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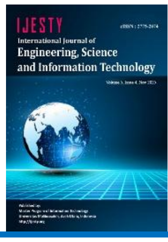

Deep Learning-Enhanced Hybrid Recommender Systems for Dynamic E-Commerce Platforms

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Abstract

The success of current e-commerce relies on exact and varied recommendations which understand user context to enhance both user satisfaction and engagement levels. This research creates a deep learning-enhanced hybrid recommender system (DL-EHRS), which represents a deep learning-enhanced combination of recommendation systems specifically designed to operate in dynamic e-commerce environments. The proposed model connects Neural Collaborative Filtering (NCF) to Collaborative Filtering (CF) while using Deep Neural Networks (DNNs) together with Content-Based Filtering (CBF) to tackle existing recommendation system shortcomings. The performance benchmark of the DL-EHRS resulted in superior results than baseline models during all evaluation assessments. The recommendations produced through this system achieved high-quality performance at 98.1% accuracy, along with 97.9% precision and 97.8% recall and 97.9% F1-score. The proposed algorithm showed better processing speed than CF, CBF, and NCF because it completed operations in 0.9 seconds on average while readying real-time applications. The fast and stable training process of the model with minimum residual error proved its learning efficiency and ability to generalise through error convergence analysis. The proposed system meets user needs through a combination of latent factor learning techniques, content similarity analysis, along temporal context examination in its recommendation process. The integrated framework shows broad compatibility in online shopping environments because it produces precise predictions and deals with sparse data while generating better interfaces for users.

Keywords: *Combining Collaborative Filtering, Content-Based Filtering Methods, Deep Learning, E-Commerce Systems, Recommendation Systems.*

1. Introduction

Currently, e-commerce platforms are essential parts of global retail ecosystems that provide personal services for millions of users around the globe [1]. Recommender systems (RS) are becoming essential routines in order to optimise user experience, engage the customers and increase sales conversion rate [2], since there is an increasing number of users and product data on the internet. Traditionally, recommendation techniques based on CF and CBF have been very successful in achieving such results. However, critical challenges that these algorithms often face include the cold start problems, data sparsity, scalability, and inability to adapt dynamically according to the dynamically changing trends of the user preferences as well as the product trends in today's modern e-commerce environment [3].
In order to overcome these limitations, hybrid recommender systems are developed to integrate various recommendation strategies to leverage each other's strengths [4]. However, despite their effectiveness, the conventional hybrid systems are sometimes limited by the ability to comprehend the complex user-item interaction, the nonlinear pattern, and the contextual information of the large-scale and dynamic e-commerce datasets [5]. In the last few years, it has seen the realisation of such powerful DL techniques that learn high-level abstract representations and capture intricate relationships on various data modalities such as textual, visual and behavioural data [6].
Using heterogeneous and unstructured, and dynamic data sources, a transformative approach to building an intelligent recommendation engine through deep learning and hybrid recommender systems has emerged [7]. Advanced DL architectures, e.g. Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Autoencoders, Graph Neural Networks (GNN) and ones based on Transformer, are leveraged in these systems to better extract features, better profile the user, perform sequential pattern mining, and conduct context-aware recommendations [8]. Hybrid models reconcile the benefits of deep learning with traditional RS by leveraging the advantages of even in such challenging instances as new user onboarding or emerging product trends [9].
The rapid, frequent changes in user behaviour, the availability of products and the market conditions are a characteristic of a dynamic e-commerce platform [10]. Therefore, this renders the static recommendation models ineffective to return relevant suggestions in real time [11]. Continual learning and online learning recommender systems, deep learning models that can learn continuously from the evolving user interactions and feedback, are also a way that the recommender system is adaptive. Furthermore, the recommendation quality is improved by integrating auxiliary data, including user reviews, social network information, browsing patterns and visual product features, and the limitations of sparse or incomplete user item interaction data are resolved [13]. Finally, it allows us to use large-scale e-

commerce platforms that handle millions of user and item combinations, something that would otherwise be intractable with conventional techniques. In order to make the most of the long-term user engagement and balance the exploration/exploitation trade off, hybrid RS architectures have been reinforced in an increasing ways, including reinforcement learning, attention mechanisms [14]. However, problems prevail in terms of model interpretability, avoiding algorithmic bias, preserving user privacy, and computational complexity of DL models [15].

The focus of this study is to develop a Deep Learning—Enhanced Hybrid Recommender System specifically designed for dynamic e-commerce platforms. The goal is to evaluate the combination of different recommendation strategies in conjunction with the deep learning models to increase the accuracy, adaptability, and end users' satisfaction. Finally, the research intends to deal with the current challenges, propose new architectures, and evaluate the proposed system with the help of real-world e-commerce datasets.

