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Provide a Recommender System for Predicting Users Favorite Music Using Gray Wolf Algorithm and Neural Networks

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Abstract

Recommender systems are systems that can recommend a good offer to users by taking limited information from users and features such as user searches in the past as well as data points. In this research, a new method is presented to suggest the favorite music of users. The proposed method of using the neural network and recommender system based on participatory filtering and using the points given by users to the products is discussed. We then optimize our data with the Gray Wolf algorithm. The results of the research show 95% accuracy of correct recommendations to users and it can be said that the proposed method of this research can greatly improve the problems of other previous methods and have good recommendations for users.

Keywords: Music recommender system; Gray wolf algorithm; Neural network; Data mining

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Introduction

Due to the growing volume of music on the Internet, and the lack of proper management on this vast volume, similarity and music recommendation systems are designed, which is the basis of the recommendation system, can automatically list the user's playlist according to similar features. There are different types of genres in music and each person is interested in a particular group and type of music. The recommender system is an important feature in an application, especially with so many choices for a particular case. With a good recommender system, users can help with suggestions and can improve the app user experience. It is best to do this using the participatory filtering (CF) method by recommending products related to personal preferences history. With the advent of big data, the performance of traditional recommendation algorithms is no longer enough to meet the demand. Most people do not leave too many comments and other data when using the application. In this case, the user data are too scattered and discrete, with obvious data sparsely problems. First, this paper describes the main ideas and methods used in current recommendation systems and summarizes the areas that need attention and consideration. Based on these algorithms and based on the user history data information and music data information that can be found now, the paper aims to build a personalized music recommendation system based on directed tags, which can provide basic music services to users and push them personalized music recommendation lists. Then, the collaborative filtering algorithm based on tags is introduced. Usually this method uses discrete tags, and the user tags and music tags are juxtaposed and leveled with each other, which does not reflect the importance and ranking order relationship of each tag and does not reflect the cognitive sequence of users when they listen to and annotate music. In order to improve this problem and increase the accuracy of recommendations, the user-tag and music-tag data are correlated through the tag sequence of tag and music-tag data are correlated and modeled analytically, and feature directed graphs are constructed. In music recommending systems, auto-resume playlist is an emerging task that aims to improve the listening experience of users by recommending music tailored to their music tastes. A common method of this method is to identify playlist features by inspecting songs in playlists [1]. Digital content has become one of the important needs that is presented in the form of attractive information in different ways. In general, digital music content providers use user behavior data when exploring the digital world over the Internet. Currently, millions of song catalogs are distributed on the Internet and users can easily access them. On average, each digitally based song content takes about 3 minutes, so it can be concluded that 1 million digital ones are completed in this time [2]. Increasing the amount of digital music content each month leads to a lot of unstructured data in the playlist and makes it difficult for users to choose the songs they want to listen to. To facilitate music catalog optimization, a music recommender-based system is needed that allows users to manage digital music content catalogs according to their needs. One of the recommended methods is participatory filtering. The proposed participatory screening techniques have lost their functionality mainly due to the increase in the number of web pages and the vast amount of information available. In this research, a new method is presented to recommend the favorite music to users. The proposed method is to use a neural network and then use a recommendatory system based on participatory filtering to suggest to users and the data optimization table using the Gray Wolf meta-algorithm. From the comparison, it was found that participatory filtering and neural network have better results than shared filtering. This process can increase the amount of people interacting with an application, especially digital online music, because appropriate recommendations can improve the user experience of an application **(Figure 1)**.

Related work

In her article in 2021, Wen provided a way to suggest users' favorite music. The researcher proposed an intelligent background music system based on deep learning and Internet of Things (IoT) technology. Accordingly, a feature extraction algorithm based on the mid-level feature structure was proposed that extracts the basic features of the scene images. Then, the vital functional components of the intelligent background music system are explained. Based on real operations, an intelligent background music system is designed based on deep learning and the Internet of Things. The results show that the detection rate of internal scenarios by the feature-based construction feature extraction algorithm is higher than the average level, which is about 87.6%. The proposed algorithm classifies and identifies the feature of the scenarios and its detection rate is always around 20% [3].

In their 2021 paper, Girsang and Wibowa presented a way to improve the music recommendation system. The researchers used data from 20,000 users, 6,000 songs and 470,000 ranked transactions to create a music recommending system. The researchers compared the two techniques of participatory filtering and the NCF method for scoring and recommending to the user. The results of this study indicate the superiority of the NCF method over collaborative filtering and provide a more accurate list of users' favorite music [4].

