



MELOMANIAC BASED ON MACHINE LEARNING

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Abstract: Mood and emotion play an important role when it comes to choosing musical tracks to listen to. In the field of music information retrieval and recommendation, emotion is considered contextual information that is hard to capture. Modern day entertainment and music streaming has largely been dependent on digital technologies. People prefer subscription based online services for buying physical copies of the music albums. online streaming services like Spotify, apple iTunes, google music offer great services to the listener with ease. However, drawbacks to these systems includes long delays in payouts for the artists, lack of transparency, confusing payments and licensing terms and so on. In order to give solution to these drawbacks the proposed system is an interface which is used between the user (fans or melomaniacs) and the independent musicians without involving the third parties and thereby satisfying the user by fetching them the songs of their mood by using the sentimental analysis. we have proposed it as a collaborative work by which the artists gets benefited as well as the user gets satisfied with the help of machine learning techniques.

Keywords: Melomaniacs, Machine Learning, Sentimental Analysis,

I.INTRODUCTION

The recommendation systems that really emerged in the 1990s have developed strongly in recent years, especially with the introduction of Machine Learning and networks. Indeed, on the one hand, the growing use of the current digital environment, characterized by an overabundance of information has allowed us to obtain large user databases. On the other hand, the increase in computing power made it possible to process these data especially thanks to Machine Learning when human capacities were no longer able to carry out an exhaustive analysis of so much information. Unlike search engines that receive requests containing precise information from the user about what they want, a recommendation system does not receive a direct request from the user, but must offer them new possibilities by learning their preferences from their past behaviour. E-commerce sites that aim to sell a maximum of items or services (travel, books, ...) to customers must therefore recommend suitable goods quickly. As for sites that offer streaming music and movies, their goal is to keep their users on their platform as long as possible. The common point is that it is necessary to make adequate recommendations. Recent progress in this field is considerable and these recommendations are as beneficial for companies that maximize their profits as they are for customers who are no longer overwhelmed by the number of possibilities. Decision-making is made easier and a good recommendation is therefore a significant time saver. In 2006, Netflix, which was an online DVD rental service, launched the Netflix Challenge with \$1 million to be won. The goal of the contest was to build a recommendation algorithm that could surpass the current one by 10% in tests. The contest generated a lot of interest, both in the research community and among movie lovers. The prize was won 3 years later and highlighted several methods and research directions to solve this kind of problem. A recommendation system will be defined according to Burke's definition: It is a system capable of providing personalized recommendations or guiding the user to interesting or useful resources (called items) within a large data space.

II.LITERATURE SURVEY

According to the paper, personalized music recommendation system (PMRS) based on the convolutional neural networks (CNN) approach. The CNN approach classifies music based on the audio signal beats of the music into different genres. In PMRS, we propose a collaborative filtering (CF) recommendation algorithm to combine the output of the CNN with the log files to recommend music to the user. The log file contains the history of all users who use the PMRS. The PMRS extracts the user's history from the log file and recommends music under each genre. We use the million-song dataset (MSD) to evaluate the PMRS. To show the working of the PMRS, we developed a mobile application (an Android version). We used the confidence score metrics for different music genre to check the performance of the PMRS. [1]. The personalized music recommender supports the user-favourite songs stored in a huge music database. In order to predict only user-favourite songs, managing user preferences information and genre classification are necessary. In our study, a very short feature vector, obtained from low dimensional projection and already developed audio features, is used for

