

A LITERATURE SURVEY ON RECOMMENDATION SYSTEMS BUILD ON DEEP LEARNING TECHNIQUES

B. Sunitha, B. Kranthi Kiran

Assistant Professor of Information Technology IT, BVRIT, B V Raju Institute of Technology, Narsapur, Medak, Telangana.

ORCID ID: 0009-0002-2278-7572,

²Professor of Computer Science and Engineering, JNTUH University College of Engineering Hyderabad (JNTUH UCEH).

sunitha.b@bvr.it.ac.in , kranthikiran9@gmail.com

Abstract

In today's world we are finding huge information in all most every domain, due drastically increase in digitalization. This scenario creating a serious problem called information overhead. To solve this problem different business creating their own search facilities to get the information whatever they are looking for, still it is not possible to achieve a good precision in the results. Recommendation systems are the frameworks which uses different algorithms to filter the data as per user requirement and produce a relevant set of recommendations. These kinds of systems are very much useful in the domains like E-Commerce, Books, Music, Movies etc but still these recommendation systems are facing problems like Cold start, New user etc . In this paper we are proposing An improved recommendation frame work which consists of product to user recommendation through Self-Attention based Generative Adversarial Capsule Network optimized with coyote optimization algorithm. Apart from that personalized add recommendation implementing through Auto-Metric Graph Capuchin Search Neural Network model. Finally in this frame work other user feedback was considered in the form of ratings and processed using Binarized Spiking Volcano Eruption Neural Network. This improved frame work definitely changes the land scape of the eco system.

Keyword: Recommendation systems, Deep learning, E-Commerce, Neural Network model Generative Adversarial Capsule Network, Cold start problem.

1.Introduction

Customers spend a lot of time and energy researching items and services through online retailers since there's so many options with many attributes. One possible approach to fixing this issue is to implement a recommender system. With the purpose of assisting users in managing information overload and making tailored suggestions. Helping consumers discover relevant products from a big pool of objects is a major challenge in this space, and recommender systems have come up as a significant solution. For more than 20 years, algorithms like these are suggesting things across many different fields, including media, academia, employment, and social networks. A number of main recommendation techniques have been created and investigated over the years. Among them, you may find content-based filtering (CBF) and a number of hybrid approaches. Online businesses like Amazon, Netflix, LinkedIn, Twitter, and Facebook rely heavily on recommender algorithms these days.

Basic so-called memory-based CF approaches used by early CF systems like GroupLens to provide predictions for recommendations depend on the levels of similarity computed between individuals or things using user's rating data. Whereas, when data is scarce and typical items are few, memory-based CF approaches provide incorrect similarity scores. A number of model-based CF techniques have been studied in an effort to overcome this constraint and improve prediction performance. The issue of scalability arises when computing resources reach unreasonably high levels, which model-based CF algorithms will encounter even as they attempt to resolve the sparsity problem, which becomes more problematic when the number of people and things increases enormously. In most cases, consumers make their thoughts known without explicitly stating them by referring to certain product features. On the other hand, the avatars in most conventional recommender systems just take into account past user ratings and exclude any characteristics. In order to improve the prediction accuracy, many hybrid recommender systems were created. These algorithms blend attribute data with previous rating data. Both qualities and previous ratings are thought to have substantial relevance in estimating the prediction function for recommendations based on the given experimental findings. Furthermore, consumers in the actual world have boundless and unexpected wants, and their tastes could change even within the same category of goods. As an example, one user could be interested in purchasing large, pricey toys, while another would prefer smaller, more affordable books. Thus, it's best to find out what people

like according to product features in each area independently. We first boost scalability and decrease issue dimensions using this strategy, and then we improve suggestion quality.

1.1 Types of Recommender systems:

Collaboration filtering, content-driven recommendation systems, and hybrid recommendation systems are just a few examples of the many varieties of referral systems available. User input, either implicitly or explicitly, is the foundation of content-based recommendation systems, which then utilize that data to generate suggestions. Collaborative filtering relies on the premise that people and various products may be compared for similarities in order to generate suggestions. To provide product recommendations, hybrid recommendation systems employ a mix of content-based and collaborative recommendation approaches. Figure 1 shows the recommendation methods in detail.

