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REVIEW ARTICLE

Deep Learning Techniques for EEG Signal Applications – A Review

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ABSTRACT
Electroencephalogram (EEG) can track the brain waves which contain the neural activity of the brain. EEG signals help to understand the physiological and functional details and activities of the brain. In the era of Artificial Intelligence (AI), machine learning algorithms were useful in brain disorder detection and classification. Recently, a rapid increase in using Deep Learning (DL) methods in various applications in EEG signals not only helps in the detection of brain disorders but also facilitates the recognition of human emotions and various psycho-neuro disorders. In order to offer a beneficial and broad perspective, a detailed survey on the application of deep learning architecture in EEG signals has been carried out in this paper. Different deep learning methods, using varied architecture in EEG signal analysis, offer an understanding to develop the next level of AI-based systems. This review will provide information about how deep learning methods are used in EEG signals and the challenges and limitations of each method in classification; moreover making it helpful for those who are exploring EEG signals using DL algorithms.

KEYWORDS
Deep learning algorithm; Artificial neural network; Electroencephalogram (EEG) signals; Convolution neural network

1. INTRODUCTION

Deep Learning (DL) networks were successful in many applications involving images, text, videos and speech recently. The application of these networks in neuro-imaging is being on the rise and recent works have started to use them for investigating cognitive tasks, epilepsy detections and human emotions. DL networks have many hidden layers, each layer is carrying a simplified representation of the input data to the next layer. These types of neural networks used in DL are also called Deep Neural Networks (DNN). Various types of deep learning architectures are used to find Human brain disorders and mental and emotion states via EEG signals. EEG (Electroencephalogram) tracks the neuro-activities of the brain usually called brainwaves. It has five different frequency waves called alpha waves, theta waves, beta waves, gamma waves and delta waves. Neuroscience community has processed these brain waves by various deep learning methods to identify brain disorders and detect the emotions of human beings. The major deep learning algorithms can be classified into Convolution Neural Network (CNN), Auto encoder (AE), Recurrent Neural Network (RNN), Deep Belief Network (DBN), Restricted Boltzmann Machine (RBM), Multilayer Perceptron Neural Network (MLPNN), Optimized deep neural network, EEG-Functional Magnetic Resonance Imaging (EEG-fMRI)-based deep learning, offering various possibilities for neuro-imaging community. The rest of this survey contains sections as follows: In Section 2, it is explained how each network has been used in EEG signals, together with diagrams and tabulation. We also discussed some crucial challenges faced in DL usage for EEG studies. The final section deals with the conclusion of the survey by offering the future road map to neuroscience community with DL algorithms. Deep Learning is gaining much popularity due to its supremacy in terms of accuracy when supplied with a huge amount of data. Deep learning models can be visualized as a set of points each of which makes a decision based on the inputs to the node. This sort of network is similar to the biological nervous system, with each node acting as a neuron within a larger network. Deep Learning is a subset of Machine Learning that achieves great power and flexibility by learning to represent the world as nested hierarchy of concepts or ideas, with each concept or idea defined in relation to simpler concepts, and more abstract representations computed in terms of less abstract ones. EEG is a complex signal and requires considerably more of training to be correctly interpreted. Recently, deep learning (DL) has shown great promise in helping make sense of EEG signals due to its capacity to learn good feature representations from raw data. In this work, we review 156 papers that apply DL to EEG, published between January 2010 and July 2018, spanning different application domains

