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Advances and Challenges in Human Emotion Recognition Systems: A Comprehensive Review

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Abstract

It's really difficult to tell what a person is feeling simply by glancing at their face or their behaviour. A basic human quality, the ability to decipher nonverbal clues from body language and facial expressions is essential for social and everyday communication. People use voice, gestures, and emotions to communicate with one another. Thus, there is a high need in various industries for systems that can identify the same. In terms of artificial intelligence, if a computer can recognize and interpret human emotions, it will be much easier for it to engage with people. A number of methods have been proposed in the past for evaluating human emotion. The traditional techniques essentially use visual and auditory cues to simulate human emotional reactions, including speech, body language, and facial expressions. Characterizing emotional states by physiological reactions has garnered more attention in recent times. Rapid advances in technology should make it possible for complex and perceptive HCI (human-computer interaction) systems to consider emotional states of humans during interactions, promoting empathy between humans and machines. Intelligent Human-Computer Interaction (HCI) applications, including virtual reality, video games, and educational systems, need the ability to recognize emotions. In the medical domain, feelings that people identify with each other could be a sign of specific functional issues, such as severe depression. The primary goal of this review is to examine alternative methods for identifying emotions using five distinct approaches, rank and explain the best methods along with their benefits, and provide

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commentary. In an effort to improve human-computer interactions, this article intends to be a resource for all academics and students researching in the field of emotion detection.

Keywords: Emotion Recognition, Machine Learning, Signal processing, EEG, ECG, Facial Recognition, Speech Recognition, Brain-Control Interface, Biosensor.

1. Introduction

When it comes to emotion detection, physiological signs have historically received less attention than audiovisual emotion mediums like voice or facial expression. It is very difficult to map precise physiological patterns for the emotional reactions. The physiological patterns of emotions may vary greatly depending on the users and situations since emotions are influenced by time, place, culture, and individual factors. The potential for physiological cues to serve as reliable medium for emotion identification is examined in this study. Respiratory changes, skin conductivity, electromyogram, and electrocardiogram were all measured using four-channel biosensors. In the days to come, this will improve the HCI and allow for improved emotional detection [1].

Electroencephalograph (EEG) recordings of ongoing brain activity may be used to identify connections between emotional states and brain activity. Four different emotional states (joy, rage, sorrow, and pleasure) were classified using a support vector machine. It has been shown that a set of characteristics taken from the frontal and parietal lobes provide discriminative information related to emotion processing that is comparatively unaffected by subject variability [2].

A human emotion identification method based on automated ECG analysis is presented in this research. Physiological ECG features are extracted from the time- and frequency-domain and nonlinearly analysed ECG signals in order to identify emotion-relevant features and associate them with emotional states. The real time emotion detection system is devised in this study using a single ECG channel to categorize four different kinds of emotions. with the help of data gathered from 61 healthy individuals, [3].

Humans have historically had no trouble detecting emotions from facial expressions, but computer algorithms find it difficult to do the same job. Emotion detection from images has become feasible with the recent advances in machine learning and computer vision. Five basic face expression classes—angry, sad, joyful, frightened, and surprised—are the subject of the present text [4].

Accurately identifying facial emotions from input images is becoming more and more common because of the recent technological improvements. These appearance-based techniques have the potential to yield a lot of ground truth label information because of crowdsourcing platforms. The most recent architecture for deep convolutional neural networks (DCNNs) and the evaluation of four distinct training approaches using crowdsourced labels to identify emotions is discussed [5].

An emotion detection system's dependability is significantly impacted by features that are taken from the speech signal. The features that are obtained from prosody, spectral envelope, and voice quality are analyzed in this work along with their emotional discrimination capabilities. A relatively new area of study in the realm of human-computer interaction (HCI) is automatic speech emotion recognition. An interface for human-computer communication that is more natural has become necessary since computers have become an essential part of our lives. Speech is seen as a effective form of communicating the emotional and intention-based communication. The ability to identify human emotion from voice data has been the subject of study in recent years. Applications of speech smotion recognition include learning environments, instructional software, intelligent toys, deception detection, psychiatric diagnosis, and identifying an operator's emotional state during phone interactions in customer service centers [8-11].

