Intelligent Systems Conference 2018
6-7 September 2018 | London, UK

Deep Learning in Classifying Depth of Anesthesia (DoA)

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***Abstract*—This present study is what we think is one of the first studies to apply Deep Learning to learn depth of anesthesia (DoA) levels based solely on the raw EEG signal from a single channel (electrode) originated from many subjects under full anesthesia. The application of Deep Neural Networks to detect levels of Anesthesia from Electroencephalogram (EEG) is relatively new field and has not been addressed extensively in current researches as done with other fields. The peculiarities of the study emerges from not using any type of pre-processing at all which is usually done to the EEG signal in order to filter it or have it in better shape, but rather accept the signal in its raw nature. This could make the study a peculiar, especially with using new development tool that seldom has been used in deep learning which is the DeepLEarning4J (DL4J), the java programming environment platform made easy and tailored for deep neural network learning purposes. Results up to 97% in detecting two levels of Anesthesia have been reported successfully.**

Keywords—Deep learning; DeepLearning4J; depth of anesthesia; DoA; neural networks

I. INTRODUCTION

Recently electrical brain signals have been researched extensively to serve different applications and especially the application in biomedical engineering. The Brain Computer Interface (BCI) has been designed around brain signals and it connects computers to human mind and translates his intention to commands that is used to communicate with other devices. A major benefit of BCI is the assistance it provides for disabled people to easily communicate with other humans. Besides that, biomedical applications such as the diagnosis of brain related disease such as Alzheimer, Epilepsy, and the severely affected brains which resulted from traumas or those leading to Nicoma. In addition to all that, BCIs has succeeded recently to effectively assist as one of the biometric Identification methods.

Electroencephalography (EEG) is a recording of brain low voltage signals emerging from currents flowing within the brain neurons and gives the unique reference for brain electrical activities which can be measured and recorded. That EEG signals contains considerable amount of information related to time and frequency classified into four different bands; Beta (13 to 30 HZ), Alpha (8 to 13 Hz), Theta (4 to 8 Hz), and Delta (0.5 to 4 Hz). The human physical and conditions can be identified from each band giving a unique feature for such conditions, as each band reflects differently to the type of physical stimulus.

Nevertheless, a major challenge in detecting (EEG) signal level arises due to the fact that brain signals come in very low amplitude. Other activities done by the patients such as eye blinks, muscular movements, teeth movements, and even heart beats could interfere with the EEG signal and introduces considerable distortion. The EEG signals needs to be processed in order to obtain appropriate features, hence it is normally analyzed by time domain algorithms, or frequency domain algorithms, beside time-frequency processing algorithms. But the frequency content of those bands is more informative and hence more often used in EEG analysis relying on the Fast Fourier Transform (FFT) or other similar types of transform [1].

Many techniques has been proposed by researchers to clean EEG signal which diverges from temporal filtering [2], [3], spatial filtering [4]-[6], feature extraction [25], [7] and selection [8]-[11], besides dimensionality reduction [12]-[14]. Power Spectral Density (PSD) is one of the dominant feature extraction technique currently and extensively used in EEG classification. Self-organizing Maps (SOM), as well as correlation [16] and entropy [17], beside Support Vector Machines [15], [18], [19], are considered some of the statistical feature extraction methods that were successfully been used in EEG preprocessing.

This paper presents a novel EEG-Anesthesia Level recognition algorithm to overcome this constraint by fully utilizing a large Deep Neural Networks (DNN) when its hyperparameters carefully tailored, to give the best performance. In this work, a supervised training method was adopted to preliminary training of each layer, then use supervised training method to fine-tune of the whole network. Finally, pattern classification is implemented by SoftMax classifier. The mentioned model accepts the raw EEG as input with complete disregard to any feature engineering solutions. When fully trained, the DNN is tested on 7 out of 23 different subjects collected from operation rooms EEG recorder collecting. The results showed that its speed while training reached up to 15 minutes with a round 10K training epochs has finally attained an accuracy of 97% in identifying 100,000 testing data samples covering the 22 patients but with special focus on 7 of them.

After discussing the Deep Learning concepts and approaches to EEG classification and deep neural networks in Section 2, we present some related works in Section 3, although there were very few which combines DoA level prediction and Deep Learning approach. We present the

978-1-5386-4185-9/18/$31.00 ©2018 IEEE

methodology of Feed Forward Deep Neural Networks which operates on different activation functions in Section 4. In Section 5, we present the material used for this study; while Section 6 shows the results. And finally, we conclude the work with discussion on future directions.

