USER FEEDBACK RATING COMPUTATION BASED ON A HYBRID RECOMMENDER SYSTEM

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Abstract

The exponential growth of information offered on the Internet leads to an exponential increase in products. Therefore, it does not make sense to display all products to the user through the site, so it needs to provide useful things that match the interests of this user. Thus, there is a need for a tool to filter the product according to the interests of some users, and the recommendation system provides these services to users, so the importance of optimizing the recommendation system is necessary to provide recommendations that are more suitable for their preferences. User profiles are commonly used to predict product ratings which are not taken into account. This system also faces several challenges or problems related to large data, failure to collect complete information about users, or adding a movie or a new user to the system. In this thesis, a hybrid system consisting of collaborative filtering and content-based filtering will be implemented in order to recommend products to different users, where the matrix factorization technique will be implemented to divide the data into two matrices in order to solve the problem of data scalability as well as solve the problem of data sparsity where according to previous studies the solutions were This problem is solved by implementing a clustering where the data is divided into several groups and each group is dealt with separately. Either to solve the cold start problem, the document content will be used, and the film type will be used.

Key words: Matrix Factorization, users, Content-Based, Feedback.

1.1 INTRODUCTION

Recommender systems (RS) are information-filtering systems, which are supposed to offer users with personalized choices, depending on their tastes and inclinations [1]. The purpose of these systems is to propose the most attractive products or content to users that is most likely to attract them and increase the user satisfaction with the system and user engagement [2]. Examples of this would be Netflix movie suggestions and Amazon product suggestions. Well applied, the recommender systems enhance convenience and experience to users, which may result in higher sales and use of the platform.

Numerous online systems are highly dependent on recommender systems to ensure that they get maximum user interaction. As an example, Facebook focuses on showing the most interesting material in the newsfeed of users to extend the time spent on the site and enhance the exposure to ads placed therein [3]. It is through such strategies that recommender systems have played a significant role in contemporary digital services.

Recommender systems gather information on preference of the user either via implicit or explicit feedback system [4]. Implicit feedback are those that are indirectly recorded and do not need direct feedback. They can be the comments of users on films that they have watched, the search history, clicks, downloaded files, and the time spent watching them. The system automatically gathers, analyses, and processes this form of data to make inferences about the users in terms of their interests and preferences [5].

Conversely explicit feedback enables their users to state clearly what they want or what they do not want. This is generally done by rating systems like five stars scale, yes/no answers or like/dislike options, which are popular on social networking sites. It is through these feedback systems that users are able to express in a clear manner whether they are interested in certain content or products as shown in Figures (1.1) and.

In general, the recommender systems are based on rating approaches in order to model the preference of the users. Extensive use of like and dislike systems is an activity of popular social media sites, such as Instagram, Facebook, LinkedIn, Twitter, and YouTube, which enable their users to share their views and assess content [6].

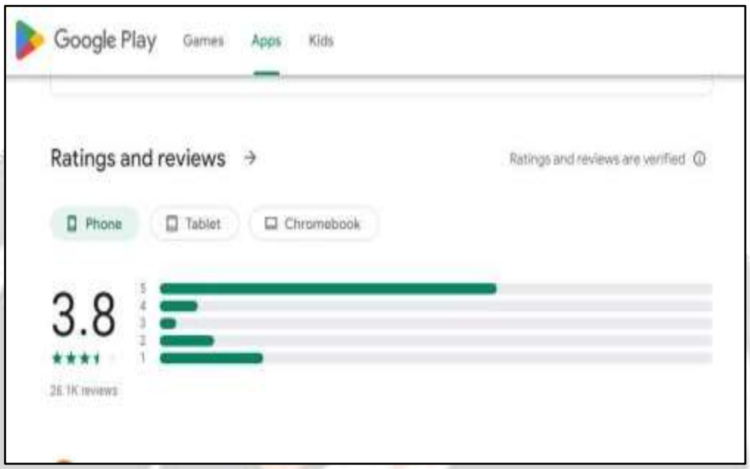


Fig-1: Sample of explicit rating (google play).

Daily, the Internet has increased exponentially in the amount of information created and exchanged in a vast amount. Such huge growth renders it more challenging to the users to find meaningful content or products that appeal to their interests without proper filtering systems. As a result, recommender systems have emerged as critical systems of organizing the information and providing users with personal recommendations.

