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Review Article

A survey of machine learning techniques in physiology based mental stress detection systems

Suja Sreeith Panicker, Prakasam Gayathri *

School of Computer Science and Engineering, Vellore Institute of Technology (VIT), Vellore, Tamil Nadu, India

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ABSTRACT

Various automated/semi-automated medical diagnosis systems based on human physiology have been gaining enormous popularity and importance in recent years. Physiological features exhibit several unique characteristics that contribute to reliability, accuracy and robustness of systems. There has also been significant research focusing on detection of conventional positive and negative emotions after presenting laboratory-based stimuli to participants. This paper presents a comprehensive survey on the following facets of mental stress detection systems: physiological data collection, role of machine learning in Emotion Detection systems and Stress Detection systems, various evaluation measures, challenges and applications. An overview of popular feature selection methods is also presented. An important contribution is the exploration of links between biological features of humans with their emotions and mental stress. The numerous research gaps in this field are highlighted which shall pave path for future research.

1. Introduction

Stress has become a buzzword of present times affecting a large number of people worldwide irrespective of gender, age group or work profile. The changing demands in work culture, increasing pressures, changing lifestyles and technological interventions could be possible reasons for this trend. Hence significance of Stress Detection systems has increased as compared to the scenario prevailing decades back. It is important to safeguard human resources worldwide from the growing impact of stress especially because stress is inevitable. Thus early detection and management of stress is crucial to enhance emotional health and overall wellness of mankind.

Just like emotions stress is also transient in nature and physiology plays an important common role in both – emotions and stress. The various negative emotions are but manifestations of high stress. Because of their inherent inter-relationship both Emotion Detection systems and Stress Detection systems have been surveyed in this paper along with highlights on the various facets and role of machine learning algorithms.

We have developed a pictorial representation of overall layout of the work carried out in this paper in Fig. 1. As illustrated in Fig. 1, Sections 2 and 3 are further elaborated in

* *Corresponding author at*: School of Computer Science and Engineering, Vellore Institute of Technology (VIT), Vellore, Tamil Nadu, India.
E-mail addresses: pgayathri@vit.ac.in (P. Gayathri).

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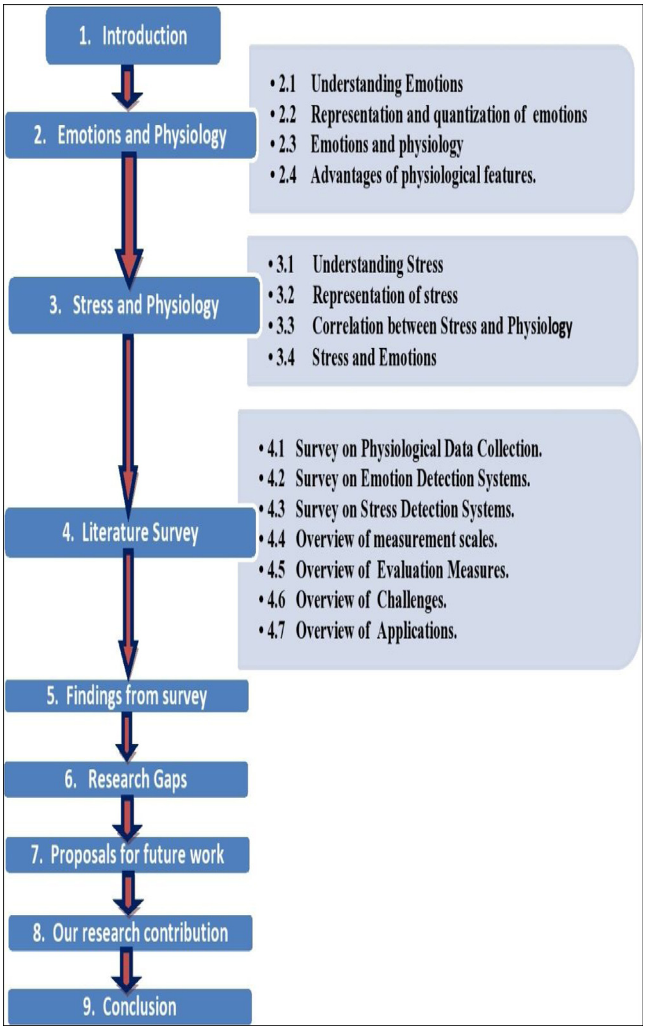

Fig. 1 – Overall layout of current work.

four subsections each while Section 4 is further divided into seven subsections.

2. Emotions and physiology

The current section presents information about the common links that exist between emotions and physiology.

2.1. *Understanding emotions*

Quest for the basic characteristics of emotions is a central question in emotion research [123] and there is a rich variety of definitions of 'Emotion' in existing literature. Highlights are presented below:

- Emotion is the process of causally linked mental and behavioral elements, where the former include action tendency, appraisal and subjective experience; and the latter include physiological reactions, vocal and facial expressions [122]. However, real life factors such as weakened (or loss of) body–mind correlation is an impediment for this definition. Hence it is worthwhile to review the subsequent ones.
- Emotion is a sequence of changes in state for each of the five organismic subsystems – Cognitive (appraisal), Autonomic nervous system (arousal), Motor (expression), Motivational (action tendencies) and Monitor (feeling). This sequence of changes could occur in interrelated and interdependent way in response to internal/external stimulus [122,125].
- Emotions are mental states hence they are in the same class as beliefs, sensations or desires [123].
- Emotion is a process having psycho-physiological nature and could be triggered by unconscious/conscious perception of objects or situations. Usually this is largely associated with the individual's temperament, mood, motivation and personality [1].
- The huge number of definitions in literature have been articulated in the seminal work [143] with the following well defined mutually-inclusive categories: affective, exterior emotional stimuli, cognitive, expressive/emotional behavior, physiological, adaptive, disruptive, multi aspect, restrictive, motivational and skeptical [143]. From these, emotion has been expounded as under:

The complicated set of communications amidst objective or non-objective determinants, intervened by hormonal/neurological systems that can

i. Generate affective experiences (characterized by conventional feelings of arousal, pleasure/displeasure).
ii. Initiate cognitive processes.
iii. Stimulate physiological adjustments.
iv. Cause behavioral change that is often but not always expressive.

2.2. *Representation and quantization of emotions*

Interrelationship between the various affective dimensions have been empirically represented by the classic circumplex model shown in Fig. 2 [122] which illustrates the 28 different emotions which are quantifiable by the varying values of pleasure and arousal. Fundamental categories of emotions are positive and negative. Some common labels of emotions found in literature include arousal, leisure, amusement, sleepiness, despair, displeasure, enthusiasm and worry [122].

The cognitive structure of affect indicates that the affective space is bipolar with the antonym emotion labels (or stimulus words, as the case may be) approximately 180 degrees away from each other. Emotion labeling is typically a mathematical function that imparts a fuzzy membership value between 0 and 1 to every emotion state such as – happy, sad, angry etc. As implied by the inherent nature of fuzzy sets, the boundaries between various emotion states illustrated in Fig. 2 are fuzzy. Clustering of emotion synonyms near axes is not found, on the contrary the emotion labels are found to be approximately spread across the perimeter [122]. Systematic application of weighted regression and Principal Component Analysis enables the efficient quantization of emotions [122].

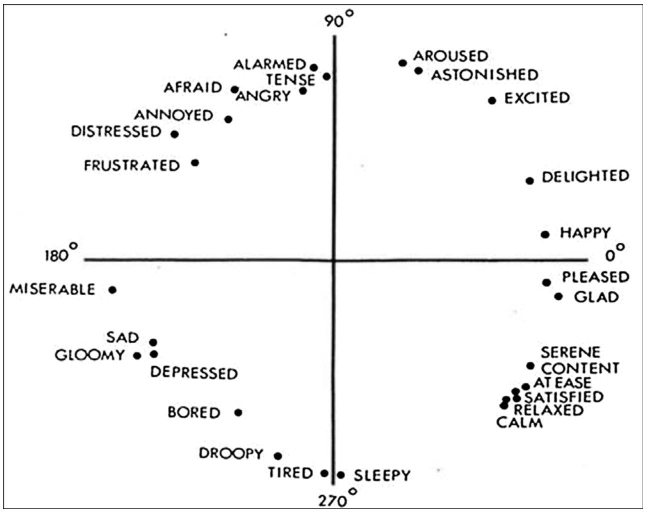

Fig. 2 – Multidimensional circumplex model [122].

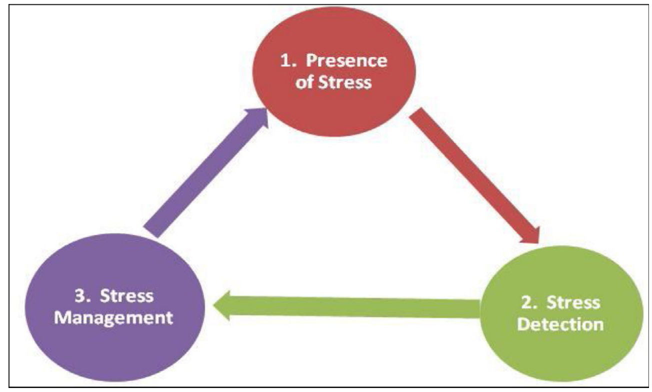

Fig. 3 – Joint role of various aspects in Emotion Detection and Stress Detection.

2.3. *Emotions and physiology*

Emotions imply accepting, deciphering and recognizing the events using one's senses. These emotions can be objectively and realistically captured by one's physiological signals [2]. Emotion is the intense experience felt at mental level and usually manifested by characteristic phenomena such as faster heartbeat, profuse sweating and atypical facial expressions [3]. Research has put forth the strong evidence that physiological signals contain human emotion related information [4]. As per the facts presented in [5] lowered heart rate variability is associated with the emotion 'happiness' while the increased value is associated with 'joy'/'amusement'. Along similar lines the role of Galvanic Skin Response (GSR) too has been investigated. It is demonstrated that GSR can differentiate between the emotions of 'fear' versus 'anger', 'fear' versus 'sadness' and 'happy' versus 'sadness'.

