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ARTICLE

HCF-MFGB: Hybrid Collaborative Filtering Based on Matrix Factorization and Gradient Boosting

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ABSTRACT: Recommendation systems are an integral and indispensable part of every digital platform, as they can suggest content or items to users based on their respective needs. Collaborative filtering is a technique often used in various studies, which produces recommendations by analyzing similarities between users and items based on their behavior. Although often used, traditional collaborative filtering techniques still face the main challenge of sparsity. Sparsity problems occur when the data in the system is sparse, meaning that only a portion of users provide feedback on some items, resulting in inaccurate recommendations generated by the system. To overcome this problem, we developed a Hybrid Collaborative Filtering model based on Matrix Factorization and Gradient Boosting (HCF-MFGB), a new hybrid approach. Our proposed model integrates SVD++, the XGBoost ensemble learning algorithm, and utilizes user demographic data and meta items. We utilize information, both explicitly and implicitly, to learn user preference patterns using SVD++. The XGBoost algorithm is used to create hundreds of decision trees incrementally, thereby improving model accuracy. Meanwhile, user demographic and meta-item data are clustered using the K-Means Clustering algorithm to capture similarities in user and item characteristics. This combination is designed to improve rating prediction accuracy by reducing reliance on minimal explicit rating data, while addressing sparsity issues in movie recommendation systems. The results of experiments on the MovieLens 100K, MovieLens 1M, and CiaoDVD datasets show significant improvements, outperforming various other baseline models in terms of RMSE and MAE. On the MovieLens 100K dataset, the HCF-MFGB model obtained an RMSE value of 0.853 and an MAE value of 0.674. On the MovieLens 1M dataset, the HCF-MFGB model obtained an RMSE value of 0.763 and an MAE value of 0.61. On the CiaoDCD dataset, the HCF-MFGB model achieved an RMSE value of 0.718 and an MAE value of 0.495. These results confirm a significant improvement in movie recommendation accuracy with the proposed approach.

KEYWORDS: Recommendation systems; hybrid collaborative filtering; SVD++; XGBoost; K-Means clustering; user demographics; meta item

1 Introduction

In recent years, the amount of data and information on various platforms has increased significantly [1]. This has resulted in users finding it difficult to choose goods or content according to their precise preferences and within a certain timeframe [2–4]. To increase profits and customer satisfaction, each platform is required to match users with products that suit their preferences [5]. This has led to recommendation systems becoming an important and inseparable part of every platform [6,7]. Recommendation systems are designed to analyze and provide more personalized recommendations to users [8,9]. Recommendation systems have undergone rapid development and are now utilized on various platforms, including e-commerce [10], streaming services [11], learning media [12], and social media [13].

For example, the most prominent application of recommendation systems is on Netflix, Amazon, and YouTube platforms, where, indirectly, the system can increase user engagement by presenting personalized content, resulting in longer user sessions, higher retention rates, and a greater likelihood of making purchases or interacting with advertisements. This increased engagement can directly generate higher revenue and a competitive advantage [14,15]. In general, recommendation systems are categorized into content-based filtering, collaborative filtering, and hybrid approaches [16,17]. The collaborative filtering approach is the most frequently used in various studies [18–20]. This approach works by analyzing similarities between users based on their preferences and behavior [21]. Despite rapid progress, the conventional collaborative filtering approach faces several challenges, such as data sparsity and cold-start [22]. Of these challenges, sparsity is the primary factor contributing to a decline in recommendation performance. This is because only a few users provide feedback on some items, so the data in the system is very sparse, which makes it difficult for the system to produce accurate recommendations [23,24]. This has an impact on decreasing user engagement because the recommended items are irrelevant.

To address these challenges, several previous studies have been conducted. For example, research [25] which developed a Hybrid Collaborative Filtering model based on Sparse Rating Matrix and User Preference (HCFDS). This model operates by combining two primary algorithms: IU-CS, which measures similarity between users, and II-CS, which measures similarity between items. Additionally, the HCFDS model provides a distinct approach to handling missing values in the rating matrix. This process begins by predicting the missing values using the II-CS algorithm and then adjusting the prediction results to consider the item category preferences of each user. In this way, the system does not rely solely on limited rating data but also incorporates more contextual preference patterns. The results show that HCFDS can reduce the MAE value by up to 7.9%.

Research [26] developed the Rec-CFSVD++ model, which combines collaborative filtering (CF) with SVD++ to consider implicit feedback in predicting ratings. By leveraging the advantages of collaborative filtering and SVD++ approaches simultaneously, the Rec-CFSVD++ model exhibits superior performance, resulting in a lower error rate that effectively addresses the issues of sparsity. Research [27] combines matrix factorization with the XGBoost algorithm. In this model, matrix factorization is used to predict the initial rating and creates hand-crafted features such as user similarity, item similarity, and global average. The results of MF and hand-crafted are used as input for the XGBoost model to produce the final rating prediction. Combining these two modules has proven effective in increasing recommendation accuracy because it utilizes the advantages of MF in capturing latent relations and the advantages of XGBoost in modeling non-linear relationships.

Meanwhile, research [28] proposed an ExtKNNCF model, which is a development of the K-NN method. This model incorporates user cognition in calculating similarities between users, making it more accurate in grouping users with similar preferences and producing more relevant recommendations. This model proved to be significantly more effective than the baseline model in increasing prediction accuracy by reducing RMSE and MAE values. Furthermore, integrating additional information from users proved to be very effective. Research [29] proposed Dem-Enh Cosine-KNN, which combines user demographic data such as age, occupation, gender, and zip code in calculating similarities between users. By utilizing user demographic data, the model has access to a wealth of information, and the results have proven to be very effective in increasing recommendation accuracy. This performance improvement confirms that utilizing user data can help overcome the sparsity problem in traditional collaborative filtering.

