Classification of Motor Imagery and Synchronization of Post-Stroke Patient EEG Signal

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Abstract— Stroke attacks often cause disability, so the need for rehabilitation to restore patient's motor skills. Electroencephalogram (EEG) is an instrument that can capture electrical activity in the brain. Some post-stroke patients have brain electrical dysfunction so that EEG signal can achieve such as amplitude decrease, and wave differences from symmetric channels. However, EEG signal analysis is not easy because it has high complexity and small amplitude. However, information from EEG signals is beneficial, including for stroke identification. This study proposes the identification of EEG signals from post-stroke patients using wavelet extraction and Backpropagation Levernberg-Marquardt. EEG signals are recorded, extracted imagery motor variables, and synchronization of symmetric channels. The results of the study provide that the accuracy for identifying post-stroke EEG signals is 100% for training data and 79.69 % for new data. Research also shows that the use of learning rates affects accuracy. The smaller the learning rate provided accuracy is better. However, it had consequences for computing time so that the optimal learning rate is 0.0001.

Keywords— post-stroke; EEG; motor imagery; wavelet; backpropagation; Levenberg-Marquardt

I. Introduction

A stroke occurs when part of the brain-damaged due to the lack of blood supply. At present, stroke is the third most common cause of death after heart disease and cancer [1]. Stroke is also the main factor causing severe disability. To restore motor skills and improve quality of life, post-stroke patients undergo the right rehabilitation program. Therefore, monitoring and evaluation are required.

In evaluating the rehabilitation of post-stroke patients, one of the methods of observation carried out by neurologists is the National Institutes of Health Stroke Scale (NIHSS). NIHSS, as an initial assessment tool in rehabilitation monitoring [2]. However, unfortunately, this method tends to be subjective. There is an instrument that can capture electrical activity in the brain, such an Electroencephalogram (EEG).

The device can obtain electrical abnormalities in the brain that occur as post-stroke patients. EEG operations are quite cheap, safe, and can be performed in real-time. However, EEG analysis is not easy given the complexity of the signal and has a small amplitude.

Previous research analyzed the relationship between EEG signals for male patients with the NIHSS method [3]. The study only looked at the comparison of EEG sub-band signals with the NIHSS score. However, it has not done a detailed pattern analysis.

Neurologist usually observes the rhythm or density of waves, amplitude, changes in amplitude, differences in amplitude between symmetric channels, and the presence of low-frequency waves such as Delta, Theta, and Mu [4]. Previous research used motor imagery parameters to identify the motor skills of paralyzed limbs [5]. Motor imagery is thinking of a movement without involving the muscles so that it is related to electrical disturbances in some post-stroke patients. Motor imagery variable of EEG signal detected stroke patients in rehabilitation period [6]. Other study used motor imagery variable to identify stir movements simulation. Motor movements that can be identified through EEG signals reflect hand movement [10]. Identification patient motor imagery supporting the evaluation of post-stroke rehabilitation [11]. Most imagery motors use Mu wave in the imagery motor classification [12].

Meanwhile, implementation of wavelet transforms for the classification of emotions in post-stroke patients [7] and identifying variables that affect post-stroke patients [4]. EEG signals are also used to detect electrical abnormalities in the brain, such as Epilepsy [8].

One of the learning algorithms used to identify EEG signals is Backpropagation Levenberg-Marquardt. In previous studies, the Levenberg-Marquardt algorithm was used for the classification of hand motion imagery motors [13]. Backpropagation Levenberg-Marquardt method has identified motor imagery of left and right-hand movement. It showed that it worked faster than ordinary Backpropagation [14].

Backpropagation Levenberg-Marquardt also classified the condition of open eyes and closed eyes through EEG signals [15]. Meanwhile, other studies identified neuropsychological emotions toward advertising videos [16].

This study proposed a method to classifying post-stroke patients of EEG signal data that has been extracted using Wavelet first. The EEG signal variables used are imagery motors and symmetrical channel wave differences. Identification was performed using learning with the Levenberg-Marquardt Backpropagation algorithm first.