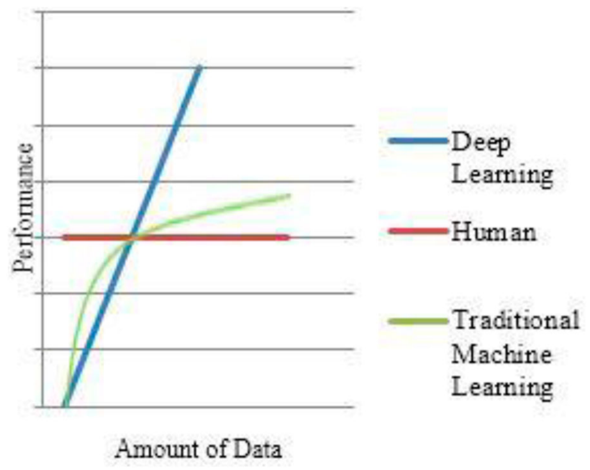

Figure 1: Performance: deep learning vs. human vs. machine learning

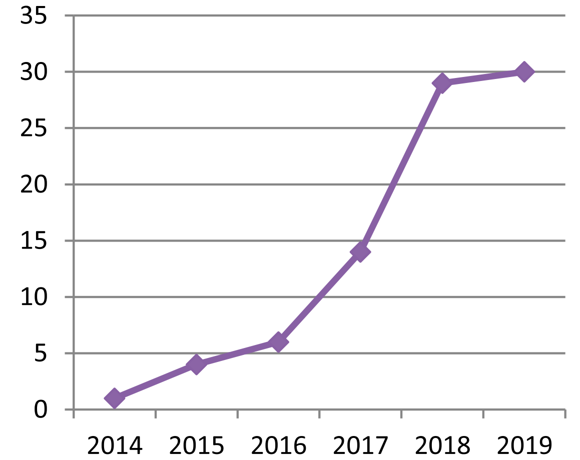

Figure 2: Published deep learning (DL) paper for EEG signals vs. published years

such as epilepsy, sleep, brain–computer interfacing, and cognitive and affective monitoring. We extract trends and highlight interesting approaches in order to inform future research and formulate recommendations.

2. METHODS AND ACHIEVEMENTS

Apart from the mentioned major architecture in the introduction section, DL algorithms are also used for detecting epileptic seizures automatically from EEG signals [1,2]. Although the limited availability of large volume of EEG data was a restriction in employing DL methods, many have attempted to use them with the databases available. The increased availability of data in recent times has slowly turned the scientific community to DL from machine learning which is depicted in Figure 1. The performance of object identification and classification has increased drastically due to deep learning methods as the data availability has increased. A graph given in Figure 2 depicts the progressive usage of deep learning algorithms in EEG which were considered for this survey. In EEG signal processing, Ocular artefacts (OA) removal (the most important form of interferences in the analysis of EEG) is a key analysis before processing those signals. To reconstruct the EEG signals, DNN is trained by samples without the interruption of OAs and this DL algorithm is used as a filter to automatically remove OAs from the contaminated EEG signals [3].

Disabled people's difficulties in expressing thoughts and communication with the external world are aided and supported by the brain–computer interface-based systems. Even though DL-applied EEG-based Brain–Computer Interface (BCI) systems are time-consuming, they perform well in expressing thoughts and communicating with better efficiency [4,5]. To predict affective levels and personal factors of people, a multi-task cascade deep neural network is designed [6]. Moreover, deep learning techniques established in an ultra-low power environment with the consumption of less memory space of device by using True North chip showed the technical advancements for EEG applications [7]. Using DL automatic prediction Intracranial Epileptic discharges (IED) was achieved. Moreover, a combination of the MLPNN with deep learning is used to detect epilepsy by extracting discrete wavelet transform (DWT) features [8–10].

2.1 Convolution Neural Networks

CNN given in Figure 3 (a) is a type of feed-forward artificial neural network which is inspired by the organization of the animal visual cortex. In CNN, a neuron in the layer will only be connected to a small region of the layer which is available unlike the traditional fully connected network, where a neuron will be connected to the entire neurons of the layer before it. CNN has multiple hidden layers and it consists of a convolution layer, ReLU layers, a pooling layer and a fully connected layer. Convolution layer and pooling layer are used to extract features and the fully connected layer serves as a classifier. As expected, CNN adapts to learn non-linear data since the real-world data to be learned in mostly non-linear. Since the convolution layer is linear in operation, the ReLu layer is introduced in helping to convert linear operation to non-linear.