Nevertheless, the calculation of user feedback ratings is one of the greatest challenges that exist in the current recommender systems. Feedback provided by users is typically inadequate, sparse, noisy, or unevenly expressed especially when one uses a single source of feedback or recommendation. Implicit feedbacks do not necessarily capture the actual user preferences whereas explicit ones can be curtailed by the unwillingness of the user.

Recommender systems are important in platforms like Netflix and YouTube because they are used to recommend movies or video content that suits the tastes of users. The success of these platforms will be determined by their capacity to precisely estimate the user preferences by means of trustworthy feedback rating computation. Poor recommendations, lower user satisfaction, and less engagement may result in inaccurate or biased ratings estimation, which will impact the performance and profitability of the platform.

Thus, it is required to have an effective method of calculating user feedback rating by combining several recommendation strategies. A hybrid recommender system provides the capabilities of various techniques of recommendation to surmount the weaknesses of a single approach, to increase the precision of the rating, and to increase the quality of personalization. This challenge is essential in coming up with more efficient and dependable recommender systems that can provide useful and valuable recommendations in environments that are data intensive.

The proposed research will be used to calculate user feedback rating with increased precision by utilizing a hybrid recommender system that incorporates various methods of delivery. The suggested solution will promote the quality of recommendations, user satisfaction, and decision making in the data-intensive web-based systems.

2. LITERATURE REVIEW

In this section, prior research has been conducted, which has used collaborative filtering (CF) and recommender system overall to improve the performance of the recommendation and user satisfaction. A number of methods, data sets, and metrics of evaluation have been considered in the literature.

The authors of [7] used the MovieLens data to create a movie recommendation website in 2018 with the help of a hybrid recommendation system. They have used a hybrid method of content-based filtering (CBF) that made use of the genre of the movies, and collaborative filtering (CF) using Pearson correlation coefficient. According to the experimental results, a figure of 0.9 was obtained after comparing the results of the experiment using the Mean Squared Error (MSE) metric.

The article in [8] offered a solution to exploit user data in a recommender system based on MovieLens data set. The information about users such as their age, gender, and occupation was brought together to manage vast data volumes. The K-means clustering was applied to cluster the users sharing similar features; K-Nearest Neighbors (KNN) algorithm was implemented to calculate the user similarity and to create a personalized recommendation.

In [9], a recommender system was established based on Neural Network to recommend movies to the users. The suggested framework involved preprocessing, clustering, and classification processes, to deal with the issue of scalability, sparsity of data, user trust, cold-start problems, and the lack of user interaction history.

In [10], the authors described a hybrid recommender system that was aimed at enhancing the accuracy of movie recommendations. The system was composed of a combination of several components such as fuzzy expert systems, content-based (CB) and collaborative filtering (CF) modules, which allowed being more flexible and more precise in predicting the preferences of user needs.

The collaborative filtering based on items was explored in [11] in which various similarity measures, including cosine similarity and adjusted cosine similarity, were tested. The adjusted cosine similarity gave the best performance with the Mean Absolute Error (MAE) of 0.712.

In [12], recommender systems were applied within an e-commerce environment to predict user preferences and identify products that best match customer needs. The proposed system utilized multiple recommendation techniques to enhance product selection accuracy, ultimately improving sales performance and profitability.

The study in [13] employed a collaborative filtering-based recommendation model using cosine similarity to analyze user sentiment and predict movie recommendations. Machine learning techniques were integrated to assess movie quality based on sentiment analysis, determining whether a movie was suitable for recommendation.

Finally, [14] proposed a graph-based recommender model that calculated user similarity while incorporating site-related and user-specific information. The model leveraged automatic feature extraction techniques and demonstrated superior performance compared to several existing algorithms, as reported in the experimental results.

3. METHODOLOGY

A recommendation system is one that deals with increasing information obtained electronically by collecting information about users and products. Its importance is that new products for users can be found through it.

the proposed model offers a recommendations system that suggests movies to consumers based on CF. as shown in the figures, the model has three basic stages: pre-processing, prediction, and assessment measures.

