WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Mood Based Music Recommendation System Using Brainwaves

Ashwati Shrimali[1], Ritika Kumari[2], Shivam Kumar[3], Dr. Bahubali Shiragapur[4]

[1]CSE department, D Y Patil International University, Akurdi, Pune, India
[2]CSE department, D Y Patil International University, Akurdi, Pune, India
[3]CSE department, D Y Patil International University, Akurdi, Pune, India

A B S T R A C T

The Mood-based Music Recommendation System using Brainwaves is a cutting-edge method for making music recommendations based on an individual's current mood, as detected by their brainwaves. The technology records brainwave activity using electroencephalogram (EEG) signals and then uses machine learning algorithms to categorize the user's mood. The system makes music recommendations based on the user's mood, which improves their enjoyment of listening to music and emotional health. The proposed method might completely transform music recommendation systems and offer a more individualized and natural listening experience. DREAMER and GUINEA BISSAU EEG data were the datasets used in this study. Both data were obtained by measuring them using an Emotive EPOC device with 14 channels. After additional preprocessing, classification, and recommendation, automatically music playlist is generated and played by identifying the current emotion of the user. Both methods yield better performance in terms of computational time, as compared to the algorithm in the existing literature. The first approach's accuracy was 94%, while the second approach's classification accuracy for valence and arousal using SVM with PCA was 96.8% and 96%, respectively.

Keywords: EEG, Music recommendation, SVM, KNN, PCA, classification, Spotify dataset.

1. INTRODUCTION

Music has long been acknowledged for having a tremendous effect on people's emotions and general well-being. It has become necessary for these systems to make recommendations based on a person's listening history, tastes, and mood as personalized music recommendation systems become more and more popular. Many of these systems, meanwhile, rely on oblique mood assessments, like user input or musical qualities, which might not always correctly reflect the user's actual emotional state.

In this paper, we provide a novel method for creating a music recommendation system based on mood, which uses brainwave data obtained using 14 channels of the Emotiv EPOC device. A wireless EEG device called the Emotiv EPOC records brainwaves and enables real-time monitoring of cognitive and emotional processes which is shown in Figure 1. This strategy may offer more thorough and accurate assessments of the user's mood, enabling more individualized and pertinent music choices. The effectiveness of music streaming services as well as the listening experience could both be enhanced by this technique.

This project's main goal is to improve the user's mood by playing music that suits their preferences. The researchers can learn more about a person's neurological responses to music by examining electroencephalography (EEG) data, which records electrical activity in the brain. They can determine a person's cognitive and emotional reactions to different musical genres by looking at EEG patterns.

By taking into account a person's interests and emotional states, this method generates personalised music recommendations that are catered to their need. Changing one's mood might aid in getting through challenging situations like depression and sadness. Many health issues can be avoided via expression analysis, and actions can be made to raise the user's mood.

Using brainwave data from the Emotiv EPOC, this new approach to developing a music recommendation system based on mood has the potential to revolutionise personalised music suggestions. By offering more pertinent and customised music options, it can improve the user's listening experience, thereby enhancing their mood and well-being.

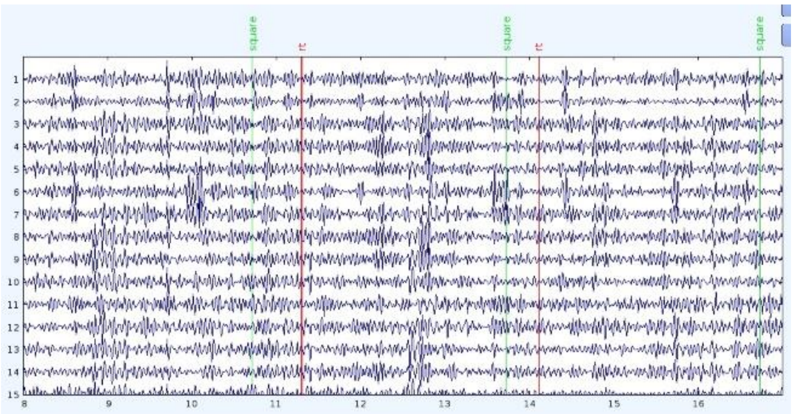

Figure 1: EEG signal of 14 channels

In this study, we applied two distinct approaches to two datasets.