Although various previous studies have contributed to reducing the impact of sparsity issues, these studies still have weaknesses. The HCFDS model only focuses on similarities between items and users. The shortcomings of this model are that it does not integrate user demographic data and meta-items. Additionally, HCFDS does not utilize matrix factorization techniques that can leverage both explicit and implicit information to reduce sparsity, resulting in a less-than-optimal model, particularly for large datasets.

Matrix factorization-based models, such as Rec-CFSVD++ [26] and HCFMR [27], do not utilize user demographic and Meta-Item data, so system performance can be less than optimal when data is very limited or specific preferences are not recorded in the rating pattern. Meanwhile, KNN-based models, such as ExtKNNCF and Dem-Enh Cosine-KNN, struggle to capture complex latent relationships between users and items, which can lead to decreased performance on large datasets. Dem-Enh Cosine-KNN has integrated user demographics but has not incorporated matrix factorization techniques that utilize implicit feedback to reduce sparsity. Thus, an integrated approach is needed that leverages the advantages of SVD++ and ensemble learning algorithms, while using user demographic and meta-item data to bridge this gap.

Table 1. shows a summary of the differences between previous studies, including the dataset, advantages, disadvantages, and evaluation metrics used by the HCFDS, Rec-CFSVD++, Ex-tKNNCF, Dem-Enh Cosine-KNN, and HCFMR models.

Table 1: Summary of differences from previous research

Model	Advantages	Limitations	Dataset	Evaluation technique
HCFDS	• Effectively reduces sparsity with IU-CS and II-CS. • This technique can improve prediction accuracy.	• Focus only on similarities. • Does not utilize implicit information or demographic data.	MovieLens 100K	MAE
Rec-CFSVD++	• Combining CF and SVD++. • Utilizing implicit feedback.	• Relying solely on similarity and implicit information.	MovieLens 100K, 1M, Book Crossing	RMSE, MAE
ExtKNNCF	• Using user cognition to calculate similarities between users. • Accurate in grouping similar preferences.	• Unable to capture latent relationships between users and items. • Does not integrate user demographics.	MovieLens 100K, 1M	MAE, RMSE, MAP, NDCG

(Continued)

Table 1 (continued)

Model	Advantages	Limitations	Dataset	Evaluation technique
Dem-Enh Cosine-KNN	• Integrating user demographic data. • The resulting accuracy is improved.	• Less efficient with data with many preferences. • Unable to capture latent relationships between users and items.	MovieLens 100K, 1M	RMSE, MAE
HCFMR	• Able to capture latent factors. • Modelling non-linear relationships.	• Not yet utilizing implicit information or user demographic data.	MovieLens 100K, 1M, Ciao DVD	RMSE, MAE

Based on the explanation of previous research and to overcome existing limitations, this study proposes a new hybrid model combining SVD++ and XGBoost, enriched with user demographic and meta-item data clustered using K-Means Clustering. This overall combination is designed to enhance the accuracy of rating prediction by reducing reliance on explicit rating data, as well as addressing the sparsity issue in movie recommendation systems. SVD++ is used to capture hidden preference patterns. By integrating SVD++, which effectively captures hidden preference patterns, and the XGBoost ensemble algorithm, which reliably models complex non-linear relationships, along with user demographic and meta-item data that have been clustered using K-Means, the proposed model is expected to provide more targeted movie recommendations, even with minimal available rating data.

In this context, the research aims to comprehensively understand how the integration of user demographic data and item metadata can affect the performance of collaborative filtering-based recommendation systems. In addition, the study examines the effectiveness of ensemble algorithms, such as XGBoost, in enhancing rating prediction accuracy, particularly in conditions of high sparsity, and evaluates whether the combination of SVD++, K-Means Clustering, and XGBoost methods collectively provides a significant improvement over the baseline model. This approach aims to provide a more comprehensive insight into the contribution of each model component to the performance of the recommendation system.

The significant contributions of the proposed HCF-MFGB model to movie recommendation systems are summarized as follows:

1. Uses SVD++ by integrating implicit feedback and explicit ratings to address sparsity.
2. Integrates user demographic and meta-item data and groups them into clusters using K-Means Clustering.
3. Uses XGBoost to process additional features, thereby improving model performance.
4. Validates the effectiveness of the HCF-MFGB model with comprehensive evaluation metrics and demonstrates its good performance in providing accurate movie recommendations.

The following is the structure of this article. Section 2 outlines the methodological steps employed; Section 3 presents the experimental setup and the results of the movie recommendation system's performance evaluation; and Section 4 summarizes the findings and implications of this research.

2 Method

This study develops a recommendation system model that combines SVD++ and one of the Gradient Boosting Algorithms, namely XGBoost. This model is known as Hybrid Collaborative Filtering Based on Matrix Factorization and Gradient Boosting (HCF-MFGB). In Fig. 1, the HCF-MFGB model comprises six stages: dataset preparation, preprocessing, temporary rating prediction using SVD++, feature engineering, final prediction using the XGBoost algorithm, and evaluation.