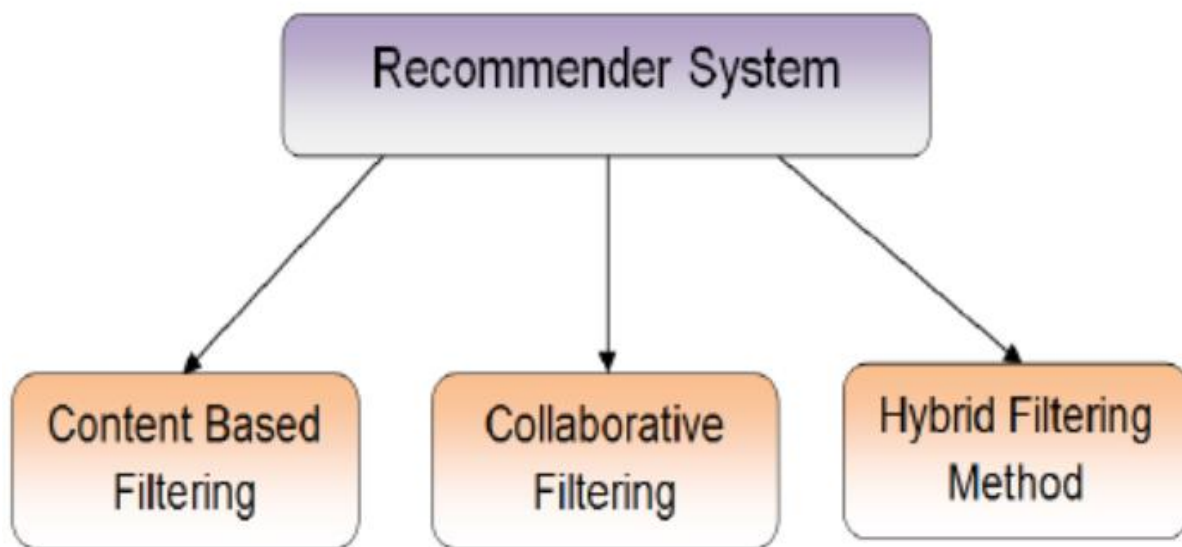


Fig.1 Different Types of Recommendation Systems

1.2 Different Generations of Recommendation systems:

There are three main generations of recommendation systems, each built on a different methodology. The very first generation relies on knowledge-based techniques, the subsequent one on matrix factorization, and the third regarding advanced deep learning algorithms. Figure 2 displays comprehensive data on the generations.

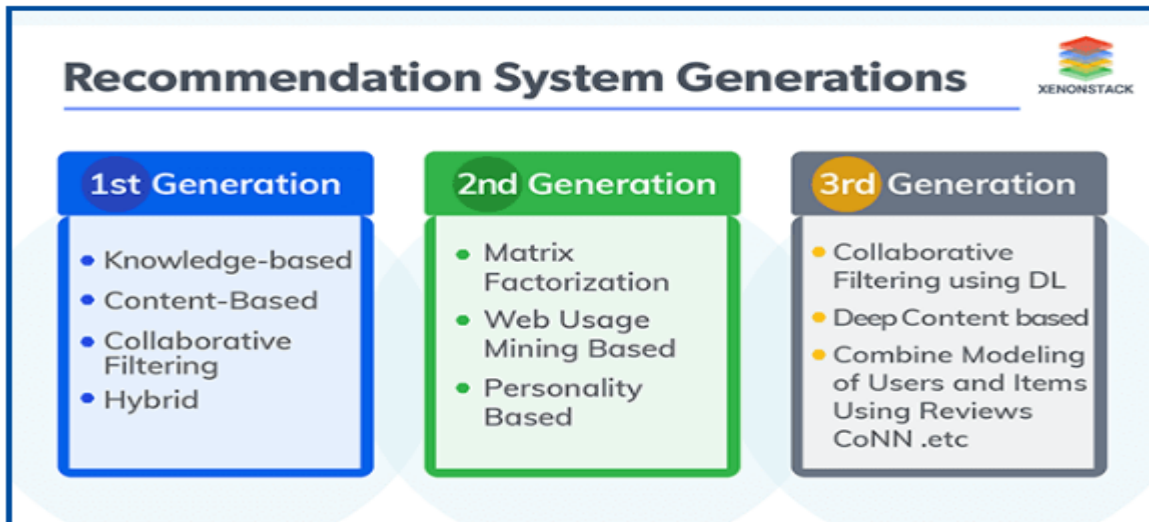


Fig.2 Different Generations of Recommendation Systems

2. Literature Survey

This section evaluated some of the most recent studies on online product suggestion, which is an area that sees a lot of study.

