A survey on Artificial Intelligence Algorithms Associated to Motor Imagery Signal Classification from Graphite/Noble Metal EEG Electrodes

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Abstract
Brain computer interfaces (BCI) are the fledgling field to rehabilitate the immobilized people. This BCI technology can succour paralyzed patients to operate wheelchairs independently for locomotion, also to lift and carry the objects based on brain-neuronal activity with robotic control. EEG (Electroencephalography) is a device used to provide information immeasurably identifying about brain conditions and disabilities with an effective stimulus using graphite or noble metals. It indicates extremely herculean and targeted EEG applications to guide devices utilizing brain activity. This study gives the survey of (ML) machine learning and (DL) deep learning associated with MI (Motor Imagery), MeI (Mental Imagery) and ME (Motor Execution) gesture classifications applicable for BCI. There are two public domain datasets (PhysioNet, BCIC- Motor Execution) and self-collected datasets were utilized for computerized process since inception. DBN (Deep belief networks), PCA (Principal component analysis) and few other transforms were applied to the recorded signal to extract the features. To categorize the features derived from the collected signal, diverse machine learning and deep learning classification algorithms are available. This article surveys on literature for multiplex weighted visibility graph (MWVG), G-CRAM (Graph based convolutional Re current attention model), FFNN (Feedforward neural network classifier), HF-CNN (Hierarchical flow conventional neural network), (Spectro temporal Decomposition – Squeeze and Excitation – Convolutional Neural Network) SSD-SE-CNN, LASSO (Least absolute shrinkage and selection operator), DML (Deep metric learning), (ASTGCN) adaptive spatiotemporal graph convolutional network, VaS-LDA (Vertical arrangements of sub-bands - Linear Discriminant Analysis), ZSL (Zero shot learning), RLS-CSP (Recursive-least squares updates of the Common Spatial Pattern filter coefficient), SW-LCR (Sliding window- Longest consecutive repetition), CNN (Convolutional Neural Networks), SVM-RBF (Radial Basis Function-based support vector machine (SVM) classifier), DJDAN (dynamic joint domain adaptation network), and S-EEGNet (Separable EEGNet) with HHT (Hilbert-Huang Transform). Eventually, this work also consolidates wide range of research progress in classification and analysis on the datasets, sampling rate, number of subjects and overall performances are discussed in specific to motor imaginary tasks.

Index Terms— Deep learning, Machine learning, Mental Imagery, Motor Execution.

1. Introduction

A brain-computer interface is one of the computerized approaches that obtains brain electrical signals, investigates them, and transcribes them into broadcast commands to an output device to achieve a convenient action. In general, variety of brain signal perhaps used to control a Brain computer interface system. The typically considered signals from brain activity are electrical signals. It can be measured from patients through different techniques. To forecast the electrical activity of the brain, a variety of electrode setups are available, like electrode cap, 64 channel EEG, 8 channel EEG, etc. BCI technology speak for a tremendously expanding field of investigation with application systems.

Its benefaction in medical sectors range from prevention to neuronal convalescence for significant injuries. Electroenceplography is the device used to predict the electrical activity of brain signals. There are mainly six type of EEG electrodes are used to identify the electrical activity of brain signals. They are disposable electrodes, reusable disc electrodes, scalp electrodes, saline based electrodes, and needle electrodes. The choice of electrodes depends on the needs of patient data and the field of application, and it is made by using graphite or noble metals such as gold, silver, silver chloride, or platinum. Combination of BCI and signal processing uses five stages to complete the task.

They are data acquisition, preprocessing, feature extraction, signal classification and finally, the classification results are given to control the device [1].

This paper will provide the comparison of various algorithms used in the data acquisition, feature extraction and classification. First stage is to acquire the EEG data, it can be acquired through public domain or real time. Next stage of data collection is preprocessing, here data filtering, down sampling, artifact removal etc. After preprocessing different feature extraction algorithms are used for extracting wide range of features from the data.

