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A Detailed Analysis of Emotion using Deep Learning with the help of EEG Signals

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ABSTRACT

Thanks to recent advances in sensor knowledge and information processing, computers can now detect and understand human emotions. Research into emotion identification is a promising avenue in many different areas. Feelings expressed by humans can take several forms. With so many uses for emotion classification—recommender schemes, cognitive load detection, etc.—EEG-based emotion identification has grown more important to the intelligence of Brain-Computer Interaction (BCI) systems. There has been a lot of recent excitement in research powered by Artificial Intelligence (AI) surrounding emotion categorization. The research paper included a comprehensive analysis of AI-powered automatic emotion identification using EEG data. The study compiles and reviews over a hundred articles on emotion recognition using literature research methodologies in this survey. The research sorts the articles into many groups based on the advances they include. When it comes to emotion identification using EEG signals, these papers are all about the methodologies and datasets. In addition, this review evaluates several sensors for emotion identification and contrasts their pros and cons. To choose appropriate algorithms and EEG datasets, researchers can benefit from a deeper grasp of current emotion identification systems, which the suggested survey can provide.

KEYWORD

Artificial Intelligence; Brain-Computer Interaction; Electroencephalogram; Human Emotion recognition; Deep Learning

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I. INTRODUCTION

A person's emotional state is an outward expression of their internal mental and physiological processes; the concept of emotion recognition was first put forth in a systematic way in the 1990s. Emotion recognition has found several applications in different domains due to the fast advancement of science and technology. These include HCI, healthcare, online education, sector, among others [1]. It is possible to implement emotion identification using a variety of detecting techniques and sensors. Robotic or human-computer interaction systems are created by combining sensors with sophisticated algorithm models and large amounts of data [2]. When used to healthcare, emotion recognition can reveal a patient's mental health status or the need for adjuvant therapy, all while enhancing both the quality of care and the efficiency of medical procedures. When it comes to BCI applications for treating brain illnesses and injuries, the industry is seeing a significant boost from the increasing usage of BCI technology. The global BCI market was worth $1,488,000,000 in 2020. Forecasts indicate that this value will reach $5,463,000,000 by 2030, expanding from 2021 to 2030 at a CAGR of 13.9% [3]. Affective reports (e.g. SAM) and biosignals have both grown in popularity as alternative methods of emotion measurement in recent years. Emotion identification has long made use of biosignals such as respiration, galvanic skin reaction, phalanx temperature, ECG, electrooculographic (EOG) signals, blood volume pulse, and cerebral blood flow [4].

A number of recent studies have concentrated on the analysis of brain signals using methods like electroencephalograms (EEGs), functional near-infrared functional magnetic resonance imaging (fMRI), and proton emission tomography (PET). One benefit of EEG over the other technologies is the improved temporal resolution it provides [5].

The recent push to conduct signal recording in settings other than clinical research labs has been a major obstacle for EEG system prototypes. Typically, subjects were monitored in hospital or laboratory settings using bulky technology. But now, thanks to efforts to develop wearable EEG equipment, we can record brain activity outside of a lab setting for longer periods of time without intrusive procedures [6]. Thus, BCI for emotion identification in many domains is becoming more feasible due to the rising wearability of prototyped systems. Neuromarketing makes extensive use of EEG in non-clinical contexts to assess consumers' responses to offerings [7]. In the past, researchers in this field have used a variety of commercially available EEG equipment.

The use of ML and DL algorithms allows for the analysis of EEG data. Classification is the last stage of conventional ML algorithms, which often begin with preprocessing and feature extraction. However, not all hidden features can be extracted manually, and the methods used to extract features from the time domains can be rather complicated [8]. In addition, electromyography artefacts can taint EEG data, severely impairing the performance of conventional machine learning methods. In light of these issues, our primary goal is to develop an emotion detection system that is both simple and effective, with small mistake rates and high categorization rates. In light of the foregoing, certain deep learning techniques are utilised to circumvent these problems. With learning, a system may automatically gain knowledge and get better over time [9].

The training of a model in deep learning, a subfield of machine learning, makes use of complex networks. One key difference between deep learning and machine learning is that the former can handle both types of data, regardless of their structure [10]. Machine learning algorithms' effectiveness degrades with increasing data volumes; so, a deep learning approach is required to preserve the model's efficacy. Many different types of businesses can benefit from deep learning. Even though it's a dangerous undertaking, automating self-driving automobiles has recently gotten closer to being a reality [11]. From learning to recognise stop signs to seeing pedestrians, models based on deep learning are trained and evaluated in simulated scenarios. The use of virtual assistants is one example of a well-known deep learning application. Alexa, Cortana, Siri, and Google Assistant are just a few examples of the virtual assistants that we all use on a regular basis [12].

