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Folk Music Recommendation Using NSGA-II Optimization Algorithm

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Abstract: Music recommendation systems can significantly improve the listening and search experiences of a music library or music application. There is simply too much music on the market for a user to navigate tens of millions of songs effectively. Because of the high demand for excellent music recommendations, the field of Music Recommendation Systems (MRS) is rapidly expanding. The main motivation for developing the rating-based recommendation system was to extract relevant information from user reviews of instrumental music. In this study, we suggest an NSGA-II-based music recommendation system based on user interest, popularity of an instrument, and total cost. Our aim is to maximize user interest and popularity while minimizing the costs. We also compared our method to the baseline algorithm and discovered that it outperforms the baseline approaches. We used real-world metrics like precession, recall, and F1-score to compare our method to the baseline approaches.

Keywords: Recommendation System, Collaborative Filtering, Folk Music, User Ratings, NSGA-II

Introduction

A software program and algorithm known as the recommender system suggests products for users based on what they find most interesting. A suggestion is connected to various sorts of practical applications, such as what commodities are purchased, what music is listened to, or what recent news is read (Niyazov *et al*., 2021). Yet, since Apple acquired Beats Music in 2014, the recorded music industry has seen a shift. In recent years, the music industry's financial model has shifted from being dependent on commodity sales to one that is centered on subscriptions and streaming. Digital music is now widely available compared to earlier times because of the new economic model in the music industry (Schiavoni and Costalonga, 2015). As a result, the importance of the music recommender system for music suppliers cannot be overstated. The music service providers may boost user happiness and sell more diversified music as a result of their ability to forecast user preferences and then recommend the right tracks to their consumers (Miranda *et al*., 2018).

Recommendation systems are widely used in various fields such as the tourism industry, music industry, and many more (Sarkar *et al*., 2020; Sarkar and Majumder, 2021; 2022; Ramasamy *et al*., 2017). A customized music recommendation system is a suggested solution to the problem of how to efficiently find the songs of interest in the huge and complex sea of music in the modern era of rich music resources. Based on data about the user's behavior and the features of the music, music recommendation algorithms forecast and promote user behavioral preferences (Niyazov *et al*., 2021). The evolution of the algorithm for music recommendations has also changed from the technical path advised by the individual tastes of users to the mutual suggestion among users. The current emphasis has been on discovering prospective preferences. The technology behind music recommendation systems is generally improving.

The cultural legacy of India's north-eastern region includes a variety of musical instruments. These musical accompaniments give the local music of this area extra vigor. North Eastern India is home to a wide range of musical instruments, such as various wind, string, and percussion instruments kinds. The North Easterners' creativity in creating one-of-a-kind and creative musical instruments, such drums, tabla, flutes, mouth organs, clarinets, harmoniums, guitars, trumpets, fiddles, Jews-harps and leaf instruments, is another indication of their musical aptitude. An in-depth examination of these instruments exposes to us another facet of people's closeness to Nature. Nature serves as both an inspiration and a source of the raw materials needed to make these instruments. Most of their instruments are original works of design by Fig. 1. A specific instrument can now be recommended to a user based on the user ratings of other instruments. The user similarity must be checked in order to locate comparable users across different places.

A specific instrument can now be recommended to a user based on user evaluations of various instruments. The user similarity must be checked in order to find similar users across multiple locations. The main contributions of this study are as follows:

- Several studies on music recommendation have been done. According to the best of our knowledge, the proposed method is the first of its kind to recommend folk musical instruments based on interest, popularity, and cost
- The proposed method takes into account the user's interest and popularity
- The suggested method maximizes user interest and popularity while minimizing the costs
- The cost is calculated based on the price accumulated from a list of instruments that can be used
- The proposed method employs the NSGA-II optimization technique

