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Music Therapy Using EEG Brain Wave Signals

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Abstract: ***Music is an emotion. Music helps us to feel things in a better way by interacting with our senses. More than 75% of people listen to music every single day and with the latest advances in technology, it has become much simpler and easier for a user to listen to music, simply via a mobile app. It has been found that people having certain disorders like anxiety, depression, stress, etc are in need of music therapy which could help them relax and make them calm. Music therapy is an evidence-based clinical use of music interventions to address physical, emotional, cognitive, and social needs of individuals. Music therapy app provides a platform for individuals to access music therapy treatment remotely, at their own convenience. Music therapy app have the potential to improve the accessibility and effectiveness of music therapy for a wider population. In this paper, we have analyzed the EEG brain wave signals of the user and developed a Music Therapy app where the user could listen to any one of the moods like Attention, Meditation, and Sleep which is based on a self-learning model.***

Keywords: Music therapy, Mobile App, Machine learning, Android Studio.

1. Introduction

In this rapidly changing society, people from all age backgrounds are facing a lot of depression and stress from external things. Children have exam tension and the forceness to get good and high marks have only led to the increase in their depression, automatically destroying their mental health. Adults are faced with work pressure, stress, humiliation which is basically affecting their physical and mental health. The World Health Organisation (WHO) have listed Heart Disease, Depression, and AIDS as the three most dangerous diseases in human beings. Depression is the second dangerous disease and about more than 20% of the world population have depression. Depression and Stress causes both physical and psychological damage to the human being. Therefore it is indeed crucial to develop a method/system to cope up with depression and provide a way to overcome them. It is medically impossible to fully recover from depression, as no medicine can provide a cure to that. But it is possible to overcome them by deploying an effective way to tackle them in a slow and steady way. Music therapy is one of the many ways to tackle depression and stress, by using music interventions to users with depression and stress. By continuously listening to music the brain wave signals of the user changes that in turn helps the user to relax and be calm. It is found that certain music pieces have the potential to soothe the user's mood and help in reducing stress.

2. Literature Survey

Lee et al., [1] developed and implemented a music recommendation system that gives consumers a list of calming emotions. This study used an EEG Bluetooth headset that is readily accessible off the shelf and had sensors that can record changes in brain waves. Data transmitted securely with the mobile device using the Bluetooth transmission mechanism. Various cognitive dysfunctions and disorders were identified from the EEG signal, which can also reveal a wealth of other information. Additional EEG signal analysis, classification, and depression level categorization was used as a basis for music therapy evaluation in addition to giving medical personnel a reference for treatment.

Llerena et al., [2] proposed a system by observing brain wave activity and stress levels recorded by an EPOC+ electroencephalogram device, this paper created a prototype that lowers students' stress levels. After implementation, the findings revealed that 76 percent of respondents were successful in reducing their stress, 19 percent did not require music therapy, and 5 percent were unsuccessful in doing so. A sample of 44 out of 274 pupils tested the prototype, with positive results.

Chen et al.,[3] proposed a detailed study to determine how the type of music listened to and brain waves are related. It was made simpler to prescribe a certain genre of music to relieve tension, anxiety, or increase mood, or even to help in better focus while executing a task, due to the study of the Electroencephalographic (EEG) on Alpha, beta, and Theta waves. This research had shown that listening to calming music lengthens the wavelength of theta and beta waves. A high level of creativity and idea flow is indicated by an increase in theta wave wavelength, aid in triggering the brain's ability to analyze numerous issues and think logically and the capacity of long-term memory has increased.

Thapaliya et al.,[4] proposed research that examines how software developers' electromagnetic brain waves change while they program with or without music and how music affects their jobs as a whole. The programmer's brain activity was measured with an EEG equipment and pre-processing techniques were used to calculate the arousal-valence coefficients. The results showed that the mean valence was higher and the mean arousal was lower when programming with music.

Gabbualoy et al.,[5] proposed a technique for stimulating human brain waves based on monaural beats conveyed through speakers and enhanced by the theory of low frequency vibrations was described. A laboratory test with dimensions of 2.60 x 4.03 x 3 meters and frequencies of 131.81 Hz and 121.81 Hz that were produced and delivered via audio speakers was constructed using the principles of music and audio engineering. The frequency was found by using a particular microphones and software. 25 subjects were chosen to wear EEG headsets to measure the brain waves, and data was collected to analyze in MATLAB using biomedical engineering techniques. The results showed that the people can hear monophonic beats.

Divya et al.,[6] proposed a case study on the impact of music therapy on various individuals of various ages, at various times, while using a variety of ragas, and while taking a reading of blood pressure was discussed. This study is used to further explain the impact of music therapy on children with autism and how robots are used to support music therapy sessions. The goal of this essay is to demonstrate and persuade readers that music therapy can be used instead of prescription medications to treat autism, reduce stress, and shorten recovery times.