- In the first method the analysis of EEG data from 97 Guinea Bissau residents. The data was pre-processed the data which was publicly accessible online data to arrive at a generalised mood categorization value. The data was categorised into ”very low,” ”low,” ”high,” and ”very high.”. The first, second, and third quantiles of the EEG data were used to calculate these levels. It was hoped to provide a more objective and accurate assessment of people’s emotional states by classifying their mood based on EEG data. This technique might increase the precision of applications like mood monitoring in hospital settings and personalised music recommendation systems.
- In the second approach, the well-known dataset for physiological signal processing and emotion analysis, DREAMER, was utilised. To cut down on noise and artefacts, the data was pre-processed, and features were extracted. Then, support vector machines (SVM) and K-nearest neighbours (KNN) classification methods were used to classify the valence and arousal of individuals from their EEG data. Each piece of music was assigned to a different emotional category after the user’s emotional state was ascertained in order to provide music recommendations. This enabled the system to make personalised music recommendations that matched the user’s emotional state. This strategy aims to deliver a more precise and customised music recommendation system by utilising machine learning techniques and EEG data analysis. This strategy has a wide range of possible applications since it might increase the efficiency of music streaming services and improve the listening experience as a whole. This method may also have effects on mental health because it may help with the treatment of ailments like sadness and anxiety by suggesting personalised musical selections that may uplift mood.

Overall, the first approach's accuracy was 94%, while the second approach's classification accuracy for valence and arousal using SVM with PCA was 96.8% and 96%, respectively.

2. PROBLEM STATEMENT

Music has been recognized as a powerful tool for uplifting mood, and researchers have dedicated significant efforts to develop more precise and effective methods of leveraging music for mood enhancement. This study focuses on the goal of improving users' moods by providing them with music that caters to their specific needs. To gain insights into an individual's neurological responses to music, this approach utilizes electroencephalography (EEG) data, which captures the electrical activity in the brain. By analysing EEG patterns, we can better understand an individual's cognitive and emotional reactions to different genres of music. This understanding enables the creation of personalized music recommendations that consider an individual's interests and emotional states. Intentionally altering one's mood from time to time can also have potential benefits in overcoming challenging circumstances such as depression and sadness. Furthermore, the utilization of expression analysis and proactive measures can help address various health concerns and facilitate mood improvement.

3. LITERATURE SURVEY

EEG, sometimes known as electroencephalography, is a non-invasive technique for observing the electrical activity of the brain. It has been demonstrated that integrating EEG with music recommendation algorithms can improve users’ listening experiences by offering more relevant and personalised music selections. This overview of the literature explores the most recent findings and developments in the area of EEG-based music recommendation systems. Studies have suggested a variety of methods, including the selection of emotive music, real-time music recommendations, the identification and recommendation of music emotions, and personalised music suggestions based on user preferences and emotional states. These methods use collaborative filtering algorithms, deep learning models, and machine learning techniques to extract information from EEG data and provide personalised music recommendations. EEG-based music recommendation systems have the potential to completely change how people discover music.

An emotive music selection system was created by Koelstra et al. (2011) [1] that tracks user emotional responses using EEG data. In their study, the system makes music recommendations based on the user’s anticipated emotional state by using machine learning algorithms to recognise EEG data associated with emotional states. However, Jin et al. (2013) [2] created a real-time music recommendation system employing a Brain-Computer Interface (BCI) to collect EEG data and identify emotional responses in order to build a recommendation model based on user preferences. Both research present promising avenues for improving user experience by generating more relevant and emotive music recommendations. The development of a music recommendation model that can represent the emotional states of listeners is made possible by the integration of EEG data with music recommendation systems.

Using EEG data, Lin et al. (2014) [3] created a system for classifying musical emotions and making music recommendations based on the user's emotional state. They identified emotions and made music recommendations depending on the user's emotional state by using feature extraction techniques to extract emotion-related features from EEG data. However, Ma et al. (2018) [4] proposed a system for providing personalised music recommendations based on user preferences and emotional states using EEG data analysis, machine learning methods, and collaborative filtering algorithms. They integrated these methods to produce a more precise and insightful recommendation system that considers the user's past listening behaviour and musical tastes in addition to their present emotional state.

In order to address the challenges faced by personalized recommendation systems, Zhang et al. (2022) [5] developed a model that focuses on studying social connections and trust relationships among users. The primary objective of their model was to recommend places of interest to users based on social impact and geographic information between users and tourist attractions. The results obtained from the data analysis demonstrated the feasibility and effectiveness of their proposed model algorithm, showing superior prediction accuracy compared to other recommendation algorithms.

Building upon the concept of social communication, Bi et al. (2021) [6] introduced an innovative social reference network model. This model integrated the attention mechanism and bidirectional LSTM (Long Short-Term Memory) within the same framework, incorporating multilayer perceptrons. By combining these techniques, they aimed to improve the accuracy and performance of social-based recommendations.

