Emotion Recognition of Humans using modern technology of AI: A Survey

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Emotion Recognition of Humans using modern technology of AI: A Survey

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***Abstract*— This comprehensive investigation and evaluation of the subject matter of emotion recognition is presented, focusing on the broader implications for society at large. The study utilizes a thorough analysis of scholarly literature and practical observations to establish a theoretical framework that facilitates comprehension of the topic under investigation. The findings have considerable implications for future investigations and pragmatic applications. Emotion recognition holds immense importance in diverse domains such as human-computer interaction and healthcare. The analysis of techniques used for emotional recognition includes facial expression assessment, speech patterns analysis, physiological signal interpretation, music perception, and written expression evaluation. The study presents a comprehensive overview of research methodologies commonly used in emotion recognition, discussing datasets, feature extraction techniques, and classification algorithms. The analysis of challenges and limitations pertaining to emotion recognition systems, including privacy concerns, is also discussed. Performance evaluation is analyzed through various methods, including machine assessment and self-report. The significance of continued investigation within the domains encompassing data integration across diverse modalities, the creation of robust classification algorithms, and the exploration of the intricate connection between the brain and affective states is underscored.**

Keywords— Emotion, Recognition, Human, Technology, Methods, Dataset.

I. INTRODUCTION

The capacity of humans to identify emotion exhibits a tremendous degree of variation. It's important to keep in mind there are various ways to obtain ground truth, or reality of actual feeling, when learning about automated recognition of emotions [1]. Personal health, industry, and smart homes are three areas where human-computer interaction is being used more and more. Having a perfect emotional interaction can help human-computer communication [2]. Emotional interactions are advantageous for various applications because they positively impact the cognitive functions of a person's brain, including memory, learning, problem-solving, and perception [3]. It may also be applicable to contemporary healthcare, particularly when dealing with patients who are stressed out or depressed [4].

Furthermore, rehabilitation software that guides patients through their exercise while responding to their emotional states would be immensely motivating and may hasten their recovery [5]. Different emotion recognition systems are appropriate for various applications, depending on the field of application [6]. Accurate emotion recognition is often enhanced by combining the examination of many multimodal human expressions, such as physiology, texts, video, and audio [7]. Several emotion types are discovered by merging data from speech, body movement, and facial expressions. [8]. The so-called emotional Internet is thought to have emerged because of technology [9]. Broadly speaking, hybrid approaches, statistical methods, and knowledge-based strategies can be used to characterize existing methodologies in emotion detection for identifying emotion types [10][11].

The first section of this research examines the idea of emotional perception and its objectives. The research is organized into five primary elements or divisions. The second section discusses the subject's primary types, or types, and provides a brief explanation of each type. The third portion discusses the most well-known data sets previously used by researchers. The last fifth section is the studies that were a crucial source for the creation and evaluation of the paper, and the fourth section is the methodologies utilized by researchers.

II. EMOTION RECOGNITION OVERVIEW

In addition to intuition, emotions also influence most of the choices we make, having a direct impact on how we live our daily lives [12]. The goal is to align people's perceptions of their feelings with those feelings themselves. One possible source is, "What would most people say the person feels" The "truth" in this situation might not match how the person feels, but it might match how most people would describe the person's appearance or emotions [13]. For instance, if someone put on a wide smile while feeling depressed, most people would assume they were cheerful. Even though an automated approach does not measure how participants feel, it can be said to be accurate if it produces comparable outcomes to an audience of observers. Asking the subject what they are feeling can provide additional "truth" about them [14].

This is effective if the individual is motivated to share their inner state, has good knowledge of it, and is able to articulate it in words or statistics [15]. Some individuals, however, suffer from alexithymia, which impairs their ability to appropriately express their emotions in both words and figures. In general, determining the cause of sentiments can be difficult, rely on the criteria used, and typically require retaining a degree of uncertainty [16]. From this Point of view, the importance of (Human Emotion Recognition) was highlighted, and many studies appeared on it, starting to shed light on the importance of the topic [17][18].

A. Fundamentals of Emotion Recognition

Emotion recognition involves the discernment and comprehension of human emotions by scrutinizing a range of indicators such as facial expressions, physiological signals, speech signals, body movement, and EEG signals. Theories pertaining to the recognition and comprehension of emotions elucidate the mechanisms underlying the processes by which individuals identify and comprehend emotional states. Various theoretical frameworks have been proposed to understand the nature of emotions. One prominent theory is the basic emotions theory, which posits the existence of universal emotions that transcend cultural boundaries. Another framework, known as the dimensional theory, categorizes emotions based on the dimensions of valence (positive or negative) and arousal (low or high intensity).

