CONTENTS

Abstract

Human brain consists of millions of neurons which are playing an important role for controlling behavior of human body with respect to internal/external motor/sensory stimuli. These neurons will act as information carriers between human body and brain. Understanding cognitive behaviour of brain can be done by analyzing either signals or images from the brain. Human behaviour can be visualized in terms of motor and sensory states such as, eye movement, lip movement, remembrance, attention, hand clenching etc. These states are related with specific signal frequency which helps to understand functional behavior of complex brain structure. Electroencephalography (EEG) is an efficient modality which helps to acquire brain signals corresponds to various states from the scalp surface area. These signals are generally categorized as delta, theta, alpha, beta and gamma based on signal frequencies ranges from 0.1 Hz to more than 100 Hz. This paper primarily focuses on EEG signals and its characterization with respect to various states of human body. It also deals with experimental setup used in EEG analysis.

Recommender systems have been based on context and content, and now the technological challenge of making personalized recommendations based on the user emotional state arises through physiological signals that are obtained from devices or sensors. This paper applies the deep learning approach using a deep convolutional neural network on a dataset of physiological signals (electrocardiogram and galvanic skin response), in this case, the AMIGOS dataset. The detection of emotions is done by correlating these physiological signals with the data of arousal and valence of this dataset, to classify the affective state of a person. In addition, an application for emotion recognition based on classic machine learning algorithms is proposed to extract the features of physiological signals in the domain of time, frequency, and non-linear. This application uses a convolutional neural network for the automatic feature extraction of the physiological signals, and through fully connected network layers, the emotion prediction is made. The experimental results on the AMIGOS dataset show that the method proposed in this paper achieves a better precision of the classification of the emotional states, in comparison with the originally obtained by the authors of this dataset.

Chapter 1

Introduction:

Affective Computing has emerged as an important field of study that aims to develop systems that can automatically recognize emotions. In 2019, the market for emotion-detection technology is worth roughly $21.6bn, and its value is predicted to reaching 56bn$ by 20241. Emotions are human responses to environmental objects or events2 that affect different aspects of human life, such as attention, memorization, achieving goals, awareness of priority, knowledge motivation, communication with others, learning development, mood status, and effort motivation3,4. During the last decade, many research and development efforts have been deployed to develop new approaches and techniques for emotion recognition. Two main approaches have evolved the way researchers analyze and classify emotions: the constructionist and locationist approaches. The first approach defines several dimensions to create an effective framework for studying and classifying emotions. The valence-arousal-dominance (VAD) descriptive model2,4 is the model most representative of this approach. Conversely, the second approach assumes that there is a specific brain structure and pattern for each emotion.

It is becoming increasingly attractive to detect human emotions using biological brain signals. Electroencephalography (EEG) is a reliable and cost effective technology used to measure brain activity. Detecting emotion using EEG signals involves multiple steps being performed in sequence to satisfy the requirements of a brain–computer interface (BCI).

Traditional methods are used to extract features from a fixed group of the same EEG channels for all subjects. However, brain-behavior is sophisticated and changes from one person to another3 and from one emotional state to another 5,6,7. Moreover, extracted features are either computed from the whole sample of the EEG signal, which contains irrelevant information, or from an arbitrarily chosen portion of the sample and not necessarily the portion of the signal that corresponds to the emotional excitation instant. There is a growing need for additional steps, such as the identification of epochs, which are the instants at which excitation is maximum during the emotion, and the selection of electrodes that show significant variation in brain activity during emotional states, to accurately detect emotional states. Experiments show that the addition of these steps drastically improves the quality of features