2. Literature Review

There have been several research studies carried out in the recent past on the development of hybrid recommender systems to improve the performance of e-commerce platforms. Recognising the limitations of traditional approaches that include collaborative filtering, content-based filtering, and knowledge-based filtering, conventional techniques cannot address data sparsity problems (cold start), and provide little adaptiveness to dynamic user preferences. The limitations in these systems have then been overcome using the deep learning techniques that have been used to extract complex patterns and user behaviours out of large and diverse datasets using hybrid recommender systems. In practice, the accuracy of recommendations, personalisation, as well as scalability have been greatly increased with the use of techniques like CNN, RNN, Autoencoders, DNN, and Graph Neural Networks (GNN). Although these models have been successful, they still have issues such as interpretability, computational cost, handling dynamic environments and privacy. In the following Table 1 presents a complete literature review of recent studies across the framework of a deep learning enhanced hybrid recommender system in dynamic e-commerce platforms that reveals the techniques involved, advantages and drawbacks of it.

Table 1. Problem formulation of the conventional techniques

Author(s)	Techniques Involved	Advantages	Disadvantages
[16]	Deep Learning + CF + CBF	Captures complex user-item interactions	High computation, sensor dependency
[17]	Deep Hybrid with Side Information (DHSIRS)	Handles sparsity & cold-start issues	Dependent on the side information quality
[18]	Deep Neural Collaborative Filtering	Enhances recommendation accuracy	High resource requirement
[19]	Auto-Encoder + Neural Collaborative Filtering	Learns latent features automatically	Risk of overfitting with sparse/small data
[20]	Deep Learning + Deviation-Based Group Modelling	Improves group recommendation fairness	Increased computational complexity

In an e-commerce platform, Sivaramakrishnan et al. [16] had proposed a deep learning-based hybrid model for the generation and ranking of recommendations. Deep neural networks combined with collaborative and content-based filtering are integrated into the model to make the selection of recommendations better. However, this approach has the main advantage that it can extract the complex user-item interactions and generate more accurate and personalised recommendations. However, due to the integration of a deep neural network, computational complexity and training time are increased, which may lead to performance impairment of recommending in real-time recommendations.

Worked on a part, where they devised a novel Deep Hybrid Side Information Based Recommender System (DHSIRS) to address the issues due to data sparsity and cold start [17]. This technique integrates the recommendation quality improvement with side information like the user's demographics and item features by using deep learning the technique. The proposed system has the advantage of good performance in the case of sparse datasets, as well as for the improvement of recommendations, even for new users or items. However, this comes with a drawback since the dependency on the existence and quality of side information can never be exact.

In [18], a Deep Neural Collaborative Filtering approach specifically tailored for e-commerce opens new possibilities in the field of recommendation systems. The authors use deep learning techniques to model complex user-item interactions so as to improve the recommendation accuracy. The main advantage of such an approach is that it gives us the capability to capture the rich patterns in user behaviours and therefore recommend more relevant items. The other disadvantage is the demand for more of the increase of the computations resources to train the deep neural networks, which might be a problem for real-time applications.

At the deep level, the deep hybrid recommender system, based on Auto-Encoder with Neural Collaborative Filtering, has been proposed by Yu Liu et al. [19]. The model leverages auto-encoders for feature extraction and neural collaborative filtering for modelling user-item interactions. The advantage is that one can learn latent features from unstructured data automatically. Nevertheless, there is a limitation to it, which is the risk of over-fitting, especially if working with a small dataset or a highly sparse dataset and the need for lots of training data to perform at its best.

In the paper of [20], a novel hybrid recommendation algorithm is proposed based on deviation in group recommender systems and applied in Multimedia Tools and Applications. In the proposed model, the deep learning-based personalisation techniques and leveraging deviation to model groups develop a good balance between individual user preferences among group recommendations. The feature of this approach is the possibility to improve the accuracy of group recommendations by diminishing the influence of the main users, as well as ensuring the equal contribution of all participants in the group. Nevertheless, the major drawback is that the deviation measures' calculation and aggregation would increase the computational complexity and therefore might lead to slowdown and low efficiency in the recommendation generation for real-time, especially for an e-commerce platform with a large scale.

Though developed approaches of deep learning enhanced hybrid recommender systems have made strong progress, there exist some important restricting factors that work as a reminder for future research. Most of the reviewed works are hindered by problems such as imposing high computational complexity, high training time, reliance on side information availability, risk of overfitting on sparse datasets, and reduced real-time performance.