Then dimensionality reduction also applicable for getting the better performance. Finally, classification algorithms are implemented to classify the signals [2]. This classification algorithms are combined with optimization techniques to provide the better results. The classification results are used for BCI with 3 degrees of freedom (DOF) of robotic exoskeleton for the paralyzed patients [51].

2. Data Collection

There are different types of data sets are available based on EEG applications either public domain or real time data. Public domain datasets can be collected through Physionet website and (BCIC) Brain Computer Interface Competition dataset [41]. But real time data can be obtained experimentally, it can be taken from the patients with the help of electrodes, electrode cap etc. [2]. Table 1. provides some of the examples of public domain datasets from Physio bank website and BCI competition dataset. CochlEEG system is used to acquire the better performance electrical activity of the brain signals for the real-life applications [3]. EEG signals can be acquired three different ways. They are CochlEEG system, SMARTING system and MASTER System. They utilized two techniques to acquire the EEG signals. They are, Event-Related Potentials and Auditory Stable Responses. The AFE (Analog Front End) design technique is used to acquire the EEG signals with high input impedance. This AFE design includes the IA (Instrumentational Amplifier) and NSS-ADC (Neural Signal Specific Analog to Digital Converter). These techniques are reducing the amount of power used by the entire system and avoids the signal attenuation. It increases AFE's input impedance at 102 GΩ with respect to 1 Hz and 5.2 GΩ with respect to 20 Hz [4].

Table 1: Different type of EEG datasets collected from the public domain.

Dataset	**Weblink**	**Subjects**	**Device**	**Sampling rate(HZ)**	**Reference**
EEG Motor Imagery / Movement Dataset	https://physionet.org/content/eegmmidb/1.0.0/	109	BCI2000 system	160	9, 10
Motion Artifact Contaminated fNIRS and EEG Data	https://physionet.org/content/motion-artifact/1.0.0/	22	International 10-20 system	25	10, 11
EEG-Biometric dataset for Auditory evoked potential	https://physionet.org/content/auditory-eeg/1.0.0/	20	10/10 international EEG system	200	10, 12
Rapid Serial Visual Presentation dataset	https://physionet.org/content/ltrsvp/1.0.0/	11	10-20 system	2048	10, 13
MAMEM SSVEP Database	https://physionet.org/content/mssvepdb/1.0.0/	11	256 channel EEG system	250	10, 14
MI based Competition dataset for BCI	https://www.bbci.de/competition/iii/desc_IVa.html	10	10/20 international EEG system	1000	38, 39

The components of the portable EEG system were composed of 2 major components. One is skin interfacing e-textile (E-Textile Headband) another one is the electronics system. There are two main circuits in the electronics system as well. They are Signal Amplification (ADS1299 module, ESP8266 microcontroller) and Transmission through Wi-Fi, SPI interface (Serial Peripheral Interface). For this setup the operating time of the system will be increased more than 24 hours. It is the low-cost EEG system [5]. EEG signals can be acquired ultra-shielded capsule. This is one of the experiments. It will be conducted at the LSBB (Low noise underground laboratory). It was situated in the Rustrel, France. This capsule technique is employed to examine the scalp EEG signals. Through the aid of this capsule low noise signals are acquired with higher level of Beta band activities. For future studies need to include the Gamma related activities, audio, video cognitive tasks [6]. Brain computer interface competition datasets coming under the public domain dataset. It is easily available. In this BCIC datasets mainly consists of five different sets. Each datasets having variety of patients information's with different sampling rate, and it can be acquired using different kind of electrode systems.

