



Review Article

A Review on Big Data Sentiment Analysis Techniques

Raed Abdulkareem Hasan^{*1, }, Tole Sutikno^{2, }, Mohd Arfian Ismail^{3, }¹ Department of Electrical techniques, Faculty of Al-Hweija Technical Institute, Noerthern Technical University, Mosel, Iraq² Department of Electrical Engineering, Faculty of Industrial Technology, Universitas Ahmad Dahlan, Yogyakarta, Indonesia³ Faculty of Computing, College of Computing and Applied Sciences, Universiti Malaysia Pahang, Malaysia

ARTICLE INFO

Article History

Received 30 Sep 2020

Accepted 23 Dec 2020

Published 15 Jan 2021

Keywords

Big data

Sentiment analysis

Natural Language
Processing,

Text Processing



ABSTRACT

The areas of Natural Language Processing, Text Analysis, Text Preprocessing, Stemming, etc. are the most important study fields at the moment. Sentiment analysis is employed for all of these areas. Study of sentiment is performed by using a variety of methods and tools to the task of analyzing unstructured data in such a way that it is possible to get objective findings from the analysis of said data. These methods, in their most fundamental form, make it possible for a computer to comprehend what a human person is saying. A variety of methods are utilized in the process of sentiment analysis in order to assess the attitude conveyed by a given text or sentence. A machine learning approach and a lexicon-based approach are the two primary categories into which it may be divided, depending on which method was used to develop it. For the purpose of gaining insights into the market and improving performance, businesses utilize sentiment analysis. The use of sentiment analysis in the process of developing a smart society is enormous, and there is a pressing need to define the trend in a comprehensive manner. The fundamental objective of this study is to present an in-depth investigation of the several platforms that are now accessible for the execution of Big Data Sentiment Analysis Methods. This study examines the various hardware platforms that are currently available for big data analytics and evaluates the benefits and drawbacks of each of these platforms based on a number of different metrics, including scalability, data I/O rate, fault tolerance, real-time processing, data size supported, and iterative task support.

1. INTRODUCTION

An individual, an organization, a problem, an event, or a topic can all be subjected to sentiment analysis[1, 2], which is a computer research aimed at understanding people's ideas and feelings towards these things. SA provides market intelligence to improve both the performance of businesses and the image of brands. SA[3] is used by customer-centric companies to gain consumer intelligence, which is then used to drive business strategy. In order to grasp the requirements of the inhabitants, analytical technologies such as text mining, machine learning, and natural language processing (NLP)[4] are utilized. A smart society is one that incorporates the use of digital technology to improve the lives of its residents, the economy, and the performance of its institutions. The building of smart governance, smart infrastructure, and smart solutions can all be accomplished with the help of SA. The voices of customers have already been included into the business structures of corporations as a means of co-creating value. For instance, SA may be utilized in the research and study of consumer behavior, as well as in the engagement and relationship marketing of consumers. Emergent research is being done in the area of the adoption and implementation of SA in city administration, and the field is now in the period of evolution. The public's opinions serve as a source of real-time social data and serve as social sensors when using social media as an information source for gaining valuable insight into society. Analysis of sentiment on social media helps to determine the feelings and perspectives of users in order to evaluate societal problems. These days, several social sites including Facebook, TikTok, and YouTube are quite popular among users. People have started sharing a big collection of videos online in order to communicate their thoughts and opinions on many topics. It has been estimated that more than five hours worth of video content is uploaded to YouTube every single second. These films provide a wide variety of information pertaining to a variety of items and services, which increases the variety of options available to customers for obtaining information about products or services from other customers. [PL08, LZ12] "Sentiment analysis" is an all-encompassing study topic that focuses on people's opinions, assessments, attitudes, and emotions in relation to different things. Since the beginning of the new millennium, sentiment analysis has emerged as a central topic of investigation in a wide range of fields, including natural language processing, web data mining, social media research, consumer research, and even stock market analysis. Sentiment

