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Providing a Recommendation System for Recommending Articles to users using Data Mining Methods

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Abstract

Due to the growing number of articles and books available on the web, it seems necessary to have a system that can extract users' articles and books from the vast amount of information that is increasing day by day. One of the best ways to do this is to use referral systems. In this research, a method is provided to improve the recommender systems in the field of article recommendation to the user. In this research, DBSCAN clustering algorithm is used for data clustering. Then we will optimize our data using the firefly algorithm, then the genetic algorithm is used to predict the data, and finally the recommender system based on participatory filtering provides a list of different articles that can be of interest to the user. Be him. The results of the evaluation of the proposed method indicate that this recommending system has a score of 94% in the accuracy of the system. And in the call section, it obtained a score of 91%, which according to the obtained statistics, it can be said that this system can correctly suggest up to 90% of the user's favorite articles to the user.

Keywords: Recommender system, DBSCAN algorithm, firefly algorithm, genetic algorithm

1. Introduction

Recommender systems are systems that, by taking limited information from the user and features such as what information the former user has searched for and what privileges he has given to the goods, can provide appropriate suggestions to the user that may be of interest to him. Recommending systems today offer attractive items to the user in many different applications. One of the most important applications of recommendation systems in the field of web, digital libraries, restaurant industry, tourism industry, film recommendation and other environments where there is a large amount of information, can provide appropriate suggestions to the user. One of the most important and popular systems that users have been interested in from the beginning until now, the recommendation system has been related to systems that offer articles and books. Due to the large number of articles on the web, which is increasing day by day, the existence of a system that can extract users' favorite articles and can suggest to the user seems necessary. Recommending systems allow articles to be suggested to the user by features such as article title, article type, or other features related to an article. The most important type of recommendation system for recommending articles to the user is the recommendation system based on participatory filtering. Provides a list of recommendations for the group's favorite items and the removal of items previously purchased by the user. This group of systems is called participatory refinement systems, which are among the most widely used systems for generating recommendations to users. The main mechanism of the participatory refinement algorithm

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is that using the similarity criterion of individuals, the preferences of large groups of users are recorded. Next, users who have the same priorities as the current user are selected as their neighbors, then the average of the priorities is calculated and the final priority function tries to recommend an item that the user has not scored. In this research, a method is provided to improve the recommending systems in the field of offering articles to the user. The method is that after collecting the articles that have already been searched by different users and given ratings to these articles, as well as information about users and their tastes, then we process this information in advance, then we cluster our data, then to produce Prediction We will use the genetic algorithm and in the last step, using a recommendation system based on participatory filtering, a list of recommendations that can be of interest to the user will be provided to the user.

2.Related Work

Gundogan & Kaya [1] presented a method for a recommender system to suggest articles to users in their article. These researchers proposed a hybrid article recommendation system based on deep learning. This method uses a combination of document similarity, hierarchical clustering and keyword extraction. The purpose of this research was to group articles in different fields such as computer science, economics, and medicine or in a specific field according to their subject and according to the entered request, provide the user with articles with high semantic similarity. This study is applied to a real dataset containing articles from different categories such as machine learning, artificial intelligence, human-computer interaction in computer science. The results of this research indicate the performance of 80% of this proposed method in recommending articles to users.

Vara & et al [2] proposed a method to improve the quality of article recommendations using K-means clustering algorithm. This study examines the feasibility of the k-means clustering algorithm in order to improve the effectiveness of the results recommended by the RICEST journal search engine. More than 15,000 articles published in the files of engineering journals during 2013-2017 were collected from their websites. Their titles, abstracts and keywords were extracted, normalized and processed to form the body of the test. According to the number of collected articles, using Cochran's formula, 400 articles completely related to the topic of each journal were randomly and proportionately selected and entered into the system as a questionnaire to receive the system's recommended journals before and after k-means clustering. Finally, the effectiveness of the system results at each stage was determined by the leave-one-out cross-validation method based on the accuracy of the high ranking K results. Also, the opinions of the referees about the relevance of the target journal were checked through a questionnaire. The results showed that before data clustering, only 40% of target journals were recommended in the first 3 ranks. But after the k-means clustering algorithm, in more than 80% of the searches, the target journal was retrieved in the first 3 ranks. Also, the effectiveness of the recommendations, according to the opinion of 210 subject reviewers, after the k-means clustering algorithm showed that more than 80% of recommended journals are completely related to the article in question. According to the results of the study, data clustering can significantly increase the effectiveness of recommended results by journal recommender systems.

