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THE DEVELOPMENT OF INTELLIGENCE BOOK RECOMMENDATION MODEL USING NEURAL COLLABORATIVE FILTERING METHOD

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Abstract:

The arrival of the digital era has significantly reshaped how readers discover and interact with books, diminishing the effectiveness of conventional recommendation approaches, such as bestseller rankings and expert reviews, in reflecting personalized tastes. This study addresses the limitations of traditional methodologies, specifically the cold start and data sparsity concerns, by developing an intelligent book recommendation system that utilizes Neural Collaborative Filtering algorithms. The aim is to achieve higher recommendation accuracy by leveraging advanced techniques in user–item interaction modelling. Data is acquired from many sources, pre-processed, and evaluated using deep learning models that detect nonlinear patterns. The system's performance is evaluated using accuracy, precision, and recall scores, with a focus on mitigating cold start and data sparsity problems. The system provides reliable recommendations to existing users. Consequently, this study

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makes a significant contribution to the power of neural collaborative filtering in transforming customized book suggestions into the digital world.

Keywords:

Book Recommendation System, Cold Start Problem, Data Sparsity, Neural Collaborative Filtering, Deep Learning

Introduction

Book recommendation systems have evolved significantly since the 1990s, providing individualized choices based on individual tastes, hobbies, and reading history. These systems use deep learning algorithms, data analytics, and user profiling to create lists of books tailored to each user's interests and preferences (Amin et al., 2025). They are widely used in various platforms, including streaming services, social media, digital governance, e-libraries, e-learning, news sites, and many more (Garapati & Chakraborty, 2025). Collaborative filtering, associative rules, multi-model ensembles, and content-based filtering are common algorithms used in recommendation systems (Bhajantri et al., 2024). These methods address challenges such as data sparsity, cold start concerns, and scalability limitations by combining multiple algorithms (Jetti & Krishna Prasad, 2025). Therefore, this approach produces more accurate and personalized suggestions, improving the overall recommendation process. As technology advances, personalized book suggestions are expected to become more sophisticated and successful, resulting in a more engaging and unique experience for users (Gao, 2025). In this study, a Neural Collaborative Filtering (NCF) book recommendation system is presented that identifies trends and preferences based on user-item interactions. It enhances the system's ability to adapt to different user preferences, increasing the overall accuracy and relevance of the suggestions.

Nevertheless, such systems commonly encounter limitations, particularly the cold-start problem and data sparsity, which remain significant challenges in real-world applications. Cold-start issues involve the lack of data, which prevents algorithms from analyzing user preferences and making reliable suggestions (Panteli & Boutsinas, 2023). This constraint makes it difficult for new users to fully benefit from the recommendation system (Mishra et al., 2024). Data sparsity is another issue in recommendation systems, particularly in collaborative filtering-based algorithms. It results from a lack of sufficient data or interactions between users and objects, leading to less tailored recommendations (Patel & Kant, 2025). This can lead to incorrect recommendations and distorted data distributions. Thus, researchers and developers are looking for new ways to improve recommendation accuracy while handling these limitations. Therefore, even with limited user data or interactions, book recommendation systems aim to competently solve cold-start and data sparsity problems by emerging solutions offering useful suggestions.

Research on intelligent book recommendation systems explores various techniques to enhance accuracy and personalization. Collaborative filtering (CF) predicts user preferences based on past interactions, but faces challenges like data sparsity and cold-start issues (Chen et al., 2025). Content-based filtering (CBF) recommends items by analyzing content and user preferences,

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but struggles with overspecialization and limited data (Javed et al., 2021). Hybrid filtering combines CF and CBF to improve accuracy and adaptability, as seen in platforms such as Netflix, though it is complex to implement (Sarma et al., 2021). These studies highlight the need for hybrid models to optimize recommendation systems.

Various Artificial Intelligence (AI) techniques have considerably improved book recommendation systems' accuracy and customization. Deep learning techniques successfully capture complicated user-item interactions, whereas convolutional neural networks (CNNs) improve feature learning (Wadikar et al., 2020). NCF predicts nonlinear user-item connections and is capable of boosting recommendation performance (Kavitha & Murugesan, 2024). Clustering techniques, such as K-means and hierarchical clustering, divide user preferences into meaningful categories (López-Oriona et al., 2025). Furthermore, matrix factorization techniques such as singular value decomposition and alternating least squares can be used to improve recommendation efficiency (Adyatma & Baizal, 2023). Therefore, these techniques improve the effectiveness of book recommendation systems.