In calculating and classifying the mental load of individuals which results in different EEG (which tracks the neuro-activity of the brain) recordings which involves

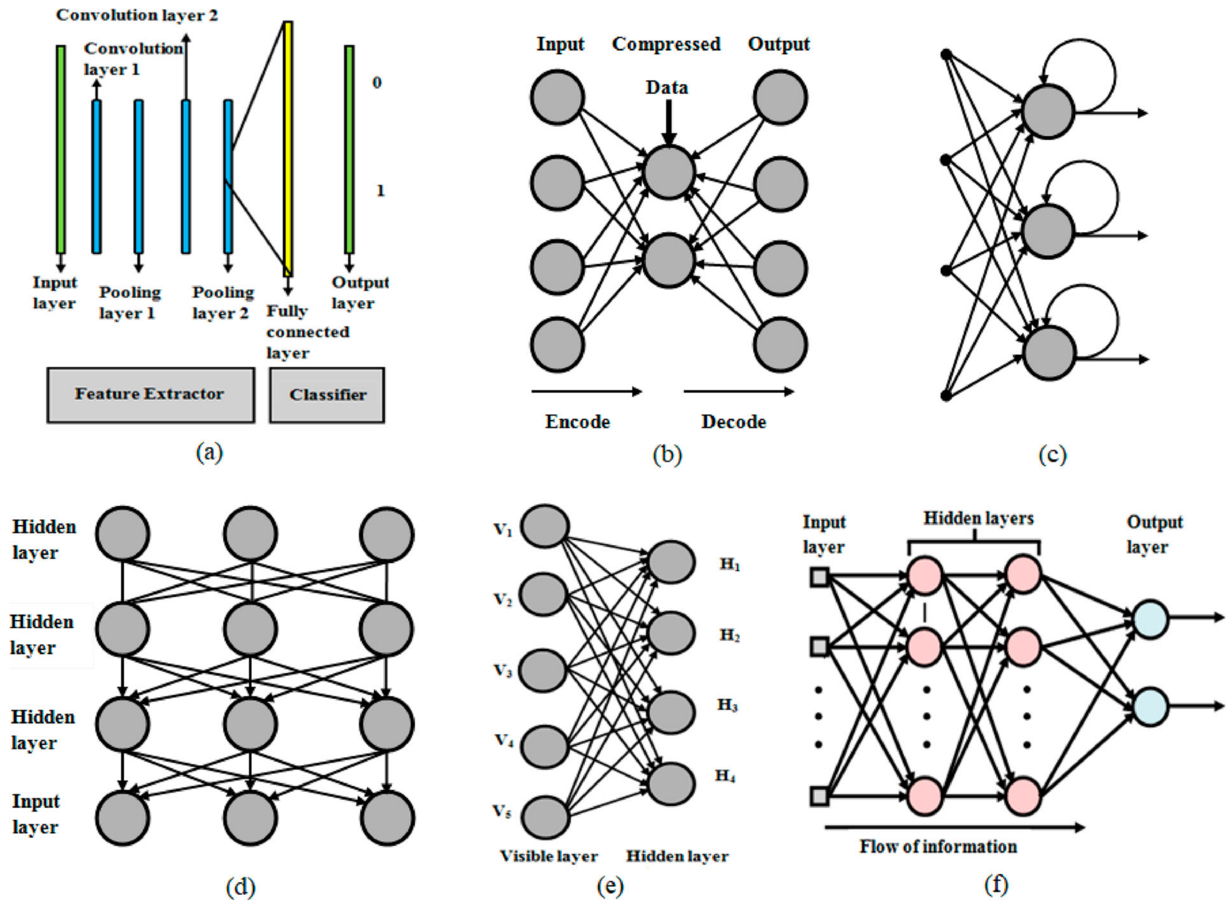

Figure 3: Various neural network architectures (a) convolutional neural network, (b) autoencoder, (c) recurrent neural network, (d) deep belief network, (e) restricted Boltzmann machine, (f) multi-layer perceptron neural network

challenges in various classification tasks as the mental conditions change frequently, CNN is achieving better results than deep recurrent CNN in classification task while supplementing pointwise gated Boltzmann machines' component in the classification process. Since CNN uses limited parameters, it could extract the various deep features from primary data on comparison with the advanced DL models.

