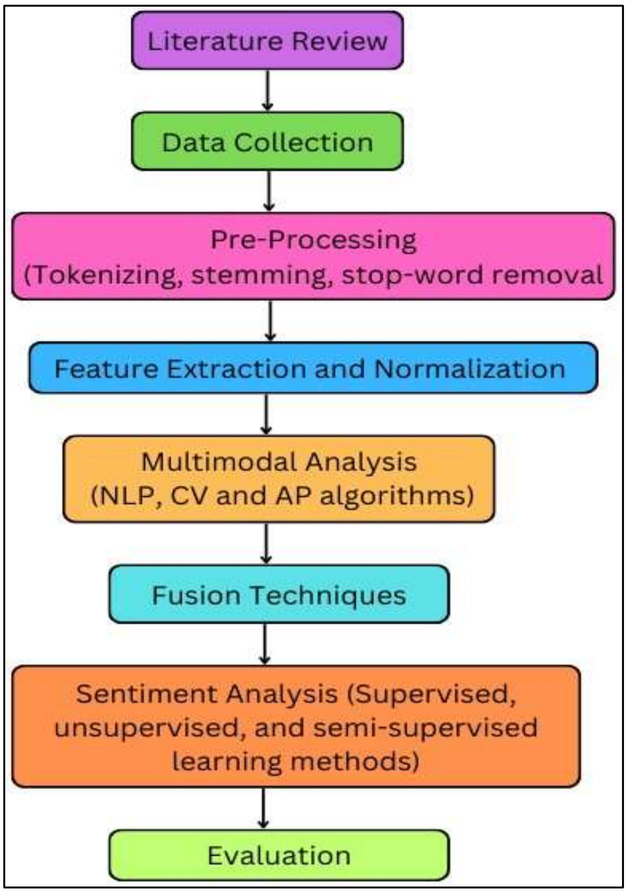

Figure 1: General methodology adopted by previous authors

A systematic review of existing literature is conducted to identify relevant studies, methodologies, and advancements in cross-media sentiment analysis. This review serves as the foundation for understanding the current state of the field and identifying research gaps. Datasets comprising social multimedia contents, including text, images, videos, and audio, are collected from various sources such as social media platforms, online forums, and multimedia repositories. These datasets represent diverse contexts and enable a holistic analysis of sentiment across multiple modalities. The collected data undergoes preprocessing to clean and standardize the content across different modalities. Textual data may be subjected to tokenization, stemming, and stop-word removal, while multimedia data may undergo feature extraction and normalization processes. A multimodal analysis approach is employed to analyze sentiment across different media modalities. Textual data are subjected to natural language processing techniques, while images, videos, and audio are analyzed using computer vision and audio processing algorithms to extract relevant features indicative of sentiment. Multimodal fusion techniques are applied to integrate insights from different media modalities and derive a holistic understanding of sentiment. Fusion approaches may include early fusion, late fusion, or hybrid fusion strategies to combine textual and multimedia features effectively. Sentiment analysis algorithms are applied to the fused multimodal features to classify sentiment polarity or intensity. Supervised, unsupervised, and semi-supervised learning methods may be utilized to train sentiment classifiers based on labeled data or through transfer learning techniques. The performance of the cross-media sentiment analysis approach is evaluated using appropriate metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve. Cross-validation techniques may be employed to assess the robustness of the model across different datasets and contexts.

By following this research methodology, this study aims to advance the understanding of sentiment analysis in the context of social multimedia contents and pave the way for innovative approaches to capture sentiment across diverse media modalities.

3.1. Tool and Techniques

Natural Language Processing (NLP): NLP techniques are employed to analyze textual data and extract sentiment-related features. Tools such as NLTK (Natural Language Toolkit), SpaCy, and TextBlob are utilized for tasks such as tokenization, part-of-speech tagging, sentiment analysis, and named entity recognition.

Computer Vision: Computer vision techniques are applied to analyze images and extract visual features indicative of sentiment. OpenCV (Open-Source Computer Vision Library) and deep learning frameworks like TensorFlow and PyTorch are utilized for tasks such as image classification, object detection, and feature extraction.

Audio Processing: Audio processing techniques are employed to analyze speech and extract acoustic features relevant to sentiment analysis. Tools such as librosa and PyDub are used for tasks such as speech recognition, feature extraction, and emotion detection from audio signals.

Machine Learning Algorithms: Supervised, unsupervised, and semi-supervised machine learning algorithms are applied to train sentiment classifiers and analyze sentiment patterns across different media modalities. Techniques such as support vector machines (SVM), decision trees, random forests, and deep learning models (e.g., Convolutional Neural Networks, Recurrent Neural Networks) are utilized for sentiment analysis tasks.

