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# Hybrid Recommendation System Based on Collaborative and Content-Based Filtering

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**ABSTRACT**

A Recommendation System (RS) is a method which filters the information and helped users' to choose the corresponding target from the huge amount of information obtainable in online. The system recommends useful and satisfactory products (items) such as books, music, jokes, and movies for targeting users based on their interest. The content-based filtering as well as collaborative are different systems used often while designing the RS that predicts the recommended item(s) based upon the user preferences. However, the collaborative filtering algorithm provides poor performance for data sparsity, and it is complex for tracking the change of user interest. Moreover, the hybrid system has combined both the techniques in multiple ways to overcome the shortcomings and optimize the outcomes. Thereby, this article plans to develop a new hybrid recommender system assisting with the optimization concept for optimal recommendation list based on user preference or interest. At first, the feature extraction process takes place, in which the content features and the collaborative features are extracted based on (a) profile construction, (b) content similarity index, (c) Neighbor finder, (d) Items generator, and (e) Items weight generator and variance generator. Consequently, the optimal recommendation is carried out on the basis of features extracted. Further, the developed work plans to carry out the optimal rating of recommendation using a FireFly with Weighted Crow Search Algorithm (FF-WCSA). At last, the outcomes of the developed model is computed to extant approaches in terms of various metrics like accuracy, FDR, MAE, MARE, MSE, MSRE, RMSE, and RMSRE, respectively.

**KEYWORDS**

Feature extraction; optimal rating; optimization; recommendation system; similarity index

## Introduction

Numerous resources are provided by the online movie platforms that provide convenience for the normal audience. Nevertheless, the users need to spend more time in searching the movies based on their interest that provide the rapid growth in the resources of network information (Dooms,

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Pessemier, and Martens 2015; Soares and Viana 2015; Deldjoo et al. 2019). Based on the requirement of the users, it helps to identify the resources as it requires quickly. The summation of novel movies may cause information overload issues in the successive movie market. RS is known as the powerful solutions to the issues of information overload as well as it is significant in the research field (Wei et al. 2016; Chang and Jung 2017; Sinha, Dhanalakshmi, and Regmi 2020).

One of the software tools is the Recommender Systems (RSs) that provide users implication based on their needs (Thorat, Goudar, and Barve 2015). RS are classified into two types: CF and CBF. The CBF suggests goods that are similar to those that the user has previously used. Item-based Collaborative Filtering is a type of collaborative filtering that finds and recommends goods that are comparable to those that the user has rated. The CF normally generates a large list of recommendations, but users only prefer a tiny percentage of products that are recommended.

RSs are employed for helping the users to cope up the explosion of the information. Moreover, the RS is used in e-commerce portals like eBay, Flipkart, and Amazon as well as digital entertainment like IMDb, Prime Video, Netflix. Further, the movies are differentiated easily based on their genres like animation, action, thriller, and comedy (Ferdaous et al. 2018; Kumar, De, and Roy 2020; Logesh et al. 2020). The movies-based metadata is categorized as director, cast, release year, or language. Certain online video-streaming services offered the experience of the personalized user through the usage of the user's historical data like rated history or viewed previously (McAuley and Leskovec 2013). RSs-based movies could help to search the preferred movies quickly online. Moreover, the primary requisite for a RS movie is trustworthy and provides the users with the movies recommendation which resemble its preferences. Recently, the RS is useful in day-to-day activities for making decisions with an exponential increase in online data. RSs are divided into two major categories such as CF and CBF (Cao, Li, and Zheng 2019; El-Ashmawi, Ali, and Slowik 2021; Kumar, De, and Roy 2020; Paleti, Krishna, and Murthy 2021). The most prevalent techniques to constructing RSs is collaborative filtering (CF), which leverages a set of users' known preferences to create recommendations or predictions for other users' unknown preferences (Nguyen, Nguyen, and Jung 2020). A user–item interaction matrix is created through recording the interactions among users and different things.

The hybrid RSs is more scalable while using the clustering algorithms (Rewadkar and Doye 2018; Gangappa, Mai, and Sammulal 2019; Kumar 2019; Nair and Muthuvel 2019; Daniya 2020; Sangtani 2020). The KNN collaborative approach is combined with the basic predictors that enhanced the timing of recommendation methods and decrease the error metrics

(Yeung, Yang, and Ndzi 2012; Hong, Jung, and Camacho 2017; Indira and Kavithadevi 2019; Liu et al. 2021). Most of the hybrid RSs used collaborative filtering extensively as an instrumental part of the entire engine. Particularly, the hybrid RSs is the most efficient model that faced the issues while applying in the scenarios of real-life (Askarzadeh 2016; Li et al. 2018; Pan and Wu 2020). Both ICF and CF has some limitations such as it selects all items that are similarity to the existing items bought by the active user usually above certain threshold. A huge list of items is generated for the active user. But it is very tough for the user to identify the suitable items. The proposed approach has shortened the recommendation list and also increases the precision value of the generated recommendations.

The main implementation of the adopted scheme is given below:

- Introduces the new recommended system, in which the optimal recommendation is performed owing to the features extracted and the optimal rating for recommendation by the new FF-WCSA.

The left over section includes: Section Literature review addresses the literature review on conventional recommendation systems. Section Overall description of the proposed optimization assisted hybrid recommended system portrays about the overall description of the proposed optimization-assisted hybrid recommended system. Section Feature extraction process: combining content and collaborative feature set describes the feature extraction process: combining content and collaborative feature set. Section Optimal recommendation via proposed firefly with weighted crow search algorithm depicts the optimal recommendation via the proposed firefly with a weighted crow search algorithm. Section Results and discussions discussed the results and discussions. At the end, Section Conclusion concludes this article.

## Literature Review

### *Related Works*

In 2016, (Wei et al. 2016) has presented a hybrid movie recommendation model by means of ratings and tags. Initially, the preference topic approach and social movie networks were constructed. Subsequently, the social tags were extracted, reconditioned, and normalized based on the user preferences depending on social content annotations. At last, the recommendation model was improved by deploying additional data depending on historical user ratings.

