CNN classification of variance-based selected topo-maps of EEG

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ABSTRACT

Epileptic activity in the EEG record can manifest in different ways over time series. A classifier that would alert physicians to the possibility of different types of epileptic activity would be an effective tool. We created image data from EEG records, which we subsequently classified using the SqueezeNet network, which has a promising potential in the field of image classification based on the results so far. On patients whose data the network did not come into contact with during training and validation, we subsequently assessed the accuracy of the classification. The accuracy for each condition was around 80%.

CCS CONCEPTS

• **Computing methodologies**; • **Machine learning**; • **Machine learning approaches**; • **Neural networks**;

KEYWORDS

EEG, epilepsy, CNN, SqueezeNet, classification

ACM Reference Format:
Tereza, TS, Simralova, Jan, JS, Strobl, Vaclava, VP, Piorecka, Filip, FC, Cerny, and Marek, MP, Piorecky. 2022. CNN classification of variance-based selected topo-maps of EEG. In *2022 9th International Conference on Bioinformatics Research and Applications (ICBRA 2022), September 18–20, 2022, Berlin, Germany*. ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3569192.3569211

1 INTRODUCTION

The brain is the control center of our body. Because it is covered by a skull, the most used non-invasive method of examination is electroencephalography (EEG), which describes the changes in its electrical activity over time. Like any physiological process, electrical activity can be disrupted. One of the disorders with a significant manifestation in the form of EEG time-series changes is epilepsy [1].

Epilepsy is a serious neurological disorder that disrupts everyday life. One of the main ways to diagnose epilepsy is EEG. Evaluation of epilepsy done only by physicians is ineffective, due to a need of examining a several hour long recording. At the same time, it is highly time-demanding to train physicians to reliably recognize certain brain manifestations in EEG recordings [2]. Thanks to digital technology and the evolving artificial intelligence (AI) for signal processing, it is possible to reduce time requirements by pre-scoring. Algorithms evaluate and highlight segments of time series in moments when the activity corresponds to the characteristics of epileptiform activity, instead of physicians. The first such algorithms date back to the second half of the 20th century [3]. With the development of AI, the possibilities of classification are constantly expanding.

AI is still evolving, so it is promising to apply new technologies for acquiring more accurate results in classification of EEG segments. If the success of the epileptiform activity detection was consistent across various patients and devices, the pressure on the physicians evaluating the recordings would be reduced. Moreover, this would speed up the entire diagnostic process.

The aim of this work is to present the success of the classification of a convolutional neural network for various manifestations of epileptic activity in EEG. Emphasis is placed on the optimization of input data, i.e. the creation of image data, as well as on the sui oftability data sets for training, testing, and validation. The success is also verified on subjects that were not used as a training dataset.

1.1 Epilepsy

Epilepsy is one of the most common neurological diseases that can affect anyone regardless of ethnicity, age, or gender [4]. It is characterised by recurrent seizures that have no immediate identifiable cause [5]. Epilepsy is not a homogenous type of disease, it is rather a set of several different syndromes. This disease is treatable in most cases (drug suppression or surgically operable). However, pharmaco-resistant variants are also emerging [6].

