A novel LSTM-based data synthesis approach for performance improvement in detecting epileptic seizures

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Abstract: Bio-electrical time signals play a significant role in assisting non-invasive observational procedures in healthcare. These bioelectrical signals are weak signals with inherently low voltage and low frequency, hidden mostly under relatively large high-voltage noise signals. Hence it is extra challenging to analyze them. In modern clinical data analysis, these signals could be further analyzed using conventional machine learning (ML) methods. Also, in the recent past, two-dimensional spectrum-based classification, predominantly with Convolutional Neural Networks (CNN), has been tried with time-series data. One of the objectives of this study is to find which approach would suit better for biomedical signal analysis when data are scarce and signals are weak. Also, in bio-medical signal analysis data is scarce. Yet, to effectively train either an ML or a deep learning (DL) model, a sample clinical dataset of a significant size is required. Hence, the second objective of this research is to present a novel data synthesis method to address data scarcity. With these objectives, the study compares the performance of the time-series-based classification with traditional ML approaches, against the 2D spectrum-based classification for bio-electrical signal classification. For this purpose the study utilizes learning models; Multi-layer Perceptron (MLP), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), Long Short-Term Memory Networks (LSTMs), Auto Encoder (AE), and Convolutions Neural Network (CNN). Also, the authors propose a novel data synthesis method based on LSTMs to improve the sample size of the standard CHB-MIT Scalp EEG dataset. The results show that with the expanded dataset, the two-dimensional spectrum-based classification architecture was able to achieve a precision level of 85% at the classification. The conventional ML-based methods showed on average a precision level of 82%. In conclusion with the proposed virtual sample generation approach, 2D spectrum-based classification with Convolutional Neural Networks showed promising performances.

Key-Words: Bio-electrical time signal classification, Long Short-Term Memory Networks (LSTMs), Convolutional Neural Networks (CNN), Time series based classification, Two-dimensional spectrum based classification, Virtual Sample Generation

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1 Introduction

The human body is a complex biological system. Its neural intercommunication system could be treated as a low-voltage and low-frequency complex electrical signaling system. The nervous system is the central communication network of the human body, which consists of billions of neurons that are responsible for carrying small electrical signals. While the central nervous system (CNS) of the body carries out the functionalities in the brain and the spinal cord, the peripheral nervous system (PNS) transports signals between the CNS and the rest of the body. As the human body works as a conductor, the neural signals can be recorded from the skin via surface electrodes. Such signals observed, especially as the changes in the electrical potential across selected locations of the human body, are referred to as “bioelectrical time signals”. Examples of bioelectrical time signals are the electroencephalogram (EEG), electrocardiogram (ECG), and nerve conduction studies (NCS) which are the recordings of the electrical activity of the body obtained on the scalp, over the heart, and nerves respectively.

In medical sciences, these bioelectrical time signals play a significant role in detecting abnormalities, such as seizure disorders, encephalopathies, and structural lesions. When making a diagnosis, these signals’ frequency and amplitude fluctuations are examined in comparison to the norm. Yet, these bioelectrical signals are extremely weak by nature and are concealed by large noise signals. They are difficult to isolate and process. As a result, signal prepossessing techniques like filtering are used to qualitatively improve the analysis and to carry out the feature extractions efficiently.

Machine learning and deep learning are sub-fields of artificial intelligence (AI), which has exhibited a dramatic development cycle in the last decade. These models possess the capacity to learn patterns and extract information from given data with minimum human intervention. They thereby open the door for real artificial intelligence in machines and electronic devices. AI has influenced and found application in modern medical science extensively in tasks such as disease diagnosis, prognosis, and treatment. In this context, biomedical signal analysis with AI has emerged as an exciting and rapidly evolving field that fuses the learning architectures of AI with biomedical signal processing to revolutionize healthcare. It integrates sensors and acquisition systems used in diagnosis with AI models for effective prepossessing, precise categorization, and meaningful interpretation, which would result in better healthcare solutions.

