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Applying Random Forests to Anticipate Music's Therapeutic Effects on Individual Patients

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Abstract

Individuals may experience stress due to a variety of factors in their everyday lives, including but not limited to work pressures, personal concerns, natural catastrophes, acts of violence, and so on. Stress has been linked to a wide range of physical and mental health issues, including but not limited to: asthma, headaches, anxiety, depression, heart disease, asthma, Alzheimer's disease, and more. Music therapy has the potential to promote the mental and physical well-being of its patients. As a kind of complementary and alternative medicine, music therapy uses musical interventions to treat psychological, physiological, and socioemotional distress. We set out to create a system for categorizing and forecasting MT-appropriate musical compositions using the Random forest machine learning technique. This study takes into account a number of factors, including the therapist's and client's musical tastes, stress and anxiety levels, and the time spent relaxing before and after music therapy. The accuracy performance of this classification is about 89, and our study elucidates critical aspects in music prediction for music therapy.

Introduction

Physical and mental health may both be improved by a variety of therapies, one of which is therapy. Music listening is a popular pastime because of the favorable psychological and neural effects it may have on the listener. The goal of music therapy is to find positive health outcomes via musical intervention. The stress and health issues like heart disease, depression, anxiety headaches, etc. that

plague many individuals may be alleviated by music therapy, which is a kind of relaxation treatment. Although music therapy has gained a lot of attention and popularity recently, little is known about the impact different genres of music have on individuals or how therapists decide which songs to use during sessions.

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Dementia, autism, cancer, aphasia, and heart disease are just few of the medical conditions that music therapy may help with. The healing effects of music vary depending on its structure. Many research have shown a correlation between musical and cognitive preferences, but have ignored therapeutic implications. Using demographic data (age, education, gender, interest in music, self-selected music choice, therapist-suggested music choice, and relaxation scale, where 0 indicates no pain/stress and 10 indicates heavy pain/stress), this proposed system predicts and classes the music preference type for music therapy using a random forest algorithm. Individuals may choose to listen to either self-selected music or music provided by their therapist, both of which are based on therapeutic goals.

Because of its increased predictive capacity compared to decision trees and its resistance to over fitting, the Random forest method was chosen for this research. This technique also allows for the extraction of features. They are a kind of ensemble model that uses a random decision tree. The machine learning method random forest may be used for both regression and classification, and it is supervised. This method builds decision trees from data and then uses voting to choose the optimal solution based on the predictions of each tree. Based on these forecasts and categorizations, we can determine which musical genres have therapeutic effects. Here, we include the patient's and the therapist's musical preferences into the forecasting process.

Related Work

In the article [1], the decision tree algorithm is used for classification and prediction of effectiveness of music therapy because they are simple to visualize. In this study the effectiveness is predicted in terms of classifying the result in positive, negative and no change category. These category deals with the relaxation level. As a result, a decision tree is produced with an overall accuracy of 0.79 in this research. Article [2] deals with the study on the link between emotional judgments and listening to music using various machine learning techniques such as linear regression, artificial neural networks, and random forests. Here the factors related to therapeutic outcomes and the relation between music listening and therapeutic results remain unexamined.

Article [3] [4] concerning the growth and importance of music therapy. This study obtained descriptive data on training needs, development of the music field, clinical trends, and practice status. They conclude that there is a positive outlook on the music therapy field's future by many therapists and music therapists provide high-quality services in mental health. Article [5] also deals with the relation between musical styles and cognitive styles. Here the study is related to cultural aspects because they influence the music tastes of the people. In this study also the therapeutic effects of music listening were not considered.

Article [7] provides a study about how music interventions lead to stress reduction and balance their mental health and aimed to assess the capability of the effect of music on both physical and mental

stress-related outcomes. They conclude that music intervention is best considering their low costs, lack of side effects and effects of music are significant for the treatment and prevention of stress-related problems.

Article [8] concerns the capability of listening music in its considerable impact on the brain. In this study, the melodic health approach is discussed and they lead way to new therapeutic perspectives and innovative neuroscience research models on the impact of music on the human brain.

Proposed System

Figure 1 shows the proposed work. Where the first step is identifying the necessary attributes needed for classification and prediction. The second step is the collection of data from various sources or people. The third step is pre-processing. It is a process of converting the raw data into proper data set (i.e.) remove noise. The fourth step is using the random forest classifier, a machine learning technique and identifying the importance of each features/attributes involved in the study. Next step is to contrivance the Random forest algorithm for both types of classification with all attributes and only with sorted out attributes respectively. In the final step predicting the music in concern to various factors is achieved and the performance of both types of classification are compared and analyzed.

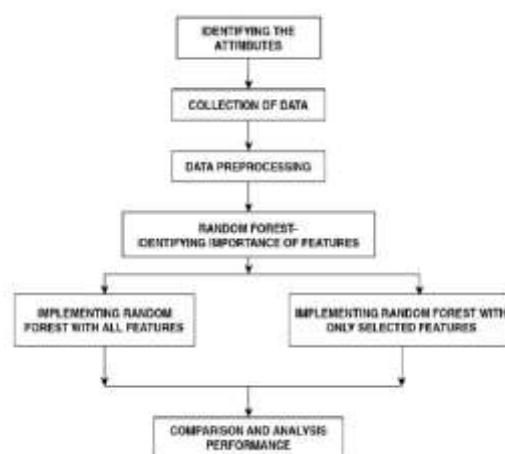


Figure 1. Proposed System

Methodology

The steps involved in our method is explained as follows

Objective

The main aim of the present study is to classify and predict the music for music therapy using random forest classifier and to investigate the importance of various factors like age, gender, education level, music practice, choice of music, and relaxation score before and after listening music involved in the study.

