Brain Melody Informatics: Analysing Effects of Music on Brainwave Patterns

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Brain Melody Informatics: Analysing Effects of Music on Brainwave Patterns

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***Abstract*—Recently, researchers in the field of affective neuroscience have taken a keen interest in identifying patterns in brain activities that correspond to specific emotions. The relationship between music stimuli and brain waves has been of particular interest due to music's disputed effects on brain activity. While music can have an anticonvulsant effect on the brain and act as a therapeutic stimulus, it can also have proconvulsant effects such as triggering epileptic seizures. In this paper, we take a computational approach to understand the effects of different types of music on the human brain; we analyse the effects of 3 different genres of music in participants electroencephalograms (EEGs). Brain activity was recorded using a 14-channel headset from 24 participants while they listened to different music stimuli. Statistical features were extracted from the signals and useful features and channels were identified using various feature selecting techniques. Using these features we built classification models based on K-nearest Neighbour (KNN), Support Vector Machine (SVM) and Neural Network (NN). Our analysis shows that NN, along with Genetic Algorithm (GA) feature selection, can reach the highest accuracy of 97.5% in classifying the 3 music genres. The model also reaches 98.6% accuracy in classifying music based on participants' subjective rating of emotion. Additionally, the recorded brain waves identify different gamma wave levels, which are crucial in detecting epileptic seizures. Our results show that these computational techniques are effective in distinguishing music genres based on their effects on human brains.**

***Index Terms*—Brain Activity, Electroencephalogram, Affective Neuroscience, Feature Extraction, Classification, Music Therapy**

I. Introduction

Music is a powerful and complex medium. It allows us to express emotions and cultural beliefs, it enhances our focus and creativity, and it stimulates physical activity. Due to music's ability to influence human emotion and physiology, it is a popular choice of stimulus for researchers in the field of affective computing and affective neuroscience. One of the most important research questions in the field of affective neuroscience is looking for patterns of brain activities related to specific emotions and investigating if the patterns are common among people [1]. These questions can be further differentiated with respect to audio or visual stimuli.

Brain anatomy researchers have highlighted that music can act as a nonverbal medium that can move through the auditory cortex directly to the limbic system, which is a crucial part of the emotional response system [2]. The most common use of music stimuli has been for therapy to reduce stress, anxiety and various mental disorders. Certain classical music pieces have been shown to reduce anxiety and improve sleep behavior [3], [4]. It has also been used as a potential way to reduce epileptic seizures, a common neurological disorder affecting around 50 million people in the world [5]. However, using music in the treatment of epilepsy has been a controversial topic for many years. There is rare form of epilepsy called musicogenic epilepsy in which seizures can be triggered by certain musical experiences [6]. Some papers in the literature have mentioned that patients reported having seizures induced by specific types of music, instrument use or singing style [7], [8]. But no specific patterns have yet been identified regarding music that can invoke seizures. In addition, there has been very little research done to understand this phenomenon at the physiological level. Studies show that music listening can significantly decrease respiration rate and heart rate, which correlates with decreased levels of anxiety [9]. Observing these patterns through computational models can be highly beneficial for future medical research. Research questions include: can people's brain activity be used to differentiate different types of music; what types of effect do different types of music have on the brain?

The electroencephalogram (EEG) is the physiological signal most commonly used to understand brain activity associated with affective reasoning. It is used to record brain wave patterns. In the wider context, it is vital in detecting conditions such as epilepsy, sleep disorders, stroke, stress and anxiety. In this paper, we explore the impact of 3 different types of music stimuli on human brain activity using EEG. Several signals from different brain regions are investigated to identify which features provide useful information regarding music type and emotion processing. Three different classifiers are used to recognize the 3 music genres based on the selected brain activity features. The subjective responses provided by the participants related to the music have also been classified using a similar approach. The rest of the sections of this paper are organized as follows: Section II describes some relevant background information and reviews recent related work. Section III explains the experiment methodology. Section IV describes the results and discusses some patterns identified through the

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process. Section V concludes the paper by highlighting future work.

