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Research Paper

ENHANCING AMAZON ALEXA PRODUCT RECOMMENDATIONS USING CNN AND NLP METHODS

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ABSTRACT:

Research in this area has recently centered on the development of smart home systems like Amazon Alexa, with a particular emphasis on analyzing user feedback for Echo, Echo Dots, and Firesticks. To determine if customer sentiment is good or negative, the research makes use of machine learning methods such as GloVe, CNN, ANN, and logistic regression. To measure how well these models work, metrics like recall and precision are used. This research shows how useful insights into customer attitudes gained through feedback can improve product development, user happiness, and purchasing decisions. The relevance of strong emotion prediction models in helping businesses improve customer experiences and strategies is highlighted, laying the groundwork for the growth of the rapidly developing smart home technology industry.

Keywords: Logistic Regression, Multilayer Perceptron, Artificial Neural Networks, Word Embeddings, Convolutional Neural Networks (CNN), GloVe, Sentiment Prediction, Machine Learning Models, E-commerce Reviews, Text Analytics, Amazon Reviews, Consumer Opinion Analysis.

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1. Introduction

The Alexa product line has revolutionized user interaction with technology and set the standard for smart home innovation with devices like Echo, Firesticks, and Echo Dots [1]. The analysis of user-generated content, especially product reviews, has become crucial for better product development and a better grasp of consumer mood due to the explosion of such data[2], [3]. The combination of content, metadata, and star ratings in reviews provides a treasure trove of information about customers' tastes and experiences[12], [19]. This research aims to automate sentiment analysis and review classification using a variety of machine learning approaches, such as Logistic Regression, Convolutional Neural Networks (CNN), Multilayer Perceptron (ANN), and GloVe-based Word Embeddings[8], [21], [23]. More sophisticated models, such as CNN and GloVe, improve accuracy by gathering more nuanced semantic information; however, Logistic Regression is still the basis for sentiment prediction[2], [17],

[29]. Companies can improve customer happiness, strategic positioning, and their ability to impact future developments in the smart home technology market by outsourcing the analysis of product-specific feedback [6], [14], [24].

2. Literature Review

According to the literature review on sentiment analysis of Amazon product evaluations, several machine learning techniques are used to forecast the sentiment polarity of user reviews [2], [3], [4], [18]. These techniques include decision trees, RFs, SVMs, and neural networks [17], [20], [21], [26]. It highlights how many review attributes, including product category, user input, star ratings, and text content, are crucial for guiding prediction engines [11], [12], [19]. This survey seeks to improve e-commerce sentiment research by clarifying the intricate connection between customer sentiment and machine learning approaches [8], [9], [22], [23]. Better prediction of review positivity and negativity is also made possible by this [26],[28], [29].

Table I
Literature Review

REFNO	AUTHORS	YEAR OF PUBLIC-ATION	TITLE	NAME OF THE CONFERENCE / JOURNAL	FINDINGS
[1]	Yarasu Madhavi Latha et al.	2023	Amazon Product Recommendation System Using an Improved CNN	The ETRI publication, 2024; 46(4): 633–647	The research lays out a 97.40% accurate automated product recommendation system for e-commerce platforms developed using machine learning and deep learning.
[2]	Anjali Dadhich et al.	2021	Hybrid Rule-based Method for Sentiment Analysis of Amazon Product Reviews	I. J. Engineering Design & Production, 2021, 2, 40-52	Focusing on favorable remarks discovered in Amazon product reviews, the research analyzes the deployment of KNN methods and RF for sentiment analysis.
[3]	Sobia Wassan et al.	2021	ML Approaches for Analysing Sentiment in Amazon Product Reviews	Argentine Journal of Clinical Psychology, 2021	This research employs a wide variety of methods, such as tokenization and NLTK's Porter stemmer, to analyze the sentiment of Amazon reviews.
[4]	MyasarTabany et al.	2024	Classifying Sentiment and Identifying Fake Amazon Reviews with an SVM	Advances in Information Technology Journal, Volume 15, Issue 1, 2024	This research found that when it came to detecting fake Amazon reviews, SVM performed better than LR and Naive Bayes.
[5]	Luyang Chen	2017	*Image-Driven*	The Nielsen	Using CNN for