3. Feature Extraction

After the features from the EEG dataset with emotional activities were extracted using Hilbert Huang spectrum and Discrete wavelet transform [13]. Here, they predicted two types of features. One is time domain features and another one is frequency domain features. Potentials associated to events, signal statistics (Mean, power, standard deviation, 1st difference, normalised 1st difference, 2nd difference, normalised 2nd difference), Hjroth features, Time domain features include higher order crossings, fractal dimensions, and non-stationary indices. Frequency domain characteristics include band power and high order spectra [40]. LP-SVD transform is a technique for separating the features from motor imagery signals. The expansion of (LP SVD) is linear-prediction and singular-value-decomposition. This transform was constructed with two step process. The process based on LPC filter coefficient estimation followed by SVD computation of the left-singular vectors of the LPC-filter IR matrix. It has been worked in two ways, time series and frequency domain analysis. If the linear prediction is used for the time domain, then it can be utilized for extraction of features, compression, and signal modelling.

Frequency domain signals should reduce the distance between the actual spectrum and all pole spectrum of the particular signal. Next, the LP coefficients and error variance were calculated [42]. Finally, it can be compared with the DCT (Discrete cosine transform) and AAR (Adaptive auto regressive) techniques for the best feature extraction. 67.35 % accuracy was predicted with LP-SVD transform [14]. For the classification of cognitive tasks, the de-mixing of EEG channel pairs with the correlation-coefficient approach was also utilized to extract the features. A 2-D rotation matrix is used to demix each pair of EEG channel signals, during the preprocessing stage. Three coefficients were calculated to extract the features. They are, Fisher ratio (FR), within class correlation coefficient distance (WCCD), and interclass correlation coefficient distance (ICCD) [43], [44]. The EEG channel pairs are used to determine these correlation coefficients. For optimization various feature selection techniques are applied and finally best features are selected based on correlation coefficient results [15]. For feature extraction (PCA) principal component analysis and deep belief networks (DBN) were combined and it was analyzed for the motor imagery features [45], [46].

Initially, they estimated the normalized second order moment of the signals. After that, principal components are calculated by using following steps. 1. From the original data average values are processed. 2. For the covariance matrix the root decompositions are carried out. 3. New coordinate system for the original data are projected. 4. Contribution of accumulation takes place. 5. To select the exact cumulative contribution. After that Deep belief networks are executed. They are two models are presented to obtain the appropriate output. They are Restricted Boltzmann Machine (RBM) and Gaussian restricted Boltzmann machine (GRBM). Then models are trained and processed. Finally, they used SoftMax classifier [16].

Table 2: Various feature extraction techniques applied for EEG signals to extract the features.

Technique	Application	Reference
Hilbert Huang Spectrum and DWT	Emotion recognition	13
LP-SVD	MI task classification	14
ICCD, WCCD and FR	Cognitive task classification	15
PCA and DBN	MI task classification	16
CSO and AAR	BCI	17

To extract the characteristics from motor imagery signals they are two algorithms were used, they are (CSP) Common spatial pattern [47] and (AAR) adaptive auto regressive. After feature extraction, they used to identify the frequency range of the signals [17]. If the frequency ranges between 100-1000 Hz it undergoes time domain frequency calculation.

After time domain calculation it will check the time domain ranges between 500-2000 milliseconds. If it is coming under this time domain range, it allows the following steps. They are decomposition level selection, conscious task classification, data testing and training and vector machine migration. After all these processes are completed feature extraction will be takes place. If the time domain ranges are not present between 500 to 2000 ms that signals are provided for error calculation. After that rectified signal will be extracted their features.

The following stages are carried out for the signal does not coming under the frequency ranges between 100-1000 Hz. They are analysis of DRD/DRS, band level decomposition, signal cross screening, data communication. After that it will move to the next stage of data testing and training. After feature extraction the comparative analysis of classifications are done. They used 3 classification techniques such as Bayesian classifier, Common space classifier and Linear discrimination classifier. There were used different varieties of feature extraction algorithms for extract the EEG features like Hilbert huang spectrum, Discrete wavelet transform, LP-SVD, ICCD, WCCD, FR, PCA, DBN, CSO and AAR (Table 2).

