Review Of Affective Computing

M.B.T.Ahamed
Faculty of Information Technology
University of Moratuwa
Katubedda, Sri Lanka
ahamedthanveer123@gmail.com

***Abstract*— Affective Computing is emerging as a new field of research in the past few years. It is a multidisciplinary research area that affects many varieties of fields such as Education, Health Care, and Gaming. Affective Computing is aimed at developing systems that automatically recognize human emotions and respond to them accordingly. This will enable emotional intelligence in the System. Emotional intelligence is important for developing successful human interactive Systems. Emotion recognition is a key aspect of Affective Computing. Understanding the emotions and behavior of a person makes it easy to control them. So, affective computing helps to build more effective educational models for the field of education and treatment techniques for the Field of healthcare. This Review paper will discuss how human emotions are recognized, the use of the Affective Computing field of education and healthcare, and issues and challenges in affective computing**.

Keywords— ***Affective Computing; Emotion Recognition; Application of Affective Systems;***

I. INTRODUCTION

Affective computing is a developing research area targeted at enabling intelligent systems to identify, perceive, conclude and understand emotions. It is a multidisciplinary research field that affects different fields. It is a collection of techniques to detect emotion or the affective state of human users. In human decision-making, learning, communication, and understanding of human emotions play a crucial role [1]. The affective computing concept became popular with the development of Al.

In the early days, theoreticians consider symbolic processes are the best way to model cognitive systems. Then formalization and discretization of human thinking become the focus. Logic, grammar, and modular understanding become a source of analysis. But such semantic approaches couldn't capture the most important dynamic and creative aspect of the human mind even after the advent of fuzzy logic and nonmonotonic. Later cognitive scientists proposed the idea as emotion and inherent interaction between human minds and bodies contribute to the cognitive process. Consequently, the Concept of Machines with emotional intelligence comes out [2].

A. *Machines with emotional intelligence*

The Concept of Machines with emotional intelligence explains that intelligent machines must be related to the emotion of human users. When building a machine with Emotional Intelligence various types of models are used but all of these models refer to the ability to connect with others by detecting, expressing, managing, and understanding the emotions of oneself and others. Efforts in building machines that are emotionally intelligent focus on a few key factors such as, empowering the machine to detect emotion, enabling the machine to express emotion, and finally, embodying the machine virtually or physically [3].

B. *Importance of Emotional intelligent systems*

Emotional Intelligent Systems (EIS) improve human-machine interaction. Emotions are the key players in decision making so emotional intelligent systems can make better decisions than normal intelligent systems. It is will help to build human-centric intelligent Systems. EIS act as a communication tool for autism patients and EIS provides more productive solutions for real-world problems.

C. *Affective Sensing*

Affective sensing is the ability to recognize emotions by the data gathered from the human body in form of signals and patterns .to accomplish affective sensing an EIS should equip with hardware and software that can sense human emotions [4]. There are 8basic human emotions according to Tomkins as *Joy, Excitement, Surprise, Anger, Disgust, Distress, Fear, and Shame* [2] . Human emotions can detect by verbal and nonverbal communication other than that we can use the bio-inspired technique to identify human emotions.

This paper would discuss how emotions are recognized, the applications of Affective Computing in different fields, and the challenges in the field of affective computing. Section 2 would discuss Emotion Recognition while Section 3 would discuss Applications of Affective Computing. Section 4 emphasizes the issues and Challenges related to Affective Computing. Section 5 discusses all the aspects of the present systems and comments on possible improvements while section 6 concludes. Section 7 mentions further work.

II. EMOTION RECOGNITION

Emotion Recognition plays a vital role in affective computing to build an affective system. First, it should be able to recognize human emotion, and then it should understand the state of emotion and react accordingly. Humans express their emotions through verbal or non-verbal behavior. So Cognitive scientists develop affective systems based on verbal and nonverbal manner depending on the motivation of the affective Systems. When measuring emotions 2 main approaches are commonly used [5].

1) *Discrete measurement*

In Discrete measurement, complex emotions form as a result of the combination of basic emotions. The discrete method has 2 main approaches, *a) Message-based measurement*

This method uses the observer to guess the type of emotion or affective condition by mapping facial expressions or features with the basic emotion model of Ekman. This Ekman model includes direct evidence of uniform signals throughout all humankind. This method is built with the assumption that an expression can directly map with basic emotions and find the type of emotion. Figure 1 shows the Ekman basic emotion model.

Figure 2. Ekman's basic emotions. from left to right: happy, sad, angry, fear, surprise and disgust *[12]*

b) Sign-based measurement

This is a descriptive method that use to model expressions as signs and then use experimental and observational methods to identify a relationship between such signs and emotions. The most used method is the Facial Action Coding System (FACS). FACS classification is developed by observing gray variations between image expressions, recording facial muscle electric activities, and tracking the effects of facial stimulations electrically. Figure 4 shows the Action units in FACS.