Related Work

Recent advances in mobile network technology have sped up the development of digital multimedia technologies. The main customers are now thought to be young people, particularly students, and one of their favorite media is now thought to be digital music (Shapiro *et al*., 2017). When users are looking for a specific piece of music, they can quickly find it by typing in the title or artist, but when they don't have a specific request in mind, or when they just want the music system to play whatever suits their tastes, personalized music recommendation may be the better option. To increase the sensitivity and accuracy of probabilistic recommendation issues, (Dai and Yu 2019) suggested a new content-based recommendation strategy based on the Gauss mixture model. Convolution neural networks were used (Waddell and Williamon, 2019) to support a content-based recommendation system. The developers of (Sarkar *et al*., 2020) introduced a rating forecasting framework to address the cold start issue. This approach enables the system to anticipate user ratings for unscripted musical compositions, producing useful suggestions. Recommendation systems seldom take users' preferences and interests into account simultaneously at the moment. In Folk Instrumental Music (FIM) improvisational elements remain available in a music recital. Performers undergo a profound learning process (tAlim), familiarize themselves with common words, learn about different aspects of ragas, and understand how to arrange different patterns of singing and playing. A raga transmits various color tones at different times and when it is carried out by a variety of people. In addition, at various times, the same performer will invoke diverse impacts from different ragas. The traditional development of FIM music inherently blends technical and descriptive components (Sarkar and Majumder, 2021). These are the components of virtuosity and ingenuity. Virtuosity components are critical for the selection and melodic variation of materials, such as tempo, rhythmic complexity, difficult decoration, and dynamic tone. Musical influences often play a vital role in the accomplishment of musical success. The auditorium's architecture, plays a critical role in sound transmission, the efficiency and adaptation of sound amplification systems, stage decoration, lighting arrangements, hosting of concerts and costumes of musicians, etc., (Ramasamy *et al*., 2017).

Background and Problem Formulation

Let $I = \{i_1, i_2, i_3, ...in\}$ be the folk musical instruments. Each instrument $i_x \in I$ $(1 \leq x \leq n)$ consists of a set of behavioral pattern $B = \{b_1, b_2, b_3, ...b_k\}$. In this study, each recommended instrument can play a number of Ragas $R = \{r_1, r_2, r_3, ...r_k\}$. Based on the user interest, the popularity of the instruments, and the cost.

Characteristics of a User U_i

A user U_i wishes to listen to various Ragas R_k from a suggested instrument. It should also be noted that if a user is belonging to a city C_y, prior histories may be unavailable due to the unreliability of such instruments.