The pharmaceutical and healthcare industries greatly benefit from deep learning due to its many uses, such as rapid diagnosis and picture segmentation. A traditional neural network (CNN), for instance, can process X-rays, MRI data, and other types of imaging. Nearly every sector of the economy has begun to use deep learning [13]. It finds use in many different fields, such as manufacturing, e-commerce, advertising, chatbots, visual recognition, NLP, visual recognition, visual recognition, fraud detection, etc. One reason to go with deep learning is that it allows for automated feature extraction, which isn't achievable with traditional ML methods. In some situations, this review article might be useful:

- ❖ A comprehensive explanation of emotions, processing of EEG signals, necessary tools, datasets that are publically accessible, popular features, and classifiers are all part of the introductory material that is offered to new researchers in order to assist them in getting up to speed as soon as possible.
- ❖ The results may assist researchers at the intermediate level in deciding what to do next by comparing the performance of DL-based classification systems.
- ❖ Emotion recognition features and databases that are accessible To further assist expert-level researchers in developing a faultless emotion identification system for real-world application, the paper analyses a number of pertinent studies, discusses their limitations, and offers recommendations for future study.

The rest of the paper is structured as shadows: Section 2 introduces the EEG device; Section 3 analyses the background of EEG based emotions; Section 4 describes the sensors used for emotion recognition in detail; Section 5 lays out the process for emotion recognition; Section 6 mentions related work; and Section 7 benevolences the challenges found in previous studies. Sections 8 and 9 conclude with the tendencies for the future.

II. EEG DEVICES

Recent developments in Brain-Computer Interface (BCI) technology have caused a meteoric rise in the consumer-grade segment, which in turn has increased the number of reasonably priced EEG devices available on the market. With consumer-grade items, researchers can easily analyse human brain activity without having to know electronics or engineering. These products are accessible, have a basic design, and are cheaper. Here you will find comprehensive descriptions of the three EEG devices mentioned earlier: Emotiv, OpenBCI, and NeuroSky.

A. Emotiv

When it comes to EEG equipment for the general public, Emotiv is among the most prominent names. EPOC products—X,+, FLEX, and INSIGHT—are on the market. Released in 2020 to celebrate the 10-anniversary, the newest product, EPOC X, has the same features as the renowned predecessor model, EPOC+. The updated EPOC X model allows for more comprehensive neuroscience studies. The electrical activity of the cerebral cortex can be monitored with the help of fourteen electrodes, plus two reference. "Emotiv EPOC X - 14 Channel Wireless EEG Headset | Emotiv," n.d., lists the following features as important: Bluetooth connectivity, better signal quality, a electrodes.

B. OpenBCI

"OpenBCI - Open Source Biosensing Tools (EEG, EMG, EKG, and more)," n.d., describes the 2014 debut of OpenBCI products as open- products do is act as an amplifier, which is less than other less expensive EEG devices. For example, the Cyton+ Daisy Biosensing Board collects data from sixteen channels at 125 Hz, while the Cyton Biosensing Board collects data from eight channels at 250 Hz. The electrical activity of the heart and muscles are also recorded by the OpenBCI boards in addition to data from the brain. One of the available headset solutions includes computer-aided drafting (CAD) software, so the customer can design and 3D print their own custom headgear to meet their specific academic needs. You can develop an open-source application using OpenBCI's programme named Processing. More and more experimental research are using OpenBCI products. Multiple studies proved that the OpenBCI device could reliably and potentially record high-quality EEG signals.

C. NeuroSky

Since its founding in 2004 NeuroSky Inc. has been manufacturing Brain-Computer Interface technology for consumer-grade applications. As far as consumer-grade EEG equipment are concerned, NeuroSky was an early trailblazer. Neurosky MindSet was their initial product introduction in 2007. After NeuroSky Mindset made a sensation, the company released multiple consumer-grade products with upgrades. While prior variants were produced for a while, only MindWave Mobile 2 is now available worldwide.

An affordable EEG gadget that has gained popularity is the MindWave Mobile 2. According to the creators, all it takes is one EEG electrode to pick up on data related to cognitive functions including attention and meditation states. The electrode on top of the skull captures impulses from brain, and the ear clip secures to the ear canal to ground the device and interpret the electrical signals. Due to their reliance on a single electrode, NeuroSky devices suffer from poor sensitivity and performance quality, despite their inexpensive price, ease of use, and speedy data processing. Other commercial EEG devices do a better job of cancelling out background noise than these do. You can find a summary of EEG devices in Table 1, and in Table 2 you can see the pros and cons of these devices.

Table 1: A summary of six reasonably priced EEG devices.

Device	Release Year	Price (USD)	Electrodes	Sampling Rate (Hz)
Emotiv EPOC FLEX+	18	1699+	up to 32 (+2)*	128
Emotiv EPOC X++	20	7999	14 (+2)*	128/256
Emotiv EPOC++	13	6999	14 (+2)*	128/256
Emotiv INSIGHT++	15	2999	5 (+2)*	128
OpenBCI	14	750/180	8/16	250/125
NeuroSky MindWave	18	199	1	512

* (+2) point to the reference sensors situated at the mastoid development.

Table 2: Advantages and difficulties of revised commercial EEG products.

