Analysis of Electroencephalograms: Application of Artificial Neural Networks for Detection of Epileptic Discharges

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***Abstract* — Algorithms based on multilayer feedforward and recurrent neural networks were employed to automatically detect epileptic discharges (spikes) in unprocessed electroencephalograms (EEG). Results were compared to two separate benchmarks: analysis provided by an expert and output of algorithm based on mathematical morphological filters [3]. Feedforward neural network was able to on average detect ~95% of spikes detected by the expert and ~60% of spikes detected by an aforementioned algorithm. Recurrent neural network was able to on average detect ~93% and 80% spikes respectively. While in some cases artificial neural network was able to outperform algorithm based on morphological filter in terms of detected spikes, the main issue remains the high number of false positives and in particular low-amplitude spike-like waveforms that cannot be utilised for diagnostic purposes.**

Keywords— Electroencephalograms, Epileptiform discharge, Artificial neural network, Machine Learning, Epilepsy

I. Introduction

Early and accurate diagnostics of epilepsy is one of the key factors in order to prescribe proper treatment and improve the quality of life for patients and caretakers alike. Electroencephalograms (EEG) remain one of the main tools used for diagnostic purposes and can be accurately analysed by professionals; however, such process is time consuming and inefficient. While many algorithms are employed to support manual EEG analysis, issues like classification quality or inflexibility still limit practical application.

Despite that currently there are many algorithms designed for automatic EEG analysis, in many cases it's still done manually by visually inspecting recording [2]. Given that EEG recordings can last from few minutes to several hours, nonetheless are composed of 21 or more channels and can be affected by various noises [2], such analysis remains difficult and time consuming. While aforementioned algorithms certainly help in EEG analysis, they are not always reliable to identify elements of interest and in most cases are hardcoded to detect specific elements thus making them non-reusable for other diagnostic purposes (see [2], [3], [4]).

The main purpose of this research is to analyse how machine learning and in particular artificial neural networks can be employed for the automatic EEG analysis. The main motivation behind selection of this method is an opportunity to develop an algorithm that can potentially solve problems mentioned earlier and improve identification of various EEG elements. Nonetheless, it would be much easier to adjust such algorithm for diagnostic of other medical conditions. Case study is done with spikes common to benign childhood epilepsy with centrotemporal spikes (referred as Rolandic epilepsy from now on), yet described methods can potentially be applied for diagnostic purposes of other types of epilepsy and brain injuries alike.

The paper is organized into three main parts: first of all we will discuss the current state of research in an automatic EEG analysis. Secondly we will describe data collection and preparation procedures as well as main research methods. Finally we will present how multilayer feedforward neural network and recurrent neural network was able to deal with aforementioned research goals.

II. Related Work

Idea to develop algorithm for automatic EEG analysis dates back to 1970s. In 1972 Carrie JR. [5] published paper describing one of the first automatic algorithms aimed to detect epileptic discharges (also called spikes) visible in EEG. Algorithm was based on calculation of certain spike features, namely specifications of spike peak and sharpness. Later Guedes de Oliveira, et al. [6] described method to identify EEG spikes based on spike curves and a certain threshold was applied to separate spikes from non-spikes. One of more recent works was published by A.V. M. Misiūnas, et al. where mathematical morphological filters were employed to identify EEG spikes associated with Rolandic epilepsy [3]. Based on expert evaluations – this algorithm is able to identify ~90% EEG spikes. This algorithm was also used in this paper for comparison purposes.

While aforementioned algorithms present good results in certain cases they all face several issues:

1) Sensitivity to noise. In most cases results are highly affected by noise, which highly depends not only on how recording was performed but on device itself

2) Being hardcoded for one specific problem. Therefore application for other purposes remains limited and in many cases – impossible.

Machine learning algorithms (and especially artificial neural networks) are in many cases employed to address similar problems. Main advantage of such method is that it's not necessary to specify spike duration and morphology [8] therefore neural network can be quickly adjusted (trained) to analyse signals recorded with different electroencephalographs and employed to detect spikes with different durations and morphologies. Research related to application of neural networks for EEG analysis can mostly fall within two distinct categories: *pre-processed EEG data* (see. Gabor and Seyal, 1992 [11]; Webber et al., 1996 [9]) and *raw EEG data* (see Ozdamar and Kalayci, 1998 [10]). Ozdamar and Kalayci was able to design a neural network that can correctly classify EEG elements (with main purpose of spike-detection) with sensitivity of ~94%, however Webber et al. [9] was not able to replicate such results (and found true positives to be ~76% and sensitivity ~40%).

