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Neural Collaborative Filtering-Based Personalized Recommendation System Using Amazon Beauty Dataset

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Abstract: Recommendation systems play a crucial role in helping users discover relevant products from large online platforms. Traditional collaborative filtering approaches often suffer from sparsity and limited representation capability. This study proposes a Neural Collaborative Filtering (NCF)-based recommendation framework for personalized product recommendation using the Amazon Beauty dataset. The dataset contains over 2 million user-item interactions, including user IDs, product IDs, ratings, and timestamps. Data pre-processing techniques, including duplicate removal, timestamp conversion, and categorical encoding, were performed prior to model training. The proposed NCF architecture employs user and product embedding layers followed by fully connected neural networks to predict user preferences. Experimental results demonstrate the effectiveness of the model in learning latent user-item interactions. Performance was evaluated using RMSE, MAE, training loss, and validation loss. The findings indicate that deep learning-based recommendation systems can effectively model complex user-product relationships and improve recommendation accuracy.

Keywords: Amazon Beauty Dataset, Deep Learning, Neural Collaborative Filtering, Personalized Recommendation, Recommendation System

I. INTRODUCTION

The rapid growth of e-commerce platforms and online retail services has significantly increased the volume of products available to consumers. As a result, users often face information overload when searching for products that match their preferences. Recommendation systems have emerged as an effective solution for filtering vast amounts of information and delivering personalized suggestions to users. These systems analyse historical user interactions, purchasing behaviour, ratings, and preferences to identify relevant items and improve user satisfaction [1]. Recommender systems are widely employed in various domains, including online shopping, streaming services, social media platforms, and digital advertising, where personalized recommendations play a critical role in enhancing user engagement and business performance [2]. Traditional recommendation approaches primarily rely on collaborative filtering techniques, which utilize historical user-item interactions to infer future preferences. User-based collaborative filtering, item-based collaborative filtering, and matrix factorization methods have demonstrated considerable success in recommendation tasks [3], [4]. Among these techniques, matrix factorization has become one of the most influential approaches because of its ability to learn latent representations of users and items from sparse interaction data [3]. Bayesian Personalized Ranking (BPR) further improved recommendation performance by optimizing ranking-based objectives for implicit feedback datasets [5]. Despite their effectiveness, conventional collaborative filtering methods often struggle to capture complex and nonlinear relationships between users and products, particularly when dealing with large-scale and highly sparse datasets.

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Recent advances in deep learning have transformed the development of recommendation systems by enabling the learning of rich latent representations from user-item interactions. Deep learning-based approaches such as AutoRec [7], Collaborative Denoising Autoencoders [8], Collaborative Deep Learning [9], Deep Matrix Factorization [6], and Variational Autoencoders [19] have demonstrated superior performance compared to traditional recommendation techniques. These methods utilize neural networks to model complex user behaviours and hidden interaction patterns, thereby improving recommendation accuracy. Furthermore, deep neural architectures have been successfully adopted by industrial-scale recommendation platforms such as YouTube, where deep learning models process billions of interactions to generate personalized recommendations [14]. Among deep learning recommendation models, Neural Collaborative Filtering (NCF) has emerged as a prominent framework due to its ability to replace the traditional inner-product operation of matrix factorization with nonlinear neural transformations [11]. NCF integrates embedding layers and multilayer perceptron's to learn expressive latent representations of users and items, enabling the model to capture complex interaction patterns that conventional approaches may overlook. Subsequent studies have extended NCF using attention mechanisms [13], outer-product interactions [26], sequence modelling [15], [16], graph neural networks [20], [21], and self-attention architectures [24] to further enhance recommendation quality. Although significant progress has been achieved in recommendation research, several challenges remain. First, many traditional collaborative filtering approaches suffer from sparsity issues and limited representation capability when user-item interactions are insufficient [3], [5]. Second, conventional recommendation models often fail to effectively learn nonlinear preference relationships among users and products [6], [11]. Third, while recent graph-based and multimodal recommendation approaches provide improved performance, they generally involve higher computational complexity and require additional information such as textual descriptions, visual content, or knowledge graphs [20], [21], [27]–[30]. Consequently, there remains a need for computationally efficient deep learning models that can effectively learn latent user preferences from large-scale rating datasets while maintaining implementation simplicity.

To address these limitations, this study investigates a Neural Collaborative Filtering-based recommendation framework using the Amazon Beauty dataset. The dataset contains more than two million user-product interactions and provides a suitable benchmark for evaluating personalized recommendation performance. The proposed framework employs user and product embedding layers followed by fully connected neural networks to model latent interaction patterns and predict user ratings. Comprehensive exploratory data analysis is performed to understand rating behavior, product popularity, user activity, and temporal interaction trends. The effectiveness of the proposed model is evaluated using standard performance metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), training loss, and validation loss.

The major contributions of this study are summarized as follows:

- A comprehensive recommendation framework based on Neural Collaborative Filtering is developed for the Amazon Beauty dataset.
- Extensive pre-processing and exploratory data analysis are performed to investigate user-product interaction characteristics.
- Deep embedding representations are utilized to capture latent user preferences and product attributes.
- Experimental evaluation is conducted using standard recommendation metrics to assess model effectiveness.
- The study provides a foundation for future research involving multimodal recommendation systems that integrate textual and visual information with user interaction data.