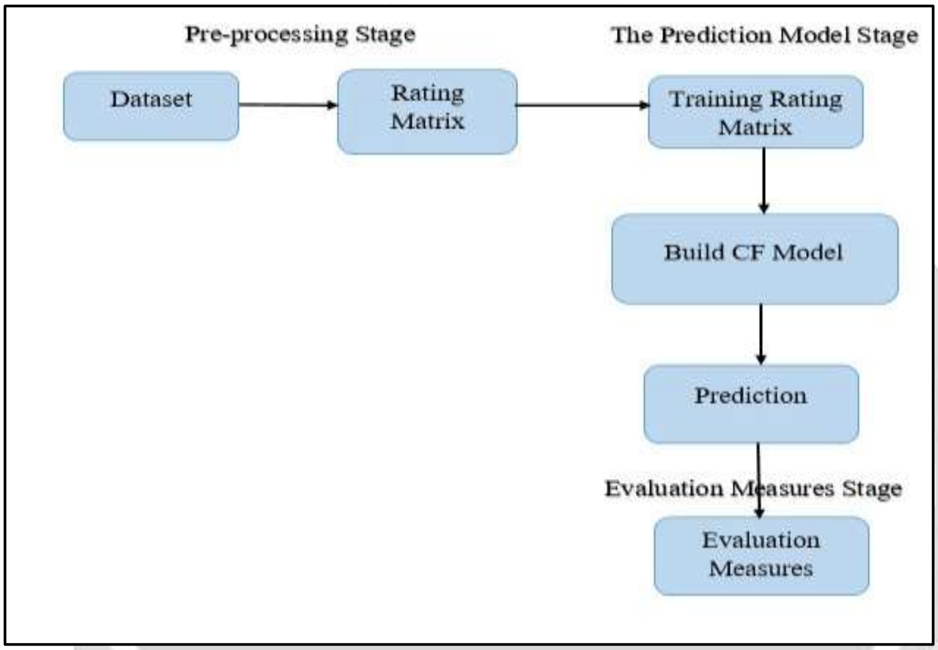


Fig-2 : flowchart of preposed method

3.1 DATASETS

The Movielens dataset is a collection of three files that includes non-context aware movie data. The first file, titled "ratings," which is associated with file

u.data, has four features: userID, itemID, rating, and date (see fig .3).

user ID	item ID	Rating	Timestamp
1	17	3	875073198
1	47	4	875072125
1	64	5	875072404
1	90	4	878542300
1	92	3	876892425
1	113	5	878542738
1	222	4	878873388
1	227	4	876892946
1	228	5	878543541
1	253	5	874965970
2	257	4	888551062
2	279	4	888551745

Fig-3: File of rating in movielens dataset.

3.2 THE PRE-PROCESSING

This step is crucial because pre-processing helps the algorithms to quickly understand the dataset's characteristics. Beginning with the creation of the user-movie matrix, which comprises of the user, the movie, and ratings. When a dataset has been split into training and testing halves, hold-out cross validation is used. To help with the prediction process, the genre is content-based. The stages of the preprocessing step are depicted in Fig (4).