Cheng-We and Hsiao-Wen [12] used feedforward neural network composed of 3 layers (with 30, 6 and 1 neuron accordingly). They also tried to replicate research of Ozdamar and Kalayci [10] and concluded that initial results was possibly biased due to errorous data preparation. One of the main issues authors encountered is overemphasis on 10^{th} neuron. Authors argue that this happened due to fixed location of spike centres, where 10^{th} element of supplied time-series always aligned to spike centre, thus resulting I high numbers of false positives. Authors tried to train neural network with varying coordinates of spike centre relative to analysed section, yet were unsuccessful to achieve satisfactory results and concluded that at that point in time computing technologies were not viable to apply neural networks for EEG analysis. Nonetheless this emphasizes importance of data preparation and training strategy.

While it's rather difficult to analyse raw EEG data, much better results were achieved while working with pre-processed datasets. Nigam, and Graupe [21] employed feedforward neural networks for spike detection, however signal was pre-processed with non-linear filters. Authors were able to achieve ~96% classification accuracy thus implying that data pre-processing is a good alternative. However, given that such filters must be individually prepared for different EEG this method has the same issues as discussed in previous chapters therefore it's not further analysed in this paper.

III. CHARACTERISTICS OF ROLANDIC EPILEPSY EEG SPIKES AND DATA COLLECTED FOR THIS REASERCH

A. EEG spikes specific for Rolandic epilepsy

Rolandic epilepsy is one of the most common types of childhood epilepsy with ~23% of early school age (mean age ~7 years) children being affected [13]. In most cases, the disease affects boys more than girls (with ration 5 to 1). EEG readings of patients diagnosed with this type of epilepsy have distinct sharp waveforms also called spikes. A typical spike is characterized by high amplitude (more than twice higher than average amplitude of normal brain activity prior spike) and change of phase (see [13], [14]). There are also non-typical EEG elements associated to epileptic discharges yet given that those only constitute from 1% to 7% of all cases (see [15], [16]); therefore, those are not further investigated. While aforementioned spikes might slightly differ, common spike characteristics remains similar among different patients.

Spikes can be classified into two main categories based on duration [22]:

- *Spikes* – duration of 20 – 70 ms.
- *Sharp waves* – duration of 70 – 200 ms.

Both can be described as short term elements, clearly distinguishable from normal brain activity with the main component having negative phase in most cases. Both (spike and sharp waves) have similar initial (or elevation) stage; however, sharp waves have longer demotion stage. In this paper spikes are not distinguished from sharp waves and are analysed together.

Second distinct characteristic can be defined as a combination of three key measurements: amplitude, duration and sharpness. Frost J.D. [17] analysed aforementioned characteristics among spikes with a duration up to 70 ms and developed CPS (composite spike parameter) index that can help to detect Rolandic EEG spikes. The author defined sharpness as second derivative of voltage at spike peak and normalized by amplitude. Among all spikes analysed by author mean values of amplitude, duration and sharpness were 160,9μV, 74ms. and 0.022 respectively.

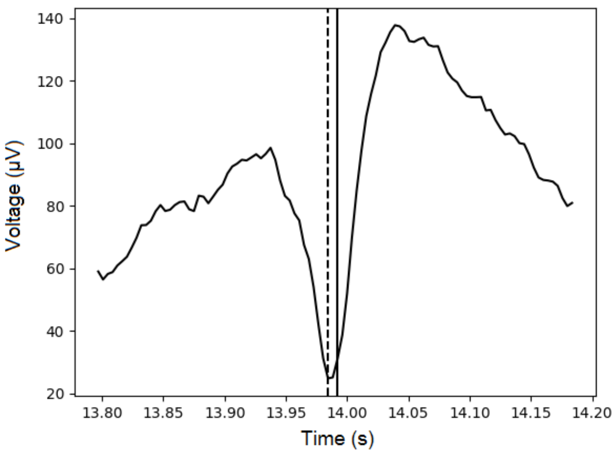
B. Data description and preparation

For this research EEG readings of 20 patients was used. Among those data of 3 patients was analysed by expert. In each of the files aforementioned expert (a paediatric neurologist) marked spikes and elements that visually resemble spikes but are definitely not. In total coordinates of 499 spikes were collected.