In 2018, (Li et al. 2018) have determined a hybrid recommendation model for resolving two problems by combining the user interest and movie feature. Here, the vector for movie feature was constructed depending on movie attributes and was merged with user rating matrix to generate the vector for user interests. These vectors were updated mutually in an iterative manner. Subsequently, depending on user interest vector, the user-related matrix was created. The findings of the developed scheme had offered better accuracy to the reported extant approaches.

In 2020, (Kumar, De, and Roy 2020) has suggested a hybrid RSs for movies, which leveraged the most excellent concepts exploited from CBF and CF together with twitter sentiment analysis from microblogs. The intention of using the movie tweets was to identify the public sentiment, user response, and movie's present trend. Finally, the experimental analysis was performed on the publically available database that has yielded better outcomes. Comparison of obtained results over the reported literature has clearly shown the superiority of the proposed model.

In 2020, (Bahl et al. 2020) have introduced a recommendation engine depending on the hybrid framework that resulted in improved accuracy. Accordingly, the collaborative recommendations were made depending on user similarity; whereas, the content-oriented recommendations were made depending on item attribute similarities. In addition, this work has exploited SVD for performing collaborative filtering united with content-oriented approach for predicting the ratings of the item for each user. The experimental outcome of the developed approach has shown minimal error than the conventional methods.

In 2020, (Tahmasebi, Ravanmehr, and Mohamadrezaei 2021) has determined a hybridized social RSs by deploying a deep autoencoder network. The adopted framework has employed content-oriented and collaborative-oriented filtering along with the social influence of users'. Further, the social influences of every user were computed depending on Twitter features as well as her/his social behaviors. In the end, simulation results have revealed the accuracy and effectiveness of the adopted schemes.

In 2018, (Deldjoo et al. 2018) have shown the users' movie preferences that were determined with respect to "mise-en-scène features," that is, the movie's visual features, which characterized design, esthetics (e.g.) color textures, and style. These features were automatically evaluated any video file that offers flexibility to handle novel items, thus eliminating the requirement of error-prone and costly human-based tagging. The simulation outcomes were compared over other methods in the literature to ensure the superior performance of the presented approach.

In 2016, (Christou, Amolochitis, and Tan 2016) have carried out extensive experimentations with recommendation software including Lens-Kit as well as Apache Mahout along the execution of numerous item-based, user-based, as well as content-based recommendation models in open-source.

**Table 1.** Review on extant recommendation systems: features and limitations.

| Author (citation) | Presented model | Features | Limitations |
|---|---|---|---|
| Wei et al. (2016) | SVD scheme | • Better recall<br>• High precision | • User preference could not be attained based on the variation in time. |
| Li et al. (2018) | Inverse feature frequency model | • High accuracy<br>• Evaluates the similarity among users | • Should be analyzed using better similarity computation model. |
| Kumar, De, and Roy (2020) | CBF method | • High precision<br>• High accuracy | • Have to consider English languages. |
| Bahl et al. (2020) | SVD | • Reduces sparsity issues<br>• Minimal errors | • The recommendation has to assist a group of people instead of a particular person. |
| Tahmasebi, Ravanmehr, and Mohamadrezaei (2021) | Deep autoencoder network | • Better efficiency<br>• Minimal error | • Need consideration on sentiment analysis. |
| Deldjoo et al. (2018) | GWO model | • Better scalability<br>• Reduced computational load. | • Low level visual features should be analyzed in terms of diversity. |
| Christou, Amolochitis, and Tan (2016) | AMORE | • Higher recall<br>• Minimal running time | • Should focus more on cost factors. |
| Vimala and Vivekanandan (2019) | KLD–FCM–MRS scheme | • High accuracy<br>• Reduced error | • Should focus more on the future behavior of the user |

The outcomes have indicated that the execution of collaborative filtering with content-oriented model outperformed the compared methods both in response time and solution quality with minimal running time.

In 2019, (Vimala and Vivekanandan 2019) have developed KLD–FCM–MRS for improving the recommendation model related to movie. In the adopted system, “KL divergence-oriented cluster ensemble factor” was integrated in FCM clustering schemes for improving the robustness and stability during clustering. Thus, the obtained outcomes were compared and evaluated to the recent literature works to demonstrate the potential as well as effectiveness of the developed model.

## *Review*

Table 1 demonstrates the review of extant recommendation systems. Initially, SVD scheme was presented in (Wei et al. 2016) that offers better recall and high robustness. Nevertheless, user preference could not be attained based on the variation in time. The inverse feature frequency model in (Li et al. 2018) evaluate the similarity among users and high accuracy is attained, but it should be analyzed using better similarity computation model. Besides, CBF method in (Kumar, De, and Roy 2020) provides high precision and accuracy; nevertheless, it should consider more on English languages. Also, SVD was employed in (Bahl et al. 2020) that reduces sparsity issues with minimal errors. However, the recommendation has to assist a group of people instead of a particular person. Likewise, Deep autoencoder network (Tahmasebi, Ravanmehr, and Mohamadrezaei 2021) results in a minimal error and better efficiency. However, it needs consideration on sentiment analysis. In addition, GWO in (Deldjoo et al. 2018) offers lower computational load and better scalability. Nevertheless, low-level visual features should be analyzed in terms of diversity. AMORE (Christou, Amolochitis, and Tan 2016) offered higher recall and minimal running time; however, cost factors should be analyzed. KLD–FCM–MRS scheme, presented in (Vimala and Vivekanandan 2019) offers high accuracy with reduced error; but, it should focus more on the future behavior of the user. These Challenges were regarded to enhance the hybrid RSs efficiently in the present work.