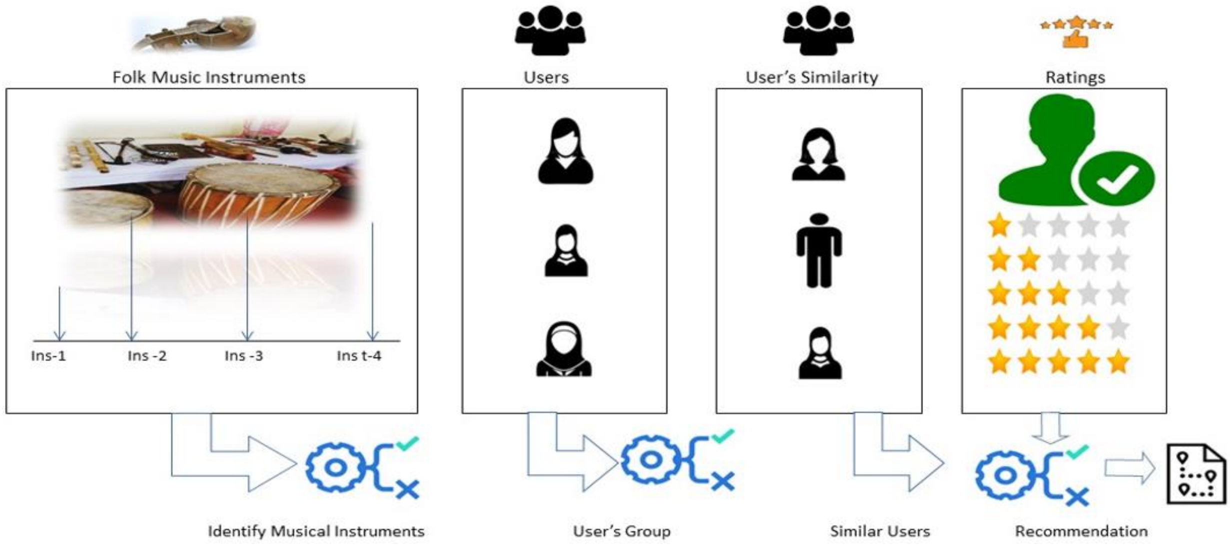


Fig. 1: Overview of the system framework

Average Instrumental Score

Considering the user's listening behavior, the average instrumental score S(I) for a particular Raga R_k is calculated using Eq. 1:

$$S(R) = \frac{\sum_{u=1}^{k}(T_j^{end} - T_j^{start})\beta(r_j = r)}{D_z\,\beta(r_j = r)} \tag{1}$$

where, T_j^{start} and T_j^{end} denotes the starting and ending time for listening R_k. D_z denotes the total number of times a user listens to a specific instrument.

Here:

$$\beta(r_j) = \begin{cases} 1, if\ r_j = r \\ 0, Otherwiswe \end{cases}$$

User Interest in a Specific Instrument

Considering the user's listening behavior, the user interest *I*(*Int*) for a particular instrument is calculated using Eq. 2:

$$I(Int) = \sum_{j=1}^{l} \frac{(T_j^{end} - T_j^{start})\beta(I_{R_j} = I)}{S(R_j)} \tag{2}$$

where, $\beta(I_{R_j}) = \begin{cases} 1, if\ I_{R_j} = I \\ 0, Otherwiswe \end{cases}$ the fact that a user spent more time listening to Ragas for a particular instrument indicates the user's greatest interest.

Popularity and Cost

The overall number of times all users listen to a specific instrument can be used to calculate popularity and is shown in Eq. 3:

$$U(I) = \sum_{u=1}^{l}\sum_{r=1}^{k} (T_j^{end} - T_j^{start})\beta(I_j = I) \tag{3}$$

The price accumulated from a list of instruments can be used to determine the cost.

User's Similarity

The user's similarity is calculated based on the cosine similarity test and is given in Eq. 4:

$$Cos(U_x, U_y) = \frac{I(Int)\ _{U_x} . I(Int)\ _{U_y}}{\left\| I(Int)_{U_x} \right\| . \left\| I(Int)_{U_x} \right\|} \tag{4}$$

Here, U_x and U_y are the two different users.

Problem Definition

The main objective of this study is to recommend a list of instruments within a specific budget *Bt*. Our goal is to maximize interest and popularity and minimizes the cost and is given in Eq. 5:

$$\frac{Max(\pi U_{Int} + (1-\pi)U_{pop})}{Cost(I)} \tag{5}$$

where, π is the weight parameter that is used for balancing the interest and popularity. The *cost* (*I*) function is devoted to calculating the *cost*:

$$I(1,x) = I(x,1) \le 1;\ x = 2, ...(m-1) \tag{6}$$

$$Cost(I) \le B_t \tag{7}$$

Equation 5 is NP-hard due to the cost-related function. We used the NSGA-II optimization algorithm to tackle this multi-objective problem which is discussed.

