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A Network Layer Dependency-Based Product Recommendation Utilizing Proposed Adaptive Filtering Of Nlp With Cbcrpoa-Shcgru Approach

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Abstract:
The recommendation system plays a major role in several online services. Dependency analysis between inter and intra-layer-centric recommendation enhancement wasn't concentrated in any of the prevailing works. Thus, a Cosine-Bray-Curtis-based Red Piranha Optimization Algorithm Soft Hexpo Clipping Gated Recurrent Unit (CBCRPOA-SHCGRU) networks-centric recommendation system is proposed in this work. Initially, the social graph is constructed from the network data. Then, by using Density-based Scree Spatial 2P Clustering of Applications with Noise (D2S2PCAN), a subset node is created. Next, for the created subset node, inter and intra-layer links are predicted. In the meantime, network attributes are extracted from the graph. Subsequently, by utilizing Truncated Gautri Gaussian Fuzzy (TG^2Fuzzy), the influential node is identified. Moreover, inter and intra-layer links are predicted for the identified influential node. In contrast, rating and review data about the product are taken and pre-processed. Next, polarity is identified; rank is estimated using polarity-identified data, user ratings, predicted inter and intra-layer links, identified influential nodes, and network attributes. In addition, the pre-processed data are inputted to word embedding by utilizing Bidirectional Encoder Representations from Transformer (BERT). Finally, for the recommendation system, word embedding output, rank calculation, and extracted network attributes are given as input to the CBCRPOA-SHCGRU. Experimental analysis displays that R-squared (R^2) and Mean Error (ME) achieved by the proposed technique are 0.526396 and 0.326541, correspondingly.
Background: *Product recommendation has advanced with Deep Learning (DL) techniques like Neural Collaborative Filtering (NCF), which combines user and item embeddings for complex interactions. However, challenges such as high computational costs, overfitting, and the failure to identify key influencer nodes limit these methods' effectiveness. The proposed work addresses these issues by introducing new techniques to enhance the accuracy, quality, and scalability of product recommendations, overcoming the limitations faced by previous approaches.*
Results: *The proposed CBCRPOA-SHCGRU technique outperforms conventional methods, achieving 98.65% accuracy and 98.21% precision. It also shows lower MSE, RMSE, MAE, and MAPE values, effectively addressing overfitting and complexity issues. Compared to other approaches, the proposed method demonstrates superior performance in link prediction and product recommendation accuracy.*
Conclusion: *The proposed method successfully identifies influential nodes, achieving 98.65% accuracy in inter- and intra-layer link prediction, with an R^2 of 0.526396 and ME of 0.326541 for product recommendations. Future work will focus on enhancing recommendation accuracy by incorporating product-centric multimedia advertisements to improve the recommendation system's efficiency.*
Keywords: *Cosine-Bray-Curtis based Red Piranha Optimization Algorithm Soft Hexpo Clipping Gated Recurrent Unit networks (CBCRPOA-SHCGRU), Truncated Gautri Gaussian Fuzzy (TG^2Fuzzy), Density-based Scree Spatial 2P Clustering of Applications with Noise (D2S2PCAN), Bidirectional Encoder Representations from Transformer (BERT), Natural Language Processing (NLP), Product recommendation system, and Adaptive filtering technique.*

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I. Introduction

A software tool that recommends items to users centered on their characteristics, behaviors, or preferences is called a Recommender System (RS) (Peng et al., 2022). Mostly, RSs are utilized in e-commerce and streaming platforms for personalizing recommendations regarding user experience and ratings (Daza et al., 2024). Here, the social networks followed by the Product Recommender System (PRS) recommend products based on their social connections, interactions, and preferences within a network (Rajput et al., 2024, Shao et al., 2021). But, inaccurate recommendations are caused because of drawbacks like privacy concerns and potential biases from echo chambers (Stöckli&Khobzi, 2021).

Neural Collaborative Filtering (NCF) that integrates user (Siji Rani et al., 2024) and item embeddings for capturing complex interactions was a prevailing Deep Learning (DL) approach utilized for product recommendation (Vedavathi&SuhasBharadwaj, 2022). Here, sequential data are leveraged by Recurrent Neural Networks (RNNs) for personalized recommendations (Yu et al., 2021). But, these approaches have drawbacks, such as computational costs and potential overfitting on sparse data (Halder et al., 2024, Almahmood&Tekerek, 2022). Moreover, the influencer node between inter and intra-layer dependencies isn't identified in this work, which leads to inaccuracies in PRS. Thus, various techniques are leveraged in the proposed work for accurate recommendation of products.

Problem Statement

Prevailing works' drawbacks are listed further:

- Prevailing works didn't identify the influencer nodes across inter and intra-layer dependencies, which limited the accurate RS.
- In (Elahi et al., 2023), the product was recommended by utilizing content-based filtering alone, which resulted in only low-quality product recommendations.
- The network node and complexity were not differentiated and reduced in (Khelloufi et al., 2024), which led to scalability issues by degrading the entire framework.
- Prevailing techniques didn't examine the trust correlation between other users and other products, which created data sparsity during training.

The proposed work's objectives are explained below:

- In the proposed work, the influencer nodes are effectively identified using TG²Fuzzy.
- The ratings and review data are collected and processed for high-quality product recommendations.
- By using the D2S2PCAN technique, the network node and complexity are differentiated and reduced.
- The proposed work calculated trust correlation for data sparsity reduction during training.