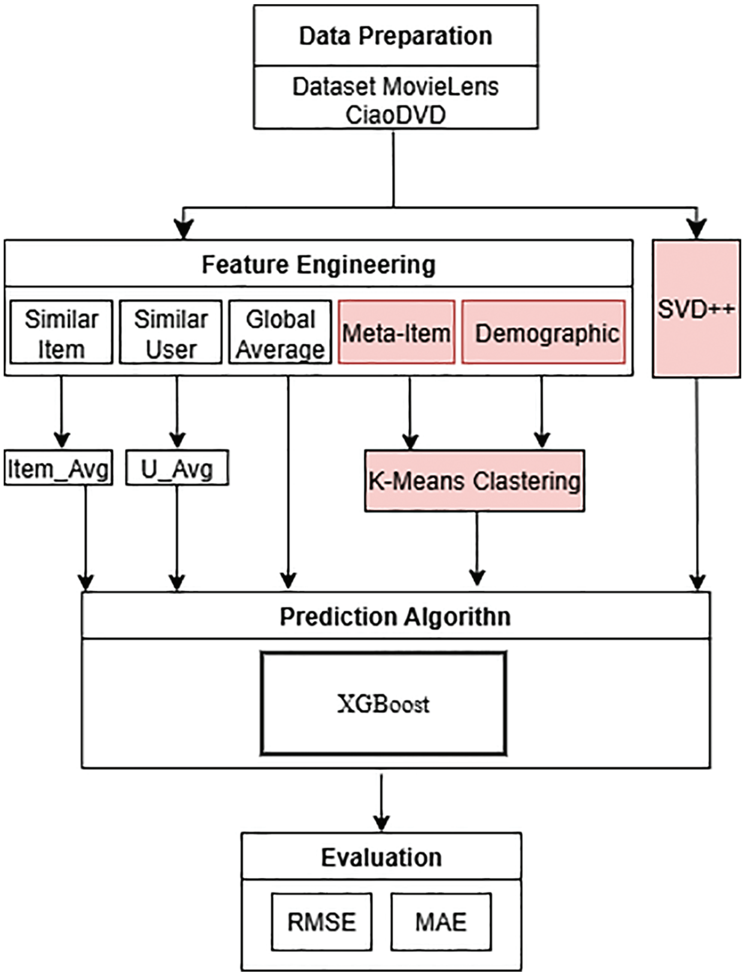


Figure 1: Research methodology

2.1 Data Preparation

This study uses two public datasets, namely the MovieLens 100K, MovieLens 1M, and CiaoDVD. These datasets are often used in recommendation system research [30,31], because they provide very complete interaction data between users and items, as well as relevant contextual information. Table 2 is the specification of the dataset used. Tables 3–5 present the structure of each data contained in the MovieLens dataset, namely item data with its meta items, and user data with its demographic data.

Table 2: Dataset description

Dataset	User	Film	Rating	Rating scala	Sparsity
MovieLens 1M	6040	3900	1,000,209	[1–5]	95.75%
MovieLens 100K	943	1682	100,000	[1–5]	93.70%
CiaoDVD	7375	99,746	278,483	[1–5]	99.90%

Table 3: Example of user data in the MovieLens dataset

User_ID	Age	Gender	Occupation	Zip_Code
97	43	M	Artist	98006
266	62	F	administrator	78756
811	40	F	educator	73013
24	21	F	artist	94533
31	24	M	artist	10003
281	15	F	student	6059
569	34	M	educator	91903
260	40	F	artist	89801

Table 4: Example of item data in the MovieLens dataset

MOVIE_ID	Movie_Title	Release_Date	Genre
1	Toy story	01 January 1995	Animation, Children's, Comedy
2	GoldenEye	01 January 1995	Action, Adventure, Thriller
3	Four rooms	01 January 1995	Action, Comedy, Drama
4	Get shorty	01 January 1995	Crime, Drama, Thriller
5	Copycat	01 January 1995	Drama

Table 5: Example of rating data in the MovieLens dataset

User_ID	Movie_Id	Rating	Timestamp
196	242	3	881250949
186	302	3	891717742
22	377	1	878887116
244	51	2	880606923
...	...	...	...
880	476	3	880175444
716	204	5	879795543
276	1090	1	874795795

2.2 Preprocessing

The preprocessing stage in this study focused on converting categorical data into numerical data so that it could be processed by algorithms and removing unused data. The MovieLens dataset used in this study contains attributes from items and user demographic data that are still in the form of categorical attributes such as genre, gender, and occupation, as shown in Tables 3 and 4. All data that is still in the form of categories is converted using one-hot encoding; each category is converted into a unique and different number to make it easier to process to the next stage. In addition, to handle missing user demographic data, we implemented an imputation procedure. Empty categorical attributes, such as gender or occupation, were filled with the mode, which is the value that appears most frequently in the dataset. In contrast, numerical attributes, such as age, were imputed using the median. This approach ensures that all users can be retained in the dataset without losing essential information, while maintaining data consistency to improve reproducibility.

2.3 SVD++

The next stage in this research is to predict the temporary ratings that users have not yet given for certain items. SVD++ is used to predict temporary ratings that have not been given by users. When compared to other types of factorization techniques, SVD++ is superior because it utilizes implicit feedback, such as access history or user interactions, including lists of items that have been opened. The use of SVD++ has been proven to be better in overcoming data sparsity problems and increasing prediction accuracy [32,33]. In predicting ratings using Eq. (1).

$$\hat{r}_{ui} = \mu + b_u + b_i + q_i^T \left(p_u + \frac{1}{\sqrt{|N(u)|}} \sum_{j \in N(u)} y_j \right) \tag{1}$$

where μ is the global average rating, b_u and b_i are user and item biases, p_u and q_i are latent vectors of users and items, $N(u)$ is the collection of items accessed by the user u, while y_j is a vector of latent contributions from users' implicit interactions.

