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Sentiment Analysis of User-Generated Content: A Bibliometric Analysis

Nunik Afriliana, Ni Made Satvika Iswari , Suryasari

Faculty of Engineering and Informatics, Universitas Multimedia Nusantara, Tangerang, Indonesia 15810

E-mail: nunik@umn.ac.id, satvika@umn.ac.id, suryasari@umn.ac.id

Abstract. User-generated content offers the opinions and sentiment analysis of numerous individuals in diverse areas, including e-commerce, marketing, health care, transportation, customer service, brand research, and many others. However, the abundance of user-generated content data makes it challenging to analyze and derive insights from it. As a result, the demand for sentiment analysis research has increased. This work intends to highlight the trends and state of the art in user-generated content sentiment analysis through a bibliometric analysis. To our knowledge, bibliometric research of sentiment analysis on user-generated content has never been conducted. The research methodology adopted for this study was essentially divided into four phases. Those phases include data collection, data cleaning, data visualization, data analysis and report writing. This bibliometric research successfully identified the trends and state of the art in user-generated content sentiment analysis. This study will give a baseline for future researchers to start another study. Big data, text analytics, text mining, tourism, covid-19, machine learning, deep learning, convolutional neural networks, making predictions, and marketing decisions are among the most recent research interests for sentiment analysis of user-generated content. However, there is a lack of research on those particular topics.

Keywords: User-Generated Content, Sentiment Analysis, Bibliometric Analysis, State of The Art

1. Introduction

A vast amount of data is available on social media, blogs, forums, e-commerce, and other digital platforms, with a substantial part of it being user-generated content. The amount of user-generated content on the Internet is constantly growing due to technological advancements and the growth of the Internet-savvy population. User-generated content, also known as UGC, is created by people based on their personal experiences and opinions. This type of content is becoming an increasingly attractive economic resource and valuable resource for commercial potential. The UGC provides the opinions of numerous individuals on a range of subjects such as e-commerce, marketing, health care system, transport system, customer service, brand research, and many other fields (Berthon et al., 2015; Krumm et al., 2008; Putra & Suryasari, 2021). Users can generate content informally on social media, websites, or product review forums (Chakravarthi et al., 2022).

To evaluate products and services, prospective customers increasingly rely on user-generated content (UGC) as e-word-of-mouth information. Simultaneously, managers are fast recognizing the need to utilize this data to obtain feedback and evaluate their own and competitors' products and performance. It increases understanding of consumer behavior and expectations and identifies market opportunities. The objectives of UGC information mining are to determine what enhances consumer satisfaction, evaluate products and services, and aid businesses in spotting potential risks (Berthon et al., 2015; Birch-Jensen et al., 2020; H. Li, 2022; M.-F. Li et al., 2022; Xu et al., 2011). Therefore, classifying sentiment from customer reviews is crucial to detect a product or service's negative or positive sentiment. It can help to identify critical issues with the product or services. However, the abundance of reviews makes it challenging for prospective consumers to get relevant insights and for management to monitor customer feedback. Consequently, the need for sentiment analysis research increases (Agarwal & Mittal, 2013; D. Li et al., 2022).

This paper aims to present the trends and state of the art of research in UGC sentiment analysis. To our knowledge, there has never been a bibliometric examination of UGC sentiment analysis. Therefore, our study will give a bibliometric analysis of UGC sentiment analysis using the following research questions (RQs).

RQ1: How are user-generated content sentiment analysis research trends evolving?

RQ2: How is the state of the art in user-generated content sentiment analysis research?

2. Literature Review

User-generated content (UGC) is content contributed by people based on their personal experiences and opinions. This content is created by ordinary people who voluntarily contribute data, information, or media that is then presented to others practically or amusingly, typically on the Internet. Examples of this UGS include restaurant ratings, wikis, and videos (Krumm et al., 2008). The UGC solicits community feedback on various issues, including e-commerce, marketing, the healthcare system, transportation, customer service, brand research, and many others. This information is becoming an increasingly important economic resource with significant commercial potential by sharing people's opinions about a specific entity or product. (Berthon et al., 2015; Krumm et al., 2008; Putra & Suryasari, 2021). However, the abundance of reviews makes it challenging for prospective consumers to get relevant insights and for management to monitor customer feedback. Consequently, the need for sentiment analysis research increases (Agarwal & Mittal, 2013; D. Li et al., 2022). In recent years, UGC has amassed vast data about individual beliefs, activities, and experiences. While the actual value of these data to public opinion or sentiment analysis research is still being debated, the potential insights gleaned from UGC are projected to be substantial (Ruelens, 2022).