Multimodal Fusion Techniques: Various fusion techniques are employed to integrate insights from different media modalities and derive a comprehensive understanding of sentiment. Early fusion, late fusion, attention mechanisms, and multimodal embeddings are

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Corresponding author. E-mail addresses: richarawal23@gmail.com

utilized to combine textual, visual, and auditory features effectively.

Sentiment Lexicons and Dictionaries: Sentiment lexicons and dictionaries are utilized to enrich sentiment analysis by incorporating domain-specific knowledge and sentiment-aware terms. Existing lexicons such as SentiWordNet, VADER (Valence Aware Dictionary and sEntiment Reasoner), and AFINN (Affective Norms for English Words) are leveraged for sentiment analysis tasks.

Evaluation Metrics: Standard evaluation metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve are employed to assess the performance of sentiment analysis models. Additionally, domain-specific metrics and qualitative analysis techniques may be utilized to evaluate the effectiveness of sentiment analysis across different contexts.

Data Visualization Tools: Data visualization tools such as Matplotlib, Seaborn, and Plotly are utilized to visualize sentiment patterns and insights derived from social multimedia contents. Graphical representations, heatmaps, and interactive visualizations aid in interpreting and communicating the results of sentiment analysis effectively.

By leveraging these tools and techniques, researchers can conduct comprehensive cross-media sentiment analysis of social multimedia contents and gain valuable insights into sentiment expression across diverse modalities.

3.2. Challenges

Social multimedia contents encompass diverse data types, including text, images, and audio, posing challenges in integrating and analyzing heterogeneous data sources. The sheer volume of social multimedia data generated in real-time presents challenges in processing and analyzing large-scale datasets efficiently. Social multimedia data often exhibit noise, inconsistencies, and subjective interpretations, affecting the accuracy and reliability of sentiment analysis outcomes. Integrating insights from different media modalities (text, images, audio) while ensuring coherence and consistency poses technical challenges in feature extraction, fusion, and interpretation. Social multimedia contents may lack context or contain ambiguous expressions, making it challenging to accurately interpret sentiment in varying contexts and scenarios. Scalability issues arise when scaling sentiment analysis techniques to handle the growing volume and complexity of social multimedia data across diverse platforms and domains.

3.3. Opportunities

Advancements in machine learning models, such as deep learning architectures, offers opportunities to improve the accuracy and robustness of sentiment analysis across different media modalities. Developing advanced fusion techniques to integrate insights from text, images, and audio can enhance the comprehensiveness and richness of sentiment analysis outcomes. Incorporating contextual information, user demographics, and situational factors into sentiment analysis models can improve the relevance and reliability of sentiment insights. Implementing real-time sentiment analysis techniques enables timely monitoring and response to emerging sentiment trends in social multimedia contents. Tailoring sentiment analysis approaches to specific domains (e.g., healthcare, finance, entertainment) offers opportunities to address domain-specific challenges and derive actionable insights tailored to industry needs. Addressing ethical considerations related to user privacy, data protection, and algorithmic bias presents opportunities to develop responsible sentiment analysis frameworks that prioritize fairness, transparency, and accountability.

IV. Conclusion

In conclusion, the cross-media sentiment analysis of social multimedia contents represents a dynamic and evolving field with significant potential for advancing our understanding of user opinions, preferences, and sentiments across diverse media modalities. Through this research paper, we have explored various challenges, opportunities, methodologies, tools, and techniques involved in analyzing sentiment in social multimedia data.Despite the challenges posed by data variety, volume, and quality, as well as the complexities of cross-media integration and contextual ambiguity, there are ample opportunities for leveraging advanced machine learning models, multimodal fusion techniques, and context-aware sentiment analysis approaches to enhance the accuracy, relevance, and timeliness of sentiment analysis outcomes. Moreover, the scalability of sentiment analysis techniques, coupled with domain-specific solutions tailored to specific industries and applications, offers promising avenues for addressing real-world challenges and deriving actionable insights from social multimedia contents. Ethical considerations remain paramount in the development and deployment of sentiment analysis frameworks, necessitating a commitment to responsible practices that prioritize user privacy, data protection, and algorithmic fairness. In summary, the continued advancement of cross-media sentiment analysis holds the potential to revolutionize various domains, including marketing, customer service, public opinion monitoring, and beyond. By embracing emerging methodologies and technologies while remaining cognizant of ethical considerations, researchers and practitioners can unlock new opportunities for extracting valuable insights from the rich tapestry of social multimedia data.

Correspondence to: Richa Rawal, Department of Computer Science and Information Technology, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: richarawal23@gmail.com

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Correspondence to: Richa Rawal, Department of Computer Science and Information Technology, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: richarawal23@gmail.com

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Correspondence to: Richa Rawal, Department of Computer Science and Information Technology, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: richarawal23@gmail.com