Another online product selection method was created by Huang et al. [16] in 2022 for company marketing purposes; it is now being used by various online media with e-commerce components. Overall gated recurrent modules for this study uses matrix factoring as well as non-negative matrix factoring methods to predict the global and long-term purchasing habits of consumers. After receiving the gathered dormant user & product characteristics, the Broyden Fletcher Goldfarb Shanno algorithm follows in order to present the finalized items to customers. The anticipated state may be used to differentiate dependencies with gated recurrent units.

In 2021, Feng et al., [17] established a grading system to assess user tastes, anticipate future needs, and provide tailored service recommendations. This study introduces a novel CF ranking model which takes a rating-oriented method known as Probabilistic Matrix Factorization (PMF) and combines them with a pairwise ranking-oriented strategy termed Bayesian Personalized Ranking (BPR). Explicit and implicit feedback data are used by this approach.

In 2021, Tahmasebi et al., [18] proposed a recommendation system which, according to theory, should be able to tailor its recommendations to the specific needs of each user by analysing their past behaviour and interests. Considering the benefits of human social impact, content-based filtering, and collaborative filtering, a hybrid social recommender system built around deep autoencoder networks is presented. Based on their online behavior and personality qualities, every user's social impact is calculated. Both the Open Access Movie Database and Movie Tweeting contributed to the databases.

In 2021, Maheswari et al. [19] included the mobile app version into a hybrid app recommendation architecture. The newly developed framework, known as the "Probabilistic Evolution based Version Recommendation Model (PEVRM)", combines the concepts of Probabilistic Matrix Factorization (PMF) and Version Evolution Progress Model (VEPM)." By analyzing the App's version history, such innovative recommendation method may help mobile users quickly select the perfect App for a certain task. Initial cold-start difficulties may also be addressed with the help of this framework.

In 2019, Sharma et al., [20] proposed an approach that takes into account the user-provided contextual characteristic to enhance the post-filter strategy, overcome its drawbacks, and combine it alongside the pre-filter method. The experimental results further demonstrate that the proposed method improves the user's recommendation ranking and accuracy. This combination of methods eliminates the sparsity problem in the pre-filter algorithm and improves the performance of the proposed system compared to the traditional post-filter method.

In 2022, Sharma et al., [21] implemented the HSC recommender system using the Movie Lens dataset to demonstrate its efficacy and utility. Results from the HSC technique and a plethora of others are contrasted. We used precision, mean absolute error, recall, and accuracy as our performance metrics to evaluate the HSC collaborative movie recommender system. The results of the study on the Movie Lens dataset show that the proposed method has great promise for scalability, performance, and personalized movie recommendations.

In 2022, Agarwal et al., [22] has brought about a change towards MOOC platforms due to its transparency and adaptable "on-the-go" character, in addition to the hybrid recommendation system that has been used in online education with the growing significance of Technology



Enhanced Learning (TEL). Even though adaptive e-learning systems have been the subject of much research within the last decade, there remains a need for investigation into personalized learning in massive open online courses (MOOCs). This research delves into the topic of customization in a massive open online course (MOOC) environment, as well as how to build a knowledge-based recommendation engine that works on semantically linked use information that draws from several domain ontologies. By integrating SWRL-defined rules via cluster-based collaborative filtering, the recommendation system becomes a genuine hybrid recommendation system. Around its heart, this is a system that uses observed use characteristics to divide students into groups based on their predicted learning preferences, as outlined by the Felder Silverman Learning Style Model (FSLSM).

In 2020, Guo, Z. ,et.al [23] We need further study on recommender systems until we can use these in industrial IoT settings, since the Internet of Things (IoT) is experiencing an issue regarding information overload. Since the number of people using different social networks continues to rise, social recommendations (SoR) are going to play an important role in providing future Internet of Things (IoT) users with more practical personalized information offerings. Almost all of the existing study was able to examine and quantify correlations amongst user preferences and social connections, but it failed to take into account the correlations underlying item attributes that may have an even greater impact on the layouts of certain social groupings. This research proposes a social recommendation system (GNN-SoR) targeting the Internet of Things that is built on deep network neural networks to tackle this problem. To begin, we establish two separate, abstract spaces containing item as well as user attributes.