Perfect	Difficulties	Rewards
Neurosky MindWave Mobile 2	Only 1 sensor Bad superiority for EEG experiments	Low price
Emotiv EPOC	10–15 min setup period	Compact
	Non- sensors, ability	Wireless
	Requires a pro license SDK for raw data admission	Practical
OpenBCI	Need to collect yourself	14 sensors
	Requires major preprocessing	High signal quality
		Ready to use assembly

III. BACKGROUND OF EMOTION DEFINITION

No one concept can adequately describe the range of human emotion. There are several facets to this multi-faceted phenomenon that have to do with the mental, physiological, and social conditions of an individual. Emotions are changes in the human brain's state that occur in response to a specific experience. Researchers often refer to emotional states as the affective state. A wide range of disciplines, including philosophy, sociology, computer science, medicine, neurology, and psychology, have long been interested in human emotion. American philosopher and father of psychology William James (1884) argued that physiological changes in the body give rise to subjective experiences known as emotions. Muscle tension, facial expressions, and visceral motor activity are some of the bodily changes he posited as the origins of human emotion.

A. *Models of emotion*

It is crucial to know how to categorise the many brain regions activated during emotion creation. No universal model has been settled upon, despite the fact that numerous researchers have put out diverse emotion classification algorithms. There are currently two main types of emotion models: those that use discrete definitions and those that use dimensional scales for emotion classification. feelings are categorised by discrete emotional models, which use a restricted set of common feelings as a basis. They are applicable to primates and other creatures, and they are universal since they are ubiquitous across cultures. Therefore, they are grown in a natural way. For many years, the six discrete emotions—happy, sad, scared, angry, shocked, and disgusted—were the basis of emotion models. When a computer is asked to forecast many emotional states, it often uses discrete emotional models. This is common in emotion identification systems. But the intricacy of emotions is beyond the capabilities of these models.

The next step in handling the difficulty of emotions is to construct a dimensional emotion model that makes use of the dimensions of various affective conditions. In this concept, emotions are categorised using a dimension. The values of a dimension can range from zero to one, and they can be either continuous or discontinuous. The values or points on each scale provide a multi-dimensional expanse that can be used to describe and understand emotions (Scherer, 2005). This manner, scientists can forget about deciding which emotion category to follow and concentrate on emotion recognition tests. When dealing with dimensions, Russel's circumplex model is a popular choice. To categorize feelings, it use a two-dimensional model. Two such scales exist: the scale. An emotion's valence can be captured on a scale from pleasant to bad. As an alternative, the arousal scale measures how active or passive a person feels.

Emotional intensity and positivity can be measured using Russell's arousal and valence levels [14]. In Figure 1, we can observe that this model classifies emotional reactions as either high arousal with arousal with low valence (LALV), or low arousal with high valence (LAHV). This study developed the DL process classes using this four-subdivision approach.

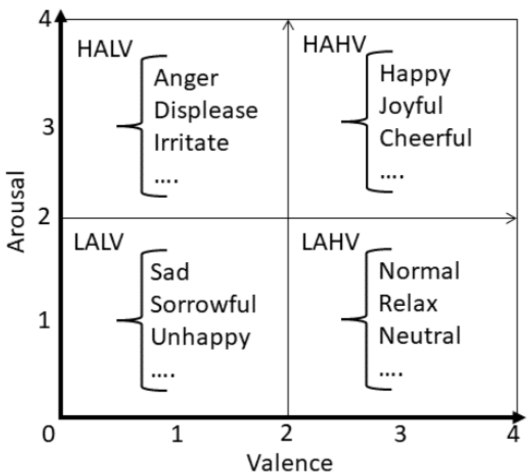

Figure 1. We use the Russell circumplex approach to distribute emotions and classes. Thanks to this framework, we were able to implement a multiclass categorization system.

IV. SENSORS FOR EMOTION RECOGNITION

Visual, auditory, radar, and other physiological signal sensors are commonly utilised for emotion recognition. These sensors may gather signals of many dimensions and, with the help of certain algorithms, accomplish emotional analysis. When it comes to emotion recognition, many sensors are useful for different things. Table 3 displays the benefits and drawbacks of various emotion recognition sensors.

Table 3. Compensations and difficulties of diverse sensors for emotion recognition.

Sensors	Disadvantages	Compensations
Visual sensor	Restricted by light; calm to cause privacy leakage	Simple data collection; high scalability
Audio sensor	Lack of robustness for multifarious sentiment investigation	Low cost; wide variety of applications
Radar sensor	Radial movement may cause disturbance	Remote monitoring of physiological signs
Other physiological sensors	Invasive, needs wearing close to the skin surface	Aptitude to monitor physiological signals representing
Multi-sensor fusion	Multi-channel info needs to be synchronized; cunning is relatively big	Richer collected information; higher robustness

A. *Importance of EEG for Emotion Recognition*

The physiological changes that accompany human emotion have a profound impact on our awareness of the world around us. Electrooculography (EOG), and blood volume pulse (BVP) are among the many other physiological signals detected by the human body. By placing electrodes on the scalp, an electroencephalogram (EEG) can detect the brain's electrical signal activity. Several brain regions have been linked to emotion regulation, including gyrus. Anxiety, impatience, sadness, concern, and anger are the feelings induced by their activity levels, in that order.