Sentiment analysis is the computational study of assessing the feelings and opinions of individuals regarding a particular entity. It determines the emotional tone of a string of words and can be used to comprehend users' attitudes, opinions, and emotions. Sentiment Analysis methods automatically classify the polarity of negative, positive, or neutral opinions (Medhat et al., 2014; Priyadarshini & Cotton, 2021; Serna et al., 2021). Sentiment analysis is utilized in numerous fields, such as smart tourism, health care, business reputation management systems, e-commerce, and even identifying sentiment on the COVID-19 pandemic (Alkhaldi et al., 2022; Antonio et al., 2020; Saura et al., 2020).

Bibliometric analysis is a popular and rigorous technique for investigating and understanding enormous quantities of scientific data. It enables us to analyze the evolutionary subtleties of a particular discipline and sheds light on new topics within that field. In recent years, bibliometric analysis has become prominent in business research (Donthu et al., 2020, 2021). Bibliometric analysis can be used to discover emerging trends in article and journal performance, collaboration patterns, and research elements, as well as to investigate the intellectual structure of a particular area in the existing literature. It helps and empowers researchers to get a unified perspective, uncover knowledge gaps, generate novel research ideas, and position their intended contributions to the discipline. (Donthu et al., 2020, 2021).

3. Research Methodology

The procedure used to carry out this study comprised four phases. These phases are as follows: data gathering, data cleaning, data visualization, data analysis and report writing.

Figure 1 illustrates how this procedure should have been carried out in greater detail.

