Comparison of Deep Learning Models in EEG Pathology

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1 Abstract

An electroencephalogram (EEG) can track the brain waves that contain neural activity in the brain. The physiological and functional details and activities of the brain are better understood with the aid of EEG signals. Machine learning algorithms were helpful in the detection and classification of brain disorders during the age of artificial intelligence (AI). Recent advances in the use of Deep Learning (DL) techniques in a variety of EEG signal applications not only aid in the early detection of brain disorders but also make it easier to identify various psycho-neuro disorders and human emotions. In this paper, a thorough survey on the use of deep learning architecture in EEG signals has been conducted in order to provide a useful and comprehensive perspective. When analysing EEG signals, various deep learning techniques using various architectures provide insight into how to create the next generation of AI-based systems. This paper considers and evluates the performance of variations of Convolutional Neural Networks (CNNs) on EEG datasets.

2 Introduction

Electroencephalography (EEG) is extensively used in research involving neural engineering, neuroscience, and biomedical engineering because of its high temporal resolution, non-invasiveness, and relatively low cost . An important first step in making the use of EEG more widely applicable and less dependent on qualified experts is the automatic classification of these signals. Artifact elimination, feature extraction, and classification are all parts of the typical EEG classification pipeline. An EEG dataset is composed of a 2D (time and channel) matrix of real values that represent brain potentials that were recorded on the scalp in connection with particular task conditions. EEG data is suitable for machine learning due to its highly structured format. On EEG data, numerous conventional ML and pattern recognition algorithms have been applied. Due to practical issues like lengthy computation times and issues with vanishing/exploding gradients, neural networks did not initially receive high attention in neural classification applications. Fortunately, the recent advancement of graphic processing units (GPUs) and the accessibility of large datasets provided neural network researchers with an affordable and effective solution to their hardware bottleneck, allowing them to research deep learning architectures (neural network architectures containing at least two hidden layers). In the past ten years, interest in and applications of deep learning have grown exponentially as a result of these innovations. In fact, performance in a variety of traditionally difficult domains, including images, videos, speech, and text, was significantly improved. Neural networks are typically thought to require less prior expert knowledge about the dataset to perform well because they automatically and iteratively optimise their parameters. The field of medical imaging, which frequently involves sizable datasets that are otherwise challenging to interpret, even by experts, saw early adaptations as a result of this advantage. Deep learning frameworks have recently been used to decode and classify EEG signals, which are typically associated with low signal-to-noise ratios (SNRs) and high dimensionality of the data. This is due to the increasing availability of large EEG datasets. We review the current deep learning models that are frequently used in this field in this paper, and then we implement several well-known deep learning models to compare their performance.

3 Literature Survey

S. et al. proposed a novel recurrent neural network (RNN) architecture termed ChronoNet. ChronoNet is formed by stacking multiple 1D convolution layers followed by deep gated recurrent unit (GRU) layers where each 1D convolution layer uses multiple filters of exponentially varying lengths and the stacked GRU layers are densely connected in a feed-forward manner.
ChronoNet outperforms previously reported results on given dataset thereby setting a new benchmark.

Alhussein et al. The fusion of CNN features of three distinct temporal segments of the EEG signal was realized using the MLP. Proposed system with the fusion achieved the highest accuracy, outperformed other related systems.
However, different fusion strategies in the proposed system are not investigated.

van Leeuwen et al. validates a convolutional neural network identifying abnormal EEGs in a large diverse set, including age and sleep stage in the model results in minimal performance gain.
Extensive prediction error analysis reveals promising future research directions.
EEG reports including words related to slowing or spike wave discharges, but labeled as normal, were more often predicted to be abnormal and were thus misclassified, presumably because such EEGs contained "suspicious" but not sufficiently distinct or obvious to be considered definitively abnormal. Scope to further improve discrimination by considering label noise

Cisotto et al. evaluate the impact on EEG classification of different kinds of attention mechanisms in Deep Learning Models. The three models that were considered were InstaGAT, LSTM with attention and a CNN with attention.
The best performing model was the baseline LSTM, not the LSTM with attention. All models considered crossed the 75-percent mark in terms of

accuracy except for the baseline CNN. Both LSTM models were the best performing with the baseline being better than the one with attention, however in the case of InstaGAT and CNN, the models with attention performed better.