1.1 Overview

In recent years, EEG classification has become an increasingly important problem in various fields. In the field of medicine, EEG detection could be incredibly promising for seizure or stroke detection in patients that are susceptible to such conditions, and a great deal of research has already been put into solving this problem. Other medical applications include manufacturing transportation devices for patients with limited motor abilities to control using simply their thoughts or extremely subtle facial movements. EEG would pick up on both of these and an efficient and accurate classifier could lead to the successful creation of such a device that would change the lives of patients with such a disability. Yet other applications exist in the fields of psychology and neuroscience, where EEG classification can give insight into the inner workings of the human brain. For this project we will explore this particular application for the purpose of classifying human response to visual stimuli. In particular, the paradigm involves presenting three conditions of visual stimulus to the subject: (1) the same undoctored image presented to both eyes separately, (2) the same image but with binocular disparity between each eye to create a 3D effect, and (3) the image enhanced with an algorithm to increase its perceived depth presented to each eye with no binocular disparity. The main goals for this project is to discriminate between EEG recorded during 2D vs 3D stimuli. From the classifier's features we can extract which regions of the brain and which time points during the recording were the most informative in distinguishing between these two classes. In synchrony this will tell us what regions of the brain respond strongly to 3D stimuli at what time after the initial onset of the image. This paper will focus on the methods and results of the discrimination task. A secondary goal, and the subject of future work, is to then use these spatio-temporal cues to compare the EEG recordings of the undoctored vs depth-enhanced images to gauge how well the algorithm does at evoking a 3D-like response in the human brain. Conventional approaches to EEG classification primarily focus on classifying frequency information of record1 052 053 054 055 056 057 058 059 060 061 062 063 064 065 066 067 068 069 070 071 072 073 074 075 076 077 078 079 080 081 082 083 084 085 086 087 088 089 090 091 092 093 094 095 096 097 098 099 100 101 102 103 ings without deep learning, extracting this information using the Fourier or other transforms. However, recent literature has indicated that there is promise in using neural networks for EEG classification. In particular, due to the temporal nature of these recordings, a primary candidate for successful classification has been a Recurrent Neural Network, where at each time step the network retains information from previous time steps. This is the approach we will be taking for this project.

1.2 Literature Survey:

Affective computing (AC) is a continuously growing interdisciplinary research field spanning psychology, computer science, cognitive science, neuroscience, and more (Tao and Tan, 2005). In Picard's landmark book, AC is defined as "computing that relates to, arises from, or deliberately influences emotion or other affective phenomena" (Picard, 1997). It mainly focuses on how technology can inform and deepen understanding of human affect and how systems can be designed to estimate the affective state using computational models from behavioral and physiological signals (Calvo and D'Mello, 2010).

Affect plays an important role in human cognition, specifically in perception processes, rational decision-making, human communication, and human intelligence (Ammar et al., 2010; Singh et al., 2013). In marketing, understanding and recognizing the affective states of users (or customers) has become a vital theme, which can reveal users' true preferences and improve and assist in the purchasing process (Malär et al., 2011; Garrido-Morgado et al., 2015).

Conventional assessment methods of AC in marketing depend mostly on personal evaluations, such as surveys, focus groups, and interviews (Ariely and Berns, 2010; Yadava et al., 2017; Lin et al., 2018). However, customers may not express their true opinions because of social desirability bias (Paulhus, 2002; Vecchiato et al., 2011a). They may not say exactly how they are feeling but rather, how they feel others would reply (Calvert and Brammer, 2012). These post hoc analysis tools are also influenced by individuals' mental states or environments at the time of self-reporting (Nilashi et al., 2020). Due to the limitations of traditional AC techniques, marketers and researchers try to supplement these shortcomings and seek alternative or complementary tools. Neuroscientific tools based on electrophysiological and neuroimaging techniques provide one such alternative, as well as a way to dig deeper into understanding the complex evaluation process and the dynamics of the affective state by directly accessing the physiological signals and fundamental cerebral structure from which an affective state occurs.

Considering its low cost and high temporal resolution (milliseconds), electroencephalography (EEG) has become common and is extensively used in the marketing industry. Furthermore, variations in EEG signals cannot be voluntarily controlled and therefore are a better objective indicator of affect (Singh et al., 2013). EEG-based AC provides a promising avenue for studying the mechanisms underlying affective states and developing recognition computational models to predict the psychological responses of customers. It can, therefore, be widely used to boost sales, advertising, pricing, package design, marketing campaigns, and so forth (Calvo and D'Mello, 2010).