Considering spike characteristics discussed previously, also given that sharp waves and spikes can be both associated with Rolandic epilepsy – a fixed spike length of 200 ms (maximum length of sharp wave) will be used in this research. Nonetheless sub-elements will not be separated in any way and will be treated as one typical epileptic discharge associated with Rolandic epilepsy. EEG readings used in this paper was presented in .edf (European data format) type files recorded in 256Hz sample rate (1 element in time series is equal to 3.90625 ms). Further data analysis was done in fixed-duration sections. In order to prepare such sections, 200 ms. (maximum spike duration used in this research) was approximated to 50 elements in time series or roughly 196 ms. Each section with spike was prepared by choosing 25 elements backwards from spike centre and 25 elements forward, thus ensuring that spike centre (peak) and centre of section will align.

While expert tried to mark spikes at the exact centre it was proven to be difficult to point exact coordinates, therefore data was further post-processed by shifting positions of spike centres to lowest voltage value in the section. While theoretically spike peaks can have positive phase it was not the case for this data therefore no further adjustments was done. Example is presented in figure 1

FIG 1. EXAMPLE OF INITIAL (SOLID VERTICAL LINE) AND ADJUSTED (DASSHED VERTICAL LINE) SPIKE CENTERS



Waveforms that morphologically resemble spikes, however have lower amplitude, were not included to initial sample. Those can be considered a non-typical spikes. While those sometimes can be associated with Rolandic epilepsy, however, as discussed with expert, final diagnosis is never based on such “non-typical“ elements. Summary of amplitude characteristics of all spikes is presented in table I where it is evident that average amplitude is approximately 12% lower when compared to research of Frost J.D. [17] with ~35% lower standard deviation. Both can be explained by usage of different measuring device, however deviations remains insignificant.

TABLE I. AMPLITUDE CHARACTERISCITS OF EEG SPIKES USED IN THIS REASERCH

Mean	142,8
Standard deviation	44,2
Minimum	51
Maximum	325,7

Aforementioned data was used for all further researches presented in this paper.

As discussed in previous chapter data pre-processing can potentially improve detection quality, however we decided to keep it to a minimum, mostly because EEG data pre-processing methods used for feature extraction or denoising are in most cases designed to work with specific data (eg. Electrooculogram (EOG) induced noise can be successfully removed in pre-procesing stage by applying regression based methods [23] or filters based on independent component analysis [24] however such approach requires to have data with separate EOG measurements which is not always available). However, main purpose of this research is to develop algorithm that can be employed to analyse data from various sources with minimal adjustments as well as to potentially work with extraction of other EEG features. Nonetheless, working with raw EEG allows to evaluate neural network’s ability to deal with variability in data. Considering aforementioned arguments only 50Hz notch filter was applied in order to reduce noise created by power supply.

IV. NEURAL NETWORK DESIGN

In this paper we employ and compare two neural network architectures: multi-layered feedforward neural network and recurrent neural network based on LSTM model.

A. *Training data*

As discussed in paragraph III data from 3 patients and 4 EEG channels were used for initial training of neural networks. Given that main purpose of this analysis is to be able to identify spikes in full EEG channel data was prepared in following manner. Each channel was divided into sections each consisting of 50 elements based on rolling window i.e. each section starts with element n and ends at n+50 while next section starts at n+1 and ends at n+1+50. Under such rules each channel is represented by number of sections equal to number of elements in channel.

In the next step segments was classified into two main categories with corresponding numeric values:

0. Non-spikes

1. Spikes

Data of full EEG channel was used for training. Each section was classified as spike, if centre of that section falls within interval:

*[v – Section size * 0,425; v + section size* 0, 425]*

Where v – centre of actual spike, section size – section size or in this case 200 ms.

Coefficient 0,425 represents 42,5 % and is calculated under main assumption that at least ¾ of spike must be visible in order to correctly classify segment it as spike. Therefore (assuming that all elements of specific segment falls within interval [0 ms.; 200 ms.] with spike centre being at 100 ms.) the earliest point when ¾ of shortest possible spike (20ms) can be visible in this segment is when x coordinate of spikes’ centre is equal to 15 ms. (3/4 * 20 ms. = 15 ms.) and latest point is 185 ms. (200 ms. – 15 ms.). This gives interval of [15 ms.; 185 ms.] or ~21 element. Summary of data used for training is presented in TABLE II.

