Emotion Detection Using Eeg Signals in Image and Video Processing: A Survey

Poorani Nivetha. R[1], DR. S. Batmavady[2]

[1]Research Scholar, Puducherry Technological University
[2]Professor, Puducherry Technological University

ABSTRACT
Brain serves as the body's processing of knowledge and management centre. The central nervous system directly produces ElectroEncephaloGram (EEG) physiological signals, which are strongly associated with human emotions. In the upcoming years, there will be an increase in interest for identifying emotion using brain waves by EEG (ElectroEncephaloGraphy) signals. It takes efficient and effective signal processing and feature extraction techniques for detection of emotions from human biological brain signals. Current approaches gather valuable information from a fixed number of ElectroEncephaloGraphy (EEG) channels utilizing variety of methodologies. This work analyses the different difficulties and problems associated with EEG signals for emotion identification and provides a comprehensive summary of several contemporary approaches. Pre-processing, feature extraction, and categorization are the first steps in the process of recognizing emotions from EEG signals. The main goal of this survey is to sought and enhance brain signal-based emotion detection ability by comparing all novel and adaptive channel selection technique that recognize the distinct changes in brain activities that varies between individuals and emotional states.

Keywords: Brain, EEG signal, emotion analysis, emotion detection, pre-processing, feature extraction, and categorization

INTRODUCTION
The human species is seen to represent the pinnacle of life on Earth. This isn't a result of the human body's strength and agility. Many other species are capable of things that humans can only imagine, and they have skills far beyond our own. The brain is one feature that sets humans apart from every other living thing on the earth, figure 1 shows the virtual structure of a human brain. The human body is controlled by the brain. But in humans, the brain is also the location of the mind, unlike in animals [1].
Humans are superior than other animals because of the mind. It gives people the capacity for thought, emotion, and adaptation. As a result, man has accomplished a great deal while simultaneously realizing that there is still a long way to go. The average adult brain weighs three pounds and is sixty percent fat and forty percent made up of water, protein, carbs, and salt. Neural tissue comprises the organ known as the brain. It's not a muscle. The cerebellum, brain stem, and cerebrum are the three primary components of the brain. Each of these is composed of multiple elements and has a distinct purpose. The nervous system is under the direction of the brain. People may experience changes in their personality, mobility, eyesight, sleep patterns, and other vital biological functions when they sustain damage to distinct areas of

the brain [1]. To control many biological processes and detect changes in the surroundings, the brain communicates chemical and electrical impulses throughout the body.

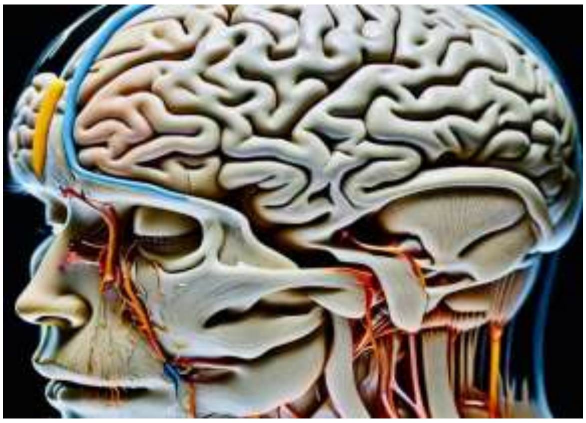

Figure 1: Human Brain

Emotions are feelings that are significant in a person's life. It makes it possible for people to communicate with one another and comprehend who they are. Most importantly, emotions are mostly in charge of what people think and do. Figure 2 shows basic types of emotions experienced by human beings [2]. Feelings like love, happiness, inspiration, pride, and many more are things you may like to experience. However, you would also want to avoid or get over bad emotions like hopelessness, loneliness, or misery if you are experiencing them. It shouldn't be considered that all positive feelings are always good and all negative emotions are bad because emotions can be both positive and negative by nature [3]. Other elements including frequency and intensity, the type of circumstance, and the stimuli aroused should be taken into account when assessing their influence. Everything in excess is harmful. Emotions have a stimulating influence; for instance, a cheerful person always makes other people happy and seems to be surrounded by happiness [4]. In a similar vein, an angry individual enrages other people. Emotion is therefore contagious. Additionally, emotions are also important in artistic and creative endeavours. Our social lives greatly depend on our capacity to comprehend and analyse the emotional states of others [5].