Some significant and popular physiological signals used in existing literature are summarized as follows – Electroencephalography, Electrocardiogram, Blood Volume Pressure, Electromyogram, Skin Temperature, GSR, Photoplethysmogram, Respiration pattern [4], Blood Pressure [6], Respiratory Volume and Heart Rate [1]. Physiological changes have been induced by a variety of stimuli to elicit human emotions in laboratory. Commonly used ones include – affective pictures/movies/video/music or texts and facial expressions [1].

Emotion detection and Stress Detection are multi-disciplinary domains and seek expertise from varied domain experts, significant ones being – medical practitioners, psychiatrists, computer engineers and researchers. We have conceptualized a simple diagram emphasizing this joint role as shown in Fig. 3. Presence of stress deals with physiological aspect, stress detection deals with research aspect while stress management tackles the psychological aspect.

Fig. 3 clearly depicts the cyclic flow of stress from initiation (as shown in phase 1 – Presence of Stress) to high levels (phase 3 – Stress Management). Stress reduction programs have a strong role in stress management. Cyclic flow from stress management back to presence of stress is indicative of ongoing entry of stress in one's life.

2.4. *Advantages of physiological features*

There are several unique advantages possessed by physiological features which make them a preferred choice of researchers worldwide. These strengths of physiological features over their non – physiological counterparts are summarized below [6]:

1. Simplicity in overall experiment (from data gathering till interpretation of results).
2. High accuracy.
3. High reliability.
4. Cost effective.
5. Uninterrupted continuous readings are possible.
6. Non invasive
7. Ease of use for the subject.
8. Is unmaskable by the subject since physiological signals are involuntary.
9. Least sensitive across cultural differences [7].

3. Stress and physiology

The current section deals with basic understanding about stress followed by information about the common links between stress, emotions and physiology.

3.1. *Understanding stress*

From the various definitions of Stress found in literature, we present some significant ones:

1. Stress is a non-specific response of the body toward the external demands. These external demands are known as Stressors, while internal bodily changes (chemical/hormonal) produced by demands form the actual stress response [145].

2. Stress is a relationship that exists between the person and his/her surroundings and is assessed by the former as being exhaustive or much beyond the available resources thereby jeopardizing one's safety or welfare [144].
3. Butler in their seminal study [143] presented the following highlights:
   i. Coercion or strong persuasion leads to stress, with rising intensities of either, leading to heightened chances of the recipient to succumb.
   ii. The response to stimuli which may be distasteful or unpleasant, paves the way for Stress. If the recipient is subjected to longer period of such stimuli, exhaustion or giving way becomes inevitable.
   iii. Stress is the dynamic progression that reflects both internal and external factors. One's thoughts, beliefs, images and attitudes constitute the internal factors, while the circumstances and interactions form external factors [143].
4. Stress is the unfavorable feedback from the recipients toward the extreme demands they are subjected to [146].

3.2. *Representation of stress*

There are three stages of stress depending upon the length of time during which the individual is confronted with it. These are – Acute stress (lesser exposure), Episodic stress (recurrent exposure) and Chronic stress (lasting exposure) [95].

Stress Detection systems rely on a fundamentally qualitative assessment, since disparity may exist between numerical scales hypothesized by different researchers. Also, since 'stress' is primarily felt and experienced by the sole individual, it is a difficult job for the third party (the research team) to quantify it. There could be factual inconsistency between the computed score of stress and the actual feelings of the individual. Various researchers have used different linguistic terms to assess stress qualitatively. Some popular class labels [27] include – (a) extremely stressed, slightly stressed, slightly relaxed, stressed, extremely relaxed, relaxed or normal; (b) low, high or medium; (c) absence or presence of stress. However some researchers have used a quantitative scale for assessing stress, ranging from 0 to 5 or from 1 to 10; with ascending numbers indicating rise in stress.

Commercial systems that provide continuous feedback to users, thus helping them in stress management include emWave [89], ThoughtStream [90] and StressEraser [91].

3.3. *Correlation between stress and physiology*

A summary of the correlation between stress and physiology is presented here. Rise in any of the physiological parameters – HR, Blood Pressure or Respiration Rate leads to increase in stress [85–87]. Galvanic Skin Response [88] is an important stress marker too. Lowered BVP values are indicative of increased stress and vice versa. Skin Temperature rises with decrease in stress levels and vice versa. Both HRV and GSR closely reflect stress as compared to respiration signal. Increased energy for the speech components having high energy, and rapid fluctuations at fundamental frequency are indicative of higher stress [27].

In the case of Multimodal techniques certain behavioral parameters too have been used in addition to one or more modalities such as – facial expression, handwriting, gesture, speech and usage of mobile phones.

3.4. *Stress and emotions*

Stress is strongly correlated to emotions and high levels of stress affects one's emotions, performance at work, physical health and mental health [77].

- An important parameter in this field – affective quality, is combination of the values of arousal and valence. Affective quality creates a state called as 'core affect' in the participant thereby initiating neurophysiological and mental processes. This suggests that the induced stimulus causes changes in one's neurons, physiology and the mind [141].
- Escalating thresholds in the various emotions has high probability of giving rise to stress. Upsurge in negative emotions such as anger, sadness, fear or frustration has high probability of giving rise to negative stress, as it originates from fundamentally negative emotions. Positive stress arises from positive emotions such as hope, joy or pride, and is conventionally believed to boost one's performance while also harmoniously maintaining the state of mind.
- Besides emotions, another important factor contributing to onset of stress is time. Lengthened exposure to positive stress is likely to establish positive mindset, while extended exposure to negative stress may lead to negative mindset of individuals. This establishes the link between stimulus, emotions, stress and mindset.

4. Literature survey

Extensive literature survey is carried out in this paper and covers the significant benchmarks encompassing entire research process commencing with collecting the suitable data right up to the varied applications as depicted in Fig. 1 previously.

4.1. *Literature survey on physiological data collection*

Data collection is crucial in all types of research, this is especially true for physiological data since this process must be error free and data be devoid of noise for better accuracy of algorithms.

Table 1 tabulates some of the popularly used devices for collecting real time physiological data. Thus a quick view of the devices with the corresponding physiological features collected by it is presented. In addition to the devices tabulated in Table 1, Kendall Neonatal electrodes [21] and Textrodes [25] have been used in literature for acquiring ECG.

The specific devices as cited in Table 1 shall serve as a roadmap for future researchers. Since literature covers a variety of feature subspace, the exact device used in major works shall be useful for fellow researchers to identify the most suitable device. This shall facilitate in the crucial decisive phase during inception of future research.

Table 1 – Summary of devices used for physiological data collection.

Reference	Name of device	Physiological parameters collected
[8–12,58,107]	Emotiv [13]	EEG (Electroencephalography)
[14]	Waveguard EEG cap [15]	EEG
[66]	Biopac MP150 and Empatica E4	Heart Rate
[67]	BrainLink Headset [16]	EEG
	Shimmer [17]	GSR and PPG (Galvanic Skin Response, Photoplethysmogram)
	Shimmer EMG [18]	EMG (Electromyogram)
[68]	BioHarness kit, SC Amplifier	Electro CardioGram, Skin Conductance, Electromyogram, Respiration
	Bioamplifier	Rate (RR), Arterial Pulse Rate, Skin Temperature
	Temperature sensor, Piezoelectric Arterial Pulse Transducer	
[69]	FlexComp Infiniti [19]	Skin Conductance, Blood Volume Pressure, Electrooculogram, Interbeat Intervals
[20]	Equivital Life Monitor	Heart Rate Variability
[94]	Wearable electrocardiograph with tri-axis Accelerometer	Heart Rate Variability
[36]	BioSemi ActiveTwo system	EEG
[21]	g.GSRsensor2	GSR
	uEye camera	HR
[22]	B-Alert X10	EEG, ECG
[23]	Truscan32 System	EEG
[12]	Tobii T60 Tracker	Points Of Regard (POR)
[24]	g.US Bamp	EEG
[25]	ECGZ2	Thoracic Electrical Bio-Impedance (TEB)
[26]	SleepSense breath belt, g.PULSEsensor, g.GSRsensor.	RR, pulse, GSR
[27]	Thought Technology FlexComp Infiniti,	
	BodyMedia Sensewear, Biopac GSR100C	Skin Conductivity
	Affectiva Q Sensor	
	Thought Technology FlexComp Infiniti, Biopac ECG100C	HRV
	Thought Technology FlexComp Infiniti	EEG
	Finapres monitor	BP
	LM34 Temperature sensors	Skin Temperature
[28]	Biopac	EEG

Large feature space adds to the complexity of physiology based systems, highlighting the importance of selecting the most prominent/relevant features for the respective experimental design. The commonly used methodologies for reducing the feature set include Independent Component Analysis, Empirical Mode Decomposition, wavelet analysis and fractals. Other methodologies include Simulated Annealing, Ant Colony Optimization, Particle Swarm Optimization, Genetic Algorithm, Differential Evolution and Deep Learning.

4.2. *Literature survey on Emotion Detection systems*

a. Emotion elicitation process:

In most Emotion Detection systems participants are subject to suitable stimulus with an aim of eliciting specific emotions. Appropriate laboratory environment is setup in a controlled manner and the participants are subject to one or more of the following affective content – audio, pictures, video or virtual reality environment (for the participants all of these may usually be unseen before). Most researchers use standard affective content which is annotated with specific emotion labels. In physiology based Emotion Detection systems, wearable sensors are continuously used in the laboratory to track and monitor the physiological states of participants – before, during and after the experiment. The preprocessed data is mathematically assessed as per the presented hypothesis and later classified into various class labels by using a suitable machine learning algorithm.

b. Overview of significant features contributing to representation of emotions:

According to the popular model, complexity of emotions can be better understood by human experts as also mathematically represented by two significant features – arousal and valence [29]. The former is the individual's level of awareness toward the impetus while the latter is the level of attractiveness [30]. By considering the emotions along both dimensions – arousal and valence, most Emotion Detection systems classify the human emotion as either positive or negative.

c. Categories of Emotion Detection systems:

We have developed a simple diagrammatic representation as shown in Fig. 4 to depict the various categories of Emotion Detection systems.