II. Related Works

A. Motor Imagery

Motor imagery is a cognitive process where the subject imagines moving his limbs without involving muscle gestures. In a movement at least there are organs involved, the brain commands to move and the muscles that execute. When there are abnormalities such as stroke sufferers, then one of the indicators of rehabilitation success is the function of moving the hands or feet, which is characterized by motor imagery. In other words, motor imagery requires a part of the brain that functions to prepare movements and movements accompanied by regulation of these movements. [17]. Several ways to measure motor imagery, one way by using EEG signals μ

(Mu) and β (Beta) to classify motor imagery using Wavelet Time-Frequency Image [12].

B. Wavelet Extraction

EEG signals have frequency components called Delta waves (<4Hz), Theta (4-7 Hz), Alpha and Mu (8-13Hz), Beta (14-30 Hz) and Gamma (> 30 Hz) [17]. Motor imagery, as an indication of the condition of post-stroke patients, is associated with the presence of Mu waves, specifically in the central area.

Wavelet transformation is suitable for non-stationary signals such as EEG [18] [19]. Wavelet means basis function Φ(n) called the mother wavelet as (1).

$$\Phi_{j,k}(n) = 2^{j/2}\Phi(2^j n - k) \quad (1)$$

Where j and k are an integer that indicates the scaling and dilate of the basis function. Φ(n) is the mother wavelet, which depends on the characteristics of signals to be decomposed. Previous studies generally used the Daubechies db4 as mother Wavelets such in seizure detection [19] and ischemic stroke [20]. The wavelet coefficient approximation is a(j,k) that implies convolution signal x(n) as (2), low frequency.

$$a(j,k) = 2^{-j/2}\sum_n x(n) * \Psi\left(2^{-j}n - k\right) \quad (2)$$

While d(j,k) is convolution signal x(n) with scaling function as (3), high frequency.

$$d(j,k) = 2^{-j/2}\sum_n x(n) * \Phi\left(2^{-j}n - k\right) \quad (3)$$

Wavelet synthesis can be written as follows (4) [19]

$$x(n) = \sum_{j,k} 2^{-j/2} a_{j,k}\Psi\left(2^{-j}n - k\right) + \sum_{j,k} 2^{-j/2} d_{j,k}\Phi\left(2^{-j}n - k\right) \quad (4)$$

C. Backpropagation Levenberg-Marquardt

The Backpropagation Levenberg-Marquardt is an algorithm that is the development of the Backpropagation through revising the weight correction. Weight values start with random, and then it is corrected in the reverse direction based on the difference between the output of the feed-forward process [21]and the actual output of each neuron [21].

The Levenberg Marquardt method uses optimize learning algorithms considering that standard algorithms have a weak convergence rate. This condition becomes many iterations to give the smallest error [15].

Neurons of the input layer are equal to the number of features, which are the result of extraction. The number of output neurons is the number of classes. Meanwhile, the number of neurons from the hidden layer can be calculated using (5).

$$\sqrt{n \times m} \quad (5)$$

The Backpropagation Levenberg-Marquardt algorithm uses the Hessian (H) matrix approach on (6). Also, the algorithm improves the computational time in the iteration of the Backpropagation method.

$$Hessian\ (H) = \boldsymbol{J}^T\boldsymbol{J} \quad (6)$$

Where $\boldsymbol{J}$ is matrix Jacobian, and $\boldsymbol{J}^T$ is the transpose of matrix Jacobian.

