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A Review on Various Mood Detection and Regulation Methods

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***Abstract*----Advancements in research and technology have made the human capacity to interact with computers or machines. The most natural way of communication is through emotions. In this era of Artificial Intelligence, Affective computing and virtual reality, to sense and regulate the person's emotional states without another person's intervention is possible. Enormous research has taken place in the field of mood detection and regulation. This paper focuses on the major highlights in the recent research of mood detection and regulation with different approaches for providing a technological perspective on society.**

***Keywords*--- Human-Human interaction, Human-Computer Interaction, Mood Detection, Mood Regulation, Self- Regulation**

I. INTRODUCTION

Moods and emotions play a vital role in our life. Emotion is nothing but the energy-in-motion, a way of expressing oneself whereas mood is the state of being emotional. Irrespective of culture a human grows with basic seven emotions (Anger, Contempt, Fear, Disgust, Happiness, Sadness, and Surprise). Emotions and moods can mutually influence each other. If emotion is strong and deep enough, it can turn into a mood [1]. Moods and emotions have significant effects on all aspects of individuals such as body, perception, cognition, actions and personality development [2]. They can be recognized through various modes like neuroimaging, speech, text, facial expressions, physiological signals, body postures, and gestures, etc. Extracting and understanding moods and emotions can help us how we act, behave, or think [3].

Mood regulation is the process in which individuals modify their emotions, respond to the emotions of the situations that evoke emotions to respond properly [4]. Mood detection used in various applications which include Personal Robots [5], Security, Medical Diagnosis [6], Web-based E-Learning, Computer Gaming [7], Call Centers, Intelligent Toys, Autonomous Cars [8]. Mood regulation used in Education [9], Car Safety [10], Mental Healthcare [11]. The notion of emotional intelligence is an active research topic in computer vision, pattern recognition, artificial intelligence and affective computing fields for more than two decades due to its diverse applications. This paper focuses on the analysis of various mood detection and regulation methodologies. This paper is organized as follows: Section II discusses different mood detection methods. Their comparative analysis is given in Section III. Section IV describes mood regulation methods and therapies and Section V concludes this survey.

II. MOOD DETECTION METHODS

All methods of mood detection have three main steps: preprocessing, feature extraction, and classification. Some of the most researched mood detection methods are given below.

A. Neuroimaging:

Brain is the main organ of the central nervous system which controls and monitors all the activities of the body. Producing imaging scans of the brain or other nervous systems (i.e. Neuroimaging) for different emotions has always been a challenging task. Since the early 1990s, development in imaging technology has allowed research in neural structures related to moods or emotions [12]. Over the years, several studies and meta-analysis described the functional neuroanatomy of emotions using Functional magnetic resonance imaging (fMRI) and Positron Emission Tomography (PET). Our brain is divided into several non-overlapping parts and each brain region is involved in different aspects of emotions [13]. However, individual imaging studies cannot fully characterize which brain regions are responsible for emotion. Some techniques like multi-voxel pattern analysis allow for the possibility that neural responses to emotional stimulation occur in many brain areas simultaneously [14]. Some of the studies to detect emotions in the brain using neuroimaging are given in Table 1.

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Table 1: Different Studies on Neuroimaging

Ref.	Method	n	Experimental Paradigm	Emotions
[15]	fMRI	26m	Viewing emotional facial expressions	S, H
[17]	fMRI	18f, 11m	Mood Induction by Tactile Task based on Discrimination of Braille-like Raised Dots Patterns & Negative F/B	FR, AN
[18]	fMRI & GNB	8f, 2m	Mood Induction by Self-Experiencing Emotions & by Viewing Pictures	A, D, E, F, H, L, P, S, SH
[19]	MRI & VBM	69 f, 41m	Viewing emotional Facial Images	F, A, D, S, N, SU, H
[20]	PET	18f, 16m	Social anxiety questionnaires & brief telephone interview	SA
[21]	fMRI & SVM	65 mix	Resting Experiment	DE
[22]	PET	53 mix	Mood Induction by self-bio recall & re-experience	S, H, A, F

