Electroencephalogram (EEG) Signals-based Feature Extraction Using Classification of various Deep Learning Techniques

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***Abstract*— A Brain-Computer Interface (BCI) is an interaction method that makes it possible for a human brain to communicate with computers or software without the use of EEGs that result from brain function. Electroencephalography (EEG) is the oldest neuroscience diagnostic tool. If a neurologist sees an EEG study, he will report critical neurological abnormalities, that many diagnoses have been overlooked. All the data in the EEG cannot be processed in the human brain. Feature extraction is to classify a certain EEG type of information measured by brain neuronal activity. So much deep architecture for machine learning is designed to understand EEG signal data. This review summarizes different literature on EEG classification using different deep learning methods and feature extraction such as CNNs, RNNs, LSTM, GANs, AEs, and RBM.**

***Keywords*— Brain-Computer Interface (BCI), Electroencephalogram (EEG), Feature Extraction, Deep Learning (DL), Classification Techniques.**

I. INTRODUCTION

BCI research was initially initiated in the 1970s and addressed an alternate transmission channel without usual peripheral nerve & muscle production pathways in the brain being dependent on them. An early definition of BCI suggested brainwave measurement and decoding signals to monitor and implement the desired behavior. Then the word 'BCI' is formally defined as the direct route among the human brain & external device. Human BCIs have received much recognition in the last decade [1]. The introduction of BCIs also makes it more efficient to connect with the world using brain signals. Various brain imaging methods are used to incorporate BCI applications to interact with LIS patients. This includes the most widely used modality of electroencephalogram (EEG), as contrasted with the rest of neuroimaging instruments, such as magneto EEG (MEG), NIRS (Near-infrared Spectroscopy) & fMRI. EEG signal has low cost, portability & decent temporal resolution that is non-invasive. EEG signal is determined by scalp electrodes. EEG signals indicate electrical activity from neurons during a task. The electrodes on the head surface test this behavior. The variation in the cellular membrane is measured here by the post-synaptic propensity of cortical neurons. As EEG and the BCI modes, capturing signals are widely used because of their portability. BCI signal originating from the steady-state visual evoked potential (SSVEP), MI, & P300 was the most common signals applied. The three signals referred to above are used for quad & wheelchair control. Applicable to EEG-based BCIs using non-linear Bayesian classifiers & linear classifier [2] are some classification algorithms. Feature extraction is to classify a certain EEG type of information measured by brain neuronal activity. Attributes are features of a signal that can distinguish emotions. The key challenge of extracting features is to draw on the outstanding features, which can map EEG data into emotions. There are different feature extraction methods used for analyzing the EEG signals. Different extraction methods are understood to select a better method, the extracted features are fed as input for further classification. It is done by a suitable classifier for the recognition and detection of emotions. A classification system is a system that separates data into groups and lists the connection between the characteristics and emotion that is part of the EEG signal [3]. Hinton et al. 8 motivated by the way people thought suggested profound learning. Deep learning (DL) forms more abstract representations of high levels by merging low-level functionality to cover attribute categories or functionality for discovering distributed properties through data. New methods need to be taken for EEG to be processed more generalized and more scalable. In this sense, deep learning can greatly simplify the pipelines of pre-processing, extraction, and classification modules, by enabling automated end-to-end learning, while at the same time achieving strategic perceptions on target challenges. DL, and ML subfield, studies computer models to learn hierarchical images of input data by successive non-linear processes. Stimulated by earlier models e.g. perceptron, Deep neural networks (DNN) are models where: (1) artificial "neuron" layered layers apply a linear transformation to the received data & (2) product of transformation matrix of each layer is fed by a non-linear activation function. Particularly by minimizing feature in costs, parameters of these transformations are learned. While the word "deep" does mean that several layers are used, no agreement has been reached on how to quantify depth in a NN &, thus, on which is a deep network & which is not [4].