In this review, we focus on EEG-based AC in marketing. First, we stress the need to incorporate the various features of neural signals that contribute to consumers' affective states and evaluation processes beyond what traditional marketing measures already provide. Second, we state that marketing studies should adopt the methodologies and algorithms used in data processing and prediction modeling that are mature in other fields such as computer science and engineering. We examine AC literature in marketing on the general features extracted from EEG recordings and conclude with a general discussion of the challenges faced by this field, providing several recommended guidelines for the road ahead.

1.3 Motivation:

The electroencephalogram (EEG) signals reflect the electrical activities of brain behaviors. The signal-processing techniques based on EEG signals analysis form an important clinical tool for monitoring and diagnosing neurological brain disorders such as autism spectrum disorder (ASD) and epilepsy disorders because they reflect the electrical activities or disorders of neurons in the human brain. Brain disorders, such as ASD and epilepsy disorders, are defined by such activities in the human brain. Currently, most brain disorder diagnoses are performed manually by neurologists or skilled clinicians through visual inspection of EEG signals. The human brain is the most complex part of the human body and provides a wide variety of information related to limbic movements and neurological disorders. In recent years, researchers in multidisciplinary fields of engineering, neuroscience, microelectronics, bioengineering, and neurophysiology have attempted to take advantage of the information provided by EEG signals for several application domains, such as controls, communications, and medical diagnosis. Currently, several types of studies are being conducted in this field to build and improve an efficient diagnosis system.

1.4 Objective:

- An EEG can find changes in brain activity that might be useful in diagnosing brain disorders, especially epilepsy or another seizure disorder.

- An EEG might also be helpful for diagnosing or treating:
  Brain tumors
  Brain damage from head injury
  Brain dysfunction that can have a variety of causes (encephalopathy)
  Inflammation of the brain (herpes encephalitis)
  Stroke
  Sleep disorders

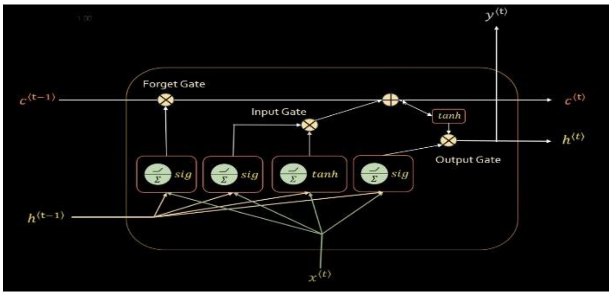
- An EEG might also be used to confirm brain death in someone in a persistent coma. A continuous EEG is used to help find the right level of anesthesia for someone in a medically induced coma.

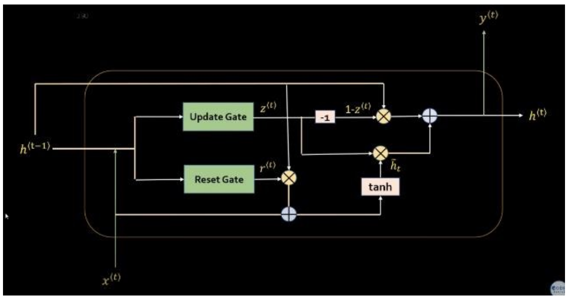
- Reading and understanding human emotions is an integral part of the human civilisation. Women are supposed to be better than men at detecting emotions, especially fear and disgust. A human can deal with any other human if the former can learn from the latter’s emotions carefully. Traders, godmen, fortune tellers and the like have always been masters of understanding emotions.