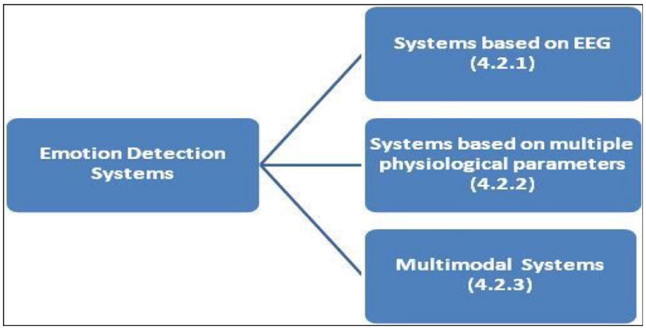

Fig. 4 – Broad categories of Emotion Detection systems.

Fig. 4 illustrates the three subsections in the ensuing literature survey on Emotion Detection systems – systems based on exclusive use of EEG signals, systems based on a combination of various physiological signals and lastly systems based on multimodal fusion techniques which is a growing trend in current research.

4.2.1. *Emotion Detection systems based on EEG*

Voltage fluctuations that occur beyond the native current flow within the millions of neurons in brain are measured by EEG. Hence EEG data has predominance in accuracy and reliability in determination of individual's state of mind [31].

Some basics into EEG measurement – every scalp electrode is located close to certain centers of human brain. To mention few significant ones of interest: F8 has proximity to sources of the emotional impulses, activities of perception and differentiation are located near P3, P4 and Pz; emotional processors are found near T3 and T4 [148]. Research indicates that negative emotions arise from left frontal lobes and positive emotions arise from right frontal lobes [24]. For accurate data, the arrangement of EEG sensors is important. After sufficient experimentation with EEG positioning, the highest variability observed was of approximately 18 degrees [142].

Compared to the conventional use of parameters such as heart rate, respiration amplitude, blood volume pulse, eye pupil rate, human speech etc.; the advantages of EEG data are multifold. Hence there has been substantial research on the use of EEG signals. The detailed Literature Survey along with advantages and disadvantages of EEG based systems is presented in Sections 4.2.1 and 4.2.2, respectively.

4.2.1.1. Literature survey for EEG based Emotion Detection systems. A brief survey in this regard is presented below:

EEG based emotion analysis was performed by initial use of DWT. Significant features were extracted based on wavelets coefficients, one group worth mentioning is the modified wavelet energy parameters. Minimum Redundancy Maximum Relevance (mRMR) was used as feature selection for reducing the redundancy and maximizing the relevance. Results of multi class SVM (Support Vector Machine) suggest the promising role of proposed algorithms [32].

Use of DWT for feature extraction marked improved results in retaining temporal information of EEG data as opposed to conventional Fourier Transform and Wavelet Transform, where there is likelihood of loosing this essential time based characteristic. SVM and Extreme Learning Machine when used with Symlets order 6 yielded accuracies of 84% and 89% respectively for two emotions – happy and sad [33]. Emotiv EPOC was used in acquiring real time EEG [34]. After pre-processing with DWT, Linear Regression and SVM were used to classify six emotions – sadness, joy, surprise, anger, disgust and fear. Low accuracy of 37.72% was obtained which could be improved further by feature selection.

A novel method for selecting better wavelet for extracting features from EEG data is used in [31]. Features from the following sub-bands were considered: gamma, beta, alpha, theta and delta. An innovative concept of energy density has been explored to distinguish between normal and abnormal persons with visualization of energy graphs [31]. The plots of normal persons indicated a higher density of energy in the central and frontal parts of lobes. These parts of brain are associated with reasoning, movement, problem solving and recognition. The plots of abnormal persons indicated a higher density in the frontal part which is associated with emotions. Multi layer feed forward network was used to classify the emotional states of persons. Highest accuracies recorded were 100% and 86% for normal and abnormal person respectively. Future work would be to consider higher number of emotional states and validation with different classifiers.

To explore the hidden features in EEG data, Empirical Mode Decomposition was employed to use the rich multidimensional information of decomposed EEG signals. Proposed technique yielded higher accuracy of 69.10% as compared to existing methods when used with following techniques – sample entropy, SVM, fractal dimension, DWT and differential entropy.

Results indicate that the high frequency component of this decomposed EEG has substantial effect on detecting various emotional states [35]. A novel approach of employing Renyi's Quadratic Entropy for distinguishing between 4 emotional states based on EEG Data was performed in Ref. [36]. As compared to conventional Multiscale Multivariate version of Sample Entropy, proposed method was found to have lowered computational intensity and demonstrate less sensitivity to the length of snippet. An important finding is the use of infrequently used public dataset of movie based emotional stressors [37].

mRMR was used to select the 40 optimal features from EEG data having 114 features initially, along the dimensions of arousal and valence. A noteworthy contribution is the use of existing samples from Enterface project database [38], with the latter being further extended with EEG data captured in real time. Neural Networks, Naive Bayes and SVM were used to classify the data into 5 classes. Although initial results yielded lower classification accuracies of 32% and 37% for valence and arousal, respectively, increased accuracies of 71% and 81%, respectively were noted with improvements on data [23].

An innovative concept of dyad – the basic building unit of interpersonal communication/relationships was explored to detect two emotions namely sadness and happiness from EEG data. A novel case of the relation between mother and child was considered with an objective to study impact of mother's emotional states on the child's ensuing interpersonal and social relations. High results of 99% were achieved with Neural Network [39].

International 10-10 system of electrode placement was used in [40] and EEG data was collected from 64 electrodes. The following techniques were used for selecting prominent features – Surface Laplacian and DWT. An important finding is a newly proposed feature – Absolute Logarithmic Recoursing Energy Efficiency which yielded high accuracies with both Linear Discriminant Analysis (LDA) and kNN as compared to conventional features subset [40].

A pioneering concept of combining time, frequency together with DWT features from EEG data was used to classify two emotions – sad and happy. Results indicated that time domain features achieved better accuracy of 81.8% for 'Happy' while frequency domain features performed better for 'sad' emotion with accuracy of 72.7% [24].

Ref. [41] presents an useful tool for co-relating the relationships between emotional states and brain activity. Indices such as – correlation, phase synchronization and coherence were employed to approximate the functional connectivity of brain by using EEG signals. Analysis of patterns was performed using Quadratic Discriminant Analysis.

While majority research suggests popularity of DEAP [42] and IAPS [43] as standard datasets for emotion elicitation, current work used the Standard Chinese Emotional Film Clips Database [44]. Future work includes the use of varied types of stimuli for eliciting emotions. Also, further experimentation can be performed by using Directed Transfer Function and Partial Directed Coherence.

Ref. [45] serves as reference for selection of EEG channels for determining emotions. Average Mean Reference and DWT were used for pre-processing and feature extraction respectively. Experimentation was done with 10, 14, 18 and 32 EEG channels with kNN as classifier. Highest results were observed on Gamma frequency band – 89.54%, 92.28%, 93.72%, 95.70% for valence and 89.81%, 92.24%, 93.69%, 95.69% for arousal. It was noted that classification accuracy increased with increasing number of channels. It was also observed that as compared to other bands, Gamma band is closely associated with emotional states [45]. Using mRMR for feature selection, Random Forests and SVM for classification; experimentation was performed by varying the following – EEG channel locations, different frequency bands, feature extraction algorithms. Random Forests proved more robust. Future work aims to extend current work for automatic depression detection with real time data [46].

In Ref. [28] EEG analysis was performed irrespective of individual subjects by considering the Event Related Potential (ERP) values. EEG features were acquired from three electrodes positioned at central line and experimentation indicated that selecting parameters directly from EEG yielded higher accuracy in emotion classification. ERP – a derivative of EEG, reduces the need for base lining and averaging operations while also contributing to higher accuracy.

A novel method of applying EEG based recognition of emotions to real world applications such as web enabled music therapy and music player is proposed in [47]. Fractal based algorithm – Higuchi, was used for quantifying these six emotions in real time – frustrated, fear, happy, sad, satisfied and pleasant. Two different experiments were conducted with both types of stressors – music and sound. Future work includes increasing the sample size, integrating the currently standalone modules of Emotion Recognition and the Applications on the web.

The EEG signals induced with specific excitatory stimulus were given as input to Duffing Oscillator. Experimentation involved plotting and interpreting the various phase portraits in accordance with the response. This work opens up new methodology of clustering based on emotions using the EEG signals in phase-space [48].

A deep learning framework called Spatial Temporal Recurrent NN [100] was used to classify into the following labels – positive, neutral and negative; after extracting features from delta, theta, alpha, beta and gamma bands. High accuracy of 89% was noted. Research gaps include – working on a larger sample size and aiming for better accuracy.

In contrast to the major works that explored conventional emotions, a novel emotion of Empathy was determined in [12]. It was observed that more than 80% of the feature-elevated fixations of eye gaze suggest presence of empathy. Important findings are: predominance of EEG data in emotion recognition, seamless fusion of the different technologies for data gathering with further advantages of low cost and non invasiveness. Permitting the participants to behave in their natural way during data collection owing to the least invasiveness of devices used, is a strong advantage. This is important for accuracy as well as reliability of collected data. Extending the current work to successfully detect deafness along with the personality trait of shyness in individuals is proposed for future research.

From the above survey it is observed that Discrete Wavelet Transformation has been popularly used in several EEG based research.

An extensive survey is tabulated in Table 2 presenting the details of – datasets used, feature space, machine learning algorithms with its corresponding advantages and disadvantages. The observations from Table 2 indicate wide use of EEG in literature and show the different statistical features which have formed various feature subspaces in the studies.

4.2.1.2. Advantages and disadvantages of EEG based Emotion Detection systems. Based on the survey of existing work [1,11,56,57,62] we have summarized the advantages and disadvantages of EEG as a modality for Emotion Detection systems.

Advantages are enlisted below:

1. Higher accuracy than other modalities since the signals arise from central nervous system.
2. Robustness.
3. Provides insights into the functional status of the neural networks present in human brain. This information can be tapped for assessing the individual's state of mind [149].
4. Tolerance to the physical/mental impairments of subjects which may inhibit the quality of physiological signals to be used for research.
5. High temporal resolution.
6. Low intrusiveness.
7. Provides objective evaluation.
8. Swift response of signal to the stimuli, thus facilitating faster data collection.
9. Less affected by social influence, hence unmasked real data is obtained.