A third perspective, known as the appraisal theory, establishes a relationship between an individual's emotions and their evaluation of a given situation. These theories provide valuable insights into the complexities and mechanisms underlying emotional experiences. Emotion recognition can be accomplished utilizing various methodologies, encompassing deep learning and shallow machine learning techniques. Deep learning utilizes neural networks to facilitate the extraction of distinctive features from data, whereas shallow machine learning employs conventional algorithms such as support vector machines, k-nearest neighbors, and naive Bayes [19].

The application of emotion recognition has proven valuable in various domains, including human-computer interaction, affective computing, virtual reality, robotics, and behavior modelling. Various approaches for assessing emotion recognition include recognizing facial expressions, detecting physiological signals, analyzing speech signals, evaluating text semantics, and analyzing body movement [20].

Emotion recognition systems employ datasets containing emotional data, including JAFFE, CK+, and Berlin Emotional Database, as well as self-generated databases [21].

Various feature extraction techniques, including wavelet transform, nonlinear dynamics, and analysis of variance, are frequently employed in the task of emotion recognition within academic research and scholarly investigations. Various classification algorithms, such as Support Vector Machines (SVM), k-Nearest Neighbors (k-NN), Naive Bayes, and random forest, are frequently employed in the classification and recognition of emotions. These algorithms are applied based on the extraction of relevant features. The assessment of performance bears immense significance for emotion recognition systems. Performance evaluation metrics such as accuracy, precision, recall, and F1 score are utilized to assess the effectiveness and efficiency of the systems being evaluated. Future research in the field of emotion recognition entails the pursuit of investigating the potential of multi-modal data fusion, the advancement of robust classification algorithms, and the exploration of the intricate correlation existing between specific brain areas and the genuine experience of emotions [22][23].

B. Emotion Recognition Challenges and Limitations

One challenge in emotion recognition is the variability and subjectivity of feelings, as they can be expressed uniquely by different people and influenced by social and contextual factors.

1) The need for standardized datasets for emotion recognition calculations makes it difficult to compare and benchmark different approaches.
2) Emotion Recognition frameworks may face difficulties in identifying and translating subtle or mixed feelings, as emotions are complex and nuanced. The proximity of noise or obstacles in the input data can pose challenges for emotion recognition algorithms. Restricting accessible labelled information for building emotion recognition models can be limiting, as collecting, and annotating extensive emotion datasets can be time-consuming and resource intensive.
3) Recognition frameworks may struggle to generalize across individuals and populations due to cultural and individual variations in expressing and recognizing emotions.
4) Protection and moral concerns are important in emotion recognition, as the use of facial or physiological data for analysis raises issues about privacy and consent.
5) Real-time handling and computational proficiency are obstacles for Emotion Recognition frameworks, as analyzing complex data streams in real-time may need substantial computational resources [24 – 28].

III. EMOTION RECOGNITION METHODS

A. Traditional Methods

Traditional methods of emotion recognition are associated with procedures used before the advent of machine learning and deep learning techniques [29]. Traditional techniques include:

1. Music Emotion Recognition (MER): is a branch of study that automatically identifies and classifies emotions expressed via music. It entails the creation of computer algorithms and strategies for analyzing and interpreting musical elements to deduce the emotional content and affective aspects contained in a piece of music. Music Emotion Recognition's ultimate objective is to record and comprehend the

emotional experiences that listeners may have when engaging with music [30].

2. Written expressions relate to the emotional content and feelings communicated via written language. It entails examining the text to discover and comprehend the writer's emotions, attitudes, and subjective moods. Happiness, sorrow, wrath, fear, surprise, and other subtle emotional states may all be expressed in writing [31].

3. Facial expression analysis: This entails evaluating facial characteristics and expressions to infer feelings. It often uses hand-designed facial work modules as well as rule-based systems [32].

4. Speech analysis: the process of studying speech signals such as pitch and duration to discover emotional clues. Techniques such as analysis of audio presentation and extraction of auditory features may be used [33].

