

## Review

# EEG-Based Emotion Recognition Datasets for Virtual Environments: A Survey

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## Article information

Received: January 3<sup>rd</sup>, 2024; Revised: March 21<sup>st</sup>, 2024; Accepted: April 1<sup>st</sup>, 2024; Published: April 12<sup>th</sup>, 2024

## Cite this article

Hamzah HA, Abdalla K. EEG-based emotion recognition datasets for virtual environments: A survey. 2024; 2(1).

doi: <https://doi.org/10.70705/ppp.ltcs.2024.v02.i01.pp18-31>**ABSTRACT**

When it comes to virtual environments (VEs), one of the biggest issues is how users struggle to handle ever-more-complicated systems. Therefore, if computers could read human emotions, it would greatly improve the quality and consistency of human-machine interactions. A system that can detect and respond to human emotions may be realized by modeling the human emotional state and then employing an electroencephalogram (EEG) device as a biosignal sensor. This paper presents a comprehensive overview of methods for emotion recognition based on electroencephalogram (EEG) data. It categorizes these methods according to time domain, frequency domain, and feature extraction. The review focuses on datasets used in recent studies that investigate EEG-based emotion classification and addresses the challenges associated with this field. Two types of artificial intelligence-based algorithms, deep learning and machine learning, have become very prominent in the area of emotion identification. Emotional ratings or labels should be included in the data used to assess the algorithms and models that are offered. Building a professional experimental setting and developing a scientifically valid experimental user model involves specific understanding in psychology, which might be challenging for certain researchers, particularly those working in computer science. As a result, a lot of people that are into researching emotion detection models want to check their ideas and see how they stack up against comparable works using certain criteria. Consequently, research is offered with the hope of laying the groundwork for future efforts to improve the virtual contact experience via modeling human impact.

**INTRODUCTION**

One of the biggest problems with VEs is dealing with people, which is becoming more complicated as a result. A framework for interaction modes that depends on the application's specific needs must be thus devised. Standard and organic user interfaces, situational awareness and personalization, individualized content management, multimedia communication, and multimedia applications are all possible components of these needs [1-4].

In order to keep the user engaged in the core aim, VEs often need human contact. Understanding emotional variability is also necessary for task engagement, which includes both cognitive engagement and motivation. In order to better understand the mental and emotional operations that go into completing a job, physiological computing technologies may be used. In particular, the incorporated as an additional input modality, the capture and analysis of electroencephalogram (EEG) data, which provide an indicator of brain activity levels, may give benefits [3, 5, 6].

In recent studies, electro-encephalography has been used to show how the brain responds to different stimuli in the environment. In most cases, these devices work as supplementary controls for

more traditional methods, such a game console, computer mouse, or keyboard. However, consumers still find this proactive engagement mode to be expensive since controlling brain activity requires substantial training, as well as considerable focus and effort. As a result, the user's focus is shifted from the main job to the interaction modality due to this condition. Achieving really seamless contact requires the system to respect the user's intentions and requirements. Using an electroencephalogram (EEG) as a base signal is one promising way to provide interaction that doesn't need user training or concentrated attention. This requires the employment of a sensor that mimics the user's mental and emotional condition [3, 7, 8]

Emotion recognition has attracted a lot of attention from scientists in many different disciplines. Within the new field of affective computing, which aims to enable computers to effectively absorb, recognize, and understand human emotional signals, this phenomena poses a significant scientific challenge. The development of virtual worlds demonstrates the importance of this factor in promoting natural interactions between humans and computers. The fields of artificial intelligence and ambient intelligence also place a high value on it. Computer science, electrical engineering, human factor engineering, psychology, neurology, and medical sciences are just a few of the many fields that stand to benefit from the interdisciplinary

approach to affective computing [7, 9, 10].

Emotion is a complex psychological construct condition, as seen by outwardly noticeable changes in behavior and body temperature. In the past, researchers have attempted to identify emotions by analyzing emotional data derived from various physiological responses and physical behaviors. This data has come from microphone recordings, data from devices that measure neurophysiological activity, camera footage, and textual content extracted from websites. Statistical machine learning techniques for differentiating between different emotional states, either offline or in real time, have been the primary emphasis of research into emotion recognition. Natural language, facial expressions, voice, body language, vital signs, text, and eye contact are all potential sources of emotional data that might be enhanced by more investigation into this matter. In the realm of affective computing, evaluating emotional states by means of physiological activities is now a hot topic. There are connections between physiological processes and emotional perception, according to a number of research in psychology and physiology [9–11]. However, the order in which these events occur is still a matter of contention. Recognition algorithms that depend on face or voice data may benefit greatly from methods grounded in computational psychophysiology. The effectiveness of these techniques can be significantly diminished when people consciously hide their true feelings behind “social masks.” Utilizing brain activity data from EEG to study the mechanisms of emotional perception and recognition of emotional states is particularly promising because the autonomic nervous system is regulated and overseen by the central nervous system during emotional processes. A good mood may improve spatial memory in virtual environments (VEs), according to studies that looked at the effects of emotional states on VEs like educational VR, gaining knowledge. Consequently, it is critical to recognize feelings while participating in VR learning [12, 13].