The rest of the paper is organized accordingly: Section 2 Brain-computer interface (BCI) & its various technologies used in the EEG signals process. EEG signal and it is used in a medical field described in Section 3. A brief introduction of Classification techniques is given in Section 4. The deep description of DL for EEG-based BCI is given in section 5. Section 6 also Provides literature on the topic of Spatial-Frequency Feature Learning & Classification of Motor Imagery EEG Based on DCNN.and lastly. Section 7 concludes our work.

II. BRAIN-COMPUTER INTERFACE (BCI)

The BCI is called a neural-control edge. It’s a communication conduit among the human brain & devices external to the body. The neurons in the brain capture thoughts of the human which are transmitted to the external device by using various algorithms and data extraction features. The first step of BCI is signal acquisition. Invasive technique, partially invasive technique, and non-invasive technique are three techniques of signal acquisition. In invasive technique, electrons are implanted neurosurgically inside the brain of a human. It provides high spatial and temporal resolution. It increases the quality of acquired signals. An intracortical method is one of the most used Invasive methods. In noninvasive techniques, external sensors are used to record the activity of the brain [5].

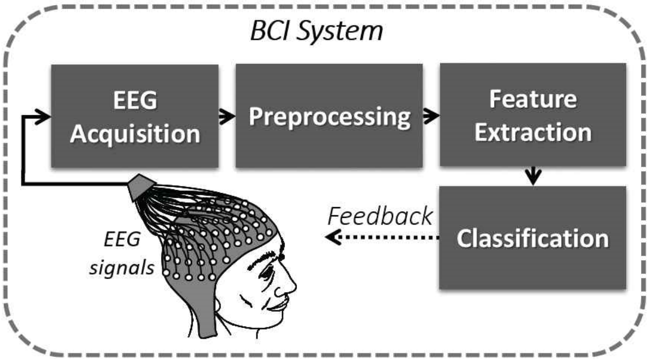

Figure 1: Block diagram of BCI

A. BCI Technology

1. *Signal Acquisition*

The physiology of the brain is discussed. By using intrusive, partially invasive, and anti-invasive methods, the electrical signals from the object can be obtained by electrical devices. Brain waves are captured in action, feelings, and distortions or excitement on a motor path or sensory trajectory of the human brain.

2. *Pre-Processing*

Preprocessing is the overall term for all the transformation of the data, including centering, normalization, rotation, shifting, shear, etc., before being transformed into the model. The pre-processing objective is to enhance image data that eliminates unwanted distortions or optimizes specific image features that are needed for more processing, while geometric image transformation is classed among pre-processing methods here, given that similar technologies are utilized for the pre-processing process.

3. *Feature Extraction*

The raw data in the FE mechanism is translated into usable information; only the appropriate signal is derived from collective signals and produced based on the individual user intention. to obtain wanted signals from raw signals, function extraction techniques such as PSD-, AAR parameters are performed. Features like amplitude, time & frequency may be removed from the subject's brain signal.

4. *External Application*

BCI is an emergent area, but there are no further external apps available and not used in use by disabled persons. In this area, the study groups are growing to support the people with disabilities to articulate their needs. More applications need to be developed and an economical BCI method can be established shortly so that individuals from any group can take advantage of it. So far, robot power, Vowel prominence, Shape distinction, Object recognition, games, so on. have been available.[6-8]

III. ELECTROENCEPHALOGRAPHY-(EEG)

EEG signals are commonly used in BCI systems to record brain impulses as they are non-invasive, are time-consoled, have consumer mobility capacity, and comparatively low costs. EEG is a technique applied to the measurement of brain electrical impulses that provide information about the brain's activity. These brain waves are taken from the electrodes on the head classified as scalp EEG. On the other hand, Intracranial EEG signals are registered when needle electrodes are put in the brain tissue. EEG is an EEG surveillance method for measured electrical activity in microvolt scale and brain fluctuation signals around the scalp as a result of ionic current streams in the brain neurons [9].