This method combines the influence of two types of important information into the model, namely explicit and implicit information, so that the resulting predictions become more personal and not generic. The latent vector y_j represents the effect of items that the user has seen, even though they are not rated. This collection of vectors allows the model to understand what the user likes, so that the resulting predictions are not only numerically accurate, but also according to the user's interests, because they consider user behavior. In this study, the prediction results from SVD++ are not the final prediction results but are used as additional features in the final prediction model.

2.4 Feature Engineering

In this stage, we create additional features to enrich the information used in the prediction process. There are four features, namely, calculating the similarity between items based on rating patterns using Eq. (2), calculating user similarity based on the ratings given to several items using Eq. (3).

$$cosine_{sim}(u_1, u_2) = \frac{\sum u_1.u_2}{||u_1||||u_2||} \tag{2}$$

$$cosine_{sim}(v_1, v_2) = \frac{\sum v_1.v_2}{||v_1||||v_2||} \tag{3}$$

where u_1, u_2 are the rating vectors of two different users, $\sum u_1.u_2$ is the dot product between the two user vectors, and $||u_1||||u_2||$ is the length of each user's vector.

After that, we calculate the Global Average value of all ratings given by users, using Eq. (4).

$$\text{Globalavg} = \frac{\sum r_{aj,i}}{\sum N_{nz}} \tag{4}$$

where $\sum r_{aj,i}$ is the total number of ratings given by all users and $\sum N_{nz}$ is the total number of ratings given by users.

Next, we used K-Means Clustering to group films based on genre combinations. Each film in the MovieLens dataset has multiple genres, such as Action, Comedy, Drama, etc., represented in binary form. The K-Means algorithm groups films that have similar genre combinations. The next clustering was applied to user demographic data, namely age, gender, and occupation, grouping users with similar demographic characteristics.

2.5 Prediction Algorithm

To predict the final rating score given by users, we use the XGBoost Algorithm. The XGBoost algorithm is a machine learning algorithm that applies ensemble learning techniques that work by building hundreds of decision trees gradually to improve model accuracy [34,35]. At each stage, a new decision tree will correct errors in the previous model so that it can gradually improve model performance. XGBoost is widely used as a machine learning algorithm, which is because of its ability to handle large datasets and produce good performance [36].

Previously generated features, such as rating results from SVD++, item-user similarity, global average, and clustering results from meta-items and user demographics generated by K-Means, these features are combined into a feature vector and used as input to XGBoost. The objective function in XGBoost consists of a loss function and a regularization term, which are defined in Eq. (5).

$$\mathcal{L}(\Theta) = \sum_{i=1}^{n} \mathrm{l}(y_i, \widehat{y_i}) + \sum_{k=1}^{K} \Omega(f_k) \tag{5}$$

where $\mathrm{l}(y_i, \widehat{y_i})$ is a loss function measuring the difference between the actual value y_i and the predicted one $\widehat{y_i}$, $\Omega(f_k)$ is a regularization term used to control the complexity of the model.

The model uses a gradient boosting technique, where the contribution at each iteration is determined by minimizing the second order using Eqs. (6) and (7).

$$g_i^{(t)} = \frac{\partial \mathcal{L}\left(y_i, \widehat{y_i}^{(t-1)}\right)}{\partial \widehat{y_i}^{(t-1)}} \tag{6}$$

$$h_i^{(t)} = \frac{\partial^2 \mathcal{L}(y_i, \widehat{y_i})}{(\partial \widehat{y_i}^{(t-1)})^2} \tag{7}$$

where g_i and h_i are the first and second order gradients of the loss function, $\partial \mathcal{L}\left(y_i, \widehat{y_i}^{(t-1)}\right)$ is the loss function that measures the prediction error in the previous iteration, and $\partial \widehat{y_i}^{(t-1)}$ is the model prediction in the previous iteration.

2.6 Evaluation

The final step in this research is to assess the performance of the proposed model, in measuring the performance of the model built in this research using two evaluation metrics, namely, Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), these two metrics are used to assess how close the prediction results produced by the model are to the rating given by the user. RMSE calculates the root of the average square error of the difference between the predicted rating and the actual rating using Eq. (8).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \|y(i) - \hat{y}(i)\|^2}{N}} \tag{8}$$

Meanwhile, MAE measures the absolute average of the difference between the predicted and actual values and provides a more direct representation of the overall prediction accuracy using Eq. (9).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\|y(i) - \hat{y}(i)\| \tag{9}$$

3 Simulation, Results and Discussion

3.1 Experimental Setup

This experiment was conducted on a computing device that has been optimally designed to support the testing process of the recommendation system model that was built. The specifications used in the experiment are summarized in Table 6. Python is the programming language used because of its stability and compatibility with various libraries. The experimental process was run on a computer with a 13th-generation Intel Core i7 specification, and the algorithm used was a combination of SVD++, K-Means Clustering and XGBoost. We used the MovieLens dataset because it provides a complete user profile, as supported by a literature study conducted by Saifudin and Widiyaningtyas [37] on 73 research papers, 61% of research in recommendation systems used the MovieLens dataset, the rest used the Book Crossing dataset 3%, Netflix 3%, Yahoo music 3%, Film trust 1%, Epinions 2%, Movie tweetings 1%, Yelp 4%, Ciao 3%, and Amazon 10% dataset. The dataset structure is presented in Tables 2–5.