CHAPTER 2

Methodology:

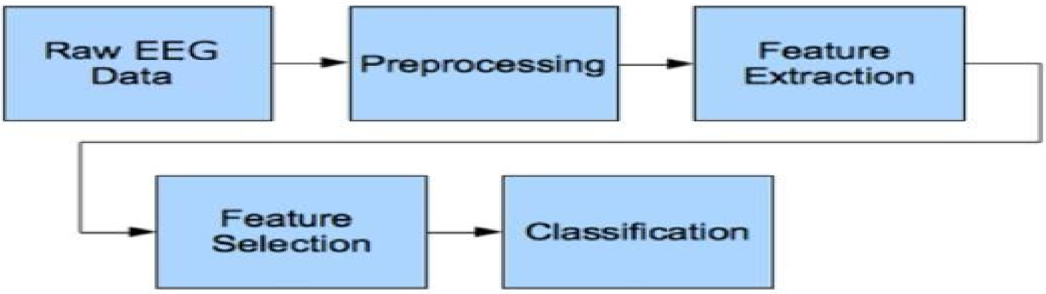
Traditional methods are used to extract features from a fixed group of the same EEG channels for all subjects. However, brain-behavior is sophisticated and changes from one person to another3 and from one emotional state to another5,6,7. Moreover, extracted features are either computed from the whole sample of the EEG signal, which contains irrelevant information, or from an arbitrarily chosen portion of the sample and not necessarily the portion of the signal that corresponds to the emotional excitation instant. There is a growing need for additional steps, such as the identification of epochs, which are the instants at which excitation is maximum during the emotion, and the selection of electrodes that show significant variation in brain activity during emotional states, to accurately detect emotional states. Experiments show that the addition of these steps drastically improves the quality of features.