There have been a lot of research looking into EEG-based emotion identification before this review was written. This research thesis must highlight survey articles published in the last three years and explain why it is critical to write a new survey study. Several survey papers need to have their content revised. Take, for instance, the following works: [12] is a survey of multimodal sentiment analysis; [13] is an AI-powered systematic review of automatic emotion recognition from EEG signals; and [14] is a survey of EEG emotion recognition and a brief review of benchmark datasets. This is why these surveys need to be enhanced with additional material regarding deep learning, various approaches to extracting EEG features for emotion recognition from four different angles, including time domain features, frequency domain features, time frequency features, and nonlinear features. The following are the primary benefits of this paper:

(1) The article provided an overview of the ways in which recognition might improve VR settings for a variety of uses, including healthcare, education, entertainment, and everyday life functions including social media, virtual tourism, and training.

(2) Here we provide a current overview of technological approaches to EEG-based emotion pattern recognition. This in-depth analysis delves into the most recent datasets that have been developed for the purpose of emotion recognition and analysis, as well as their

associated difficulties.

(3) We examine the possible benefits and downsides of EEG emotion detection and have a conversation about them. We also note and describe possible future research directions in this area.

Presented below is the structure of this document. We discuss the many ways VR is changing our lives and how technological approaches to pattern recognition and EEG feature extraction and selection might improve VR environments for a variety of uses, with a focus on emotion identification. We take a look at new datasets. We examine supplementary studies that detail the sample size, gender distribution, emotional expressions measured, elicitation stimuli (images, videos, etc.), electrode placement, and EEG equipment. Here we give you the big picture of what’s happening right now and where things are headed. Finally, a few remarks.

## 2.DUC Background

Numerous fields, including healthcare, lifestyle, education, entertainment, and gaming, stand to benefit from a system that can detect and adapt to the user’s current emotional state.

VEs in medical practice (section 2.1). In addition to helping people deal with stressful and anxious emotions, VEs have shown promise in treating a wide range of physical problems. A prominent example of this is the increasingly popular virtual reality exposure treatment (VRET) for anxiety and particular phobias. A user is immersed in a virtual reality (VE) and subjected to stimuli designed to induce anxiety inside an appropriately designed setting. Kids on the autistic spectrum have shown promise in improving their social skills after receiving VEs. These cases show how a system that modulates emotions might be useful, letting doctors see how a patient’s disease is developing alongside their emotional states. Additionally, this data might be used to tailor treatments in real-time, reducing the likelihood of patients being overexposed [13, 16].

2.2. Using VEs in the Classroom. Affective learning (AL) describes the relationship between affective computing and learning. This phrase describes a set of technologies that may detect when a learner is experiencing certain emotions and respond accordingly to enhance the learning process. Intuitive reasoning and the application of constructivist ideas are the primary foundations for the understanding that interest and active involvement are critical components of the learning process. The use of AL might bring about a sea change in this regard by providing unparalleled quantitative assessment, modeling, investigation, and support for the affective component of learning. Virtual environments (VEs) and adaptive learning (AL) have been shown to improve student performance in the past. Questionnaires and other forms of objective assessment of emotional state have been the backbone of several earlier techniques. Using biosensors like electroencephalograms (EEGs), educational systems might mimic a teacher’s ability to detect affect and decipher nonverbal clues [17, 18]. The technological features of VR support the concepts of constructivism in education, which stress the need of students actively building their understanding and knowledge via hands-on experiences. Using these guidelines as a foundation, a framework called VRID (Virtual Reality Instructional Design) provides guidance on creating instructional virtual environments. Vir-

tual reality (VR) education often takes constructivism as its guiding principle, with experiential learning being considered most suited to VR settings. The immense potential for future applications in virtual reality education is likewise acknowledged when it comes to gaming's incorporation into educational settings [19]. Investigating the use of narrative immersive virtual reality (IVR) as a pre-lesson resource, this research [20] found that students retained more information after using narrative IVR before a multimedia lesson. According to these findings, virtual reality may improve academic performance in the area of cognitive development. In addition, it was noted to influence the way people felt. It has research [21] used a dual-path model to look at how VR affects students' academic performance.

It found that variables like immersion, interest, control, and active learning impact VR's affective and cognitive pathways, which in turn affect students' academic performance. Research and theory suggest that ecosystems, especially those designed with pedagogical principles in mind, can provide students with opportunities for active learning and increased student engagement, both of which improve the quality of their education. Research efforts are being focused on studying and improving methodologies for the more effective exploitation of virtual environments (VEs) in educational settings, which is a rapidly expanding subject. environment that is totally immersed in it.

**2.3 Virtual Encounters in the Leisure and Amusement Industries.** The gaming business is the most obvious user of virtual consoles, which have generated a lot of buzz in the entertainment sector overall [22]. Given that many video game developers aim to build and sell emotionally engaging experiences, this upsurge in interest is not surprising. Previous study has shown a favorable association between emotions and the psychological sensation of presence in immersive virtual reality environments, lending credence to the idea that virtual reality has the ability to evoke both good and negative emotions. As an example, consider *Second Life*, a virtual world that was created using virtual environments [23]. A user's avatar may get their facial expressions in real-time thanks to the High-Fidelity platform. The system's goal is not to detect affect, but it can imitate facial expressions linked to words and emotions. Nevertheless, by integrating EEG technology, the high-resolution platform can respond to human influence, making it even better. Paralyzed people, for example, can't change their facial expressions, but that doesn't mean they can't benefit from a platform like High Fidelity. Using the well-established correlation between presence and emotional state, there is a great deal of room for automated modification of user emotional states in virtual environments [24]. Some of the many fields that have felt the profound influence of VEs include online social networks, virtual training environments, and virtual tourism. There will be an in-depth discussion of how VEs impact and enhance each of these industries.