Rao et al.,[7] proposed research that focuses on auditory signal processing and brain signal processing are condensed in this article. The reviewed articles in audio signal processing pertain to both Western and Indian music. In the field of brain signal processing, BCIs created for western music, such as brain signals controlled music players, music production, music evaluation, changes in brain signals when listening to various types of music, musical interfaces, etc. Details about Indian classical music's impacts on brain waves are provided in a later paper. The goal of this study is to draw attention to a survey of BCIs that concentrate on music before, in the end, focusing only on Indian music.

Nugroho et al.,[8] proposed that the EEG recordings made during patient recordings will be useful in this study for assessing and diagnosing EEG signal behavior patterns. Gamma, alpha, beta, theta, and delta signal behavior exhibits specific medical meanings related to changes occurring in the patient's brain. Medical professionals will be greatly helped in their diagnosis of all patient medical opportunities by changes in patterns. The results of monitoring the electrical activity in the brain captured by this prototype will be highly beneficial in supporting subsequent medical decision-making. This schema can also act as a forewarning to prevent potential severe flaws in human health and brain function.

Rahman et al.,[9] proposed a system where classification models based on these features using K-nearest Neighbor (KNN), Support Vector Machine (SVM), and Neural Network technologies (NN) were created. The algorithm also achieves 98.6% accuracy when categorizing music based on the subjective ratings of emotion provided by the participants. The recorded brain waves also reveal various gamma wave levels, which are essential for spotting epileptic convulsions. The findings demonstrate that these computational methods are useful for classifying musical genres according to how they affect listeners' brains.

Summary:
This work in contrast to the above mentioned works implemented both machine learning and deep learning techniques to analyze the performances of both and to conclude the best, which is based on various validation factors.

3. Problem Definition

Music can be used as a therapy in many different ways depending on the specific needs and goal. Some of the ways include listening to music, singing, song writing, playing instruments, and Guided Imagery and Music (GMI). Singing can be used to help users express their feelings and emotions and improve communication skills. It is used to promote relaxation and reduce stress. Playing a particular music instrument is also one of the ways used by Music Therapists, as it is used to promote motor coordination and fine tune motor skills. Playing an instrument is also used as a form of self-expression. We have used the first method as the primary method in our paper. Listening to particular pieces of music has a positive impact on the brain wave signals and this can be used as an analysis metric to detect user's current mood and recommend them music accordingly.

The basic steps involved in a music therapy session are included in Fig. 1.

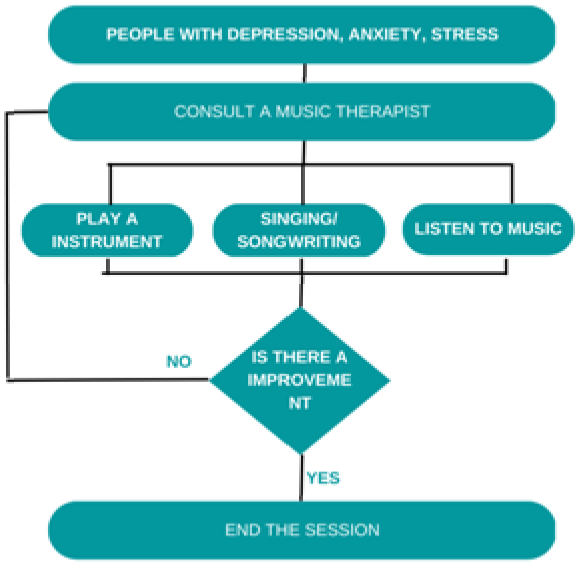

Figure 1: Process flow in music therapy

This manuscript is mainly divided into 8 sections: Section I: Introduction, Section II: Literature Survey, Section III: Problem Definition, Section IV: Architecture of the proposed work, Section V: Implementation, Section VI: Evaluation and Results, Section VII:Conclusions & Future Scope, Section VIII: References.

4. Architecture of the Proposed Work

The proposed architecture is shown in Fig. 2. The architecture mainly consists of analyzing the brain wave signals, preprocessing it, building the machine learning model, developing the mobile app using Android Studio.

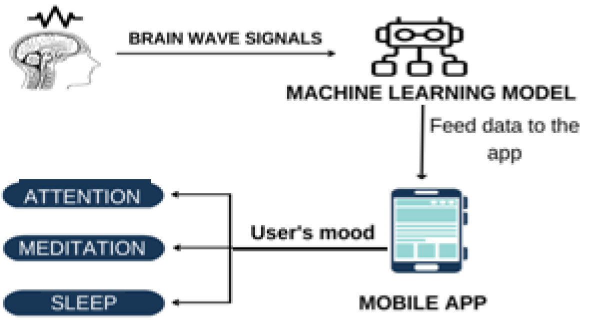

Figure 2: Architecture diagram of the proposed work

4.1 Brain Wave Signals

The brain wave signals are captured using the Electroencephalography (EEG) sensors and represent the measurement of voltages that should be captured in an accurate way. These brain waves can be categorized into five major types: Delta(0.5 - 3 Hz), Theta(3.5 - 7.5 Hz), Alpha(8-14 Hz), Beta(14-30 Hz), Gamma(30-70 Hz). These brain waves also have some significance of their own, that can be used to identify a particular state of the user. The significance is listed in Tab 1.