Figure 2: Various types of Emotions

EEG-based brain-computer interface (BCI) technology has emerged as an intriguing development. Essentially a brain-computer interface (BCI) facilitates direct communication between the brain and an external device. This has numerous applications of differing degrees of applications as possible [6]. Patients with severe impairments in their ability to control their muscles due to trauma, including complete spinal cord lesions, or debilitating diseases like brainstem stroke or amyotrophic lateral sclerosis can communicate with each other because the BCI output bypasses peripheral nerves and muscles [7].
Electrodes are affixed to the scalp to measure electrical activity in the brain through a process called electroencephalography [8]. Figure 3 shows the position of electrodes in the skull to determine the output signals from the brain. The produced wave's amplitude, frequency, and shape are examined in order to interpret EEG data. Information specific to the patient, such as age, condition, and where the electrodes are placed on the scalp, determines how significant the results are. Wave patterns can develop from almost all brain regions [9]. Wave shapes come in four varieties: alpha, beta, theta, and delta. Normal EEG frequencies range from 0.5 to 500 Hertz, and frequency is crucial in distinguishing between aberrant and normal EEGs. Since every wave type has unique properties of its own, each wave type has a range of normal frequencies. Since the EEG represents brain function, it is a useful tool for enhancing all of the recent treatments rather than serving as a pointless substitute [10].
The third primary application of electroencephalography involves examining individuals with specific neurologic conditions that result in distinctive EEG irregularities. These abnormalities, while non-specific, aid in indicating, validating, or bolstering the diagnosis. If recurring slow-wave complexes are observed in patients with an acute brain disease, this diagnosis should be suggested because these abnormalities are well-exemplified by the complexes occasionally seen in herpes simplex encephalitis [11]. It is advisable to consider the electrical results as an additional physical indicator, and as such, they must be assessed in combination with the other medical and laboratory information.

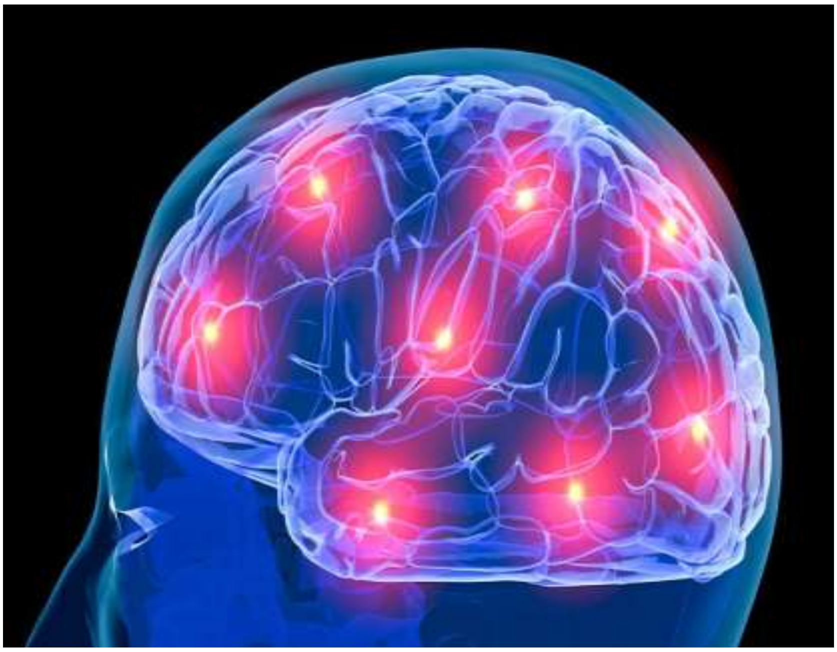

Figure 3: ElectroEncephaloGraphy (EEG)

The initial EEG signals consist of a sequence of evolving curves. The original data comprises numerous sounds and interferences throughout the acquisition process, which have an impact on the categorization.