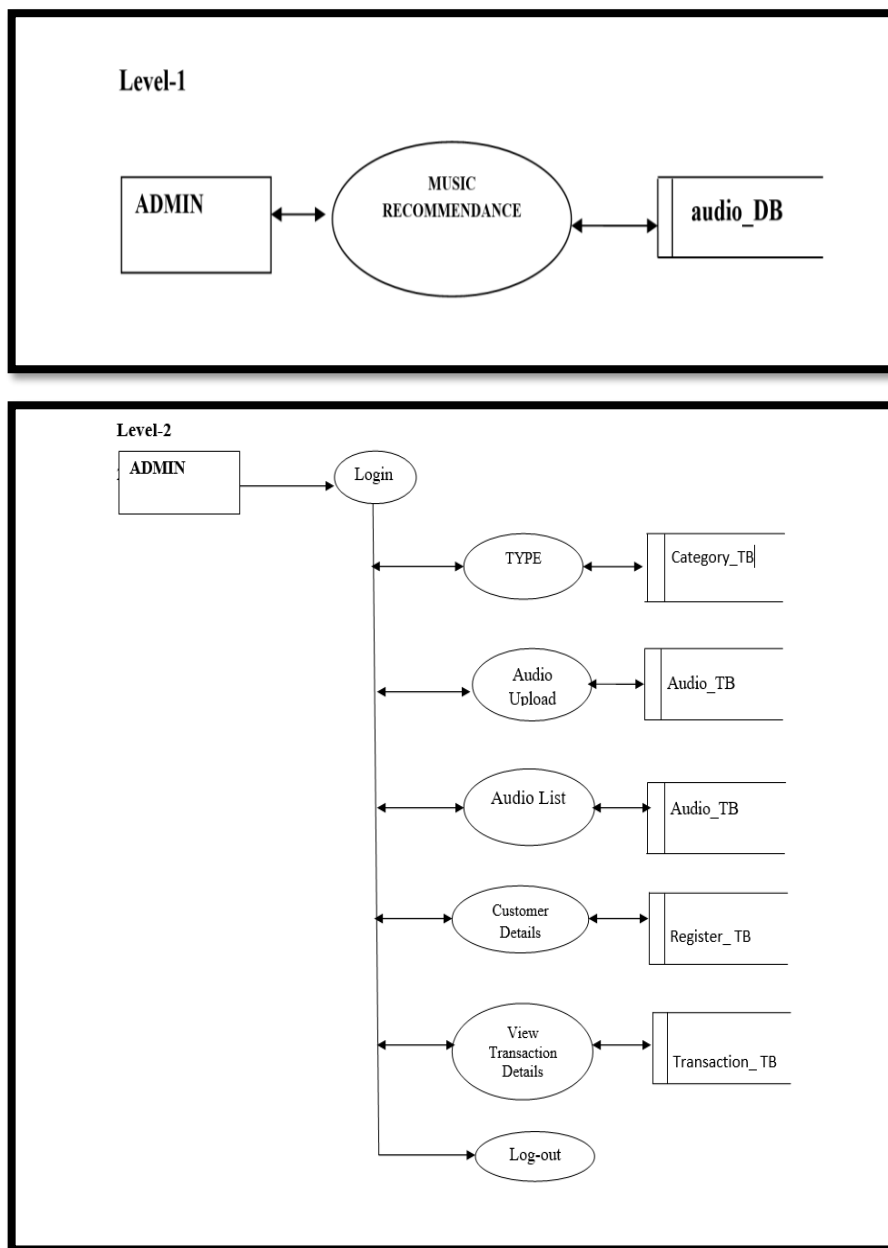


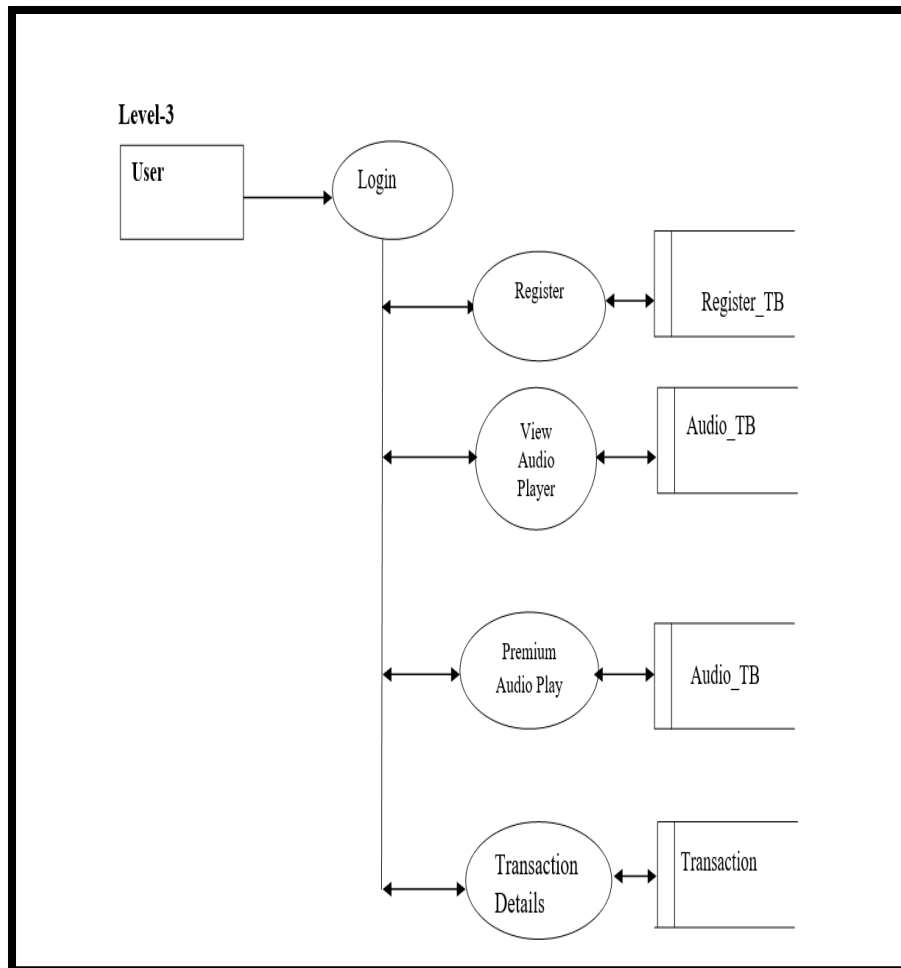
music genre classification problem. We applied a distance metric learning algorithm in order to reduce the dimensionality of feature vector with a little performance degradation. We propose the system about the automatic management of the user preferences and genre classification in the personalized music system. [2].