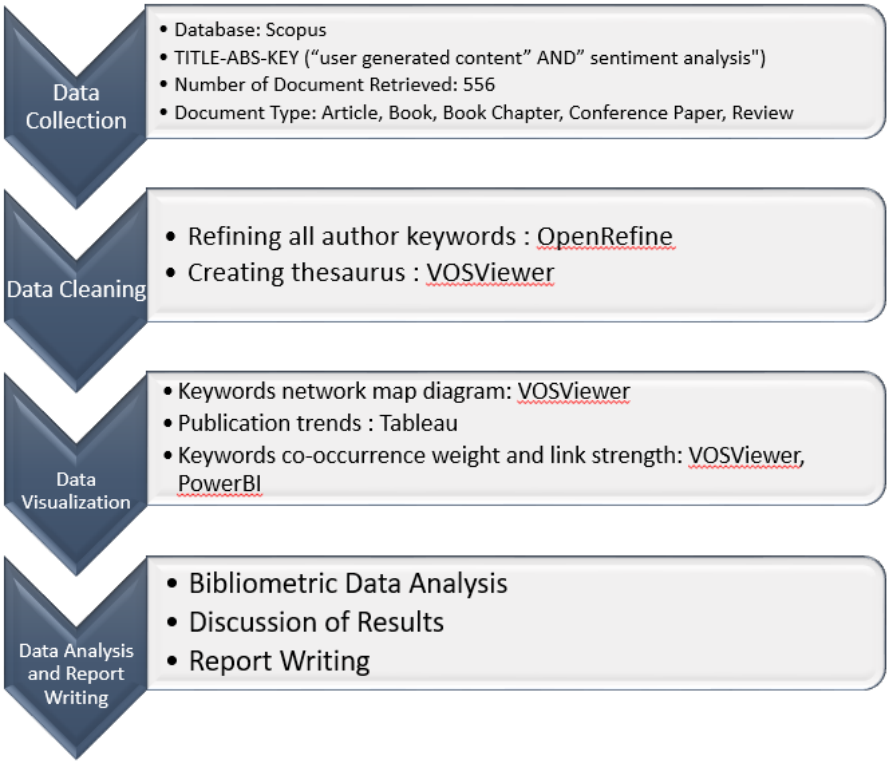

Fig. 1: Research Methodology

3.1. Data Collection

We collected articles from the Scopus database on August 15, 2022, as part of the data collection phase. There was no restriction on the publishing year applied. TITLE-ABS-KEY ("user-generated content AND sentiment analysis") was used as the search phrase. This search technique returned 556 documents spanning the years 2007 to 2022. This search was restricted to the following document types: conference paper, article, book chapter, review, and book. Conference papers and articles are the two most popular documents, with 258 and 255, respectively. Figure 2 provides a breakdown of the document type's distribution.

3.2. Data Cleaning

The second phase involves data cleaning. All of the author's keywords were refined using the OpenRefine software. This process aimed to combine the lexically or semantically related document keywords. Therefore, the keyword analysis would be free of duplicate keywords that could potentially influence the result. The thesaurus was then created using VOSViewer to eliminate the remaining unidentified duplicate keywords from the previous refining process.

3.3. Data Visualization

Data Visualization phases were conducted by constructing a network map based on the co-occurrence of article keywords using VOSviewer (van Eck & Waltman, 2010). In this phase, we highlighted all the relationships between all of the document's keywords. Then, we utilized Tableau and PowerBI to illustrate some bibliometric data, including the number of documents each year, the number of documents per document type, and the ten most productive nations in this study field.

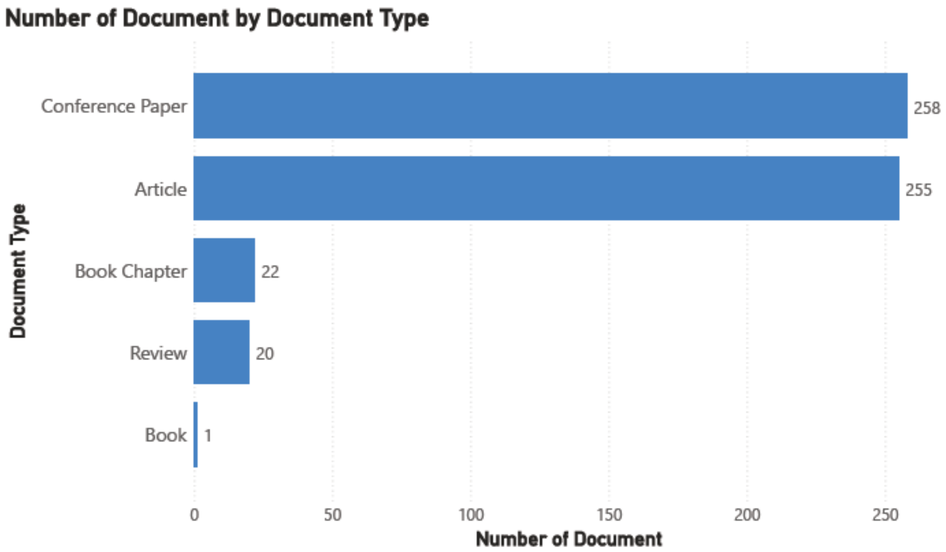

Fig. 2: Number of Documents by Document Type

3.4. Data Analysis and Report Writing

The final stages of this research were data analysis and report writing. The previously shown bibliometric data were then evaluated and interpreted based on the articles included in the study. The result interpretation was based on the bibliometric data visualized in the previous stage. It includes the interpretation of the network map based on the co-occurrence of article keywords. The understanding, discussion, and conclusion were then summarized in a report.

4. Result and Discussion

A bibliometric and content analysis were developed to respond to the study's research question. State of the art in sentiment analysis for UGC was determined by examining trends over time, keyword analysis, and content analysis.

4.1. Research Trends of Sentiment Analysis for User-Generated Content

Research on the sentiment analysis of user-generated content was first carried out in 2007, beginning with two publications. Between 2007 and 2022, the number of publications in this field of study showed a steady upward trend during most of those years. Nevertheless, there was an exception in 2015: the decline in the total number of publications. The year 2019 saw the most significant number of publications, with 82 Scopus-indexed articles published; this is a 43% increase from the previous year's total. The tendency indicates that studies in this field will continue to receive increasing focus until 2022 (Figure 3).