Table 2 – Literature survey for pure EEG based Emotion Detection systems.

Ref. No.	Machine learning algorithm used	Features extracted	Class labels used	Dataset used	Results	Advantages	Disadvantages
[1]	SVM	Brain asymmetry, power spectral density of EEG data	Disgust, neutral, happy, sad, tense	Real data	Results of within stimulus experiment are superior: 93.31% accuracy for power spectral density.	• Affective data has been built with real time collected data. • Extensive experimentation performed on various feature extraction methods.	Number of subjects considered is small.
[10]	PNN	EEG data	Positive and negative labels with respect to valence and arousal	MAHNOB and DEAP [42]	96% with MAHNOB data	Features were combined from all 3 domains of EEG data as opposed to single domain in many works.	1. Low accuracy. 2. More experimentation using tuning parameters such as number of iterations, algorithms to improve the accuracy.
[11]	SVM, k NN	EEG data	Scared, sad, calm, happy	International Affective Picture System	Average recognition of 55% for kNN, 58% for SVM	1. Extensive experimentation performed with various types of feature extraction methods, and respective feature subsets. 2. The novel method of feature extraction focused primarily on the event related characteristics of EEG data, hence stands apart from majority.	Low recognition rate.
[14]	Multilayer Perceptron (with one hidden layer), SVM (using Pearson Kernel function), C4.5	EEG data	High arousal or low arousal, positive valence or negative valence	DEAP and real dataset	Highest accuracy of 87.80% was obtained with SVM	1. The experimentation On real EEG data collection is advantageous over DEAP with respect to Annotation, as the former allows users to report the emotions on continuous basis for each stimulus on the item. 2. Responses by users to unfamiliar music stimulus, is more accurate in detecting emotion.	1. Small number of subjects considered in real dataset collection. 2. Extending the work as an Emotion Detection System.
[50]	Long-short-term-memory recurrent neural network, SVM	Rational asymmetry parameters from the 14 pairs of electrodes	Positive, negative	DEAP [42]	Average accuracy of 76.67%	All three important areas for characteristics of EEG frequency, temporal and spatial are considered.	1. Obtained accuracy is not suited for practical purposes. 2. The number of features considered in the frequency space is less. 3. Total subjects considered were only 32. 4. Should have been validated on more classifiers. 5. Proposed classifier can be further improved to obtain better results.
[51]	SVM	EEG data	Low arousal and low valence, high arousal and low valence.	DEAP [42]	86.28%	The combination of feature extraction method successfully yielded higher accuracy as compared to those in literature.	1. More features should be considered. 2. Validation using more classifiers is required.

Table 2 (*Continued*)

Ref. No.	Machine learning algorithm used	Features extracted	Class labels used	Dataset used	Results	Advantages	Disadvantages
[62]	Binary-LIBSVM (RBF)	Wavelet features of EEG	Anxiety, neutral, sadness, amusement, joy, anger, disgust, surprise, fear	MAHNOB-HCI	0.73 and 0.77 (arousal and valence respectively)	1. Less number of features used, as compared to existing literature 2. Only 8 electrodes used as compared to 32, in most previous work. 3. Good results obtained as compared to previous works. 4. Ease of use for the user. 5. No discomfort for the wearer.	The interface of human and machine could be further reduced, for more comfort by wearer, as the number of electrodes used is more.
[52]	Artificial Neural Networks, SVM using Radial Basis Function k- NN, Decision Tree, LDA	EEG Data from 32 electrodes.	Positive, negative	DEAP [42]	1. Results for Leave one out method are: 84.63%, 88.54% and 87.03% for valence, arousal and liking respectively 2. LSM achieved more than 94% accuracies for Subject Video Independent and Independent Subject scenarios.	1. Four different scenarios were conceptualized and experimented. 2. Results indicated better accuracy than existing work.	1. More fine tuning could be performed for parameters while using the classifiers – ANN and SVM. 2. Data from lesser number of channels (instead of the conventional number 32) could be experimented with. 3. More experimentations could be performed on the various possible configurations of LSM. 4. Use of fMRI and facial features to be combined with EEG, to build a more robust Emotion Detection system. 5. Validate the system with real EEG data collected from wearable devices.
[53]	Multiple class SVM, Artificial Neural Networks	Hjorth parameters, statistical features, differential entropy, combination on symmetric electrodes (RASM-Rational Asymmetry and DASM-Differential Asymmetry)	Negative, positive, neutral	SJTU Emotion EEG Dataset [54]	1. For multi class classifiers: 2. High accuracy of 91.2% obtained for ANN, as opposed to 40% for SVM 3. For binary classifiers: 4. Both ANN and SVM yielded accuracy over 94%	1. Fusion method of Feature Extraction was experimented successfully. 2. High accuracies were obtained on the standard datasets.	1. Experimentation on real data is lacking. 2. Validation with more classifiers is lacking. 3. Further experimentation with different combinations of feature subsets with the different classifiers can be performed, for better accuracy and generalized results.
[55]	LDA, Gaussian Naive Bayes, SVM (Linear Kernel and Radial Basis Function), kNN, MLP, Decision Tree	Oscillation, spectral power, Shannon entropy features EEG data	Not mentioned	DEAP [42]	SVM with linear function yielded following accuracies: 79.99%, 76.84%, 79.45% and 77.66% dominance, valence, liking and arousal respectively.	1. Benchmarking of results with previous existing works indicate a 9% increase in accuracy with current method. 2. Proposed method with suggested set of features are robust compared to existing work.	Validating the system with more experimentations on feature subsets and classifiers to obtain higher accuracy.

Table 2 (*Continued*)

Ref. No.	Machine learning algorithm used	Features extracted	Class labels used	Dataset used	Results	Advantages	Disadvantages
[6]	kNN, ANN	Entropy, correlation-based and spectral properties of 18 channels	High or low valence, High or low arousal	DEAP [42]	ANN performs better with accuracy of 75% and 72.87% respectively for the 2 classes	Data from only 18 relevant channels is used, instead of conventional 32 channels.	1. To further improve the accuracy 2. To validate on more number of subjects. 3. To reduce the dimensionality of feature space (currently 250)
[57]	SVM, Logistic Regression	EEG data	Positive, negative, neutral	SJTU Emotion EEG Dataset	Accuracy of session 81.81, accuracy of subject evaluation 77.88%	Extensive experimentation performed with number of experiments and various classifiers	1. Validation on more datasets. 2. Further improving the accuracy
[58]	VM with RBF	EEG data	Happiness, calm, anger	Real Data	Average accuracy of 60%, highest accuracy of 80% for emotion of happiness	Instead of conventional 32 electrode data, 14 electrode data was considered. Thus reduced feature subspace and time is achieved.	1. Improve the accuracy rate. 2. Increase the number of subjects 3. Experiment with more number of emotion classes 4. Experiment with Classifier combinations
[59]	Deep Kohonen NN, Circular Back Propagation Neural Network	Peak to peak signal, ratio of latency to amplitude, kurtosis, mean, power spectral density, signal power, entropy and energy	Angry, happy, sad, relax	DEAP	Average 95–98% of accuracy	High accuracy obtained.	To consider more complexity in the emotions. To test system with Deep Learning. To further experiment with modifications in BPNN and Kohonen algorithm.
[3]	SVM (RBF, Linear, Polynomial)	ElectroDermal activity, Photoplethysmogram	Boredom, joy, acceptance	Real data	Highest accuracy of 90% obtained by Linear kernel for Boredom – joy.	1. Real dataset was built. 2. Extensive experimentation performed with various feature extraction methods. 3. Number of subjects is 100, which is good number as compared to existing work.	1. To test the system for more emotions such as: surprise, anger, sadness. 2. To extend the system to test for children with/without autism. 3. To test the system with more classifiers.
[61]	Linear SVM, common spatial patterns	EEG data from gamma band	Happiness, sadness	Real data	Highest accuracy was 93.5%	1. Time length was varied for experimentation. 2. Results indicate the potential of gamma band (30–100 Hz) for successful emotion classification.	1. To test the system for more emotions, besides happiness and sadness alone. 2. To validate the system with larger sample size.
[40]	LDA, kNN	EEG data	Disgust, surprise, happy, neutral, fear	Real data	1. Highest average accuracy of 83.26% with kNN, 75.21% with LDA	1. Novel method of feature extraction used. 2. New features are proposed, which have impact classification accuracy.	1. To test the system with more classifiers 2. To experiment with a larger dataset.

10. It is a popular non-invasive method.

Disadvantages are mentioned below:

1. Sophisticated techniques of signal processing are required to extract patterns from EEG data.
2. EEG based emotion classifier trained on a certain stimulus may not generalize to unseen EEG data that is trained on other stimuli. Thus building generalized models is a challenge.
3. Connectivity issues exist in data collection.
4. Exact placement of electrodes is a crucial task, failure of which may lead to deviations in data.
5. High cost.
6. Inherent characteristic of being non-stationary adds to the overall complexity.
7. Process of data acquisition may cause fatigue to user.
8. Different values for impedances may affect data processing.
9. Possibility of mismatch between training data and test data exists if the gathered data has been sampled differently or collected from various sessions.
10. Discrepancy of distribution between the subjects.

4.2.2. *Emotion Detection Systems based on combination of physiological signals*

A brief survey of existing work on the use of a combination of various physiological signals (apart from pure EEG) is presented below.

To perform data labeling in accordance with emotion criteria, data preprocessing techniques were experimented with an aim to increase classification performance. EEG and GSR were used from DEAP dataset. The former was filtered with wavelet functions, the latter with Short Time Zero Crossing Rate. Convolution Neural Network was trained with Maximum Likelihood Estimation to classify the multimodal data. The proposed deep model obtained an accuracy of 73.4% which is higher than the ones obtained in existing methods. Future work shall investigate the changes to existing framework by combining multiple networks [63].

With the goal of investigating heartbeat dynamics, the linear and non-linear analysis was performed for features selected from the ECG signal. Vector distance classifier, Linear discriminant classifier, kNN, Quadratic discriminant classifier, Probabilistic Neural Network and Multi Layer Perceptron were used to ascertain the four basic emotions. Highest accuracies recorded were: 79% on valence and 83.55% on arousal. Being fully personalized, this framework is not dependent on the majority population for sampling. This system can be explored in the diagnosis and further treatment of mood disorders since the latter always produces altered response of emotions. Such tracking and monitoring systems shall be very useful to society at large, to check for the progression of disorders in a well-timed and efficient way [64].