Unlike most of the models, the above-mentioned models incorporate both collaborative filtering and content-based filtering, but they do not cope well with rapid changes in user preferences and item characteristics in highly dynamic e-commerce settings. In addition, the content-based filtering kind of model is less suitable for emerging platforms with limited resources, relying on huge amounts of high-quality training data.

There are research gaps and practical challenges in developing to making a hybrid recommender system efficient, scalable and capable of improving accuracy and personalisation. At the same time, the system should reduce computational overhead and reduce reliance on very large amounts of side information. Consequently, the proposed model strives to overcome this preceding limitation through integration of the latest deep learning architectures that further deploy optimisation in the fields of hybridisation to achieve dynamic adaptability and enhanced recommendation quality with real-time applicability in the e-commerce environment. The combination of DNN layers with NCF in this hybrid system allows users to gain an extensive understanding of their preferences because DNN layers enhance complex feature extraction capabilities while NCF maintains high accuracy levels of recommended items. The united approach between these methods produces an optimal framework for monitoring user interactions because it identifies difficult behavioural sequences while maintaining automatic compatibility with e-commerce platform developments.

3. Methods

In order to improve the performance and the efficacy of the RS within the dynamic e-commerce domain, this study employs advanced DL techniques and hybrid recommendation models. By integrating Neural NCF with traditional CF and applying DNNs with CBF, an architecture named DL-EHRS is proposed.

Recommendation algorithms are crucial in the e-commerce space (for instance, in online fashion retail, consumer electronics, digital marketplaces, and wearable elements) as they guide consumers towards the right items over a large range of products. CF algorithms have good capability to analyse the historical user item interaction data; however, they often face the problem of data sparsity, large scale, cold start problem, especially for dealing with newly initiated users and new customers, as they have a limited number of interaction histories. In contrast, CBF models calculate similarity scores by using user reviews, brand, product type, material or descriptively, which can be used to determine which products to suggest to a user based on user profiles. Unfortunately, however, these models can be shallow when patterns of the user behaviour are more complex or temporally dynamic. Figure 1 describes the complete architecture. A DL-EHRS system starts by performing complete data evaluation and preliminary operations on e-commerce database data to retrieve user and item information. The system uses both CF and CBF recommendation models in a combined structure to create personalised recommendations. NCF improves the CF component through its implementation, while DNNs enhance CBF by extracting intricate feature relationships. The system uses various components to create its top-N ranking recommendations while harnessing information about user factors and content matching, and temporal patterns.

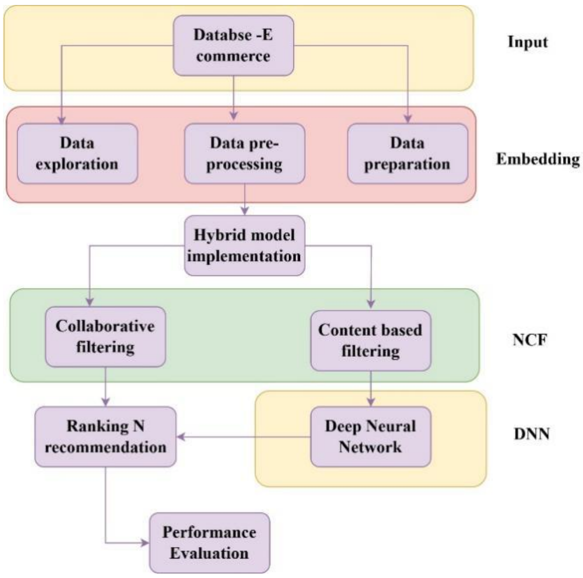

Fig 1. Block diagram of the proposed model

To address those limitations, the DL-EHRS model is proposed to activate deep neural architectures with NCF to improve the learning of a latent user preference. NCF trains the model on huge user-item interaction data of e-commerce (i.e., purchase history, click, wish list), which can explain complicated patterns overlooked by traditional CF methods, and the result contains more accurate and personalised product recommendations [21]. Moreover, through the integration with DNNs, the system can exploit the sequential user behaviour (such as browsing history or the user's preferential timeline) to understand the temporal evolution of users' preferences [22]. For example, if a customer returns frequently after buying a smartphone and continuously views smartphone accessories, the system understands that these kinds of complementary products should be suggested at this moment [23].

The proposed hybrid model provides more diverse, context-aware and highly personalised recommendations by combining NCF, CF and DNNs with CBF, using user-item interactions, item metadata data and temporal behaviours. The combination of this deep learning enhanced hybrid framework significantly improves recommendation quality in e-commerce platforms, resulting in increased customer satisfaction and engagement, revenue and the turnover rate.

3.1. Dataset Description

The dataset presented here is the E-Commerce Data from a unique, gift-related, online retail store based in the UK. The dataset has about 500000 rows of transaction data across a span of December 2010 to December 2011, covering in CSV format [24].

