Human Emotion Detection with ECG and EEG Signals Using ML Techniques

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I. Introduction

Emotions are one of the most important phenomenons that revolve around human day-to-day life, we encounter emotions in every activity that we perform. Therefore understanding and accurately detecting human emotions is widely important in many fields of work.in the fields like health care [1], Human-Computer Interaction(HCI)[2], and psychology [3] can be some fields that are benefited from the precious identification of emotion that a person is experiencing on a given time. Initially, we have been depending on self-reporting to identify emotions. That process of identification can be biased and subjective on the perspective that the person who is giving out the self-report has. Now we are in an era where physiological signals generated by the human body are used as an emotion-measuring technique. which can be hectic but will give good outputs.

Over the years there have been many ways to tackle emotion recognition through physiological signals and in this research ECG and EEG signals are used for human emotion detection, signal processing, Machine learning technique, and other state-of-the-art techniques are used for the enhancement of the signal that was acquired and processed. the final aim of the project was to create a robust framework for detecting and classifying human emotions into different categories which can be used in the future for the above-mentioned applications.

II. Related Works

A. Scientific perspective on emotion

1) What is an emotion: Emotion is a complicated state that shows human consciousness in response to environmental stimuli. In general, they are reactions to ideas, memories, or events that occur in our environment. It involves a variety of individual thoughts, feelings, behaviors, and psychological experiences, which play a vital role in human decision-making and mutual interaction [4].

2) Models of emotions: All along, scientists and researchers adhered to using the basic discrete emotion model and the dimensional emotion model as the two main approaches to studying and categorizing emotions. When considering the basic discrete emotion model, It categorizes a variety of core emotions such as joy, sadness, fear, anger, disgust, etc., while the dimensional model [5] categorizes emotions in various matrices such as valence, arousal, dominance, etc. These models provide the basis for researchers to understand, organize, and study various emotions in order to explore more complex aspects of emotions in different fields.

Drawing was the first researcher who come up with a novel knowledge of emotions, which was further improved by a scientist called Tomkins. Tomkins introduced a discrete emotion model [6] that covers nine core emotions: interest (excited), surprise (startled), amusement (joy), distress (angry), disgust (disgust), scared (terrified), anger (anger), contempt (disgust), and shame (humiliation). These nine emotions are thought to be the building blocks for complex emotions. Another famous discrete emotional mode is the Ekman model. It introduced six core emotions that are universally recognized. They are sadness, surprise, happiness, disgust, fear, and anger. Moreover, Izard offered 10 fundamental emotional categories, while Cicero and Graver proposed four. However, according to these studies, all the other emotions that were not in the base model were considered to be variations or combinations of the core emotional states.

The discrete emotion model has drawbacks when representing a range of different emotions because it categorizes only core, basic emotions in a distinct way. To mitigate the above-mentioned drawback, a novel emotion classification model, the dimensional emotion model, has been introduced. In this model, emotions are organized in a multidimensional space,

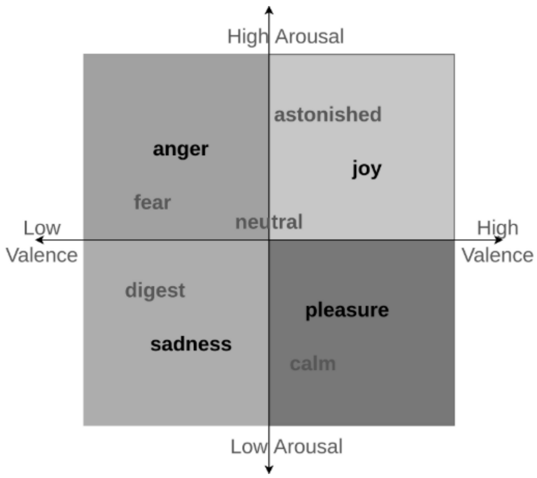

Fig. 1: The 2D emotion model

with each dimension representing a different emotional aspect or measure. There are numerous dimensional emotion models that can be used to aid in research. The first one is Russell‘s circumplex 2D model [5]. It uses arousal and valence as the dimensions and shelters up to 150 different effective emotions. The second one is Whissell’s continuous 2D space, which uses evaluation and activation as the dimensions. Both these are 2D emotion models, and Schloberg introduced a three-dimensional emotion model [7] that adds an attention-rejection dimension to the two-dimensional model. Out of these models, Russell’s 2D emotion model is the most frequently used.