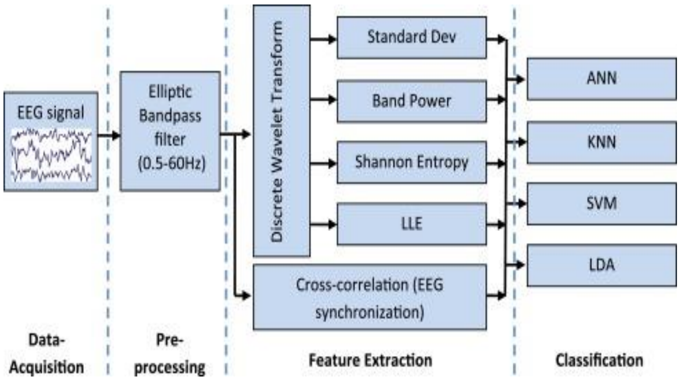

Figure 2: Example of EEG signals Classifications

Table 1: Transformations of brainwaves from EEG signal

Transformations of brainwaves from EEG signal				
Alpha Waves	Frequency 8- 13 Hz	Measured in the central field	Closed-eyed waking human	disappears safely
Beta Waves	Frequency 13-30 Hz	The parietal and frontal lobes are detected	Consider that people who are nervous and eye-open are natural and superior.	
Delta Waves	Frequency 0.5-4 Hz	Observable in kids and parents who sleep	Cerebral damage or brain disease suggestion	
Theta Waves	Frequency 4- 8 Hz	It can be seen in children and adults sleeping	This develops while sleep and during those phases of sleep	In awake adults abnormal but usual in children under the age of 13 and at bedtime
Gamma Waves	Frequency >30 Hz	Concerning the status of active cortical information processing		

A. EEG Signal in Medical

EEG is a procedure for medical imaging that reads electrical scalp activity produced by brain structures. EEG signals have been in concert a significant role in health & medical applications [10]. Signal of EEG and meditation Joseph et al. studied the EEG Signal dynamics using nonlinear parameters such as CD, LLE, and H at various meditation points. They stated that during the khumbaka stage, the variability of EEG signals reductions meaningfully. It was found that the practice of transcendental meditation (TM), mostly between anterior and posterior areas, increased the level of audio phase synchrony. You also found that increased phase synchrony in alpha frequency increases functional integration during meditation. Using wavelet tests and flouted c-means, EEG meditation signals were analyzed. They suggested a distinct grey chart from the characteristics derived to show a particular state of meditation. brain reduced parallel functional operation (part of pranayam-breathing for relaxation). During this time, nonlinear measures such as CD, LLE, ApEn, & z-score have been reduced [11,12].

IV. FEATURE EXTRACTION IN EEG SIGNALS

The features were derived from many different types of algorithms, including autoregressive power spectrum density-dependent feature and entropy-based features, rather than depending on the use of a single feature extraction algorithm. Autoregressive algorithms have been selected because, while the data are short, they provide higher frequency resolution. Another common approach for the analysis of complex biological processes was Entropy. Entropy essentially gives an insight or difficulty measurement of a signal which has been widely used in the analysis of brain epileptic signals as well as Alzheimer's and sleep surveys. Since EEG signals are not stationary and non-linear, entropy estimation as an extraction tool is simple to use. To find out where EEG signals are most influenced by various forms of imagined motions in the brain, the channels that capture variations of EEG signals have to be identified [13]. The extraction method refers to the extraction by domain information of distinguishing characteristics by input signals [14].