There are currently two fundamental approaches for AI-based bioelectrical signal analysis: time series-based analysis and two-dimensional spectrum-based analysis. The authors of this study compared these two methods for the use of EEG-based seizure detection on a qualitative and quantitative level. The CHB-MIT dataset, [1],[2], which is a publicly available standardized seizure detection dataset, was used by the authors to train each learning algorithm. Furthermore, this study utilizes learning models Multi-layer Perceptron (MLP), Recurrent Neural Network (RNN), Gated Recurrent Unit (GRU), Long Short-Term Memory Networks (LSTMs), and Auto Encoder (AE) to perform time series-based analysis, while Convolutions Neural Network (CNN) is used to model two-dimensional spectrum based analysis. The lack of data, as in any AI-based research, is one of the key limitations of bioelectrical signal analysis. Deep learning models in particular need a lot of data to make appropriate choices. The authors propose a novel data synthesis method based on LSTMs to solve the bottleneck caused by data scarcity. The proposed method was able to qualitatively improve the size of the standard dataset. Finally, through simulations, the authors demonstrate the suitability of the proposed data synthesis method for improving the detection accuracy of epileptic seizures using EEG signals.

2 Background on Bio-electrical time signal analysis methods

More often than not, bioelectrical time signal analysis is carried out by first viewing the received signals as groups of time series. These groups of signals are either directly visualized or analyzed using techniques such as time-frequency distributions (TFD), fast Fourier transform (FFT), eigenvector methods (EM), and autoregressive methods (ARM), [3].

In the research presented in this manuscript, the authors analyze the EEG signals for seizure classification. According to the literature, the most popular machine learning algorithms for seizure classification are the support vector machine (SVM), extreme learning machine (ELM), and linear discriminant analysis (LDA), [3]. Along with the wave decomposition techniques (WDT), SVM, ELM and LDA have shown 63.85%, [4], 42.8%, [5], and 50.14%, [6], of accuracy in EEG based seizure classification, respectively.

Many supervised deep-learning techniques are also tested for seizure classification. For instance, in [7], 74.3% of seizure classification accuracy was recorded with stacked auto-encoders. The deep belief networks (DBN), [8], and multi-layer perceptron neural networks (MLPNN), [9], have performed with 80.4% and 85.0 % accuracy in seizure detection, re-spectively. The long short-term memory network (LSTM) has returned an accuracy of 87.0% for recog-nition of emotion from raw EEG signals, [10].

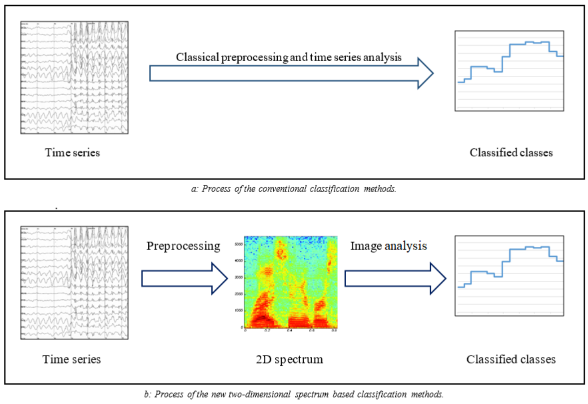


Fig. 1. The two main approaches of EEG classification architectures.

The literature highlighted above, analyzes EEG signals as time series representations. An emerging alternative approach for classifying EEG signals is to first map the time series signal to a two-dimensional (2D) image base representation as shown in Fig. 1, and then to perform classification using 2D image analysis models. In this alternative approach, the mapping of a one-dimensional time series signal into a two-dimensional spectrum is carried out using pre-processing methods such as FFT, and power spectral density (PSD). Next, the resultant spectrum images are analyzed using either machine learning or deep learning-based image analysis techniques.

The commonly used image classification method in literature is the CNN, which has shown 87.3% accuracy in EEG seizure classification, [11]. Also, more promising results were obtained, when the CNN models were combined with other pre-processing and post-processing techniques. For instance, combining a sparse representation classification (SRC) model with a fast compression residual convolutional neu-ral networks (FCRes-CNN) led to an improvement in average accuracy from 88.79% to 98.82% in the de-tection of EEG seizures, [12].

In the presented study, the authors, present a qualitative and quantitative comparison of the classification performances of time series-based and two-dimensional spectrum-based machine learning and deep learning architectures for EEG-based seizure detection. This objective is approached by applying those two types of classification architectures on the same standard seizure detection dataset (CHB-MIT) [1],[2], under a similar environment and comparing the classification performances against each other.

3 Dataset

The famous EEG classification dataset, CHB-MIT Scalp EEG Database, [1],[2], provided by the Mas-sachusetts Institute of Technology (MIT, USA) is uti-lized in this study. This dataset is used to differentiate epileptic seizures from the normal state in pediatric and young adolescent patients.