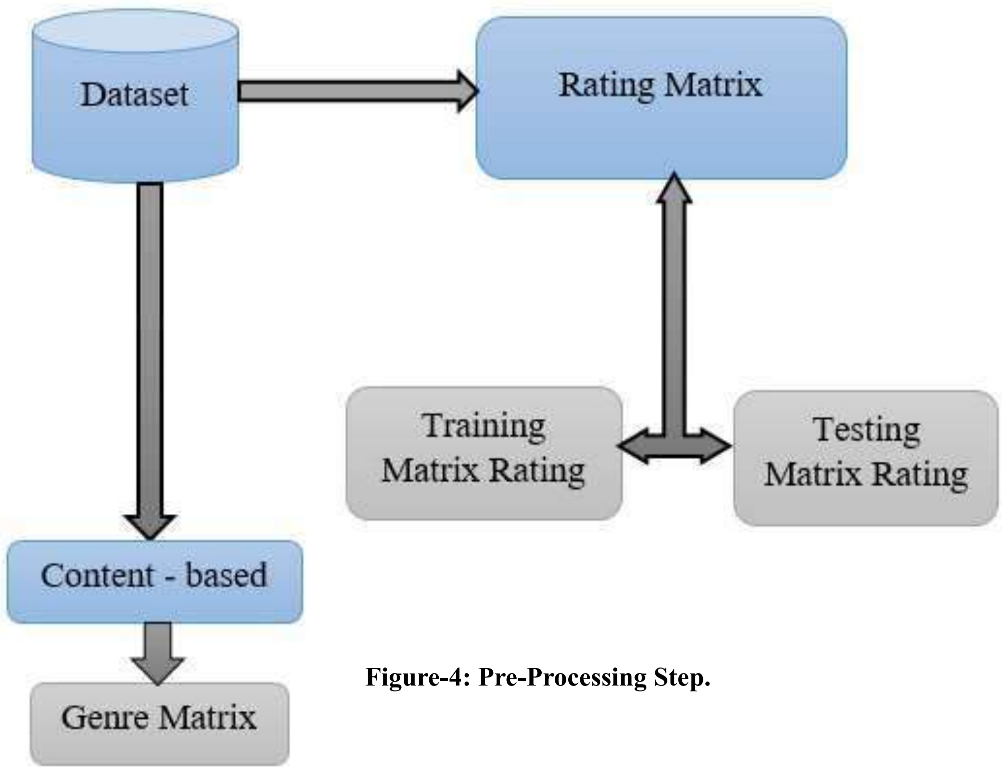


Figure-4: Pre-Processing Step.

3.3 MATRIX FACTORIZATION CONSTRUCTION

Import the data from the rating file to create a two-dimensional training matrix. The user, movie, and rating fields make up the sole three fields in the rating matrix, which has been split into two matrices for training and testing using hold-out cross validation. The test matrix is needed after the model has been trained, during the model assessment step.

The users (P) and movies (Q) are represented by the first and second matrices, respectively, of the training matrix.

In this model the SGD equation is applied on MF. Following the Netflix contests, the use of stochastic gradient descent (SGD) gained popularity.

Simon Funk popularized an SGD optimization of equation (3.1) "wherein the algorithm loops through all ratings in the training set" (https:// sifter.org/ simon/ journal/ 2006121).

According to Koren et al. (2009), "the system predicts r_ij and computes the related prediction error for each given training example.

$$\min \sum (r_{ui} - \hat{r_{ui}})^2 + \lambda(\|P\|^2 + \|Q\|^2) \quad \ldots.. (3.1)$$

Equations (3.2 and 3.3) provide the update rules.

$$P_u = P_u + \boldsymbol{\alpha}.\ (e_{ui}.\ Q_i - \lambda\ .\ P_u) \qquad (3.2)$$

$$Q_i = Q_i + \boldsymbol{\alpha}.\ (e_{ui}.\ P_u - \lambda\ .\ Q_i) \qquad (3.3)$$

4. RESULTS DISCUSSION

4.1 Dataset Analysis

When implementing the model, the data set used in this model must first be analyzed. In this section the Movielens dataset will be analyzed. The Figures below show the percentage of genres in a dataset of movielens, see the figures (5.6.7).

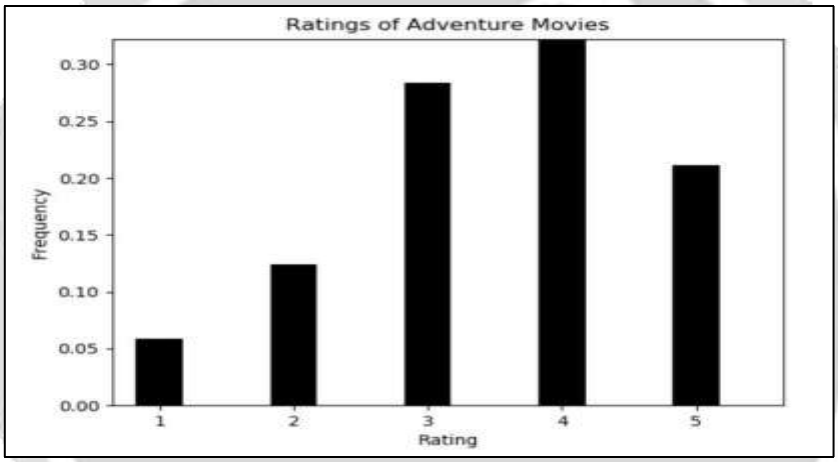


Fig-5: Rating of Adventure Movies.