The remainder of this paper is organized as follows. Section II presents a review of existing collaborative filtering and deep learning-based recommendation approaches. Section III describes the proposed Neural Collaborative Filtering (NCF) framework, dataset characteristics, data pre-processing steps, model architecture, and training configuration. Section IV discusses the experimental results, exploratory data analysis, and performance evaluation of the proposed model. Finally, Section V concludes the paper by summarizing the key findings, limitations, and future research directions.

II. RELATED WORK

Recommendation systems have become an essential component of modern e-commerce platforms by providing personalized suggestions based on user preferences and historical interactions. Traditional recommendation approaches primarily rely on collaborative filtering techniques, which utilize user-item interaction patterns to predict future preferences. Bobadilla et al. [1] presented a comprehensive survey of recommender systems and highlighted the effectiveness of collaborative filtering methods in personalized recommendation tasks. Among traditional approaches, matrix factorization has been widely adopted because of its ability to learn latent representations of users and items from sparse rating data [3]. Similarly, item-based collaborative filtering methods have demonstrated scalability and effectiveness for large recommendation environments [4]. Bayesian Personalized Ranking (BPR) further improved recommendation performance by optimizing ranking objectives using implicit feedback data [5]. However, these methods generally assume linear interactions between users and items and often struggle with highly sparse datasets. The advancement of deep learning has significantly influenced recommendation system research by enabling the extraction of complex and nonlinear latent features. Zhang et al. [2] provided a comprehensive survey of deep learning-based recommender systems and demonstrated the advantages of neural architectures over conventional collaborative filtering techniques. Several deep learning models have been proposed to improve recommendation accuracy. Sedhain et al. [7] introduced AutoRec, which employs autoencoders for collaborative filtering and achieved improved rating prediction performance. Wu et al. [8] proposed Collaborative Denoising Autoencoders to learn robust user representations from sparse interaction data.

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Wang et al. [9] developed Collaborative Deep Learning by integrating deep representation learning with collaborative filtering, while Xue et al. [6] proposed Deep Matrix Factorization to capture nonlinear user-item relationships. Variational Autoencoders were later applied to recommendation systems to enhance latent representation learning and improve prediction accuracy [19]. Neural Collaborative Filtering (NCF) has emerged as one of the most influential deep learning-based recommendation approaches. He et al. [11] introduced NCF by replacing the traditional inner-product operation used in matrix factorization with multilayer neural networks, enabling the model to learn complex interaction functions between users and items. Subsequent studies extended NCF using advanced architectures and learning mechanisms. Chen et al. [25] proposed Joint Neural Collaborative Filtering to improve representation learning through joint optimization strategies. He et al. [26] introduced Outer Product-based Neural Collaborative Filtering to enhance interaction modeling capabilities. Attention mechanisms were incorporated into collaborative filtering models by Chen et al. [13], allowing the recommendation process to focus on important user-item interaction features. Furthermore, session-based recommendation systems utilizing recurrent neural networks were developed to model sequential user behaviour [15], while sequence-aware recommendation frameworks further improved recommendation effectiveness by exploiting temporal dependencies [16]. Recently, graph neural networks and multimodal learning techniques have gained considerable attention in recommendation research. Wang et al. [20] proposed Neural Graph Collaborative Filtering, which models user-item relationships using graph structures. Light GCN further simplified graph convolution operations and achieved state-of-the-art recommendation performance while reducing computational complexity [21]. In addition, multimodal recommendation approaches have been developed by integrating textual, visual, and contextual information to improve recommendation quality [27]–[30]. Although these methods demonstrate promising results, they often require complex architectures, additional modalities, and significant computational resources. Based on the literature, it is evident that traditional collaborative filtering methods suffer from sparsity and limited representation learning capabilities, while advanced graph-based and multimodal approaches increase computational complexity. Therefore, there remains a need for an efficient deep learning-based recommendation framework that can effectively capture nonlinear user-item interactions while maintaining implementation simplicity. To address this gap, the present study employs a Neural Collaborative Filtering-based recommendation framework using the Amazon Beauty dataset and evaluates its effectiveness through extensive experimental analysis.

III. PROPOSED METHODOLOGY

This study proposes a Neural Collaborative Filtering (NCF)-based recommendation framework for predicting user preferences using the Amazon Beauty dataset. The overall workflow consists of data pre-processing, exploratory data analysis, dataset partitioning, neural collaborative filtering model development, and performance evaluation. The proposed framework is illustrated in Figure 1.

