Melodious Micro-frissons: Detecting Music Genres From Skin Response

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***Abstract*—The relationship between music and human physiological signals has been a topic of interest among researchers for many years. Understanding this relationship can not only lead to more enhanced music therapy methods, but it may also help in finding a cure to mental disorders and epileptic seizures that are triggered by certain music. In this paper, we investigate the effects of 3 different genres of music in participants' Electrodermal Activity (EDA). Signals were recorded from 24 participants while they listened to 12 music stimuli. Various feature selection methods were applied to a number of features which were extracted from the signals. A simple neural network using Genetic Algorithm (GA) feature selection can reach as high as 96.8% accuracy in classifying 3 different music genres. Classification based on participants' subjective rating of emotion reaches 98.3% accuracy with the Statistical Dependency (SD) / Minimal Redundancy Maximum Relevance (MRMR) feature selection technique. This shows that human emotion has a strong correlation with different types of music. In the future this system can be used to distinguish music based on their positive of negative effect on human mental health.**

***Index Terms*—Music Therapy, Physiological Signals, Electrodermal Activity, Classification**

I. Introduction

Music is a popular form of entertainment that plays a significant role in our day to day life. Listening to music or playing musical instruments can be an enjoyable experience for anyone. Music also has the power to elicit different emotions in people. Some types of music make us happy or excited, some can make people sad or depressed. Music is also an integral part of a country's culture so it shapes the preferences and emotional responses of their people. It has also shown to improve memory and cognitive function [1]. These multiple applications of music have caused music to be used in a wide range of applications.

Music has been used as an alternate form of medicine to reduce stress and anxiety among people for many years. It appears that it can affect the emotional and physiological state of a person, though this is controversial. Some experiments have demonstrated that music creates specific patterns in heart rate, blood pressure etc [2]. Moreover, according to brain anatomy researchers, music can affect brain functions in two ways. First, it 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. Second, it stimulates release of endorphins and allows these polypeptides to act on specific brain receptors [3].

Music is said to be able to influence autonomic nervous system reactions both in a relaxing and arousing fashion [4]. Due to the power of stimulating different emotional reactions, music therapy has been used to treat different mental disorders such as stress, anxiety, depression. It has also been used to treat epilepsy which is a neurological condition affecting around 65 million people all over the world. This condition affects 1 in a 100 people of the world [5]. While 70 percent of patients with epilepsy can reduce their frequency of seizures with currently available antiepileptic medications, the other 30 percent are diagnosed with medically refractory epilepsy which cannot be helped by drugs [6]. People belonging to this category have a higher risk of death, depression and anxiety [7]. Music therapy has been used to reduce the frequency of epileptic seizures among patients. However, little research have been done to understand exactly how music changes the physiological states of these patients to reduce the frequency of seizures, or how it causes changes in mental state in general.

In this paper, we explore the effects of electrodermal activity (EDA) while listening to 3 different genres of music. Electrodermal activity is a useful physiological signal which is seen to be sensitive to emotional changes [2]. A neural network is applied to classify the physiological responses into the 3 given genres of music. Classification is also performed based on the subjective responses of the participants.

The paper is organized as follows: Following this Section I Introduction, Section II discusses necessary background and reviews the related work. Section III explains the materials,

978-1-7281-2009-6/$31.00 ©2019 IEEE

methods and evaluation measures used in this study. Section IV shows classification performances using different feature selection techniques and discusses the factors that influence the systems performance. Section V concludes the paper and mentions future work.

