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Emotion Detection Analysis using EEG and Physiological Signals for Hybrid Systems

Namrata D Rupani, R. Roseline Mary

***Abstract:** Emotions are an inevitable and integral part of human existence. They form the basis of decisions taken by individuals and the way they perceive their surroundings. Method of articulation of emotions have changed with the increment in dependency between people and innovation. Now the need to recognize emotions has increased with the increasing role of human-Computer Interface (HCI) technology. There are many ways to record and identify human's emotion using different neurophysiological measurements/ technologies like GSR(Galvanic Skin Response), Electromyography (EMG), Electrocardiogram (ECG) and Electroencephalography (EEG). In this paper, the focus is on emotion detection using EEG signals and other physiological signals and further analyzing them. There exist various machine learning techniques that have been used to pre-process and classify EEG data, have been reviewed in the paper. The analysis involves major aspects of the emotion recognition process like feature extraction, classification and comparison of the approaches. Different supervised machine learning algorithms have been applied to classify the EEG data. This paper focuses on comprehensive analysis of existing systems and based on the result propose the techniques which when applied will reap high-quality results.*

***Keywords:** Emotions, Emotion Recognition, Human Computer Interface (HCI), Electroencephalogram (EEG), EEG Analysis, Physiological Signals, Valence – Arousal Model.*

I. INTRODUCTION

Emotions are crucial to human existence. As humans understand, in general, emotions are their spontaneous reaction or mental state towards a situation. It acts as the foundation for one's perception of the surrounding. Some common emotions are happy, sad, calm or angry, etc. They define how a person is feeling. There are two different notions of emotions adapted by neuroscientists and researchers. According to researchers, emotions are mere states of an individual's mind, feeling, while for neuroscientists, emotions are a result of physiological interactions with their surroundings [1]. Nowadays, technology paradigms are shifting to human centric and human- driven applications. Emotion detection and its analysis has become quite an important topic to utilize these technologies up to their full potential and improve human-computer interaction.

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***** Correspondence Author

Namrata D Rupani*, Research Scholar Master of Computer Applications (MCA) Department of Computer Science CHRIST (Deemed to be University), Bangalore – 560029, Karnataka, India

R. Roseline Mary, Assistant Professor Department of Computer Science CHRIST (Deemed to be University), Bangalore – 560029, Karnataka, India

Technologies like Human Computer Interface (HCI) and Brain Computer Interface (BCI) involves human cognition, humans interacting with machines, decision making, etc. and requires good understanding and analysis of human emotions [2].

There exists numerous ways to recognize and then analyze human emotions. Emotions elicited by a person can be identified mainly in two ways; one through external signals gathered through facial expressions, speech, eye movements, etc. But these signals can be subject to modification (a person can feign his/her expression), i.e. may not be authentic. Second, internal signals comprises of certain physiological signals which provide more reliable results by displaying the underlying emotions of a person. Physiological signals are a combination of recordings collected from the central and the peripheral nervous system. The brain and spinal cord forms the central nervous system. The peripheral nervous system is further sub-divided in the autonomous nervous system (ANS) and somatic nervous system (SNS) [32, 41]. The regulation of bodily functions like heart rate, pupillary response and sexual arousal are unconscious reactions to the control system, i.e. the peripheral nervous systems [2, 4]. The signals from brain are referred as electroencephalogram (EEG) while other signals considered for emotions are Galvanic Skin Response (GSR), Electromyography (EMG), Heart Rate (HR), Electrocardiography (ECG), etc. [33, 34]. Apart from these signals, there are certain sensors attached with the applications which contribute in recording and detecting our emotional state during a particular activity. All these recordings are closely monitored and devised to detect emotions for further proceedings.

Emotions of a person are detected from signals recorded through different sensors.

For research purpose, there are certain data repositories designed and developed for this purpose such as DEAP dataset, SEED dataset, IAPs dataset, etc. There are two models proposed for an emotion recognition system, the Discrete Model and the Multi-Dimensional Model. In the discrete model by an American psychologist, Ekman, there are six universal emotions; happiness, sadness, anger, surprise and fear. But sometimes the complex human state of mind cannot be categorized within the set of these six emotions. In the second model, the emotions are categorized with multiple dimensions using continuous measuring scales. This helps the person to reflect on his/her elicited emotion. The two common emotion models under the Multi-Dimensional models are the valence – arousal (VA) model and pleasure, arousal and dominance (PAD) model [5, 37]. These models are required to classify emotions of a person into certain categories or simply label them.

The recordings collected in data format require further processing to be finally categorized into specific emotions. There are varied steps involved in processing these recordings and there is no definite way to follow. The data is first subjected to some pre-processing filtering wherein the unwanted or garbage data is disposed off, down sampling the required relevant data.

Some of the techniques used in filtering are spectral filtering, band-pass filtering, average mean reference(AMR), etc. [6,11,17]. These refined recording then undergo for feature extraction. Some of the used feature extraction techniques involve discrete wavelet transform (DWT), Fourier transform, fast Fourier transform (FFT), etc. [8, 13, 14, 17]. Then certain machine learning algorithms are used to classify emotions by preparing an appropriate classifier. Classifier can utilize one or many algorithms such as support vector machine (SVM), principle component analysis (PCA), linear discriminant analysis (LDA), naïve Bayes (NB), k-nearest neighbor (KNN), etc. [7,8,12,16,18]. The output of these classifiers gives us the information about the emotional and mental state of a person.

In this paper, we will be reviewing the works done to recognize human emotions and its analysis using EEG signals and physiological signals.

The paper focuses on understanding the entire process involved in emotion detection and its analysis which includes understanding of the signals, data acquisition, pre-processing techniques, feature extraction methods and later the classification of emotions. Comparison between the approaches of EEG signals and physiological signals is also done based on the current works.