Lee et al. (2018) [7] focused their research on the automatic extraction of melodies using deep learning. They proposed an algorithm that utilizes a feature image generated by the band energy extracted from the chord audio file. By leveraging deep learning techniques, their algorithm aimed to automate the process of extracting melodies from musical data.

A lot of attention has been given to EEG based music recommendation systems recently. The ability to recognise emotions has been greatly enhanced by the combination of deep learning techniques. Although it is a long-term project, EEG based music recommendation system still require constant invention and advancement. Personalised music recommendations can be carried out with accuracy using music emotion recognition. Individual differences can be effectively solved and music retrieval techniques can become more varied by adjusting the music according to the emotional demands of the listeners. Recent years have seen a rise in the effectiveness of music-based psychiatric therapy due to the expansion of emotion-based music recommendation systems in the medical industry. As a result, the study of EEG based music recommendation is crucial to the thorough development of many fields

4. METHODOLOGY

All We have applied two distinct approaches to two datasets i.e., Guinea-Bissau EEG Data and DREAMER dataset.

4.1 Data and Sources of Data

4.1.1 DREAMER Dataset

The DREAMER dataset is a freely accessible multimodal dataset created for research on emotion recognition. It consists of physiological signs, auditory and visual cues, and information gathered from participant self-reports when they were exposed to various emotional cues. Following each stimulus, 23 individuals recorded their signals as well as their self-reported ratings of their affective states in terms of valence, arousal, and dominance. 18 different movie snippets were played for the participants. These movie clips served as stimuli during the data gathering procedure and were carefully chosen to induce a range of emotions. The participant's physiological signals, auditory and visual stimuli, and self-report data were all recorded as they watched these 18 movie snippets, and these recordings are included in the dataset.

4.1.2 Guinea-Bissau EEG Data

The EEG data from the Emotiv Epoc X was obtained via the internet repository *https://www.zenodo.org*. The dataset is made of 5 minutes of EEG recordings taken from 97 people in rural Guinea Bissau and Nigeria utilizing 14 channels.

4.2 APPROACH 1

4.2.1 DATA PREPROCESSING

Before classification is performed, the data are preprocessed. To remove undesired frequency components from the EEG data in this step, digital filters are applied. Removing any undesired frequencies that can interfere with the analysis, helps improve the data's signal-to-noise ratio. The filter coefficients are shaped by the hamming window function, which reduces frequency domain spectral leakage. Power spectral density (PSD) was applied to the filtered signals. The PSD gives details on how power is distributed throughout the frequency range and can provide crucial details about the signal's properties.

Different types of brain waves are associated with different frequency bands, including delta waves (0.5-4 Hz), theta waves (4-8 Hz), alpha waves (8-13 Hz), beta waves (13-30 Hz), and gamma waves (30-100 Hz). By calculating the PSD of an EEG signal, we can identify the frequency bands that are most active during different tasks or states, and use this information to better understand the underlying neural processes. The data is transformed using scaling which guarantees that each feature has the same scale. To facilitate future analysis, we combined all the data into a single data frame. The final dataset created utilizing the aforementioned processes was then split into two datasets for valence and arousal classification.

4.2.2 EMOTION CLASSIFICATION

The valence and arousal dataset was classified using four supervised machine learning classifiers.

- **Support Vector Machines (SVM) classifier -** Support Vector Machines (SVM) is a potent supervised learning technique used for regression and classification tasks. It seeks to locate an ideal hyperplane that, with the greatest margin, divides the data points of several classes. As long as the data is mapped into a higher-dimensional space using the kernel method, SVM can handle both linear and non-linear data. The support vectors, or critical points that are most near the decision border, are found by the algorithm. The features are standardized. The hyperparameters tuned for SVM is the kernel function. Since the assessment requires multidimensional classification, only the radial basis function (RBF) kernel is taken into account.
- **Support Vector Machines (SVM) with Principal Component Analysis (PCA) -** Principal Component Analysis (PCA) is used to achieve dimensionality reduction, and after the features have been modified, the SVM classifier is used. The features are standardized and dimensionality is decreased using PCA. The modified features generated by PCA are used to design and train an SVM classifier. The labels for the test set are then predicted using the classifier.
- **K-Nearest Neighbours (KNN) classifier -** A straightforward and understandable machine learning technique called K- Nearest Neighbours (KNN) is employed for both classification and regression applications. In KNN, a data point's prediction is based on the consensus of the nearest K neighbours in the feature space, or on their average. The features are standardized. The number of neighbours is the tuned hyperparameter value used in this study. The test set's labels are predicted by the classifier, which has been trained on the training set of information.
- **K-Nearest Neighbours (KNN) with Principal Component Analysis (PCA) -** Principal Component Analysis (PCA) is used to conduct dimensionality reduction, after which the altered features are subjected to the K-Nearest Neighbours (KNN) classifier. The features are standardized and dimensionality of the features is decreased using PCA. Both the training and testing sets are subject to change. The number of neighbours is a tailored hyperparameter value. In order to predict the labels for the test set, the classifier is trained on the training data.