*Corresponding author. Email: raed.isc.sa@ntu.edu.iq

analysis places more of an emphasis on the detection of overall sentiment at the document level or at the phrase level in its early stages [Tur02, PLV02, DC04, DLP03, LLS03, MYTF02, NY03, PL08]. [These studies] [Tur02, PLV02, DC04, DLP03, LLS03, MYTF02, NY03, PL08] Each document has the potential to be categorized as either positive or negative, with the entire document being taken into consideration as the atomic input. There are several Big Data Sentiment Analysis Techniques accessible, each of which possesses a unique set of qualities; hence, selecting the appropriate platform calls for an in-depth understanding of the capabilities offered by each of these platforms. When determining whether or not it is acceptable to construct analytics-based solutions on a certain platform, one of the most important considerations to take into account is the capability of the platform to adjust to rising demands for data processing. In order to achieve this goal, we will begin by providing a comprehensive overview of all of the prevalent big data platforms that are presently being utilized in the industry and highlighting the benefits and downsides associated with each of these platforms in turn. When a user has to select the appropriate platforms from which to pick, he or she will often have to do an investigation into the requirements of the application or algorithm. Before arriving at the best choices, one will inevitably grapple with a number of fundamental questions in their head.

2. BACKGROUND

Based on the literature and research articles published over the course of the previous few years, this section offers a synopsis of the numerous research projects that have been carried out in the field of sentiment analysis by a large number of scholars. Big data sentiment analysis is the phrase used to describe the real-time processing of enormous volumes of data collected at high rates from a variety of sources with minimum latency. This type of analysis is known as "big data" sentiment analysis. Moemeng and Porntrakoon[5] came up with the idea for SenseComp, which is a technology that uses multidimensional lexicons and a technique called sentiment compensation to automatically assess the Thai sentiment of a consumer's review in terms of the product, the price, and the delivery dimensions. We spoke about multi-dimensional trust measurement as well as Thai sentiment analytics, in which the opinions of customers are analyzed to determine the trust score of a product or an online seller. The review that ChhayaChauhan[6] is concentrating on focuses on the algorithms and approaches that were used to extract a feature-wise summary of the product and examine those summaries in order to write an honest assessment. In 2017, Maria et al.[7] proposed using a hybrid approach for the prediction of sentiment. In this approach, context-sensitive coding provided by Word2Vec and sentiment/emotion information provided by a lexicon were combined. This was done in order to get the best results possible in terms of efficiency, accuracy, and the amount of time it took to complete the task. A hybrid system solution to the Sentiment Analysis issue at the sentence level was suggested by Orestes Appel et al. in 2016[8]. This technique gives a high degree of accuracy of 88.02 percent and precision of 84.24 percent. A approach known as natural language processing (NLP) is utilized here. The results obtained using the hybrid approach are compared to those obtained using the Naive Bayes (NB) and Maximum Entropy (ME) techniques. The hybrid method is presented for use with three distinct data sets. Abinash Tripathy et al.[9] attempted to categorize movie reviews using a variety of supervised machine learning algorithms. They did this by applying the algorithms to the data. Ioannis Korkontzelos and colleagues[10] conducted a study to investigate the impact that sentiment analysis has on the process of collecting adverse medication responses from online forum postings and tweets. The automatic identification of ADR was difficult because to its vast size; but, with the help of this technology, it became much simpler. Using a deep learning approach to the sentiment analysis of tweets, Aliaksei Severyn and Alessandro Moschitti[11] predicted polarities at both the message and the phrase level. For this, they used an unsupervised neural language model that trained initial word embedding, and further was tuned to find the polarities.