TABLE II. SUMMARY OF TRAINNG DATA

Patient	Chanel	Spikes	Segments classified as spikes	Total segments
1	T4	177	4248	47310
2	T3	144	3456	185550
2*	T5	28	672	185550
3	P4	150	3600	66510

** Due to low number of spikes, data from patient 2, cahnnel T5 was used only for training purpose and not utilized for testing.*

B. Measuring Classification quality

At this point it‘s important to establish criteria to evaluate algorithm performance. Typical binary classification accuracy is not suitable here for several reasons:

First of all, given that in typical 60 second EEG channel (that is consisted of 15360 segments), only less than 1% of those segments can be typically classified as spikes, simple binary accuracy will provide relatively good results despite that spikes was not necessarily found. Nonetheless main purpose of such algorithms is spike detection. Also when using binary classification accuracy, a case where multiple sections was detected next a single spike, is treated in a same manner as when multiple sections were detected next to different spikes. Yet again – given that main purpose is to detect all spikes this would not represent desired performance.

Therefore 3 main criteria was defined:

1) Ratio of all detected spikes with spikes detected by expert (true spikes)
2) Elements (group of sections) falsely classified as spikes
3) Spikes falsely classified as non-spikes

Given that exact coordinates of spikes were well-known following methodology was employed:

1) All algorithms were design in a way that only sections that were classified as spikes will be outputted. If section was classified as spike it‘s coordinate is adjusted in following manner:

$$x_n = x_o + section\ size / 2$$

where x_n – new coordinate of segment;

x_o – old coordinate of segment (number of first element);

section size – 200 ms

2) Each x_n is then compared to known spike coordinates. Whenever it falls within aforementioned interval of:

$$[v – section\ size * 0,425;\ v + section\ size * 0,425]$$

(where v – centre of actual spike)

that section is considered correctly classified and spike is considered detected.

According to our evaluation methodology - each spike can be only detected once, therefore more sections (classified as spikes) around single spike will not inflate result. All sections outside interval are classified as non-spikes. Those sections were further grouped in order to assess number of false positives where each group was composed of up to 42 sections starting from first false positive section, with last one being not further than 42 elements while ignoring true positives.

C. Application of Multilayer Feedforward Neural Network

In order to design optimal structure of neural network (number of neurons in hidden layers) a k-fold cross validation was employed (with k = 3). Due to non-standard measurement, data was not shuffled but instead neural network was trained with data from two patients, while tested on data from third one. As in typical cross validation such technique was repeated 3 times. In order to have a starting point several researches were taken into consideration:

Based on research by Cheng-Wen Ko and Hsiao-Wen Chu [12] a network architecture consisting of 3 layers with 30 (segment size), 6 and 1 neurons accordingly were chosen;

Cheng-wen et. al. [18] used four layered neural network with 4,5 and 1 neurons (input layer is excluded since it always holds number of neurons equals to segment size)

Weng and Khorasani [19] used four layered neural network with 9, 90 and 1 neurons.

Mirchandani and Cao [20] presented an idea that number of neurons in hidden layer can be calculated using following formula:

$$H = \log_2 M$$

Where H – number of neurons in hidden layer, M – largest number of linear separable regions in input data (in this M = 50 – 1 = 49).

Using aforementioned researches as a starting point and employing k-fold cross validation optimal feedforward network architecture was found to be 4 layers with following distribution of neurons in each corresponding layer: 50, 25, 90, 1. Averaged results of cross validation is presented in table III (TP and FP refers to True Positives and False Positives respectively).

TABLE III. CLASSIFICATION RESULTS OF FEEDFORWARD NEURAL NETOWRK WHEN COMPARING TO ANALYSIS PROVIDED BY EXPERT

Average detected spikes	Δ found spikes	Average FP sections	Δ FP sections
95%	4%	30%	48%

While algorithm was able to detect ~95% spikes detected by expert, there were ~30% of segments (not spikes) falsely classified as spikes. Nonetheless ~48% difference of FP and TP segments in channels indicated that results are highly dependent upon channel. Nonetheless at this point analysis was only performed on 3 EEG files therefore results are not good representation of algorithm’s performance.

