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Research Article

Fake Review Detection Techniques on Online Products: An Empirical Study

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Abstract: E-commerce websites are becoming an essential component of daily living. The epidemic has quickly moved into the digital era and changed people's online buying habits. Many individuals research items before making an online purchase by reading product reviews. Thus, reviews are crucial to a customer's decision to purchase any goods. As a result, social media platforms and e-commerce sites like Flipkart, Amazon, and others get more bogus reviews. Robust and dependable approaches are required to identify phony reviews, which may be advantageous to both the seller and the client. Phony reviews have the power to promote poor items and disparage good ones. The goal of this survey article is to provide a broad overview of the many strategies used to these sorts of problems. This paper provides a thorough examination of several techniques to spam detection in machine learning (ML), natural language processing (NLP), sentiment analysis, and deep learning (DL).

Keywords: Fake Reviews, Machine Learning, Sentimental Analysis, Deep Learning, Natural Language Processing.

1. Introduction

Online reviews are increasingly significant and appealing to e-commerce companies. Before making a purchase, consumers utilize product reviews as a starting point for their research. Sometimes, however, these reviews are fake. Companies could create these fictitious endorsements in order to boost product sales. Fake reviews may also be produced as a result of competition between firms. Customers may be duped into buying a product by these phony reviews. False reviews have the potential to undermine buyers' faith in the product and the website, as well as harm online purchasing platforms. Therefore, identifying bogus reviews is the first step in fixing the issue. Therefore, it is necessary to create a system that can differentiate between real and fraudulent reviews.

Numerous writers have previously put up a number of strategies for creating a system that can identify phony reviews. The suggested strategies and approaches based on sentiment analysis, deep learning, machine learning, and natural language processing have all been examined in this research. Some of the techniques are explained in this paper.

The use of several machine learning techniques to detect fraudulent reviews.
• Fake review detection using deep learning.
• The use of sentiment analysis to spot phony reviews.
• False Review Detection via Natural Language Processing.
The following sections follow the introduction; part II provides background information on techniques for identifying fake reviews. Section III provides an overview of current techniques for writing phoney reviews. Section IV covers the study's objective and viewpoint.

2. Related Work

The literature survey is divided into four sections based on four techniques. The sections are as follows:

2.1 Recognizing Inauthentic Reviews via Diverse Machine Learning Techniques

This section of the literature review's primary goal is to look at machine learning methods that may be used to the identification of phony reviews. The supervised [4][8], unsupervised [4], semi-supervised [5–6], and ensemble machine learning techniques [7] are the primary topics of this portion of the literature review. In the realm of machine learning, a machine learning model is what learns and produces predictions. As such, in [2], Patel et al. discussed the basic steps involved in creating a machine learning model for the collection of fake assessments. The steps include selecting and extracting various attributes, collecting and evaluating data, and creating a classifier model.

Etaiwi et al. investigated and evaluated the effects of character selection strategies on the acquisition of fake reviews via the application of several machine learning algorithms in [3]. In an analysis, parameters including recall, accuracy, and accuracy are considered. Both word count and bag-of-words are used as the criteria. It is determined that the feature selection strategy significantly affects the choice of phony reviews as well as the functionality of each classifier system independently.

In [4], the solution is proposed using supervised and unsupervised machine learning approaches. While reviewer, review content, and product information are taken into consideration when extracting features in unsupervised learning methods, supervised machine learning techniques such POS tagging, N-gram, sentiment analysis, and linguistic characteristics are employed. Furthermore, even with excellent findings, the spam analysis remains incomplete if the IP address, the quantity of reviews submitted, and the posting time of the review are not taken into consideration for the reviewer.

A machine learning strategy based on semi-supervised learning is presented in [5]. Grammar, emotion polarity, bigram frequency count, and total word count are some of the factors that are considered. The sentiment polarity of an element is only determined by the direction of the expressed feeling. Here, the author just considers the barest minimum of functionality while categorizing, which has an impact on the expected result.

A strategy using semi-supervised machine learning techniques was introduced by Yılmaz and colleagues in [6]. Both textual and network-based components are used. The IP address and quantity of reviews a reviewer has submitted are considered in the features generated by using network-based approaches. The obtained results confirm that including both review data characteristics and network-based criteria significantly improves the detection of spam reviews. The drawback is that the best results can only be obtained by combining the textual content of the review with the analyzed product network.

