Electroencephalogram classification of brain states using deep learning approach

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ABSTRACT

The oldest diagnostic method in the field of neurology is electroencephalography (EEG). To grasp the information contained in EEG signals, numerous deep machine learning architectures have been developed recently. In brain computer interface (BCI) systems, classification is crucial. Many recent studies have effectively employed deep learning algorithms to learn features and classify various sorts of data. A systematic review of EEG classification using deep learning was conducted in this research, resulting in 90 studies being discovered from the Web of Science and PubMed databases. Researchers looked at a variety of factors in these studies, including the task type, EEG pre-processing techniques, input type, and the depth of learning. This study summarises the current methodologies and performance results in EEG categorization using deep learning. A series of practical recommendations is provided in the hopes of encouraging or directing future research using EEG datasets to use deep learning.

Introduction

The human cerebral cortex, which is made up of the brain, has a great and flourishing spatiotemporal dynamics that is unique to humans. Chemical and electrical signals are used by millions of neurons in the brain to communicate with one another (action potentials). Seizures are abnormal electrical disturbances in the brain. Epilepsy occurs when the brain experiences repetitive seizures. Electroencephalogram (EEG) analysis gives essential information about brain activities and can be used to detect brain disorders, particularly epilepsy. Waveforms of varying frequencies, amplitudes, and spatial dispersion are included in EEG. Delta waves occur below 3.5 Hz (0.1–3.5 Hz), theta waves occur between 4 and 7.5 Hz, alpha waves occur between 8 and 13 Hz, beta waves occur between 14 and 40 Hz, and gamma waves occur above 40 Hz. When a brain disorder arises, the EEG may display atypical electrical discharge. The placement of electrodes in the frontal pole (Fp), frontal (F), parietal (P), temporal (T), and occipital (O) areas of the brain allows for meaningful communication. To distinguish the hemispheres of the brain, even and odd integers as subscripts were used.

Electroencephalography (EEG) is widely used in neural engineering, neurology, and biomedical engineering research (e.g., brain computer interfaces, BCI); sleep analysis; and seizure detection) due to its high temporal resolution, non-invasiveness, and low financial cost. With the automatic classification of these signals, EEG will become more widely applicable and less reliant on specialised expertise. Removing artefacts, identifying features, and classifying them are all part of a typical EEG classification pipeline. An EEG dataset, at its most basic level, is a two-dimensional (time and channel) a matrix of actual values representing scalp recordings of brain-generated potentials under specific task circumstances. EEG data is excellent for machine learning because of its highly organised format. The EEG data has been subjected to a variety of classic machine learning and pattern recognition methods. In neural classification.

EEG signal categorization techniques based on deep learning have grown in popularity in recent years. Researchers often utilise DL designs to capture both spatial and temporal information in EEG data since they are recordings of biopotentials across the scalp across time. Typically, a CNN cascade is employed, followed by an RNN, commonly an LSTM. The nature of neural networks dictates that the preceding layers serve as feature extractors for the subsequent layers in these cascade structures.

Methods

- **Search Methods for Identification of Studies**

The systematic review and meta-analysis approach PRISMA (Preferred Reporting Items for Systematic Reviews as well as Meta-Analyses) found studies and reduced the amount of data collected to evaluate deep learning applications for EEG data classification using this technique. On December 22nd, 2018, a search was conducted in both the Web of Science and the PubMed databases using the following keywords: (“Deep Neural Network*” OR “Deep Learning” OR “Deep Belief Network*” OR “Deep Machine Learning” OR “Deep Convolutional” OR “Representation Learning” OR “Boltzmann Machine*” OR “Deep Recurrent” OR “Deep LSTM”) AND (“EEG” OR “ Duplicates across the two databases were eliminated, as were studies that did not meet the inclusion criteria (described below). The remaining papers' full texts were then examined.

Unqualified studies were excluded using the following criteria:

- Electroencephalography alone — Research involving multi-model datasets, such as EEG analysis in combination with other physiological signals (electrooculography, electromyography) or on films, for instance. were omitted to limit variability in the studies.
- Task classification – This study focused entirely on the use of EEG data to classify tasks done by humans. Other research were omitted, including power analysis, non-human studies, and feature selection with no end classification.
- Deep learning - Deep learning is defined as neural networks with at least two hidden layers in this review.
- Time – Due of the rapid pace of research in this field, this evaluation only included articles published within the last five years.

