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Unmasking Sentiments: A Comprehensive Review on Emotion Detection Technologies

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Abstract
Stress is a state of tension, either physical or emotional, that can be brought on by any idea or incident that leaves you feeling anxious, irate, or disappointed. It is a basic human reaction that drives us to confront obstacles and dangers in our lives. Stress can elicit a variety of emotions, such as worry and irritation, and makes it difficult for us to unwind. This paper reviews many techniques [ECG, EMG, EDA, EEG, etc..,] for identifying stress.
Keywords: *Electro-Dermal Activity, Electrocardiogram, Electromyography, Electrooculography, Galvanic Skin Response, AgCl, Ag, Silver Chloride, Silver.*

1. Introduction
Human stress is a very subjective phenomenon since different people experience stress for different reasons under the same circumstances, causing the stress response to differ significantly [1]. Hospitalization has been recognized as a major source of stress for patients, irrespective of the ailment, particularly in cases when surgery is required. It is generally established that pre-surgery stress negatively impacts a person's ability to cope and maintain their physical and psychological health. Most of the earlier research has been on the use of physiological markers for stress detection [2]. Many studies have employed various physiological signals, such as the galvanic skin response (GSR) or Electro Dermal Activity (EDA), electrocardiogram (ECG), electrooculography (EOG), electromyogram (EMG), and multiple physiological signals to identify stress in binary (stress / no stress) or multi-Level (e.g., low, moderate, and high) forms. These studies made the case that a person's stress reaction cannot be fully assessed by using a single marker [4][3]. On the other hand, a few earlier research relied on advantages such as lower computing costs, better real-time system conditions, and the use of conventional wearable device data to identify stress levels using only one signal—typically the ECG or GSR [2]. The measurement of the constant changes in the electrical properties (conductance) of the skin brought on by changes in the body's sweating activity is called GSR or EDA. This idea is predicated on the idea that skin resistance fluctuates according to the health of the skin's sweat glands [3]. The conductance was found by simply reciprocating the resistance. This theory is based on how the Autonomic Nervous System (ANS) functions. When the ANS's sympathetic branch is strongly aroused, the sweat glands become active as well. As a result, skin conductance increases and skin resistance decreases. Human sympathetic nerve system (SNS) reactions, which are directly related to

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the control of emotional behavior in humans, are measured in this instance [2]. One of the most used methods for identifying both short and long-term stress is the electrocardiogram (ECG) [4]. The electrocardiogram (ECG) measures the heart's electrical activity by interpreting heart rate characteristics. Something stressful triggers a series of things [3]. When your body releases the hormone adrenaline, your heart rate, respiration, and blood pressure all momentarily increase. The "fight or flight" response is one of these reactions that gets you ready for the circumstance [4]. The upper trapezius muscle generates an EMG signal, which has been employed as a stress indicator [4]. Most of the earlier research has been on examining changes in certain EMG signal characteristics for binary stress detection [1]. Numerous research has examined the use of the EMG signal for stress detection. studied the effects of statistical analysis on the properties extracted from the left trapezius muscle's EMG signal during stress and rest. The right hand's extensive movements destroyed the right trapezius muscle's EMG signal. In a prior study, it was demonstrated that the right and left erector spine muscles' EMG signals were affected by stress and that these muscles could detect stress just as well as the trapezius muscles [5]. Emotion-optimized gaming (EOG) represents an exciting frontier in stress detection technology, transcending traditional methods. By harnessing the power of artificial intelligence and sophisticated sensors, EOG systems aim to revolutionize the understanding and interpretation of human emotions [1]. These systems, designed for applications ranging from healthcare to immersive gaming experiences, hold the promise of providing real-time insights into users' emotional states. As we explore the intricate landscape of stress detection, the incorporation of EOG into existing methodologies opens new avenues for more accurate and personalized assessments, marking a significant stride toward a future where technology seamlessly integrates with emotional intelligence [5].

2. Stress Theory

2.1 The theory of prolonged activation and stress

Stressful psychological situations can influence how a physical illness develops and progresses.