Later, all the work is well comprehended and a conceptual framework is suggested depending on the purpose of recognizing and analyzing human emotions.

II. DISCUSSION

In this section of the paper, initially we will get to know about the background of emotions and its representation, EEG signals, other physiological signals. We then will get to know about the different datasets available for research work on emotion detection and its analysis.

After that we will learn about the various steps involved in this research which comprises of pre-processing techniques, feature extraction and classification.

Since the papers aims at comparing two different approaches towards emotion detection using EEG signals and physiological signals.

We will later be drawing comparisons between their approach towards classification. Lastly, we aim at proposing a conceptual framework for better outcomes, inferred from the review work.

In this section, we will understand about Emotion and its models, EEG and other physiological signals.

A. Emotion and Emotion model

Emotions

Emotions are elemental to our daily lives. It is complex psychological experiences that affect our lives in every aspect such as decision- making, forming a perception, human intellectual and intelligence.

Importance of emotions have also been surfaced with the evolution of Human cognition technology [2, 3, 31]. Emotions are prolonged spontaneous state of a mind while the mood is pre-dominant conscious effort in time [32]. Mood can be regarded as the initial phase of the emotional state of a person which is further accompanied by physiological changes in human body.

Emotions, also referred as mental states, can be understood as production by instrumental stimuli. Instrumental reinforces are stimuli which affects the output of future response. Sometimes reinforces are unlearned and some are made reinforcing by learning due to their association with primary reinforces therefore also called “secondary reinforces”.

Amygdala is referred to as brain’s network of emotions. Autonomic and motivational responses can be produced by re - directing the outputs of the amygdala and orbitofrontal cortex to the hypothalamus.

The emotional functioning of amygdala is vitally dependent on sensory inputs[40, 43]. Emotions are expressed through brain and different parts of human body.

Detection of emotions require both, sensory input from various body parts which are recorded as physiological signals and brain signals referred to as EEG. Depending on the objective of emotion recognition we can utilize internal and other physical signals.

Emotion Models

For Emotion identification, a model of emotion need to be described and attained quantitatively. There are different theories of emotions and based on the field of work many models have also been developed. The major two approaches proposed by psychologists are discrete model and multiple dimensional model [2, 31, 32].

First model, Discrete Emotion Model, was introduced by an American psychologist Ekman. It consists of basic six emotions like joy, anger, surprise, sadness, fear and disgust. The second model, divides emotions into multiple continuous scales called Multi- dimensional model.

I Discrete Model

According to Ekman, emotions are discrete, quantitative, and physiological in nature. He has proposed certain features of basic emotions.

Emotions cannot be learned, humans are born with it.

Emotions exhibited in a particular situation remains same.

They way of expressing emotions do not change.

The physiological patterns remain same while expressing the similar emotion.

Plutchik’s Wheel of Emotion was introduced in 1980 by Plutchik. It includes primary eight emotions of joy,trust,fear,surprise, sadness, disgust, anger and anticipation as displayed in Figure 1. This wheel model is designed based on the intensity of emotions. Weak emotions are placed outward, at the flower bloom while strong emotions are at the center of the flower.

Their can be various combinations of emotions making it complex. and Arousal, VA) or three (Pleasure, Arousal, and Dominance, PAD). Valence refers to the positive and negative characteristics.

Arousal indicates the intensity level of emotion. And Dominance reflects an individual’s status, that is, in control or being controlled.

Figure 1: Plutchik's Wheel of Emotions

II Multi- dimensional Model

As research progressed, psychologists identified the relation between emotions and their intensities. Intensity of a particular emotion demonstrated its certain degree of emotional level. For example, a person is happy while another person is happy, as in on ninth cloud happy. Their emotion is same, happy, but level of intensity is different. Mostly there are two multi-dimensional models, 2D model and 3D model. In 2D model, the two constituent dimensions are Valence and Arousal, VA. In 3D model, the three dimensions are Valence, Arousal, and Dominance. In these models, the negative and positive characteristics are referred as Valence while the magnitude of their intensity is measured by Arousal. Dominance displays the level of dominance from submissive to dominant which means the controlling ability of a human over a certain emotion.

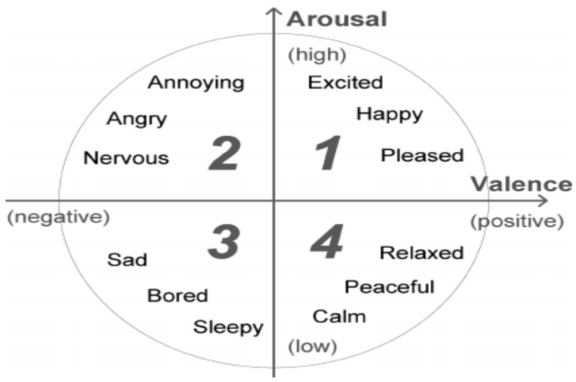

Figure 2 a): 2D Emotion Model

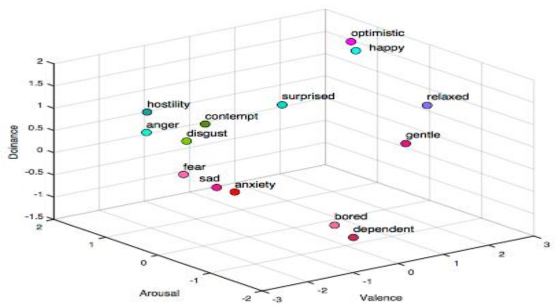

Figure 2 b): 3D Emotion Model

Electroencephalogram

The human brain largely comprises of neurons. These neurons have dense interconnection through synapses. These become the source of both, inhibitory and exhibitory, activities. Postsynaptic potential refers to the delicate electrical impulse generated by any synaptic activity. Since, an impulse generated by a single neuron has very low magnitude therefore can only be detected when in direct contact with it. When multiple neurons are excited in sync then an electrical field is generated which is strong enough to spread across tissue, bone and skull. This makes it measurable on the surface of the head[47, 48, 50].

