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Automatic Detection of EEG Epileptiform Abnormalities in Traumatic Brain Injury using Deep Learning

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Abstract— **Traumatic brain injury (TBI) is a sudden injury that causes damage to the brain. TBI can have wide-ranging physical, psychological, and cognitive effects. TBI outcomes include acute injuries, such as contusion or hematoma, as well as chronic sequelae that emerge days to years later, including cognitive decline and seizures. Some TBI patients develop post-traumatic epilepsy (PTE), or recurrent and unprovoked seizures following TBI. In recent years, significant efforts have been made to identify biomarkers of epileptogenesis, the process by which a normal brain becomes capable of generating seizures. These biomarkers would allow for a higher standard of care by identifying patients at risk of developing PTE as candidates for antiepileptogenic interventions. In this paper, we use deep neural network architectures to automatically detect potential biomarkers of PTE from electroencephalogram (EEG) data collected between post-injury day 1-7 from patients with moderate-to-severe TBI. Continuous EEG is often part of multimodal monitoring for TBI patients in intensive care units. Clinicians review EEG to identify the presence of epileptiform abnormalities (EAs), such as seizures, periodic discharges, and abnormal rhythmic delta activity, which are potential biomarkers of epileptogenesis. We show that a recurrent neural network trained with continuous EEG data can be used to identify EAs with the highest accuracy of 80.78%, paving the way for robust, automated detection of epileptiform activity in TBI patients.**

I. INTRODUCTION

Traumatic brain injury (TBI), physical injury to brain tissue that temporarily or permanently impairs brain function [1], can have wide-ranging physical, psychological, and cognitive effects. TBI outcomes include acute injuries, such as contusion or hematoma, as well as chronic sequelae that emerge days to years later, including cognitive decline and seizures [1], [2]. Post-traumatic epilepsy (PTE) is one consequence of TBI that can affect up to 50% of patients [3], with the highest incidences of PTE corresponding to severe penetrative head injuries. A person with PTE suffers from unprovoked and recurrent post-traumatic seizures (PTS) more than one week after TBI [4]. Currently, the Epilepsy Bioinformatics Study for Antiepileptogenic Therapy (EpiBioS4Rx) is enrolling moderate-severe TBI patients with the goal to identify biomarkers of epileptogenesis [5], [6], [7]. These biomarkers will help conduct more targeted clinical trials for antiepileptogenic interventions by identifying TBI patients who have the highest probability to develop PTE [2].

Although the mechanisms underlying epileptogensis are still under debate, recent investigations suggest that injury severity and lesion characteristics evidenced by neuroimaging, as well as epileptiform abnormalities (EAs) on electroencephalogram (EEG) are high risk factors of PTE. Kim et al. showed that the presence of EAs such as seizures, periodic discharges (PDs), and abnormal rhythmic delta activity (ARDA) in the EEG signal during the acute period following TBI independently predicted PTE in the first year post injury [8]. In another study, Vespa et al. suggested that seizures and PDs are one mechanism for metabolic crisis in TBI patients [9]. Fig. 1 displays sample EAs in EEG signals from the EpiBioS4Rx dataset. This evidence suggest that identifying EAs in EEG recordings is of fundamental importance to deepening our understanding of PTE. However, automated detection of EAs yields imprecise results, so EA detection is generally conducted via manual labeling, which requires both extensive expertise and time to mark these events [10]. In this paper, we address this issue by developing deep learning (DL) models to automatically detect EAs in EEG signals. These automatic methods will allow us to accelerate the process of biomarker identification, and ultimately PTE prediction.

DL models are a subset of machine learning models, which consist of multiple hidden layers of artificial neural networks and can be used to apply nonlinear transformations in large databases [11]. In recent years, DL has been used for analyzing medical data and has shown excellent performance in various applications such as medical image [12], [13] and signal [14] analysis. DL approaches have recently been applied to EEG data to address a range of neurological problems, such as sleep monitoring, braincomputer interface implementation, Alzheimers disease diagnosis, and seizure detection [15], [16], [17]. In previous studies, various DL architectures for detection of epileptiform EEG data have been proposed. Zhou et al. used a convolutional neural network (CNN) on raw EEG signals to identify segments of epileptic seizures with accuracy greater than 90% [18]. Another CNN based study [19] implemented a deep CNN algorithm to detect different seizure classes with an average

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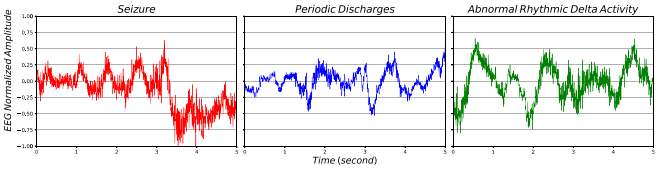