## Overall Description of the Proposed Optimization Assisted Hybrid Recommended System

The collaborative/Content hybrids is the type that will illustrate the ramp-up issue as both techniques requires proper rating datasets. Though, this hybrid model is more popular, since in many situations, the ratings already exist or it could be inferred from data. In these circumstances, this work initiates meta-techniques to avoid the problem of sparsity. As per the proposed work, initially, the feature extraction method takes place in which the collaborative features as well as content features are extracted based on "(a) profile construction, (b) content similarity index, (c) Neighbors finder, (d) Items generator, and (e) Items weight generator and variance generator." Based on these hybrid feature sets (both content and collaborative), the optimal recommendation is carried out by considering this as the optimization issue. For solving this, a new FF-CSWA is implemented in this article. Figure 1 illustrates the architecture of the proposed scheme.

## Feature Extraction Process: Combining Content and Collaborative Feature Set

### *Feature Extraction*

The feature extraction process includes the following constraints.

- Profile construction
- Content similarity index
- Neighbors finder
- Items generator
- Items weight and variance generator

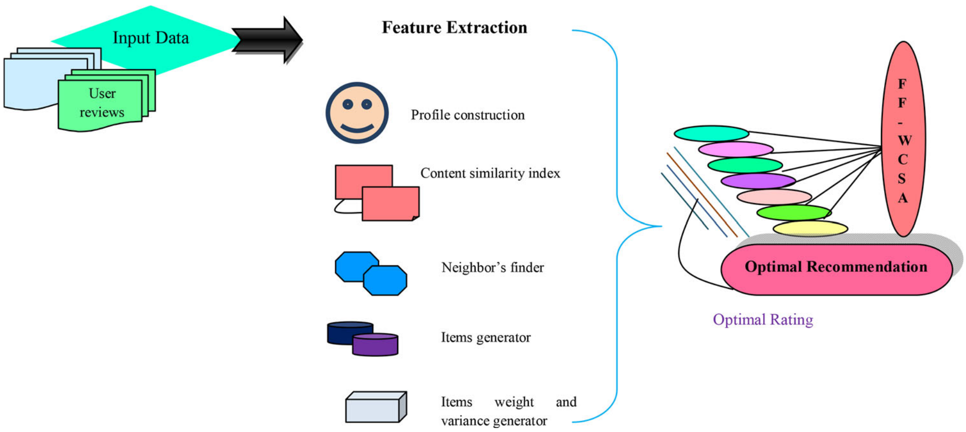


**Figure 1.** Architecture of the developed methodology.

**Table 2.** Parameters and notation.

| Parameters | Notation |
|---|---|
| $(U_1, U_2)$ | Refers to the user |
| $\vec{u}_1, \vec{u}_2$ | Vectors of user1 and 2 |
| $C$ | Cosine Similarity |
| $AB_{a,U_1}$ | Average Rating of user1 |
| $AB_{a,U_2}$ | Average Rating of user2 |
| $B_{a,U_1}$ | Rating of the item$a$ by user 1 |
| $B_{a,U_2}$ | Rating of the item$a$ by user 2 |
| $I_{1,2}$ | Common items for both users |
| $N_i$ | Neighbor count |
| $N_{\max}$ | Maximum count |
| $P_i$ | average item rating of item $i$ |
| $\text{count}_i$ | the number of users who have rated an item$i$ |
| $\text{Rating}_{\max}$ | Maximum Rating |
| $\text{Count}_{\max}$ | Maximum count |
| $R_{\max}$ | Highest rating in a rating scale |
| $d$ | Total number of users |
| $IW_{i_t}$ | Common item weight |
| $H_j$ | Final Rating of an item |

### *Profile Construction*

Here, the profile construction of each user and item is carried out. It creates the item profile via the keywords set given through e-commerce website. Moreover, it creates the profile for each user in terms of KV. The Parameters and notation are depicted in Table 2.

### *Content Similarity Index*

It finds same users who comprise same interests on the basis of user's profile constructed already as the target user (Tewaria 2020). Here, the cosine similarity $C$ is used, which is given in Eqs. (1) and (2).

$$C(U_1, U_2) = \cos\text{ine}(U_1, U_2) \tag{1}$$

$$C(U_1, U_2) = \frac{\overrightarrow{U}_1, \overrightarrow{U}_2}{|\overrightarrow{U}_1| \times |\overrightarrow{U}_2|} \tag{2}$$

### Neighbor Finder

It collects the target user's rating for various items from a profile that has previously been built. Pearson's analysis is conducted to determine user similarities.

$$S(U_1, U_2) = \frac{\sum_{a \in I_{1,2}} (B_{a,U_1} - AB_{U_1})(B_{a,U_2} - AB_{U_2})}{\sqrt{\sum_{a \in I_{1,2}} (B_{a,U_1} - AB_{U_1})^2 \sum_{a \in I_{1,2}} (B_{a,U_2} - AB_{U_2})}} \tag{3}$$

In Eq. (3), $U_1$, and $U_2$ refers to the users, $I_{1,2}$ denotes the common items of both users, $B_{a,U_1}$ and $B_{a,U_2}$ portrays the rating of the item $a$ by user 1 and user 2, $AB_{a,U_1}$ and $AB_{a,U_2}$ represents the average rating of user 1 and user 2.

### Item Generator

The items are generated from the neighbor finder phase. It chooses target user's each neighbors. It also picks every neighbor's related items not related through the user's target.

### Item Weight & Variance Generator

It helps to find the popularity of different items among all users in the form of weights. The target user item-specific weight is calculated as per Eq. (4), where, $N_i$ indicates the neighbor count.

$$W_{u,i_t} = \frac{N_i}{N_{\max}} \tag{4}$$

The common item weight indicates the likeness degree in any exacting item between all users and determined using Eq. (5).

$$IW_{i_t} = \frac{P_i}{Rating_{\max}} \times \frac{count_i}{count_{\max}} \tag{5}$$

In Eq. (5), $P_i$ indicates the average item rating of item $i$, and count$_i$ denotes the count of users with an item $i$ rated. The variance of the item rating is calculated using $SD$, which is expressed in Eq. (6).

$$SD_i = \frac{\sqrt{\sum_{k=1}^{count_i} (x_k - P_i)^2}}{count_i} \tag{6}$$

## Optimal Recommendation via Proposed Firefly with Weighted Crow Search Algorithm

The final optimal recommendation is performed by a developed FF-WCSA scheme that hybridizes the concept of FF and CSA.

