HUMAN EMOTION BASED MUSIC RECOMMENDATION SYSTEM USING PHYSIOLOGICAL SENSORS

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Abstract- *This report is intended to present the proposed design and implementation of the "Human Emotion Based Music Recommendation System Using Physiological Sensor" system. The proposed design is for a system that will import human's real time emotion and recommend media based on that. The parameters used to analyze the said emotion of a particular person are: Attention and Meditation level of a person which are based on alpha, beta, gamma, delta, and theta waves of that particular person's brain. In order to capture this we are going to make use of a hardware device, neurosky mindwave for the purpose of capturing real time human's emotion state and recommending media based on that. Most of the current media recommendation systems use collaborative or content-based recommendation models. Because, the media choice of a user is not only dependent to the historical preferences or music contents but also dependent to the mood of that user. Thus, we are going to analyze the real time emotional state of a person in order to propose our design of recommending media based on that. In particular, the emotion of a user is classified by a wearable computing device which is integrated with an electroencephalogram (EEG) sensors (Here, we have made use of neurosky mindwave device). This information is fed to our recommendation model as data and then our predictive model give media recommendations to current user as per their emotion classified in real time. In this paper emotion recognition problem is considered as an emotion label prediction from physiological signals. Our experimentation conducted during this process has resulted in a 99.88% accuracy rate being obtained using the SVM Classifier.*

Keywords- Machine learning, SVM , K-means ,EEG , Neurosky mindwave , music ,recommendation system

I. INTRODUCTION

Wearable computing is the study or practice of inventing, designing, building or using body-worn computational and sensory devices that leverage a new type human-computer interaction with a body-attached component that is always up and running. With increase in wearable devices every year, there areas of applications are also increasing rapidly. They have influenced medical care, fitness, aging, disabilities, education, transportation, finance, gaming and music industries. [1] [2]

Recommendation engines are algorithms which aim to provide the most relevant items to the user by filtering useful information from a huge pool of data. Recommendation engines may discover data patterns in the data set by learning user's choices and produce the outcomes that correlates to their needs and interests. [3]

Most of the recommender systems do not consider human emotions or expressions. However, emotions have noticeable influence on daily life of people. For a rich set of applications including human-robot interaction, computer aided tutoring, emotion aware interactive games, neuro marketing, socially intelligent software apps, computers should consider the emotions of their human conversation partners. Speech analytics and facial expressions [4], [5] have been used for emotion detection. However, in case of human beings prefer to camouflage their expressions, using only speech signals or facial expression signals may not be enough to detect emotions reliably. Compared with facial expressions, using physiological signals is a more reliable method to track and recognize emotions and internal cognitive processes of people.

In our project, we are going to study emotion recognition using electroencephalogram (EEG) device by making use of Neurosky Mind Wave game tools.

Electroencephalography is an electrophysiological monitoring method to record electrical activity of the brain, where EEG is the device which is placed around a human's head to monitor the electrical signals of the brain. Refer the figure below for a clear picture about how an EEG device looks

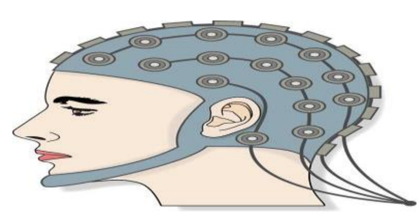

Chart -1 : EEG Device

To achieve our goal of recognizing electrical signals of a human's brain as per the EEG terminology we are going to make use of a gaming device, Neurosky Mind Wave. Neurosky Mind Wave is basically a game which makes use of the electrical signals of the brain to measure the concentration intensity and moves the ball as per the intensity. To have a clear idea about Neurosky Mind Wave device refer the figure below.

