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A Comprehensive Study On Human Emotion Classification Framework Through EEG Signals

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Abstract: This review study highlights the ongoing complexities in understanding nonlinear brain dynamics despite recent researches. Neuroscience addresses these challenges by integrating brain structure and function, exploring innovative methods to map and model neurobiological systems. It leverages an empirical method for comprehensive mapping and dynamic pattern recording, alongside some proposed networks theories. This study comprises of the computational advancement along new scientific frontiers: probing network dynamics, controlling brain architecture, and integrating processes across diverse domains. The Electroencephalography (EEG) signal is a precise method for recognizing emotions during computer interactions. The review study explores emerging techniques of the neuroscience, aiming to illuminate brain understanding. It offers a compelling roadmap toward a deeper comprehension of complex brain functions and cognition.

Keywords: Emotion, Electroencephalogram signal, emotional intelligence, state of the art, Comprehensive study

Abbreviation:

Adaptive Neuro-Fuzzy Interference System (ANFIS)

Asymmetry (ASM)

Bayes neural networks (Bayes NN)

Band-pass filter (BPF)

Blood volume pressure (BVP)

Canonical Correlation analysis (CCA)

Convolution neural networks (CNN)

CNN+RNN (C-RNN)

Differential asymmetry (DASM)

Density estimate (DE)

Discrete wavelet transform (DWT)

Differential caudality (DCAU)

Electroencephalography (EEG)

Empirical mode decomposition (EMD)

Electromyograms (EMG)

Electrooculography (EOG)

Event-related oscillations (ERO)

Evoke event-related potential (ERP)
Flexible analytic wavelet transform (FAWT)
Fast Fourier transform (FFT)
Fisher linear discriminant (FLD)
Hilbert-Huang spectrum (HHS)
Hilbert–Huang transform (HHT)
Higher-order statistics (HOS)
Intrinsic mode functions (IMF)
K-Nearest neighbors (k-NN)
Leave-one-subject-out (LOSO)
Long-short term memory (LSTM)
Mahalanobis discriminating analysis (MDA)
Multi-fractal detrended fluctuation analysis (MFDFA)
Normalized length density (NLD)
Non-stationarity index (NSI)
Probabilistic Neural Network (PNN)
Power spectra density (PSD)
Quadratic discriminate analysis (QDA)
Rational asymmetry (RASM)
Random decision forest (RDF)
Recurrent neural networks (RNN)
Residual Wavelet Transform (RWT)
Transfer recursive features elimination (TRFE)
Spearman correlation coefficient (SCC)
SJTU emotion EEG dataset (SEED)
Short-time Fourier transform (STFT)
Support vector machine (SVM)
Transformer Capsule Network (TCN)
Temperature (TEM)
Time-frequency (TF)
Wavelet transform (WT)
Dataset for emotion analysis using EEG physiological, and video signals (DEAP)

1. Introduction

Emotion has an essential character in human intelligence, and the essence of artificial infiltration lies in its capacity to understand and acknowledge to emotions. Human-machine interaction become more essential in smart homes, industry 4.0, and personal wellness. A seamless interchange of emotions can improve human-computer interface. Emotions have an enormous impact on cognitive functions, including learning, understanding, remembrance, perception, and problem-resolving, making emotional interactivity beneficial for various appeals. It may also be pertinent in current healthcare, particularly in interactions with person suffering from despair or stress. Rehabilitation apps that guide patients via workouts while considering their emotional condition might boost motivation and speed up recovery. Minsky, in early eighties states that the absence of emotion leaves a machine lacking true intelligence [1]. The available literature suggests that the exploration of human emotion identification has practical applications across diverse domains, including entertainment [2], safe driving [3, 4], healthcare [5], and social security [6]. Picard [7] further asserted that human emotional changes manifest through various channels, namely, audio [8], facial [9], body posture [10], physiological activities [11], and more, which involves both the autonomic and central nervous systems. As a result, the investigation of human emotions via physiological, facial, behavioral attributes has earned considerable attention. However, deliberate concealment of audio and facial utterances in specific social contexts has led researchers to explore emotions using physiological time series such as EMG, BVP, TEM, EOG, EEG and many more. Out of these, EEG signals have captured researchers' interest as it directly reflect the instant brain dynamics. Hence, any disturbances in EEG signals accurately mirror shifts in emotional levels. The preference for physiological signals, particularly EEG, arises from its direct connection to brain activity, providing a direct insight into the kinetics of human emotions. This channel of research into EEG signals is more promising for a deeper understanding and more precise recognition of human emotions, overcoming the limitations posed by intentional concealment in other observable channels like vocal or facial expressions. Thus, delving into the complexities of EEG time series becomes imperative in evolution of distinction in emotional experiences. The high value of temporal resolution allows the transient activities. Moreover, the EEG signal allows measurements on impaired patients such as facial paralysis, psychological disorders, paraplegia, etc, in lab conditions. The rhythms of the EEG signal play an essential part in comprehending emotional recognition. It unveil sophisticated brain activities and specific states of the brain, characterized by rhythmic patterns falling into five fundamental bands based on frequency range: alpha (0.5–3 Hz), theta (4–8 Hz), alpha (9–13 Hz), beta (14–30 Hz), and gamma (>31 Hz). The unique activities are reflected with rhythmic bands in EEG, provide vital look into cognitive processes and therefore emotional states. This understanding of this transaction aids in research works of emotional identification, offering valuable insights into mental states and contributing to advancements in emotional recognition technologies.