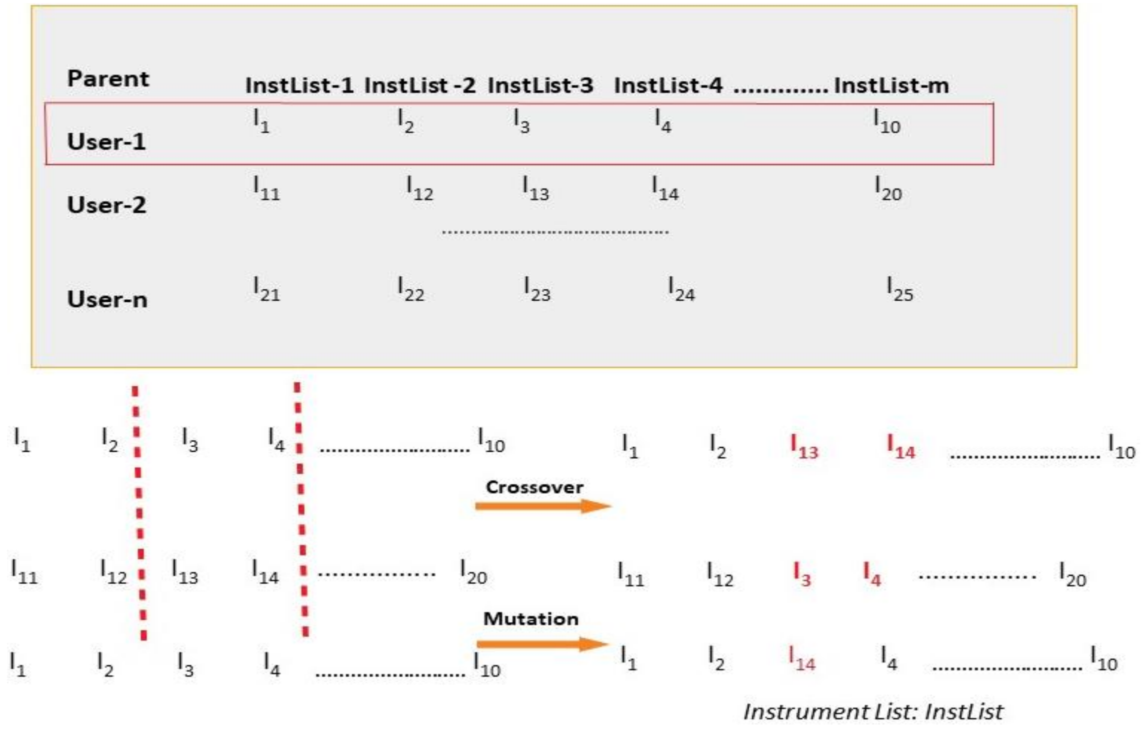


Fig. 2: Crossover and mutation process

NSGA-II Based Optimization Algorithm

Our aim in this study is to recommend a list of instruments that maximize interest and popularity while minimizing cost. As a result, the objective can also be written as:

$$Maximize(I(Int)\ _{U_x}) \tag{8}$$

$$Maximize(I(Pop)\ _{U_x}) \tag{9}$$

$$Minimize\ (Cost(I) \tag{10}$$

$$I(1,x) = I\,(x,1) \leq 1;\ x{=}2,.....(m\text{-}1) \tag{11}$$

$$Cost(I) \leq B_t \tag{12}$$

NSGA-II algorithm stops when the maximum number of generations is reached. In other words, the optimum top-N suggestions of each solution are considered. However, the total travel cost of the suggested itinerary should be within the given budget (Miranda *et al*., 2018). The crossover and mutation process of the NSGA-II algorithm is shown in Fig. 2. NSGA-II utilizes 2 fitness functions, as described in Eqs. 13-14:

$$Fitness\text{-}1{=}\ Max(\pi U_{Int} + (1-\pi)U_{pop}) \tag{13}$$

$$Fitness\text{-}2{=}\ Minimize\ (Cost(I)) \tag{14}$$

Materials and Methods

To implement and test our proposed method, we use the following hardware and software configuration: Hardware: A desktop computer with an Intel Core i5 processor and 32 GB of RAM. Python 3.8 as the programming language, and PyCharm as the software.

Dataset Description

In this section, we categorize three types of datasets, namely dataset (A), dataset (B), and dataset (C). In this study dataset (A) consists of Sumui, Saroj Veena, and Rosem, dataset (B) consist of Adhuri, Twitreng, Wakhorok, and Dataset (C) consists of Tipara flute, Chongpreng, Tintrong. In each Instrument, three different types of Ragas were played. The detailed Dataset description has been given in Table 1. The different user ratings are also given in Tables 2-3.