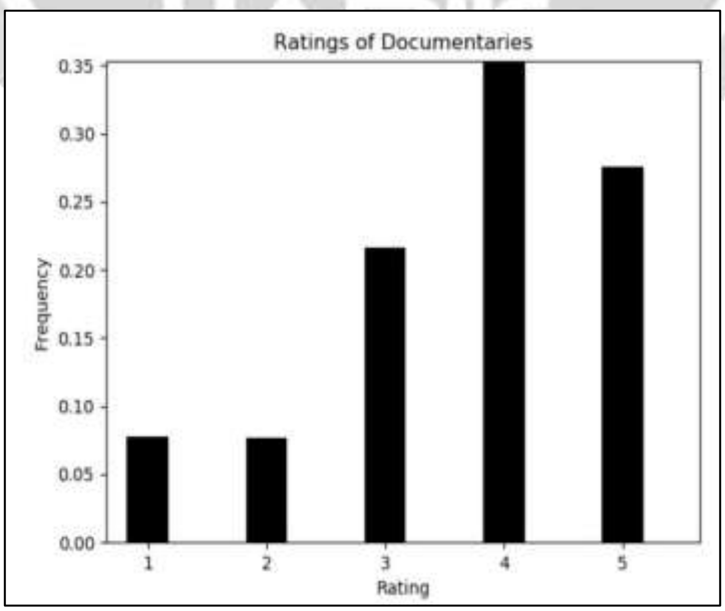


Fig-6: Rating of Documentaries Movies.

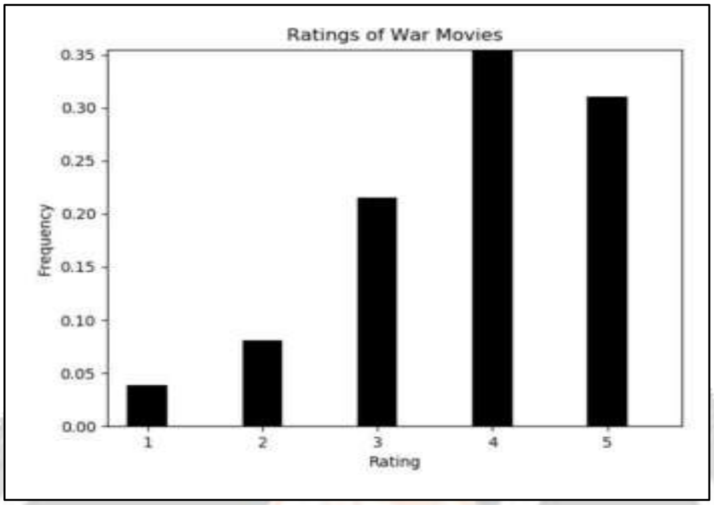


Figure-7: Rating of War Movies.

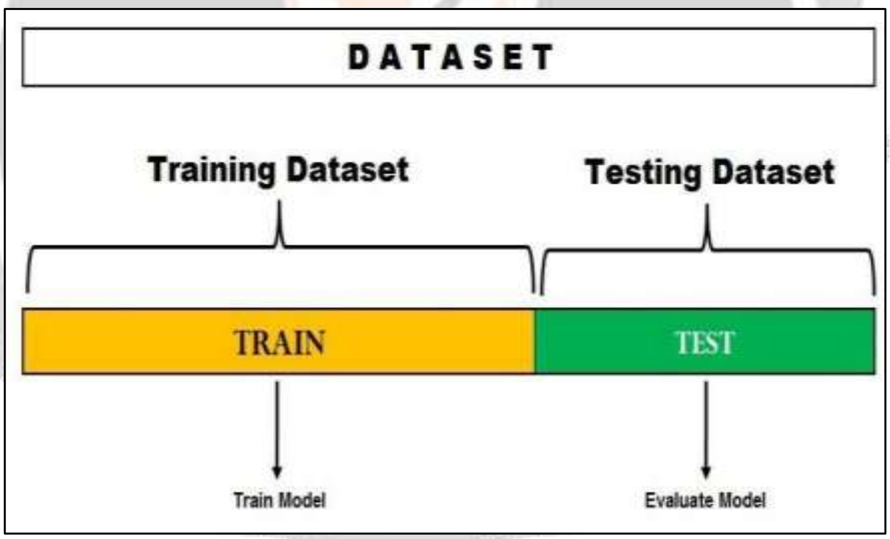


Fig-8: Splitting the dataset into 80:20.