II. Background

The data captured by EEG are brain waves which can be divided into multiple frequency bands. Each of these bands are associated with different functions in the brain. These brain waves are:

- Delta (δ) waves – These waves are the slowest, having the lowest frequency range of $0.5 - 4$ Hz. These waves are not seen in adult brains while they are awake. These waves are generally associated with deep sleep, as well as disfunction such as hypoxia and schizophrenia.
- Theta (θ) waves- Having the frequency of $4-8$ Hz, theta waves are produced during sleep and drowsiness.
- Alpha (α) waves – Alpha waves have the frequency of 8–12 Hz, and are found in almost every part of the brain, but mostly in the occipital lobe. These waves are highly associated with any relaxed state. Alpha waves are often boosted during meditation or any other stress relieving activities.
- Beta (β) waves – Beta waves (12–30 Hz) are the most frequently seen brain waves that reflect the active state of the brain. They are mostly associated with increased attention and alertness.
- Gamma (γ) waves – These are the fastest brain waves ($>$ 30 Hz), which are thought to increase cognitive function and boost memory and focus. These waves can also be found in stroke and epileptic patients [10].

EEG is typically recorded by placing electrodes on the scalp. The number of electrodes and what information they capture differs based on the device that is used to capture the signals. The electrodes have distinguishable names, which reflects the placement location on the head. The name consists of a letter and a number, where the letter represents the brain lobe and the number represents the position and hemisphere. Our experiment uses the popular EEG device - the Emotiv EPOC headset [11], which is a 14-channel wireless headset that also has 9-axis motion sensors. Emotive also provides software that can be used to record raw EEG data, from which different brain waves and related information can be extracted. Figure 1 shows the channels' names and locations of Emotive EPOC electrodes.

Over the last few years there have been many researchers who focus on analysing EEG signals from the human brain, including investigation of the role of music in brain wave production. Thammasan et. al. [12] used EEG signals to continuously identify emotion based on valence and arousal levels in participants while they listen to music. However, they do not discuss specific emotions and which brain regions contribute to identifying emotions. Shedeed et. al. [13] collected EEG signals associated with 3 arm movements and analysed data from 4 channels located in the pre-frontal, frontal and supplementary motor cortex. Their model, based on a multi-layer perceptron neural network reaches the highest accuracy of 91.1%. They did not explain why only those 4 channels were used. In one of the more recent works, Ieracitano et al [14] collected EEG recordings from patients with Alzheimer's disease and healthy controls using a 19-channel EEG system. They achieved the highest accuracy of 95.76%, using a 1-hidden layer multi-layer perceptron. Some papers in the literature have discussed identifying brain regions that provide useful information while participants are engaging with stimuli. Zheng and Zhu [1] collected EEG signals from a 62 channel device and selected data from a combination of 4, 6, 9 and 12 fixed channels to classify 3 categories of emotions evoked by emotional movie clips. It is not clear how these channel combinations were derived. Lin et al. [15] used excerpts from Oscar-winning film soundtracks to evoke emotions in participants and classify their self-reported emotions using a support vector machine (SVM). They also reported useful features to be found in the frontal and parietal lobes of the brain. However, to the best of our knowledge, there has not been any work that investigates human brain activity while participants listen to popular music, or music that is said to be effective for music therapy. This paper explores this research area in greater detail.

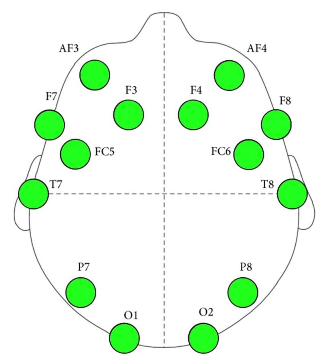

Fig. 1. Emotiv Headset Channel Location and Names [16]

III. Materials and Methods

A. Participants and Stimuli

EEG signals were recorded from 13 male and 11 female students (total = 24) studying at the Australian National University. All of the students participated voluntarily and signed a written consent form before their participation, as required by our ethics approval. Twelve music pieces were chosen for this experiment and divided into 3 categories. They are:

- Classical - These pieces were chosen based on their long lasting periodicity, a feature that has been useful in music therapy [17].
- Instrumental - These pieces include jazz, rock and binaural beats. Binaural beats in particular are purported to enhance specific brainwave patterns [2].
- Pop - We chose these pieces based on the top song of Billboard Hot 100 year-end chart from year 2014-2017 [18].