**2.3.1. Virtual Environments for Tourists.** Virtual reality (VR) allows users to immerse themselves in a world, complete with interactive features and captivating 360-degree movies, allowing would-be tourists to virtually explore various locations. In the field of marketing and promotion, virtual reality is being used to promote locations by presenting pictures to prospective visitors. This helps to evoke more emotions and increases the likelihood that they will visit. In addition,

when completely immersed in a new culture,

Cultural events, museums, and historic locations may now be experienced by people without requiring them to leave their homes, allowing for a more profound understanding and admiration. When it comes to accessibility, virtual reality opens up new worlds to those who may otherwise be unable to access them, whether it's due to a lack of resources or a physical disability [23, 24].

**2.3.2. Virtual Entities in Social Networks.** When it comes to immersive communication, social VR apps let people communicate in virtual worlds using VR goggles, creating a deep feeling of being there and being part of something bigger. Furthermore, people may attend concerts, conferences, and meetings virtually, expanding networking opportunities beyond physical borders, via virtual gatherings. Lastly, when it comes to augmented reality, it allows for more complex social interactions that aren't always possible on traditional social media sites because of the lack of non-verbal clues like gestures and body language [23, 24].

**VEs in Learning Settings (2.3.3).** In the field of skill improvement, virtual reality environments provide a safe and supervised way to practice and hone abilities by simulating real-life scenarios. When used to the field of education, virtual reality has the ability to provide engaging course materials that boost student engagement and retention. Educators may foster empathy and improve educational practices by exposing themselves to varied opinions, including those of students in a classroom environment [23, 24]. One of the most important aspects of contemporary technology and culture, virtual reality apps are changing the way we see the world, interact with one another, and learn new skills.

**3. Emotion Recognition Based on EEG as an Input Modality** Various methods for collecting information about people and their emotions are already available. In most cases, input may be provided by means of visual and aural components of communication, such as monitoring eye and gaze movements, analyzing facial expressions, detecting body mobility, analyzing speech patterns, and testing auditory perception. Further, sensor-derived input signals may also be used to acquire physiological measures, such as electroencephalography, galvanic skin reaction, and electrocardiogram. However, electroencephalography has several benefits that make it a good choice for practical applications, such as the fact that it is noninvasive and sensitivity to motion. Both independent and combined use of electroencephalograms (EEGs) with other biometric sensors is possible. Case in point: iMotions has built a business platform that can track users' mental and physiological states while they're in a VR environment. This is a perfect example of how visual recognition of emotions may improve VR experiences. The discrete model and the dimension model are two often used frameworks for describing emotional space. The first is to symbolize the emotional domain with a single, universal emotion. Joy, sorrow, surprise, fear, wrath, and contempt are the emotions that have been used in many research, however none can agree on which ones are the most fundamental. Emotional space is characterized by continuous coordinates in two or three dimensions in the dimensional model, as shown in Figure 1. The valence-arousal dominance dimensions and the dominance-arousal dimensions are names for these coordinates. To be more specific,

the arousal dimension progresses from calm to active, and finally to excited states, while the valence dimension reverses the order of negative to positive. The dominance dimension, on the other hand, is a measure of a person's level of control over their environment. [26 and 27].

There are two types of brain signals, invasive and noninvasive, depending on the methods used to gather data. The surface of the brain's cortex is directly sampled for intrusive waves, while external sensors that pick up on the brain's electrical activity provide noninvasive data. A leading example of a noninvasive physiological signal is the electroencephalogram (EEG). When it comes to noninvasive brain imaging, electroencephalography (EEG) is the gold standard for evaluating brain electrical processes with the use of electrodes. For this technique, electrodes are placed on the outside of the skull to measure the strength of EEG impulses. As a result of the restricted number of electrodes used to collect EEG data, the signals' spatial resolution is low [28]. A cap or headset containing a multitude of connected and wireless electrodes or sensors meant to be put on the surface of the skull is the most common kind of EEG gear used for acquisition. Electroencephalogram (EEG) devices collect brain impulses, particularly post-synapse potential neurons, by inserting electrodes on the human skull or even the cortex and using conductive gel and abrasion to improve contact. Five notable electrical patterns or waves produced by the human brain are shown in Figure 2 as ( $\alpha$ ), ( $\theta$ ), ( $\beta$ ), ( $\delta$ ), and ( $\epsilon$ ). There are two separate ways that EEG data may be captured: via wired and wireless devices [9, 30]. There are benefits and drawbacks to each of the two methods stated above. In order to capture brain activity with a conventional wired EEG equipment, the participant has to stay still for the whole procedure. But, wireless EEG devices have the advantage of being able to record brain activity even while moving about with very few constraints on mobility. Also, you won't have to connecting the EEG cap to the data acquisition system via cords. By inserting electrodes into certain areas on the skull's exterior, EEG data may be retrieved from the brain's electrical activity. According to Figure 3, the American EEG Society has suggested the universally accepted 10/20 electrode placement scheme. The numbers 10/20 show the distance, in percentage terms, between two electrodes placed strategically on the skull; 10% and 20%, respectively. The conventional wisdom is that the right side of the scalp should have electrodes with even numbers and the left side should have electrodes with odd numbers. Various areas, including the frontal, parietal, temporal, occipital, central, and midline electrode regions, are assigned these electrodes [32]. Recording reference electrode locations may be chosen from four possible locations: the vertex (Cz), the tip of the nose, the contralateral ear, or connected ears. In the wireless EEG industry, you'll find both established and up-and-coming players. A wireless EEG device can be integrated into a larger ecosystem to acquire physiological (neuro) data if the device is offered by a well-established company. This is because these companies typically have a wider range of products that may interface well with wireless EEG devices. A visual representation of the hardware may be seen in Figure 4 [33].