EEG stands for electroencephalogram, which is the measuring of human scalp electrical activity using electrodes. False facial expressions are known to be used by certain persons to conceal their true feelings. The recording of the human brain's electric field, or electroencephalogram (EEG) data, is one of these sources. By analysing brain waves, this study aims to identify or detect human emotion. A further goal of the study is to create computer programs that can swiftly and accurately identify human emotions. With the use of brain signals, this research aims to design, build, and test an intelligent and interactive emotion detection system that can be used by both healthy and unhealthy users to identify and classify emotions via eye movement [12-15].

The base objective of this review article is to:

- Study five different methods employed in detection and recognition of human emotions.
- Compare and explicate the results found including the advantages, disadvantages in a tabular manner to help the budding researchers interested in the field of emotion recognition.

A range of methods were used in the selection of the research publications related to emotion recognition. In the context of non-invasive screening techniques, terms such as "emotion recognition + EEG," "emotion + ECG," "emotion + facial recognition," " emotion recognition + speech" and others were used. The fact that almost all of the articles were chosen from IEEE explore, MDPI, and Springer journals attests to the quality of the works. The aforementioned keywords have been frequently used in Google Scholar searches for manuscripts.

2. Methodology

The five methods for recognizing emotions using different technology are explained in this section. By grouping the articles according to distinct criteria, it becomes simple to comprehend the fundamental interface and apply it to one's own work.

2.1 Emotion Recognition based on Physiological Changes

The main goal of this research is to identify emotional signals in several physiological indicators. To identify human emotions via physiological changes, precise sensors that measure things like

- skin conductance,
- heart rate, and
- face temperature are used.

Sturdy signal processing, including feature extraction, and records unique emotional trends. Sophisticated machine learning models that have been trained on a variety of datasets improve classification accuracy are used. Nuanced emotion detection is facilitated by context-aware analysis and real-time processing, and responsible implementation is ensured by ethical concerns such as privacy protections. The electromyogram, skin conductivity, electrocardiogram, and respiration were the physiological signals recorded using a Pro-comp Infiniti fitted with four biosensors as shown in Figure 1. The basic block diagram of the system based on physiological changes is depicted in Figure 2 [1].

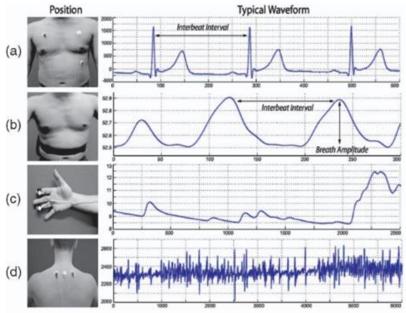

Figure 1. Position and Typical Waveforms obtained from the Biosensors [1].

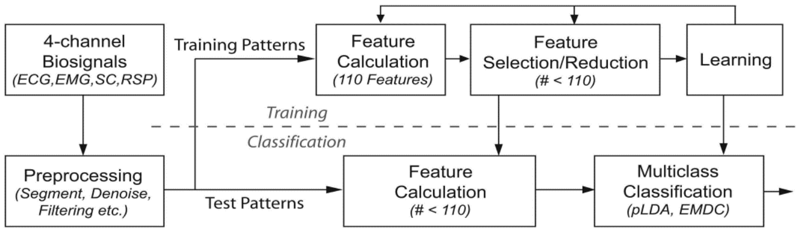

Figure 2. Block Diagram of the Emotion Recognition System using Physiological Changes [1].

2.2 Emotion Recognition using EEG

In human emotion recognition using EEG, key features include precise electrode placement for data accuracy, robust signal preprocessing to minimize artifacts, and feature extraction capturing neural patterns. Ethical considerations, such as privacy protection, are essential for responsible implementation. Electrodes positioned in close proximity to the parietal and frontal lobes were the main source of the highlighted characteristics. The picture depicting the international 10-20 system for placement of EEG electrodes is shown in Figure 3. Before any significant and evident motion artifacts could be seen, the collected EEG data were preprocessed to provide artifact-free data. Multilayer perceptron (MLP) and support vector machines (SVM) were the two classifiers used in this work to sort EEG data. To put it briefly, the pairs of electrodes located in front and parietal regions were the most influential in shaping mental states. Four emotional states are possible to distinguish by combining SVM with EEG spectral estimates [2]. Using convolutional neural networks (CNNs), a new deep learning technique for EEG-based emotion identification is presented in this research. Apply certain brain connection components that haven't been used in previous deep learning model research. choose CNNs since its convolutional layers' two-dimensional filters allow them to take into account spatial information. In this study, three CNN models—Non-Negotiable Neural Networks, CNN-2, CNN-5, and CNN-10—were used [13]. The frequency classification of EEG bands is shown in Table 1. The basic information on the specification of the EEG electrode kit is explicated in Table 2.