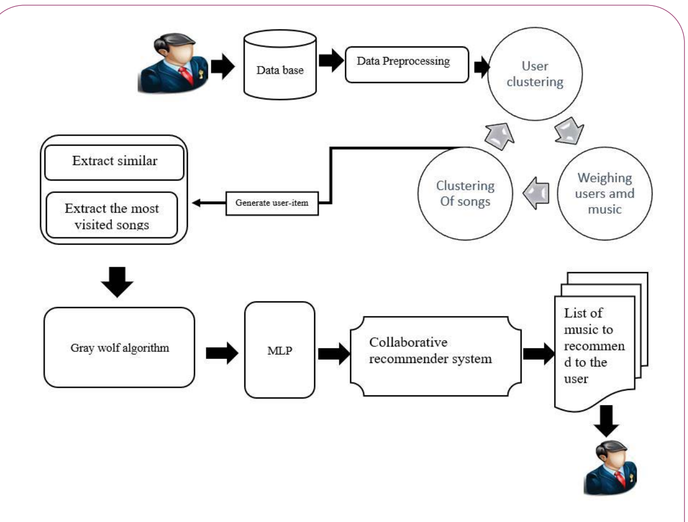

Figure 1 An overview of the proposed method.

In their article in 2021, Fathollahi and Razzazi presented a new method for an effective recommender system. The researchers classified the different genres of music using convolutional neural networks to extract high-level features from neural network layers and used the Euclidean method to calculate the similarity between the data. The results of the research of these researchers indicate a 10% improvement in the results of this method compared to other existing methods [5].

In their 2021 paper, Jazi et al. presented a music recommending system using emotion-aware music. In their research, these researchers presented two motivations for expanding the existing system. First, according to their knowledge, current systems first estimate the user's emotions and then suggest music based on it. Second, according to existing studies, the pattern of users' interactions with input devices can reflect their emotions. Based on these two methods, a music recommendation system was proposed that offers music based on users' mouse click and click patterns. Unlike previous systems, the proposed system draws these patterns directly on the user's favorite music without tagging its current emotions. The results of this study show that even if the system does not use any additional devices, it can be more accurate than other available methods [6].

In their 2021 paper, Kim et al. presented a way to recommend music to the user using emotion. These researchers from used a support vector machine (SVM) algorithm and selected an optimal kernel function for recognizing the six target emotions. Performance evaluation results for each kernel function revealed that the radial basis function (RBF) kernel function yielded the highest emotion recognition accuracy of 86.98%. Additionally, content data (images and music) were classified based on emotion information using factor analysis, correspondence analysis, and Euclidean distance. Finally, speech information that was classified based on emotions and emotion information that was recognized through a collaborative filtering technique were used to predict user emotional preferences and recommend content that matched user emotions in a mobile application [7].

Recommender system

Recommender systems have become very important in recent years. The goal of any offering system is for consumers to be able to find new goods or services, such as the web, books, music, restaurants, or even people, based on information about the consumer or the recommended item [8]. The recommender system is a system that, according to the user's preferences, recommends items jointly to a group of users [9]. Recommending systems are systems that help to find the user's interests in situations of over-information. Where the user's preferences are estimated based on the behavior observed in the past and can provide the user with a ranked list of suggestions [10].

Collaborative recommendation system

Collaborative technique analyzes a large amount of data collected from user responses to an item as rating and then recommends items to user. Here, analyzing item content is not compulsory and information is shared between two users so the base of method depends on relationship between user and items and also on the rating feedback matrix where each element representing a specific rating on a specific item.

Mi music recommender system

Music recommender systems allow a user to identify songs of his interest from a plethora of artists and albums. A recent development of music recommender systems is emotion- or mood-based recommender systems that can suggest songs relative to the user's current mood [11].

Neural network

Artificial Neural Networks (ANNs), or more simply neural networks, are new systems and computational methods for machine learning, knowledge display, and finally the application of knowledge gained to maximize the output responses of complex systems. The main idea of such networks is (to some extent) inspired by the way the biological neural system works, to process data, and information in order to learn and create knowledge. The key element of this idea is to create new structures for the information processing system. The system is made up of a large number of highly interconnected processing elements called neurons that work together to solve a problem and transmit information through synapses (electromagnetic communications). In these networks, if one cell is damaged, other cells can make up for its absence and contribute to its regeneration. These networks are capable of learning. Neural network is a method of calculation that is based on the interconnectedness of several processing units. These types of networks consist of an arbitrary number of cells or nodes or units or neurons that connect the input set to the output [12-14].