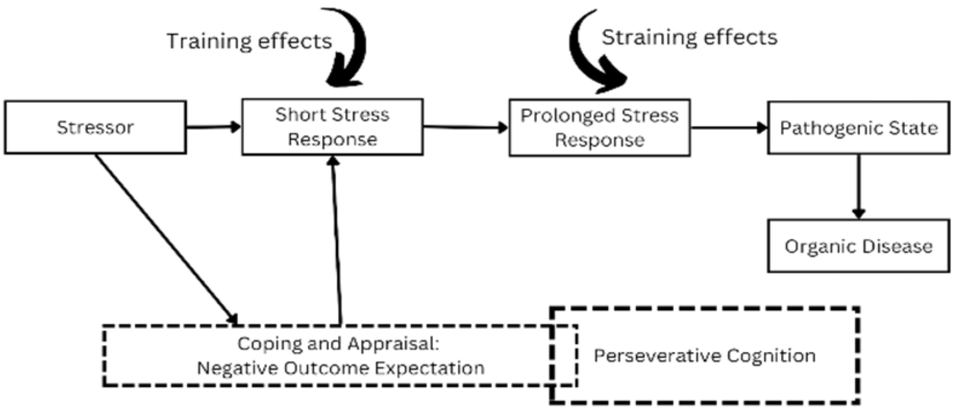

Figure 1 In a model of extended stress-related activation, perseverative cognition serves as a mediator between stressors and persistent stress responses [4]

The majority of stress scientists concur that extended physiological activity brought on by stressors—rather than just the activity during stressors—is responsible for a significant portion of this influence [4]. The pathogenic condition that ultimately gives rise to organic illness can only be reached by sustained activation. Three types of prolonged physiological stress activity exist recurrent activity associated with previous stressors, protracted recovery from stressors, and anticipatory reactions to (future) stressors. Early stress is marked by prolonged activity or the

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duration of the stress response. However, throughout the course of the last 50 years, researchers studying stress have not, as a result, made extended activation a central component of their ideas and investigations [4]. In a model of extended stress-related activation, perseverative cognition serves as a mediator between stressors and persistent stress responses are shown in Figure 1.

2.2 Mediator of prolonged activation: Perseverative Cognition

What therefore sustains physiological activity before or after a stressor? The development of a theory of this mediator has been hindered by the prevailing stress theories' absence of the extended activation element [2]. Although several theories have included the prolonged activation element, they have not specifically proposed a cognitive mechanism that genuinely extends activation in response to stresses or how they perceive them. It is crucial to understand that prolonged activation only results from extended stressor or perception (i.e., negative outcome expectation) rather than from the stressor or perception alone. Similar to the biological responses that occur during moderate activity, the average physiological response to a stressor is a "medium-sized" response. When not provoked, this type of reaction recovers swiftly. Thus, after a psychological stressor has ended, the organism continues to respond for reasons other than physiological needs. Similarly, metabolic demands at the time of anticipation cannot account for large anticipatory reactions that occur well in advance of a stressor [4]. Lastly, modifying stressors including perceived unpredictability, inadequate coping mechanisms, inadequate social support, and hostile personality traits also do not result in a sustained activation of oneself. To put it succinctly, a system that mediates between sustained activation and stressors and stress factors must exist [3]. In a model of extended stress-related activation, perseverative cognition serves as a mediator between stressors and persistent stress responses.

3. Methods of Stress Detection

Since stress detection is a major social contribution that improves people's quality of life, it is covered in a variety of literary works. Below is a review of various stress monitoring techniques.