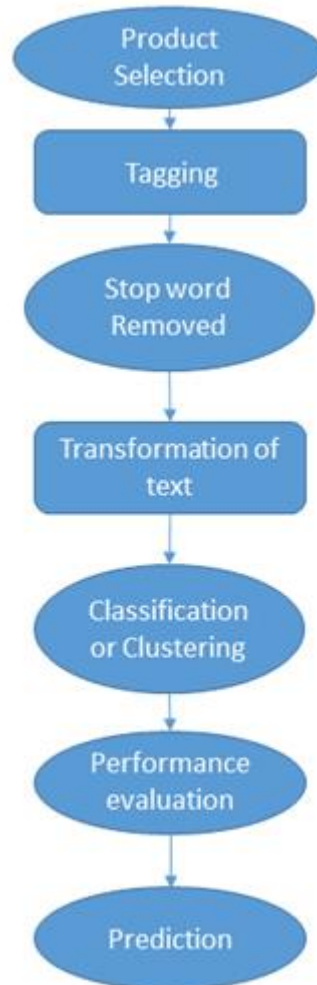


Fig.1. Flow of general model

3. BIG DATA SENTIMENT ANALYSIS

Analysis of opinions expressed in text is the focus of ongoing research in the subject of natural language processing, which is known as sentiment analysis. Analysis of sentiment is used in a wide variety of contexts, including product evaluations[12], comments from customers, political discussions, and more. Sentiment analysis is an issue that has been investigated extensively in the field of Natural Language Processing (NLP)[13, 14]. It has recently gained popularity as a method for collecting the thoughts of customers based on online reviews or social networking websites. Analysis of sentiment based only on texts may be broken down into two categories: those that are knowledge-based and those that are statistical. At first, knowledge-based techniques were employed extensively; however, given that this kind of strategy is not based on the requirements and preferences of customers, researchers have steadily favored using statistical approaches, particularly supervised ones. Even while there have been studies that have focused on emotion detection[15, 16] based on auditory and visual modalities, very few of those studies have combined text with the other modalities, which is what is meant by the term "using multimodal characteristics." Several different pieces of research have employed visual clues to do sentiment analysis on evaluations of products and films. Recent work in multimodal sentiment analysis has focused on approaches from artificial intelligence, such as the combination of neural networks. For instance, multiple-kernel Convolutional Neural Networks (CNN) and Select-Additive Learning (SAL) CNNs are capable of learning characteristics that are generalizable across speakers. Tensor Fusion Network (TFN) was presented by[16]. as a method for learning the intra-modality and intermodality

of various modalities (T, A & V). On the other hand, the contextual linkages have not been taken into account in any of the investigations that have been discussed. In order to solve this issue, Poria et al. suggested using hierarchical LSTMs to learn the contextual information of multimodal features in conjunction with CNN for the extraction of context-independent unimodal features. Poria et al. offered an architecture that combined a variety of different modalities that was based on the opinions of customers. In their study, [16]. offered multi-attention blocks as a means of capturing the interaction between several modalities. Chen et al. came up with the concept that a model need to have the ability to "gate" important modalities at each and every instant. Additionally, the modalities that do not offer essential information can be turned off.

- Aspect Term Extraction

The goal of the basic job known as aspect extraction (AE)[17,18] in the ABSA system is to identify the aspects on which reviewers have provided their feedback. Finding noun phrases, making use of opinion and target relations, supervised learning, and topic modeling are some of the methods that may be utilized to extract aspects. Dictionary-based or rule-based techniques come in first, while deep learning-based methods come in second. These are the two primary categories that are used to classify AE problems in terms of the methods that are used to solve them. In supervised learning, the problem is typically modeled as a sequence labelling job. To begin, a review is broken down into individual tokens, and then it is deduced whether or not the token corresponds to any certain facet. Each token has a label that indicates either "Begin," "Inside," or "Outside." A continuous group of tokens that are labeled with a single B and then followed by either one or more I until the O forms an aspect. The example 1.1 battery life demonstrates what the aspect word looks like.

- Aspect Sentiment Classification

Aspect Sentiment Classification (ASC)[19] is a subsequent task of AE that aims to classify the sentiment polarity of the extracted aspect terms of the review sentence as either positive, negative, or neutral. This can be accomplished by categorizing the extracted aspect terms as "positive," "negative," or "neutral," respectively. Prior to the development of BERT, the designs of recurrent neural networks (LSTMs) and convolutional neural networks were the two types of deep neural networks that were utilized most frequently for the ASC problem. On the objective of aspect-based sentiment classification, state-of-the-art results were achieved by BERT-based models and modifications of such models.