Rosli and Ishak [3] presented a method to recommend articles and books using a recommender system. A recommender system is a program that analyzes data and makes recommendations for things a user might be interested in. For example, a book and article recommender system uses user information to recommend relevant books. However, many systems do not include recommendations based on the interests and backgrounds of other readers. Therefore, this study proposes a recommender system model for book and article recommendations that incorporates the background and interests of other readers. This data was combined with reader information to generate a list of articles and books that would be of interest to the reader. In addition, the system has a comment section that allows users to provide information about articles and books, whether they like it or hate it. System development is divided into two parts: user interest survey and prototype development. The purpose of this survey was to collect information about the backgrounds and interests of book readers. This data serves as the initial data for the recommender system. The waterfall model has been used in the construction of the recommender system. The proposed recommender system is critical to helping readers find and select articles and books that are relevant to their interests. This saves the reader considerable time when browsing the book collection. Comments from past readers provide a general summary of the book. This helps the reader to decide whether or not to continue reading. The system was tested on a group of readers who served as respondents for this study. The findings show that more than 80% of the respondents were generally satisfied (agree and strongly agree) with the interface design and system content.

Renuka et al [4] presented a method to recommend articles to users using TF-IDF technique. This paper discusses two approaches based on content-based recommender systems. These two approaches include retrieving similar articles using cosine similarity and clustering, then the results of the respective approaches are compared. The textual data that this paper deals with includes 230 web articles related to various fields of machine learning and data science, such as natural language processing, reinforcement learning, and deep learning. The data preprocessing steps involved in the method are stop word removal and word vectoring using TF-IDF. Using cosine similarity, K-means, and cumulative clustering methods to retrieve articles of interest and relevance to the user, based on the articles read by the user. The results of the evaluation of this method show that the system has demonstrated better performance compared to other similar articles.

Sharma & et al [5] propose a hybrid system-based book recommendation system that predicts recommendations. The proposed system is a combination of collaborative filtering and content-based filtering, which can be explained in three steps: In the first step, it identifies users who are similar to the active user by matching users' profiles. In the second step, it selects the candidate item for each similar user by obtaining the vectors VC and Vm related to the user profile and item contents. After calculating the prediction value for each item using the Resnick prediction equation, the items are suggested to the target user in the final phase. In the evaluation of the proposed system, which was compared with advanced proposed models, such as collaborative filter and content-based filter, it was shown that the proposed method shows an acceptable performance. In the experimental part, it is also shown that the proposed hybrid filter approach performs better than the joint filter and the content-based filter.

3. Proposed Method

In the proposed method, a new method is presented to improve the recommending systems in the field of offering articles to users. In this method, after collecting information about users as well as articles previously searched by users, we must perform data preprocessing operations on our data. We perform data preprocessing operations because our data is raw data and this data cannot be injected raw into data mining algorithms. After data preprocessing, in order to be able to extract similar users as well as more articles used by users, we need to cluster our data and thus obtain the weight of the obtained pages for the user's interest in these items .Each user has a list of items that are explicitly or implicitly ranked. This produces a user-item matrix called ‘R’, a matrix that represents the user preferences for items. To find unknown rankings, various methods are used, such as finding the "nearest neighbor" so that items offered to new users are based on rankings provided by their nearest neighbors after the clustering operation, we have to optimize our data for a better output using the firefly algorithm. Then, in order to produce an accurate prediction, we evaluate our data using a genetic algorithm. Then, in the last step, using a recommendatory system based on participatory filtering, we provide the user with information that this information can be used. In the figure below, you can see an overview of the proposed method.