The electroencephalogram (EEG) is a method of recording and analysing data pertaining to the electrical of the brain. Neuronal impulses in the brain, which are both spontaneous and rhythmic, are what create EEG signals. Anxietiespheric EEG data may be able to characterise emotional brain states and behavioural patterns, according to the fields of neuroscience and psychology [15]. Emotion recognition research often makes use of EEG. Electroencephalogram (EEG) signals may detect even the most minute changes in people's emotional states. It is challenging to record EEG signals because of how weak they are. Other physiological signals, such as those from (EMG), electrooculography (EOG), and electrocardiography (ECG), might readily interfere with them. So, electroencephalogram (EEG) signals are non-linear and chaotic in structure. It is common practice to denoise and pre-process raw EEG signals.

V. EEG-BASED EMOTION RECOGNITION PROCESS

The precision of emotion identification can be enhanced by selecting the appropriate approach [16]. Figure 2 explains how various sensors use emotion recognition.

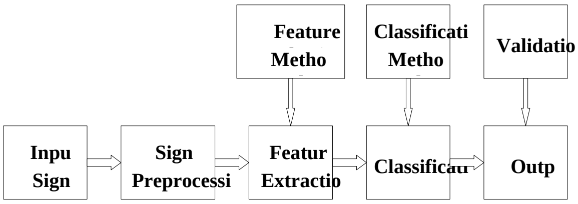

Figure 2. Process of emotion recognition method.

The term "signal preprocessing" describes the steps used to lower noise and improve signal quality. Finding the properties of various signals and reducing the amount of math needed for classification are the major uses of feature extraction. When features are retrieved, they are fed into a specific classification model. This process is called classification. Finally, analysis is used to derive the matching emotion of the signal.

A. *Dataset Details*

Truer emotions can be conveyed by physiological signals, which are immune to the influence of people's covert emotional actions. Table 4 [17] displays common datasets that are based on physiological markers

Table 4. Datasets of physiological signals.

Sum of Emotion Categories	Name	Type	Details	Physiological Signals
Dimensional emotion (arousal valence)	DECAF *	Induced	30 participants	EMG; NIR; hEOG;
ECG; tEMG				
Dimensional emotion (arousal valence dominance)	DEAP *	Induced	32 participants; regular age is 26.9 years old	EEG; EMG; RSP; GSR; EOG; plethysmograph; skin high temperature
3	SEED *	Induced	15 participants; average age is 23.3	EEG; EOG
Dimensional emotion (arousal-valance dominance)	DREAMER *	Induced	23 participants; composed by wireless low-cost off-the-self plans	EEG; ECG

A person's respiration rate or heart rate may be detected without physical touch using the radar sensor. The most common types of these sensors are RFID tags, millimetre wave radar, continuous wave radar, and continuous frequency modulated wave (FMCW) radar. Our survey shows that most academics prefer to create their own databases, while datasets based on signals from radar sensors are not very popular. As an emotional trigger, most radar data include short films or images. In order to compile datasets, participants' physiological signals are recorded using radar sensors.

B. *Signal Preprocessing*

- An essential first step in emotion identification using several sensors is signal preprocessing. In the initial phases of emotion recognition, preprocessing can lessen the effect of noise.

- Primarily employ signal preprocessing techniques such as cropping, rotation, scaling, and grayscale when dealing with visual inputs. Among the primary components of the signal preprocessing approach for audio signals are
- To decrease calculation consumption, silent frame removal is used.
- To compensate for components, is applied.
- To decrease the impact of different environments on the results, regularisation is applied. - To prevent signal edge leakage from affecting feature extraction, window is used.
- To reduce background noise, noise reduction procedures like minimum mean square error (MMSE) are used.

Radar and physiological signal preprocessing techniques mostly comprise:

- Filtering: Utilise various filters to eliminate background noise, signal interference, or baseline wander. - Wavelet transform: Define the local properties of physiological signals by using a time frame and a frequency window.
- In nonlinear dynamics, you can get a smooth signal estimate and get rid of temporary disruptions by using approximation transfer entropy.

C. *Feature Extraction*

By reducing the amount of work, improving the model's generalizability, ignoring irrelevant information, and overcoming the curse of dimensionality, feature extraction can achieve these goals. In order to feed signals into some classical classification models, feature extraction is frequently necessary.

Fast Fourier Transform (FFT): One common way to handle signals is via fast Fourier transforms (FFTs). You may use it to change signals from the time domain to the frequency domain and back again. The Power Spectral Density (PSD) is often calculated for spectral analysis by taking the square of the FFT's magnitude. You may use PSD to see how much power a certain frequency range adds to the signal as a whole.

Maximal-Relevance Minimal-Redundancy (mRMR): mRMR applies the greatest dependency criteria and the minimal redundancy criterion to mutual information in order to quantify correlation. It can pick out traits that are highly correlated.