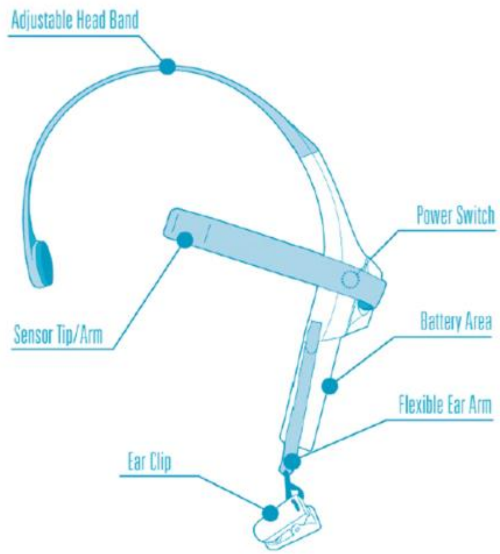

Chart -2:mindwave device

A. Motivation behind project topic

There are three things which motivated me the most for coming up with an idea of Human Emotion and Opinion recognition through his or her online activities. They are as follows:

1.The movie Imitation Game. This movie is based on the life of Alan Turing who is also known as the father of Artificial Intelligence. Alan Turing was the one who broke the "ENIGMA", enigma was basically the code through which Germany, during the Second World War used to send message to its troops about where to drop the bomb and Alan Turing along with his team developed a machine called Christopher which could decode the entire code and could tell the exact latitude and longitude of the locations where the next bombs would be dropped.

2.Our motivation in this work is to use emotion recognition techniques with wearable computing devices to generate inputs for music recommender system's algorithm, and to enhance the accuracy of the resulting music recommendations. Apart from this, the existing models which are making use of physiological devices or sensors are making use of galvanic sell response (GSR), Photo Plethysmography (PPG), Electrocardiogram (ECG), and so on. All of these devices cannot be worn in real time scenario and they can only be used for only some kind of routine checkup. In our case, we are going to make use of a very comfortable device of Neurosky mindwave as show in fig (2) which will be embedded with a head phone. This will help us in achieving our goal of collecting electrical signals of the human's brain who is using our device which ultimately benefit us for our recommendation model.

B. Aim and Objective(s) of the work

1. To measure the following mental characteristics of a person by using a custom smart headphone/earphone:
a. Attention
b. Meditation

2. To develop a machine learning system to analyze the above measured data and identify the emotion of the person.
To recommend media (Audios/Videos) based on the emotion class recognized..

II. METHODOLOGY

A. Proposed Approach

Proposed framework involves using EEG to capture physiological signals from the user via a wearable computing device, and using these signals to enhance the accuracy of the recommendations made by the recommender system by tracking the user's emotional state through these signals. Emotional effects of the past recommendations on the user are stored in the system's database and used in future recommendations, as the same musical track's effects can be varied between different users.

B. Algorithm

Input: Source Data Signal Electroencephalogram SEEG
Output: Predicted Target emotion labels LE based on arousal and Valence values
Output: Recommended Songs Rs
Step 1: Get signal data from EEG SEEG
Step 2: Sample and extract features from SEEG
Step 3: Predict Target Labels LE by clustering
Step 4: Use this dataset obtained during real time emotion classification
Step 5: Classify the Emotion of user EUser
Step 6: Give EUser as input to the Apriori Algorithm
Step 7: Get suggested results Rs and send it to the player

C. System Architecture

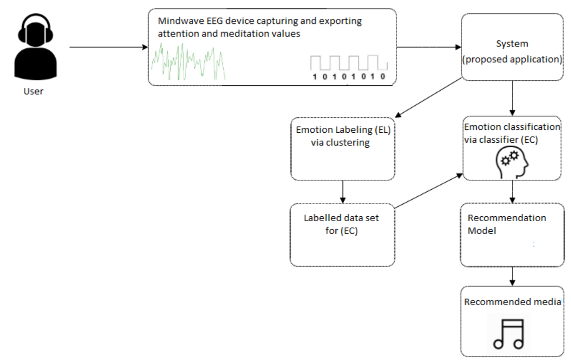

Chart -3: System Architecture

D.Data Collection:

Data collection will be done by making use of either a typical EEG device or the head gear of neurosky mindwave on the basis of their availability and feasibility. The electrical signals from any of these two devices will be analogue in nature and can be seen on the software which comes along with them. This analogue signal will then be fed to the python's library of PYB in which we are having the ADC (Analog to Digital Converter) class and from that class we will be able to get numerical values within the range of 0 to 4095 of alpha, beta, gamma and delta waves of the mind. Thereafter for each user in each song we will divide the entire time in 5 seconds slots and take the values of alpha, beta, gamma and delta respectively for each time slot and then take their average to obtain single/unique values of alpha, beta, gamma and delta for a single user for a single song. Thus, we will be creating our dataset on this basis on more than one thousand students on ten different songs.

E.Feature extraction via PCA

After creation of the dataset the second most important work is feature extraction because we are going to work on algorithms which will work on 2-Dimensional data and by feature extraction we will be able to achieve that goal.

For feature extraction we are going to make use of PCA algorithm. The theory of PCA Algorithm is given below.

Principle Component Analysis:

The Principle Component Analysis is a mathematical procedure that transforms the d dimensions inputs into the new k-dimensional space, with minimum loss of information where the value of k is always less than the value of d. Here, in our case the value of k will be 2 as we are requiring 2-dimensional feature space.

Algorithm:

Step 1. Find the mean vector.
Step 2. Assemble all the data samples in a mean adjusted matrix.
Step 3. Create the covariance matrix.
Step 4. Compute the Eigen vectors and Eigen values.
Step 5. Compute the basis vectors.
Step 6. Represent each sample as a linear combination of basis vectors.

F.Labelled Dataset Creation Using K-Means Clustering

The K-means problem is NP-complete, which means that there is no efficient solution to find the global minimum and we need to resort to a heuristic algorithm. The best known algorithm is usually also called K-means, although the name 'Lloyd's algorithm' is also used. The outline of the algorithm is given in algorithm below.

Algorithm:

Algorithm 8.1: KMeans(D, K) – K-means clustering using Euclidean distance Dis_2.

Input : data $D \subseteq \mathbb{R}^d$; number of clusters $K \in \mathbb{N}$.
Output : K cluster means $\mu_1, \ldots, \mu_K \in \mathbb{R}^d$.

randomly initialise K vectors $\mu_1, \ldots, \mu_K \in \mathbb{R}^d$;
repeat
  assign each $\mathbf{x} \in D$ to $\arg\min_j \mathrm{Dis}_2(\mathbf{x}, \mu_j)$;
  for $j = 1$ to K **do**
    $D_j \leftarrow \{\mathbf{x} \in D \mid \mathbf{x}$ assigned to cluster $j\}$;
    $\mu_j = \frac{1}{|D_j|} \sum_{\mathbf{x} \in D_j} \mathbf{x}$;
  end
until no change in $\mu_1, \ldots, \mu_K$;
return $\mu_1, \ldots, \mu_K$;

Chart -4: K-Means Algorithm

III. ANALYSIS

A. Emotion Classification

After clustering, we will get a labelled dataset which will be fed to our classification model for classifying the real time human emotion. There are multiple classification techniques available and we will be experimenting each one of them, the process will be followed by calculating the accuracy of each classification technique and choosing the technique with highest accuracy. The following classification techniques can be used:

a.Decision Tree

Classification Tree:

Decision tree learning uses a decision tree (as a predictive model) to go from observations about an item (represented in the branches) to conclusions about the item's target value (represented in the leaves). It is one of the predictive modelling approaches used in statistics, data mining and machine learning. Tree models where the target variable can take a discrete set of values are called classification trees.