In this case, J contains the first derivative of the network error against network weight and bias. The Gauss-Newton method was modified as in (7) for the matrix with the expression of the Hessian equation.

$$\boldsymbol{W}_{i+1} = \boldsymbol{W}_i - \left(\boldsymbol{J}_i^T\boldsymbol{J}_i + \mu\boldsymbol{I}\right)^{-1}\boldsymbol{J}_i^T e_i \quad (7)$$

Where (JT J) is a positive value of the function of network weights and biases, and e is a vector declaring all errors in the network output shown in (8) as the identity matrix.

$$\boldsymbol{J} = \begin{bmatrix} \frac{\partial e_{11}(x)}{\partial x_1} & \frac{\partial e_{11}(x)}{\partial x_2} & \cdots & \frac{\partial e_{11}(x)}{\partial x_n} \\ \frac{\partial e_{k1}(x)}{\partial x_1} & \frac{\partial e_{k2}(x)}{\partial x_2} & \cdots & \frac{\partial e_{k1}(x)}{\partial x_n} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{\partial e_{kp}(x)}{\partial x_1} & \frac{\partial e_{kp}(x)}{\partial x_2} & \cdots & \frac{\partial e_{kp}(x)}{\partial x_n} \end{bmatrix} \quad (8)$$

Mean Square Error (MSE) based on the output error value using (9) [22].

$$MSE = \frac{1}{N}\nabla e \quad (9)$$

Where N is the amount of output neuron. For accuracy calculations using (10).

$$accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)}.100\% \quad (10)$$

Where TP is True Positive, TN is True Negative, FP is Positive False, and FN is False Negative.

III. RESEARCH METHOD

Classification of EEG signals from post-stroke patients uses imagery motor components and synchronization of symmetric channel pairs. Nevertheless, the elements of the Theta and Delta waves are included.

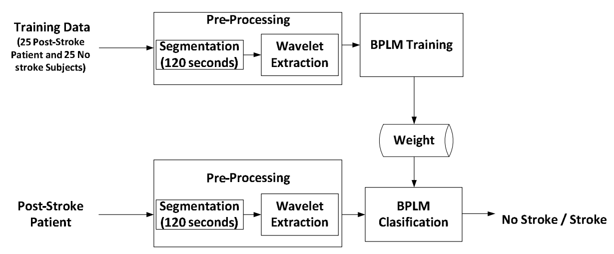

Fig. 1. Classification of EEG signal post-stroke based on motor imagery and synchronization of symmetric channel

They are extracting waves from the EEG signal using Wavelet. After that, the classifications of two classes "Stroke" and "No Stroke" was conducted, with training first using the Backpropagation Levenberg-Marquardt algorithm. As in Fig. 1.

This research used data from the previous study [4] were recorded from 25 post-stroke patients at Al-Islam Bandung Hospital and 25 no stroke people. EEG signal was taken using Epoc Emotiv from 14 channels particularly AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 during three minutes. This EEG instrument has a 128 Hz sampling frequency. Subjects were asked to follow the instructions as in Fig. 2. EEG signal of the post-stroke patient.

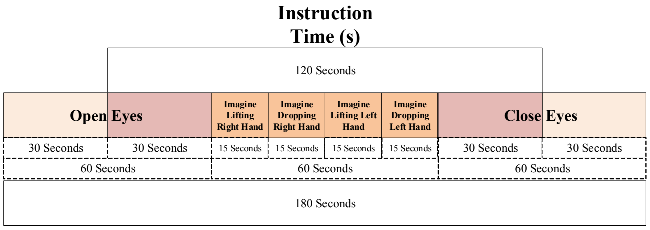

Fig. 2. Recording instruction

A. Wavelet Extraction

Data extraction is carried out for each segment so that the wave components obtained are by the instructions given. The waves taken in this study are Delta, Theta, and Mu, which are segmented every two seconds to produce 256 data obtained from 128Hz × 2 seconds. The signal decomposition process is carried out up to five levels using Wavelet, which can be seen in Fig 3.