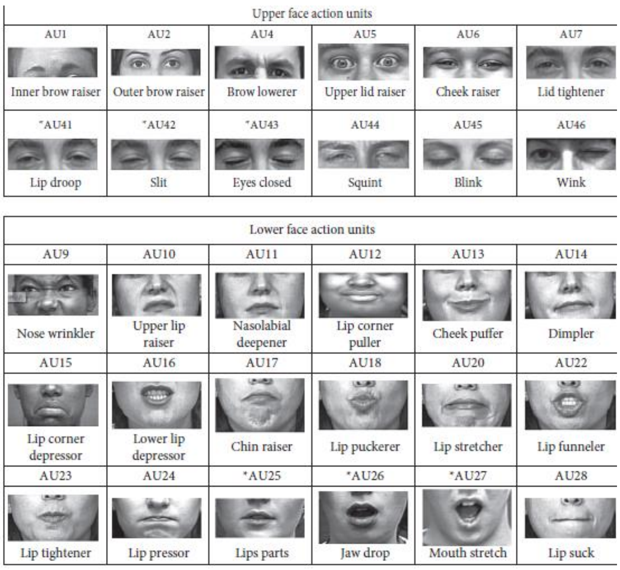

Figure 3. Action Units in a face in FACS *[12]*

2) Dimensional models-based measurement

This method explains similarity or the intensity of emotion. These methods model emotions by representing a fundamental property that is common to all emotions in each dimension of a multidimensional space. This method gives the intensity of emotion detected. Figure 5 shows the intensity variation of an action unit.

Figure 6. Different Dimensions of AU 12. *[12]*

NON VERBAL BEHAVIOR OF EXPRESSING EMOTIONS

This means expressing human emotions through gestures, facial expressions, eye movements, body language, and posture. It also includes biological changes that occur in human organs when expressing emotions. The affective system can recognize human emotions mainly in 2 ways as bio-sensing and computer vision.

3) Bio-Sensing technique

In this technique, affective systems measure biometric signals transmitted by human organs when expressing emotion and infer the types of emotion that human being expresses [6]. In biosensing, Approach emotions are measured by electrocardiogram (ECG), electroencephalogram (EEG), galvanic skin response (GSR), photoplethysmography (PPG), and using neuromodulating cognitive architecture (NEUCOGAR) [6] [2].

a) Electrocardiography (ECG)

ECG is a technique used in affective computing to infer emotions by using the heart-related activities of a person. When humans express an emotional heart rate (HR) and heart rate variable (HRV) changes. For example, when a person gets stressed his HR starts to rise. HRV provides more information than HR.HRV is the calculation of the standard difference in interval between successive R waves. There are four key components of a standard heartbeat as the baseline, P wave, QRS complex, and T wave. The R spike of the QRS complex is most often used for testing HRV as it is the most important spike in the waveform. HRV is a product form as a result of changes in self-contained nerve function consisting of sympathetic and parasympathetic modulation. The main role of the sympathetic nervous system (SNS) is to accelerate HR to increase the body's blood supply. The function of the parasympathetic nervous system (PNS) is to slow down the HR That increases as a result of an emotion. When a person gets stressed, this helps to examine how fast the body is reacting to stress and how long it takes to respond to the stimulus and how quickly the PNS reacts and slows down HR to reduce stress [7].

ECG is a device that use to measure electrical signals produced by depolarization and repolarization of the heart. When ECG is used to get reading about a person's HRV electrodes are positioned strategically on the body of the person. The data that is measured and collected by ECG and extracted as HRV is used filter as frequency content for examining purposes. Examining frequency content is mainly divided into 3 main categories as very low frequency (VLF/0-0.08Hz), low frequency (LF/0.08-0.15Hz), and high frequency (HF/0.15-0.5Hz). This classification is important because the SNS function is related to LF frequency content and the PNS function is associated with HF frequency content.

$$Power\ Ratio(ECG) = \frac{Power(LF)}{Power(HF)} \quad (1)$$

The power values are computed by using power spectral density (PSD) which uses fast Fourier transformation to convert data from time to frequency domain. by using these measurements ECG can infer the emotions like stress, and happiness and infer affective state in arousal and valence perception [5].

b) Electroencephalography (EEG)

All simulations related to the nervous system are controlled brain. For detecting emotional responses, it is important to closely track the functions of the human brain. Most emotional responses like fear and stress originate in the amygdala which communicates with the hypothalamus to generate an autonomic nervous system (ANS) response. psychological and physical emotional responses are generated as a result of this ANS stimulation. potentials generated at the cerebral cortex correspond to the signals transformed between the amygdala and hypothalamus, by this, it is possible to track and record the brain functions at this moment.to examine the frontal cortex EEG is used [8].