ICBRA 2022, September 18–20, 2022, Berlin, Germany

ACM ISBN 978-1-4503-9686-8/22/09…$15.00
https://doi.org/10.1145/3569192.3569211

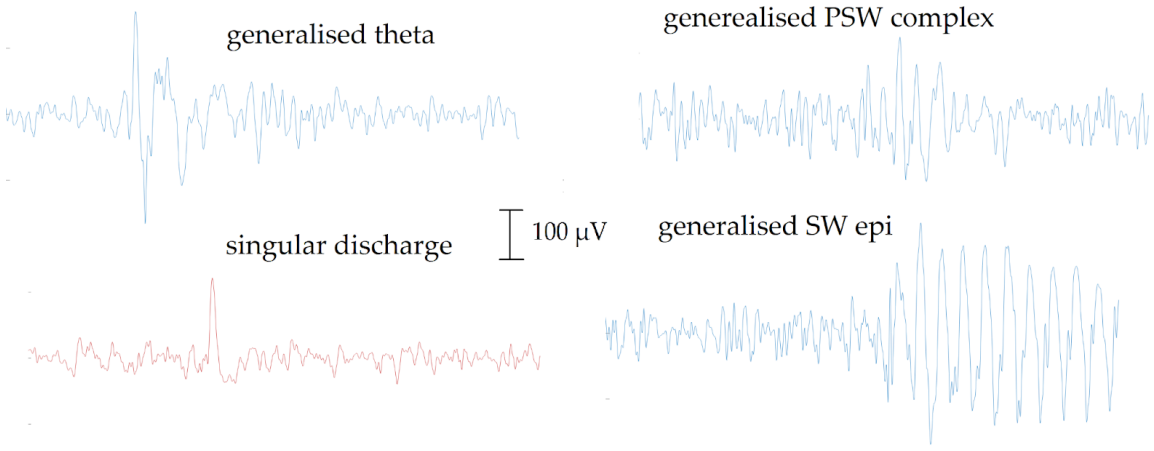

Figure 1: Example of epileptogenic activity in collected EEG signals.

Epileptic activity can manifest itself in a variety of seizures. The basic ones are generalised and further divided into types such as: absence of symptoms, tonic-clonic, myoclonic or clonic, atonic, and tonic seizures. Another type are focal seizures, which are further divided into with and without consciousness [7]. At figure 1 can be seen different types of epileptic activity recorded by EEG.

EEG is a summation signal of neuronal electrical activity on the scalp surface. Standard clinical EEG is often measured in a 10-20 system with 19 measuring channels. The change in voltage over time produces a quasi-stationary signal. Certain periods of EEG activity reflect the physiological or pathological activity. In the frequency domain, we most often describe brain manifestations using the power spectrum. Here, the 4 basic EEG spectral bands, concretely delta (1 - 4 Hz), theta (4 - 8 Hz), alpha (8-13 Hz) and beta (13-30 Hz) are most often distinguished.

1.2 Convolutional neural network

One of the types of neural networks (NN) are convolutional neural networks (CNN). This type of neural network seeks to mimic the way people perceive the world around them. Convolutional neural networks are used in various areas of computer vision [8, 9]. Recently, CNNs have been used for automatic classification of epileptic seizures from EEG recordings [10]. However, for this type of NN, the EEG signal must be converted to image data.

CNN is currently a widely used method for classifying epileptic activity with relatively good results. For example, in the study by Mandhouj et al. [11], the authors used Short time Fourier transformation (STFT) to create an entry on CNN. The authors claim that they had a high accuracy of about 98%. However, the authors used the same data for training and testing. In the study by Naseem et al. [12] the continuous wave transformation (CWT) in combination with CNN has been used instead of the STFT. Here, the authors used a large online database (500 records) of EEG data from healthy subjects, subjects with epilepsy diagnosis and subjects that had a tumor. In this study, EEG segments from individual subjects were divided evenly between the training, validation and testing branches. The accuracy of this method was 74-78%. In the study by Qin et al. [13], the authors achieved a high accuracy of 98.67% using the feature fusion convolutional neural network. However, the authors used same data for training and validation. In the study by Sameer et al. [14] the 1D CNN for automatic feature extraction has been used and then the epileptiform activity was classified by the conventional classification methods. The authors again obtained training and test data from the same datasets, so it is not possible to evaluate the accuracy of new unknown records. Even in the study by Shoji et al. [15], the authors randomly mixed segments from the same records, which they then divided into training and test data. Again, they used sections from the same EEG records for testing and training. In this study, the authors specifically focused on the detection of paroxysmal discharges.

2 METHODS

As part of the research, standard EEG clinical data from patients with suspected epilepsy were preprocessed. Subsequently, the appropriate time points were selected to create an image from the EEG signal, which then entered the selected convolutional neural network of the SqueezeNet architecture.