In the below Table (4.1), The movies are the highest rated by users according to the type of occupation for the user, as this occupation is found in the user's file and includes several occupations for each user.

Table-4. 1: The movies are the highest rated by users according to the type of occupation.

No.	Occupation	Movie title	Rating
0	administrator	When We Were Kings	5.0
1	administrator	Winter Guest	5.0
2	administrator	World of Apu, The (Apur Sansar)	5.0
3	artist	39 Steps	5.0
4	artist	Adventures of Pinocchio	5.0
...	...	...	...
No.	Occupation	Movie title	Rating
58	technician	Basquiat	5.0
59	technician	Beautiful Thing	5.0
60	writer	Faster Pussycat! Kill! Kill!	5.0
61	writer	Faust (1994)	5.0
62	writer	Fille seule, La (A Single Girl)	5.0

4.2 The Standard Experiments

In this section, the proposed method will be implemented and then the results obtained from this method will be found. In the beginning, the ideal condition of the parameters used in MF is implemented, where the program is executed on several different parameters to find the best parameter to be used, meaning in the parameters (Learning rate, Latent factor), As the best result obtained is as shown in the table below (Table 4.2).

Table-4. 2: Best parameters according to testing process.

Latent K	Learning rate	Regularization	RMSE testing	MAE testing
5	0.002	0.1	0.935327	0.739782

In the table below, the results obtained before and after prediction are shown Table (4.5).

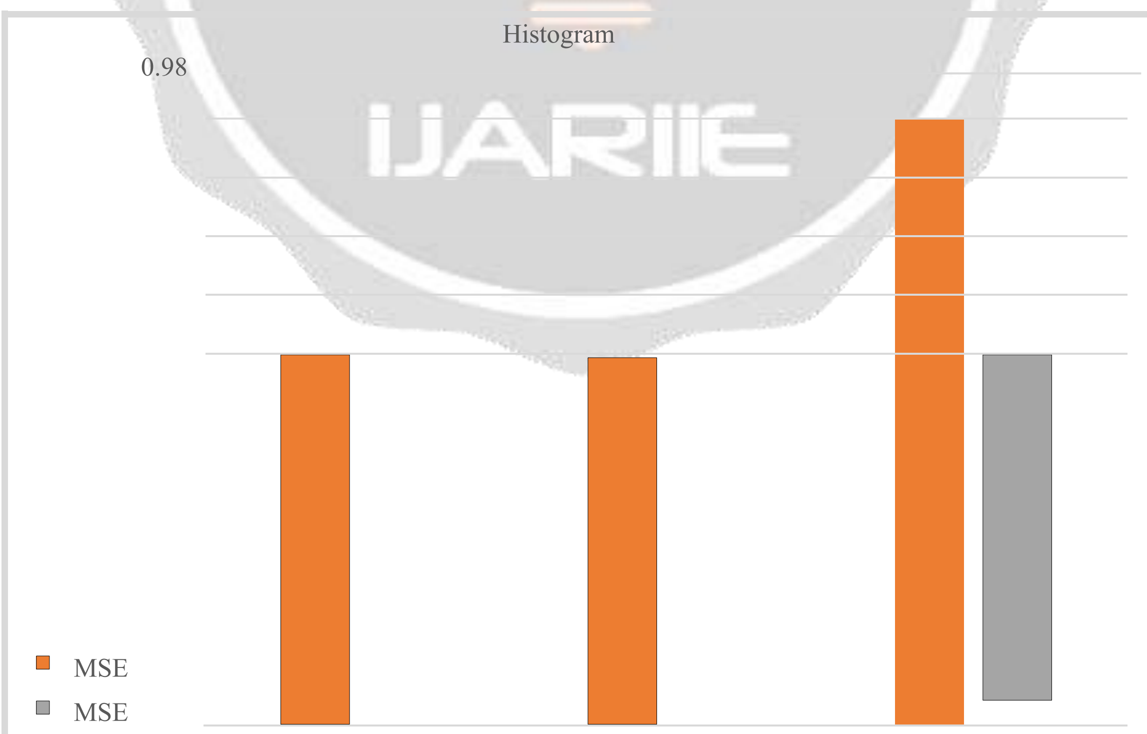
Table-4. 3: Real and Predictive Rating Sample