The rest of the paper is arranged as: The related works are discussed in Section 2, the proposed technique is explained in Section 3, the results and discussion are given in Section 4, and lastly, the proposed work is concluded in Section 5 with future development.

II. Related Work

(Elahi et al., 2023) presented a hybrid recommendation system centered on advanced techniques. Primarily, the data was acquired from the Amazon dataset. Then, for the recommendation, BERT and Principal Component Analysis (PCA) were utilized. According to the experiment outcome, the propounded model achieved superior outcomes. But, as only content-based filtering was concentrated, low-quality recommendation systems might be present.

(Khelloufi et al., 2024) propounded a latent-centric Social Internet of Things (SIoT) recommendation system. At first, the input data were pre-processed. Next, the graph was constructed. As per the result, this system achieved higher accuracy. But, network nodes were present in different sizes that failed to differentiate the networks, thus resulting in increased network complexity.

(Da'u et al., 2020a) recommended a recommendation system using aspect-centric opinion mining and DL approaches for enhancing the recommendation process's accuracy. Experimental outcomes displayed that this research model attained significant improvements compared with the baseline techniques. However, the research work wasn't reliable since it focused less number of source information.

(Da'u et al., 2020b) propounded a weighted aspect-centric opinion mining by utilizing the DL technique. Primarily, the aspect-centric opinion mining model extracted the product aspects from the review text. The experimental analysis assessed the research model's performance. This model attained better results. Nevertheless, it had overfitting issues, which affected the framework's performance.

(Chiu et al., 2021) presented a personalized recommendation model in a smart product service system centered on an unsupervised learning model. For examining the user-provided data, the unsupervised NLP model was utilized. As per the experimental evaluation, this model attained higher performance. Yet, the in-depth information of users was not covered, which affected the model's performance.

III. Proposed Product Recommendation System Using Cbcrpoa-Shcgru

In this work, a product recommendation system is proposed by utilizing advanced techniques. Figure 1 presents the proposed research's structural representation,

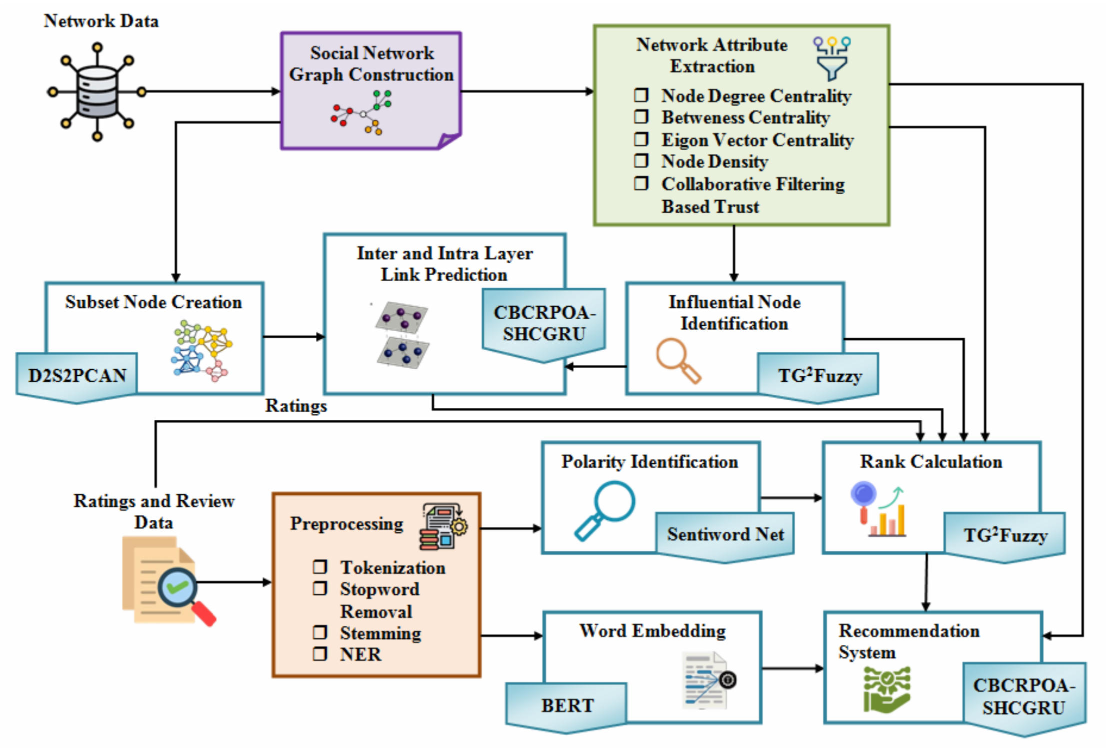


Figure 1: Structural representation of the proposed system

Network data

Initially, the network data is gathered. It consists of the social network's user details. The acquired data is indicated as,

$$\aleph_{ob} = \{\aleph_1, \aleph_2, \ldots\ldots, \aleph_n\} \tag{1}$$

Here, $\aleph_{ob}$ is the collected dataset, and $\aleph_n$ is the n-number of gathered data.

Social network graph construction

Here, to extract the depth information of the network, the graph is constructed based on the collected network data.

$$G_g = (V_{tx}, E_{gs}) \tag{2}$$

Here, G_g is the constructed graph, and V_{tx} and E_{gs} are the vertex and edges of the graph, correspondingly.