EEG is used to measure electrical potentials generate in the brain when there is an occurrence of brain stimulation. The electrode is placed according to the international 10/20 system (fig 2). This system is based on 19 electrodes positioned at intervals of 10% and 20% across the cranium. Like ECG measurement of electronic potentials can transform to frequency content and emotions can analyze by power values computed by PSD. These brain waves (electronic potentials) can classify as delta(0-3Hz), theta(3-8Hz), alpha(8-12Hz), beta(12-38Hz) and gamma(38-45Hz).The frequency range of brain waves is changed from 0.01Hz to 60Hz.gamma waves are induced when emotional activity is generated. Alpha wave is stimulated when a person is in a calm situation. Theta and beta wave exists between the emotional status of alpha-delta and alpha-gamma simultaneously data was collected and analyzed by using audio-visual stimulation to identify basic emotions. measurement features collected by independent component analysis (ICA) and classify these features using the K nearest neighbor (KNN) algorithm.

Emotions are detected by applying KNN for power ratio values computes by using PSD and to infer emotions to classify the emotional response as fear, sad, disgust, neutral and happy. The point of maximum spectral energy is identified, and corresponding x and y coordinates are considered when inferring emotion. When a person is happy frontal cortex is become active and primary centroids shows (26.58, −99.97) reading. The neutral emotional status relaxes the brain activities and almost every part of the brain gets affected but the left part of the brain is significantly affected, and the primary cortex shows a reading of (-69.18,12.89). The sad emotions spread in the region of the right occipital and left frontal cortex of the brain KNN shows the reading of (66.45,29.53). Emotion fear affects the frontal cortex, right amygdala, and the centers of the left hypothalamus this state indicates (74.22, -9.65). Disgust affects the Right occipital, prefrontal temporal, and right prefrontal/temporal regions and shows (63.05,38.68) reading. BioSemi. The Emotiv EPOC+ and ABM B-Alert are used as EEG devices. Figure 8 shows how the brain gets affected when different emotions have occurred.

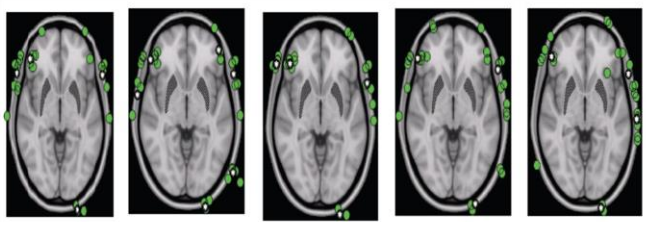

Figure 7. Modeling Emotions by EEG. from left to right: happy, neutral, sad, disgust, fear *[8]*

c) Galvanic skin response (GSR)

This method mainly focuses on measuring emotions by using skin conductivity. Skin conductivity is sensitive to the skin to conduct electricity. When a person is emotionally affected human sweat glance also starts to function and as a result, it would generate more sweat on human skin. activities of sweat glance are controlled by SNS and PNS. When the emotional state is occurred similar SNS accelerate the sweating process and the conductivity of the skin increases. This skin conductivity is directly proportional to psychological arousal and emotions like fear, and stress can detect by this method [7].

GSR which focuses on skin conductivity in response to physiological arousal measures skin conductivity while activity change is tracked. In a humid environment, skin conductance is naturally increased, this is called tonic skin response, and this is used as a reference point. Phasic skin response is considered in measuring, these are quickly changing peaks generated as a result of the stimulation. Observed values are mostly in the range of microsiemens (nS), this specifies the sensing range. ProComp, Biopac MP150, and Shimmer3 are used as GSR devices. Basic emotions can recognize by extracting features from data collected from GSR and classification of those features to find corresponding emotions. Immune Hybrid Particle Swarm Optimization (IH-PSO) is used to extract relevant features from the GSR data and Fisher classifier with a linear discriminated function is used for classifying those features to infer the type of emotion. Identifying the rate of emotion in data with mixed other emotions (IRE) is considered a variable to detect emotion. Table 1 shows the data used to infer the type of emotions [9].