Heartbeat Extraction method was employed to determine the intervals between heartbeats and exploit this data for recognizing emotion. In contrast to most work surveyed so far, Radio Frequency was used for data collection. Results suggest the use of heartbeat as potentially rich source of information in the field of Emotion Recognition and Non-invasive Diagnostics [65].

In a classic work [12], successful experimentation was performed on the novel approach of combining varied data sources. Thus a rich variety of features – acceleration, Electro-Dermal Activity, Heart Rate, Blood Volume Pulse, eye tracking information and temperature was collected in real time. Results were tested on several classifiers such as – kNN, Repeated Incremental Pruning to Produce Error Reduction, Naive Bayes, SVM, Logistic Regression, Random Forest, C4.5, Logistic, Multilayer Perceptron and Radial Basis Function.

SVM was used for classifying the features extracted from ECG, ST and EDA into four labels – sadness, anger or surprised with 78% accuracy. Gaps include: increasing the sample size, improving the accuracy and testing with more classifiers [101]. Multiclass least squares SVM [103] was used with various functions for classifying the group of statistical features derived from EMG into happy, neutral, sadness or fear. 84% accuracy was observed, gaps include – working on a larger sample size and aiming for better accuracy. Logistic regression was used for classifying EDA, HR, EMG, ST and statistical features of RR into two levels – low or high [102]. Gaps include increasing the complexity of system and considering more emotions for study.

A detailed survey on use of variety of physiological signals is presented in Table 3, along with details of the machine learning algorithm used, its advantages and disadvantages, datasets used, feature space. Observations from Table 3 suggest the popular use of GSR and ECG in Emotion Detection systems.

4.2.3. *Multimodal emotion classification systems*

Multimodality in emotion research is an important element of affective HCI since the basic human response to events is inherently multimodal in nature. Recent literature shows fusion of several modalities such as speech, physiological signals, facial expressions, body gestures, user's information (from smartphone data/keyboard strokes) into a robust multimodal emotion classification system. Table 4 tabulates some important highlights in this field.

As observed from Table 4, choosing the optimum subset of modalities combined with the best feature selection and machine learning algorithm are important issues in design of any efficient multimodal system. In addition to the conventional emotion class labels, multimodal classification deals with interesting labels such as – emphatic, helpless, ironic, reprimanding, touchy, uncertainty, disbelief, puzzle, interest, embarrassment and shame [133]. An important challenge in this field is integrating all the nonverbal modalities into a single HCI system to demonstrate the analysis of true human behavior [128].

4.3. *Literature survey on Stress Detection systems*

Several literatures have reviewed and analyzed the ill effects of stress on the mind and body. Stress has been found to be a major culprit in the onset of several disorders from mild to chronic [76–83], and a potential factor for negative emotions such as anger, anxiety or fear. Stress has emerged as a major health concern in today's world, hence efficient Stress

Table 3 – Literature survey for Emotion Detection systems based on combination of physiological signals\.

Ref. No.	Machine learning algorithm used	Features extracted	Class labels used	Dataset used	Advantages	Disadvantages	Results
[4]	Logistic Regression	Respiration signal data	Positive, negative	DEAP, Affection dataset by Augsburg University, Germany	1. Is a fully data driven model. 2. Results are better than existing work.	Results are still low to be applied to real world.	73.06% and 80.78% for valence and arousal respectively on DEAP, 80.22% for Augsburg dataset
[6]	Probabilistic Neural Network	Electrocardiogram (ECG), Galvanic Skin Response (GSR)	Peacefulness, sadness, happiness, scary	Real data	1. Real dataset was built by collecting physiological signals. 2. The emotion class labels are innovative and different from the ones used in majority of research.	1. The number of subjects considered is small. 2. The current work should be extended for use in real life.	1. Highest recognition of 100% with PCA. *2. Performance of ECG data was better than GSR data.
[7]	Backpropogation Neural Network	Electro Cardiogram, Electro Encephalogram, Respiration, Photo Plethysmogram, Galvanic Skin Response	Fear, joy, happiness, despair, anger, sadness	International Affective PictureSystem as stimulus	High accuracy yielded for all the emotion classes.	1. Testing to be performed with more number of classifiers 2. Validate the system with more datasets.	1. Highest Recognition Rate was obtained for happiness (91%). 2. All remaining emotions fared more than 79%
[66]	SVM (one model for valence, another for arousal)	AVSCL, AVNN, RD, SDNN, HR, LF, rMSSD, HF, pNN50	High, low and medium	International Affective Picture System [43]	The two types of sensors – laboratory and wearable were validated with respect to each one's capability at Emotion recognition.	1. Number of subjects considered is small. 2. Only single classifier used, more classifiers could be used for better validation of results. 3. Motions could be considered as stimulus. 4. Less controlled lab setup would be more useful.	66% accuracy obtained for valence, 70% for arousal
[67]	SVM, J48, Naïve Bayes	Mean, minimum, maximum, variance, standard Deviation for channels of EEG data GSR: Phasic component features,	Positive and negative aspects of valence and arousal	DEAP [42]	1. Several experimentation setups were conducted using single features and subset of features on different classifiers. 2. Cross subject classification is performed, thus yielding robustness to system. 3. Individual training/tuning of classifiers is not required. Thus saving	1. Validation with larger number of subjects is required 2. To extend the system for real life cases of patients with impairment and check the accuracy of present system.	Highest accuracy of 64% obtained by SVM

Table 3 (Continued)

Ref. No.	Machine learning algorithm used	Features extracted	Class labels used	Dataset used	Advantages	Disadvantages	Results
[68]	Statistical Methods	m, Skin Conductance,, Electro MyoGram, Respiration Rate, Arterial Pulse Rate, ST	Low and high label combinations of arousal and valence respectively, neutral	International Affective Picture System	Extensive experimentation performed by considering time and frequency domain of features.	Results of t tests were not found to be significant, the same should be investigated.	Highest standard deviation of 4 obtained in LVHA
[69]	SVM, kNN	Skin Conductance, Blood Volume Pressure, Electrooculogram, Interbeat Intervals	Fear, anger, sadness, happiness, disgust, surprise	Real data	Dynamic weighting method enables the system to adapt to each new user, thus increasing generalization and accuracy of system. Complexity of system is less. Data collection process is less obtrusive, hence easy for subjects to use.	Small sample size per emotion. Lack of generalization to additional sessions in future.	Higher accuracy of 84.7% was obtained by SVM as opposed to 80% accuracy by kNN
[70]	SVM, kNN	EMG, EEG, Electro OculoGraphy (EOG), Respiration Pattern, Skin Temperature e, GSR, Blood Volume Pressure	Low and high label combinations of arousal and valence respectively	DEAP [42]	1. Data from only 10 channels was used, as opposed to convention use of 32 channels, thus reducing feature dimensionality. 2. Results indicate an important finding – superior role of higher frequency bands as opposed to lower frequency bands for classification of emotions	1. Validation using Poincare map analysis can be performed. 2. Use of chaotic features for better generalization. 3. Integrate the current research with appropriate hardware for a complete Emotion Classification System.	Using kNN higher results obtained: arousal: 86.75%, valence: 84.05%
[71]	Linear Kernel Least Square SVM, Backpropagation Neural Networks	EEG and physiologic al signals	Positive, negative	DEAP [42]	Efficient feature selection method used.	1. To obtain combination of time and frequency domain features and test the same on ensemble classifiers for higher accuracy. 2. To extend the system for real world.	Higher accuracy of 64.84% obtained for Low/High Arousal
[72]	ANN	EEG and ECG Data	Not mentioned.	IAPS for stimulus, University of California Riverside and CLAW for data processing	1. Efficiency in processing of the data stream. 2. Optimum usage of memory	1. Exact features of ECG used in the study are not mentioned.	Average MSE of 3.5 $\times$ (10^{-7})
[73]	Group based Individual Response Specificity algorithm, Decision Tree, Multilayer Perception, Naïve Bayes, Random Forest.	Galvanic Skin Response, Electrocardiogram, and Photo Plethysmography	Sadness, neutral, fear, pleasure	Real data	1. Real time physiological dataset is constructed 2. Differences in the individual responses to same stimulus are dealt with successfully, thus ensuring user independent system.	1. Not dealing with missing data. 2. To fuse the current physiological features with more modalities such as facial features.	Highest accuracy of 88% obtained by Random Forests

Table 3 (Continued)

Ref. No.	Machine learning algorithm used	Features extracted	Class labels used	Dataset used	Advantages	Disadvantages	Results
[74]	CART, C4.5, random forest	Parameters from financial trading, heart rate, skin conductance	Rejoice, regret	Real data	1. Novel application of financial domain was applied. 2. Fusion of physiological data with financial data performed. Such methods have been rare.	1. Improve the accuracy. 2. Validate on more datasets. 3. To test the system with SVM	CART yielded highest accuracy of 67%, binary-rejoice
[75]	SVM	Variability in pulse rate, heart rate variability	Fear, happiness, peacefulness sadness	Real data	1. Impact of both fusion schemes – decision level, feature level were confirmed by the research. 2. High accuracy is achieved.	1. To further improve the accuracy for use as a real time system. 2. To validate the research with more classifiers. 3. To consider a larger sample size.	92% accuracy achieved

Monitoring is a growing concern for human society globally [84]. There is an increased need for timely and efficient Stress Detection systems that could effectively aid the individuals to know their stress levels thereby enabling them to combat and manage stress [92]. Artificial Intelligence has been popularly used in literature for stress detection [93,105]. A survey on Stress Detection systems is presented below.