Subset node creation

Here, to enhance the recommendation system output, the user's subset node is created in G_g by the D2S2PCAN technique. The traditional DBSCAN technique efficiently creates the subset nodes centered on the density of connections within a region. Noise and merge problems are presented owing to the small radius value. Thus, this research work utilizes the Scree plot for calculating the distance between each point. Moreover, incorrect MinPts lead to under or over-clustering. Thus, for solving this problem, 2P MinPts are used. Primarily, the neighborhood around a G_g is determined based on the Scree plot, which is calculated based on the cumulative variance between the G_g and is displayed in equation (3),

$$\beta_{eps} = \frac{\sum G_g}{\sum \varpi_{dg}^{cv}(G_g)} \tag{3}$$

Here, β_{eps} is the radius value of constructed graph plots, and $\varpi_{dg}^{cv}(G_g)$ is the diagonal element of the covariance matrix for the graph G_g. Then, the minimum number of MinPts is chosen centered on the β_{eps}. Here, two MinPts are chosen to enhance the clustering efficiency.

$$2MinPts \geq G_g + 1 \tag{4}$$

Lastly, the created subset node output is indicated as Q_j.

Network attributes extraction

Here, the network attributes are extracted from G_g, namely node degree centrality, betweenness centrality, eigenvector centrality, node density, and collaborative filtering-centric trust.

$$\delta_{ex} = \{\delta_1, \delta_2, ..., \delta_{nq}\} \text{ (or) } \delta_i, \; i = 1,2,....,nq \tag{5}$$

Here, δ_{ex} is the extracted network attribute set, and δ_{nq} specifies the nq-number of extracted network attributes.

Influential node identification

To enhance the recommendation system using the TG²Fuzzy technique, the influential node of the social network is identified. Here, δ_{ex} is taken as the input. The traditional fuzzy provides efficient solutions for complex issues. But, the conventional technique had issues in membership function related to scaling factors and control issues. For solving this problem, the research work utilizes the Truncated Gautri Gaussian (TG²) membership function. Primarily, the membership function $\xi_A(\delta_i)$ is constructed in the fuzzification stage centered on equation (6),

$$\xi_A(\delta_i) = \begin{cases} 0 & if\ \delta_i < u \\ \dfrac{1}{1 + \exp\left(\dfrac{|\delta_i - v|}{c_w}\right)^{2\partial}} & if\ u \leq \delta_i \leq \kappa \end{cases} \tag{6}$$

Here, u and κ are the truncation limits, v signifies the center of the Gaussian function, and c_w and ∂ are control unit and shape unit, correspondingly. Next, a rule τ_{rl} is generated, which is expressed in equation (7),

$$\tau_{rl} = \begin{cases} \lambda_{il}, & \delta_{ex} == high \\ NI_{fl}, & \delta_{ex} == low \end{cases} \tag{7}$$

Here, λ_{il} is the influential node, and NI_{fl} is the non-influential node. Then, rule strength is determined in equation (8).

$$\tau_{rl} = \max(\xi_A(\delta_i), \xi_B(\delta_{i+1})) \tag{8}$$

The proposed TG²Fuzzy technique's pseudocode is expressed below,

Pseudocode: TG²Fuzzy

Input: δ_{ex}

Output: (λ_{il}, NI_{fl})

Begin

Initialize u, κ, v, c_w, and ∂

For each δ_{ex} **do**

Construct $\xi_A(\delta_i)$

If $(\delta_i < u)$ {

$\xi_A(\delta_i) = 0$

} else {

$$\xi_A(\delta_i) = \frac{1}{1 + \exp\left(\frac{|\delta_i - v|}{c_w}\right)^{2\partial}}$$

} **end if**
Generate rule
If $(\delta_{ex} == high)$ {
$\tau_{rl} = \lambda_{il}$
} **else** {
$\tau_{rl} = NI_{fl}$
} **end if**
End for
Return (λ_{il}, NI_{fl})
End

Lastly, the defuzzification process is handled.

Inter and intra-layer link prediction

Here, for inter and intra-layer link prediction, Q_j and λ_{il} are given as input to the CBCRPOA-SHCGRU. The traditional GRU technique takes less memory for large datasets, and it is supported for large-scale data. But, it had overfitting and vanishing gradient issues. For solving these issues, this research work utilizes an adaptive filtering approach like CBCRPOA. Moreover, for solving the vanishing gradient problem, the Soft Hexpo Clipping (SHC) activation function is utilized. Figure (2) exhibits the proposed CBCRPOA-SHCGRU's architecture,