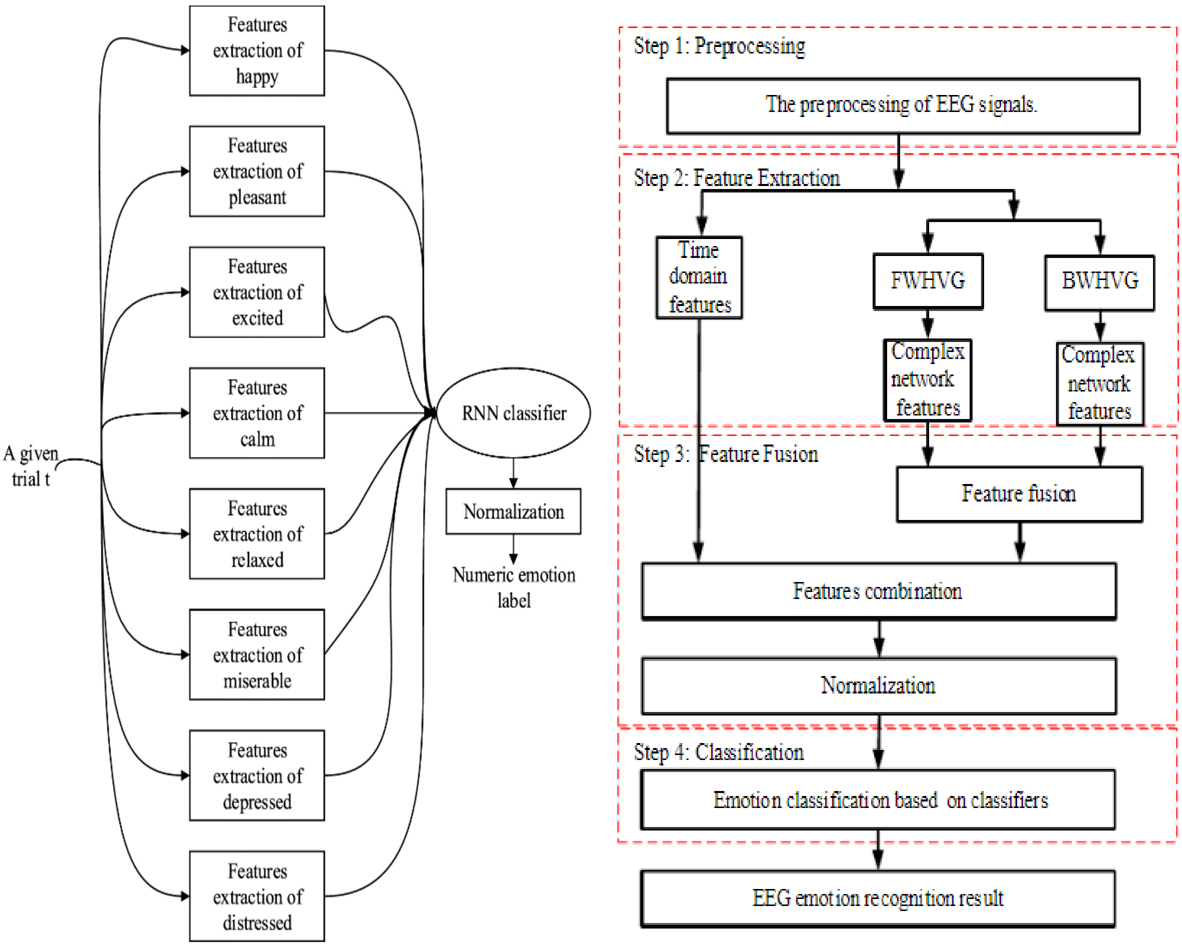
LSTM GRU

We propose a novel method for EEG channel selection based on signal epoch estimation using the zero-time windowing (ZTW) method20. The ZTW method was used to extract instantaneous spectral information from EEG signals at a good temporal resolution. The spectral information obtained using the Numerator Group Delay (NGD) function on the emotional EEG signal was analyzed using the ZTW method to identify the epoch locations on every EEG channel. A majority voting technique was used to select the location that was commonly identified as the epoch instant by most of the electrodes. Only EEG channels that had a vote that matched the selected epoch location were considered for further processing. The other channels were ignored. The brain activity of the selected channels was analyzed to determine which channels showed significant changes during each emotional state. The retained electrodes were used as sources to extract relevant features. The experimental results show that the proposed method is highly competitive compared with existing studies on multi-class emotion recognition. We also found that the proposed method works well, even when applying deep learning algorithms.



The motivation for this study is discussed in “Related works” section, and the most widely known research works in this area are mentioned. “Proposed method” section presents our approach to epoch identification, channel selection, and emotion recognition. “Performance evaluation of the proposed method” section describes the performance of our approach and compares it with related works. Finally, “Conclusion” section summarizes the study and discusses future perspectives of this work.

2.1 Block Diagram



CHAPTER 3

Comparison Tables:

The key difference between a GRU and an LSTM is that a GRU has two gates (*reset* and *update* gates) whereas an LSTM has three gates (namely *input*, *output* and *forget* gates).

GRU is related to LSTM as both are utilizing different way if gating information to prevent vanishing gradient problem. Here are some pin-points about GRU vs LSTM-

The GRU controls the flow of information like the LSTM unit, but without having to use a *memory unit*. It just exposes the full hidden content without any control.

GRU is relatively new, and from my perspective, the performance is on par with LSTM, but computationally *more efficient* (*less complex structure as pointed out*). So we are seeing it being used more and more.

LSTM	GRU
3 Gates: Input, output, forget	2 Gates: reset, update
More accurate on longer sequence, less efficient	More efficient computation wise. Getting more popular
Invented: 1995 - 1997	Invented: 2014

GRU

```
inputs = tf.keras.Input(shape=(X_train.shape[1],))

expand_dims = tf.expand_dims(inputs, axis=2)

gru = tf.keras.layers.GRU(256, return_sequences=True)(expand_dims)

flatten = tf.keras.layers.Flatten()(gru)

outputs = tf.keras.layers.Dense(3, activation='softmax')(flatten)

model = tf.keras.Model(inputs=inputs, outputs=outputs)
```