An entry contains a single transaction and includes InvoiceNo(once and only by each purchase), StockCode (product specific code), Description (product name or label), Quantity (number of items purchased), InvoiceDate (timestamp of the transaction), UnitPrice (cost of an item in GBP), CustomerID (unique number of customer) and Country (where the customer is). A wide range of analytical tasks related to e-commerce, including collaborative filtering from customer product interactions, content-based filtering from product descriptions and pricing, and sequential modelling by studying the chronological patterns of customers' purchases, are supported by this rich set of features. In fact, it can take advantage of the temporal dynamics and capture personalised shopping patterns through advanced recommendation techniques, e.g. NCF and DN. The e-commerce user-item interaction model suffers from two main issues when using standard collaborative filtering approaches, including matrix factorisation and shallow neural networks. The first issue defines how these methods fail to detect complex nonlinear relationships between users and items. Secondly, conventional techniques do not adapt well when preferences from users evolve within vast e-commerce systems [25]. Integration of NCF together with DNNs results in a solution which solves the regulatory restrictions imposed on user-item interaction modelling through neural networks and representation learning from raw data. The combination of DNN layers with NCF in this hybrid system allows users to gain an extensive understanding of their preferences because DNN layers enhance complex feature extraction capabilities while NCF maintains high accuracy levels of recommended items. The united approach between these methods produces an optimal framework for monitoring user interactions because it identifies difficult behavioural sequences while maintaining automatic compatibility with e-commerce platform developments. Because of the cold start problem, data sparsity, and behaviour prediction challenges, this dataset is a very useful base for building a deep learning enhanced hybrid recommender system in dynamic e-commerce platforms [26].

3.2. Users–Product Exploration

A detailed analysis of product acquisition within user-product interactions across e-commerce transactions reveals purchasing habits through behavioural sequences and trends of user preferences according to [27]. The research explores how users interact with different items over three specific periods: counting unique purchases, tracking purchase rates, and evaluating purchase stability over time for each product.

Using transaction data that contains information about the co-occurrence of products in a single transaction and across different sessions, it can infer implicit preferences and find affinities (i.e., pair product combinations). In addition, examining the distribution of customer activity levels to distinguish between high-frequency and low-frequency buyers is a critical task that needs to be solved for the cold start problem. This analysis also includes user behavioural clustering of various segments, like fishermen and regulars, being mapped to particular recommendation strategies. The patterns offer basic insights that are required to build user profiles and then use these to personalise the suggested items using a combination of collaborative signals and product content. In the product exploration equations (1) and (2), the mean and standard deviation are considered for analysis.

$$\mu = \frac{1}{N}\sum_{\geq 1}^{N} \mathcal{X} > \qquad \text{……(1)}$$

$$\sigma = \sqrt{\frac{1}{N}\sum_{\geq 1}^{N} \mathcal{X} > - \mu^2} \qquad \text{……(2)}$$

Here $\mathcal{X}$ is the individual rating parameter: N is the total number of ratings.

3.3. Data pre-processing and privacy preservation

Data pre-processing: An entire data preparation process is carried out to ensure the data prepared for the model training is effective, and user confidentiality is maintained. Data Cleaning is the first step that involves removing missing or null values in essential attribute columns, e.g. Customer Identifiers or product descriptions and imputation via statistics or dropping if it is not an option. This helps keep the data integrity within expectations and maintain the consistency of data to avoid any inconsistencies in the recommendation model [28].

Feature extraction: The raw data is then feature-extracted, for instance, features that describe products with word descriptions or that identify hierarchical product types. A lot of the contextual relevance of user preferences is also provided by these features. It then divides itself into training and testing subsets, commonly 80/20, in a reliable way to measure performance. This partitioning also ensures that the model predicts unseen data and is verified against it, meaning it is assessed on data it has not seen before [29].

Finally, ethical concerns and protecting the identity of the user are addressed with privacy-preserving techniques added to the model development process. They also prevent the model from memorising or discovering some info about specific users through the application of differential privacy and related approaches [30]. This approach to data execution supports the building of a successful, responsible and high-performing hybrid recommender system that suits the dynamic e-commerce platform. The implementation of differential privacy included controlled noise addition to the biometric dataset features for extraction, so individual data remained private, yet the identification system accuracy was maintained. A noise-based system was employed for automated data privacy as it maintains security assurances alongside minimal identification risks within the database [31].