Dataset

The collection of numbers or values that relate to a particular subject is called a data set. In this study, we collected data on personal information and their experience on music therapy from various people. The data set contains personal information of an individual and the relaxation score in terms of Visual Analog Scale [VAS] before and after music listening on both individual and therapist choice of music. 10 attributes are involved and the attributes are as follows

- Age
- Gender
- Education level
- Music interest
- Individual music choice
- VAS score before listening to self-choice music
- VAS score after listening to self-choice music
- Therapist music choice
- VAS score before listening to therapist choice music
- VAS score after listening to therapist choice music

Data Preprocessing

Data pre-processing is used to process collected data before feeding it into the algorithm. Usually, data are collected from various sources so there is any noise in data. So pre-processing removes noise and converts the raw data into feasible data used for analyze. Here transformation of data is carried out which involves converting the data type of features from one form to another form. (I.e. string to numeric form).

Input Parameters

User input details such as age, gender, education level, music interest, individual choice of music, therapist choice of music, VAS score before and after listening to music are the 10 attributes involved.

Train and Build Machine Models

Here the dataset is randomly divided into two parts such as a training dataset and a testing dataset which is 60% and 40% respectively.

Feature Importance

The decrease in node impurity weighted to the probability of reaching node measure the feature significance the more important feature has the higher value. From each tree the feature importance

values are total normalized as illustrated in equation 1.

$$RFI_i = \frac{\sum_{k=1}^N \sum_{j=1}^M f_{ij}^k}{\sum_{j=1}^M \sum_{k=1}^N f_{ij}^k} \quad (1)$$

Results and Discussion

The collected data set is pre-processed and fed into the random forest model. Here the classification and prediction is carried out. Performance metrics like Accuracy, Precision, recall, F1-score are evaluated. The feature importance is also determined with the ratio to the normalized feature importance for n in tree k and total number of trees.

In Figure 2, the feature importance score of the features is depicted. This feature importance illustrates the important factors that are involved in the classification and prediction of music dataset.

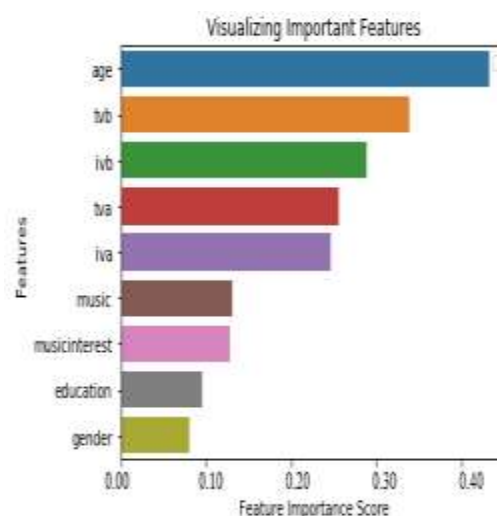


Figure 2. Visualizing Importance features

The Table 1 illustrates the performance metrics of the model that involves all 10 features. The overall

accuracy obtained from this model is 83.4%. The total number of instances taken for testing is 84 and misclassified instances are 14.

Table 1. Predictive analytics for model that involves all features

	PRECISION	RECALL	F1 SCORE	SUPPORT
CLASSIC	0.92	0.83	0.87	17
POP	0.85	0.83	0.81	27
HIPHOP	0.82	0.84	0.83	40
ACCURACY	0.83			

The Table 2 illustrates the performance metrics of the model implemented with selected highest six features according to its importance. The features that are involved are age, relaxation value before and after hearing music for both individual and therapist music choices. The overall accuracy obtained from this model is of about 89.28%. The total number of instances taken for testing is 84 and misclassified instances are 9.

Table 2. Predictive analytics for model that involves selected features

	PRECISION	RECALL	F1 SCORE	SUPPORT
CLASSIC	0.97	0.89	0.94	14
POP	0.88	0.86	0.87	31
HIPHOP	0.86	0.90	0.88	39
ACCURACY	0.89			

Conclusion and Future Work

For the sake of music therapy, this study developed a system of categorization and prediction. When evaluating music therapy, it is important to consider how subjective preferences and therapeutic goals

influence the categorization of music. Also discussed are comparative analyses of feature participation in system performance, with emphasis on the visualization of key characteristics. Since the random forest approach may be used for both regression and classification, it is more flexible and hence more valuable. Overall, the algorithm's results are rather impressive. The positive benefits of music therapy on both physical and mental health are also highlighted in this research. This categorization will help music therapists choose music that is appropriate for their therapeutic goals and help their patients improve their mental health.

After identifying parameters like age group, gender, education level, present mood condition, and so on, this study may be improved by different machine learning algorithms for prediction. If more qualities are required for prediction, they may be added.

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