In 2020, Leong, L.Y,et.al[24] Confidence is a major concern in online shopping. Little is known regarding the elements that impact confidence in e-commerce, despite prior research addressing the link among trust and purchase intention. The purpose of this research is to identify the social support or social presence variables that impact e-commerce trust. compared to most business research, we employed a hybrid SEM-ANN approach that can discover non-compensatory correlations and non-linear relationships. Linear compensating models suggest that other variables may compensate from a factor shortage. Yet, linear models sometimes reduce consumer decision-making too much due to its complexity and lack of compensation. Using criteria sampling, 462 datasets of social commerce clients were

collected utilizing a mall intercept approach. Supporting people socially is more effective than providing them with knowledge alone.

In 2020, Yang, Y., et.al.,[25] were able to demonstrate operation-aware neural networks that could anticipate the user's reaction. The importance of learning interaction between features has been highlighted in several publications. A novel neural model called Operation-aware Neural Networks (ONN) has been proposed for various operations with the goal of automatically learning relationships between high-order features. Whether training in an offline or online setting, the findings demonstrate that ONN routinely surpasses the state-of-the-art models using two large real-world ad click/conversion datasets.

In 2020, Leong, L.Y., et.al.,[26] have shown a SEM-artificial neural network method for forecasting the reliability of internet advertisements. This research will assess the elements that impact trust by integrating a Trust Building Model into the ADTRUST scale. Instead of using linear models, that have become more common in the present literature, a method dubbed Structural Equation Modelling-Artificial Neural Network (SEM-ANN) was implemented. So, to understand how internet advertising builds confidence, the results using linear models were insufficient and wrong.

In 2020, Gharibshah, Z., et.al.,[27] online digital advertising relies heavily on consumer curiosity and behavior modeling. The study presents two deep learning-based frameworks enabling user interest modeling & click prediction: LSTMcp and LSTMip. Forecasting accurately the likelihood about a user clicking on an advertisement and the likelihood of a user clicking upon a certain sort of ad campaign represented the objective. Employ a long short-term memory (LSTM) network to acquire latent characteristics that indicate user interests in order to accomplish the aim of collecting page information shown to users within a temporal sequence.

In 2020, Saumya, et, al [28] demonstrated the recommendation-based helpfulness score prediction using a convolutional neural network. Based of the hundreds of reviews about this product which are presently accessible, this project aims to use review representations learning to anticipate which one will prove to be most valuable. The characteristics may be easily adjusted to any sort of review as they can be identified from the review text alone,

without any extra domain expertise. To make the forecast, a model of a two-layered convolutional neural network was used. This led to a rise in the mistake rate.

In 2020, Guo, et, al [29] Providing an emotional component from internet reviews impacts purchasing choices via recommendation-based positive suggestions. The research assumptions were tested empirically through a 106-person laboratory experiment that utilized a heuristic-systematic model to examine the impact of personal feelings on purchase decisions as well as the moderating role for emotional literature on non-emotional content and purchase decisions. A larger chance of purchase is associated with positive online customer evaluations compared to negative ones, according to the research. As a result, precision decreased.

In 2020, Guo, et, al [30] have offered a An analysis of client recommendations for airlines is conducted using a text mining technique applied to online customer reviews. This method provides the airline industry with a state-of-the-art framework for measuring customer satisfaction. Read OCRs (Online Customer Reviews) and use text mining to identify suggestions. Learn about 400 airlines plus 170 countries' worth of passengers by perusing this database with nearly 55,000 OCRs. Here, accuracy was diminished.

In 2020, Xu, et, al [31] have shown how to use a naive Bayes ongoing learning framework to analyze product evaluations for online shopping and provide recommendations. The purpose of this study is to offer an ongoing naive Bayes learning strategy for sentiment analysis of product evaluations on large-scale, multi-domain internet marketplaces. The original naive Bayes model's outstanding computing efficiency may be preserved by adapting its parameter estimation approach to an alternative constantly evolving style. Because of this, the level of complexity.

In 2020, Da'u et al., [32] has suggested an approach for making better recommendations by using deep learning-based aspect-based opinion mining (ABOM). Two stages are involved, including ABOM and rating prediction. To improve aspect extraction and rating generation, the first step is to use a multichannel deep convolutional neural network (MCNN) to determine the polarity of user sentiment on various aspects. Step two involves feeding the aspect-specific ratings into the TF machine to overall rating prediction. In comparison to the

baseline methodologies, the experimental findings demonstrate the efficacy of the suggested model.

