

A Review on EEG-Based Emotion Recognition: Methods, Challenges, and Future Directions

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Abstract: Electroencephalography (EEG) is a non-invasive and objective method to evaluate the emotional states of human beings with high temporal resolution and robustness to subtle or hidden facial expressions. This review systematically explores EEG based emotion recognition from signal acquisition to preprocessing, feature extraction and classification. We review both classical machine learning and modern deep learning frameworks along with a comprehensive taxonomy of existing methods. Publicly available EEG datasets and benchmark results are compared to allow critical evaluation of approach efficacy. It addresses challenges such as inter-subject variability, signal noise and limited dataset sizes. Future directions of research include optimization of deep learning architectures, multimodal fusion with other physiological signals, transfer learning and lightweight models for wearable EEG systems. EEG-based methods achieve a good performance in emotion classification and deep learning methods outperform the traditional methods, which indicates the practical applicability in affective computing and human-computer interaction. In summary, these approaches offer a reliable framework for advancing academic research and practical applications in the area of emotion recognition from EEG signals..

Keywords: EEG; Deep learning; Machine learning; signal processing

1. Introduction

Emotions guide human cognition, decision-making and behavior through engaging neural systems that are important for processing feelings. They are so important for effective decision making as conscious knowledge alone is not enough. It also triggers that complex interplay of emotion and rational thought which is not an aside but a complete process. Artificial Emotional Intelligence (AEI) is the combination of cognitive and emotional skills in human computer interaction (HCI) [1]. It allows computers to imitate human feeling skills. In other words it allows systems to have a more nuanced emotional awareness so that the interaction feels less mechanical and more human like, even though it is still only an engineered process[2]. AEI can sense, analyze, and understand the change in emotion by using advanced algorithms such as natural language processing and machine learning [3]. AEI also allows AI systems to become more intuitive, adaptable and responsive to learn to understand and respond to human emotions. Emotional intelligence in computers involves some vital human-like qualities such as self-awareness, self-regulation, intrinsic motivation, empathy and social skills but these are embedded into the design of the technology to make interfaces more natural, context aware and emotional engaging in practice [4][5]. This combination improves the user.

Experience and creates better bonds between humans and machines. With the advancement of AI, the potential of these emotionally intelligent systems to transform

various industries from healthcare to entertainment is becoming increasingly evident. These systems combine emotion with artificial intelligence, going beyond mere data

driven processing to a more empathetic, user centered way of interacting, and somehow, they are able to respond in a way that fits users' affective states. Finally, this integration improves user experience and satisfaction in a variety of domains, such as healthcare, education, and customer service, by facilitating more human-like and meaningful human-machine interactions [6]. Emotion recognition is very important in artificial intelligence, medicine, and education, because it improves how people communicate and interact. It improves the user experiences, and also helps to achieve better outcomes by sensing the human feelings which becomes important in the domains of health care, teaching, client support and entertainment [7]. Standard approaches to emotion recognition have several limitations. One problem is that facial and behavioral expressions differ from culture to culture. And then there's the case of voluntary masking, where people are actively masking their feelings. Moreover, environmental noise can interfere with the presence of auditory cues and make it difficult to reliably identify emotions in real-life situations [8]. Physiological signals are an objective indicator of emotional reactions that are representative of involuntary responses mediated by the autonomic nervous system, ANS [9]. These signals are recorded using methods such as EEG, ECG, EMG, EOG, PPG, EDA and GSR providing a more detailed view of the neurophysiological events associated with different affective states. These bio signals are less prone to the deliberate manipulation of aware people and are, therefore, more reliable for the purpose of emotion recognition than the traditional and common techniques [10]. The theory of emotion recognition began in the 90s and was enhanced with better sensors and algorithms. In time it spread across many different domains, bridging psychological frameworks with new technological ideas. This improved human computer interactions, supports medical health settings and also feeds entertainment because better emotion analysis approaches became available, more precise and more usable [11]. Emotion recognition research has been systematically developed from Psychology, where theories were constructed and emotions were defined. In this progress dimensional models were introduced, such as the valence-arousal model [12], which provided a conceptual basis for emotional states. According to psychophysiology, emotions are related to the body responses that can be measured, including neural and cardiovascular signals. This approach highlights the relationship between physiological arousal and mental interpretation [13]. Then, Signal Processing came to the rescue to handle the noise and general complexity of physiological signals. It involves things like filtering, artifact removal, and feature extraction, specifically of EEG data. The idea is to convert raw bio signals into something that can be analyzed. And yes, this is to make things more tractable. With the processed features in place, the Machine Learning methods were presented for the automatic classification of emotional states. The standardized datasets, such as DEAP, enabled systematic model evaluations and comparisons. In other words, the approach became more formalized, less ad hoc and it was possible to compare different learning algorithms without guessing [14]. Then the subject moved towards Deep Machine Learning, which at some point reduced the reliance on manually engineered features by learning layered representations directly from the data, and that actually improved performance when modeling complex emotional structures, which are, you know, more nuanced than before [15]. In recent years, research has shifted towards Wearable Bio-AI, where emotion recognition systems are realized in real-life scenarios via wearable devices working in real-time and dealing with practical constraints such as noise in signals, energy efficiency, user-specific adaptation, and data privacy [16]. Figure 1 explain the evolution of emotion recognition.