A real time Stress Detection system with monitoring over three days in a simulated office work yielded a high average detection rate of 98.3%. Future work includes deploying the system for Health Monitoring of patients suffering from vertigo [94]. In a noteworthy work [95], extensive survey is carried out on Stress Detection Systems with focus on work life of individuals; since work-related stress is an important cause of stress worldwide. Worklife stress has been appropriately defined as the mental state characterized by presence of high amounts of arousal and distress. It invariably deals with the various dimensions of an individual's reaction to the event. Significant dimensions include: cognitive, behavioral, emotional and physiological. The three important modalities of stress – physiological, psychological and behavioral have been extensively reviewed with details of target application and extracted features. This contrasts the majority works in literature that experimented with a confined subset of feature space and/or singular modality. Current work experimented with three groups of features: physiological, behavioral and context. The wide range of physiological features reviewed in current work include – EMG, ECG, EDA, blinks, EEG, ST, BP, BVP, fMRI, Resp, eye gaze, pupil diameter and thermal imaging. The following behavioral features were considered: use of keyboard, text linguistics, mouse use, speech, posture, computer exposure, smart home sensor events, facial expressions, smartphone use. File activity, calendar, ambient sound and GPS were considered as Context features [95].

In Ref. [95] a multimodal Stress Detection system is proposed and some crucial challenges in this field are surveyed in detail. These include – ethical issues, reliability, privacy, efficiency, security, legislation, cost and interoperability. It was also observed that other data acquisition techniques such as hormonal, questionnaires-based are unsuitable for real time stress monitoring.

As opposed to the predominant works that used conventional lab-based stressors, a word-based system was used in Ref. [96] to differentiate between the affective words (positive/negative) and the neutral ones. Rapid Serial Visual Presentation was used in this system which was composed of three different stages. Stage numbers two and three indicated the association with nouns having emotional content significance.

Through experimental setup in Ref. [26] a protocol to distinguish between psychosocial stress and mental stress is proposed. It was demonstrated that higher workload is associated with increased mental stress and lowered performance, also the same is marked with raised Heart Rate. Skin Conductance and Heart Rate were acquired from participants along with their responses to State-Trait Anxiety Inventory questionnaire. It was observed that higher STAI scores indicated 'stress' state, as compared to other states such as 'relaxation', 'baseline'. Future work includes extending the current work to classify more emotional classes for applicability in real life and experimentation on pure EEG signals to build a robust Stress Detection system [26].

Table 4 – Overview of survey on multimodal Emotion Detection systems.

Ref. No.	Multimodal features extracted	Class labels used	Dataset used	Algorithm	Research gap
[126]	Pupil diameter, eye blinking, gaze distance, EEG, answers to Self Assessment Manikins questionnaire	Calm, activated and aroused based on Arousal. Pleasant, unpleasant and neutral based on valence.	Real data	1. Both decision level and feature level fusion techniques were used. 2. Classifier used was SVM (RBF)	1. Using a sophisticated tool for self reporting. 2. Use of lighting effect similar to real life to be used to remove reflex to papillary response. 3. Increasing the sample size. 4. Further investigation with more classifiers.
[127]	Forehead, eyebrow, right cheek, low eye, left check, speech	Anger, sadness, neutral and happiness.	Real data	1. SVM using the second order polynomial kernel functions. 2. Both decision level and feature level fusion techniques were used.	1. Captured facial information can be erroneous if the participant has a beard. mustache or is wearing glasses. 2. Developing a system that perceives the feedback from humans and respond suitably to improve his/her experience.
[129]	EEG, EMG, GSR, ST, RR, BVP, EOG, video features	1. Active and passive based on Arousal. 2. Pleasant, neutral and unpleasant based on Valence.	DEAP	SVM with Recursive Feature Elimination algorithm (RFE) to choose optimal feature subset.	1. Improving the classification accuracy. 2. To include the non linear dynamics of physiological signals. 3. To compare RFE with other feature selection algorithms to choose optimal subset.
[130]	• Features of eyes, mouth, eyebrows and nose. • Following statistical features from body cues – Initial & final slope, mean, the main peak duration/duration, distance between the centroid and max, shift index of maximum, symmetry index, number of maxima. • Following speech features – Pitch, MFCC, intensity, bark spectral bands, pause length and voiced segment characteristics.	Anger, interest, despair, sadness, pleasure, joy, irritation and pride.	Real data	1. Viola Jones algorithm for face detection. 2. Bayes Classifier for multimodal classification.	1. Developing methods for multimodal fusion by considering common relationships concerning the feature space from different modes. 2. Investigating the association of neurological information with the magnitude of information communicated by every modality regarding a certain emotion.
[131]	Features from facial expression and body movements	Anger, boredom, disgust, fear and anxiety.	FABO (Face And Body) dataset	CNN	1. To test the system on real world situations. 2. Extend the system for indoor human-robot interactions.
[132]	EEG, pulse, ST, BP, answers from SAM questionnaire	Horror, boredom, happiness, relaxation.	Real data	Reputation-driven imbalanced fuzzy support vector machine	1. Use of advanced wearable technology to reduce current hardware restrictions adverse effects of motion artifacts. 2. To achieve better recognition by optimizing – label estimation, feature extraction and data fusion techniques.

The finding that color plays an imperative role in eliciting varied physiological responses was studied in [2]. The Poincare's plot was used to compute a numerical measure for one's mental state. Red, blue, green, yellow – main colors of psychology served as stimulants, and ECG signals were acquired from participants. Rule based classifier was used to differentiate between four emotions – anger, pleasure, joy and sadness. Results indicated the superior association of red color with increased intensities of anger while the feelings of anxiety were marked for having similar traits with green color.

Several works that correlate changes in physiological signals with stress exist in literature. These are presented below:

In Ref. [97] a novel approach of using EEG data is implemented for quantification of three different levels of mental stress while the participants were assigned a puzzle. Time pressure and negative feedback served as stressors. Wavelet Transform was used for feature selection and a novel technique of employing SVM along with Error Correction Code was used for classification. High average accuracy of 94.79% was obtained. Limitations include: all participants were males and only seven electrodes were used for recording EEG.

In another innovative work [98] the learning styles of participants were decoded by performing cluster analysis performed in two steps on EEG data. A significant measure to determine brain asymmetry was used to perform correlation between learning style, stress and intelligence quotient with 100% accuracy.

EEG parameters from nine channels were used in conjunction with stress questionnaire in a radical work [22] which performed comprehensive experimentation for detecting mental stress level of participants in controlled setup. The following EEG metrics were used: low engagement, sleep onset, high engagement, distraction and cognitive state. Statistical features such as mean, median, variance and mode were used in building the feature set comprising of sixty features. SVM was used to classify each participant into either of the two levels – high stress or low stress. In Ref. [21] participants were subject to a novel real time stressor of singing a song, during which their HR, GSR were monitored to detect real time changes in their physiological parameters. The latter was declared as Stress. Two detectors based on HR and two more based on GSR were used. Social anxiety, possible embarrassment and mental workload were computed. Raised HR and GSR were found to be associated with increased mental stress.

Research indicates that the huge wealth of information in ECG is highly useful in predicting mental stress and cardiovascular diseases. However, challenges in denoising the signal may lead to inaccurate feature extraction. This issue has been addressed in [99] where three wavelet functions (coif5, db4, sym7) and four thresholding rules (Sqtwolog, Rigrsure, Minimaxi, Heursure) were experimented with. Based on the following performance measures – noise power, signal to interference ratio, power spectral density, percentage root mean square difference; it was observed that coif5 wavelet with rigrsure rule yielded optimal performance in noise reduction for real time ECG signals.

An innovative technique of three-fold analysis of participants based on carefully designed application scenarios was performed in Ref. [25]. An innovative feature – Thoracic Electrical Bioimpedance was used in conjunction with ECG signals. Smartphone was used for data processing, Genetic Algorithm for feature selection of the original 112 features. The application scenarios are summarized below: analysis 1 noted the four activities of neutral, emotional, mental and physical; analysis 2 conducted viewing of movies to elicit various emotions such as neutral, disgust and sadness; analysis 3 had Games as stressors, and aim was to classify mental activity into low or high based on workload. This work is a novel and realistic manifestation of adapted systems to monitor the health of individuals by detecting their stress and psychological load. In terms of probability error, results for the three scenarios with Neural Networks are 21.2%, 4.8% and 32.3%, respectively [25].

In a distinguishing work [84], experimentation was performed to estimate the shape of the stress signal – linear, symmetric saturating linear or hyperbolic, using Genetic Algorithm, SVM, Artificial Neural Network. Real data was collected by acquiring physiological signals as well as physical signals.

A summary of machine learning algorithms used to predict the stress levels in Stress Detection systems is presented in Table 5.

The findings from Table 5 are as follows:

- From the ones surveyed in this paper, very few studies built a real time affective dataset and hence did not deal with the important phase of data gathering.
- With respect to the above, there are several benchmarking issues for fellow researchers.

There is significant research on the efficient detection of presence/levels of stress by collecting a variety of physiological feature subsets [109–118]. All works cited above indicate the strong correlation between mental stress and physiology.

4.4. *Overview of measurement scales for emotion and stress*

This section presents an overview of the popular self-reports used in literature for assessment of emotion or stress; followed by observations based on these reports and important limitations.

4.4.1. *Questionnaires for measuring emotion*

Discrete Emotions Questionnaire [134], Self Assessment Manikin [135], NEO Five Factor Inventory Empathy Quotient [12], Jefferson Scale of Physician Empathy [12], Assessing Emotions Scale [136] are some popular questionnaires for emotion measurement. The literature survey covered in this paper suggests the popularity of SAM questionnaire.

4.4.2. *Questionnaires for measuring stress*

Perceived Stress Scale [138], Standard Stress Scale [139], Ardell Wellness Stress Test and Stress Coping Resources Inventory [140] are some examples of questionnaires for measuring

Table 5 – Survey of machine learning algorithms in Stress Detection.