Table 2.Inferring emotions using IRE values

Emotion	IRE value (Average%)
Happy	45.79
Surprise	40.37
Disgust	33.44
Sad	40.07
Angry	32.27
Fear	15.44

d) Photoplethysmography (PPG)

Table 2. Modeling computational Parameters

Type	Process	Monoamines	Description
Generic	Computing power	noradrenaline	The higher noradrenaline levels, the more computing power on current activity must be Concentrated
	Memory distribution	noradrenaline	Memory distribution and concentration is impact by noradrenaline
	Learning	serotonin, dopamine	Learning is impact by dopamine and serotonin
	Storage	serotonin, dopamine	Dopamine is important in activation of previously recalled pattern and serotonin important to generate pattern
Decision Making / Reward processing	Confidence	serotonin	Serotonin induces confidence
	Satisfaction	serotonin	Serotonin induces satisfaction in the system
	Motivation, wanting	dopamine	The systems are more motivated by dopamine
	Amount of options	noradrenaline	Systems tend to select risky measures under noradrenaline influence
	Risky choices	noradrenaline	The system makes Noradrenaline find a limited number of options

When the emotional status is generated the HR and HRV are changed accordingly. This change affects the change of blood volume and blood pressure of that person. The blood volume pulse (BVP) is the cycle of blood volume change that match each frequency of the heartbeat of a person. BVP is used to identify changes in blood pressure when blood volume is changing. The process of widening the blood vessels and narrowing blood vessels happens due to variations occurring in blood pressure, this process can distinguish by the BVP test. These variations of blood pressure happen due to actives related to the heart so BVP can use to infer emotions [5].

PPG is an optical technique used to identify the changes that occur in the blood volume of the microvasculature. PPG is designed with near-infrared (NRI) as the source of light and uses a photodetector as the receiver for reflected light. This NRI is focused on the blood capillaries of the person's body and the photodetector check for the reflected light rays from the body. The amount of light reflected is used as the measurement of PPG. If less amount of light is reacted, then the light emitted from NRI should have been absorbed by the site of illumination this means microvasculature contains a large volume of blood. when the pulse is at enough rate this approach can use to detect BVP. By using BVP data HR and HRV also can compute. So, using data of HRV and using optimal classification method this system can detect human emotion like the ECG technique.

e) Neuromodulating cognitive architecture (NEUCOGAR)

This model is developed biometrically to adopt the functionalities of brain neuromodulators into the computational environment. This model aims to provide more efficient AI Solutions to build an Artificial cognitive system that can perform complex task such as creativity and innovation as well as engage with human users in a sustainable relationship. In Neuromodulating Cognitive Architecture (NEUCOGAR) monoamine neuromodulators mapped as parameters of the affective system. [10]

There are several considerations in NEUCOGAR as,

1. Emotions are natural and necessary modulators, reinforced and simultaneously modeled by social factors
2. Geneva emotion wheel, Plutchick's emotion wheel, and Lövheim Cube of emotion are models used to explain strategies used to model emotion in this method
3. Monoamine is used in modeling emotional responses in the human cognitive system.

This method is considered a basis for an affective computing paradigm and plans to use in a variety of domains. three monoamine structures presumably represent a different emotional aspect. Noradrenaline, serotonin, and dopamine cannot direct mapping for computation systems for some obvious reasons as computer systems don't have anything like a biochemical process in a neuron. So, in NEUCOGAR indirect mapping is done base on the role of each neuromodulator involve in human emotion. Mapping is done between computer and brain neuromodulator processes and the relevant biochemical effect of neuromodulatory systems on neuron effect by virtual neuromodulator levels on the machine computational method.

Types of monoamines,

- **Dopamine** - It is important for linking feelings, perception, and knowledge from simple motivation processes up to the working memory system. In computer systems, it is modeled as memory distribution and decision making.
- **Serotonin** – It has played an essential role in the regulation of aggression and agonist social interactions in various species. it is correlated with confidence, internal intensity, and pleasure. In a computer system, it influences machine training and strong learned information.

- **Noradrenaline**- It contributes to regulatory impacts related to excitement and the opportunity to respond and contribute to storing recuperating memory, particularly affecting emotionally intense events.

When modeling this to the computational system those parameters are divided into 2 parts according to their nature, Generic and Decision Making.

Table 2 shows the types of parameters and what kind of task they use to perform in the affective system after mapping neuromodulators to computer parameters.

NEUCOGAR is a smoothly built architecture to detect human emotion by using the human neuromodulatory system. It is a good example of a biosensing model.

4) Vision-based technique

In this technique, affective systems recognize the pattern of expression human is expressing using a deep neural network. Affective System uses facial recognition and computer vision-based techniques to understand the pattern of emotion expressed and uses fuzzy logic to detect the type of emotion [6]. Automatic facial expression analysis is the main method used to detect emotions in this technique [11].

a) . Automatic facial expression analysis (AFEA)

The face is an important organ in the human body that can convey much important information about a person. Face holding 2 types of information about humans demographical information (age, origin, and gender) and psychological status-related information (emotions) of a human. AFEA use to identify and classify the physiological status of a person. Human conveys emotion in the face by utilizing facial expressions. This facial expression is used to detect emotions. AFEA uses an important protocol Kwon as a facial action code system (FACS). FACS use to measure the intensity and frequency of facial expression and these measurements are converted as an action unit (AU).AU is the smallest distinguishable pattern that can identify from a facial expression.AU works with pupil adjustment, brow adjustment, lip movements, and cheek adjustments that import in detecting emotions so AU considers an important concept in AFEA.AFEA can use both Discrete and dimension model-based measuring techniques to compute emotions [12].