(GNB - Gaussian Naïve Bayes Classifier, VBM – Voxel-Based Morphometry, SVM – Support Vector Machines, n – Number of Participants, f – Female, m - Male, F/B – Feedback, FR - Frustration, AN - Annoyance , A - Angry , D - Disgust , E - Envy , F -Fear , H - Happy , L - Lust , P - Pride, S - Sad , SH - Shame , N - Neutral , SU - Surprised, SA - Social Anxiety, DE - Depression)

Scans of fMRI shown in Fig.1 depict an activation multi-voxel patterns when a brain experiences an emotion – sad and happy. Color coding is used to detect the level of neural activity in the brain.

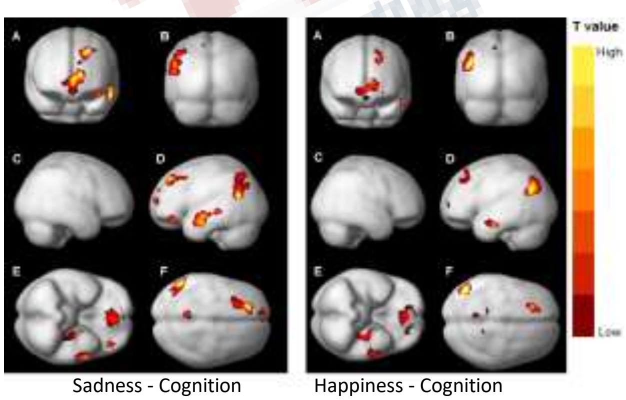

Fig. 1: Activation pattern of emotions in brain - (A) - Anterior, (B) - Posterior, (C) - Right, (D) - Left, (E) - Ventral, (F) - Dorsal view [15]

In fMRI and PET, if greater the activation, greater the flow of blood in that region of the brain which gives activation pattern of emotions in the brain, however, their low time resolution makes it difficult to investigate temporal aspects of emotional states [16].

B. Speech Emotion Recognition (SER) :

Speech is one of the important ways of communication. Emotion recognition from the speech signal has been a research topic for more than two decades. Speech processing came into existence in 1920 when a celluloid toy named "Radio Rex" was made [23]. In SER, Feature selection is based on the type of features such as Prosodic, Spectral, etc. Patterns of derived speech features such as Energy, Pitch, Formant Frequency, Mel-frequency Cepstrum Coefficients (MFCC), Linear Prediction Cepstrum Coefficients (LPCC) and Modulation Spectral Features (MSFs) are mapped using Classical ML classifiers like k-nearest neighbors (KNN), Artificial Neural Network (ANN), SVM, Hidden Markov Model (HMM), Gaussian Mixture Model (GMM) [24], Modified Brain Emotional Learning Model [25] or Deep Learning-Based Classifiers. Other models are Decision Tree, Fuzzy Classifier and many more. Overview of Speech emotion recognition is given in Fig. 2.

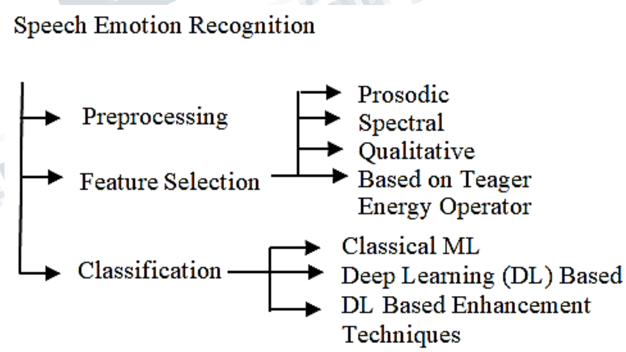

Fig. 2: Overview of SER [26]

The important issues in speech emotion recognition system are choice of database, signal processing unit in which appropriate features are extracted from available speech signal and another is a classifier which recognizes emotions from the speech signal [8]. Some of the studies on SER are given in Table 2.