The Relief-F technique, Locality Preserving Projections (LPP), Empirical Mode Decomposition (EMD), and (LDA) are further feature extraction methods for physiological and radar data.

D. *Feature selection*

Feature selection approaches seek to improve model accuracy by narrowing the set of available characteristics to just those that are truly necessary. They work well for feature extraction when there is a high degree of correlation between the two variables. Filter, wrapper, and embedding approaches are the three main groups into which features selection strategies fall according to the method used for merging them. These frameworks allowed many specialists to test the waters with different approaches. Choosing the optimal characteristics for EEG-based emotion identification is a challenging task. In addition, because of the input parameter and the qualitative output, the ANOVA and Kendall's rank coefficient—both of which depend on connexion—are commonly used in emotion categorization from EEG.

Machine learning is increasingly automating the process of feature selection. L1 regularisation is used by feature-selection approaches such as sparse modelling and LASSO. The random search technique also finds global minima. Nowadays, most learning algorithms take care of feature selection automatically, therefore very few researchers really use a feature selection approach specifically for facial emotion recognition. The Ant Colony (AC) methodology, Particle Swarm Optimisation (PSO), the GA, (Binary Harris Hawks' Optimisation, BHHO), CFS, SA, SFS, Welch's t-test, and many more

E. *Classification*

By taking in a variety of input signals, the classifier can determine which emotion category each one belongs to. The precision of emotion recognition is influenced by the quality of the classifier. There are two main schools it comes to modern categorization techniques: classical machine learning and deep learning. Since most of the research concentrated on deep learning, this part will introduce some widely used deep learning methods.

Deep learning approaches include classification, making them more efficient than conventional machine learning techniques. In order for deep learning algorithms to learn more complex semantic characteristics, they rely on massive datasets. Their capacity to distinguish between various emotions is superior. On top of that, they are better at generalising.

1) *CNN*

The area of emotion identification greatly benefits from convolutional neural networks (CNNs), a network. layers, and classification layers make up the bulk of a convolutional neural network. For the purpose of feature extraction, the convolutional layer filters the input signal. To improve the model's expressiveness, nonlinear elements can be included using activation functions. The pooling layer decreases the calculation consumption and the number of parameters. The last step in classifying the incoming classification layer. Parameter sharing and local connection are features of convolutional neural networks that enable more efficient model training.

2) *LSTM*

An outstanding recurrent neural network for learning long-term dependences from input data is (LSTM). Additionally, it is able to solve issues like disappearing gradients and bursting gradients. Input gate it, output gate o_t, and forget gate are the three major types of gate units in the conventional LSTM architecture. f_t. These gate units are used to regulator the statistics transfer of hidden state h_t, candidate state c_t, and candidate core state $\tilde{c}_t$.

Each control are calculated by the ensuing formula:

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i) \quad (1)$$

$$f_t = \sigma\left(W_f x_t + U_f h_{t-1} + b_f\right) \quad (2)$$

$$\tilde{c}_t = f(W_{ct} x_t + W_{ch} h_{t-1} + b_c) \quad (3)$$

$$o_t = \sigma(W_o x_t + W_o h_{t-1} + W_{oc} c_t + b_o) \quad (4)$$

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (5)$$

$$h_t = o_t \odot f(c_t) \quad (6)$$

Among them, W and U characterize the weight, b is the bias, the matrix s characterizes the function, f is function, and $\odot$ characterizes the elements.

3) DBN

In most cases, a Deep Belief Network (DBN) will include a number of restricted Boltzmann machines (RBM). RBM is able to evade the trap of a local optimum. The RBM is built layer by layer, with each layer building upon the one before it. The outputs of a DBN are based on joint probability distributions and unsupervised learning. Extraction of layer is accomplished using units of the hidden layer. Primarily, pre-training and fine-tuning comprise DBN training.

4) Other Classification Methods

Many new models have been suggested in fresh years, thanks to improvements in computer dispensation power and other technology. Their categorization performance is often greater, and their structures are more intricate.

