Iranian Journal of Science and Technology, Transactions of Electrical Engineering
https://doi.org/10.1007/s40998-026-01064-9

RESEARCH PAPER

Sentiment Analysis for Product Recommendation Using Graph Neural Network with Cosine Migration Optimization

Sangeetha M[1] · R. Manjula Devi[2] · Lalitha Krishnasamy[3] · Kumaravel T[4]

Received: 16 September 2025 / Accepted: 17 February 2026

Abstract
The main goal of this article is to devise an effective method named Cosine Migration Optimization-based Graph Neural Network (CMO_GNN) for product recommendation. Initially, the input data, such as user buying sequence, product id, name of the product, reviewer ID, and user review, is considered. Then, graph generation is performed, where the sequence is encoded. Later, a Graph Neural Network (GNN) is utilized to identify the relevant user by training it based on the user graph. The training of GNN is done on the proposed hybrid Cosine Migration Optimization (CMO). Then, product recommendation is performed by using the user's buying behavior query as input to the GNN, which performs node classification to identify the relevant user. Later, the product buying sequence of the particular user is tracked from the user feature vector. Finally, the product recommendation is refined by analyzing the product's sentiment using a trained sentiment classification model. Here, sentiment analysis is performed by considering the product review data. Subsequently, feature extraction is performed, and sentiment classification is performed by a Hierarchical Attention Network (HAN) trained by the CMO. Experimental results demonstrate that the proposed CMO_GNN achieves superior performance, attaining a precision of 90.995%, a recall of 91.945%, and an F-measure of 91.468%.

Keywords Migration algorithm · Hierarchical attention network · Graph neural network · Sine cosine algorithm · Product recommendation

1 Introduction

Recommendation systems use users' historical activity to generate personalized product recommendations through automated software. They are employed in numerous applications, including social media, music streaming, and online shopping (Javaji and Sarode 2023). Initially created in the middle of the 1990s, recommender systems have grown significantly in the last several years. Recommender systems are based on the ratings and preferences of users. They now play a particularly significant role in the media, banking, utilities, e-commerce, and media industries. Utilizing this kind of technology, Facebook recommends users connect with and follow certain individuals, YouTube suggests related videos for auto-play, and Amazon suggests recommended products for users (Dang et al. 2021). The recommendation system in an e-commerce setting benefits both the community of sellers and buyers. These systems are essential to obtain relevant products and more individualized recommendations based on user purchase behavior and interests from an extensive range of products (Qomariyah

✉ Sangeetha M
sangeethcse@gmail.com

R. Manjula Devi
rmanjuladevi.gem@gmail.com

Lalitha Krishnasamy
vrklalitha24@gmail.com

Kumaravel T
kumarengineer@gmail.com

[1] Department of Computer Science and Engineering, PSG Institute of Technology and Applied Research, Coimbatore, Tamilnadu, India

[2] Department of Computer Science and Engineering, KPR Institute of Engineering and Technology, Coimbatore, Tamil Nadu 641407, India

[3] Department of Artificial Intelligence and Data Science, Centre For Interdisciplinary Research, Nandha Engineering College, Erode 638052, Tamilnadu, India

[4] Department of Computer Science and Engineering, School of Computer Science and Engineering, Presidency University, Rajanukunte, Yelahanka, Karnataka 560119 Bengaluru, India

Published online: 06 April 2026

and Fajar 2019). The two core approaches to recommendation systems are collaborative filtering and content-based filtering. Users are recommended products by collaborative filtering systems based on the preferences and ratings of people with similar tastes. For instance, if you rate several movies on Netflix, the system will suggest films that others with comparable ratings have liked. Users are given recommendations by content-based filtering systems based on the content of the items themselves (Chen et al. 2020; Javaji and Sarode 2023). More relevant and engaging product recommendations are now given to customers by context-based recommendation systems and demographic recommendation algorithms (Karthik and Ganapathy 2021). Using statistical methods and knowledge discovery technologies, the product recommendation system suggests products that satisfy customer needs with a concentration on marketing and cross-selling (Cho et al. 2020).