- **Extraction and Presentation of Data**

The following categories of data were gathered:

a. Task information
   - Task type
   - Number of subjects
   - Total length of analyzed data

b. Artifact removal strategy
   - Manual
   - Automatic
   - No cleaning or removal

c. Frequency range used for analysis

d. Formulation of Input
   - Signal features of EEG
   - Channel selection methods

e. Deep learning strategy, main characteristic, number of classifier layers, and output classes
   - Deep Belief Network (DBN) and number of Restricted Boltzmann Machines (RBM’s)
   - Recurrent Neural Network (RNN), number of RNN layers, type of RNN unit
   - Convolutional Neural Network (CNN), number of convolutional layers, activation
   - Hybrid architectures, types of algorithms, corresponding main characteristics, activation

- Stacked Auto-Encoders (SAE), number of hidden layers, activation
- Multi-Layer Perceptron Neural Network (MLPNN), number of hidden layers, activation

f. Highest achieved accuracy or other performance metric

Result and Discussion

This section initially goes through the pre-processing techniques used in this study. The general categories of activities, input formulations, and architectural trends are next investigated. The findings section concludes with a case study based on a publicly available dataset, allowing for comparisons of various deep learning design choices.

- **Has deep learning been used to investigate EEG classification tasks?**

The tasks presented in these studies were divided into six categories: emotion recognition (17%), motor imagery (20%), mental workload (15%), seizure detection (15%), sleep stage scoring (10%), event related potential detection (9%), and other studies (14%), which included Alzheimer's classification, bullying indices detection, depression, and gait panning. The general protocols for these jobs are described in the following sections.

Tasks for Recognizing Emotions

Emotion recognition tasks often require individuals to watch videos that have already been pre-assigned by specialists with specific feelings. As a result of these viewings, an EEG was recorded along with an assessment of one's own emotions. It was decided to adopt a generally accepted way to describe emotions by using the original emotion class and self-assessment. Understanding a patient's emotional state will help the underlying algorithm determine whether a particular movement was the movement requested by the patient, which is the major motivation behind emotion recognition research. Emotion recognition research, in general, aid computers in better understanding the user's present emotional state.

Tasks Requiring Motor Imagery

The individual is asked to envision various motor imagery involves having the subject make muscle movements on their arms, legs, and/or tongue. Most of their applications are based on BMI, which means that BMI applications will eventually have to classify a user's intended movements accurately.

Tasks Requiring Mental Workload

EEG data was collected while the patient was performing a variety of mental activities of varied complexity. Approaches like as driving simulation studies, genuine pilot studies, and responsibility tasks have been used to determine the mental workload levels of drivers and pilots, among other things Driver and pilot studies used statistics such as reaction time and path deviation to classify mental effort. Responsibility studies used a workload classification system based on an individual's increasing number of acts. To track cognitive stress or BMI performance, this test can be utilised in one of two ways.

Tasks for Detecting Seizures

For seizure detection investigations, the EEG signals of epileptic patients are captured both during and after seizures. There was also a control class of non-epileptic patients' EEG signals captured for some datasets. These research projects were created with the goal of identifying impending seizures and alerting the epileptic patient ahead of time.

Tasks for Assessing Sleep Stages

The EEG signals of individuals are recorded overnight in The task type with the fewest studies was sleep stage scoring. For the purposes of classification, the signals were sorted into four groups: sleep phases 1, 2, 3, 4, and rapid eye movement (REM). With this research, the ultimate goal is to lessen the reliance on medical professionals for the analysis and comprehension of patient sleep stages.

Tasks Related to the Event

EEG is frequently recorded from participants in experiments examining the detection and classification of event-related potentials while presenting a visual display. A person views a quick sequence of pictures or letters in order to focus attention on specific markers in these tasks. When a certain letter or image appears, the EEG data shows a stereotyped reaction, usually in the form of a P300 response. Due to the reasonably clean signal (minimization of artefacts) and high signal-to-noise ratio, which are qualities not generally seen in EEG data, these tasks are beneficial in study. EEG research into event-related potential tasks will aid in the development of better nonverbal communication systems.