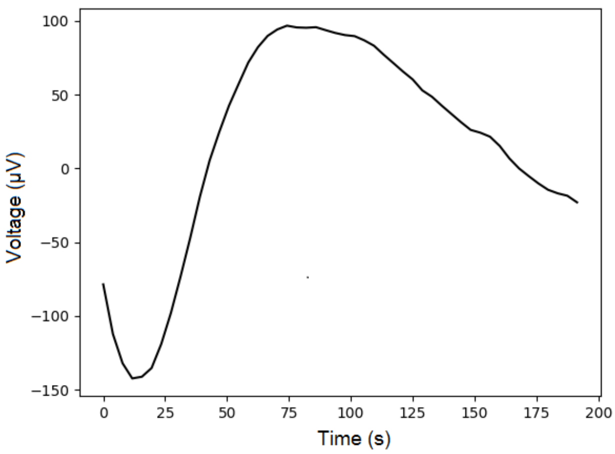
In order to expand analysis results from single channel were further processed. In order to ensure that each false positive segment will represent a new spike results were grouped. First of all true positives were properly identified and matched to corresponding spikes. Then each false positive is grouped so that each group was filled with segments that are no further from the false positive (that is not part of any other group) than 50 elements. E.g. whenever segment is classified as false positive a new group is formed where that segment is a first group member and all other segments that are distanced no more than 50 elements from the first one are assigned to the same group. One distant segment can have its’ own group.

T3 channel of patient 2 was further processed using aforementioned technique thus resulting in 53 false positive groups that will be referred as 53 false positives from now on. Further analysis of false positives revealed that such elements can be classified into 3 main categories:

1) Segments that are close to spike, however falls outside pre-defined range.
2) Spike-like waveforms with low amplitude
3) Elements that are not related to spikes

Technically 1st group is classified correctly, however given that spike peak is on the edge of the segment (at least 3/4 of spike is not visible) it would be impossible to tell without any further references that this is actually a spike therefore such elements won‘t be included or reclassified. See fig.2 for example.

FIG 2. BARELY VISIBLE SPIKE CLASSIFIED AS FALSE POSITIVE



Despite all efforts – due to low amount of high quality data it is difficult to came up to conclusions therefore data sample (of 3 patients) was increased by 17 more EEG files without spike coordinates. To prepare more results for validation an algorithm based on morphological filters were employed [3]. All 17 files were analysed and results were compared with ones produced by algorithm based on neural network. Comparison was done in the same manner as previously discussed.

Summary of results are presented in table IV. All numbers (True positives or false positives) are in relation to results of algorithm based on morphological filters. Also 3 channels, where aforementioned algorithm identified less than 10 spikes, were removed from final results.

TABLE IV. CLASSIFICATION RESULTS OF FEEDFORWARD NEURAL NETOWRK COMPARED TO ALGORITHM BASED ON MORPHOLOGIC FILTERS

	Detected spikes	TP	FP
St. dev	37%	19%	19%
mean	60%	22%	78%
min	0%	0%	44%
max	99%	56%	100%

On average feedforward neural network was able to detect 60% of spikes, detected by algorithm based on mathematical morphological filters, however a lot of elements were falsely identified as spikes (average of ~78%). Nonetheless in 11 out of 17 (with 3 channels removed from initial sample) cases neural network was able to detect more than 50% spikes with 86% detected spikes on average.

At this point false several examples of positives were sent to expert for detailed analysis. Due to limited time and resources expert was able to analyse only 12 false positives however this potentially reveals certain trend. Among 12 results were distributed in following order:

- 2 were identified as spikes
- 2 were identified as non-spikes
- 8 were identified as either spike-like waveforms with low amplitude or true spikes, however expert was not able to correctly classify those with certainty.

FIG 2. EXAMPLE OF SPIKE (CICRLED ON THE LEFT SIDE) AND LOW AMPLITUDE SPIKE-LIKE WAVEFORM (ON THE RIGHT)

Therefore we conclude that the main problem remains low amplitude or low sharpness spike-like waveforms that are constantly identified as spikes although are unwanted for diagnostic purposes.

To sum up we conclude that multilayer feedforward neural network can potentially be used for primary analysis of EEG with a purpose to identify spikes associated with Rolandic epilepsy and can detect ~60% of spikes on average when comparing with algorithm based on morphological operations or ~95% when comparing to data prepared by expert. However main problem remains low amplitude, spike-like waveforms identified as spikes that can potentially be removed by certain filters. Finally, algorithm discussed in this paragraph did not detected spikes in channels where there potentially were no spikes (or low number of spikes, eg. 1).

D. Recurrent Neural Network

Given that too many low-amplitude spike-like waveforms were falsely classified as spikes, a recurrent neural network was employed to address this issue. Main rationale for this type of neural network is that it captures information from previous elements therefore it‘s actually possible to estimate spike amplitude relative to the background brain activity.