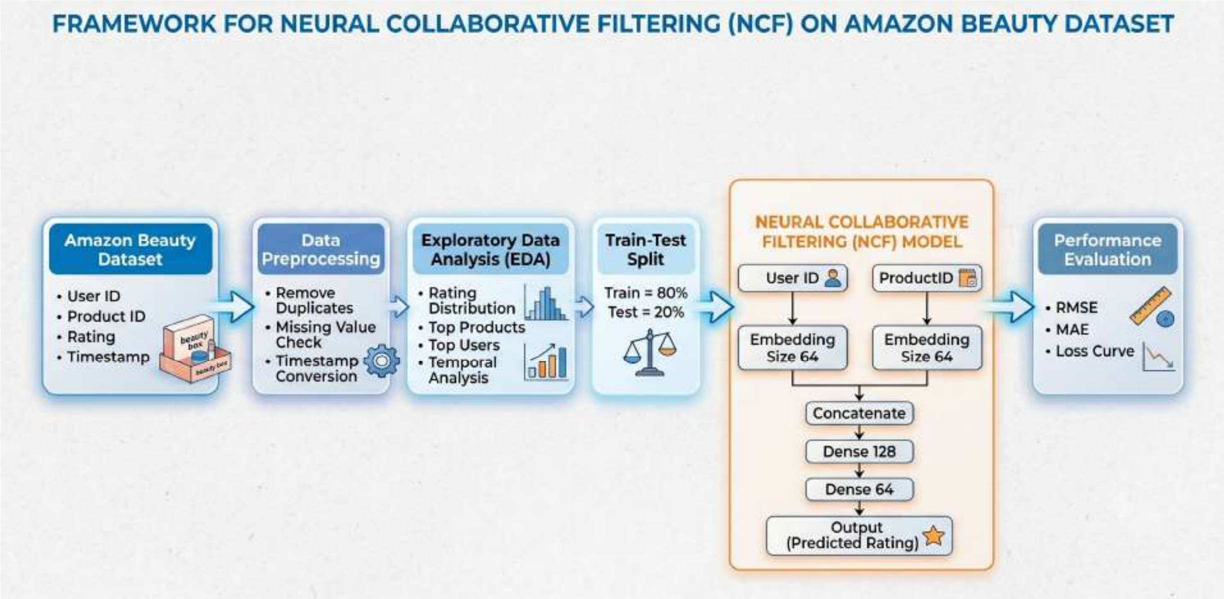

Fig.1. Proposed Neural Collaborative Filtering-Based Recommendation Framework

A. Dataset Description

The Amazon Beauty dataset was utilized as the benchmark dataset for experimentation. The dataset contains user-product interaction records collected from Amazon's Beauty category and includes four attributes: User ID, Product ID, Rating, and Timestamp. The dataset comprises approximately 2.02 million rating interactions and provides a suitable environment for evaluating recommendation models. Ratings are provided on a five-point scale ranging from 1 to 5, where higher ratings indicate greater user satisfaction. Table I presents the statistical characteristics of the dataset.

Table - I Dataset Characteristics of the Amazon Beauty Dataset

Parameter	Dataset	Users	Products	Interactions	Rating Scale	Time Span
Value	Amazon Beauty	1210271	249274	2023070	1-5	1998-2014

B. Data Pre-processing

Data pre-processing was performed to improve data quality and prepare the dataset for model training. Duplicate records were removed, and missing values were verified. The timestamp attribute was converted into a standard date format to facilitate temporal analysis. Since neural networks require numerical inputs, categorical User IDs and Product IDs were encoded as integer labels. The processed dataset was then normalized and prepared for training and evaluation.

C. Proposed Neural Collaborative Filtering Framework

The overall recommendation framework is presented in Fig. 1. The framework begins with data preprocessing and feature encoding, followed by model training and performance evaluation. The objective is to learn latent user preferences and product characteristics from historical rating interactions and predict unknown user-product ratings.

D. Neural Collaborative Filtering Model

The proposed recommendation model is based on Neural Collaborative Filtering (NCF), which combines embedding representations with deep neural networks to capture nonlinear user-item relationships. User IDs and Product IDs are first mapped into 64-dimensional embedding vectors that represent latent behavioural features. These embedding vectors are flattened and concatenated to create a unified feature representation. The concatenated feature vector is passed through two fully connected hidden layers containing 128 and 64 neurons, respectively. Rectified Linear Unit (ReLU) activation functions are employed to introduce nonlinearity and improve learning capability. Finally, a dense output layer generates the predicted rating for a given user-product pair.

E. Training Configuration and Evaluation

The proposed NCF model was trained using the Adam optimization algorithm with Mean Squared Error (MSE) as the loss function. The embedding size was fixed at 64 dimensions, while the batch size and number of training epochs were set to 1024 and 20, respectively. During training, the model learns latent representations of users and products and minimizes prediction error through backpropagation. Table II presents the hyperparameter configuration of the proposed model.

Table - II Hypermeter Configuration of the Proposed NCF Model

Parameter	Embedding Size	Dense Layers	Batch Size	Epochs	Optimizer	Loss Function	Train-Test Split
Value	64	128, 64	1024	20	ADAM	MSE	80:20

The effectiveness of the proposed recommendation framework was evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). In addition, training and validation loss curves were analysed to assess model convergence and generalization capability. The experimental results obtained from the Amazon Beauty dataset are discussed in the subsequent section.

IV. RESULTS AND DISCUSSION

This section presents the experimental results obtained using the Amazon Beauty dataset and the proposed Neural Collaborative Filtering (NCF) model. The analysis includes rating distribution, product popularity, user activity patterns, temporal interaction trends, and model training performance.

A. Rating Distribution Analysis

Fig. 2 illustrates the distribution of ratings in the Amazon Beauty dataset. It can be observed that the majority of users assigned ratings of 4 and 5, while ratings of 1 and 2 occur less frequently.