### Objective Function

The fitness can be calculated as per Eq. (7), which defines the maximization of the recommendation factor.

$$Fitness = \frac{(H_j - SD_i) \times W_{u,i_t}}{R_{\max}/2} + IW_{i_t} \tag{7}$$

Here,

$$H_j = AB_{a,U_1} + \frac{\sum_{n=1}^{d} (B_{a,U_1} - AB_{U_1}) * S(U_1, U_n)}{\sum_{n=1}^{d} S(U_1, U_n)} \tag{8}$$

In Eq. (8), $d$ denotes the total number of users, as well as $R_{\max}$ indicates the maximum rating in a rating level.

### Proposed FF-WCSA Model

Even though, the existing FF (Wang et al. 2017) model is known to be the well-known optimization tool for solving various optimization problems; it suffers from high computational time complexity. For overcoming the issues of extant FF, the concept of CSA (Manimurugan et al. 2020) is merged with it since the hybrid optimization model were reported to be capable for various search issues (Beno et al. 2014). FF is the population-based stochastic search algorithms. Each FF indicates a candidate solution in the population of search space. FF identifies the potential candidate solutions and it move toward other positions. The attractiveness of the FF is examined through the intensity of the emitted light, which is calculated by the fitness value. Consider, $Z^l$ as the population of $l$th FF, where $l = 1, 2, \ldots, V$ and $V$ represents the size of population. Moreover, the attractiveness among the two fireflies $Z^l$ and $Z^m$ is expressed as per Eq. (9). The value of $g_{lm}$ is calculated as per Eq. (10).

$$\beta(g_{lm}) = \beta_0 e^{-\gamma g_{lm}^2} \tag{9}$$

$$g_{lm} = \|Z^l - Z^m\| = \sqrt{\sum_{f=1}^{F} (z_{lf} - z_{mf})^2} \tag{10}$$

In Eq. (10), $f = 1, 2, \ldots, F$, $F$ portrays the problem dimension, $g_{lm}$ depicts the distance among $Z^l$ and $Z^m$, and $z_{lf}$, $z_{mf}$ represents the $f$th dimension of $Z^l$ and $Z^m$, correspondingly. Moreover, $\gamma$ specifies the light absorption coefficient, as well as the parameter $\beta_0$ specifies the attractiveness at $g = 0$. Further, $\lambda$ set to $\frac{1}{\lambda^2}$, here, $\lambda$ denotes the length scale of the intended variables. Each FF $Z^l$ is computed with all other FF$Z^m$, here, $m = 1, 2, \ldots, V$ and $m \neq l$. $Z^l$ is attracted to and move toward $Z^m$ only if $Z^m$ is better than $Z^l$.

The adopted contribution is given as: Conventionally FF is updated on the basis of $Z^l$ movement. As per the adopted FF-WCSA scheme, the FF update integrates the position update of the CSA. Thereby the final proposed update evaluation is as per Eq. (11).

$$Z^{l,\,\text{iter}+1} = wt \times Z^{l,\,\text{iter}} + \text{rand}_l \times L^{l,\,\text{iter}}\left(Z^{m,\,\text{iter}} - Z^{l,\,\text{iter}}\right) \tag{11}$$

In Eq. (11), $\text{rand}_l$ is a random value ranges from 0 to 1 and $L^{l,\,\text{iter}}$ depicts the flight length of crow. Here, $wt$ represents the weight of experience of a crow being a thief in order to predict the behavior of other crows, and it ranges from 0 to 1. The main steps of the developed FF-WCSA scheme are determined in Algorithm 1, $FE(.)$ is the fitness evaluation function, NEs indicates the count of fitness assessment, as well as $\text{MAX}_{\text{NEs}}$ denotes the higher count of fitness assessment.

**Algorithm 1:** Proposed FF-WCSA model

Population initialization and generate $V$ fireflies $Z^l$,
The fitness value is computed for each firefly
NEs $= V$;
While (NEs $\leq \text{MAX}_{\text{NEs}}$) do
  For $l = 1$ to $V$ do
    For $m = 1$ to $V$ do
      If FE($Z^m$) $<$ FE($Z^l$) then
        Move $Z^l$ toward $Z^m$ as per the proposed update given in Eq. (11)
        The fitness value is computed for the new $Z^l$;
        NEs$^{++}$;
      end
    end
  end
End while

## Results and Discussions

### *Simulation Procedure*

The adopted RS with FF-WCSA scheme was implemented in PYTHON as well as the outcomes were established. One of the common-purpose programming language is Python is with a high level of abstraction. Its design philosophy prioritizes code readability through the use of substantial indentation. The adopted FF-WCSA scheme was evaluated to extant approaches such as GWO (Mirjalili, Mirjalili, and Lewis 2014), MFO (Mirjalili 2015), PSO (Pedersen and Chipperfield 2010), GWSO (Wu et al. 2012), CSA (Manimurugan et al. 2020), as well as FF (Wang et al. 2017), correspondingly. In addition, the outcomes was evaluated for different recommendations from top 10 to top 50 based on various metrics including accuracy, MAE, FDR, MARE, MSE, MSRE, RMSE, and RMSRE, correspondingly.

### Dataset Description

The dataset has collected from (Vuong Nguyen et al. 2021). This dataset is made up of Amazon reviews. The data covers an 18-year period and includes 35 million reviews upto march 2013. Product and user information, ratings, and a plaintext review are all included in reviews. The total amount of reviews in this dataset is 34,868,770, with a total of 6,643,669 people. A total of 2,441,053 numbers of product were used.

