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INTELLIGENT COLLABORATIVE FILTERING RECOMMENDATION SYSTEM FOR MOVIE REVIEW RATING

SRINIVASA RAO MANDALAPU[1], B. NARAYANAN[2], SUDHAKAR PUTHETI[3]

[1]Research Scholar, Department of CSE, Annamalai University, Chidambaram,Tamilnadu, India.
[2]Assistant Professor, Computer Science and Engineering Wing, Directorate of Distance Education, Annamalai University, India.
[3]Professor, Department of CSE, Vasireddy Venkatadri Institute of Technology, Namburu, Pedakakani, Guntur, Andhra Pradesh, India.

Email: sree.mandalapu.sree@gmail.com, narayanan.bk@gmail.com, sudhakarp0101@gmail.com

ABSTRACT

Recommendation system used to analyze the data concept and discovery of data to provide the modified approvals on the web. Various techniques have been suggested to capture the user's interest and effectively provide accurate recommendations. User-based collaborative filtering technique was popular and utilized in practice extensively. Still, the system faced several vital tasks to provide adequate scalability and qualified recommendations because of increasing items daily and users on various webpage. So, a novel technique named Eagle Deep Neural based Movie Recommender System (EDNbMRS) to recommend movies related to ratings from the review. Consequently, the data was collected for the training process. In the preprocessing phase, the noise features were eliminated from the dataset for the recommendation process. Next, the best features were selected based on the developed model in the feature extraction process. Then, a rating for the movie was necessary for recommending the film to the user to perform the similarity and prediction computation process. Finally, the recommendation process was done using the predicted rating score for the target user. Meanwhile, the developed mechanism was executed in the Python tool with several performance measurements such as accuracy, Recall, f-measure and precision. This developed model produced outstanding results compared with the previous studies by providing accurate results for the recommendation process.

Keywords: *Recommendation, Target User, Feature Analysis, Eagle Optimization, Collaborative Filtering.*

1. INTRODUCTION

Recently, technology was developed quickly and increased knowledge dissemination; consumer needs were too complex [1]. Manufacturers and suppliers attain complicated processes in contributing the products and services that meet the customer's requirements for the opportuneness of buying the service due to business which made the active competition [2]. In this type of competition, the information which was too complex produced overload issues. A recommender system (RS) is the filtering of an information system that tends the user to predict the rating or item preference based on the consideration of the user [3, 4]. This system has been an essential software tool and approach to producing recommendations since the 1990s. The tailored offers are delivered to the customer based on preferences that the users would give an item. Typically, methodologies applied from related areas included Machine Learning, human-computer interaction and retrieval of information [5, 6]. These played a broader role in real life and were adopted by numerous internet platforms, namely Google, Facebook, Netflix, and Amazon [7]. A film recommender system was an essential tool for the user to choose The user-provided ideas made it easy to identify the correct movies quickly. While compared to personal computers (PCs), mobile services (MS) provide quick handling and estimation from internet service providers. The movie recommendations were promoted in MS by certifying that they were accurate and timely [8, 9].

Collaborative filtering (CF) was considered the most critical approach and was typically used in the online retail site Netflix to promote the extra items and increase sales. The essential methods made the recommendations using the user ratings of the items as the information source [10]. Furthermore, CF was categorized into two classes such as memory type and modelling type class. First, the memory-based class focused on relating among the user or item, but the model-based class was trained based on the rating matrix [11]. The RS would query the user to rate the restricted items when the new user enters the real-life scenario. Thus, this was not enough to get accurate recommendations for the user because ratings were very sparse [12]. So, for the user to acquire precise recommendations, high-quality data was produced using active learning. In addition, these RS provides the user unauthorized access to the entire digitized world depending on interests, behaviour and experiences [13, 14]. IoT helps the RS work efficiently. Hence, the data gathered from the various sources provide numerous works. The IoT data movie recommendations had user data included with the viewer's behaviour, filtering process, site activity, and movie ratings depending on the user's ratings and other viewer data [15, 16].