print(model.summary())

```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, 2548)]            0

 tf.expand_dims_1 (TFOpLambd  (None, 2548, 1)          0
 a)

 gru_1 (GRU)                 (None, 2548, 256)         198912

 flatten_1 (Flatten)         (None, 652288)            0

 dense_1 (Dense)             (None, 3)                 1956867

=================================================================
Total params: 2,155,779
Trainable params: 2,155,779
Non-trainable params: 0
_________________________________________________________________
None
```

```
    y_train,
    validation_split=0.2,
    batch_size=32,
    epochs=2,
    callbacks=[
        tf.keras.callbacks.EarlyStopping(
            monitor='val_loss',
            patience=5,
            restore_best_weights=True
        )
    ]
)
```

```
Epoch 1/2
38/38 [==============================] - 233s 6s/step - loss: 30.4759 - accuracy: 0.8625 - val_loss: 19.3537 - val_accuracy: 0.9097
Epoch 2/2
38/38 [==============================] - 221s 6s/step - loss: 3.6220 - accuracy: 0.9606 - val_loss: 7.1764 - val_accuracy: 0.9398
```

Test Accuracy: 96.06%

Lstm

inputs = tf.keras.Input(shape=(X_train.shape[1],))

x=tf.keras.layers.Dense(64, activation='relu')(inputs)

x-tf.keras.layers.Dense(64,activation='relu')(x)

outputs = tf.keras.layers.Dense(3, activation='softmax')(x)

outputs = tf.keras.Model(inputs=inputs, outputs=outputs)

print(model.summary())

```
Epoch 1/2
38/38 [==============================] - 223s 6s/step - loss: 38.4135 - accuracy: 0.7527 - val_loss: 16.7722 - val_accuracy: 0.8863
Epoch 2/2
38/38 [==============================] - 220s 6s/step - loss: 7.7516 - accuracy: 0.9053 - val_loss: 4.5407 - val_accuracy: 0.9197
```

```
model_acc = model.evaluate(X_test, y_test, verbose=0)[1]
print("Test Accuracy: {:.3f}%".format(model_acc * 100))
```

```
Test Accuracy: 93.750%
```

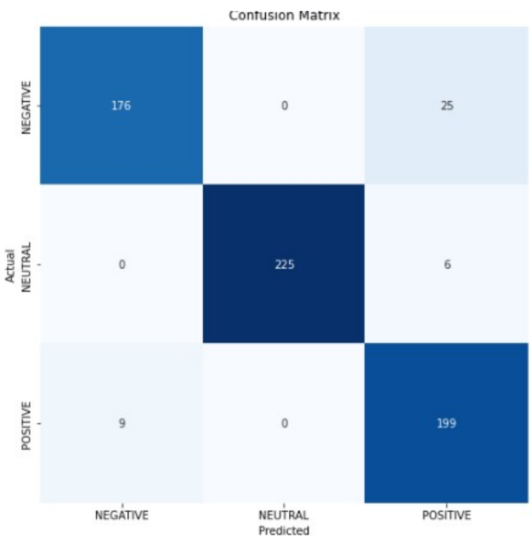
Result And Discussion:

Predicted

Classification Report:
----

	precision	recall	f1-score	support
NEGATIVE	0.95	0.88	0.91	201
NEUTRAL	1.00	0.97	0.99	231
POSITIVE	0.87	0.96	0.91	208
accuracy			0.94	640
macro avg	0.94	0.94	0.94	640
weighted avg	0.94	0.94	0.94	640

a confusion matrix, also known as an error matrix,[9] is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one (in unsupervised learning it is usually called a matching matrix). Each row of the matrix represents the instances in an actual class while each column represents the instances in a predicted class, or vice versa – both variants are found in the literature.[10] The name stems from the fact that it makes it easy to see whether the system is confusing two classes (i.e. commonly mislabeling one as another).



CHAPTER 4

4.1 Conclusion

This paper presented a new approach for emotion recognition using EEG signals. The proposed approach consists of applying the ZTWBES algorithm to identify the epochs, pre-selecting the electrodes that successfully identified the epochs and for every emotional state, determining relevant electrodes in every frequency band. Brain activity changes compared with neutral emotional states were extracted as features. As such, unlike previous studies, the set of electrodes processed to extract relevant features for the distinct emotions changed in every frequency band from one emotion to another, and from one subject to another.