In Russell’s 2D emotion model, the vertical axis represents the arousal dimension, indicating the intensity of the emotional experience from low to high, while the horizontal axis represents the valence dimension, representing the degree of cheerfulness from negative to positive. Based on this coordinate system, emotions can be categorized into four main groups as shown in Figure 1.

B. *Electrocardiography in the field of emotion recognition*

The cardiovascular system is a network of blood vessels that carries blood throughout the body. The human heart is the main organ and plays a vital role in the cardiovascular system by pumping blood through the entire network of blood vessels. The heart has mostly four chambers. The upper chambers are called the atria, and the bottom chambers are called the ventricles. The right atrium receives oxygen-poor blood from the body through large veins, while the left atrium receives oxygen-rich blood from the lungs through veins. As well, the right ventricle pumps oxygen-poor blood to the lungs through arteries, while the left ventricle pushes oxygen-rich blood into the body’s circulation through arteries. This pumping activity of the heart is controlled by the heart muscle, which beats regularly to pump blood efficiently. Electrical signals that start in a place called the Sinus Node act as the main energy source for this rhythmic beat of the heart. These signals travel along specific pathways in the heart, allowing for regular contraction (depolarization) and relaxation (repolarization). By using sticky electrodes, the electrical activity of the heart can

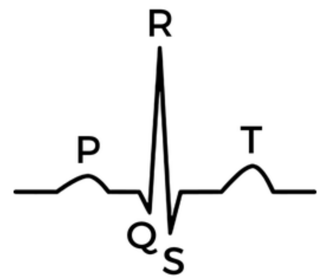

Fig. 2: Illustration of the PQRST wave-form

be detected on the surface of the body and converted to a form of graph known as an electrocardiogram (ECG).

ECG provides valuable information on heart activity based on the electrical pulses of the heart, which helps with research on complex aspects of heart activity in various fields. ECG signals have been widely used in developing machine learning and deep learning solutions, such as for detecting improper heart rhythms, identifying emotions, and even for biometric identification purposes. Scientific studies conducted in the domain of emotion detection using psychological signals have shown a strong relationship between cardiovascular activity and emotions, as emotions can affect the autonomic nervous system that governs heart activity. To obtain ECG signals, electrodes are placed on the skin‘s surface. Common configurations of ECG acquisition systems include single-channel, 3-lead, 5-lead, or 12-lead [8], [9]. When considering a detailed ECG, generally consists of three main waves, as shown in Figure 2. These are P, QRS, and T waves. The P wave represents atrial depolarization, the QRS wave marks the beginning of ventricular contractions, and the T wave appears when the ventricles repolarize. Each of these waveforms contains valuable information that helps understand an individual’s cardiac condition[8].

So these physiological aspects of the ECG can be used as a parameter which is coinciding with the change of emotions. therefore these correlating features of the ECG can be used in experiments to identify the emotional state of a person.

C. *Electroencephalography in the field of emotion recognition*

EEG is used to monitor brain activity or brain waves [8]. EEG can be recognized as one of the most efficient ways to measure brain waves. The process of measuring these signals includes placing electrodes on the scalp to detect tiny electrical signals generated by the brain’s neurons and it will be amplified for further analysis.

By analyzing and studying those brain waves, emotional states, and emotional changes can be identified. When an electrode is placed on the scalp it will measure the electrical activities of a group of neurons rather than a single neuron. Those neuronal signals include functional and physiological changes in the central nervous system(CNS). Therefore, the EEG signals contain useful and meaningful psychological and physiological information.