5. Analyze physiological signals: This entails monitoring physiological signals such as heart rate, skin conductance, and electroencephalography (EEG) to infer emotional states. Focuses on the physiological changes caused by different emotions [34].

Traditional techniques often rely on manual characteristics and rule-based systems, which may be limited in their ability to capture the richness and diversity of human emotions. Because emotions are expressed and perceived differently between people and cultures, these methodologies may struggle with generalization to other individuals and cultural situations.

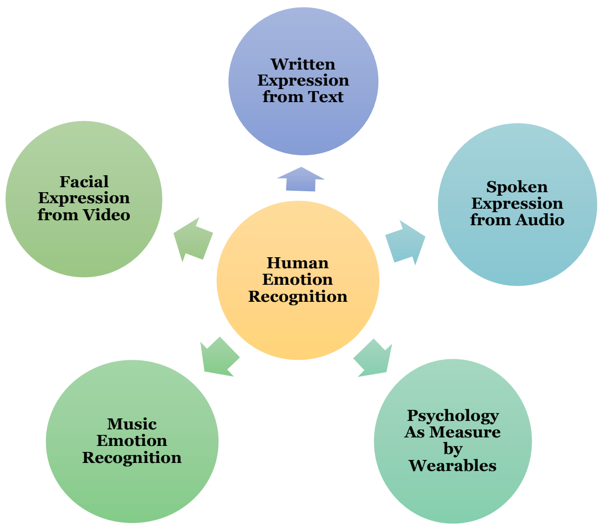

Figure 1: **Types of Human Emotion Recognition.**

B. *Modern AI Methods*

Machine learning and deep learning algorithms have been employed to facilitate emotion recognition, thereby enabling the automatic identification and classification of human emotions. This is accomplished by leveraging diverse input modalities such as facial expressions, speech patterns, and physiological signals.

The objective underlying the utilization of algorithms is to enhance the precision and efficacy of emotion recognition systems, thereby facilitating their application in diverse domains including healthcare assessment, human-computer interaction, and robotics.

Nevertheless, a multitude of challenges and issues are intertwined with these algorithms. One primary concern pertains to the accessibility and calibre of labeled training data, given that the process of gathering and annotating extensive emotion datasets can be arduous and prone to subjectivity.

This issue pertains to the difficulty surrounding the extrapolation of trained models to varying individuals and environments. The manifestation of emotions can exhibit significant diversity across individuals, and the recognition thereof is subject to contextual influences.

The limitations inherent in machine learning and deep learning algorithms in the context of emotion recognition encompass the requisite utilization of substantial volumes of training data, the propensity for overfitting, and the interpretability challenges pertaining to the acquired models. Deep learning algorithms possess a notorious reputation for their intrinsic opaqueness, rendering the comprehension of the principal decision-making course a challenging endeavour [35 – 41].