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Table 2: Different Studies on Speech Emotion Recognition

<table>
<tr><th>Ref.</th><th>Emotions</th><th>Database</th><th>Technique</th><th colspan="3">Recognition Rate in %</th></tr>
<tr><td>[7]</td><td>J, S, A D, F, N, SU,</td><td>Berlin & Spanish</td><td>MLR, SVM, RNN</td><td colspan="3">Berlin - 83
Spanish - 94</td></tr>
<tr><td>[25]</td><td>H, S, A</td><td>EMO-DB</td><td>BEL, ANFIS, MLP</td><td colspan="3">72.50</td></tr>
<tr><td rowspan="4">[27]</td><td rowspan="4">H, S, A, N</td><td rowspan="4">IEMOCAP</td><td rowspan="4">RNN</td><td></td><td colspan="2">Overall</td></tr>
<tr><td>Features</td><td>WA</td><td>UA</td></tr>
<tr><td>Raw Spectral</td><td>57.7</td><td>53.78</td></tr>
<tr><td>Emotion LLDs</td><td>59.1</td><td>55.63</td></tr>
<tr><td>[28]</td><td>H, S, A, SU, F, N</td><td>Vocal Data from Social Media</td><td>LS-SVR</td><td colspan="3">82.43</td></tr>
<tr><td>[29]</td><td>H, S, A, N</td><td>SEMAINE</td><td>FPCA & QDC</td><td colspan="3">75.8</td></tr>
<tr><td>[30]</td><td>H, S, A, N</td><td>MHMC, EP-DB, LM-DB</td><td>DAE & LSTM</td><td colspan="3">64.5</td></tr>
<tr><td>[31]</td><td>H, S, A, F, N, D, B</td><td>EMO-DB</td><td>FT AlexNet & AlexNet-SVM</td><td colspan="3">FT AlexNet - 76
AlexNet-SVM - 68</td></tr>
<tr><td>[32]</td><td>H, S, A, F</td><td>LDC & UGA</td><td>SVM</td><td colspan="3">LPCC - 73.125
MFCC - 85.085</td></tr>
<tr><td>[33]</td><td>H, S, A, N</td><td>IEMOCAP</td><td>DCNN</td><td colspan="3">WA - 71.8
UA - 68</td></tr>
</table>

(J - Joy, B - Boredom, IEMOCAP - The Interactive Emotional Dyadic Motion Capture, EP-DB - Emotion with Personality Database , LM-DB - Long -Term Mood Database , EMO-DB - Berlin Emotional Speech Database , LDC - Linguistic Data Consortium, UGA - University of Georgia, RNN - Recurrent Neural Network, LS-SVR - Least Square Support Vector Regression, FPCA - Functional Principal Component Analysis, QDC - Quadratic Discriminant Classifier, DAE - Denoising Autoencoder, LSTM - Long Short Term Memory, BEL - Brain Emotional Learning, ANFIS - Adaptive Neuro-Fuzzy Inference System, MLP - Multi Layer Perceptron, FT AlexNet - Fine Tuned AlexNet , DCNN - Deep Convolution Neural Network, WA - Weighted Accuracy, UA - Unweighted Accuracy)

C. *Text-Based Emotion Recognition:*

Emotion recognition from text has been promising research over the years. Texts reflect a writer's emotional state and feelings which can be detected using different methods. Emotion recognition from text is nothing but the classification problem which comes under Text data mining [34]. Social media has facilitated an increase in online communication, blogs, public review sites, micro-blogging sites like Twitter have opened the newer approaches to detect the emotions from that text data. Recognizing emotions conveyed by a text can give an insight into the author's intent and may lead to better understanding of the text's content. Mainly, there are four approaches for emotion recognition from text data: keyword spotting based, Lexical affinity-based, Machine learning (ML) based and hybrid-based methods [35].