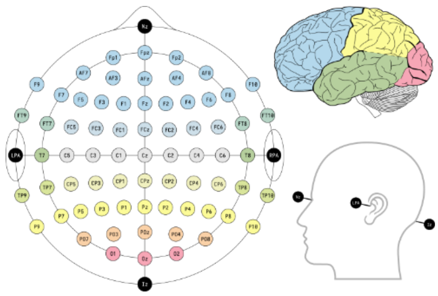

Figure 3. Placement of EEG Electrodes according to International 10-20 System [12].

Table 1. Bands of EEG Signal

EEG Frequency band	Frequency range (Hz)	Brain State	Level of Consciousness
Delta	0.5 - 4	Deep sleep	Very low
Theta	4 – 8	Mild sleep	Low
Alpha	8 – 12	Awake quiet, closed eyes	Medium
Beta	12 – 30	Mind active, focused, highly alert	High
Gamma	30 – 100	Meditation	Very High

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Table 2. Specification of the EEG Sensor Kit utilized in the Reviewed Articles

citation / Parameters	[2]	[12]	[13]	[14]	[15]
Toolkit name	Neuroscan	CONTEC KT88-3200	DEAP	-	DEAP
Channels	32	32	32	1	32

2.3 Emotion Recognition using Electrocardiogram

Key elements for successful feature extraction in ECG-based human emotion identification are precise data collection, low noise interference, and strong signal processing. In order to ensure nuanced classification, machine learning models need a diverse range of emotional states during training. An ethical framework that protects privacy, real-time processing power, and ongoing model improvement all go into creating a trustworthy and accountable emotion identification system. With the help of physiological changes in just one ECG channel, this algorithm uses least squares support vector machine (LS-SVM) classifiers, the generalized discriminant analysis (GDA) feature reduction method, and a sequential forward floating selection-kernel based class separability-based (SFFS-KBCS-based) feature selection algorithm to effectively recognize music-induced emotions [3]. The block diagram of the reviewed article on emotion recognition using ECG is depicted in Figure 4.

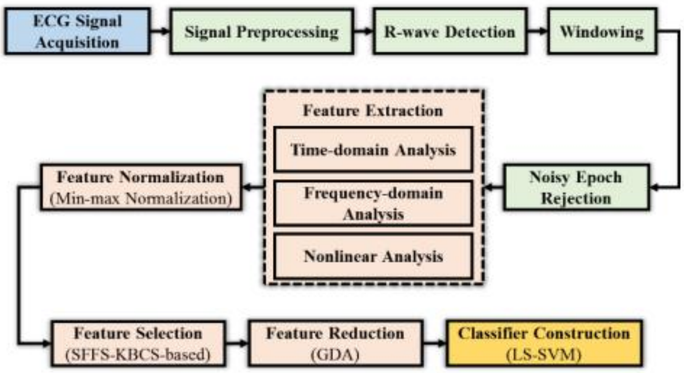

Figure 4. Block diagram of the Emotion Recognition System based on ECG [3].

2.4 Emotion Recognition using Facial Recognition

Key elements for human emotion detection using face recognition include high-quality image data, reliable feature extraction that captures a range of facial expressions, and large training datasets that cover a range of emotional states. While detecting emotions from facial expressions has always been a simple process for humans, using a computer system to do the same objective may be difficult. Figure 5 shows the different facial expressions of a human. Recent developments in machine learning and computer vision allow for the detection of emotions in images. For image analysis, convolutional neural networks, or CNNs, are the most often used method. CNNs are distinct from multi-layer perceptrons (MLPs) in that they have convolutional layers, which are hidden layers. The suggested approach is based on a CNN architecture with two levels [4]. When it comes to image recognition and classification, convolution outperforms feed-forward neural networks. This is so that convolution may benefit from spatial locality and minimize the number of parameters in a network [6].

Figure 5. Different Facial Expressions for Recognition of Emotions [6].

