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Convolution Neural Network Architectures for Motor Imagery EEG Signal Classification

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ABSTRACT

This paper has made a survey on motor imagery EEG signals and different classifiers to analyze them. Resolution for medical images like CT, MRI can be improved using deep sense CNN and improved resolution technology. Drowsiness of a student can be analyzed using deep CNN and it helps in teaching, assessment of the student. The authors have proposed 1D-CNN with 2 layers and 3 layers architecture to classify EEG signal for eyes open and eyes closed conditions. Various activation functions and combinations are tried for 2-layer 1D-CNN. Similarly, various loss models are applied in compile model to check the CNN performance. Simulation is carried out using Python 2.7 and 1D-CNN with 3 layers show better performance as it increases number of training parameters by increasing number of layers in the architecture. Accuracy and kappa coefficient increase whereas hamming loss and logloss decreases by increasing number of layers in CNN architecture.

KEYWORDS

Artifacts, EEG, Epilepsy, Motor Imagery, Seizures, Sleep Scoring

1. INTRODUCTION

EEG signals may be affected by artifacts at the time of recording. Adaptive classifiers with weighted distance nearest neighbor classifiers with auto regressive models, power being the features considered can give better classification performance (M. Sabeti et. al, 2013). Generalized RNN is used to detect prestate seizures in EEG. Ten sub frequency bands are created from EEG, features are extracted using regression neural network and then applied to ten threshold mechanisms for classification (C. Sudalaimani et. al, 2018). Gradient descent, optimization techniques are used in logistic regression and βfunction for sigmoid helps in incrementing accuracy for the identification of malignant or benign tissue presence for cancer analysis (Laila Khairunnahara et. al, 2019).

Section 2 gives an overview on brain related issues, Section 2.1 describes motor imagery classification methods. Section 2.2 explains the availability of different classifiers for EEG, Section

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3 illustrates the proposed architectures for 1D-CNN, Section 4 show the results obtained using python 2.7 and narrates the possibility to increase the performance of CNN, Section 5 concludes the work carried out.

2. SURVEY OF BRAIN RELATED ISSUES

2.1 Motor Imagery Classification

5-layer CNN extract features and classify motor imagery EEG with left hand and right-hand movements (Zhichuan Tang, et. al, 2016). Conventional methods like SVM with power, SVM with common spatial pattern and SVM with autoregression are used in motor imagery classification. CNN performs better than the conventional classification methods. Combining deep learning with data augmentation for 2-way motor imagery classification (Zhiwen Zhang et. al, 2018). EMD decomposes EEG, mixes their IMFs to form new artificial frames of EEG, applied as inputs to complex morlet wavelets. CNN with wavelet NN helps in obtaining higher classification accuracy. STFT trains EG and give frequency domain representation. CNN and LSTM are deep NN used for EEG motor imagery classification with promising results (ZijianWang et.al, 2017).

Spatial distributions, β and μ rhythms help in imagery activities classification of EEG signals. Gradient descent, MLP are used for training the neural network which may lead to less accuracy, speed of convergence, PSO-GSA attains better accuracy, convergence speed in motor imagery classification (Sajjad Afrakhteh et. al, 2018), (Rahul Kala et. al, 2011). EEG muscular motor imagery is approximated based on RBF, further conventional MLP-NN and asynchronous NN are applied to increase accuracy, speed of control for the EEG classification (I. E. Shepelev et. al, 2018). Unclean EEG filtering, low SNR problems can be addressed using traditional BPNN, however an improved BPNN with weight splitting technique and PSO for appropriately training the low weights help in better motor imagery classification (Long Liu, 2019). Table 1 shows various techniques on motor imagery EEG

Table 1. Various motor imagery EEG aspects and techniques used

Authors	Year	Type of Disease	Approaches	Achievement
Sunny T. D. et. al	2016	Motor imagery classification	Bayesian spatio-spectral filters	Classification performance
Rami Alazrai et. al	2018	Decoding finger movements-EEG	Choi William, quadratic T-F	2-way classification
Akara Supratak et. al	2017	Sleep stage scoring	CNN, bidirectional LSTM	Accuracy, F1 score
Nicola Michielli et. al	2019	Sleep stage classification	Cascaded LSTM RNN	Neuro cognitive performance
Arnaud Sors et. al	2017	Sleep stage scoring	CNN	Cohort study, class wise patterns
Irene Sturm et. al	2016	Motor imagery classification	Layer-wise propagation	Neural activity complex perception

2.1.1. Inferences

- Motor imagery classification with left hand, right hand movement can be done using conventional methods, CNN.
- Gradient descent, MLP are conventional training NN methods, PSO-GSA can give better convergence speed in motor imagery classifications.

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