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A Review on Deep Learning For Electroencephalogram Signal Classification

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ABSTRACT

RECENTLY, THE RESEARCH ON ELECTROENCEPHALOGRAM (EEG) SIGNALS HAVE BEEN OBTAINED MORE FOCUS AT THE SAME TIME THE EEG SIGNAL IS REGARDED AS THE BASIS FOR THE PREDICTION OF DIAGNOSIS DISEASE AND THE BRAIN BEHAVIOR. EEG IS AS SIGNIFICANT TOOL FOR MANY CONDITIONS THAT CAN BE RECORDED THE BRAIN HUMAN WAVES WHICH ACCOMMODATE THE BRAIN ACTIVITY. IN THE RECENT DECADES, EEG DATA HAS BEEN EXTENSIVELY APPLIED IN THE APPROACHES OF DATA ANALYSIS SUCH AS TIME SERIES ANALYSIS. WITH THE CONSIDERABLE ACHIEVEMENT OF DEEP LEARNING (DL) IMPLEMENT ON THE TIME SERIES DATA, MULTIPLE STUDIES HAVE BEEN BEGAN APPLYING DEEP LEARNING ALGORITHMS ON THE PROCESSING OF EEG SIGNAL. SEVERAL DEEP LEARNING TECHNIQUES THAT ASSISTANT IN THE DETECTION VARIOUS PSYCHO-NEURO DISORDERS, HAVE BEEN PROPOSED IN ORDER TO AUTOMATE EEG DETECTION AND CLASSIFICATION WITH GREAT DEVELOPMENT IN MULTIPLE APPLICATIONS OF EEG SIGNALS. ALSO, DIFFERENT MACHINE LEARNING (ML) ALGORITHMS HAVE BEEN PRESENTED IN SUCH RESEARCH FOR BRAIN SIGNALS IDENTIFICATION AND CLASSIFICATION IN THE ERA OF ARTIFICIAL INTELLIGENCE (AI). IN AN ATTEMPT TO SUMMARIZE THE EEG SIGNAL PROCESSING TECHNIQUES, WE HAVE PERFORMED A LITERATURE REVIEW AROUND DEEP LEARNING ALGORITHMS FOR DECODING THE HUMAN'S BRAIN ACTIVITY AS WELL AS DIAGNOSIS DISEASE AND CLARIFIED PARTICULARS ABOUT SEVERAL DEEP LEARNING ALGORITHMS. WE ALSO CONDUCTED SOME OF ML PAPERS ABOUT EEG SIGNALS CLASSIFICATION. BASED ON THE ACHIEVEMENT RESULTS OF THE RESEARCH MENTIONED IN THIS ARTICLE APPEARS AN ADVANCED SCIENTIFIC DEVELOPMENT IN TERMS OF DEEP LEARNING.

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1. Introduction

Latest advances in smart health sensors and communication technology have impacted the field of healthcare by means of new services, availability, accuracy, and speed of response, as well as the collection of a huge amount of producing enormous amounts of clinical data[1]. Electroencephalogram (EEG) is a technique for analyzing the electrical signals of the brain. EEG records can reveal the electrical activities of the brain which enables it to give useful insight into brain activity disorders. Due to its high temporal resolution, relatively minimal financial cost, and non-invasive nature it's frequently

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utilized in neural and biomedical engineering research (for example brain-computer interfaces(BCI))[2], seizure detection [3], and sleep analysis[4]. The first recorded brain activity in the form of electrical signals was performed by Richard Caton (1842-1926) in 1875 who utilized a galvanometer and put a pair of electrodes over a human subject's scalp. Since then, some concepts have been used to denote the EEG which are electro-(denoting to registration of electrical activities in the brain), encephalo-(relating to the signals head emitting), and gram (or graphy) indicating drawing or writing were combined to denote the brain's electrical neural activity [5].

In the past few decades, EEG data has been widely applied in data analysis techniques such as time/frequency series analysis [6]. The neurons of the brain have ionic currents that generate voltage fluctuations, which EEG can record. This electrical activity is recorded from several scalp electrodes during a period of time to generate an EEG signal [7]. Over the past few decades, deep learning(DL) approaches have been effectively developed and widely employed to extract information from variety kinds of data.