### Performance Analysis

The performance of the proposed RS with FF-WCSA model is computed to extant schemes including GWO, MFO, PSO, GWSO, CSA, as well as FF, respectively, with respect to different metrics is represented in Figures 2 and 3, correspondingly. Likewise, the metrics including FDR, accuracy, MAE, MARE, MSE, MSRE, RMSE, and RMSRE of the adopted FF-WCSA scheme holds superior results to extant schemes. As per Figure 2(a), the adopted FF-WCSA model attains higher accuracy for top 40 recommendation, and it is 50%, 16.67%, 22.22%, 33.33%, 18.88%, 44.44%, and 11.11% superior to the existing models like conventional (hybrid recommendation system), GWO, MFO, PSO, GWSO, CSA, and FF, correspondingly. It establishes the betterment of the developed scheme in optimal recommendation than the other traditional methods with a better convergence rate. The adopted FF-WCSA method holds minimum FDR value ($\sim$0.5) for top 10 recommendation; still, the extant approaches attains the value of hybrid recommendation system ($\sim$0.7), GWO ($\sim$0.8), MFO ($\sim$1.0), PSO ($\sim$1.4), GWSO ($\sim$0.9), CSA ($\sim$1.7), and FF ($\sim$0.75), respectively, in Figure 2(b). Similarly, the MAE of the adopted FF-WCSA approach is given in Figure 2(c) holds the lowest values ($\sim$0.06), which is the better performance for sorting the top 30 recommendation. However, the extant approaches demonstrate their reduced performance with high value. Likewise, the MARE of the adopted FF-WCSA model achieves superior outcomes ($\sim$0.1) for top 20 recommendations than other existing models like hybrid recommendation system, GWO, MFO, PSO, GWSO, CSA, and FF, respectively, in Figure 2(b).

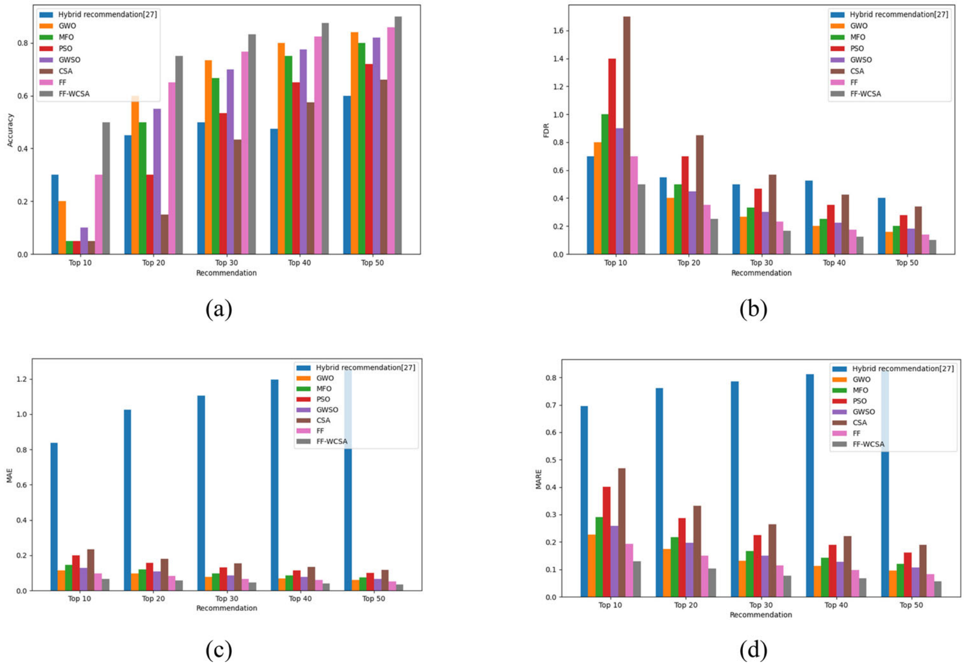


**Figure 2.** Performance analysis of the developed FF-WCSA scheme to extant approaches for (a) Accuracy (b) FDR (c) MAE (d) MARE.

Likewise, the MSE of the adopted FF-WCSA scheme for top 10 recommendations attains the least value (~0.01), which is superior to extant approaches including hybrid recommendation system, GWO, MFO, PSO, GWSO, CSA, and FF, respectively (Figure 3(a)). Further, the MSRE of the implemented FF-WCSA method for top 10 recommendation holds the least value (~0.02) than the other conventional models such as hybrid recommendation system (~0.54), GWO (~0.05), MFO (~0.08), PSO (~0.17), GWSO (~0.07), CSA (~0.24), and FF (~0.04), respectively, as per Figure 3(b). In addition, the adopted FF-WCSA algorithm holds minimum RMSE for the top 20 recommendations, which is 80% better than the traditional hybrid recommendation system as per Figure 3(c). The RMSRE of the developed FF-WCSA scheme is 90%, 37.5%, 87.5%, 75%, 62.5%, and 25% better to extant schemes including hybrid recommendation system, GWO, MFO, PSO, GWSO, as well as FF, respectively, for top 50 recommendations as in Figure 3(d). Thus, the development of the proposed work is established to conventional models for various measures.