II. Related Work

A. Music as Therapy

Music therapy has been a well-known method to reduce many mental health issues and epileptic seizures. In Li and Xiong [8], 90 students were divided into three groups where one group received music therapy, one group received music therapy along with biofeedback training and the other was the control group. The results demonstrated that music therapy in combination with biofeedback training has a significantly greater effect in reducing anxiety among students. In Yang et al. [9], 22 psychiatric patients were divided into three groups based on their level of anxiety. They listened to 20 minutes of music for 10 days and their finger temperature and EEG were measured before and after music intervention. The results showed a significant decrease in anxiety across all three anxiety levels after the music intervention. Lee et al. [10] performed a randomized controlled trial on 64 students to measure effects of music therapy on stress. They found significant difference in blood pressure, diastolic blood pressure, pulse, SDNN, normalized low frequency, normalized high frequency, and subjective stress after music therapy. One study on the effects of music in sleep quality was performed by Huang et al. [11]. They did a randomized controlled trial on 71 adults and divided them into control group, music group and music video group. Results showed that the music group had significantly longer subjective total sleep time than the control group and music video group. Coppola et al. [12] used a set of Mozart's compositions for 2 hours per day for fifteen days on 11 patients with drug-resistant epileptic encephalopathy. They found out that 5 out of 11 patients had a 50% reduction in their frequency of seizures. They also reported a significant improvement in the patients sleep and daily behaviour.

While music can be highly influential in reducing seizure frequency in many patients, some reports have demonstrated that music can also *trigger* seizures. One form of epilepsy called musicogenic epilepsy is prevalent in 1 out of 10,000,000 people. It is classified as a rare form of epileptic disorder [13]. In this kind of epilepsy, seizures can be provoked by listening to music, playing or even thinking of music [14], [15]. According to a review done by Pittau et al. [16], between 1884 and 2007 there were 110 reports of music-evoked seizures. One third of these cases showed epileptic seizures happened only because of music, while the rest reported other factors as well. Different types of music for instance classical, instrumental, or jazz, or specific instruments or even composers are said to have an impact on these type of seizures. A case study [17] reported a patient who has seizures while listening to music by certain singers having a voice with throaty and metallic quality.

Music seems to have both proconvulsant and anticonvulsant effect on epilepctic disorders, but to the best of our knowledge there is no research to understand these effects on a physiological level. Current clinical studies have not been able to explain why more neutral music (e.g. a specific sound) can invoke seizures in epileptic patients [18]. A review by Hughes [19] discusses the presence of gamma brain waves in a majority of the seizures, particularly during ictal activity in extratemporal and regional onsets. On the other hand, it is commonly known that increasing gamma waves in the brain can be beneficial as these waves are known to improve focus, cognition and memory formation. This is why many music therapy sessions use music or video stimuli to increase gamma waves in the brain to enhance cognitive ability. These multiple applications of music are fascinating and it is certainly worthwhile to explore how human physiological signals change pattern in response to music stimuli.

B. Physiological Signals as Evidence

A number of researchers have identified different categories of emotion using physiological signals. A variety of audio and visual stimuli have been used to elicit different emotions. Most of the work involves the use of images, text or videos as the stimuli for emotion recognition. Sharma et al. [20] used stress inducing and non-stress inducing texts to collect various physiological and physical signals from subjects. The model achieved 98% accuracy. Picard et al. [21] collected many physiological signals such as heart rate (HR), temperature, skin conductance (SC) and used personalized imagery to evoke emotions in 1 subject. They achieved an accuracy of 81% for eight emotions. Hossain et al. [22] collected different physiological signals from subjects by showing them videos consisting of genuine and fake smiles. The highest classification accuracy they got was 96.5%. Physiological signals have been used to design experiments to reduce epileptic seizures as well. Nagai et al. [23] conducted biofeedback training using a series of animated pictures as stimuli to collect galvanic skin response (GSR) signals from 18 patients with drug-refractory epilepsy. Compared to the control group, the biofeedback group showed a correlation between their GSR responses and reduction in frequency of seizures. In a recent study done by Alessandro et al. [24], Mozart Sonata for two pianos in D major, K448, was used on 12 patients with epilepctic disorder for six months. They observed an average of 20.5% reduction in their frequency of seizures.

Based on the literature it is evident that there are certain kinds of music that are being used to reduce stress, anxiety and epileptic seizures. However, this intuitive approach has not been empirically explored by experimentation to understand if different music genres have different effects, and what specific physiological signals are beneficent to detect these effects. Our research explores this phenomena in greater detail.

III. Materials and Methods

A. Subjects

24 students (13 male and 11 female) participated in this study. Among them 19 were undergraduate students and 5 were postgraduate students. The mean age was 21 years old with a standard deviation of 4.6. Participants were asked to sign a written consent form before their voluntary participation in the study. The study was approved by the Australian National University's Human Research Ethics Committee.