Fig. 1. Sample Epileptiform Abnormalities: Seizure, Periodic Discharges, and Abnormal Rhythmic Delta Activity in EEG signal from the EpiBioS4Rx study.

accuracy of 88.7%, a specificity of 90% and a sensitivity of 95%. More recently, recurrent neural networks (RNNs) have gained attention in time series analysis because of their ability to learn sequential information from data and effectively exploit temporal dependencies in time series [17], [20]. Hussein et al. used an RNN based model with long short-term memory (LSTM) cells for robust detection of epileptic seizures achieving 100% classification accuracy, 100% sensitivity, and 100% specificity [17]. An important advantage of many of these DL methods is that they eliminate the need for preprocessing the EEG signal and performing manual feature selection in order to achieve robust detection [18], [17]. We follow this approach in our implementation and relaxed the need for any major preprocessing.

While other approaches have used DL to detect the presence of epileptic seizures, to the best of the authors' knowledge, this is the first EEG study to employ DL for the automated classification of *four* classes of EEG (Normal and three EAs) on continuous EEG data collected from *TBI patients*. In this study, a Multi-layer Perceptron (MLP) and an RNN based model are developed to categorize normal, seizure, PD, and ARDA classes in EEG signal. This paper is organized as follows: Section II briefly presents the dataset. Section III presents the proposed DL methodologies. Experimental results are presented in Section IV, and final conclusions and future work are discussed in section V.

II. DATASET

The dataset used in this investigation is from the EpiBioS4Rx study and described in [5], [6]. Continuous EEG data are acquired during first week of post-injury. The selected EEG data are gathered from four male TBI patients enrolled in EpiBioSRx with average age of 45.25 (SD=19.8) and average Glasgow Coma Score of 8.25 (SD=4.6) upon arrival to the emergency department. EEG for each patient contains 12 single channels, with seven day duration for each subject. Data have been reviewed by EEG experts, and segments with EEG abnormalities (Seizure, PD, and ARDA) were extracted with their corresponding labels. The experimental procedures involving human subjects described in this paper were approved by the medical institutional review boards of each of the collaborating institutions.

III. METHODOLOGY

In this study, we propose two DL based models for the purpose of automatic EA detection. The EA detection problem is formulated as a classification task between four

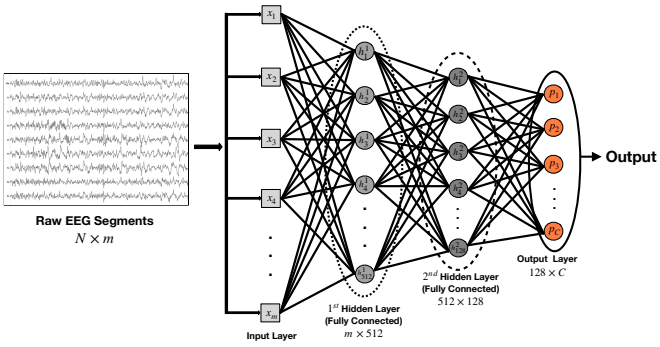

Fig. 2. Schematic diagram of the MLP Model for epileptiform abnormality detection approach: Raw EEG is segmented into 5 second epochs, leading to features of dimension $N \times m$, where N is the number of input samples and $m = 5 \times 250 = 1250$ is the total number of data points in each EEG segments (due to the 250 Hz sampling rate). These segments are used as the input to the model; h represents fully connected (dense) layers unit; p_1, p_2, p_3, ..., and p_m are the probabilities produced by output layer for the C-classes; Out indicates the predicted label for the corresponding input.

different EEG classes: normal, seizure, PD, and ARDA. In spite of the abundant research in seizure prediction, there is no highly precise and automatic method for EA detection in TBI patients. The first classification model is based on a simple feed-forward deep neural network, also known as a Multi-layer Perceptron (MLP). The network structure of the proposed MLP model is shown in Fig. 2. The MLP model does not explicitly take into account temporal aspects of the data so to leverage temporal information, the second model uses a Recurrent Neural Network (RNN) structure [20], shown in Fig. 3.

A. EEG Segmentation and Data Reshape

Raw EEG data without any preprocessing are used as the input to all the models, which allows the discriminative features of a given EEG time course to be learned automatically using the DL algorithms. This allows the trained DL models to be more widely applicable by reducing the overhead, in preprocessing time and expertise, needed to perform classification. The raw EEG data take the form of 12 channels per subject, covering a 7 day period for each subject. Clinician defined labels of EAs are used to separate out specific channels and specific time periods where EAs occurred. All the EEG signals containing EAs are divided into non-overlapping segments of a specific time length (L). One important reason for EEG segmentation in this study is the need for a large number of labeled data samples to train the neural networks. In real-life applications, it is hard to obtain sufficient well-labeled data for training deep neural networks to have a reliable output. The data segmentation, however, can help obtain more training samples, and hence improve the performance of the DL architecture under study[17]. A small segment time window, L=1 second, would result in a computationally slow process thus L was chosen as *5 seconds* to balance computational complexity with getting enough samples for training [17], [21]. As a result of the segmentation, each sample used for training is a 5 second window of a single EEG channel. Across all subjects, 2138