Methods of Pre-Processing

Because EEG devices pick up external electrical physiological signals such eye blinks and neck muscles' electromyograms, EEG data is inherently noisy. When the subject moves, there are also worries regarding motion artefacts caused by cable movement and electrode displacement. The detection and elimination of EEG artefacts has been widely researched in the past literature, and this review will not go over that ground again. The artefact removal procedure was approached in one of three ways (shown in Figure below), with the exception of the 40.9% of research that did not address any specific artefact removal process. 1) human removal (28.8%) 2) automatic removal (8.2%), and 3) no cleaning or removal (22.1 percent).

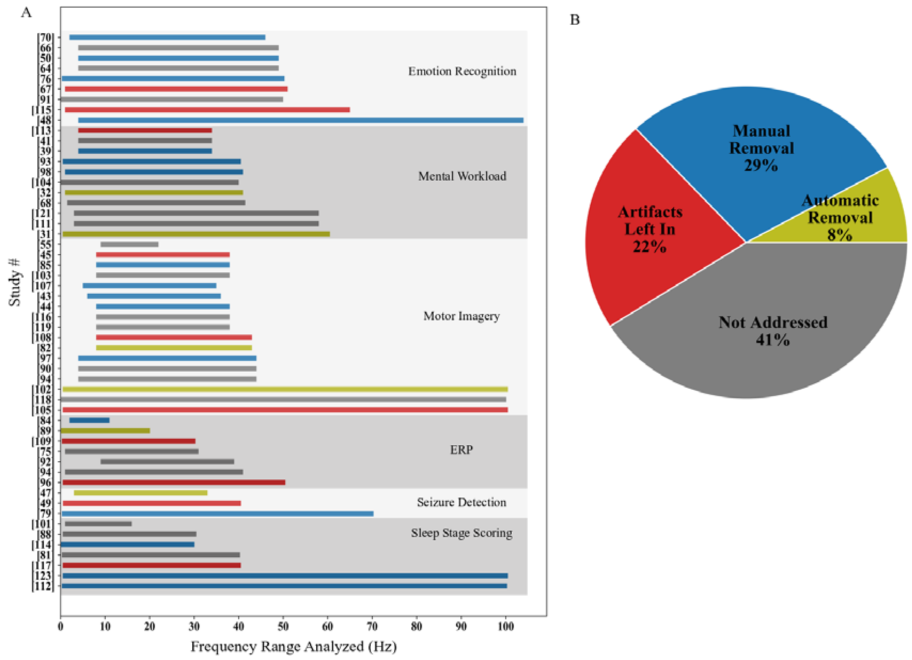

Figure 1: Filtering and artefact removal techniques. A) In the EEG analysis, the frequency range is grouped by task type. B) The percentage of different artifact removal strategies across all studies.

Different artefact removal strategies are shown by the different colours of the bars. Artefacts were purposefully left in studies with red bars to serve as contaminants, whereas studies with dark grey bars took no steps to remove them from their results. The studies are divided into categories based on the type of application they are used for.

Surprisingly, more than a quarter of the research (26 out of 90) used manual methods to eliminate artefacts. A sudden outlier is easy to identify visually when signals are lost or strong EMG artefacts are present. Finding persistent noisy channels in multi-channel recordings, on the other hand, may be difficult. Other researchers will have a hard time replicating the procedures because manual data processing is highly subjective as well. The studies that did not eradicate EEG artefacts in a systematic manner included 22% of the studies that did not take any steps to do so. The remaining 80% of the research analysed used ICA and Discrete Wavelet Transformation as their primary artifact-removal strategies (DWT). Frequency domain filters were commonly utilised in EEG studies to keep the signal's bandwidth in check. The rest of the spectrum can be safely ignored if only a small portion of it is of interest. Around half of the trials used a low pass filter to keep the signal in the low gamma band or lower. It is clear from Figure 1 that most studies used an artefact removal method in addition to limiting the frequency ranges they were studying.