B. Stimuli

The music we have chosen was divided into three categories: classical, instrumental and modern pop music. In terms of classical music, pieces that have high values for long lasting periodicity have shown beneficial effects for music therapy [25]. Two of the four chosen music pieces are Mozart Sonatas K.448 and K.545, which have been used in a wide number of music therapy experiments [12], [26]. The other two music pieces were F. Chopin's "Funeral March" from Sonata in B flat minor Op. 35/2 and J.S Bach's Suite for Orchestra No. 3 in D "Air" [25].

When choosing instrumental music, we chose a different solo instrument for every piece of music. We used two music pieces used in Hurless et al. [27]. They are, "The Feeling of Jazz" by Duke Ellington and "YYZ" by Rush. The songs represent Jazz and Rock genres, respectively. A particular type of brainwave can be increased by using an audio tone called binaural beats as stimuli. Binaural beats can effectively synchronize brainwaves to enhance any specific brainwave pattern [3]. Therefore the other two pieces are binaural beats chosen from YouTube search results on relaxing music. One is called "Gamma Brain Energizer", which is said to boost gamma waves in the brain and regain focus and awareness [28]. The other piece is called "Serotonin Release Music with Alpha Waves", which is believed to be a relaxing music piece increasing alpha waves in the brain [29].

Modern pop music pieces were chosen by looking at the top song of Billboard Hot 100 year-end charts from year 2014-2017. Thus the selected songs are, "Happy" by Pharrell Williams, "Uptown Funk" by Mark Ronson featuring Bruno Mars, "Love Yourself" by Justin Bieber and "Shape of You" by Ed Sheeran [30].

In total we have chosen 12 songs, 4 from each category as our stimuli. For our experiment each participant listens to 2 out of the 3 categories. Thus each participant listens to a total of 8 songs. This number has been chosen as a result of a pilot study where different numbers of music were used with multiple participants. Eight has been chosen as the optimum number as beyond that subjects become tired and do not focus in the experiment. Although many papers focused on using only 1 or 2 music pieces as the stimuli, a comparison experiment has shown that using a set of music pieces is more effective and less monotonous than using just one music piece [31]. All music pieces were around 4 minutes in length. The music categories were order balanced in order to avoid any bias caused by keeping the same order for all participants.

C. Methods

Participants were comfortably seated in a chair in front of a 17.1 inch monitor. They were given a participation information sheet where all the instructions were written. Then the consent form was given for them to sign. After completion of this part we started the connection and calibration process of the physiological sensors. The participants were asked to wear a Empatica E4 device [32] on their left wrist which was used to record electrodermal activity at a sampling rate of 64 Hz. All participants were asked to limit any unnecessary movement during the experiment to prevent adding artefacts in the signals. For listening to music participants wore Bose QuietComfort 20 Acoustic Noise Cancelling headphones. Using a noise cancelling headphones helped participants to not get distracted by any outside noise. The entire process of listening to music and collecting subjective response was done through an interactive website prepared for the experiment.

Participants were asked some demographic questions at the beginning of the experiments. Then we started the experiment and participants listened to each music piece wearing the earphones. After the music finished they were automatically redirected to a page where they were asked to answer some questions about the music they just finished listening to. The questions included general comments as well as subjective ratings based on a 7-point Likert scale. For subjective rating the most common approaches used are 5-point and 7-point Likert scale. A 7-point scale is shown to be more reliable than a 5-point scale whereas having a scale with more than 7 ratings is shown to be impractical [33]. Hence we chose a 7-point Likert rating scale for our experiment. We asked questions about how the music made them feel. The emotional scales were categorized as i) $sad \rightarrow happy$ ii) $disturbing \rightarrow comforting$ iii) $depressing \rightarrow exciting$ iv) $unpleasant \rightarrow pleasant$ v) $irritating \rightarrow soothing$ vi) $tensing \rightarrow relaxing$. These metrics were taken from [34]. The first 4 ratings seek a general impression about the music itself, whereas the last 2 ask about the participant's feeling while listening to that music. Participants also answered the post-experiment questionnaire which asked them to give additional comments about any music pieces causing them discomfort.