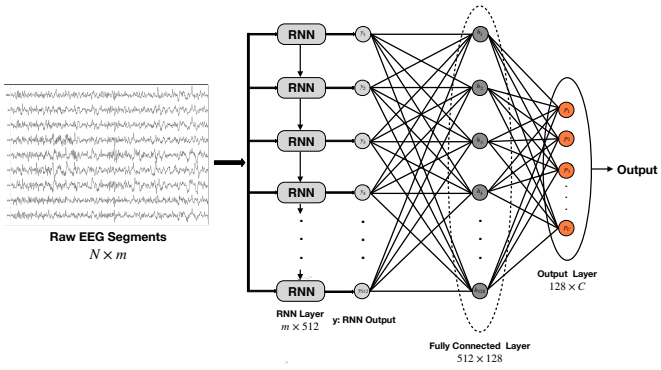

Fig. 3. Schematic diagram of the RNN Model for epileptiform abnormality detection approach: Raw EEG is segmented into 5 second epochs, leading to features of dimension $N \times m$, where N is the number of input samples and $m = 5 \times 250 = 1250$ is the total number of data points in each EEG segments (due to the 250 Hz sampling rate). These segments are used as the input to the model; y is the output of RNN layer; h represents a fully connected (dense) layer unit; p_1, p_2, p_3, ..., and p_m are the probabilities produced by output layer for the C-classes; Out indicates the predicted label for the corresponding input.

samples with EAs where extracted, with around 700 samples from each of the 3 EA types. A matching number of nonevent (normal) EEG samples were extracted to provide balanced data for classification.

B. Multi-Layer Perceptron

MLP is one of the most popular and widely used artificial neural networks (ANNs). In general, MLP consists of three successive layers: an input layer, hidden layers, and an output layer [22]. The ANN idea is motivated by the structure of the human brains neural system in which the activation function of a node defines the output of that node given an input or set of inputs [21]. Nonlinear activation functions help the network to learn the features better. Final output at the output layer is an indication of the appropriate predicted class of the corresponding input data. The first MLP model classifies signals in two classes: normal and any EA in the EEG segment. It consists of two hidden layers, with 512 and 128 units respectively. The model is trained with backpropagation and optimized using stochastic gradient descent (SGD) algorithm, and the loss function used is the binary cross entropy as defined by (1).

$$l(y, \hat{y}) = -[y\, log(\hat{y}) \; + \; (1 - y)\, log(1 - \hat{y})]] \tag{1}$$

where y and $\hat{y}$ are true and predicted outputs respectively.

The Rectifier Linear Unit (ReLU) activation function was used to add nonlinearity and to ensure robustness against noise in the input data [21]. ReLU is defined in (2).

$$f(x) = max(0, x) \tag{2}$$

where x is the sum of the weighted input signals and $f(x)$ is the ReLU activation function.

To map from output probabilities to class labels, the LogSoftmax function was used, which is defined in (3).

$$LogSoftMax(x_i) = log\Big(\frac{exp(x_i)}{\sum_{c=1}^{C} exp(x_c)}\Big) \tag{3}$$

where x_i is the sum of the weighted input signals and C is the number of classes.

The second MLP model classified signals into one of four classes: normal and each of three EAs as separate classes. Again the model consists of two hidden layers with same structure as the first MLP model. The only difference is in loss function since there are more than two classes. The cross entropy loss for more than two classes is defined in (4).

$$l(y, \hat{y}) = -\sum_{c=1}^{C} y_c\, log(\hat{y}_c) \tag{4}$$

where C is the number of classes.

C. Recurrent Neural Network

RNNs are a type of neural network that can maintain state along the sequential inputs, meaning they can process a temporal sequence of data depending on the processing done on the previous sequences [20]. It is this property of RNNs that makes them suitable for applications such as time series prediction. The first RNN model is trained to perform classification between two classes: normal and any EA. It consists of two hidden layers: first layer with 512 RNN cells and second layer with 128 dense and fully connected units. The model is trained with backpropagation and optimized using SGD algorithm and the loss function used is the binary cross entropy defined by (1) and ReLU activation function defined by (2) and also LogSoftmax activation function (3) is selected for the output layer.

The second RNN model has the same structure as the first one except that it classifies between four classes: normal and each of EAs as separate classes and the lost function is cross entropy given by (4).

