A New Method of EEG Classification for Motor Impairment Neural Disorders using Deep Learning

Binh Tran, Duc M. Duong, Hoai Su, Nhan Trinh

University of Information Technology VNU-HCM, Ho Chi Minh, Vietnam
ducdm@uit.edu.vn

Abstract. The research recent, convolutional neural networks (CNN) was usually used to automatically identify patterns on the medical signals. Among them, the EEG signal is receiving the most attention. The studies are looking for ways to represent the EEG signal to input the CNN model with the best results. Our study will present a method for analyzing EEG signals as time-frequency representations and will use it to execute end-to-end deep learning. Our proposed method will build a network without expert manipulation which automatically learns features from extracting the EEG signals as time-frequency representations. Our research propose methods of representing the EEG signals as time-frequency and it was used the input of the CNN to identify disorders. We have experimented with two time-frequency representations (Scalogram, Spectrogram) and two CNN (AlexNet, LeNet). After the experiment, we were very good results and evaluated them. The results show that the performance of the CNN was affected by the representation of the EEG signal and using AlexNet with the Scalogram images as input data is the most suitable with the accuracy 76.92%.

Keywords: Convolutional neural networks, AlexNet, Scalogram, Electroencephalography.

1 Introduction

In recent years, many researchers have involved in the processing and analyzing electroencephalogram (EEG) signals in order to use signal information for diagnose some kind of neurological disorder in a person.

The possible diagnoses identified in this way has been increasing over the years and covers a wide range of neurological diseases, from mild cognitive impairments [10], through neurodegenerative diseases such as Alzheimer Disease [17], to the most severe forms of neurological disorders such as amyotrophic lateral sclerosis or cerebral palsy, where the patients may be severely physically impaired or even completely paralyzed [15]. Thereby, it shows the high feasibility of diagnosing neurological diseases from the analysis of EEG signals. From that, the motivation of our work for analysis EEG.

In the EEG analysis, we found 7 methods J. Kaur [11]. However, recent studies have shown that the Wavelet Transform (WT) or the Short-Time Fourier

Transform (STFT) are good methods D. Verstraete [19]. In S. P. Ghael [8] paper, the signals transform from time to frequency domain which will help us understand more. For example A. Vilamala [20], transforming the signal into frequency over time helps to classify sleep stages. We decided to choose WT for signal analysis based on the result of Haya Alaskar [2]. In addition, we chose STFT that compared WT.

There are many popular convolutional neural networks such as AlexNet, VGGNet, GoogLeNet, ResNet, MobiLeNet. However, end-to-end learning is commonly chosen AlexNet because it achieves very good results. At Y. Dong [6], cells infected with malaria were classified by traditional machine learning tools and it achieved an accuracy of 91.66%. While AlexNet obtained a higher accuracy of 98.13%. Therefore, we chose AlexNet for EEG analysis to diagnose motor neuron impairment disorder. Besides, the LeNet is also chosen because it also gives high performance in classifying motor impairment neural disorders G. Vrbancic [21].

2 Methods

The proposed methods will explore two CNN architectures, evaluate them and will analyze the learning rate. In addition, we will evaluate Scalogram images and Spectrogram images.

The research experiment will be implemented using eight-channel the recorded the EEG signals of 13 participants, which were then analyzed to classify the spinal cord injuries and multiple sclerosis (ms) and unimpaired person. Figure 1 illustrates our experiment process in using time-frequency representation as input data for end-to-end learning.

The obtained result, a CNN architecture is suitable for diagnosing neurological disorders and good image type to use for EEG analysis.

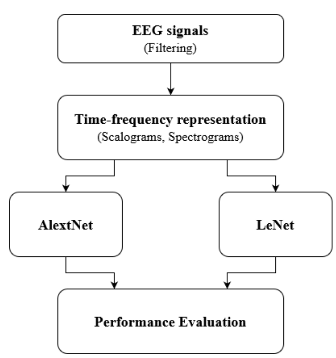


Fig. 1: The experiment process

2.1 EEG data set

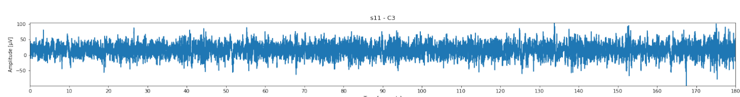
In this paper, we selected an EEG database from Colorado State University [5]. In data sets, we used g.Tec g.GAMMASys machine data. It includes 8 channels with 256 Hz sampling frequency and hardware range filters from 0.5 Hz - 100 Hz (-3dB) E. Forney [7].