D. Preprocessing

Physiological signals collected during the experiment are highly prone to artefacts caused by subject movements, blinking etc. Therefore it is very important to use some preprocessing techniques to remove these artefacts before doing any further analysis. Also the values that we get from these physiological signals are subject-dependent, which means they have different range of values. So it is necessary to use some normalization methods on these raw signals to bring all the values within one range. We used Min-Max normalization technique for this. The equation for min-max normalization is,

$$v\prime = \left(\frac{v - min\_v}{max\_v - min\_v}\right) * (new\_max - new\_min) + new\_min \quad (1)$$

Where, $v\prime$ corresponds to min-max normalized data and v is the range of raw data, max_v and min_v are the maximum and minimum value of v respectively. Here we chose $new\_min = 0$ and $new\_max = 1$. So all the values were normalized to have a value within the range of 0 to 1. Data from each participant were normalized individually.

After normalizing the data we move on to filtering them. Data that corresponds to skin conductance and skin response activities are commonly filtered using a median smoothing filter [35]. Thus we used this filtering technique for our study. Choosing a high value as the parameter for filtering might cause the loss of valuable data, on the other hand a low value will result in the data remaining too noisy. We chose a 10 point median filter in order to avoid the loss of too much data [36].

E. Features

Physiological signals collected using devices give a large amount of data for each participant. Not only is it difficult to analyze the entire set of recorded features, it is also computationally very expensive. Therefore, a number of features were extracted from the data after finishing the data normalization and filter process. Based on a number of previous examples in the literature on emotion recognition and physiological signals [21], [22], [37], [38], the following 14 features were calculated.

- Mean of Filtered and Normalized Signals
- Maximum and Minimum of Filtered Signals
- Standard Deviation and Interquartile Range of Filtered Signals
- Variance and Kurtosis of Filtered Signals
- Number of Peaks for Periodic Signals
- Means of the absolute values of the first and second differences of the normalized and filtered signals
- Mean of the first 10 points derived using Welch Power Spectral Density

13 features out of 14 are time domain features, and power spectral density is the frequency domain feature. Converting physiological signals from time domain to frequency domain to extract features is commonly done to find features that are more apparent in the frequency domain [39]. The conversion is done using Fourier Transformation. In total, there were 14 extracted features for each music stimuli for every participant. The signals were segmented according to the song length to get 8 samples from each participant. We also tried calculating features using 60 seconds and 30 second segments but the results showed a decline in terms of classification accuracy. So a total of 2688 features (14*8*24) were used in the classification process.

F. Feature Selection

The feature selection process is often used before classification in order to reduce the dimension of the feature space. Sometimes the extracted feature set can contain redundant or noisy features. Feature selection algorithms can identify those features and remove them from the set. A reduced number of features can also result in a shorter run time for the classification process which means it helps create a robust system. [40] provides a detailed explanation and comparison of many of the state-of-the-art feature selection methods. Based on that and some other literature [41] we have used 3 feature subset selection algorithms and 2 feature scoring algorithms in this study. They are briefly described below:

- Genetic Algorithm (GA) - A heuristic optimization method that selects a subset of features having the best fitness value.
- SFS (Sequential Forward Selection) - This is a greedy search method that starts with an empty feature set and adds feature according to their contribution in maximizing the output
- SFFS (Sequential Floating Forward Selection)- This is an extension of SFS where after each forward step, the method executes backward steps till the objective function increases.
- Statistical Dependency (SD) - SD ranks all the features by measuring if the values of a features are dependent on their class labels or not.
- Minimal-redundancy-maximal relevance (MRMR) - Features are ranked according to the mutual information between features and their associated class labels.

G. Evaluation Measures

We have used 6 well-known evaluation measures to evaluate the results of this study. Along with classification accuracy, we have calculated precision (fraction of the predicted labels matched), recall (fraction of the reference labels matched, also called sensitivity), specificity (true negative rate), F measure (harmonic mean of precision and recall, also known as F score or F1 score) and geometric mean (of true positive and true negative rate) to validate our classification results.