Methodology

Proposed methodology

In this research, a new method is proposed to suggest users' favorite music using neural network and participatory filtering and then data optimization using gray wolf algorithm. In this paper, we design a desirable music genre classification using neural networks to extract high-level features from intermediate network layers. To measure similarity, we considered the cosine similarity and the Euclidean distance between the feature vectors. We applied this automated recommendation system to three databases of different genres and showed that the recommender would gain considerable accuracy in identifying his favorite music using this method.

Data set: The taste profile subset used in the million-song dataset challenge has over 47 million triplets (user, song, count) describing the listening history of over 1 million users and 380.00 songs. We select 20,000 songs with top listening count and 100,000 users who have listened to the most songs. Since this collection of listening history is a form of implicit feedback data, we use the approach proposed in to perform negative sampling.

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 [15]. 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 [16].

Data clustering: In this step we have to cluster the data obtained from the previous steps. Clustering or cluster analysis is the process of grouping physical or virtual objects into classes of similar objects. The desired clustering method is using DBSCAN 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 or neighboring points). 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 original point. If there are enough min points in this range, the clustering process starts (found) 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 noise point may become part of the cluster). In both cases this point is marked as visited. For this first point in the new cluster, the points in the ε 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, i.e. all points in the ε range of the clusters are visited and tagged. In order to understand the DBSCAN algorithm, it is necessary to first introduce some of the definitions used in this algorithm:

DBSCAN algorithm needs to specify 2 parameters Minpts and Eps. These two parameters are used to determine the minimum density of a cluster.

Definition 1: Neighbors of the radius Eps of a point: Neighbors in the radius of Eps A point such as p denoted by NEPs (p) are a set of points whose distance from p is less than the radius of Eps:

$$NEP(P)=\left\{q\in\frac{D}{Dist(p,q)}\leq EPs\right\} \quad (1)$$

Definition 2: A central object is an object that has at least the number of Minpts of an object in the neighborhood of its Eps radius [17-20].

Data weighting: A simple approach capable of combining acoustic features and user access patterns for similarity measurement is to compute the similarity based on each representation and then combine the two similarity measurements linearly. By incorporating the user access patterns of music, the combined similarity measurement can more accurately reflect human perception of music than the one based only on acoustic features. A major drawback with such an approach is that user access patterns are usually sparse. Only for a relatively small number of pieces of music, their user access data are adequate to provide robust estimation of similarity with other pieces of music. This drawback will substantially limit the impact of the use of user access patterns. Also, since the approach uses the Murkowski distance for the audio-based similarity calculation, it does not provide a means for estimating the weights on acoustic features, the essential component sin making similarity measurement that is both genre-dependent and user-dependent.

We first present a simple matrix factorization model for collaborative filtering music recommendation. Then, we point out major limitations of this traditional CF algorithm and describe our proposed approach in detail. Suppose we have m users and n songs in the music recommender system. Let $R=\{r_{ij}\}_{m\times n}$ denote the user song rating matrix, where each element r_{ij} represents the rating of song j given by user i.

Matrix factorization characterizes and songs by vectors of latent factors. Every user is associated with a user feature vector $u_i \in R^f, i=1,2,\ldots,m$ and every song a song feature vector $V_j \in R^f, i=1,2\ldots,n$ for a given song j, v_j measures the extent to which the song contains the latent factors. For a given user I, u_j measures the extent to which he likes these latent factors. The user rating can thus be approximated the inner product of the two vectors.

$$r_{i,j}=u_i^T v_j \tag{2}$$

To learn the latent feature vectors, the system minimizes the following regularized squared error on the training.

$$\sum_{(i,j)\in I}\left(r_{ij}-u_i^T v_j\right)^2+\lambda\sum_{i=1}^{m}n_{u_i}\|ui\|^2+\sum_{j=r}^{n}n_{v_j}\|vj\|^2 \tag{3}$$

Where I is the index set of all known ratings, λ a regularization parameter, n_(u_i) the number of ratings of song j. We use the alternating last squares (ALS) technique to minimize Eq.