2.1 Dataset

The dataset consists of signals acquired from 6 patients in total. Age range of the patients is between 19 to 58 years. Signals were measured on Brain-Quick (Micromed S.p.A.) digital system. Standard 19-channel EEG electrode placement was used, corresponding to the 10-20 system with reference electrodes placed on the earlobes. The recordings' duration ranged from 9 to 20 minutes. The study protocol has been approved by the Hospital Na Bulovce ethical committee. The sensitivity was 100 μV per 10 mm and electrode impedance was below 5 *kOhm*. The sampling frequency was 256 Hz.

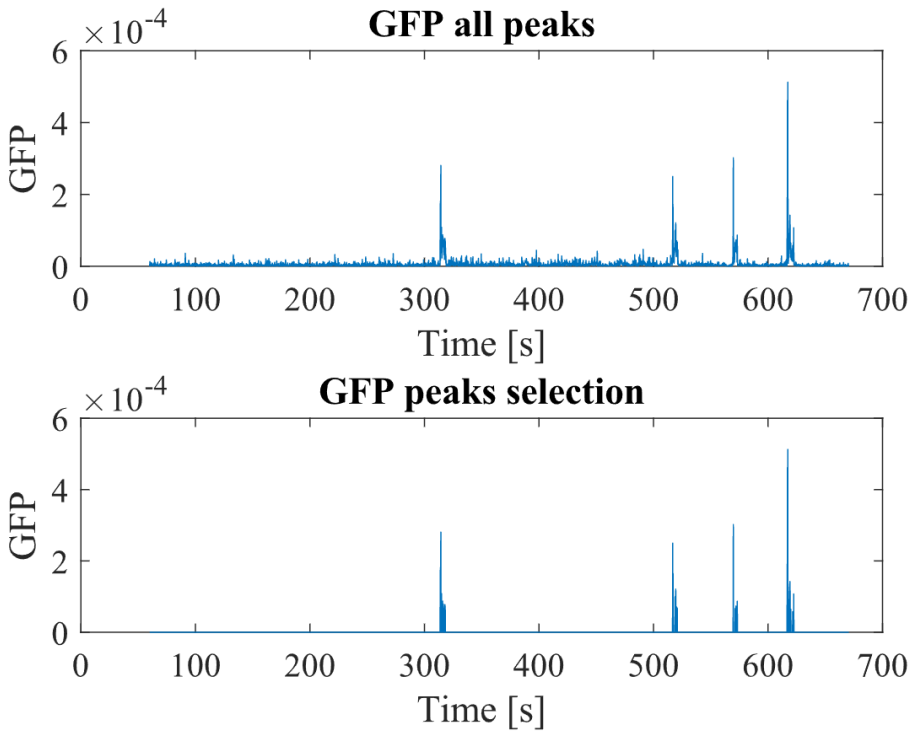

Figure 2: Graph shows the GFP curve (top) and selected time point defined by local maxima of GFP curve higher than threshold (bottom).

2.2 Preprocessing

The data were filtered with a bandpass filter 0.5–30.0 Hz. Two-way FIR filter was used. Filter order was set to 1000. Also demean and detrend was applied. Data were segmented into 6 second length trials with 10% overlapping. Time-frequency analysis was done by convolution with the Hanning window. The time resolution was set to 500 ms. Power spectrum in the range of 1-30 Hz with 1 Hz resolution was investigated. With regard to the number of time points, a selection of certain time points was chosen, which serves as a source for creating maps (images). Variance across electrodes can reflect brain activity, which appears to be typical and can be used to describe short-term brain conditions. This is an approach to the analysis of microstates, where the so-called GFP curve is calculated, see Figure 2. GFP curve is calculated like [16]:

$$GFP\,(t) = \sqrt{\frac{\left(\sum_i^K \left(V_i\,(t) - V_{mean}\,(t)\right)^2\right)}{K}}$$

where V means amplitude value and K represent the number of channels. Local maxima were automatically selected from GFP curves. In figure 2 a GFP curve of one subject is shown. Selected GFP peaks correspond to epileptogenic activity (SW complex) scored by a physician.