Recent advances in EEG-based emotion identification have made tremendous strides, especially with the use of cutting-edge deep learning techniques. These developments have been essential in advancing our understanding of emotional states and the brain connections that underlie them. Convolutional neural networks (CNNs)

and recurrent neural networks (RNNs) are two examples of the deep learning models used in integration, which have improved the accuracy of EEG-based emotion identification systems. The capacity to obtain complex feature representations from EEG data is a key component in complex emotional states are being recognized. The development of EEG emotion recognition benchmark datasets has allowed for the evaluation and comparison of different approaches and models. This study's goal—a systematic analysis of such normative data—is in line with the current state of knowledge on the way emotional states appear in EEG data. Emotion identification using EEG is an area of multidisciplinary study that calls for knowledge from computer scientists, psychologists, and biologists. Thanks to this kind of multidisciplinary research, we now know more about the computational methods needed to identify emotions as well as their psychological and physiological components. Advancements in EEG-based emotion identification have an outsized impact on human-computer interaction (HCI) applications. Computers may learn to understand and interpret human emotions more accurately, which opens the door to more intuitive and empathetic user interface design [12]. Neuroscientists have gained important insights into the brain circuits involved in emotion processing via the use of EEG data for emotion identification. This helps us better understand the brain's emotional circuitry by linking certain emotional states to specific neuronal activities. The trend towards using models that are influenced by biology in the field of electroencephalogram-based emotion recognition shows that people are starting to see the possibility of improving the accuracy and naturalness of these systems by learning more about the brain processes that underlie emotions [34].

Improvements in these areas have the potential to the field of emotion recognition technology, as well as substantial advancements in the vast fields of affective computing, neurology, and psychology. The complex nature of emotions and how they manifest in the brain may then be better understood. EEG, study of facial expressions, and analysis of speech patterns are highly regarded methods for detecting emotions, with diverse benefits and best-suited situations for each.

Because of its capacity to directly monitor brain activity and its better temporal precision, EEG is known to be less susceptible to intentional intervention by people. It shines in cases when quick changes in emotional processes need to be observed, or when other methods aren't feasible, as when there aren't any audible sounds or face expressions to work with. A more objective evaluation that takes into account a wider variety of contextual information may be possible using an electroencephalogram (EEG) [7, 35, 36].

Visual cues that are intrinsically associated with emotional states are the basis of facial expression analysis. When it comes to recognizing different emotional states, these signals are quite effective and have a high degree of intuitiveness. Use of this method is useful in situations requiring evaluation in real-time, especially in contexts involving human contacts, such as security or customer service. Furthermore, it eliminates the need for particular technical gear and acts as a helpful tool for studying emotional responses in auditory contexts [37, 38].

The study of the varying acoustic features of speech is known as

speech pattern analysis. to factors like as pitch, tempo, and emotional states. The absence of visual clues makes this method very useful in speech modulation systems and other communication applications. Additionally, it is useful for analyzing emotional reactions when visual expressions are restricted or hidden, but vocal intonations reveal how someone is feeling emotionally [39, 40].

Factors like as the situational environment, the requirement of equipment, the possibility of intentionally regulating people' emotional manifestations, and the precise category of emotion under inquiry might be considered while choosing amongst various methodologies. In fields like as medicine or academia, where exactness and completeness in emotion recognition are of the utmost significance, electroencephalography (EEG) may be preferred. In user experience or interactive technology studies that value genuine responses, evaluating facial expressions can be the way to go. For cases requiring the examination of vocal interactions or telecommunications infrastructures, the study of speech patterns may be the best option. There are a variety of approaches, and each one has its own set of benefits and uses. Most of the time, a better understanding of emotional conditions may be achieved by combining different approaches in an integrated way [35, 36].

**3.1. Methods for Evoking and Recognizing Emotiond States.** A recording technique must be in place in order to generate and document active signals. This approach involves having the individual do activities within a certain time limit while monitoring their brain activity. Because distinguishing between tasks is so important, the participant is instructed to take a break while tasks are changed.

performance and nonperformance, and to differentiate between different kinds of work. But there is no constant steady situation, therefore the resting state en-counters problems. Regional neuronal activations undergo continuous spontaneous changes in the brain. Signal variations might be caused by auto-activation altering local blood circulation. As a result, the brain is always working, suggesting that when an individual is not engaged in sensory or cognitive tasks, their brain is not actively processing their external environment. As seen in Figure 5, some of the most common ways to generate emotions from people in the datasets include stimulating their recollections of emotional experiences, showing them videos, and having conversations. Most commonly used tools for emotion elicitation, such as the International Affective Picture System (IAPS) and the International Affective Digitized Sound System (IADS) [41], provide standardized emotional stimuli. Experimental research benefit from these datasets. Using the IAPS dataset as an example, there are 1200 pictures total, with 60 shots each set and valence and arousal levels labeled on each photo. Similarly, the latest edition of the IADS dataset includes 167 digitized recordings of everyday natural sounds tagged with valence, arousal, and dominance. Participants labelled the dataset using the Self-Assessment Manikin method.

Section 3.2 discusses the pattern recognition's technical routes. Using preexisting data to assess the emotional categories of target samples, the study of emotion recognition follows the tenets of pattern recognition research.

measurement criteria. A flowchart, depicted in Figure 6, presents an overview of the pattern recognition approaches utilized in related works, with diverse technical routes being clearly distinguished. The

emergence and advancements of deep learning (DL) in domains such as graph and image processing, as well as natural language processing, have captured the interest of researchers in this field, with existing works demonstrating efficacy [42]. Consequently, this review directs more attention towards DL-based studies, with Table 1 providing a summary of these technical routes and representative works.