Data g.GAMMASys were taken from 13 people with a sample length of almost 3 minutes. In which, one person had a disease of spinal cord injury, 3 people had multiple sclerosis disease and the other had no history of the disease.

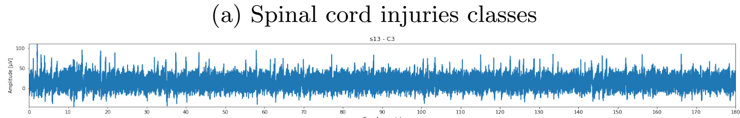
Data sets	
Subject	s16, s13, s15, s11, s28, s23, s24, s27, s20, s21, s26, s25, s22,
Electrode	8 channels (C3, F3, O1, P3, C4, F4, O2, P4)
Multiple sclerosis classes	s16, s13, s15
Spinal cord injuries classes	s11
Unimpaired person classes	s28, s23, s24, s27, s20, s21, s26, s25, s22
Length of EEG signals	3 seconds

Table 1: The data set description

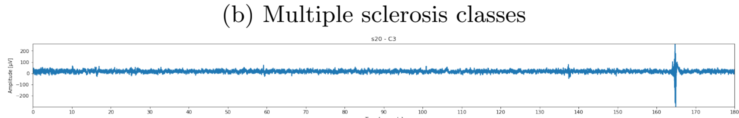
About Figure 2 was shown the data EEG signals sample about spinal cord injuries, multiple sclerosis and an unimpaired person.



(a) Spinal cord injuries classes



(b) Multiple sclerosis classes



(c) Unimpaired person classes

Fig. 2: Data EEG signals samples

2.2 Data preparation

About the experiment data, we will download the raw EEG signals of each subject from Colorado State University [5]. The result was shown in Figure 2. According to research V. Podgorelec [17], the EEG signal rhythms are characterize:

- delta waves (0 Hz – 4 Hz)
- theta waves (4 Hz – 8 Hz)
- alpha waves (8 Hz – 14 Hz)
- low beta waves (14 Hz – 20 Hz)
- high beta waves (20 Hz – 30 Hz)
- low gamma (30 Hz – 50 Hz)

Among the above characterization, our primary focus was on delta and theta waves frequency range. Because based on previous V. Podgorele [17], R. Schirrmeister [18] research, their frequency was characteristic enough to indicate some brain diseases. Therefore, we filtered frequency band from 0.5 Hz–7.5 Hz to remove low and high frequency noises and non-signal artefacts. Then, we ware used the Wavelet transform and the short-time Fourier transform to generating the Scalogram and Spectrogram images. About input data to the CNN, the signals were cuted into segments of about 3.84s with 20% overlapped which produce one Scalogram image and the same with Spectrogram image.

Overall, the EEG data was used to created 6,032 Scalogram or Spectrogram images, including 464 images generated from spinal cord injuries and 1,392 images generated from multiple sclerosis and 4,176 images generated from unimpaired person.

Time-frequency representation

The EEG signal is represented in time-frequency which helps us to obtain the signal's characteristic. Scalograms and Spectrograms are popular methods in time-frequency representations. About creating a Scalogram, we used the Wavelet Transform (WT), whereas a Spectrogram uses The Short-Time Fourier Transform (STFT). The two methods are one of the ways to analyze the EEG signal J. Kaur [11] and recent studies have shown that WT or STFT are good methods D. Verstraete [19].

In this study, we will evaluate the two types of time-frequency representation. The two methods would create 2-D images and passed into the AlexNet.

Wavelet Transform (WT)

Wavelet Transform was used to generate Scalogram images. In M. P. G. Bhosale [3] paper, non-stationary and transient signals were commonly processed by the WT. Basically, WT is extracted on wavelets to produce Scalogram images where the x-axis represents time and the y-axis represents frequency. Scalogram color is very important which represents the amplitude of the frequency..

The WT of EEG signal represented by:

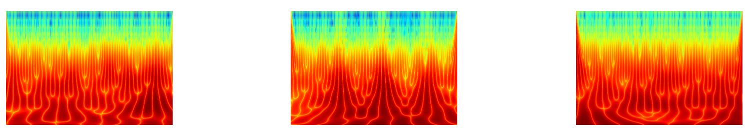
$$W(s,b) = \frac{1}{\sqrt{(s)}} \int_{-\infty}^{+\infty} f(x)\psi_O^* \left(\frac{x-b}{s}\right) dx \tag{2.1}$$

Where:

- $f(x)$ is the 1-D signal
- $W(s,b)$ is the continuous Wavelet transformation coefficient of $f(x)$, where s is the ratio (reciprocal of the frequency) and b is the position characteristic displacement.
- ψ_O^* a complex conjugate called the analysis Wavelet function.