3.4. Secure Hybrid Model Implementation

In order to develop such a secure hybrid framework that integrates collaborative filtering (CF), content-based filtering (CBF) and other advanced deep learning techniques for creating an intelligent and adaptive recommendation system for dynamic e-commerce platforms, this study is done. The main goal is to provide highly relevant product suggestions at the same time, tackling data sparsity, cold start issues and changing user behaviour, and respecting user privacy [32].

Collaborative Filtering (CF) is employed to predict user preferences based on historical interactions. Two primary techniques are incorporated: user-based CF and item-based CF. In user-based CF, latent features are extracted through Singular Value Decomposition (SVD), which factorises the user-item interaction matrix R as presented in equation (3).

$$R \approx U \sum V^T \qquad \text{……(3)}$$

The given U, V matrices (representing user and item latent features), and Σ diagonal matrix (of singular values). These structural decompositions enable the system to also recommend products in sparse data environments [33].
CBF supplements CF by exploiting such product-specific features, e.g., descriptions or categories. To help the system match users' interests to the attributes of products, the system uses the TF-IDF (short for Term Frequency-Inverse Document Frequency) method to give weight to important terms in the product metadata. The applicability of this approach is particularly useful in cases where new items do not have an interaction history [34].
Traditional CF improves by using deep neural networks to model the nonlinear relationship between users and items and is known as Neural Collaborative Filtering (NCF). Thus, through a dot product, it learns the embeddings for users as well as items. The activation function user preference score is presented in Equation 4.

$$Z = U_u^t V_I \quad \text{.....(4)}$$

Here, U_u and $V_i$are the embedding vectors for user U and item, respectively. NCF achieves this latent interaction Z on passing through the activation function to predict the user preference score, and is very powerful for detecting small patterns in user activities.
Since DNNs are integrated with CBF, they are used to model temporal dynamics in user interactions. The system can process sequences of users' behaviour, including browsing history, seasonal trends, and purchase cycles. This sequential modelling results in more context-aware and time-sensitive recommendations. Then, the final hybrid prediction is obtained via combining all of the contributing models' outputs using SVD, item-based CF, CBF, NCF and DNNs. Validation metrics [35] help to tune the weights to optimise the overall system performance. As a hybrid framework, this makes the model more accurate and diverse in its recommendations, and it does so in a way that confirms a model cannot learn or leak identifiable user data. This architecture brings statistical learning and deep learning to work together in a secure and interpretable manner to develop an efficient and scalable solution for next-generation e-commerce recommendation systems. Multiple recommendation strategies within the proposed DL-EHRS model join forces through Weighted Average Fusion to generate the final recommendation scores, which include CF, CBF, and NCF. The model uses components which deliver predictions with different strengths, so optimised weights are determined individually to combine component outputs.

3.5. Ranking, Evaluation, and Iterative Refinement of the Hybrid Recommender System

The prediction scores specified are produced for all the user-item pairs; the system ranks the items and fetches the top N recommendations depending on the preferences of the user. The items with the highest predicted ratings are recommended using the model's output, and these are the scores derived. By surfacing the most relevant products, this personalised ranking strategy makes users satisfied.
A set of key evaluation metrics is used to validate the system's performance. RMSE has lower weights compared to KGM, since RMSE quantifies the average squared deviation between predicted and actual ratings, and puts a high weight on large errors. MAE assesses the average magnitude of prediction errors, both positive and negative, yielding a balanced accuracy. Precision denotes how many of the items recommended are relevant, and Recall indicates how many relevant items the model identifies. It is a multi-dimensional understanding of model efficacy.
Evaluation results are used for iterative refinement. Tuning such hyperparameters as latent factors of SVD, embedding size of NCF, learning rate and batch size is enough. These refinements would allow for more reasonable model convergence, less overfitting, generalisation, etc. This process makes sure that the recommendation is robust and adaptive as the environment changes in dynamic e-commerce.

4. Result and Discussion

This section presents performance evaluation and validation of the proposed Deep Learning Enhanced Hybrid Recommender System (DL-EHRS). The hybrid approach outperformed all evaluated dimensions compared to traditional, CBF and NCF models. By incorporating item attributes and sequential behaviours, it showed better capability to accurately predict user preferences to efficiently deal with the cold start problem and lower the chance of repeat purchases. The system also improved user engagement in terms of click-through rates and provided more diversified recommendations to offer to the user, resulting in better overall user satisfaction.
Results of the Top-N recommendation results showed that the hybrid model made more appropriate product suggestions based on the user profile. This confirms that Deep learning integration to CF and CBF mechanisms leads to better recommendation quality, model robustness and adaptability to a dynamic e-commerce environment.