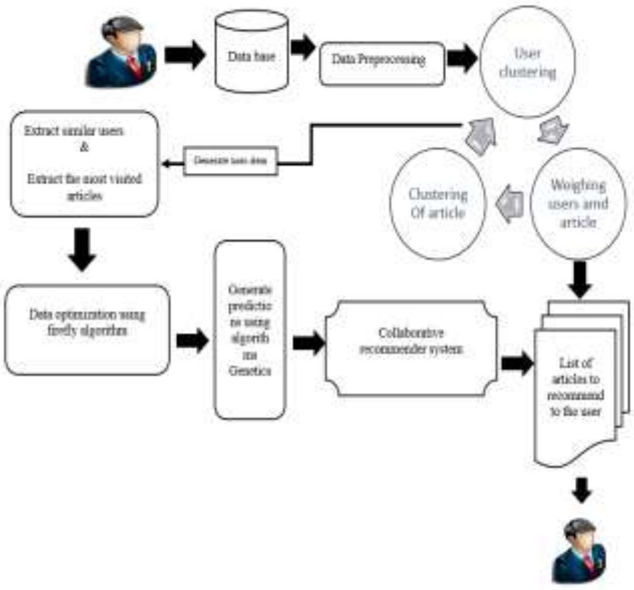

Fig. 1. An overview of the proposed method

3.1.Data Preprocessing

In the first step of the proposed method, we must first perform the data preprocessing operation, because it is usually not possible to extract the data in raw form into data algorithms. In order to prepare the data, it is necessary to take them out of their original form and state and transform them into a form that is suitable for the algorithm. If different data are pre-processed, the same reliable and effective performance will occur in all datasets [6, 7, 8]. Also, the available data usually have different extras that may confuse the algorithm. In data mining we also need to remove extra data that does not help the problem and the algorithm. Data preprocessing operations are usually performed before the main operation of data mining algorithms and facilitate and assist the algorithms. Data processing is an important step towards successful data mining.

3.2.Clustering Users and Articles

Next we need to cluster our data. The preferred method for data clustering is the use of the DBSCAN clustering algorithm. The way this algorithm works is that DBSCAN starts with a desired starting point that has not been visited. The range of this point is extracted using the epsilon distance (all points in the distance ε are group points or neighbors). It should be noted that the algorithm uses the Euclidean distance to find a neighbor in a two-dimensional and three-dimensional space, thus the neighborhood is defined by the least distance from the main point. If there are enough $minpoints$ in this range, the clustering process starts (border point) and the current data point becomes the first point of the cluster in the new cluster, otherwise the point is considered as noise (later this the noise point may be part of the cluster). In both cases this point is specified as visited. For this point in the new cluster, the points in the ε-distance range are also part of a cluster. This method is used to construct all points in the ε group belonging to the same cluster and then it is repeated for all new points that are only added to the cluster group. This process is repeated until all points in the clusters are entered, if all points in the range of ε clusters are visited and tagged [9, 10].

3.3.Exreact Similar Users

Once a new user of a cluster or class has been identified, its neighbors, which include users in that cluster, are extracted. The comments of these neighbors are effective in the final offer of the film to the new user; But not all neighbors are alike similar to the new user, and a similarity criterion should be used for closer neighbors. Suppose system users are set U=$\{u_1, u_2, u_3, \dots, u_m\}$ with features D=$\{d_1, d_2, d_3, \dots, d_n\}$ and collection articles I=$\{i_1, i_2, i_3, \dots, i_k\}$ is defined. Then the similarity of a new user and each of the neighbors is calculated based on the following equation [11].

$$\boldsymbol{d(x,y)} = \sqrt{\sum_{\boldsymbol{i=1}}^{\boldsymbol{m}} (\boldsymbol{xi} - \boldsymbol{yi})^{\boldsymbol{2}}} \qquad (1)$$

To do this, consider C as all users and S as all items (articles) that can be suggested to the user. The u utility function expresses the utility of the s item for c users. The total set of orders is denoted by R, which we define as C × R → R. Then, for each c ∈ C user, we define a clause such as s ∈ S that maximizes the user's usefulness as a contract according to the following relation.