The equation (2.1) shows that the WT is a mapping that converts from a variable $f(x)$ to function $W(s,b)$ dependent on two variables which are the scale variable s and the shift variable b. The normalization coefficients $1/\sqrt{s}$ in (2.1) ensures standardized the wave of Wavelet with analysis rates s other $\|\psi_{0(s,b)})\| = \|\psi_0\|$.

In research, we used the widely applied Morlet function and obtained the Scalograms Figure 3.

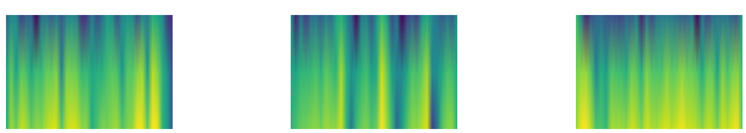


(a) Spinal cord injuries (b) Multiple sclerosis (c) Unimpaired person

Fig. 3: Scalogram images of EEG recording on channel C3

Short-Time Fourier Transform (STFT)

Short-Time Fourier Transform was used to generate Spectrogram images which is a method for sinusoidal functions. Classification tools H. M. Alaskar [1], P. Xia [22] commonly used spectrogram images as input data that achieving better performance because the spectrogram images hold more unknown features of EMG signals.



(a) Spinal cord injuries (b) Multiple sclerosis (c) Unimpaired person

Fig. 4: Spectrogram images of EEG recording on channel C3

The STFT of EEG signal represented by:

$$S(\tau, w) = \int_{-\infty}^{+\infty} w(t-\tau)x(t)e^{-iwt}dt \tag{2.2}$$

Where:

- $x(t)$ is the input signal.
- $w(\tau)$ is widonw function using the signal analysis, commonly a Hann window or Gaussian window centered around zero
- e^{-iwt} is basic function.

In the article, we had used the Hann window function that creating the Spectrogram images and Figure 4 was our result.

LeNet

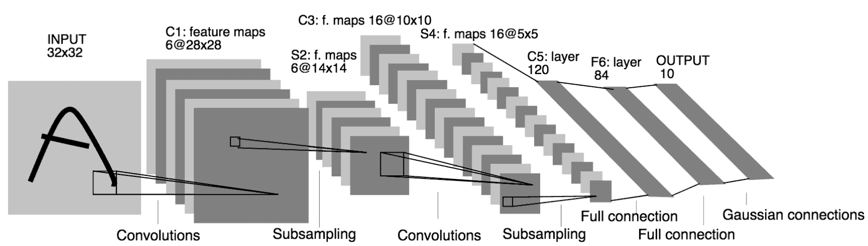


Fig. 5: LeNet Architecture [13]

In the last decade, Convolutional Neural Network (CNN) is one of the most competitive neural network architectures for image classification tasks, in some cases even outperforming human performance D. Ciresan [4]. In the research Y. LeCun [14], Y. LeCun et al. proposed the original form of LeNet. Which is one of the improved architectures of CNN. LeNet architectures are two convolutional layers with filter size 5×5 and stride 1×1, each of them followed by a pooling layer using maximization function with filter and stride size 2×2.

AlextNet Architectures

The AlexNet architecture was one of the top performers in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) competition in 2012. It is one of the typical convolution neural networks published by the A. Krizhevsky team [12]. The Alex Krizhevsky team built the AlexNet architecture based on the following ideas:

- Processing on multiple GPUs.

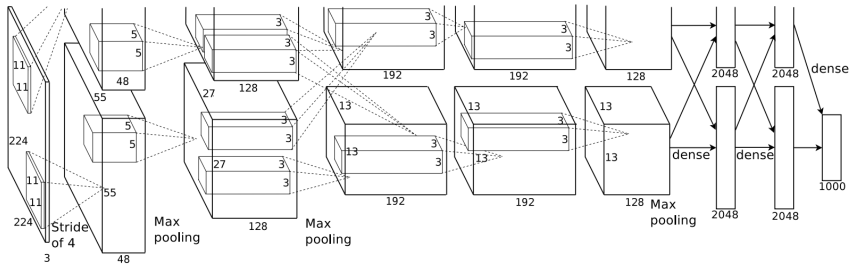


Fig. 6: AlexNet Architecture [12]

- ReLu Nonlinearity to speed up calculation.
- Local Response Normalization to normalize each layer.
- Overlap pooling to reduce the size of the network.
- Using Dropout as a new mainstream method for CNN. Dropout helps the model to avoid overfitting and reduced model training time.
- Enhancing data by translations, horizontal reflections.