4. Classification

Kaniska Samanta et al [18] predicted the novel method to categorize the motor-imagery EEG signals. For extracting the deep features of the EEG signals they used auto encoder structure. After the deep feature extraction, they introduce the graphical algorithm to classify the EEG signals. They named this algorithm into MWVG-multiplex weighted visibility graph. To apply this technique, they calculated the correlation, mutual correlation, and clustering coefficients. It is used to mapping the temporal properties of the univariate time series into the graphical representation.

These techniques were utilized for the analysis of the multivariate time series of the EEG signals. With the help of clustering coefficient, the complex functional brain connectivity network was constructed. It is fully based on mutual correlation between the signals between the different electrodes. Another one method also implemented to identify the lack of generalized features from the signals. That was called as cross-categorization. Finally, random forest classifier is used to identify the precision, specificity, sensitivity, and accuracy for two kinds of databases. This graphical approach was used to classify the motor imagery signals. That approach is called as G-CRAM (Graph based convolutional Re current attention model) [19]. In this model each positioning information of the EEG nodes will be graphically plotted with the help three types of graphs like N-graph, D-graph, S-graph.

It is utilized to contrast the motor imagery signals temporal and spatial dimensions. In the end, the temporal characteristics will be graphically plotted with the help of Graph based convolutional Re current attention model [48]. The combination of decomposition and neural network algorithms were used to classify the motor imagery signals [20]. Initially denoising of the signals takes place using MSPCA (multiscale principal component analysis) with the help of covariant matrix calculation of wavelet transform. Next stage is decomposition of EEG signals.

Here, (Empirical Fourier decomposition)-EFD was utilized for the decomposition of non-stationary and nonlinear MI and MeI EEG waves into subsequent modes. After that, these subsequent modes of the EEG signals were selected into single conspicuous mode using (IEFD) Improved Empirical Fourier-decomposition. In this IEFD and EFD decomposition techniques are used to extract the collected signals' time and frequency features.

They used the HF-CNN (Hierarchical flow conventional neural network) technique used to classify the motor execution, motor imagery signals of the datasets collected from experimental task (Real time) and public domain [21]. Here, ICA (Independent component analysis) are used to eliminate the contaminated factors. Next stage is to classify the signals using HF-CNN. Here, they used two steps they are, CNN I and CNN II. CNN I was used to detect the movement of the signals and CNN II was used to detect the rotation of the forearm signals. Finally, the classified results were verified with ANOVA test.

The comparative results of the experimental and public domain datasets with motor execution and motor imagery classification accuracy results were discussed.

The SSD-SE-CNN (Spectro-temporal-Decomposition – Squeeze and Excitation – Convolutional-Neural-Network) approach to classify the motor imagery EEG signals [22]. In this process mainly consists of three stages. First stage is to extract the features with the help of Spectro temporal Decomposition (SSD) algorithm. Second stage is to classify the motor imagery signals used by the Convolutional Neural Network (CNN) depends on convolution and scaling. Third stage is recalibration of classified signals with Squeeze and Excitation approach.

The LASSO (Least-absolute-shrinkage and selection-operator) algorithm were a new model for classifying the motor imagery signals [23]. To simulate the group sparsity of signals, LASSO was used. Here, wavelet packet decomposition technique was applied to the motor imaging signals to derive three features. The signals can be classified, and accuracy will be calculated with five different LASSO techniques using SLEP toolbox. They are, LASSO, Enet (Elastic net), fLASSO (fused LASSO), gLASSO (group LASSO) and sgLASSO (sparse group LASSO).

Table 3: Various classification algorithms applied for EEG signal classification.