The present study explores various algorithms for classifying emotionally labeled EEG signals at different levels of cognition. These algorithms demonstrate the capability to extract impulsive, busty, and transient variations of the EEG signal which are stimulated through different emotional labels. The article delves into the exploration of diverse algorithms and provides a comparative analysis to further our understanding of emotional signal processing. This article examines the various algorithms of emotion detection, including its benefits and limitations for certain applications.

2. Process of Emotion recognition

The process of emotions identification requires various steps that begin with eliciting emotions. Subsequently, the emotional characteristics derived from physiological signals must be identified and isolated. Emotions are then identified through the use of specialized classifiers. The subsequent sections outline various methods, as well as the challenges and constraints involved in this process.

1.1 Emotion Stimulation: The quality of dataset is very crucial for eliciting emotions and producing comparable outcomes. Emotions can be elicited by their memories or events. The database uses emotional acoustic stimuli that may be individuals or combination of image, video, audio, physiological signals. An affective norms database offers a wide range of normative emotional ratings that induce due to cognitive and physical stress.

1.2 Feature Extraction: Given the stochastic and semi-periodic behaviour of physiological events, it becomes imperative to extract specific attributes in order to facilitate the subsequent identification of emotions. Once the raw brain signals are measured, distinct features are extracted and computed. Nevertheless, it is crucial to examine each bio-signal individually as the extracted features may differ in their efficacy for emotion classification.

1.3 Classifier: Once the features matrix has been extracted from EEG signals, various classifiers are utilized to recognize the emotional levels. Notable among these classifiers are CCA, FLD, ANFIS, SVM, KNN, Bayesian network method, ANN, and many more. The accuracy of different classifiers varies when applied to the same data with different kernel functions, loss functions, iterations, stopping criteria, validation methods, etc. It is necessary to test both classifiers with different training sets to determine which one yields higher accuracy.

1.4 Evaluation: Emotion assessment poses a significant challenge that is not easily resolved. One approach is to compare the findings with a benchmark, like facial recognition or EEG, but these measurements may be susceptible to inaccuracies due to potential false emotional triggers. Another method involves categorizing emotions based on a variety of parameters and then comparing the outcomes with a self-assessment survey. Nevertheless, the interpretation of emotions can greatly differ based on individual experiences, cultural disparities, age, and various other factors, thereby making the evaluation process quite complex.

1.5 Limitations: Emotion analysis through facial conditions, gesture, or audio can be influenced by cultural, age, gender, environmental, and more. This reliance on outward physical expressions can result in inaccurate emotion classification due to social masking. To accurately determine emotional states, internal parameters must be considered. Utilizing multimodal systems may also aid in detecting genuine emotions. The autonomic nervous system responds to an individual's emotional state and is less susceptible to deception. There are no set guidelines for eliciting, classifying, or evaluating human emotions. The purpose of a study can also impact how subjects experience emotions. It's important to note that laboratory conditions are not the same as real-life situations, and results may not directly translate.

Classification module can be dependent or independent to subject. The dependent model need calibration for each participant, while independent model can identify emotions from unseen person without calibration. Dependent model typically have higher identification accuracy, while another is better for a broader audience. The latter technique often has lower identification accuracy and demands more advanced methods for correct emotion detection.