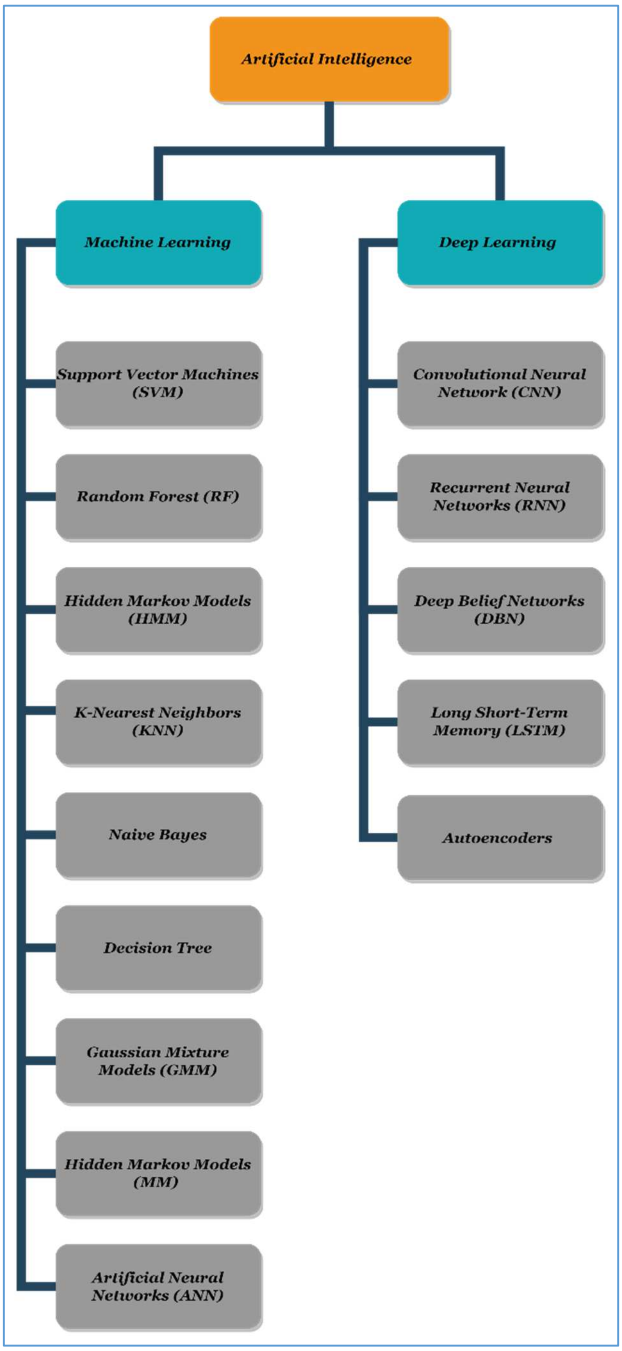

Figure 2: ML and DL technologies used for Emotion Recognition

The following point describes the above figure: -

I. *Machine learning Techniques*

1. Support Vector Machine (SVM): is a machine learning algorithm that divides data points into distinct classes, maximizing the margin between these classes. It is widely used in fields like image classification, text categorization, bioinformatics, and sentiment analysis. SVM's versatility in handling linear and nonlinear data makes it a valuable tool for classification purposes. It accurately classifies unfamiliar data by identifying the best decision boundary using patterns learned from training data. SVM's versatility makes it a valuable tool in various fields [42]
2. Random Forest (RF): is a machine learning technique that uses decision trees to make predictions for classification and regression tasks. It aims to enhance accuracy by addressing overfitting and effectively managing datasets with large dimensions, enhancing the overall effectiveness of machine learning [43].
3. Hidden Markov Models (HMM): are statistical models that capture temporal changes and shifts between different emotional states. They represent observed data points as unknown states associated with specific emotions, allowing for the analysis of facial expressions, speech signals, and physiological signals to determine hidden emotional states. HMMs are valuable tools for understanding emotions' dynamic nature and capturing transitions between emotional states. They are suitable for examining sequential data and deducing emotional fluctuations in specific contexts or interactions. Researchers aim to use HMMs to enhance the precision and comprehension of emotional dynamics, potentially impacting fields like affective computing, human-computer interaction, and psychological research [44].
4. K-Nearest Neighbor (KNN): is a simple yet efficient method of categorization that classifies a sample based on its proximity to nearby samples in the feature space. It recognizes that items with similar attributes typically fall into the same category. The algorithm uses a user-defined parameter k to determine the class of a test sample based on its k closest neighbors. KNN is versatile and widely used in various fields, such as image identification, textual categorization, suggestion systems, and pattern recognition, due to its simplicity and effectiveness [45]
5. Naïve Bayes: is a probabilistic classifier based on Bayes' theorem that classifies instances into predefined categories by calculating the probability of each class given input features. It is widely used in various domains, including text classification, spam filtering, sentiment analysis, recommendation systems, and medical diagnosis. Naive Bayes is particularly effective in natural language processing tasks, where discrete or categorical features are often used. It has applications in analyzing email content, determining sentiment polarity in customer reviews, and categorizing documents into different topics. Its simplicity and efficiency make it a popular choice for situations where data exhibits conditional independence and the classifier needs to be trained and deployed quickly [46].
6. Decision Tree: is a machine learning algorithm that creates a tree-like model for making decisions or predictions based on labeled data. It is widely used in classification and regression tasks, and has proven effective in various fields like healthcare, finance, marketing, and customer relationship management.

Decision Tree models can classify diseases, predict customer behavior, analyze financial data, and make informed business decisions. Its versatility and interpretability make it a valuable tool in data analysis and decision-making processes across various domains [47].