II. Deep Learning

Deep Machine Learning is based on the concept of computational models used to represent information with similar characteristics close to that of the human brain. It tries to model the high-level abstractions contained in data. The “Deep Learning” topic, the hottest in the artificial intelligence and machine learning techniques, is one of the recently gained the most of the researcher’s attentions and currently and widely used in solving many engineering problems. Those solutions diversify from those related to computer vision [20], speech recognition [22], and even in natural language processing [21]. Basically, is known that the Deep Learning is considered a hierarchical structural that has the capability of extracting advanced level features from lower ones constructed within a multi-layer network and hence overcomes the traditional problem faced by shallow neural networks.

Based on neural networks, the Deep Learning (DL) is a machine learning network topology that tries to model high level abstractions contained in data. Different from older learning algorithms or so called shallow learning, but now deep learning can process ultimately huge numbers of data using many layers containing many neurons. In detail the DNN comprises of layers of nonlinear processing units or nodes called neurons. These neurons change their parameters during learning process to reach best fit. A deep neural network consists of an input layer, output layer and multiple hidden layers in between. Now each layer processes the output from the previous layer and deliver to the next layer. The layers memorize low-level features up to high-level features embedded in data as layers go deeper and deeper. So, when further we dive into the network, the more complex features the network can represent and memorize. Nevertheless, in order to find the best network to do such a good work, many variations of hidden layer configurations beside other learning parameters need to be tested.

Many types of activation function for the neuron are employed. This makes it another axis of freedom to be considered during the creation of a deep neural network. Examples of activation functions are *ReLU* (Rectified Linear Unit), the Logistic, the *TanH*, and the *SoftExponential*. The output layer for classification of multiple classes normally uses the *softmax* function for the activation. The function that learns the weight vector is called the optimizer function. A popular optimizer is *SGD* (Stochastic Gradient Descent) is typically used in training. The training dataset is fed into the network in batches. The process of passing of each data in the training dataset is called an epoch. In training a deep neural network, the optimizer, number of epochs, and batch size are parameters to be considered and makes the great difference in the final layer (*softmax* layer).

It has been noted that Deep Learning not yet been widely used in detecting Anesthetic levels although of its early applications covered most of bioengineering applications. Only few studies pinpointed the deep learning importance in EEG-based Anesthetic level detection.

III. Related Works

Underneath the deep learning model, we can find deep neural networks, convolutional neural networks, beside recurrent neural networks. For our classification of Anesthesia level using EEG signal the deep neural network (DNN) is successfully applied. The first researches combining EEG signals and DL, has started with classifying brain's motor activity [23], then brain-computer interface [24], [26], in addition to BCI using motor imagery [25], and more. Although, Anesthetic level detection in EEG is studied extensively, little research has been done to implement end-to-end detection and classification networks. In this thesis, Deep Neural Networks (DNNs) are used to detect and classify the EEG data for possible Anesthetic levels for patients under surgery, and their further classification into two classes (Wake and Anesthetized).

Artificial neural network (ANN) based detection of anesthetic levels have been researched by several researchers. Watt [27] uses a three-layered feed forward neural network for detection of the spectral signatures within EEG recording giving three distinct levels of anesthesia. He claimed the overall accuracy rate obtained is 77%. Krikic [28] suggested a new method which uses spectral entropy and embedded eigen-spectrum features. He used a type of neural network namely radial basis pattern classifier to reach overall accuracy rate of 98%.

IV. Methodology

The general form of computation done in neurons in any neural network is following the next two operations: to combine linearly inputs

$$y = w0 + \sum_{i=1}^{n} wi \,.\, xi \tag{1}$$

And a non-linear transformation

$$z = f(x) \tag{2}$$

Using some of the non-linear activation functions, usually two activation functions are widely used in classical ANN framework and they are the sigmoidal function beside the tanh function as shown next, respectively:

$$f(x) = \frac{1}{1+e^{-x}}. \tag{3}$$

$$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{4}$$

We can have fully connected layers of those neurons following previous paradigm, but conventional ANN paradigm shows limit to the approximations and conversion. Based on that researchers have proposed some alteration on the number of hidden layers as to be deeper beside some presentation of newer activation functions. Loss function is also another newer concept in Deep Learning with its Deep Neural Networks. Activation functions such as *Rectified Linear Units (RLU)* and *SoftMax* are newly introduced with deep Neural networks. The next shows their formulas, respectively:

$$f(x) = max(0;\, x) \tag{5}$$

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$$f(x) = \frac{e^{xi}}{\sum_{j=1}^{n} e^{xj}} \quad (6)$$