The main drawbacks of the RS were analysis of restricted Content, specialization and cold start problems. Using this system, it was too complex to analyze excellent or bad documents with similar terms and phrases [17]. It was very tough to extract the feature factors for multimedia data, video streams, audio streams and graphic images [18]. In cold start problems, the items could not be recommended because of a lack of information about the item and the user. There would not be any previous information for the new user, such as interested items and browsing history etc., so it was very tough to recommend the item to the user [19]. Also, there would be no rating for the new user. Another area for data sparsity enhancement refers to the fewer ratings than potential ratings. Sparsity is the inverse of the ratio between the given and possible ratings [20]. To overcome those issues, the present article described the novel technique named EDNbMRS model for the Movie Recommendation System. The critical contribution of this research was described as follows:

- Initially, the Movielens dataset was used in the RS to collect the data for the initialization process.
- Consequently, preprocessing and feature analysis were done to eliminate the noise features, transform data into matrix format and select the best features using the proposed model.
- Then, the similarity and prediction computation process was involved in computing the movie's overall rating in this process.
- Moreover, the movies were recommended based on the predicted ratings with the weights of the items.
- Finally, the performance measurements were validated based on accuracy, precision, Recall and F-measure.

The remaining part of the paper was determined as Section 2 defines literature review studies with their outcomes. The problem statement with the system model was described in Section 3. The proposed methodology is represented in section 4. Section 5 discusses the experimental results and analysis finally, conclude with the conclusion in Section 6

2. LITERATURE REVIEW

A few associate works of literature related to the Movie recommendation System were described as follows:

RS was one of the requests to the data burden issue grieved through the website sender that allowed the specific item rated score. So, Choudhury *et al.* [21] proposed the Multimodal trust-based recommendation system (MTRS) that combines user similarity with trusted weight propagation to recommend the item to the user. In this technique, the CF handled the similarities between the object and the user for performing the recommendations. The movies were initially recommended to the trusted user depending on the trustful value and ML techniques. Here, matrix factorization recognizes the features that interest the specific user. Using the trust-based filter, the thrust value was calculated with the ML mechanism's help. However, due to the linear model, the complex relationship in data could not capture the RS.

Darban *et al.* [22] proposed that Graphical-based Hybrid RS(GHRS) was used to recommend the film associated with the user similarity ratings. Initially, the graph was constructed with the nodes, which were said to be the process's users. Then, a similar graph was used to extract the dataset for each user. Next, the lateral data included gender and age to retrieve the movies to the user with several features. Also, the autoencoder was applied to extract the new features, and their dimensions were diminished. By k-means clustering, the novel features were encrypted for the clustering of the user data. Finally, the item rating was computed based on the similarity of another item for each user because of the cluster's average rating for the movie recommendation system. However, various graphs increased the time complexity and not considering the meaningful features included in the review.

Here, the genre data was considered to capture the consumer behaviour assessment. So, Widiyaningtyas *et al.* [23] presented the user profile type Correlation-based Similarity (UPCSim) used to examine the variety and user profile types data. This system needed the similarity weight value for user rating and behaviour to identify each user. Finally, the correlation coefficient between the rating of users and the user profile data was estimated to obtain both similarities' weights for the recommending process. This approach provides the scalability issue using an extensive database for increasing the computing period.

The RS was vital to help the customer select the preferred movie with the existing feature. But, the user provided a complicated process to find a suitable film because of the increased number of movie information. Therefore, Cintia *et al.* [24] suggested the ML-based movie recommendation system. The designed augmented groups from various approaches were utilized to compare the nest approach regarding similar user grouping based on movie tag, genre, and ratings using the MovieLens dataset. Finally, each cluster was optimized, which did not increase the variance (Error) for selecting the file for the customer. However, the system's enactment needed to be enhanced with more features.

Tahmasebi *et al.* [25] discussed the deep autoencoder system that aimed to recommend the movie using Twitter data—the developed model employed Content-based and collaborative-based filtering. The required dataset was taken from the MovieTweetings and Open Movie databases for recommendations. Finally, the estimate of the social influence of each one of the users depends upon the social characteristics and behaviours on Twitter. In this process, the data sparsity problem was increased due to the extensive data for the movie recommendation system.

3. SYSTEM MODEL AND PROBLEM STATEMENT

RS was the software gear and approach that produced recommendations for the user. The proposals were of various categories, included with music tracks, movies, and news recommendations. The RS provided recommendations with user interest and contextual information. It was the building block of the filtering of data. The goal of constructing the RS was to give the complete information needed for personalized learning and interests based on the interactive client pattern. Contextual information was utilized to make essential recommendations in several fields.

