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Emotion Based Music Recommendation System

Mr. Malige Gangappa
Assistant Professor, Department of Computer Science Engineering, VNR Vignana Jyothi, Institute of Engineering and Technology

Avuluri Nikhitha
B. Tech, Department of CSE, VNR Vignana Jyothi, Institute of Engineering and Technology.

Bondugula Reshma
B. Tech, Department of CSE, VNR Vignana Jyothi, Institute of Engineering and Technology.

Gundabathina Manasa
B. Tech, Department of CSE, VNR Vignana Jyothi, Institute of Engineering and Technology.

Pooja singh
B. Tech, Department of CSE, VNR Vignana Jyothi, Institute of Engineering and Technology.

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Music recommendation; CF; Model based on Content; emotion-based model

ABSTRACT

Many consumers believe it is quite difficult to compile a list from a lengthy tracklist. As a result, customers often opt to play the following music in a random mode or through suggestion. There are a wide range of scientific environments and procedures used in track remedy for health assistance. As a result, an effective personalised track guidance method has become important. With the use of generalised track treatment tactics and synthetic intelligence technology, an advise machine is focused on assisting people in making the best choices for their lifestyles and maintaining their mental and physical health. As a result, this research investigates a modern framework and offers cutting-edge track models. We used the algorithms for CF and model based on content because they work well in recommender systems. Due to the difficulty in finding a track related to contemporary feeling, two user-centric strategies—context- and emotion-based versions—were receiving more attention.

1. INTRODUCTION

Music has a wonderful impact on people and is frequently used to unwind, control mood, heal from illnesses and pressure, and preserve mental and physical artwork. We now understand how important music is to our lives. And people regularly listen to music, considering it to be a vital part of their lives. A good music recommendation system should be able to discern preferences automatically and generate tracks that suit such tendencies. Additionally, recommender systems are a great strategy for expanding search engines because they help users identify products they otherwise might not have found. In essence, the consumer should be recommended some things based on his tastes. Users can be profiled in a number of ways, such as by watching how they interact with others, pressuring them to engage in particular activities, or asking them to fill out forms with private information. Anyone who is depressed, anxious, or excited will choose to listen to music. It features rigorous sports, including cut-off dates, which have a predisposition to temper swings, study stress in college students, painting stress in particular fields, along with IT, and the personal flavour of track changes based entirely on those temper swings. By using listeners' interest contexts, such as pulse rate, coronary heart rate, sleep duration, steps taken, energy expended, etc., this assignment will reveal the design of the personalised track recommendation system [1]. The main goal of our project is to create a system for recommending music to users depending on their mood as determined by several health factors, like heart rate, pulse rate, number of steps taken, etc. With the help of this project, users may be able to avoid getting off to a slow start and to choose a music that suits their mood at the time. Since our software considers health parameters as the key datasets depending on their current health characteristics, it can handle users' mood fluctuations and offer the greatest music that can help them unwind and return to work with a lot of enthusiasm and energy.

The four main topics covered in this work are audio processing, human emotion analysis, emotion to music production, and music recommendation [2]. However, there isn't a mechanism for recommending music based on a user's present state, which includes things like pulse rate, how many hours they slept, how many steps they took, etc. [1]. To achieve this, we create a deep learning-based music recommendation system that uses human health indicators as its main metric [1].

RELATED WORK

The findings of our examination into the current music recommendation algorithms and systems are presented in this section.

A. Currently operational music recommendation systems

Music recommendation systems have seen a substantial transition in the current era as a result of the expansion and popularity of online streaming services, which at times put practically all of the world's music at the user's fingertips. Even if the large amount of music available now almost makes it possible for people to find fascinating music, research on music recommendation systems still faces several challenges. Research on music recommendation systems is essential, especially when it comes to developing, implementing, and assessing recommendation strategies that take into account factors other than straightforward interactions between users and items or based on content descriptors that and instead delve deeply into the changing needs, preferences, and intentions of listeners. Despite the success of music information retrieval (MIR) approaches over the past 10 years, the development of music recommendation systems is still in its infancy. In contrast to more traditional music recommendation systems, which make playlist suggestions based on the user's preferences, more contemporary systems provide playlist recommendations based on the user's heartbeat in order to stabilise and keep it within normal ranges. If the user's heartbeat is faster or slower than the average heart rate, either way, in order to stabilise the user's mood and return their heartbeat to a normal range in the shortest period of time, the system uses the Markov decision approach to construct a user-preferred music playlist[11]. Similar to Spotify, Pandora, and iTunes, T-RECSYS is another recommendation system that uses deep learning to learn a user's musical interests in order to provide music recommendations. Both content-based and collaborative filtering are used to enter data into this model.