Figure 1. Evolution of Emotion Recognition Research: From Psychology to Wearable Bio-AI.

Physiological signals are indeed very important for reliable emotion recognition, as they directly reflect the internal responses of the body to emotion changes, such as neural activity and autonomic nervous system. Physiological traces are more objective and involuntary measures of emotional states, than behavioral cues, which can be intentionally steered or even masked. They thus improve the accuracy, stability and robustness of emotion recognition, especially in real-life scenarios [17]. This review then provides a broad synthesis of emotion recognition studies based on physiological signals, including single and combined, multimodal setups. It looks at EEG, ECG, EMG, EOG, PPG, and GSR signals, and it walks

through the usual signal processing pipelines, plus feature extraction strategies and machine learning and deep learning methods. A comparative view of data fusion tactics is also provided, along with a survey of public datasets. The review also points out major challenges such as motion artifacts, inter-subject variability, sparse labeling, and privacy limitations. By combining views from neuroscience, signal processing and artificial intelligence, this work offers a complete taxonomy of existing methods and suggests new avenues for research in the design of robust, interpretable and privacy-aware affective computing systems for real-world deployment.

2. EEG (Electroencephalography)

Emotion recognition from Electro-encephalography. It is the recognition of emotional states by means of electroencephalography to capture the brain processes [18]. EEG has some practical advantages, e.g. detection of emotional changes in real time when combined with spatial clues and temporal and frequency related features for emotion recognition. However, newer approaches such as convolutional neural networks as a way to help to improve the accuracy, but the older approaches tend to miss this [19]. EEG is less prone to voluntary masking than traditional cues (e.g. facial behavior or spoken language) resulting in more stable and reliable decoding. Therefore, EEG is especially useful in affective computing and human-computer interaction, where quick and reliable emotion recognition is highly significant [20]. Technically EEG technology measures emotions in the moment. It does this issue by measuring brain activity with electrodes placed on the scalp. This measurement is stable and instantaneous, which helps to understand better how a person adapts to environmental cues, thus improving the accuracy and reliability of emotion assessment. It also helps system designers refine spatial layout and elevate user satisfaction [21]. The electroencephalogram basically mirrors electrical brain activity coming from ionic motion across neuronal membranes. Neurons keep a resting membrane potential around -70 mV, largely because ion distribution is not balanced [22]. Neural communication shows up through depolarization and action potential generation. EEG does not directly record action potentials, rather it measures extracellular field potentials. These field potentials are produced by the combined effect of excitatory and inhibitory postsynaptic potentials from big populations of pyramidal neurons [23]. The scalp EEG signal is strongly influenced by how neuronal dipoles are oriented. There are several layers that affect signal propagation, such as brain tissue, cerebrospinal fluid, skull and scalp [24]. The laminar structure of the cortex favors synchronization of neurons and produces recognizable EEG rhythms. However, EEG mainly measures activity of the cortical surface and has only limited sensitivity to deeper brain regions [25]. Real-time EEG acquisition and monitoring system consists of hardware and software that allow for continuous analysis of brain activity and timely clinical responses. wireless electrodes of EEG devices receive and transmit neural signals in real time [26]. Later on, the data processing units use signal analysis methods to identify abnormal patterns and allow real-time decision-making [27]. The communication modules allow for a reliable transfer of data from the EEG hardware to the cloud-based platforms for remote monitoring [28]. HealthSOS is a mobile system that enables remote monitoring of EEG from hospital settings and provides immediate feedback on neurological alterations [29]. The EEG-driven brain-computer interface (BCI) pipeline is shown in Figure 2. First the brain activity is captured. Then it is pre-processed to remove noise and artifacts. Then relevant features are extracted and moved to a classifier for identifying mental states like attention or meditation. The classification output is translated into a control signal for further applications which again feed back to the brain forming a closed loop system.