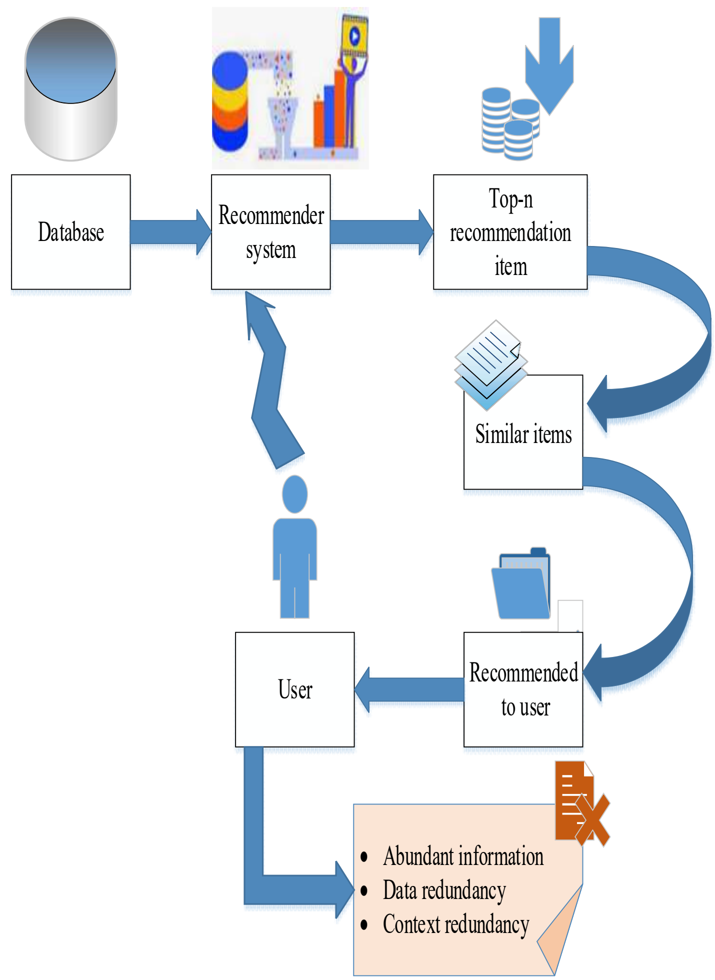

Fig.1 System Model With Its Problems

The RS system allowed the target user to find the item related to the user's needs and preferences. Also, the features were analyzed to find the similarity among the users who preferred the thing. Next, consumer preferences were calculated based on past choices. Furthermore, the items were identified based on comparing items, and the item recommendation was made based on the rating of the object. However, the issues were much information, data redundancy and context redundancy, which would affect the effective

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recommendation process. The system model with the problem statement is illustrated in Fig. 1.

4. PROPOSED EDNbMRS FOR MOVIE RECOMMENDER SYSTEM

In this research, a novel technique named Eagle Deep Neural based Movie Recommender System (EDNbMRS) was designed to recommend the movie to the receiver upon movie review ratings for the recommendation purpose. The main goal was to provide the film's recommendation based on the user's ratings. The basic structure of the designed EDNbMRS strategy is illustrated in Fig. 2.

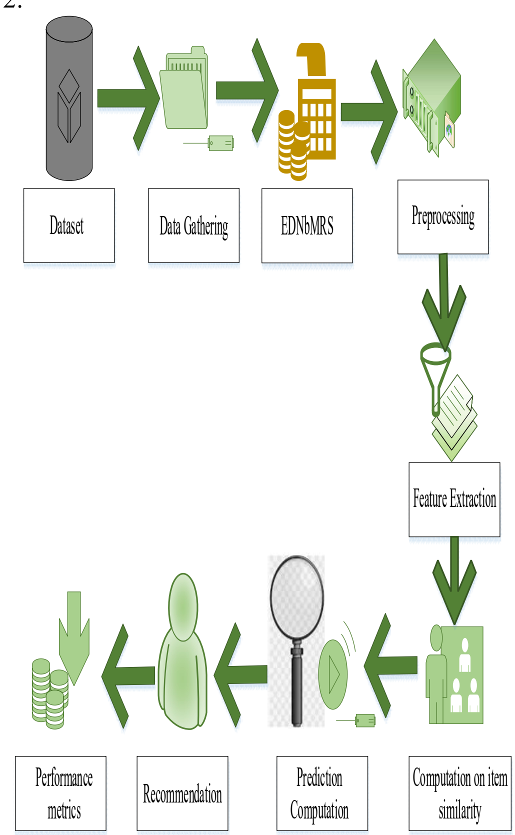

Fig.2 A Systematic Diagram Of The Proposed EDNBMRS Model

Initially, the data was collected for the training process in the RS. In this process, the Movielens dataset was used for the RS. Then, the data was eliminated with the noisy features and transformed the features into a matrix format using the designed model. Next, the features were extracted using the fitness function of the proposed model. Moreover, the similarity calculation was done for the items and predicting computation process was performed to predict the ratings for the feature (movie). Finally, the film was recommended to the customer with the recommendation engine's predicted movie review ratings.