VI. RELATED STUDIES FOR EMOTION ANALYSIS

Table 5: Studies on existing techniques

Author's Name	Technique used	Merits	Dataset	Performance analysis	Demerits
Hossain, S et al. [18] (2023)	The multiple model, a parametric-based frequency-spectrum-estimation technique, is applied for EEG-based emotion recognition	Utilizes a parametric-based model (MUSIC) for frequency-based feature extraction, potentially providing more robust results than non-parametric methods.	SEED dataset is utilized for EEG-based emotion recognition	97% accuracy on average is achieved for classifying three emotional states using the proposed MUSIC model and an artificial neural network	The dataset flaws mentioned may impact the generalizability of the proposed model to other datasets or real-world scenarios
Iyer, A., et al. [19] (2023)	A hybrid model combining (CNN) and Long Short-Term Memory (LSTM) is proposed for human emotion recognition using electroencephalogram (EEG) signals.	Segregates EEG signals into five frequency bands, providing a detailed analysis of different EEG rhythms	Validation is performed on two datasets, namely SEED and DEAP, for EEG-based emotion investigation	The proposed approach achieves a high accuracy of 97.16% on the SEED dataset for emotion classification.	The effectiveness of the proposed approach is demonstrated on specific datasets (SEED and DEAP), and generalization to other datasets may vary.
Garima et al. [20] (2023)	combining signal processing Coefficients, Flexible Analytic Wavelet Transform, and Tunable Q Wavelet Transform), post-processing (using Modified Multidimensional Scaling), and classification	Offers advantages in measuring correspondence based on both orientation and magnitude, contributing to a more robust distance metric.	The publicly available DEAP dataset.	Achieves a notable accuracy of 80.93%.	The work is evaluated on a single dataset (DEAP), potentially limiting the generalizability of the proposed approach to other datasets.
Shanmuga Priya, K., & Vasanthi, S [21] (2023)	employs a novel Convolutional Deep Belief Network with Long Short-Term Memory (CDB-LSTM) for accurate classification	Addresses a diverse range of emotions, including happy, relax, sad, fear, anxiety, anger, and stress, enhancing the granularity of emotion recognition.	The publicly available DEAP dataset.	The projected CDB-LSTM network achieves a high accuracy range of 97.27%.	The work is evaluated on a single dataset (DEAP), potentially limiting the generalizability of the proposed approach to other datasets.
Nour, M., et al. [22] (2024)	employs a 2-dimensional Convolutional Neural Networks (2D-CNN) for the accurate diagnosis and classification of Alzheimer's disease (AD)	Enhances model diversity and performance by incorporating five distinct internal classifiers within the DEL model	Utilizes EEG datasets, including Dataset-A (24 AD subjects and 24 HC subjects) and Dataset-B (80 AD subjects and 12 HC subjects).	DEL exemplary achieves an impressive average accuracy of 97.9% in AD classification through 5 cross-fold training	Acknowledges that further efforts are required to enhance the accuracy of the proposed model, suggesting ongoing refinement.
Fan, C., et al. [23] (2024)	a dual module EEG emotion recognition method combining an improved capsule network (as the spatial module) and a residual (ResLSTM) network (as the temporal module).	Addresses the importance of considering spatial and temporal correlations in dual modules, aiming to capture comprehensive emotional	Evaluates the method on the DEAP dataset, achieving high accuracy for arousal, valence, and dominance. Additionally, tests the method on the	DEAP Dataset: Arousal: 98.06% Valence: 97.94% Dominance: 98.15% DREAMER Dataset: Arousal: 94.97% Valence: 94.71% Dominance: 94.96%	The work is evaluated on a dataset, potentially limiting the generalizability of the proposed approach to other datasets.

		representations in EEG signals.	DREAMER dataset, demonstrating competitive performance		
Bengalur, M. D et al. [24] (2024)	Employs Laplacian Eigenmaps, a nonlinear dimensionality reduction technique, to extract discriminative features from EEG signals. Applies ensemble machine learning classifiers, specifically Random Forest (RF) and eXtreme Gradient Boosting (XGB), for emotion classification based on the reduced features.	Utilizes Laplacian Eigenmaps for nonlinear dimensionality reduction, effectively capturing the underlying structure of high-dimensional EEG data.	Conducts experiments on the widely used DEAP dataset	Random Forest (RF): 98.1% accuracy in emotion classification. eXtreme Gradient Boosting (XGB): 98.7% accuracy in emotion classification.	The paper may benefit from discussing the proposed method on other EEG datasets or scenarios, providing insight into its broader applicability beyond the DEAP dataset.
Çelebi, M., et al. [25] (2024)	a novel method for EEG-based emotion recognition using the Empirical Wavelet Transform (EWT) signal decomposition method. The method involves the extraction of frequency-based, linear, and nonlinear features, mapping them to a 2-D axis based on EEG electrode positions, constructing 3-D images, and implementing a 3-D deep learning framework named EWT-3D–CNN–BiLSTM-GRU-AT	Combines frequency components, linear, and nonlinear features into 2-D images, creating 3-D images that incorporate multichannel brain frequency, spatial, and temporal relationships	Evaluates the proposed framework on the DEAP dataset	Valence Axis: 90.57% classification accuracy. Arousal Axis: 90.59% classification accuracy.	The inclusion of multiple components in the deep learning framework may lead to increased complexity
Mahmoud, A., et al. [26] (2023)	a innovative approach utilized Convolutional Neural Complexes (CNNs) for EEG emotion recognition.	Utilizes CNNs for EEG emotion recognition, enabling the model to learn discriminative features directly from raw EEG signals	Evaluates the proposed CNN-based approach on benchmark SEED datasets	SEED Dataset: 96.32% accuracy. DEAP Dataset: 92.54% accuracy.	The study does not explicitly discuss the generalization of the proposed CNN-based approach to other EEG datasets.
Hosseini, M. S. K., et al. [27] (2023)	A pre-trained CNN is utilized to extract emotion-related features directly from raw EEG data. An LSTM network is employed to extract features related to the Big Five personality traits from the EEG data	Incorporates the Big Five personality traits into the emotion recognition model, enhancing its utility and providing a more holistic understanding of emotional states	The study recruited 60 participants, and EEG data were recorded while they viewed unique arrangement stimuli. The dataset includes EEG recordings along with information about the Big Five personality traits	The classifier achieves a high accuracy of 93.97% in predicting emotional circumstances within the dimensions.	While the study reports high accuracy, there is a need for detailed validation metrics and exploration of the model's generalization to different datasets and populations.
Alotaibi, F. M. [28] (2023).	Utilization of a bag-of-hybrid-deep-features (BoHDF) extraction prototypical. Implementation of a K-nearest neighbor (KNN) clustering algorithm for emotion classification.	Transformation of EEG signals into 2D spectrograms to capture time-varying behavior, suitable for analyzing EEG patterns	Evaluation conducted on the DEAP and SEED databases	Recognition accuracy of 93.83% on the DEAP database and 96.95% on the SEED database.	The paper does not address potential ethical considerations related to EEG data usage, privacy, and potential biases, which are essential in human-centric applications like emotion recognition for human-robot interaction
Zhang, L., et al. [29] (2023)	Utilization of spatial clustering of applications with noise (DBSCAN) for constructing emotion classification labels	Adoption of a serial network combining CNN and LSTM for feature learning and classification.	Emotion classification experiments conducted on the DEAP dataset.	Regular classification accuracy of 92.98%	No explicit discussion on potential ethical considerations related to emotion analysis, particularly in healthcare and mental health care contexts