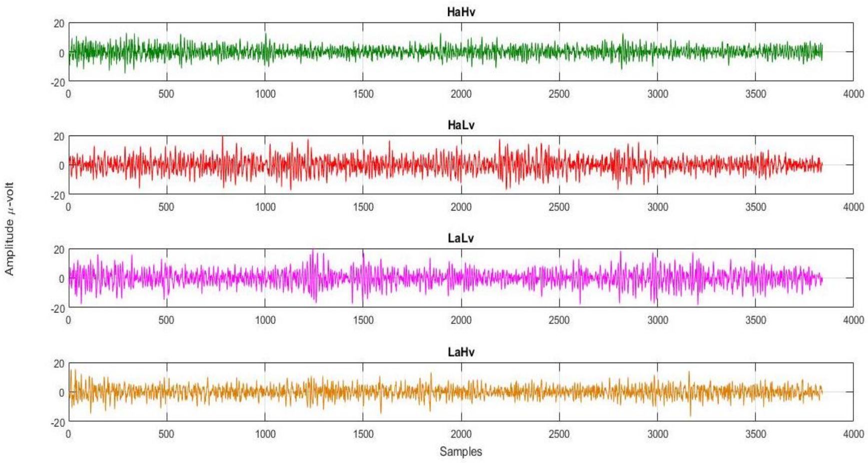

Figure 1. Labelled EEG signals from DEEP dataset.

3. Dataset

There are various datasets have been employed in the literature on emotions recognition through EEG time series. This study focuses on two specifically labeled EEG emotion datasets namely DEAP [12] and SEED [13] database. These datasets are authentic and publicly which are available on web. They consist of recordings capturing diverse brain activities stimulated during the generation of various emotions. The brief description of the databases are as follows:

DEAP dataset: It is an authentic and web-available emotions labelled EEG recordings. It encompasses time series of 32-neurological events and 8-peripherals, comprising 40-channel recordings. Thirty-two volunteers were instructed to numerically rate fourth one-minute music concerts based on different emotional dimensions, including dominance (1-9), arousal (1-9), familiarity (1-5), like/dislike (1-9), and valence (1-9). These recordings are classified into four classes of emotions based on the mean-standard deviation limit of arousal and valence. This representation includes low arousal and high valence (LaHv), high arousal and low valence (HaLv), low arousal and low valence (LaLv), and high arousal and high valence (HaHv). Figures 1 and 2 display the labelled non-linear brain signals and number of time series, associated to different emotions respectively. The recordings undergo filtering to eliminate many artifacts and are down-sampled at 128 Hz. To address concerns about emotions initiating early during concert watching, a 3-second duration is designated as baseline data, and remaining 30 seconds of recordings are earmarked for analysis.

SEED dataset: The SEED database comprises EEG recordings of 15-volunteers (8 females and 7 males), with emotions categorized into positive, neutral, and negative states. Each participant contributed data through three sessions over a three-week period, involving 15 trials per session. The emotional events are recorded through 62-channels.

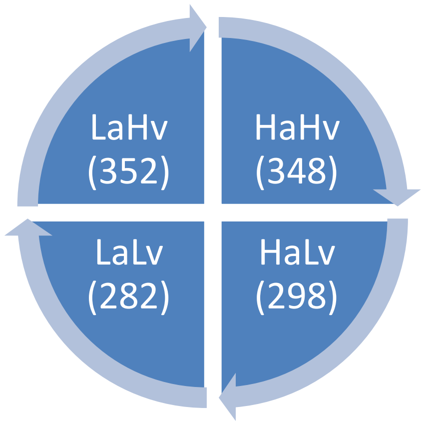

Figure 2: The number of emotional events associated to various emotions

4. Literature review

Human emotions act as neurophysiological indicators that become evident in the context of psychiatric disorders associated with emotion regulation. Figure 3. shows the intelligence algorithm of human-computer interface associate to emotion recognition. Human intelligence and computational intelligence are the two components of this system. Human intelligence is influenced by memory, experiences, and surrounding conditions, and is responsible for eliciting emotions. On the other hand, artificial intelligence involves synthesis, adaptation, and expression. It attempts to imitate human behavior by applying specific mathematical rules to the brain's event potential signature.