Table 1: Dataset description with respect to northeastern regions, users, folk instruments and ragas

Northeastern regions	# Of user	# Of folk instruments	# Of ragas
Tripura	35	18	5
Meghalaya	21	15	4
Arunachal Pradesh	08	3	3
Assam	40	11	4

Table 2: User ratings: Slow comparison

	Slow comparison Part				
	Ratings				
Participants	W(1)	M(2)	A(3)	G(4)	E(5)
# 33					●
# 33				●	
# 33			●		

Table 3: User ratings: Middle/first comparison

	Middle/first comparison Part				
	Ratings				
Participants	W(1)	M(2)	A(3)	G(4)	E(5)
# 33					●
# 17				●	
# 14			●		

Baseline Algorithms

For our findings analysis, we used the following benchmark approaches. There are no benchmark methods in the field of folk musical instrument recommendation that we are aware of.

Greedy Most Popular (G-POP)

By selecting the best three instruments based on the amount of time users have spent listening to them.

Greedy Random (G-RAND)

By picking instruments at random from a list of instruments.

Greedy Near (G-NEAR)

Based on the user's location, by identifying the nearest instrument. The highest priority should be given to instruments from the northeast, for instance, for a northeastern.

Real-Life Evaluation

We decided to assess our response to several benchmarks using the following matrices. Based on the visitors' past history, a variety of real-world sequences are picked for our experiments.

Instrument Recall (InsRec(I))

Let R_{rec} be the list of ragas available in the recommended instruments. R_{eal} is a collection of ragas that are listened to in a real-life by users. The *InsRec*(*I*) is presented with Eq. 15:

$$InsRec(I) = \frac{||R_{rec} \cap R_{real}||}{||R_{real}||} \tag{15}$$

Instrument Precession (InsPre(I))

The tour precession is shown in Eq. 16:

$$InsPre(I) = \frac{||R_{rec} \cap R_{real}||}{||R_{rec}||} \tag{16}$$

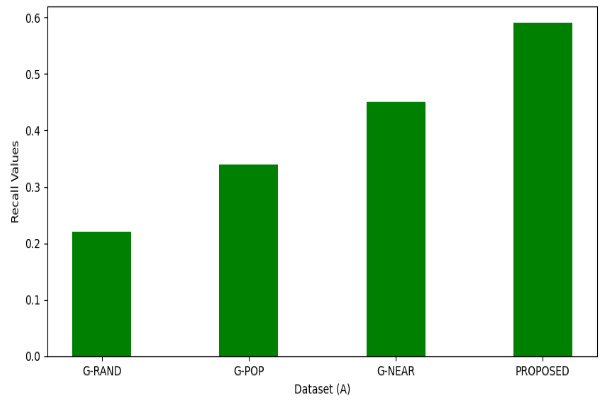
Instrument F1-score (F1-score(I))

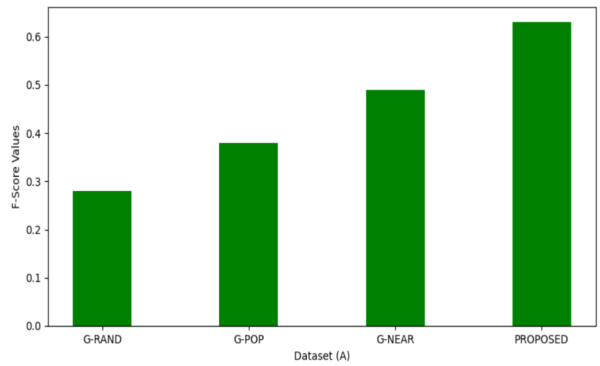
Tour F1-score can be calculated using Eq. 17:

$$F1\text{-}score(I) = \frac{2 \times InsPre(I) \times InsPre(I)}{InsPre(I) + InsPre(I)} \tag{17}$$