In the classification of 2-D spectral maps obtained by t-distributed stochastic neighbour embedding (t-SNE) method from EEG signal, deep features that are contained in the dataset samples reveal the potential of the deep models while obtaining typical features and classification performance [11]. In the case of Global anoxia (absence of oxygen) problems of the brain lead to postanoxic coma, where a state of unconsciousness due to cardiac arrest is experienced, a suitable prediction model needs to be developed. To predict "good" neurological outcome or "poor" neurological outcome [Where the scale of good- (Cerebral Performance Categories (CPC) 1–2); poor-(CPC 3–5)] after cardiac arrest, CNN-based classifier , which provides reliable and objective prognostic information, is used. In the ongoing EEG recordings of cardiac arrested patients at and after 12 and 24 h of cardiac arrest, 5-minute artefact-free spans are used for training and validating the CNN. The accuracy of outcome prediction for postanoxic coma patients is more accurate at after 12 h of cardiac arrest [12]. To classify reaching targets earlier than movements begin, CNN is used unified with the discriminant power of EEG images. In general, visualization process in human brain conditions the brain to more readily perceive the desired outcomes. Virtual Reality (VR) approaches use decoded EEG images for understanding the visualization measures in the human brain while it identifies different images [13]. CNN can decode task-related information from the raw EEG without handcrafted features and with innovative visualization techniques for EEG-based brain mapping, thus highlighting its potential in decoding [14]. The analysis of brain signals from human interactions with a robot may help to identify robot errors. CNN is more accurate than widely used EEG classifiers (regularized linear discriminant analysis (r-LDA) and filter bank common spatial pattern (FB-CSP) combined with r-LDA) in decoding robot errors from the EEG of a human observer [15]. ConvNets is the best method for error decoding which shows better results than r-LDA classifier. This error recognition method of CNN can be trained by different error models [16]. To detect the normal, preictal and seizure classes, Pyramidal one-dimensional (P-1D) CNN model and CNN combined with Computer Aided Diagnosis (CAD) systems are used which can distinguish the EEG signals automatically.

This overcomes the drawback of direct visual inspection which is very tedious and cumbersome [17,18,19]. The advantage of these systems is feature extraction and feature selection done in a single step, by applying a bagging algorithm, and a vast database can get better results [20]. In automatic sleep stage scoring, CNN overcomes the burdens in the manual scoring of sleep stages from raw polysomnography signals. Visually interpretable images of sleep patterns from EEG signals are created by resorting multilayer spectral analysis and used as input to a CNN to solve visual recognition tasks and to score sleep stages automatically [18]. Through these EEG signals, screening the depression of a person and thus the result shows that the right hemisphere of the human brain shows more depression signals than the left hemisphere [19]. We can differentiate the sleep stages of the human brain by using unsupervised sleep stage method, Complex-valued Unsupervised Convolution Neural Networks (CUCNN) [21]. To improve the current stroke rehabilitation strategies, CNN-based Motor Imagery (MI) BCI system is used [22]. To identify subjects from EEG signals captured by low-cost device, a security system with CNN outperforms other traditional classification-based methods [23]. In Parkinson's disease (PD), certain nerve cells (neurons) gradually break down or die in the brain. While a 13-layer CNN architecture is used to determine these PD Signals [24], a 5-layer CNN-based models EEG-Conv and EEG-Conv-R were used to predict the mental state of the drivers where fatigue of driver leads to traffic accident [25]. Achievements and applications of CNN in various brain-related disorders and conditions are listed, as shown in Table 1.

2.2 Autoencoder

Data denoising and Data dimension reduction are the two applications of AE for data visualization. AE given in Figure 3 (b) is an unsupervised neural network that uses DL to do data compression (to convert the input into a smaller representation and vice versa). A BCI system being an alternative pathway of communication between the human brain and external devices, signal classification is an important issue to be resolved. Among various brain activity monitoring modalities, EEG technique (A new form of input is extracted from EEG signal combined with time, frequency and location information) provides an easy and low-cost solution for non-invasive BCI systems using DL algorithms. In stacked autoencoder (SAE)-based deep network, the gain of each network is unified and the performance increases when the features are extracted in CNN which are applied to classify EEG Motor imagery signals [26]. Adaptive Stacked De-noising Auto Encoder (ASDAE) uses back propagation to upgrade the weights of the node. Back propagation reduces the error, and it can subsequently classify the cross session of mental workload (MW) levels in EEG-signals which outperform advanced MW classifiers [27]. Achievements and applications of AE are listed as shown in Table 1.