VII. CHALLENGES

The study has discovered possible obstacles in previous research after conducting an extensive examination of automated emotion identification systems. Below is a summary of the most significant difficulties encountered by automated emotion detection systems.

A. Dataset Availability

There are a few issues with the publicly available datasets, including a lack of subjects, inadequate data, and biassed coverage. Although electroencephalogram (EEG) data is inconsistent, difficult to compare, and often used in experiments, many researchers still use it. Therefore, it is beneficial to the development of emotion identification to

the EEG collection process, and the current denoising approaches typically only address one type of noise. Higher levels of precision are required by the denoising method in real-world applications. Researchers often used full-channel EEG signals to gather data in their trials. Experiment accuracy is compromised due to the complete channel signal, which is not favourable to the experiment. Research on channel selection technologies is booming right now since nobody knows which channels can convey changes in mood the best.

Also, all of the existing datasets only include data collected using one modality, such as electrocardiogram (ECG), electroencephalogram (EEG), gadolinium-induced potential (GSR), speech, or face pictures. Emotion recognition studies that combine data from different sources on the same subject are so lacking. Healthcare, brain-computer interfaces, and other applications suffer from a shortage of publicly available emotion datasets, thus restricting the scope of such study. The EEG data was often disregarded in favour of data obtained while subjects were feeling intense emotions, according to many research. Simple EEG impulses are the source of spontaneous EEG data in humans. According to some research, there is a noticeable difference between an EEG signal taken when at rest and one taken during an emotional response. Secondly, they may provide far better results if they consider it a feature.

B. Solving Technical Issues from the existing Deep Learning

Since feeling emotions is a multi-faceted physiological process, it is difficult to advise on the best feature or feature extraction method. principal component analysis (PCA), and wavelet transformations are all very useful tools for the emotion recognition system. The connection between data and brain processes (including cognition) that are independent of EEG has been the subject of recent research. Nonetheless, these incidents will necessitate more thorough examination in the future. Emotion identification using EEG data has shown some success in recent years because to the fast advancement of deep learning. There seems to be a continuous stream of models for emotion identification using mixed neural networks.

A deep learning-based hybrid neural network model is now the centre of attention in the field of research. The researchers discovered that the hybrid model exhibited superior stability and accuracy when comparing the build a broad range, a small difference, and a huge number of public data sets. Wet electrodes are the standard for obtaining EEG signals. Applying conductive glue to the scalp is necessary due to the high cuticle. While collecting EEG data, the electrical conductivity naturally declines with time, making for a weaker signal and a more difficult experiment overall. Although the method for acquiring data from dry electrodes is straightforward, the signal strength is low.

The method of acquiring dry electrodes has been enhanced. After collecting signals, this method's basic tenet is to filter and amplify them before compressing them as experimental data. Design refinement is ongoing. Any sort of noise can interfere with

experimental findings. However, this study is in its early stages, and the results may vary greatly depending on the people and methods used to elicit emotions. Just pretend that emotion detection technology is useful for people. Therefore, it's important to set up a suitable emotion identification framework in order to eradicate or at least significantly lessen the impact of age, location, personality, and other forms of individual variation. Emotion identification using EEG data is a very new field of study, thus there is a lot of room for growth. In humans, emotions permeate all facets of existence. In addition to its high theoretical merit, this study has promising practical implications. Finding a better way to acquire EEG signals and increase the pace of emotion identification is still a challenging topic.