Current book recommendation platforms employ AI-driven algorithms that learn from readers' preferences and behaviours, thus providing more relevant, engaging, and personalized book suggestions. It tailors recommendations based on user preferences, reading history, and emotional states (Wayesa et al., 2023). Librarian AI, which focuses on deep customization, continuously refines recommendations through user interactions. WhichBook introduces an innovative approach by allowing users to filter books based on mood and story elements, while BookSloth enhances the experience with social engagement features (Payne, 2022). These developments highlight the shift from traditional recommendation methods to more adaptive, user-centric systems, enhance book discovery, and foster deeper reader engagement.

The rest of the paper is organized as follows. Section 2 presents the related works of the book recommendation system. Section 3 outlines the research methodology steps, and Section 4 presents the experimental results and analysis. Lastly, Section 5 gives a discussion and future work.

Literature Review

As online retailers, digital libraries, and reading platforms continue to grow, book recommendation systems have received increased attention in recent years. There are many titles available, and it can be challenging for readers to select novels that align with their favorites. In order to improve user satisfaction and engagement, recommendation systems analyze user behavior, preferences, and trends, providing relevant book recommendations. By boosting the visibility and sales of a variety of titles, these platforms are able to help publishers, retailers, and individual readers with book recommendations.

Cold start and data sparsity are common problems in a book recommendation system. Cold start relates to the recommendation difficulty in recommending items or providing an inference to new users (Roy & Dutta, 2022). It identifies new users and new items (new books), which are new sign-up users and new book titles with no interactions (Son, 2016). Conversely, data sparsity arises when there is a lack of user input reviews or ratings, which stops the system from recommending a more accurate item (Dwiputriane et al., 2022). In addition, it takes on

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other forms, such as interaction and text sparsity (Kim et al., 2024). Accordingly, these are the common problems in a book recommendations system.

Information filtering theory requires tailored recommendations, which are the basis of recommendation systems. The aim is to reduce information overload by choosing relevant data from big datasets. This idea is directly applied via collaborative filtering and content-based filtering strategies, which seek to rank and filter items based on user behavior and preferences (Natarajan et al., 2020). Collaborative Filtering (CF) is also based on the social influence concept, which holds that other people's beliefs and actions influence people's choices (Batmaz et al., 2019). Similarity between users or between items in CF illustrates how social norms and group behaviors impact personal decisions. This theoretical viewpoint explains why it is possible to make accurate predictions about future preferences by examining user ratings and interactions.

In improving accuracy and flexibility, recommendation systems use a variety of techniques. The NCF approach is one of the most significant developments in recommendation system research. NCF uses deep neural networks to simulate intricate, non-linear relationships, in contrast to conventional collaborative filtering techniques that depend on linear interactions between users and items (Alam & Ahmed, 2025). Higher-order interactions that conventional models frequently miss can be captured by NCF. This method improves suggestion accuracy and flexibility, especially in areas where user preferences are complex and multifaceted, like book recommendations. By tackling problems like data sparsity and cold-start concerns, recent research has shown that NCF performs better than traditional collaborative filtering, making it a promising method for personalized recommendation systems.

The development of book recommendation systems has evolved dramatically with the use of Artificial Intelligence (AI), making it possible to create highly customized and context-aware recommendations, utilizing deep learning models, reinforcement learning, and natural language comprehension (Alam & Ahmed, 2025). AI-driven systems are effective tools for improving the reading experience on digital platforms since they not only increase recommendation accuracy but also adjust to changing user interests.

Table 1. Summary of Past Findings in Recommendation System Research

Study	Technique	Main Findings	Limitations / Gaps
(Roy & Dutta, 2022)	Collaborative Filtering	Addressed large-scale data retrieval challenges	Difficulty in identifying the most relevant items
(Fkih, 2022)	Collaborative Filtering	Similarity metric selection strongly impacts performance	Wrong metric choice reduces accuracy
(He et al., 2017)	Neural Collaborative Filtering	NCF introduces non-linearities, outperforming matrix factorization	Early stage; limited domain testing
(Ullah et al., 2020)	Neural Collaborative Filtering	Improved accuracy for book recommendations	Dataset-specific, may lack generalizability

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(Batmaz et al., 2019)	Deep Learning	Deep learning improves accuracy and scalability	Computationally expensive

Table 1 shows the evolution of several recommendation system strategies over time. Although collaborative filtering is still extensively used, it has problems with accuracy and relevance, especially when it comes to handling vast amounts of data and using similarity metrics. Deep learning techniques offer notable gains in scalability and accuracy, but come with a high computational cost (Batmaz et al., 2019). Although there are still problems with early-stage development, NCF shows promise as a substitute by capturing non-linear user–item interactions and outperforming conventional methods (He et al., 2017; Ullah et al., 2020).