$$\forall_{c} \in \boldsymbol{C}\,, \quad \boldsymbol{S_c} = \mathbf{arg\,max}\, \boldsymbol{u}\,(\boldsymbol{C}, \boldsymbol{S}) \tag{2}$$

In the recommender system we have to create a matrix of users and items. In this method, each user votes for an item, that point is stored in the desired cell in the matrix. Once a user's vote is determined, it can be used to determine a bid for similar users. Obviously, this matrix will be thin and solitary. A recommender system should predict these dispersions and suggest them to the user if the prediction score is high. The most widely used criteria for evaluating the system are the use of MSE and MAE criteria. Items that two users voted for (user to user) or all user ratings from two items (item to item) are compared [12, 13, 14].

$$\mathbf{MSE} = \frac{\mathbf{1}}{\mathbf{n}} \sum_{\mathbf{i=1}}^{\mathbf{n}} (\mathbf{Y_i} - \mathbf{Y_i})^{\mathbf{2}} \tag{3}$$

$$\mathbf{MAE} = \frac{\sum(\mathbf{u.i}) \in \mathbf{Rtest}\ \left|\mathbf{R_{u.i}} - \mathbf{R_{u.i}}\right|}{\left|\mathbf{Rtest}\right|} \tag{4}$$

3.4.How to Score

This section deals with the concept of points and the point’s matrix. Since user feedback plays a key role in the participatory filtering technique, it is necessary to design methods and templates to collect it. In the literature of recommending systems, different methods have been introduced to collect user feedback, but the common method used by most refining-based recommending systems is to consider a numerical interval (for example, 1 to 5) for each item, defining the meaning of each. These numbers (for example, 1: very bad, 2: bad, 3: average, 4: good, 5: very good) and ask the user to map one of these numbers to each of the items he sees. These numbers are called scoring systems in the literature and this method is called scoring. CF techniques use a database of preferences for items by users to estimate additional topics or create new users.

In a typical CF scenario, there is a list of m users {u1, u2, u3...um} as well as a list of n items {i1, i2, i3 ... in} and each Ui user has a list of items Has lui that the user has rated or those whose preferences have been inferred through their behavior. The rank can be explicit references and ... which is on a scale of 1 to 5 or it can also be an implicit reference.

3.5.The Nearest Neighbor – Based Algorithm

These types of algorithms use the scores given by a similar user to predict a user's interest in a particular item. These similar users are called user neighbors. If n is the same as user u, n is said to be a neighbor of u. To predict user u interest in item i, the average score given by u neighbors (including user n) to i should be calculated equal to (1.2). In this equation, rni is the score that user n gave to item i. We see how to calculate this algorithm in the following relation.

$$\boldsymbol{pred}(\boldsymbol{u.i}) = \frac{\sum \mathbf{ncneighbors(u)r\ ni}}{\mathbf{number\ of\ neighbors}} \tag{5}$$

The prediction of the score that user u will give to item i is obtained by calculating the weighted sum of user points u on similar items i.

$$\mathbf{Pred(u,i)} = \frac{\sum_{\mathbf{j \in rateditems(u)}} \mathbf{itemsim(i,j).\,rui}}{\sum_{\mathbf{j \in rateditems(u)}} \mathbf{itemsim(i,j)}} \tag{6}$$

3.6.Data Optimization using Firefly Algorthm

At this stage we have to optimize our data using the firefly algorithm. The idea of the firefly algorithm is inspired by the optical connection between fireflies [15]. This algorithm can be considered as one of the manifestations of congestion intelligence, in which the cooperation and possibly competition of simple and low-intelligence members creates a higher level of intelligence that can certainly not be achieved by any of the components. This algorithm is a collective intelligence algorithm. Each person (called a firefly in this algorithm) in the population represents a potential solution in a multidimensional space. Due to the power of absorption between fireflies, they move to other places to find better solutions [16, 17]. In the firefly algorithm, the degree of absorption is determined based on the radiant power of the light and the brightness of that person [18]. This amount is basically proportional to a person's level of competence. Consider finding a maximum. For firefly x, the relationship between the suitability and the amount of light and brightness of that cream can be expressed as I (x) ∝f (x). The degree of adsorption indicated by β will be proportional to r. As this distance increases, the rate of adsorption will gradually decrease [19]. Consider that Xi represents the i-th person in the population, in which case the degree of attractiveness of the i-th person by the j-th person will be expressed using the following relation [20].