Table 6: Simulation environment

System resource	Description
Programming language	Python 3.5
Operating system	Linux
CPU	Intel Core i7 13th
Algorithm	SVD++, K-Means Clustering, and XGBoost

To optimize the performance of the proposed recommendation system model, hyperparameter selection through an experiment-based approach repeatedly adjusts the three main models used, namely SVD++, XGBoost, and K-Means Clustering. The XGBoost hyperparameter tuning process focuses on balancing the model's ability to understand complex patterns and its capacity to provide accurate results not only on training data, but also on test data or previously unseen data. The parameters used in XGBoost are summarized in Table 7.

The hyperparameters of SVD++ summarized in Table 8 are used by considering several aspects, including adjusting the number of latent factors so that the model can capture a wide range of user preferences as a whole, maintaining the training process by setting the number of iterations and learning rate so that the model can adjust gradually, and controlling the complexity of the model by using regularization parameters.

Meanwhile, the hyperparameters for K-Means Clustering, summarized in Table 9, were used to cluster meta-items and user demographics, designed to produce informative and stable clusters. The number of clusters was selected based on the complexity of the data and the analysis purpose, which was to capture patterns of similarity between items and user group characteristics. Additionally, the random_state parameter was set to ensure reproducible clustering results in each experiment, facilitating the validation and replication of the experiment.

Table 7: Hyperparameter for XGBoost

Parameter	Dataset	
	MovieLens 100K	MovieLens 1M
n_estimators	200	800
learning_rate	0.03	0.015
max_depth	5	7
Subsample	1.0	0.9
colsample_bytree	1.0	0.9
reg_alpha	0	0.01
reg_lambda	1	0.05
Gamma	0	0.1
min_child_weight	1	3
random_state	42	42
n_jobs	1	1

Table 8: Hyperparameter For SVD++

Parameter	Dataset	
	MovieLens 100K	MovieLens 1M
n_factors	50	200
n_epochs	50	80
lr_all	0.005	0.003
reg_all	0.05	0.005
random_state	42	42

Table 9: Hyperparameter For K-means clustering

Parameter	Value
n_cluster (Genre)	5
n_cluster (Demo)	5
random_state	42

3.2 Experiments and Performance Ablation Analysis of Each HCF-MFGB Model Module

To evaluate the contribution of each principal component in the HCF-MFGB model, we conducted ablation experiments by removing one module at a time, namely K-Means Clustering and SVD++. The aim is to assess the extent to which each module contributes to the model's performance, as well as to validate the effectiveness of integrating the three components in improving rating prediction accuracy. The results of the experiment on the MovieLens 100K dataset, summarized in Table 10, show that when we developed the model without using K-Means Clustering, the RMSE value rose from 0.853 to 0.908, while the MAE rose from 0.674 to 0.718. This increase in error indicates that grouping users and items provides additional important information, enabling the model to identify hidden patterns between features more effectively.

Table 10: Performance comparison of each functional module of HCF-MFGB

Dataset	Model	RMSE	MAE
	HCF Without K-Means Clustering	0.908	0.718
	HCF Without SVD++	0.920	0.722
MovieLens 100K	HCF-MFGB	0.853	0.674

Meanwhile, the model we developed without using SVD++ showed a decline in performance, with the RMSE value increasing from 0.853 to 0.920, and the MAE rising from 0.674 to 0.722. This error rate is lower than that of the model without K-Means Clustering. This indicates that utilising both explicit and implicit user feedback is very important. By utilizing SVD++, the model can better understand user preferences. The results of this experiment prove that each component used has a significant contribution to the model's performance. Without K-Means, the model's ability to identify user and item group patterns decreases, while without SVD++, the model loses its ability to effectively capture user preferences.

3.3 Evaluation Based on Subset Sparsity

To assess the model's robustness to various levels of sparsity, we divided the three groups of users in the 100K dataset into three categories based on the number of ratings they provided. The first group consisted of users who provided more than 70 ratings, the second group consisted of users who provided 50–70 ratings, and the third group consisted of users who provided fewer than 50 ratings.

The analysis results summarized in Table 11 indicate that the HCF-MFGB model maintains good performance on user subsets with low and moderate sparsity; however, there is an increase in error on high-sparsity subsets. This decline in performance can be explained logically. First, in the high sparsity subset, information about user preferences is very limited, making the estimation of latent factors in SVD++ less accurate. Second, due to the small number of user interactions, cluster formation using K-Means becomes less stable, resulting in the model losing additional support from the cluster structure between users and items.

Table 11: Model performance based on sparsity subset

Subset sparsity	RMSE	MAE
Low (First Group)	0.8532	0.6748
Medium (Second Group)	0.8435	0.6558
High (Third Group)	0.8784	0.6940

3.4 Results and Discussion

To determine the overall performance of the proposed HCF-MFGB model and compare it with baseline models on the dataset used. In the first step, we divided the dataset used into 80% training data and 20% test data. This was done because it considers the balance between the needs of model training and model performance evaluation. 80% training data allows the model to learn patterns in the dataset optimally. Meanwhile, the 20% test data is quite representative in measuring the model's ability on previously unseen data. Next, we used SVD++ to predict temporary ratings. In addition, we created feature engineering, including item similarity, user similarity, global average, meta-item, and user demographics, which were used in the cluster again using K-Means Clustering. The rating results from SVD++ and feature engineering are used as input to the final prediction model. We also adjusted the hyperparameters used for SVD++, XGBoost, and K-Means Clustering, which are summarized in Tables 7–9.