IV. Results and Discussion

A. Statistical Analysis of Participants' Subjective Ratings

Subjective ratings provided by the participants were analyzed using analysis of variance (ANOVA) test. We computed the significance level of each music category based on the six questions about emotional response to the music stimuli. The results show statistical significance ($p < 0.05$) for two emotions ($Sad \rightarrow Happy$, $Depressing \rightarrow Exciting$), but it did not show significant difference for other emotions.

B. Selected Features

Table 1 shows the features that were selected by each feature selection method for 3 music genre classifications. Note that the first 3 methods select a features subset while the others rank all 14 features. For these latter methods, we have chosen the best 10 features from the feature scoring algorithms.

TABLE I
SELECTED FEATURES BY EACH METHOD FOR GENRE BASED CLASSIFICATION

Selection Method	Number of Selected Features	Selected Features
GA	11	1,2,3,5,6,8,9,10,11,12,14
SFS	5	3,4,7,10,11
SFFS	4	3,4,10,11
SD	10	1,2,3,5,6,7,9,10,12,14
MRMR	10	1,2,3,5,6,7,9,10,12,14

[1]Features Corresponding to the Numbers

Table 2 shows the total number of features chosen by each feature selection method for classification based on different subjective rating. Note that in all cases SD and MRMR choose the same 10 best features (in sometimes different orders). That is why we combined the classification results of both methods in the following section.

C. Classification Results

1) Classification based on Music Genre: All the music stimuli were labelled as one of the following 3 categories: classical, instrumental and modern pop. A leave-one-observer-out process was performed using a 3 class classifier to distinguish among the 3 music categories. Classification was done using MATLAB R2017a software with an Intel(R) Core(TM) i7-5200U processor with 3.60 GHz, 16.00 GB of RAM and Microsoft Windows 10 Enterprise 64-bit operating system.

For the classification process, a pattern recognition network was constructed with one input layer, one hidden layer and one output layer. The hidden layer consisted of 30 nodes. Choosing the optimum number of hidden nodes is the most crucial task in building the neural network. Too many neurons in the hidden layer may result in overfitting, while too few neurons may cause underfitting. We ran the neural network using hidden node sizes from 5-50 and compared the classification accuracy. The result is shown in Fig. 1.

We can observe that from the hidden node size of 30 the network produces a pretty stable result in terms of accuracy. Therefore we chose this as the optimum number of hidden nodes for our network. Other parameters of the network were: Levenberg—Marquardt methods as network training function and mean squared normalized error as performance function.

[1]1 = Mean of normalized signals, 2 = Mean of filtered signals, 3 = Maximum of filtered signals, 4 = Minimum of filtered signals, 5 = Standard deviation of filtered signals, 6 = Interquartile range of filtered signals, 7 = Variance of filtered signals, 8 = Kurtosis of filtered signals, 9 = Number of peaks in filtered signals 10 = Mean of the first difference of normalized signals, 11 = Mean of the second difference of normalized signals 12 = Mean of the first difference of filtered signals 13 = Mean of the second difference of filtered signals 14 = Mean of the first 16 data points from Welch power spectrum density analysis

TABLE II
TOTAL NUMBER OF FEATURES SELECTED BY EACH METHOD FOR SUBJECTIVE RATING BASED CLASSIFICATION

Emotion	GA	SFFS	SFS	SD	MRMR
sad → happy	9	3	4	10	10
depressing → exciting	10	2	1	10	10
disturbing → comforting	10	4	4	10	10
unpleasant → pleasant	7	2	2	10	10
irritating → soothing	11	2	3	10	10
tensing → relaxing	10	2	1	10	10

Fig. 2 shows the average results based on all evaluation measures mentioned in the previous section using all 7 feature selection methods. The leave-one-observer-out process is done 20 times for all methods and the average results are shown.