#### 4. EEG Feature Extraction and Selection

An essential part of studying emotion recognition with EEG is extracting relevant features. Its main goal is to analyse people' emotional states by reducing the dimensionality of EEG data by the extraction of key features [11, 30]. The performance of the sensory recognition model is strongly affected by the quality of the features, making this relationship in emotion recognition very important. Accurate emotion detection relies on features that both accurately portray emotions and have a strong correlation with them. At present, time-domain, frequency-domain, time-frequency, and nonlinear features are the four most used ways to analyze EEG signals [30].

Brain network analysis algorithms, multistep algorithms, and global algorithms are all part of the neural decoding algorithms that are summarized in Figure 7 [149].

**4.1. Features Regarding the Time Domain.** The temporal domain is where most EEG signal acquisitions take place since it is easy and straightforward to do so. Research on electroencephalograms (EEGs) has made heavy use of the signals' temporal characteristics, making frequent use of the following time-domain attributes: amplitude, variance, mean, root mean square, peak detection, analysis of waveform parameters, linear prediction, and zero-crossing and variance analyses [30]. The author explored the location of the event-related potentials that were induced in participants by stimulation in [150]. The EEG characteristics used were statistical ones, such as the mean and standard deviation of the signals. The authors of [61] used the DEAP to extract EEG signal properties including skewness and kurtosis. data set. In this study, researchers used deep neural networks (DNNs) for valence identification and convolutional neural networks (CNNs) for arousal recognition. There was a favorable effect of recognition in the classifying process. The amplitude difference between symmetrical electrodes was used as an EEG characteristic in [151]. In order to accomplish emotion identification, these traits were integrated with facial expressions.

**Section 4.2: Features Dependent on Frequency.** In order to study EEG waves throughout time, time-domain analysis is used. In contrast, frequency-domain analysis is used to evaluate EEG waveforms in relation to frequency conditions [30]. The basic idea behind frequency-domain analysis is to use an algorithm to convert the signal's domain from time domain to frequency domain. This will reveal the signal's properties in relation to frequency changes. Using this method, the dispersion of each EEG rhythm may be more easily seen intuitively. To facilitate feature extraction, frequency-domain analysis often entails separating the EEG signal into several frequency bands, such as the delta (0-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-25 Hz), and gamma (25-50 Hz) sections. Power, power spectral density, and energy quantities are common frequency-domain characteristics derived from EEGs. Power spectrum estimate, which is known for its straightforward computation, good signal adaptation, and simple reasoning, is the main basis for feature extraction [11,

30]. The five frequency bands used to record electroencephalogram (EEG) data were beta (13–25 Hz), alpha (8–13 Hz), theta (4–8 Hz), and gamma (25–50 Hz) [152]. As EEG characteristics for emotion identification, the power spectral density of these bands was then estimated. At the same time, the authors of [11] implemented band-pass filtering on the theta, alpha, beta, and gamma signals after converting the EEG data from the time domain to the frequency domain using fast Fourier transform. For every frequency band, we computed power characteristics and then used the Relief-F method to identify the best ones. After that, we ran emotional recognition tests across the four dimensions of valence, arousal, dominance, and liking; we got an accuracy rate of 85–92% on average. The authors used deep neural networks and power spectral density characteristics collected from EEG to

make sense of feelings. Similarly, the authors of [154] computed the theta, alpha, beta, and gamma band characteristics of facial expression and power spectral density using the short-time Fourier transform for time-frequency conversion. A better recognition impact was achieved after fusing these characteristics and using the long short-term memory network to emotion recognition.

4.1. Features Relating to Time. Since processing an EEG signal is inherently nonstationary, frequency-domain analysis is required. The temporal appearance of each signal component is unknown, even if their frequency components may be detected [30, 32]. A crucial instrument that has arisen to meet the demand for a thorough comprehension of signal frequency variations across time is time-frequency analysis. This study takes into consideration the signal's temporal and frequency properties, which together provide a fuller picture of how the signal evolves with time and frequency. Thus, time-frequency analysis can accurately represent the unique data contained in brain electrical impulses. Splitting a time period into many time windows allows for time-frequency analysis, a popular method in signal processing. The output signal is then partitioned into a number of smaller, equally-sized processes, where each of these processes may be thought of as stationary. Every single little process then undergoes a time-to-frequency signal transformation, after which characteristics in the frequency domain are retrieved. One way to estimate the signal's instantaneous frequency and amplitude is to use a sliding time window, which allows one to examine different time periods. This sheds light on how long feelings last. Several approaches are often used for time-frequency analysis, such as the wavelet transform, the Hilbert-Huang transform, and the short-time Fourier transform (STFT) [11, 27, 155].