The weights in the ANN is adjusted during the training phase until the correct output vector is generated from a given input. This operation continues until the global error is minimized to an acceptable value. It is worth noting that we use the Feedforward Neural Network (FNN) to refer to the a more basic ANN architecture used. The neurons are connected forward in series way and its activation propagates in unidirectional from the input layer to the output layer [1].

V. MATERIALS

It has been known that there is a strong relation between Bispectral Index and the EEG graphic features and found that the anesthetic features are linearly correlated with the BIS reading for all levels of anesthesia. As many literatures has approached the classification of anesthetic levels, only the next levels illustrated in Table I are of concern to us. Human experts have assessed the anesthetic levels and reached 5 classifications labels; Awake state, light anesthesia, moderate anesthesia, deep anesthesia, and near suppression level. As noted earlier, we are implementing an artificial deep neural model to extract most dominant features from EEG signal in supervised manner that were classified by human experts in prior. The resulted DNN would then be used to classify test sets of data. In this work, the raw EEG data were not being processed by any preprocessing algorithms or filter intentionally done, therefore bandpass filters were not used beside down or up sampling or even baseline removals. The reason behind that is two folded, one for leaving the processing light and fast to work noticeably fast for real time applications, while the other is to show the effectiveness of the deep learning when used in processing raw EEG data.

The EEG data generated from the 22 subjects were taken under full Anesthesia for different surgery time spanning from ½ hour to 2 hours. Although noise and deformation of the EEG were quite high with the beginning of the surgery giving unclear EEG signal patterns, but some were in good shape and were successfully extracted for training the DNN model. Finally, the resulted good records that span equally between the two anesthetic levels were only witnessed in only 7 subjects in which we based our training sets on.

For each experiment only one second epoch was extracted (128 samples). And to investigate performance of the proposed DNN model for DoA prediction, we created 7 test data that were showing quite clear Awaken epochs and plenty of Anesthetized epochs. For each subject (patient) 2 sets of datasets create, i.e., one for Awaken state and the other for Anesthetized state. Two schemes to organize training datasets were also followed; one to construct data set for a particular subject for sole training; while the others work as test sets; and in another scheme, all datasets except one are used for training leaving the one set for testing.

Totally 121,000 epochs were obtained from 7 subjects and later the other 15 subjects were taken some of their epochs for testing. We have to bear in mind that, the datasets were measuring different brain activities for different stages of hypnosis stages.

Training sets were intentionally extracted to fill 90% of the total available sets while the remaining 10% epochs were selected for testing. Anyway, we further re-distributed trainig_to_testing datasets to balance different configuration that we thought would be more helpful in determining the best distribution raises to the best DNN performance.

We have used a so-called comma-separated values (CSV) data, the recorded data organized to, in this work (series of EEG data till 128 samples per epoch). It was exported from MATLAB program responsible to open the long EEG file and cut to small epochs. Then the result is de-normalized on multiple sets of data then joined together resulting in the CSV data that the DeepLearning4J the JAVA programming uses for all neural network computation.

VI. RESULTS

The complete data of five subjects have been used to train and test the network with. In a total of 3610 epochs each with 128 readings giving a total of 462,080 data readings. Then data has been arranged such that the one which gives a specific class are to be grouped together then comes the other class group. In a total of two classes cover the two anesthetic levels, Waken and Anesthetized.

Three different configuration of data training has been implemented: the *train_and_test_all* in which 65% used for training and remaining 35% is kept for testing. Another configuration is the train one and test all. Also, *train_all_except_one* for test. And finally, *train_one_and_test_on_each* other alone. Next table shows results.