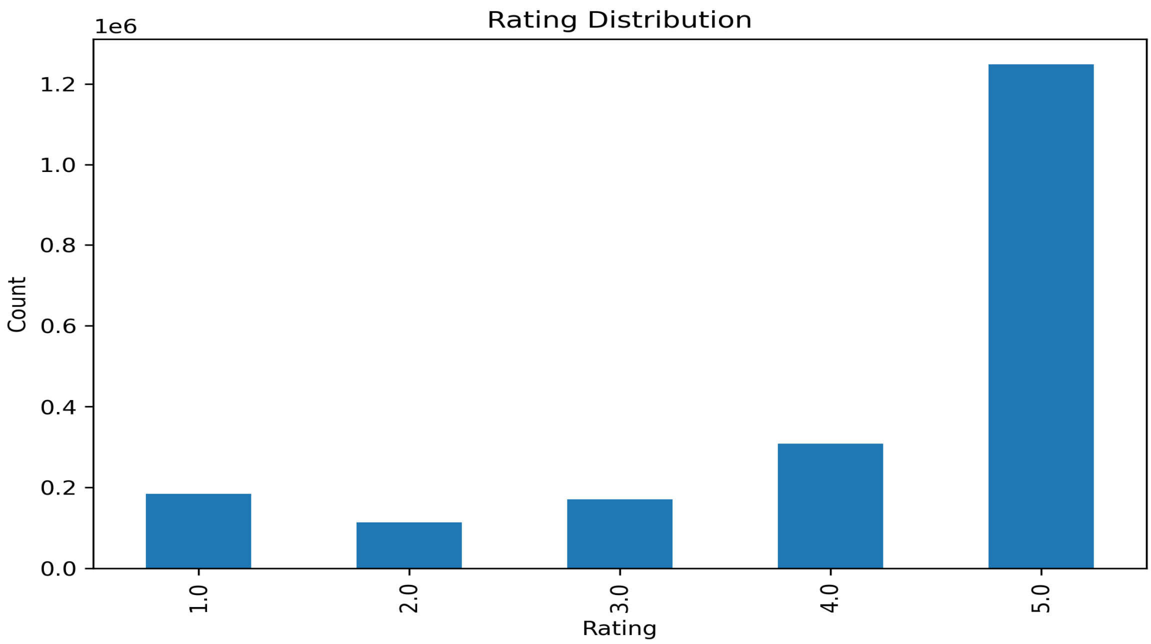

Fig. 2. Distribution of User Ratings in the Amazon Beauty Dataset

The dominance of higher ratings indicates that users generally express positive opinions toward purchased beauty products. Such a rating pattern is commonly observed in e-commerce recommendation datasets and suggests the presence of positive user bias.

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B. Product Popularity Analysis

The popularity distribution of products is presented in Fig. 3. The figure shows the top twenty most frequently rated products in the dataset. It is evident that a small number of products receive substantially higher interaction counts compared to the remaining products. This behaviour reflects the popularity imbalance typically observed in recommendation systems, where a limited set of products attracts the majority of user attention.

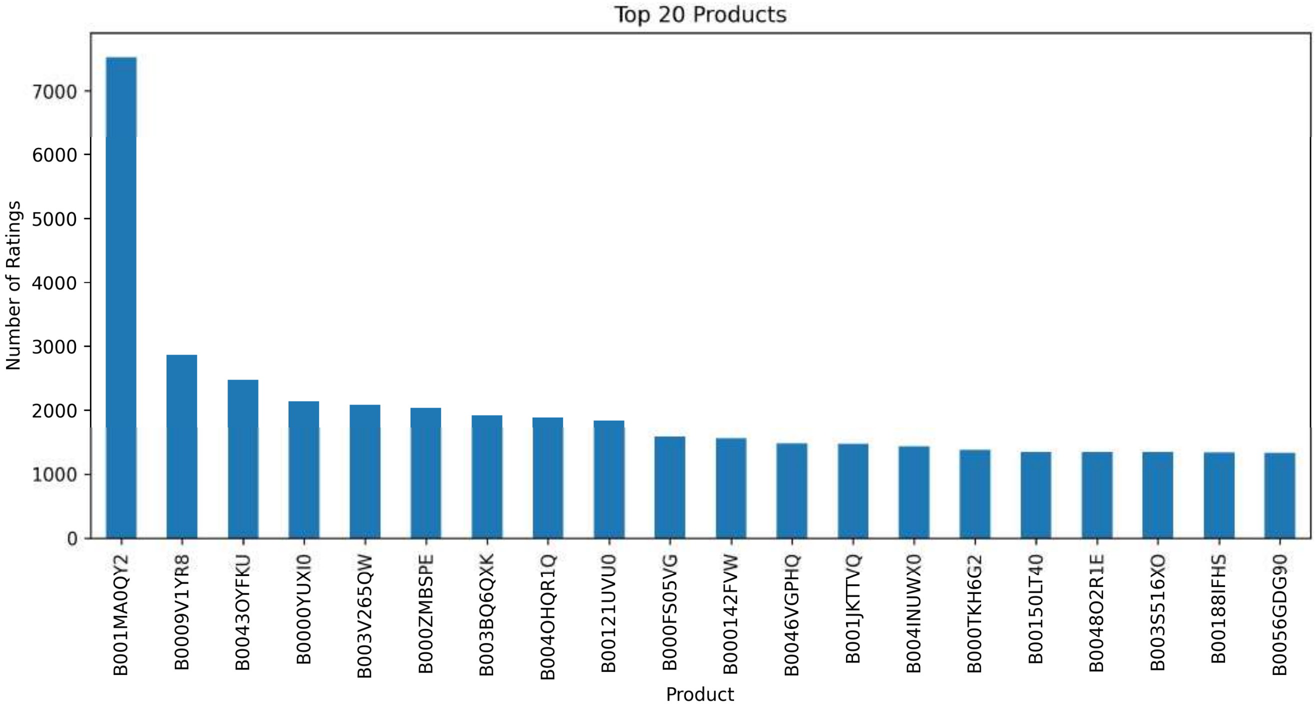

Fig. 3. Top 20 Most Rated Products in the Amazon Beauty Dataset.