These can be caused by the EEG device itself or the transmission line itself [12]. The original EEG signal has to be de-interfered and de-noised in order to enhance the classification performance. A reasonably clean signal is obtained following appropriate preprocessing. The original EEG signal was pre-processed using several techniques such as filtering, independent principal component analysis, baseline correction, channel localization.

The process of changing a signal, identifying the relevant signal features, removing unnecessary components, computing the features associated with the target task, and communicating the results in a concise or comprehensible way for preceding execution is known as feature extraction [13].

This study examines the various challenges and issues related to using EEG data to identify emotions and offers a thorough overview of a number of modern methods. The following session discuss about various existing methods in identifying emotions using EEG signals, followed by a comparison of all the methods their advantages, uses and drawbacks. The last session contains the conclusion by comparing all the existing methods that were compared in this survey.

TECHNIQUES FOR IDENTIFYING EMOTIONS

The general architecture of the EEG signal model, including preprocessing, feature extraction, and classification are discussed in this section. Figure 4 gives the general structure for recognizing emotions from raw input EEG signals given as input to the system to be processed for identifying the emotion. EEG signal processing for identifying emotions is mainly divided into three categories namely, pre-processing, feature extraction and emotion classification.

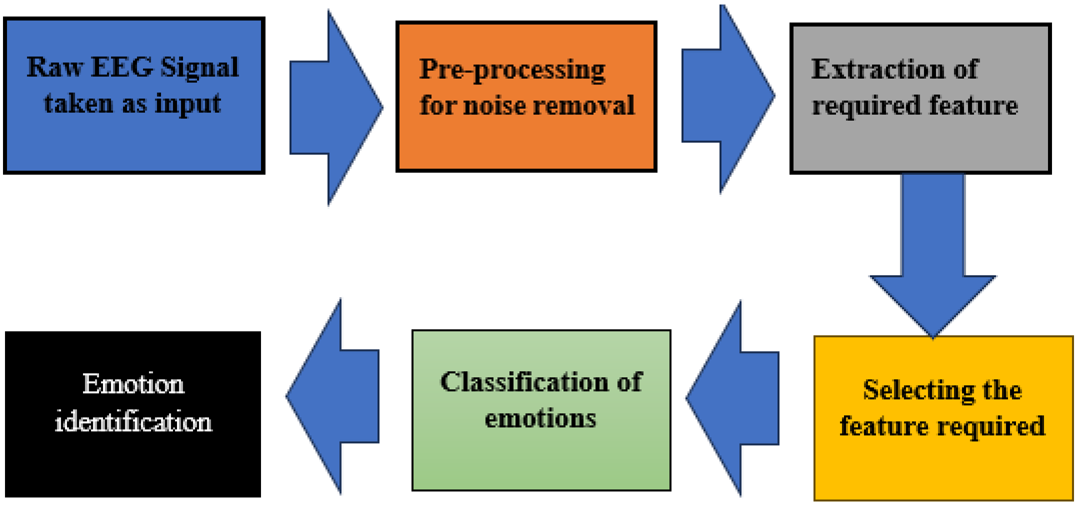

Figure 4: The overall structure for recognizing emotions

1) PRE-PROCESSING

An EEG signal can be defined as anything other than the planned electrical activity produced by a coordinated electrochemical process. To make brain activity more measurable, it is required to reduce noise in the temporally location of interest, and to include data from a specified geographical region. The pre-processing of raw EEG signals is necessary because the input image data typically require certain measures for removing noise and other unwanted artefacts from the input. The two main artifacts are biological artifacts and environmental artifacts. Distortions like because of electrodes, electricity cables, human interaction, and room shielding comes under environmental artifacts and distortions like ECG