4. SCALABILITY

Because of the enormous quantity of data involved, the difficulty of scalability is one of the most difficult challenges to solve in massive data streaming analysis and sentiment analysis. This is one of the most difficult problems to overcome. The quantity of big data that is being produced is growing at an exponential rate, which is a significant amount quicker than the rate at which computer resources are being added. Despite the fact that processors adhere to Moore's law, the quantity of data being created is expanding at an exponential rate. The development of scalable frameworks and algorithms that will accommodate the data stream computing mode, as well as the development of an effective resource allocation strategy, and the resolution of parallelization issues, should be the primary focus of research efforts in order to deal with the ever-increasing size and complexity of data. This should be the primary focus of research efforts in order to deal with the ever-increasing size and complexity of data.

5. TEXT PREPROCESSING

Because the computer cannot instantly grasp English words while working with text data, it is required to preprocess the corpus. Different goals are served by each stage of the preprocessing. Some of them get rid of letters that aren't necessary, some condense many words into a single root phrase, while yet others give each word its own own number identification. Each step is necessary, however the text preparation stages differ from corpus to corpus, thus it is necessary to justify each component individually. Each step plays a crucial function.

- Cleaning Text

The correction of contractions was the initial stage in our cleaning process. We separated the words into their two individual components so that the complete meaning would be maintained. If nothing more is specified, the computer will differentiate between "don't" and "do not." After doing all of this, we went on to the following phase after conducting a search in the dictionary for probable contracted terms. We removed all of the punctuation from the corpus so that the text would be easier to understand, the learning process would go more quickly, and the model would be more reliable. Networks that use punctuation become increasingly reliant on its proper use. The model will produce inaccurate results if any marks are omitted, as is typical with reviews, or if the punctuation is altered in any way. In addition, the work that is being done is restricted by the hardware that is running the models, which is why accelerating training is vital. After removing all of the punctuation, we were left with non-standard characters to work with. Since the data comes from Amazon customers in the United States and is in English, we got rid of any characters that weren't alphanumeric. Other characters shouldn't have any

bearing on the interpretation of the data. Emojis and other expressions of emotion are not permitted in customer evaluations on Amazon. The subsequent preprocessing approach that we used helped the machine read information more quickly.

- Stop Word Removal

Because not every word contributes substance to a phrase and many only give structure, we have eliminated certain terms that are unnecessary. The only use that stop words serve is to act as determiners, namely for marking nouns such as "the" or coordinating conjunctions such as "but" or prepositions such as "in." The meaning of the text is not affected in any way by these words, despite the fact that they contribute to the formation of a language. Eliminating these terms requires merely a search using the NLTK package, and it results in the model being trained more quickly and receiving a greater boost as a result. We have avoided dealing with or cleaning any bits of the text that may have significance up to this point, but the step that comes after this one breaks with that pattern.

- Lemmatization

Lemmatization is the process of converting words into their root terms, which saves the computer from having to learn each and every form of a word. As an illustration of this procedure, the statements "I loved this product," and "I adore this product" are consolidated into the single sentence "I love this product." The only thing that differentiated them was the tenses that they used to express the content and mood. Converting the input to a single root helps the computer learn from it more effectively because we are not concerned about tenses. Unfortunately, lemmatization is not a straightforward process due to the prevalence of homophones, which are words that share the same spelling but have different meanings. As a result, we made use of the NLTK package so that every word in the text could have its respective part of speech tagged. After that, we were able to determine whether a phrase has a base root by conducting a search in the dictionary alongside the search. This method was repeated for each word in the corpus, and once a root was found, the phrase was transformed in accordance with that root. The lemmatization stage was the final significant step in the high-level text alteration process.