Table I shows the accuracy of the five subjects validation results emerged from DeepLearning4J package when all are used for train and subsequent test. The percentage of the taken epochs for train to the test is 65% to 35%. Accuracy up to 100% reached when chosen a batch size of less than 1000. Table II shows validation results for the configuration of taking one subject for training and leaving the others for testing. This one has resulted in an accuracy up to 93%. The reason behind other lower accuracies is the EEG subject difference and the abundance of clean signals prior to and during anesthesia.

Tables III and IV depict the other two training configurations where one subject is taken for training and the others are grouped in one set for testing and vice versa. An accuracy of 90% and 99% for the consequent two methods has been reached. The result indicators in the following tables are based on the next interpretations:

1) Accuracy: is defined as the percentage of epochs that were correctly identified by our model.

2) Precision: is the number of true positives divided by the number of true positives and false positives.

3) Recall: The number of true positives divided by the number of true positives and the number of false negatives.

4) F1 Score - Weighted average of precision and recall.

Here the Accuracy measures the model overall performance, while the Precision, Recall and F1 measure a model's relevance.

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For Comparison purposes another four references has been used for benchmarking. In [29] studied the use of neural networks in the classification of anesthesia depth level using recurrent neural networks (shallow neural networks) and reached an accuracy of 99.6%. Another work [30] has used Elman Neural Networks and Multilayer Perceptron MLP to reach an accuracy of 95% and 99%, respectively. Both of those works have used three Anesthetic levels of low, medium, and high. A combined wavelet and neural network classifiers has been studied in [31] with an accuracy of classification reaching 96.6%. All those works have reported results based on three level of anesthesia and inclusively using features extracted from the EEG signal for trained data, beside using shallow neural networks. Nevertheless, our works have used a deep neural network based on deep learning operating exclusively on raw EEG signals, classifying only two anesthetic levels and reported a maximum accuracy of 97%.

VII. Conclusion

This experimented study demonstrated that the DL training with EEG data set is able to detect two levels of anesthesia in an untrained (unseen) data set corresponding to new subjects with high accuracy up to 97%. Experiments have shown that multiple factors increase the training and the recognition accuracies, such as increasing training data, having more subject's diversities contributing those data, beside choosing cleaner training epochs, in addition to tuning the hyperparameters of the network and in particularly the training batch size.

TABLE I. Test Results Conducted on All Subject's Data But Distributed based on 65% for Training and 35% for Testing. Batch Size are Different, But the Data Epochs Is 3610 X 128

Batch Size	**Accuracy**	**Precision**	**Recall**	**F1 Score**
< 1000	**100%**	100%	100%	100%
1000	**92%**	85%	73%	77%
3610	**90%**	87%	86%	87%

TABLE II. Test Results on the 5 Subjects Data But Taken as Train One and Test One. The Training Data Size Is Different According to Subject Trained

Epochs	**Trained**	**Tested**	**Accuracy**
235 Class 0 235 Class 1	P1	P2 P6 P7 P19	85% 71% **93%** 86%
141 Class 0 558 Class 1	P2	P1 P6 P7 P19	68% 44% **74%** 69%
157 Class 0 1032 Class 1	P6	P1 P2 P7 P19	40% 61% 68% **75%**
290 Class 0 290 Class 1	P7	P1 P2 P6 P19	**85%** 84% 72% 79%
60 Class 0 623 Class 1	P19	P1 P2 P6 P7	**35%** 38% 38% 38%

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TABLE III. TEST RESULTS ON THE SAME SUBJECTS DATA BUT TAKEN AS TRAIN ONE AND TEST ALL. READINGS ARE GIVEN FOR DIFFERENT BATCH SIZES. THE TRAINING DATA SIZE IS DIFFERENT ACCORDING TO SUBJECT TRAINED

Trained On	**Tested**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
P1	P (2, 6, 7, 19)	78% 71% **82%** 79%	76% 67% 50% 50%	76% 76% 82% 79%	76% 66% 90% 88%
P2	P (1, 6, 7, 19)	**90%** 87% 82% 69%	85% 87% 83% 50%	83% 83% 86% 69%	84% 85% 82% 82%
P6	P (1, 2, 7, 19)	**82%** 79% 67% 48%	81% 80% 71% 50%	74% 74% 76% 48%	76% 75% 66% 65%
P7	P (1, 2, 6, 19)	**87%** 85% 83% 78%	84% 84% 84% 82%	73% 73% 73% 73%	77% 76% 76% 74%
P19	P (1, 2, 6, 7)	**80%** 77% 72% 64%	80% 80% 78% 73%	67% 67% 67% 66%	69% 68% 66% 62%