B. Popular Algorithms

As technology advanced, a variety of algorithms for recommendation systems emerged. Currently, the following techniques or algorithms are primarily employed for music recommendation systems: models that use CF and CBM content-based models . The difference between them is determined by the type of data used.

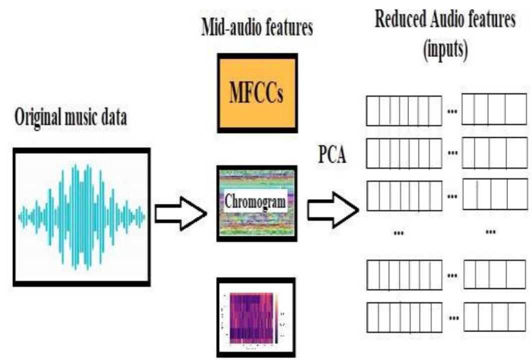
First-person predictions are developed based on user-item interactions, historical experience, and input from users on the things in question. The second one calls for distinctive qualities in the objects. It must be aware of both the user and item content. Additionally, some systems make use of the K-Nearest Neighbour (K-NN) method, which is frequently employed in recommendation systems due to its capacity to manage vast volumes of data and make accurate predictions. The K-NN method operates by identifying an item's k nearest neighbours. The rating of the item is then decided by the neighbours. These are the most popular algorithms for music recommendation systems, according to our research.

2. METHODOLOGY

The aforementioned figure displays the proposed system. The system is built to extract several health metrics, like heart rate, steps taken, hours slept, etc. These parameters are then used to train and test the system. The user's current mood is recognised and classified as neutral, happy, furious, or sad by the music suggestion system module [4]. Additionally, the music that is meant to be recommended is also categorised such that it has something to do with the user's current circumstance. For instance, if the user's mood is determined to be depressed, the system suggests music that will uplift and motivate them.

The four main topics covered in this work are: Audio feature processing; human emotion analysis; emotion to music production; and music recommendation [2].

- Feature processing for audio



Numerous studies have been conducted on the examination of auditory functions. Audio characteristic retrieval is the most important stage in audio characteristic analysis [2]. The current approach takes into account spectral elements including MFCCs, spectral centroid, and chromogram, which reflect the loudness, tone, and pitch of the music [1]. Additionally, the rhythmic components have been taken away. To obtain the spectral ability, each snippet sampler was considered at a rate of 22050 Hz, which was a successful method. The electricity spectrogram was then obtained using a short-time Fourier transform [1]. We calculated the discrete Fourier transforms over Hann home windows, and for each sample, we produced a spectrogram with a size of 1025 1077. The computing of various spectral features was the outcome of the preprocessing indicated earlier. . As an illustration, we developed a Mel-scale spectrogram for MFCCs by clearing out the spectrogram with a Mel clean out financial institution [1]. Following that, we decide to compute the MFCCs using the diminishing cepstral coefficients [1].

Once the chromogram had been calculated using Ellis' method, centroid function of tonal were produced by projecting the Chromatogram functions onto a basis of 6-dimensions The labours toolset had also been used to calculate additional functions, such as spectral contrast, spectral centroid, zero-crossing fee, and spectral roll off [3]. Following that, by connecting the spectral and rhythmic functions, the utilisation of fundamental thing analysis was decreased (by 99% of the variance). By using the decreased feature, audio inputs had finally been made.

Analysis of human emotions As a result of demanding jobs, money worries, and problems with their families or personal life, people nowadays commonly suffer high levels of stress [7]. Unwinding by listening to music is one way to do this. However, those for whom music best conveys their current state of stress, concern, or other emotion will benefit from our project more. The programme then provides songs in exactly the same condition dependent on the user's health data. Happy, sad, angry, and neutral emotions could all be distinguished by the algorithm with ease [8]. Wearable technology that provides emotion recognition and tracking can be very helpful in monitoring psychological wellness and facilitating human-computer interaction.