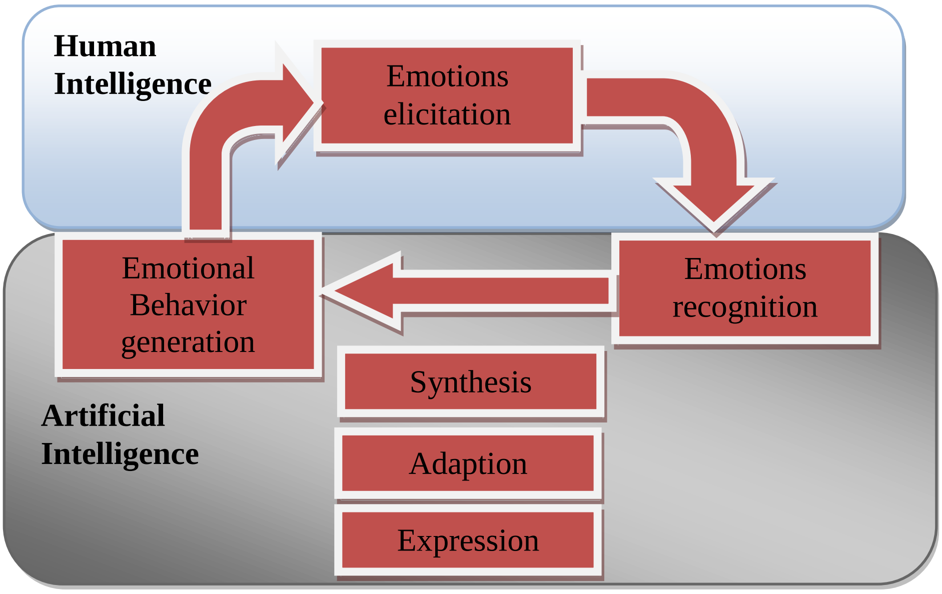

Figure 3. Human-computer interface associate to emotion recognition

The literature reveals a wealth of studies dedicated to understanding the constructs beneath the dynamic phenomena and their proportionate reflections in EEG signals. Numerous algorithms have been proposed diverse time, frequency, and mixed domain analogies [14–19]. Kroupi et al. [20] introduced a correlation approach and leveraging the SCC among NLD, PSD, and NSI features vectors discriminate three categories emotions. The decomposition techniques are used to break down the series into its rhythms, and various attributes, namely, sub-band PSDs of these rhythms were computed to discern emotions labels [21, 22]. Authors of an article measured mixed features matrix, including the Zhao Atlas-Mark distribution, spectrogram, and HHS of the studied data and classified them using various classifiers, namely, kNN, MDA, and QDA respectively. The achieved classification accuracy was 86.52% with kNN algorithm [23]. Several nonlinear signatures such as Hjorth parameter [24, 25], fractal dimension [26, 24, 27], and variants of differential entropy [24, 28] are introduced to explore the underlying dynamics of labelled EEG signals. A two-level emotion categorizing method were proposed by Frantzidis et al. [30]. The features, such as, EROs and ERP are measured and classified with the MDA and SVM classifiers. They achieved accuracies on order of 79.5% and 81.3% to respective classifiers. Zheng and Lu listed 86.65% emotions categorization accuracy with differential entropy feature [29].

Neurophysiological signals are having non-stationary dynamics, which cannot be adequately characterized by time or spectral domain algorithms alone. Therefore, various TF methods are employed to explore the non-stationary dynamics of neurological events, offering insights into frequency dispersity on time axis. It limited the resolution over TF axes. To overcome the limitations of traditional methods, these TF analysis approaches simultaneously break-down the signal along on TF coordinates, providing improved temporal localization of frequency components. The STFT has been introduced for emotion recognition [32], its fixed window length often results in suboptimal performance in localizing impulsive and oscillatory behaviours of studied signals. The WT is extensively employed for automated emotion identification due to its exceptional TF resolution through utilization of a variable-length wavelet basis [33–34]. However, DWT exhibits vulnerability to shift-variance and lacks adjustable TF coverage, especially at higher frequencies. To mitigate these issues, various variant of WT, namely, multiwavelet transform [35], FAWT [28], and more have been introduced in the literature. However, it is a data-dependent method which outcomes may vary with alter in basis of mother wavelets. The EMD is another alternative nonlinear tool for emotion identification [37, 38]. The authors in [33, 37], measured zero-crossing count from each sub-band that obtained through DWT and EMD algorithms. In addition to above discussed methods, the CNN has been proposed for automated human emotion classification [39, 40]. These advanced approaches demonstrate the evolving landscape of techniques applied to better capture the nuanced and dynamic nature of emotional states through EEG signal analysis.

Table 2: Emotion recognition algorithm in different domains.