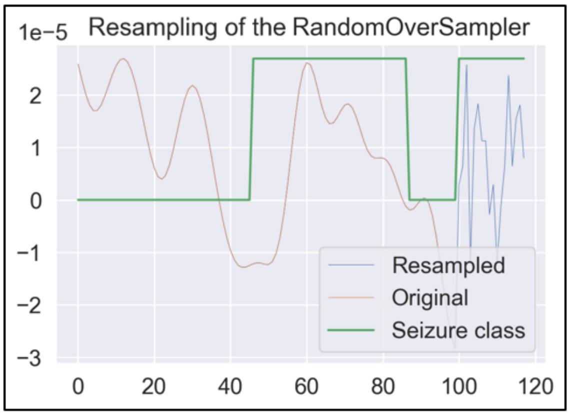
The EEGs were recorded at the Children's Hospital Boston with 23 children with epileptic seizures using scalp electrodes. The study included 17 female patients with ages ranging from 1.5 to 19 years and 5 male patients with ages ranging from 3 to 22 years. All subjects stopped the related treatments and medications several days before the data collection.

Most EEG files in the dataset contain EEG signals with 23 leads per seizure detection instance, while very few cases consist of 24 or 26 leads. These groups of EEG signals were collected using the International 10-20 system of EEG electrode positions and nomenclature, [1]. The signals were recorded at a 256 Hz sampling rate with 16-bit resolution. Throughout the 844 hours, i.e. over 900,000 time points, of observations presented in the dataset, a total of 686 recordings with 198 seizures were captured. The database consists of onsets and ends of 182 annotated seizures.

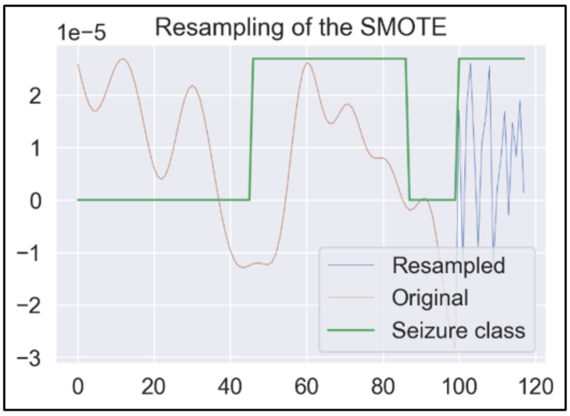
4 Methodology

It was observed that this dataset largely contains EEG signals of a "normal" state compared to the interested "epileptic seizure" state, with an average distribution of 98:2 of the total dataset. Due to the class imbalance present within the dataset, in general, machine learning or deep learning classification models would fail to learn the correct patterns and they would eventually produce a biased output. 5

To address this shortcoming in the dataset, first, outlier detection methods such as isolation forest and local outlier factors were tested by considering the seizures as the positive outliers of the dataset. Alternatively, corrective sampling techniques such as classifications with sample weights and random oversampling (ROS), synthetic minority oversampling technique (SMOTE), and adaptive synthetic method (ADASYN) were also tried in order to adjust the shortage of samples in the seizure class. Out of these tested methods, ROS and SMOTE showed promising results as seen in Fig. 2. It can be observed that the amplitudes of the oversampled data points lie within the same range as the actual seizure signals. However, since these tested methods do not preserve the temporal properties of the original samples and only consider each instance as an individual sample, the reconstructed time signals appear completely random. This shortcoming has given rise to the necessity of developing a new data reconstruction method to overcome class imbalance.



a: Oversampling of the ROS.



b: Oversampling of the SMOTE.

Fig. 2. Original and reconstructed signals of random oversampling (ROS) and synthetic minority oversampling technique (SMOTE).