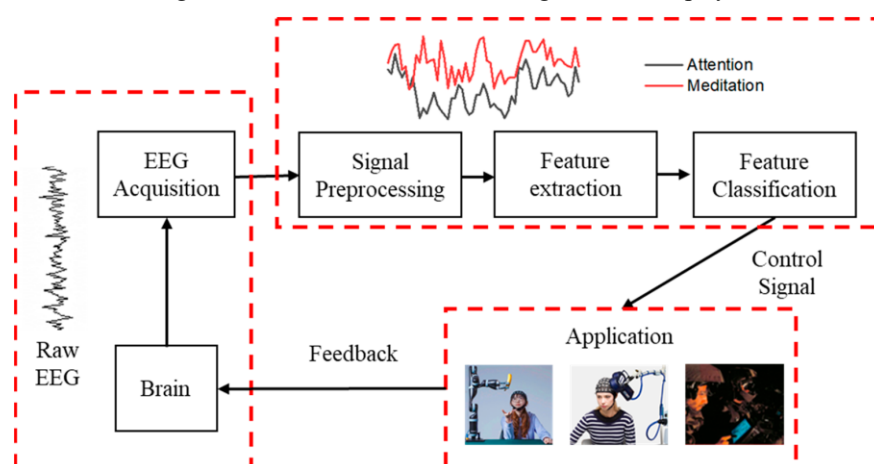


Figure 2. Block Diagram of an EEG-Based Brain-Computer Interface (BCI) System for Real-Time Signal Processing and Control Applications [30]

It consists of some simple components of the known EEG which collectively allow for a proper assessment and evaluation of electrical activity in the neural system. Electroencephalogram electrodes are usually mounted on caps or patches and they detect the potential on the scalp while maintaining a sufficiently low skin-electrode impedance to preserve the quality of the signal which is of utmost importance [31]. Amplification modules to amplify weak EEG signals and filtering strategies to remove noise and artefacts achieve this [32]. Digitization occurs using an analog-to-digital converter to generate the output signal data that will be analyzed [33]. Signal processing modules have been used in analyzing features in online analysis. Data from EEGs have been stored using storage systems during clinical trials or in research [34]. In the development of EEG technology, a lot of advancements have been achieved, with the most important being the increase in the channel numbers, which determine the quality of data collected. Moreover, several studies on different applications and technological advances discuss the advantages and novelties of single and multi-channel EEG systems [35]. Furthermore, single channel EEG devices have received increasing attention due to their low cost and ease of operation, and can be used in practical applications such as sleep staging and emotion recognition. Such devices with bipolar or unipolar electrode configurations reduce the hardware assembly and signal processing burden, enabling rapid deployment in clinical and consumer applications [36]. Meanwhile, multi-channel EEG devices are used to obtain better data through the recording of neural activity that is spatially distributed across multiple cortical areas. More channels (8, 16 or 32) are available for a more detailed study of brain dynamics and improve classification for more challenging problems such as emotion recognition and monitoring of cognitive states [37]. Many of the current multichannel platforms have wireless communication tools that provide the user with more natural and comfortable feeling of movement, no wires. Moreover, the recent multi-channel systems provide other features such as lead-off detection and real-time signal processing that provide more reliable data and more accurate measurements for practical applications [38][39]. Figure. 2. Difference of bipolar and unipolar conductive electrode configuration in EEG recording. In the bipolar mode the EEG signal is the difference between the voltages of two neighboring electrodes. This removes the normal noise but the spatial resolution is still poor. In a unipolar configuration, however, each electrode is measured against a common reference electrode. This allows for multi-channel recordings and provides a more spatially distributed picture of brain activity.