6. DISCUSSION OF BIG DATA STREAMING TOOLS

Within the scope of this review are a number of works that investigate the analysis of sentiment by making use of deep learning models. Since emotion analysis is used to predict user opinions, deep learning models revolve around predicting or imitating the human mind, and deep learning models provide more accuracy than shallow models, it has been demonstrated that with deep learning methods, feeling can be analyzed in a more effective and accurate way. This has been shown after analysis, and it has been demonstrated that with deep learning methods, feeling can be analyzed in a more accurate and effective way. Deep learning networks feature a greater number of hidden layers than traditional neural networks, which only have one or two hidden layers. This gives deep learning networks an advantage. It has been demonstrated that private architectural RNNs equipped with gateways consisting of LSTMs are extraordinarily effective at capturing the statistical importance of string inputs. LSTM is the first network to offer a gateway mechanism, which was developed to overcome the problem of fading gradients and capture long-range dependencies. LSTM is also the network that introduced the term "gateway mechanism." The training that may be received from deep learning networks can be either supervised or unsupervised. Deep Learning Networks do not include any kind of human interference, but Morale Analysis incorporates a wide variety of issues of their own. You are able to install a number of activities by making a few straightforward modifications to the system. Additionally, this technique has several restrictions, such as the use of SVM. Training needs a substantial financial investment and extensive amounts of data. In contrast to LSTM, these more involved models might take many weeks to complete. There are other models, such as LSTM, that perform exceptionally well in deep learning models. When compared to the other study, which utilized 470,000 tweets and had an accuracy of 70 percent, the one in which the author employed less data points is the superior one. This study used only 10,000 tweets and had a high accuracy of 64.46 percent. A total of 100,000 items were gathered by the author, and they were accurate 89.5 percent of the time. As a result, it is possible to reduce the amount of time spent on feature engineering. In contrast to other models, such as SVM, which might take weeks to complete and have very high associated costs.

TABLE I OPEN-SOURCE TOOLS AND TECHNOLOGY FOR BIG DATA SENTIMENT ANALYSIS

No.	Tools	Source
1.	Quadratic LSTM-RNN	[19]
2.	LSTM and Dynamic CNN	[20]
3.	RNTN and RNN	[21]
4.	Markov Model, SVM, NB	[22]
5.	CNN,LSTM, CNN+LSTM	[23]
6.	Deep Intelligent Contextual Embedding	[24]
7.	Bi-LSTM with attention mechanism	[25]
8.	NB, ANN, SVM	[26]

A platform that has a high spike load profile, such as a gaming platform, may find that a deployment that is structured as a platform as a service is the most suitable option. According to the information provided by the corporation, customers won't be charged until after their data has been processed if the platform distribution can be accomplished using an Infrastructure as a Service cloud platform. On-premises deployment is a potential option worth considering when dealing with needs that are either predictable or ongoing. In the event that the workloads are diverse, it is possible that an implementation strategy that includes both the cloud and on-premises components will be investigated (i.e., consisting of consistent flows and spikes). This makes it possible to integrate web-based services or apps in a smooth manner, as well as to have remote access to key tasks while traveling without sacrificing speed.

7. CHALLENGES IN SENTIMENT ANALYSIS

The conduct of sentiment analysis is fraught with a number of difficulties, the likes of which include high processing costs, informal writing, and the prevalence of linguistic diversity. In this section, we examine the difficulties associated with sentiment analysis that are more likely to arise with specific types of sentiment structures, as indicated in Table 1. A few of the significant difficulties encountered in sentiment analysis are as follows: Formal sentiment reviews provide structured feelings; these evaluations concentrate more on formal issues; such as books or research. Due to the fact that the authors are trained experts, they are able to provide views or observations that are relevant to scientific or factual issues. Sentiments that are semi-structured lie between those that are structured and those that are unstructured. These demand a grasp of a wide variety of topics pertaining to reviews. This method, which is based on benefits and disadvantages, is mentioned individually by the writers; the pros and cons sections are often consisting of brief phrases. This method is dependent on both benefits and downsides. Unstructured Sentiment is a sort of writing that is casual and free-flowing, and the writer is not restricted by any rules when they are writing it. The passage could have more than one sentence, and every one of those phrases might have the potential to incorporate both positives and negatives. For instance, unstructured reviews provide more information about the authors' opinions than their more formal counterparts do. An explicit feature of the product is one that is described in a section or chunk of a review sentence. This type of feature is referred to as a "explicit feature" of the product. To provide just one example, the visual in that portion is just stunning. The picture is a clear aspect of the product. When a feature of the product is not specifically spoken out in the review section but is nevertheless understood to be there, we refer to this feature as an implicit feature of the product. For example, in that part of the section, it is quite costly, and one of the feature signs for that portion is expensive. In view of the important importance of sentiment analysis, the purpose of this study is to investigate the link between the perspective structures of respondents and the difficulties that pertain to sentiment analysis.