It is clear from the examined literature that recommendation systems have progressed from conventional filtering techniques to increasingly complex AI-driven strategies. Particularly in the book arena, neural collaborative filtering shows great promise for improving recommendation accuracy and personalization. These results support the investigation of AI-based collaborative filtering techniques, such as NCF, in order to create more individualized and efficient book recommendation systems.

Methodology

This section describes the systematic approaches and methods utilized in a study on book recommendation systems, which used a variety of data sources and analytical tools. It explains the tools, methods, dataset selection, and algorithms used to provide accurate and meaningful results.

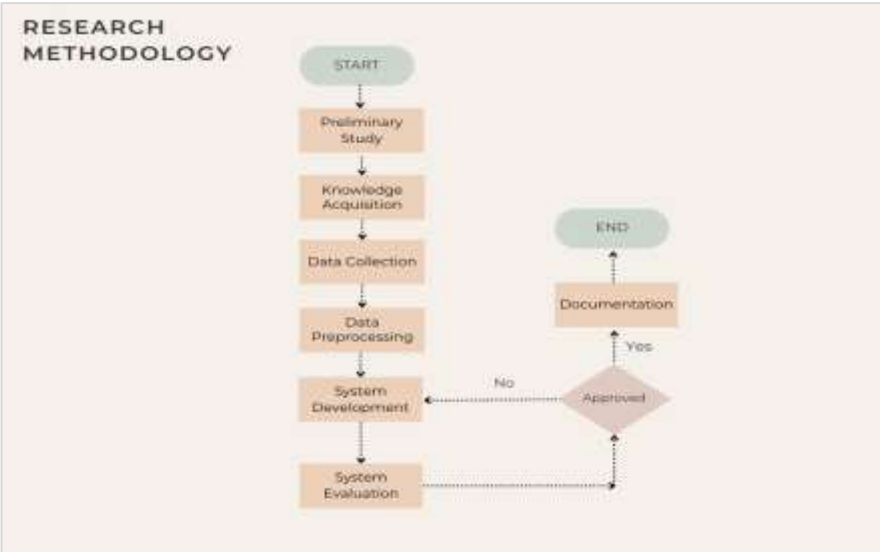

Figure 1: Research Methodology

The Preliminary and Knowledge Acquisition phase aims to recognize the need for creating a recommendation model to deal with the problem of information overload in book selection. Users are frequently overwhelmed by the large number of books available due to the quick expansion of digital libraries and online marketplaces such as Goodreads and Amazon, which

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makes it challenging to find the right material that fits their interests. In this stage, a thorough literature assessment of recommendation systems, deep learning methodologies, and collaborative filtering strategies is carried out. Existing models are examined to determine their advantages and disadvantages. Thus, the theoretical foundations for creating the suggested intelligent book selection model are established in this step.

In the Data Collection phase, the project's dataset was sourced from Kaggle and Goodreads. While Kaggle gives publicly accessible datasets with user ratings and interactions, Goodreads offers book-related information, including titles, authors, and genres. Kaggle's user-rating datasets and Goodreads metadata are combined to guarantee that the suggested model has access to both collaborative data (user-book interactions) and content-based data (book features). In order to maintain representativeness while maintaining computational manageability, a subset of users, books, and ratings is chosen due to the size of the original datasets. To make a complete dataset, the two sources merge together using common markers like ISBNs or titles, ensuring that each book is shown with both content-based and collaborative features.

To make sure the raw dataset is appropriate for training a machine learning model, the Data Preprocessing stage is essential. First, duplicate records are removed, missing values are addressed, and unnecessary or noisy items that might degrade the model's quality are removed. Then, standardization is used to preserve uniformity across characteristics such as book details and ratings. To make them compatible with machine learning algorithms, categorical information like book genres, categories, and user preferences is converted into numerical values. To make embedding easier during model training, user and item identifiers are also re-indexed into continuous integer IDs. The dataset is also divided into subgroups for testing and training in order to compare performance and assess the model. Building train-test splits is another crucial step in assessing the model's generalizability. In order to maintain the chronological order of interactions when timestamps are available, the dataset is separated into subsets for training, validation, and testing. By guaranteeing that the model is tested on "future" interactions that it hasn't observed during training, this method replicates real-world recommendation scenarios.