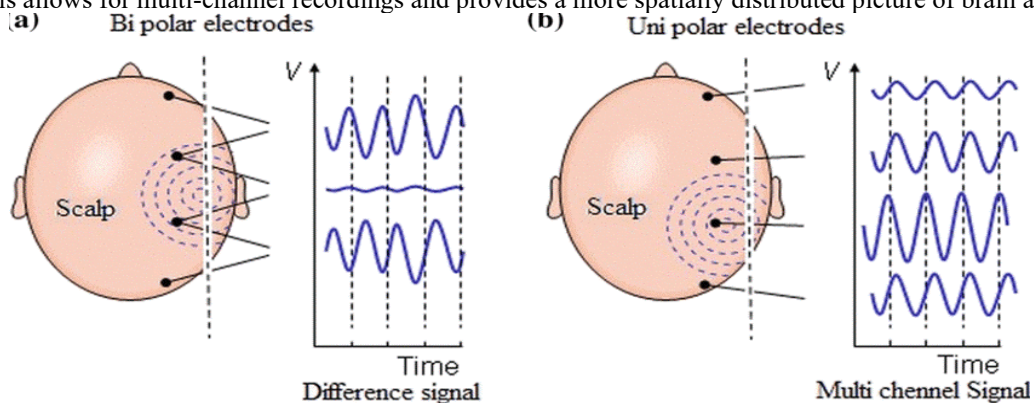


Figure 3. Comparison of Bipolar and Unipolar Electrode Configurations in EEG Signal Acquisition [36]

The choice of both wet and dry EEG equipment is not only relevant for neurophysiological research, but also for clinical application. The most common differences between wet and dry EEG systems are typically found in their setup, the quality of the output signal, and the day-to-day ease of management. Most wet electrodes require conductive gel and careful skin preparation, which can slow things down and make them awkward for nonclinical environments. However, the dry electrodes are more user friendly and allow faster montage and keep portability as a strong point [37]. In general, dry electrodes have a higher skin-electrode impedance than wet electrodes which can impact signal quality. However, recent advances in dry electrode materials and design have improved performance so that noise levels and signal fidelity can approach those of conventional wet electrodes [38]. Dry electrodes also do not need any conductive gel as in wet electrodes and this greatly reduces the preparation time and discomfort to the user [39]. This difference makes dry systems especially suitable for mobile, wearable and real-time EEG applications. Dry electrodes can be more appropriate in nonclinical and in-world settings as they allow for extended EEG recording while a person is engaged in daily activities with minimal impact on signal integrity. Thus, the use of EEG continues to grow outside of traditional laboratory settings. The advent of wearable EEG devices is a major development in neurotechnology because they can monitor the brain in real-time in a more user-friendly manner [40].

These devices make use of sensor technology improvements and signal processing strategies, so EEG can be used for stress estimation, sleep tracking, and braincomputer interfaces. The next sections summarize key parts of wearable EEG technology [41]. Types of wearable EEG devices are shown in Table 1.

Table 1. Types of Wearable EEG Devices and Their Functional Characteristics

Ref.	Type	Examples	Design	Application
[42]	Headset Devices	Emotiv Epoc, Emotiv Insight, InteraXon Muse, Imec EEG Headset	Head-mounted EEG headsets with multiple electrodes	Detect neurological activity to assess attention, stress, and engagement; typically connected to smartphones via Bluetooth
[43]	Flexible Dry Sensor Devices	Flexible dry EEG sensors	Flexible silver-ink, screen-printed dry sensors without conductive gel	Enable long-term EEG monitoring without skin preparation and skin irritation
[44]	Sleep Monitoring Devices	Forehead-, ear-, or neck-mounted EEG devices	Lightweight EEG electrodes placed on non-scalp locations	Analyze sleep patterns and lifestyle-related sleep factors
[45]	Brain-Computer Interface (BCI) Devices	Wearable BCI systems	Scalp, forehead, or ear-EEG configurations	Decode brain signals for medical and assistive applications, including patient care and disease management