(ElectroCardioGram), heart rate, respiration, and muscle contraction and relaxation comes under biological artifacts [14]. There are various techniques to remove the unwanted artefacts from the input signal. The main filters or pre-processing methodologies that are used widely that have better output are considered and discussed as follows.

a) 2D- Finite Impulse Response Filters

Images restoration, image enhancement, and de-noising applications frequently employ 2D finite impulse response filters (2D-FIR) because for their greater efficiency and less complexity as said by *Soumica Cheemalakonda, Sudeeksha Chagarlamudi et al (2023)* in [15]. Using an efficient network of adders, subtractors, and shifters, the 2D FIR filter architecture incorporates proper functioning with multipliers. The area is optimized by reducing total number of partial products and multipliers through the use of Radix -2 r multiplication during implementation of area-efficient 2D FIR filter design. For three kernel sizes—7x7, 5x5, and 3x3—a symmetric filter is developed in gate level HDL (Hardware description language) using a direct form design. To verify that 2D FIR works, Intel DSP Builder is utilized, and Intel Quartus Standard edition is used for synthesis.

b) L-Band Band Pass Filters

A band pass filter is a filter that have signals that has non-overlapping and near-zero frequency bands as output. Bandpass filters admit signal frequencies within a specific range but reject all other frequencies. The EEG signal pattern spans from 1-50Hz and is divided into five frequency bands: Alpha, Beta, Delta, Theta, and Gamma as said by *Eric Lützow Holm, Diego Fernandez Slezak et al (2024)* in [16]. Bandpass filters are categorized as low pass or high pass based on their frequency range. Digital bandpass filters are often implemented by categorizing a continuous response to frequency toward finite discrete samples through the use of methods such as space-domain filtration and Fourier transformations. The two filter's main role is to limit the bandwidth of the output signal to ensure it communicates data at the desired speed and level.

c) Event Related Adaptive Filters

Guruprasad Madhale Jadav, Jonatan Lerga et al (2024) in [17] introduces a new way for analysing noisy EEG data. The toolbox comprises an adaptive, data-driven noise removal methodology based on an enhanced Intersection of Confidence Interval (ICI) algorithm. The toolbox now includes a local entropy-based approach for analysing EEG data, while the local Rényi entropy-based analysis of EEG representation in the time-frequency domain effectively detects the presence of P300 Event Related Potential (ERP) at specific electrodes.

d) Intelligence Cascade Analysis

Chun-Hsiang Chuang, Kong-Yi Chang et al (2022) in [18] created Intelligence Cascade U-Net (IC-U-Net), a new artifact removal model for removing common EEG artifacts and reconstructed brain signals. IC-U-Net was trained with combinations of brain and non-brain components dissected through intelligence cascade analysis. Simulation study and four real-world EEG studies indicated successful recovery of brain activity and removal of artifacts such as eye blinks, muscle movements, and line/channel noise. IC-U-Net is a potential system for automatically removing artifacts from EEG recordings, capable of reconstructing multi-channel signals and addressing various artifact kinds.

e) Independent Component Analysis (ICs)

These components are clustered within subjects and assigned a Quality Index (QIc) indicating their stability during data resampling in [19] proposed by *Fiorenzo Artoni, Arnaud Delorme et al (2022).* Sets of individual ICA decompositions obtained after PCA was used to reduce data variance by 85%These bootstrap ICs could be utilized as Benchmarks for various data pretreatment processes. ICA uses non-Gaussianity, or higher-order information, to identify distinct elements. Because of this, ICA is better suited for images which are not regularly organized. ICA algorithms can be used to analyse how noise or inadequate data affects the quality of ICA decompositions.