TABLE IV. TEST RESULTS ON THE SAME SUBJECT'S DATA BUT TAKEN AS TRAIN ALL EXCEPT ONE THEN TEST THAT ONE. READINGS GIVEN FOR DIFFERENT BATCH SIZES. THE TRAINING DATA SIZE IS DIFFERENT ACCORDING TO SUBJECT TRAINED

Trained On	**Tested**	**Accuracy**	**Precision**	**Recall**	**F1 Score**
P (2, 6, 7, 19	P1	**82%** 79% 73%	86% 82% 72%	82% 82% 82%	81% 79% 70%
P (1, 6, 7, 19)	P2	**99%** 99% 99%	99% 99% 99%	99% 99% 99%	99% 99% 99%
P (1, 2, 7, 19)	P6	**85%** 82% 75%	6*% 73% 73%	67% 67% 66%	67% 69% 67%
P (1, 2, 6, 19)	P7	89% 90% **92%** 91%	89% 87% 62% 50%	89% 88% 86% 91%	89% 88% 67% 95%
P (1, 2, 6, 7)	P19	**96%** 96% 96% 96%	89% 92% 94% 94%	91% 91% 91% 91%	90% 93% 92% 93%

REFERENCES

[1] Yuan, L. and Cao, J., 2017, June. Patients' EEG Data Analysis via Spectrogram Image with a Convolution Neural Network. In International Conference on Intelligent Decision Technologies (pp. 13-21). Springer, Cham.

[2] K. P. Thomas, G. Cuntai, C. T. Lau, A. P. Vinod, and A. Kai Keng, "A New Discriminative Common Spatial Pattern Method for Motor Imagery Brain Computer Interfaces," IEEE Transactions on Biomedical Engineering, vol. 56, pp. 2730-2733, 2009.

[3] Q. Wei and Z. Wei, "Binary particle swarm optimization for frequency band selection in motor imagery based brain-computer interfaces,"Bio-Medical Materials and Engineering, vol. 26, pp. 1523-S1532, 2015.

[4] A. S. Aghaei, M. S. Mahanta, and K. N. Plataniotis, "Separable Common Spatio-Spectral Patterns for Motor Imagery BCI Systems,"IEEE Transactions on Biomedical Engineering, vol. 63, pp. 15-29, 2016.

[5] X. Li, X. Lu, and H. Wang, "Robust common spatial patterns with sparsity," Biomedical Signal Processing and Control, vol. 26, pp. 52-57, 4// 2016.

978-1-5386-4185-9/18/$31.00 ©2018 IEEE

[6] W. Wu, Z. Chen, X. Gao, Y. Li, E. N. Brown, and S. Gao, "Probabilistic Common Spatial Patterns for Multichannel EEG Analysis," Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 37, pp. 639-653, 2015.

[7] A. Zhang, B. Yang, and L. Huang, "Feature Extraction of EEG Signals Using Power Spectral Entropy," in International Conference on BioMedical Engineering and Informatics, Sanya, 2008, pp. 435 - 439.

[8] A. Sharma, S. Imoto, and S. Miyano, "A Top-r Feature Selection Algorithm for Microarray Gene Expression Data," IEEE/ACM Trans. Comput. Biol. Bioinformatics, vol. 9, pp. 754-764, 2012.

[9] J. Luo, Z. Feng, J. Zhang, and N. Lu, "Dynamic frequency feature selection based approach for classification of motor imageries," Computers in Biology and Medicine, vol. 75, pp. 45-53, 8/1/ 2016.

[10] A. Sharma, K. K. Paliwal, S. Imoto, and S. Miyano, "A feature selection method using improved regularized linear discriminant analysis," Machine Vision and Applications, vol. 23, pp. 775-786, April 2014.

[11] A. Sharma, K. K. Paliwal, S. Imoto, and S. Miyano, "A feature selection method using improved regularized linear discriminant analysis," Machine Vision and Applications, vol. 25, pp. 775-786, 2014.

[12] A. Sharma and K. K. Paliwal, "A deterministic approach to regularized linear discriminant analysis," Neurocomputing, vol. 151, Part 1, pp. 207-214, 3/3/ 2015.