The above ideas, the AlexNet team created a structured network consisting of 5 convolution layers (11x11, 5x5, 3x3 convolution), 3 fully connected layers (3x3, 3x3, 3x3 max pooling), with middle layers are sampling classes and ReLu, which trained in parallel on two GPU graphics cards.

3 Experiments

In this study, we had training experiments about classifying the patterns on EEG signals as either spinal or multiple sclerosis or normal class with AlexNet and LeNet models.

In the first step, signals were filtered to remove noise. Then, we extract two types of images from time-frequency representation. Their size are 384 px x 384 px. For AlexNet, we proportionally resized images from original 384 px x 384 px resolution to 227 px x 227 px according to AlexNet input standards. About the training-test data of each CNN, I. Goodfellow [9] recommended to randomly chosen as 80% to 20%.

After the training was run 50 epochs with a learning rate of 0.000001, we received the model separately from each EEG channel. Then, we received the model separately from each EEG channel. Then, we will randomly choose 20% of images from each EEG channel and passed the vote to evaluate. Subjects denoted as s20–s28 represented persons without known neural disorders (marked as F – false cases), while subjects s11–s16 represent patients with motor impairments (marked as T – true cases). If more than half of the votes are neural disorders, the result will be impairment and vice versa. Next, the results of each experiment was presented.

3.1 The Scalogram

	C3	F3	O1	P3	C4	F4	O2	P4	class
ms	0	0	0	1	0	0	0	0	0
spinal	1	1	1	1	1	1	1	0	1
normal	12	12	12	11	12	12	12	13	12

Table 2: Scalogram - AletNet (LR=0.0001)

	C3	F3	O1	P3	C4	F4	O2	P4	class
ms	0	0	0	1	0	0	0	0	0
spinal	0	0	0	0	0	1	0	0	0
normal	13	13	13	12	13	12	13	13	13

Table 3: Scalogram - LeNet (LR=0.0001)

	C3	F3	O1	P3	C4	F4	O2	P4	class
ms	0	1	0	2	0	0	0	0	0
spinal	1	1	1	1	1	1	0	1	1
normal	12	11	12	10	12	12	13	12	12

Table 4: Scalogram - AletNet (LR=0.000001)

	C3	F3	O1	P3	C4	F4	O2	P4	class
ms	0	0	0	0	0	0	0	0	0
spinal	0	1	0	0	0	1	1	0	0
normal	13	12	13	13	13	12	12	13	13

Table 5: Scalogram - LeNet (LR=0.000001)

In this section, the results of using the Scalogram images as input AlexNet were shown in Table 2 (LR=0.0001) and Table 4 (LR=0.000001). Besides, we also apply that the Scalogram images as input LeNet. The results were shown in Table 3 (LR=0.0001) and Table 5 (LR=0.000001).

	LR=0.0001		LR=0.000001	
	AlextNet	LeNet	AlextNet	LeNet
Accuracy	76.92%	69.23%	76.92%	69.23%
Sensitivity	25.00%	0.00%	25.00%	0.00%
Specificity	100.00%	100.00%	100.00%	100.00%
F1 score	71.65%	56.64%	71.65%	56.64%

Table 6: The performance for Scalogram images

From the results obtained, we comparing the performance of AlexNet and LeNet as Table 6. From Table 6, LeNet performance was lower compared to AlexNet. However, the performance did not increase as the learning rate decreases and neither did LeNet.

3.2 The Spectrogram

In this section, we have replaced the Scalogram image with the Spectrogram image which is the input data of AlexNet and LeNet. The results were displayed as follows: Table 7 (LR=0.0001) and Table 9 (LR=0.000001) and Table 8 (LR=0.0001) and Table 10 (LR=0.000001).

	C3	F3	O1	P3	C4	F4	O2	P4	class
ms	0	1	0	1	0	0	1	0	0
spinal	0	1	0	0	0	0	1	0	0
normal	13	11	13	12	13	13	11	13	13

Table 7: Spectrogram - AletNet (LR=0.0001)

	C3	F3	O1	P3	C4	F4	O2	P4	class
ms	0	0	0	0	0	0	0	0	0
spinal	0	0	0	0	0	0	0	0	0
normal	13	13	13	13	13	13	13	13	13

Table 8: Spectrogram - LeNet (LR=0.0001)

	C3	F3	O1	P3	C4	F4	O2	P4	class
ms	0	0	0	0	0	0	0	0	0
spinal	0	0	0	0	0	0	0	0	0
normal	13	13	13	13	13	13	13	13	13

Table 9: Spectrogram - AletNet (LR=0.000001)

	C3	F3	O1	P3	C4	F4	O2	P4	class
ms	0	0	0	0	0	0	0	0	0
spinal	0	0	0	0	0	0	0	0	0
normal	13	13	13	13	13	13	13	13	13

Table 10: Spectrogram - LeNet (LR=0.000001)

For Table 11, it could be observed that the AlexNet performance same as the LeNet performance. Which did not increase as the learning rate decreases.