Algorithm (Courtesy Xoriant's Machine Learning Classification Algorithm of Decision Trees):

Step 1: Create root node for the tree
Step 2: If all examples are positive, return leaf node 'positive'
Step 3: Else if all examples are negative, return leaf node 'negative'
Step 4: Calculate the entropy of current state H(S)
Step 5: For each attribute, calculate the entropy with respect to the attribute 'x' denoted by H(S, x)
Step 6: Select the attribute which has maximum value of IG(S, x)
Step 7: Remove the attribute that offers highest IG from the set of attributes
Step 8: Repeat until we run out of all attributes, or the decision tree has all leaf nodes.

b. Support Vector Machine (SVM)

Linearly separable data admits infinitely many decision boundaries that separate the classes, but intuitively some of these are better than others. For example, the left and middle decision boundaries seem to be unnecessarily close to some of the positives; while the one on the right leaves a bit more space on either side, it doesn't seem particularly good either. To make this a bit more precise, we defined the _margin of an example assigned by a scoring classifier as c(x) ˆs(x), where c(x) is +1 for positive examples and −1 for negative examples and ˆs(x) is the score of example x. If we take ˆs(x) = w· x−t , then a true positive xi has margin w· xi − t > 0 and a true negative xj has margin −(w· xj − t) > 0. For a given training set and decision boundary, let m ⊕ be the smallest margin of any positive, and m_ the smallest margin of any negative, then we want the sum of these to be as large as possible. This sum is independent of the decision threshold t, as long as we keep the nearest positives and negatives at the right sides of the decision boundary, and so we re-adjust t such that m⊕ and m_ become equal. The training examples nearest to the decision boundary are called support vectors: as we shall see, the decision boundary of a support vector machine (SVM) is defined as a linear combination of the support vectors.

The margin is thus defined as m/||w||, where m is the distance between the decision boundary and the nearest training instances (at least one of each class) as

Algorithm:

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Algorithm 7.3: PerceptronRegression(D, T) – train a perceptron for regression.
Input   : labelled training data D in homogeneous coordinates;
          maximum number of training epochs T.
Output  : weight vector w defining function approximator ŷ = w·x.
w ← 0; t ← 0;
while t < T do
    for i = 1 to |D| do
        w ← w + (y_i − ŷ_i)^2 x_i;
    end
    t ← t + 1;
end
```

Chart-5: SVM Algorithm

c. K-Nearest Neighbours Classification

In pattern recognition, the k-nearest neighbors algorithm (k-NN) is a non- parametric method used for classification and regression. In both cases, the input consists of the k closest training examples in the feature space. The output depends on whether k-NN is used for classification or regression:

In k-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbours, with the object being assigned to the class most common among its k nearest neighbours (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbour.

In k-NN regression, the output is the property value for the object. This value is the average of the values of its k nearest neighbours.

Algorithm:

Step 1: Load the data
Step 2: Initialize K to your chosen number of neighbors
Step 3. For each example in the data
Step 3.1 Calculate the distance between the query example and the current example from the data.
Step 3.2 Add the distance and the index of the example to an ordered collection
Step 4. Sort the ordered collection of distances and indices from smallest to largest (in ascending order) by the distances
Step 5. Pick the first K entries from the sorted collection
Step 6. Get the labels of the selected K entries
Step 3. Return the mode of the K labels

B. Recommendation Engine Modelling via Apriori Algorithm

Apriori algorithm is a classical algorithm in data mining. It is used for mining frequent itemsets and relevant association rules. It is devised to operate on a database containing a lot of transactions, for instance, items brought by customers in a store.

It is very important for effective Market Basket Analysis and it helps the customers in purchasing their items with more ease which increases the sales of the markets. It has also been used in the field of healthcare for the detection of adverse drug reactions. It produces association rules that indicates what all combinations of medications and patient characteristics lead to ADRs.

Algorithm:
Step 1: Create a frequency table of all the items that occur in all the transactions.