B. Methods

Participants were first given a brief description of the experiment and signed the consent form. Afterward, they sat in a chair in front of a 17.1 inch monitor and were fitted with the Emotiv EPOC headset. The headset electrodes were properly hydrated for good connectivity prior to the calibration process. Participants were asked to keep their eyes open for 15 seconds and keep their eyes closed for another 15 seconds to complete the calibration. Then the data collection process began at the sampling rate of 128 Hz. Participants also wore a pair of noise cancelling earphones to listen to the music so that no other sounds distracted them.

The complete experiment was conducted through an interactive website prepared for this purpose. Participants answered some initial demographic questions after which they started listening to each music piece. Every participant listened to a total of 8 pieces of music from the 12 chosen - the music pieces were order balanced. After participants finished listening to a music piece they gave ratings to the music based on their general impression and their feelings while listening. The ratings were given on a 7-point Likert scale based on 6 emotion scales [19]. The scales are i) *sad* → *happy* ii) *disturbing* → *comforting* iii) *depressing* → *exciting* iv) *unpleasant* → *pleasant* v) *irritating* → *soothing* vi) *tensing* → *relaxing*. The scales were chosen according to [20]. Continuous scales were chosen to reflect the real world, where human emotions are usually blended and therefore cannot be put in a discrete space. Figure 2 shows the emotion scales for our experiment in a 2D emotion model, a conceptual model frequently used in the field of affective computing [21].

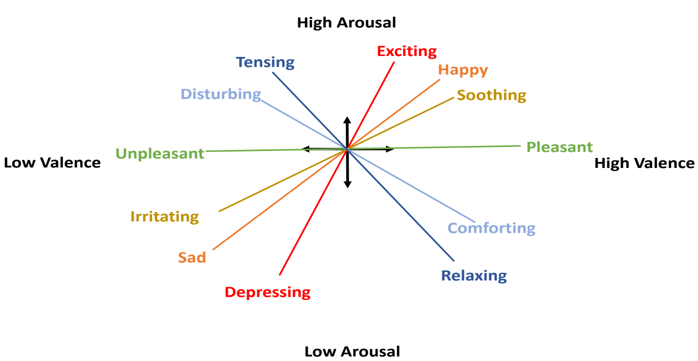

Fig. 2. Two Dimensional Emotion Model based on Valence and Arousal

The EEG data was collected from all 14 channels of the headset using EmotivPRO Academic software [16].

Figure 3. shows the overall steps of the experiment. These are discussed in detail in the following sections.

C. Preprocessing

Raw EEG signals collected from participants can be sensitive to subject movements. In addition, sometimes a few channels could not receive a good connection and therefore added noise artefacts to the collected signals. Therefore, we

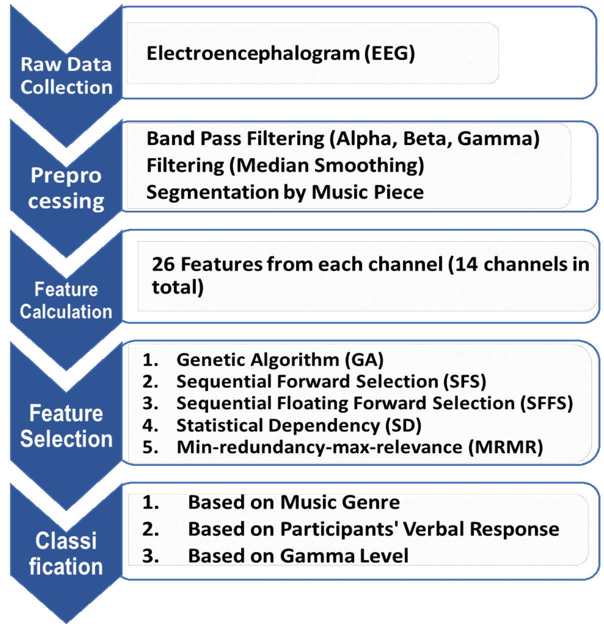

Fig. 3. Experimental Design

applied a median smoothing filtering to smooth out the noisy signals [22]. Then the EEG data is band-pass-filtered between 3 to 60 Hz. This is done primarily to separate the band frequency ranges of our interest, which are: Alpha [8-13 Hz], Beta [14-30 Hz] and Gamma [31-50 Hz] Band. Then the data was segmented into the lengths of the music pieces for feature extraction.