The short-time Fourier transform is a method

Gabor first suggested the form in 1946. This method of time-frequency analysis is based on the idea of adding a window function to the Fourier transform. In order to ensure that the signal stays steady for a short period of time before applying the Fourier transform, a window function is used. In order to divide the EEG signal into comparable time units, the window function moves along the time axis. They are then all transformed using a Fourier series [9, 11]:

looked at in the realm of time and frequency. This kind of modification is called a continuous wavelet when both parameters  $a$  and  $\tau$  may take on continuous values, in where  $(\omega)$  represents the frequency and  $w_n$  stands for the window function, and

$(t)$  stands for the time index. After that, we can easily derive the signal frequency fluctuation over time by computing the frequency-domain parameters of each window function. Careful consideration of the appropriate time window length is of the utmost importance when dealing with the short-time Fourier transform. The precision of the frequency-domain analysis is compromised when the time frame is too small, as there will be insufficient signals. On the other side, if the time frame is too broad, the time-domain resolution will be too low [156]. The sweet spot for emotion detection re-search right now is between one and two seconds. As an analytical approach to time-frequency transformation, Morlet presented the wavelet transform in 1982. By adding a frequency-dependent variable window, the wavelet transform improves upon and expands upon the short-time Fourier transform's localization principle [156]. This method improves upon the short-time Fourier transform's drawback of having an unchangeable temporal frame. This brings us to the following procedure for wavelet transform calibration:

transform. The discrete wavelet transform is used when these parameters take on discrete values, albeit [11, 156]. A time window truncation transformation of variable length based on the short-time Fourier transform is the basis of the wavelet transform, which modifies the time window function. While overcoming the problem of fixed time frames, this method takes on the characteristics of time-frequency analysis. There may be a relationship between the signal frequency and the amount of variance. Both the continuous wavelet transform (CWT) and the discrete wavelet transform (DWT) are essential components of the wavelet transform; for an example, see Figure 8. Two main parts, empirical mode decomposition (EMD) and Hilbert spectrum analysis (HSA), make up the Hilbert-Huang transform, a non-linear approach to time-frequency feature extraction. Each of the time-frequency analysis approaches has its own set of pros and cons. Research on emotion recognition may make use of a variety of methods, depending on the needs of the experiment.

5.2. SEED-VIG Dataset. The SEED-VIG dataset was assembled by Zheng et al. [164] for the purpose of gauging driver attentiveness. A cohort of 23 individuals, consisting of 12 females and 11 males with a mean age of  $23.3 \pm 1.4$ , was enlisted to participate in the study. EEG recordings were obtained from 17 channels at a sampling rate of 1000 Hz, with each experiment extending over duration of approximately two hours, resulting in a total of 885 EEG trials. Participants were instructed to operate a simulated vehicle within a virtual environment, with the majority of sessions conducted post-lunch to facilitate the induction of driving-induced fatigue. The PERCLOS metric [164], ascertained through the employment of eye-tracking spectacles, was utilized to estimate vigilance.

5.3. SEED-V Dataset. The SEED-V dataset was assembled by the authors of [165]. The dataset consists of 45 brief videos, which were carefully selected based on their ability to elicit five distinct emotions: happiness, fear, neutrality, sadness, and disgust. The participants who took part in the studies totaled 16 individuals, 10 of whom were female and 6 of whom were male. Each participant

engaged in the experiment three times, and each iteration included different stimuli. The experiments themselves involved 15 trials, with each emotion represented by three trials. In each trial, the participants were subjected to three stages: 15 seconds of start hint, 2 to 4 minutes of a film clip, and 15 or 30 seconds of self-assessment. All in all, 62 EEG recordings were collected, with each recording having a sampling frequency of 1000 Hz [165].

Section 5.4 contains the German Dataset (SEED-GER). From the dataset generated by the authors of [166], 18 stimulus materials were meticulously chosen; these materials fall into one of three clear emotional categories: positive, neutral, or negative. There was only an English version of the stimulation materials as there was no German version. The studies included eight native German subjects, seven of whom were men and one of whom was a woman. The subjects' ages ranged from 22.25 to 1.98 years, with a mean. The subjects' EEG and eye movements were tracked simultaneously as they subtly studied the stimulation materials. Unfortunately, we could only collect data from 20 sessions of the multimodal assessment due to equipment failure and participant withdrawal. Out of the eight participants, four made it through all three sessions, while the other four could only make it through two [166].

Consistent facial expressions for these emotions across cultures provide credence to the hypothesis that Charles Darwin had advanced about this system, which includes the thalamic hippocampal nuclei, hypothalamus, and cingulate cortex. Nevertheless, new dimensional models have emerged that divide the emotional spectrum into two or even three halves [197]. Emotional phenomenologists are born from the union of these parts, which map onto established neural pathways in the brain's cortex and spinal cord. The criticism that subjective emotional states might sometimes be diffused and mixed into one another led to the adoption of this new method. A mountain of EEG and fMRI research points to this conclusion.

It is suggested in [198] that cortical structures are pivotal in feelings via these routes, opening the door to electrophysiological investigation using noninvasive techniques like as EEG and MEG. The use of noninvasive, wearable EEG-based methods for emotion categorization also has strong backing from the fMRI data. Notably, these methods mostly collect information from the brain's cortex. When referring to these core emotional components, authors have used a wide variety of terms. In this work, we use the naming scheme proposed by Posner et al. [199], where "valence" means a range from extreme happiness to extreme sadness. Some speculate that this spectrum originates in the dorsal raphe nucleus and its serotonergic projections to the ventricular striatum, as well as the mesolimbic dopamine system.

An orthogonal component is one of the most important parts. Arousal goes under a lot of different names, including approach/withdrawal and behavioral activation. Arousal seems to influence memorization abilities, which are crucial for the formation of declarative memory. The amygdala is more strongly linked to stimulus intensity than sensory valence, according to studies using gustatory stimuli [200]. In addition, the amygdala and reticular formation have

been shown to be activated by emotional inputs [201]. There is a clear association between the activation of the amygdala and the assessment of the skin conductive response [202].