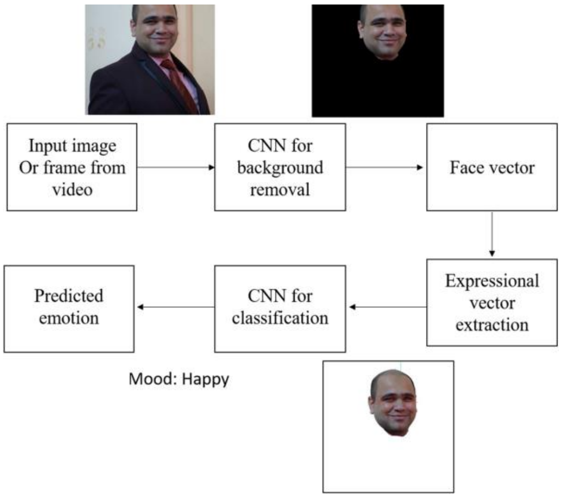

Figure 6. Block diagram of Facial Emotion Recognition System [4].

2.5 Emotion Recognition based on Audio (Speech) Signals

Essential elements for speech-based human emotion recognition are clean audio recordings, efficient feature extraction from voice intonations, and a range of emotional states for thorough model training. Accuracy is ensured by robust signal processing, which reduces noise. The method of utilizing artificial intelligence to anticipate human emotions from audio inputs is known as speech emotion recognition (SER). The different non-verbal facets of language that enable individuals to express or comprehend emotion are known as emotional prosody, or affective prosody. It comprises the way a person speaks—their pitch, volume, timbre, speech tempo, and pauses—and how they express that tone of voice. An emotion detection system's reliability is significantly impacted by features that are derived from the speech signal. Both the vocal tract and the spectral qualities of the voice are impacted by the emotional state. Every frame, a basic auto correlation analysis is carried out to characterize immediate pitch.

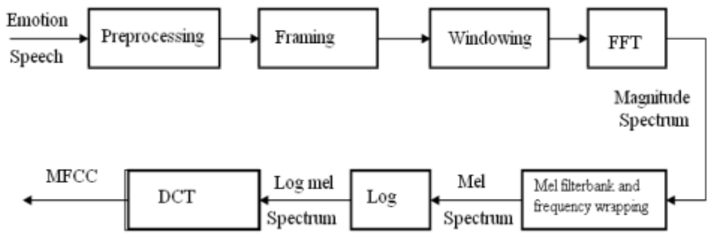

Figure 7. Mel Frequency Cepstral Coefficient-based Emotion Recognition from Speech Signals [11].

3. Analysis of the Articles Reviewed

The top five techniques for identifying human emotions have been covered in this part, along with a tabulation of different technology-based characteristics that emphasize the hardware used, error rate, accuracy, and experiment budget.

3.1 Emotion Recognition based on Physiological Changes

110 features were computed from the four-channel biosignals after the preprocessing step for signal segmentation and denoising, and the sequential backward search approach was used to identify the most important features. In all four-channel signals, several kinds of

abnormalities were seen, such as brief noise resulting from the participants' movements during the recording, which mostly occurred at the start and finish of each recording. EMG, SC (skin conductivity), and RSP (respiration) were sampled at 32 Hz, whereas the ECG was sampled at 256 Hz. Pre-gelled single Ag/AgCl electrodes are attached to a pre-amplified electrocardiograph sensor, which is used to detect ECG waves (band width: 0.05 Hz-1 KHz). MyoScan-Pro sensor with pre-gelled single Ag/AgCl electrodes and an active range of 20–500 Hz for EMG. EMG signals up to 1,600 µV may be recorded using it. By identifying the surface voltages that arise during a muscle contraction, electromyography quantifies muscle activity. The individuals' respiratory activity was recorded with a stretch sensor that employed a latex rubber band fastened with a Velcro RSP belt. It may be placed over clothes in an abdominal or thoracically orientation. The skin's electrical conductivity is measured using the SC sensor. The skin's resistance to current flow or conduction is measured when a little voltage is applied to it. As a result, it is thought that skin conductance depends on how active the eccrine sweat glands are. Table 3 summarizes the results obtained in emotion recognition using physiological changes comparing the accuracy, error rate and other parameters.