D. Feature Extraction

Raw EEG signals were collected using all 14 channels at the sampling rate of 128 Hz. This resulted in a large amount of data from every participant which can be very hard to analyse due to high computational cost. Therefore, we extracted a total of 26 linear and non-linear statistical features from our recorded data. The features were extracted from the 3 chosen band frequency ranges. Table 1 shows the 26 linear and non-linear features extracted from every participant's music segment. The process was done in the same manner for all 14 channels. The channel names and locations are also noted in Table 1. Channel names follow the convention of the International 10-20 locations system. The features are chosen from [23]–[26].

E. Feature Selection

In the feature extraction process we extracted 26 features from each of the 14 channels of the Emotiv for each participant's music listening periods, or 364 features per song segment for every participant. Thus we end up with a large number of features, which increases the computation cost of classification, and importantly, decreases classification models performance [27]. To address these concerns, we applied a total of 6 feature selection methods [28], [29] of 2 types: feature ranking methods and feature subset selection methods:

TABLE I
EMOTIV CHANNEL NAMES AND LOCATIONS AND EXTRACTED FEATURE LIST

Channels	Location	Names
	Pre-Frontal Lobe	AF3, AF4
	Frontal Lobe	F3, F4, F7, F8, FC5, FC6
	Temporal Lobe	T7, T8, P7, P8
	Occipital Lobe	O1, O2
Features	**Type**	**Names**
	Linear	Mean, Maximum, Minimum, Standard Deviation, Interquartile Range, Sum, Variance, Skewness, Kurtosis, Root Mean Square, Average of the power of signals, Peaks in Periodic Signals, Integrated Signals, Simple Square Integral, Means of the absolute values of the first and second differences, Log Detector, Average Amplitude Change, Difference Absolute Standard Deviation Value
	Non-Linear	Detrended Fluctuation Analysis, Approximate Entropy, Fuzzy Entropy, Shannon's Entropy, Permutation Entropy, Hjorth Parameters, Hurst Exponent

- Feature Ranking Methods
  - Statistical Dependency (SD)
  - Minimal-redundancy-maximal-relevance (MRMR)
- Feature Subset Selection Methods
  - Genetic Algorithm (GA)
  - Random Subset Feature Selection (RSFS)
  - Sequential Forward Selection (SFS)
  - Sequential Floating Forward Selection (SFFS)

F. Classifiers and Evaluation Measures

The classification was executed using MATLAB® R2018a software with an Intel® Core™ i7-5200U processor with 3.60 GHz, 16.00 GB of RAM and Microsoft Windows 10 Enterprise 64-bit operating system. We used 3 different classification methods for comparing our results. They are: Neural Network (NN), K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). For the 2 feature ranking methods SD and MRMR, we chose the top 150 features to use in the classification process. This number was chosen because the feature subset selection methods generally resulted in around 100-180 features. We chose 150 as an optimum level to lead to good classification performance and not be computationally heavy. A leave-one-observer-out process was performed as the validation approach.

For the neural network, a pattern recognition network was constructed with one input layer, one hidden layer and one output layer. The hidden layer consisted of 30 nodes. This was chosen based on the comparison of different hidden layer sizes done in our previous study [20]. Other parameters of the network were: Levenberg—Marquardt method as network training function and mean squared normalised error as performance function. The classification process was done 20 times and the average of those results were selected. For KNN, we performed the process using node sizes 3 to 30 and chose the best results. K = 9 resulted in best outputs for most cases. We used Minkowski as the distance metric. The multiclass SVM chosen for this study uses tree learner and one-versus-all coding design.