On e-commerce sites, users' purchasing decisions are heavily shaped by the reviews of products. The abundance of reviews can make it challenging for users to locate the ones most relevant to their interests. A few particular product attributes, such as "quality," "appearance," "price," and so on, are typically the focus of most users. The difficulty in locating the most beneficial reviews for specific people emerges from the wide variations in both the reviews' attributes and users' preferences (Huang et al. 2020). Sentiment analysis is a field within Natural Language Processing (NLP), computational linguistics, and text mining that seeks to identify a writer's feelings, personality, etc., in relation to particular subjects (Ray et al. 2021). Numerous studies in recent years have introduced different sentiment analysis models applicable to areas such as social media, finance, and tourism. Numerous studies have been conducted to examine attitudes in the financial sector (Li et al. 2014; Ray et al. 2021). Text classification with respect to sentiment analysis involves classifying texts and making decisions based on the classified text. Sentiment analysis counts the frequency of words that indicate sentiments, in addition to considering syntactic and semantic analysis. Nevertheless, most studies in the literature focus on using syntactic words for opinion mining, which often results in lower prediction accuracy (Lei et al. 2016; Munuswamy et al. 2021). Approaches to sentiment classification are typically divided into machine learning methods and lexicon-based methods. The sentiments expressed in the unstructured data are identified through the application of deep learning techniques (An and Moon 2022). In recent years, multimodal data such as hashtags and micro videos have also been subjected to sentiment analysis (Karthik and Ganapathy 2021).

Recommendation systems can be developed using various methods. Using machine learning algorithms is one typical technique. It is possible to train machine learning algorithms to determine which items a user will like by providing them with large datasets of user ratings or preferences. Using techniques from Artificial Intelligence (AI) is another method for creating recommendation systems (Darban and Valipour 2022). Recommendation systems can be made more advanced and potent by utilizing AI techniques like deep learning. Now, people depend heavily on recommendation systems to help us make wise choices about the goods and services we use on a daily basis (Javaji and Sarode 2023). In online shopping product recommendation systems, fuzzy logic improves the accuracy of recommendations, providing customers with highly personalized and relevant products (Ray et al. 2021). Fuzzy-based recommendation systems have been used recently in government sectors (Meza et al. 2018) for tasks like tax payment, which gives some assurance that the public will become more aware of tax payments. The majority of applications use fuzzy logic to choose the best vendor from a group of vendors because fuzzy logic is used to increase decision accuracy in decision support systems (Karthik and Ganapathy 2021). Recently, GNNs have shown great promise in addressing this issue, enabling recommendation methods to effectively incorporate relational data. In recent years, GNNs have emerged as a strong tool for addressing issues in recommendation systems. Utilizing their prior behavior and preferences, recommendation systems seek to suggest products to users that are useful and relevant to them (Javaji and Sarode 2023).

The main objective of this research is to develop an effective and accurate personalized product recommendation system that addresses the limitations of existing methods, such as being unable to effectively train GNNs with different models (Javaji and Sarode 2023), failing to analyze the node classification process thoroughly (Lai and Tseng 2022), not introducing novel processing techniques (Karthik and Ganapathy 2021), and ignoring important user and product features that could enhance recommendation performance (Abbasi-Moud et al. 2021). To tackle these shortcomings, we present a novel CMO_GNN framework that fuses user behavior modeling, node classification, and sentiment analysis, trained via the CMO algorithm, with the goal of boosting recommendation accuracy, relevance, and user experience. Reviewer ID, user review, product name, product id, and user buying sequence are among the first set of input data that are considered. Then, graph generation is performed based on the user vector, where the sequence is encoded. The relevant user corresponding to the input feature vector is then identified using the GNN, which is trained on the user graph. The devised CMO, integrating the Migration Algorithm (MA) and Sine Cosine Algorithm (SCA), is employed to train the GNN. Later, product recommendation is performed. Node classification is carried out using

of CMO_GNN concerning f-measure while comparing with context-aware tourism recommendation is 2.28%.