There are considerable issues in the first three methods such as a collection of data, feature choice, labeling of emotions, ambiguity in keyword, incapability of recognizing sentences without emotional keywords, incapability of recognizing sentences without emotional keywords, and difficulties in determining emotion Indicators. Thus, the hybrid-based method combines in keyword-based and ML-based methods to increase the performance [35] [36]. Systematic classification of Text-Based Emotion Recognition methods is given in Fig. 3.

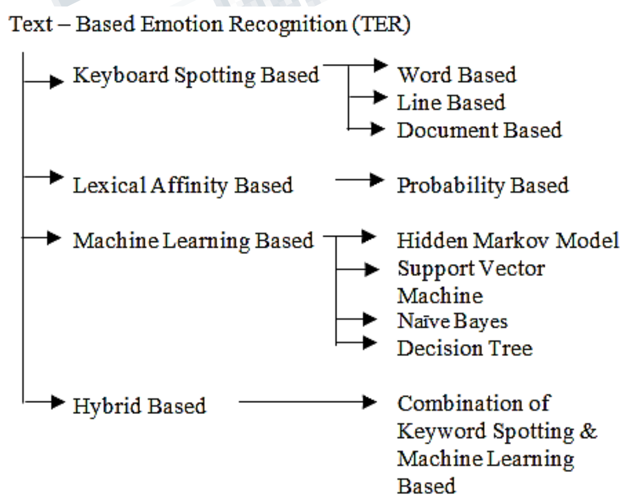

Fig. 3: Classification of TER Methods [35]

Text based emotion recognition system still requires attraction of researchers. Some of the recent studies on Text Based Emotion Recognition are given in Table 3.

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Table 3: Different Studies on Text Based Emotion Recognition

Ref.	Emotions	Database	Technique	Recognition Rate in %
[38]	H, S, A	On-line website text	Fuzzy Logic & NN	90
[39]	J, A, D, F, S, SH, G	Keystroke Analyzed & Text pattern analyzed data	Vector Space Model	80
[40]	H, S, A, F, D, SU	HC Corpora Punjabi Text Data	Naive Bayes & SVM	—
[41]	J, S, A, F, D, G, SH	ISEAR	Lexicon & Word Embedding	81
[42]	H, S, A, F, D, SU	ISEAR	Line based Keyword Spotting	65
[43]	H, S, A, F, D, SU	Aman 2007, Twitter Data	K-NN & PMI	84 (F-Score)
[44]	PO, NE	News Summary	CNN	Headlines – 67.95 Blogs – 60.73

(G - Guilt, Po - Positive, NE – Negative, ISEAR - International Survey on Emotion Detection Antecedents and Reactions, PMI - Point Mutual Information, CNN – Convolution Neural Network)

D. Facial Emotion Recognition (FER):

In 1977, Ekman and Friesen developed Facial Action Coding System (FACS) to code facial expressions in which the movements on the face are described by action units. This system inspired many researchers to analyze facial expressions by means of image and video processing. In this work, tracking of facial features and measuring the amount of facial movements is done to classify different facial expressions [37]. The most effective non-verbal communication is through facial expressions. In communication, most of the message contribution is in the form of non-verbal communication especially facial expressions. There are multiple approaches to recognize mood using facial expressions including Machine Learning, Deep Learning, and Fuzzy Logic. Facial Emotion Recognition basic architecture is given in Fig.4. In this, facial features such as geometric and appearance features which include shapes and locations of eyes, nose mouth, facial regions or patches are extracted from the face.

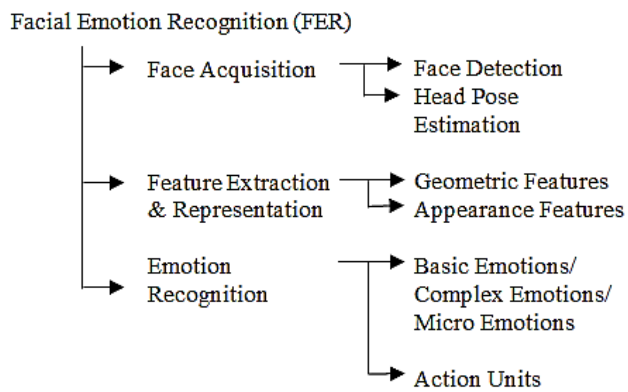

Fig. 4: FER Architecture [37]

Facial expression recognition becomes difficult in case if a human face has multiple variations such as color, orientation, expression, posture, and texture, etc. [51]. Some of the methods that detect emotions from facial expressions are given in Table 4.