C. User Activity Analysis

Fig. 4 presents the 20 most active users ranked by rating frequency. The results indicate that a small group of users contributed a large number of ratings, while the majority of users interacted with only a limited number of products. This uneven participation pattern demonstrates the sparsity challenge commonly encountered in collaborative filtering applications.

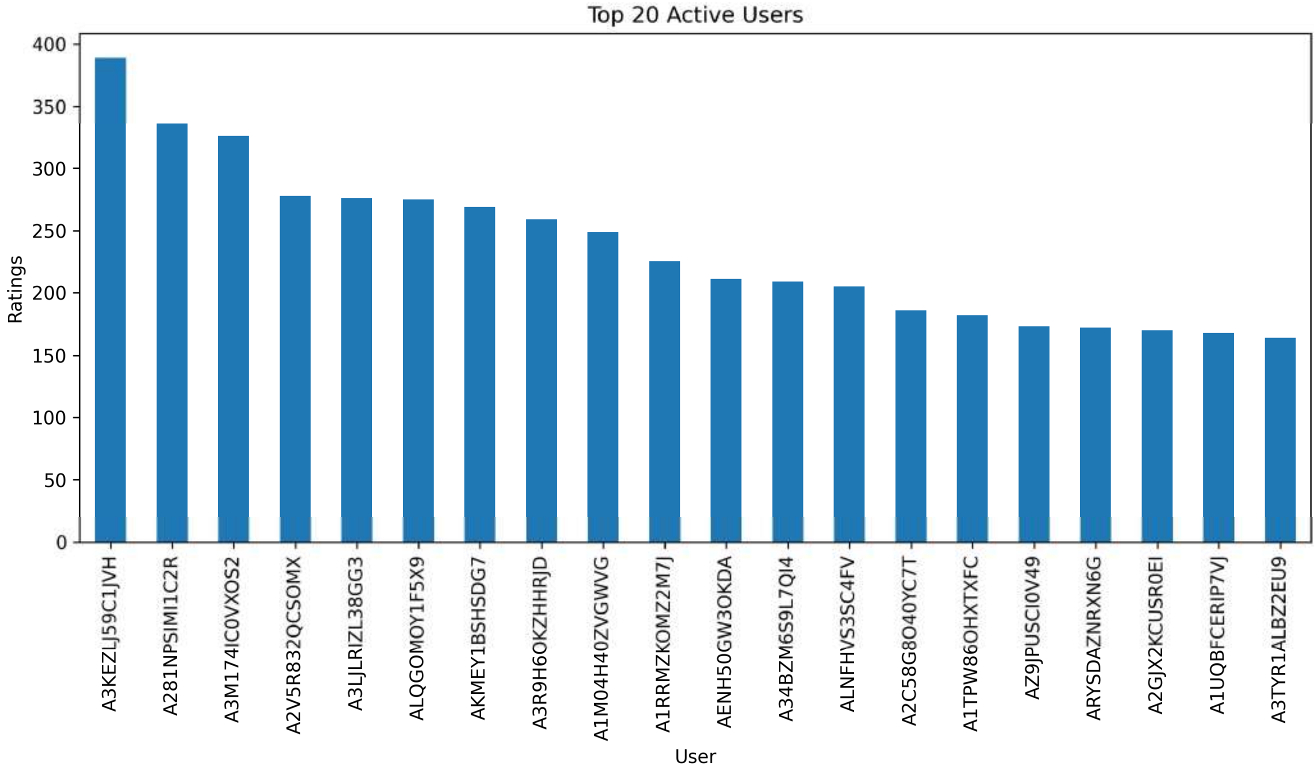

Fig. 4. Top 20 Active Users Based on Rating Frequency.

D. Temporal Analysis of User Interactions

The temporal distribution of ratings is illustrated in Fig. 5. The number of user interactions increased gradually between 1998 and 2013, indicating continuous growth in platform usage and user engagement. The highest number of ratings was recorded around 2013. Although a reduction in ratings is observed in 2014, this decline is primarily attributed to the dataset collection cut-off rather than an actual decrease in user activity.