$$\boldsymbol{\beta(r_{i,j}) = \beta_0 e^{-r^{r_{ij}^2}} \; where \; r_{ij} = \|X_i - X_j\|} \tag{7}$$

For each Xi firefly, compared to the Xi worm, if Xi is brighter than Xi, it will move toward Xi based on how absorbent Xj is. The amount of this motion is obtained based on the following equation.

$$\boldsymbol{x_{id}(t+1) = x_{id}(t) + \beta_0 e^{-r^{r_{ij}^2}} \left(x_{jd}(t) - x_{id}(t)\right) + a\varepsilon_i} \tag{8}$$

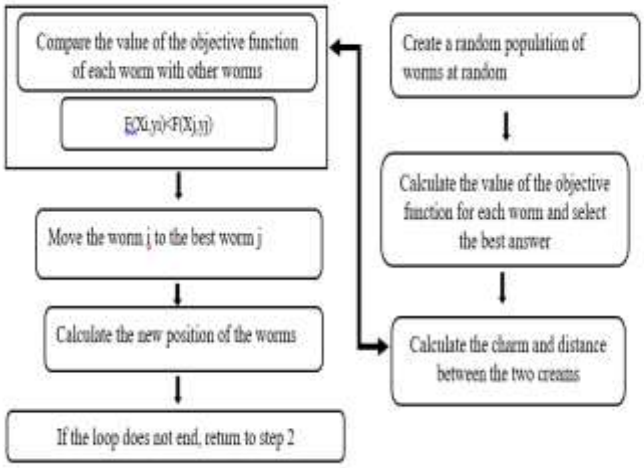

Fig. 2**.** Firefly algorithm framework

At the end of this step and after using the firefly algorithm, we will see the optimization of the recommendations in the proposed method. The results of optimization can be seen in the evaluation section of the proposed method and compared with other existing methods.

3.7.Generate Prediction using Genetic Algorithms

We use genetic algorithms to generate predictions. In order to be able to solve a problem with a genetic algorithm, we have to convert them to the special form required by this algorithm. In this process, we must define the required solution to the problem in such a way that it is represented by a chromosome. The method of work is that first the most suitable member of each community is selected. Then the element with the most fitting number is selected. As the average fit of society increases, so does the weight of choice. This method is useful when the set contains elements that have a large number of fit and only small differences distinguish them. A subset of the attributes is selected and the members of that set compete with each other, eventually the selected attributes will be used to generate a prediction.

In genetic algorithms, "probability" mechanisms are used for "transition" from one state in the problem space to another state. While in conventional search algorithms, information related to the target is used for such work. Such an important feature of genetic algorithms, they become "general purpose" (general purpose) search algorithms. Also, genetic algorithms are used to search irregular search spaces. In general, genetic algorithms are used to solve problems in applications such as function optimization, parameter estimation, and machine learning.

Since the search operation starts from a set of answers (initial answers are randomly scattered in the answer space) in the solution space of the problem, a powerful and unbiased search will be guaranteed in the genetic algorithm. In the next step, all the initial solutions generated are evaluated to determine the value of the objective function of each of them. At this stage, an "Exterior Penalty Function" is usually used to transform the "Constrained Optimization Problem" into an "Unconstrained" optimization problem. Such transformation will be different depending on different optimization problems (problems whose optimal solutions are supposed to be generated). In the third step, the objective function of the problem is mapped to a fitness function. Through the fitness function, the "fitness value" of each member of the initial population is determined. After determining the fitness value of the candidate answers, genetic algorithm operators are used to make changes on the candidate answers.