Table 4: Different studies on FER

Ref.	Emotions	Database	Technique	Recognition Rate in %
[45]	H, S, A, F, D, SU	Real time Images	K-NN Classifier	90
[46]	H, S, A, F, N, D, SU	JAFFE	ASM, CT, SVM	RBF Kernel– 63.0 Expo. Kernel – 68.5
[47]	H, S, A, F, N, D, SU	JAFFE	ICA, ANN, K-NN	ICA_ANN – 91.43 Ratio_KNN- 90.48 Combine - 92.38
[48]	H, S, A, D, N, SU, AF	KDEF	CNN, AOD	Average 84.9
[49]	H, S, A, D, F, N, C, SU	CK, JFFE	AlexNet	90
[50]	H, S, A, D, F, SU	CK, MMI	Deep Convolution NN	CK – 99.6 MMI – 98.63

[51]	H, S, A, N, D, SU	JAFFE	GFE, NN, PCA, Gabor Feature Extraction	__
[52]	H, S, A, N, F, D	SAVEE	Graph Mining, BCSO, NN	90
[53]	H, S, A, N, F, D, SU	SFEW & RAF	Random Forest Classifier	SFEW- 57.7 RAF- 59.0
[54]	H, S, A, F, D, SU	CK+ &JAFFE	Feature Descriptors, KNN, SVM	CK+ - 98.5 JAFFE - 98.3

(AF - Afraid, C - Contempt, JAFFE - Japanese Female Facial Expression, KDEF - Karolinska Directed Emotional Faces, CK - Cohn-Kanade, SAVEE - Surrey Audio-Visual Expressed Emotion , SFEW - Static Facial Expressions in the Wild, RAF - Real-World Affective Faces, K-NN - K-Nearest Neighbour, ASM - Active Shape Model, CT- Census Transformation, ICA - Independent Component Analysis, AOD – Audio on Demand, GFE - Gabor Feature Extraction , PCA – Principal Component Analysis, BCSO - Binary Cat Swarm Optimization, RBF- Radial Basis Function)

E. Emotion Recognition by Physiological Signals

Physiological signals which are controlled by the autonomic nervous system are increasing attention in the field of emotion recognition. However, a single signal may not describe emotions completely and accurately [58]. So, one or more signals such as EEG, ECG, GSR, EMG, PPG, RSP, HRV, etc. are sensed using sensors and wearable devices to recognize mood and emotion. Some research findings of physiological signals are given in Table 5. Physiological signals are easily influenced by many factors such as the human body and external environment which makes it difficult for data acquisition [56].

Table 5: Emotion Recognition by Physiological Signals

Ref.	Signal	Emotions	Database	Technique	Recognition Rate in %
[55]	ECG & GSR	Arousal & Valence	AMIGOS	DCNN	Arousal-76 Valence-75
[56]	ECG, GSR, EMG & PPG	P, F, S, A	Sensor Data	KPCA & GBDT	93.42
[57]	RSP & HRV	H, S, A, F, N, D, SU	Sensor Data	CNN	94.02
[58]	EEG, EOG & EMG	Arousal & Valence	DEAP	K-NN, RF, CART	Arousal – 94.42 Valence – 94.02