DL is a trendy branch of machine learning that recently become increasingly popular due its significant advancements in computational power, deep neural networks, and bunch collected data. The architecture of DL is considered a development of the classic neural network (NN) framework because it involves multiple hidden layers between the input and output layers to mimic more complicated nonlinear connections[7][8]. DL networks have lately proven to be effective in a variety of applications including text, images, videos, and speech. The usage of these networks in neuroimaging is increasing, and recent studies have begun to employ them to investigate cognitive activities, epilepsy detections, and human emotions[9].

One of the most common types of DL are convolutional neural networks(CNNs), these kind of DL algorithms have mimicked the behavior of a biological neural system (e.g. the human brain)[10][11]. Different types of deep learning architectures are utilized to detect the disorders of the human brain and emotional and mental states using EEG waves. Because CNN for EEG data training may decrease the influence of noise, most research employed CNN for EEG signals to identify disorders using anomaly signal classification [12].

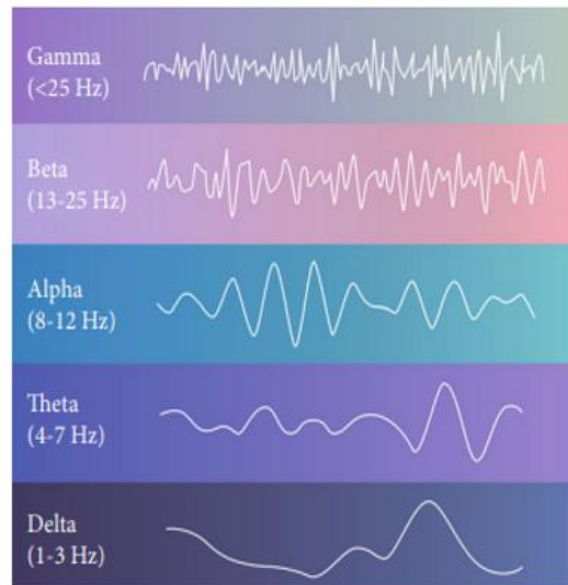
2. Disease diagnosis based EEG signal

EEG may also indicate human health; many diseases, and the diagnosis of many diseases, need anomalous EEG signal analysis, which records when the diseases occur. As a result, a system that can give the best diagnostic accuracy has become a direction for a range of areas. One of the most famous diseases known by EEG is epilepsy. It is the most common neurological disorder seen in primary health that affects around 1% of the world's population worldwide[13][14]. Epilepsy is a serious neurological disorder caused by transient aberrant discharges of electrical activity in the brain, resulting in uncontrolled movements and shaking. As a result, epilepsy diagnosis allows for the selection of either medical or surgical therapy[15]. When EEG is measured immediately onto the cortical surface (head surface), it is referred to as an electrocortigram, this type of reading does not request any invasive therefore it can be performed repeatedly to patients, and children, and normal adults with virtually no limitation or risk. however, when depth probes are used then it is called electrogram[16].

EEG is widely used in many research due to its non-invasiveness, low financial cost, and high temporal resolution. EEG signals track the neuro-brain's activities commonly known as brainwaves that has five distinct frequency waves known as alphawaves, betawaves, deltawaves, thetawaves, and gammawaves [9] as shown in Table 1. and Fig.1.

TABLE 1 - Wave's amplitude and frequency

Wave	Amplitude	Frequency range
Delta band	High	0.5-4 Hz
Theta band	Low-medium	4-8 HZ
Alpha band	Low	8-15 HZ
Beta band	Very low	15-30 HZ
Gamma band	Smallest	30-60 HZ

**Fig. 1 - Brain wave samples with dominant frequencies belonging to beta, alpha, theta, and delta band[17].**

EEG is a non-invasive process contracted to monitor brain responses and states and has been employed to observe and diagnose stroke, seizures, dementia, depth of anesthesia, encephalitis, obstructive sleep apnea, coma, and brain tumors[18]. It can represent set of bioelectrical signals from human's brain as shown in Fig. 2.

**Fig. 2 - Set of bioelectrical signals using EEG[17].**

One of the most significant step that making the using of EEG signal more practical in applications and fewer dependent on the trained professionals is the automatic classification.

3. EEG classification methods

One of the most significant step that making the using of EEG signal more practical in applications and fewer dependent on the trained professionals is the automatic classification.