3.1 EDA [Electro-Dermal Activity] or GSR [Galvanic Skin Response] for Stress Detection

Emotions govern the neurological system, which governs variations in skin-surface sweating as well as variations in heart and breathing rates. The physiological signal known as GSR, or electro-dermal activity (EDA), is simpler to measure and less expensive [6]. Excitement-producing physiological responses are replicated in GSR. Sweating is a response to arousal and is most frequently seen on the face, hands, fingers, and toes. For example, people sweat, their skin's salinity increases, and their electrical resistance shifts when they are happy [7]. It is imperative to ensure good conductivity in the event of EDA by attaching the electrodes to clean skin. Applying two electrodes to the finger so that at least the fingertips are covered is the primary method used to measure EDA [6]. These sensors can be inserted into gloves when mobility measurement is necessary. Regarding the human body, the ermine glands regulate thermoregulation. Compared to other sweat glands, these glands in the palm are more responsive and active when there is behavior associated to emotions. Therefore, a little voltage is delivered to the skin to measure the electro-dermal reaction of the skin at the palm. The primary relationship between skin conductance and arousal is that as arousal rises, so does skin conductance. The self-reported assessment of arousal and the measurement results are correlated [6]. The amplitude of the GSR signal is linked to anger, frustration, excitement, stress, and engagement. Using one or more sensors, the GSR method determines the skin's electrical conductivity. The sensors are made up of particular electrodes with skin-contact Ag/AgCl (silver chloride) contact patches [7]. The process of analyzing a GSR signal usually involves using several approaches in the temporal and frequency domains to extract statistical metrics such the ratio of minimum to maximum, minimum, maximum,

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median, mean, and standard deviation. This is because a GSR signal's amplitude and frequency provide important information [7]. Amplitude and frequency are examined when analyzing Galvanic Skin Response (GSR) signals, usually using a variety of methods in the time and frequency domains.

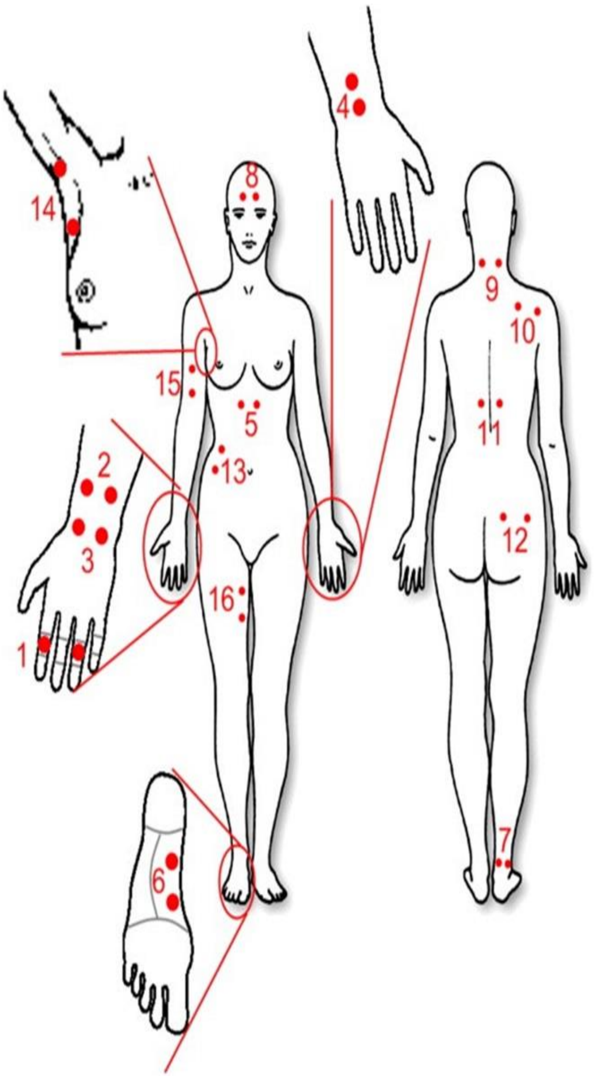

Figure 2 Potential locations for GSR electrode attachment [7]