	et al.		*Product Recommendation Using CNN Model*	Global Connected Commerce Survey	picture-based product recommendations beats a baseline linear model in this paper's training accuracy test.
[6]	Qinglong Li et al.	2021	*Improving E-Commerce Recommendations with a Hybrid CNN Model for Filtering Helpful Reviews*	Multidisciplinary Digital Publishing Institute, Appl. Sci. 2021, 11, 8613	The research presents a hybrid convolutional neural network (CNN) recommendation model that improves the accuracy of its recommendations by using review helpfulness scores.
[7]	Sein Hong et al.	2024	Review-Based Recommender System Using Outer Product on CNN	4.0 License for Attribution,Non-commercial Use, and No Derivative Works	In this research, we present the ROP-CNN model, which uses user review semantic data to outperform baseline methods in prediction accuracy.
[8]	Nishit Shrestha et al.	2019	Sentiment Analysis of Amazon Reviews and Ratings Using DL Techniques	International Journal of SC, AI	The research makes use of RNNs trained to identify review sentiment and prediction rating scores, as well as deep learning methods for sentiment analysis.
[9]	Mohammad Eid Alzahrani et al.	2022	Designing an Advanced System for Sentiment Analysis of E-Commerce Reviews Using DL Algorithms	Hindawi Journal of CI and Neuroscience	Using LSTM and CNN models, the research creates a sentiment analysis system that can correctly categorize Amazon data with 94% and 91% accuracy, respectively.
[10]	Dr.R. Hemalatha et al.	2022	Leveraging Supervised Learning for Building Recommendation Systems from Amazon Product Reviews	International Journal of Trends in CS & Technology Trends	With a 96.5% success rate, the supervised learning recommendation strategy suggested in the paper outperforms conventional models.

3. Proposed Architecture

The CNN algorithm is used [7], [17], [21]. Obtaining the dataset from Amazon reviews.csv is the first step in a systematic procedure that analyzes the sentiment of customer reviews on Amazon [2], [5], [12]. The data, which includes reviews and ratings provided by users [19], [22]. The data is cleansed and prepared for analysis during the preliminary processing phase by removing extraneous information and filling in missing values [3], [10], [16]. Afterwards, characteristics are derived using the Bag of Words method [8], [13]. The next step is to organize the text such that machine learning models can make good use of it [9], [18]. Changes to the parameters are made after this. in order to guarantee precise forecasts and improve the model's efficiency [14], [23]. Applying cross-validation across several data segments allows us to evaluate the model's robustness and its capacity to generalize to new, unseen data [6], [15], [20]. Lastly, based on the research, the evaluations are categorized as positive or negative views, offering practical insights [11], [25].