Table :1 Review of various Pre-processing methods in Image Processing

REF.,	AUTHOR	METHODOLOGIES	ADVANTAGES	DISADVANTAGES
[15]	Eric Lützow Holm et al (2023)	2D finite impulse response filters (2D-FIR)	Less Complexity	filter requires less space, depending on the kernel size.
[16]	Jonatan Lerga et al (2024)	L-Band Band Pass Filters	Communicates data at the desired speed	signal pattern spans within a certain range
[17]	Guruprasad Madhale Jadav et al (2024)	Intersection of Confidence Interval (ICI) algorithm	More Efficient	Dependant on the data given through electrodes.
[18]	Kong-Yi Chang et al (2022)	Intelligence Cascade U-Net	Automatically remove artifacts	Not used in mobile environments.
[19]	Fiorenzo Artoni et al (2022)	Independent Component Analysis	Quality Index is used	Stability is based on data re-sampling.

The above table implies that Independent Component Analysis give more stability in the output as Quality index plays the major role in determining the desired result without any noise and other interferences. In conclusion, independent component analysis is a flexible image processing method that may be used to extract separate, appropriate elements from complicated picture data, providing insights and potential uses in a variety of fields.

2) FEATURE EXTRACTION

In image processing, feature extraction is the process of automatically choosing and focusing important details from an image, thereby minimizing data while keeping significant qualities. Feature extraction in the segmentation of images is a procedure of selecting and changing raw pixel information into a more relevant representation for the task of segmenting the image [20]. To apply image processing methods to EEG signals, time-frequency representations are converted into visual formats (pictures) and then important features are extracted using image processing, few feature extraction methods used widely are as follows.

a) Scalable and Adaptive Feature Extraction

Zainab Loukil, Qublai Khan, Ali Mirzaan et al (2023) in [21] examined pre-trained algorithms for feature extraction in picture classification. This study evaluates the performance of various pre-trained neural networks for feature extraction in picture classification tasks. This research presents a novel hybrid feature extraction methodology which concentrates on the combination and optimum choosing of higher-level and lower-level characteristics. The suggested method's scalability and reliability are achieved through the automated modification of the final ideal features depending on real-time circumstances, resulting in an accurate and effective medical image illness categorization.

b) Deep Residual Learning

Deep Residual Networks were recently demonstrated by Wu, S., Zhong, S., Liu, Y. et al (2022) in [22], to greatly increase the effectiveness of neural network models trained on ImageNet. they endeavour to clarify how Deep Residual Networks have been, their ability to generate such good results, and why their effective implementation in practice constitutes a huge step forward over prior methodologies. They also cover several unanswered problems about residual learning, as well as potential uses for Deep Residual Networks outside ImageNet.

c) Harris Corner Detector

Hatipoglu, B., Yilmaz, C. M., et al (2020) in [23] said in image processing, the Harris corner detectors is a widely used technique for locating corners or other interesting areas in an image. The detector's purpose is to locate important spots in an image which stand out due to significant intensity variations in all directions. These crucial locations are frequently the image's corners or intersections, that are utilized in situations when matching key-points are essential, such as picture registration and object recognition. helpful in visual tracking jobs where keeping tracking between frames is aided by the identification of distinguishing locations. When it comes to changes in parameters, like the dimensions of the Gaussian window, the detector is comparatively resilient. Noise can affect the Harris corner detector's sensitivity, which may affect the overall output.

d) Speeded-Up Robust Features (SURF)

It does this quickly by quickly calculating box filtration systems, which are employed by Hatipoglu, B., Yilmaz, C. M., et al (2021) in [24] for estimating Gaussian derivatives, through integral pictures, also called summed-area tables. The discipline of image processing is continuing to widely adopt it for both research and commercial applications. Because of this, SURF may be used for both large-scale image processing jobs and real-time applications. Because SURF is built using integral pictures, it can efficiently handle fluctuations in image circumstances and is immune to modifications in distortion and luminance. Although SURF is effective in analysing scale space, the scale selection might not be as sensible or adaptive.