2. EEG Signal Characteristics and Frequency Bands

Electroencephalography (EEG) is a technique that records the electrical activity of the brain by means of electrodes placed on the scalp. It provides high temporal resolution and a relatively direct window into neural processes associated with emotion [46][47]. Typically, EEG signals are divided into “named” frequency bands, delta theta alpha beta and gamma, each one associated with specific neurophysiological and affective functions [48]. Delta, around 1–4 Hz, is present during deep sleep, low arousal, and in emotional situations, it’s often reported with calmness or sadness. Theta (around 4–8 Hz) is linked to drowsiness, memory encoding and emotional regulation, and it can rise in sadness or when people are in a meditative-like state [49]. Alpha (8–13 Hz) reflects relaxed wakefulness; in emotion research, increased alpha power is associated with joy and anger, while reductions are found in fear and sadness [50]. Beta (13–30 Hz) is associated with active thinking, attention and arousal so increased beta activity is often associated with active feelings such as anger or joy [51]. Gamma (>30 Hz) is associated with higher order cognition, sensory joining and tends to peak when emotions feel intense [52]. The location of these signals in space is really important for emotion decoding. Frontal alpha asymmetry (FAA), greater left frontal alpha suppression than right, is a robust indicator of positive valence whereas the converse pattern indicates negative valence [53]. The temporal lobes are also involved in arousal and the processing of auditory emotions, and negative emotions tend to have less periodicity in the temporal EEG traces [54]. The parietal cortex tends to help regulate arousal and attention, because changes in it mirror changes in alertness, engagement, and the intensity of the emotion felt. In the meantime, occipital regions are mostly visual, but their responses are not limited to simple visual attributes. On the contrary, their response can be influenced by the emotional significance associated with what they perceive. As such, there exists a close relationship between vision and emotions with neural differences being identifiable when the former are exposed to emotionally charged images rather than neutral visual objects [55]. Time also comes into play since the faster high frequency waves (beta, gamma) change with shifting emotions. Gamma is often maximal during a stimulus perception while beta is more related to sustained attention [56]. These oscillations are found in networks that

involve the amygdala, frontal cortex, and occipital areas suggesting multi-region teamwork in emotional processing[57]. In clinical groups EEG-emotion links can be altered. For instance, patients diagnosed with epilepsy or depression may have reduced or even abnormal FAA patterns, which calls for population-specific models [58]. In conclusion, EEG frequency bands provide the neurophysiological basis for emotion recognition. EEG can be useful input to machine learning and deep learning in terms of spectral content and spatial arrangement. Frequency and spatial-temporal pattern sensitive markers can lead to more accurate and more interpretable decoding of emotions [59]. Table 2. Relationship between EEG frequency bands and emotional states. Lower bands like Delta and Theta are mostly associated with calm, sadness and emotional regulation. Alpha and Beta bands are associated with relaxation, attention and emotional arousal. High frequency gamma activity is an indicator of higher involvement and integration of sensory-cognition

Table 2. Emotional Correlates of EEG Frequency Bands

Ref	Band	Frequency Range	Emotional Associations
[47]	Delta	1–4 Hz	Calmness, sadness
[49]	Theta	4–8 Hz	Sadness, emotional regulation
[50]	Alpha	8–13 Hz	↑ in joy/anger, ↓ in fear/sorrow
[51]	Beta	13–30 Hz	Active emotions, attention, arousal
[52][60]	Gamma	>30 Hz	Intense engagement, sensory integration

4. EEG Data Acquisition and Electrode Placement

The primary instruments for data collection remain the non invasive multi channel scalp EEG setups which usually span around 14 to 64 channels [61]. Consumer-style tools like Emotiv and Muse are portable and cheap, but research-grade platforms like BioSemi and Neuroscan generally offer clearer signals and better artifact rejection, even if they come with more operational hassle [62]. In practice, emotion induction protocols heavily rely on multimodal audio visual stimuli. Standardized datasets like DEAP, SEED and DREAMER enable the method to be stable and are a more consistent approach of cross study benchmarking [63]. The international 10-20 system remains the standard electrode placement scheme, because it allows reproducibility and comparison across different studies [64]. High-density arrays with 64 to 256 electrodes are becoming more common in lab settings, primarily to pick up subtle changes in neural activity, especially when the emotion state is more complex. While lean configurations often 2-8 sensors located over frontal, parietal and occipital parts have shown solid accuracy as well at the same time. This supports wearable, and even real time use [65]. Some results show that electrodes placed on the frontal and parietal areas can achieve classification accuracy above 95% which makes them attractive for portable systems with no significant drop in performance [66]. Researchers used optimization routines such as particle swarm optimization, ReliefF-mRMR and hybrid sequential forward selection for selecting most important sensors. These techniques reduce the computational load with relatively stable accuracy [67]. Recent studies also study the tension between the number of electrodes and the spatial topology. In general, the number of electrodes may sometimes outweigh the expected benefits of advanced spatial arrangements, at least for the classification of emotion recognition. This is important in the design of affordable EEG systems, which still aim at high performance [68]. Spatial modeling methods, for example hierarchical dynamic local-global graph representations, have improved the ability of models to represent both intra-regional and inter-regional brain dynamics. The enhancement of the accuracy of emotion classification and augment the interpretability of the models by exploiting the spatial relations among electrodes [69]. In general, the trend seems to be towards more intelligent ideas for electrode placement that combine hardware miniaturization with adaptive spatial modeling. The goal is to build efficient, compact and reliable EEG emotion recognition systems. These changes are also creating the opportunity for real time, wearable workflows in mental health monitoring, human computer interaction and affective computing where electrode placement needs to balance accuracy, comfort and day to day usability [60].