8. CONCLUSION AND FURTHER WORK

Controlling and predicting people's sentiments and views is what sentiment analysis is all about. In this particular piece of research, sentiment analysis is carried out by utilizing deep learning methodologies. Since deep learning is composed of a large number of correct models, it may be used to the resolution of a wide variety of issues in an efficient and precise manner. This review takes a look at a number of different research to gain an understanding of the many effective uses of deep learning in the field of emotional analysis. Acquiring a high degree of accuracy has shown to be the solution to a great number of issues that have arisen in the fields of deep learning and sentiment analysis. Next, we will put into action the Kaggle model that was developed to evaluate Arab emotions and achieve an accuracy rate of 96 percent. This model consists of a CNN layer, then an LSTM layer, and finally a prediction layer that is completely connected at the end. The prediction layer will have one output class that is one of three emotional categories (positive, negative and neutral).

Conflicts of Interest

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgment

The authors would like to express their gratitude to the Al-Hweijja Technical Institute, the Informatics Institute for Postgraduate Studies, and the Al Salam University College for their moral support. Please accept my sincere gratitude for the useful recommendations and constructive remarks provided by the anonymous reviewers.

Funding

The authors receive no funding for this work.

References

- [1] B. Liu, "Sentiment analysis and opinion mining," *Synthesis lectures on human language technologies*, vol. 5, no. 1, pp. 1-167, 2012.
- [2] G. Alexandridis, I. Varlamis, K. Korovesis, G. Caridakis, and P. Tsantilas, "A Survey on Sentiment Analysis and Opinion Mining in Greek Social Media," *Information*, vol. 12, no. 8, p. 331, 2021.
- [3] G. Vinodhini and R. Chandrasekaran, "Sentiment analysis and opinion mining: a survey," *International Journal*, vol. 2, no. 6, pp. 282-292, 2012.
- [4] Y. Kang, Z. Cai, C.-W. Tan, Q. Huang, and H. Liu, "Natural language processing (NLP) in management research: A literature review," *Journal of Management Analytics*, vol. 7, no. 2, pp. 139-172, 2020.
- [5] P. Porntrakoon, C. Moemeng, and P. Santiprabhob, "Text Summarization for Thai Food Reviews using Simplified Sentiment Analysis," in *2021 18th International Joint Conference on Computer Science and Software Engineering (JCSSE)*, 2021, pp. 1-5: IEEE.
- [6] C. Chauhan and S. Sehgal, "Sentiment analysis on product reviews," in *2017 International Conference on Computing, Communication and Automation (ICCCA)*, 2017, pp. 26-31: IEEE.
- [7] J. R. Alharbi and W. S. Alhalabi, "Hybrid approach for sentiment analysis of twitter posts using a dictionary-based approach and fuzzy logic methods: Study case on cloud service providers," *International Journal on Semantic Web and Information Systems (IJSWIS)*, vol. 16, no. 1, pp. 116-145, 2020.
- [8] O. Appel, F. Chiclana, J. Carter, and H. Fujita, "A hybrid approach to the sentiment analysis problem at the sentence level," *Knowledge-Based Systems*, vol. 108, pp. 110-124, 2016.
- [9] A. Tripathy, A. Agrawal, and S. K. Rath, "Classification of sentiment reviews using n-gram machine learning approach," *Expert Systems with Applications*, vol. 57, pp. 117-126, 2016.