e) Convolutional Neural Networks

Yuying Wang, Pengfei Hu, Jianjun Qian, et al (2022) in [25] offers a deep learning-based method for classifying and extracting features from computed tomography (CT) images that show lung nodules. The suggested technique automatically extracts hierarchical characteristics of lung nodule patches using convolutional neural networks (CNNs). The CNN-based method is effective in differentiating between malignant and benign lung nodules, according to experimental data, which bode well for computer-assisted diagnosis in clinical settings.

Table :2 Comparison of various Feature-extraction methods in Image Processing

REF.,	AUTHOR	METHODOLOGIES	ADVANTAGES	DISADVANTAGES
[21]	Ali M., et al (2023)	Scalable and Adaptive Feature Extraction	Flexibility in Handling Large	Loss of Interpretability,

			Data, Reduced Computational Complexity.	Sensitivity to Parameter Settings.
[22]	Liu, Y. et al (2022)	Deep Residual Networks outside ImageNet	Handling Deep Architectures Efficiently, State-of-the-Art Performance.	Computational Complexity, Overfitting Concerns.
[23]	Yilmaz. et al (2020)	Harris corner detector	Detector is comparatively resilient	Noise sensitive can affect overall output
[24]	Padhy., et al (2024)	Speeded-Up Robust Features (SURF)	effective in analysing scale space	he scale selection might not be as sensible or adaptive
[25]	Yuying, et al (2022)	Hierarchical characteristics using convolutional neural networks	Effective-Parameter Sharing, Translation Invariance.	Computational Complexity

From the above table it can be noted that feature extraction using hierarchical characteristics in Convolutional Neural Networks (CNN) have more advantages and less drawbacks compared to other feature extraction methods in image processing. The development in upcoming CNN methods can overcome the drawbacks and provide the desired output with more percentage of accuracy and efficiency.

3) EMOTION IDENTIFICATION

Various classifiers are used to separate the signals into multiple groups based on the retrieved features. the process of building and evaluating classifiers that identify the main characteristics of an individual's emotional state based on recorded EEG data. The issue was categorized as one of classification. To categorize emotional states with positive to negative and high to low stimulation, there are numerous classification systems. We can categorize emotions like relaxed, joy, frustration, despair, and sorrow using the classifiers [26]. Classification frequency bands mostly pertain to emotions, which can manifest in various ways. Various emotion identification methodologies are used widely, few outstanding methodologies are discussed below.

a) K-Nearest Neighbours (KNN)

One flexible technique that can be used for image processing applications is K-Nearest Neighbours (KNN), which is used for categorization as examined by Hoang, V. H., Nguyen, N. L., Bui, et al (2024) in [27]. KNN can categorize new photos into these groups based on their visual characteristics given a series of tagged images. KNN may be used to locate similar photos in the database according to their visual resemblance. When it comes to imaging in medicine, KNN can help with tasks like identifying various tissues or organs according to their visual features that are taken from pictures that include histopathology slides or MRI scans. Since the "training" portion of a KNN only involves storing data, it is easy to comprehend and apply, and it can work well for picture classification applications when class boundaries are clearly defined. Because KNN requires the computation of distances for every sample used for training, it can be operationally costly for big datasets.

b) Support Vector Machine (SVM)

Khadidos, A. O., Alshareef, A. M. et al (2024) in [28] said that SVMs are strong machine learning models that work well for a range of image processing applications. By categorizing image patches or regions according to whether they contain a particular object of interest, SVMs can be utilized for object detection tasks. SVMs are used in medical imaging to perform tasks like tissue segmentation and tumour classification using image features taken from CT, MRI, and histopathological scans. SVMs are capable of classifying complete photos into groups according to the visual material they contain, allowing them to differentiate between various scene types. When the total amount of features is high in comparison to the total amount of samples, SVMs are less likely to overfit. When dealing with very big datasets or domains requiring real-time analysis, SVMs could not scale effectively.