For our evaluation measures we report the classification accuracy of the models in predicting the 3 music genres and also the subjective ratings given by the participants. While accuracy is crucial to show the predictive power of the model, it does not always provide complete information on the value of the model [30]. Therefore, we report some additional measures along with the accuracy of our models. These are:

- Precision (Fraction of the predicted labels matched)
- Recall/Sensitivity (True Positive Rate)
- Specificity (True Negative Rate)
- F-measure (Harmonic mean of Precision and Recall)

IV. RESULTS AND DISCUSSION

A. Statistical Analysis

The statistical analysis was conducted using Analysis of Variance (ANOVA). We analysed the classification accuracy using NN for all feature selection combinations. The results show high statistical significance ($p < 0.01$) across all the selection methods. However, there is no statistical significance observed for classifications using KNN and SVM. Thus, different feature selection methods have significant impacts just on the NN model in our model. In the later sections we will discuss optimal feature selection methods further.

B. Best Features

We counted the frequency of every feature chosen by each feature selection method in all 7 classification processes. Table 2. shows the list of top 25 features in decreasing order of frequency.

The table gives us two types of useful information. Firstly, it tells us which extracted features are providing useful information as derived by a number of feature selection models. Secondly, it tells us which channels (parts of brain region) are useful in the classification process. From the top 25 features, 10 come from the channels F3 and F7, both located in the frontal lobe of the brain. Most of the other features were also from the channels located in the frontal and pre-frontal region of the brain (except 4 of them which were features from the temporal lobe). This shows that the frontal lobe can reveal important information related to music processing in the brain. Frontal and pre-frontal lobes are considered to be the emotional control centre of the brain [31], [32]. Frontal lobes are also involved in decision making [33]. Our observations align with the literature where high activity in the frontal lobe has been seen during various activities. Khushaba et.al. [34] reported high delta and theta activity in F3 and F4 region during decision making. This finding can also be beneficial for future research in making

TABLE II
TOP 25 FEATURES SELECTED BY FEATURE SELECTION METHODS

Channel	Feature Name
F3	Standard Deviation
FC5	Permutation Entropy
P8	Permutation Entropy
F3	Maximum
F8	Permutation Entropy
F7	Shannon's Entropy
AF3	Skewness
AF3	Shannon's Entropy
P7	Permutation Entropy
F4	Permutation Entropy
FC5	Skewness
T7	Skewness
F3	Mean of the First Difference
F7	Approximate Entropy
T7	Permutation Entropy
F7	Hurst Exponent
AF3	Maximum
F7	Skewness
F7	Kurtosis
FC6	Root Mean Square
P8	Approximate Entropy
FC6	Permutation Entropy
AF4	Permutation Entropy
F3	Hurst Exponent
F3	Mean

wearable devices to capture EEG. One of our observations while conducting the experiment was that participants often felt uncomfortable wearing the 14 channel headset for a longer period. This often hampered their concentration in listening to the music and answering questions. A comfortable wearable device which captures data only from the frontal region of the brain, requiring less points of pressure on the head, may be beneficial for longer experiments in such cases.

Another observation from this feature list is the usefulness of the entropy features. From this list we can see that permutation entropy of 8 different channels appeared in the top features list. Furthermore, entropies cover 12 out of the top 25 features. Entropies in general reflect the randomness and complexity properties of physiological signals. Permutation entropy analyses various permutation patterns of these signals to identify the complexity level [35]. These features highlight useful properties from non-stationary signals like EEG. Entropies have also been shown to be effective features for building models for epileptic seizure detection [36]. Using these features and relevant channel data we can significantly reduce the computational cost of our system without compromising its predictive power.

C. Classification

We performed the classification using NN, KNN and SVM based on the labels of music genres and participants' subjective rating on 6 emotion scales described in section 3. The ratings were categorized into positive, neutral and negative ratings. Thus, all of them were 3 class classification problems to match the human subjective ratings. This approach allowed us to tease out human response distinctions not just at the level of genre, but at the more fragmented level of individual music pieces. The classification labels are listed below, based on the music genre and subjective rating on emotion given by the participants:

- Classical Genre - Instrumental Genre - Pop Genre
- Disturbing - Neutral - Comforting
- Depressing - Neutral - Exciting
- Sad - Neutral - Happy
- Unpleasant - Neutral - Pleasant
- Irritating - Neutral - Soothing
- Tensing - Neutral - Relaxing

In general, for all cases, NN performed significantly better than KNN and SVM. Figure 4 shows the classification accuracy of all 3 models using all 6 feature selection methods based on the ratings on emotion *Tensing* $\rightarrow$ Neutral $\rightarrow$ *Relaxing*.