Table 3. Parameters for Emotion Recognition based on Physiological Changes

Cited Work / Parameters	[1]
Objective of the cited work	Emotion recognition using physiological changes such as EMG, ECG, Skin conductivity, Respiration
Accuracy (%)	95
Error rate (%)	5
Hardware employed	4 separate sensors for data acquisition of different parameters.
Algorithms / Software req.	sequential forward selection (SFS), Fisher Projection

3.2 Emotion Recognition using EEG

Due to its ease of use, non-invasive nature, and superior ability to detect emotions, electroencephalography (EEG) is the most optimal method for measuring brain activity. Prior to moving farther with data classification and clustering, feature selection is a must. Finding a subset of features by eliminating superfluous characteristics while keeping informative features is the aim of feature selection. The electrode pairs that provided the greatest information regarding the emotional states were, in summary, the frontal and parietal pairings. In order to identify the emotions of both patients and criminals, hospitals and police agencies may utilize the study's findings. Some individuals who are able to divulge human emotions during questioning are able to do so because the information is easy to comprehend. Table 4 tabulates the existing works carried out on recognition of human emotion using EEG using various algorithms, sensors and computational methods along with filtering.

Table 4. Parameters for Emotion Recognition using EEG.

Cited Work / Parameters	[2]	[12]	[13]	[14]	[15]
Accuracy (%)	74	70	85	80	92
Error rate (%)	26	30	15	20	8
Hardware employed	NEUROSCAN -32 channel	CONTEC KT88-3200	DEAP	-	DEAP
Algorithms / Software req.	MLP, SVM	Software Application – Safenet Microdog	CNN-2, CNN-5, CNN-10s	MATLAB - ANFIS module	3D-CNN

3.3 Emotion Recognition using Electrocardiogram

ECG signals, which are derived from the heart, may objectively and in real-time indicate an individual's emotional state. LS-SVM classifiers employing just the ECG signal evoked by listening to music and the SFFS-KBCS+GDA feature reduction approach comprises an automated ECG-based emotion identification system. Combining sequential forward selection (SFS) with sequential backward selection (SBS) to lessen the nesting effect is known as sequential forward floating selection (SFFS), a suboptimal feature selection technique. Table 5 explains the parameters and software methods used for ECG-based emotion identification.

Table 5. Parameters for Emotion Recognition using Electrocardiogram

Cited Work / Parameters	[3]
Accuracy (%)	73
Error rate (%)	27
Hardware employed	NeXus-10 instrument with Biotrace
Algorithms / Software req.	GDA, LS-SVM, SFFS - KBCS

3.4 Emotion Recognition using Facial Recognition

Since facial expressions reflect emotions, they are essential indicators of human moods. A person's facial expression is a nonverbal means of expressing their emotions, and it may be used as hard proof to determine whether or not they are telling the truth. For image analysis, convolutional neural networks, or CNNs, are the most often used method. Prior to extracting the edges of each layer during the convolution procedure, the facial expression picture is first normalized. To maintain the texture image's edge information, the retrieved edge information is placed on each feature image. Next, the maximum pooling approach is used to perform the dimensionality reduction of the retrieved implicit features. Table 6 compares the previous studies on emotion detection by facial recognition, often referred to as image processing, and includes details on the datasets and algorithms used.

Table 6. Parameters for Emotion Recognition using Facial Recognition.

Cited Work / Parameters	[4]	[5]	[6]	[7]
Accuracy (%)	95	84.9	60	90
Error rate (%)	5	14.1	40	10
Hardware employed	-	-	-	-

Algorithms / Software req.	CNN	DCNN	FFNN, CNN, DT	CNN
Dataset	Cohn-Kanade extended (CK+)	FER+	FER-	FER-, LFW

3.5 Emotion Recognition based on Audio (Speech) Signals

To get the labeling and characteristic curves required for feature extraction, the recordings were processed. The processing included pitch-period marking, voiced-unvoiced labeling, vowel recognition, vocal activity detection, estimate of the glottal source signal and of the intonation curve [8]. The main way to determine a speaker's emotional state is often via prosodic characteristics. These two features—the Mel Frequency Cepstral Coefficient (MFCC) and the Mel Energy spectrum Dynamic coefficients (MEDC)—are recovered throughout the feature extraction procedure [10]. The results of using different algorithms on different datasets and utilizing audio signals for emotion recognition are tabulated in Table 7.