The synchronized activity of brain is measured by the electroencephalogram (EEG) in volts (V) or microvolts (mV), from the scalp. The waveforms of the recorded signals signify the cortical electrical activity.

Electrical activity generated by the brain is monitored by EEG over a period of time. This is used to understand the underlying working of different areas of cortex, being responsible for processing information at particular time. Different parts of cortex and their functions are:

Occipital Cortex

This section of the brain processes visual information. To study the effects on occipital region, experiments are held with visual stimuli (videos, images).

Parietal Cortex

This cortex is accountable for motor functions. It becomes active for self-referential tasks like when a person encounters an object or information related to him/her.

Temporal Cortex

Temporal cortex has lateral aspects. It makes them responsible for processing of language and production of speech. During spatial navigation medial regions are more active.

Frontal Cortex

In comparison with other mammals, frontal cortex is an enlarged part of a human brain. This cortex deals with executive functions like helps a person maintain control, future planning and behavior analysis. Along with the origination of electrical activities, analysis of frequencies responsible for an ongoing activity is also considered.

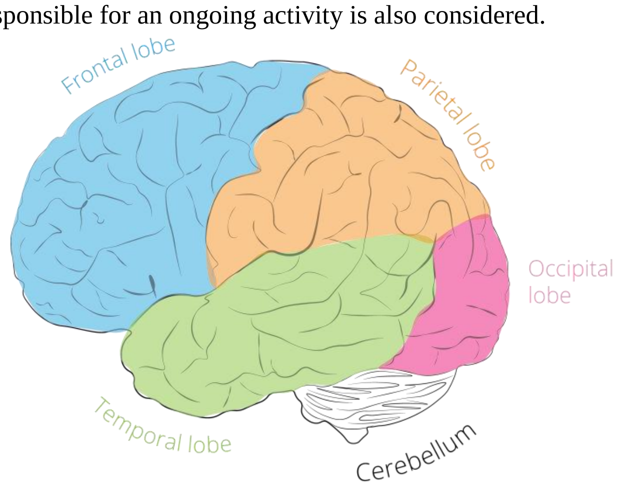

Figure 3: Different lobes in human brain

To understand the internal cognitive process of a brain, we observe its different states and monitor its effect on frequency patterns. Humans have 5 following EEG waves:

i. *Delta*

Frequency Range: 1 – 4 Hz

Occurrence: Its occurrence might be focally and generally distributed with subcortical lesions and diffuse lesions, deep lesions(or metabolic encephalopathy hydrocephalus), respectively.

Features:

- Highest in amplitude and slowest in waves
- Depth of sleep can be examined through this
- It is mostly experienced frontally in adults (e.g. FIRDA - Frontal Intermittent Rhythmic Delta) and posteriorly in children e.g. OIRDA - Occipital Intermittent Rhythmic Delta).

ii. *Theta*

Frequency Range: 4 -7 Hz

Occurrence: It mostly occurs in sleep and also observed during deep meditations. It is observed as manifestation of focal subcortical lesions

Features:

- Classified as “slow activity”
- Becomes prominent during difficult tasks which require concentration
- Normal for children in sleep, up to 13yrs of age. But abnormal when adults are awake.

iii. *Alpha*

Frequency Range: 7 – 12 Hz

Occurrence: It occurs at the posterior regions of the head on each side when eyes are closed. It disappears when eyes are opened or made alert by any activity.

Features:

- Higher in amplitude on the dominant side
- Major rhythm observed in normal relaxed adults
- Often used in Biofeedback trainings to monitor relaxation
- Inhibition and attention are linked with these waves

iv. *Beta*

Frequency Range: 12 – 30 Hz

Occurrence: It could be prominent on both sides in symmetrical distribution and is evident frontally. These can be observed clearly over the motor regions when a person makes any movement.

Features:

- Referred as “fast activity” and normal rhythm
- It gets intensified by certain sedative drugs like the benzodiazepines and the barbiturates
- Its activity is reduced or becomes absent in the part of cortical damage
- If patients are alert, anxious or their eyes are wide open then it becomes dominant rhythm

v. *Gamma*

Frequency Range: 30Hz and above, typically 40 Hz

Occurrence: nothing specific, gets activated when data has to be exchanged between different brain regions.

Features:

- Can be observed when a person is focusing or attentive

  Associated with rapid eye-movement, also known as micro-saccades

Physiological Signals

The devices use many different sensors for measuring selected physiological signals [27, 36, 37].

Some sensors used in emotion recognition are shortly described below:

- **Blood volume pulse** (BVP, also called photo plethysmography): These sensors are used detect flow of blood flow using infrared light from the tip of a finger and measuring the amount of reflected light.
- **Electrocardiography (ECG):** This device is used detect the electrical changes on the skin caused due to depolarization of the heart muscle during every single heartbeat.

  To detect the physiological change related to activities of heart both, BVP and ECG, are used. They function based on different specific principles.
- **Temperature (T)** sensor : It detects the temperature of body. Signals can be easily measured through this sensor and it also records variations caused in time. Skin Temperature (SKT) sensor is the most widely used sensor. It records the temperature from the skin surface and is commonly attached on fingers.

  Electromyography (EMG) sensor: It records the impulses exhibited during a muscle movement in body. The power of muscle contraction is directly proportional to the amplitude of an electric signal.

  Since it is difficult for valence to measure small values, therefore only strong emotions can only be depicted through the muscle activity.
- **Skin Conductance (SC**) sensor: It is used to measure the skin’s electrical conductance. It is mostly fixed on finger.
- Sometimes, Galvanic Skin Resistance (GSR) can also be used based on the purpose of recording.
- **Respiration (RSP)** sensors: It is used to measure the breathing rate of a person, i.e. how quickly and deeply a person is breathing. Their breathing rate is related to their emotional state.