The integration of deeper brain areas in emotion processing poses a significant obstacle to direct, noninvasive electrical monitoring, because only their cortical equivalents can be acquired. Nonetheless, the autonomic nervous system's responses are regulated by the limbic system. Vital indications such as skin resistance, heart rate, and breathing frequency are among those that may be monitored [203]. It was as early as 1993 [204] that these auxiliary indicators were used to assess valence. Quantification techniques provide a noninvasive way to track the limbic system, but it's important to remember that variables other than the subject's mood significantly affect the secondary responses [205].

When first extracting features from EEG data, autonomic reflexes are often disregarded as "noise" from an electrophysiological perspective, despite the possible incorporation into the relics themselves [197]. Several autonomic reactions make up the EEG artifacts:

- (i) Pulse Pressure. When cardiac artifacts manifest in an electroencephalogram (EEG), it's because the signal is in a frequency and amplitude range that's comparable to that of cerebral activity. Nevertheless, these artifacts display regularity and are clearly archetypal, which makes their identification easier. Implementing independent component analysis (ICA) has been effective in differentiating between these signals and the EEG [206].
- (ii) The spectral power of the (c) band is significantly affected by breathing frequency, which allows one to predict the individual's arousal level based on their breathing rate [207].
- (iii) Muscle artifacts may be seen on the frontal electrodes, which indicate oculomotor activity. Despite the fact that some EEG analyzers would want to eliminate this artifact [208], it is intriguing to note that an individual's sympathetic arousal is connected with their eye blink rate, suggesting that this phenomenon might be a new secondary indication of emotions in EEG recordings.

The fourth property is the skin's impedance. Performing a skin electrode impedance test, which is standard on many commercially available EEG systems, facilitates the proper placement of wet electrodes. Wearable devices have been developed as a consequence of the significant research into continuous skin impedance measurements conducted by the affective computing community [203, 209]. When used with an EEG-based emotion categorization system, these wearables might provide useful supplemental data that would make the emotion inference engine much more accurate.

Applying a sudden, unexpected stimulus to the subject, usually in the form of a burst of white noise, is one common psychophysiological paradigm for studying autonomic reactions. How much of an unconscious response there is to this sudden shock depends on the person's emotional state. Considered a kind of sensory evoked potential, electroencephalographic (EEG) responses to shocking stimuli have real-world applications in the diagnosis and treatment

of mental diseases such as schizophrenia and alexithymia [211, 212]. Also, those with neurological diseases like Alzheimer's may benefit greatly from having their EEG responses evaluated in order to gauge their emotional skills. Combining the spatial information of brain activity with biomarkers in the frequency-domain representations of EEG data is another important paradigm in the neuro-anatomical basis of emotion categorization [213, 214]. Traditional spectral content analysis involves partitioning the signals into distinct

( $\gamma$ ), ( $\alpha$ ), ( $\theta$ ), ( $\beta$ ), and ( $\delta$ ) bands are investigated further in this research. This study takes into account the unequal distribution of power in the frontal alpha band between the two sides of the brain. The degree of tonic approach and withdrawal reactions is assessed using the results of this experiment.

Although these approaches show promising results [215], we may need to do further research to understand the neural basis of electrode pair selection in IHPA. The development of an emotion classifier that is hardware-based and able to collect EEG data in real-time is anticipated to speed up the investigation of questions related to neuroscience. The capacity to capture unprocessed data is thus critical for EEG acquisition devices, which must also allow for reliable electrode placement. The use of visual markers on the electrodes, which may be a powerful tool for capturing any variation from recognized clinical norms (10-20), can help achieve this goal. More information on how EEG hardware platforms are used in neuroscience research may be found in [197].

4.1. Understanding EEG Datasets. A complete EEG dataset that includes all types of stimulation is still missing, which is a major problem for EEG emotion identification. Since there is a limit on the number of multimodal signals used by existing datasets, ML engines can only train and infer using these signals [197]. Due to these restrictions on sensing modalities, harmful biases in sensors are introduced, which hinder the training of networks. Here are some qualities that future datasets for EEG-based emotion identification should have:

(1) A wider variety of multimodal markers should be included in the dataset to reduce the impact of sensory biases.

(2) A dataset with a global scope, including people from varied areas, ethnic origins, vocations, and health problems, is necessary for fully addressing the similarities and differences in emotional reactions to stimuli across cultures.

To the best of our knowledge, the dataset in [171] meets all of the aforementioned criteria. But a tried-and-true procedure is required to successfully remove distortions while emotional elicitation is underway. Because the length and timing of the experiment affect the data obtained, a specific distortion emerges. Research shown in [174] showed that people's emotional states might change over long periods of time, which can introduce bias into the results. Uncertainty about the correlation between the stimulus and the data obtained could arise because different emotions might emerge during the 60 seconds allotted for data collection [197]. Additional recommendations are necessary to improve the quality of datasets:

(1) White noise bursts and other rapid stimuli may help reduce the bias in more traditional forms of media including video games, music snippets, and movie excerpts. Emotions evoked by the latter types of stimuli depend on the subject's emotional state just before the stimulus begins, a phenomenon known as the "history effect" [197].

(2) It is important to establish and follow methods to label EEG data consistently among participants and over the whole EEG recording period. This consistency should be maintained all the way through the dataset development process, not only during the collecting session. Consistency is especially important in the intermediate areas of the valence-arousal dominance dimensions, where the data is much lower. Making sure the data is consistent will increase its value and make it better for training and validation [197].