Table 7. Parameters for Emotion Recognition using Audio Signals.

Cited Work / Parameters	[4]	[5]	[6]	[7]
Accuracy (%)	76	70	92	57
Error rate (%)	24	30	8	43
Hardware employed	-	-	-	-
Algorithms / Software req.	LPFC	HMM	LIB-SVM, RBF, Polynomial Kernel	LSTM, RNN
Dataset	Berlin emotional speech	INTERFACE Emotional Speech	Berlin Emotional speech	IEMOCAP

4. Discussions

This section provides a brief, critical analysis of the benefits and drawbacks of the studied approaches across various fields. Table 8 discusses the tabulated findings.

Table 8. Advantages and Disadvantages based on Reviewed Methodologies.

Number	Methodology	Advantages	Disadvantages	Essential Features required
1	Physiological Changes	Four distinct biosensors are used to show how accurately and clearly an emotion is recognized, leaving no room for error or misunderstanding of human emotions. In order to get precise, exact answers during interrogation without producing outcomes that are manipulative, this capability may be used in several Army and Police aspects.	The inapplicability of voice and face recognition technology might be one of the main drawbacks. This system has more potential and could be used in several dimensions for different purposes if these two characteristics could be included.	Sensitive biometric sensors such as skin conductance, heart rate, and others are necessary for accurate physiological changes associated with human emotions. Robust signal processing and feature extraction are able to capture complex reactions. Accurate classification is ensured by machine learning models that have been trained on a variety of emotional states, and real-time processing improves responsiveness.
2	EEG	Based on data coming from the brain, this is able to identify emotions. The primary benefit is in the ability to identify emotions without requiring verbal	To enable the use of this system, high-quality sensors, electrodes, and processing systems must be used, which raises the expense and increases risk.	EEG data capture with low artifacts is necessary for accurate human emotion recognition based on EEG. Strong signal pre-

		expression; instead, the signals openly portray the feelings.		processing is necessary, and this includes feature extraction and noise reduction. Emotionally varied machine learning models allow for efficient classification. EEG signal emotion identification that is accurate and responsive is made possible by real-time processing capabilities and ongoing model improvement.
3	ECG	Through the use of a sensor that is linked to a processing system, this system records heartbeats. This system's capacity to precisely identify emotions is one of its advantages; whether anger, pleasure, calmness, or tears are conveyed, heart rates differ.	Fugitives are often taught how to manipulate their breathing patterns to get against this ECG-based emotion detection system. This alters the emotion that is being detected and may lead to incorrect interpretation.	Signal quality is important because dependable ECG data gathering is necessary for efficient ECG-based human emotion recognition. It is essential to extract precise features from cardiac patterns. It is possible to accurately classify emotions by using machine learning models that have been trained on a variety of emotional states. Emotion identification from ECG data is more

				responsive when it is continuously improved and processed in real time.
4	Facial Recognition	Using the least amount of expenditure in image processing, this method uses FERC to identify human emotions.	While FERC has made it possible to detect human emotions rather precisely, people sometimes have a propensity to conceal their feelings, making it difficult to assess them effectively all the time.	High-quality picture data, reliable feature extraction that captures face emotions and a range of emotional states are required for facial emotion identification. Sophisticated machine learning algorithms guarantee accurate emotion categorization since they are trained on large datasets. Privacy protection is one of the most important ethical issues.
5	Audio (Speech) based emotion recognition	In distant areas when additional elements like facial recognition, EEG, ECG, or respiration data are unavailable, this technique may sometimes be used. This method is often used to analyze and comprehend the person the government is tracking for security reasons during phone tracing and tapping.	This method yielded an accuracy rate that falls into the lowest category. This is because of the influence of the weather, which might be chilly. The voice of the person experiencing cold symptoms may seem weeping or exhausted, but this is entirely untrue.	Accurate audio-based human emotion recognition relies on clear and crisp recordings, efficient noise reduction, and voice intonation-capturing feature extraction. Accurate categorization is ensured by sophisticated machine learning models that are

				trained on a variety of emotional states. Adaptability and real-time processing are key components in the accurate identification of emotions from audio data.