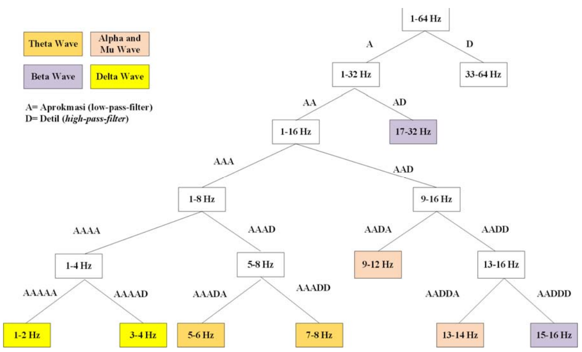

Fig. 3. Decomposition of multilevel Wavelet

Wavelet extraction is carried out in the Delta area (8x14 canals), Theta waves (8x14 canals), and Mu (12x2 canals). Meanwhile, synchronizing of the symmetric channel value is obtained comparing the waves of symmetric channel pair that is 110 points for each second. If the EEG signal is recorded every two seconds, then it gets 2 x 358 = 716 seconds. This extraction is an input feature of artificial neural networks.

B. Backpropagation Levenberg-Marquardt

Classification is accomplished by Artificial Neural Networks with the Multilayer Perceptron (MLP) architecture, as shown in Fig. 4. MLP has three layers, i.e., the input layer, hidden layer, and output layer. The input layer has 716 neurons following the features number. The output layer has two neurons as two-class. Also, the hidden layer has 38 neurons from the computation (4).

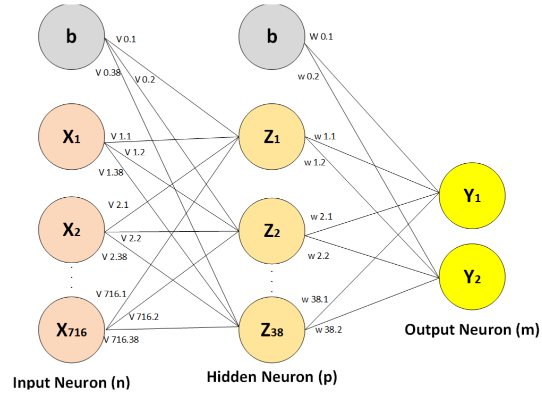

Fig. 4. Multilayer perceptron architecture

IV. Result and Discussion

This study used 50 data consisting of 25 post-stroke patient data and 25 no stroke data, 80% of the data was used as training data, and 20% was test data.

The results and discussion consisted of three parts, particularly parameter optimization, using Levernberg-Marquardt algorithm. So the third, it examines the accuracy of the parameter synchronization component of the symmetric channel.

A. Parameter Optimization

Dynamic weight correction is an improvement from the Backpropagation Levernberg-Marquadts (BPLM) algorithm. First tested the accuracy and computation of several learning rate values. In this case, the experiment uses a variety of learning rates 0.0100, 0.0010, and 0.0001. Correctness and losses up to epoch 100 can be seen in Table I.

TABLE I. Parameter Optimization Using BPLM

Learning Rate	Training Data		Validation Data	
	Accuracy (%)	*Loss*	*Accuracy (%)*	*Loss*
0.0100	93.40	0.0517	75.00	0.2002
0.0010	100.00	1.6085	78.65	1.6297
0.0001	100.00	1.7545	79.69	1.5481

The experiment used BPLM algorithm with a learning rate of 0.0100 of 100 epochs resulting in training data accuracy of 93.40% and validation data of 75%, shown in Fig. 5.

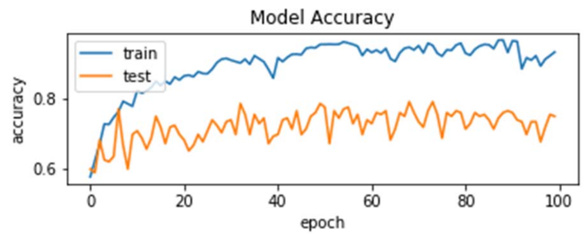

Fig. 5. Accuracy of BPLM using 0.0100 learning rate

Meanwhile, losses or the difference in target output and actual output shown in Fig. 6. The learning rate of 0.0100 for training data provides losses of 0.0517 and variance data of 0.2002. With a training time of 2.7828 seconds per epoch.