China has 98 publications, making it the leader in the research field of sentiment analysis of user-generated content. This puts China in the lead from the perspective of country productivity. The United States of America and India are currently in second and third place, respectively, with 84 and 80 publications. As seen in Figure 4, the remaining publications were distributed throughout numerous nations, including Spain, the United Kingdom, Italy, Germany, and Singapore.

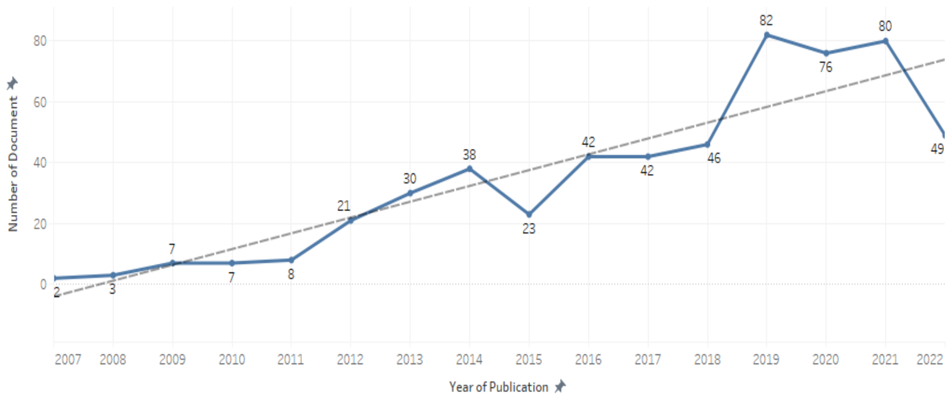

Fig. 3: Number of Documents Per Year

Fig. 4: Number of Publications Based on Country

4.2. Network Map Diagram Analysis

The research trends of sentiment analysis on user-generated content were identified by creating a bibliometric analysis. A network map based on the article's keywords co-occurrence was created using VOSviewer (van Eck & Waltman, 2010). The term "keyword co-occurrence" refers to the occurrences of a single keyword in several publications. The number of co-occurrence that might be considered a threshold can vary greatly depending on the targeted outcomes of the research. The lower the threshold used, the greater the number of keywords that will be displayed, and vice versa.

We established all the connections among 1182 keywords from all 556 articles retrieved. The minimum threshold for keyword co-occurrences has been set to three. Thus, 102 keywords met the minimum requirement. Figure 5 depicts the entirety of the connections between these 102 keywords. The weight of an object determines the label's size and the item's circle. The greater the item's weight, the larger the item's label and circle. The item's color is defined by the cluster to which it belongs.