Electrode Positioning

A typical EEG recording follows a standard positioning of scalp electrodes after adapting the 10/20 system.

This system is vital because of the distance recorded in percentage between Naison – Inion and fixed points.

The five fixed points marked on the scalp are the Frontal pole (Fp), Central (C), Parietal (P), occipital (O), and Temporal (T).

The brain is divided into two hemispheres, right and left, by a midline.

Subscript z, stands for zero, is used to mark the midline electrodes.

For points lying in left hemisphere, subscripts with odd numbers are used and for points lying in right hemisphere, even numbers are used as subscripts

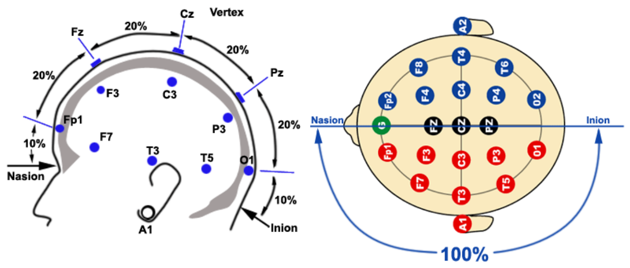

Figure 4: 10/20 Electrode Positioning system

B. Datasets Referred

In this section we list out the features of the dataset from where we collected the required data. Some of the datasets were exclusively designed for EEG data while others have both EEG as well as Physiological data. Below are some of the used dataset:

i. DEAP dataset

DEAP is a dataset used for emotion analysis through EEG, physiological and video signals. It is recorded by Sander Koelstra, Christian Mühl, Mohammad Soleymani and et al. This multimodal dataset was recorded at two different locations, Geneva and Twente, in 2012. The dataset comprises of two sections, firstly, fourteen to sixteen participants were asked to undergo an online self-assessment where they were supposed to rate one-twenty music videos, each of sixty seconds, on the basis of valence – arousal – dominance model. Secondly, participant ratings, facial recordings, physiological and electroencephalogram recordings of thirty - two participants are stored. For the dataset, thirty-two participants were made to watch subset of 40 one - minute duration (60 seconds), excerpts from music videos. Amongst thirty-two participants, frontal face video was also recorded for twenty-two of them. The dataset contain original data files as well as pre- processed files. In original data files, have recordings of forty-eight channels at 512Hz. From these forty-eight channels, thirty – two are for EEG, twelve are peripheral channels (4 EOG signals, 4 EMG signals, 2 GSR signals and 2 Erg signals), three unused channels and one status channels. In pre – processed dataset, the data was down sampled to 128Hz, band pass filter from 4.0Hz to 45.0Hz was applied and EOG artifacts were removed. The dataset is appropriate for further classification purpose and gives well- reasoned dataset. To understand the dataset better visit https://www.eecs.qmul.ac.uk/mmv/datasets/deap/readme.html.

ii. SEED dataset

SEED dataset is abbreviation for SJTU Emotion EEG Dataset. The dataset is recorded at BCMI laboratory by Prof. Bao-Liang Lu for the experiment, seventy – two film clips were selected with basic emotions like happy, sad, fear or neutral emotion. . It consists of EEG signals of fifteen participants. 62 – channel system has been adapted while recording EEG signals and eye movements. There exist three sessions recorded on different days and each session consist of twenty-four trials. Participant's EEG signals and eye movements are recorded while watching each and every video. Further on data pre – processing techniques have been applied and features have been extracted. Now, the latest dataset also provide vigilance dataset along with emotions.

iii. MAHNOB-HCI dataset

MAHNOB-HCI is a multimodal dataset designed for emotion recognition. It has a feature of implicit tagging. There are thirty subjects for the experiment done to collect the data for the database. The experiment setup includes six cameras, a head-worn microphone, tracker to eye-gaze, different physiological sensors like ECG, EEG (32 channel-system), respiration amplitude and skin temperature, to monitor the subject. For each individual subject, the experiment has been recorded in two sections. The first section comprises of various movie fragments which were shown to the participants. Based on the movie clip, these participants were asked to rate their emotional state on the valence – arousal graph. In the second section, they were made to press either green on red button based on their choice between whether they agree or not. Further to enhance the synchronization between sensors, the audio, video, eye - gaze data, we record it simultaneously.

iv. The International Affective Picture System (IAPS) dataset

The purpose of IAPS dataset is to supply a collection of emotional stimuli which can be acquired for experiments to thoroughly and practically understand the functioning of attention and emotions. The objective is to build up an enormous arrangement of institutionalized, inwardly reminiscent, globally available, shading photos that incorporates substance over a wide scope of semantic classes. The Centre for Emotion and Attention (CSEA) at the University of Florida has been creating and distributing the IAPS (articulated eye-aps) dataset.

v. USTC-ERVS dataset

The USTC – ERVS is a dataset developed for understanding mechanism of emotions using EEG signals. In total it consists of 197 EEG responses to the 92 video stimuli recorded from 28 users along with their emotional self-assessments. But, the USTC-ERVS dataset is now unavailable online. Either its URL was entirely deleted from its earlier database or its page is moved.

Table 1: Different referred datasets

S.NO.	Dataset	Remarks
1.	DEAP dataset	This is amongst the most used dataset by both EEG and Physiological signals. It is detailed and provide raw as well as pre-processed data.
2.	SEED dataset	SEED dataset is good for EEG signals. However, the higher versions of it like SEED – IV and SEED – V can be used for physiological signals.
3.	MANHOB- HCI dataset	This dataset is suitable for EEG signals and certain physiological signals such as ECG, skin temperature.
4.	IAPS dataset	IAPS dataset is designed and developed to monitor EEG signals only to understand the mechanism of emotions and attention.
5.	USTC-ERVS dataset	This dataset can only be used for EEG signals.