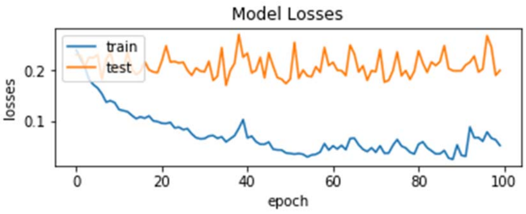

Fig. 6. Losses of BPLM using 0.0100 learning rate

Decreasing the learning rate to 0.0100 from 0.0100 can improve the accuracy of 100% training data and decrease computing time each epoch into 0.8908 of 2.7828. It seems that the learning rate value of 0.0010 has given good results, and the decrease in learning rate has less effect on increasing accuracy. The value of accuracy and losses from the use of the learning rate 0.0010 are shown in Fig. 7 and Fig. 8.

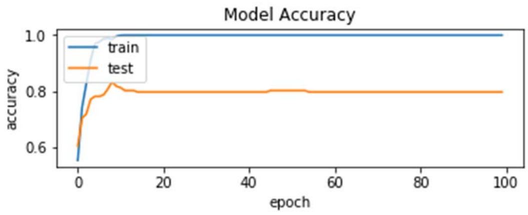

Fig. 7. Accuracy of BPLM using 0.0010 learning rate

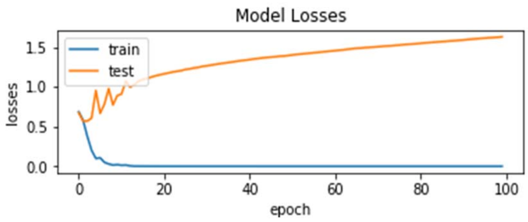

Fig. 8. Losses of BPLM using 0.0010 learning rate

Decreasing the learning rate to 0.0010 from 0.0100 can improve the accuracy of 100% training data. However, the decrease in the learning rate to 0.0001 turned out to only increase the correctness of the validation data only 1%. The accuracy of the use of the learning rate 0.0001 is shown in Fig. 9, and losses are shown in Fig. 10.

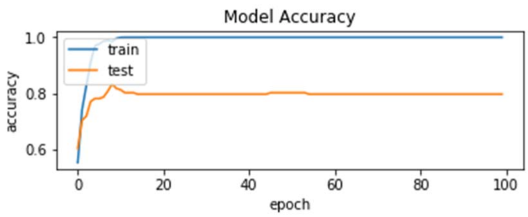

Fig. 9. Accuracy of BPLM using 0.0001 learning rate

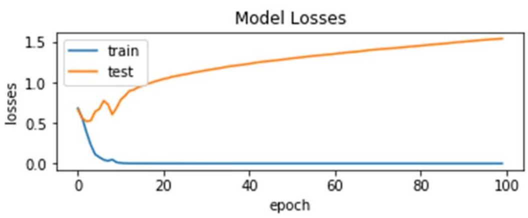

Fig. 10. Losses of BPLM using 0.0001 learning rate

B. Backpropagation Levenberg-Marquardt Compare than Backpropagation

Using the Backpropagation Levenberg-Marquardt algorithm requires to compare than Backpropagation accuracy as in Table II.

TABLE II. BACKPROPAGATION LEVENBERG-MARQUARDT VS. BACKPROPAGATION

Method	**Learning Rate**	***Accuracy (%)***	
		Training Data	***Validation Data***
BPLM	0.0100	93.40	75.00
	0.0010	100.00	78.65
	0.0001	100.00	79.69
BP	0.0100	53.99	54.17
	0.0010	53.12	53.76
	0.0001	58.97	53.65

The comparison results of using the Backpropagation Levernberg-Marquardt can increase accuracy almost twice from the training data and about half of the validation data. Therefore BPLM can improve the Backpropagation algorithm. This accuracy increase occurs from all learning rate uses, which are shown in Fig. 11 – Fig. 14.