Size of spectrum estimation for each subject was 30 frequencies for 19 channels over time. Size of GFP information was 30 frequencies per time. Spectral power estimation was performed by convolution (frequency domain multiplication) using the Hanning window. Power spectral values on electrodes are plotted through a scalp in a 2D image using extrapolation and subsequent interpolation. Resulting maps (in 875x656 resolution) are exported to .png format. Figures are then rescaled to 227x227 and continue into the classification process. The images are also normalised, creating 2 sets of images for the same time points. Normalisation allows unification of the range of the colour gamut across maps. On the other hand, non-normalized maps reflect the distribution of activity at a given moment and therefore provide higher contrast. The difference between normalised and non-normalised spectral power can be seen at figure 3. From 4 individuals, segments that correspond to epileptiform activity and physiological activity are randomly selected. Therefore, a database of two groups is created. Each group contains 1000 topographical maps which were subsequently divided in 7:3 ratio into training and validation groups.

2.3 Neural Networks

Deep neural networks are used predominantly with an interest to improve accuracy. However, greater complexity of the structure requires more communication between servers during distributed training and has higher hardware requirements. SqueezeNet is therefore designed as a small architecture that seeks (18 layers) to compensate for these shortcomings. SqueezeNet [17] achieves AlexNet accuracy with 50x fewer parameters. For the purpose of this work, a ready-made neural network SqueezeNet was chosen,

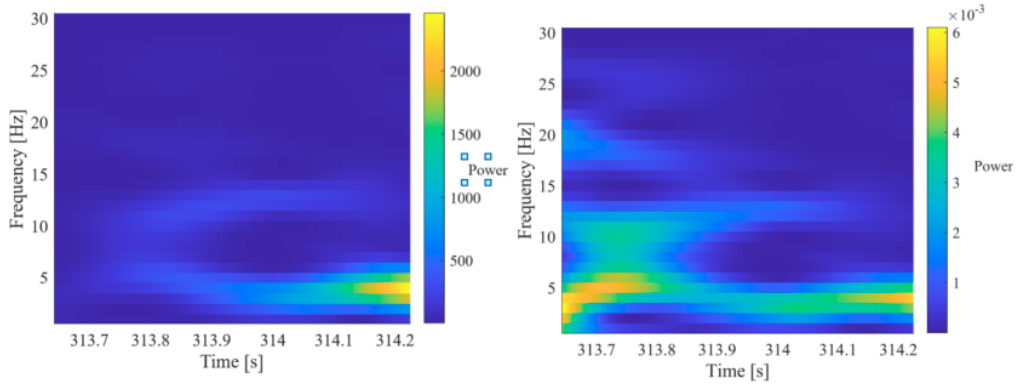

Figure 3: Time-frequency analysis shows the difference between normalised (left) and non-normalised (right) spectral power.

Table 1: Parameters for CNN for different types of normalisation/scaling data input.

	Normalised	Non-normalised	Unscaled
InitialLearnRate	0.0001	0.001	0.0003
L2Regularization	1.28E-10	0.0018	2,8512e10-8
ValidationFrequency	17	18	9
MaxEpochs	15	24	12
MiniBatchSize	20	13	25
LearnRateDropPeriod	5	10	10
LearnRateDropFactor	0.4998	0.4629	0.4608
	80.83%	81.67%	81.50%

which was re-taught to our type of dataset using the method of so-called transfer learning. The selection of the network was governed by several criteria, namely availability in the MATLAB software environment, low computational complexity, and suitability for our type of dataset. Transfer learning consists of replacing the last few layers of the network with completely new layers. These layers then, after setting the appropriate parameters, re-learn the network and distribute the new knowledge among other layers. In Bayesian optimization, the maximum accuracy of verification on the validation set was chosen as the evaluation criterion. The number of iterations was set to 500 and the final value of WeightLearnRateFactor and BiasLearnRateFactor was set to 15. The algorithm used for network training was Stochastic Gradient Descent with Momentum (SGDM). The CNN was trained with the following parameters in the specified range of parameter values: RandRotation [-90 90], RandScale [0.5 2], InitialLearnRate [1.10^{-4} 1.10^{-3}], L2Regularization [1.10^{-10} 1.10^{-2}], ValidationFrequency [5, 20], MiniBatchSize [10 30], MaxEpochs [10 25], LearnRateDropPeriod [1, 10], LearnRateDropFactor [0.1 0.5].Optimised parameters for different types of input data are shown in Table 1.