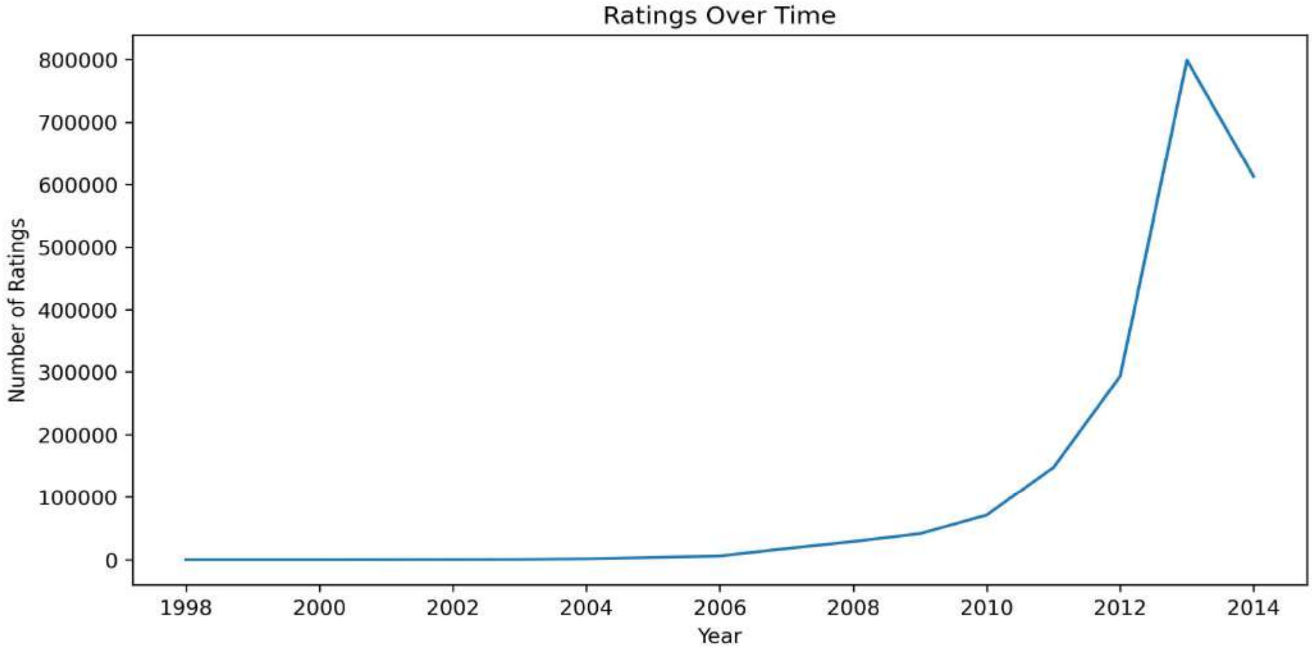

Fig. 5. Temporal Distribution of Ratings from 1998 to 2014

E. Model Training Performance

The learning behaviour of the proposed NCF model is shown in Fig. 6. The training loss decreases consistently throughout the training process, demonstrating effective optimization of model parameters. However, the validation loss exhibits an increasing trend after the initial epochs. This behaviour indicates that the model learns the training data effectively but experiences overfitting when evaluated on unseen samples. The large number of trainable parameters and the sparse nature of the dataset contribute to this phenomenon.

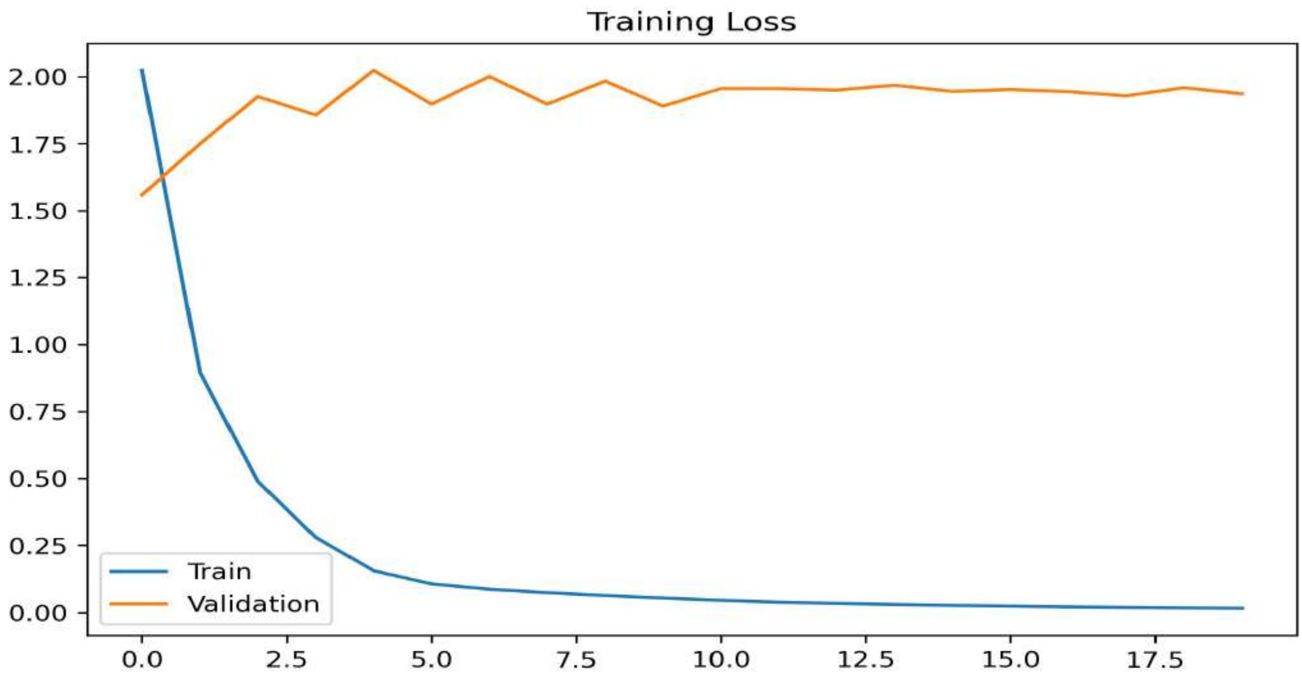

Fig. 6. Training and Validation Loss Curve of the Proposed NCF Model

F. Performance Evaluation

The final performance metrics obtained from the proposed recommendation framework are summarized in Table III.