4.1 Data reconstruction

As presented earlier most EEG files in the dataset contain EEG signals with 23 leads per each seizure detection instance, while very few cases consist of 24, 25, or 26 leads, as extra leads or dummy signals. At the data reconstruction, the first filter-based prepossessing was utilized to remove these dummy signals

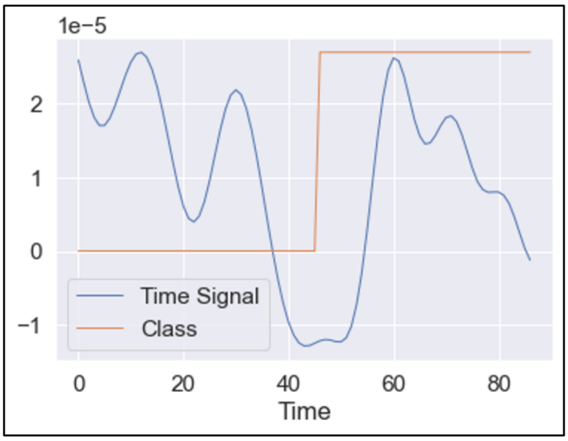


Fig. 3. Sample of extracted seizure and normal time signal.

and occasional extra lead signals. Next, frequencies between 0.2Hz – 25Hz were extracted from the signals of all EEG leads. Thereafter the segment of the seizure signal, as well as a random segment from the normal state section of the EEG, were extracted. The time duration of the normal state signal was made equal to the time duration of the seizure signal. Both the normal and seizure signals were combined to produce a new EEG signal of twice the length of the seizure segment. This process was repeated with all the EEG signals and all EEG leads. A sample output of the newly generated EEG signal data is shown in Fig. 3.

Next, an LSTM network was trained with the new dataset to predict the next observation of the input signal when the previous observation was known to the system. A sample of the training data for this LSTM network is shown in Fig. 4. Once the network is trained, the test input signals are fed to the network to synthesize new signals similar to the original signals. A sample of the synthesized new EEG signal generated by the LSTM network is shown in Fig. 5. The proposed new EEG signal synthesizing process was repeated for all the usable seizures present in the original dataset and a newly synthesized signal was created for each seizure signal in the dataset. All the original and reconstructed signals were separated into two classes; normal and seizure, in order to create a balanced dataset with more volume of data, especially from the seizure class.

The proposed new data synthesizing process was further improved by randomly grouping seizure and normal signal segments to create a more generalized dataset. In this refinement stage, three segments of either seizure (S) or normal (N) EEG signals from the same patient were randomly selected and concatenated into one continuous signal. This approach offers 8 possible combinations i.e NNN, NNS, NSN, NSS, SNN, SNS, SSN, and SSS, per EEG data recording of a single patient. This in turn helps to enhance the dataset in a qualitative manner. Since data in medical research is scarce, this proposed approach provides a practical solution to the problem identified.

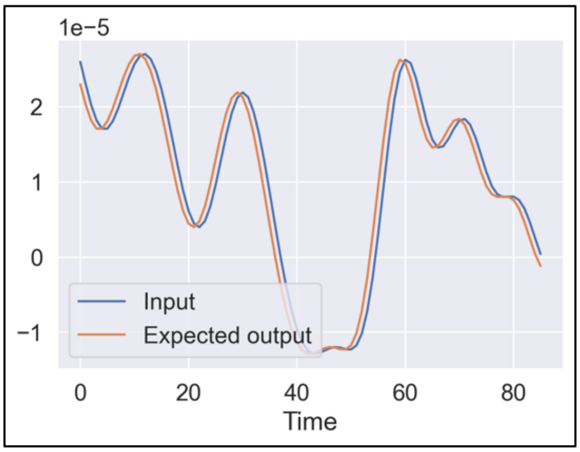


Fig. 4. Sample of training data for the LSTM network.

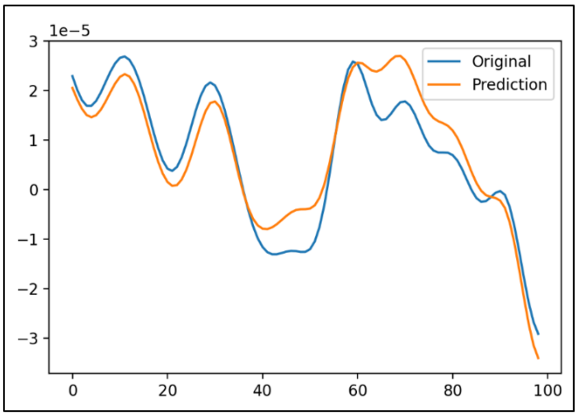


Fig. 5. Reconstruction of a new signal.