### *Convergence Analysis*

The convergence analysis of the developed FF-WCSA scheme to extant approaches like GWO, MFO, PSO, GWSO, CSA, and FF for diverse

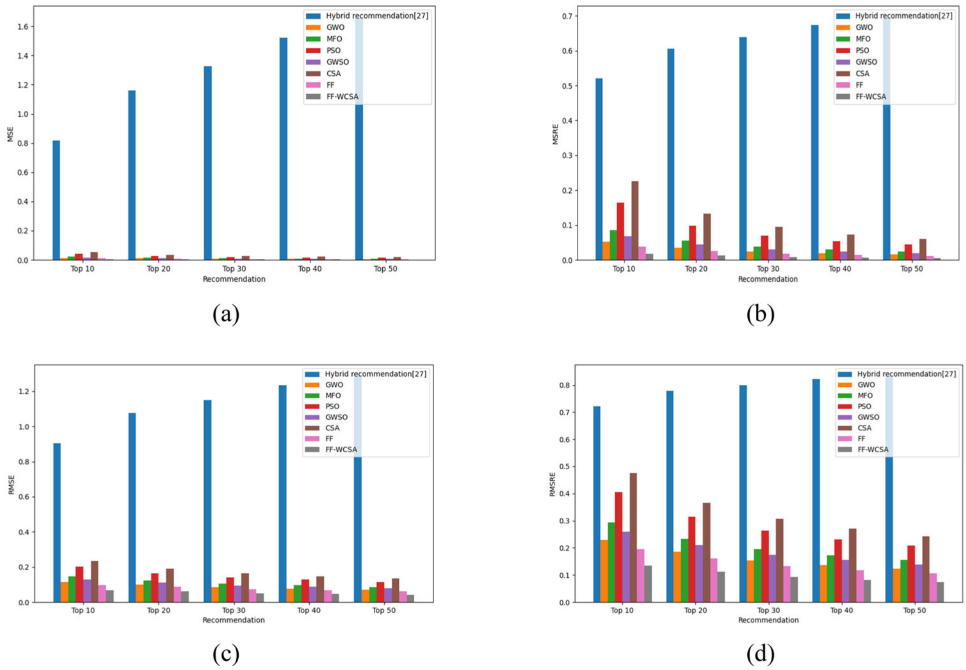


**Figure 3.** Performance analysis of the developed FF-WCSA scheme to extant approaches for (a) MSE (b) MSRE (c) RMSE (d) RMSRE.

iterations among 0 to 50 is represented in Figure 4. As the iteration increases, the cost function gets minimized as reaches to the least value at the 50th iteration. The convergence analysis is evaluated by determining the reciprocal of the objective function (i.e.), $\frac{1}{\text{Fitness}}$. From the graph, the proposed FF-WCSA scheme attained least cost values to extant schemes. The outcomes of the developed FF-WCSA scheme is 58.62%, 40%, 36.84%, 33.33%, 14.28%, and 7.69% higher than the traditional models MFO, GWSO, CSA, FF, PSO, and GWO correspondingly at 30th iteration. Therefore, the outcome of the adopted scheme is confirmed to extant schemes for the optimal recommendation.

### Comparative Analysis on Top Recommendations

The comparative analysis of the adopted FF-WCSA model to extant schemes including GWO, MFO, PSO, GWSO, CSA, as well as FF, respectively, for varied top recommendations 10, 20, 30, 40, and 50, is summarized in Tables 3–7. In table, the adopted FF-WCSA scheme has proved higher recommendation outcomes for all top recommendations to other extant schemes including GWO, MFO, PSO, GWSO, CSA, and FF, correspondingly. Furthermore, the developed FF-WCSA scheme holds larger accuracy values (75%) for top 20 recommendations to extant schemes including hybrid recommendation system, GWO, MFO, PSO, GWSO, CSA,

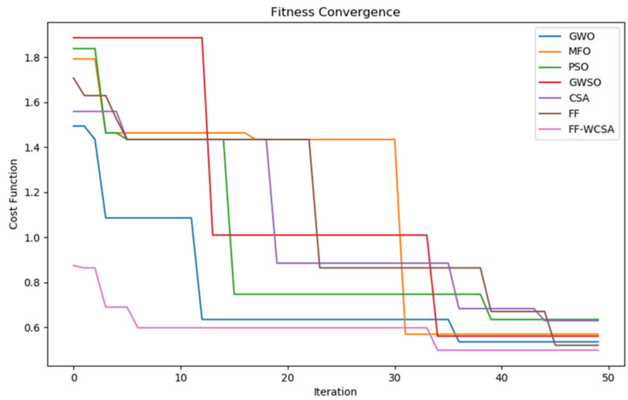


**Figure 4.** Convergence analysis of developed FF-WCSA scheme to extant schemes.

and FF, respectively, in Table 4. On observing Table 4, it is shown that the adopted FF-WCSA method is 58.72%, and 70.26% higher RMSRE to the extant schemes such as hybrid recommendation system, GWO, respectively, for top 10 recommendations. Likewise, the FDR, MSE, MAE, RMSE, MARE, MSRE, and RMSRE of the proposed FF-WCSA model holds least values for all top recommendations to extant approaches. Altogether, the proposed model has proved its betterment over other conventional models for an optimal recommendation, which shows its improved convergence rate.

### *Statistical Analysis*

In terms of accuracy, Table 8 compares the proposed FF-WCSA strategy to other standard technologies. The optimal mean performance of the ICSFF is 0.587068, which outperforms the existing models GWO = 0.738019, MFO = 1.134495, PSO = 0.953288, GWSO = 1.09346, CSA = 1.0042598, and FF = 1.086962. Other metrics show that the adopted model outperforms the standard method. As a result, the proposed model's enhancement was successfully validated.

### *Computation Complexity Analysis*

In this section, the computational time of the FF-WCSA and traditional models such as GWO, MFO, PSO, GWSO, CSA, and FF is discussed and shown in Table 9. In comparison to other methods, such as GWO (81,397), MFO (77,218), PSO (90,542), GWSO (96,325), CSA (75,842), and FF (87,516). The proposed model, conversely, has the shortest running time (72,258). As a result, the proposed model is guaranteed to be efficient in terms of computational time.