The system is developed using NCF, which enhances collaborative filtering with deep learning to better capture complex user–item relationships. In this system, user and item IDs are first transformed into embedding vectors, which efficiently convey their properties in a dense and significant manner, and then mapped into a continuous latent space. Following their concatenation and passage through several neural network layers, these embeddings allow the model to discover hidden patterns and higher-order interactions that surpass the basic similarity metrics employed in traditional techniques. The network's ability to identify non-linear correlations between users and books is made possible by activation functions and hidden layers, which enhance the precision and customization of suggestions. After training, the NCF-based recommendation algorithm predicts user preferences for unseen titles to produce personalized book recommendations. This results in a system that can provide data-driven and customized recommendations based on learned interaction features and collaborative patterns.

Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), two error-based metrics, are used to assess the recommendation model's performance. By contrasting the anticipated ratings produced by the algorithm with the actual user ratings in the test set, these measures

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measure prediction accuracy. While RMSE penalizes greater errors more severely, MAE offers a simple way to evaluate the average absolute difference between projected and true ratings, which makes it useful for detecting situations in which the model generates predictions that are noticeably off. The dataset is separated into training and testing subsets to provide a rigorous and equitable evaluation. The testing set is used just to evaluate generalization performance on unseen data, while the training set is utilized to build and optimize the model. The performance of the suggested NCF method is then compared with baseline collaborative filtering techniques, including item-based and user-based similarity models. The benefits of NCF in capturing intricate user-item interactions and generating more precise and tailored book suggestions are demonstrated by this comparison.

In the documentation phase, the entire research process and system development are recorded in detail. The dataset description, preprocessing stages, model design, training methods, assessment outcomes, and findings discussions are all included in this. The documentation guarantees that the approach and findings are open, repeatable, and suitable for use as a guide for further studies or enhancements to the recommendation model.

Results and Discussion

The findings and evaluation of the suggested Neural Collaborative Filtering (NCF) book recommendation system are shown in this part. To ascertain the efficacy of the algorithms and recommendation models, it also looks at their performance. Accuracy, precision, recall, RMSE, Mean Squared Error (MSE), and MAE are used to evaluate the system's capacity to offer precise and tailored recommendations. These results provide information about the model's advantages and disadvantages as well as how effectively it can improve user experience in general.

Model Training and Testing Processes

In this study, a 90/10 train-test split was used to assess the NCF model's performance. Performance was evaluated using RMSE, MSE, MAE, accuracy, precision, and recall after training for 10, 20, and 50 epochs. The evaluation's findings are reported in Table 2 along with comparisons to earlier research.

Table 2. The Evaluation Results from Different Studies

	Epochs		RMSE	MSE	MAE	Accuracy	Precision	Recall
This study	10		0.85	0.72	0.70	0.75	0.89	0.57
	20		0.72	0.52	0.58	0.86	0.90	0.82
	50		0.81	0.65	0.67	0.80	0.89	0.70
(Verma et al., 2025)	100		0.48	0.23	0.29	Null	Null	Null
(Kavitha & Murugesan, 2024)	5		1.15	Null	Null	Null	Null	Null
	10		1.08	Null	Null	Null	Null	Null
	20		0.99	Null	Null	Null	Null	Null

The findings of this study are contrasted with those of earlier research in Table 2 above. In contrast to Verma et al.(2025), which obtained 0.48 RMSE at 100 epochs, and Kavitha & Murugesan (2024), which only reported RMSE values over 0.99, this study offers a more comprehensive evaluation that includes MSE, MAE, accuracy, precision, and recall. For

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accurate book suggestions, the suggested model is the most practical option due to its more balanced and effective performance.