Extract 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 music to the new user; but not all neighbors are equally similar to the new user, and a similarity criterion should be used for closer neighbors. Assume system users as a set $U=\{u_1,u_2,u_3,\ldots,u_m\}$ with properties $D=\{d_1,d_2,d_3,\ldots,d_n\}$ and the set of movies should be defined as $I=\{i_1,i_2,i_3,\ldots,i_k\}$. Then the similarity of a new user and each of the neighbors is calculated based on the following equation.

$$d(x,y)=\sqrt{\sum_{i=1}^{m}(xi-yi)^2} \tag{4}$$

Data optimization using the gray wolf algorithm: Next, we need to optimize our data. The method to optimize the data is to use the gray wolf algorithm. The GWO Gray Wolf Algorithm is a metaheuristic algorithm inspired by the hierarchical hierarchical structure and social behavior of gray wolves while hunting. This algorithm is population-based, has a simple process, and can be easily generalized to large-scale problems. Gray wolves are considered apex predators, which are at the top of the food chain pyramid. Gray wolves prefer to live in a group, each group has an average of 5-12 members. All members of this group have a very precise hierarchy of social domination and have specific tasks. In each herd of wolves there are 4 degrees to hunt, which is modeled as a pyramidal structure as shown below [21,22] **(Figure 2)**.

Wolves are called alpha group wolves, which can be male or female. These wolves dominate the herd.

Beta wolves: Help alpha wolves in the decision-making process and are also prone to be chosen instead.

Delta Wolves: Lower than beta wolves and include older wolves, predators and baby care wolves.

Omega Wolves: The lowest rank in the hierarchy that has the least rights over the rest of the group. After all, they eat and do not participate in the decision-making process. Method of hunting gray wolves

In explaining and teaching the gray wolf algorithm, we can say that this algorithm consists of 3 main steps:

1. Observing hunting, tracking and tracking (tracking and approaching).

2. Approaching, encircling (hooping) around the prey and misleading it until it stops moving (Pursing and encircling).

3. Attacking hunting.

Optimization is done using alpha, beta and delta wolves. A wolf is assumed to be the main alpha of the algorithm, a wolf beta and a delta are involved, and the rest of the wolves follow them. Gray wolves have the ability to estimate the hunting position. To model this process, see the following steps: In the initial search, we have no idea about the hunting position. Alpha, beta, and delta wolves are thought to have better first-hand knowledge of hunting position (optimal answer point).

Description of Gray Wolf Optimizer (GWO): In GWO Gray Wolf Optimizer, we consider the most appropriate solution as alpha, and the second and third appropriate solutions are named beta and delta, respectively. The rest of the solutions are considered omega. In the GWO algorithm, hunting is driven by α β and δ. Solution ω follows these three wolves **(Figure 3)**.

When the hunt is surrounded by wolves and stops moving, the attack led by the wolf alpha begins. Modeling of this process is

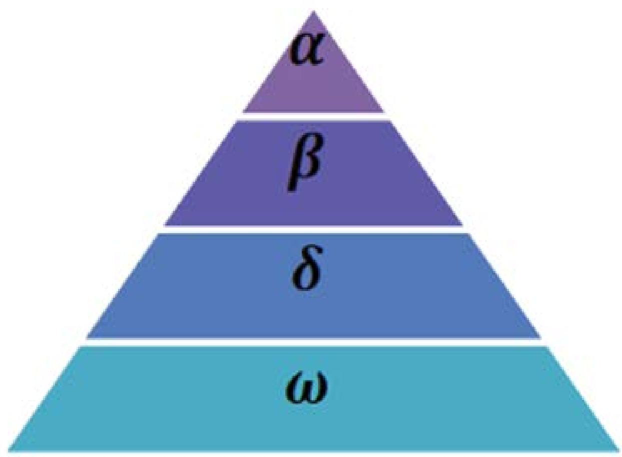

Figure 2 The pyramidal structure of the gray wolves.

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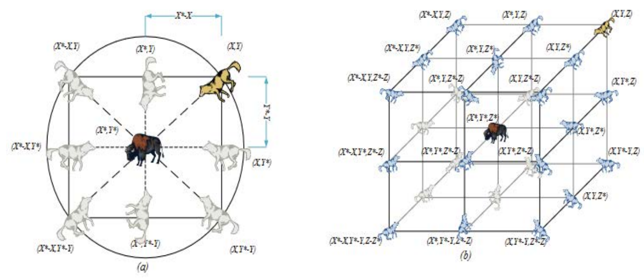

Figure 3 How and coordinates how wolves hunt in groups.

done using the reduction of the vector A. Since A is a random vector in the range[-2a,2a], as a decrease, the vector of coefficients A also decreases. If | A |<1 is, the alpha wolf will approach the prey (and the rest of the wolves) and if | A |>1 the wolf will be away from the prey (and the rest of the wolves). The gray wolf algorithm requires all wolves to update their position according to the position of alpha, beta, and delta wolves.