The experimental results on the MovieLens 100K dataset, summarized in Tables 12 and 13, demonstrate that the performance of our proposed model has improved compared to other baseline models, with an RMSE of 0.853 and an MAE of 0.674. These figures indicate that our proposed model can reduce errors in the prediction process compared to other baseline models, both in terms of RMSE and MAE. We provide a detailed comparison of the HCF-MFGB model with some of the best models, the HCF-MFGB model consistently outperforms the previous models on the 100K ML dataset, by increasing RMSE and MAE by 17.7% and 16.8% when compared to the ExtKNNCF technique, 10.8% and 8.7% when compared to the SVD technique, 10.5% and 9.7% when compared to the Co-Clustering technique, 9.9% and 6.9% when compared to the KNN+XGBoost technique, 9.4% and 8.8% when compared to the Dem-Enh Cosine-KNN technique, 7.3% and 6.5% when compared to the Rec-CFSVD++ technique. The HCFMR technique is a complex model that previously yielded the best results, with an RMSE value of 0.885 and an MAE of 0.697. Our proposed model still achieves the smallest RMSE and MAE values, at 3.6% and 3.3%, respectively.

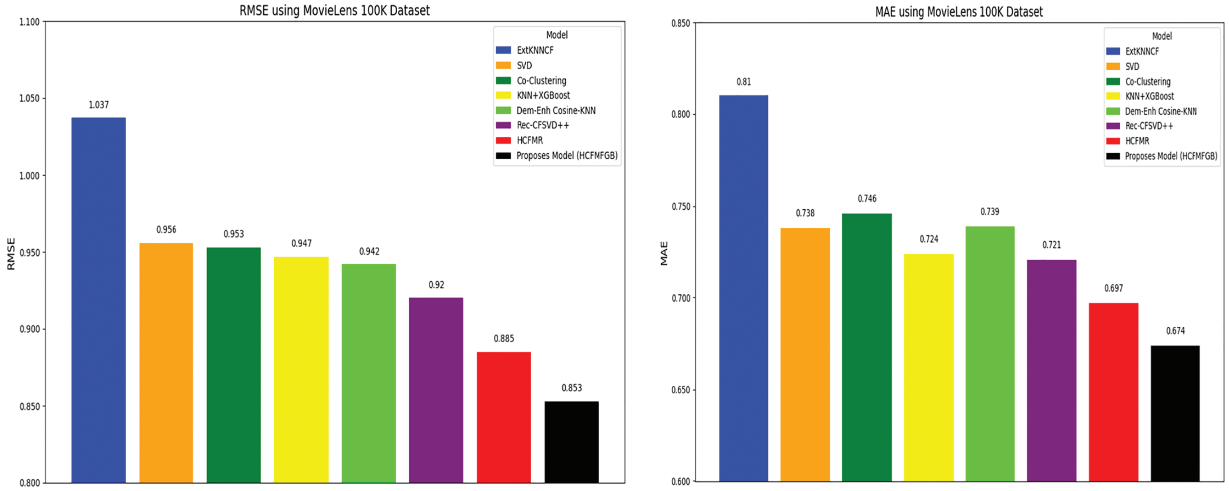
Table 12: Comparison of the proposed Model with the baseline Model on ML 100K dataset

Model	RMSE	MAE
ExtKNNCF [28]	1.037	0.810
SVD [38]	0.956	0.738
Co-Clustering [39]	0.953	0.746
KNN+XGBoost [40]	0.947	0.724
Dem-Enh Cosine-KNN [29]	0.942	0.739
Rec-CFSVD++ [26]	0.920	0.721
HCFMR [27]	0.885	0.697
Proposed Model (HCF-MFGB)	**0.853**	**0.674**

Table 13: Percentage improvement of HCF-MFGB model

Model	ML 100K(in Percent)		ML 1M(in Percent)	
	RMSE	MAE	RMSE	MAE
ExtKNNCF	17.7	16.8	10.6	20.2
SVD	10.8	8.7	12.7	11.1
Co-Clustering	10.5	9.7	15.8	14.1
KNN+XGBoost	9.9	6.9	13.5	9.9
Dem-Enh Cosine-KNN	9.4	8.8	8.7	11.2
Rec-CFSVD++	7.3	6.5	11.5	9.4
HCFMR	3.6	3.3	7.1	3

Furthermore, Fig. 2a,b shows a graphical comparison of the performance of the HCF-MFGB model against several baseline models on the 100K ML dataset. Our proposed model achieves the lowest prediction error value among all models.