NO	Technique	Dataset	Subjects	Accuracy (%)	Sampling Rate (Hz)	Application	Reference
1	MWVG	BCICIII-IVa dataset - Right hand (RH) and Right foot (RF) MI tasks	5	99.92	1000	Cross - subject MI task classification	18
		BCICVI-IIa dataset - Feet, Left hand (LH), Tongue and RH MI tasks	9	99.96	250		
2	NG-CRAM	PhysioNet MI- Fist open and close dataset	105	74.71 ± 04.19	160	MI task classification	19
		BCICIV2a dataset -LH, RH, Feet, Tongue movements	9	60.11 ± 09.96	250		
3	IEFD with	BCICII-IVa dataset -	5	93.33	1000	MI and MeI	20

	FFNN	RH, RF movements				task classification	
		BCICII-IVb dataset LH, RF movements	5	91.96	1000		
		BCICII-III dataset - RH, LH movements	1	88.08	128		
		BCICIII-V dataset - MeI tasks	3	82.70	512		
4	HF-CNN	Public dataset - ME tasks	10	73.00 ± 04.00	1000	Forearm movement imagery classification	21
		Public dataset - MI tasks	10	65.00 ± 09.00	1000		
		Experimental dataset - ME tasks	15	52.00 ± 03.00	100		
		Experimental dataset - MI tasks	15	51.00 ± 04.00	100		
5	SSD-SE-CNN	BCICIV-IIb dataset – RH, LH movements	9	79.30 ± 01.60	1000	MI task classification	22
		Tianjin University dataset - RH, LH movements	12	85.70 ± 04.90	1000		
6	fgLASSO	BCICIII-IVa dataset – RH, RF MI related tasks	5	79.24 ± 10.13	100	MI task classification for BCI	23
		BCICIII-IIIa dataset - LH, RH, Feet, Tongue MI tasks	3	86.64 ± 09.24	250		
		Experimental dataset - LH, RH MI tasks	8	81.09 ± 07.05	250		
7	DML	PhysioNet MI-Imagination of right- or left-hand movements	109	64.70	160	MI task classification for BCI	24
8	ASTGCN	Tianjin University dataset – MI tasks	25	90.60 ± 03.40	1000	MI task classification	25
9	VaS – LDA	BCICIV-I dataset - MI LH and RH movements	7	89.84 ± 07.80	1000	MI task classification for BCI paradigm	26
		Open dataset (General - purpose BCI research) – MI grasping objects task	54	86.10 ± 15.30	1000		
10	RLS-CSP	BCICIII-IVa dataset – MI tasks for RH, RF.	5	80.42 ± 18.22	1000	MI task classification	28
	ISCDC	BCICIII-V dataset – LH and RH movements, Word generation tasks	3	88.53 ± 07.44	512		
11	SW-LCR	BCICIV-IIa dataset (Healthy) – MI tasks for LH, RH, both feet and tongue movements	9	72.99	250	MI task classification for BCI	29, 36
		Experimental dataset -	10	88.13	500		

		Stroke patient Dataset					
12	CNN	BCICIV-IIa dataset - MI tasks for LH, RH, both feet and tongue movements	9	78.00 ± 02.00	250	MI task classification for BCI	30
		BCICIV-IIb dataset- MI tasks for LH, RH movements	9	57.00 ± 03.00	250		
		BCICIII-IVa dataset - MI tasks for RH and RF movements	5	90.52	1000		

NO	Technique	Dataset	Subjects	Accuracy (%)	Sampling Rate (Hz)	Application	Reference
13	ZSL	Tongji University dataset – MI tasks for hand movements	9	91.81	500	MI task classification for BCI	35
14	CNN - CycleGAN	Self-collected data – Shandong university (Qilu hospital) – Cognitive tasks	50	78.30 ± 25.00	1000	Right and left-hand movement MI task classification	31
15	CTFSP	BCICIII-IVa dataset - MI tasks for RH and RF movements	5	85.00 ± 18.96	1000	MI task classification	32
		BCICIII-IIIa dataset - MI tasks for RH, LH, foot or tongue movements	3	96.20 ± 03.07	250		
		BCICIV-I dataset - MI tasks for RH and RF movements	7	75.00 ± 18.34	1000		
16	DJDAN	BCICIV-IIa dataset - MI tasks for LH, RH, both feet and tongue movements	9	81.52	250	MI task classification	33
		BCICIV-IIb dataset- MI tasks for LH, RH movements	9	83.00	250		
17	CNN – Bilinear interpolation	BCICIV-IIa dataset - MI tasks for LH, RH, both feet and tongue movements	9	77.90	250	EEG classification	34, 37
		DEAP signals – Emotional tasks	32	89.91	512		
18	CNN	Experimental dataset – MI tasks for Simple limb and compound limb	10	74.75	1000	Robust MI task classification	27