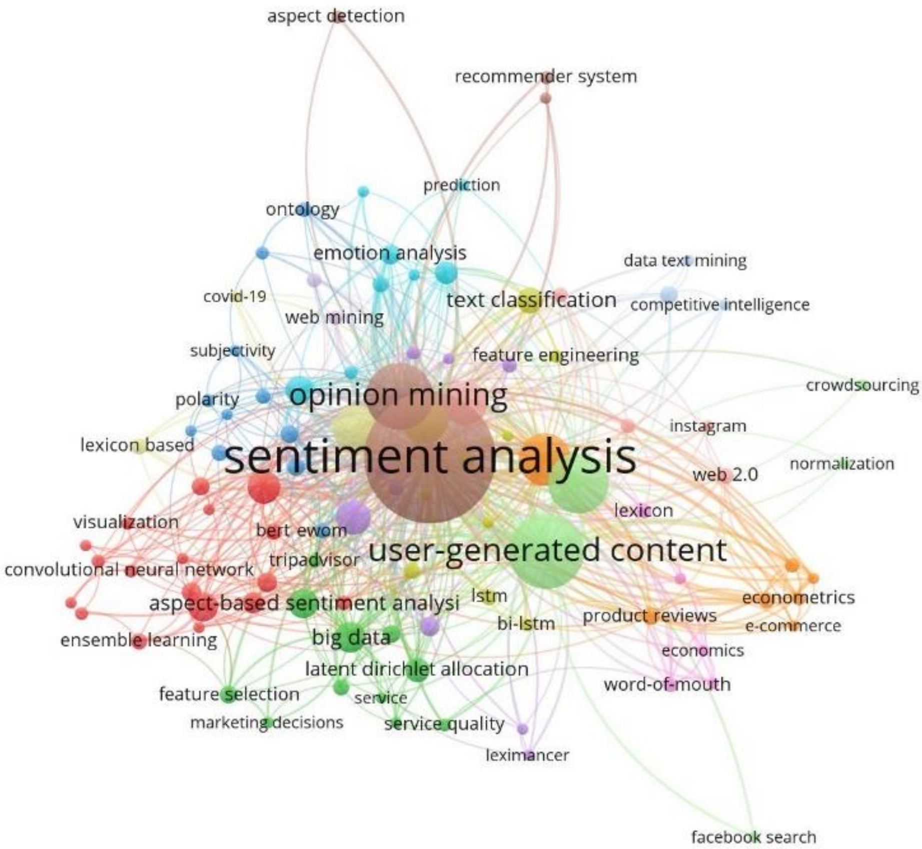

Fig. 5: Network map based on keyword co-occurrence

Each of the fourteen colors seen in Figure 3 corresponds to a distinct cluster. The clustering approach was based on the proximity and similarity of the keywords detected throughout all of the included articles. It implies that elements clustered together are more related to one another than those outside the cluster. Therefore, we can conclude that the elements clustered together in the same cluster may share a similar research focus. The detail of keywords in every cluster is summarized in Table 1.

The term "sentiment analysis" appears the most frequently, with 328 occurrences, followed by "user-generated content" with 110 occurrences and "opinion mining" with 88 occurrences. Sentiment analysis has the strongest link to other keywords, with a total link strength of 694 and 100 keywords connected to it. It thus makes it the most notable of all the keywords. Figure 6 displays the fifteenth most frequent keyword occurrences and the total link strength.