A thorough examination is conducted by extracting statistical data such the minimum, maximum, median, mean, standard deviation, and the ratio of minimum to maximum. When low- and high-frequency components are present in the signal together with different responses to the same stimulus, traditional signal analysis is confronted with difficulties. When it comes to detecting certain emotions that are connected to arousal levels, such as tension or excitement, machine learning algorithms present a promising way to improve emotion detection accuracy. GSR has certain benefits over ECG and EEG, although providing less information regarding emotional states: It makes it easier to employ wearable technology to identify emotional states during daily activities since fewer measuring electrodes are needed. GSR produces less raw data overall, particularly in long-term monitoring, which allows for faster analysis without requiring a lot of processing capacity. GSR measurement equipment is less complicated and more reasonably priced. Common components like microcontrollers and ADC converters can be built into a measurement device with the availability of specific electrodes. Nonetheless, a significant disadvantage of GSR is its incomplete valence level information. Usually, various emotion identification techniques are integrated to overcome this constraint. A more thorough examination of emotional states is made possible by the complimentary outcomes produced by various techniques. The two main areas of focus are: Developing and evaluating methods for emotion recognition that combine GSR with other techniques. Creating a variety of wearable sensors. The third topic focuses on establishing systems that can identify emotions with a high degree of reliability by utilizing contemporary signal processing and analysis techniques. [8] An example is provided in [9], which describes a stress detection system that depends just on two physiological signals: heart rate and GSR. The study promotes an ideal strategy that uses fuzzy logic to combine precision and real-time applicability. This entails simulating a person's behavior under various stress and non-stress conditions. The suggested approach, which uses fuzzy logic, has an impressive 99.5% accuracy rate in detecting stress. [8] Table 1 shows an Analysis of Scientific Studies Centered on the Identification and Assessment of Emotions by GSR Potential locations for GSR electrode attachment are shown in Figure 2.

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Table 1 An Analysis of Scientific Studies Centered on the Identification and Assessment of Emotions by GSR

Aim	Emotions	Methods	Hardware & Software
Stress level evaluation in computer-human interaction.	Stress	GSR, eye activity	Mindfield eSense sensor, Tobii eye-tracker environment (Tobii Studio) [10]
Development of a wearable textile system with the ability to assess exosomatic EDA using both AC and DC techniques.	Level of arousal	GSR	Textile electrodes, from Smartex s.r.l. (Pisa, Italy), installed into special glove [11]
Examination of suggested techniques for identifying emotions from physiological cues	Valence and arousal levels	GSR, heart rate	Polar-based system, Armband from Bodymedia [12]
Evaluation of human emotions over brief intervals of time utilizing peripheral and EEG physiological data	High/neutral/low valence and arousal	GSR, EEG, blood pressure	Biosemi Active II system, plethysmograph to measure blood pressure [14]
Assessment of human emotion from physiological signals by means of pattern recognition and classification techniques	High/low valence and arousal	GSR, EEG, blood pressure, a respiration, temperature	Biosemi Active II device, GSR sensor, plethysmograph, respiration belt and a temperature sensor [13]
Development of a wearable technology to measure physiological markers related to emotion	-	GSR, heart rate, skin temperature	Originally designed glove with installed sensors [12]
Validation of a novel technique for assessing emotional experiences by deriving semantic data from the autonomic nervous system	High/low valence and arousal	GSR, ECG, heart rate,	Bodymedia Armband, InnerView Research Software 4.1 from Bodymedia [14]
Creation of two mobile phone state emotion recognition engines	Pleasant unpleasant	GSR, Photoplethysmogram (PPG), Skin Temperature [11]	-

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3.2 ECG

Electrocardiography (ECG), one of the most potent diagnostic instruments in medicine, is frequently used to evaluate heart function since the heart is one of the most vital organs in the human body. ECG is a physiological signal and is used as a traditional method to non-invasively interpret the Electrical activity of the heart in real time. [15] Recognizing emotions may be done with ECG in addition to assessing heart activity since cardiac activity is connected to the human central nervous system. A detailed description of the ECG recording procedure is provided below. The 12-lead ECG is the technique that is most often utilized. There are nine sensors on the human body that are utilized by this technology. [16] There are three main sensor sites on the body: the left arm (LA), right arm (RA), and left leg (LL). The right leg (RL), which is the only part that is wired, serves as a ground for all attached sensors. A 3-lead ECG is a technique that a physician can employ if he has only these three sensors. Although it lacks some cardiac information, this is nevertheless helpful in emergency scenarios where prompt analysis is necessary. [15] On the thorax, six sensors (V1–V6) are added to provide greater resolution. These sensors register data up to the ground (right leg, or RL) (G). The results of attaching all nine sensors to a 12-lead ECG are Lead I, Lead II, Lead III, aVR, aVL, aVF, V1, V2, V3, V4, V5, and V6. [7] The peaks P, Q, R, S, T, and U are the most significant locations on the ECG signal. Every one of these peaks has unique properties and is connected to cardiac function. Because physiological signals are more sensitive to movement aberrations and cannot visually discern emotion from data, emotion detection using physiological signals is a more sophisticated procedure than emotion recognition using electroencephalograms. [16] To get rid of noises coming from outside sources, such the person moving around during measuring procedure, ECG is often carried out when a person is quiet in locations shielded from environmental influences.