Craik et al. performed a systematic literature survey to answer certain questions including the EEG classification tasks explored by Deep Learning, input formulations used for training, and specific deep learning network structures used.
Tasks that used deep learning fall into five categories: Emotion Recognition, Motor Imagery, Mental Workload, Seizure Detection, and Sleep Scoring.
For EEG classification, CNNs, RNNs and Deep Belief Networks outperform stacked auto-encoders and multi-layer perceptron networks.

4 Motivation

An electroencephalogram (EEG) is a test that measures the electrical activity in the brain. An EEG is one of the main diagnostic test for epilepsy and other brain disorders such as brain tumors, damage from head injury, dysfunction, stroke, sleep disorders, Alzheimer's, etc.The role of the EEG is to help the doctor establish an accurate diagnosis. Study of an EEG is highly interpretive and hence cannot be used as a confirmatory diagnostic tool without appropriate consultation by a physician.EEGs generally take around 20 to 40 minutes to complete and hence generate a significant amount of data per EEG unlike a single scan like that of X-Rays. This takes a long time to analyse and form a diagnosis based on that data solely.This creates an opportunity to build an assistive system for doctors which analyses the EEG data and provides a diagnosis. This diagnosis can be used to assist the physicians in finalising the diagnosis based on consultation and other tests that the physician may have ordered.It is meant to be an aid to help confirm a diagnosis or warrant further investigation into the condition of the patient.

5 Problem Statement

Medical tests such as EEG generate a large amount of data and consequently are difficult to analyse and provide a diagnosis. As EEG is an inconclusive test on its own, an assistive system would prove very helpful for doctors in diagnosing brain disorders with greater accuracy.

6 Objective

To evaluate the performance of different kinds of Deep Learning (DL), neural network models on classification of Electroencephalography (EEG) patterns into normal and abnormal (i.e., artifactual or pathological).

7 Proposed Architecture

The model proposed is a deep learning model, and consequently entails a neural network. Deep neural networks have produced high accuracy on classification tasks.Convolutional Neural networks, which involve the use of convolutional layers in conjunction with activation layers, have produced high accuracy on EEG datasets according to the literature, as have Recurrent Neural Networks, which produce state-of-the-art results on time-series data.