4.2 Time series based classification

In order to analyze the EEG signals in practical environments such as at healthcare facilities for diagnostics, it is necessary to have a trained classifier that could deliver excellent performance with unseen data. For this purpose, state-of-the-art time series-based deep learning classifiers, namely MLP, RNN, GRU, LSTM, and AE were first trained and tested using the original dataset. It was observed that feeding the original data directly to machine learning classifiers did not return the expected performance. This was mainly due to the class imbalance and the smaller sample size associated with the original dataset. To address this bottleneck, the offline synthesized dataset created above, with improved 2000 data points from each class, was utilized to retrain the MLP, RNN, GRU, LSTM, and AE classifiers.

The created dataset was split into training:validation:testing as in 60:20:20 ratio. The training subset of the created dataset was used to train the models along with the Random Search and Tree of Parzen Estimators as the parameter optimization methods. The trained classifier was tested using the testing subset of the dataset. The results were averaged over 10 iterations of training and testing sessions.

4.3 Two-dimensional (2D) spectrum based classification

The 2D spectrum-based classification has emerged in the literature as an alternative analysis method for time-series data, [13]. In such an approach, the time series signal is first converted to the 2D representations using either spectrograms or Frequency Spectrum (FS) with FFT or Power Spectral Density Spectrum (PSDS). However, as of literature, [13], [14], [15], we have noticed that the performance of the CNN-based classifiers with the spectrogram converted 2D representation was very poor. This probably may be due to the fact that spectrograms illustrate only signal strengths.

The FS-based imaging visualizes frequencies of the signals at each instance along the time axis. It was observed that FS imaging-based classification exhibited better performance than spectrogram images. The PSDS image of each class shows, the power present in the signal as a per unit frequency at a time. Although PSDS is almost similar to the corresponding FS, PSDS itself adds slightly more contrast to the spectrum image by revealing extra features of the time series signal. This results in PSDS performing better with CNN-classifier than FS.

In order to address the lack of sample data, data augmentation approaches are widely utilized in 2D space-image-based classification techniques. Following this trend, we also propose a novel augmentation technique to create new 2D spectrum data samples out of the previously created dataset which comprised both actual and synthesized EEG signals. This approach provides a solution to the key bottleneck associated with deep learning models in the healthcare sector, i.e. scarcity of data. The augmented dataset is used to train the CNN models, while the testing of the trained model is carried out using only the originally acquired EEG data. The proposed augmentation mechanism is presented as follows.

1. For every other 25 time points of the input signal, the immediate next 100 neighboring time points of the same signal are appended to create an epoch of 125-time points of length as shown in Fig. 6. In this approach, the current 25-time points will be repeated 4 more times (i.e. the same 25-time points contained in 4 consecutive epochs (=100/25)), creating redundancy in the dataset.

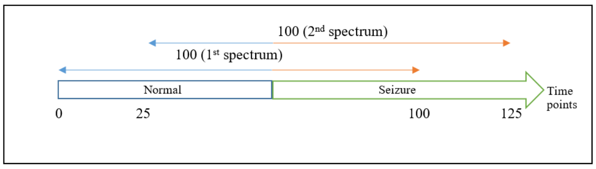


Fig. 6. Example of epoch separation for the spectrum calculation.

2. Next, FFT and PSDS were created for each epoch as shown in Fig. 7.

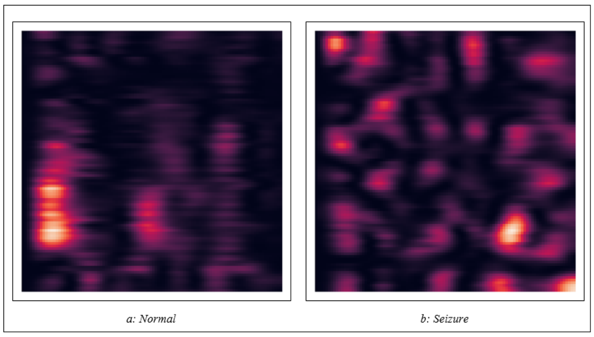


Fig. 7. Sample frequency spectrum of each class.

3. The target class probabilities for each epoch were calculated as the percentage of the seizure time points contained inside the epoch. So, it indicates the fraction of seizure signals present in each spectrum in comparison to the normal signals as shown in Fig. 8.