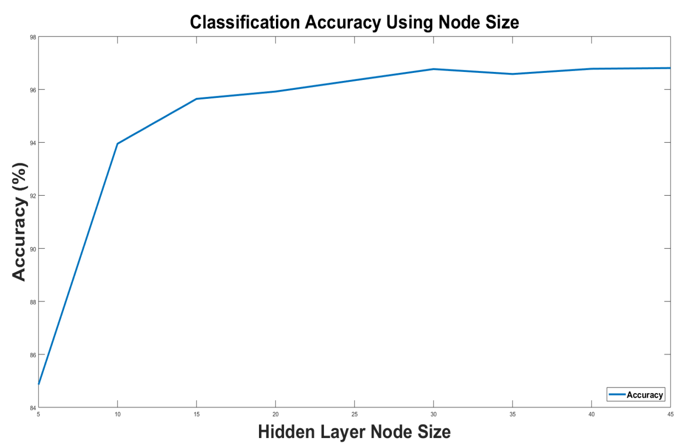

Fig. 1. Classification Accuracy Using Different Hidden Node Size

From Fig. 2 it can be observed that classification using neural network along with GA feature selection method can give a high accuracy of 96.8% for 3 different music genres. This implies that EDA can be a good measure in classifying music categories. Neural network with GA gives best results in terms of all 6 evaluation measures. Table 3 gives a comparison of GA results with SD/MRMR (which performed moderately) and SFFS (which performed the worst). It can be seen that the difference between GA and SFFS method is quite significant (Around 15% and 13% for precision and F measure respectively).

2) Classification based on Participants' Subjective Ratings: Based on the responses provided by the 24 participants of this study, we have given 3 labels to each of the questions and labelled all the responses according to those labels. So the

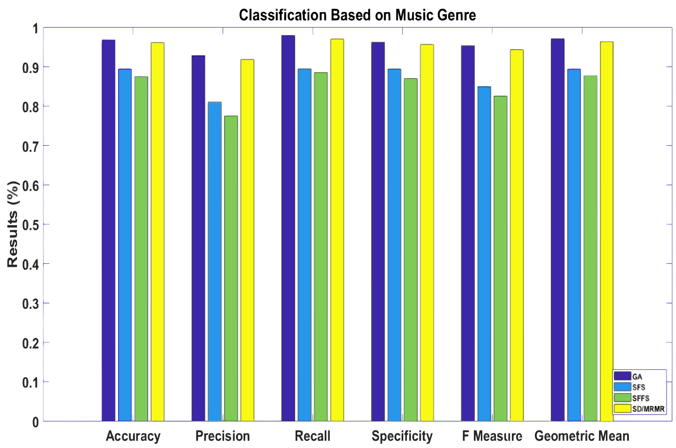

Fig. 2. Classification Based on 3 Music Genres

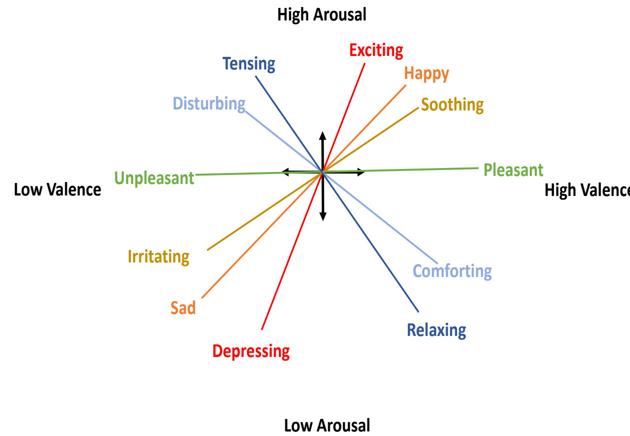

Fig. 3. Two Dimensional Emotion Model by Valence and Arousal

labels for the 6 questions were: i) $sad \rightarrow neutral \rightarrow happy$ ii) $disturbing \rightarrow neutral \rightarrow comforting$ iii) $depressing \rightarrow neutral \rightarrow exciting$ iv) $unpleasant \rightarrow neutral \rightarrow pleasant$ v) $irritating \rightarrow neutral \rightarrow soothing$ vi) $relaxing \rightarrow neutral \rightarrow tensing$. We have used these labels to perform the classification using the 3 class classifier described in the previous section. Below we will describe the details of results based on two emotions ($disturbing \rightarrow neutral \rightarrow comforting$ and $depressing \rightarrow neutral \rightarrow exciting$)

Researchers of affective computing often use two kinds of emotions to model different emotions. The first one is using discrete labels, and the other one is using multiple dimensions or scales to categorize emotions. The main drawback of discrete labels is that stimuli can contain blended emotions which cannot be fully expressed just with one label [2]. Therefore a multidimensional space is more appropriate to express these emotions. The common scales used for this are valence (intrinsic goodness or badness) and arousal (alertness/response readiness). Fig. 3 shows the valence-arousal diagram of the emotions we constructed for this study.