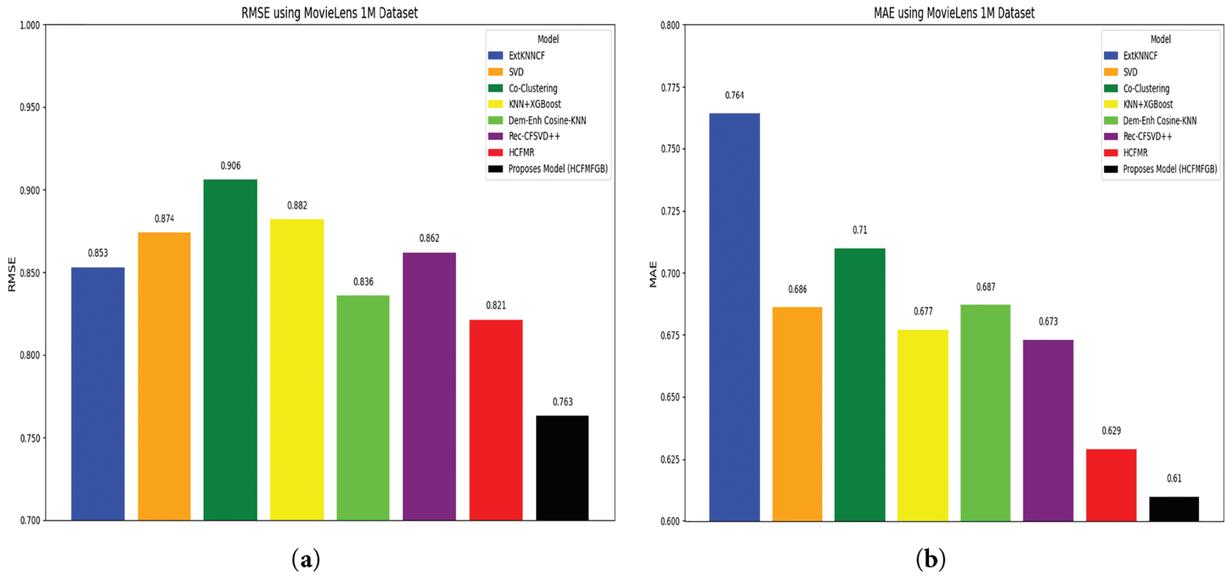


(**a**) (**b**)

Figure 2: Model performance on the MovieLens 100K dataset: (**a**) Performance on RMSE evaluation metric; (**b**) Performance on MAE evaluation metric

After achieving better results on the MovieLens 100K dataset, we tested the proposed model on a larger dataset, the MovieLens 1M. This dataset presents more challenges than the 100 K dataset, as it includes more user-item interaction data and a greater diversity of preferences. This was done to test the extent to which the proposed model can maintain its performance on a larger and more diverse dataset.

Tables 9 and 10 compare the performance of the proposed model with several advanced models, such as ExtKNNCF, SVD, Co-Clustering, KNN+XGBoost, Dem-Enh Cosine-KNN, Rec-CFSVD++, and HCFMR., the results found that our proposed model obtained an RMSE value of 0.761 and MAE of 0.61, with this value obtained indicating that the HCF-MFGB model's performance has increased compared to other baseline models by being able to reduce errors in the prediction process, both RMSE and MAE. We compare the performance with the ExtKNNCF technique, the HCF-MFGB model increases by 10.6% and 20.2% for RMSE and MAE, when compared with the SVD technique 12.7% and 11.1%, when compared with Co-Clustering 15,8% and 14.1%, when compared with the KNN+XGBoost technique 13.5% and 9.9%, when compared with the Dem-Enh Cosine-KNN technique 8,7% and 11.2%, when compared with the Rec-CFSVD++ technique 11.5% and 9.4%, and when compared with even the best technique such as the HCFMF technique, our proposed model is proven to be able to increase the RMSE value by 7.1% and MAE by 3%. Fig. 3a,b shows a graphical comparison of the performance of the HCF-MFGB model with the baseline model on the 1M ML dataset. Our proposed model achieves the lowest prediction error value.



(**a**) (**b**)

Figure 3: Model performance on the MovieLens 1M dataset: (**a**) Performance on the RMSE evaluation metric; (**b**) Performance on the MAE evaluation metric

This study presents a novel approach to a hybrid-based recommendation system by leveraging meta-item features, user demographics, and combining SVD++ to factorize the matrix and XGBoost to predict the final rating. Overall, the experimental results obtained demonstrate that our proposed model outperforms several baseline models, including ExtKNNCF, SVD, Co-Clustering, KNN+XGBoost, Dem-Enh Cosine-KNN, Rec-CFSVD++, and HCFMR, on all datasets. This confirms that our proposed model produces more accurate recommendations.

On the MovieLens 100K dataset, our proposed model outperformed various other models, achieving an RMSE value of 0.853 and an MAE of 0.674. Compared to the HCFMR model, which achieved the best performance on the baseline, our proposed model improved its performance by 3.6% for RMSE and 3.3% for MAE. On the 1M ML dataset, which has a larger and more diverse amount of data, our proposed model maintains its best performance with an RMSE value of 0.761 and an MAE of 0.61. Compared to the baseline, our model improves its performance by 7.1% and 3% for RMSE and MAE, respectively. These results demonstrate that our proposed model remains stable in handling large dataset types and maintains prediction accuracy, even with datasets of high sparsity and diverse preferences.

In addition to the MovieLens dataset, HCF-MFGB was also tested on the CiaoDVD dataset to validate the model's capabilities in different domains. The CiaoDVD dataset is a dataset with extremely high sparsity, specifically 99.90%, comprising 99,764 items and 7375 users. For traditional approaches, data with this high sparsity makes it difficult for the system to find users with similar rating patterns, because only a few items are rated by more than one user. However, the HCF-MFGB model is designed to mitigate this issue by integrating latent factors to learn hidden preferences by combining explicit feedback and implicit feedback, so that the model remains capable of producing accurate predictions even when the number of ratings is minimal. Meta item information, such as genre, acts as an additional feature that enriches the item representation, enabling the model to recognize similarities between items even if not all items have been rated by users. Furthermore, the XGBoost ensemble algorithm processes all available features by gradually building a series of decision trees, enabling the system to capture complex, non-linear relationships and enhance the accuracy of the final prediction.

The evaluation results on the CiaoDVD dataset demonstrate that the HCF-MFGB model achieves good performance, yielding an RMSE value of 0.718 and an MAE value of 0.495. These results indicate that the prediction error rate achieved by the model is relatively small. This performance is slightly better than the results on Movielens, which are summarized in Tables 12 and 14, despite its data characteristics indicating less interaction data between users and items. This suggests that the HCF-MFGB model continues to perform well, even when applied to datasets other than MovieLens.