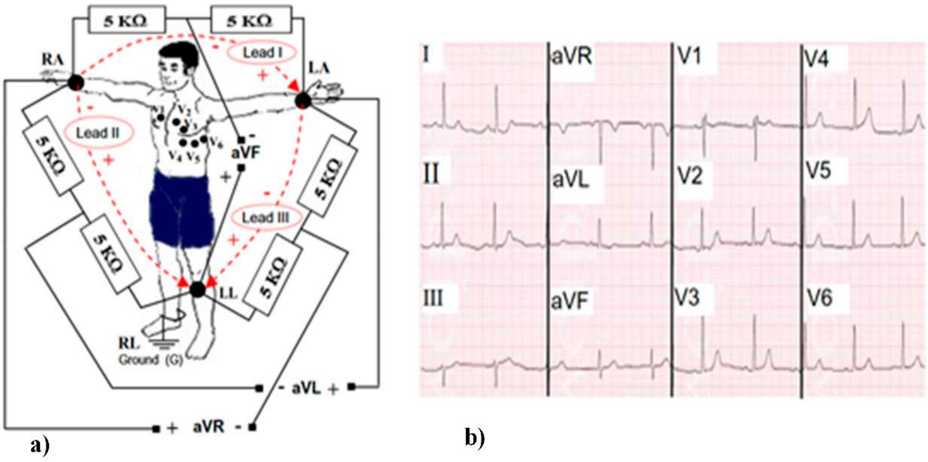

Figure 3 Schematic Illustration of Electrocardiography (ECG): (A) 12-Lead ECG: RA, LA, LL, RL; (B) Sample of ECG Signals [7]

The primary five metrics that are frequently used to assess ECG signals are listed in Table 2. Typically, an analysis of all five parameters is conducted solely for medical purposes to characterize aberrant cardiac activity and determine its deviation parameter. The QRS Complex, which describes heart activation associated with the human emotional state and is a suitable indicator to recognize main emotions, is typically used for emotion recognition. [16] However, there are

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difficulties in recognizing emotions because of this indicator's varying sensitivity to different emotions. The research findings presented by Cai, Liu, and Hao demonstrate that melancholy is a more simply and accurately recognized emotion than joy. [17]

Table 2 Description of Main Parameters of Electrocardiography (ECG) Signal [15]

Parameter	Duration, s	Amplitude, mV	Short Description
P	0.04	0.1–0.25	The cause of this wave is striatal contraction, also known as depolarization. A P wave that is larger than usual could be a sign of atria hypertrophy.
PR	0.12- 0.20	-	Measured from the beginning of the P wave to the beginning of the Q wave is the PR interval. It represents the duration of the atria's depolarization (contraction).
QRS Complex	0.08-0.12	-	Measured from the beginning of the Q wave to the conclusion of the S wave is the QRS complex. It is a measure of the ventricle's contraction (depolarization) time. Extended periods of time may indicate the presence of bundle branch blocks.
QT/ QTc	0.41	-	That's measured from the start of the Q wave to the end of the T wave. The QT interval represents the duration of the ventricles' contraction and relaxation. An inverse correlation exists between heart rate and QT/QTc duration.