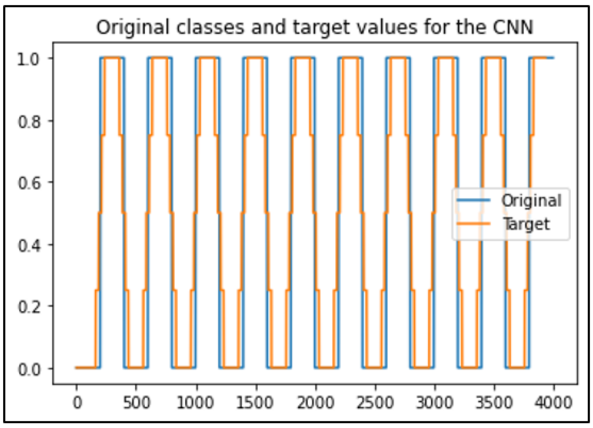


Fig. 8. Original classes and target values for the CNN.

4. The new dataset with the spectrum and targeted class probabilities was utilized to train a CNN model as the classifier.

5 Results and Discussion

As presented in the introduction, two hypotheses related to biomedical signal classification are addressed in this research. The authors first explore the possibilities of using a novel LSTM-based EEG signal generation method to address the data shortage problem in EEG research. The study then assesses the hypothesis of whether the conventional time-series-based EEG classification approach is superior to the two-dimensional spectrum-based approach. In order to achieve this, we first train the chosen machine learning and deep learning algorithms using the new dataset that has been synthesized, and then we test each of them using authentic EEG data from clinical collections available through the CHB-MIT dataset. This decision was made because we want to see how well the classification algorithms that were developed using the synthesis dataset, perform during deployment.

Table. 1 and Table 2 shows the classification results for each classifier, namely MLP, RNN, GRU, LSTM, AE and CNN. The classifiers MLP, RNN. GRU, LSTM and AE were trained using the time-series data han-dling approach, whereas CNN was trained using the two-dimensional spectrum-based approach. The pre-sented results are averaged values over 10 iterations of independent training and testing sessions. Fur-thermore, the two-dimensional spectrum-based clas-sification architectures appeared to be doing well in the seizure classification, according to the results pre-sented in Table. 1 and Table 2. The performance sum-mary of the CNN-based classification has reached al-most 98% accuracy with better precision in each class. Also, we did not notice a significant change in the performance of either FFT or PSDS spectrum-based analysis.

The enhanced performance displayed by 2D spectrum-based classification approach has been caused by two aspects. One is that each 2D spectrum sends the classifier a single input containing all the frequencies and amplitude information of each epoch, and the classifier automatically extracts the features to learn from these inputs. The classifier that was trained using input data from a sequential time series, however, relies on manually extracted input features. The redundancy added by the overlapping epochs at the generation of 2D spectrum data is the second factor that contributed to the performance enhancement. Due to this factor, the classifiers could further validate the occurrences of seizures by looking at the subsequent spectrum data and assessing the temporal domain behavior.

Table 1: Time series-based deep learning classification results.

Classif-ier	***Precis-ion of class 0***	***Precis-ion of class 1***	***Recall of class 0***	***Recall of class 1***	***Accur-acy***
MLP	0.99	0.72	0.98	0.61	0.94
RNN	1.00	0.78	0.99	0.73	0.95
GRU	0.99	0.80	0.99	0.74	0.97
LSTM	1.00	0.82	0.99	0.79	0.98
AE	0.98	0.71	0.98	0.31	0.94

Table 2: Two-dimensional spectrum-based deep learning classification results.

Classif-ier	***Precis-ion of class 0***	***Precis-ion of class 1***	***Recall of class 0***	***Recall of class 1***	***Accur-acy***
FFT+ CNN	1.00	0.83	0.99	0.79	0.99
PSDS+ CNN	1.00	0.85	0.99	0.80	1.00

As of Table. 1 RNN and LSTM showed better performance under the time series-based signal analysis approach. According to Table. 2 CNN which utilized the 2D spectrum generated with PSDS outperformed the scenario where the 2D Spectrum was generated using FFT. Fig. 9 presents a detailed classification report of RNN while Fig. 10 presents a detailed classification report of CNN with PSDS to give further insight into the performance achieved by the two classifiers under the two different training scenarios, with the same input.

The classification report of an RNN classifier trained exclusively utilizing the original data, which had a sizable class imbalance, is shown in Fig. 11. Due to the intrinsic class imbalance in the original data, the classification accuracy of this approach is close to 100 %. This in turn shows that the EEG-based seizure detection applications necessitate a data reconstruction technique, and the suggested data synthesis strategy aids in enhancing the overall effectiveness of the AI models employed for this purpose.