III. PROPOSED SYSTEM

The expected outcome is to provide a user interactive interface for both the users as well as the pop stars. It will be a transparent medium through which the user gets to know that their subscriptions reach their beloved artists without the intervention of the third parties. The artists will be benefitted in time. The fans will be able to hear the albums of their artists at any time with any number of streams. Users will be able to hear the songs using hashtags or keywords using the movie or album name or song name etc., according to their moods. It will be an Interactive web application that benefits the artists and fans.

IV. FLOW DIAGRAM





V.SYSTEM MODULES

There are Six modules in this system:

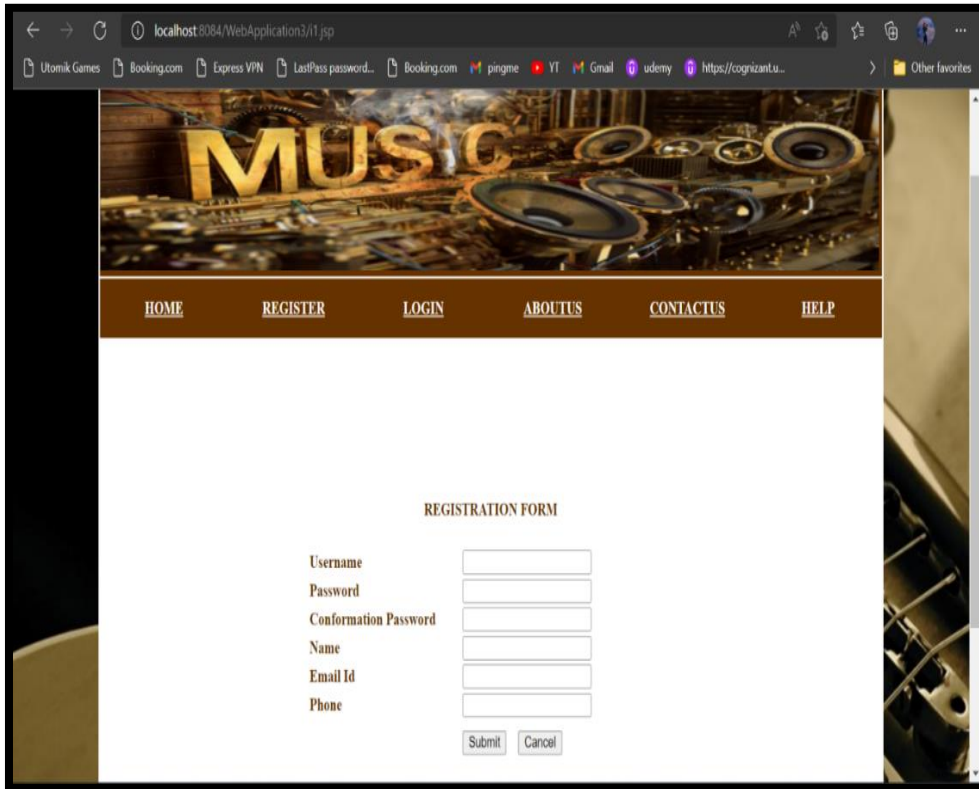
1. **Recommendation Module**
2. **File Server Module**
3. **Web Application Module**
4. **Popularity Module**
5. **Content Based Module**
6. **Collaborative Filtering Module**