5. Public Datasets

The real backbone of today's EEG emotion recognition are public datasets which allow reproducible benchmarking and some much fairer comparisons of methods. Most research is based on a few core databases, then they add a newer large scale, VR oriented, game driven resources [70]. It is clear from systematic reviews that a few datasets dominate the field; for example, DEAP is used in around 40 to 45 percent of recent studies, along with SEED, DREAMER, and SEED IV [71][72][73]. DEAP provides synchronized peripheral signals and continuous valence arousal ratings while people watch music videos, and provides 32 channel EEG. It becomes the de facto testbed for both classic machine learning and deep learning approaches, including CNN, RNN, transformers and also mixed or hybrid architectures [74]. SEED and SEED IV, recorded with 62 channel EEG during film clips, give researchers the opportunity to work with both discrete and dimensional labels, and are extensively used for deep learning experiments, for domain adaptation tasks and for cross subject generalization studies [75]. DREAMER also demonstrates that low cost wireless devices can deliver performance comparable to medical grade systems in valence, arousal and dominance recognition [76]. On the other hand, AMIGOS and MAHNOB HCI provide multimodal recordings, EEG plus ECG, GSR, video and other streams, which helps people study feature fusion and affective brain computer interfaces in more social or multimedia scenarios [77]. GAMEEMO uses computer games to evoke boredom, calmness, horror and fun with a 14 channel EMOTIV setup. You get raw recordings and preprocessed versions as well as self-assessment score tags [78]. VR based sets like VREED capture EEG response to 3D immersive video supporting positive vs. negative emotion labeling. It also points to different involvement patterns in frontal and occipital regions [79]. Finally, HBUED was proposed as a large-scale emotional EEG dataset, which was designed to alleviate the well-known problem of too few subjects in previous collections [80]

Table 3. Major Public EEG Emotion Datasets

Dataset	Modality / Device	Stimuli & Labels	Typical Uses	Citations
DEAP	EEG + peripherals, 32 ch	Music videos; valence–arousal	Benchmark for ML/DL, cross-subject, evaluation frameworks	[72][71][81]
SEED / SEED-IV	62-ch EEG	Film clips; discrete + dimensional labels	Deep learning, transfer learning, cross-subject analysis	[73] [82][83]
DREAMER	EEG + ECG, low-cost device	Audio-visual clips; valence–arousal–dominance	Wearable affective computing, feature comparison	[84] [20]
MAHNOB-HCI	EEG + peripherals + video	Video clips; continuous ratings	Multimodal HCI, evaluation across datasets	[85]
GAMEEMO	14-ch EMOTIV	Games; four emotions + valence–arousal	Wearable EEG, game-based induction	[86]
VREED	EEG in VR	3D VR videos; positive/negative	VR emotion recognition, network analysis	[87]
HBUED	Large-scale EEG	Emotional videos; valence–arousal	Large-sample deep learning, generalization studies	[88]