Ref No.	Machine learning algorithm used	Features selected/extracted	Class labels	Results achieved	Limitations of study
[85]	Fuzzy logic and SVM, Decision tree and random forest, expectation maximization	EEG, SpO2, BP, ECG and RR Environmental parameters of location, temperature and weather.	Stress levels – normal, low, middle and high	Not mentioned	1. Use of advanced biosensors for more accuracy. 2. Customized healthcare service for mental wellness making use of smart healthcare system.
[92]	SVM, kNN	ECG, RR, blood oximeter, GSR and BP	Stress, no stress	Individualized model yielded 95.8% accuracy, generalized model yielded 89.3% accuracy.	Integrating more medical sensors in one common platform, to enable the collection of more physiological parameters. One wearable platform as mentioned above shall ensure ease of use and comfort to the participant. Making the system more user friendly by displaying relevant options in a menu to the participant. Considering a larger sample size for generalization of results. Considering more events that induce stress. Detecting the presence of stress in the form of detailed levels, as opposed to mere presence/absence
[104]	SVM	Self-reports and SC Mean, standard deviation, variance, magnitude, median, root mean square, average squared power. Power spectral density features: weak, median, and Mean Frequency	Stress, no stress	Average rate 94%	i. To depict relationship between the levels of stress and the two elements of GSR – phasic and tonic. ii. Develop a system with enhanced reliability in real world situation. iii. More focus on exploring the association between stress of drivers and the elements of driving style.
[106]	Fuzzy logic	GSR, HR, breath	Relaxed, stressed	GSR showed highest indication of stress.	To experiment with more classifiers such as Neural Networks
[107]	k-NN, Gaussian Discriminant Analysis, SVM with Gaussian, linear, quadratic, cubic functions, decision trees, logistic regression, HMM	EEG, salivary cortisol		Highest accuracy of 80% with Gaussian SVM	Limited experimentation with feature subspace
[108]	C 4.5, Linear SVM, Ada Boost, Naïve Bayes	Heart Rate Variability, Heart Rate, SCL, psychological features, behavioral features.	Relaxed, stressor, normal, pressure	Mean Absolute Error of 2.53 with SVM	To build a dataset of behavioral features, independent of stressors and physiology.
[8]	Deep learning	EEG data	Stress, workload	20% increase in performance with 4 levels of assessment	• Lacks extensive experimentation. • Small sample size considered. • Real world crew members were not used in study.
[9]	FFNN	Temporal and peak features of EEG data	Normal, stress	60% accuracy for 25 hidden layers.	Small sample size used. Difficult to benchmark. More validation required on other classifiers.
[60]	MLP, Bayes, Random forest, k star, random tree, J48, ZeroR	EMG, ECG, foot GSR, RR, intermittent HR	Low, medium, high stress	100% accuracy obtained for k star	• Features related to T wave is not considered. • Small dataset is used • Test the system with hierarchical algorithms

stress. Survey covered in this paper suggests the high popularity of Perceived Stress Scale.

4.4.3. *Findings from above questionnaires*

In most of the controlled lab setups for eliciting emotions or stress as the case may be, an important biological phenomenon called 'startle' (which is a sudden response to some intense stimulus) occurs which intersects several response systems of the human body – Peripheral physiology (ANS), Central physiology (CNS) and behavior. Hence laboratory experimentations confront an inherent challenge to deal with this response while measuring the emotion or stress [137]. However, in cases when the participants fill a self-report questionnaire the issue of being able to successfully capture the magnitude of startle response, looms over the researchers. Hence in several works on Emotion Detection/Stress Detection systems, questionnaires have been used in addition to lab setup (for real time monitoring).

4.4.4. *Limitations of using questionnaires for eliciting emotion or stress*

1. It is likely that individuals who are ailing from alexithymia do react to the lab induced stimulus but have difficulty in envisaging their feelings in the way which is favorable for responding to the self-report [137].
2. Another common problem with questionnaires is the willingness of participants to respond truthfully without barriers of culture, society or other such factors.
3. From psychological point of view, self-reports relate more to the currently experienced emotions.
4. Not all the individuals may be capable of reporting their mental states accurately.

4.5. *Overview of evaluation measures*

4.5.1. *Analysis of the number of subjects*

This subsection covers an important measure from the research surveyed so far – the number of human subjects who participated in experimentation and contributed their physiological data to be used in research. This measure is useful in determining the generalization ability of the developed system. We have developed a graph as shown in Fig. 5 to illustrate the main highlights of this measure.

Observations from Fig. 5:

1. Although it is true that number of subjects per study can be compared only if the same experimental design is followed, it is a fitting metric for indicating robustness and generalization of the proposed work. Unless tested on sufficiently large number of subjects, applicability to real world situations is questionable.
2. However, the crisp value of sample size is debatable. Fig. 5 is developed to guide the fellow researchers with main highlights of this measure. Fig. 5 indicates relatively small sample size with the minimum and maximum size being 2 and 100, respectively, with the former being a relatively small figure to make substantial impact. Hence there is a compelling need for systems that have been tested on larger sample size preferably more than 100, to reflect true sampling from the real world population.
3. However it is to be noted that a smaller sample size may have been the only solution to certain uncommon research problems. In such cases, it may be otherwise infeasible to collect data from more individuals due to the inherent unavailability of large number of suitable participants. Also, several researchers may prefer prototyping of their research ideas on relatively smaller sample size, say for example less than 10, with plans of extended work with revisions in feature space/design/algorithm etc. then applied on larger samples.

4.5.2. *Analysis of the referred papers*

A representative plot of the number of references from each publication year surveyed in this paper, is visualized in a diagram and illustrated in Fig. 6.

Fig. 6 illustrates that the papers referred in current work span as early as 1956 till the latest works in 2018. The ones in the comparatively earlier chronological period were referred

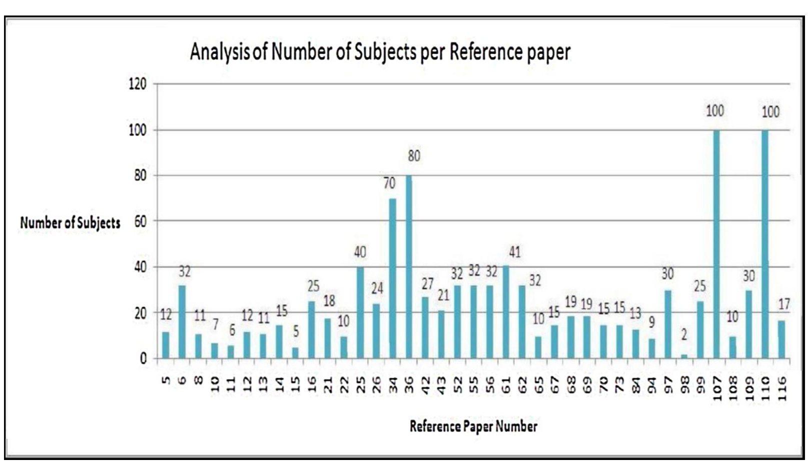

Fig. 5 – Summary of the number of subjects.

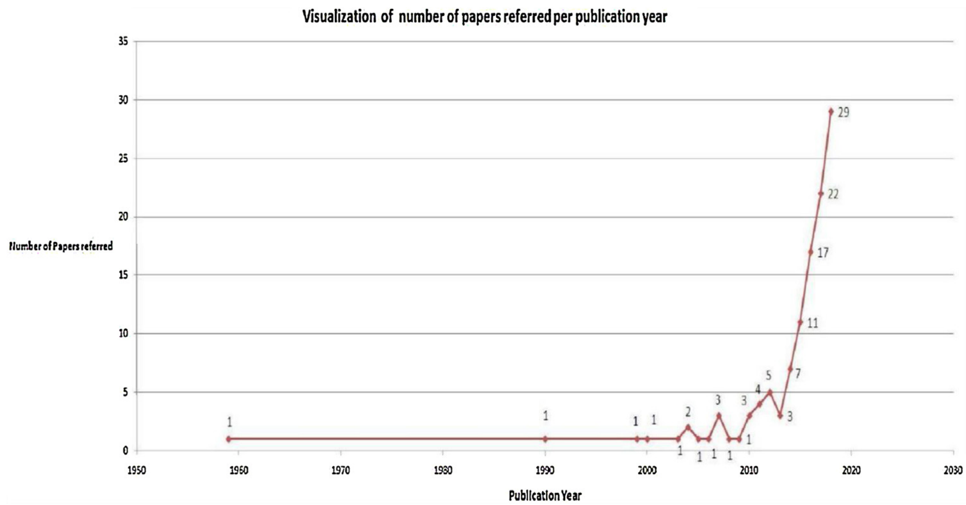

Fig. 6 – Summary of referred papers per year of publication.

for being seminal. Fig. 6 depicts the usage of maximum chunk of latest years from 2015 till date.

4.6. Challenges

This subsection covers the various challenges encountered in the different phases of developing a robust system for detecting either emotion or stress.

4.6.1. Challenges in developing general Emotion Detection systems

1. Certain important individualistic factors such as one's native mood, baseline mood should be considered prior to the data collection and annotation [69].
2. Health issues such as those related to blood sugar, hormones, sleep pattern/cycle etc. are very likely to cause large changes in one's physiology. Hence it is important to attend to these issues as they may hamper the accuracy of system [69].
3. Vast majority of research have predominantly used DEAP dataset [42] for benchmarking, the latter being an unanimous choice. Although existing literature is rich with the use of DEAP, we observed the presence of certain fundamental lacunae which are reflected in all research work that used it. These include:
   - The subject's familiarity with input stimulus may not have been considered during data collection process. This is important factor that determines the user's response to stimulus (along with its intensity), and hence affects accuracy of systems.
   - Cannot be extended to adapt to real world scenarios.

   These factors could be accommodated in DEAP in the interest of research community of Emotion Detection. This gap could also be bridged by fellow researchers to facilitate robust and real time systems useful to society in the future.
4. Very few research from the ones surveyed in this paper built a real dataset and hence did not deal with the important phase of Data Gathering. Real datasets need to be encouraged by making such datasets publicly available so as to foster research and benchmarking.
5. More research needed to further improve the recognition accuracy [11].
6. More research needed to determine the various unknown areas in human brain dealing with one's emotional behavior [11].
7. Representation of human emotion is a complex problem [73].
8. Utility, scope and authenticity of data as well as of the developed system [119].

4.6.2. Challenges in developing Multimodal Emotion Detection systems [119]

1. Deciding on the most suitable subset of modalities.
2. Collecting the real data, removing noise, ensuring accuracy.
3. Deciding the fusion techniques for selecting appropriate features.
4. Deciding the evaluation protocols to test the system.

4.6.3. Issues in EEG related works

Features of the EEG have been commonly used in both the systems – Emotion Detection and Stress Detection. However, certain significant issues should be dealt with carefully so as to improvise the design and maximize the results while using EEG data. Highlights of issues are presented below:

1. Comparatively less number of works focus on the significance of ample covering of the lower regions of head while performing EEG measurements [147].