(ECG - Electrocardiogram , GSR – Galvanic Skin Response, EMG - Electromyogram , PPG - Photoplethysmography , RSP - Respiration , HRV - Heart Rate Variability, EEG - Electroencephalogram , EOG - Electrooculography , P - Pleasure, AMIGOS - A dataset for Mood, personality and affect research on Individuals and GrOupS, DEAP - A Database for Emotion Analysis using Physiological Signals, KPCA – Kernel Principal Component Analysis, GBDT – Gradient Boosting Decision Tree , K- NN - K Nearest Neighbor, RF -Random Forest , CART - Classification and Regression Tree)

F. Emotion Recognition by Body Postures and Gesture

Recognizing emotions through body gestures are still less explored in the research. However, the influence of mood and emotion on body postures, movements and gestures is undeniable. They give information that is not present in speech and facial expression. The gesture itself is an expressive movement of the body through which emotions can be expressed. Body gestures do not have obvious emotional traits, unlike facial expressions and speech. For the same emotion, a different person can express different body gestures [59]. Humans can easily predict a person's emotions through body movements. But for computers to detect emotions using body movements is still challenging.

Fig.5 Body Gestures of Different Emotions [59]

Some of the methods to recognize emotions using deep learning are discussed in Table 6.

Table 6: Emotion Recognition using body postures and gestures

Ref.	Emotions	Gestures	Database	Technique	Recognition Rate in %
[59]	H, S, A, F, D, S U	Jump, Squat, Throw, Stand, Recede, Turn & Walk away	Captured Images	TSN, ST-GCN, FCN	—
[60]	H, S, A, F, D, SU	Positions & orientation of joints	Captured by Kinect Sensor	CNN, RNN & RNN-LSTM	RNN-LSTM -72
[61]	H, S, A, F, U	Jump, Sit, Walk	University of York emotion action dataset	FDCNN	94.2

(U - Untrustworthy, TSN - Temporal Segment Network, ST-GCN - Spatial-Temporal Graph Convolutional Networks, FCN – Fully Connected Network, RNN-LSTM – Recurrent Neural Network Long Short-Term Memory, FDCNN - Feed Forward DCNN)

G. Emotion Recognition using Daily Activities

As we discussed earlier, Moods influence all activities of individual including day to day activities. Life logging is digitally recording user's daily lives for various purposes and in a variety of details. Such information can be recorded to identify daily life activities and boost the person's experience. Daily lifelog including sleep quality, diet, physical activities, and our environment influence our moods and emotions [62]. Table 7 gives recent study on emotion recognition using daily activities.

Table 7: Emotion Recognition using Daily activities

Ref.	Emotions	Database	Technique	Recognition Rate in %		
					SVM	C 4.5
[62]	Happy, Anxious, Content, Depressed	Daily Lifelog	SVM & C4.5	Valence	75.43	71.92
				Arousal	89.03	83.33

III. COMPARATIVE ANALYSIS OF DIFFERENT MOOD DETECTION MODALITIES

We have discussed briefly about different modalities to recognize different emotional states of human. Each Modality has some pros and cons. Some has great background of research however; some has not so explored. Among all studies facial and speech recognition for emotion detection has been explored and studied widely by researchers. All methods are compared on basis of dependency, complexity and applications as shown in Table 8.

Table 8: Comparative Analysis of Different Mood Detection Methods

	Depends on	Complexity	Applications
Neuroimaging	Small Movements	More	Medical Diagnosis
Speech	Speaking Style, Culture, Environment	Less	Call Centers Intelligent Toys
Text Based	Language, Writing Style	Moderate	Opinion Mining
Facial	Culture, Gender, Age, Person	Less	Mental Healthcare, Education, Security
Physiological S/G	Person & Time	More	Personal Robots, Mental Healthcare
Body Postures & Gestures	Culture & Gender	Moderate	Video Surveillance
Daily Activities	Person	Less	Sleep Monitoring

IV. MOOD REGULATION METHODS

In the last decade, mood regulation has received increasing attention and has become one of the most studied topics within the psychological field. Mood regulation is a dynamic process that every person implements to down-regulate or up-regulate positive and negative emotional states to reach desirable states [63]. Based on interaction there are two types of regulations first is self-regulation and the other is regulation using digital technology.