4.2.3 MUSIC RECOMMENDATION

Based on the user's assessed mood, the Music Recommendation System can offer tailored music choices. The algorithm may make song suggestions that fit the user's mood by assessing their emotional condition. For music recommendations, a data set from Spotify is used, and K-means clustering based on valence and energy is performed. As a result, the algorithm can divide the music into four groups according to the user's mood. The system can deliver more precise and individualized recommendations that are suited to the user's emotional state by giving the songs mood labels. This strategy might improve the user's listening experience and offer a more satisfying and customized musical experience. The Music Recommendation System may deliver more precise and individualized recommendations that are catered to each user's unique preferences by utilizing Spotify's dataset and K-means clustering.

- High valence, high arousal – Happy
- High valence, low arousal- Relaxed
- Low valence, high arousal – Angry
- Low valence, low arousal – Sad

Each data point is given a name based on the cluster to which it belongs, and these labels are then mapped to the appropriate feelings and moods. A selection of tracks from a music dataset is suggested based on the user's mood.

4.3 APPROACH 2

4.3.1 DATA CLASSIFICATION

EEG dataset obtained from the Emotiv Epoc X needs to be categorized, hence a set of universal values must be created. The first quantile (q1), second quantile (q2), and third quantile (q3) values for each of the 97 participants are calculated, and these quantile values are then averaged across all participants. The quantiles, where q1 represents the 25th percentile, q2 the 50th percentile (median), and q3 the 75th percentile, are used to show how the data are distributed. We can determine the range of values that are most prevalent across the entire group by computing these values for each participant. As a result, we are able to build a baseline or reference point for each channel and characteristic, which we can use to classify new data into groups depending on how it contrasts with the values we have already defined as the standard.

After getting the generalized values for q1, q2, and q3, the dataset was categorized using the following criteria:

- very low if value < q1
- low if q1<value<q2
- high if q2<value<q3
- very high if q3 < value

After the data has been grouped, we can individually find each group's quantiles. Given that the quantiles will be determined using data from comparable populations, this will result in a more accurate depiction of the data.

4.3.2 SETTING INTERVAL

Emotiv Epoc X produces data at a rate of 128Hz, or 128 observations per second. We categorized the dataset before calculating the modes for each of the 128 observations in order to analyze the data. The total amount of brain activity for that second was then determined. Through this procedure, we were able to obtain a second dataset that represents the user's brain activity more precisely. We computed the mode of the data across the 60-second period in order to identify the user's predominant mood during that time. Using this method, we determined the user's typical mood over a longer time period, which may alter over time.

4.3.3 MUSIC RECOMMENDATION

We have categorized the Guinea-Bissau EEG data using a generalized quantile value, which offers useful insights into a person's emotional state. With the Spotify music dataset, we intend to accomplish the same, enabling us to produce song suggestions depending on a person's present mood. We established the data dispersion for the audio qualities of Tempo, Danceability, and Energy in order to achieve this. This will entail figuring out the quantile values for each attribute, which will provide the data with a more precise representation.

The Spotify dataset was divided into four categories—very low, low, high, and very high activity—after determining the data dispersion. This enabled us to create music recommendations by segmenting the dataset according to a person's current mood. We can identify which songs are most likely to improve a person's mood and make listening more enjoyable by examining the auditory characteristics of each song. This strategy helped us improve the user's listening experience and offer a more satisfying and customized musical experience.

4.3.4 PLAYING MUSIC

The suggested songs are played by opening a tab on YouTube based on the user's mood. We are able to give users a flawless and delightful listening experience by automating the process of playing music on YouTube.

5. RESULTS AND ANALYSIS

The use of four different algorithms, namely SVM, SVM with PCA, KNN, and KNN with PCA—have been tested for classifying emotions. In assessing arousal and valence, the study discovered that SVM with PCA had the highest classification accuracy. EEG-valence and EEG- arousal accuracy rates were 96.8% and 96%, respectively which is shown in Figure 2 and Figure 3.