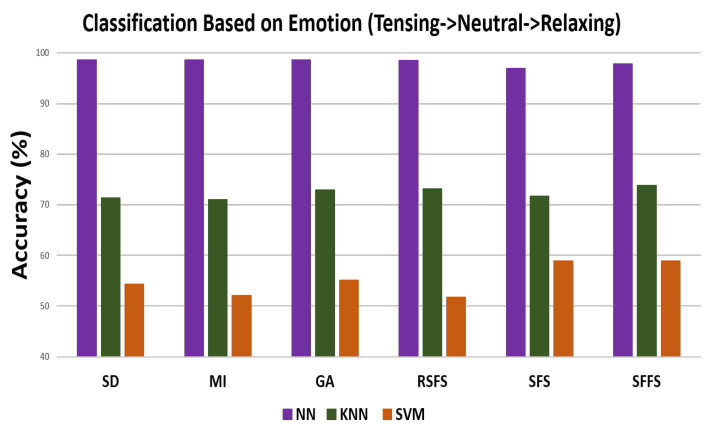

Fig. 4. Classification Results Based on Subjective Rating (*Tensing* $\rightarrow$ Neutral $\rightarrow$ *Relaxing*), Range 40-100 Chosen for Better Visualization

Figure 4 shows that NN can reach the highest accuracy of 98.6% based on the average of 20 runs, whereas KNN and SVM reached 73.8% and 58.9% respectively. Similar patterns are observed in other emotion scales as well across all evaluation measures. Figure 5 shows the 6 evaluation measures for classification based on the music genres using NN. We can observe that NN achieves a high accuracy of 97.5% and 96.3% in F-measure. The F-measure is the harmonic mean of precision and recall and it is often considered a stronger measure than arithmetic mean because it reveals more useful information on groups having different properties [37]. For KNN and SVM, even though the models achieve reasonable results in terms of accuracy, it often gets a low score ($< 40\%$) for F-measure. Therefore, we suggest NN as an effective model, as it achieves high scores for all evaluation measures.

We wanted to identify which feature selection methods are most suitable to use for our classification model. Figure 6

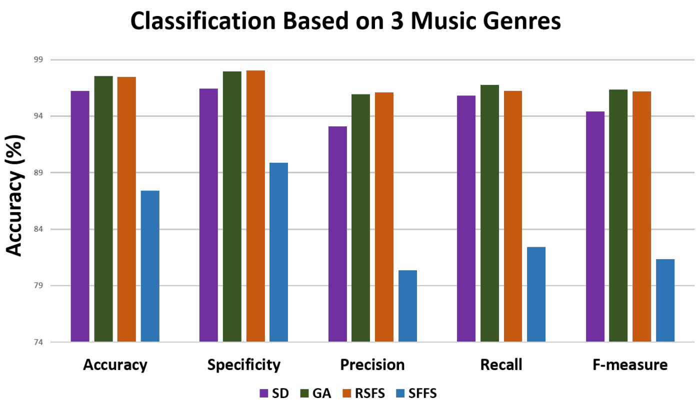

Fig. 5. Classification Results Based on 3 Music Genres, Range 75-100 Chosen for Better Visualization

shows the NN accuracy results of 3 emotion scales using the SD, GA, RSFS and SFFS. Similar patterns are observed for other emotion scales as well. It can be seen in Figure 6 that the feature selection methods achieve very close results in terms of accuracy. But when comparing other measures we found that GA and RSFS achieve the highest results in all evaluation measures for most cases. Table 3 shows the results of all evaluation measures for the same combinations shown in Figure 6.