Siege of prey by gray wolves: During the hunt, gray wolves surround the prey. A Mathematical model of the siege behavior is presented in the following equations. In the relations below the current iteration t, A and C are coefficient vectors, Xp is the prey position vector, and X is the gray wolf position vector.

$$\vec{D} = |\vec{D}.\vec{X}_P(t)\vec{X}(t)| \quad (5)$$

$$\vec{X}(t+1) = \vec{X}_P(t) - \vec{A}.\vec{D} \quad (6)$$

Vectors A and C are calculated as follows:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \quad (7)$$

$$\vec{C} = 2.\vec{r}_2 \quad (8)$$

In the above relations, the variable a decrease linearly from 2 to 0 during the iterations, and r1, r2 are random vectors in the range [0, 1]. Hunting operations are usually led by Alpha. Beta and Delta's wolves may occasionally hunt. In the mathematical moel of gray wolf hunting behavior, we assumed that alpha, beta, and delta had better knowledge of the potential prey position. The first three solutions are best stored and the other agent is required to update their positions according to the position of the best search agents according to the following equations.

$$\vec{D}_{X} = |\vec{C}_1.\vec{X}_X - \vec{X}|, \vec{D}_\beta = |\vec{C}_2.\vec{X}_\beta - \vec{X}|, \vec{D}_\delta = |\vec{C}_3.\vec{X}_\delta - \vec{X}| \quad (9)$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.(\vec{D}_\alpha), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.(\vec{D}_\beta), \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.(\vec{D}_\delta) \quad (10)$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \quad (11)$$

Explain the search step: The search phase is exactly the opposite of the attack process: during the search, the wolves move away from each other to track the prey (| A |>1), while after tracking the prey, the wolves approach each other in the attack phase. Are (| A |<1). This process is called divergence in search - convergence in attack.

$$\text{Exploitation}: |A| > 1 \quad (12)$$

$$\text{Exploitation}: |A| < 1 \quad (13)$$

Vector C: Vector C is considered as an obstacle in nature that slows down wolves approaching prey. Vector C gives weight to the prey and makes it more inaccessible to wolves. Unlike a, this vector does not decrease linearly from 2 to zero.

Algorithm sequence:

• The suitability of all answers is calculated and the top three answers are selected as alpha, beta, delta until the end of the algorithm.

• In each iteration, the top three answers (alpha, beta, delta wolves) are able to estimate the hunting position and do this in each iteration using the following equation:

• In each iteration, after determining the position of alpha, beta, delta wolves, the position of the rest of the answers is updated by following them.

• In each iteration, vectors a (and consequently A) and C are updated.

• At the end of the repetitions, the position of the alpha wolf is introduced as the optimal point.

Gray wolf algorithm flowchart: According to the contents of the flowchart, the gray wolf algorithm can be considered as follows. This flowchart will only work by specifying the values of vectors A and C. Explaining this flowchart is very simple by studying the steps mentioned above **(Figure 4)**.

Use neural networks to predict data: In the next step, we have to deliver the data obtained from the previous steps for training and then suggest the data overnight. The neural network processes the input signals and converts them into the desired output signals. Typically, once a neural network has been designed and implemented, the parameters w and b for the sets of input signals must be adjusted to form the desired output network output signals. Such a process is called neural network training (in the first stage of training, the values w and b are randomly selected, because until these parameters have no value, the neural network will not be usable) while training the neural network (ie gradually increasing the number of time the parameters of the parameters are adjusted to achieve a more desirable output) the value of the parameters to their true and final be. We use the Back Propagation method to learn the weights of a multilayer

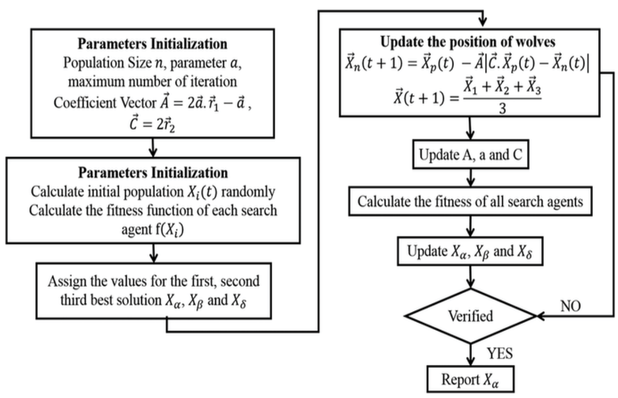

Figure 4 Gray wolf algorithm flowchart.

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network. In this method, using a gradient descent, we try to minimize the error square between the network outputs and the objective function. The error is defined as follows:

$$E\left(\overrightarrow{W}\right)=\frac{1}{2}\sum_{d\in D}\sum_{k\in outputs}\left(t_{kd}-o_{kd}\right)^2 \quad (14)$$

Outputs are the output of a set of output layer units, and t_kd and o_kd.