There are 6 major steps in AFEA to process a facial expression to infer an emotion,

1. Inputting the image or the video that contains facial expression details
2. Detecting and tracking facial boundaries and landmarks
3. Face alignment
4. Extracting features from the data
5. Reducing the dimensionality in the extracted features
6. Classifying AU to infer the emotion

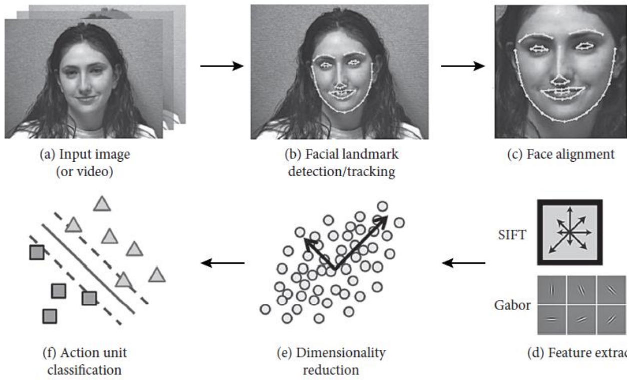

Figure 9. Process of inferring emotions from facial image *[12]*

Figure 10 shows how these steps are executed. To detect face AFEA need a frontal view of the face as the image data. Viola-jones object detection framework is used as a face detection technique. After detecting the face AFEA used to track facial features, these features [13]may be dense or sparse. AFEA uses Active appearance models (AAMs) or constrained local model (CLM) technique. These models 1st uncouple the image and use predetermined linear appearance models with linear variations of facial expressions to match with the uncouple image and to track facial details. The image must fix to canonical size and orientation to eliminate the dimensionality in position, and rotation in facial proposition these alignments are fixed by AAMs and CLM.

When extracting features from the filtered data several types of features are considered geometric, appearance, and motion. Geometric features are denoted as specific shapes related to the face like eyes and brows. Appearance features represent changes in skin tone such as dimpling and deeper facial holes. The motion feature is representing changes in the physical shapes of the face or the movement of facial muscles.

Extracted features contain high dimensionality of data, to reduce dimensionality AFEA different types of Algorithms. FACS has used classification techniques and detect emotions. Affectiva and Emotient systems have been developed to detect emotion using AFEA these systems use cloud facilities and distributive networks and Machine learning techniques to detect emotions.

III. APPLICATIONS OF AFFECTIVE COMPUTING

The key objective of designing an affective system is to recognize human emotions and collect emotional information to enhance the communication between the human user and the intelligent system. The affective computing concept is used in many fields such as education, gaming, and healthcare.

1) Field of HealthCare

Affective Computing systems are used in the healthcare field as an emotion development tool in medical treatment. A project was developed to understand the emotional communication of children with an autism spectrum disorder (ASD) and respond to their emotions.

The system is designed to improve the social and emotional functioning of children with autism spectrum disorder using robots [14].

This system measures the emotion of a child with ASD using a computer vision method that recognizes detailed emotions from the expression of the face when the child is communicating with parents. Children and parent communication are stronger with emotions. So, research use this strategy to collect data on child emotion. Collected data use to measure emotion using a continuous rating method. And System is used as an efficient Machine learning algorithm to infer emotions.

2) *Field of Education*

In the field of education, there are several learning models and methods designed using Affective Computing. As an example, an e-learning platform was designed to provide personalized support by considering the emotions and personality of the user and by recognizing the affective state of the learner to provide appropriate affective support in the e-learning platform. The platform can identify the learner's emotions and react accordingly [15].

This method mainly focuses on collecting and detecting the emotion of learners in the personality dimension. Researchers explain that personality is diverse from user to user and they use data gathered from Five-Factor Markers (FFM) questionnaires and model them and categorize them into groups of personalities and provide them facilities according to their personality.

IV. ISSUES AND CHALLENGES IN AFFECTIVE COMPUTING

As affective computing is an emerging multidisciplinary research area, this field is facing many issues and challenges. The main issue of affective computing is an ethical consideration.

A. *Ethical consideration*

There is a strong belief in the general public that if the machine gets intelligent with emotions, the machine could easily understand the weakness of humans and if any case machine has gone rogue it would be catastrophic. This chapter will help to conclude which kind of intelligent systems should have the capability of affective computing. And what kind of constraints should be considered when building affective computing. Let's discuss some factors that should consider in building affective systems.