4.8 Comparative Discussion

The results obtained by CMO_GNN in comparison to current techniques are delineated in Table 1. Moreover, it is seen that CMO_GNN attained the highest precision, recall and f-measure values of 90.995%, 91.945%, and 91.468%, while contemplating k-value as 9. The precision values calculated by GNN is 83.990%, ADLRP is 85.878%, Fuzzy logic-based product recommendation is 87.990%, context-aware tourism recommendation is 89.018%, MLA-EDTCNet is 89.368%, and SPCM is 89.777%. Recall values measured by traditional methods like GNN, ADLRP, Fuzzy logic-based product recommendation, context-aware tourism recommendation, MLA-EDTCNet and SPCM is 84.756%, 86.957%, 88.006%, 89.755%, 90.368%, and 90.776%. Conventional model gained f-measure values of GNN is 84.373%, ADLRP is 86.418%, Fuzzy logic-based product recommendation is 87.998% and context-aware tourism recommendation is 89.387%, MLA-EDTCNet is 89.865%, and SPCM is 90.274%. Furthermore, CMO_GNN efficiently exploits the label contents and graph topology of the graph-structured data. The superior performance of the CMO_GNN framework arises from the combined effect of optimized GNN training, effective node classification, and sentiment analysis. The CMO algorithm enhances GNN performance by generating optimal weights and biases, improving convergence, and avoiding local minima, which allows the network to learn richer representations of user–product interactions. Node classification captures relational patterns and behavioral similarities among users, enabling the identification of relevant users whose purchasing behavior aligns with the query user, thereby improving the behavioral relevance of recommended products. Sentiment analysis, performed using the HAN model trained with CMO, evaluates product reviews to filter out negatively perceived items and prioritize positively reviewed products, enhancing the overall accuracy and satisfaction of recommendations. This combination of techniques allows CMO_GNN to effectively exploit graph topology and label content, resulting in higher precision, recall, and F1-score compared to traditional methods. The framework provides personalized recommendations, robustness to sparse or noisy data, and practical applicability in e-commerce, online marketplaces, and other platforms requiring user-centric recommendation systems.

Implementing the CMO_GNN framework in a real-world recommendation system may face several challenges. Large-scale user–product graphs can increase computational and memory requirements, slowing down training and inference. Dynamic user behavior and constantly changing product inventories require frequent model updates to maintain relevance. Sparse data for new users or products can cause the cold-start problem, reducing recommendation accuracy. Additionally, sentiment analysis may be affected by ambiguous or noisy reviews, leading to misclassifications. These challenges can be addressed by employing scalable graph processing techniques such as mini-batch training, incremental or online learning strategies, hybrid feature-based models for cold-start scenarios, and text preprocessing or noise filtering to improve sentiment classification accuracy. Incorporating these solutions ensures the CMO_GNN framework can be effectively deployed in practical recommendation systems.

5 Conclusion

A technique for product recommendation using CMO_GNN is proposed here. At first, graph generation is performed based on the user vector. Training of GNN is carried out based on the user graph, and GNN is utilized to identify relevant users. The training of GNN is done by the proposed hybrid CMO, which is designed by a combination of MA and SCA. Later, the Query of User buying behavior is fed as input to the GNN for a product recommendation, which does node classification to find the relevant user. Based on the relevant user, the product buying sequence of the particular user is tracked from the user feature vector. Once the product recommendation sequence is identified, the final product recommendation is made by checking the sentiment of the product using a trained sentiment classification model. For sentimental analysis, product review data is taken as input, and feature extraction is performed. Then, sentiment classification is performed by HAN trained by CMO. The CMO_GNN recorded a high precision of 90.995%, recall of 91.945%, and F-measure of 91.468%. Future work aims to implement other datasets to check the feasibility of the proposed model.

Acknowledgements I would like to express my very great appreciation to the co-authors of this manuscript for their valuable and constructive suggestions during the planning and development of this research work.

Author Contribution Author Contribution: All authors have made substantial contributions to conception and design, revising the manuscript, and the final approval of the version to be published. Also, all authors agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Funding This research did not receive any specific funding.

Data Availability The data that support the findings of this study are

openly available in Amazon Review Data (2018) at https://nijianmo.github.io/amazon/.

Code Availability The source code for the proposed method is available at "https://github.com/KumaaravelT/CMO_GNN.git".

Declarations

Ethical Approval Not Applicable.

Conflict of Interest The authors declare no competing interests.

Informed Consent Not Applicable.

References

Abbasi-Moud Z, Vahdat-Nejad H, Sadri J (2021) Tourism recommendation system based on semantic clustering and sentiment analysis. Expert Syst Appl 167:114324

Amazon Review Data (2018) https://nijianmo.github.io/amazon/,on January 2024.