Three classification strategies were applied to measure the efficiency of the proposed method. Our findings showed that the proposed method was a competitive approach in this field and it outperformed that of previous studies. The QDC obtained an average accuracy of 82.37%, and the RNN reached an accuracy average of 91.22% and 85.64% during classification schemes 1 and 2, respectively. Compared with the best performance obtained by previous studies, the proposed method increased the accuracy of emotion recognition by 2.37%, 11.22%, and 5.64% using the QDC, RNN-scheme 1, and RNN-scheme 2, respectively.

Contrary to the image processing based approach, emotion detection using EEG signals requires multi-disciplinary skills including neuroscience, engineering, computer science and psychology. However, going beyond performances of current algorithms for emotion detection, requires further discovery in neuroscience and psychology or by applying a multi-modal approach that combines EEG-based emotion recognition models with image processing based approaches.

4.2 Future Scope

Various fields including medicine, advertising, robotics, virtual reality, gaming, education, working conditions and safety, automotive, home appliances and so on will significantly benefit from the use of emotion-sensing technology. Newly-developed smart devices will be able to arrest emotional reactions and convert these into data and facts to analyse situations and come up with appropriate recommendations accordingly.

At present, healthcare and automotive industries are among the most eager to adopt emotion-sensing features. Car manufacturers are exploring the implementation of in-car emotion-detection systems to improve road safety by managing the driver's drowsiness, irritation and anxiety.

Owing to achievements in computer vision, the emotion-sensing technology field is progressing on understanding human emotions, speech recognition, deep learning and related technologies. Every year, we see new mood sensor technologies being realised. While most of the existing emotion-sensing inventions are based on the use of on-body devices or voice/facial recognition software, research and development efforts are increasingly being directed towards sensing technology that can measure emotions in a contactless manner.

Though artificial intelligence (AI) is unleashing a wave of digital disruption, the limitation of AI to understand human emotion is still a challenge. However, in the past few years, increasing access to data, low-cost computing power, and evolving NLP combined with digital learning are enabling the systems to analyze human emotions.

A detailed understanding of emotion is a factor that challenges the EDR market, as emotions can be expressed in multiple ways and can also be deceptive. Despite this challenge, technological advancements in AI are expected to drive the market for EDR during the forecast period.

Other key influencers of the market include the rising need for better customer experience (as emotional connection also plays a key role along with customer satisfaction), the increasing need for a human touch in digital communications (chatbots), and challenges in language context and facial recognition.

Many prominent companies are using emotion detection and recognition to their advantage. This technology facilitates consumer behavior detection and, thus, helps in contributing significantly to consumer behavior studies. For instance, Disney has been using technology to determine how audiences enjoy its movies, specifically creating an AI-powered algorithm that can recognize complex facial expressions and even predict upcoming emotions.

Moreover, the technology has gained a significant amount of focus from the video game companies. Video games are designed to induce a series of emotions in players, with these reactions often being essential for the overall enjoyment of the game. The developers are integrating emotion-detection into user experience, in order to adjust or tweak sequences in real-time. This has also resulted in more immersive experience for gamers.

4.3 Limitation:

One of the big disadvantages of EEG/ERP is that it's hard to figure out where in the brain the electrical activity is coming from. By putting lots of electrodes all over the scalp (in our lab we use 64 or 128 electrodes), we can get some idea of where the ERP components are strongest. This doesn't really tell us where in the brain the signals are coming from, but it can be useful in telling us whether two ERP components come from the same place or not. For example, let's say we want to know if different parts of the brain are used when you see a picture of an apple, and when you read the word "apple". Maybe the ERP components to the picture and the word are biggest at the same time, but they are biggest over different parts of the head. This would tell us that different parts of the brain were being used.

Reference:

Literature Review on EEG Preprocessing, Feature Extraction, and Classifications Techniques - Athar A. Ein Shok, Mohamed M. Dessouky, A. S. El-Sherbeny

Using Deep Convolutional Neural Network for Emotion Detection on a Physiological Signals Dataset (AMIGOS) - Luz Santamaria-Granados , Mario Munoz-Organero, (Member, Ieee), Gustavo Ramirez-González , Enas Abdulhay4 , And N. Arunkumar