In 2020, Zhou [33] developed a distributed expression plus recurrent neural network–based recommendation method. This study improves upon previous work with recurrent neural networks by adding a temporal frame to regulate the transmission of data from the network's hidden layers. In terms of recommendation system accuracy, results from experiments demonstrate that the suggested method outperforms the conventional recurrent neural network model.

In 2019, Zhang et al., [34] used cutting-edge deep convolutional neural networks (CNNs) to build a new learning-based architecture for DeepLink and video content-driven advertising. The initial step in detecting and retrieving garments from ad photos using state-of-the-art deep CNN models is to move them into our data domain. Following that, using our newly generated large-scale clothes datasets, train the associated models. We have conducted extensive experiments that prove our clothing-based video advertising technique is both feasible and effective.

In 2020, Kang, S., et.al.,[35] in internet broadcasting have devised a real-time ad suggestion system based on trees. The authors of this piece suggest a recommendation system that can provide targeted ads in real time. Tree models are generated by the proposed system using user historical data. In an effort to reduce the cost of preference prediction, HashMap enables quick tree searches. Using the characteristics that comprise the user's tree model for complicated preference prediction, the suggested technique standardizes their preferences. Lastly, put the suggested tree-based system of recommendations through its paces by conducting experiments to evaluate its performance.

3. Conclusion

In this thesis we are implementing a recommendation frame work using advanced deep learning algorithms to deliver user to product recommendation for reducing information overhead. Apart from that this frame work includes personalized add recommendation to covert browser to buyer. The major achievement in this work we are considering the existing customer feedback available in the form of ratings while recommending the products. This

improved frame work definitely change the land scape of this Eco system and creates comfort to customer as well as business owner.

References

- [1] Al Fararni, K., Nafis, F., Aghoutane, B., Yahyaouy, A., Riffi, J. and Sabri, A., 2021. Hybrid recommender system for tourism based on big data and AI: A conceptual framework. *Big Data Mining and Analytics*, 4(1), pp.47-55.
- [2] Wang, H.C., Jhou, H.T. and Tsai, Y.S., 2021. Adapting topic map and social influence to the personalized hybrid recommender system. *Information Sciences*, 575, pp.762-778.
- [3] Sharma, S., Rana, V. and Malhotra, M., 2022. Automatic recommendation system based on hybrid filtering algorithm. *Education and Information Technologies*, 27(2), pp.1523-1538.
- [4] Javed, U., Shaukat, K., Hameed, I.A., Iqbal, F., Alam, T.M. and Luo, S., 2021. A review of content-based and context-based recommendation systems. *International Journal of Emerging Technologies in Learning (iJET)*, 16(3), pp.274-306.
- [5] Singh, P.K., Pramanik, P.K.D., Dey, A.K. and Choudhury, P., 2021. Recommender systems: an overview, research trends, and future directions. *International Journal of Business and Systems Research*, 15(1), pp.14-52.
- [6] Jabeen, F., Maqsood, M., Ghazanfar, M.A., Aadil, F., Khan, S., Khan, M.F. and Mehmood, I., 2019. An IoT based efficient hybrid recommender system for cardiovascular disease. *Peer-to-Peer Networking and Applications*, 12(5), pp.1263-1276.
- [7] Maheswari, M., Geetha, S., Kumar, S.S., Karuppiyah, M., Samanta, D. and Park, Y., 2021. PEVRM: probabilistic evolution based version recommendation model for mobile applications. *IEEE Access*, 9, pp.20819-20827.
- [8] Tran, T.N.T., Felfernig, A., Trattner, C. and Holzinger, A., 2021. Recommender systems in the healthcare domain: state-of-the-art and research issues. *Journal of Intelligent Information Systems*, 57(1), pp.171-201.
- [9] Chen, R., Hua, Q., Chang, Y.S., Wang, B., Zhang, L. and Kong, X., 2018. A survey of collaborative filtering-based recommender systems: From traditional methods to hybrid methods based on social networks. *IEEE Access*, 6, pp.64301-64320.