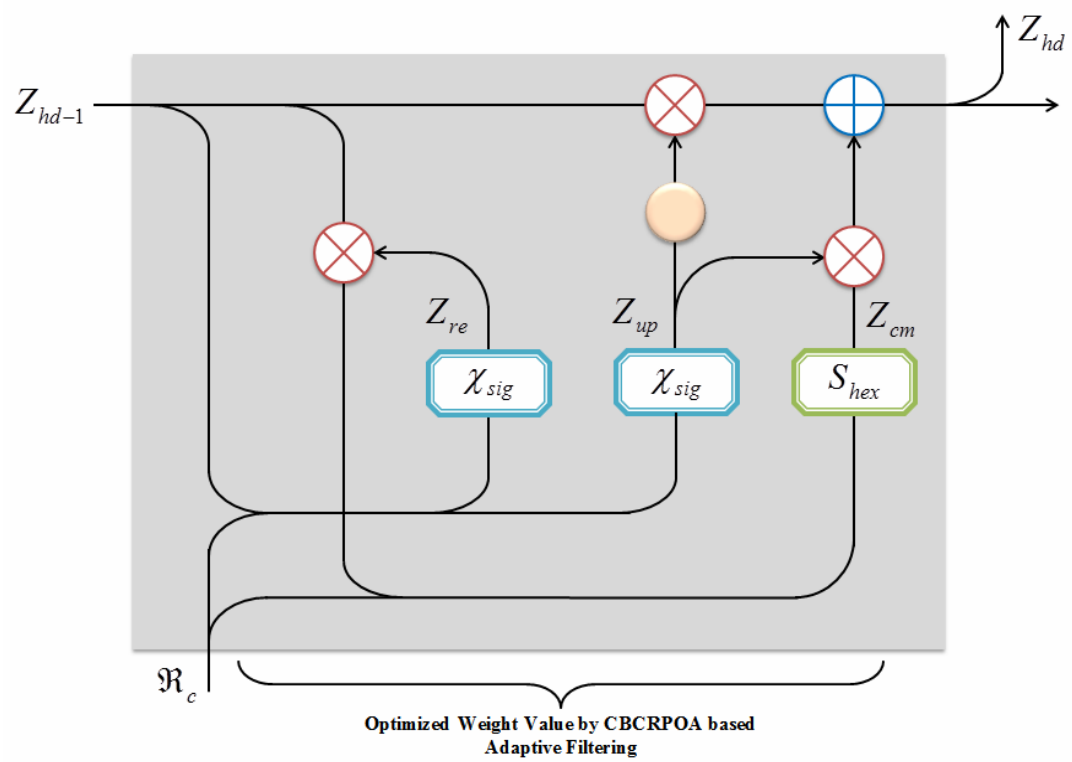


Figure 2: Structure of CBCRPOA-SHCGRU

Primarily, the derivation for the update gate Z_{up} is expressed in equation (9),

$$Z_{up} = \chi_{sig}\left(\wp_{up} . [Z_{hd-1}, \Re_c] + \;_{up}\right) \qquad (9)$$

Where, χ_{sig} is the sigmoid activation function, $\Re_c$ depicts the combination of Q_j and λ_{il}, Z_{hd-1} signifies the previous hidden state, and $\wp_{up}$ and $_{up}$ are the weight and bias values of the update gate, correspondingly. Next, reset gate Z_{re} derivation is expressed in equation (10),

$$Z_{re} = \chi_{sig}\left(\wp_{re}.\left[Z_{hd-1}, \Re_c\right] + \ _{re}\right) \quad (10)$$

Where, $\wp_{re}$ and $_{re}$ are the reset gate's weight and bias values, correspondingly. Equation (11) presents the expression of current memory Z_{cm}.

$$Z_{cm} = S_{hex}\left(\wp_{cm}.\left[Z_{re} \otimes Z_{hd-1}, \Re_c\right] + \ _{cm}\right) \quad (11)$$

Here, S_{hex} is the soft hexpo clipping activation function, which is given as,

$$S_{hex} = \frac{\Re_c}{1 + \exp\left(-a\left(\Re_c - b\right)\right)} \quad (12)$$

Here, a and b are the control parameters. Hidden state is derived as,

$$Z_{hd} = \left(1 - Z_{up}\right) \otimes Z_{hd-1} + Z_{up} \otimes Z_{cm} \quad (13)$$

Where, the weight values of all gates are initialized by using the CBCRPOA technique. The traditional RPOA technique had a perfect ability to bypass local optima. But, encircling pray was done by utilizing Manhattan distance. While applying this optimization model in high-dimensional spaces, it becomes difficult to visualize. Thus, the Cosine-Bray-Curtis distance is utilized. Initially, the weight values of all gates are signified as $\wp$, and it is regarded as red piranha. Next, the position of the population is randomly initialized, and the fitness is evaluated. Here, maximum accuracy $\max\left(\ _{ccy}\right)$ is considered as a fitness function η_{fft},

$$\eta_{fft} = \max\left(\ _{ccy}\right) \quad (14)$$

After fitness evaluation, the position of the population is updated $_{t+1}$ based on equations (15) to (17),

$$_{t+1} = L_{sco}^{t} - \Phi_c.G_{ds} \quad (15)$$

$$G_{ds} = \frac{1 - Cos(\wp) + BC(\wp)}{2} \quad (16)$$

$$\Phi_c = q_1 * \left(-2 + q_2\right) + \left(1 - q_1\right)\left(1 + q_3\right) \quad (17)$$

Here, L_{sco}^{t} is the position vector of the scout, G_{ds} is the distance between the population, $Cos(\wp)$ signifies the cosine similarity function of the population, $BC(\wp)$ depicts the Bray Curtis similarity, Φ_c is the coefficient, and q_1, q_2, and q_3 are the random vectors. The proposed CBCRPOA-SHCGRU's pseudocode is expressed below,

Pseudocode: CBCRPOA-SHCGRU

Input: $\Re_c$

Output: υ_{cc}

Begin

Initialize Z_{up}, Z_{re}, Z_{cm}, Z_{hd}, and S_{hex}

For each $\Re_c$ **do**

Derive update gate

Derive reset gate

Derive $Z_{cm} = S_{hex}\left(\wp_{cm}.\left[Z_{re} \otimes Z_{hd-1}, \Re_c\right] + \ _{cm}\right)$

Estimate weight value by CBCRPOA

#CBCRPOA

Evaluate η_{fft}

Update position

If $\eta_{fft}\left(\ _{t+1}\right) \geq \eta_{fft}$ {

Update by, $_{t+1} = L^{t}_{sco} - \Phi_c . G_{ds}$
} else {

Consider $_t$
} end if
End for

Return υ_{cc}
End

Lastly, the obtained inter and intra-link layer of the user is signified as υ_{cc}.