4.1 Data Gathering

The Movie Lens dataset collected data for the movie recommendation system, whereas 610 people provided ratings of 1,00,837 for 9743 movies. The database contains the user supplied with user ratings of more than 20 movies. This dataset consists of films with genre-named URLs, movie IDs, titles, and user details such as movie IDs, time stamps, and user ratings. Each of the data records indicates the movie ratings for various users. The movies.csv, user.csv and ratings.csv files were used in the RS. The user review was developed based on a rating scale from 1 to 5 numbers. Then, the data gathering process in Eqn. (1)

$$T = \{F_1, F_2, F_3, \ldots F_n\} \tag{1}$$

Where, T denoted as the dataset, $\{F_1, F_2, F_3, \ldots F_n\}$ represented as the n number of samples. The film RS was done based on collecting the data for the user.

4.2 Preprocessing

The preprocessing phase was performed after the information was collected in the RS. In the database, the data contains noise features and standard features. So, the denoising process was done to remove noise features from the data. It would be too complex to perform the RS for the item to the customer if the noise was present in the data. Then, the dataset was preprocessed into the proper format, and the data frame of ratings was transformed into the appropriate form. So, the data was transformed into $l \times n$ the matrix, where l and n was the number of movies and users. The denoising process and matrix transformation process were described in Eqn. (2).

$$L = T + \sigma(l,n)\left[h(j) - h(k)\right] \tag{2}$$

Here, L represented as the preprocessing parameter, the dataset was denoted as T the matrix transformation process, h which was the tracking parameter for eliminating the noise features, $j\ and\ k$ which were the typical and noisy features. However, the noisy data was neglected from the trained database and transformed into a suitable format in the preprocessing stage using Eqn. (3).

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4.3 Feature Extraction

The system was tested with the dataset; each motion picture had several features such as title, movie identifier and 19 genre attributes. Here, the feature could be selected by a feature extraction process that helped diminish the characteristics of the selection process. Then, the fitness value was calculated based on the proposed EDNbMRS model for each feature matrix and comparing the fitness function value with the eagle optimized to produce the best and worst features. The highest value attained was said to be the best feature which was selected as the feature for the recommendation system. The feature extraction process was determined in Eqn. (3).

$$E = T + \alpha[\max\{\sigma(l,n)\}] \tag{3}$$

Here, E indicates the feature extraction phenomena, T represented dataset, α was the fitness function of the features, σ denoted the transformation of matrix parameter, $l\, and\, n$ were the number of features such as movies and users. The term $'\max'$ illustrates the maximum value identified based on the fitness function to select the feature for the recommendation of films based on review.

4.4 Computation of item similarity

The mean-squared difference (MSD) was used for the similarity score of the two users. The mean of the inverse of the difference square among the user ratings on the same objects used to assess similarity among two users' p and q was defined in Eqn. (4).

$$MSD(p,q) = \frac{|S_{pq}|}{\sum i \in S_{pq}\left(r_{pi} - r_{qi}\right)^2} \tag{4}$$

Here, S_{pq} denoted as the similarity between two users, r_{pi} and r_{qi} represent the ratings of p^{th} any q^{th} user. The MSD was the similarity measure among two items for the recommendation system. Then, the negative correlation within the user's preference was ignored, which enhanced the accurate rating prediction. The process of collaborative filtering was used to overwhelm the data sparsity issue of the product instead of using it directly to predict the ratings. Thus, the similarity between the two users was estimated in the RS.