3.1. EEG Machine Learning methods

Machine learning (ML) is a branch of artificial intelligent that is essential for every researcher who want to transform raw data into prediction and patterns. Over the last few decades, many machine learning algorithms are accessible and frequently used to solve different problems in the community. Due to the excellent performance of the machine learning approaches when dealing with multiple kinds of complex, dynamic, and real problems (by applying techniques such as classification, and regression, as well as unsupervised learning like as clustering) many researchers employing machine learning approaches for computing the valuable information that collecting from EEG signals.

choose scripting the algorithm for collecting significant data from EEG signals and compute that data by employing machine learning approaches[12]. These algorithms have enabled to extract the information of electroencephalographic (EEG) data of brain activity, and hence play an essential role in numerous major EEG-based research and application domains such as Support vector machine (SVM), Random forest (RF), and Artificial neural network (ANN) [19].

The typical pipeline of EEG classification involves preprocessing, extraction of features, and classification depicted in the Fig. 3.

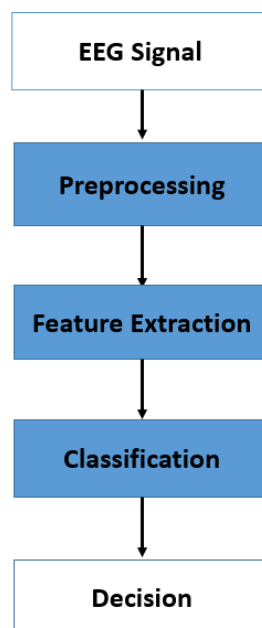


Fig. 3 - EEG signal classification steps

Within the 2D, an EEG dataset consists of matrix of real values that represent the time and channel, these values reflect the brain-generated potentials that recoded on the scalp linked with specific application conditions [20].

- **Preprocessing stage:** One of the basic steps of EEG detection is preprocessing. In this step, the noise and artifacts that are presented in raw EEG data have to be detected in order to reduce their effect on the next stage (feature extraction)[17]. As EEG is produced by several electrodes, it is also critical to determine frequency and channel in this stage [21][22].
- **Feature extraction stage:** After the preprocessing step of the EEG signal has been completed, several approaches such as discrete wavelet transform (DWT), Independent Component Analysis (ICA), and Empirical Mode Decomposition (EMD) are applied for selecting and retaining the relevant information of the original EEG signal[20]. The features extracted in this step such as Min, Max, Entropy, Median, Mean, Standard deviation, Skewness, Variance, Energy, and Relative will assist the classifier in detecting some cases such as epilepsy efficiently[22]. The applications of machine learning on EEG have been developed depending on supervised learning that categorized into classification and regression and unsupervised learning that categorized into clustering and dimensionality reduction as illustrated in Fig.4.

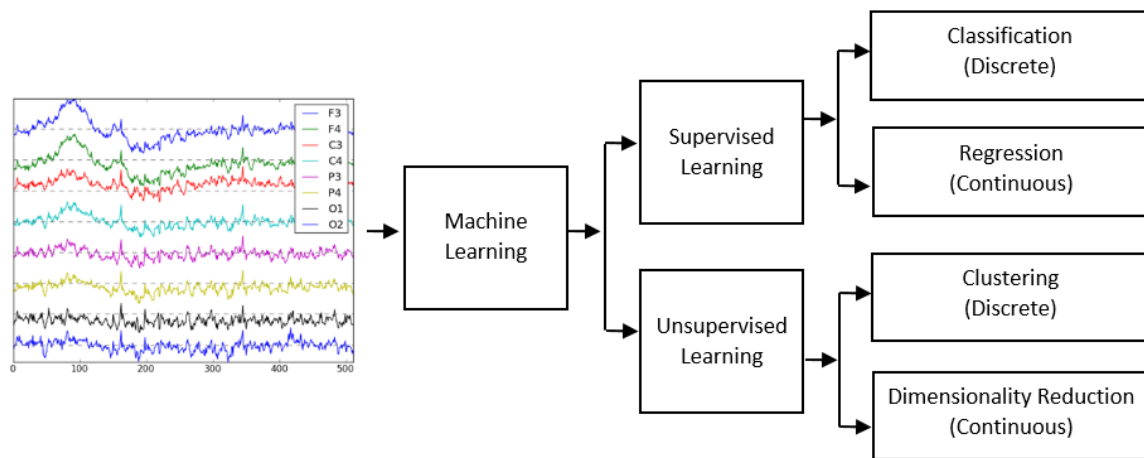


Fig. 4 - Machine learning applications on the EEG signal [6].