2.4 Statistical evaluation

The output of Bayesian optimization is the determination of the best network of all its iterations, the training graph, and the network itself. After the training, the network has a certain percentage value in accuracy in the training and validation set. However, this may not yet correspond to its true accuracy in dividing the images into learned categories. This needs to be verified on new data, i.e. images that have not been used for training. Sensitivity, specificity, and positive predictive value (PPV) parameters were also calculated [18].

3 RESULTS

In the study, we trained CNN SqueezeNet to classify clinical EEG records of patients with epileptiform activity. The aim was to compare the input image data - their nature (e.g. normalisation) and their effect on CNN accuracy. We also propose a methodology of evaluation on an unknown dataset for CNN. In case of non-normalised maps, the accuracy changes more homogeneously in comparison to normalised one. In case of normalised maps (see figure 5) the decrease and increase of accuracy between 500 and 1000 iterations is changing. The accuracy is more stable in higher numbers of iterations, see Figure 4. For unscaled input the instability of accuracy in the iteration step is also typical, see figure 6.

We calculated the sensitivity, specificity and PPV of CNN for 3 input generation methods (see table 2). The first input was a normalised time-frequency graph, the second input was a non-normalized time-frequency graph and the third one was an unscaled time-frequency spectrum. Validation was performed on data that was not used for CNN training and testing. For all validated methods, we calculated the accuracy for 4 different randomly

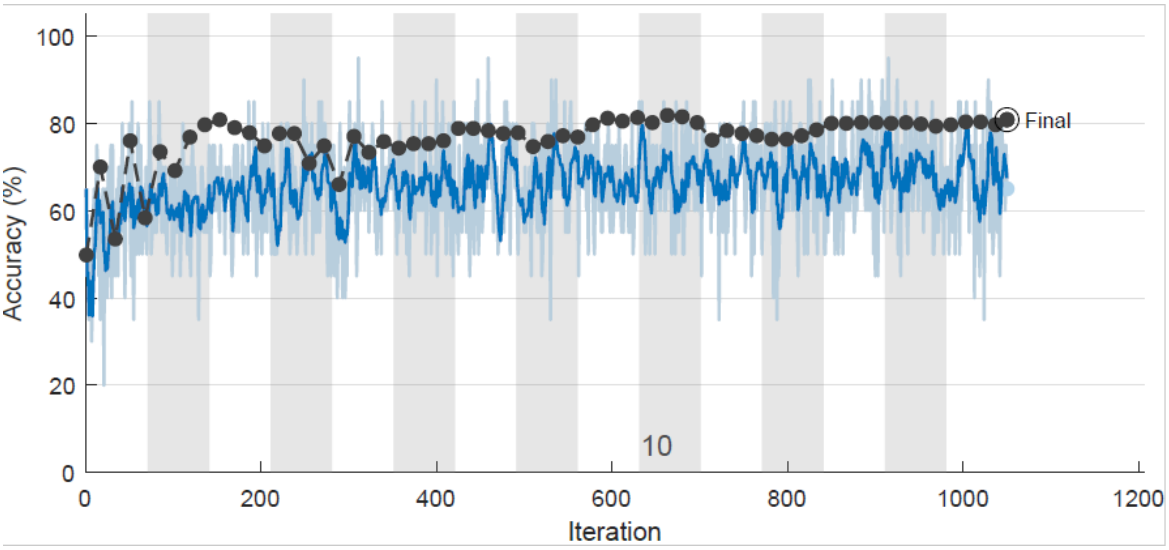

Figure 4: Changing of accuracy during the training process for non-normalised data input.