1) *Privacy*

This topic mainly focuses on how much assurance an affective system gives on data collected about human emotion to achieve the purpose of the affective system. According to Picard, he states that emotion is the ultimate personal and private thing of humans [16]. Since affective systems are built with the foundation of Machine Learning and Deep Neural networks these systems need past emotional states of the user to make decisions so if those data are stored in a less secure manner hackers may be able to access very sensitive emotional detail about the user and it would create a negative impact on a particular user. Therefore, maintaining privacy is a very important task in affective computing [4].

2) *Emotional Dependency*

Affective systems can develop as moral agents as a tool to guide the emotional happiness of a human user. But if the user gets complete dependence on a moral agent it would negatively impact on user's ability to maintain a happy life. Therefore when designing moral agents developers must ensure that the role of the moral agent should be clearly defined only to act as emotional guidance not to be a drug to the human user [17] [4].

3) *Emotional Manipulation*

All affective systems are intelligent systems. But if an intelligent system can recognize human emotion and understand human feeling it could also be able to manipulate human emotion. If an affective system negatively manipulates human emotion it would cause many bad results. As an example, the affective system detects a user in an angry emotional state and if it manipulates the user to beat some other person to balance the emotion. Therefore, when designing the affective system, its moral agents should always motivate the goodwill of humanity [4].

B. *challenges in affective computing*

The rapid development of the affective computing research field opens many research fields related to an affective intelligent system. The focus of this section is on discussing challenging research topics in affective computing.

1) *Affective Understanding and Adaptation*

Most of the affective models discussed in this paper are static approaches to analyzing the affective state of humans, not real dynamic emotional states. Real human emotions occur due to numerous factors like personality, culture, and environment. but old affective systems are not cable enough to understand the dynamic emotion of humans. Psychological research sate that emotion depends on past affect states. So to build a perfect affect system it is important to focus to integrate adaptation and dynamic affective understanding concepts when designing affective models.

2) *Multi-model Based Affective Computing*

When building a Multimodal based system, it is hard to develop a system that could manage different models to build a mutual relationship between them. The mutual relationship will help to create a system with better integration. So, the motivation for building an affective system can achieve more effectively and accurately [18].

3) Affective Feature Capturing in Real Environments

Most of the devices and systems that are used to gather data about emotion or affect from human users are not developed or advanced in technology, so the data received from those systems pretend to be noisy. So, when inferring highly sensitive emotions from those data, most of the results are not reliable. So, it is important to have more advanced and powerful systems to capture more reliable and detailed affective data from the real environment.

4) Affective Computing with Multi-agent System

The study of agent-based systems started with the development of distributed Artificial intelligent fields. Due to some factors it challengeable to design such a multi-agent system. The affective status of an agent could affect another agent, Agents intercommunication to achieve their task. how an agent is reacting in an unpredictable and changing environment [19].

5) Affective Database

Most affective systems results are produced by Machine learning algorithms. Those algorithms need a large amount of heterogeneous data to produce the best result. But in the real world, there is a big vacuum of affect data so it is a big challenge to build more powerful and efficient affective systems.

V. DISCUSSION

All the result obtained from the affective system depends on how emotions are recognized and modeled in the affective system. Human users expressed their emotions in a verbal or nonverbal manner. Affective systems are designed by considering their purpose. When considering the system that used to detect emotions of children with ASD, that system uses an approach of detecting nonverbal emotions as their technique as children are express their emotions nonverbal manner with their parents. The verbal way of emotion detection is used in systems with an educational purpose.

Nonverbal emotions are detected by using computer vision or biosensing technology. when comparing computer vision and biosensing systems can obtain more reliable results from biosensing than computer vision but when considering datasets and resources that use to model these data to the affective system computer vision has more advantages over that.

When considering measuring emotions there are several issues related to the message-based measuring approach. The assumption related to message-based measurement is quite problematic as the same expression can express different emotions according to where, with what, and how the expression occurs. This means expression depends on the context. It was difficult to match an emotion without having an understanding of the context.

Sign based emotion recognition method considers modeling expressions to action units and then inferring emotion by mapping action units with a relevant emotion. This method coverup the main drawback of the message-based emotion measuring method but this method doesn’t provide a good accuracy of inferred an emotion. That means this method doesn't provide a level of assurance of emotion that detect by this method [5].

The dimension method provides a good accuracy of inferred emotion. This method is much better than discrete methods. This method has several advantages as it can represent any emotion in terms of two or more fundamental dimensions. emotions continuously portraying their intensity. The affective state can represent positive and negative and it can be measured over a range of hundreds of points. If several independent ratings are obtained, scores over several emotions can be aggregated to generate a result with high reliability. This method is not suitable for detecting discrete emotions. Like the message base method, this method can’t exactly distinguish between joy and pleasure [5].