The EEG signals can be classified into five categories based on the variation in frequency bands: delta (0.5–4 Hz), theta

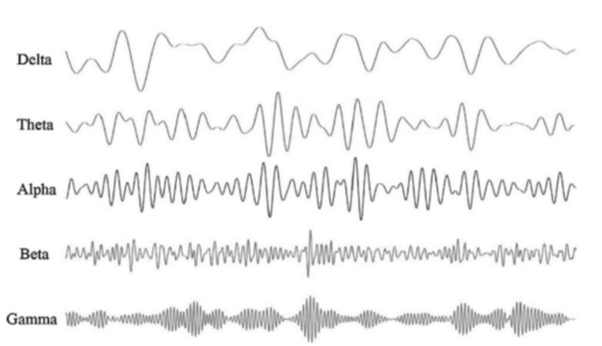

Fig. 3: The wave-forms of EEG bands

(4–8 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (¿30Hz). It can be identified a strong correlation among these EEG signals with respect to frequency range and different brain activities.

From all five frequency bands, the delta waves are the slowest brain waves (0.5 - 4 HZ). They can be obtained during deep sleep or in some people who have certain neurological disorders. Delta waves are associated with the unconscious mind, physical healing, or with restorative processes.

Theta Waves (4 - 8 Hz) can be obtained during light sleep, meditation, or deep relaxation. Theta waves are associated with the dream state or emotional processing.

Alpha Waves (8 - 13 Hz) can be obtained when a person is awake but relaxed with their eyes closed. Alpha waves are associated with a state of calmness and relaxation.

Beta Waves (13 - 30 Hz) can be obtained when a person is awake and actively doing some mental activities or in the stimulation of senses. Beta waves are associated with concentration and alertness.

Gamma Waves (30 - 100 Hz or higher) can be obtained with cognitive processes such as attention, memory, and perception. Gamma waves are associated with information processing and the coordination of various brain regions.

In order to learn computers to recognize emotions, recognizing and understanding them is important in the first place. Those emotions can be identified through different ways such as words, facial expressions, and voice tones. But physiological changes like the brain and nervous system are more reliable compared to facial expressions or voice tones because they cannot be faked. Therefore to measure those electrical activities, EEG is the most efficient way.

EEG provides valuable information about different emotional states. By understanding them it can be seen that low-frequency brain waves are highly related to emotions than high-frequency waves, and also negative emotions are usually stronger than positive emotions. By analyzing specific brain waves such as Beta, Alpha, and Theta waves, we can identify emotions like happiness, sadness, and fear. Also, it can be identified that certain brain areas are connected to specific emotions. For example, enjoyment activities are associated with the left front of the brain, while fear will reduce the activity in the left front of the brain.

So the possibility of understanding the relationship between the EEG data and the emotion elicitation can be used to detect emotions. Which will be great from the perspective of using physiological signals to detect the emotions of humans.

D. How Different experimental processes are done

The field of study of using the physiological signals for human emotion detection is not that novel but it is so vast there can be an infinite number of research done, going on, and will happen in the future as well. With the advancement of technology, research has also grown. In this section, we talk about the works that are relative to the research that is presented in this paper.

Emotion detection or emotional intelligence in detecting an emotion can help in many fields as healthcare systems, computer games, entertainment systems, and safe driving modes. In the elaboration of the above examples usage of emotional intelligence in dynamic game content is discussed [10], [11], [12]. Also when considering the vehicle safety systems emotion recognition models are used [13], [14]. So it is evident that the usage of emotional intelligence is vital in technological development in the future.

For the purpose of emotion recognition, there have been many methods used, few notable ones are speech analysis, facial feature analysis, and physiological signal processing [15]. All these methods come with pros and cons, speech-based emotion recognition needs continuous speech [16], [17] while in the facial feature analysis method, some personal might hide and mask their facial features so the emotion recognition will be harder [18], [19]. Therefore using physiological signals might be a better approach because they are continuously produced and extremely hard to mask unless you are an extremely trained professional and using physiological signals has provided some great results as well [15], [19], [20].