- **Trends in Deep Learning Architecture**

<u>Design Options for Architecture</u>

This section of the review focuses on identifying patterns deep learning architectures like the major characteristic and end classifier have been developed. This data has been compiled and is shown in the diagram below.

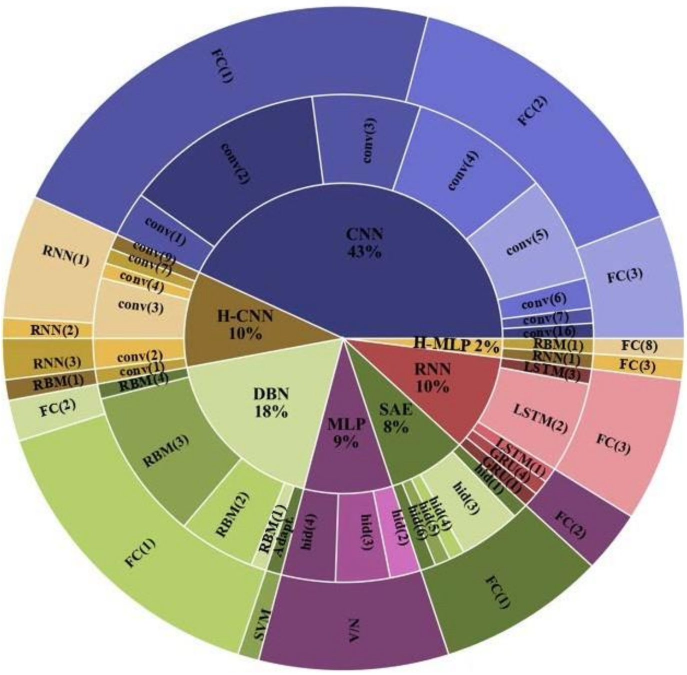

Figure 2: Architectures of Deep learning in all researches.

Above Figure, the centre circle symbolises a general deep learning technique while the middle and outer circles reflect a specific deep learning approach's major design element. The key to success is flexibility. CNN stands for Convolutional Neural Network, and DBN stands for Deep Belief Network. NFC: number of fully connected layers; Nhid: number of hidden levels H-CNN stands for Hybrid Convolutional Neural Network, whereas H-MLP stands for Hybrid Multi-Layer Perceptron. Restricted Boltzmann Machines (#): the number of such machines, The following acronyms stand for Recurrent Neural

Network: RNN, RNN(#), and Stacked AutoEncoders

CNN's (43%) architecture design approach involves alternating pooling of convolutionary layers (typically maximum pooling layers). a classifier's number of convolutional layers and sort of classification end were the two most important design features for CNNs. The second most popular pick was DBN, which received 18 percent of the vote. DBNs are made up of a series of limited Boltzmann machines built on top of each other, followed by an end classifier, which is usually a series of fully-connected layers. The second group, hybrid architectures, accounted for 12% of all research and were separated into two categories, as shown in Figure 2, Hybrid CNNs and Hybrid MLPs. Hybrid CNNs have addition to convolutional and pooling layers, such as multiple recurrent layers or constrained Boltzmann machines. Hybrid MLPs combine a deep learning method with multiple thick layers. Next in terms of percentage of total study count were RNNs (10 percent), which are composed of a number of repeating layers (each layer including a study-specific number of repeating units), followed by a number of fully linked layers. In the second place, MLPNN's single reviewed characteristic was the number of hidden layers, which is an important design aspect. Finally, an SAE (eight percent) was used, in which the total number of fully linked layers was followed by a single entirely connected layer under all conditions.

Functions of Activation

All research collected activation functions for appropriate deep learning architectures. Rectified Linear Unit (ReLU) was employed as the layer's activation function in 70% of research using convolutional layers for deep learning systems. No other activation function accounted for more than 9% of all studies that used activation functions. Exponential Linear Unit (ELU) (7%), leaky Rectified Linear Unit (leaky ReLU) (9%), and hyperbolic tangent (tanh) are some of the less common activation functions (6 percent). There were also single experiments using the parametric ReLU (PReLU), scaled Exponential Linear Unit (SELU), and split tanh types of activation functions. The discussion section goes into greater detail about the activation functions of convolutions. Fully-connected layers with activation functions other than classifiers are referred to as non-classifier fully-connected layers. Most completely connected classifier layers employed the softmax activation function, while non-classifier fully connected layers used the sigmoid activation function. No consensus was obtained by any of the three SAE studies that looked at activation functions. For non-classifier AE layers, sigmoid activation functions were utilised, while ReLU was used. More research is needed to better understand SAE designs' most effective activation function.