Table 2 summarize set of studies that applying different of machine learning algorithms for EEG signal classification.

TABLE 2 - different machine learning algorithms for EEG classification

Study	Feature extraction	Decoding problem	Architecture	Accuracy
[19]	Energy	Seizure detection	KNN, Naive Bayes, SVM, MLP	98.75
[23]	Raw data	Emotion detection	SVM	
[24]	DTCWT, MSPCA	Elliptic seizure detection	SVM and K-NN	100%
[25]	Energy and PSD	Emotion detection	SVM and LDA	92.5% for SVM and 87.5% for LDA
[26]	PCA, EDA	Emotion detection	SVM, KNN, Decision Trees, Naive Bayes, Logistic regression, and LDA	Between 55 and 75%
[27]	Spectral power	Seizure detection	RF-KNN	80.87
[28]	Mean, Power, kurtosis, skewness,	Seizure detection	RF, ANN, SVM, KNN	100

	absolute mean std dev.			
[29]	HPF	EEG signal analyzing	KNN, SVM, NN	66.7
[30]	PCA, Time and frequency domain	Emotion detection	Decision tree, gradient boosting, and RF	99%
[31]	HRV features	Emotion recognition	Decision Tree	Very low performance

3.2 EEG deep Learning methods

Deep learning (DL) is a new subfield in machine learning that comprises training neural networks along with multiple layers. DL showed great success in multiple applications such as speech and image recognition[32]. As long as different attributes of input data, there are diverse types of architectures to deep learning, such as the recurrent neural network(RNN), convolutional neural network(CNN), and deep neural network(DNN).

3.2.1 Convolutional neural network (CNN)

Convolutional neural networks (CNNs) are the most popular deep learning algorithms. Yann LeCun is a pioneer in the research of CNN which presented the first application classifier on the handwritten digits[33]. CNNs were created initially to imitate the human visual systemic and for easier brain classification and perception of the image, the complex and simple cortical cells of the visual cortex break down the visual information as simpler representations[34]. A CNN involves an input and output layer including multiple hidden layers as shown in Fig.5.

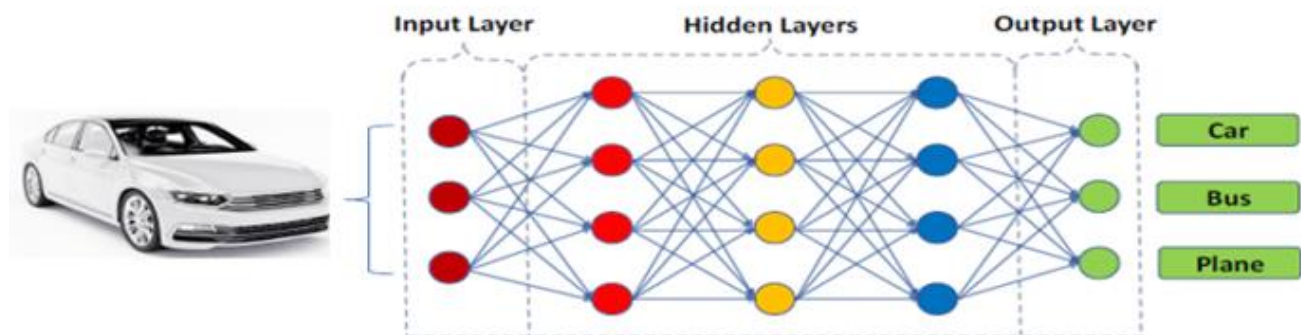


Fig. 5 - A simplified example of a CNN network [35].

The hidden layers consist of convolutional layers which, are followed by pooling and fully connected layers as shown in Fig. 6. The convolutional layers use mathematical operation layers use mathematical operation (convolution) to the input as well as the resulting transfer to the next layer[36]. Convolutional layers involving filters that consist of number of kernels for extracting the image features. In this layers, some of parameters are applied such as activation function, size of kernels, stride, regularization type, and padding [37]. Pooling layers are used for reducing the dimensionality of feature map that resulted from convolutional layer. The last layer (fully connected layer), is considered the general final classification used for aggregate information from the final features [37].