The critical examination leads to the conclusion that there is a bright future for human emotion detection systems, which will soon be used in more public spaces such as banks and airports. When combined with sound and face recognition software, the physiological signal-based system may improve current work and become a universal solution. Because many people are trained to overcome these obstacles and generate manipulations in the reading by managing their breathing pattern in order to stay calm at all times, the ECG and audio recognition systems are less often used.

Robust datasets with a range of demographic and cultural backgrounds are necessary for the accurate identification of human emotions. These datasets are required for the training of sophisticated machine learning algorithms, including deep neural networks. For a thorough study, feature extraction should take into account physiological signals, verbal intonations, and facial emotions. Dynamic emotional state adaptability is ensured by real-time processing capabilities and ongoing model improvement. It is important to take into account ethical factors, such as reducing the limitations and enhancing the privacy protections. Contextual knowledge is improved by the integration of multimodal inputs and context awareness. A sophisticated and culturally aware method of recognizing human emotions is fostered by ongoing research cooperation and user input, which aid in the evolution of models.

4.1 Future Perspectives of Human Emotion Recognition Systems

Human-robot interaction: One exciting problem in the realm of human-robot interaction is the development of emotional intelligence in robots. Within the more general domains of effective computing and human-machine interaction, emotion recognition has been extensively studied. The focus of recent developments in emotion recognition, particularly in the context of human-robot interaction, has been on modeling emotions through the definition of neurocomputational models, their formalization in pre-existing cognitive architectures, their adaptation of existing cognitive models, or the creation of specialized effective architectures. Additionally, covered are the crucial problems and future possibilities for creating human-robot interaction systems that are more efficient

- **Automated Emotion Recognition**: Applications for automated emotion identification may be found in a variety of fields, including e-learning, healthcare, and surveillance. Human emotions may now be automatically recognized because to the advancement of computer-aided diagnostic (CAD) technologies. The goal of this field's future research is to enhance emotion identification systems' resilience, accuracy, and generalizability in uncontrolled contexts. Promising outcomes have been seen in the enhancement of emotion detection systems' performance via the use of deep learning methods.

5. Conclusion

Technology-driven solutions known as emotion recognition systems are made to recognize and interpret human emotions from a variety of indicators, such as physiological signals, voice tones, and facial expressions. These systems evaluate data and classify emotional states using machine learning methods, such as deep learning and natural language processing. They find usage in marketing, education, healthcare, and human-computer interaction; they also improve user experiences, keep an eye on mental health, and improve instructional strategies. However, difficulties like as cultural differences and moral dilemmas have surfaced, igniting conversations on consent and privacy. The creation of multimodal techniques to increase accuracy may be a future breakthrough for emotion recognition systems. Although these technologies provide encouraging prospects, their appropriate and ethical usage need cautious control because of the possibility of emotional privacy invasion.

The revolutionary potential of a human emotion recognition technology to transform human connection and well-being is what makes it so important. These technologies may improve human-computer interactions and make technology more intuitive and user-responsive by properly identifying emotional states. Emotion detection in healthcare may help with immediate assistance, early mental health problem management, and general well-being improvement. Understanding customer emotions may also result in more successful marketing and advertising campaigns and goods that are suited to certain emotional reactions. Emotion detection in education may enhance classroom settings and modify instructional strategies to meet the requirements of certain students. These methods may also promote more sympathetic and fruitful connections in domains like customer service and work settings. In the end, there are significant ramifications for enhancing both the efficacy of diverse sectors and applications as well as the standard of living for individuals when it comes to precisely identifying and addressing human emotions.

To summarize, the field of human emotion identification systems has a bright future ahead of it. Research will concentrate on creating more realistic and efficient systems for human-robot interaction as well as enhancing the precision and resilience of electronic emotion detection systems.

References

[1] J. Kim and E. André, "Emotion recognition based on physiological changes in music listening," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 30, no. 12, pp. 2067-2083, Dec. 2008, doi: 10.1109/TPAMI.2008.26.

[2] Y. -P. Lin, C. -H. Wang, T. -L. Wu, S. -K. Jeng and J. -H. Chen, "EEG-based emotion recognition in music listening: A comparison of schemes for multiclass support vector machine," 2009 IEEE International Conference on Acoustics, Speech and Signal Processing, Taipei, Taiwan, 2009, pp. 489-492, doi: 10.1109/ICASSP.2009.4959627.