In contrast, the results of this study extend the evaluation to include accuracy, precision, and recall, all of which are critical for recommendation systems, in addition to reporting RMSE, MSE, and MAE. At 20 epochs, the model used in this investigation had an accuracy of 0.86, precision of 0.90, recall of 0.82, RMSE of 0.72, and MAE of 0.58. The inclusion of extra performance measures demonstrates that the model in this study offers a stronger balance between correctness (precision), coverage (recall), and overall dependability (accuracy), even though the RMSE is marginally higher than that of Verma et al.(2025), 0.48. Additionally, this study's model is more computationally efficient and feasible for real-world deployment because it converges at just 20 epochs, while Verma et al.(2025) needed 100 epochs to achieve optimal performance.

In conclusion, the study by Verma et al.(2025) shows that the model has the lowest RMSE, it requires a lot more training epochs, and is not well evaluated. With constantly high RMSE values, Kavitha & Murugesan (2024) model exhibits the poorest performance. With competitive error rates and excellent accuracy, precision, and recall in fewer epochs, the model suggested in this study proves to be the most appropriate and well-balanced method for personalized book recommendation tasks.

Evaluation Metrics Graph

Error-based assessment measures were investigated in order to offer a more profound understanding of the training behavior of the suggested NCF model. Specifically, throughout several training epochs (10, 20, and 50), MSE and RMSE were monitored. These metrics are frequently used to evaluate prediction accuracy; higher alignment between predicted and actual scores is indicated by lower values. It is feasible to determine the moment at which the model achieves the optimum generalization without underfitting or overfitting by looking at their trends over several epochs.

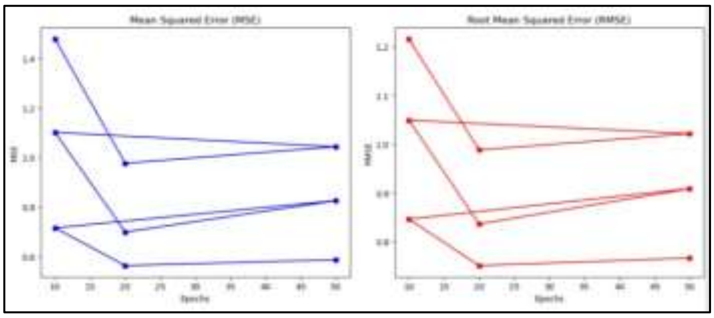

Figure 2. RMSE and MSE Evaluation Metrics Graph

The variance of RMSE and MSE throughout 10, 20, and 50 training epochs is shown in Figure 2. Between 10 and 20 epochs, both error measures significantly decline, indicating efficient learning and model development in this range. The ideal training point for the model is confirmed to be at 20 epochs, when the lowest error values are observed (RMSE = 0.72, MSE = 0.52). The onset of overfitting, in which the model learns patterns from training data rather than generalizing to new inputs, is indicated by a modest rise in both RMSE and MSE at 50

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epochs.

According to this pattern, the suggested model performs best when 20 epochs are used, limiting errors while avoiding the drawbacks of undertraining (10 epochs) and the dangers of overfitting (50 epochs).

Recommendation For New Users
This study assesses the system's capacity and provides insightful recommendations to new users. The cold start issue affects new users who have no previous interaction history. In handling this problem, the system uses content-based filtering to produce suggestions based on preferences during registration (such as genres, authors, or themes).

The findings show that the technique used has successfully addressed sparsity and cold start problems, providing even novice users with appropriate and flexible book recommendations. This demonstrates the system's ability to preserve customization and enhance the reading experience.

Conclusions
The present study develops an intelligent book recommendation system using NCF to improve recommendation accuracy while addressing the cold-start problem and data sparsity. The objectives were achieved, as the model demonstrated strong performance in accuracy, precision, and recall, particularly at the optimal training epoch, confirming the contribution of deep learning to improving collaborative filtering.

The results suggest that neural-based frameworks can significantly enhance personalization, thereby improving user engagement, satisfaction, and retention. This highlights the broader potential of integrating advanced deep learning architectures into recommendation systems to meet the growing need for adaptive and user-centric digital platforms.

This research contributes to the validation of NCF's ability to capture complex user–item interactions and introduces a fallback mechanism to mitigate cold-start issues. These contributions advance research on intelligent recommendation systems and demonstrate practical value for applications in digital libraries, e-commerce, and e-learning environments. Despite these contributions, it has limitations, including dependence on Goodreads data, high computational requirements, and only partial resolution of the cold-start problem. Future direction should explore hybrid approaches that combine NCF with content-based or knowledge graph models, incorporate contextual and temporal factors, and evaluate performance through real-world deployment and user feedback.

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