3.8.Collaborative Refinement Recommender System

In the last step, we will store the data obtained from the previous steps in a recommender system based on participatory filtering and provide it to the user for recommendation. This type of recommender system starts with finding users who have preferences and purchase history of subscriptions with the current user, then collects information about the group's favorite items and deletes those items previously purchased by the user. Provides recommendations. This group of systems is called participatory refinement-based systems, which are among the most widely used systems in order to generate recommendations to users. The main mechanism of the participatory refinement algorithm is that using the similarity criterion of individuals, the preferences of large groups of users are recorded. Next, users who have the same priorities as the current user are selected as their neighbors, then the average of the priorities is calculated and the final priority function tries to recommend an item that the user has not scored.

4. Evaluation the Proposed Method

We use MSE and MAE criteria to evaluate the user-item matrix. You can see the results obtained from these two criteria in the following tables. According to the chart below and the evaluation of the mean square error, we see a reduction in error in the proposed method. The closer the MSE criterion is to zero, the lower the error rate. According to the evaluations of the proposed method, the proposed method can have about 1% less error. Also, in the absolute mean value of point error and evaluations made in this section, MSE has less error than other available methods.

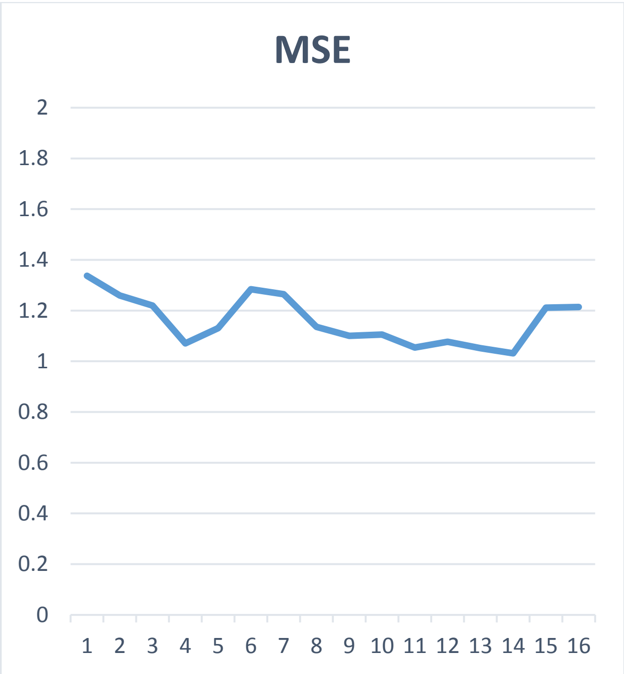

Fig. 3.MSE value of the proposed method

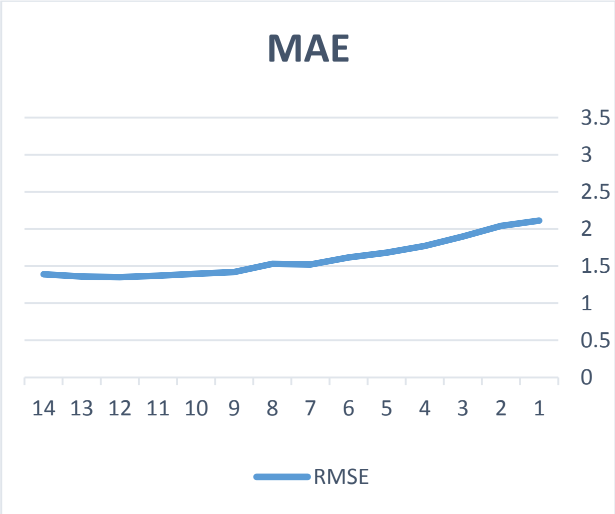

Fig. 4.MAE value of the proposed method

It is often used to validate recommender systems such as system accuracy and item recall. In this research, these criteria have been used to evaluate the system. Accuracy and recall in recommender systems are calculated using the following two equations.
Accuracy is calculated using the following equation.

$$\textbf{Precision} = \frac{|\{\textbf{relevant item}\cap\{\textbf{retrved item}\}|}{|\{\textbf{retrived item}\}|} \qquad (9)$$