		movements [49]					
		PhysioNet - MI tasks for RH and LH movements	109	77.21	160		
		BCICIV-IIa dataset - MI tasks for LH, RH, both feet and tongue movements	9	79.42	250		

*DEAP: A Database for Emotion Analysis Using Physiological Signals

The effectiveness of the classification technique was improved by using primal-dual theory optimization techniques. DML (Deep metric learning) technique were used to classify the motor imagery signals [24]. It used triplet pairs to achieve the better performance results. The motor imagery classification and emotional classification employed for brain computer interface use many sorts of classification methods. Table 3 will talk about it. The (ASTGCN) adaptive spatiotemporal graph convolutional network also used to classify the motor imagery signals [25]. Here 25 healthy persons were tested to acquire the input signals.

The STB (spatiotemporal block) was utilized to identify the characteristics of the motor imagery signals. Here, they assigned the AGCL (adaptive graph convolutional layer) for entire work. The grid data of Euclidean space are convoluted and graphed into non-Euclidean space using graph convolution. The classification accuracy and the standard deviation results was compared with four techniques. They were CNN-SAE, EEGNet, STGCN and ASTGCN. Finally, they concluded ASTGCN was provided the better accuracy performance. The classification algorithms based on decomposition of the signals into sub bands were developed [26].

To classify the signals deep learning approach also used. The number of hidden layers increased hyperparameters also increased. To handle this hyperparameter problems (CNN) convolutional neural network with ad hoc method was used [27. Here, CNN with ConvNet was applied to get the better performance. This network was tested with various input, hidden and output layers to vary the hyperparameters. The RLS-CSP (The CSP filter coefficients are updated using recursive least squares) method to classify the EEG signals with SSS (Small Sample Sitting) [28]. The sliding window technique was used to categorize the motor imagery EEG bio signals. This sliding window was divided into two stages. Initial stage was SW-LCR (Sliding window- Longest consecutive repetition) used to predict all the sliding windows with the calculation of longest consecutive repetition. Second stage was SW-Mode used to predict all the sliding stages with the calculation of the mode of the sequence. For feature extraction the CSP were used for feature extraction. LDA was used to categorize the signals. However, SW-LCR was able to deliver better outcomes for healthy individuals, whereas SW-Mode was able to deliver better outcomes for stroke patients. The approximate value of the classification accuracy and kappa value for both SW-LCR and SW-Mode was 80% and 0.6 [29].

CNN (Convolutional Neural Networks) are used for the categorization of MI EEG signals. Two alternative convolutional layer types are present in the end-to-end shallow architecture. The characteristics were extracted using those layers. The temporal characteristics were extracted using one convolutional layer. The signals' spatial characteristics were extracted using a second convolutional layer. In this study, event-related synchronization and desynchronization of the CNN input were employed to improve the calibration at each stage using ERD and ERS. Three public domain datasets are utilized in this study [30]. CNN with CycleGAN generated signals were used for the classification purpose [31].