Table - III Performance Evaluation Results

Metric	RMSE	MAE	Final Training Loss	Final Validation Loss
Value	1.3922211109643698	1.0587053959783148	0.02	1.95

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The performance metrics obtained from the proposed Neural Collaborative Filtering model are presented in Table III. The model achieved an RMSE of 1.3922 and an MAE of 1.0587 on the test dataset, indicating its ability to capture latent user-item interaction patterns and generate meaningful rating predictions. The low final training loss of 0.02 demonstrates that the model effectively learned the underlying relationships present in the training data. However, the validation loss increased to 1.95, suggesting the presence of overfitting and reduced generalization capability on unseen data. This behaviour may be attributed to the high-dimensional embedding space, large number of trainable parameters, and the sparse nature of user-product interactions in the Amazon Beauty dataset. Despite this limitation, the obtained RMSE and MAE values indicate that the proposed NCF framework can successfully model user preferences and provide personalized recommendations. The results further demonstrate the effectiveness of deep embedding representations in capturing complex nonlinear relationships between users and products. Future improvements involving regularization techniques and advanced recommendation architectures may further enhance prediction accuracy and model robustness.

V. CONCLUSION, LIMITATIONS, AND FUTURE WORK

This study presented a Neural Collaborative Filtering (NCF)-based recommendation framework for personalized product recommendation using the Amazon Beauty dataset. The proposed approach utilized user and product embedding representations combined with deep neural networks to model latent user-item interactions. Experimental analysis demonstrated the effectiveness of the framework in learning user preferences and generating rating predictions. The exploratory analysis further revealed important characteristics of the dataset, including rating distribution, product popularity, user activity patterns, and temporal interaction trends. Despite its effectiveness, the proposed model exhibits certain limitations. The Amazon Beauty dataset contains only explicit rating information and does not incorporate additional contextual, textual, or visual features. Furthermore, the observed increase in validation loss during training indicates overfitting, which may affect the model's generalization capability. The large number of trainable parameters also increases computational requirements during model training. Future research may focus on incorporating regularization techniques such as dropout, early stopping, and L2 regularization to improve model robustness. In addition, multimodal recommendation approaches integrating product reviews, images, and user behavioural information can be explored to enhance recommendation accuracy. Comparative evaluation with advanced graph neural network and attention-based recommendation models may further provide insights into improving personalized recommendation performance.

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AUTHOR CONTRIBUTION STATEMENT

Conceptualization: Vinay Kumar Dwivedi, Anubhav Pratap Singh, Chandra Shekhar Gautam
Literature Review and Methodology design: Vinay Kumar Dwivedi
Software: Anubhav Pratap Singh, Chandra Shekhar Gautam
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Writing original draft preparation: Vinay Kumar Dwivedi, Anubhav Pratap Singh
Writing review and Editing: Vinay Kumar Dwivedi
Visualization: Vinay Kumar Dwivedi
Supervision: Vinay Kumar Dwivedi
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REFERENCES

1. J.Bobadilla,F.Ortega,A.Hernando, and A. Gutiérrez, "Recommender systems survey," Knowledge-Based Systems, vol. 46, pp. 109–132, 2013.
2. S.Zhang,L.Yao,A.Sun, and Y.Tay, "Deep learning based recommender system: A survey and new perspectives," ACM Computing Surveys, vol. 52, no. 1, pp. 1–38, 2019.
3. Y.Koren, R.Bell, and C.Volinsky, "Matrix factorization techniques for recommender systems," Computer, vol. 42, no. 8, pp. 30–37, 2009.