The call is calculated using the following equation.

$$\textbf{Recall} = \frac{|\{\textbf{relevant item}\cap\{\textbf{retrved item}\}|}{|\{\textbf{relevant item}\}|} \qquad (10)$$

To evaluate the accuracy and convenience of the system, a comparison was made between the proposed method and the algorithms of gray wolf, ant colony and PSO, The proposed method could have a better performance than other existing methods, and in the system call part, it was able to obtain a 91% call score and could have better optimization than other optimization methods. Also, in terms of accuracy, a comparison was made between the proposed and proposed methods and the algorithms of gray wolf, ant colony and PSO, The proposed method could have a better performance than other existing methods, and in the system calling part, it was able to obtain a 94% calling point. And according to this comparison, it can be said that the proposed method works better than other available methods and can offer more than 90% better recommendations to the user.

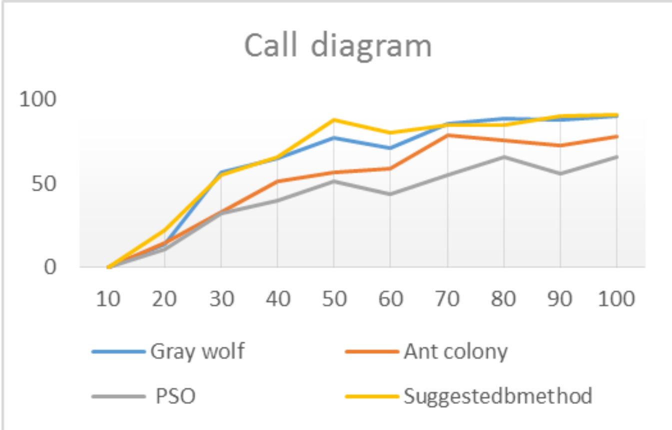

Fig.5. Comparison diagram of the proposed method with other methods

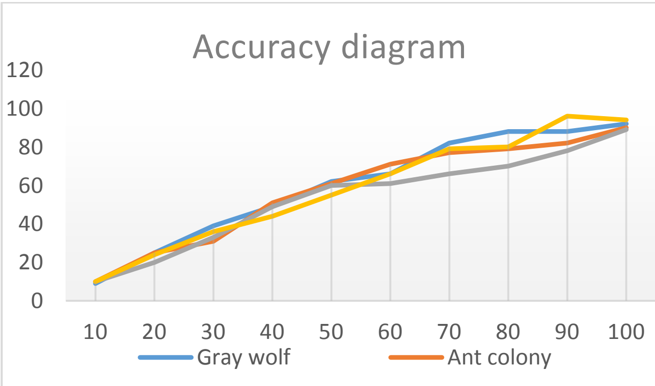

Fig.6. Diagram comparing the accuracy of the proposed method with other methods

5. Conclusion

In this research, a new method was presented to users in order to improve the recommending systems in the field of articles. Due to the growing content and articles on the web, the existence of a system that can extract users' favorite articles on the web and suggest to the user, is necessary. To do this we need to personalize our systems. One of the best ways to do this is to use referral systems. Recommender systems are systems that can provide the user with a list of items that may be of interest to the user by obtaining limited information from the user and features such as items searched by a past user. In this research, using a recommender system based on participatory filtering and data mining methods, we tried to design a system that can solve the problems of previous systems and provide appropriate suggestions to the user. In this system, after collecting the database of articles related to the user's favorite, first the data preprocessing operation was performed on the desired database. We then clustered our data to evaluate the interest and similarity of the items using the DBSCAN clustering algorithm. The results of evaluating the efficiency of the DBSCAN algorithm showed that this clustering method was more efficient than other existing methods. Then we optimized the obtained data by firefly metamorphosis algorithm and finally we used genetic algorithm to generate predictions. The results of the evaluation of the proposed method indicate that this recommending system has a score of 94% in the accuracy of the system. And in the call section, it obtained a score of 91%, which according to the obtained statistics, it can be said that this system can correctly suggest up to 90% of the user's favorite articles to the user.

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