Fig. 4 shows the evaluation results of the subjective rating based on the emotion $depressing \rightarrow neutral \rightarrow exciting$. Similar to the genre based classification, all evaluation measures are calculated from an average of 20 runs.

It can be observed that GA is again performing better than all other feature selection methods. A comparison between the evaluation measures value of GA and two other methods is given in Table 4. Similar to genre based classification, it can be seen that GA performs much better than the worst performing method, SFS in this case (Around 35% difference in accuracy). Similar outcomes are observed for classification based on 2 other emotions ($sad \rightarrow neutral \rightarrow happy$, and $irritating \rightarrow neutral \rightarrow soothing$). In all of the cases GA performs better than all other feature selection methods. The

TABLE III
CLASSIFICATION RESULTS BASED ON MUSIC GENRE

	GA	SD/MRMR	SFFS
Accuracy	**0.968**	0.961	0.875
Precision	**0.929**	0.918	0.775
Recall	**0.979**	0.97	0.885
Specificity	**0.962**	0.957	0.869
F Measure	**0.953**	0.943	0.825
Geometric Mean	**0.971**	0.963	0.877

average accuracy based on these 2 emotions are 93.8% and 95.1% respectively.

However, different patterns are observed for the other 3 emotion based classification ($disturbing \rightarrow neutral \rightarrow comforting$, $unpleasant \rightarrow neutral \rightarrow pleasant$ and $relaxing \rightarrow neutral \rightarrow tensing$). Fig. 5 shows the results of 6 evaluation measures based on the emotion $disturbing \rightarrow neutral \rightarrow comforting$.

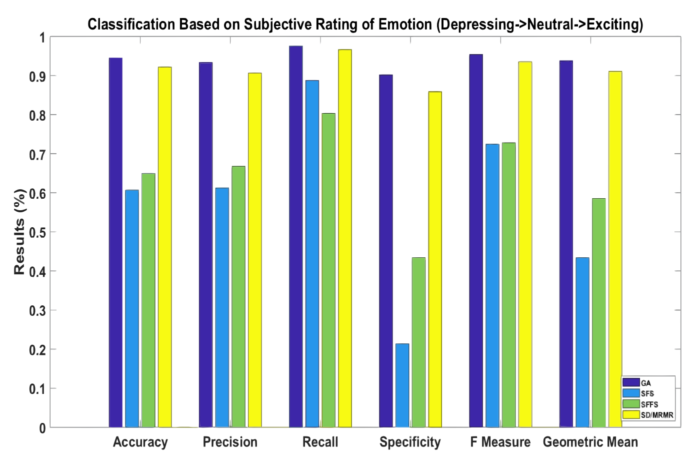

Fig. 4. Classification Results Based on Subjective Rating ($depressing \rightarrow neutral \rightarrow exciting$)

TABLE IV
CLASSIFICATION RESULTS BASED ON SUBJECTIVE RATING
($Depressing \rightarrow Neutral \rightarrow Exciting$)

	GA	SD/MRMR	SFS
Accuracy	**0.945**	0.922	0.607
Precision	**0.933**	0.906	0.612
Recall	**0.975**	0.967	0.888
Specificity	**0.902**	0.859	0.214
F Measure	**0.954**	0.935	0.725
Geometric Mean	**0.938**	0.911	0.434

TABLE V
CLASSIFICATION RESULTS BASED ON SUBJECTIVE RATING
($Disturbing \rightarrow Neutral \rightarrow Comforting$)