In [7], Espinoza et al. developed an approach based on group learning. It uses the Doc2vec approach to produce features. The author employs stacking, bagging, and boosting as her three main methods for creating an ensemble learner. As a result, ensemble learning-based techniques are claimed to outperform conventional machine learning algorithms in recognizing false data.

[8] describes a technique that leverages supervised machine learning. Here, the study's behavioral and linguistic features were selected by the author. The recommended solution uses supervised machine learning techniques for its classifier approaches. It may be inferred from the observed results that KNN (k=7) outperforms the other classification techniques. The drawback, however, is that factors like the frequency of reviewer writing, the length of time it takes them to complete, etc., were not considered.

Table 1: Using various machine learning algorithms, summarizes the literature survey for bogus review identification.

Ref. and Year	Insights	Approach	Dataset	Conclusions
[4] 2017	An answer based on both supervised and unsupervised machine learning techniques has been put forward by the author.	Decision trees, KNN, SVM, and Naive Bayes (NB)	paid unidentified online labourers to create fictitious hotel evaluations in order to obtain a dataset of such reviews.	The findings obtained are good; nonetheless, the spam analysis lacks critical information about the reviewer.
[5] 2017	A method that makes use of semi-supervised machine learning methods has been covered by the author.	Random, Logistic Regression, and K-Nearest Neighbour classifiers	Look at textual information on 20 hotels in the Chicago area; phoney reviews generated by Amazon Mechanical Turk (AMT); more reviews collected from Yelp, TripAdvisor, Expedia, and Hotels	F-score rose with the use of PU learning-based categorization.
[6] 2018	An strategy using semi-supervised machine learning techniques has been described by the author. The author utilises both textual and network-based features.	Naive Bayes, Decision Trees, Support Vector Machines, k-Nearest Neighbors, Logistic Regression, The Node2vec and Doc2vec	The Yelp dataset	The detection of spam reviews is significantly improved by combining textual review data with representations obtained from reviewer product networks.
[7] 2020	The author has presented a method that utilises ensemble learning.	Extreme Gradient Boosting Trees, Decision Trees, Random Forests, Support Vector Machines, and Multilayer Perceptrons	Created a fabricated review dataset called "Restaurant dataset" and included reviews from verified users sourced from Google.	Ensemble learning approaches have proven to be superior to conventional machine learning algorithms in detecting deceptive information.
[8] 2021	Approach that makes use of supervised machine learning methods has been provided by the author.	Decision trees, Naive Bayes, closest neighbor, and support vector machines tree, Random-forest, Logistic regression	The Yelp dataset	KNN outperforms other classifier algorithms in terms of accuracy.

2.2 Fake Review Detection Using Deep Learning

The deep learning technique has been used over the last several decades to handle a wide range of issues, including fraud detection, picture identification, illness diagnosis, and video processing. The specifics of the various deep learning approaches utilized to address the issue of phoney reviews are given below.

In [10], problems with the existing Twitter spam detection approach were investigated, and a deep learning-based categorization solution was suggested. Additionally, a comparison was made with the current syntax-based and feature extraction methods. On some datasets, the outcome is superior and more precise. The author provides a thorough examination of automated Mis-Information Detection (MID) on various types of misleading content such as spam, rumours, false or disinformation, and fake news in their publication [11]. It provides a forward-looking analysis of MID development, where DL enables the automation of data processing and the generation of distinct patterns to achieve improved results and assist in extracting global features.

A novel strategy for the problem of false review identification was presented in [13]. In this method, a self-organizing map, or SOP, is used to collect words that are semantically related to one another. The grid map is used to depict them once a fixed-size picture has been constructed. The algorithm was then trained on these photographs, and with CNN's assistance, it was able to distinguish between actual and fraudulent images. The method primarily extracts the lexical variety dispersed with these reviews by using linguistic factors.

In order to enhance and increase the efficacy of opinion spam review detection techniques, a deep structure based on attention was developed in [15]. The model consists of a Multi-Headed Self-Attention mechanism paired with a bidirectional LSTM. An input embedding layer, a BiLSTM layer, an attention layer, and a SoftMax layer comprise the model's architecture. It looked into the misleading issue mentioned above. They emphasize that one of the most effective strategies for handling this kind of issue is the DL [16]. In order to prevent confusion caused by the spread of false information and news, [18] suggested a method that employs N-gram to solve four kinds of neural network models that are comparable to each other.