- [10] Singh, P., 2022. Recommender Systems. In *Machine Learning with PySpark* (pp. 157-187). Apress, Berkeley, CA.
- [11] Chang, J.L., Li, H. and Bi, J.W., 2022. Personalized travel recommendation: a hybrid method with collaborative filtering and social network analysis. *Current Issues in Tourism*, 25(14), pp.2338-2356.
- [12] Dadhich, A. and Thankachan, B., 2022. Sentiment analysis of amazon product reviews using hybrid rule-based approach. In *Smart Systems: Innovations in Computing* (pp. 173-193). Springer, Singapore.
- [13] Stavrotheodoros, S., Kaklanis, N., Votis, K., Tzovaras, D. and Astell, A., 2022. A hybrid matchmaking approach in the ambient assisted living domain. *Universal Access in the Information Society*, 21(1), pp.53-70.
- [14] Harshvardhan, G.M., Gourisaria, M.K., Rautaray, S.S. and Pandey, M., 2022. UBMTR: Unsupervised Boltzmann machine-based time-aware recommendation system. *Journal of King Saud University-Computer and Information Sciences*, 34(8), pp.6400-6413.
- [15] Walek, B. and Fojtik, V., 2020. A hybrid recommender system for recommending relevant movies using an expert system. *Expert Systems with Applications*, 158, p.113452.
- [16] Suresh, A. and Carmel Mary Belinda, M.J., 2022. Online product recommendation system using gated recurrent unit with Broyden Fletcher Goldfarb Shanno algorithm. *Evolutionary Intelligence*, 15(3), pp.1861-1874.
- [17] Feng, J., Xia, Z., Feng, X. and Peng, J., 2021. RBPR: A hybrid model for the new user cold start problem in recommender systems. *Knowledge-Based Systems*, 214, p.106732.
- [18] Tahmasebi, H., Ravanmehr, R. and Mohamadrezai, R., 2021. Social movie recommender system based on deep autoencoder network using Twitter data. *Neural Computing and Applications*, 33(5), pp.1607-1623.
- [19] Maheswari, M., Geetha, S., Kumar, S.S., Karuppiah, M., Samanta, D. and Park, Y., 2021. PEVRM: probabilistic evolution based version recommendation model for mobile applications. *IEEE Access*, 9, pp.20819-20827.

- [20] Sharma, M., Ahuja, L. and Kumar, V., 2019. A hybrid context aware recommender system with combined pre and post-filter approach. *International Journal of Information Technology Project Management (IJITPM)*, 10(4), pp.1-14.
- [21] Sharma, B., Hashmi, A., Gupta, C., Khalaf, O.I., Abdulsahib, G.M. and Itani, M.M., 2022. Hybrid Sparrow Clustered (HSC) Algorithm for Top-N Recommendation System. *Symmetry*, 14(4), p.793.
- [22] Agarwal, A., Mishra, D.S. and Kolekar, S.V., 2022. Knowledge-based recommendation system using semantic web rules based on Learning styles for MOOCs. *Cogent Engineering*, 9(1), p.2022568.
- [23] Guo, Z. and Wang, H., 2020. A deep graph neural network-based mechanism for social recommendations. *IEEE Transactions on Industrial Informatics*, 17(4), pp.2776-2783.
- [24] Leong, L.Y., Hew, T.S., Ooi, K.B. and Chong, A.Y.L., 2020. Predicting the antecedents of trust in social commerce—A hybrid structural equation modeling with neural network approach. *Journal of Business Research*, 110, pp.24-40.
- [25] Yang, Y., Xu, B., Shen, S., Shen, F. and Zhao, J., 2020. Operation-aware neural networks for user response prediction. *Neural Networks*, 121, pp.161-168.
- [26] Leong, L.Y., Hew, T.S., Ooi, K.B. and Dwivedi, Y.K., 2020. Predicting trust in online advertising with an SEM-artificial neural network approach. *Expert Systems with Applications*, 162, p.113849.
- [27] Gharibshah, Z., Zhu, X., Hainline, A. and Conway, M., 2020. Deep learning for user interest and response prediction in online display advertising. *Data Science and Engineering*, 5(1), pp.12-26.
- [28] Saumya, S., Singh, J.P. and Dwivedi, Y.K., 2020. Predicting the helpfulness score of online reviews using convolutional neural network. *Soft Computing*, 24(15), pp.10989-11005.
- [29] Guo, J., Wang, X. and Wu, Y., 2020. Positive emotion bias: Role of emotional content from online customer reviews in purchase decisions. *Journal of Retailing and Consumer Services*, 52, p.101891.