- [10] I. Korkontzelos, A. Nikfarjam, M. Shardlow, A. Sarker, S. Ananiadou, and G. H. Gonzalez, "Analysis of the effect of sentiment analysis on extracting adverse drug reactions from tweets and forum posts," *Journal of biomedical informatics*, vol. 62, pp. 148-158, 2016.
- [11] A. Severyn and A. Moschitti, "Twitter sentiment analysis with deep convolutional neural networks," in *Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval*, 2015, pp. 959-962.
- [12] Z. F. Hussain et al., "A new model for iris data set classification based on linear support vector machine parameter's optimization," *International Journal of Electrical and Computer Engineering*, vol. 10, no. 1, p. 1079, 2020.
- [13] J. Serrano-Guerrero, F. P. Romero, and J. A. Olivas, "Fuzzy logic applied to opinion mining: a review," *Knowledge-Based Systems*, vol. 222, p. 107018, 2021.
- [14] K. S. Kalyan, A. Rajasekharan, and S. Sangeetha, "Ammus: A survey of transformer-based pretrained models in natural language processing," *arXiv preprint arXiv:2108.05542*, 2021.
- [15] A. H. Ali, M. N. Abbod, M. K. Khaleel, M. A. Mohammed, and T. Sutikno, "Large scale data analysis using MLlib," *Telkonnika (Telecommunication Computing Electronics and Control)*, vol. 19, no. 5, pp. 1735-1746, 2021.
- [16] A. H. Ali and M. Z. Abdullah, "A novel approach for big data classification based on hybrid parallel dimensionality reduction using spark cluster," *Computer Science*, vol. 20, no. 4, 2019.
- [17] Y. Mao, Y. Shen, C. Yu, and L. Cai, "A joint training dual-mrc framework for aspect based sentiment analysis," *arXiv preprint arXiv:2101.00816*, 2021.
- [18] E. S. Alamoudi and N. S. Alghamdi, "Sentiment classification and aspect-based sentiment analysis on yelp reviews using deep learning and word embeddings," *Journal of Decision Systems*, vol. 30, no. 2-3, pp. 259-281, 2021.
- [19] D. Wu and M. Chi, "Long short-term memory with quadratic connections in recursive neural networks for representing compositional semantics," *IEEE Access*, vol. 5, pp. 16077-16083, 2017.
- [20] Y. Wu, B. Zheng, and Y. Zhao, "Dynamic gesture recognition based on LSTM-CNN," in *2018 Chinese Automation Congress (CAC)*, 2018, pp. 2446-2450: IEEE.
- [21] Q. Qian, B. Tian, M. Huang, Y. Liu, X. Zhu, and X. Zhu, "Learning tag embeddings and tag-specific composition functions in recursive neural network," in *Proceedings of the 53rd Annual Meeting of the Association for Computational Linguistics and the 7th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, 2015, pp. 1365-1374.
- [22] S. Yu, H. Chen, and R. A. Brown, "Hidden Markov model-based fall detection with motion sensor orientation calibration: A case for real-life home monitoring," *IEEE journal of biomedical and health informatics*, vol. 22, no. 6, pp. 1847-1853, 2017.

- [23] J. Wang, L.-C. Yu, K. R. Lai, and X. Zhang, "Dimensional sentiment analysis using a regional CNN-LSTM model," in *Proceedings of the 54th annual meeting of the association for computational linguistics (volume 2: Short papers)*, 2016, pp. 225-230.
- [24] U. Naseem, I. Razzak, K. Musial, and M. Imran, "Transformer based deep intelligent contextual embedding for twitter sentiment analysis," *Future Generation Computer Systems*, vol. 113, pp. 58-69, 2020.
- [25] X.-m. Yu, W.-z. Feng, H. Wang, Q. Chu, and Q. Chen, "An attention mechanism and multi-granularity-based Bi-LSTM model for Chinese Q&A system," *Soft Computing*, vol. 24, no. 8, pp. 5831-5845, 2020.
- [26] R. Moraes, J. F. Valiati, and W. P. G. Neto, "Document-level sentiment classification: An empirical comparison between SVM and ANN," *Expert Systems with Applications*, vol. 40, no. 2, pp. 621-633, 2013.