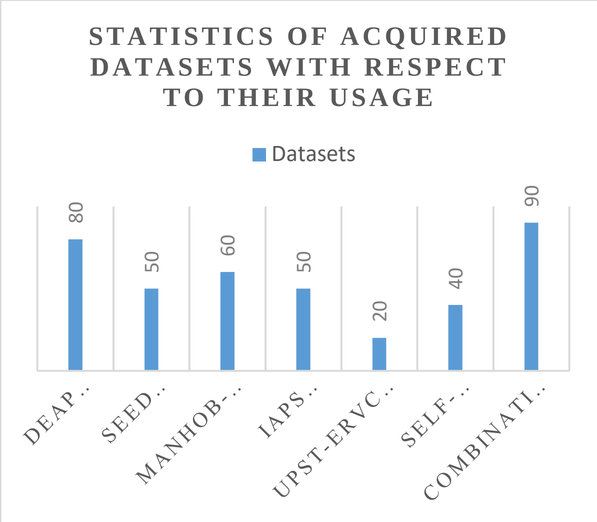

Figure 6: Statistics of acquired datasets

As mentioned earlier, different datasets have been acquired for the analysis purpose. But based on the features offered by them their usage vary. The combination of these datasets have proved to give optimum solutions. Since DEAP dataset provides data for both EEG and Physiological signals, it is widely used. Then based on the requirement and accessibility other datasets are used subsequently.

C. Pre-Processing

In this section different pre-processing techniques are discussed. Pre-processing aims at removing noise from the data and preparing it for further feature extraction process. Following are the techniques:

i. Bandpass filter

A bandpass channel is an electronic gadget or circuit that permits flags between two explicit frequencies to pass, however that oppresses signals at different frequencies. Some bandpass channels require an outer wellspring of intensity and utilize dynamic parts, for example, transistors and incorporated circuits; these are known as dynamic bandpass channels. Different bandpass channels utilize no outside wellspring of intensity and comprise just of inactive segments, for example, capacitors and inductors; these are called aloof bandpass channels.

ii. Average Mean Reference (AMR)

Pre- processing phase requires removal or reduction of electronic amplifier, power line and external interference noise for which AMR method can be used. Every single channel is selected and its mean is calculated. Then this mean is subtracted from each sample of that sample. Normalization of all the values is done between [0, 1] to reduce the individual difference effect.

iii. Butterworth filter

The Butterworth filter is a type of signal processing filter designed to have a frequency response as flat as possible in the passband. It is also referred to as a maximally flat magnitude filter.

iv. Surface Laplacian (SL) filter

To apply emphasis on the electrical activities that are near to a recording electrode (i), spatially, SL filter can be utilized. It also filters out the activities whose origin is outside the skull.

D. Feature Extraction

1. Discrete Wavelet Transform

DWT is a linear signal processing and is applied to particular data. If the data has same length then these techniques can be applied for its reduction. Following are the steps to apply this technique:

i. The Length of L, input vector should be a power of 2
ii. Data smoothening(sum or weighted average) is applied. To obtain detailed features of data, weight difference is performed.
iii. The output shall be L/2 after this function is applied and either has low frequency or high frequency, respectively.
iv. When these functions are applied to the output dataset, the length of 2 is obtained.
v. Values from the obtained data is selected and applied to the coefficient of transformation.

2. Principal Component Analysis

PCA is a statistical technique that has used for face recognition, image compression, and it is common techniques for finding patterns in data of huge dimension. It has used some mathematical terminology like mean, standard deviation, variance, co-variance, covariance matrix, matrix algebra, Eigenvector, Eigen value. It has the following steps.

i. Gather the input data
ii. Calculate mean vector
iii. Computing co-variance Matrix
iv. Find corresponding Eigen Vector and Eigenvalue.
v. Ranking and Choosing K Eigenvector and generate the new feature vector
vi. Transform the samples on the new subspace. New Data=Row Feature vector*Row Data Adjust

3. Higher Order Crossing

The time series used in almost all the feature extraction techniques progresses(grows). This implies that series means the finite zero and that level zero can be expressed through the zero count. Therefore, HOC is used to refer zero crossing. To extract a particular feature HOC can be applied in combination with discriminate and spectral analysis.

4. Statistical Based Feature

This techniques is applied on physiological signals. It has certain following steps:
It was applied to the physiological signals. It has to be follow some of the mathematical steps.

i. Mean of Raw signal
ii. Standard Deviation
iii. Calculate the mean of absolute values of the first different raw signal
iv. Calculate the mean of absolute values of the second different raw signal
v. Calculate the mean of the absolute value of second standard signal.

Based on these steps the exact patterns can be extracted from EEG.

5. *Short Time Fourier Transformation and Mutual Information*

STFT is utilized to extricate from every cathode sliding window of 512 examples and its covering between two sequential windows. Mutual Information is dependent on how every single anode pair's and how those factual conditions the highlights are separated which are utilized for feeling examination.