7. Gaussian Mixture Model (GMM): represents a dataset's probability distribution as a mixture of multiple Gaussian distributions, enabling applications in pattern recognition, data clustering, and density estimation. They capture variability and characteristics of speech patterns, partition data points based on probability density, and estimate density functions [48]
8. Artificial Neural Network (ANN): develop computational models inspired by human brain structure, performing tasks like pattern recognition, classification, regression, and decision-making. They learn from input data and adapt parameters through training, enabling accurate predictions and solutions in various fields [49].

II. Deep Learning Techniques

1. Convolutional Neural Network (CNN): use deep learning techniques for efficient image analysis and recognition, processing visual data and extracting meaningful features. They are used in various domains like computer vision, autonomous driving, medical imaging, surveillance, and natural language processing, revolutionizing image analysis tasks and advancing understanding of visual information in diverse fields [50].
2. Recurrent Neural Networks (RNN): are artificial neural networks used in sequence modeling and analysis to capture temporal dependencies and sequential information in data. They excel in tasks like natural language processing, speech recognition, and handwriting recognition, capturing context and dependencies between words or characters. RNNs are also employed in time series analysis for accurate predictions, weather forecasting, and anomaly detection. Overall, RNNs provide solutions for tasks requiring sequential data analysis and modeling across multiple disciplines [51].
3. Deep Belief Networks (DBN): are deep learning models that learn hierarchical representations of data, capturing complex patterns and dependencies in high-dimensional data. They are used in various domains, including computer vision, natural language processing, speech recognition, and bioinformatics. DBNs are used for image classification, object detection, and image generation, while RNNs excel in sequential data analysis, time series analysis, and handwriting recognition. Both domains provide solutions for tasks requiring sequential data analysis and modeling [52].
4. Long Short – Term Memory (LSTM): a recurrent neural network architecture designed to handle sequential data with long-term dependencies. It captures and retains important information over extended time intervals, enabling it to model and predict sequences effectively. LSTM is particularly effective in natural language processing tasks like translation, sentiment analysis, and speech recognition, as well as time series forecasting tasks like stock market prediction and weather forecasting. It also excels in image and video analysis, improving understanding and interpretation of visual sequences by considering temporal dependencies between frames or regions [53].
5. Autoencoders: are neural networks that learn efficient representations of input data by compressing it into a lower-dimensional latent space and reconstructing the original data. They are used in fields like image processing, natural language processing, and anomaly detection, enabling tasks like image denoising, compression, and generation. Autoencoders are versatile and powerful in various domains, facilitating tasks like data representation learning, dimensionality reduction, and generative modelling [54].

IV. Previous Studies

A. Previous Methodologies

Previous researchers reviewed many studies on the topic (Recognition of Human Emotion) in various fields and types. However, this research was selected on two bases: the amount of useful scientific information that serves new researchers in getting to know the subject beneficially. The second basis is that it has a high quotation from It is accepted by researchers and considered a review-type article that briefly reviews concepts [15][25]. The following table (4) summarizes the studies.

Tabel 1: Summarized studies.

Related Studies / Year	Author	Scoop	Aim
[55] 2010	Ykim. et al.	MUSIC	Explores music's emotion detection using language of emotion.
[4] 2012	S. Koolagudi & K. Sreenivasa Rao	Speech	International data sets for speaker-based emotion recognition.
[56] 2019	E. Maria. et al.	Physiological Signal nalysis	Summary of techniques for identifying emotions and comparing their function using Physiological Signal Analysis research.
[57] 2020	S. Saganowski. et al.	Wearables	Discover how feelings are affected by omnipresent

Related Studies / Year	Author	Scoop	Aim
			computing in our daily lives. Critical research steps were identified, and key field constraints and issues were explored using a systematic literature review.
[58] 2022	A. Dzedzickis.et al	All Type	Emotion assessment aids goal-setting, and alternative choices in IoT and affective computing systems.

B. The Dataset Used in human emotion recognition

Many studies have appeared around Human Emotion Recognition, using different methods of artificial intelligence and different methods. The following is a table (2) that summarizes essential global data sets used and the scope of their use.