Table 1: Brain waves and their significances

Brain waves	Significance
Delta	deep sleep
Theta	drowsy, light sleep
Alpha	relax, non-active thinking
Beta	concentrating, critical thinking, problem solving
Gamma	memory access, recognition, perception

4.2 Machine Learning Model

There are various machine learning models that can be used to analyze EEG signals, some of the most popular ones include:

Support Vector Machines (SVMs): SVMs are a type of supervised learning algorithm that can be used to classify EEG signals. They find a hyperplane in the feature space that maximizes the margin between different classes.
Random Forest: Random Forest is an ensemble learning method that can be used to classify EEG signals. It creates a set of decision trees and combines their predictions to improve the overall performance of the classifier.

Recurrent Neural Networks (RNNs): RNNs are a type of neural network that can be used to process sequential data such as time series or natural language. They can be used to classify EEG signals by analyzing the temporal dependencies between different EEG samples.

Convolutional Neural Networks (CNNs): CNNs are a type of neural network that can be used to analyze image data. They can be used to classify EEG signals by analyzing the spatial dependencies between different EEG channels.

4.3 Mobile App

The detected mood of the user, after the data has been pre processed and sent to the model, is fed to the mobile app. The mobile app is created using Android Studio and Java is used as the programming language to create the app. The songs are stored in Firebase RealTime Database storage which can be integrated in the Android Studio. The user can also upload music of their own by uploading it in the firebase storage.

Three kinds of music are stored in Firebase storage, where each one of them contains different sets of music. The user can select any one of them and the list of music gets played in a continuous manner. Each music has a duration of not more than 240 seconds, since there is a chance for the user to get a feeling of repeatedness.

5. Implementation of Proposed System

The Brain Wave EEG signals are preprocessed using various standardization techniques to remove any kind of outliers since the values in the dataset are mostly continuous. The preprocessed data is splitted into training and testing sets. Various machine learning algorithms like Random Forest, Decision Tree, Support Vector Machine (SVM), K-NN, etc. The accuracies are tabulated to provide a comparison analysis with deep learning models. The Long-Short Term Model is used to provide further depth for the preprocessed data. The model with higher accuracy and the one that performed the best during the validation phase is chosen as the primary model for further analysis.

The detected state of the user is used as the input for the mobile app. Accordingly, the app gets users a list of music that can be played continuously depending on the user's choice. The mobile app is built upon Android Studio Platform, integrated with Firebase RealTime Database Storage.

EEG Brainwave Dataset is a dataset of EEG data that has been processed with statistical extraction methods. The data has been collected from two people(1 male, 1 female). The data is collected for 180 seconds in a continuous manner, each per state. They have used a EEG Muse band using dry electrodes to collect data from four scalp locations which includes temporoparietal (TP9, TP10),frontal(AF7, AF8). These locations are majorly used to track the four kinds of brain waves and continuous recording of these waves are tabulated in the dataset. The various kinds of locations and their uses are shown in Fig. 3.

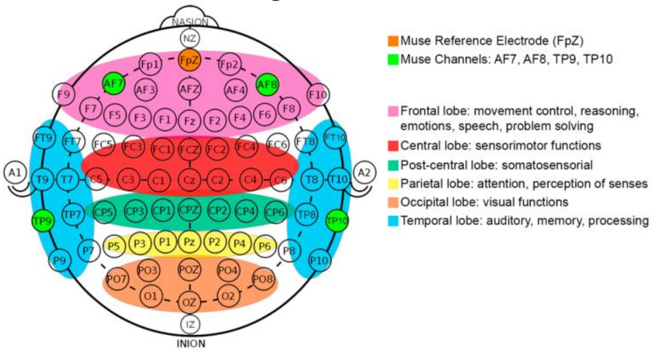

Figure 3: Electrode locations and their uses

5.1 Preprocessing dataset

The EEG Brainwave dataset is loaded into the dataframe and the whole dataset is splitted into three parts: Meditation, Attention, Sleep. The corresponding dataframe are then visualized to analyze the spread of data across time. Standardization techniques and One Hot Encoding is used to categorize the output states as: 0-Meditation, 1-Attention, 2-Sleep. The dataset is then splitted into training and testing sets and used for building the model.

The distribution of data for three states is shown in Fig. 4.