4.5 Prediction Computation

The collaborative filtering technique was used to predict the unknown ratings, the most critical process in the RS. Here, the weights of the item prediction to the specific user (u) were estimated for predicting the ratings. The prediction computation process was indicated in Eqn. (5)

$$C_{(p,q)} = \frac{\sum_{l \in N_{(u)}(p)} w_{(p,q)} r_{(p,q)}}{\sum_{l \in N_{(u)}(p)} |w_{p,q}|} \tag{5}$$

Here, $w_{(p,q)}$ it represents the similarity weight among the items $p\, and\, q$; the ratings known by the user to the items $p\, and\, q$ were defined as $r_{(p,q)}$, $N_u(p)$ indicated by the users that had rated the item, $C_{(p,q)}$ which was the prediction computation process. Thus the prediction was estimated based on the weight computation process of the items for the RS.

4.6 Recommendation System

The recommender stage was based on the similar predicted score value of the film. Furthermore, the whole item rate was essential for the recommending strategy. The expected rating is given as input to the recommendation engine, which acclaims the motion picture to the user based on its rating value. The recommendation process based on movie review rating was in Eqn. (6)

$$R = \omega[E + C_{(p,q)}(w_{(p,q)})] \tag{6}$$

Where, R was denoted as the recommendation parameter, ω indicates the recommendation engine helped to recommend the item to the user, $C_{(p,q)}$ was the prediction evaluation process, $w_{(p,q)}$ represents the similarity weight among the items. Therefore, the similarity weight score between the items based on high ratings was used to provide the item (movie) to the user using the proposed model.

Algorithm 1. EDNbMRS
Start
{
Data Initialization ()
$\text{int}\, T, F;$
// Collect the input data from Eqn. (1)

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Preprocessing ()
{
$\text{int}\, L, T, \sigma, l, n, h, j, k$;
//The preprocessing variable was defined
$L \rightarrow denoise(j,k) + \sigma(m,n)$
// noise features were removed, and the data was transformed into a suitable format using Eqn. (2)
}
Feature extraction ()
{
$\text{int}\, E, T, \alpha, \sigma, l, n;$
//The variables of item features were initialized
$E \rightarrow select[\alpha(m,n)]$
//The features were analyzed by Eqn. (3)
}
Item Similarity Computation()
{
$\text{int}\, S, p, q, r, MSD;$
//The estimation of item similarity variables was initialized
$MSD \rightarrow similarity\left[S_{(p,q)}, r_{(p,q)}\right]$
//The item similarity process was computed from Eqn. (4)
}
Prediction Computation()
{
$\text{int}\, C, p, q, N, w, r, u;$
//The prediction evaluation variables were initialized
$C \Rightarrow \Pr edict\left(w_{(p,q)}, r_{(p,q)}\right)$
//The prediction of user rating for the recommendation function was evaluated in Eqn. (5)
}
Recommendation ()
{
$\text{int}\, R, \omega, E, p, q, w, C;$
//The initialization process performed for the recommendation
$R \rightarrow recommend\left(E, Cw_{(p,q)}\right)$
//The recommendation process was done for the target user
}
}
End