Table 2: Summarises the literature survey for fake review detection using a deep learning approach.

Ref. and Year	Insights	Approach	Dataset	Conclusions
[1] 2022	Customers are placing more and more trust in reviews as a source of product information. Nevertheless, online reviews are hindered by the presence of fraudulent reviews that distort the true representation of product quality.	Universal Language Model Fine-tuning (ULMFiT)	Amazon E-Commerce Dataset	It can accurately predict both computer- and human-generated reviews, but it is limited by the specificity of the dataset and needs to be updated frequently.
[9] 2019	Explored various DL models for identifying fake reviews, employing a range of techniques such as CNN, LSTM, RNN, and WORD2VEC, in combination with ML classifiers.	CNN, RNN, LSTM, ML Classifiers	Yelp (unlabeled), Ott(labeled)	After carefully analysing the results, the author proceeded to compare them with previous work. Expertly achieved a highly accurate and efficient solution.
[10] 2017	The author presented a model that utilises sentimental analysis in conjunction with deep learning. Here, the structures are utilised to identify patterns in the data. Patterns resembling question marks, uncommon symbols, and so on.	Sentimental analysis algorithm along with deep learning models	Politifact	The performance of ensemble networks surpasses that of additional types of construction.
[12] 2019	In this planned method, a new approach is utilised, which is rooted in Deep Learning. The author utilises Word2Vec and constructs binary classifiers using the existing dataset.	CNN, RNN, Word2Vec	NA	Successfully proposed a new organization method
[14] 2021	The suggested method employs analysis based on machine knowledge and deep learning. It involves a reactive approach that displays pop-ups on the browser to alert users of any issues or potential spam.	ML Classifiers along with DL algorithms	NA	99.4% of accuracy

2.3. Detecting fake reviews using Sentiment Analysis

There are many ways to create the bogus review detecting system. Among them is the sentiment analysis method. A number of algorithms are included into the sentiment analysis methodology. Among the algorithms are support vector machines (SVM), k*, decision trees, Naive Bayes, and others.

The algorithms are predicated on several methods of mathematics. The sentiment analysis method efficiently arranges the data and classifies reviews as authentic or fraudulent. The intended technology will search through available reviews to identify fraudulent ones.

The sentimental analysis technique has been outlined by Punde et al. [17] writers utilizing the Naive Bayes and Decision tree algorithms. Mathematical ideas of probability are used by the naive Bayes method. It computes the relative probability for the dataset using the two independent occurrences as input. The training dataset is subjected to 1.0 laplacian smoothing in order to estimate a value. This method has a 96.89% accuracy rate, which is superior.

Kauffmann et al. [18] provide a brief summary of the sentimental analysis case study. Many data points are considered in a dataset. Sentiment analysis is a natural language processing research approach that focuses on identifying the attitude or point of view of subjective textual elements. First, while categorizing, both positive and negative judgments are taken into account. Pujari et al.'s comparison of many sentiment analysis methods is done [19]. Support Vector Machine (SVM), Maximum Entropy, and Naive Bayes are a few of the algorithms. The performance of many algorithms is assessed in order to identify the best efficient approach for identifying fraudulent reviews. When it comes to this, SVM performs better than the others.

Elmurngi et al. [20] predicted the accuracy using sentiment analysis and a bag of words. Positive and negative emotions were taken into consideration by the author while classifying emotions. The author used a mixed textual analysis in this investigation. The research paper's methodology mixes a lexicon with machine learning techniques. The lower-dimensional datasets are best served by SVM and k-NN algorithms.

The Naive Bayes approach, which is based on the concept of probability distribution, is used in sentiment analysis. In the event that A and B are two separate events, the probability is calculated as follows:

$$Pr (A, B) = Pr(A).Pr(B)$$

The Naive Bayes assumption can be expressed using the following equation:

$$Pr (y\text{-}x1 \ldots\ldots X) = Pr (x1 |y) Pr (x2|y) .. Pr (x_n|y) Pr (y)/ Pr (x_1) Pr (x_2)\ldots Pr (x_n)$$

In this equation, y represents the class variable while x represents the dependent feature of a vector with size n. Naive Bayes calculates the likelihood of an event occurring based on the probability of a related event occurring.

Table 3: presents a summary of the literature survey on fake evaluation detection through sentimental analysis.