- **RECOMMENDATION MODULE:** Recommendation module generates recommendation based on the user profile. it analyses the previous listening history and preferences of a user and provides a list of songs that user might prefer to listen. we have used a global popularity model, content based model and collaborative filtering model.
- **FILE SERVER MODULE:** We have implemented the file server using java, jsp, servlet and MySQL modules for efficient upload and retrieval of items. grids for MySQL provide many advantages over traditional file systems.
- **WEB APPLICATION MODULE:** Web application provides an intuitive user interface to the user and interacts with file server and recommendation module.
- **POPULARITY MODEL:** It is a basic model which sorts the songs in the training set according to popularity in descending order and recommends most popular songs. this method doesn't take users preference into account.
- **CONTENT BASED MODEL:** Content-based filtering methods are based on a description of the item and a profile of the user's preferences. these methods are best suited to situations where there is known data on an item (name, location, description, etc.), but not on the user.

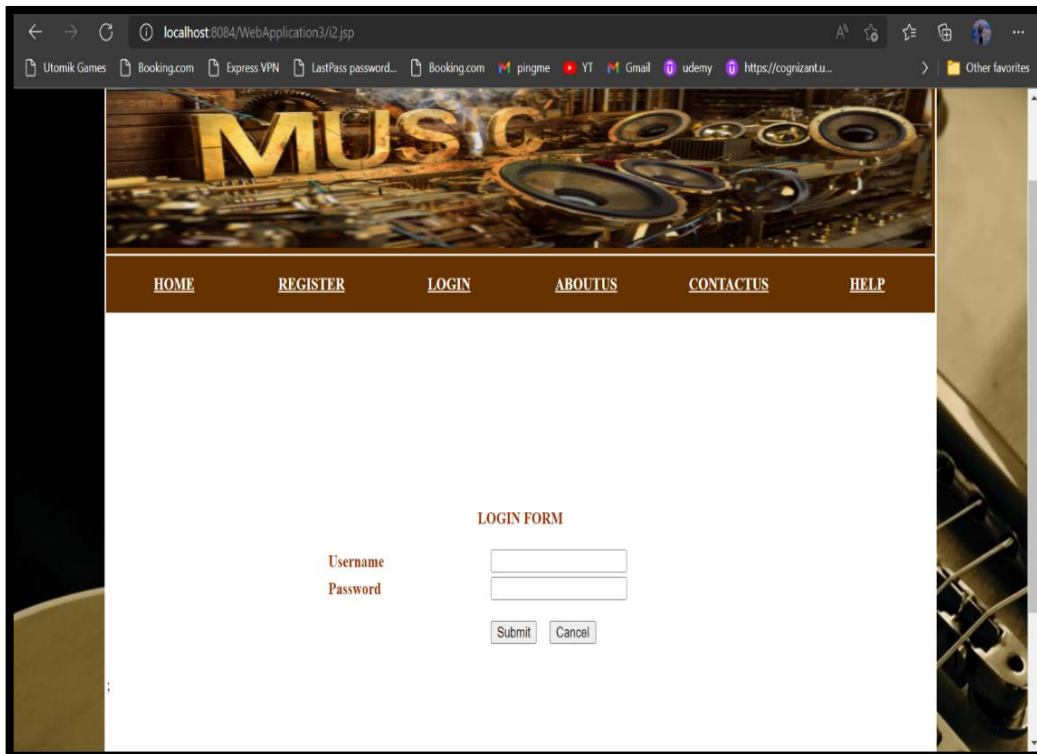


VI.SCREENSHOTS

USER REGISTRATION

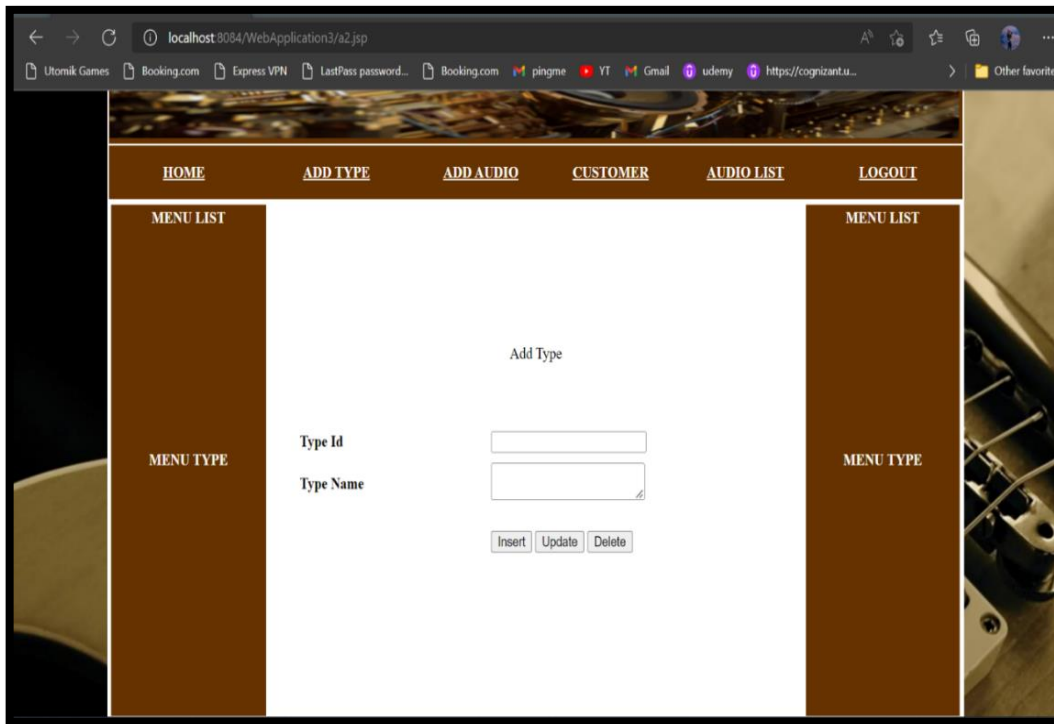


LOGIN PAGE

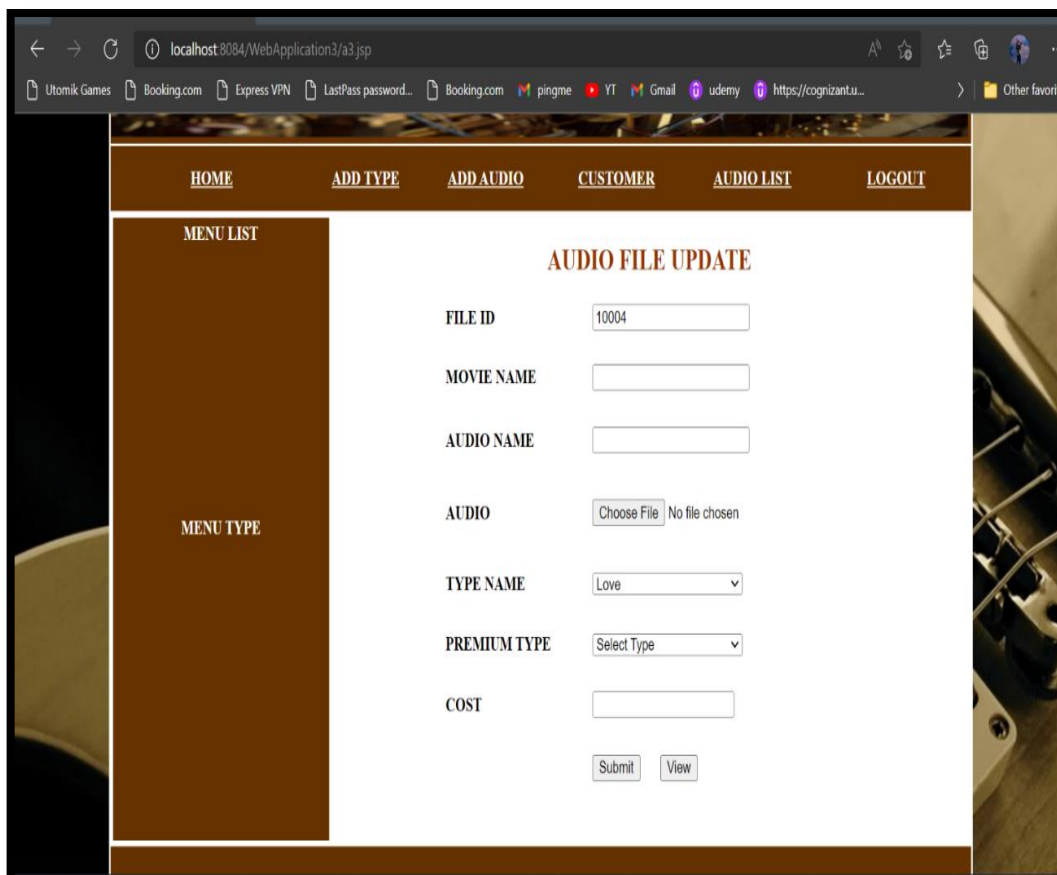




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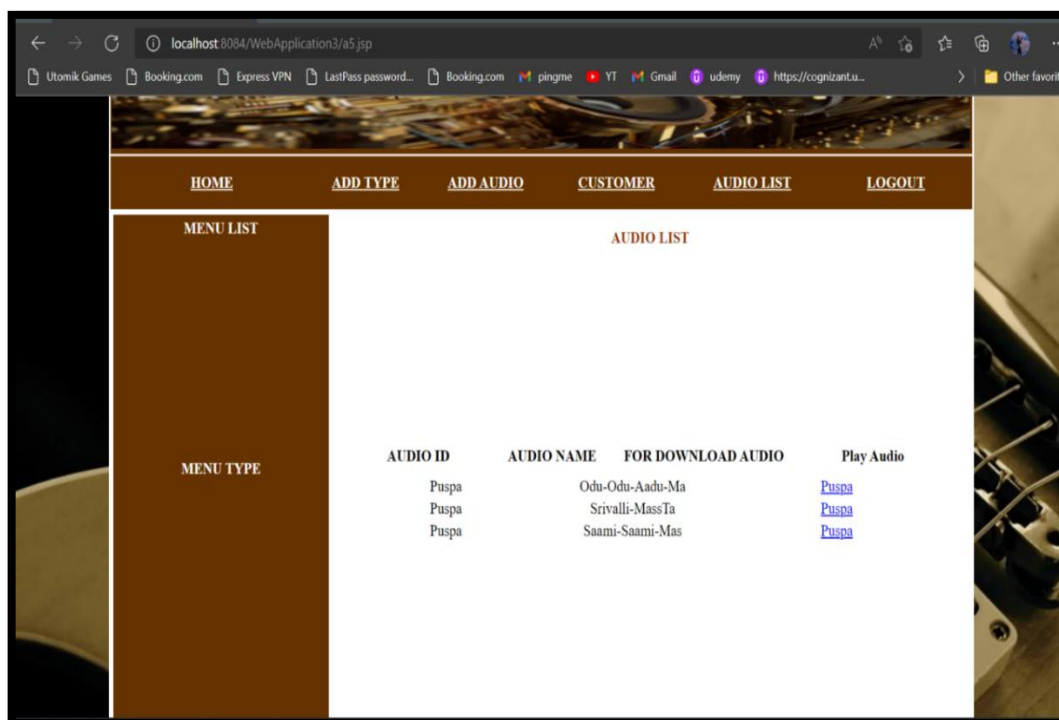


AUDIO FILE UPDATE PAGE





AUDIO LIST DETAILS



VII.CONCLUSION

Thus, by doing this project we will be able to create a user-friendly music interface for both the users and the independent musicians since they the users can hear n number of streams according to their needs as well as the independent musicians will be paid as per the no of streams being played without involving the third parties. And so, both the fans (users) and the musicians are been benefitted by using our application.

VIII.FUTURE ENHANCEMENTS

In the future, we would like to try the following things: 1. Using audio signal (e.g., audio frequency) to recommend songs 2. Trying content-based algorithm 3. Trying Convolutional Neural Network 4.Making the recommender system a real-time system 5, trying clustering techniques to recommend music. Designing a personalized music recommender is complicated, and it is challenging to thoroughly understand the users' needs and meet their requirements. As discussed above, the future research direction will be mainly focused on user-centric music recommender systems. A survey among athletes showed practitioners in sport and exercise environments tend to select music in a rather arbitrary manner without full consideration of its motivational characteristics. Therefore, future music recommenders should be able to lead the users to reasonably choose music. In the end, we are hoping that through this study, we can build the bridge among isolated research in all the other disciplines.

IX.REFERENCES

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