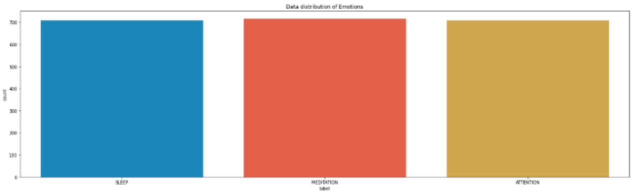

Figure 4: Distribution of three states

5.2 Building the model

Neural network model is built using Tensor Flow's Keras API. The function takes no input arguments. It consists of an input layer for the model with shape specified as the number of columns in the input data (x_train.shape[1]). It adds a GRU (Gated Recurrent Unit) layer with 256 units and set return_sequences=True, this layer will be used to process the input data. GRU is a type of recurrent neural network that can be used to process sequential data such as time series or natural language. Flatten layer is used, it will reshape the output of the GRU layer into a one-dimensional array. Finally it creates an output layer with 3 units and using the activation function 'softmax' which is commonly used in multi-class classification problems. The model is then compiled using the 'adam' optimizer, categorical crossentropy loss function and accuracy as the evaluation metric.

5.3 Mobile App Development

Android Apps are developed using Java programming language. The Android app serves as the frontend of the system. The frontend is responsible for the user interface, handling user input, and displaying data. The backend, on the other hand, is responsible for handling data processing, logic and communication with other external systems like databases (Firebase).

The backend in this case is a web application built using Flask, a micro web framework for Python. The Android app communicates with the Flask app through API requests. When the user clicks on a specific mood button on the Android app, it sends an API request to the Flask app. The Flask app receives the request, processes it, and sends a response back to the Android app. The Android app then processes the response and plays the appropriate songs based on the user's mood selection.

The Android app sends an API request to the Flask app using the Volley library, which is an HTTP library for Android that makes networking for Android apps easier and faster. Volley is designed to be efficient, for both small and large transfers, as well as for handling a large number of concurrent network connections.

The Flask app receives the API request, processes it and uses a pre-trained LSTM (Long Short-Term Memory) model to generate a list of recommended songs for the specific mood that was requested by the user. LSTM is a type of recurrent neural network (RNN) that is trained to recognize patterns in sequential data, such as music data in this case. The model uses the user's mood selection to generate a list of recommended songs that are likely to match the user's current mood.

The Flask app sends a response to the Android app containing the url links of the recommended songs. The Android app then uses the MediaPlayer library, which is an inbuilt android library, to play the songs using the url links. The media player also provides controls for the user to pause, play, change to the next or previous song.

The app also has the functionality for the user to provide feedback on whether the recommended song satisfies their mood or not. This feedback is sent to the Flask app as an API request, where it is processed and used to improve the music recommendation system. The Flask app can use this feedback to update the LSTM model and make the recommendations more accurate.

Overall, the architecture is a client-server model where Android app is the client and Flask app is the server. Volley library is used to handle the API requests and MediaPlayer library is used to play the songs in the Android app. The Flask app uses an LSTM model to generate recommended songs based on the user's mood selection. The feedback provided by the users is used to improve the music recommendation system.

6. Evaluation and Results

The proposed work has used many evaluation parameters for calculation of accuracy. The classification report is used to derive the performance of the trained model using various parameters like precision, support, etc. The performance of the random forest classifier is analyzed using classification reports and tested during the validation phase. It is shown in Tab. 2.

Table 2: Classification Report of Random Forest classifier

	Precision	Recall	f1-score	Support
0	99	98	98	153
1	94	94	94	142
2	94	95	95	132
Accuracy	96	96	96	427

The classification report for the deep learning LSTM model is shown in Tab.3.

Table 3: Classification Report of LSTM Model.

	Precision	Recall	f1-score	Support
0	99	97	98	153
1	95	88	91	142
2	89	98	94	132
Accuracy	94	94	94	427

For the Deep Learning model the 5 layer neural network produced an accuracy of 94.37% after 10 epochs and the accuracy and loss plots are shown in Fig. 5.

Figure 5: LSTM Model's Accuracy vs Loss Plot

The music app developed using Android Studio is shown in Fig. 6.

Figure 6: Music app

7. Conclusion & Future Scope

In conclusion, this paper presents the development of a music therapy app that utilizes self-learning to classify EEG brainwave signals and provide personalized music selections for moods such as Attention, Meditation, and Sleep. The app has the potential to improve the accessibility and effectiveness of music therapy for a wider population, particularly for individuals with disorders such as anxiety, depression, and stress. The performance of the app was evaluated using various parameters, including precision and support, and the results showed that the random forest classifier had a high level of accuracy of 94.37%. This paper highlights the potential for music therapy app to provide convenient and effective treatment for individuals seeking to improve their mental well-being.

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