Ref. and Year	Insights	Approach	Dataset	Conclusions
[17] 2019	When it comes to classifying data, one common approach is to tokenize the data using a bag of words perfect. The outline primarily relies on data mining techniques.	Naive Bayes and conclusion tree algorithm	NA	Naive Bayes gives an competence of 96.89%.
[18] 2019	The data is organized according to positive and negative reviews. The customer's rating is an important factor in determining the classification. Classifying polarity is a fundamental task.	Probability-based algorithm, algorithm based on decision trees, and Support Vector Machine (SVM).	Out of the total of 1971, appraisals were taken into consideration for evaluation. From the total, 1328 reviews were identified as fake, while the rest were accurately predicted.	Out of 781 reviews, only a small fraction of 14.47% were identified as inaccurate predictions of fake reviews.
[18] 2018	An investigation into various sentiment analysis algorithms has been conducted. Several factors are taken into account when making comparisons.	Utilizing various algorithms such as Maximum Entropy, Decision tree, Naive Bayes, and support vector machine (SVM)	NA	SVM achieves better efficiency among all algorithms.
[20] 2017	There are two overall approaches: machine learning and dictionary-based.	Support Vector Machine (SVM), Naive Bayes, KNearest Neighbour.	NA	SVM achieves better with large datasets.

2.4. Fake Review Detection Using NLP

In opposition to the current changes in the world, more and more everyday tasks—such as reading the news and staying up to date on pertinent subjects—are shifting online. As a result of the increased amount of information accessible, the spread of false news became a popular issue on the Internet. Current occurrences, like the COVID-19 epidemic, have shown how false news highlights things that may not be factual and has a major detrimental impact on society. Furthermore, bogus news misleads individuals and shapes their perceptions for a variety of reasons. Researchers, alarmed by the flood of misleading information, created automated techniques based on Natural Language Processing (NLP) techniques to distinguish fake news. In this paper, we investigate potential techniques for identifying false news in

Romanian, reference previously released datasets and related studies in the analysis of false news in English, and outline future directions for this research endeavor.

Datasets: Creating a relevant corpus of labelled articles is a difficult but essential step in the detection of false news. A huge number of items in a clearly objective collection of articles takes a lot of work to produce. In an effort to cut down on the time and effort required for these kinds of tasks, some research groups claim that information produced by certain organizations—like CNN and PolitiFact—is factual and impartial.

Challenge of Fake News: One of the most significant datasets that is often used to test machine learning models is this one. The title and the article's content are sent into the algorithm, which then decides whether or not the material is discussed, agrees with the subject, or is unrelated. A technology like this may help humanities analysts get several viewpoints on a given issue, which will cut down on the amount of time they need to investigate it.

ClaimBuster: This tool highlights passages from candidates' statements that could need further attention by identifying check-worthy phrases in political discourse and debates. This approach shortens the amount of time journalists spend deciphering intricate discourses by identifying key words that need thorough examination before becoming viral and spreading false information. A total of almost 20,000 phrases were chosen for examination and classification as "False Judgement," "NonTrue Judgement," and "Improper Judgement."

Politifact: The 12,800 brief claims were chosen at random based on the six categories that Politifact pants defined: false, mainly false, slightly true, half true, and true. By constructing a structured, specified, and sufficiently big database for such testing, the LIAR database presented in the study, on paper, presents the capability of using machine learning algorithms to analyze such assertions and categorize politically important data.

FEND: The authors' design, called FEND (Fake News Detection), is based on the notion of grouping news stories with related topics together so that it would be simple to distinguish between phoney and authentic pieces that discuss the same issue. First, each news article's events and subjects were identified, and then clusters were constructed based on which clusters in that group share a comparable subset of topics, whereas other clusters in that representative subset do not share common topics. The fundamental premise was that reputable news sources like CNN and the New York Times existed.

3. Results

Many writers have suggested and explored a wide range of methods and techniques for identifying fraudulent reviews. The process of selecting features, how different machine learning approaches impact the performance of different classifier algorithms based on features, and the effectiveness of using different machine learning techniques for fake review identification have all been examined by the authors. After reading them, we discovered the typical procedure followed by a number of methods for identifying phoney reviews, as seen in figure 1.