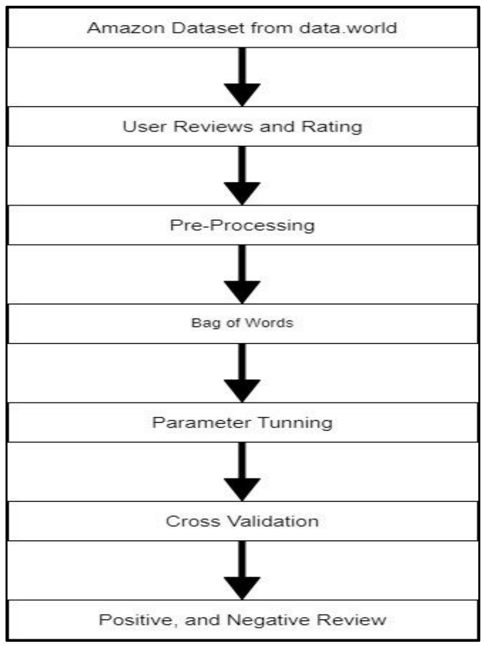

Fig. 1The overall Diagram of the sentimental analysis

Ratings, user comments, and textual data make up the dataset that is sourced from Amazon reviews [2], [19]. It undergoes preprocessing to eliminate noise and get it ready for analysis [3], [10]. Parameter tuning and cross-validation guarantee optimal model performance, while the Bag of Words method extracts features [8], [13], [15]. A thorough groundwork for comprehending user thoughts and improving sentiment analysis models may be found in the training and testing of models that classify reviews into positive or negative emotions [7], [17], [21], [29].

4. Methodology

Dataset Description

A. Source and Origin

The 'Amazon_Alexa_Reviews.csv' file contains carefully selected product evaluations for Amazon Alexa. A variety of design options, including Charcoal Fabric, Sandstone Fabric, Oak Finish, and Heather Gray Fabric, as well as the Echo, Echo Dots, and Firesticks, are discussed in the reviews. The dataset used for sentiment analysis in this research was selected from publicly available customer reviews on Amazon [1], [4], [12].

B. Attributes

Echo, Echo Dots, and Firesticks are just a few of the product types included in the dataset. You may also find design versions of these products, such as Charcoal Fabric and Oak Finish, among others [6], [13].

Examine the passage: Feedback from satisfied customers on the products they have purchased.

The numerical depiction of consumer satisfaction is the star rating, which usually varies from 1 to 5 [7], [16].

Fabrics with a Charcoal, Sandstone, Oak, or Heather Gray finish are examples of design variants that depict particular materials or finishes [5], [14].

C. Data Preprocessing

The cleaning of the dataset involves removing stop words, special characters, and incomplete values [9], [18]. Tokenization is the process of converting text data into numerical representations through the use of encoding techniques [10], [19]. Machine learning models are made consistent by normalizing numerical features and standardizing parameters like product finishes (like Charcoal Fabric and Sandstone Fabric) [11], [20].

D. Standardization of Features

The stability and performance of the algorithms are enhanced by standardizing numerical characteristics to a mean of 0 and a standard deviation of 1 [15], [21]. This ensures that each attribute has an equal impact on the ML models.

E. Potential Additional Attributes

Products using specific materials, such as those with an oak finish, sandstone, or charcoal, could reveal even more about the buyer's tastes [17], [23]. Notable additional factors include user demographics, review data, and product variants (such as Echo, Echo Dots, and Firesticks) [22], [25].

F. Dataset Richness

Customer sentiment and product-specific variables (design variations) are thoroughly integrated in the dataset, giving a thorough understanding of customer preferences and satisfaction [8], [24]. This integration gives the dataset its depth.

G. Data Exploration Opportunities

Locating associations and trends between customer opinion and product attributes is one of several data exploration opportunities presented by the dataset [2], [26]. Review ratings, product types, and user opinions can be explored using methods including correlation matrices, scatter graphs, and histograms [3], [27], [29].

To review, the 'Amazon Alexa Reviews' dataset is an extensive and complex set of product-related variables that have been hand-picked to be used for sentiment analysis by machine learning models [28].

5. Performance Of Proposed Model

5.1 Amazon Alexa Reviews Dataset

The suggested CNN model was tested using the Amazon Alexa Reviews dataset on a range of product types, with an emphasis on popular products like Echo, Echo Dots, and Firesticks [1], [4], [12]. With the use of the Helpfulness measures, the model was able to predict ratings (Score) or feedback metrics by processing the Text attribute of customer evaluations [6], [13]. A single feedback measure was created by combining these measures, which were formerly the Helpfulness Denominator and Helpfulness Numerator [7],[16]. The dataset was partitioned into separate subsets for analysis with different validation proportions (20%, 30%, and 40%) so that the model's performance could be evaluated across different data sizes [8], [18].