Jezusefovich et. al [7] analysed more than 10000 recurrent neural network architectures and proven that there is no alternative that can consistently outperform LSTM model and

GRU (gated recurrent unit). While there are not many researches where LSTM was applied for EEG analysis, considering previous statement this model was selected as potentially offering the best performance.

While working with the same data, first step was to identify optimal network architecture. Same three-fold cross validation was applied as previously discussed with feedforward neural network. Optimal network depth (layers) was proven to be 1 input layer, 2 LSTM layers and 1 output layer (feedforward neural network). Each LSTM layers had 90 units (also referred as cells). Results of cross validation (when algorithm output was compared to analysis performed by expert) are presented in Table V. Only results of network with aforementioned optimal structure is included. It is evident that while recurrent neural network performed slightly worse in comparison to feedforward neural network (eg.93% detected spikes versus 95%), deviation is minor and given low number of test and training samples in each case we conclude that there are no major differences in performance when testing on similar type of data.

TABLE V. CLASSIFICATION RESULTS OF RECURRENT NEURAL NETOWRK WHEN COMPARING TO ANALYSIS PROVIDED BY EXPERT

Average detected spikes	Δ found spikes	Average FP sections	Δ FP sections
93%	10%	30%	10%

Furthermore, research was repeated in a same manner as previously (compared to results of algorithm based on morphological filters [3]). Data of same 20 patients were used. Results are presented in TABLE VI. Same as previously - all numbers (True positives or false positives) are in relation to results of algorithm based on morphological filters. Also 3 channels where aforementioned algorithm identified less than 10 spikes was excluded.

TABLE VI. CLASSIFICATION RESULTS OF RECURRENT NEURAL NETWORK COMPARED TO ALGORITHM BASED ON MORPHOLOGIC FILTERS

	Detected spikes	TP	FP
St. dev	26%	16%	16%
mean	78%	19%	81%
min	8%	2%	49%
max	100%	51%	98%

At this point recurrent neural network was able to detect mores spikes on average, however at the expense of false positives with a small increase from 78% to 81%. After visual analysis of false positives it was clear that same low amplitude waveforms are dominant in this group as well therefore it is evident that shift from feedforward to recurrent neural network alone can’t significantly improve results.

V. RESULTS AND DISCUSSION

Two algorithms aimed to detect spikes in unprocessed EEG data were analysed in this research.

The algorithm based on recurrent neural network was able to on average detect 78% of spikes (see table VI) when comparing results to an algorithm based on mathematical morphological filters. Also, it outperformed algorithm based on feedforward neural network by ~10% (see table V) on average in terms of detected spikes, but increased number of false positives by 3% on average. While neither algorithm developed in this paper is sufficient on its’ own for diagnostic purposes, neural networks can be used for data preparation or primary analysis.

While neural networks can effectively classify EEG spikes in some cases, the main issue is false positives and in particular - low amplitude spike-like waveforms (see figure 2). While in some cases such waveforms can be classified as spikes, those are not used for diagnostic purposes thus are undesirable and should be removed from the result set. It can possibly be achieved by applying amplitude based filters thus making such combined algorithm an effective tool for EEG analysis, however, this is beyond scope of this paper and is recommended for future research.

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REFERENCES

[1] EEG SIGNAL PROCESSING. Saeid Sanei and J.A. Chambers Centre of Digital Signal Processing Cardiff University, UK

[2] Samaitienė R. Rolando epilepsija sergančiu vaiku EEG pakitimu, miego bei elgesio sutrikimu ir klinikiniu charakteristikų sąsajos. Vilniaus universitetas, 2013.

[3] Misiūnas, A. V. M., Meškauskas, T., & Juozapavičius, A. On the implementation and improvement of automatic EEG spike detection algorithm.In: Proceedings of the Lithuanian Mathematical Society, Ser. A, Lietuvos matematikos rinkinys, 56, pp. 60–65, 2015. ISSN: 0132-2818.

[4] Wilson, S. B., & Emerson, R. (2002). Spike detection: a review and comparison of algorithms. Clinical Neurophysiology, 113(12), 1873-1881.

[5] Carrie JR. A hybrid computer technique for detecting sharp EEG transients.Electroencephalography and clinical Neurophysiology 1972;33(3):336–8.