This study identified four distinct emotional states associated with music: joyful, sad, angry, and neutral. Songs isolate the emotions in the music using an SVM-based technique. derived from the study. Depending on the type of happiness, the heart rate of a neutral state ranges from 60 to 80 beats per minute, whereas that of a happy state ranges from 70 to 140 beats per minute [4]. While the heart rate associated with rage ranges from 110 to 135 beats per minute, that of sadness is often between 80 and 100. To differentiate between the four emotional states (happy, sad, neutral, and furious), real-time pulse evaluation is used. The various states are closely tied to the variation in sign. Neutral = 60–80 bpm Happy =70-140.

Music that evokes emotion There are no large-scale tuning datasets available right now with annotated human emotion labels. Since creating music based on emotion labels is no longer natural, [3] it is no longer intuitive. In this essay, we propose a gadget that may capture the modern consumer's mood, which is an emotion, and create a tune based on that emotion [5]. To be more precise, we first programme the device with the user's fitness parameters, such as pulse rate, the number of steps they take each day, the number of hours they sleep, etc. Next, an automatic emotion popularity version is built, which analyses the emotion and categorises it as sad, happy, angry, or neutral [9]. Now, the songs related with various emotions have been grouped together. For each emotion, a class of songs is created, with each class of songs being connected with a specific emotion, and so on. In this way, the emotion is examined, and the exact music that corresponds to that emotion is created.

4. Recommendations for music

As the entire subject is tied to this recommendation, music selection is one of the survey's most important elements. Users are recommended music using two of the most well-liked ML algorithms, Collaborative Filtering (CF) and Filtering based on content (CBF)[6]. After the algorithm has evaluated the user's current mood, it searches for music that are appropriate for that mood [3]. This technique is a part of the production of emotions in music that was previously covered. After this music generating process is complete, the user is given recommendations for music that best suits their present state of mind [14].

3. IMPLEMENTATION DETAILS

There was data exploration. This module is used for loading data into the system. The data is read using this module and processed. This module is used to split the data where we have train and test. The creation of models uses different algorithms.

Login & user sign-up are modules. is employed to obtain registration and login. User input serves as a module for providing input for predictions, and predictions are used to display the final predictions.

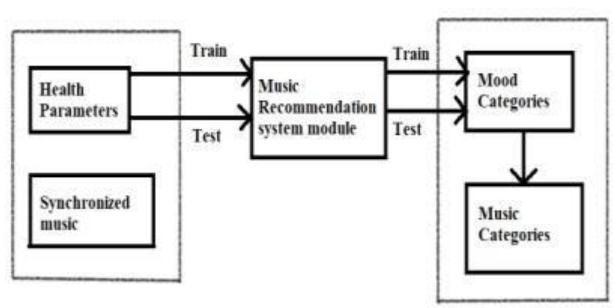


Fig 3.1: System Architecture

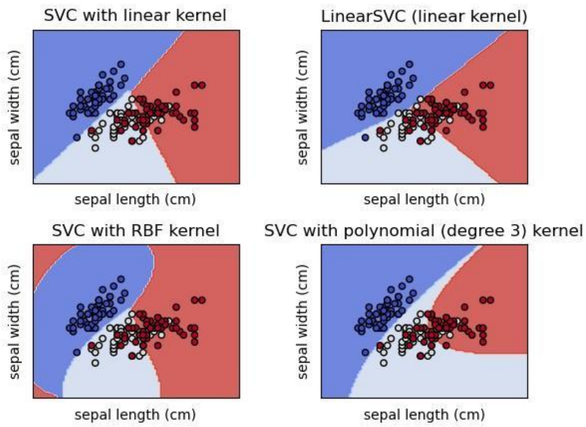


Fig 3.2: SVM

A supervised ML method called SVM can be used to solve classification or regression issues. However, it is most typically used for categorization of texts and other categorisation-related problems.

B. K-Nearest Neighbours: The KNN algorithm is a supervised learning[8], non-parametric classifier that makes predictions or classifications about how a single data point will be grouped [8].

A network of neurons is a group of algorithms that seeks to find underlying links in a set of data by employing a method that is similar to how the brain works in humans. In this context[4], neural networks are collections of neurons which can have a synthetic or organic origin [4].

Random Forest, developed by Leo Breiman, PhD, and Adele Cutler, is a popular machine learning technique which combines the results of numerous decision trees to obtain a single result[10]. Its adaptability and usefulness, as well as the fact that it can address classification and regression concerns, are what drive its extensive adoption[10].