	LR=0.0001		LR=0.000001	
	AlextNet	LeNet	AlextNet	LeNet
Accuracy	69.23%	69.23%	69.23%	69.23%
Sensitivity	0.00%	0.00%	0.00%	0.00%
Specificity	100.00%	100.00%	100.00%	100.00%
F1 score	56.64%	56.64%	56.64%	56.64%

Table 11: The performance for Spectrogram images

4 Discussion

We present methods that extracted EEG signals to create time-frequency images for inputting data to CNNs. Above results, the AlexNet will obtain the performance highest when using Scalogram image as the input data. It completely identified completely 9 subjects unimpaired persons and 1 out of 4 subjects with the disease of motor neuron impairment. The results are very good with an F1-score of 71.65% and an accuracy of 76.92%. In addition, sensitivity and specificity were respectively achieved at 25% and 100%.

For the purpose of improving AlexNet's performance, we have reduced the learning rate. The overall result is no performance increase, but performance increase in some EEG channels. For example, channel P3 of s15 in Table 2 was misclassified as persons without known neural disorders. Whereas, channel P3 of s15 in Table 4 was correctly classified as patients with motor impairments. This is also important for our further research work.

LeNet does not correctly patients with motor impairments (s11 - s16) at all EEG channels when using Spectrogram images as the input data. About AlexNet with the Spectrogram images as input data, the result obtained was low. From there, draw conclusions that the Scalogram image will improve the performance of CNNs.

We also compared the model performance with a paper working on motor impairment neural disorders. G. Vrbancic [21] and our paper were matched because using the same data set. G. Vrbancic [21] took a different approach which was using Spectrogram images to display data for each EEG channel. Also through G. Vrbancic [21], we also compared further with some traditional classification methods: Linear Regression (LR), Linear Discriminant Analysis (LDA), K-Nearest Neighbours (KNN), Classification and Regression Trees (CART), Naïve Bayes (NB) and Support Vector Machine (SVM).

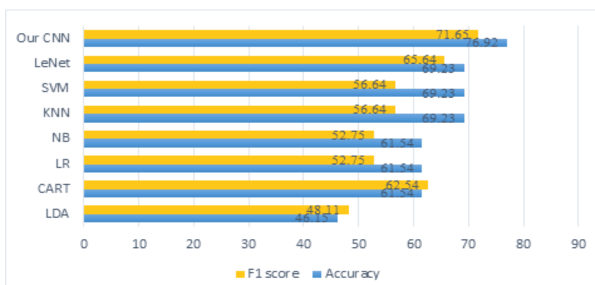


Fig. 7: Comparison of all tested classification methods

As illustrated as Figure 7, regarding to the analysis of F1 score, we have shown that our method gave the highest result of 71.65%, 6.01% more than LeNet. In addition, regarding to the analysis of accuracy, our diagnostic model also gave the highest result at 76.92%. Thereby, it can be seen that our method is the best method in diagnosing motor neuron impairment disorder.

5 Conclusions

In this paper, we presented two types of time-frequency images for the analysis of the EEG signal. Before extracting time-frequency images from the EEG signal, we filtered Butterworth Bandpass for the EEG signal that will increase the CNN's performance. Through the experiment results shown that the classification of motor impairment neural disorders should use the AlexNet architecture with Scalogram images as input data. Because the EEG signal of motor impairment neural disorders is non-stationary and transient signals, while the Scalogram images were created by WT which is a method for non-stationary and transient signals M. P. G. Bhosale [3]. Therefore, our proposed model for the accuracy and F1-score was higher than the previous studies G. Vrbancic [21]. In addition, we have seen a method for increasing CNN's performance that reducing learning rates.

For future work, we will applying the Scalograms as input data of AlexNet for the classification of motor impairments neural disorders. Then, we will adjust the parameters to get better results K. G. Pasi [16]. This has been proven in the experiments. In addition, we would like to expand our work with the use of a larger EEG dataset and using the combined model to increase the performance.

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