4. Preprocessing and Artifact Removal

The main goal of preprocessing for emotion recognition is basically to increase the signal-to-noise ratio, so that the next steps of feature extraction and classification are working with data that looks clean, reliable, at least enough. Filtering is a very common step in preprocessing pipelines. Bandpass filters are used a lot, to keep the frequency parts that matter for emotional processing, usually falling in the theta, alpha and beta ranges. Thus, the low frequency drift and high frequency noise are eliminated and the physiological signals can be analyzed more accurately [89]. Notch filters are also applied tuned to 50 or 60 Hz to calm down power line interference [90]. In some cases, a more selective trap filtering scheme is chosen, targeting very specific noise bands, without stepping on adjacent frequencies [26]. Downsampling is typically performed after anti-aliasing low-pass filtering and it reduces the data size and computational effort while preserving the frequency band of interest [91]. For artifacts, approaches have changed from single-method routines to mixed or hybrid plans that employ more than one algorithm. ICA (Independent Component Analysis) is a widely used blind source separation method to extract and remove ocular and muscular artifacts [92]. But ICA can have problems like possible signal distortion. Also, the component selection part may need manual checking. This results in the frequent use of complementary tools such as Empirical Mode Decomposition (EMD) and wavelet transforms [93]. It has been reported that hybrid setups such as EMD-BSS and wavelet-ICA work better for removal of overlapping artifacts, especially those that share spectral traits with neural signals [26]. Recent work has included the development of mutual information-based BSS methods using Epanechnikov kernels (which have better artifact separation and lower computational overhead than Gaussian kernel variants) and automated artifact identification methods such as MARA have been integrated into preprocessing pipelines. Hence, the results are more reproducible and efficient, and require less manual review [94]. Wavelet transform and meta-heuristically optimized Non-Local Means filters have been found effective for muscle artifact removal in low-channel studies and significantly improve the signal quality [95]. Normalization procedures such as z-score scaling also address inter-subject amplitude differences. Hence signals between individuals or between sessions become [77].

5. Machine Learning Approaches for EEG-Based Emotion Recognition

EEG based emotion recognition has really progressed beyond those pipelines that rely on handcrafted features plus old school ML classifiers such as SVM, KNN, Random Forest, and Naïve Bayes and it seems to be moving towards end to end deep learning architectures. But, traditional ML is still very common. SVM and RF generally outperform KNN and NB. For benchmark datasets such as DEAP, SEED the reported accuracies often lie in the range of approximately 61% to above 90% though it depends on the feature choice and the protocol and sometimes on how people set up the experiment [91]. The use of deep learning approaches continue to gain popularity, especially CNNs for analyzing spatial topography or connectivity maps and RNN or LSTM parts for recording temporal flow dynamics, often achieving around or above 90% accuracy in subject-dependent cases [96]. Meanwhile, CNN LSTM hybrids keep popping up, because it combines the spatial encoding with sequence memory, which is a parallel style thing. And then also transformer based models are becoming more common, since they fold in long range spatiotemporal dependencies, which also tends to bring improved interpretability, or at least that is what people claim, in a bit of a clearer way [97]. These deep models tend to perform better in terms of accuracy but they also have a heavier computational cost and more data demands as well. It's obvious but still. All approaches show performance drops when you do subject independent validation it shows limited generalization and not just a small adjustment. This is why evaluation metrics like accuracy precision recall F1 score confusion matrices are very important. Also, cross validation strategies should be used so results are not over promoted, or over optimistic [98]. EEG based emotion recognition is useful for healthcare and mental health monitoring but also for affective BCI, HCI and adaptive interfaces for learning, gaming and VR, where real time constraints and robustness are crucial, even under weird conditions [99]. But there are still problems like high inter-subject variability and the noise and different artifacts and small or weakly labeled datasets. There are computational burdens as well which make the real time deployment problematic. Also, there are no standard datasets, consistent labeling schemes, and clear evaluation protocols. However, many papers report promising research level performance which makes reproducibility hard and limits real world translation [100].

6. Conclusion

In this review, current status of EEG based emotion recognition is reviewed from the way we acquire the data, preprocessing, feature extraction and then machine learning or deep learning approaches. EEG has demonstrated great promise as an objective and reliable modality to track emotional states. It provides a high temporal resolution and is often

more robust to subtle or even concealed facial and behavioral cues. Classical machine learning approaches, such as SVM and Random Forest, have also achieved moderate results. However, in recent years, the development of deep learning, such as CNNs, LSTMs and hybrids, greatly improves the accuracy of classification, and also enhances the feature representation. These improvements do not solve a few difficulties. The results are not very generalizable to everyday settings due to inter-subject variability, signal noise, less than ideal dataset sizes and lack of uniform experimental protocols. Future work includes pushing multimodal integration, using transfer learning, pursuing explainable AI and designing light-weight models that fit wearable EEG devices. And bigger and more diverse datasets and standardized evaluation protocols matter a lot, because that's really what's going to move the field forward. Finally, EEG based emotion recognition appears to be a promising method in affective computing and human-computer interaction. As the methods and technology improve, it might impact healthcare, adaptive learning, virtual reality and other areas, bridging cognitive neuroscience with intelligent systems.

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