	GA	SD/MRMR	SFS/SFFS
Accuracy	0.968	**0.983**	0.946
Precision	0.967	**0.983**	0.957
Recall	**0.998**	**0.998**	0.979
Specificity	0.819	**0.913**	0.781
F Measure	0.982	**0.99**	0.968
Geometric Mean	0.874	**0.954**	0.874

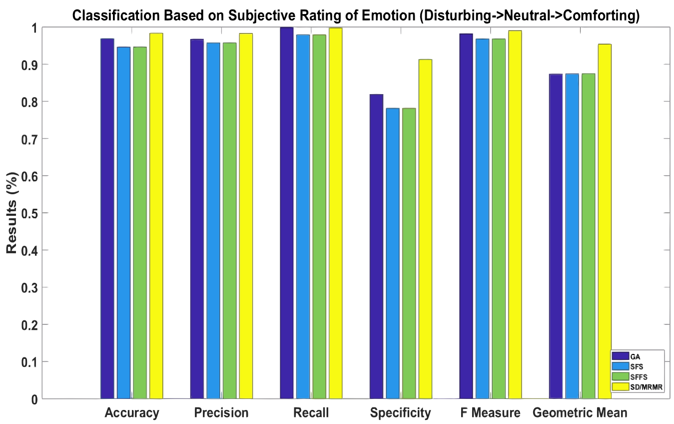

Fig. 5. Classification Results Based on Subjective Rating ($Disturbing \rightarrow Neutral \rightarrow Comforting$)

As seen in Fig. 5, SD/MRMR feature selection method gives the best results in all measures. Comparing with the worst performing method (both SFS and SFFS in this case as they have selected the same set of features), the difference is high in terms of specificity (around 13%). The values are given in Table 5.

As for the other 2 emotions ($unpleasant \rightarrow neutral \rightarrow pleasant$ and $relaxing \rightarrow neutral \rightarrow tensing$), the best results for all evaluation measures is also found by using SD/MRMR feature selection method with the average accuracy of 98% and 96.4% respectively. Although the values of GA and SD/MRMR are quite similar, t-test analysis shows a significant difference in terms of accuracy for $depressing \rightarrow neutral \rightarrow exciting$ ($p < 0.01$), but not for the case of $disturbing \rightarrow neutral \rightarrow comforting$. Further experiments might be able to show a significant difference. Values of other evaluation measures also show the same pattern for both cases.

From the emotion model in Fig. 3, we can observe that for the 3 emotions that have a negative slope ($depressing \rightarrow neutral \rightarrow exciting$, $sad \rightarrow neutral \rightarrow happy$ and $irritating \rightarrow neutral \rightarrow soothing$) GA feature selection methods works the best. But for the emotions that have a slope of 0 or positive value ($disturbing \rightarrow neutral \rightarrow comforting$, $relaxing \rightarrow neutral \rightarrow tensing$ and $unpleasant \rightarrow neutral \rightarrow pleasant$) SD/MRMR method works the best. Further experiment and analysis are required to understand this phenomenon in greater detail. But based on the current results it is evident that there is a correlation between human emotion and their physiological signals which can be differentiated by different feature selection methods during classification.

V. CONCLUSION AND FUTURE WORK

In this paper, we conducted a preliminary study to collect participants' EDA activity while listening to different types of music. Signals were first normalized then smoothed, then multiple features were extracted. Then a set of feature selection methods were applied to find the best features.
Empirical analysis demonstrated that physiological signals are capable in identifying the differences in these various categories of music. Neural network analysis showed the highest accuracy of 96.8% and 98.3% in classifying music based on genre type and human emotions respectively. This could certainly be useful for medical and affective computing researchers as our analysis has shown that different types of music do indeed change the states of physiological signals. It is anticipated that future work will involve including more physiological signals such as electroencephalogram (EEG), heart rate variability (HRV), pupillary response to build a more robust system with more features and deep learning models. We will also apply visualization techniques to understand the effects of different music genres and physiological state changes on a deeper level. Future research in this area will be beneficial in improving music therapy treatments and perhaps to finding a cure for musicogenic epilepsy.

ACKNOWLEDGMENT

The authors would like to thank the participants who took part in this research. Data relating to this study will be made publicly available upon completion and publication of the complete study.

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