(3) To achieve coherence and limit undesirable interferences, pre-processing of multimodal data is essential. This data includes skin impedance, EEG, auditory, visual, respiratory, pulse, and temperature data. There is a lack of cohesion in the preprocessing since different research groups employ different techniques to clean up the data and draw conclusions from the EEG sub-band signals. As a consequence, there are inconsistencies in the training data due to algorithmic and preprocessing issues. Together with standardized libraries of preprocessing tools, we propose the creation of global multimodal datasets. All classification systems will use consistent inputs because of this [197].

(4) The community must prioritize standardized benchmarking in order to adopt a set of universal standards for emotion categorization engines. In order to validate the clinical use of wearable devices based on electroencephalogram (EEG) for emotion recognition, it is essential to implement such standards [197].

## 5. Future Work

Passive approaches are used in datasets intended for applications, such as IAPS, IADS, music videos, and movie clips, to trigger emotions. Conversely, public databases like DEAP and SEED rely on using movie clips and music videos, respectively, to evoke certain emotions. It should be highlighted, nonetheless, that only a small number of research studies use active emotion technologies like video games and flight simulators to elicit feelings. It is anticipated that in the future, active elicitation techniques will be used to produce datasets since they are more accurate in replicating "real life" occurrences and more successful in evoking emotions. However, conducting these kinds investigations necessitates a far more intricate setup for the experiments. In addition, studying personal feelings has become more and more common lately. An analysis called Fear Discovery, which has ramifications for the study of phobias and other psychological diseases, is an example of such work. It is important to note that our poll revealed that it is harder to recognize negative emotions than happy ones. We found in our assessment of the literature that there is a dearth of studies on EEG-based emotional recognition of mixed emotions, such as sweet and bitter, which involve both positive and negative affect experienced simultaneously. These emotional integrations are especially intriguing because of

how important emotions are to the arena of highly creative performance. Figure 30 illustrates the prospective directions for research, challenges, and advancements in EEG-based recognition of human emotions as perceived by us. The elucidation encompasses numerous challenges related to emotion recognition within the context of brain-computer interface (BCI), which is commonly categorized into two domains: technology-oriented and user-centric. Furthermore, it delineates the potential impact of technological progress and trends on the realm of research concerning EEG-based recognition of human emotions. The identification of emotions within the domain of BCI continues to pose a significant challenge, necessitating further investigation and empirical studies. The imperative task of senior researchers in formulating a dependable system for classifying emotions remains essential to facilitate seamless interaction between individuals and automated systems.

## 6. Conclusion

The objective of this research was to investigate the feasibility of using electroencephalogram (EEG) data to enable virtual environments to detect and understand users' emotional states. Hence, the possibility of using EEG signal data is shown by the results of several tests using different combinations of features, especially those obtained from brain oscillations.

Exploring real-time implementations and understanding how they play out in the real world of virtual phenomena requires a broader range of research and methods. Not only is the computational cost being considered, but also embedded and real-time systems. Furthermore, it explores the ways in which the user's perceptions and the virtual environment will be affected by this new way of thinking and interacting. When a model is trained using data from one set of people or one set of tools, it may not perform as well when applied to another set of people or another set of tools. Many contributing factors may be identified as causing this difference.

(i) **Difference(s) Among Participants.** Brain architecture, functional organization, and neuro plasticity all contribute to the unique patterns and traits shown by each individual. Such variations may show up in distinct electroencephalographic electrical brain waves, which are most noticeable while doing similar mental activities.

ii) **Differences between Experiments.** Because of things like sleepiness, focus, and the time of day, a person's brain signals could change from one trial to the next.

(iii) **The Misalignment of Electrodes.** Variability may occur due to small differences in electrode placement between sessions or between people. Human error, differences in cranial anatomy, and variances in hair thickness are among potential causes of this variability.

(iv) **Prejudices that are unique to individual devices.** Inconsistencies in the obtained data may arise from the fact that different EEG devices may have different calibration setups, sampling frequencies, or signal-to-noise ratios.

v. **Environmental Disruption.** When trying to compare different people, it might be complicated since external elements like room temperature, noise, or light can affect an individual's brain activity.

**Conquering Obstacles.** To tackle this difficulty, we need to use sophisticated approaches that can standardize and account for the internal variables. This will make sure that BCI models are resilient and can be used with more than just one dataset. Domain adaptation

techniques provide an interesting avenue for research as they adjust a model that was trained in one domain to effectively function in another separate but related domain. Furthermore, it might be beneficial to improve performance by using more targeted datasets for fine-tuning or by using approaches such as meta-learning, which allow models to quickly adapt to new tasks.

Recently, there has been a lot of interest in researching brain-computer interface (BCI) emotion identification using electroencephalogram (EEG). Numerous research initiatives have been sparked by notable advancements in the development of cost-effective BCI devices with progressively improved usability. Here, we took a look at the various EEG recording datasets that have been developed for emotion identification. The current research efforts in the EEG dataset for emotion categorization are expected to be thoroughly reviewed and updated in this publication. Additionally, new researchers planning to enter this area of study might use the anticipated benefits for research in this domain as a springboard. The essay delves further into the topic, exploring how different industries including healthcare, education, entertainment, and lifestyle might benefit from a focus on the virtual environment's effective features to improve the user experience. The user's level of immersion is directly correlated to the virtual world's emotional qualities, and vice versa. When considering the subjective aspects of VR may ruin the user's experience if it doesn't match their expectations or how they're feeling in that specific situation. The user experience may be greatly enhanced by giving more attention to the often-overlooked aspects of virtual reality and emotional intelligence during development.

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