6 Conclusion

This study makes two contributions to the field of bio-electrical signal processing, particularly for auto-

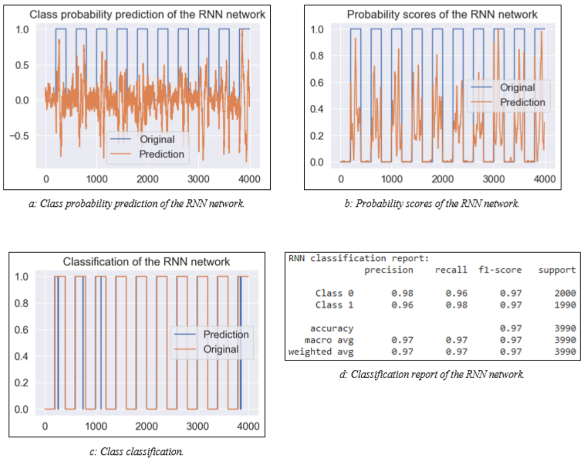


Fig. 9. Classification results of the RNN network with synthesis data.

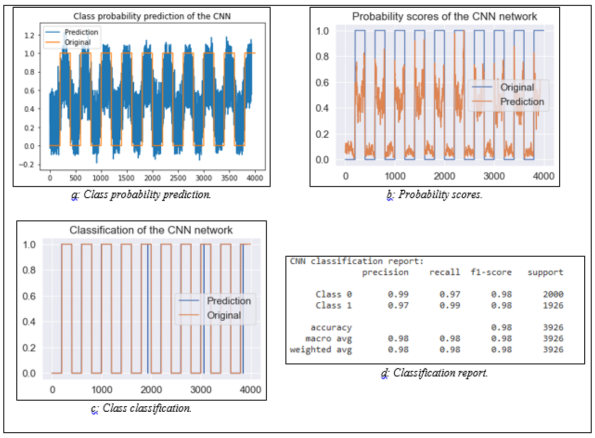


Fig. 10. Classification results of the CNN network with synthesis data.

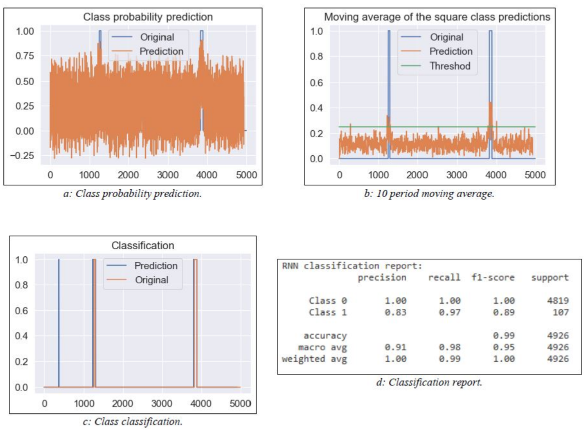


Fig. 11. Classification results of the RNN network with original data (without synthesis data).

mated EEG seizure detection using artificial intelligence (AI). When actual clinical data are hard to get by for EEG research, it first offers a time-series data synthesis method. The proposed remedy focuses in particular on the high-class imbalance, which is a non-seizure-to-seizure ratio of 98:2 in the CHB-MIT Scalp EEG database. Modern deep-learning-based classification architectures that use 2D spectrum have the potential to improve classification results by automatically extracting and processing more features from the inputs at once. In order to categorize bioelectrical signals, this research suggests with evidence that the 2D spectrum-based deep learning classification approach is an efficient and effective substitute for conventional time-series-based machine learning.

The LSTM network is adopted in the proposed novel seizure signal synthesizing architecture. The proposed architecture is able to synthesize new seizure signals that replicate and keep epileptic characteristics while randomly injecting some fluctuations to the signal to create the flaws that are intrinsically present in a real seizure signal. The study then examines the effectiveness of the suggested data synthesis approach in the time-series classification of bioelectrical signals. To assess the validity of the research hypothesis, the performance of the 2D spectrum-based CNN technique and the traditional time series-based machine learning and deep learning classification architectures were also evaluated. For this analysis, 2D spectrums were generated using FFT and PSDS methods. Also, classifiers MLP, RNN, GRU, LSTM, and AE were trained using time series data analysis methods.