The hypothesis space sought in this method is the large space defined by all possible values for the weights. The gradient descent method tries to achieve a suitable hypothesis by minimizing the error. But there is no guarantee that this algorithm will reach the absolute minimum.

a. Create a network with n input nodes, hidden nodes, and n_out output nodes.

b. Number all weights with a small random value.

c. Follow the steps below to reach the final condition (error reduction):

For each x belong to the training examples:

a. Post example X forward on the network.

b. Spread the E error backwards on the network.

Evaluate the proposed method: To evaluate and compare our music recommendation systems, we used regression evaluation criteria: mean absolute error (MAE), mean absolute error percentage (MAPE), mean square error (MSE), and root mean square error (RMSE). Regression evaluation criteria are used because of the output of the proposed system, the predicted ranking. Therefore, it calculates the difference between the actual and the predicted amount of music rating. The formula of each evaluation criterion is shown as an equation **(Figures 5-7)**.

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.

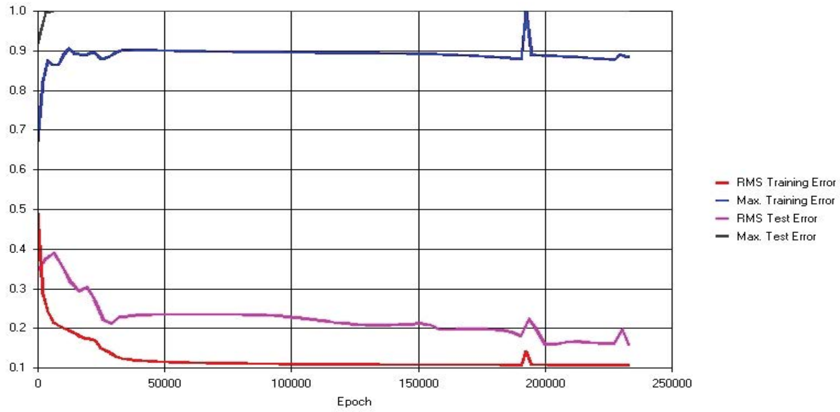

Figure 5 RMS curves and maximum learning and test error in three-layer perceptron.

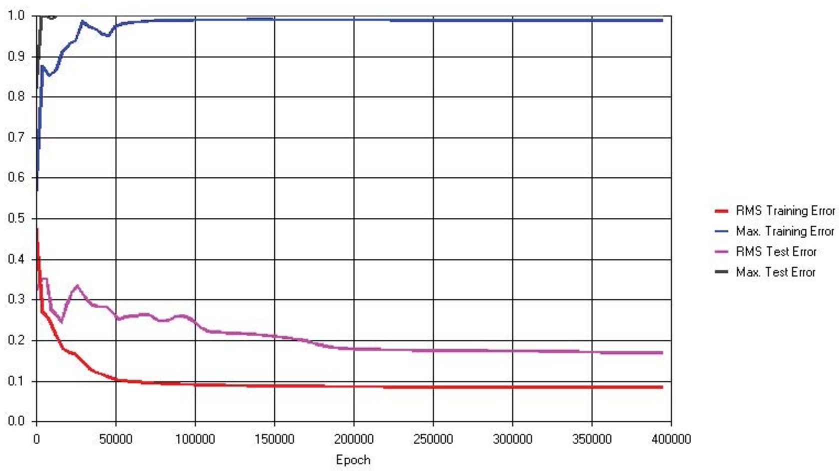

Figure 6 RMS curves and maximum learning and test error in selected four-layer perceptron.

$$precision = \frac{|\{relevantitem \cap retrveditem\}|}{|\{relevantitem\}|} \quad (15)$$

The call is calculated using the following equation.

$$Recall = \frac{|\{relevantitem \cap retrveditem\}|}{|\{relevantitem\}|} \quad (16)$$

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 results of this comparison can be seen in the following diagrams **(Figures 8-10)**.