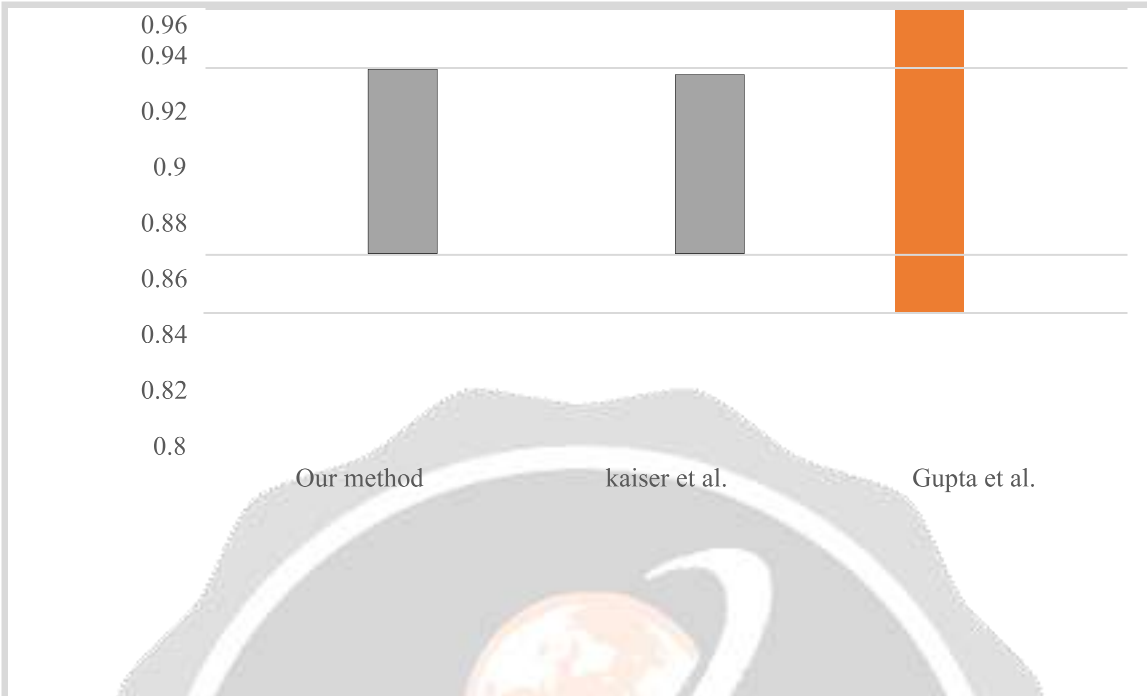
UserId	MovieId	Real Rating	Predict Rating
125	72011	4	3.7326
414	7454	2.5	2.8414
477	4008	3.5	3.6142
448	9809	2.5	3.1678
472	1678	3.5	3.0541
144	4993	4.5	4.1891
317	4255	4	3.9154
290	3095	5	4.1478
177	1027	3	2.8742

Table-4.4: compare between the previous studies and our method.

Citation	Methods	Dataset	Advantage or Result
[15]	CF based KNN and Cosine similarity	Movielens	The results were (0.501) based on (Precision) according to Content-based method, and (0.782) according to Collaborative filtering.
[3]	Matrix Factorization	Movielens	Solve the cold start problem through using the demographic information
Our method	Matrix Factorization and Genre movie	Movielens	Solve the cold start problem through using the genre movie, and the results were (0.9353) and (0.7397) according to RMSE and MAE.

Through the above Table (4.4), we find that the feature that was worked on in our model is the use of the type of film from the movie data of Movielines. By comparing the obtained results, we find that the results are good, especially that the system has adopted the collaborative filter and the content-based filter, and learning techniques have not been used. It is possible to use the same model that was applied and then implement one of the deep learning techniques. The model also addressed one of the common problems in films and how to solve them while maintaining the accuracy of the system used.





5. CONCLUSION

The proposed hybrid recommender system achieved promising results, as evaluated using error metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Utilizing movie types proved effective for generating recommendations based on similar films, where cosine similarity was employed to measure similarities between movies. Furthermore, incorporating movie genres facilitated recommendations for new users, allowing the system to analyze their initial evaluations and provide a personalized set of movie suggestions. Overall, the model demonstrates the effectiveness of combining multiple recommendation strategies to enhance prediction accuracy and user satisfaction.

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