**Table 3.** Comparative analysis of presented and traditional schemes with top 10 recommendations.

| Metrics | Hybrid recommendation system (Li et al. 2018) | GWO (Mirjalili, Mirjalili, and Lewis 2014) | MFO (Mirjalili 2015) | PSO (Pedersen and Chipperfield 2010) | GWSO (Wu et al. 2012) | CSA (Manimurugan et al. 2020) | FF (Wang et al. 2017) | FF-WCSA |
|---|---|---|---|---|---|---|---|---|
| Accuracy | 0.3 | 0.2 | 0.05 | 0.05 | 0.1 | 0.05 | 0.3 | 0.5 |
| FDR | 0.7 | 0.8 | 1 | 1.4 | 0.9 | 1.7 | 0.7 | 0.5 |
| MAE | 0.836136 | 0.113349 | 0.145178 | 0.200131 | 0.128777 | 0.232723 | 0.097028 | 0.065259 |
| MARE | 0.818514 | 0.012974 | 0.02115 | 0.04026 | 0.016628 | 0.0545 | 0.00958 | 0.004516 |
| MSE | 0.904718 | 0.113902 | 0.14543 | 0.20065 | 0.128951 | 0.233453 | 0.097876 | 0.067202 |
| MSRE | 0.695178 | 0.22666 | 0.290994 | 0.401854 | 0.258156 | 0.46899 | 0.193557 | 0.130187 |
| RMSE | 0.520407 | 0.052184 | 0.08585 | 0.164535 | 0.067518 | 0.225874 | 0.038146 | 0.018 |
| RMSRE | 0.721393 | 0.228439 | 0.293001 | 0.405629 | 0.259842 | 0.475262 | 0.19531 | 0.134165 |

**Table 4.** Comparative analysis of adopted and extant schemes with top 20 recommendations.

| Metrics | Hybrid recommendation system (Li et al. 2018) | GWO (Mirjalili, Mirjalili, and Lewis 2014) | MFO (Mirjalili 2015) | PSO (Pedersen and Chipperfield 2010) | GWSO (Wu et al. 2012) | CSA (Manimurugan et al. 2020) | FF (Wang et al. 2017) | FF-WCSA |
|---|---|---|---|---|---|---|---|---|
| Accuracy | 0.45 | 0.6 | 0.5 | 0.3 | 0.55 | 0.15 | 0.65 | 0.75 |
| FDR | 0.55 | 0.4 | 0.5 | 0.7 | 0.45 | 0.85 | 0.35 | 0.25 |
| MAE | 1.023983 | 0.096348 | 0.119511 | 0.156023 | 0.108556 | 0.180107 | 0.083784 | 0.057612 |
| MARE | 1.159357 | 0.009918 | 0.015384 | 0.026831 | 0.01258 | 0.035752 | 0.007519 | 0.003658 |
| MSE | 1.076734 | 0.099587 | 0.124034 | 0.163802 | 0.112161 | 0.189081 | 0.086713 | 0.06048 |
| MSRE | 0.761222 | 0.174158 | 0.217607 | 0.286717 | 0.19695 | 0.331916 | 0.150782 | 0.103221 |
| RMSE | 0.605559 | 0.034346 | 0.054641 | 0.098476 | 0.044135 | 0.133307 | 0.025612 | 0.012287 |
| RMSRE | 0.778177 | 0.185326 | 0.233754 | 0.313809 | 0.210083 | 0.365112 | 0.160036 | 0.110848 |

**Table 5.** Comparative analysis of adopted and extant schemes with top 30 recommendations.

| Metrics | Hybrid recommendation system (Li et al. 2018) | GWO (Mirjalili, Mirjalili, and Lewis 2014) | MFO (Mirjalili 2015) | PSO (Pedersen and Chipperfield 2010) | GWSO (Wu et al. 2012) | CSA (Manimurugan et al. 2020) | FF (Wang et al. 2017) | FF-WCSA |
|---|---|---|---|---|---|---|---|---|
| Accuracy | 0.5 | 0.733333 | 0.666667 | 0.533333 | 0.7 | 0.433333 | 0.766667 | 0.833333 |
| FDR | 0.5 | 0.266667 | 0.333333 | 0.466667 | 0.3 | 0.566667 | 0.233333 | 0.166667 |
| MAE | 1.105413 | 0.076201 | 0.095592 | 0.130459 | 0.086151 | 0.152834 | 0.065734 | 0.045094 |
| MARE | 1.325066 | 0.00706 | 0.011041 | 0.020026 | 0.008976 | 0.027072 | 0.005313 | 0.002589 |
| MSE | 1.151115 | 0.084024 | 0.105074 | 0.141512 | 0.094744 | 0.164536 | 0.07289 | 0.050878 |
| MSRE | 0.786039 | 0.131761 | 0.165883 | 0.225722 | 0.149318 | 0.26418 | 0.113449 | 0.077577 |
| RMSE | 0.639283 | 0.023661 | 0.037763 | 0.069293 | 0.030427 | 0.094419 | 0.017587 | 0.008449 |
| RMSRE | 0.799552 | 0.153821 | 0.194326 | 0.263236 | 0.174434 | 0.307277 | 0.132618 | 0.091919 |

**Table 6.** Comparative analysis of adopted and extant schemes with top 40 recommendations.

| Metrics | Hybrid recommendation system (Li et al. 2018) | GWO (Mirjalili, Mirjalili, and Lewis 2014) | MFO (Mirjalili 2015) | PSO (Pedersen and Chipperfield 2010) | GWSO (Wu et al. 2012) | CSA (Manimurugan et al. 2020) | FF (Wang et al. 2017) | FF-WCSA |
|---|---|---|---|---|---|---|---|---|
| Accuracy | 0.475 | 0.8 | 0.75 | 0.65 | 0.775 | 0.575 | 0.825 | 0.875 |
| FDR | 0.525 | 0.2 | 0.25 | 0.35 | 0.225 | 0.425 | 0.175 | 0.125 |
| MAE | 1.195879 | 0.068957 | 0.085828 | 0.114689 | 0.077706 | 0.133407 | 0.059821 | 0.041092 |
| MARE | 1.522773 | 0.00589 | 0.009141 | 0.016215 | 0.007464 | 0.021775 | 0.004453 | 0.002182 |
| MSE | 1.234007 | 0.076747 | 0.095611 | 0.127338 | 0.086392 | 0.147563 | 0.066732 | 0.046715 |
| MSRE | 0.810887 | 0.113309 | 0.141795 | 0.189984 | 0.128072 | 0.221191 | 0.097986 | 0.067079 |
| RMSE | 0.674148 | 0.018648 | 0.029638 | 0.053792 | 0.023933 | 0.073052 | 0.013899 | 0.006698 |
| RMSRE | 0.821065 | 0.136558 | 0.172158 | 0.23193 | 0.154704 | 0.270282 | 0.117892 | 0.081838 |