Decision Tree: The not parametric supervised learning approach known as a decision tree can be used to carry out both classification and regression tasks[9].It has a single root node, divisions, internal nodes, and nodes for the leaves and is arranged hierarchically[9].

The independence of predictions in Bayes' Theorem is the foundation of the classification approach known as Naive Bayes [5]. Simply expressed, a classifier based on Naive Bayes thinks that the existence of one feature within a class has no bearing on the existence of any more features[5].

Logistic regression: Logistic regression is an example of supervised learning. It is employed to ascertain or predict the probability that an event with two possible outcomes will take place. Logistic regression is one method of using machine learning to determine if a person is likely to carry the COVID-19 virus or not[2].

XGBoost is an ensemble ML method built on decision trees and a gradient boosting framework. For prediction problems involving unstructured data (images, text, etc.), artificial neural networks frequently outperform all existing algorithms or frameworks. [11].

Voting Classifier: It is a particular kind of machine learning estimator that develops a number of different initial models or estimators and then generates predictions by averaging the output of each base estimator. The aggregating criterion may be taken into consideration while casting a vote for each estimator output[13].

Adaboost: An AdaBoost [6] classification algorithm is a meta-estimator which initially fits a classifier on the initial data set, and then fits more copies of the classification algorithm on the exact same dataset with the weighting of incorrectly classified instances changed to ensure that subsequent classifiers focus more on difficult cases[6].

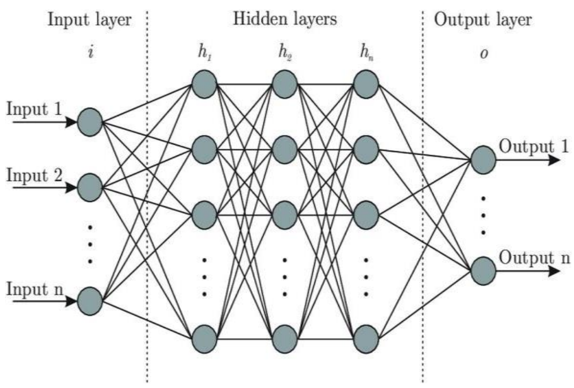


Fig 3.3: Neural network

The model was developed with the aid of SVM, KNN, NN, Random Forest, DT Decision Tree, Naive Bayes, LR Logistic Regression, Xgboost, Voting Classifier (LR + SVM + DT), Adaboost, and Voting Classifier (Adaboost + Xgboost). We selected collaborative filtering (CF) and content-based modelling (CBM), two well-known algorithms that perform well in recommender systems. Two user-centered approaches—context- and emotion-based versions—are garnering increased attention as a result of the challenge of choosing a track relevant to modern sentiment. After completing all the training procedures, the model is trained and ready for testing.Data from 25% of the dataset were used for testing.

4. RESULTS

We offer datasets with about 304 items that include user health parameters for training and testing. In order to create a better model, we slightly altered the binary digits value in a few column columns. We also enhanced the model accuracy by increasing the number of epochs to 5, while at the same time decreasing the loss. Training on multiple datasets resulted in the creation of distinct models. The use of the multiple health parameters that need to be considered increased the music recommendation model's accuracy rate.

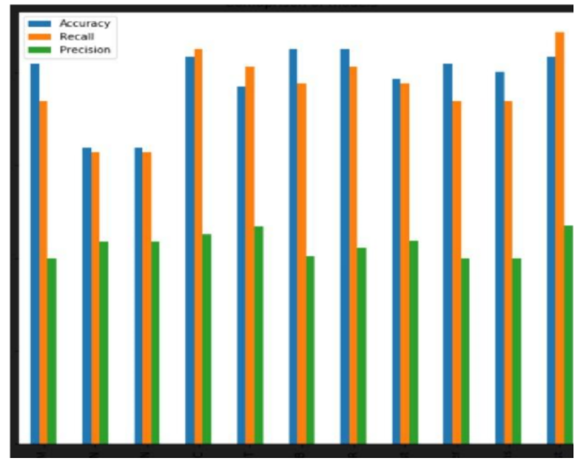


Fig 4.1: Accuracy

By determining the user's mood and then playing the suggested song, the series of graphics below shows the steps involved in producing music recommendations. We can see the algorithm playing the recommended song and inferring the user's mood from the given information.