[6] De Oliveira, P. G., Queiroz, C., & Da Silva, F. L. (1983). Spike detection based on a pattern recognition approach using a microcomputer. Electroencephalography and clinical neurophysiology, 56(1), 97-103.

[7] Jozefowicz, R., Zaremba, W., & Sutskever, I. (2015). An empirical exploration of recurrent network architectures. In Proceedings of the 32nd International Conference on Machine Learning (ICML-15) (pp. 2342-2350).

[8] Valenti, P., Cazamajou, E., Scarpettini, M., Aizemberg, A., Silva, W., & Kochen, S. (2006). Automatic detection of interictal spikes using data mining models. Journal of neuroscience methods, 150(1), 105-110.

[9] Webber, W. R. S., Lesser, R. P., Richardson, R. T., & Wilson, K. (1996). An approach to seizure detection using an artificial neural network (ANN). Electroencephalography and clinical Neurophysiology, 98(4), 250-272.

[10] Ozdamar O, Kalayci T. Detection of spikes with artificial neural networks using raw EEG. Comput Biomed Res 1998;31:122–142.

[11] Gabor, A. J., & Seyal, M. (1992). Automated interictal EEG spike detection using artificial neural networks. Electroencephalography and clinical Neurophysiology, 83(5), 271-280.

[12] Beritelli, F., Capizzi, G., Sciuto, G.L., Napoli, C. and Scaglione, F. (2018) Automatic heart activity diagnosis based on gram polynomials and probabilistic neural networks. Biomedical Engineering Letters, 8(1), pp.77-85.

[13] Ko, C. W., & Chung, H. W. (2000). Automatic spike detection via an artificial neural network using raw EEG data: effects of data preparation and implications in the limitations of online recognition. Clinical neurophysiology, 111(3), 477-481.

[14] Kramer U (July 2008). "Atypical presentations of benign childhood epilepsy with centrotemporal spikes: a review". J. Child Neurol. 23 (7): 785–90. doi:10.1177/0883073808316363. PMID 18658078

[15] Gloor P. Contributions of electroencephalography and electrocorticography inthe neurosurgical treatment of the epilepsies. Adv Neurol 1975;8:59–105.

[16] Fejerman, N., Caraballo, R., & Tenembaum, S. N. (2000). Atypical Evolutions of Benign Localization‐Related Epilepsies in Children: Are They Predictable?. Epilepsia, 41(4), 380-390.

[17] Panayiotopoulos, C. P. (1999). Benign childhood partial seizures and related epileptic syndromes (Vol. 15). John Libbey Eurotext.

[18] Frost, J. D., Hrachovy, R. A., & Glaze, D. G. (1992). Spike morphology in childhood focal epilepsy: relationship to syndromic classification. Epilepsia, 33(3), 531-536.

[19] Ko, C. W., Lin, Y. D., Chung, H. W., & Jan, G. J. (1998). An EEG spike detection algorithm using artificial neural network with multi-channel correlation. In Engineering in Medicine and Biology Society, 1998. Proceedings of the 20th Annual International Conference of the IEEE (Vol. 4, pp. 2070-2073). IEEE.

[20] Damaševičius, R., Napoli, C., Sidekerskienė, T. and Woźniak, M. (2017). IMF mode demixing in EMD for jitter analysis. Journal of Computational Science, 22, pp.240-252.

[21] Weng, W. D., & Khorasani, K. (1996). An adaptive structure neural networks with application to EEG automatic seizure detection. Neural Networks, 9(7), 1223-1240.

[22] Mirchandani, G., & Cao, W. (1989). On hidden nodes for neural nets. IEEE Transactions on circuits and systems, 36(5), 661-664.

[23] Nigam, V. P., & Graupe, D. (2004). A neural-network-based detection of epilepsy. Neurological Research, 26(1), 55-60.

[24] IFSECN, International Federation of Societies for Electroencephalography and Clinical Neurophysiology. A glossary of terms most commonly used by clinical electroencephalographers. Electroencephalogr Clin Neurophysiol 1974; 37:538–53.

[25] Princy, R., Thamarai, P., & Karthik, B. (2015). Denoising EEG signal using wavelet transform. International Journal of Advanced Research in Computer Engineering & Technology, 3.

[26] Vorobyov, S., & Cichocki, A. (2002). Blind noise reduction for multisensory signals using ICA and subspace filtering, with application to EEG analysis. Biological Cybernetics, 86(4), 293-303.