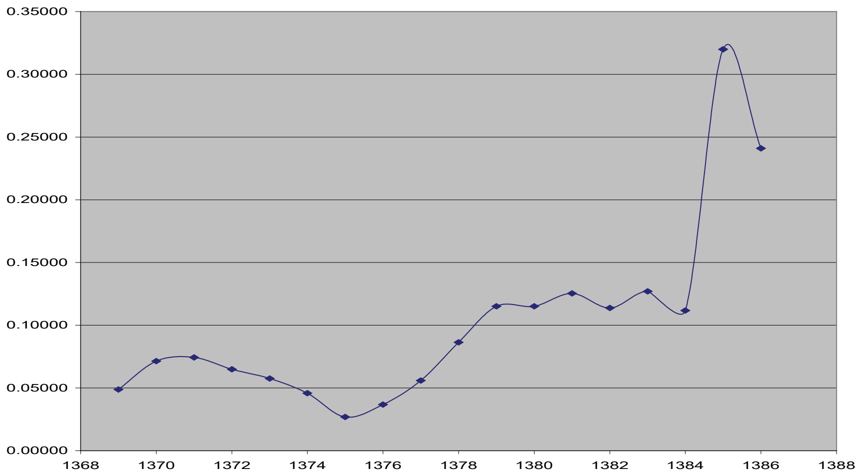

Figure 7 Diagram of system growth after the use of neural networks.

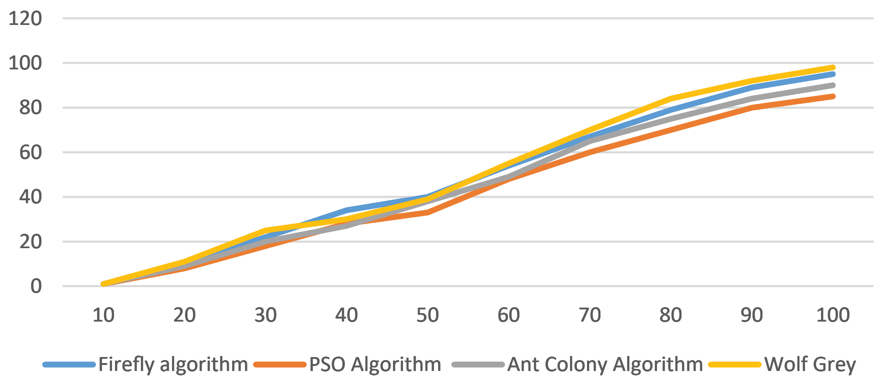

Figure 8 Comparison diagram of the proposed method with other methods.

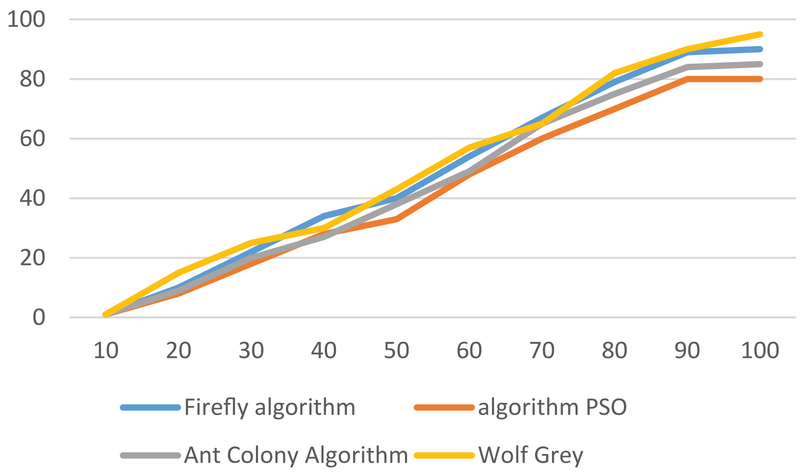

Figure 9 Diagram comparing the accuracy of the proposed method with other methods.

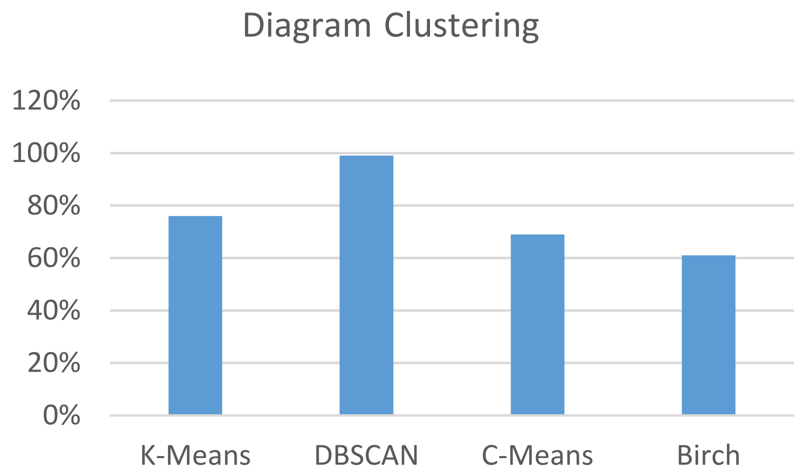

Figure 10 Performance diagram of DBSCAN and other clustering methods.