Table 2: **Summarized of the Dataset in Human Emotion Recognition**

Related Studies	Dataset Name	Domain
[59]	BED	EEG recordings provide emotion annotations for images, valence and arousal information, and stimuli for developing EEG-based biometrics, including cognitive activities and SSVEP.
[60]	UIT-VSMEC	is a typical Vietnamese Social Media Emotion Corpus (UIT-VSMEC) that has 6,927 words that have been human-annotated with six emotion classifications. It is a low-resource language that helps research on emotion recognition in Natural Language Processing (NLP).
[61]	MuSe	displays audiovisual recordings of real-world interactions between objects and humans. Along with discrete and continuous emotions annotation for trustworthiness, arousal, and valence, it includes speech subjects that are useful for multisensory assessment of mood and emotion identification.
[62]	MELD	consists of a collection of multiparty conversations where every word has a feeling and emotion assigned to it. MELD. Evaluation of feelings and multimodal emotion recognition are suitable for conversations because they are supplied in video format. Talking about dialogue systems, multimodal sentiment analysis, and emotion identification is helpful while using MELD.
[63]	DREAMER	Electrocardiography (ECG) recordings and delivers electroencephalography (EEG), as well as emotion annotations for viewers of film clips in terms of dominance, arousal, and valence.
[64]	DEEP	delivers electrocardiography (ECG), electroencephalography (EEG), facial video records, and emotion annotations for viewers of film clips in terms of valence, arousal, and dominance.

C. Evaluation Methods

According to the fundamental methodologies employed for emotion recognition, the evaluation methods provided in the literature can be separated into two primary sets [65].

1. Machine assessment methods are based on measurements of various human body parameters.
2. approaches for self-repair based on feelings self-evaluation by completing different surveys.
3. Additionally, there are many instances where many techniques are used simultaneously to improve the accuracy of results.

To evaluate emotion, it is possible to look at each of the five main elements of emotion: behavioural propensities, subjective feelings, motor manifestations, and physiological reactions. Only the first four, however, may be evaluated effortlessly and convey a user's emotional condition without interfering with the conversation. Subjective emotions are typically only assessed through self-assessment approaches [66]. Automatic emotion recognition is often carried out by evaluating changes in a variety of bodily characteristics or electrical impulses in the nervous system. Electroencephalography, measurements of skin resistance, eye activity, heart rate, blood pressure, and motion analysis are the most often used methods. The following Point summarizes the methods [67].

1. **Respiration Rate Analysis (RR)**[65]**:** With excellent precision, respiratory monitoring data can be used to infer emotional states. Breathing in and out quickly and deeply are often influenced by human emotion. For instance, shallow breathing denotes stress while deep breathing denotes excitement, which is frequently accompanied by the feelings of happiness, rage, or terror. Shallow breathing suggests a calm or negative state, while deep breathing shows relaxation. For instance, enthusiasm can produce 40–50 breaths per minute, whereas tranquillity typically results in 20–40.

2. **Electroencephalography (EEG)** [68]**:** A non-invasive electrophysiological method for capturing electrical activity generated by the human brain is the EEG. Typically, EEG signals are recorded using a special tool called an electroencephalogram. The major components of this apparatus are specific metal plate electrodes that must be applied to a person's head; alternate needle electrodes may also be used in rare circumstances to apply the electrodes directly to the scalp.
3. **Electrocardiography (ECG)** [69]**:** The heart is the most important organ in the human body, and ECG, one of the most effective diagnostic techniques in medicine, is frequently used to evaluate the heart's performance. The common technique for noninvasive real-time assessment of the heart's electrical activity is the electrocardiogram (ECG), a physiological signal. Furthermore, since heart activity is connected to the human central system ECG, it is helpful in assessing the heart's activity and can be applied for emotion recognition.
4. **Galvanic Skin Response (GSR)** [70]**:** Electrodermal activity (EDA), skin conductance (SC), and galvanic skin response (GSR) are other names for the continuous measuring of the electrical characteristics of human skin. The key variable in this method is frequent skin conductions. Since the traditional idea holds that the electrical properties of the skin depend on the fluctuation of sweat reaction, which primarily reflects changes in the activity of the sympathetic nervous system, these properties are not under the conscious control of the human being. It has been demonstrated that changes in skin conductance occur in response to several of the sympathetic nervous system's output signals. The surface of the hand's fingers and soles become noticeably sweatier in response to emotional changes. Human skin's electrical resistance changes as a result of sweat reaction, which changes the amount of salt in the skin. More active sweat glands produce moisture towards the direction of the skin's surface. This alters the ratio of negative to positive ions and alters how readily electrical current travel through the skin.
5. **Electromyogram (EMG)** [71]**:** An electromyo-graphy technique can be used to monitor and record the electrical potential generated by muscle cells. In the realm of emotion detection and in medicine, this test is used to determine the link between mental feelings and physiological reactions. Because it is believed that facial mimicry plays a role in the emotional response to different stimuli, the majority of EMG-based research focuses on examining facial expressions. The following Figure (2) summarizes the above Point.
6. **Gesture Analysis (GA), Body Posture (BP), and Facial Expressions (FE),** [72]**:** The use of emotion identification techniques that examine facial expressions, body language, and gestures has seen a considerable rise in popularity over the past ten years. Recent advancements in vision systems for computers may help to explain this increase in interest. Methods for identifying emotions are based on the examination of facial expressions, body postures, and gestures, much like EMG. According to these methods, bodily movements and postures can be utilized to recognize the same basic emotions and play a part in how people react to them. The idea is that facial expressions of basic emotions, like sadness or happiness, may also be expressed through body language. Furthermore, people from quite diverse cultures utilize the same muscles to communicate their feelings.