Author	Year	EEG Features	Method	Dimensions
Horlings [43]	2008	Band power, Cross-correlation band powers, Peak frequency in alpha band and Hjorth parameters	NN, SVM, Naïve Bayes	Frequency
Schaaff [45]	2009	Peak alpha frequency, Alpha power, Cross-Correlation.	FFT, SVM	TF
Murugappan et al. [32, 34]	2010	Power	DWT	Time
Petrantonakis and Hadjileontiadis [33, 37]	2010	Zero crossing	DWT	Time
Frantzidis [30]	2010	Amplitudes and latencies of ERP components and amplitude of ERO	DWT, SVM	TF
Hosseini [47]	2010	HOS	Direct FFT, SVM	Frequency and Spatial

Nie et al. [31]	2011	Sub-band	STFT	Frequency
Kroupi et al. [20]	2011	Sub-band, NSI, NLD	Welch's Method	Frequency
Brown [46]	2011	Alpha Power Ratio, Band power, Peak alpha Frequency	QDC, SVM, k-NN	Frequency and Spatial
Liu and Sourina [22]	2012	β/α	FFT	Frequency
Hadjidimitriou et al [23]	2012	HHS Vectors	HHS	Time and Frequency
Chung [48]	2012	Bayesian features	Bayes NN	Frequency
Reuderink et al. [44]	2013	Asymmetry in α rhythm	Welch's Method	Frequency and Spatial
Rozgic et al [15]	2013	Spectral Power	FFT	Frequency and Spatial
Lee and Hsieh [17]	2014	Correlation and Coherence	FFT	Frequency
Zheng et al. [27]	2014	PSD, RASM, DE, and DASM	STFT	Frequency
Lahane and Sangaiah [41]	2015	Density estimate	Kernel density estimation	Frequency
Paul et al. [28]	2015	Sub-bands power	MFDFA	Frequency
Thammasan et al. [26]	2016	FD and PSD	Welch's Method	Frequency
Li [49]	2016	ML	C-RNN	-
Zheng et al. [29]	2016	DE, DASM, ASM, RASM, and DCAU	STFT	Frequency
Li et al. [38]	2017	Entropies	HHT	TF
Yin et al. [39]	2017	TF Features	FFT	TF
Youjun [50]	2017	Multi-dimensional features	CLRNN	-
Zheng et al. [13]	2020	Multi-dimensional convolution layers and ADL	RACNN	Spatial
Sharma et al. [42]	2020	HOS	LSTM-DL	-
Cui et al. [51]	2020	MM	RACNN	-
Tuncer et al. [52]	2022	DWT	SVM	Time
Tuncer et al. [53]	2022	TQWT	PatNet19	TF

5. Discussion and Conclusion

This article demonstrates the existing algorithms for emotion labelled EEG signals classification accuracy, as summarized in Table 2. Liu et al. [22] proposed a pre-trained convolutional capsule network, based on Mobile-Net for extracting the relative distribution of emotionally labeled EEG signals. They were able to achieve a recognition accuracy of 95.08% for 3-emotion classes. Murugappan et al. [32] computed power spectral density (PSD) from DWT coefficients and achieved a classification accuracy of 71.3% using the kNN classifier for binary emotions classification. However, the algorithm experienced scale variance issues, resulting in a decrease in resolution at higher frequency. Gupta et al. [36] utilized the FAWT for EEG signal decomposition and achieved a classification accuracy of 71.43% for four-class emotions with the random forest classifier. Yi et al. [39] implemented the TCN to gather the details of global contextual from different domains. They achieved 98.82% emotions categorization accuracy. Sharma et al. [42] proposed a HOS based features-independent algorithm, achieving enhanced classification accuracy by using the entire HOS transformed features matrix for labelled emotions. They reported 82% accuracy using SVM with radial basis function kernels. In [49], a novel approach for automated emotion recognition was introduced, which combines C-RNN using LSTM techniques. They achieved a classification accuracy of 75.21% using multidimensional features images (MFIs). Youjun Li et al. [50] introduced innovative research methods, integrating spatial, frequency, and mixed characteristics into two-dimensional images. They employed a hybrid DNN merging C-RNN and LSTM to recognize human emotional states, achieving 75.21% accuracy on the DEAP dataset.

Table 3: Comparison study of emotion recognition algorithms through EEG signals.