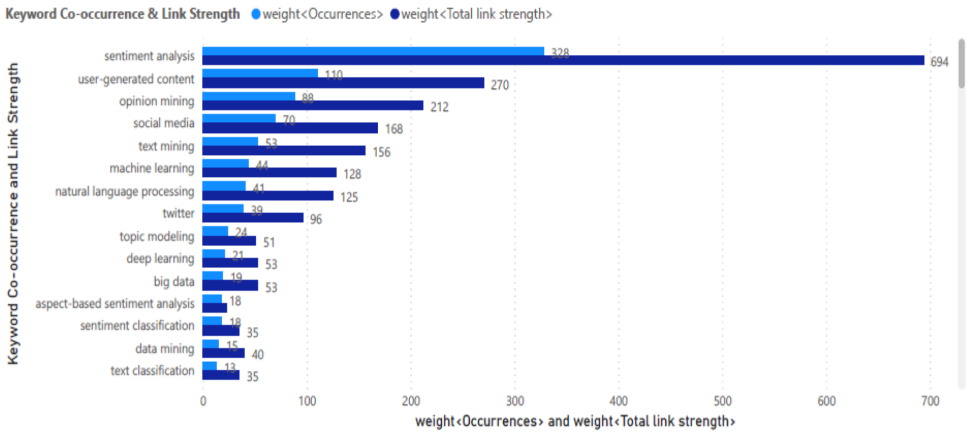

Fig. 6: Keyword Co-occurrence and Link Strength

Table 1: Keywords in every network map cluster

Cluster	Keywords
Cluster 1 (18 keywords)	attention, bert, convolutional neural network, customer satisfaction, deep learning, deep neural network, ensemble learning, feature extraction, long short-term memory, microblogging, multimodal sentiment analysis, multimodality analysis, opinion summarization, sentiment classification, sentiment lexicon, support vector machine, visualization, word embedding
Cluster 2 (11 keywords)	aspect-based sentiment analysis, big data, big data analytics, content analysis, feature selection, hospitality, latent dirichlet allocation, marketing decisions, service, service quality, tripadvisor
Cluster 3 (11 keywords)	aspect extraction, classification, ewom, lda, online reviews, ontology, opinion, polarity, semantic analysis, sentiment, subjectivity
Cluster 4 (11 keywords)	bi-lstm, decision tree, feature engineering, lstm, natural language processing, naïve bayes, neural network, nlp, supervised learning, text classification
Cluster 5 (9 keywords)	leximancer, social media analytics, social media data, spatial analysis, text analytics, topic detection, topic modeling, tourism, youtube
Cluster 6 (8 keywords)	artificial intelligence, data mining, emotion analysis, emotion recognition, emotions, microblog, prediction, social networks
Cluster 7 (7 keywords)	consumer reviews, e-commerce, econometrics, electronic commerce, electronic markets, product reviews, text mining

Cluster	Keywords
Cluster 8 (5 keywords)	aspect detection, **opinion mining**, recommender system, **sentiment analysis**, social network analysis
Cluster 9 (5 keywords)	algorithm, economics, lexicon, online communities, word-of-mouth
Cluster 10 (5 keywords)	facebook, information retrieval, instagram, twitter, web 2.0
Cluster 11 (5 keywords)	crowdsourcing, facebook search, normalization, social media, **user-generated content**
Cluster 12 (3 keywords)	business intelligence, competitive intelligence, data text mining
Cluster 13 (3 keywords)	covid-19, lexicon-based, machine learning
Cluster 14 (2 keywords)	information extraction, web mining

In cluster 1, the largest cluster in general, methods extensively used for UGC sentiment analysis are described, including deep learning, convolutional neural networks, deep neural networks, support vector machines, and word embedding. It demonstrates that numerous sentiment analysis research on user-generated content employ these methodologies. The "sentiment analysis" were placed in cluster 8, which has a close association with opinion mining. While user-generated content was grouped with crowdsourcing, social networking, and facebook search in the eleventh cluster.

4.3. Overlay Visualization Analysis

An overlay visualization is created to determine the most recent research topics, which can be seen in Figure 7. The color gradation from darker to lighter indicates the publishing year going from the earliest to the most recent. The darker blue represents older issues, whereas the yellow represents more current discussions. According to overlay visualization in Figure 7, the most recent research interests for Sentiment Analysis for User Generated Content include big data, text analytics, deep learning, convolutional neural networks, covid-19, prediction, marketing decisions, tourism, and data text mining, along with a number of other issues.

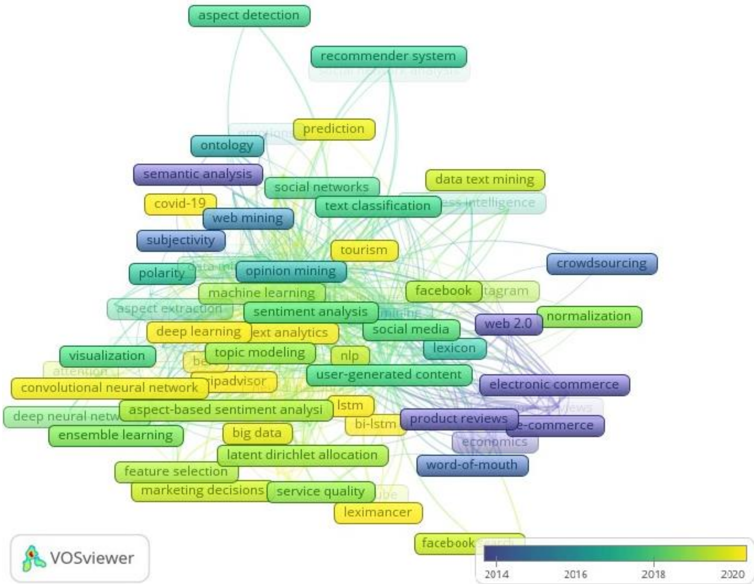

Fig. 7: Overlay Visualization Based on Keyword Occurrence

As shown in Figures 6 and 7, although the yellow topics are current issues, they do not have a high co-occurrence rate. For instance, deep learning and big data are just tenth and eleventh among the 15 most significant items. It indicates that there is a dearth of research analyzing big data, particularly for sentiment analysis on user-generated content. Thus, new opportunities for this research remain abundant.