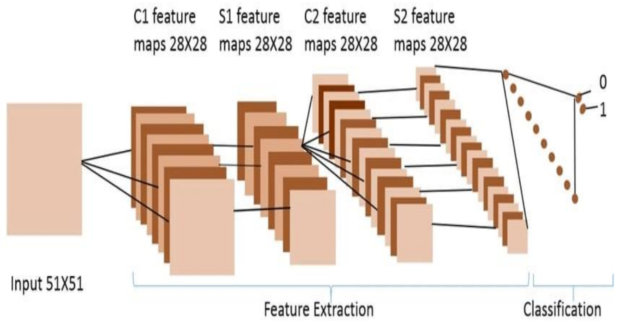

Figure 3: Structure of Feature Extraction

A. Diverse Methods of FE

1. *PCA (Principal Component Analysis)*

PCA pre-processing approach is used & also used for the extraction phase of functions. Information can be studied & data measurements compact by this technique without loss of detail. PCA function extraction benefits from improving efficiency over other extraction methods. The technique is limited by the requirement that information is linear or continuous & cannot be carried out with complex designs.

2. *ICA (Independent Component Analysis)*

It is a better technique for the pre-processing & extraction of EEG signals. Specific ICA components are completely separate, and points are obtained from these components. The simplest example of ICA is blind root isolation. It is established using ICA and is used for signal identification & brain noise separation. ICA is very powerful computationally & helps to quantify high efficiency for EEG signals.

3. *WT (Wavelet Transform)*

It is a math method applied to determine data from numerous kinds of continuous data (such as pictures & speech) on a very wide scale. The use of Wavelet's properties of a material is used to process non-stationary signals due to representing them in a time-frequency domain. Various benefits of WT exist, for example, the analyses of signals with a discontinuity using variable window sizes, the localization of signals in the frequency & time domains, extraction of power, cluster, or distance.

4. *WPD (Wavelet Packet Decomposition)*

It is an advanced method for WD. WD differs in a way from the WPD because WD uses approximation and all knowledge in more depth in each separate resolution stage by breaking down approximation. Furthermore, when comparing, accurate & effective frequency resolution is achieved using the WPD technology rather than WD.

5. *Parametric Approach*

The autoregressive system (AR) contains parametric approaches. Applications for AR are the processing of EEG signals utilizing linear combination signal representation on previous levels in a different system. AR is applied with decreased data record time to maximize the best frequency resolution & decrease spectral loss. This method provides the best results when the input parameters are AR, e.g. in non-stationary EEG signals. Some of the drawbacks are also present in this solution, one of which is the characteristic AR parameter.

6. *FFT (Fast Fourier Transform)*

FFT adds EEG data mathematics. The method of estimating PSD is applied for calculating properties of signals that have been collected from EEG that have to be processed for sample EEG signals. Features of the signal are derived from the time domain to the frequency domain. The random linear procedure also stationary signals provide improved show by FFT. Though, FFT does not process non-stationary signals and does not calculate both frequency and time. [15].

Method	Advantages	Disadvantages
PCA	Carries out dimensional reductions with no Invalid data loss collection should not be processed	It is not possible to handle complex data
ICA	It is good for huge data sizes. Small calculations.	Data analysis needs further calculations
WT	Analyze the aspect of signal time-space. Especially suitable for non-stop signals.	No clear noise removal tool.
WPD	Carries out nonstationary signal processing.	Tends to increase work time
Parametric approaches	Location of time. Position of the frequency with loss of spectra	Not appropriate for stationary signals
FFT	Decent performance for fixed signals	Does not function with non-stop signals Cannot locate frequency and time

V. Classification of EEG Signals

Classification is one of the key applications for ML which, using the available data and skill information, can group and identify cases based on learning and growth. Classification is the process by which categories or classes are identified based on their similarity. Biological and medical classification is commonly used. Classification is a method for classifying pictures, based on their similarity, into many groups. By classifying pictures, we can easily interpret or analyze our environment... However, classifying an image is not always simple, particularly if it contains noisy and bubbling materials. A database is used by users of the classification system and the database includes certain patterns or images that are previously defined or categorized. The purpose of classification is to predict the correct class efficiently for each data record. For instance, a classification model for identifying low, medium, or high credit risk loan applicants[16].