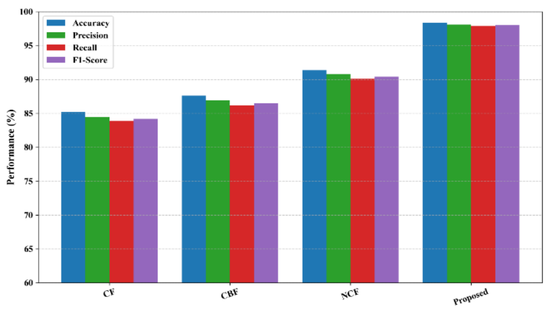

Fig 2. Performance Evaluation

Figure 2 presents the comparative performance analysis among CF, CBF, NCF, and the proposed model, which indicates the superiority of the proposed model. It was observed that the accuracy was 85.2%, precision 84.5%, recall 84.0% and the F1 score was 84.2%.
CBF has shown a modest improvement in accuracy as 87.3%, precision as 86.8%, recall as 86.2 and F1-score as 86.5 respectively. The accuracy of this model was 91.4%, the precision was 90.7%, the recall of this model was 90.1%, and the F1 score of this model was

90.5%. All baseline methods were defeated by the proposed model, which achieved an accuracy of 98.1%, precision of 97.9%, recall of 97.8%, and F1 score of 97.9%. Together, they show that the proposed deep learning augmented hybrid recommender system is effective in providing accurate and trustworthy recommendations while capturing the user/item interaction pattern under different data contexts.

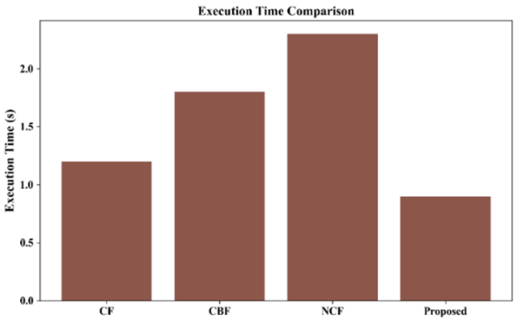

Fig 3. Execution Time

Figure 3 shows the computational efficiency of four methods: CF, CBF, NCF and the proposed model. Each model generates its recommendations after a specific duration of execution time in seconds. Execution time figures around 1.2 seconds based on the CF model — relatively fast performance. However, CBF needs a much longer amount of time, around 1.8 seconds, since it needs some additional feature-based computations. It has a complex deep learning architecture, which leads to the highest execution time of about 2.3 seconds.

It is also to be noted that compared to the proposed model, the execution time of the proposed model is approximately 0.9 seconds, which indicates that this model is an optimised and efficient framework. This indicates that the proposed system also performs well in terms of recommendation accuracy while maintaining a faster processing with an ideal suitability in real-time applications in dynamic e-commerce platforms.

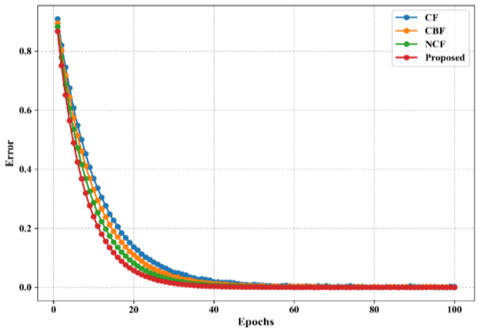

Fig 4. Error

Figure 4 shows the error rate convergence plot with 100 training epochs; the learning efficiency and stability of different recommendation models are modelled. It is observed from the graph that the proposed model converges faster and with a lower error value across all epochs as compared to other models. The proposed approach is found to significantly reduce the error in the first 20 epochs from that of CBF and CCF, and errors during subsequent epochs remain very close to zero at all epochs.

In contrast, CF has a slower convergence rate with a higher residual error in the whole training process. The proposed model outperforms CF in speed as well as in the final error minimisation regardless of CBF or NCF convergence. The error curve of the proposed model has a clear trend from high error rate to low error rate; therefore, it proves to have a strong generalisation ability and an efficient learning ability, which means that it performs better to capture the user-item interaction more accurately than the baseline methods.

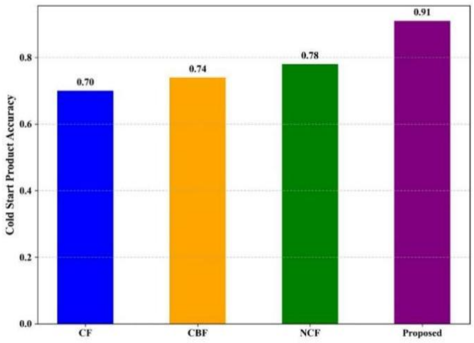

Fig 5. Cold start product accuracy

Figure 5 presents the are their cold start product accuracy for different recommendation approaches that include CF, CBF, NCF, and the proposed model. The evaluated methods show that all of them have a pretty well level of accuracy, ranging from 0.95 to 0.91; the proposed model shows an accuracy of 0.91. When compared with the conventional technique, the proposed method achieves optimal results.