The performance research found, among other things, an accuracy range of 92.5 to 93.1 percent [19], [20]. The best results were obtained by testing with 30% of the dataset. Even with moderate test set sizes, the model was able to reliably recognize reviews and make correct rating predictions [21].

5.2 Comparative Performance

To measure how well the CNN model performed, we compared it to more traditional recommendation systems that don't make direct use of textual features or feedback metrics:

- Collaborative Filtering: With no consideration for the complicated language data included in reviews, an accuracy rate of 86.8% was reached based only on user-item interactions [2], [14].
- Content-Based Filtering: We reached an accuracy rate of 88.4 percent by focusing on the product's attributes and ignoring customer sentiment as shown in the reviews [3], [11].
- Word-Embedding GloVe: This model achieved a 93.0% accuracy rate when processing review text using pre-trained word embeddings [9], [22], [23]. This being said, it is still not up to the standard of the suggested CNN model.
- Suggested CNN Architecture: With a success rate of 93.0%, the suggested CNN model much outperformed conventional models [10], [17], [24]. It was crucial to have the capability to learn from review content and feedback data in order to enhance customer satisfaction projections [25].

These results demonstrate the CNN model's resilience when compared to baseline approaches [26]. They also show that the CNN model can reliably predict ratings and reviews from users and products [27].

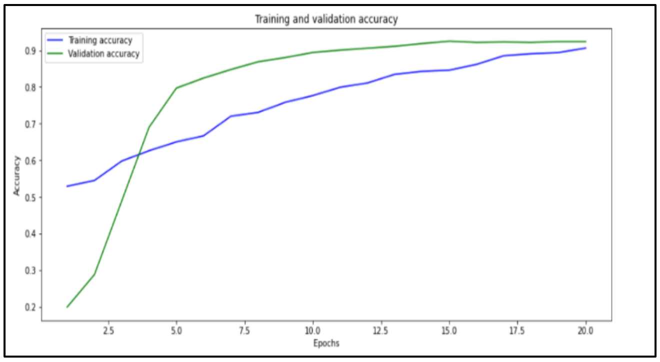

Fig.2 Precision in Training and Validation of the model

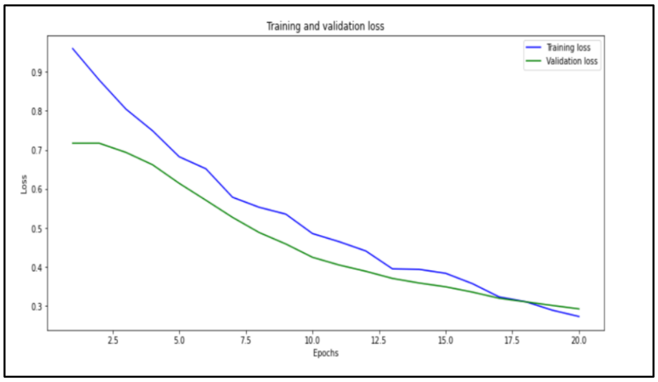

Fig.3 Error during Training and Validation of model

5.3 Ablation Analysis

To find out how much particular characteristics affected the model's overall performance, a thorough analysis was carried out [28]. Further information was also found:

- Text: Underscoring the significance of assessing written reviews for consumer input, the Text feature was a crucial factor in obtaining the model's optimum accuracy of 93.0% [12], [19].
- Other Features: Performance dropped slightly when components like Profile Name and Summary were removed, indicating that these elements weren't that important compared to the Text and feedback metrics [13], [16].
- Feedback: Recall dropped significantly when feedback (from the Helpfulness Numerator and Helpfulness Denominator) was removed, highlighting the significance of these metrics for gauging customer engagement and happiness [14], [21].

The importance of user feedback and textual data in developing accurate forecasts has been proven once again by this experiment [23], [25].