8 Flowchart

1. CNN

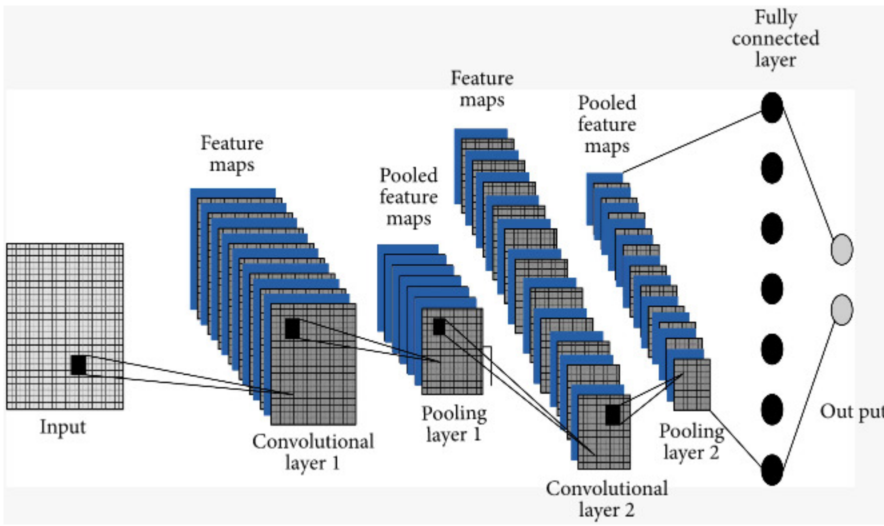

Figure 1: CNN Architecture Diagram

2. Max Pool CNN

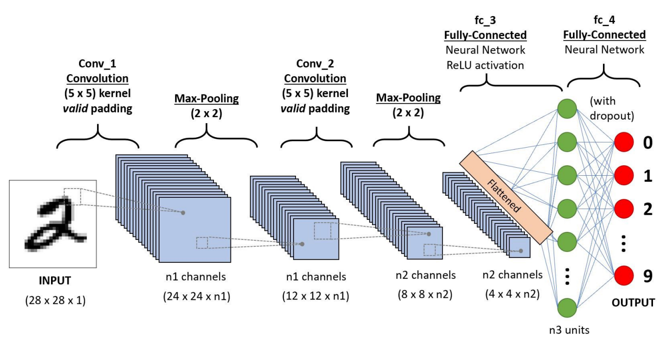

Figure 2: Max Pool CNN Architecture Diagram

3. LSTM

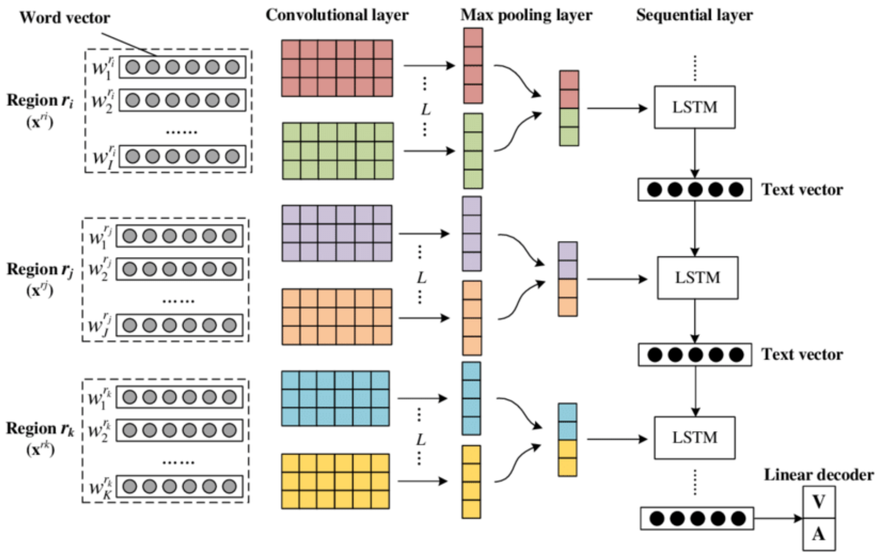

Figure 3: LSTM Architecture Diagram

9 Results

Among the major trends that emerged from our analysis, we found that (1) DL was mainly used for classifying EEG in domains such as brain–computer interfacing, sleep, epilepsy, cognitive and affective monitoring, (2) the quantity of data used varied a lot, with datasets ranging from 1 to over 16000 subjects (mean = 223; median = 13), producing 62 up to 9750000 examples (mean = 251532; median = 14000) and from two to 4800000min of EEG recording (mean = 62602; median = 360), (3) various architectures have been used successfully on EEG data, with CNNs, followed by RNNs and AEs, being most often used, (4) there is a clear growing interest towards using raw EEG as input as opposed to handcrafted features, (5) almost all studies reported a small improvement from using DL when compared to other baselines and benchmarks and (6) while several studies used publicly available data, only a handful shared their code—the great majority of studies reviewed thus cannot easily be reproduced.