2.3 Recurrent Neural Network

RNN given in Figure 3(c) is also called backpropagation through time (BTT) as it uses backpropagation for every timestamp. Long short-term memory (LSTM) network is a special kind of RNN that is capable of learning long-term dependencies is a method flawless for epilepsy since it provides seizure prediction as rock-hard achievement and reduces false alarm rates in pre-ictal EEG signals [28]. Even though the EEG signals are complicated due to their high amplitude and non-stationarity, the ability to understand EEG signals by RNN was an interesting feature. The pre-processing step (sequence of topology) transforms the EEG time series into comparable EEG frames and it causes various EEG dataset to be integrated together. Spatial coordinates of electrodes for each set-up are required to complete this transform and the data are trained via deep RNN. RNN perceives robust representations between inter-subject variations and intra-subject variations which are unchanging and to find typical noise bounded with EEG data collection helps in Cognitive load classification task to exhibit outstanding improvements in classification accuracy. It also helps in overcoming the challenges in modelling cognitive tasks from EEG data [29]. Achievements and applications of RNN are listed, as shown in Table 1.

2.4 Deep Belief Networks

DBN shown in Figure 3 (d) is the unsupervised network wherein each subnetwork, hidden layers serve as the visible layer for the next layer. DBN can overcome local minima (error surface contains multiple grooves) by pre-training with RBM. Feed-forward backpropagation network helps in refining the further results. DBN and DBN-HMM models outperform the state-of-the-art

Table 1: Achievements and applications of various neural networks in EEG-related tasks

S. No	Neural network	Author	Applications	Results
1	CNN	R. T. Schirrmeister (2017)	EEG Decoding and Visualization	FB-CSP ACC:82.1%, DCN ACC:84.0%
2		M. J. Van Putten (2017).	Outcome prediction of post-anoxic coma	SEN:58%, SPEC:100%
3		S. L. Oh (2018).	PD diagnosis from EEG	ACC: 88-25%, SEN:84-71% SPEC: 91-77%
4		H. Zeng (2018).	Driver mental states	EEG conv-R:92.68% EEG conv-R:91.78%
5		U. R. Acharya (2018).	Detection and diagnosis of seizure	ACC:88%, SPEC:90%, SEN:95%
6		Z. Jiao (2018)	Mental load classification.	ACC: 7.63%
7		Ullah (2018)	Epilepsy detection	ACC: 99.1 $\pm$ 0.9%
8		H. Dose (2018)	MI-EEG Signal Classification for BCIs	ACC: 86.49%,
9		J. Zhang and Y. Wu (2018)	Sleep Stage Classifications: Rapid eye movement and Non rapid eye movement	Total accuracy: 87.2%
10		P. Arnau-Gonzalez (2017)	Security systems	ACC: 94%
11		J. Behncke (2018)	The signature of robot action by Virtual Reality in deep convolution method.	ACC 75% $\pm$9%, rLDA65% $\pm$10% FB- CSP + rLDA63% $\pm$6%
12		M. Völker (2018)	Decodes error from Non-Invasive EEG signals.	Within subject- ACC:84.1%; Unknown subjects – ACC:81.7%;
13		S. R. Carvalho (2017)	Classification of Reaching Targets (Right, left, up and down)	G1-(69.06 $\pm$ 0.33), G2-(65.33 $\pm$ 0.94) and G3-(50.34 $\pm$ 0.38)
14		U. R. Acharya (2018)	Screening of Depression	93.54%-LH 95.49%-RH
15		A. Vilamala (2017)	Sleep Stage Scoring	ACC:86% ACC: 83%
16	AE	Y. R. Tabar and U. Halici (2016)	EEG Motor Imagery signals classifier.	ACC:90.0%
17		Z. Yin and J. Zhang (2017)	Mental workload levels classifier.	SEN:0.8830, SPEC:0.8328, PRE:0.844, NPV:0.8809, ACC:0.8579
18	RNN	K. M. Tsiouris (2018)	Prediction of epileptic seizures	MIN:15 Sen:99.28, SPEC:99.28 FPR: 0.11 MIN:60 Sen:99.63, SPEC:99.78, FPR: 0.03, FPR: 0.03 MIN:30SEN:99.38, SPEC:99.60, FPR: 0.06 MIN:120 SEN:99.84, SPEC:99.86, FPR: 0.02
19		P. Bashivan (2015)	Learning representations (speech, text, video recognition)	Frame arch ConvNetArch.D ERR-12.39% Multi-Frame ConvNet+ LSTM/1D-Conv 8.89
20	DBN	W. L. Zheng (2014)	Emotion Classification	ACC:87.62%
21	RBN	Y. Gao (2015)	Emotion Recognition	Integrated Subject −28.6% Channel selection: 57.2%, Bound Subject:68.4%
22	MLPNN	Orhan (2011)	Classification	Sen Max: 100% Spec Max: 100%
23		Raghu (2017)	Classification	Maximum Classification Accuracy Obtained: 97.68%