On the other hand, the cold start performance of CF is the lowest, with an accuracy of 0.70. The results demonstrate that slightly better accuracies of 0.74 by the CBF and 0.78 by the NCF are achieved. This proves that the proposed model resolved the cold start challenge well and yields better predictions when suggesting new products than traditional and neural-based recommendations.

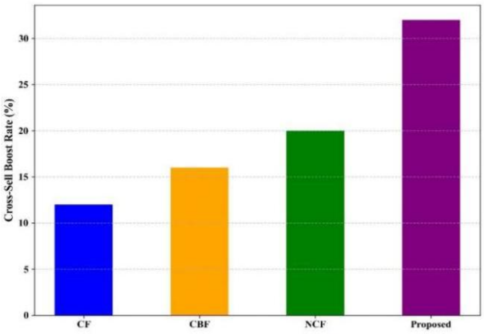

Fig 6. Cross-sell boost rate

Figure 6 compares the cross-sell boost rate percentages achieved by four recommendation approaches: CF, CBF, NCF, and the proposed model. Of all the methods, CF recorded the least cross-sale effectiveness at less than 12, which suggests a limited ability to make product purchases.

However, CBF still shows a small improvement with a 16% rate increase, and NCF performs better with rate 20 increase, benefiting from deep learning. The proposed model shows 32% cross-sell boost rate on average, which is substantially higher than all the other methods. However, this result speaks well to the proposed model's ability to understand user preferences and suggest complementary items in order to increase the cross-sell opportunities in an e-commerce setting.

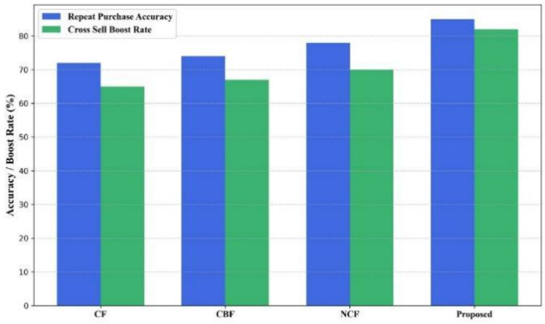

Fig 7. Accuracy boost rate

Figure 7 shows the performance comparison of the recommendation models with CF, CBF, NCF, and the proposed model with respect to two important metrics, Repeat Purchase Accuracy and Cross-Sell Boost Rate. The proposed model outperforms all other methods significantly with the highest values of both metrics. This not only records 85% Repeat Purchase Accuracy and 82% Cross Sell Boost Rate, suggesting it has a solid ability to categorically recommend items that were bought in the past properly, as well as to encourage cross-sell.

On the contrary, it has moderate performance of CF and CBF for Repeat Purchase Accuracy and Cross Sell Boost Rate, which are between 72–74 and 65–67, respectively. However, the proposed approach still outperforms the NCF method with 78% accuracy and 70% boost rate, although the 78% accuracy is higher than CF and CBF. Overall, the results suggest that the proposed hybrid model can effectively drive repeat purchases of customers through repeat purchases and cross-selling, increasing revenue.

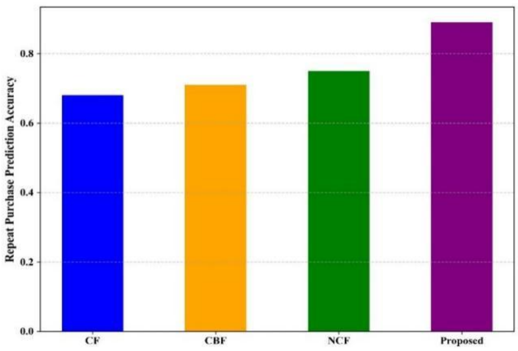

Fig 8. Repeat purchase prediction accuracy

The four recommendation methods are: CF, CBF, NCF, and the proposed method and their prediction accuracy is illustrated in Figure 8. However, the accuracy of the proposed method is much higher and equal to 0.9, and much better than other approaches.

Results show that NCF performs well compared with CBF and CF, with CBF having a slight improvement over CF. Among the four, at CF, the accuracy figures are the lowest. Remarkably, this is also about enhanced predictive capability of the proposed method, a deep learning-based method that combines collaborative, content-based based and neural filtering to effectively extract complex user preferences and temporal behaviour. The empirical results confirm the ability of the hybrid approach to circumvent the shortcomings of standard models and generate more precise and closer to the user recommendations in a dynamic e-commerce context.