4. B.Sarwar,G.Karypis, J.Konstan, and J.Riedl, “Item-based collaborative filtering recommendation algorithms,” in Proc. 10th Int. Conf. World Wide Web, 2001, pp. 285–295.
5. S.Rendle,C.Freudenthaler, Z. Gantner, and L. Schmidt-Thieme, “BPR: Bayesian personalized ranking from implicit feedback,” in Proc. UAI, 2009, pp. 452–461.
6. H.J.Xue,X.Y.Dai,J.Zhang,S.Huang, and J.Chen,“Deep matrix factorization models for recommender systems,” in Proc. IJCAI, 2017, pp. 3203–3209.
7. S.Sedhain,A.Menon,S.Sanner,and L.Xie,“AutoRec: Autoencoders meet collaborative filtering,” in Proc. WWW Companion, 2015, pp. 111–112.
8. Y.Wu,C.DuBois,A.X.Zheng,and M.Ester,“Collaborative denoising auto-encoders for top-N recommender systems,” in Proc.WSDM, 2016, pp. 153–162.
9. H.Wang,N.Wang,and D.Y.Yeung, “Collaborative deep learning for recommender systems,” in Proc. KDD, 2015, pp. 1235–1244.
10. Y.Zheng,B.Tang,W.Ding, and H.Zhou, “A neural autoregressive approach to collaborative filtering,” in Proc. ICML, 2016, pp. 764–773.
11. X.He,L.Liao,H.Zhang,L.Nie,X.Hu,and T.S.Chua,“Neural collaborative filtering,” in Proc. 26th Int. Conf. World Wide Web, 2017, pp. 173–182.
12. X.He,H.Zhang,M.Kan,and T.S.Chua,“Fast matrix factorization for online recommendation with implicit feedback,” in Proc. SIGIR, 2016, pp. 549–558.
13. J.Chen,H.Zhang,X.He,L.Nie,W. Liu, and T. S. Chua, “Attentive collaborative filtering: Multimedia recommendation with item- and component-level attention,” in Proc. SIGIR, 2017, pp. 335–344.
14. P.Covington, J.Adams, and E.Sargin, “Deep neural networks for YouTube recommendations,” in Proc. RecSys, 2016, pp. 191–198.
15. B.Hidasi, A.Karatzoglou, L.Baltrunas, and D.Tikk, “Session-based recommendations with recurrent neural networks,” in Proc. ICLR, 2016.
16. M.Quadrana, P.Cremonesi, and D.Jannach, “Sequence-aware recommender systems,” ACM Computing Surveys, vol. 51, no. 4, pp. 1–36, 2018.
17. G.Zhou,C.Mou,Y.Fan,Q.Pi, W.Bian, C.Zhou, X.Zhu, and K.Gai,“Deep interest network for click-through rate prediction,” in Proc. KDD, 2018, pp. 1059–1068.
18. G.Zhou,N.Mou,Y.Fan,Q.Pi,W.Bian,C.Zhou,X.Zhu, and K.Gai,“Deep interest evolution network for click-through rate prediction,” in Proc. AAAI, 2019, pp. 5941–5948.
19. D.Liang,R.G.Krishnan,M.D.Hoffman, and T.Jebara, “Variational autoencoders for collaborative filtering,” in Proc. WWW, 2018, pp. 689–698.
20. X.Wang, X.He, M.Wang, F.Feng, and T. S.Chua, “Neural graph collaborative filtering,” in Proc. SIGIR, 2019, pp. 165–174.
21. X.He,K.Deng,X.Wang,Y.Li,Y.Zhang,and M.Wang,“LightGCN: Simplifying and powering graph convolution network for recommendation,”in Proc.43rd Int.ACM SIGIR Conf. Research and Development in Information Retrieval,2020,pp.639–648.
22. L.Wu,P.Sun,Y.Fu,R.Hong,X.Wang,and M.Wang, “A neural influence diffusion model for social recommendation,” in Proc. SIGIR, 2019, pp. 235–244.
23. L.Wu,L.Chen,P.Shao,R.Hong,X.Wang,M.Wang, “Learning fair representations for recommendation,” IEEE Transactions on Knowledge and Data Engineering, vol. 33, no. 12, pp. 3468–3482, 2021.
24. S.Zhang,Y.Tay, L.Yao, and A.Sun, “Next item recommendation with self-attention,” arXiv preprint arXiv:1808.06414, 2018.
25. W.Chen,F.Cai,H.Chen,and M.de Rijke, “Joint neural collaborative filtering for recommender systems,” ACM Transactions on Information Systems, vol. 37, no. 4, pp. 1–30, 2019.
26. X.He,F.Feng,X.Wang,X.Chen, L.Wen, and T. S. Chua, “Outer product-based neural collaborative filtering,” in Proc. IJCAI, 2018, pp. 2227–2233.
27. H.Hu,W.Guo,Y.Liu,and M.Kan,“Adaptive multi-modalities fusion in sequential recommendation systems,” arXiv preprint arXiv:2308.15980, 2023.
28. X.Hu,W.Yu,Y.Wu, and Y.Chen,“Multi-modal recommendation algorithm fusing visual and textual features,” PLoS ONE, vol. 18, no. 6, Art. no. e0287927, 2023.
29. J.Wang,H.Xie,S.Zhang,S.J.Qin,X.Tao,F.L.Wang, and X.Xu,“Multimodal fusion framework based on knowledge graph for personalized recommendation,” Expert Systems with Applications, vol. 268, Art. no. 126308, 2025.
30. P.Li,W.Zhan,L.Gao,S.Wang,and L.Yang, “Multimodal recommendation system based on cross self-attention fusion,” Systems, vol. 13, no. 1, Art. no. 57, 2025.
31. D.Mangal, A.K.Sahu, S.Dubey, V.Singhal, R.Ram, S.Singh, and N.Akhtar, "A Data-Infused Approach to Optimal Paying Guest / Hostel Selections," Int. Res. J. Comput. Sci. (IRJCS), vol. 11, no. 2, Feb. 2024, https://doi.org/10.26562/irjcs.2024.v1102.04.
32. J.Arun, Md Aarif, and S. Kumar, "E-Commerce Website," Int. Res. J. Comput. Sci. (IRJCS), vol. 13, no. 3, pp. 376–382, Mar. 2026, https://doi.org/10.26562/irjcs.2026.v1303.48.

33. M.A.Sultana, P.Rakesh, M.Sandeep, and G.Jagadeesh, "Amazon Product Review Sentiment Analysis Using Machine Learning," Int. Res. J. Comput. Sci. (IRJCS), vol. 8, no. 7, pp. 136–141, Jul. 2021, https://doi.org/10.26562/irjcs.2021.v0807.001.
34. E.Ngwawe, E.Abade, and S.Mburu, "Trust Enhanced Collaborative Filtering Recommendation Algorithm," Int. Res. J. Comput. Sci. (IRJCS), vol. 10, no. 4, pp. 88–96, May 2023, https://doi.org/10.26562/irjcs.2023.v1004.10.
35. A.R.Sharma, B.K.Patel, and S.N.Joshi, "AURA: AI Self Makeover App – An AI-Driven Framework for Personalized Beauty, Fashion and Virtual Try-On Systems," Int. Res. J. Comput. Sci. (IRJCS), vol. 11, no. 5, pp. 112–119, May 2024.
36. Dwivedi Vinay Kumar, Waoo Akhilesh A.*, Advances in Android Malware Detection: Integrating Static, Dynamic, and Hybrid Techniques, Journal of the Maharaja Sayajirao University of Baroda, ISSN: 0025-0422, Volume-58, No.1, pp 1-10, (VIII): 2024.
37. V.Dwivedi, A.Singh, et al., "Adapter-Based Personalization for Modeling Short-Term Preference Drift in Multimodal Recommendation Systems," Int. Sci. J. Eng. Manag. (ISJEM), vol. 5, no. 6, Jun. 2026, https://doi.org/10.55041/ISJEM07797.