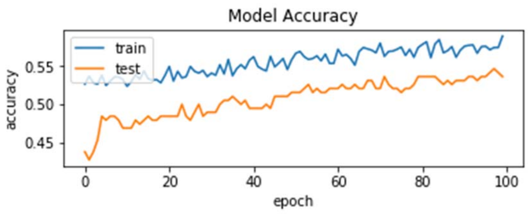

Fig. 11. Accuracy of Backpropagation using 0.0100 learning rate

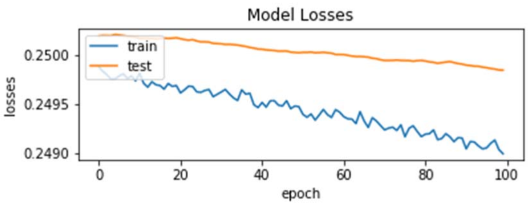

Fig. 12. Losses of Backpropagation using 0.0100 learning rate

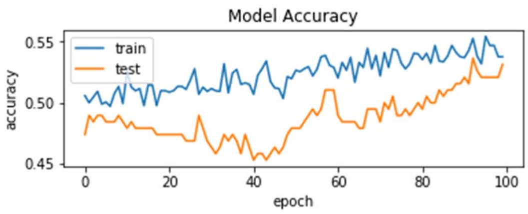

Fig. 13. Accuracy of Backpropagation using 0.0010 learning rate

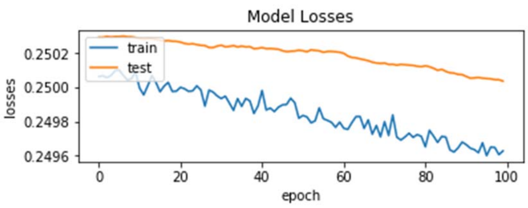

Fig. 14. Losses of Backpropagation using 0.0010 learning rate

Synchronization of symmetric channel variables is shown in Table III. It can be seen that the symmetric channel synchronization parameters in the learning rate 0.0001 have an accuracy of 97% -99% of the training data and 69-81% of the validation data. The highest accuracy of validation data is on the O1-O2 channel with an accuracy of 81.25% in 100 epochs. However, the accuracy of the entire channel and the results of symmetric synchronization are 69.27-81.25%.

TABLE III. SYMMETRIC CHANNEL SYNCHRONIZATION

No	Channel	Validation Data	
		Accuracy (%)	Loss
1	AF3-AF4	77.60	0.1959
2	F7 – F8	77.60	0.2190
3	F3 – F4	77.08	0.2136
4	FC5-FC6	73.96	0.2398
5	T7 - T8	76.04	0.2237
6	P7 – P8	75.52	0.2196
7	O1 – O2	81.25	0.1562
8	AF3-AF4 , F7-F8	75.52	0.2255
9	F7-F8 , F3-F4	75.52	0.2307
…	…	…	…
14	O1-O2, AF3-AF4	71.35	0.2619
15	AF3-AF4 , F7-F8 , F3-F4	69.27	0.2773
16	F7-F8 , F3-F4 , FC5-FC6	77.08	0.2088
…	…	…	…
21	O1-O2 , AF3-AF4 , F7-F8	71.87	0.2550
22	AF3-AF4 , F7-F8 , F3-F4 , FC5-FC6	74.47	0.2358
23	F7-F8 , F3-F4 , FC5-FC6 , T7-T8	80.20	0.1842
…	…	…	…
28	O1-O2 , AF3-AF4 , F7-F8 , F3-F4	75.00	0.2061
29	AF3-AF4 , F7-F8 , F3-F4 , FC5-FC6 , T7-T8	77.08	0.2125
30	F7-F8 , F3-F4 , FC5-FC6 , T7-T8 , P7-P8	76.04	0.2174
…	…	…	…
35	O1-O2 , AF3-AF4 , F7-F8 , F3-F4 , FC5-FC6	71.87	0.2704
36	AF3-AF4 , F7-F8 , F3-F4 , FC5-FC6 , T7-T8 , P7-P8	72.39	0.2528
…	…	…	…
42	O1-O2 , AF3-AF4 , F7-F8 , F3-F4 , FC5-FC6, T7-T8	71.87	0.2618
43	All Channel	79.69	1.5481