According to the results and observations, the 2D spectrum-based deep learning classification architecture overpowers the time series-based deep learning classification architectures in terms of recall, precision, and accuracy. Additionally, both approaches were able to prevent the negative effects of biaseness found in the original dataset thanks to the data synthesis architecture. The 2D spectrum-based deep learning classification architectures, however, were shown to use up more processing power and memory due to their intricate computations. The needs for processing and memory may be easily met thanks to the development of the modern hardware sector. In future research, the authors wish to investigate further, novel signal synthesis approaches for biomedical time series data analysis to assist the data scarcity present at the biomedical signal process.

References:

[1] Ali Shoeb. *Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment.* PhD Thesis, Massachusetts Institute of Technology, September 2009.

[2] Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R. and Stanley, H. E. Components of a new research resource for complex physiologic signals. *PhysioBank, PhysioToolkit, and PhysioNet. (2000).* Circulation [Online]. 101 (23), pp. e215–e220.

[3] Prasanna J, Subathra M S P, Mohammed M A, Damaševičius R, Sairamya N J, George S T. Automated Epileptic Seizure Detection in Pediatric Subjects of CHB-MIT EEG Database—A Survey. *J. Pers. Med.* 2021, 11(10), 1028; https://doi.org/10.3390/jpm11101028

[4] Park Y, Luo L, Parhi KK, Netoff T. Seizure prediction with spectral power of EEG using cost-sensitive support vector machines. *Epilepsia.* (2011) 52:1761–70. doi: 10.1111/j.1528-1167.2011.03138.x

[5] Yuan Q, Zhou W, Zhang J, Li S, Cai D, Zeng Y. EEG classification approach based on the extreme learning machine and wavelet transform. *Clin EEG Neurosci.* (2012) 43:127–32.

[6] Gadhoumi K, Lina JM, Gotman J. Seizure prediction in patients with mesial temporal lobe epilepsy using EEG measures of state similarity. *Clin Neurophysiol.* (2013) 124:1745–54. doi: 10.1016/j.clinph.2013.04.006

[7] Yin Z and Zhang J, Recognition of cognitive task load levels using single channel EEG and stacked denoising autoencoder, *Chinese Control Conf. CCC* vol 2016 pp 3907–12.

[8] Yu Z and Song J, Multi-class motor imagery classification by singular value decomposition and deep Boltzmann machine, *2017 IEEE 3Rd Inf. Technology Mechatronics Engineering Conf.* pp 376–9

[9] Yohanandan S A C, A robust low-cost EEG motor imagery-based brain–computer interface, *2018 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)* pp 5089–5092

[10] Salma Alhagry, Aly Aly Fahmy, Reda A. El-Khoribi. Emotion Recognition based on EEG using LSTM Recurrent Neural Network, *International Journal of Advanced Computer Science and Applications (IJACSA),* Vol. 8, No. 10, 2017.

[11] Qiao R, Qing C, Zhang T, Xing X and Xu X, A novel deep-learning based framework for multi-subject emotion recognition, *Int. Conf. Information, Cybernetics and Computational Social Systems, ICCSS 2017* pp 181–5.

[12] Jing-Shan Huang, Yang Li, Bin-Qiang Chen, Chuang Lin and Bin Yao, An Intelligent EEG Classification Methodology Based on Sparse Representation Enhanced Deep Learning Networks, *Front. Neurosci.*, 30 September 2020 | https://doi.org/10.3389/fnins.2020.00808.

[13] Hasan, M.J., Shon, D., Im, K., Choi, H.-K., Yoo, D.-S.,; Kim, J.-M. Sleep State Classification Using Power Spectral Density and Residual Neural Network with Multichannel EEG Signals. *Appl. Sci.* 2020, 10, 7639.

[14] Christensen, J.A.E., Munk, E.G.S., Peppard, P.E., Young, T., Mignot, E., Sorensen, H.B.D., Jennum, P. The diagnostic value of power spectra analysis of the sleep electroencephalography in narcoleptic patients. *Sleep Med.* 2015, 16, 1516–1527.

[15] Rahi, P.K., Mehra, R. Analysis of power spectrum estimation using welch method for various window techniques, *Int. J. Emerg. Technol. Eng.* Vol. 2, 2014, 106–109

Conflict of interest disclosure
The authors declare that they have no conflict of interest.

Ethical approval
For this type of study formal consent is not required.

Informed consent
The dataset used in this article is freely available.

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