Results and Discussion

With respect to the benchmark approaches like G-POP, G-RAND, and G-NEAR, the efficiency of our approach is maximum. Figures 3-5 show the values of Precision, Recall, and F1-Score of our approach and other benchmark approaches. The results show that in comparison with benchmark approaches, the proposed approach performs better. The Recall scores are higher compared with other benchmark approaches. The Recall value depends on values $||R_{real}||$ and $||R_{rec} \cap R_{real}||$. In the case of our algorithm, the value $||R_{rec} \cap R_{real}||$ is higher than the various benchmark approaches. This results in increased recall values. With respect to the benchmark approaches like G-POP, G-RAND, and G-near, the efficiency of our approach is maximum. The Precession scores are higher compared with other benchmark approaches.





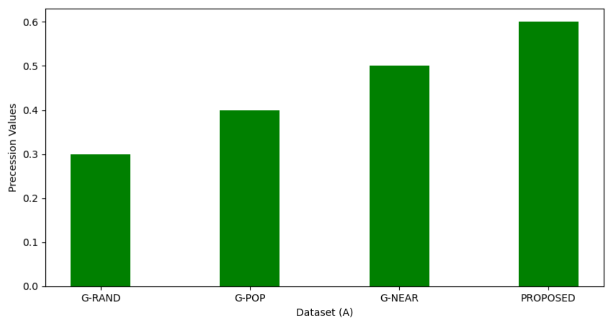
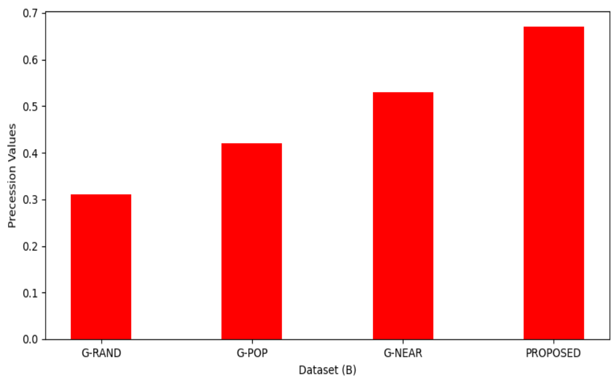
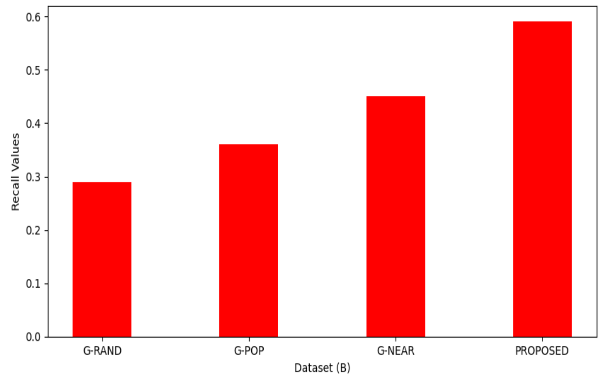


Fig. 3: Precision, recall, and F1-score values for proposed approach and benchmark approaches for dataset (A)