This study used motor imagery variables and the wave difference of the symmetric channel pairs with 79.69% accuracy. This result is higher than previous studies using the features of Alpha - Beta - Mu - Amplitude - Asymmetric of Alpha - Asymmetric of Beta - Asymmetric of Amplitude that gave 74%. In meanwhile, using all features obtained an accuracy of 70% [4]. However, other study involved emotional variables of post-stroke patients, which used Wavelet, KNN, and Probabilistic Neural Networks provided 82% of accuracy [7]]. This result is considering that emotions reflect the overall stroke disorder. While motor imagery variables and synchronization of symmetric channels only include electrical abnormalities in the brain.

V. CONCLUSION

Motor imagery and synchronization of symmetric channel pair information can be used to detect EEG signal abnormalities from post-stroke patients. The EEG signal is extracted first to get both of this information, which are features for identification using the Levenberg-Marquardt Backpropagation algorithm.

The results of the study also showed that the realization of training data with a small learning rate of 0.0001 provided convergent training and accuracy of training data 100% and 79.69% of the validation data. After several experiments, the same learning rate has different results because the initial weight is random.

The Backpropagation Levernberg-Marquardt algorithm can improve the weight update in the Backpropagation algorithm so that it can improve accuracy and reduce losses by almost 90% of training data and around 50% of the validation data for all learning rate parameters.

Meanwhile, for big training data, the Levenberg-Marquardt Backpropagation algorithm requires a very long learning time, more than a day considering it cannot be done in parallel for some data but must be done simultaneously without batching. The experimental results also show that although the learning rate of 0,0001 provides high accuracy, the loss of the best and most stable learning is given at the 0.0100 learning rate, which is equal to 0.2002.

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REFERENCES

[1] P. Langhorne, J. Bernhardt, G. Kwakkel, R. Infi, and P. P. Langhorne, “Stroke Care 2 Stroke rehabilitation,” *The Lancet*, vol. 377, no. 9778, pp. 1693–1702, 2011.

[2] S. E. Kasner, “Clinical Interpretation and Use of Stroke Scales,” *Lancet Neurology*, vol. 5, no. 7, pp. 603–612, 2006.

[3] W. R. R. Omar, R. Jailani, M. N. Taib, N. A. A. Razak, N. H. A. Wahab, and W. N. Nafisah, “An analysis of male stroke patients’ brain signal according to NIHSS score,” *IEEE Conference on Systems, Process and Control (ICSPC 2014)*, pp. 183–187, 2014.

[4] E. C. Djamal, D. P. Gustiawan, and D. Djajasasmita, “Significant Variables Extraction of Post-Stroke EEG Signal Using Wavelet and SOM Kohonen,” *Telkomnika*, vol. 17, no. 3, 2019.

[5] S. Shahid, R. Sinha, and G. Prasad, “Mu and Beta Rhythm Modulations in Motor Imagery Related Post-Stroke EEG: A Study Under BCI Framework for Post-Stroke Rehabilitation,” *Bio-Med Central Neuroscience*, vol. 11, no. Suppl 1, p. P127, 2010.

[6] Y. Liu *et al.*, “Computational Neuroscience A tensor-based scheme for stroke patients ’ motor imagery EEG analysis in BCI-FES rehabilitation training,” vol. 222, pp. 238–249, 2014.

[7] S. Z. Bong, K. Wan, M. Murugappan, N. M. Ibrahim, Y. Rajamanickam, and K. Mohamad, "Implementation of Wavelet Packet Transform and Non-Linear Analysis for Emotion Classification in Stroke Patient Using Brain Signals," *Biomedical Signal Processing and Control*, vol. 36, no. April, pp. 102–112, 2017.

[8] A. Ouelli, B. Elhadadi, H. Aissaoui, and B. Bouikhalene, “Epilepsy Seizure Detection Using Autoregressive Modelling and Multiple Layer Perceptron Neural Network,” vol. 2, no. 4, pp. 26–31, 2015.