Step 2: We know that only those elements are significant for which the support is greater than or equal to the threshold support. Here, support threshold is 50%, hence only those items are significant which occur in more than three transactions.
Step 3: The next step is to make all the possible pairs of the significant items keeping in mind that the order doesn't matter, i.e., AB is same as BA. To do this, take the first item and pair it with all the others such as OP, OB, OM.Similarly, consider the second item and pair it with preceding items, i.e., PB, PM. We are only considering thepreceding items because PO (same as OP) already exists.
Step 4: We will now count the occurrences of each pair in all the transactions.
Step 5: Again only those itemsets are significant which cross the support threshold, and those are OP, OB, PB, and PM.
Step 6: Now let's say we would like to look for a set of three items that are purchased together. We will use the itemsets found in step 5 and create a set of 3 items.

IV. DESIGN

A.System Architecture

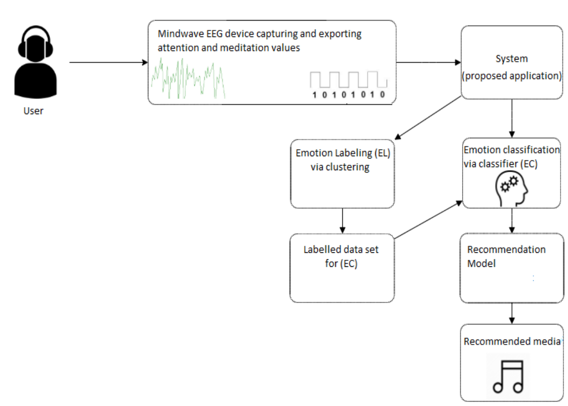

Chart-6:System Architecture

B. Data Flow Diagram

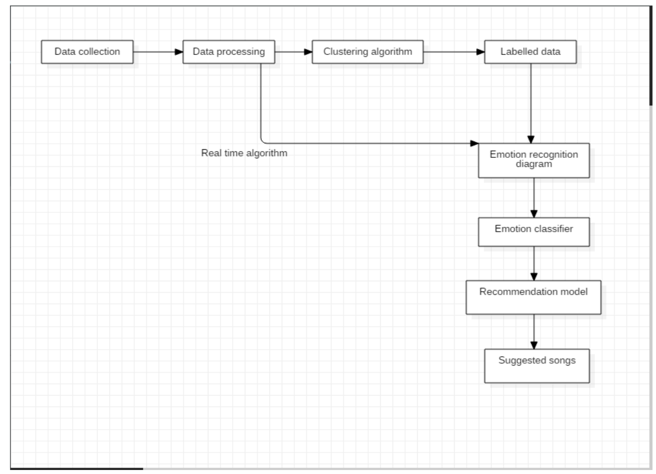

Chart-7:Data Flow diagram

C. Sequence Diagram

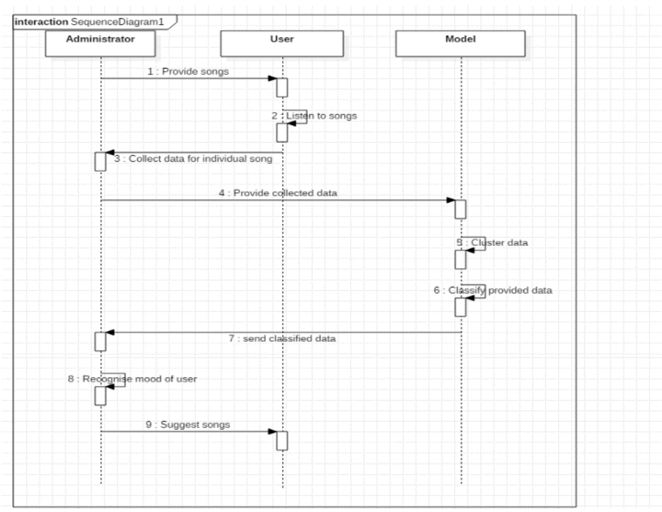

Chart-8:Sequence diagram

D.Use Case Diagram

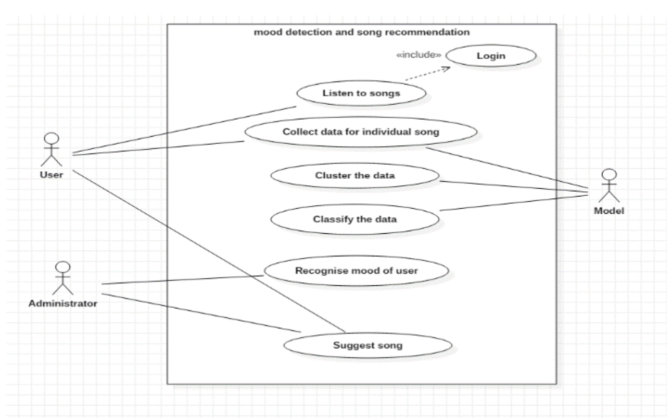

Chart-9:Use Case Diagram

E. class diagram

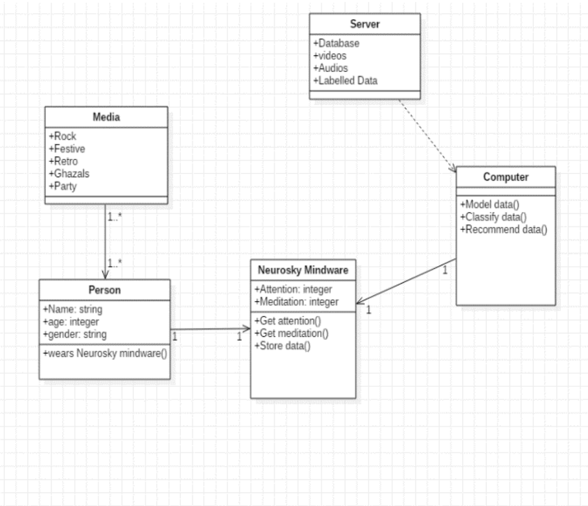

Chart-10:class diagram

F. Activity diagram

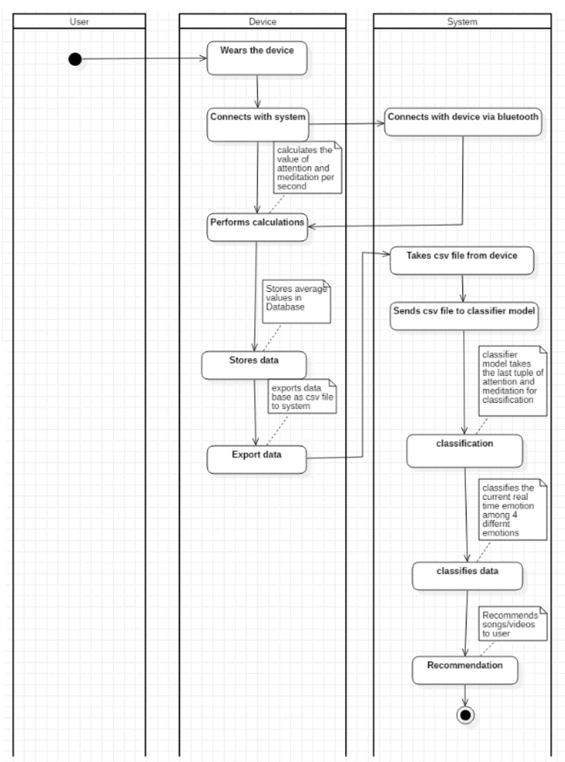

Chart -11:Activity diagram

V. CONCLUSION

In this project, we have proposed a system to determine the "Emotion" of a particular person while listening or watching any media. Our proposal cites certain mental characteristics and monitoring of these characteristics with the help of the EEG head gear embedded with headphone/earphone, the data can be analyzed and the average level of attention and meditation of the person can hence be obtained and notified to the user with the help of the user interface.

The analysis of the data takes place via a machine learning algorithm which makes use of SVM in order to correctly identify the emotion of the person. The system then recommends media based on the emotion classified of the person during the course of the listening/watching media.

The system eventually will be improving the recommendation models which are already existing to ensure maximum accuracy of understanding what a person wants, which eventually means better suggestions and experience of users while listening or watching any media on any platform.

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