Predicting the Effects of Music on Patients Using Random Forests

PRATYUSH RANJAN MOHAPATRA
ASSISTANT PROFESSOR, Mtech,Ph.D
Department of CSE
Gandhi Institute for Technology,Bhubaneswar.

Abstract

Many things in daily life, including professional demands, personal issues, natural disasters, acts of violence, and so on, may cause stress for individuals. Asthma, headaches, anxiety, depression, heart disease, asthma, Alzheimer's disease, and a host of other physical and mental health problems may all be attributed to stress. Both the emotional and physical health of its patients may be improved by music therapy. Music therapy is a kind of alternative medicine that employs music to address mental, physical, and emotional health issues. Our goal here was to use a machine learning method called Random forest to build a system for classifying and predicting musical compositions for use in music therapy. Individual and therapist music preferences, levels of stress and anxiety, and pre- and post-music-therapy relaxation are all considered in this research. Our research elucidates key factors in music prediction for music therapy, and this classification achieves an accuracy performance of about 89.

Introduction

Therapy is one of the types of treatments that aim to improve one's physical and mental fitness. Listening music is a widespread habit among people which can activate the brain structures combined with the positive mood of an individual. Music therapy is a field that pursues a connection between music and health. Music therapy is also a relaxation technique that helps people to come up with their stress and stress-related health problems like heart diseases,

Depression, anxiety headaches, etc. The importance and interest of music therapy among people is well

known still what type of music produces what type of effects and how the therapist determine the choice of music for therapy remains unknown.

Music therapy is used to improve the quality of life of people who suffer from medical disorders like Dementia, Autism, Cancer, Aphasia and heart disease. Various music structures have various therapeutic results. The link between musical styles and cognitive styles has also shown in many studies but the therapeutic aims are not considered. In this proposed system the music preference type for music therapy is predicted and classified by random forest algorithm using the information of the people such as age, education level, gender, interest on music, self- selected music choice, a therapist suggested music choice and their relaxation scale from 0 to 10(i.e. 0 indicates no pain/stress and 10 indicates heavy pain/stress) before and after listening music are taken respectively. Self-selected music is an individual interested music choice and the therapist suggested music is a therapist choice of music according to therapeutic aims.

For this study we use Random forest algorithm because this algorithm increases the predictive power when compared to decision tree and avoids over fitting. Feature extraction is also possible in this method. They are also known as ensemble model of randomized decision tree. Random forest is a supervised machine learning algorithm that is used for both regression and classification. This algorithm generates decision trees on data and finally selects the best solution from the prediction from each of the trees by means of voting. From this prediction and classification, we can able to identify the music with their therapeutic results respectively. Here we include both individual and therapist choice of music in prediction.

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.

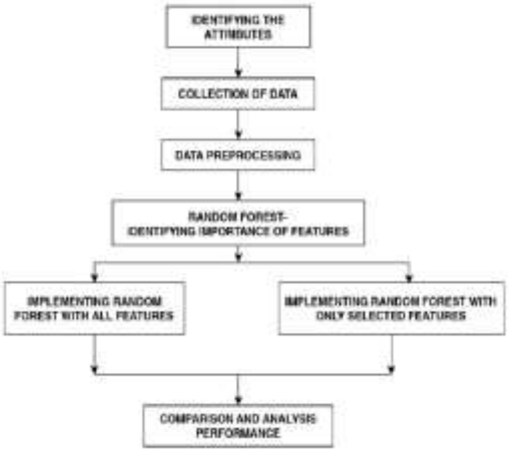

Figure 1. Proposed System

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 eqaution1.

$$RFfi_i = \frac{\sum_{j \in} normfi_{ij}}{\sum_{j \in all\,features, k \in all\,trees} normfi_{jk}} \qquad (1)$$

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.

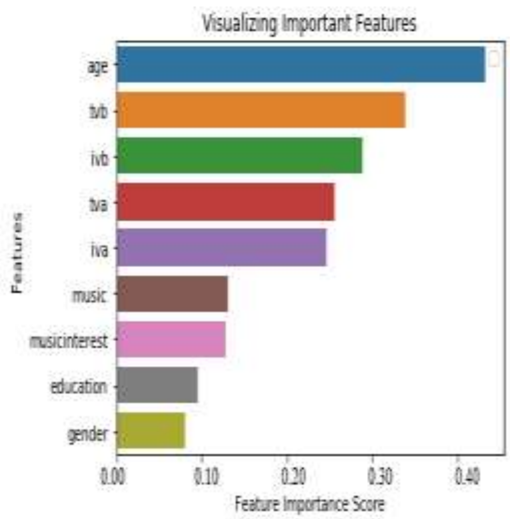

Figure 2. Visualizing Importance features

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.

References

[1] Raglan A, Umbrian M, (2019), Machine learning techniques to predict the effectiveness of music therapy: A randomized controlled trial in computer methods programs in biomedicine.

[2] N.N. Vempala, F.A. Russo, Modeling music emotion judgments using machine learning methods, Front. Psychol. 8 (2017) 2239, doi: 10.3389/fpsyg.2017.02239.

[3] M. de Witte, A. Spruit, S. van Hooren, X. Moonen, G.J. Stams, Effects of music interventions on stress-related outcomes: a systematic review and two meta-analyses, Health Psychol. Rev. (2019) 1– 62, doi: 10.1080/17437199.2019. 1627897. [4] Kelly Muphy, Winston Liu, Daniel Goltz, Emma Fixsen, Stephen Kirchner, Janice, Heidi White, (2018), Implementation of personalized music listening for assisted living residents with dementia https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6812488/.

[5] David M. Greenberg, Simon Baron, Cohen,David J. Stillwell, Michal Kosinski, Peter J. Rentfrow Mean Preferences are linked to Cognitive Styles (2015) https://doi.org/10.1371/journal.pone.0131151.

[6] Raglio, A. (2011). When music becomes music therapy. Psychiatry Clan. Neurosis. 65, 682– 683. doi: 10.1111/j.1440-1819.2011.02273.

[7] Effects of music interventions on stress-related outcomes: a systematic review and two meta- analyses by Martina de Witte, Anouk Spruit, Susan van Hooren, Xavier Moonen &Geert-Jan Stams (2019) doi.org/10.1080/17437199.2019.1627897

[8] Levitin, D. J., and Tirovolas, A. K. (2009). Current advances in the cognitive neuroscience of music. Ann. N.Y. Acad. Sci. 1156, 211–231. doi: 10.1111/j.1749- 6632.2009.04417.

[9] A Comparative Study on Decision Tree and Random Forest Using RToolhttps://ijarcce.com/wpcontent/uploads/2015/02/IJARCCE3L.pdf

[10] Wei Peng, Juhua Chen, and Haiping Zhou. An Implementation of ID3 -- Decision Tree Learning Algorithm. Retrieved March 10 (2009)