[9] E. Yulianto, A. Susanto, T. S. Widodo, and S. Wibowo, “Spektrum Frekuensi Sinyal EEG Terhadap Pergerakan Motorik dan Imajinasi Pergerakan Motorik,” *Forum Teknik*, vol. 35, pp. 21–32, 2013.

[10] M. K. Hazrati and A. Erfanian, “An online EEG-based brain-computer interface for controlling hand grasp using an adaptive probabilistic neural network,” *Medical Engineering and Physics*, vol. 32, no. 7, pp. 730–739, 2010.

[11] K. K. Ang *et al.*, “Clinical Study of Neurorehabilitation in Stroke using EEG-Based Motor Imagery Brain-Computer Interface with Robotic Feedback BT - 2010 32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBC’10, August 31, 2010,” pp. 5549–5552, 2010.

[12] H. K. Lee and Y. S. Choi, "A Convolution Neural Networks Scheme for Classification of Motor Imagery EEG Based on Wavelet Time-Frequency Image," *International Conference on Information Networking*, vol. 2018-Janua, pp. 906–909, 2018.

[13] M. M. or Rashid and M. Ahmad, "Classification of Motor Imagery Hands Movement using Levenberg-Marquardt Algorithm based on Statistical Features of EEG Signal," *2016 3rd International Conference on Electrical Engineering and Information Communication Technology (ICEEICT)*, no. October 2017, pp. 1–6, 2016.

[14] Y. Chen and S. Zhang, "Research on EEG Classification with Neural Networks Based on the Levenberg-Marquardt Algorithm," *Communications in Computer and Information Science*, vol. 308 CCIS, no. PART 2, pp. 195–202, 2012.

[15] U. N. Wisesty, "Levenberg-Marquardt Neural Network for Eye States Detection Based on Electroencephalography Data," *International Journal on Information and Communication Technology (IJoICT)*, vol. 2, no. 1, p. 23, 2016.

[16] K. N. Oktaviani, E. C. Djamal, and A. Komarudin, "Identifikasi Neuropsikologi Emosi terhadap Video Iklan menggunakan Fast Fourier Transform dan Levenberg-marquardt Backpropagation," in *Seminar Nasional Aplikasi Teknologi Informasi (SNATI)*, 2018, pp. 1–5.

[17] M. Lotze and U. Halsband, "Motor imagery.," *Journal of physiology, Paris*, vol. 99, no. 4–6, pp. 386–95, 2006.

[18] E. C. Djamal and Suprijanto, "Recognition of Electroencephalogram Signal Pattern against Sound Stimulation using Spectral of Wavelet," in *Tencon 2011*, 2011, pp. 767–771.

[19] Y. Liu, W. Zhou, Q. Yuan, and S. Chen, "Automatic Seizure Detection Using Wavelet Transform and SVM in Long-term Intracranial EEG.," *IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society*, vol. 20, no. 6, pp. 749–755, 2012.

[20] O. N. Rahma, S. K. Wijaya, Prawito, and C. Badri, "Electroencephalogram Analysis with Extreme Learning Machine as a Supporting Tool for Classifying Acute Ischemic Stroke Severity," in *2017 International Seminar on Sensors, Instrumentation, Measurement and Metrology*, 2017, pp. 180–186.

[21] R. Rahmat, R. Setiawan, and M. H. Purnomo, "Perbandingan Algoritma Levenberg-Marquardt dengan Metoda Backpropagation pada Proses Learning Jaringan Saraf Tiruan untuk Pengenalan Pola Sinyal Elektrokardiograf," *Seminar Nasional Aplikasi Teknologi Informasi (SNATI)*, no. Juni, pp. 39–43, 2006.

[22] S.Sapna, Dr.A.Tamilarasi, and M. P. Kumar, "Backpropagation Learning Algorithm Based on Levenberg Marquardt Algorithm," *Computer Science & Information Technology (CS & IT)*, pp. 393–398, 2012.