Deep Learning Trends based on a Task

There was no agreement on the deep learning algorithms to use in the emotion recognition, motor imagery, or sleep stage scoring tasks. In comparison to other tasks, seizure detection studies were almost evenly split between CNNs and RNNs, with the highest percentage of research using RNNs. Only one study used an SAE or MLPNN, and none used DBNs for seizure detection. When comparing studies employing CNNs to studies using hybrid formulations, research using The most hybrid formulations were found in sleep stage scoring tasks, with an equal number of each. According to ERP research, CNN came out on top (the highest percentage of CNN studies compared to all other tasks). Figure 5 shows the many deep learning strategies that can be used depending on the situation.

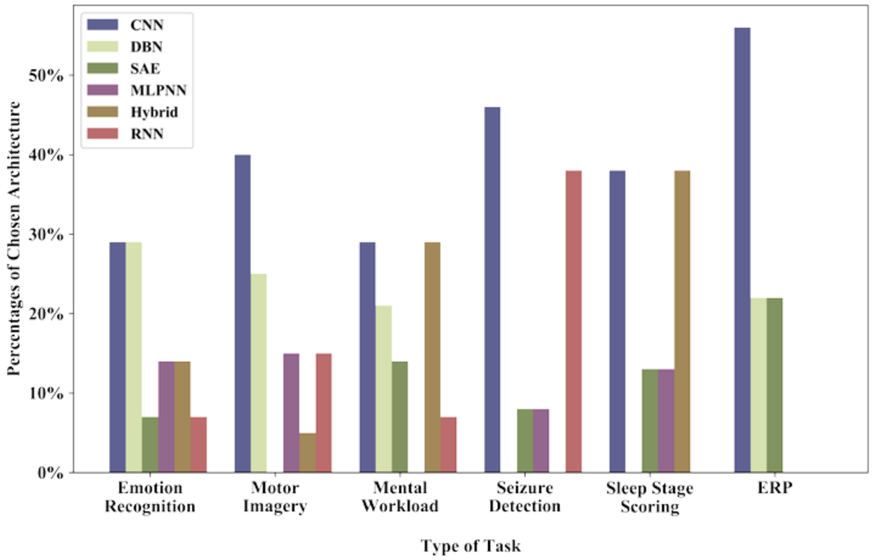

Figure 3: Deep learning architecture dimensions on the basis of different tasks.

While there was no clear consensus when all research was considered together, seizure detection studies revealed a definite preference for either CNNs or RNNs, whilst ERP studies revealed a bias for CNNs. In comparison to other architecture types, hybrid architectures were used more often in sleep stage scoring tasks and mental stress tasks for classification.

Conclusion

This paper tried to review studies which used deep learning approach for EEG classification. With deep learning classification many EEG tasks have been performed effectively such as motor imaging and seizure detection. Mental workload has also been successfully implemented using deep learning classification. The design of these deep network research differed substantially depending on the input formulation and network configuration. We were able to compare classification performance between datasets because of the large number of studies that looked at various public datasets. In general, CNNs, RNNs, and DBNs outperform other forms of deep networks, such as SAEs and MLPNNs. When signal values or (spectrogram) images were used as inputs, CNNs performed better than DBNs, but when signal values or computed features were utilised, DBNs performed better than CNNs as well. Later, we discussed deep network recommendations tailored to each task's unique requirements.

It is hoped that this map will help guide future research using EEG datasets for deep learning. Convolutional layers with recurrent layers, as well as restricted Boltzmann machines, showed promise in classification accuracy and transfer learning as compared to typical designs. The number and configuration of different layers including RBMs, recurrent layers, convolutional layers and fully linked layers should be investigated further. For now, research understanding how deep networks read raw versus denoised EEG is more important than network architecture.

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