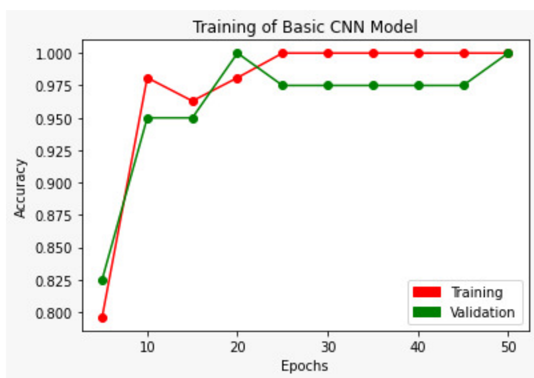

Figure 4: Baseline CNN Model

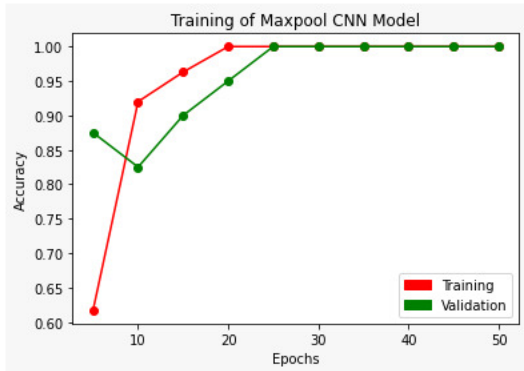

Figure 5: Maxpool CNN Model

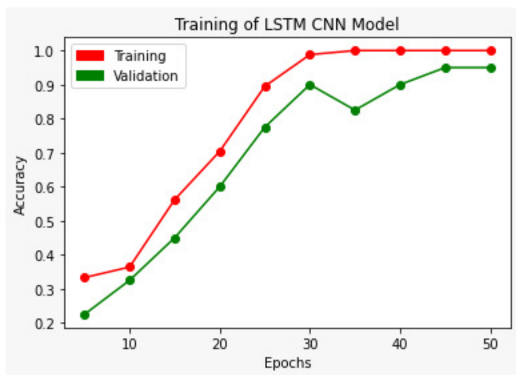

Figure 6: LSTM Model

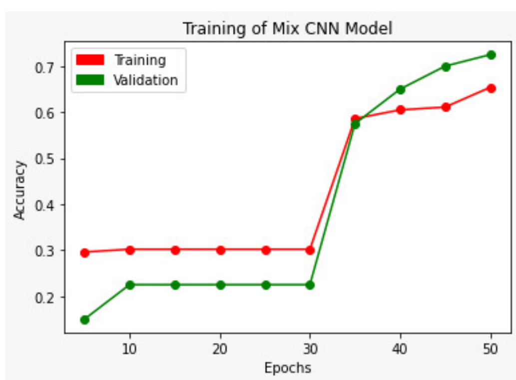

Figure 7: Mix CNN Model

10 Conclusion

There is no doubt about the value of EEG as a functional neuroimaging tool: clinical diagnosis of epilepsy and sleep disorders, monitoring of cognitive and affective states, and brain-computer interface all heavily rely on EEG analysis. DL has been suggested as a potential contender to take on these difficulties. As a result, over the past few years, the number of publications using DL to process EEG has grown exponentially, which is clearly indicative of the community's growing interest in these kinds of techniques. In this study, we compared how different DL models performed on an EEG dataset. Future research could examine the relationship between performance and data volume, performance and data augmentation, and the relationship between performance, data volume, and network depth.

11 Datasets

1. Primary Dataset
    - BCI Competition Dataset
    - https://www.bbci.de/competition/
2. Secondary Dataset
    - NMT Scalp EEG Dataset: An Open-Source Annotated Dataset of Healthy and Pathological EEG Recordings for Predictive Modeling
    - https://www.frontiersin.org/articles/10.3389/fnins.2021.755817/full
3. Tertiary Dataset
    - The Temple University Hospital EEG Data Corpus
    - https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4865520/

12 References

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