According to the research done by Atefeh GosHvar pour, Ataollah Abbasi, and Ateke Goshvarpour at the Sahand University of Technology, Iran they have experimented with measuring emotion by dimension approach with help of ECG and GSR. This experiment was designed in a two-dimensional space of emotional classes with four segments taking valance and arousal as two dimensions. This study's main purpose is to collect data related to emotional responses generate due to music. Fig 1 shows categories of emotions represented in the two-dimensional model. In this study, emotions are categorized as 5C, 3V, and 3A. 5C represents happiness, sadness, scary, peacefulness, and rest condition. 3A represents positive arousal, negative arousal, and rest condition.3V represents pleasant, unpleasant, and rest condition. The result of this study shows that ECG shows high accuracy in measuring emotions related to all these emotion categories (5C,3V, and 3A) [7]. In the market there 2 types of ECG devices Biopac’s MP150 which is not portable and Shimmer3 which is portable, but all these devices are expensive [5].ECG can give more accurate information because it directly checks with HR [20]. Therefore, more complex emotions can detect by ECG. but ECG is less portable, and less wearable and to get more sensitive measurements it needs to have a more powerful electrode to measure HR.

EEG is the most advanced technology for tracking and detecting brain activities. EEG has limitations in measuring electrical potential emit from the brain. To measure more accurate and highly sensitive data power of the device used to measure EEG signals also be high these kinds of devices are highly expensive and not portable enough [21]. When emotion is generated the quickest organ to respond to the emotion in the human brain as it controls all human emotional activities and different parts of the brain get stimulated for different types of emotions so EEG-based emotion recognitions techniques can identify different types of complex emotions with the use of efficient and effective technique to extract features and classify feature to infer emotion. In this review, KNN is used for extracting features and ICA is used to classify those extracted features KNN shows less than 20% of error when classification is done. To use a wireless and portable EEG it is better to choose Emotiv EPOC+ or ABM B-Alert X10. But when EEG devices get more portable accuracy of the measurements should consider a prominent factor [22].

GSR is a technique that develops to measure the skin reaction when an emotional potential occurs. GSR measures skin conductivity when sweating is happening as a result of emotional potential. When compared with EEG and ECG, GSR doesn't need a big setup as most GSR devices are designed with portability and GSR measurements are collected by the fingers of a person. Sweat glance of humans working with related to SNS and PNS which responsible for managing brain functions related to emotional response. Therefore, it is easy to model GSR measurement to infer emotion. GSR systems increase wearables and it doesn't require applying the gel on the body to fix electrodes like in EEG and ECG. When comparing GSR with ECG and EEG both ECG and EEG provide more accuracy in inferring emotions. Sweat glands do not respond to all kinds of emotions it only reacts to a subset of emotions like fear, stress, and arousal this is a big drawback of GSR systems. GSR systems are more suitable for designing mobile emotion detection devices as stress detection systems as they are less expensive and show more accuracy in stress detection [23].

PPG is an optical technique that is designed to detect changes that occur in blood volume in the microvasculature. PPG is the cheapest device that can use to design an emotion recognition system. As PPG is deal with blood volume the measurements of PPG can map with BVP and by using the transformation technique features can represent in the frequency domain and like ECG. So, the Accuracy of inferring emotions is just like ECG.PPG provides measurement with less noise. Although PPG has many benefits it is also able to detect a subset of emotions to compute complex emotional response PPG need more sensitive measurements it would cost high.

When discussing designing emotion recognition systems with biometric signals, EEG is the best option for detecting complex patterns of emotions as the human brain is the only organ that provides highly accurate information about human emotions. If an affective system needs to design with less expense and with high portability it is better to choose GSR or PPG techniques. But PPG has less maintenance compared to the GSR system. ECG provides more accurate details about emotions after EEG. All the biometric signals can't use directly to map emotional status as measurements are raw data mixed with noise so all these measurements should denoised and filer. Those filtered data present various types of features, to detect emotions accurately it is needed to extract more relevant features according to the subject and context. There are many varieties of extracting techniques to extract features such as Fourier transform, Wavelet Transform, Empirical Mode Decomposition (EMD), Hilbert Huang Transform (HHT), Robust Singular Spectrum Transform (RSST), etc. After extracting features, it needs to reduce the dimensionality of features as these features may not correlate with different emotional states. And those features should use to classify emotions.

For classifications, different types of classification algorithms are used. K-Nearest Neighbor (KNN), Regression Tree, Bayesian Networks, Support Vector Machines (SVM), Canonical Correlation Analysis (CCA) Artificial Neural Network (ANN), Linear Discriminant Analysis (LDA), and Marquardt Back Propagation (MBP) use as classifiers. There are 2 types of approaches to designing an emotion recognition system as a user depends on (UD) systems and user-independent systems (UI). UD is highly dependent on the subject a UI use unknown measurement independent from the subject. UI approach is now becoming more popular.