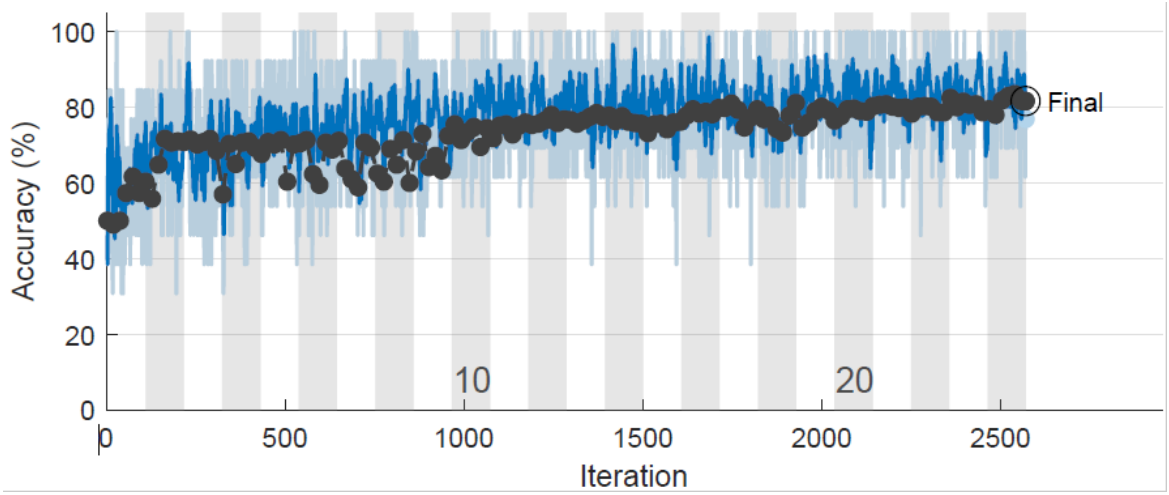

Figure 5: Changing of accuracy during the training process for normalised data input.

Table 2: Sensitivity, specificity and PPV of classification on the new subject for all three types of picture preprocessing

	Normalised	Non-normalised [uV2/Hz]	Unscaled [-]
Sensitivity	82.06%	67.53%	77.09%
Specificity	42.00%	84.00%	55.00%
PPV	96.29%	98.95%	97.45%
Accuracy	80.34%	68.24%	76.14%

selected CNN training and testing sections (see table 3). This validation tested the robustness of each method.

4 DISCUSSION

The aim of this work was to verify the classification of various manifestations of epileptic activity in EEG records on real clinical datasets. This data also includes segments that are difficult to classify. In contrast to studies that classify only selected segments of

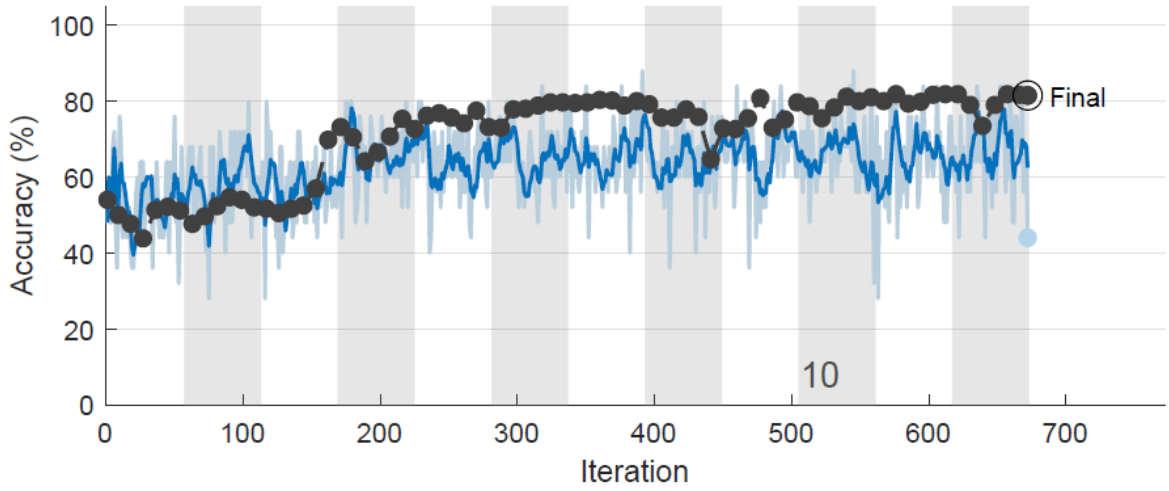

Figure 6: Changing of accuracy during the training process for unscaled data input.