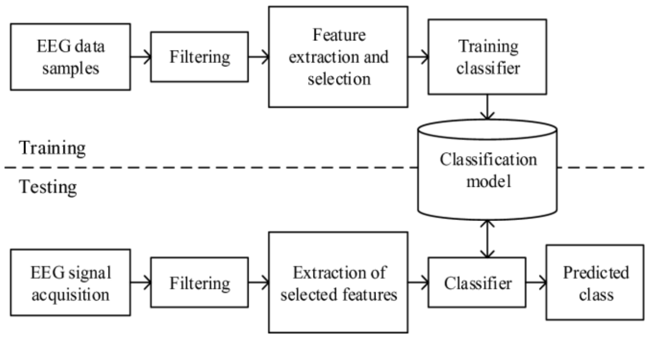

Figure 4: EEG-based Classification Model

A. Classification Techniques

The extracted functional is fed into a certain classifier to put related extracted functionalities in one class.

1. *Linear Discriminant Analysis (LDA)*

LDA is a technique of classification that generates models of very good precision in comparison with complex models. The mathematical specifications are very limited. It produces a linear combination of variables, which better divides two groups and which is described in a model of probability density function as a linear combination of variables. If this data is a non-Gaussian distribution, the dynamic form of the data cannot be preserved. If the biased function is dependent on data variation, the LDA does not work.

2. *Support Vector Machine (SVM)*

SVM is a linear classifier that is a popular algorithm applied all over the BCI in machine learning. First proposed by Vapnik, it was decided by the head of mathematical theory of learning and systemic risk reduction. SVM follows a line that divides the data set into a designated division. The difference between the hyperplane and the points closer to each class that is considered the support vectors is called the divided line hyperplane.

3. *Naïve Base Classifier (NBC)*

NBC generates nonlinear boundary decisions. The hypothesis is founded on the Bayesian theorem by which the backward probabilities of feature vectors are estimated and the functions with the largest posterior probabilities are allocated to its class. They also outperform and dismiss ambiguous samples more reliably relative to the discriminatory classifiers.

4. *Nearest Neighbor Classifiers (NNC)*

NNC is a non-parametric classification system; it first saves entirely patterns & then searches pattern NN, and assigns a class to it. NNC intense is k-NN classifier. If the function vector is from a training set, so classifier is called KNN. The class associate is assigned to a function vector based on KNN patterns of space. It compares the label of a research sample with the main label of its NN. K-NN is transparent very simple to understand & is easy to use in comparison with other approaches.

5. *Artificial Neural Network (ANN)*

ANN is a nonlinear approach to classification that consists of a vast number of associated cells known as neurons. MLPNN has 3 layers in MLPN: input, secret layer & output layer. The MLPNN network is the most common in use. The number of functions chosen in the initial layer is essentially indicated and no. of labels or groups is seen in the output level. If the secret neurons are complex, the AAN would be complex. The secret layer determines the classification accuracy as well. There may be a likelihood of classification errors if fewer secret layers are used. There are no clear selection criteria for secret neurons picked with hit and test procedure [17-.20].

VI. Deep Learning for EEG-based BCI

In recent years, ML has been common with analysts in several applications such as image recall, image classification, video advice, social media analysis, text mining, etc. DL is widely used in this application by various ML algorithms, also known as representation learning. Deep learning (DL), which is embedded in deep neural networks (DNN), exceeds its predecessors substantially. It uses graphic technologies for developing multi-layered learning models of neuronal transformations. DL is a sequence of complex ML algorithms that are put on to DNN scheme & is applied for the study of EEG patterns. A significant no. of neurons in numerous cascades is used to detect characteristics that are strongly connected to the cognitive level of the human being. CNN, RNN & GAN are common schemes for DL. For EEG-based BCI applications, DL is commonly used to remove EEG features &, then, to perform an advanced classification or regression task is combined with standard ML technology. This section contains an introduction of spontaneous BCI EEG-based applications with the CNN method, the use of GANs, the RNN mechanism & operation, & especially CNN and LSTM space-time combinations.