User reviews or collaborative filtering can increase the accuracy of music recommendation systems. EEG data gives essential details about users' emotional states, levels of interest, and attention spans, allowing for more specialized and individualized recommendations. The use of EEG-based music recommendation systems has the potential to revolutionize the music industry. Music companies may raise user satisfaction and revenue by offering customers personalized recommendations based on their emotional state, engagement level, and attention span.

The study's findings conclude that utilizing SVM with PCA for emotion classification and EEG data for music recommendation may result in increased precision and more customized recommendations. The possibilities of EEG-based music recommendation systems and their effects on the music industry need to be further investigated.

Model	Accuracy
SVM	95.1807
SVM-PCA	96.8
KNN	78.3133
KNN-PCA	86.747

Figure 2: Accuracy comparison for Valence

Model	Accuracy
SVM	95.1807
SVM-PCA	96
KNN	86.747
KNN-PCA	93.9759

Figure 3: Accuracy comparison for Arousal

4. CONCLUSION

An intriguing possibility to provide unique music suggestions depending on the user's current emotional state is presented by the development of a mood-based music recommendation system employing EEG data obtained from the Emotiv EPOC headset. The system provides accurate recommendations and improves the user's music-listening experience and the effectiveness of music streaming services by utilizing machine learning algorithms to classify the user's mood based on EEG data.

Future research might concentrate on enlarging the system by including more physiological and environmental factors. To improve the precision and applicability of suggestions, these parameters can include heart rate variability, skin conductance, and ambient temperature, among others. Additionally, the system might be adjusted to respond to each user's unique musical preferences, further personalizing the suggestions.

The music industry could experience significant effects from a successful mood-based music recommendation system. Users may be more likely to sign up for music streaming services if they are given a more customized listening experience, increasing the companies' income. Additionally, music consumption has been associated with mood regulation, and tailored recommendations may improve people's mental health and general well-being.

In conclusion, the mood-based music recommendation system has enormous potential to provide customers with tailored recommendations depending on their emotional condition. With more investigation, it might develop into a crucial instrument for the music business, enhancing user experiences and producing fresh sources of income.

ACKNOWLEDGEMENTS

With due respect, we express our deepest sense of gratitude to our respected supervisor and director Dr. Bahubali Shiragapur, for his valuable help and guidance. We are thankful for the encouragement that he has given us in completing this project successfully.

References

[1] Koelstra, S., Muhl, C., Soleymani, M., Lee, J. S., Yazdani, A., Ebrahimi, T., & Patras, I. (2011). DEAP: A database for emotion analysis using physiological signals. IEEE Transactions on Affective Computing, 3(1), 18-31.

[2] Jin, J., Wang, J., Qi, G., & Zhu, S. (2013). An efficient k-means clustering algorithm. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 34(2), 994-1000.

[3] Lin, Y. P., Yang, Y. H., & Jung, T. P. (2014). Fusion of electroencephalographic dynamics and musical contents for estimating emotional responses in music listening. *Frontiers in neuroscience*, *8*, 94.

[4] Ma, Y., Liu, Y., Wang, L., & Lu, L. (2018). Emotion recognition in music based on multimodal features and multiple kernel learning. IEEE Transactions on Affective Computing, 9(4), 525-538.

[5] Li, X., Zhang, Y., Tiwari, P., Song, D., Hu, B., Yang, M., Zhao, Z., Kumar, N., & Marttinen, P. (2022). EEG based emotion recognition: A tutorial and review. *ACM Computing Surveys*, *55*(4), 1-57.

[6] Bi, Z., Jing, L., Shan, M., Dou, S., & Wang, S. (2021). Hierarchical social recommendation model based on a graph neural network. *Wireless Communications and Mobile Computing*, *2021*, 1-10.

[7] LEE, J., YOON, K., JANG, D., JANG, S. J., SHIN, S., & KIM, J. H. (2018). MUSIC RECOMMENDATION SYSTEM BASED ON GENRE DISTANCE AND USER PREFERENCE CLASSIFICATION. *Journal of Theoretical & Applied Information Technology*, *96*(5).

[8] Katsigiannis, S., & Ramzan, N. (2017). DREAMER: A database for emotion recognition through EEG and ECG signals from wireless low-cost off-the-shelf devices. *IEEE journal of biomedical and health informatics*, *22*(1), 98-107.

[9] Vincent van Hees, & Wim Otte. (2018). EEG data collected with Emotiv device in people with epilepsy and controls in Guinea-Bissau and Nigeria (1.0) [Data set]. Zenodo. https://doi.org/10.5281/zenodo.1252141.