Ratings and review data

Here, the product's rating and user review are considered. The collected data μ_{cl} is given as,

$$\mu_{cl} = \{\mu_1, \mu_2, ..., \mu_{rk}\} \tag{18}$$

Here, μ_{rk} depicts the rk -number of collected data.

Pre-processing

Here, μ_{cl} is pre-processed for reducing error. Initially, μ_{cl} is split into tokens. Next, stop words are removed. Then, stemming is handled, and the Named Entity Recognition (NER) is executed for identifying the category of the word. The pre-processed output is given as X_{gg}.

Polarity identification

Here, the polarity of the sentence is identified from X_{gg} by using the Sentiword Net dictionary and is determined in equation (19),

$$P_{score} = X_{gg}(po, ne, ob) \tag{19}$$

Here, P_{score} is the polarity score, and po, ne, and ob are the positive, negative, and objective score values of X_{gg}.

Rank calculation

Here, the obtained P_{score}, user rating uu_r from μ_{cl}, υ_{cc}, λ_{il}, and δ_{ex} are inputted to the TG[2]Fuzzy method to estimate the rank. Section 3.5 describes the TG[2]Fuzzy technique. The rule for rank calculation RA_{ru} is derived in equation (20),

$$RA_{ru} = \begin{cases} H_{ig}(K), & P_{score}, \mu_{cl}, \lambda_{il}, \upsilon_{cc}, \delta_{ex} == high \\ L_{ow}(K), & P_{score}, \mu_{cl}, \lambda_{il}, \upsilon_{cc}, \delta_{ex} == low \end{cases} \tag{20}$$

Here, $H_{ig}(K)$ signifies the high rank K, $L_{ow}(K)$ is a low rank, and rank output is indicated as O_R.

Word embedding

Here, the words of X_{gg} are transformed into numerical values centered on the BERT technique, which understands the context around words and sentences. Primarily, the attention mechanism Att is derived for X_{gg} centered on derivation (21),

$$Att = \sigma\left(\frac{(X_{gg})^T}{\sqrt{\alpha}}\right) \tag{21}$$

Here, σ and α are the sigmoid activation function and dimension, correspondingly, and T is the transpose function. Here, α is given as,

$$\sigma = \frac{e^{Att}}{\Sigma e^{Att}} \tag{22}$$

Here, e is the exponential factor. The word embedded output is depicted as y_{em}.

Recommendation system

Here, O_R, y_{em}, and δ_{ex} are inputted to the CBCRPOA-SHCGRU method for the recommendation system. Section 3.6 describes the CBCRPOA-SHCGRU, and the recommendation system's output is signified as F_{rs}.

IV. Results And Discussion

Here, the proposed technique's performance assessment is analogized with prevailing approaches and related works. The entire work is implemented in the python.

Dataset Description

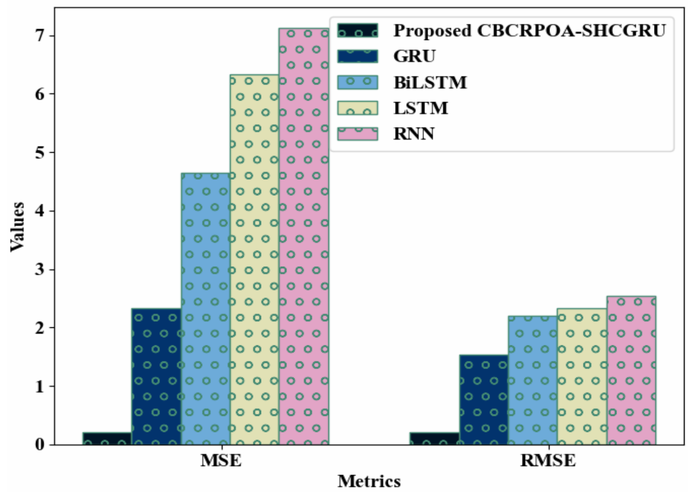
In the proposed work, two datasets, namely Social Recommendation Data (SRD) and MultiLayer Social Network Dataset (MLSND) gathered from publicly available sources are used. Hence, Table 1 explains the number of data utilized for the proposed work,

Table 1: Dataset Description

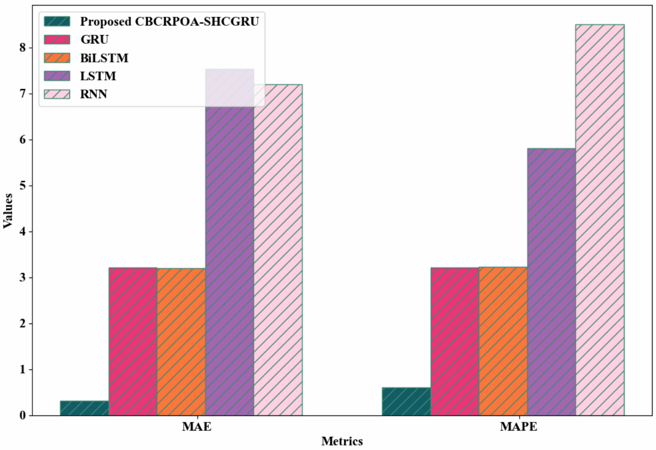
Datasets	Training (80%)	Testing (20%)
SRD	152,114	38,028
MLSND	129769	32442
Total	281883	70470

Performance Analysis of the Proposed Work

This section analogizes the performance of the proposed CBCRPOA-SHCGRU, TG²Fuzzy, and D2S2PCAN with conventional approaches.