c) Naive Bayes

Amini, T. A., Setiawan, K. et al (2024) in [29] found that depending on the Bayes theorem along with high independence assumption made between the features, the Naive Bayes classifier is probabilistic. Using a feature array of the incoming image as input, Naive Bayes calculates the following odds for each class. The new image belongs to the class with its greatest posterior probability. Because Naive Bayes is simple to use and computationally effective, it may be quickly prototyped and used to handle enormous datasets. Although Naive Bayes' probabilistic approach makes choosing as well as model interpretation obvious, some image features will exhibit feature independence, which could result in less-than-ideal performance.

d) Linear Discriminant Analysis (LDA)

There are numerous uses for the classification method such as LDA. Xu, S., Liu, R., et al (2023) in [30] used LDA as a method for controlled categorization or reduction of dimensionality. Its objective is to identify a linear feature combination that distinguishes or defines multiple sets of objects or occurrences. LDA is useful in medical imaging for tasks like identifying tumours using features collected from CT or MRI data. A type of regularization that LDA inherently includes helps manage overfitting in situations when the total amount of samples is constrained in comparison to the total amount of features. When classifications have equivalent matrices of covariance and the data dispersion is roughly Gaussian, LDA works well. Changes from these presumptions may have an impact on how well it performs.

e) Efficient-Net

Efficient-Net is a group of convolutional neural network (CNN) topologies with the goal of achieving cutting-edge efficiency yet being computationally efficient. There are multiple varieties of Efficient-Net, labelled B0 through B7, each of which is broader and more precise than other methods. Nguyen, H. T., Chung, W. Y. et al (2024) in [31] studies studied that utilizing learnt representations, previously trained Efficient-Net algorithms on large-scale datasets may be quickly adjusted for particular tasks using smaller datasets. Larger Efficient-Net variations may require a significant amount of time and computational resources to train from scratch.

Table :3 Comparison of various Feature-classification methods in Image Processing

REF.,	AUTHOR	METHODOLOGIES	ADVANTAGES	DISADVANTAGES
[27]	Setiawan, K. et al (2024)	K-Nearest Neighbors (KNN)	class boundaries are clearly defined.	requires computation of every sample.

[28]	Alshareef, A. M. et al (2024)	Support Vector Machine (SVM)	differentiate various scene types.	Scaling issues, not suitable for Real-time applications.
[29]	Setiawan, K. et al (2024)	Naive Bayes	Quickly prototyped, handle enormous datasets.	less-than-ideal performance.
[30]	Liu, R., et al (2023)	Linear Discriminant Analysis (LDA)	have efficient matrices of covariance and data dispersion.	Changes of presumptions affects accuracy.
[31]	H.T., Chung et al (2024)	Efficient-Net	Task Specific, Large-scale datasets, more accurate.	More time and computational resources.

In summary, EfficientNet is a major step forward for CNN designs because it maximizes both computational efficiency and model size. It is a well-liked option for a variety of computer vision applications in the machine learning domain because to its scalability and exceptional performance, it can select the method for pre-processing as per the requirement of the task given.

CONCLUSION

This study provides a thorough overview of the many approaches and strategies used in the EEG signal-based emotion identification process. According to the survey findings, there is a lot of room for researchers to find a person's emotion using various EEG readings. With the available dataset, a variety of evaluation parameters are employed to enhance the emotion's performance and accuracy. This survey concludes with several challenges to the current model, along with few information about Efficient-Net, a major step forward in Convolutional Neutral Network (CNN) designs that help to improve the outcome in the recognition of emotions in EEG signal.

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