The primary disadvantage of the 12-lead ECG is the massive amount of data it generates, particularly when it is used for extended periods of time.[15] The 12-lead ECG method is used by doctors because it gives them a three-dimensional view of the heart, which makes it possible to discover abnormalities that the 3-lead or 6-lead ECG approaches would miss. Sophisticated signal processing techniques are needed for the automatic emotion recognition of ECG applications. These approaches allow the relevant parameters to be extracted and detected from the raw signal. [16] Most QRS complex extraction methods operate under the premise that, since the signal structure is stable, defining P or R peaks at first is sufficient, and other parameters will be calculated using these peaks. Numerous studies focusing on various feature extraction techniques are currently accessible. Heart rate variability (HRV), with-in-beat analysis (WIB), empirical mode decomposition (EMD), FFT analysis, and several wavelet transformation techniques are a few of these techniques. A thorough summary of the several techniques for identifying emotions from ECG is provided below. [17] Schematic Illustration of Electrocardiography is shown in Figure 3. From the Table 3 An Analysis of Scientific Research Utilizing Electrocardiogram (ECG) To Identify and Assess Emotion.

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Table 3 An Analysis of Scientific Research Utilizing Electrocardiogram (ECG) To Identify and Assess Emotion

Aim	Emotion	Methods	Hardware & Software
Studies focus on the perception of emotions by service robots in their natural habitats.	Valence: high, neutral, or low. Feelings classified as negative arousal include sadness, wrath, contempt, and fear.	ECG	Wireless bio sensor RF-ECG[15]
This study proposes an ensemble learning strategy for creating a machine-learning model that can identify the four main emotions experienced by people.	Anger; sadness; joy; and Pleasure	ECG	Spiker-Shield Heart and Brain sensor[16]
development of a novel methodology for the assessment of interactive media.	Level of arousal	ECG, galvanic skin response (GSR), electromyography of the face, heart rate	Digital camera, ProComp Infiniti system and sensors, BioGraph Software from Thought Technologies. [17]
introduction of a novel AfC technique that can identify a subject's emotional state.	High/low valence and arousal	ECG, EEG	B-Alert X10 sensor (Advanced Brain Monitoring, Inc., USA) [15]
A novel approach to automatically locate P-QRS-T waves and extract features has been proposed.	Joy and sadness	ECG	BIOPAC System MP150 [17]

3.3 EMG

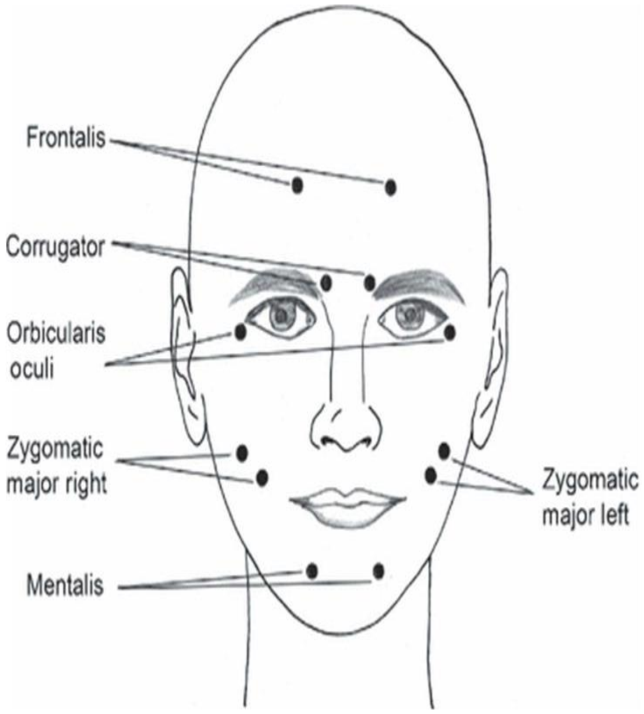

Figure 4 Facial Electromyography: Location of Electrodes

Electromyography is a technique for measuring and recording the electrical potential generated by muscle cells. The technique is used in the medical field to detect neuromuscular abnormalities and in the emotion detection industry to ascertain the connection between cognitive emotion and physiological reactions.[21] Because facial imitation is thought to have a role in the emotional response to different stimuli, most EMG-based research focuses on face expression analysis.[20] Ekman and Friesen (1978) originally put forth this idea when they observed connections between fundamental emotions, facial muscles, and the behaviors they elicited. Depending on the purpose of the study, the occipitofrontalis, corrugator supercilii, levator labii superioris, zygomaticus major, and orbicularis oculi are among the face muscles whose activity can be recorded. [19] Facial electromyography: location of electrodes is shown in Figure 4. From the Table 4 shows relationships between Facial Expressions and Emotions.