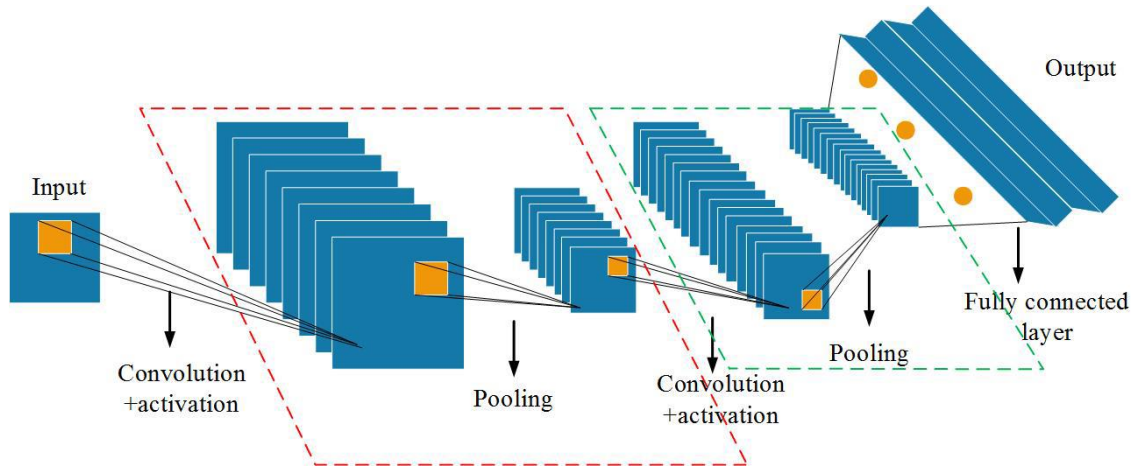


Figure 6. Convolutional neural network architecture[32].

3.2.2 Recurrent Neural Network (RNN)

Artificial neural networks (ANNs) involving recurrent (closed loop) connections are known as recurrent neural networks (RNNs) which have been a significant focus of research attention and development through the 1990's. Due to some networks such as the CNN and deep neural network (DNN) cannot deal with the temporal information in input data. Therefore, in research aspects that contain sequential data, like text, video, and audio, RNNs are dominant[39]. RNNs as shown in Fig.7 are composed of high dimensionally hidden states along with non-linear dynamics, where the structure of hidden states is employed as the network memory to remember, store, and process prior complex signals over a long period of time. RNNs are designed to learn time-varying or sequential patterns, so they enable modeling of sequential data due to sequence prediction and recognition. Several researchers such as Hinton, Williams, and Rumelhart were introduced to a simplistic recurrent neural network in the late 1980's for learning strings of characters. Later, many applications have addressed problems composing dynamic systems along with the time sequence of events.[40][41].