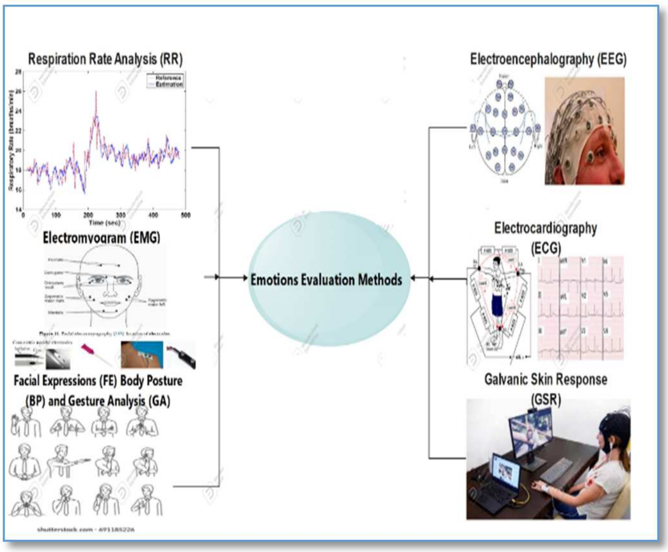

Figure 3**: Emotions Evaluation Methods.**

V. Conclusion

To summarize, the recognition of emotions assumes a paramount significance within the domains of human-computer interaction, healthcare, as well as other multifarious fields wherein comprehension and appropriate response to human emotions are of pivotal importance. This survey has presented a comprehensive overview of emotion recognition, encompassing both conventional and contemporary methodologies.

This study delved into the essential aspects of emotion recognition, encompassing diverse theoretical frameworks, as well as emphasizing the importance of integrating multimodal data fusion. This article shed light on the diverse methodologies utilized in the realm of emotion recognition, encompassing facial expression analysis, speech analysis, physiological signal analysis, music emotion recognition, and analysis of written expressions. The study addressed the various constraints and obstacles related to the detection of emotions, encompassing elements such as subjectivity, data accessibility, and apprehensions regarding privacy.

Additionally, the survey examined prior research investigations and approaches employed in emotion recognition, highlighting the significance of trustworthy datasets and assessment techniques. The highlighted research underscores the importance of employing machine learning and deep learning methodologies to enhance the accuracy of emotion recognition. The present study focused on exploring the application of various specialized methodologies, including respiratory rate analysis, gesture analysis, electroencephalography, galvanic skin response, electrocardiography, and electromyography, in the domain of emotion recognition.

In summation, this survey has furnished researchers and practitioners with an extensive comprehension of the various techniques, obstacles, and prospective avenues pertaining to the detection of emotions. Further investigation in this discipline ought to center on mitigating the constraints and difficulties. These comprise the establishment of standardized datasets, resilient classification algorithms, as well as the exploration of the fusion of multi-modal data. The continued progression of emotion recognition systems will facilitate enhanced human-computer interaction, personalized healthcare, and improved user experiences across diverse applications.

In conclusion, the implementation of contemporary AI technologies for emotive discernment exhibits promising prospects for revolutionizing human-computer interaction and exerting profound influence across diverse domains. The precise identification and comprehension of human emotions can allow systems to offer enhanced personalized experiences, bolster mental health and well-being, and foster improved human-machine communication at large.

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