Results

In this research, a new method was presented to users in order to improve the recommending systems in the field of Music. Due to the growing Music on the web, the existence of a system that can extract users' favorite Music 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 Recommender 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.

Conclusion

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 Music 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 Gray wolf metamorphosis algorithm and finally we used neural network algorithm to generate predictions. The results of the evaluation of the proposed method showed the accuracy and recall of the proposed method compared to other available methods, and according to the obtained statistics, it can be said that the proposed method can offer up to 95% of the user's desired information.

References

1 Yürekli A, Bilge A, Kaleli C (2021) Exploring playlist titles for cold-start music recommendation: an effectiveness analysis. J Ambient Intell Humaniz Compu 3: 1-20.

2 Sang L, Xu M, Qian S, Wu X (2021) Knowledge graph enhanced neural collaborative recommendation. Expert Syst Appl 164: 113992.

3 Wen X (2021) Using deep learning approach and IoT architecture to build the intelligent music recommendation system. Soft Compu 25: 3087-3096.

4 Girsang, AS, Wibowo A (2021) Neural Collaborative for music recommendation system. IOP Conf Ser Mater Sci Eng 1071: 012021.

5 Fathollahi MS, Razzazi F (2021) Music similarity measurement and recommendation system using convolutional neural networks. Int J Multimed Inf Retr 10: 43-53.

6 Jazi SY, Kaedi M, Fatemi A (2021) An emotion-aware music recommender system: bridging the users interaction and music recommendation. Multimed Tools Appl 2: 1-16.

7 Kim TY, Ko H, Kim SH, Kim HD (2021) Modeling of recommendation system based on emotional information and collaborative filtering. Sen 21:19-21.

8 Beg S, Anjum A, Ahmad M, Hussain S, Ahmad G et al. (2021) A privacy-preserving protocol for continuous and dynamic data collection in IoT enabled mobile app recommendation system (MARS). J Netw Comput Appl 174:102874.

9 Fu Z, Xian Y, Zhang Y, Zhang Y (2021) IUI 2021 Tutorial on conversational recommendation systems. In26th International Conference on Intelligent User Interfaces 1: 1-2.

10 Deldjoo Y, Noia TD, Merra FA (2021) A survey on adversarial recommender systems: from attack/defense strategies to generative adversarial networks. ACM Compu Sur 54: 1-38.

11 Rashmi KA, Kalpana B (2021) A Mood-Based Recommender System for Indian Music Using K-Prototype Clustering. InIntelligence in Big Data Technologies Beyond the Hype 31: 413-418.

12 Minaee S, Boykov YY, Porikli F, Plaza AJ, Kehtarnavaz N et al. (2021) Image segmentation using deep learning: A survey. IEEE Trans Pattern Anal Mach Intell 21: 1-5.

13 Gholami A, Kim S, Dong Z, Yao Z, Mahoney MW et al. (2021) A Survey of Quantization Methods for Efficient Neural Network Inference. arXiv preprint.

14 Chicco D (2021) Siamese neural networks: An overview. Artif Neu Netw 14: 73-94.

15 Zyblewski P, Sabourin R, Woźniak M (2021) Preprocessed dynamic classifier ensemble selection for highly imbalanced drifted data streams. Inform Fus 66: 138-154.

16 Luengo J, García-Gil D, Ramírez-Gallego S, García S, Herrera F (2020) Big data preprocessing.

17 Giordani P, Ferraro MB, Martella F (2020) Introduction to Clustering. Clus 1: 3-5.

18 Sheridan K, Puranik TG, Mangortey E, Pinon-Fischer OJ, Kirby M et al. (2020) An application of dbscan clustering for flight anomaly detection during the approach phase. AIAA Scitech 21: 1851-1853.

19 Li Z, Li Y, Lu W, Huang J (2020) Crowdsourcing logistics pricing optimization model based on DBSCAN clustering algorithm. IEEE Access 8: 92615-92626.

20 Rad MH, Abdolrazzagh-Nezhad M (2020) A new hybridization of DBSCAN and fuzzy earthworm optimization algorithm for data cube clustering. Soft Comp 24: 15529-15549.

21 Zareie A, Sheikhahmadi A, Jalili M (2020) Identification of influential users in social network using gray wolf optimization algorithm. Expert Syst Appl 142: 112971-112974.

22 Karakoyun M, Ozkis A, Kodaz H (2020) A new algorithm based on gray wolf optimizer and shuffled frog leaping algorithm to solve the multi-objective optimization problems. Appl Soft Compu 96:106560-106563.