According to the emotional recognition researches done with regards to biometrics ECG and GSR have proven 98% accuracy in recognition of emotion class with 5C,3V and 3A.and 95.4% accuracy is obtained for detecting 4 emotions with happy, angry, sad, and pleasure by using EEG, ECG, and GSR .91.89 % accuracy has recorded when detecting basic emotions with ECG, GSR, and PPG.UI approach has gained 84.59% accuracy to detect happy and sad with ECG and EEG.70.12% accuracy is gained to detect 4 emotions with ECG and GSR in this UI approach.

The physiological signal-based emotional recognition systems are important to build real-time emotion recognition systems. Although there are many methods available to extract features and classify emotions it is still challenging to find an optimal and perfect method for the system to extract features and classify them. Most of the emotion recognition systems developed are still in early-stage so most results are not reliable enough. UI approach provides more reliability to the system, but it is still in the research and engineering stage [24]. It is better to develop a management system to identify relevant feature extraction and classify methods with the concern of optimality and accuracy of the solution.

NEUCOGAR is a bio-inspired model that develops to model the emotions of human users by considering neuromodulatory activities that connect with emotions. Researchers explain that it helps an affective system with more flexibility than other emotional modeling techniques used in biosensing. This model helps to easily manage emotions in the affective system. The main drawback of this model is this not suitable for affective systems that design simple tasks and this model is still under development level. More knowledge and specialization are needed to develop these systems [25].

AFEA is the most popular facial emotion recognition system that uses a vision-based approach to emotion recognition. AFEA is suitable to detect emotions in a static context it is not built for recognizing real-time or dynamic emotion recognition [13]. But it could develop a real-time emotion recognition system with many datasets related to different varieties of human emotional expressions and with the use of high optimal algorithms and powerful and distributive systems to do computations. It makes the system very expensive. There are some significant challenges in AFEA systems as,

1. The system can't record facial expressions when the image is not a frontal post of the face or with head movements.
2. Most facial expression is naturally delicate so it is difficult to model those expressions.
3. The motions of the facial expression can be extremely variable.
4. Discrete AUs can change their expression with each other.
5. It is difficult to generalize a subject detail because it contains details about the appearance and shape of the induvial.
6. IF there are not enough extracted features the classifiers may face difficulty to infer a correct emotion.

AAMs is a subject-dependent face Tracker so it faces many difficulties when distinguishing a face with different appearances and global lightning conditions on the subject, but CLM can fix these issues. Both techniques can do online face tracking. the common drawback of these face trackers is the precision of detecting a shape of a subject is very less. When fixing the image rotation is a more challenging factor to consider as 3D rotation changes the meaning of the subject as the subject expresses different expressions in different dimensions. To classify emotion accurately AFEA needs more features sometimes so System should be able to collect more features according to the context. Table 3 contains a summary of the techniques used to recognize emotions.

Table 3. Comparison of different emotion recognition techniques

Factors considering	EEG	ECG	PPG	GSR	AFEA
Wearability	Low	Low	High	High	High
Accuracy	High	High	High	High	High
Cost	High	High	Low	Low	High
Maintenance	High	High	Low	Middle	Low
Nosiness	Middle	Middle	Low	Low	Low

When considering about Affective system used to detect the emotion of children with ASD it is a single dimension system that develops only considering the emotional relationship between child and parent. The system could design more effectively if they consider a biosensing approach to detect emotion using the wearable device. The system also provides more accurate information by optimizing the result they obtain through the affective model.

The affective system that designs to detect the learner's personality and based on his personality recommends relevant education support. As the system uses a predefined set of questions that use to detect emotion and personality with answers, this is a verbal technique. this system could improve by considering learners' styles and increasing more dimensions to achieve a perfect result.

VI. CONCLUSION AND FURTHER WORK

As Intelligent Systems become an important tool in solving complex real-life problems to solve problems related to human life intelligent systems with emotional intelligence will be a greater tool in the future.

The affective system will be able to create human emotional assistance systems in the future, which would help many psychological patients and humans who suffering from communication problems with society. Systems can build to understand the ideologies of the general public, that are important to the government.

There are more challenging areas to improve and develop in this field but when considering the research and systems that develop, in the future this field will be a prominent field in Artificial intelligence.

The affective computing field is still a growing research field because of there are no specific and well-defined guidelines for designing an affective system. So this is the time to consider Affective computing as a science and introduce more scientific and biological methodologies to improve the wisdom of this field. Affective computing provides more flexibility to design applications focusing on the emotion of the subject as further work designing a commercial application with Affective computing will change the landmarks of the business field.

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