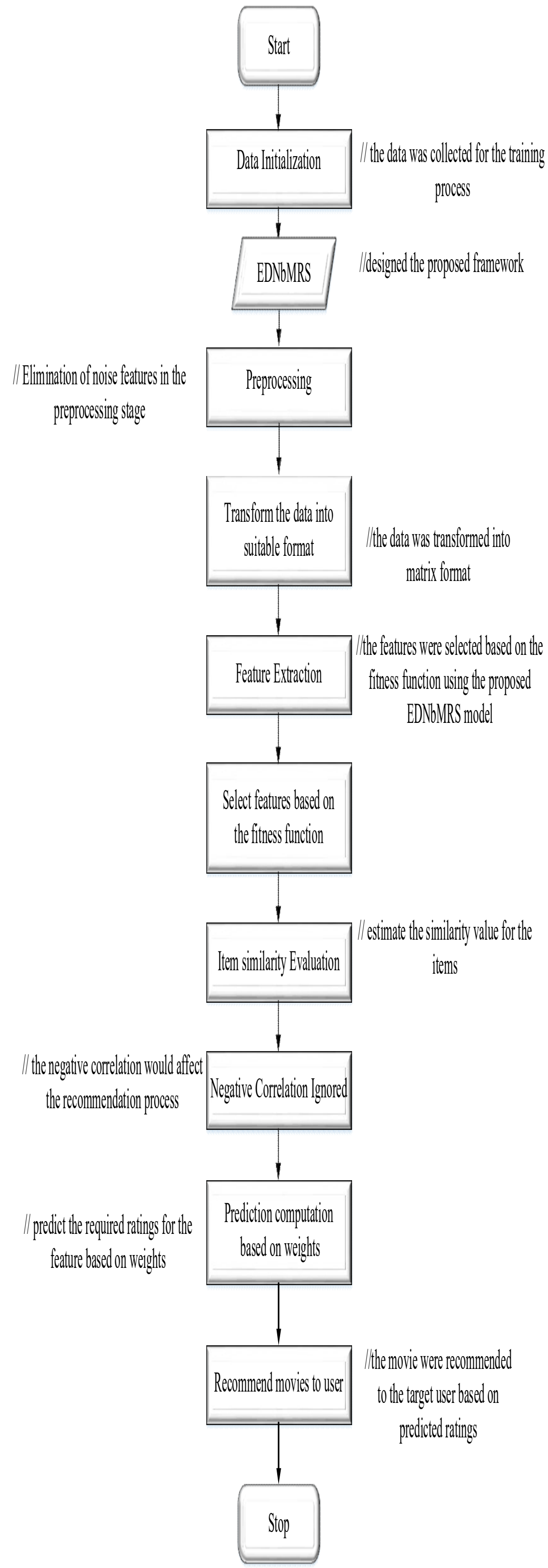

Fig. 3 Flowchart Of Ednbmrs Model

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Fig. 3 and Algorithm clearly illustrate the steps for the developed mechanism. The Python code was executed, and the outcomes were verified using the processing steps. In the pseudocode format, the algorithm was written by incorporating entire parameters of the mathematical function.

5. RESULT ANALYSIS

The implementation of the designed framework proceeded in the Python platform. The operating system used for the implementation process was Windows 10. This process aimed to recommend the movies to the target user based on movie review ratings. Table 1 represents the parameter specification for the proposed design.

Table1. Parameter Specification

Operating System	Windows 10
Dataset	Movie Lens dataset
Programming Platform	Python
Version	3.7.6

5.1 Case Study

This work developed a novel deep-learning approach to recommending movies to the target user using Collaborative filtering. Initially, the dataset was collected for training the proposed EDNbMRS model for the recommendation process. Here, the performance assessment graph shows that the performance rate was maximized. Henceforth, the performance assessment for the proposed model has been validated in Fig. 4. It has verified that the proposed design can recommend the item to the user

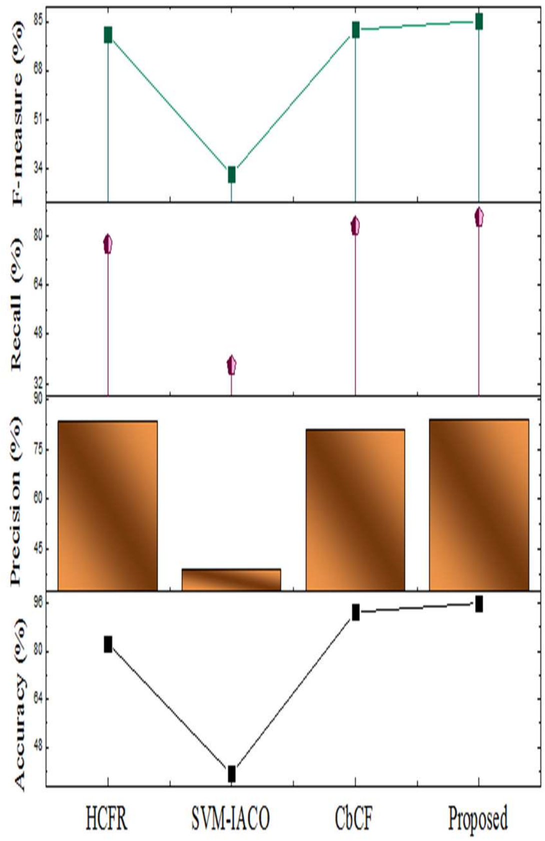

Fig. 4 Overall Performance Assessment

The performance assessment graph shows that the performance rate was maximized; the recommendation process was developed efficiently. Henceforth, the performance assessment has been validated in Fig. 4.

5.2 Performance analysis

In the proposed EDNbMRS, the accurate performance outcome of optimizing the RS is provided with several metrics, including precision, Recall, accuracy and F-measure. Then, the system was compared with several existing mechanisms such as a Hybrid Collaborative Filtering Recommendation (HCFR) [26], Support Vector Machines-Improved Ant Colony Optimization (SVM-IACO) [27], and Content-based Collaborative Filter (CbCF) [28].