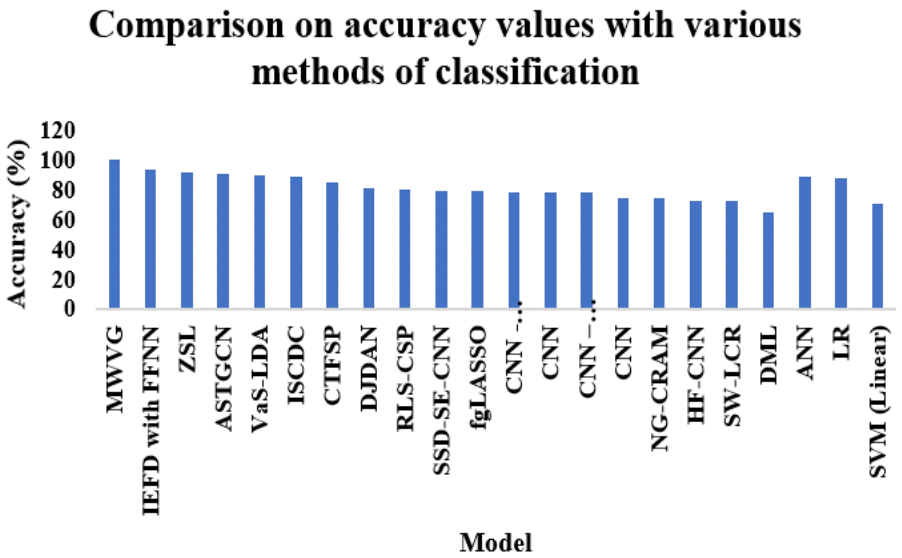

Fig 1: Accuracy ranges of various classification techniques

The identify the localization of time frequency signals using modified S transform. Then EEG2Image technique was used to convert the time-frequency signals into spectral topographies of the EEG. Both spectral and spatial information of the EEG signals are included in this EEG spectral topographies. The data structure was similarly created in this case using CycleGAN. This CycleGAN was the combination of two discriminators and two generators. It was also used to restore the EEG topographies. After that CNN and SVM classifier were used to classify the generated signals and direct motor imagery signals. Finally, they concluded there is no changes in the classification accuracy for both signals using SVM classifier. But using CNN the classification accuracy was improved using CycleGAN generated signals compared to normal motor imagery signals. The purpose of processing motor imagery tasks for classifying EEG signals with multiple support vector machines and RBF (Radial Basis Function) [32]. Here, the CSP features from the MI signals are extracted using CTFSP (Common temporal frequency spatial patterns). In this work they used to sliding-time window approach to decade the MI task. In each window the CSP features were extracted. Finally, the extracted features were classified using fusion works.

DJDAN (dynamic joint domain adaptation network) was created as a novel approach for learning the representation of the domain invariant feature and improving classification performance [33]. S-EEGNet (Separable EEGNet) with HHT (Hilbert-Huang Transform) [50] and separable CNN based on bilinear interpolation were used to classify the EEG signals [34]. Using HHT the EEG signals were converted into time-frequency representation. Using the bilinear interpolation method, the convolutional layer of the separable CNN was improved to allow free deformation of the sampling-grid. The three components of the EEG signal have a role in that distortion. They are the local, dense, and flexible input qualities of the signal. They experimented using two different dataset types: public domain MI datasets and emotion datasets. The motor imagery categorization accuracy was 77.9%, while the accuracy of the emotion classification was 89.91%. The new approach ZSL (Zero shot learning) was used to classify the known and unknown imagery tasks present in the motor imagery signals [35].

5. Conclusion

BCI technology plays a major role to assist the paralyzed patients. The classification will be used to know the exact action what the BCI technology wants to do. The dataset was used for the research using EEG with electrodes using graphite or noble metals such as gold, silver, silver chloride, or platinum. This survey summarizes huge set of machine learning (ML), and deep learning (DL) algorithms are used for classification of sensory signal. The accuracy ranges varied between 64.20% to 99.92% can be plotted Figure 1. Multiplex weighted visibility graph (MWVG) method were used to provide 99.92% accuracy. Compared to ML algorithms, DL algorithms are used to provide the better performance accuracy. These classification results gain its significance as decision support systems for robotics in medical rehabilitation applications.

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