To get a broad perspective, we analyzed the articles related to the most recent issues identified in the overlay visualization in Figure 7. Consider, for instance (Althobaiti, 2022), which created sentiment analysis models for automatically detecting offensive language and hate speech in Arabic tweets using deep learning. This study evaluated Bidirectional Encoder Representations from Transformer (BERT) with two traditional machine learning methods (Support Vector Machine and Logistic Regression). Experiments demonstrate that the BERT model produces the best results. A BERT-MDLP-Bayesian Network model was proposed to investigate the enhancement strategy of UGC-based e-commerce products (M.-F. Li et al., 2022). This study employed text mining on social media UGC to generate sentiment analysis. The model can successfully identify the underlying issues with a product and provide advice for e-commerce to improve their marketing strategies.

The deep learning model was also used in some other recent studies. For instance, (D. Li et al., 2022) created a sentiment analysis on customer opinions and experiences expressed in UGC using deep learning. This model delivers a personalized accommodation recommendation, which aids in interpreting consumer decisions and enhancing products and services. Following are summaries of studies from many disciplines that utilized deep learning or other computational intelligence (Afriliana et al., 2021) to construct a sentiment analysis for UGC.

- (Bigne et al., 2021) proposed sentiment analysis for TripAdvisor UGC using deep learning and logistic regression approach. The database contained 2,023 TripAdvisor reviews of two renowned Venetian cultural attractions, St. Mark's. This study implies that managers should look beyond individual ratings and concentrate on the sentiment analysis of online reviews, which has been demonstrated to be influenced by the nature of the attraction (free vs. paid-for).
- Twenty machine-learning classification models for assessing text reviews were compared by (Alantari et al., 2022). The study discovered that neural network-based machine learning approaches, especially pre-trained models, provide the best accurate predictions.
- (Nawaz et al., 2021) and (Priyadarshini & Cotton, 2021) applied Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) to classify the review as positive or negative. The technique is highly recommended for the sentiment analysis of unstructured text-based user-generated content, according to the findings of this study.

Text mining, Natural Language Processing (NLP), machine learning, and deep learning models show a trend that is increasingly being used to make sentiment analyses on user-generated content. The model is applied in various fields of healthcare services, transportation, e-commerce, smart tourism, smart cities, marketing research, sports events, stock market, or even public opinion on political issues (Alantari et al., 2022; Antonio et al., 2020; Cheng et al., 2021; Fang et al., 2021; Fino et al., 2021; Ghorbanian & Jalali, 2020; Haralabopoulos et al., 2020; Jessica & Oetama, 2019; Jia et al., 2022; Kar et al., 2021; Liu et al., 2019; Ng et al., 2021; Priyadarshini & Cotton, 2021; Renganathan & Upadhya, 2022; Ruelens, 2022; Vollero et al., 2021). However, research on the subject of deep learning has not yielded substantial results. There are still numerous prospects for research on this topic, particularly concerning large data sets or big data. As a result of digital technology advancements, more UGCs are being produced in massive quantities, making big data analytics a necessity.

5. Conclusion and Future Work

Over decades, the amount of user-generated content on the Internet has been overgrown. In general, the research trend on UGC sentiment analysis is increasing year after year, paralleling the growth in the volume of UGC data. China, America, and India are the three countries that provide the most research and publications in this field. Big data, text analytics, text mining, tourism, covid-19, machine learning, deep learning, convolutional neural networks, making predictions, and marketing decisions are among the most recent research interests for sentiment analysis of user-generated content. However, there is a lack of research on those particular topics. As a result, new opportunities and novelties for this research continue to emerge.

In the future, machine learning methods, particularly deep learning, are projected to be widely employed for user-generated content sentiment analysis, especially in big data analytic fields. Various enhancements will be made to improve the accuracy of the model generated by integrating deep learning with other algorithms.

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