5.2.1 Accuracy

Accuracy described how to evaluate the efficiency of the recommender systems using review ratings, while Eqn. (7) provided information on the number of false alarms affecting the success rate. Here, use accuracy to provide the most accurate result for the recommendation process.

$$A = \frac{TP + TN}{FP + TN + TP + FN} \quad (7)$$

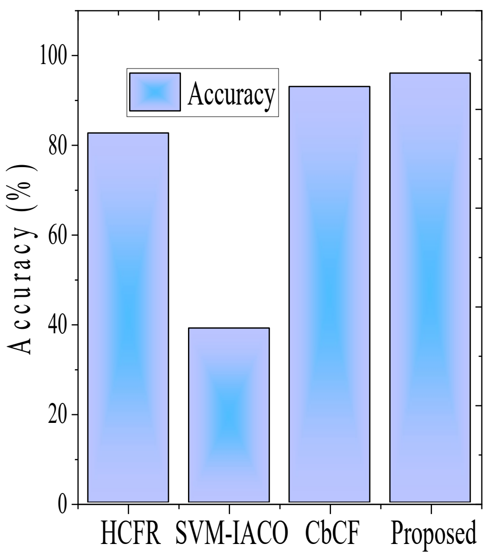

Fig.5 Comparison Of Accuracy Metrics With Existing Techniques

The prevailing models' accuracy, including HCFR, had gained 82.636%, SVM-IACO was 39%, and CbCF provided 93%. In this instance, the suggested model outperformed the other approaches, offering a reliable result of 96%. Figure 5 provides an overview of the accuracy of various suggestion methods.

5.2.2 Precision

The ability of the system to provide Content suitable for a particular user was described as precision. It was the ratio of appropriate solutions to user ideas. Eqn. (8) could be used to define precision.

$$\Pr ecision(PREC) = \frac{Correctly\ recommended\ items}{Whole\ recommended\ items} \quad (8)$$

The number of pertinent ideas that the user deemed to be correctly suggested. The total number of recommended items was the total number of recommendations made to the user.

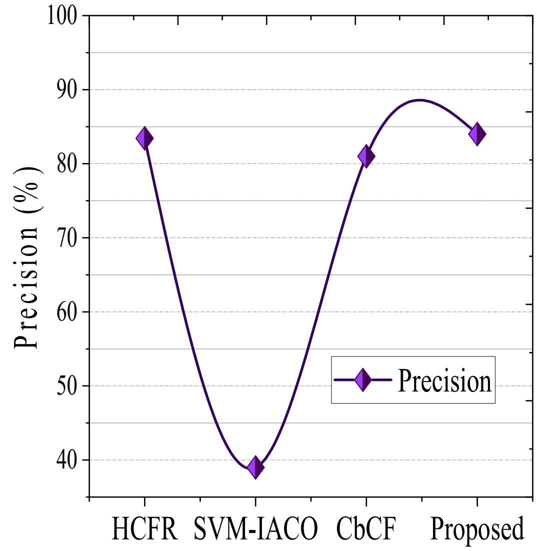

Fig.6 Comparison Of Precision

The existing methods' precision ranged from 83.433% for HCFR to 81% for CbCF to 39% for SVM-IACO. The new EDNbMRS model, however, outperformed the existing models with a precision value of 84%. The precision comparison was obtained in Fig. 6.

5.2.3 Recall

The ability of the systems to provide the users with critical data was referred to as the Recall. It stated the proportion of rapid recommendations in the pertinent recommendations set. Eqn. (9) provided a representation of the recall estimation.

$$\operatorname{Re} call = \frac{Correctly\ recommended\ items}{\operatorname{Re} levant\ items} \quad (9)$$

Where, the number of recommendations that were recommended for the item correctly. Depending on user recommendations, the highest recommendations are included with the appropriate items.