[13] A. Sharma and K. K. Paliwal, "Rotational Linear Discriminant Analysis Technique for Dimensionality Reduction," IEEE Transactions on Knowledge and Data Engineering, vol. 20, pp. 1336-1347, 2008.

[14] A. Sharma and K. K. Paliwal, "A Gradient Linear Discriminant Analysis for Small Sample Sized problem," Neural Processing Letters, vol. 27, pp. 17-24, 2008.

[15] X. Li, X. Chen, Y. Yan, W. Wei, and Z. J. Wang, "Classification of EEG Signals Using a Multiple Kernel Learning Support Vector Machine," Sensors, vol. 14, pp. 12784-12802, July 2014.

[16] D. L. Rocca, P. Campisi, B. Vegso, P. Cserti, G. Kozmann, F. Babiloni, et al., "Human Brain Distinctiveness Based on EEG Spectral Coherence Connectivity," IEEE Transactions on Biomedical Engineering, vol. 61, pp. 2406-2412, September 2014.

[17] M. Sabeti, S. Katebi, and R. Boostani, "Entropy and complexity measures for EEG signal classification of schizophrenic and control participants," Artificial Intelligence in Medicine, vol. 47, pp. 263-274, November 2009.

[18] N.-H. Liu, C.-Y. Chiang, and H.-C. Chu, "Recognizing the Degree of Human Attention Using EEG Signals from Mobile Sensors," Sensors, vol. 13, pp. 10273-10286, August 2013.

[19] L. Brown, B. Grundlehner, and J. Penders, "Towards wireless emotional valence detection from EEG," in Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2011, pp. 2188-2191.

[20] Krizhevsky, A., Sutskever, I. & Hinton, G. E. ImageNet classification with deep convolutional neural networks. Adv. Neural Inf. Process. Syst. 1–9 (2012).

[21] Graves, A., Mohamed, A. & Hinton, G. Speech recognition with deep recurrent neural networks. IEEE Int. Conf. Acoust. Speech Signal Process. (2013). doi:10.1109/ICASSP.2013.6638947.

[22] Collobert, R. & Weston, J. A unified architecture for natural language processing: deep neural networks with multitask learning. Proc. Twenty-fifth Int. Conf. Mach. Learn. 20, 160–7 (2008).

[23] Tania Morimoto and Sean Sketch. Classifying brain's motor activity via deep learning. Stanford University, CS 229 Machine Learning., 2014.

[24] Ewan Nurse, Benjamin S. Mashford, Antonio Jimeno Yepes, Isabell Kiral-Kornek, Stefan Harrer, and Dean R. Freestone. Decoding eeg and lfp signals using deep learning. CF '16 Proceedings of the ACM International Conference on Computing Frontiers, pp. 259, 266, 2016.

[25] Ian Walker. Deep convolutional neural networks for brain computer interface using motor imagery. Thesis, Department of Computing, Imperial College London., 2015.

[26] A. Zaitcev, G. Cook, L. Wei, M. Paley, and E. Milne, "Feature extraction for BCIs based on electromagnetic source localization and multiclass Filter Bank Common Spatial Patterns," in Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE, 2015, pp. 1773-1776.

[27] R. C. Watt, M. J. Navabi, P. J. Scipione, S. R. Hameroff, E. S. Maslana, "Neural network estimation of anesthetic level using EEG spectral signatures" , Annu International conference of the IEEE engineering in medicine and biology society. November 1990.

[28] M. Krkic. S. J. Roberts, I. A. Rezek, and C. Jordan. "EEG-based assessment of anesthetic-depth using neural network'. Proc Inst. Elect Eng. AI methods in biosignal analysis. Vol.10. pp.1-6. April 1996.

[29] Srinivasan, V., Eswaran, C., and Sriraam, N., "EEG based automated detection of anesthetic levels using a recurrent artificial neural network". International Journal of Bioelectromagnetism. 7:267–270, 2005.

[30] Lalitha, V., and Eswaran, C., "Automated detection of anesthetic depth levels using chaotic features with artificial neural networks". Journal of Medical Systems. 31(6):445–452, 2007.5.

[31] Benzy, V. K., and E. A. Jasmin. "A combined wavelet and neural network based model for classifying depth of anaesthesia." Procedia Computer Science 46 (2015): 1610-1617.

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