(a)



(b)

Figure 3: Comparative Analysis based on (a) MSE, RMSE (b) MAE and MAPE

Figures 3 (a) and (b) depict the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) of the proposed CBCRPOA-SHCGRU and prevailing GRU, Bidirectional-Long Short Term Memory (Bi-LSTM), LSTM and RNN approaches. Here, the proposed CBCRPOA-SHCGRU achieved minimum MSE (0.214578), RMSE (0.203652), MAE (0.326014), and MAPE (0.602147) values. Here, CBCRPOA-SHCGRU effectively processes large datasets by utilizing CBCRPOA and SHC approaches, which solve overfitting vanishing gradient issues. But, the conventional approaches display maximum MSE, RMSE, MAE, and MAPE values, which degrades the entire work process.

Table 2: R^2 and ME validation

Techniques	R^2	ME
Proposed CBCRPOA-SHCGRU	0.526396	0.326541
GRU	3.214578	3.201453
Bi-LSTM	3.547898	4.320147
LSTM	5.256398	7.320635
RNN	10.124578	10.210632

Table 2 displays that the R^2 and ME for the proposed CBCRPOA-SHCGRU are 0.526396 and 0.326541, correspondingly. When analogized to the proposed CBCRPOA-SHCGRU, the prevailing GRU, Bi-LSTM, LSTM, and RNN had maximum average R^2 and ME values of 5.535863 and 6.26321675, correspondingly, which affects the accurate recommendation process.

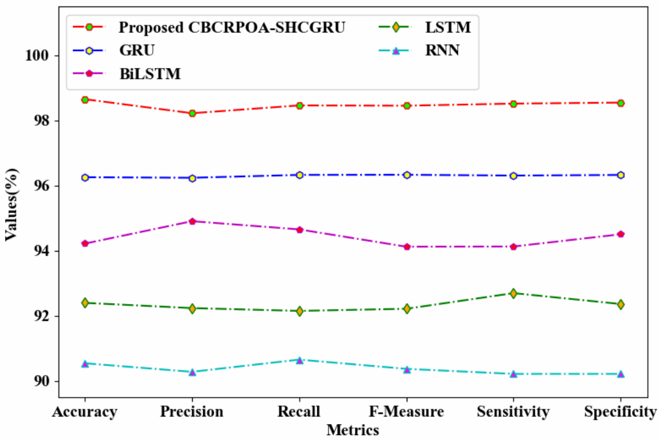


Figure 4: Performance Analysis of the Proposed CBCRPOA-SHCGRU

In Figure 4, performance analysis of the proposed CBCRPOA-SHCGRU and conventional GRU, Bi-LSTM, LSTM, and RNN approaches are exhibited. The proposed work achieved high accuracy (98.6507%), precision (98.2195%), recall (98.4595%), f-measure (98.4512%), specificity (98.5471%), and sensitivity (98.5147%). But, the conventional approaches achieved low performance, thus leading to inaccurate link predictions.

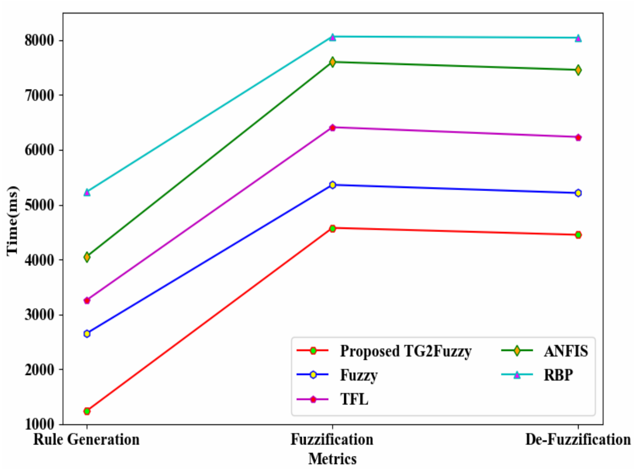


Figure 5: Performance Validation of the proposed TG²Fuzzy

The performance validation of the proposed TG²Fuzzy is analogized with conventional Fuzzy, Transfer Function Learning (TFL), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Rule Based Prediction (RBP) approaches in Figure 5. Here, the Fuzzification Time (FT), Defuzzification Time (DFT) and Rule Generation Time (RGT) of the proposed TG²Fuzzy are 4578ms, 4452ms, and 1245ms, correspondingly. This enhancement is because of the usage of the TG² approach. However, the prevailing techniques achieved maximum FT (5362ms to 8065ms), DFT (5214ms to 8044ms), and RGT (2658ms to 5236ms) values, which hinders the overall performance.