6. *Independent Component Analysis*

It is used for the conversion of the multivariate signals into signals with single interdependent component.
All the noise is removed from the EEG signals and a particular feature is extracted that is not inter- related.
Suppose the signal X (t) assume vector has zero mean then, $P(x(t))=\Sigma\ p(xi(t))$

E. Classification

i. Support Vector Machines (SVM)

A Support Vector Machine (SVM) is a discriminative classifier officially characterized by an isolating hyperplane. At the end of the day, given marked preparing information (administered learning), the calculation yields an ideal hyperplane which arranges new models. In two dimensional space this hyperplane is a line separating a plane in two sections where in each class lay in either side.

ii. Radial Basis Function (RBF)

RBF intends to round off multivariable (likewise called multivariate) works by direct combination of terms dependent on a univariate work (the radial basis function). This is radicalized so that it can be utilized in more than one measurement. They are normally applied to approximate capacities or information (Powell 1981,Cheney 1966,Davis 1975) which are just known at a limited number of focuses (or too hard to even consider evaluating something else), for the efficient and often use of evaluating the approximate functions.

iii. Multi-class Support Vector Machine(ML-SVM) or Least Squares Support Vector Machine(LS-SVM)

Multiclass SVM aims to assign labels to instances by using support vector machines, where the labels are drawn from a finite set of several elements. The implemented approach for doing so is to reduce the single multiclass problem into multiple binary classification problems via one-versus-all. The one-versus-all approach is the process of building binary classifiers which distinguish between one of the labels and the rest. Least-squares support-vector machines (LS-SVM) are least-squares versions of support-vector machines (SVM), which are a set of related supervised learning methods that analyze data and recognize patterns, and which are used for classification and regression analysis.

iv. k-Nearest Neighbors (kNN)

The KNN algorithm assumes that similar things exist in close proximity. In other words, similar things are near to each other.
K nearest neighbors is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure (e.g., distance functions).
KNN has been used in statistical estimation and pattern recognition already in the beginning of 1970's as a non-parametric technique.

v. Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) is a dimensionality reduction technique. As the name implies dimensionality reduction techniques reduce the number of dimensions (i.e. variables) in a dataset while retaining as much information as possible. For instance, suppose that we plotted the relationship between two variables where each color represent a different class.

vi. Quadratic Discriminant Analysis (QDA)

QDA is a variant of LDA in which an individual covariance matrix is estimated for every class of observations. QDA is particularly useful if there is prior knowledge that individual classes exhibit distinct covariance. A disadvantage of QDA is that it cannot be used as a dimensionality reduction technique.

vii. Naive Bayes (NB)

The Naive Bayesian classifier is based on Bayes' theorem with the independence assumptions between predictors. A Naive Bayesian model is easy to build, with no complicated iterative parameter estimation which makes it particularly useful for very large datasets. Despite its simplicity, the Naive Bayesian classifier often does surprisingly well and is widely used because it often outperforms more sophisticated classification methods.

viii. Multi-Layer Perceptron Back Propagation (MLP-BP)

The Backpropagation neural network is a multilayered, feedforward neural network and is by far the most extensively used. It is also considered one of the simplest and most general methods used for supervised training of multilayered neural networks. Backpropagation works by approximating the non-linear relationship between the input and the output by adjusting the weight values internally. It can further be generalized for the input that is not included in the training patterns (predictive abilities).

ix. Comparison between classification of emotions through EEG signals and Physiological Signals

Table 2: Comparison between EEG and Physiological signals

S.No.	Classification Algorithm	EEG Signals (applied or not)	Physiological Signals (applied or not)
1.	Support Vector Machine (SVM)	Applied	Applied
2.	Radial Basis Function (RBF)	Applied	Not – Applied
3.	Multi-class Support Vector Machine(ML-SVM) or Least Squares Support Vector Machine(LS-SVM)	Applied	Not – Applied
4.	k-Nearest Neighbors (kNN)	Applied	Applied

5.	Quadratic Discriminant Analysis (QDA)	Applied	Not - Applied
6.	Naive Bayes (NB)	Applied	Applied
7.	Multi-Layer Perceptron Back Propagation (MLP-BP)	Applied	Not - Applied
8.	Artificial Neural Network (ANN)	Applied	Applied
9.	Power Spectral Analysis (PSA)	Applied	Applied
10.	Multi-Linear Regression (MLR)	Applied	Not - Applied
11.	Deep Neural Network	Applied	Not - Applied
12.	Gradient Boosting Decision Tree classifier	Not - Applied	Applied

In the above table different classifiers used for emotion detection and analysis have been listed out. But not all are used by both the signals, i.e. EEG and Physiological. This is because their approach is different. In brain signals, EEG, we require to decide and remove the baseline, filter the recordings according to particular frequencies and then move ahead with the classification. Whereas in physiological signals we sometime apply same approach as EEG like in EMG and sometimes do not s in GSR, BVP etc. Since in physiological signals we collect data from sensors so filtering is hardly require and considering this classification is done.

F. Conceptual Framework

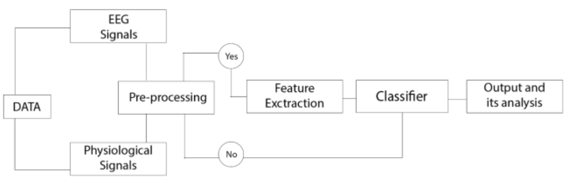

Figure 5: ***Conceptual Framework***

This framework is designed for the analysis of both, EEG and other physiological signals. Pre-processing is dependent on the quality of collected signals. Sometimes frequency, band-pass filters are taken care of at the time of recording signals and therefore do not require pre-processing. After the signals are pre-processed, they undergo the algorithms to identify particular features. Then on these features classification techniques are applied. Further, based on the result, inference is deduced.

III. CONCLUSION

In this paper a short survey of utilizing EEG signals and physiological signals to detect emotions and its analysis was discussed. Emotions have evolved to be complex in nature. There are many theories explaining it through emotion model. Selecting an emotion model for the research is quite important. Discrete emotion model can be used with passive signals. But if data is being acquired actively through sensors then multi-dimensional modal would be appropriate. Emotions being hard to detect, though can be recognized using either of the two signals. But for optimum result, combination of both would be great. They have different approach towards classifying based on the source emotion elicitation. Also, the purpose of recognizing emotions plays an important role, i.e. the ethnographic conditions need to be considered. If the emotion detection is to be used in any mobile application, different sensors recording physiological signals will be used. And if it is done for some medical purpose, EEG signals will be beneficial. Thus, EEG signals and physiological signals can be used to detect and analyze emotion based on its purpose.