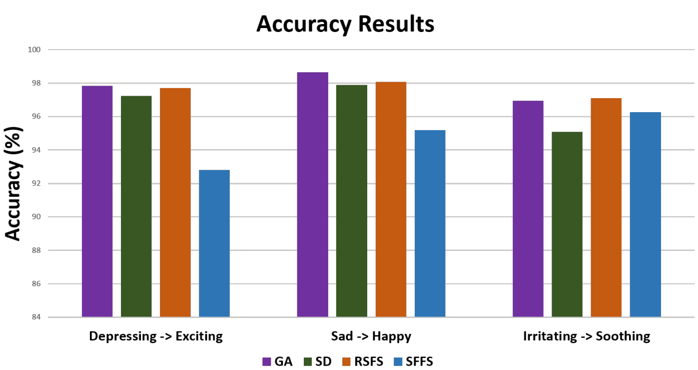

Fig. 6. Classification Accuracy Based on Participants' Subjective Response Based on 3 Emotion Scales, Range 85-100 Chosen for Better Visualization

The results are also statistically significant ($p < 0.001$). It should also be mentioned that both these methods are feature subset selection algorithms, and they produced better results than feature ranking algorithms. Although the feature ranking algorithms get the highest accuracy in some cases, they do not consistently achieve high scores in other measures.

D. Observation of Gamma Levels

We further analysed the frequency band data collected by the EmotivPro Software. We observed the gamma level of every participant when they listened to different music pieces. We labelled the songs based on the gamma levels seen in participants brain activity while they were listening to a particular music piece. We then divided the pieces into high, mid and low gamma levels. We made this division by averaging the gamma level score for every participant listening to every piece of music. This procedure was repeated for all 14 channels' gamma level information. We performed a voting among all channel data to finally label the music piece. The results were the following:

- Low Gamma - Music pieces no. 5, 7, 9, 11, 12 (mostly pop)
- Mid Gamma - Music pieces no. 1, 2, 3, 4 (all classical)
- High Gamma - Music pieces no. 6, 8, 10 (mostly instrumental)

This division was very closely aligned to our different genres with some interesting differences. It also poses some questions for future research and confirms some other assumptions we had about the music pieces. For instance, we picked music pieces 5 and 6 (both are binaural beats) from Youtube and they were said to be inducing alpha waves and gamma waves in the brain respectively. Our gamma level observation confirms this fact as music piece 5 appears in the low gamma category (the piece was meant to be used for relaxation so low gamma level would be expected). Music piece 6 appears in the high gamma category which also matches the description of the music. Both the binaural beats were able to induce the specific brain waves we expected. Another observation was that all 4 of the classical music pieces appeared in the mid gamma level category. These music pieces are frequently used in music therapy as classical music pieces are said to be beneficial to reduce stress, anxiety and improving sleep patterns [38]–[40]. However, they might not be very relaxing for all people. Pieces like binaural beats that induce more alpha waves can be of higher benefit in these cases. On the other hand, binaural beats that

TABLE III
EVALUATION MEASURES OF PARTICIPANTS' SUBJECTIVE RESPONSE BASED ON 3 EMOTION SCALES

		SD	GA	RSFS	SFFS
Depressing → *Exciting*	Accuracy	0.972	**0.978**	0.976	0.928
	Precision	0.879	0.899	**0.905**	0.758
	Recall	0.968	**0.981**	0.964	0.865
	Specificity	0.973	0.977	**0.979**	0.941
	F-Measure	**0.958**	0.938	0.933	0.849
		SD	GA	RSFS	SFFS
Sad → *Happy*	Accuracy	0.979	**0.987**	0.981	0.952
	Precision	0.911	**0.954**	0.924	0.824
	Recall	**0.968**	0.967	0.965	0.909
	Specificity	0.981	**0.991**	0.984	0.961
	F-Measure	0.939	**0.96**	0.944	0.863
		SD	GA	RSFS	SFFS
Irritating → *Soothing*	Accuracy	0.951	0.969	**0.971**	0.963
	Precision	0.875	0.918	**0.926**	0.907
	Recall	0.915	**0.965**	0.961	0.948
	Specificity	0.963	0.971	**0.974**	0.967
	F-Measure	0.941	0.941	**0.943**	0.927

increase gamma levels can contribute to epileptiform activity. A detailed review on musicogenic epilepsy by Maguire [7] mentioned that it has been hard to understand why neutral music like a specific sound triggers seizures, reported by some clinical studies [8]. Our research findings may contribute to understanding this effect in the future.