[3] Y. -L. Hsu, J. -S. Wang, W. -C. Chiang and C. -H. Hung, "Automatic ECG-Based Emotion Recognition in Music Listening," in IEEE Transactions on Affective Computing, vol. 11, no. 1, pp. 85-99, 1 Jan.-March 2020, doi: 10.1109/TAFFC.2017.2781732.

[4] V. Hosur and A. Desai, "Facial Emotion Detection Using Convolutional Neural Networks," 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon), Mysuru, India, 2022, pp. 1-4, doi: 10.1109/MysuruCon55714.2022.9972510.

[5] Emad Barsoum, Cha Zhang, Cristian Canton Ferrer, and Zhengyou Zhang. 2016. Training deep networks for facial expression recognition with crowd-sourced label

distribution. In Proceedings of the 18th ACM International Conference on Multimodal Interaction (ICMI '16). Association for Computing Machinery, New York, NY, USA, 279–283. https://doi.org/10.1145/2993148.2993165

[6] Z. Rzayeva and E. Alasgarov, "Facial Emotion Recognition using Convolutional Neural Networks," 2019 IEEE 13th International Conference on Application of Information and Communication Technologies (AICT), Baku, Azerbaijan, 2019, pp. 1-5, doi: 10.1109/AICT47866.2019.8981757.

[7] H. Zhang, A. Jolfaei and M. Alazab, "A Face Emotion Recognition Method Using Convolutional Neural Network and Image Edge Computing," in IEEE Access, vol. 7, pp. 159081-159089, 2019, doi: 10.1109/ACCESS.2019.2949741.

[8] I. Luengo, E. Navas and I. Hernáez, "Feature Analysis and Evaluation for Automatic Emotion Identification in Speech," in IEEE Transactions on Multimedia, vol. 12, no. 6, pp. 490-501, Oct. 2010, doi: 10.1109/TMM.2010.2051872.

[9] Tin Lay Nwe, Say Wei Foo, Liyanage C De Silva, emotion recognition using hidden Markov models, Speech Communication, Volume 41, Issue 4, 2003, Pages 603-623.

[10] Chavhan, Yashpalsing & Dhore, Manikrao & Pallavi, Yesaware. (2010). Speech Emotion Recognition Using Support Vector Machines. International Journal of Computer Applications. 1. 10.1007/978-3-642-21402-8_35.

[11] Houssein, E.H., Hammad, A. & Ali, A.A. Human emotion recognition from EEG-based brain–computer interface using machine learning: a comprehensive review. Neural Comput & Applic 34, 12527–12557 (2022). https://doi.org/10.1007/s00521-022-07292-4

[12] S. -E. Moon, S. Jang and J. -S. Lee, "Convolutional Neural Network Approach for Eeg-Based Emotion Recognition Using Brain Connectivity and its Spatial Information," 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Calgary, AB, Canada, 2018, pp. 2556-2560, doi: 10.1109/ICASSP.2018.8461315.

[13] U. Wijeratne and U. Perera, "Intelligent emotion recognition system using electroencephalography and active shape models," 2012 IEEE-EMBS Conference on Biomedical Engineering and Sciences, Langkawi, Malaysia, 2012, pp. 636-641, doi: 10.1109/IECBES.2012.6498051.

[14] Elham S. Salama, Reda A.El-Khoribi, Mahmoud E.Shoman and Mohamed A.Wahby Shalaby, “EEG-Based Emotion Recognition using 3D Convolutional Neural Networks” International Journal of Advanced Computer Science and Applications(IJACSA), 9(8), 2018. http://dx.doi.org/10.14569/IJACSA.2018.090843

[15] Shasidhar. R and Sanjay. S. Tippannavar, "EEG based Smart Wheelchair using Raspberry Pi for Elderly and Paralysed Patients," 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon), Mysuru, India, 2022, pp. 1-5, doi: 10.1109/MysuruCon55714.2022.9972433.

[16] R. Shashidhar, Sanjay S. Tippannavar, K. B. Bhat, N. Sharma, M. Rashid and A. Rana, "EEG-based Brain Wave Recognition using GRU and LSTM," 2022 5th International Conference on Contemporary Computing and Informatics (IC3I), Uttar Pradesh, India, 2022, pp. 1083-1087, doi: 10.1109/IC3I56241.2022.10072419.