In future, our work shall focus on exploiting the full potential of emotion recognition. Individuals can perceive feeling based on comprehensive images of humans: outward appearance, manner of speaking, words expressed, signals and so on. Further, we might utilize bio-signals in combination with outward appearance, standard information gadgets and sound sign.

REFERENCES

1. M. Z. Soroush, K. Maghooli, S. K. Setarehdan and A. M. Nasrabadi, A Review on EEG Signals Based Emotion Recognition, Tehran, Iran: Int Clin Neurosci J., 2017.
2. T. Xu, Y. Zhou, Z. Wang and Y. Peng, Learning Emotions EEG-based Recognition and Brain Activity: A Survey Study on BCI for Imtelligent Tutoring System, China: The 9th International Conference on Ambient Systems, Networks and Technologies(ANT 2018), 2018.
3. S. M. Alarc˜ao and M. J. Fonesca, Emotions Recognition Using EEG Signals: A Survey, Portugal: IEEE TRANSACTIONS ON AFFECTIVE COMPUTING, 2017.
4. P. J., S. M. and D. A., A Survey on EEG Based Emotion Analysis using various Feature Extraction Techniques, Coimbatore: International Journal of Science, Engineering and Technology Research (IJSETR), Volume 3, Issue 11, 2014.
5. Y. Liu, O. Souria and M. K. Nguyen, Real-Time EEG-Based Emotion Recognition and Its Applications, Singapore, 2011.
6. N. Kumar, S. M. Hazarika and S. M. Hazarika, Bispectral Analysis of EEG for Emotion Recognition, Assam,India: Elsevier B.V, 2016.
7. N. Zhuang, Y. Zeng, L. Tong, C. Zhang, H. Zhang and B. Yan, Emotion Recognition from EEG Signals Using Multidimensional Information in EMD Domain, China: Hindawi BioMed Research International, 2017.
8. Y. Dasdemir, S. Yildrim and E. Yildrim, Emotion Analysis using Different Stimuli with EEG Signals in Emotional Space, Turkey: International Journal of Natural and Engineering Sciences , 2017.
9. M. Sloeymani, S. A. Esfeden, M. Pantic and F. Yun, CONTINUOUS EMOTION DETECTION USING EEG SIGNALS AND FACIAL EXPRESSIONS, Imperial College London, UK, 2 Northeastern University, USA, 3University of Twente, Netherlands, 2013.
10. Y. Gao, H. J. Lee and R. M. Mehmood, Deep learninig of EEG signals for emotion recognition, Korea: IEEE, 2015.