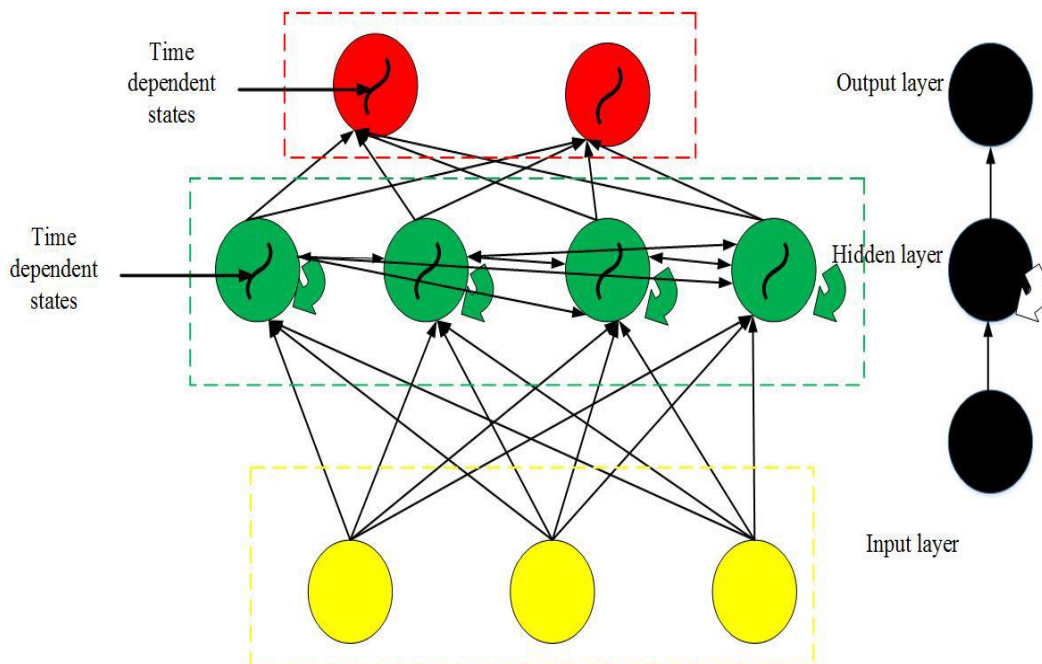


Figure 7. A typical structure of recurrent neural network (RNN)[32]

3.2.3 Stacked Autoencoder (SAE) network

Autoencoder (AE) is one of the few architectures of the artificial neural networks that involving asymmetrical structure. It is consider one of the unsupervised learning algorithms that can be divided into three basic parts (code, encoder, and decoder blocks) as illustrated in Fig. 8 - [42]. SAE is a consider one of the successful deep learning applications for prediction. In this deep neural network structure, the layers are staked for encode and decode the data [43].

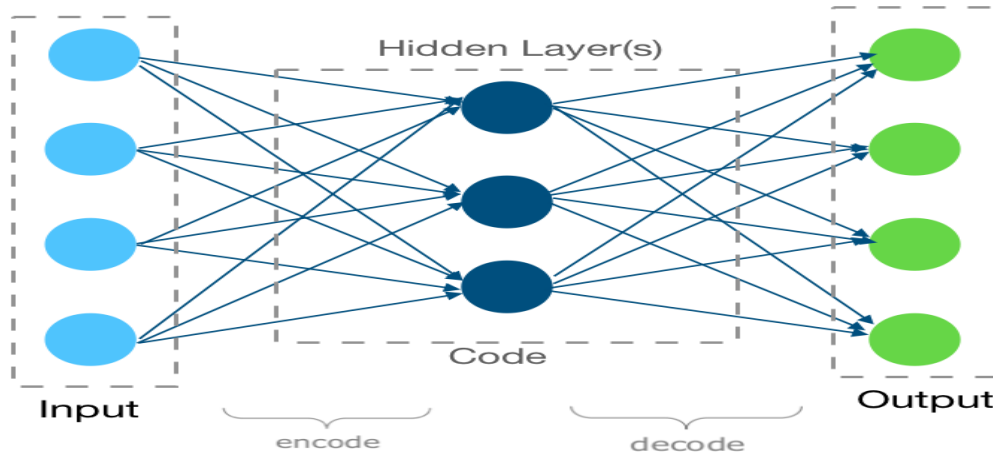


Fig. 8 - General autoencoder process.

3.2.4 Long short-term memory (LSTM)

The original LSTM paper presented by Hochreiter and Schmidhuber in 1997 [44], the researchers enhanced the remembering capacity of the typical recurrent cells through inserting (gate) into cell[39]. Following this pioneering work, various theoretical and experimental research have been published on the issue of such type of an RNN, many of them remarking on the astounding results obtained over a wide variety of application areas where data is sequential. The impact of the LSTM networks has been notable in speech to text transcription, language modeling, machine translation, and many other applications[45]. LSTM networks are tend to be suitable for modeling variable time series and time-variant platforms[46]. LSTM is an RNN style architecture that includes gates to control information flow between cells, its architecture addresses the vanishing gradient problem through including mechanisms for regulating information which allowing it to be retained for extended periods of time[47]. See a basic architecture of LSTM in Fig.9.