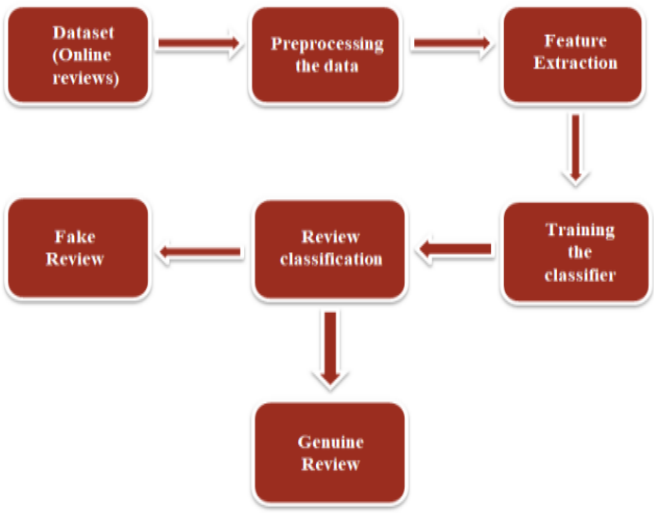

Figure 1: Outlines the Procedures Used to Find False Reviews

Multiple searches have been conducted in an effort to locate the fake review. Various techniques were used to differentiate between genuine and phony reviews. After analyzing the algorithms, we were able to determine the level of effectiveness of these techniques.

4. Discussion

Recently, there has been increased awareness of the impact of review detection on customer behaviour and purchasing decisions. We investigated and assessed the various approaches that have been proposed so far for the detection of fraudulent reviews. The survey includes techniques based on machine learning, deep learning, sentiment analysis, and natural language processing. We have discussed machine learning-based recommended solutions using supervised, unsupervised, semi-supervised, and ensemble learning methodologies. Combining feature engineering techniques with machine learning and deep learning methodologies yields the best outcomes. Moreover, the paper's discussion focused mostly on research that was applied to the real-time dataset.

It could be feasible to develop a model in the future that can identify reviews that are fake and reviewers that repeatedly use one or more accounts to spam reviews. After that, the model may be integrated with a system that limits or disables these review accounts. Furthermore, as the dataset becomes larger, the fake review detecting algorithm's efficacy increases. Consequently, other datasets may be used in the future to boost the effectiveness of the system. The methods discussed in this study will help eliminate false information, which will be beneficial to the domains of research and quality control.

5. Conclusions

The research study focusses on how fake reviews are becoming more common in online markets, which can confuse customers and change the way competition works. Different ways of finding things, like mood analysis, machine learning methods, and behavior analysis, are tested to see how well they work. The study finds that while no single method can completely solve the problem, using a mix of methods, including supervised learning models, pattern recognition, and emotion polarity checks, makes spotting much more accurate. The results show how important it is to keep improving and adapting these methods to deal with how dishonest judges' methods change over time. In the future, researchers may work on improving these methods and looking into mixed models that combine several methods to make real-time apps more reliable and scalable.

Future Recommendations

To make models more accurate and flexible, future study should focus on creating mixed models that combine machine learning, deep learning algorithms, mood analysis, and behavioral analytics. Real-time detection systems should be made to handle more and different kinds of data, and detection methods should be able to change to how bad actors act. Cross-platform analysis should be made so that review data from different sources can be analyzed and matched up, which will make identification more accurate. It is possible to look into advanced methods for handling natural language, analyzing user and network behavior, working together to filter information, and finding strange patterns. When collecting data for monitoring systems, ethical issues should be thought about, such as how to protect users' privacy. This method with many parts will help keep customers safe and build trust in online sites.

Conflict of Interest

In the context of Fake Review Detection Techniques potential conflicts of interest might arise in several ways: Affiliation with E-commerce Platforms, Algorithm and Tool Development, Data Source and Access, Addressing these potential conflicts of interest would require transparent disclosures of funding sources, affiliations, and any commercial relationships. Ethical research standards and unbiased peer review play crucial roles in maintaining the study's integrity, ensuring that findings are both reliable and objective.

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Author's Contribution

The people who wrote a review paper probably helped with coming up with the research idea, reviewing the literature, making a comparison framework, collecting data, putting the plan into action and trying it, talking about and summing up the results, writing and droughting the text, revising and finishing it, and making ethics statements. They came up with the idea for the study, did a full review of the literature, made a comparative framework, gathered and processed data, put detection algorithms to work, put together a summary of the results, wrote the paper, and worked together to revise and finish it. To be honest, they also said if they had any conflicts of interest. Their work together to give an in-depth, unbiased, and well-thought-out analysis of methods for finding fake reviews is helpful for future study.