Another significant observation relates to the pop music pieces we chose for this experiment. Out of the 4 pop music, only 1 appeared in the high gamma category and the other 3 appeared in the low gamma category. Our assumption was that all of them would be in the mid or high gamma range as these music pieces contain a lot of lyrics and instrument usage and thus would require more concentration (usage of beta and gamma waves) while listening. One possibility might be the fact that these music pieces were all very popular in recent times, and most of the participants had listened to these pieces before (as reported in the questionnaire). The fact that these pieces were already in their memory might have caused them to not concentrate as much while listening to the pieces. It has been reported before that there is correlation between high gamma activity and memory in the temporal locations of the brain [41]. We tested this by observing the gamma activity in the temporal locations (Channel P7, P8, T7 and T8). The results align with the literature (e.g. all 4 pop songs induce high gamma activity in P7 and mid gamma activity in P8). However, channels in the other locations do not follow the same patterns. It should also be noted that both temporal and frontal lobes have been shown to be regions where most epileptic seizures occur, especially in children [42], [43]. Thus any music that reflects or induces these patterns in the brain of epileptic patients should be avoided. Further analysis using features from these regions can reveal the potential of identifying brain regions and music pieces that contribute to musicogenic epilepsy. We can also compare brain activity with other physiological signals to identify if there is correlation among them.

To observe if the division of the music pieces based on participants brain wave level can be reflected computationally, we performed classification using NN using all 26 features from every channel. The labels were given according to the gamma levels of the music pieces. The model achieves the highest accuracy of 91.4% using the features from channel F3. This also aligns with our observation in section 4(B) where some of the features extracted from channel F3 data were chosen a high number of times by all feature selection methods. We also compared these results based on all 6 evaluation measures from all channels using ANOVA test and the results show very high statistical significance ($p < 0.001$). Therefore, it can be concluded that signals obtained from specific channels have significant impact on the system.

V. Conclusion and Future Work

In this paper, we conducted a study that collects participants' brain activity via EEG signals while they listened to 3 different categories of music. Signals were collected using a 14-channel wearable headset Emotiv EPOC. Signals were first pre-processed by filtering them and dividing them into frequency bands alpha, beta and gamma. Then a number of linear and non-linear features were extracted from the frequency bands of all channels. A total of 6 feature selection methods were applied to select a feature set which were then used in a NN, KNN and SVM classifier. Analysis on the data showed that, a NN model reached a high accuracy of 97.5% in classifying the music pieces based on genre and 98.6% in classifying the pieces based on the subjective rating on emotions given by the participants. The analysis also reveal that most of the useful features selected were coming from the frontal region of the brain. This study has multiple prospects in future medical and affective computing research such as

- Categorising relaxing music pieces for music therapy. Music pieces that induce more alpha waves in brain are more appropriate for music therapy, rather than just choosing any classical or instrumental piece.
- Categorising music that can potentially trigger seizures and thus should be avoided by musicogenic epilepsy patients. Categorising music via genre alone is insufficient to distinguish the best pieces for music therapy; the brain wave activity induced by a specific piece of music may potentially trigger seizures.
- Creating a wearable device using only the regions of interest (e.g frontal) which can then be worn more comfortably for longer duration experiments .

There are certain limitations to our work. We applied generalized methods to pre-process the signals. However, we did not observe in detail if different participants had different connectivity levels for the channels. The device is sensitive to movement and might show poor connections in some channels during the experiment. These need to be analyzed further. Furthermore, even though the number of participants for our experiment can be considered reasonable according to some literature [44], it is not enough to generalise the brain activity of humans at scale. A larger number of participants need to be observed to see if we can identify similar patterns that we observed in this study. Weight magnitude of the features will be analysed to compare with the best features found by frequency. Another element of future work is to investigate the factor that account for the significantly better performance of NNs over KNN and SVM. Also, since some of the music pieces were already in participants' memory and might have caused them to not concentrate as much while listening to the pieces, we need to investigate the relationship of music and memory in greater detail. Nevertheless, our study uncovers potential advancement in the field of affective computing and affective neuroscience.

Acknowledgment

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