**Table 7.** Comparative analysis of adopted and extant schemes with top 50 recommendations.

| Metrics | Hybrid recommendation system (Li et al. 2018) | GWO (Mirjalili, Mirjalili, and Lewis 2014) | MFO (Mirjalili 2015) | PSO (Pedersen and Chipperfield 2010) | GWSO (Wu et al. 2012) | CSA (Manimurugan et al. 2020) | FF (Wang et al. 2017) | FF-WCSA |
|---|---|---|---|---|---|---|---|---|
| Accuracy | 0.6 | 0.84 | 0.8 | 0.72 | 0.82 | 0.66 | 0.86 | 0.9 |
| FDR | 0.4 | 0.16 | 0.2 | 0.28 | 0.18 | 0.34 | 0.14 | 0.1 |
| MAE | 1.253033 | 0.058917 | 0.073775 | 0.099185 | 0.066596 | 0.117295 | 0.050927 | 0.034832 |
| MARE | 1.657369 | 0.004788 | 0.007449 | 0.013254 | 0.006074 | 0.018006 | 0.003615 | 0.001767 |
| MSE | 1.287389 | 0.069192 | 0.086309 | 0.115128 | 0.077938 | 0.134187 | 0.060127 | 0.042038 |
| MSRE | 0.824678 | 0.094913 | 0.11925 | 0.160437 | 0.107496 | 0.18896 | 0.081886 | 0.055894 |
| RMSE | 0.694144 | 0.015016 | 0.023887 | 0.043398 | 0.01928 | 0.059197 | 0.011188 | 0.005386 |
| RMSRE | 0.833153 | 0.122541 | 0.154553 | 0.208322 | 0.138853 | 0.243303 | 0.105771 | 0.073387 |

Table 8. Statistical analysis of traditional and proposed method.

| | Mean | Median | Std-Dev | Minimum | Maximum |
|---|---|---|---|---|---|
| GWO | 0.738019 | 0.634218 | 0.266427 | 0.534826 | 1.493056 |
| MFO | 1.134495 | 1.433333 | 0.450188 | 0.568783 | 1.791667 |
| PSO | 0.953288 | 0.746528 | 0.382495 | 0.634218 | 1.837607 |
| GWSO | 1.093461 | 1.00939 | 0.507313 | 0.559896 | 1.885965 |
| CSA | 1.042598 | 0.884774 | 0.345084 | 0.628655 | 1.557971 |
| FF | 1.086962 | 0.863454 | 0.376037 | 0.519324 | 1.706349 |
| FF-WCSA | 0.587068 | 0.597222 | 0.089112 | 0.497685 | 0.873984 |

Table 9. Analysis in-terms of computational time.

| Methods | Time (s) |
|---|---|
| GWO | 81,397 |
| MFO | 77,218 |
| PSO | 90,542 |
| GWSO | 96,325 |
| CSA | 75,842 |
| FF | 87,516 |
| FF-WCSA | 72,258 |

## Conclusion

This article has developed a novel hybrid RS assisting with optimization concept for optimal recommendation list based on user preference or interest. At first, the feature extraction process takes place, in which the content features and the collaborative features were extracted based on (a) Profile construction, (b) Content Similarity index, (c) Neighbor finder, (d) Items generator, and (e) Items weight generator and variance generator. Consequently, the optimal recommendation was carried out on the basis of features extracted. Further, the developed work plans to carry out the optimal rating of recommendation using FF-WCSA. At the end, the outcomes of the adopted model was evaluated to extant approaches based on various metrics including accuracy, FDR, MAE, MARE, MSE, MSRE, RMSE, and RMSRE, respectively. In graph, the developed FF-WCSA scheme attains higher accuracy for top 40 recommendation, and it was 50%, 16.67%, 22.22%, 33.33%, 18.88%, 44.44%, and 11.11% superior to the existing models like conventional (hybrid recommendation system), GWO, MFO, PSO, GWSO, CSA, and FF, respectively. Moreover, the MSRE of the implemented FF-WCSA method for top 10 recommendation holds the least value (∼0.02) than the other conventional models such as hybrid recommendation system (∼0.54), GWO (∼0.05), MFO (∼0.08), PSO (∼0.17), GWSO (∼0.07), CSA (∼0.24), and FF (∼0.04), correspondingly. In Table, it is shown that the developed FF-WCSA scheme was 58.722%, and 70.26% RMSRE higher to extant schemes including hybrid recommendation system, GWO, respectively, for top 10 recommendation.

## Abbreviations

| | |
|---|---|
| FCM | fuzzy C-means |
| CBF | content-based filtering |
| CSA | crow search algorithm |
| FF-WCSA | firefly with weighted crow search algorithm |
| MAE | mean absolute error |
| CF | collaborative filtering |
| KLD | Kullback–Leibler divergence |
| MSE | mean square error |
| GWSO | glowworm swarm optimization |
| IMDb | internet movie database |
| FF | firefly |
| KV | keyword vector |
| FDR | false discovery rate |
| GWO | grey wolf optimization |
| MARE | mean absolute relative error |
| MFO | moth flame optimization |
| RSs | recommendation systems |
| PSO | particle swarm optimization |
| SVD | singular value decomposition |
| RMSRE | root mean square relative error |
| MSRE | mean squared relative error |

## Data Availability Statement

The data that support the findings of this work are openly available at "https://kavita-ganesan.com/user-review-datasets/#.YCOpIWgzY2y".

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