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References

[1] Joni Salminen, Chandrashekhar Kandpal, Ahmed Mohamed Kamel, Soon-gyo Jung, Bernard J. Jansen, *"Creating and Detecting Fake Reviews of Online Products"*, Journal of Retailing and Consumer Services, **2022**, https://doi.org/10.1016/j.jretconser.2021.102771

[2] Patel, N. A. and Patel, K., *"A survey on fake review detection using machine learning techniques"*, In 4th International Conference on Computing Communication and Automation (ICCCA), pp.**1-6, 2018.**

[3] Wael, E. and Awajan, A., *"The effects of features selection methods on spam review detection performance"*, In International Conference on New Trends in Computing Sciences (ICTCS), pp.**116-120, 2017.**

[4] Rout, J. K. et al., *"Deceptive review detection using labeled and unlabeled data"*, Multimedia Tools and Applications, Vol.**76**, Issue.**3**, pp.**3187-3211, 2017.**

[5] Rout, J. K. et al., *"Revisiting semi-supervised learning for online deceptive review detection"*, IEEE Access, 5: pp.**1319-1327, 2017.**

[6] Yilmaz, C. M. and Durahim, A. O, *"SPR2EP: A semi-supervised spam review detection framework"*, In IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM). New Frontiers in Communication and Intelligent Systems, pp.**306-313, 2018.**

[7] Espinoza, G. et al., *"Ensemble learning for detecting fake reviews"*, In IEEE 44th Annual Computers, Software, and Applications Conference (COMPSAC), pp.**1320-1325, 2020.**

[8] Elmogy, A. M. et al, *"Fake Reviews Detection using Supervised Machine Learning"*, International Journal of Advanced Computer Science Applications, 12: pp.**601-606, 2021.**

[9] Shahariar, G. M. et al., *"Spam review detection using deep learning"*, In IEEE 10th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON), pp.**0027-0033, 2019.**

[10] Wu, T. et al., *"Twitter spam detection based on deep learning"*, In Proceedings of the Australasian Computer Science week Multiconference, pp.**1-8, 2017.**

[11] Islam, Md R. et al., *"Deep learning for misinformation detection on online social networks: a survey and new perspectives"*, Social Network Analysis and Mining, Vol.**10**, Issue.**1**, pp.**1-20, 2020.**

[12] Kumar, S. et al., *"Fake news detection using deep learning models: A novel approach"*, Transactions on Emerging Telecommunications Technologies, 31(2): e3767, **2020.**

[13] Neisari, A., Luis, R. and Saad, S., *"Spam review detection using self-organizing maps and convolutional neural networks"*, Computers & Security, 106: 102274, **2021.**

[14] Sahoo, Ranjan, S. and Gupta, B. B., *"Multiple features-based approach for automatic fake news detection on social networks using deep learning"*, Applied Soft Computing, 100: 106983, **2021.**
[15] Sedighi, Z. et al., *"Opinion Spam Detection with Attention-Based Neural Networks"*, Florida Artificial Intelligence Research Society Conference, pp.**1-5, 2019.**
[16] Lee, D. H. et al., *"Fake News Detection using Deep Learning"*, Journal of Information Processing Systems, Vol.**15**, Issue.**5**, pp.**1119-1130, 2019.**
[17] Punde, A. et al., *"Fake Product Review Monitoring & Removal and Sentiment Analysis of Genuine Reviews"*, International Journal of Engineering and Management Research, 9: pp.**107-110, 2019.**
[18] Kauffmann, E. et al., *"A framework for big data analytics in commercial social networks: A case study on sentiment analysis and fake review detection for marketing decision-making"*, Industrial Marketing Management, 90: pp.**523-537, 2020.**
[19] Pujari, C., Aiswarya and Shetty, N.P., *"Comparison of Classification Techniques for Feature-Oriented Sentiment Analysis of Product Review Data"*, Advances in Intelligent Systems and Computing, 542. Springer, Singapore, **2018.**
[20] Elmurngi, E. and Gherbi, A., *"Detecting Fake Reviews through Sentiment Analysis Using Machine Learning Techniques"*, In the Sixth International Conference on Data Analytics, pp.**65-72, 2017.**