ECGs and EEGs are widely used in the field of emotion recognition and one of the most used databases by the research fellows is the DREAMER database [20]. The DREAMER database has followed the multi-model approach including ECG and EEG signals. Data was collected using signal elicitation by audio-visual stimuli which was similar to the pattern that was followed in this research. Here the resources are included in how to perform the experiment using valence, arousal, and dominance model.

MPED a multi-model physiological emotion database for discrete emotion recognition was also a similar research that was done in the field of emotion recognition through physiological signals [21]. The design and constructions that were done in this research were exemplary. This model has four types of signals. Electroencephalography, galvanic skin response, electrocardiogram, and respiration, make them extremely good in comparing each other. In this research, the researchers talk about the limitation of culture-dependent stimuli. Here the experiment was done for seven distinct emotions including the neutral emotion. The MPED research introduces a method to use the attention-long short-term memory model that increases the effectiveness of the sequence analysis and the feedback is taken to compare the predicted and self-reported outputs.

The paper ”A Survey on Psycho-Physiological Analysis and Measurement Methods in Multi-modal Systems” [22] provide a nice analysis of the multi-model systems about the participant's emotional state during the experiment. Here the important feature is that they reviles many measurements that can be used to identify the emotional state by a physiological signal. This model has an extremely high accuracy rate, therefore, can be used for emotion classification using EEGs and the accuracy was measured using the self-reported data and predicted output.

The paper by Morteza et al[23] uses EEG signals for emotion recognition, this research provides a good step-by-step procedure where the emotion recognition can be carried on. The problem in this research was it is not multi-model therefore there is no comparison between different physiological signals and furthermore the accuracy that it provides can be improved as well. But an excellent paper for understanding the challenges and progress of emotion recognition using EEG.

The paper ECG Pattern Analysis for Emotion Detection [24] is uni model research that was conducted using ECG signals, this research understands the complexity of emotion recognition using physiological signals and how to tackle some of the issues that every researcher will face while conducting similar researches. This model has a relatively high accuracy of the predictions on the valence-based emotion recognition so it emphasizes the importance of comparing only one dimension of the emotional model as well. The paper follows a nicely explained procedure which can be used as a reference for following similar research. But the research itself says that there might be an accuracy increment in using multi-model approaches.

The review paper by Essam H. Houssein et al. [25] discusses the usage of brain-computer interfaces (BCI) along with machine learning to detect human emotions. The paper reviews various approaches to recognizing emotions through EEG-based BCI, along with an overview of the datasets and techniques used in emotion stimuli. Moreover, the paper focused on the general architecture of research based on BCI and ML techniques. The complete architecture involves distinct steps, such as EEG signal acquisition, data preprocessing, feature extraction, feature selection, emotion classification, and performance evaluation. According to the review paper, machine learning algorithms such as k-nearest neighbour, support vector machine, decision tree, artificial neural network, random forest, and naive Bayes, as well as deep learning algorithms such as convolutional and recurrent neural networks with long short-term memory, were used in previous studies conducted by the scientists. The paper reviews more details of the usage of the above algorithms in the field of study. Finally, it suggests several challenges and directions for future research in the recognition and classification of human emotions using EEG. One suggestion is to adhere to deep learning techniques such as convolutional (CNN) and recurrent neural networks (RNN) with long short-term memory for significantly improving emotion recognition performance. Another important point emphasized by the paper is that improving feature extraction and selection methods is crucial to enhancing the performance of emotion detection systems. So the paper suggests a more novel research direction based on using multimodel data (combining EEG data with other psychological data such as ENG and ECG) to improve the accuracy of emotion recognition.