Table 3: Accuracy of classification on the new subject for all three types of picture preprocessing

	Normalised	Non-normalised [uV2/Hz]	Unscaled [-]
group 1	86.00%	90.00%	72.00%
group 2	93.00%	94.00%	89.00%
group 3	87.00%	87.00%	76.00%
group 4	90.00%	93.00%	81.00%
mean	89.00%	91.00%	79.50%

epileptic activity from online databases, for example studies [11–13 and 19], this is a more complex problem. Next difference, compared to other studies, is the character of the input dataset [20] of images. In our case, the image is not made of time series but used topographical maps - extra and subsequently interpolation of values from electrodes. Such a topographic map can then be compared to microstate analysis. Our approach is selective, it is not the data for training from every point in time. We thus assumed lower accuracy compared to other studies, but the result should reflect the clinical impact more precisely.

SqueezeNet type CNN was chosen due to a small number of layers (18). Validation was performed on sections from EEG recordings which weren't selected for training and testing of CNN. Table 2 shows the sensitivity, specificity and PPV calculated for normalised, non-normalised and unscaled methods. The PPV was high for all validated methods, ranging between 96.29% and 98.95%. Therefore, if one of the methods detected epileptic activity, it is very likely true. The specificity was high only for the non-normalised data, specifically 84.00%. Thus, only the non-normalised method identified the non-epileptic activity correctly. The sensitivity was highest for the normalised method, namely 82.06%. Thus, the normalised method was able to find the most epileptic activities. Although the other two methods found most of the epileptic activity, they did not find a relatively large part of the epileptic activity. The reason is probably the inhomogeneous selection of training segments and the use of real EEG segments instead of pattern samples.

We compared the individual methods in 4 different groups to obtain more robust results. The individual sections were selected randomly for training and testing. Each group was created as a different random combination of selected sections. Table 3 shows the accuracy for each group and the individual methods. The highest non-normalised method had an average accuracy of 91%. On the contrary, the unscaled method had the lowest accuracy of 79.5%, and also the highest variance of individual success rates. The non-normalised method had individual robust success rates, ranging between 87% and 94%.

The best results are based on the non-normalised method, due to robust results, high specificity, PPV and higher sensitivity. The accuracy of 80% that we achieved in this work is lower than some research [21], but it can still be used in practice. Most studies use online databases containing several-second segments of normal activity or attack. These databases achieved high accuracies, but these do not reflect how the resulting algorithms would work on real data. For example, we achieved higher accuracy compared to research [22] methodologically similar to real data. In the future, CNN will need to be trained with more homogeneous segments in order to improve sensitivity of the non-normalised method, The segments for validation were selected from two EEG records. In future work, we will focus on the non-normalised method and validate it on a larger set of EEG data on which no CNN training and testing has taken place. However, the non-normalised method demonstrated the ability to detect epileptic activity in real EEG

recordings that had not previously been used for CNN training and testing.

5 CONCLUSION

The classification accuracy of approximately 80 % of various origins of epileptiform activity for completely new subjects gives promising use in supporting physicians in clinical practice in the evaluation of EEG recordings. Because the brain stays in similar activity across the scalp repeatedly, it is possible to use the image of the topographic map for classification. The manuscript offers a methodology for image extraction and subsequent classification. In the future, it would be appropriate to validate the accuracy on a wider dataset, as the current results are promising.

ACKNOWLEDGMENTS

This work was supported by the Grant Agency of the Czech Technical University in Prague, reg. no. SGS22/200/OHK4/3T/17 and SGS21/140/OHK4/2T/17.

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