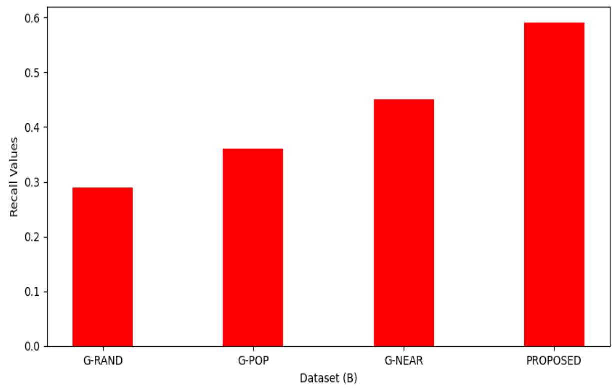
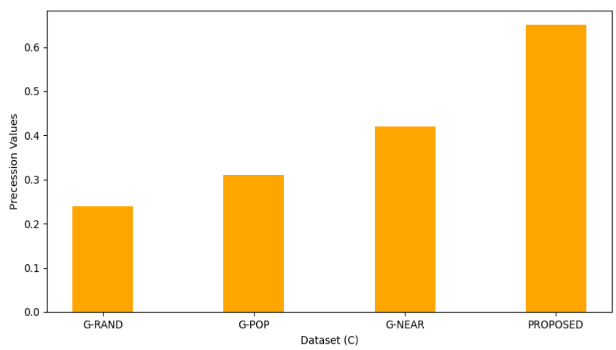
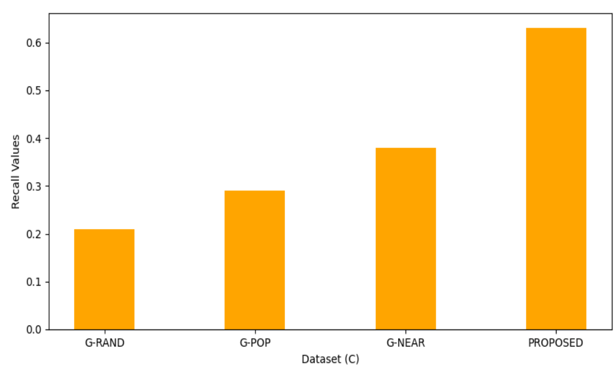


Fig. 4: Precision, recall, and F1-score values for proposed approach and benchmark approaches for dataset (B)





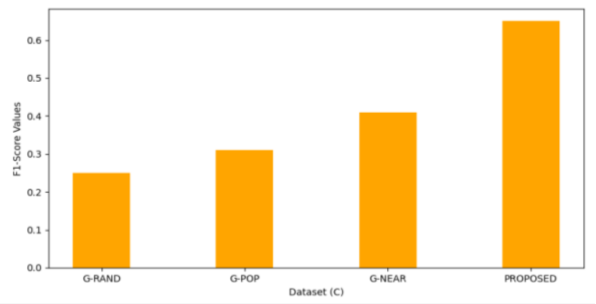


Fig. 5: Precision, recall, and F1-score values for proposed approach and benchmark approaches for dataset (C)

The Precession value depends on values $||R_{rec}||$ and $||R_{rec} \cap R_{real}||$. In the case of our algorithm, the value $||R_{rec} \cap R_{real}||$ is higher than the various benchmark approaches. This results in increased precession values. The F1-score value of our proposed is higher compared to other benchmark approaches, as the F1-score values depend on precision and recall values.

Conclusion

In this study, an NSGA-II-based folk music recommendation system based on different folk musical instruments is proposed. The proposed approach takes into account the situation where the user does not listen to a specific instrument in his life. The proposed method takes into account the cosine-similarity test based on user interest in a specific musical instrument. The proposed system maximizes user interest and the instrument's popularity while minimizing overall expense. Because the problem is NP-hard, an NSGA-II-based optimization algorithm was used and it was found that that our approach outperforms various baseline approaches. Real-life metrics such as precession, recall, and F1-score were used to compare our method to the baselines.

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The authors confirmed that there is no funding agency exists in this study.

Author's Contributions

Joyanta Sarkar: Conceptualization, written original drafted, written reviewed, edited and visualization.

Anil Rai: Conceptualization, methodology, supervision, written, reviewed and edited.

Kayala Kiran Kumar, Venkata Nagaraju Thatha, Sowmiya Manisekaran, Sayantan Mandal and Sudeshna Das: Written reviewed and edited.

Joy Lal Sarkar: Conceptualization, written original drafted, written reviewed and edited.

Ethics

The authors conducted their research ethically, following the ethical principles and guidelines of their field and institution.

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