Table 14: Comparison of the proposed Model with the baseline Model on ML 1M dataset

Model	RMSE	MAE
ExtKNNCF [28]	0.853	0.764
SVD [38]	0.874	0.686
Co-Clustering [39]	0.906	0.710
KNN+XGBoost [40]	0.882	0.677
Dem-Enh Cosine-KNN [29]	0.836	0.687
Rec-CFSVD++ [26]	0.862	0.673
HCFMR [27]	0.821	0.629
Proposed Model (HCF-MFGB)	**0.763**	**0.61**

The ability of our proposed model to outperform baseline models in various datasets ensures the effectiveness of combining SVD++ and gradient boosting techniques. The advantages of the XGBoost algorithm in handling large datasets, such as 1M ML, and its ability to improve prediction performance through ensemble learning techniques are key factors in the success of this model, as it maintains its performance at the lowest prediction error level. In addition, the feature engineering approach, which utilizes cosine similarity to calculate item similarity, user similarity, and global average, can provide a positive contribution to enriching the input to the XGBoost model. The clustering process on meta-item features and user demographics, using K-Means clustering, plays a crucial role in improving model accuracy. This is because the model becomes more effective in understanding complex patterns in user and item interactions. The findings of this study have implications for recommendation systems, as they integrate meta-item features and user demographics, thereby enhancing the system's ability to provide accurate recommendations and overcoming the problem of sparsity found in the dataset. Furthermore, understanding meta-item features and user demographics, including user preferences, provides benefits in creating effective marketing strategies that contribute to user satisfaction.

3.5 Limitations and Future Directions

In the previous section, we demonstrated the potential of our new HCF-MFGB model, which proved that this model provides significant progress in overcoming sparsity issues in recommendation systems. However, this study also has several limitations that could be topics for future research. First, it does not model temporal dynamics, which can potentially reduce the accuracy of recommendations due to changes in user preferences over time. Second, the model still focuses on the accuracy of rating predictions and does not consider the quality of the resulting recommendation sequence. Third, the HCF-MFGB model does not address the cold-start problem, which occurs when there are completely new users or items with no historical data. Finally, the scope of the model is limited to the MovieLens domain.

Future research could develop more comprehensive hybrid approaches to address cold-start problems, including the integration of deep learning methods, such as neural collaborative filtering, which enable systems to understand complex patterns automatically. Additionally, for new users, approaches that leverage explicit user preferences during registration can be an effective solution. For example, users can provide initial preference information by selecting preferred movie genres or categories, allowing the system to begin providing recommendations even when explicit rating data is not yet available. For the temporal aspect, methods that understand data sequences, such as Recurrent Neural Networks (RNN) or transformers, can be developed to capture changes in user preferences and model long-term dependencies. These methods can also expand the domain coverage beyond MovieLens by using other evaluation metrics to measure recommendation diversity.

4 Conclusion

This study proposes an HCF-MFGB model that combines SVD++ to predict initial ratings, cosine similarity to calculate item-user similarity, K-Means Clustering to cluster meta-items and user demographics, and XGBoost to predict final ratings. The purpose of this model is to overcome the sparsity problem in movie recommendation systems. The datasets used in testing this model are MovieLens 100K, MovieLens 1M, and CiaoDVD, each with varying levels of sparsity. Overall, the HCF-MFGB model outperforms the baseline models in all metrics and datasets. On the 100K dataset, the HCF-MFGB model achieves an RMSE value of 0.853 and an MAE of 0.674, outperforming the previous best baseline model by 3.6% for RMSE and 3.3% for MAE. On the 1M dataset, the HCF-MFGB model achieved an RMSE of 0.763 and an MAE of 0.61, representing a 7.1% increase in RMSE and a 3% decrease in MAE compared to the previous best-performing model. On the CiaoDVD dataset, the HCF-MFGB model achieved an RMSE value of 0.718 and an MAE of 0.495. This combination not only improves accuracy but also produces more relevant and personalized recommendations.

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Availability of Data and Materials: The data supporting the findings of this study are openly available in GroupLens at https://grouplens.org/datasets/movielens/100k/ (accessed on 23 June 2025) for MovieLens 100K and at https://grouplens.org/datasets/movielens/1m/ (accessed on 23 June 2025) for MovieLens 1M.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

Nomenclature/Abbreviations

μ	Global average of all ratings in the dataset
$\hat{r}_{ui}$	Predicted rating for user u for item i
r_{ui}	The actual rating given by user u to item i

b_u	User bias u
b_i	Item bias i
p_u	Latent vectors for users u
q_i	Latent vectors for item i
y_j	Latent contribution vector of implicitly accessed items
$N(u)$	Set of items that have been accessed by user u
N	Total number of predictions
$\mathrm{l}(y_i, \widehat{y_i})$	Loss function between actual and predicted values
$\Omega(f_k)$	Regularization function to control the complexity of decision trees
g_i and h_i	First and second order gradients of the loss function
$\sum u_1.u_2$	The dot product between the two user vectors
$\sum r_{aj,i}$	Total number of ratings given by all users
$\sum N_{nz}$	Total number of ratings submitted by users
$\lVert u_1\rVert\lVert u_2\rVert$	The length of each user's vector
XGBoost	eXtreme Gradient Boosting
SVD++	Singular Value Decomposition
RMSE	Root Mean Squared Error
MAE	Mean Absolute Error
Avg	Average
KNN	K-Nearest Neighbors

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