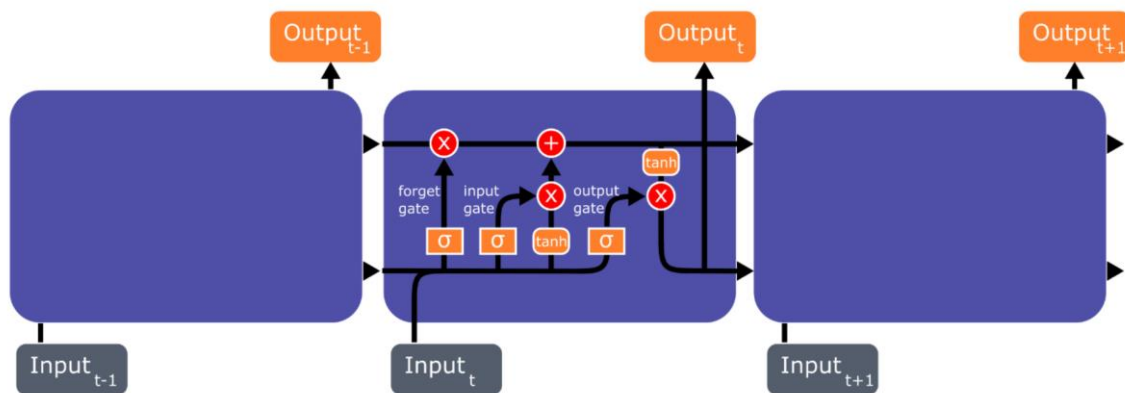


Figure 9. Basic architecture of LSTM[34].

3.2.5 Deep Belief Networks (DBNs)

Deep Belief Network (DBN) is a well-known deep learning algorithm, which was firstly proposed in 2006 by Hinton et al.[48][49]. The DBN has shown significant performance in several area such as applications of remote sensing image, face detection and face recognition[32]. It represents advanced learning technique, deeper architecture, and high-level biological modelling abstraction, resulting in simplifier mathematical models. Its network design that influenced by artificial intelligence (AI) research investigations that attempt to reproduce human- level intelligence. DBN, an alternative Deep Neural class, is a graphical model with numerous layers of 'hidden units' with connections between layers rather than inside each layer [50].

3.2.6 Multi-layer perceptron (MLP)

Multi-layer perceptron (MLP) is a famous deep learning classifier. it's a feed-forward layered network composed of artificial neurons that the data circulates in only one direction, from the input layer to its output layer[51]. MLP network has beneficial properties such as, easy implementation, smaller training set requirements, and fast operation. As shown in Fig. 10, MLP containing three primary layers: input layer, hidden layer, and output layer as shown in Fig.10[52].

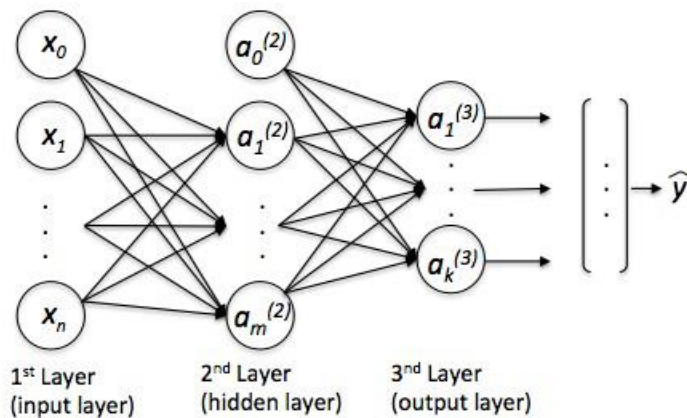


Figure 10. Multilayer perceptron(MLP) architecture[51].

Table 3. Illustrated set of research using different deep learning classifiers, feature extraction has been used, decoding problem and it classifier's achievement.

TABLE 3 - Different deep learning algorithms for EEG classification.

Study	Feature extraction	Decoding problem	Architecture	Accuracy
[35]	EEG motor imagery signals	BCI	CNN+SAE	90.0%
[54]	EEG data	BCI	CDBN	88%
[55]	EEG data	Epileptic Seizure Detection	CNN	90.5