A. DL Techniques

1. Convolutional NNs (CNNs)

CNN is a feedforward DNN model in which input data is streaming through the EEG patterns through the three basic stacked layers: convolutional layer, pooling layer, & fully connected layer. fully convolutional layer compresses the tensor to form & then simplifies computations required to reduce data dimension. In end, every neuron in the previous level is associated with a novel layer to anticipate or categories target objectives. CNN is a deep, feed-forward ANN class used for visual imaging analysis. CNN is equipped for image data processing. It is being applied in mining ST data, in particular spatial maps & ST rasters, because of its powerful capacity to measure correlations in the spatial domain...

2. Recurrent NNs (RNNs) & Long Short-Term Memory (LSTM)

RNN will approach human reasoning by creating a directed graph among neurons with temporal sequence to document the users can select. The generalized RNN network should only look for new dependencies to ensure that any long-term information could not be retained. Long-term learning dependency capacity was offered to address a certain form of RNN, the LSTM networks. Researches on the EEG-based EEG RNN or LSTM system have significantly improved with reports in recent years suggesting that RNN or LSTM-based approaches exceed conventional ML. It can extract secret EEG feature displays as well as RNN in combination with CNN can improve feature representations by integrating both temporal & spatial EEG signal data. A big issue with regular RNN is the short-term memory because of the problem of gradients that disappear. LSTM is an abstraction for RNNs, which can acquire long-term input data dependencies. Owing to the special memory chip, RNN allows LSTM to recall its inputs for a long time. There are three gates in an LSTM unit: Input, Overlooked & Output Gate. This gate defines whether the information is to be entered or not to be deleted (forget Gate) by input or to affect the output at present (output gate).

3. Generative Adversarial Networks (GAN)

In some scenarios, EEG data from the real world are small, which may be vulnerable if any ML or DL models are trained. To solve this issue, it has recently been suggested, in particular for data augmentation purposes, that the GAN, including two synchronous NN's called "generator networks" and "discriminatory networks." It says that the GAN produces new samples to mimic data from real-world models.

4. Autoencoder (AE) & Stacked AE

An AE is an ANN form designed to acquire effective, unauthorized data coding. It features a hidden layer (or more layers) encoder function that holds input code. A decoder is then created to rebuild input from a secret layer. An AE produces a compact sign of dataset in a compressed layer or bottleneck layer utilizing studying similarities of data.

5. Restricted Boltzmann Machines (RBM)

RBM is a stochastic NN of 2 layers that can be used to reduce dimensionality, classify, teach function and work together. The regular RBM form has binary nodes & bias weights. RBM attempts to learn binary code or input representation, & RBM may be conditioned, either in supervised or unattended ways, depending on a specific mission. RBM is normally used for learning features [21, 22].

VII. LITERATURE REVIEW

Z. Mao et al. (2017) suggested a modern CNN-based solution. The proposed CNN operates with raw EEG data directly, thus reducing engineering requirements. they examine the results of CNN on datasets of 100 subjects from one fatigue test. Our findings show that the CNN model is highly effective in training and highly resilient and achieves 97 percent precision in the identification of 14K test times for 100 subjects with unlocked natural fatigue data and far greater than from a randomly sampled period. The findings demonstrate that the CNN model is swift and efficient in training (90 percent). In general, the ability of DL solutions is demonstrated to identify EEG-based biometrics [23].

J. Zhang et al. (2018) The proposed approach can automatically learn feature representation from raw EEG signals without any pre-processing. They develop and shape the classifier base on TCN to classify EEG data to test the obtained results. The best performance of the 14 different combinations of two-class epilepsy detection gives an accuracy of 100.00%. their outcomes show that TCN can accurately distinguish epileptic data from non-epileptic data. In terms of computation cost and accuracy, this novel approach proposed in this paper is more competitive than others, such as wavelet transform, Naïve Bayesian, and KNN, etc [24].