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Table 4 Relationships between Facial Expressions and Emotions

Emotion	Involved Muscles	Actions
Happiness	Orbicularis oculi, Zygomaticus major	dragging the corners of the mouth laterally and upward, closing the eyelids [18]
Surprise	Frontalis, Levator palpebrae superioris	eyebrows and upper eyelid raised [19]
Fear	Frontalis, Corrugator supercilii, Levator palpebrae superioris	bringing up the top eyelid, lowering the brows, and lifting them [20]
Anger	Corrugator supercilii, Levator palpebrae superioris, Orbicularis oculi	Raising the top eyelid, lowering the brows, and shutting the eyes [21]
Sadness	Frontalis, Corrugator supercilii, Depressor angulioris	bringing up, bringing down, and depressing the corners of the lips [22]
Disgust	Levator labii superioris, Levator labii superioris alaeque nasi	Wrinkling the skin around the nose and lifting the top lip [23]

3.4 EOG

Electrooculography is the process of measuring the corneo-retinal standing potential, which is found between the front and back of the human eye. The two primary applications are for ophthalmology diagnosis and monitoring eye movements. To measure eye movement, electrodes are often placed in pairs, either above or below the eye or to the left and right of the eye. If the eye moves from its center location toward either of the electrodes, an electrical potential reflecting the eye's position arises between them. The idea supporting EOG's common use as a supplementary technique is the same one that supports EMG and EOG implementations for emotion recognition. [25] When identifying emotions such as tension or surprise, EOG often involves the detection of eye-blinking. EOG may also be used to measure fatigue, sleepiness, and attention. EOG response signals may be compared to EMG response signals using touch and non-contact measurement techniques. Utilize the same tools and EMG electrodes to quantify contact as appropriate. Measurements without touch may be made using infrared camera infrared oculography (IROG) and video camera video oculography systems (VOG). [24] An EOG signal is timescale correlated with EMG, despite the signal amplitude being much Less and a noticeable lag between the vertical and horizontal EOG. The level of sophistication of the EOG signal processing depends on the measuring method and the quantity of information that can be extracted from the signal. Identifying blinks, which are represented by peaks in the time-domain data derived from electrode recordings, is the most basic situation. [27] Eye position requires careful recording of baseline and aware eye movements to establish a link between voltage variation and eye location. Time-dependent feature extraction will require some frequency domain analysis, such as FFT or Wavelet transformation. [26]

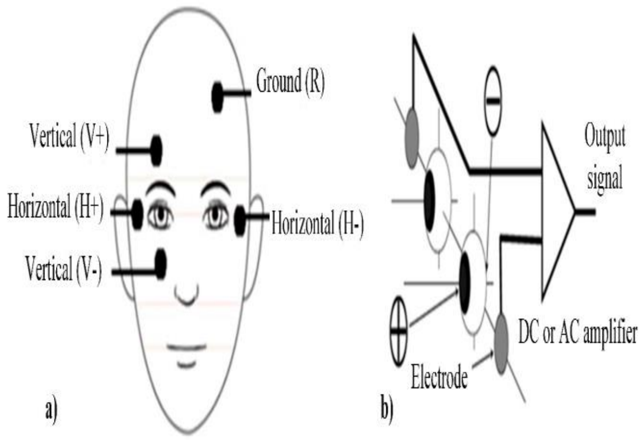

Figure 5 Electrode Insertion Technique (A) And Measuring Principle (B) Are the Fundamental Concepts of Electrooculography (Eog)