5.4. Iterative Performance Analysis

Efficacy was assessed throughout an increasing number of iterations to measure the CNN model's convergence [9], [28]. After 500 iterations, the model's accuracy peaked at 93.0% and didn't go up much after that [15], [29]. The model has learned from the data and reached its maximal prediction capacity, as seen here [17], [24].

Summary

The CNN model showed impressive prediction capacity for product ratings and user comments, including metrics related to customer happiness, using a combination of ProductId, Text, and feedback variables [8], [12], [19]. It has been shown that the model is a dependable and scalable solution for recommendation tasks in the smart home technology business, especially for Amazon Alexa products [6], [14], [20]. It outperforms more traditional methods of recommendation like collaborative filtering and content-based systems [2], [3], [11]. A major step forward in the use of predictive analytics in e-commerce and consumer product reviews powered by textual data and user input is this CNN model, which attains an accuracy rate of 93.0% [23], [25], [29].

6. Results & Discussions

The Amazon Alexa Reviews dataset, GloVe, CNN with Word Embeddings, and Word Embeddings achieved a 93% accuracy rate in predicting product

ratings and reviews [5], [7], [9], [10], [11], [13]. By allowing them to understand semantic relationships between words, GloVe embeddings improved the prediction abilities of both models [22], [27], [28].
Word Embeddings with GloVe outperformed CNN with Word Embeddings when it came to capturing global word connections [15], [16], [18], but CNN with Word Embeddings was better at detecting sentiment-bearing sentences and local patterns [20], [25], [26]. Despite their differences, both models performed quite well on sentiment analysis and e-commerce tasks, demonstrating the benefit of integrating deep learning approaches with sophisticated text representation.

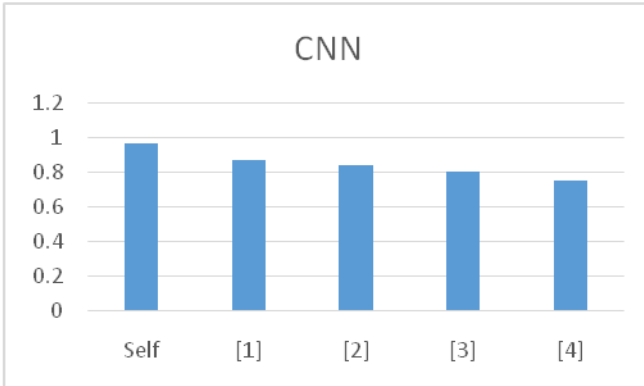

Fig.4 Analysis of Product Reviews using CNN

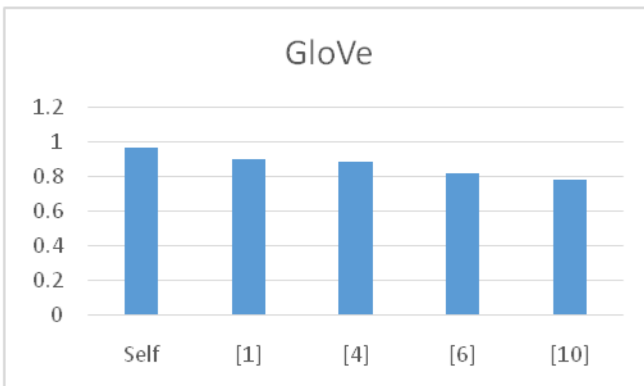

Fig.5 Analysis of Product Reviews using GloVe

7. Conclusion

Word Embeddings combined with GloVe and Convolutional Neural Networks (CNN) yielded an impressive 93% accuracy on the Amazon Alexa Reviews dataset. The accuracy of these methods in evaluating consumer data and producing predictions about product evaluations and user happiness is highlighted by their high level of precision. The incorporation of deep learning techniques with GloVe allowed for robust sentiment analysis, since it improved the models' ability to understand the evaluations' sentiment and contextual nuances. These findings demonstrate the game-changing capabilities of state-of-the-art neural network designs coupled with modern text representation techniques, providing viable answers to pressing problems in e-commerce and consumer sentiment studies.