Authors	**Methods**	**Classifier**	**Accuracy (%)**
Liu et al [22]	FFT	CCN	95.08
Frantzidis [30]	ERP and ERO	SVM	81.30
Murugappan [32]	DWT	k-NN	71.30
Gupta et al. [36]	FAWT	RF	71.43
Yi et al [39]	TCN	SVM	98.28
Sharma et al. [42]	HOS+LSTM	Softmax	82.01
Horlings [43]	DWT	SVM	81
Schaaff [45]		SVM	66.7
Brown [46]	WT	SVM-KNN	82
Hosseini et al. [47]	HOS	SVM	82
Chung [48]	-	Bayes-NN	66.6
Li et al. [49]	CLRNN	-	75.21
Youjun [50]	ML	CLRNN	75.21
Chi et al [51]	ML	RACNN	95

Tuncer et al. [52]	DWT	SVM	99
Tuncer et al. [53]	TQWT	PatNet19	94.58
Nakisa et al. [54]	TF features	LS-SVM	67.47
Yin et al. [55]	T-F features	PNN	78
Abdullah et al. [56]	TQWT	SVM	99
Sharma R. [57]	RWT	DL	78.37

In [52], an innovative multi-levels parameter estimation method for affective emotion recognition. They utilized a tetromino game-based approach and decomposing brain signals using the DWT and tetromino algorithms. This process aims to maximize relevance and minimize the redundant (mRMR) attributes from each sub-signals. Remarkably, the proposed method achieves an impressive 99% accuracy with the SVM method. Tuncer [53] introduces a comprehensive three-levels module for generating fused parameters in affective emotion recognition. The proposed model used the TQWT with LEDPatNet19 to measure various statistical and nonlinear texture attributes with 18-levels of decomposition. ReliefF and iterative Chi2 (RFIChi2) parameter selector is applied to choose the effective feature-vectors, resulting in outstanding discrimination accuracies of 99.29% and 94.58% for two different datasets, respectively. Nakisa et al. [54] conduct a thorough analysis of EEG time series in mixed domains. Various evolutionary algorithms are utilized to select informative attributes from the measured feature matrix. This approach achieves a classification accuracy of 67.47±3.38% for discriminating four emotion categories with the PNN classifier. Similarly, work by Yin et al. [55], 16 features are computed from studied EEG signals in frequency and time domains separately and the significant features are selected using the TRFE algorithm and classified with the Least Squares-SVM method, resulting in a notable 78% discrimination accuracy for binary classes.

The TQWT and Clefia-cipher extractor are used for signal decomposition and generation of total 798-local attributes are measured from different labels sub-signal and the original one. The minimum redundancy maximum relevance feature-selector is utilized to select 399-attributes form feature matrix and classified with the SVM classifier. They achieved an impressive accuracy exceeding to 99% with the LOSO method. Sharma R. [57] proposes the RWT to explore the transient and nonstationary aspects of studied signals in TF-plane. This algorithm provides excellent domain resolution to measure variations of instantaneous energy with different frequencies. It measures some remarkable edges of frequency with instantaneous time, especially at smaller signal frequencies such as δ and θ, which contain valuable information about underlying non-linearity as compared to larger frequency rhythms. The non-linear dynamics and complexity on the WT coordinate is assessed through the application of various entropies, which are subsequently processed by the LSDA. It reveals the hidden structural information to map the class-labeled attributes that enhance the marginal differences. The norm of the attributes from the marginal vector is used to rank them in ascending order. The ranked feature serves as a safeguard against impulsive and swift variations in the analyzed data, thereby minimizing error learning rates and increasing the number of iterations. The LSTM conducts a thorough analysis of sequential events, exercising control over information exchange to maximize the probabilistic error. A self-learning model is employed to bring out the subtle information embedded in studied dataset. The processing of the network exclusively based on the probabilistic criteria, and each decision is made based to error minimization.

6. Conclusion

This in-depth review thoroughly investigates EEG-based emotion recognition, encompassing its mechanisms, triggers, classification models, and algorithms. It delves extensively into the exploration of feature identification, selection, ranking, and classification within neurophysiological signals analysis for emotion identification. Furthermore, it critically examines various classification methods through a literature review to assess their efficacy. Despite notable advancements, challenges persist, particularly concerning the limited emotion categories and datasets available for practical applications. Addressing these gaps is imperative for the advancement of this field. Future research should prioritize expanding emotion categories and enhancing existing datasets to improve and broaden the average accuracy, ultimately laying the groundwork for more robust and comprehensive emotion identification technologies.

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