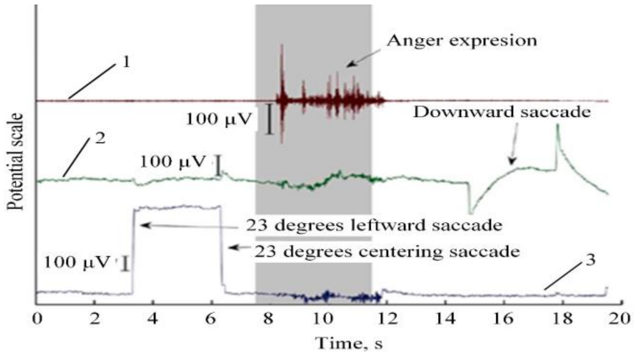

Figure 6 Eog and EMG Signal Comparisons during Three Distinct, Consecutive Actions: 1 – Corrugator Supercilii EMG; 2 – Vertical Eog; And 3 – Horizontal Eog

This technique uses non-contact measurement through analysis using several vision-based object recognition and tracking algorithms. Non-contact measurements are a benefit of EOG, despite its lower sensitivity compared to EMG (which can detect a limited range of fundamental emotions). EOG and EMG have similar disadvantages. When using this approach in a real office situation, unrelated external elements like bright sunshine, background noise, or human intervention may cause test eye movement. [28] Electrode Insertion Technique (A) And Measuring Principle (B) the Fundamental Concepts of Electrooculography (Eog) are shown in Figure 4.

Table 5 EOG Review of Scientific Research on Emotions Recognition and Evaluation

Aim	Emotions	Methods	Hardware & Software
Give an innovative method for recognizing emotions (ASFM).	Positive, neutral, negative emotions	EMG, EOG	An offline experiment was conducted with datasets from SEED. [24]
Provide a cutting-edge method for an E-Healthcare system that uses sensors.	Positive, neutral, negative emotions	EOG, IROG	The infrared camera on the Neuroscan system (Compumedics Neuroscan, Charlotte, NC, USA) has a resolution of 1280 x 720. [25]
outlined a novel method for identifying emotions via stimulated EOG data.	Positive, neutral, negative emotions	EOG	Personalized EOG data collection apparatus, ABIAgCl electrodes [26]
An emotion identification system based on human eye movement is presented by the suggested system.	Happy, sad, angry, afraid, pleasant	EOG	Eye trackers based on videos [27]
Demonstrate a fresh approach to identifying human activity: eye movement analysis.	Arousal level	EOG	Twente Medical Systems International (TMSI) offers the Mobi commercial system. [28]

The Table 5 above displays the scientific studies that use EOG technology for emotion identification and intensity measurement. Most techniques make a distinction between positive and negative mood levels. The measurement of emotional intensity level remains unclear and inadequately described in many instances. Video-based systems are very promising for deployment due to their capacity to do online analysis of current video footage and the widespread availability of technology. [26] Eog and EMG Signal Comparisons during Three Distinct, Consecutive Actions: 1 – Corrugator Supercilii EMG; 2 – Vertical Eog; And 3 – Horizontal Eog are shown in Figure 5.

Conclusion

Emotion identification is a strong and incredibly useful technique that is vital for tailoring advertising content for marketing or educational reasons when it comes to predicting human emotional states and behavior. Furthermore, the use of emotion assessment and identification broadens its relevance to the creation of additional systems for human-machine interaction. Uncertainties remain in the choice of measurement

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and data processing techniques, despite the long-established links between particular emotions and related physiological responses in humans. In addition to a wide range of data analysis techniques targeted at real-world applications, the area primarily uses eight widely-used methodologies that are based on various parameter measurements. After the review from many articles, Affective Emotion Recognition (AEE) techniques were categorized as a result of this thorough review. In order to improve result dependability, the study provides a brief summary of popular emotion identification techniques. It also presents AEE approaches from an engineering point of view, evaluating their stability, sensitivity, and dependability. In the future, a possible path entails combining these techniques in a way that works well together and adding machine learning to data analysis. From advertising and marketing to industrial engineering applications, this dynamic union has the potential to bring about advances in a variety of disciplines.

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