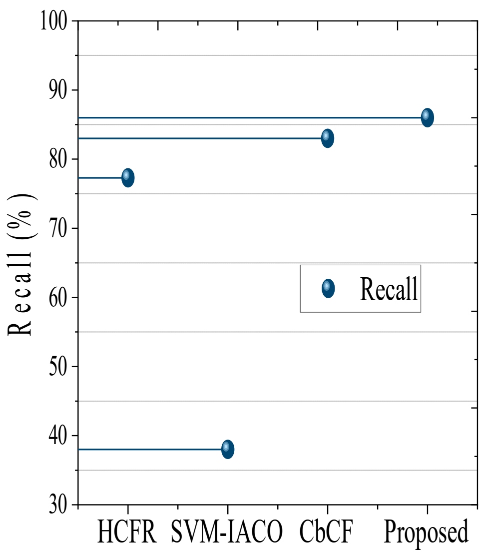

Fig.7 Comparison Of Recall Metrics In RS

Different currently used models, like HCFR, had a recall of 77.301%, SVM-IACO had 38%, and CbCF had 83%. In this instance, the suggested EDNbMRS model gained 86%, which offered a high recall value compared to the current models and presented the Recall comparison in Fig. 7.

5.2.4 F-measure

F-measure is the name given to the single statistic that integrates Recall and precision. It stood for Recall and precision's harmonic mean. Eqn. (10) showed how the F-measure was evaluated.

$$F-measure = \frac{2*\Pr ecision * \mathrm{Re}\,call}{precision + \mathrm{Re}\,call} \tag{10}$$

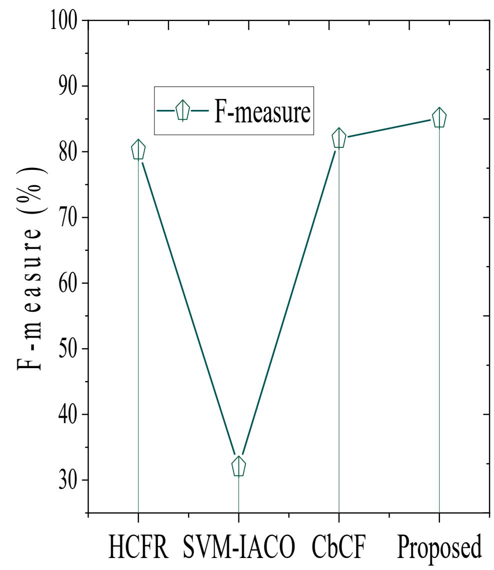

Fig.8 Comparison Of F-Measure Metrics For Several Recommending Mechanisms

The F-measure of the current models, such as HCFR, CbCF, and SVM-IACO, was 80.25%, 82%, and 32%, respectively. In this case, the generated model outperformed the current approaches in terms of F-measure. The comparison of the f-measure is shown in Fig. 8. Table 2 shows an assessment of the developed model's performance.

Table.2 Performance Estimation Of The Suggested Model

Method	Metrics			
	Accuracy (%)	Precision (%)	Recall (%)	F-measure (%)
HCFR [26]	82.636	83.433	77.301	80.25
SVM-IACO [27]	39	39	38	32
CbCF [28]	93	81	83	82
Proposed	96	84	86	85.1

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5.3 Discussion

The current model, somewhat superior to the prior studies, captured the best recommendation system output from the measuring performance. So, it was possible to confirm these performance gains by carrying out the comparative experiments in the last part. Gather the information in the dataset first, and then use the suggested EDNbMRS model to preprocess the data to eliminate undesirable noise features. The proposed model also extracted features, matched prediction calculations, and recommended processes to provide movies to the target audience. The table.3 includes details regarding the suggested model's overall performance.

Table.3 Performance Of The Developed EDNBMRS

Overall Performance statistics	
Precision	84%
Accuracy	96%
Recall	86%
F-measure	85.1%

Thus, the overall performance statistics with the performance metrics included accuracy, PREC, Recall and f-measure of the proposed model, such as 96%, 84%, 86%, and 85.1%. Hence, the designed model scored a high accuracy rate associated with the existing models. So, the recommendation process for this developed model was very effective.

6. CONCLUSION

This study deals with Collaborative filtering that aims to perform the recommendation process for the item to the target user. Here is a novel Eagle Deep Neural-based Movie Recommender System for the recommendations. Initially, the system starts with gathering the data for the training process using the proposed method. Then, preprocessing, feature analysis, similarity score and prediction computation, and recommendation process were performed in this system. The performance of several existing systems was analyzed to provide a better outcome for the recommendation process. The accuracy of the proposed model in this recommendation process was 96%, and the improvement score for this developed model was 11%. The advantage of this extended model performed the period for the recommendation process in less time. In future, the hybridization of Deep learning with an efficient, optimized technique will be used for the recommendation process.

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