The research, which focuses on emotion recognition using cardiographic waves and is titled "Research on Emotion Recognition Based on ECG Signal" [26] explores various aspects of how ECG signals control human emotions. This study is based on using existing, well-formed machine learning algorithms for human emotion detection using correlation features and time-frequency domain statistical features of ECG signals. It compares the performance of commonly used classification algorithms such as SVW, CART, and KNN in emotion detection. The main output of the study indicates that using correlation features of ECG has a greater impact on the performance of the above-mentioned classification algorithms than using time-frequency domain features, which give accuracy of 19.7% and 16.7%, respectively. When considering algorithmic performance, K Nearest Naibhour, also known as KNN, gives the highest accuracy over other algorithms. Furthermore, this research paper introduces a possible optimization of the KNN algorithm to improve performance in emotion recognition based on combining the Max-Min Ant system with the KNN algorithm. It totally improves the emotion recognition performance of the KNN algorithm by up to 92% compared to direct use of the KNN algorithm, which gives 16.9%. The data collection procedure used for this study is based on video stimuli. For exploring algorithmic performance over different emotion dimensions, one emotion from each quadrant is selected from the two-dimensional emotion model. Further, this paper suggests some future research areas in the emotion recognition domain. These suggestions include developing multimodel emotion recognition algorithms that have higher accuracy by integrating ECG signals with other physiological signals such as EEG, EMG, and SC. Moreover, it suggests a newer research area on emotion detection using deep learning techniques, which holds the possibility of improving the accuracy of emotion recognition.

Taking the above-related works as the basis for the research "Human Emotion Detection with ECG and EEG Signals using Machine Learning Techniques", it is aimed to explore novel knowledge in the field of emotion recognition involving both EEG and ECG signals. The data set is planned to be collected through video stimuli while targeting five predefined emotions (Joy, Fear, Sadness, Relaxation, and Neutral) that cover a broader range of affective emotion dimensions in the 2D emotion model. This simplification allows for the capture of a more accurate set of data and allows for easier supervision of the data during the training phase.

In summary, existing literature and previous studies done in the domain of human emotion recognition manifest the potential of using ECG and EEG signals for emotion recognition. Furthermore, the combination of various physiological signals, such as ECG and EEG, along with deep learning techniques offers improved classification accuracy compared to pure machine learning techniques. Integrating those models into computerized systems leads to more effective and personalized human-computer interaction systems.

Following table indicates the comparison of the work that is similar to the experiment carried on here and their outcomes.

TABLE I: Summary of other research work carried out relevant to the experiment - comparison of metadata

Source	Dataset	Signal Type	Adapted Emotion	Emotion Elicitation Method	Number of Subjects	Classifier	Validation	Accuracy
[20]	OWN (DREAMER)	ECG and EEG	Amusement, Excitement, Happiness, Calmness, Anger, Disgust, Fear, Sadness and Surprise	Audio and Video Stimuli	23	SVM	10 fold cross validation	Spearman correlation features of EEG and ECG utilized and generated, $\rho >$ 0.97 of classification accuracy for all rating scales.
[21]	OWN (MPED)	EEG, ECG, GSR, and RSP signals	7 Emotions	Not Specified (IAPS is recommended)	40	Deep Learning Models	-	higher accuracy in emotion recognition compared to traditional machine learning methods.
[26]	OWN	ECG	Happy, Angry, Pleasant, and Sad. Mentioned emotions are selected from each of the four quadrants of the emotional dimension model.	Video Stimuli	20	SVW, CART, and KNN	-	Considering the three well-known classification algorithms, KNN algorithm can generate the highest emotion detection performance. The paper introduces an optimization of the KNN algorithm combining the Max-Min Ant System. This further improves the accuracy of emotion detection of the KNN algorithm which increases the overall recognition rate up to 92%.
[24]	Not Specific	ECG	-	Physical Activities and Pictures	44	LDA	leave-one-out cross-validation (LOOCV)	Up to 89%
[22]	Not Specific	ECG, GSR, EEG, EMG, RR, EOG, ST Facial expression	-	Music, Virtual reality simulations, Multimedia presentations such as video and image, and gaming scenarios.	-	-	Artificial Neural Networks, Support Vector Machines, k-Nearest Neighbors, Decision Trees, and Naive Bayes	The paper concludes accuracy of $>$ 90% has been achieved utilizing EEG signals

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