ACC – Accuracy, SEN – Sensitivity, SPEC- Specificity, DCN – Deep Convolution Nets, NPV – Negative Predictive Value, PRE – Precision.

methods in the accuracy of EEG-based emotion classification [30]. Achievements and applications of DBN are listed, as shown in Table 1.

2.5 Restricted Boltzmann Machines

RBM shown in Figure 3 (e) is a shallow network method that can automatically find patterns in our data by reconstructing the input which has visible layers and hidden layers. It consists of both the forward pass and backward pass which leads to activation and reconstruction, respectively. RBM gives higher accuracy than the conventional algorithm to recognize the emotions of human beings. Through BCI systems, it can predict the disabled person's emotions [31] and assist them according to their requirements. Achievements and applications of AE are listed, as shown in Table 1.

2.6 Multilayer Perceptron Neural Network

MLPNN shown in Figure 3 (f) is a feed-forward artificial neural network that consists of multiple layers or node in a directed graph with each layer fully connected to the next one. Using DWT, EEG signals have been decomposed into frequency sub-bands and these decomposed EEG signals are used as inputs to MLPNN model classifier for better classification accuracy rates in epilepsy treatment [32]. MLPNN classifies intracranial EEG recordings by using entropy-based features [33]. Achievements and applications of MLPNN are listed, as shown in Table 1.

2.7 Optimized Deep Neural Network

These networks use algorithms, which can automatically design and customize an optimal architecture with high generalization ability for achieving higher performance and results. Classification accuracy, sensitivity and specificity were high using optimized deep neural network in EEG classification. A combination of FC layer followed by LSTM network is connected with softmax layer to get the predicted output labels. This architecture is proving its high performance in detecting seizure in both noisy background and common EEG artefacts [34].

2.8 EEG-Functional Magnetic Resonance Imaging (fMRI)-Based Deep Learning Method

FMRI measures brain activity by detecting changes associated with blood flow. EEG-fMRI allows measuring both neuronal and haemodynamic activity which comprises two important components of the neurovascular coupling mechanism. Using fMRI images and the marked interictal epileptic form discharges, General Linear Model (GLM) analysis is applied to reveal the haemodynamic changes linked to IED and seizures, and it has been established as a valid scientific tool. The manual marking burden can be reduced and reproducibility can be improved in this deep learning-based automatic seizure detector for EEG-fMRI [9].

3. CONCLUSION

Deep Nets are the current state of the art in pattern recognition and identification tasks. To analyse a simple pattern, a basic classification tool like a Support Vector Machine (SVM) or logistic regression is typically good enough, but when the data have a very large volume of different inputs or more, neural nets start to win over the other methods. Moreover, when the patterns get even more complex, neural networks with a small number of layers can become unusable. For an intricate data, the practical choice is deep neural networks. This survey provides an understanding of how deep networks used in EEG signal for various purposes. In unsupervised learning for extracting patterns from a set of unlabelled data, either an RBM or an auto encoder performs better in EEG signals. In supervised learning for a set of labelled data, different deep nets well performed in classification tasks for various applications are as follows: RNN, DBN and convolution nets. RNN and Convolution nets performed well in text processing and speech recognition, image recognition, object recognition also. In general, ReLu with MLP or DBN becomes an effective choice for classification purposes. With the development of more architecture on the anvil, the classifications tasks will be faster and more accurate. More datasets needed to learn various patterns are a challenge faced in deep learning methods. Multi-channel real-time EEG signals can be incorporated in the DL architecture to get more applications benefiting neuroscience.

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