2. Analysis of EEG data may be inaccurate if there is confusion about artifacts. Hence it is pivotal to use suitable mechanisms for recognizing and cleaning the artifacts, especially in those cases where data from the neck is being acquired [147].
3. In the experimentations of various sampling concentrations of EEG sensors with the extent of coverage, it was noted that the error occurring due to estimation of source is lessened if adequate EEG sensors are used (typically 128 or 256); along with suitable coverage of head, neck and face [150].
4. For an improved precision, modeling the conductivity of (head) tissue and assessing direction of the cortex are crucial factors [147].
5. Exactness of the dipole approximation depends on factors such as – accuracy of models used (head, source), separation (temporal, spatial) of the causal sources, information about noise (type, level) [142].

4.6.4. *Other issues*

In the systems that are trained to detect certain deviations from normal conditions as a possible step toward the presence of stress or some negative emotion (for example fear, anxiety, surprise etc.), it is highly likely that some unintentional and involuntary confounds in the movements of some participant be considered as true positive. However, factually these cases should have been considered as false positive. This poses an important challenge in stress research as well as emotion research.

4.7. *Applications*

The wide spectrum of applications under physiology based Stress Detection systems covers Virtual Reality [7], automobile industry [8], intelligent tutoring [10], robotics [69,120], medical diagnosis [2–4,14,36,47], stress recognition [20,107], Human Computer Interaction [59,121], decision support [74] and emotion recognition[6,9,53,62,67,68,70–72].

5. Findings from literature survey

The significant observations are enlisted below:

a. It is observed that Emotiv device has been popularly used for data collection.
b. Conventionally used stimulus include – images, music and videos [53].
c. It is noted that IADS [49] and IAPS [43] have been the popular standard datasets which researchers have used for providing various stimuli to subjects during experimentation process.
d. DEAP [42] has been the most popularly used standard dataset for providing the researchers with affective physiological data for their research work.
e. All research covered above have a common impediment of being conducted in controlled laboratory setups.
f. Classification accuracies obtained with specific models have been mentioned (in Tables 2, 3 and 5) with a clear motive of providing a guideline for fellow researchers in this field to be able to make a better choice of algorithms for similar problems as mentioned in literature survey. Very few standard affective datasets are publicly available and most researchers build their own real time datasets (which are not made public for varied reasons). Owing to this there are issues in benchmarking. Since various researchers may be working with altogether different data, though the classification accuracy achieved previously in existing literature may not be the sole deciding factor, it can definitely serve as a pointer for optimal choices in prototyping or experimentation phases.

6. Research gaps

From the survey presented in this paper a highlight of research gaps is briefed below:

1. Different assumptions pertaining to the conditions under which emotion/stress elicitation was performed should be specified explicitly, which shall be useful in standardizing the protocol. Conventionally these conditions are classified into two groups – optimal or suboptimal [145]. Most works have not mentioned the detailed assumptions. This leads to gaps in benchmarking.
2. Appraisal variables play a crucial role in the experimental design of every successful research in this field. These five variables are – goal relevance, congruence, coping potential, certainty and agency/blame [145]. Each research may hypothesize a differing number of these variables adding to difficulty in benchmarking for fellow researchers.
3. While comparing the results with existing literature an important gap is the use of different devices for physiological data acquisition. Even in cases where the same device may be used, the differing feature subspace in each research shall definitely be influenced by the specific classifier leading to bias in benchmarking.
4. It is vital for studies on Emotion Detection systems to address the challenges of mechanism used and representation followed for – elicitation, intensity and differentiation. Since most studies hypothesize these differently, it is difficult to benchmark the results achieved across various works [141].
5. Mathematically ensuring that exactly the same intended emotions are being induced in all the participants when exposed to certain stimulus [2] is a challenge. Human psychology plays important role here, since different persons might respond to the same stimulus in entirely different ways. This could be attributed to the individual's inherent disposition and behavior. Also the experiential feeling of emotion should be labeled by the participant in an error-free manner so as to avoid further inaccuracies in the model. This psychological aspect wholly depends upon the individual's understanding about the experience and strong ability to label it correctly. Hence role of Psychologists as one of the domain experts is important. Very few works surveyed here have considered this aspect.

6. Only few researchers have built and used real dataset for experimentation. However these are not publicly available for fellow researchers. Hence the problem of benchmarking exists in this field.
7. The number of class labels (for emotion or stress), number of participants, prior probability of the classes, validation methods vary across the different works in literature hence fellow researchers confront an important gap of comparing their results.
8. Vast majority of works have induced the stressors and recorded physiological features in controlled experimental setups which cannot be easily extended to real world. This holds special importance since Emotion Detection systems or Stress Detection systems should be of convenient use without any constraints of time, place or event since individuals could be facing real life stressors in most unprecedented ways.
9. Tradeoff between accuracy and authenticity is important in research. Lower accuracy obtained from real world setup is more useful than higher accuracies obtained in strict and controlled laboratory setups.
10. The following are fundamental categories for issues in the area of research concerning emotions: affective, exterior emotional stimuli, cognitive, expressive/emotional behavior, physiological, adaptive, disruptive, multi aspect, restrictive, motivational, skeptical [124]. In order to explore more dimensions of the human emotion, it is needed that substantial research be carried out in the following – multi aspect, adaptive, disruptive and skeptical.

7. Proposals for future work

1. Emotion causation should effectively address challenges for emotion elicitation, intensity and differentiation at the following three levels – functional, algorithmic and implementational. This shall pave path for substantial future research [141].
2. Developing a generic Stress predictor system to quantify mental stress in real life applications.
3. Building a robust system to model the response of meditators to the varied stressors/stress management programs across multiple environments [84].
4. Developing a fuzzy rule based decision support system based on the participants' responses to stress and having an user friendly interface to facilitate monitoring of mental health [84].
5. Developing a real time multimodal Stress Detection system that efficiently detects the progressing levels of stress thus enhancing quality of life for individuals [95].
6. Investigating the results of fusion of several hybrid computational techniques for stress detection at multiple dimensions [27].
7. Audio-visual stressors have been commonly used, the use of haptic stressors has great potential in future.
8. Correlating physiological data with physical measures (gestures, body language, facial expression etc.) and psychometric indicators such as NEO Five Factor Inventory Empathy Quotient, Jefferson Scale of Physician Empathy, Interpersonal Reactivity Index [12] can be a promising move.
9. As previously mentioned in this paper, prolonged exposure to negative emotions leads to negative stress which should be an important consideration in design of any Stress Detection system. However there is dearth of well defined time frames which may be hypothesized to initiate positive or negative stress. Experimentation or protocols in this direction shall be useful for future work.

8. Our research contribution

- After surveying more than 140 research papers we have presented comprehensive survey with respect to important aspects of Stress Detection systems. The current challenges and research gaps in both Stress Detection systems and Emotion Detection systems are covered meticulously. This shall be greatly beneficial for future researchers to have first-hand information of these fields and possibly address the numerous challenges.
- Our proposed model is briefed below.

A multimodal system capable of detecting episodic stress is proposed. As illustrated in Fig. 7 suitable standard physiological dataset shall be used to train the machine learning based model which shall be used further for predicting class labels of unseen real time physiological signals. Numerical class labels shall be used with class 0 indicating 'no mental stress' and class 1 indicating 'presence of mental stress.'

Knowledge of the patterns shall be recursively used to strengthen the training model, also Sub Group Discovery shall be employed to detect interesting patterns and knowledge over a period of time. The innovative concept of generating User Profiles for the individuals shall also be implemented.

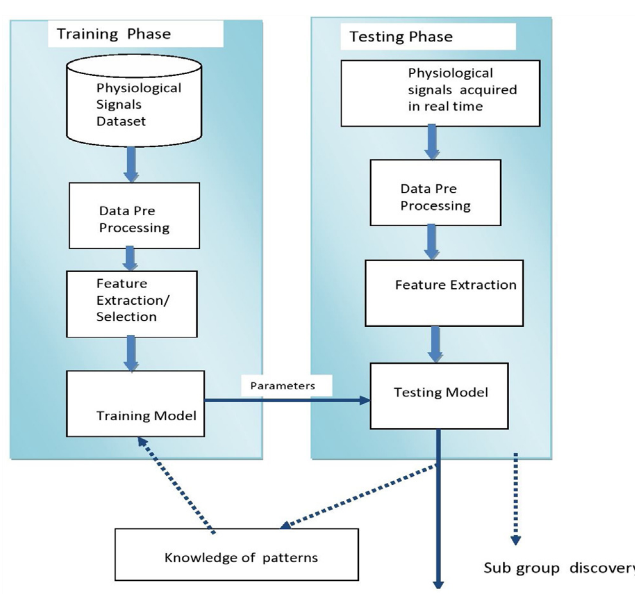

Fig. 7 – Schematic of proposed model.

9. Conclusion

Stress directly affects a nation's expense and increases the workload on medical fraternity. The most significant damage is a hampered quality of life at an individual level, which by all means directly affects one's personal, professional and social life. Mental stress adversely affects one's physiology, emotional health, physical health and overall wellness. Hence the need for generalized, efficient and robust Emotion Detection systems or Stress Detection systems is crucial. The growing pervasiveness of machine learning techniques and wearable technology in healthcare is a radical development bound to benefit the society directly. Since physiology holds a treasure of accurate and unmaskable information, we propose to use the same in our future model to predict the presence of mental stress.

In this paper we have presented a comprehensive survey on each of the following: physiological data collection, Emotion Detection systems using machine learning, Stress Detection systems using machine learning, evaluation measures of such systems, the myriad challenges in developing such systems and the variety of applications. Our work shall definitely be useful for fellow researchers in getting a clear picture of this field.

Authors' contributions

The first author was primarily responsible for Conceptualization, Data curation, Formal analysis, Methodology, Visualization and drafting of original manuscript. At every stage, substantial support and technical guidance was mentored by second author. Second author was primarily responsible for following roles – overall technical guidance for flow of content, use of proper graphics to illustrate concepts, investigation, administration, providing all resources, conducting able and prompt supervision and editing the draft.

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