[56]	Wavelet preprocessing for intra- and extracranial EEG Raw EEG data	Epileptic Seizure Detection	RNN	-
[57]	Time and frequency features	Sleep stage	CNN+Bi-LSTM	94.17%
[36]	EEG + frequency domain signals	Epileptic Seizure Detection	CNN	96.7%
[58]	EEG data	Epileptic Seizure prediction	CNN + BiLSTM	99.6%
[59]	EEG data	Epileptic Seizure Detection	CNN-RF	Sen=82%
[60]	EEG data	Emotion recognition	CNN	80.63%
[61]	EEG data	Emotion recognition	AlexNet, VGG16, ResNet50, and configurable CNN	AlexNet=90.98% ResNet50=91.91% VGG16=92.71% CNN=93.01%
[62]	EFDMs with STFT based on EEG signals	Emotion recognition	CNN	90.59%
[63]	EEG data	Sleep stage detection	CNN+LSTM	55%
[34]	EEG signals	CAP detection and sleep stage classification	1D-CNN	90.46% for sleep stage classification and 92.06% for CAP detection
[64]	EEG+ EOG signals	Sleep stage classification	1D-CNN	91%
[65]	EEG data	driver's fatigue detection	SAE	90%
[52]	EEG signals	Sleep stage classification	MLP	83%
[66]	EEG data + fast ICA	Epileptic detection	MLP	Spec=90%
[67]	EEG data	Stroke detection	VGG-16 + RESNET-50	90%
[68]	EEG signal	Stroke classification	RNN + Genetic algorithm	90%

4. Discussion

Deep learning gets the forefront of worldwide scholars and has an extensive variety of interests. It is a novel investigation in the AI field, which has achieved dramatic success in numerous applications comparing to classical ML algorithms. Convolutional neural networks are a powerful tool for a large range of applications especially the health sector. In EEG signals, having a good advance with deep learning to achieve the anticipated results. In this research, we illustrated the EEG signal and basic distinct frequency waves of the human's brain. In addition, we described some common machine and deep learning architectures that adopted by the researchers for EEG classification. Even more, the kind of EEG data used as input data for deep learning. The benefits of deep learning for raw EEG data processing were observing, and in focused recent research publications on deep learning in various architectures such as CNN, LSTM, MLP, RNN, and DBN for EEG signal processing. Preprocessing, feature extraction, and classification, which are the main steps for EEG signal detection, were reviewing in this paper. Table 2 summarizes some of research that used ML algorithms for EEG signal classification. Table 3 illustrates number of modern works for EEG signal detection and classification using deep learning architectures. As comparing, the two mentioned tables we find that most of the works, which depended on ML approaches, are accompanied more than one algorithms for gain higher accuracy whereas one deep learning model in almost articles was sufficient for achieve superior results. The using of multiple architectures make the model much complicated and may spend more time for accomplishing the goal of study.

5. Conclusion

In this article, various deep learning algorithms for classify EEG data are described. We analyzed EEG signal due to it is significant for detecting serious disorders in human brain such as epileptic seizures and stroke. In addition to serious conditions, EEG can detect some of the human activations such as sleep stages and emotion. Also we have learned about the usage of several deep learning based algorithms for EEG classification. We also notified to some machine learning approaches that applying in different works for classifying EEG signal. We concluded that almost of the works that depend on machine learning approaches are using many algorithms in the same search, despite this, it does not reach superior achievements compared to deep learning algorithms. Deep learning approaches proven it is prevalence in detection and classification of EEG signal with high achievement in many algorithms especially CNN. Overall, future research may focus on improving the robustness, interpretability, and versatility of ML algorithms to enable their use in a wider range of domains and applications with higher achievements and lower complicated.

Appendix A: Abbreviations

Artificial intelligence	AI
Brain computer interface	BCI
Cyclic alternating pattern	CAP
Convolutional neural network	ML
Deep believe network	DBN
Deep convolutional neural network	DCNN
Deep learning	DL

discrete wavelet transform	DWT
Electrode-frequency distribution maps	EFDMs
Electroencephalogram	EEG
Electrooculogram	EOC
Empirical Mode Decomposition	EMD
Heart Rate Variability	HRV
High Pass Filter	HPF
Independent Component Analysis	ICA
<i>k</i> -nearest neighbor	k-NN
linear discriminant analysis	LDA
Long short term memory	LSTM
Machine learning	ML
Multi-scale principal component analysis	MSPCA
Negative predictive value	NPV
Neural network	NN
Precision	Pre
Positive predictive value	PPV
Random forest	RF
Recurrent neural network	RNN
Schizophrenia	SCZ
Sensitivity	Sen
Short-time Fourier transform	STFT
Specificity	Spec
Stacked Autoencoder	SAE
Standard deviation	Std
Support vector machine	SVM

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