An HW, Moon N (2022) Design of recommendation system for tourist spot using sentiment analysis based on CNN-LSTM, Journal of Ambient Intelligence and Humanized Computing, pp.1–11

Ayyarao TS, Ramakrishna NSS, Elavarasan RM, Polumahanthi N, Rambabu M, Saini G, Khan B, Alatas B (2022) War strategy optimization algorithm: a new effective metaheuristic algorithm for global optimization. IEEE Access 10:25073–25105

Chen L, Wu L, Hong R, Zhang K, Wang M, (2020) Revisiting graph based collaborative filtering: A linear residual graph convolutional network approach, In Proceedings of the AAAI conference on artificial intelligence 34(01):27-34

Cho BD, Potluri RM, Youn MK (2020) A study on the effect of product recommendation system on customer satisfaction: focused on the online shopping mall. J Industrial Distrib & Business 11(2):17–23

Dang CN, Moreno-García MN, Prieta FDL (2021) An approach to integrating sentiment analysis into recommender systems. Sensors 21(16):5666

Darban ZZ, Valipour MH (2022) GHRS: graph-based hybrid recommendation system with application to movie recommendation. Expert Syst Appl 200:116850

Huang C, Jiang W, Wu J, Wang G (2020) Personalized review recommendation based on users' aspect sentiment. ACM Transa Internet Technol (TOIT) 20(4):1–26

Javaji SR, Sarode K (2023) Hybrid Recommendation System using Graph Neural Network and BERT Embeddings, arXiv preprint arXiv:2310.04878

Karthik RV, Ganapathy S (2021) A fuzzy recommendation system for predicting the customers interests using sentiment analysis and ontology in e-commerce. Appl Soft Comput 108:107396

Lai CH, Tseng KC (2022) Applying deep learning models to analyze users' aspects, sentiment, and semantic features for product recommendation. Appl Sci 12(4):2118

Lei X, Qian X, Zhao G (2016) Rating prediction based on social sentiment from textual reviews. IEEE Trans Multimedia 18(9):1910–1921

Li X, Xie H, Chen L, Wang J, Deng X (2014) News impact on stock price return via sentiment analysis. Knowl Based Syst 69:14–23

Meza J, Terán L, Piaún A, Tomalá M (2018) A fuzzy-based recommender system for public tax payment, In proceedings of 2018 International Conference on eDemocracy & eGovernment (ICEDEG), 235–240, IEEE

Mirjalili S (2016) Sca: a sine cosine algorithm for solving optimization problems. Knowl Based Syst 96:120–133

Munuswamy S, Saranya MS, Ganapathy S, Muthurajkumar S, Kannan A (2021) Sentiment Analysis Techniques for Social Media-Based Recommendation Systems. Natl Acad Sci Lett 44(3):281–287

Phalguna Krishna ES, Bhargava Ramu T, Krishna Chaitanya R, Sitha Ram M, Balayesu N, Prasad Gandikota H, Jagadesh BN (2025) Enhancing E-commerce recommendations with sentiment analysis using MLA-EDTCNet and collaborative filtering, Scientific Reports 5 6739

Qomariyah NN, Fajar AN (2019) Recommender system for e-learning based on personal learning style, In proceedings of 2019 international seminar on research of information technology and intelligent systems (ISRITI), pp. 563–567, IEEE

Ray B, Garain A, Sarkar R (2021) An ensemble-based hotel recommender system using sentiment analysis and aspect categorization of hotel reviews. Appl Soft Comput 98:106935

Rozinek O, Mareš J (2021) The duality of similarity and metric spaces. Appl Sci 11(4):1910

Scarselli F, Gori M, Tsoi AC, Hagenbuchner M, Monfardini G (2008) The graph neural network model. IEEE Trans Neural Networks 20(1):61–80

Shukla S, Balasubramanian S, Pavlović M (2016) A generalized Banach fixed point theorem. Bull Malays Math Sci Soc 39:1529–1539

Thakur RK, Deshpande MV (2019) Kernel Optimized-Support Vector Machine and Mapreduce framework for sentiment classification of train reviews. Int J Uncertain Fuzziness Knowl-Based Syst 27(06):1025–1050

Trojovský P, Dehghani M (2022) A new optimization algorithm based on mimicking the voting process for leader selection. PeerJ Comput Sci 8:e976

Trojovský P, Dehghani M (2023) Migration Algorithm: A New Human-Based Metaheuristic Approach for Solving Optimization Problems. CMES-Comput Model in Eng Sci 137:2

Wang J, Chen Z (2024) SPCM: A Machine Learning Approach for Sentiment-Based Stock Recommendation System, IEEE Access, 12

Yang Z, Yang D, Dyer C, He X, Smola A, Hovy E (2016) Hierarchical attention networks for document classification, In Proceedings of the 2016 conference of the North American chapter of the association for computational linguistics: human language technologies, pp. 1480–1489