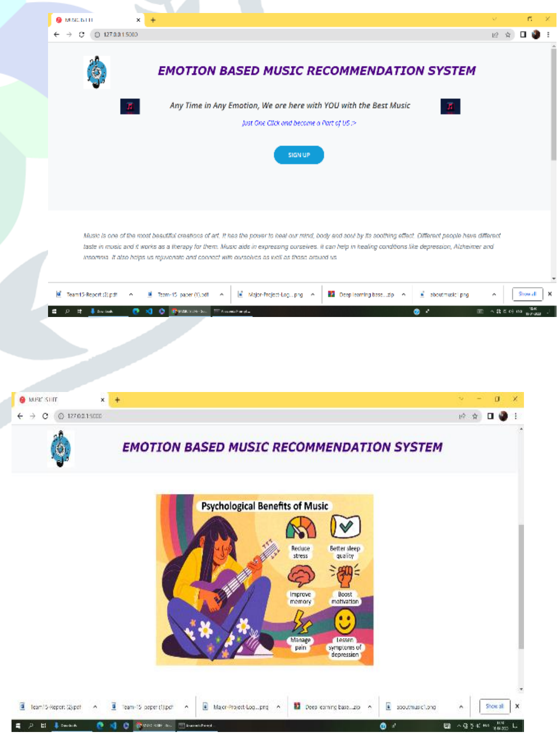


Fig 4.2: The home page

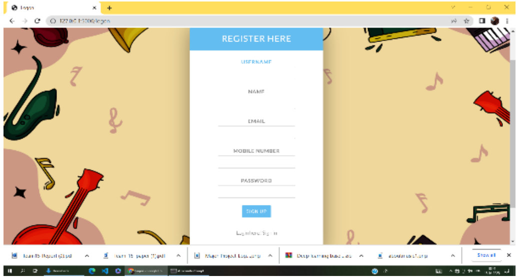


Fig 4.3: Registration page

If the user is a new one, they are then routed to the registration page; otherwise, they are forwarded to the login page illustrated in fig. 4.4.

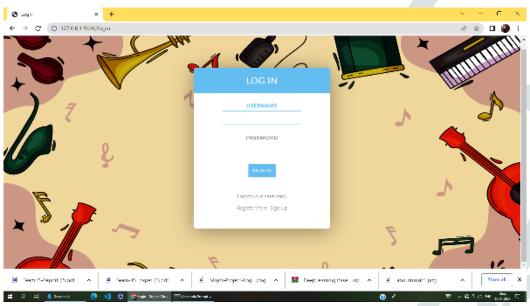


Fig 4.4: login page

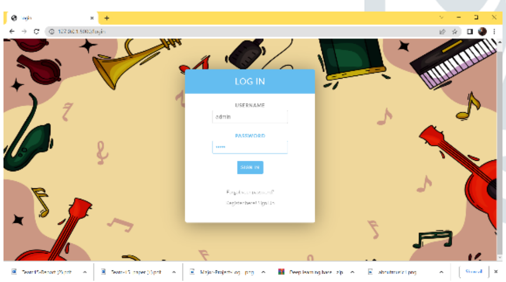


Fig 4.5: Entering details in login page

Following registration, the user must input their username and password in order to access the system.

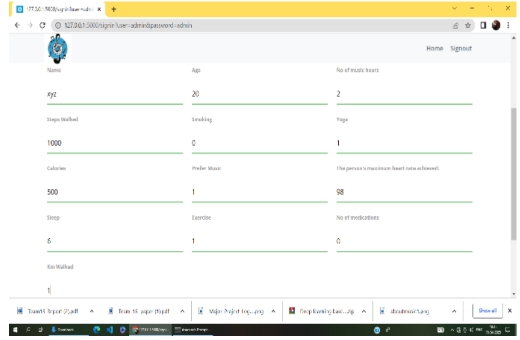


Fig 4.6: GUI interface 1

The data entry screen for users' health characteristics and habits is shown in Fig. 4.6. It asks for information like heart rate, sleep duration, number of steps taken, and sleep hours in order to assess and recommend music based on the user's mood.