- [30] Lucini, F.R., Tonetto, L.M., Fogliatto, F.S. and Anzanello, M.J., 2020. Text mining approach to explore dimensions of airline customer satisfaction using online customer reviews. *Journal of Air Transport Management*, 83, p.101760.
- [31] Xu, F., Pan, Z. and Xia, R., 2020. E-commerce product review sentiment classification based on a naïve Bayes continuous learning framework. *Information Processing & Management*, 57(5), p.102221.
- [32] Da'u, A., Salim, N., Rabi'u, I. and Osman, A., 2020. Recommendation system exploiting aspect-based opinion mining with deep learning method. *Information Sciences*, 512, pp.1279-1292.
- [33] Zhou, L., 2020. Product advertising recommendation in e-commerce based on deep learning and distributed expression. *Electronic Commerce Research*, 20(2), pp.321-342.
- [34] Zhang, H., Ji, Y., Huang, W. and Liu, L., 2019. Sitcom-star-based clothing retrieval for video advertising: a deep learning framework. *Neural computing and applications*, 31(11), pp.7361-7380.
- [35] Kang, S., Jeong, C. and Chung, K., 2020. Tree-based real-time advertisement recommendation system in online broadcasting. *IEEE Access*, 8, pp.192693-192702.
- [36]. Qiu, X., Zhang, L., Suganthan, P.N. and Amaratunga, G.A., 2017. Oblique random forest ensemble via least square estimation for time series forecasting. *Information Sciences*, 420, pp.249-262.
- [37]. Ramkumar, M., Lakshmi, A., Rajasekaran, M.P. and Manjunathan, A., 2022. Multiscale Laplacian graph kernel features combined with tree deep convolutional neural network for the detection of ECG arrhythmia. *Biomedical Signal Processing and Control*, 76, p.103639.
- [38]. Sun, G., Ding, S., Sun, T. and Zhang, C., 2021. SA-CapsGAN: using capsule networks with embedded self-attention for generative adversarial network. *Neurocomputing*, 423, pp.399-406.
- [39]. Abaza, A., El-Sehiemy, R.A., Mahmoud, K., Lehtonen, M. and Darwish, M.M., 2021. Optimal estimation of proton exchange membrane fuel cells parameter based on coyote optimization algorithm. *Applied Sciences*, 11(5), p.2052.

- [40]. Lin, F., Liang, Z., He, J., Zheng, M., Tian, S. and Chen, K., 2022. StructToken: Rethinking Semantic Segmentation with Structural Prior. *arXiv preprint arXiv:2203.12612*.
- [41]. Tao, X., Ren, C., Li, Q., Guo, W., Liu, R., He, Q. and Zou, J., 2021. Bearing defect diagnosis based on semi-supervised kernel Local Fisher Discriminant Analysis using pseudo labels. *ISA transactions, 110*, pp.394-412.
- [42]. Yang, Y., Wang, S., Zeng, N., Duan, W., Chen, Z., Liu, Y., Li, W., Guo, Y., Chen, H., Li, X. and Chen, R., 2022. Lung Radiomics Features Selection for COPD Stage Classification Based on Auto-Metric Graph Neural Network. *Diagnostics, 12(10)*, p.2274.
- [43]. Braik, M., Sheta, A. and Al-Hiary, H., 2021. A novel meta-heuristic search algorithm for solving optimization problems: capuchin search algorithm. *Neural computing and applications, 33(7)*, pp.2515-2547.
- [44]. Zhao, T. and Wang, Y., 2020. Non-parametric simulation of non-stationary non-gaussian 3D random field samples directly from sparse measurements using signal decomposition and Markov Chain Monte Carlo (MCMC) simulation. *Reliability Engineering & System Safety, 203*, p.107087.
- [45]. Khare, S.K. and Bajaj, V., 2020. Constrained based tunable Q wavelet transform for efficient decomposition of EEG signals. *Applied Acoustics, 163*, p.107234.
- [46]. Kheradpisheh, S.R., Mirsadeghi, M. and Masquelier, T., 2022. Bs4nn: Binarized spiking neural networks with temporal coding and learning. *Neural Processing Letters, 54(2)*, pp.1255-1273.
- [47]. Hosseini, E., Sadiq, A.S., Ghafoor, K.Z., Rawat, D.B., Saif, M. and Yang, X., 2021. Volcano eruption algorithm for solving optimization problems. *Neural Computing and Applications, 33(7)*, pp.2321-2337.