C. Solving the issues in EEG Signal channels

Electrodes are mainly positioned along the sagittal that link Fpz to Oz in studies that use commercial solutions that are already based on few channels. At the end of the day, the most popular electrode for wearable devices was Fp1. Indeed, data-driven based channel reduction investigations also discovered Fp1 and Fp2 to be important. In contrast to what is found in scholarly articles, P7 and P8 are currently proposed by a number of commercial solutions. Since these channels maximise the distance from the midline, they might provide useful information within the scope of asymmetry theories. Although P3 and P4 aid in detecting arousal, they are totally absent here. The widespread use of F3, F4, F7, and F8 channels is in line with the neurophysiological evidence that these channels play a crucial role in emotion assessment. C3 and C4, as well as O1 and O2, are extensively used despite the lack of evidence from neurophysiology that these channels play a crucial role in emotion detection. Due to differences recording performance analysis on the classification outputs was not performed for both prior solutions. Actually, manufacturers are obligated to disclose conformity with the standard in the technical documentation. Out of all the devices and Enobio8 are considered standard.

The anatomical-physiological study had predicted that the frontal region channels would be informative, and this prediction was confirmed by reviewing the articles that dealt with data driven-based minimization. In a channel lessening experiment using the DEAP dataset for 4-class emotion classification, more informative electrodes were clustered in the brain's frontal regions. According to the results of the 2-category emotion detection exercise, the valence dimensions were best conveyed by the F4 channel. Oddly enough, F3 was exempt from this. The arousal dimension was significantly improved by using electrodes inserted in the parietal region, specifically P3 and P4.

It is not simple to suggest a comparison among the examined algorithms, even if we limited the assessment to those that were tested on the same public dataset. There were many variations in the following areas: (i) the focus of the study (either dimensions alone or both), (ii) the amount of classes, (iii) the scope and placement of the reduced approach. Lastly, the statistical significance of the data is undermined since the example size does not reach 30 participants in many investigations.

VIII. CONCLUSION

As far as pattern recognition and identification tasks are concerned, Deep Nets are at the cutting edge of technology. Basic classification tools such as Support Vector Machines (SVMs) or logistic regression are usually enough for analysing simple patterns. However, neural nets begin to outperform these methods when the data has a very big volume of diverse inputs or more. In addition, simple neural networks can't handle more complicated patterns. Deep neural networks are the practical choice for complex data. The many applications of deep networks to EEG signals are explained in this overview. When it comes to unsupervised learning, using a collection of unlabeled data to uncover patterns, RBMs or auto encoders work better with EEG signals. The following are examples of deep networks that have shown effective in classification tasks for different applications: RNNs, DBNs, and convolution nets. These networks were trained using supervised learning with a set of labelled data. Both RNNs and convolution nets were effective in recognising objects, images, and voices, as well as processing text. For most classification tasks, ReLu combined with MLP or DBN is the way to go. More architecture on the anvil means faster and more accurate classification operations. One difficulty with deep learning approaches is the increasing number of datasets required to discover different patterns. Additional applications that enhance neuroscience can be achieved by incorporating multi-channel real-time EEG signals into the DL architecture.

IX. FUTURE TRENDS

Understanding and managing one's emotions is crucial to personal and societal growth. Technical and security-related considerations are at the heart of the present difficulties and future directions in emotion recognition.

The first is to improve user acceptance. Some emotional computing sensors need users to wear them, and many people are still unfamiliar with them. Practitioners should provide users with detailed instructions to upsurge the level of user cooperation. In adding to focusing on the user's needs, the detecting system should prioritise the user's emotional and physical well-being.

The second point is security. Recognising human emotions requires access to sensitive data, such as a person's location, health status, and physiological traits. Rather than being utilised to generate legal issues or prejudice, emotion detection technology should be applied to socially useful studies. As a result, one of the biggest problems with emotion recognition is keeping user data private. Right now, we can get around the problems with centralised data storage and make data more private and secure with decentralised AI.

The third point is robustness and accuracy. Various facets of human emotions are beyond the capabilities of the present emotion recognition model. Multimodal emotion recognition has surpassed all others as the preferred method for researchers seeking a more complete approach. Multimodal techniques perform better with bigger models and datasets. In most cases, more data is needed for emotion recognition, because elements that are people's mental public at a certain moment. Extensive follow-up is necessary for studies involving personality analysis, including those pertaining to intelligence testing and autism diagnosis. Hence, it is very important to study how to extract long-term features for emotion recognition, yet it is also a tough task.

Stricter standards for datasets are necessary to achieve an effective emotion recognition model. Unsupervised and reinforcement learning's benefits are becoming more apparent with the constant generation of large-scale datasets. Neither labels nor specifications are needed for unsupervised learning. On top of that, it can finish categorization even when given no category data. Through the use of trial and error, reinforcement learning allows the model to maximise incentives and continuously optimise the system's performance. It might be wise to investigate these emotion recognition techniques as well.

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