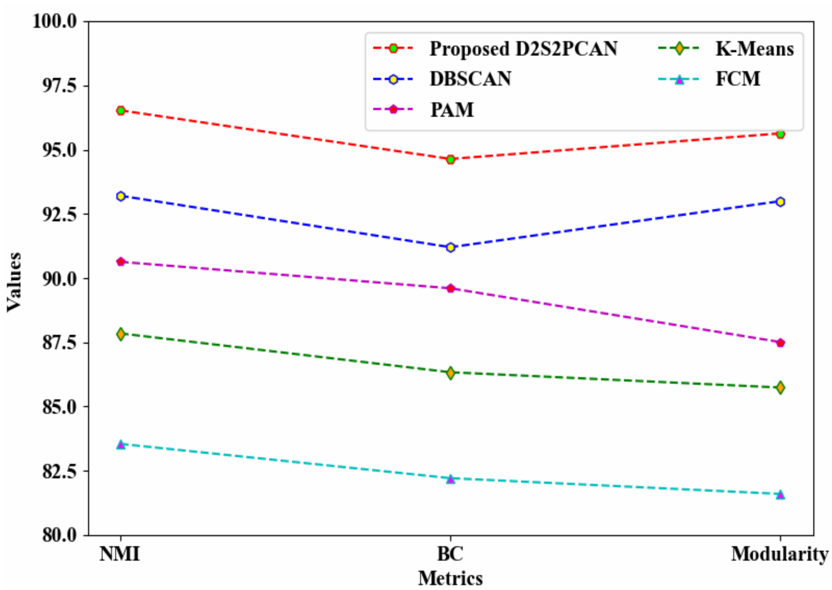


Figure 6: NMI, BC, and Modularity analysis

Figure 6 represents the Normalized Mutual Information (NMI), Betweenness Centrality (BC), and Modularity of the proposed D2S2PCAN and the prevailing DBSCAN, Partitioning AroundMedoids (PAM), K-Means, and Fuzzy-C Means (FCM) techniques. Here, owing to the inadequate neighborhood radius (Epsilon), the prevailing DBSCAN, PAM, K-Means, and FCM achieved low NMI, BC, and Modularity values. But, due to the usage of the Scree-plot technique for adequate Epsilon, the proposed D2S2PCAN achieved high NMI (96.526321), BC (94.635984), and modularity (95.630214) values. Hence, the proposed D2S2PCAN outperformed the conventional techniques.

Table 3: Comparative Analysis with Related Works

Study	Techniques Used	Accuracy (%)	Precision (%)
Proposed Work	CBCRPOA-SHCGRU	98.65	98.21
(Gulzar et al., 2023)	OCA	-	83
(He et al., 2023)	AAIN	81.24	-

(Suresh & Carmel Mary Belinda, 2022)	GRU	64.69	65
(Durga&Godavarthi, 2024)	GARNET	97.16	96.54
(Suvarna&Balakrishna, 2024)	DEC	91.07	90.23

In Table 3, the proposed works are compared with related works. Here, (Gulzar et al., 2023, Durga&Godavarthi, 2024) utilized an Ordered Clustering-centric Algorithm (OCA) and Gated Attention-centric Recurrent Networks (GARNET) with 83% and 96.54% precision, whereas (He et al., 2023, Suvarna&Balakrishna, 2024) utilized Attentional Aggregative Interaction Network (AAIN) and Deep Ensemble Classifier (DEC) approaches with 81.24% and 91.07% accuracies, correspondingly. Thus, the performance is reduced because of the drawbacks like overfitting and slow learning efficiencies. In the meantime, the proposed work that utilized the CBCRPOA-SHCGRU approach attained 98.65% accuracy and 98.21% precision. Thus, the proposed work predicted the links for effective recommendations of products more accurately than prevailing works.

V. Conclusion

Here, the influential node to predict inter and intra-layer links was effectively identified for effective product recommendation. This work is initiated by gathering network data, ratings, and review data. Here, the graph was constructed for social networks, followed by network attribute extraction. In the meantime, the sub-node was detected with an NMI of 96.526321. The influential node was identified from the extracted attributes within 1245ms RGT. Then, the inter-intra layer link was predicted with 98.65% accuracy. Lastly, the product was recommended with 0.526396 R^2 and 0.326541 ME. Therefore, the proposed work effectively recommended the products for future usage.

VI. Future Recommendation

In the proposed work, the inter-intra layer link, review, and ratings for effective PRS were effectively predicted. But, the recommendation accuracy could be enhanced by the consideration of product-centric advertisements. Thus, for more efficient RS, the PRS centered on multimedia advertisements will be considered in the future.

VII. Reference

[1]. Almahmood, R. J. K., &Tekerek, A. (2022).Issues and Solutions in Deep Learning-Enabled Recommendation Systems within the E-Commerce Field.*Applied Sciences (Switzerland)*, *12*(21), 1–20. https://doi.org/10.3390/app122111256

[2]. Chiu, M. C., Huang, J. H., Gupta, S., &Akman, G. (2021). Developing a personalized recommendation system in a smart product service system based on unsupervised learning model. *Computers in Industry*, *128*, 1–19. https://doi.org/10.1016/j.compind.2021.103421

[3]. Da'u, A., Salim, N., Rabiu, I., & Osman, A. (2020a). Recommendation system exploiting aspect-based opinion mining with deep learning method.*Information Sciences*, *512*, 1279–1292. https://doi.org/10.1016/j.ins.2019.10.038