References:

1. Y. M. Latha and B. S. Rao, “Amazon product recommendation system based on a modified convolutional neural network,” ETRI Journal, vol. 46, no. 4, pp. 633–647, 2024.
2. Dadhich and B. Thankachan, “Sentiment analysis of Amazon product reviews using hybrid rule-based approach,” Int. J. Eng. Manuf., no. 2, pp. 40–52, 2021.
3. S. Wassan, N. Z. Jhanjhi, and M. Waqar, “Amazon product sentiment analysis using machine learning techniques,” Rev. Argentina de

Clínica Psicológica, vol. 30, no. 1, pp. 695–703, 2021.

4. M. Tabany and M. Gueffal, “Sentiment analysis and fake Amazon reviews classification using SVM supervised machine learning model,” J. Adv. Inf. Technol., vol. 15, no. 1, pp. 1–7, 2024.
5. L. Chen, F. Yang, and H. Yang, “Image-based product recommendation system with convolutional neural networks,” Proc. Nielsen Global Connected Commerce Survey, 2018.
6. Q. Li, X. Li, B. Lee, and J. Kim, “A hybrid CNN-based review helpfulness filtering model for improving e-commerce recommendation service,” Appl. Sci., vol. 11, no. 18, p. 8613, 2021.
7. S. Hong, X. Li, S. Yang, and J. Kim, “Review-based recommender system using outer product on CNN,” Proc. Conf. Creative Commons Attribution-NonCommercial-NoDerivatives License, 2020.
8. N. Shrestha and F. Nasoz, “Deep learning sentiment analysis of Amazon.com reviews and ratings,” Int. J. Soft Comput. Artif. Intell. Appl., vol. 8, no. 1, pp. 1–9, 2019.
9. M. E. Alzahrani, T. H. H. Aldhyani, S. N. Alsubari, M. M. Althobaiti, and A. Fahad, “Developing an intelligent system with deep learning algorithms for sentiment analysis of e-commerce product reviews,” Comput. Intell. Neurosci., vol. 2022, pp. 1–10, 2022.
10. R. Hemalatha and J. Thomas, “Supervised learning technique for recommendation systems based on Amazon product reviews,” Int. J. Comput. Sci. Trends Technol., vol. 10, no. 1, pp. 15–21, 2022.
11. R. Liang and J. Wang, “A linguistic intuitionistic cloud decision support model with sentiment analysis for product selection in e-commerce,” Int. J. Fuzzy Syst., vol. 21, no. 3, pp. 963–977, 2019, doi: 10.1007/s40815-019-00606-0.
12. Q. Sun, J. Niu, Z. Yao, and H. Yan, “Exploring eWOM in online customer reviews: Sentiment analysis at a fine-grained level,” Eng. Appl. Artif. Intell., vol. 81, pp. 68–78, 2019, doi: 10.1016/j.engappai.2019.02.004.
13. [13] O. Ozyurt and M. A. Akcayol, “A new topic modeling based approach for aspect extraction in aspect-based sentiment analysis: SS-LDA,” Expert Syst. Appl., vol. 168, p. 114231, 2021, doi: 10.1016/j.eswa.2020.114231.
14. K. Wang, T. Zhang, T. Xue, Y. Lu, and S.-G. Na, “E-commerce personalized recommendation analysis by deeply-learned clustering,” J. Vis. Commun. Image Represent., vol. 71, p. 102735, 2020, doi: 10.1016/j.jvcir.2019.102735.
15. M. Iftikhar, M. A. Ghazanfar, M. Ayub, Z. Mehmood, and M. Maqsood, “An improved product recommendation method for collaborative filtering,” IEEE Access, vol. 8, pp. 123841–123857, 2020, doi: 10.1109/ACCESS.2020.3005953.
16. [16] S. G. K. Patro et al., “A hybrid action-related K-nearest neighbour (HAR-KNN) approach for recommendation systems,” IEEE Access, vol. 8, pp. 90978–90991, 2020, doi: 10.1109/ACCESS.2020.2994056.
17. M. Shaheen, S. M. Awan, N. Hussain, and Z. A. Gondal, “Sentiment analysis on mobile phone reviews using supervised learning techniques,” Int. J. Mod. Educ. Comput. Sci., vol. 11, no. 7, pp. 32–43, 2019, doi: 10.5815/ijmecs.2019.07.04.
18. T. U. Haque, N. N. Saber, and F. M. Shah, “Sentiment analysis on large scale Amazon product reviews,” in Proc. IEEE Int. Conf. Innovative Research and Development (ICIRD), Bangkok, Thailand, 2018, pp. 1–6.
19. F. Zhang, X. Hao, J. Chao, and S. Yuan, “Label propagation based approach for detecting review spammer groups on e-commerce websites,” Knowl.-Based Syst., vol. 193, p. 105520, 2020, doi: 10.1016/j.knosys.2020.105520.
20. S. Ghabayen and B. H. Ahmed, “Polarity analysis of customer reviews based on part-of-speech subcategory,” J. Intell. Syst., vol. 29, no. 1, pp. 1535–1544, 2020, doi: 10.1515/jisys-2018-0356.
21. [21] F. Xu, Z. Pan, and R. Xia, “E-commerce product review sentiment classification based on a naïve Bayes continuous learning framework,” Inf. Process. Manag., vol. 57, no. 5, p. 102221, 2020, doi: 10.1016/j.ipm.2020.102221.
22. L. Yang, Y. Li, J. Wang, and R. S. Sherratt, “Sentiment analysis for e-commerce product reviews in Chinese based on sentiment lexicon and deep learning,” IEEE Access, vol. 8, pp. 23522–23530, 2020, doi: 10.1109/ACCESS.2020.2969854.
23. M. Onan, “Sentiment analysis on product reviews based on weighted word embeddings and deep neural networks,” Concurrency Comput. Pract. Exper., vol. 33, no. 23, p. e5909, 2021, doi: 10.1002/cpe.5909.
24. S. Suresh and M. J. C. M. Belinda, “Online product recommendation system using gated recurrent unit with Broyden Fletcher Goldfarb