A. Self-Regulation

Human regulates their mood through cognitive processes such as Distraction, Rumination, Reflection, Reappraisal, and Acceptance and using modulation like

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Discharge, Emotion suppression and physical modulation [64]. Patients with mental health issues take some medications like Cholinergic Medication and Nicotinic Medication. These medicines are used to change the activities of the autonomic nervous system and to cope up with feelings such as depression [65]. Mindfulness is another method to overcome negative emotions. Mindfulness means focusing on present body sensations, thoughts, and feelings without judging them [66]. It can also be mindful eating or drinking so as focus on present. Sometimes a person seeks help from another person to cope up with anxiety and stress through social contact [67]. These methods are Human-Human Interaction.

B. Regulation using Digital Technologies

With the advancement in science and technology, there are methods to regulate mood using Human-Machine Interaction. The therapies using advance technologies are mentioned below.

1) Virtual Reality and Augmented Reality

Augmented Reality (AR) is a set of techniques and tools that add information to the physical reality. In AR, virtual elements provide the real-world view, hearing, smell and touch with remarkable and valuable information. These tools have used to reduce anxiety and fear by psychologists [68]. On the other hand, Virtual Reality (VR) allows generating real-life simulated scenarios that may provide a contextualized situation to measure a certain construct through significant environments, though controlled way [63]. In Virtual Reality Exposure Therapy (VRET) system, the therapist can manipulate the exposure elements in a safer, manageable and cost-effective way. So, this method is used by therapist to treat social anxiety, Social Stress and Fear [69].

2) Biofeedback techniques

Biofeedback Technique comprises an effective and noninvasive procedure, whose fundamental operating principle is the conscious registration of normally unconscious body procedures (e.g., brain activity, physiological signal etc.) [70]. Biofeedback with mobile app and gaming style app are used to capture changes in skin conductivity. This method provides greater reductions in psychological and physiological levels of stress [71]. Heart Rate Variability biofeedback has used to reduce stress and anxiety effectively [72]. Neuro feedback signals have used to control activity of brain to regulate emotions [73].

3) Wearable Sensors and Devices

Wearable devices have become popular in everyday life, which serve a range of functions, from measuring physical activity and physiological variables to providing feedback on emotional states. The 'doppel' wearable device delivers an on-demand, discrete, user-controlled, heartbeat-like vibration applied through a wristband. It is used to provide calmness in case of high anxiety and stress [74]. A recent mHealth technology, 'Calm Mom', included of a mobile app and a wrist-worn sensor band for the ambulatory measurement and alerting of increased electro dermal activity (EDA), a physiological measurement of stress has become an integral tool for managing stress [75].

4) Mobile applications

Smartphones have been and are part of a technology revolution that has deeply changed people's daily life. Mobile apps such as mental health mobile (mHealth) applications, Emotional help assistant chatbot, self-care, mood trackers and mindfulness-based applications are used to regulate emotional states [76]. Almost all mobile phones provide music player or FM Radio. Music is often used for regulating emotions in everyday life and they have both beneficial and harmful effects on emotional health. Person can regulate mood by listening music. Music can increase positive emotions and reduce negative emotions. Music therapy has been used with depressed and non- depressed people for mood regulation [64].

V. CONCLUSION

Emotional Intelligence has attracted increasing attention in last few decades by psychiatrists, researchers, academicians, automobile industries and many more. Researchers are still working on this topic to optimize existing methods and to increase their accuracy. The objective of this research paper is to provide brief introduction towards methods, applications and limitations of mood detection and regulation based on the available work in literature. As we mentioned earlier, mood or emotional state can be recognized using one or more modalities from Neuroimaging, Speech, Facial Expressions, Text, Physiological Signals, Body Postures or Gestures and Our Daily Activities. Mood has great impact on human's personal and interpersonal life. This mood has to be regulated time to time otherwise it may turn into a serious mood disorder. In this paper we have reviewed two methods of regulation i.e. self-regulation and regulation employing digital technology.

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