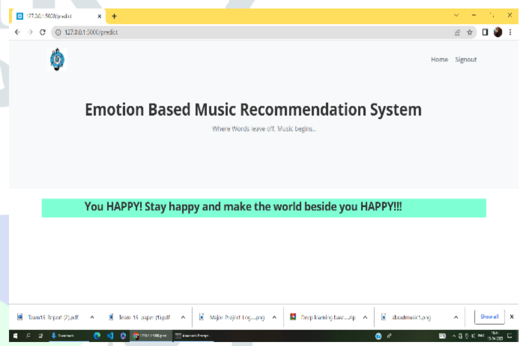


Fig 4.7: GUI interface 2

When you complete the form in Fig. 4.6, a result will appear with the quote that best describes your mood, and the suggested song will begin to play immediately.

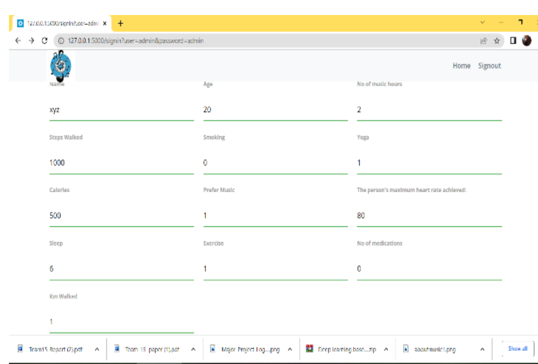


Fig 4.8: GUI Interface 3

Figure 4.8: The system must determine the user's mood in relation to the given data in order to play the suggested music. The entered data includes the user's heart rate as 143, the fact that he exercised, and 230 calories.

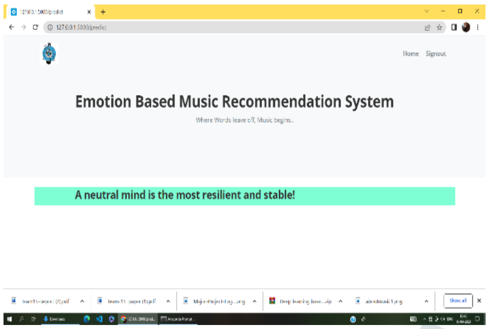


Fig 4.9: GUI Interface 4

Figure 4.9: The anticipated mood is a melancholy one, thus to uplift the viewer, a quote is displayed and the suggested song is playing in the background.

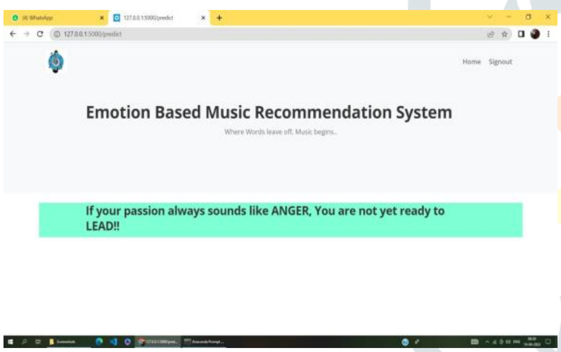


Fig 4.10: GUI Interface 5

Figure 4.10 shows the outcome, which shows anger, and plays the suggested song.

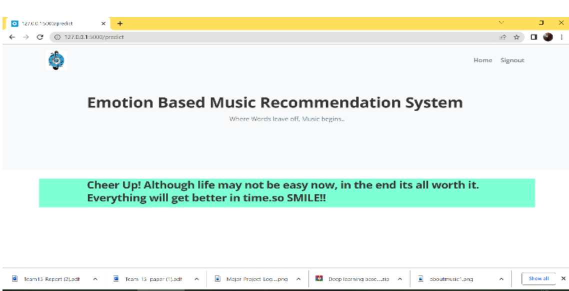


Fig 4.11: GUI Interface 6

5. CONCLUSION

This study covers the findings of the existing research on music recommendation from a variety of angles, including recommendations based on user ratings, hashtag usage, users in comparable circumstances, and people with apparent shared musical preferences. This demonstrates that the current recommendation systems where a new user finds it challenging to listen to music because there is no user-listening history. A user's historical listening habits, song ratings, most commonly liked songs, most listened to songs, etc. are all used by contemporary music recommendation systems to determine which songs to suggest. A system that recommends songs to users based on their mood swings does not, however, exist for music suggestions. As a result, the concept is to develop a music recommendation system that allows users to get songs based on their mood swings. The user's mood is analysed along with the user's health parameters, such as pulse rate, number of hours slept, number of hours worked, number of steps taken, etc. We then try to create music from emotion using collaborative filtering before recommending music to the user that is in line with their current mood.

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