[4]. Da'u, A., Salim, N., Rabiu, I., & Osman, A. (2020b). Weighted aspect-based opinion mining using deep learning for recommender system.*Expert Systems with Applications*, *140*, 1–12. https://doi.org/10.1016/j.eswa.2019.112871

[5]. Daza, A., González Rueda, N. D., Aguilar Sánchez, M. S., Robles Espíritu, W. F., &ChaucaQuiñones, M. E. (2024). Sentiment Analysis on E-Commerce Product Reviews Using Machine Learning and Deep Learning Algorithms: A BibliometricAnalysisand Systematic Literature Review, Challenges and Future Works. *International Journal of Information Management Data Insights*, *4*(2), 1–20. https://doi.org/10.1016/j.jjimei.2024.100267

[6]. Durga, P., &Godavarthi, D. (2024). ERS - GARNET: An Ensemble Recommendation System for Sentiment Analysis Using Gated Attention-Based Recurrent Networks. *Ingenierie Des Systemesd'Information*, *29*(3), 839–852.https://doi.org/10.18280/isi.290305

[7]. Elahi, M., KhoshKholgh, D., Kiarostami, M. S., Oussalah, M., &Saghari, S. (2023). Hybrid recommendation by incorporating the sentiment of product reviews. *Information Sciences*, *625*, 738–756. https://doi.org/10.1016/j.ins.2023.01.051

[8]. Gulzar, Y., Alwan, A. A., Abdullah, R. M., Abualkishik, A. Z., &Oumrani, M. (2023). OCA: Ordered Clustering-Based Algorithm for E-Commerce Recommendation System. *Sustainability (Switzerland)*, *15*(4), 1–22. https://doi.org/10.3390/su15042947

[9]. Halder, S., Lim, K. H., Chan, J., & Zhang, X. (2024). A survey on personalized itinerary recommendation: From optimisation to deep learning. *Applied Soft Computing*, *152*(December 2023), 1–14. https://doi.org/10.1016/j.asoc.2023.111200

[10]. He, H., Zhang, R., Zhang, Y., &Ren, J. (2023). AAIN: Attentional aggregative interaction network for deep learning based recommender systems. *Neurocomputing*, *547*, 1–11. https://doi.org/10.1016/j.neucom.2023.126374

[11]. Khelloufi, A., Ning, H., Naouri, A., Sada, A. Ben, Qammar, A., Khalil, A., Mao, L., &Dhelim, S. (2024). A Multimodal Latent-Features-Based Service Recommendation System for the Social Internet of Things.*IEEE Transactions on Computational Social Systems*, *PP*, 1–16. https://doi.org/10.1109/TCSS.2024.3360518

[12]. Peng, S., Cao, L., Zhou, Y., Ouyang, Z., Yang, A., Li, X., Jia, W., & Yu, S. (2022).A survey on deep learning for textual emotion analysis in social networks.*Digital Communications and Networks*, *8*(5), 745–762. https://doi.org/10.1016/j.dcan.2021.10.003

[13]. Rajput, I. S., Tewari, A. S., &Tiwari, A. K. (2024). An autoencoder-based deep learning model for solving the sparsity issues of Multi-Criteria Recommender System. *Procedia Computer Science*, *235*, 414–425. https://doi.org/10.1016/j.procs.2024.04.041

[14]. Shao, B., Li, X., &Bian, G. (2021).A survey of research hotspots and frontier trends of recommendation systems from the perspective of knowledge graph.*Expert Systems with Applications*, *165*, 1–20. https://doi.org/10.1016/j.eswa.2020.113764

[15]. Siji Rani, S., Shilpa, P., &Menon, A. G. (2024). Enhancing Drug Recommendations: A Modified LSTM Approach in Intelligent Deep Learning Systems. *Procedia Computer Science*, *233*, 872–881. https://doi.org/10.1016/j.procs.2024.03.276

[16]. Stöckli, D. R., &Khobzi, H. (2021). Recommendation systems and convergence of online reviews: The type of product network matters! *Decision Support Systems*, *142*, 1–11. https://doi.org/10.1016/j.dss.2020.113475

[17]. Suresh, A., & Carmel Mary Belinda, M. J. (2022).Online product recommendation system using gated recurrent unit with Broyden Fletcher Goldfarb Shanno algorithm.*Evolutionary Intelligence*, *15*(3), 1861–1874. https://doi.org/10.1007/s12065-021-00594-x

[18]. Suvarna, B., &Balakrishna, S. (2024). Enhanced content-based fashion recommendation system through deep ensemble classifier with transfer learning.*Fashion and Textiles*, *11*(1), 1–29. https://doi.org/10.1186/s40691-024-00382-y

[19]. Vedavathi, N., &SuhasBharadwaj, R. (2022).Deep Flamingo Search and Reinforcement Learning Based Recommendation System for E-Learning Platform using Social Media.*Procedia Computer Science*, *215*, 192–201. https://doi.org/10.1016/j.procs.2022.12.022

[20]. Yu, J., Shi, J., Chen, Y., Ji, D., Liu, W., Xie, Z., Liu, K., &Feng, X. (2021). Collaborative filtering recommendation with fluctuations of user' preference.*2021 IEEE International Conference on Information Communication and Software Engineering, ICICSE 2021*, 222–226. https://doi.org/10.1109/ICICSE52190.2021.9404120

[21]. Dataset - https://www.kaggle.com/datasets/pypiahmad/social-recommendation-data

[22]. Dataset - http://multilayer.it.uu.se/datasets.html