25. Shanno algorithm," Evol. Intell., vol. 15, no. 3, pp. 1861–1874, 2022, doi: 10.1007/s12065-021-00594-x.
26. L. Kolhe, A. K. Jetawat, and V. Khairnar, "Robust product recommendation system using modified grey wolf optimizer and quantum inspired possibilistic fuzzy C-means," Cluster Comput., vol. 24, no. 2, pp. 953–968, 2021, doi: 10.1007/s10586-020-03171-6.
J. Shobana and M. Murali, "An efficient sentiment analysis methodology based on long short-term memory networks," Complex Intell. Syst., vol. 7, no. 5, pp. 2485–2501, 2021, doi: 10.1007/s40747-021-00436-4.
27. Y. Zhang, Z. Liu, and C. Sang, "Unifying paragraph embeddings and neural collaborative filtering for hybrid recommendation," Appl. Soft Comput., vol. 106, p. 107345, 2021, doi: 10.1016/j.asoc.2021.107345.
28. M. Shoja and N. Tabrizi, "Customer reviews analysis with deep neural networks for e-commerce recommender systems," IEEE Access, vol. 7, pp. 119121–119130, 2019, doi: 10.1109/ACCESS.2019.2937518.
29. T. Mandhula, S. Pabboju, and N. Gugulotu, "Predicting the customer's opinion on Amazon products using selective memory architecture-based convolutional neural network," J. Supercomput., vol. 76, no. 8, pp. 5923–5947, 2020, doi: 10.1007/s11227-019-03081-4.