11. A. Alnafjan, A. A.-. Wabil, Y. A.-. Ohali and I. M. Hosny, Classification of Human Emotions from Electroencephalogram (EEG) Signal using Deep Neural Network, Saudi Arabia: (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 8, No. 9, 2017.
12. Y.-P. Lin, C.-H. Wang, T.-P. Jung, T.-L. Wu, S.-K. Jeng, J.-R. Duann and J.-H. Chen, EEG-Based Emotion Recognition in Music Listening, IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 57, NO. 7, 2010.
13. P. S. D. V. Renu Bhoria, ANALYSIS OF EFFECT OF SOUND LEVELS ON EEG, Haryana,India: International Journal of Advanced Technology & Engineering Research (IJATER), 2015.
14. S. Hsieh and Y.-Y. Lee, Classifying Different Emotional States by Means of EEG-Based Functional Connectivity Patterns, Taiwan: PLOS ONE, April 2014 , Volume 9 ,Issue 4, 2014.
15. C. T. Yuen, W. S. San, M. Rizon and T. C. Seong, Classification of Human Emotions from EEG Signals using Statistical Features and Neural Network, International Journal of Integrated Engineering (Issue on Electrical and Electronic Engineering).
16. T. A. Sohaib, S. Qureshi, J. Hagelb¨ack, O. Hilborn and P. Jerˇci´c, Evaluating Classifiers for Emotion Recognition Using EEG, Karlskrona, Sweden: Springer-Verlag Berlin Heidelberg, 2013.
17. M.Teplan, FUNDAMENTALS OF EEG MEASUREMENT, Bratislava, Slovakia: MEASUREMENT SCIENCE REVIEW, Volume 2, Section 2, 2002.
18. O. Bazgir, Z. Mohammadi and S. A. H. Habibi, Emotion Recognition with Machine Learning Using EEG Signals, Tehran, Iran: 25th national and 3rd International Conference on Biomedical Engineering (ICBME), 2018.
19. P. Rani, C. Liu and E. J. Vanman, "An Empirical Study of Machine Learning Techniques for Affect Recognition in Huuman-Robo Interaction," *Pattern Analysis and Applications*, p. 7, 2006.
20. P. C. Petrantonakis and L. J. Hadjileontiadis, "Emotion Recognition From EEG Using Higher Order Crossings," *IEEE TRANSACTIONS ON INFORMATION TECHNOLOGY IN BIOMEDICINE*, Vols. VOL. 14, NO. 2, 2010.
21. C. Tang, D. Wang, A.-H. Tan and C. Miao, "EEG-Based Emotion Recognition via Fast and Robust Feature Smoothing," *Brain Informatics: International Conference, Beijing, China*, BI 2017.
22. N. A. Abeer , M. Hosny, O. A. Yousef and A. A. Wabil, Review and Classification of Emotion Recognition Based on EEG Brain-Computer Interface System Research: A Systematic Review, Saudi Arabia, 2017.
23. M. M., R. M., N. R., Y. S., Z. I. and H. D., Lifting scheme for human emotion recognition using EEG, Malasiya: IEEE, International Symposium on Information Technology, 2008.
24. P. C. Petrantonakis and L. . J. Hadjileontiadis, Adaptive Emotional Information Retrieval From EEG Signals in the Time-Frequency Domain, IEEE TRANSACTIONS ON SIGNAL PROCESSING, VOL. 60, NO. 5, MAY 2012.
25. D. Garrett, C. Anderson, D. Peterson and M. Thaut, Comparison of linear, nonlinear, and feature selection methods for EEG signal claasification, IEEE Transactions on Neural Systems and Rehabilitation Engineering, July 2003.
26. M. Murugappan , N. Ramachandran and Y. Sazali, Classification of human emotion from EEG using discrete wavelet transform, Malaysia: J. Biomedical Science and Engineering,, 2010.
27. S. Koelstra, M. Soleymani, A. Yazdani and A. Nijholt, DEAP: A Database for Emotion Analysis Using Physiological Signals, IEEE TRANSACTIONS ON AFFECTIVE COMPUTING, VOL. 3, NO. 1, 2012.
28. Y. Liu, O. Sourina and M. K. Ngyuen, Real-time EEG-based Human Emotion Recognition and Visualization, Singapore: IEEE, International Conference on Cyberworlds, 2010.
29. M. Li and B. -L. Lu, Emotion Classification Based on Gamma-band EEG, Minnesota, USA: 31st Annual International Conference of the IEEE EMBS, 2009.
30. X. -W. Wang, D. Nie and B. -L. Lu, Emotionalstateclassification from EEG data using machine learning approach, China: Elseveir, Neurocomputing, 2014.
31. S. Wioleta, Using Physiological Signals for Emotion Recognition, Sopot, Poland: IEEE, 6th International Conference on Human System Interactions (HSI), 2013.
32. L. Shu, J. Xie, M. Yang, Z. Li, D. Liao, X. Xu and X. Yang, A Review of Emotion Recognition Using Physiological Signals, China: Sensors, 2018.
33. E. Maria, L. Matthias and H. Sten, Emotion Recognition from Physiological Signal Analysis: A Review, Vienna, Austria: Elseveir, 2019.
34. C. Breazeal, Emotion and sociable humanoid robots, Cambridge, USA: Elseveir, 2003.
35. A. M. Brennan, A. W. Harris and L. M. Williams, Neural processing of facial expressions of emotion in first onset psychosis, Australia: Elseveir, 2014.
36. A. M. Khan and M. Lawo, From Physiological data to Emotional States: Conducting a User Study and Comparing Machine Learning Classifiers, Germany: Sensors & Transducers, Vol. 201, Issue 6, 2016.
37. F. Agrafioti, D. Hatzinakos and A. . K. Anderson, ECG Pattern Analysis for Emotion Detection.
38. B. P. Simon and E. C., An ECG Classifier Designed Using Modified Decision Based Neural Networks, Madras, India: COMPUTERS AND BIOMEDICAL RESEARCH.
39. F. Nasoz, K. Alvarez and C. . L. Lisetti, Emotion recognition from physiological signals using wireless sensors for presence technologies, USA: Springer-Verlag London Limited, 2003.
40. J. E. LeDoux, Brain mechanisms of emotion and emotional learning, New York, USA: Current Biology Ltd ISSN.
41. Autonomic Nervous System Activity Distinguishes Among Emotions, SCIENCE, 6 September 1983.
42. C. Collet, E. V. -Maury, G. Delhomme and A. Dittmar, Autonomic nervous system response patterns specificity to basic emotions, France: Elseveir, Journal of the Autonomic Nervous System 62 , 1997.
43. E. T. Rolls, A Theory of Emotion, and its Application to Understanding the Neural Basis of Emotion, UK: COGNITION AND EMOTION, 1990.
44. E. Rolls, Information Representation, Processing, and Storage in the Brain: Analysis at the Single Neuron Level, England: The Neural and Molecular Bases of Learning, eds. J.-P. Changeux and M. Konishi, pp. 503-540.John Wiley & Sons Limited., 1987.
45. D. I. Perrett and E. T. Rolls, NEURAL MECHANISMS UNDERLYING THE VISUAL ANALYSIS OF FACES, UK: J.-P. Ewert et al. (eds.), Advances in Vertebrate Neuroethology, 1983.
46. P. Thagard, "Introduction to Cognitive Science," in *Mind*, Hong Kong, Massachusetts Institute of Technology, 2005, p. .
47. "The McGill Physiology Virtual Laboratory," [Online]. Available: http://www.medicine.mcgill.ca/physio/vlab/default.htm. [Accessed Wedesday March 2020].
48. P. Bryn Farnsworth, "iMotions," [Online]. Available: https://imotions.com/blog/what-is-eeg/. [Accessed Wednesday March 2020].
49. T. D. Fulvio, "Medium," March 2019. [Online]. Available: https://towardsdatascience.com/using-machine-learning-to-categorise-eeg-signals-from-the-brain-to-words-728aba93b2b3. [Accessed 4 March 2020].
50. D. Chen, J. Sleigh and D. Li, "Classification of EEG Signals Based on Pattern Recognition Approach," *Frontiers in Computational Neuroscience.*

AUTHORS PROFILE

Namrata D Rupani, a research scholar, at present is pursuing MCA at CHRIST (Deemed to be University), Bangalore, Karnataka, India. She obtained her BCA from MGKVP University. At this early stage in research, her interests include Machine Learning, Deep Learning and Data Mining.

Prof Roseline Mary. R currently serves as an Assistant Professor in the Department of Computer Science, CHRIST (Deemed to be University). She obtained her BSc (Mathematics), MCA from Bharathidasan University, MPhil from Alagappa University and MTech from Karnataka State Open University and currently pursuing her doctorate from Bharathidasan University in Deep Learning. Her Research interests include Database Systems, Big Data, Data Mining and Deep Learning.