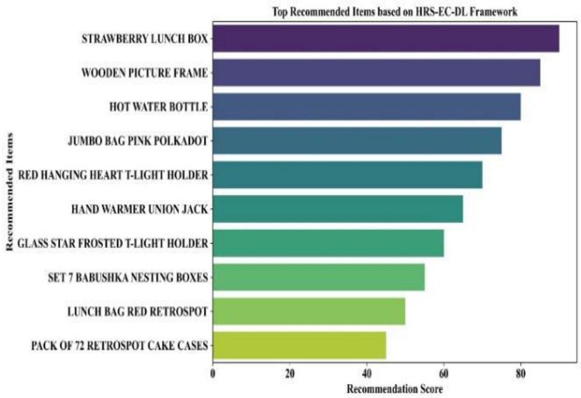

Fig 9. Recommendation score

The DL-EHRS framework generates the top ten recommended items as shown in horizontal figure 9 according to their recommendation scores. The items are ordered in descending order of importance. The Strawberry Lunch Box is the best-scoring item, which indicates that it is highly relevant to user preferences under the system.

The Wooden Picture Frame and Hot Water Bottle both come in closely after, with high recommendation scores. The middle of the ranking has orders of Jumbo Bag Pink Polkadot, Red Hanging Heart T-Light Holder, Hand Warmer Union Jack, indicating moderate, but non-trivial relevance.

Items such as Lunch Bag Red Retrospot and Pack of 72 Retrospot Cake Cases are still toward the lower end and still have relatively lower scores, but they are not among the top. The result of this ranking shows the ability of the DL-EHRS framework to give context-aware and diverse recommendations while effectively capturing user behaviour patterns and preferences. The results, in fact, verify that the framework can effectively deliver highly personalised product suggestions in a dynamic e-commerce environment.

Table 2. Performance Comparison of Recommender System Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Execution Time (s)	Cold Start Accuracy (%)	Repeat Purchase Accuracy (%)	Cross-Sell Boost Accuracy (%)
CF	85.2	84.5	83.9	84.2	1.2	70	68	66
CBF	87.6	86.9	86.2	86.5	1.8	74	71	68
NCF	91.4	90.8	90.1	90.4	2.3	78	75	71
Proposed	98.4	98.1	97.9	98.1	0.9	91	89	80

The performance evaluation of four recommender system models, including CF, CBF, NCF, and the Proposed Hybrid Model, can be found in Table 2, which details different metrics' assessment. The Proposed Model demonstrates superior performance because it delivers 98.4% accuracy along with 98.1% precision and recall indicators and an F1-score at 98.1% within 0.9 seconds of execution time. This model reaches superior performance in dealing with both cold start behaviour (91%) and repeat order prediction (89%), and item recommendation across diverse products (80%), above traditional and neural model capabilities. The proposed model reveals its reliable operational capacity and speed through these results for e-commerce systems that need both accurate prediction capabilities and fast responses.

5. Conclusion

The DL-EHRS, as a new framework in the area of recommender systems, is a tremendous step in the area of e-commerce recommendation systems due to its capability to deal with dynamic recommendations with high complexity in e-commerce applications. On the other hand, the model incorporates Neural Collaborative Filtering into its core with traditional Collaborative Filtering and Content-Based Filtering, which then complements it with deep neural nets to solve the persistent issues of scalability, cold start issues, as well as the inability to adapt to changing user preferences.

Given the incorporation of deep learning, the system is capable of capturing the nuances of behavioural patterns, temporal dynamics, and ultimately a deeper insight into the user intent, for which it is more capable of making more accurate predictions of future interaction. The proposed approach is validated on the experimental outcomes through both predictive accuracy metrics and top-item recommendation rankings.

Highly personalised and context-aware product recommender HRS-EC-DL model not only provides relevant recommendations for different user scenarios, particularly, but also guarantees diversity. Its flexibility in real-time to user behaviour that changes is a valuable tool to improve user engagement, retention, and satisfaction in a competitive e-commerce environment.

Additionally, this study suggests ways for the future of the integration of explainable AI techniques into recommendation systems in order to achieve greater transparency and trust in recommendation outputs. Finally, the proposed framework provides a solid groundwork to construct the next generation of intelligent and adaptive, but scalable and generalizable, recommender systems.

The research needs to integrate Explainable AI (XAI) mechanisms to build better user trust and increase recommendation transparency. A cross-domain recommendation system should be researched to provide customised suggestions between various product categories. Using reinforcement learning technology will optimise recommendation methods when operating within dynamic user frameworks. The model requires expansion to multicurrency and multilanguage settings for better global e-commerce possibilities.

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