Y. Yang et al. (2018) this study analyzes basic signals, intending to increase recognition accuracy by suggesting a simple but efficient pre-processing tool. Meantime, by essentially studying the compositional spatial-time representation of raw EEG sources, a hybrid neural network that incorporates 'CNN and 'RNN' is used to characterize the states of human emotions. The CNN module is being used to mine the inter-channel association between the EEG signals by transforming the EEG chain-like series into a 2D frame series. The test outcomes show that the suggested who was before method will improve the accuracy of emotion detection by around 32%, with an average accuracy of high output of 90.80% and 91.03% simultaneously for valence as well as excitement grading tasks. [25].

X. Zhang et al. (2018) the new proposed DNN-based learning system provides a perceptive overview of MI-EEG and brain activity relationships. A large-scale public MI EEG data set & a small but easy-to-implement data set were obtained in our laboratory have tested the proposed solution thoroughly. Their methodology is based on a range of guiding principles and competitive advanced approaches, resulting in 95.53 percent of our rating accuracy. A realistic BCI typing method shows the application of their proposed solution [26].

P. Sandheep et al. (2019) In this paper, an extensive analysis of the approach founded on the classification of depression using EEG signals is carried out. A computer-aided machine learning approach: CNN, a deep learning method is used in this work. deep CNN was trained using EEG signals from 30 normal & 30 down persons. The network achieved 99.31 percent of the highest precision in classifying depression from EEG signals from the right brain hemisphere and 96.3 by 10-fold cross-validation of the left brain hemisphere [27].

B. Xu et al. (2019) In this training, it is proposed to derive functionality of the EEG motor imagery signal from wavelet transformation-based feedback combining the time-frequency images from C3, Cz & C4 channels. The classification and convolutional kernels with various sizes were verified by the 2-layer CNN. Exactness and Kappe significance are assessed for the success of the proposed solution. The precision of BCI Competition II data set III amounts to 90%, the best Kappa value on dataset 2a is larger than numerous other approaches. [28].

W. Fadel et al. (2020) In the EEG signal classification, the latest pattern has been adopted where the signal is converted into images, making the classification of these signals an image classification issue for DL. For this same dataset, our outcomes were good (70.64% average exactness) & 5% higher than SVM results. We found that considering the Delta band, the rating accuracy is increased by 2.51%. [29].

A. Akrout et al. (2020) this article suggest leveraging two methods in DL e.g. ANN & CNN, which are new in extraction & recognition of left and right hand, including foot & tongue expression. EEG signals for mental functions are derived from these architectures & graded accordingly. The suggested approaches are further tested and contrasted with the EEG data collection of the BCI IV-2a competition. The findings reveal that the CNN model exceeds the ANN model by 60.55%. [30].

S. Hoshino et al. (2021) suggested a user-controlled interface for the personal mobility robot PMR. The interface is called the BMI interface for brain and mobility. The BMI is used for DNN. DNNs. The EEG signals, based on the user's purposes, are listed as controls at the output. The control commands consist of PMR linear & angular speeds. Via network training, both classifiers have an estimated output of more than 99 [%]. In a test, we also demonstrate that designation of BMI is sufficient for users to monitor the PMR since only mental commands are designed. [31].

K. -W. Ha, et al. (2021) the suggested model integrates multilayer multiscale pooling and the fusion processes that can usually be found in the modern CNNs to capture different features of an EEG signal. The test findings depended on the BCI competition IV dataset show that CNN's multi-layer pyramid pooling model improves classification accuracy in comparison to the original networks. [32].

VIII. CONCLUSION

The human brain is a complicated structure that has rich spatiotemporal mechanics. EEG offers a direct indication of cortical function with millisecond time resolution among noninvasive strategies for the examination of human brain dynamics. EEG is a map of the electrical potential of the brain cortical nerve cells. This research is based on the Deep Learning approach to Detection of Motor Imagery (MI) tasks in EEG, use of BCI techniques for direct communication among the human body & outside world, which has important forecast applications in the area of cognitive science & medical rehabilitation. In this paper, we have presented the analysis of the EEG signal with different techniques and also we observed the behavior of the EEG signal.

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