D. Performance Assessment

The EEG dataset was split into two sets, the first set was used for training (80% of the available data), and the second set for validation (20% of the available data). To assess the performance of our models, we calculate measurement matrices, such as precision, sensitivity (recall), f1-score, and accuracy as defined by (5), (6), (7), and (8) respectively.

$$Precision = \frac{tp}{tp + fp} \tag{5}$$

$$Sensitivity\ (Recall) = \frac{tp}{tp + fn} \tag{6}$$

$$f1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{7}$$

$$Accuracy = \frac{tp + tn}{tp + tn + fp + fn} \tag{8}$$

where tn, tp, fn and fp are the true negative, true positive, false negative, and false positive respectively.

TABLE I

PERFORMANCE EVALUATION OF THE PROPOSED MODELS.

model	number of classes	precision (%)	sensitivity (%)	f1-score (%)	prediction accuracy (%)
MLP	2	94.43	94.52	94.41	94.41
	4	78.85	77.61	77.20	78.12
RNN	2	95.34	95.42	95.28	95.28
	4	80.05	79.70	79.47	80.78

IV. RESULTS

In this section, we evaluate our proposed models by calculating some performance measures, such as precision, sensitivity, f1-score, and prediction accuracy. We initially examine the capability of the proposed methods to recognize whether the EEG is normal or if it contains any EAs. We then study the potential of the proposed DL models to address the four-class EEG classification problem between the EEG sets of normal, seizure, PD, and ARDA. This is a more challenging problem compared to the two-class classification problems.

Table I summarizes the performance of each method for two-class and four-class problem. For the two-class classification, we observe that the RNN model has a better performance in terms of accuracy (95.28%), precision (95.34%), sensitivity (95.42%) and f1-score (95.28%) than the MLP model (accuracy (94.41%), precision (94.43%), sensitivity (94.52%) and f1-score (94.41%)). This problem formulation is distinct from, but most similar to, seizure classification tasks in the literature. Comparable seizure classification studies [18], [19], perform at around 90% accuracy and 95% sensitivity, suggesting that for the simpler of the two classification tasks our models perform as well or better than models in the literature. For four-class problem, we can see that, again, the RNN model outperformed MLP in terms of accuracy (RNN: 80.78%, MLP: 78.1%), precision (RNN: 80.05%, MLP: 78.85%), sensitivity (RNN: 79.70%, MLP: 77.61%) and f1-score (RNN: 79.47%, MLP: 77.20%).

V. CONCLUSIONS

In this study, DL was applied to two novel classification tasks using TBI patient's EEG data. Results from the first task, identifying the presence of any EA, compared favorably to the most closely related results in the literature. This paper introduces the second task, identifying each of the specific EAs. Even though this problem was more complicated, we still obtained promising results that provide a baseline for future studies. Future work will consider improving the usability of these methods by removing the channel selection step and using these EA features as a stepping stone for interpretable classification of PTE. As such, on top of their novelty and their intellectual value as an independent object of study, these results also provide the foundation for the prediction of PTE in TBI patients.

REFERENCES

[1] S. Parikh, M. Koch, and R. K. Narayan, "Traumatic brain injury," *International Anesthesiology Clinics*, vol. 45, pp. 119–135, 2007.

[2] R. M. Verellen and J. Cavazos, "Post-traumatic epilepsy: an overview." *Therapy*, vol. 7, pp. 527–531, 2010.

[3] M. L. Rocca, R. Garner, N. Amoroso, E. Lutkenhoff, M. M. Monti, P. Vespa, A. W. Toga, and D. Duncan, "Multiplex networks to characterize seizure development in traumatic brain injury patients," *Frontiers in Neuroscience*, vol. 14, p. 1238, 2020.

[4] A. Agrawal, J. Timothy, L. Pandit, and M. Manju, "Post-traumatic epilepsy: an overview," *Clinical Neurology and Neurosurgery*, vol. 108, pp. 433–439, 2006.

[5] P. M. Vespa, V. Shrestha, N. Abend, D. Agoston, A. Au, M. J. Bell, T. Bleck, M. Blanco, J. Claassen, R. Diaz-Arrastia *et al.*, "The epilepsy bioinformatics study for anti-epileptogenic therapy (epibios4rx) clinical biomarker: Study design and protocol," *Neurobiology of disease*, vol. 123, pp. 110–114, 2019.

[6] D. Duncan, G. Barisano, R. Cabeen, F. Sepehrband, R. Garner, A. Braimah, P. Vespa, A. Pitkänen, M. Law, and A. W. Toga, "Analytic tools for post-traumatic epileptogenesis biomarker search in multimodal dataset of an animal model and human patients," *Frontiers in Neuroinformatics*, vol. 12, p. 86, 2018.

[7] R. Garner, M. La Rocca, P. Vespa, N. Jones, M. M. Monti, A. W. Toga, and D. Duncan, "Imaging biomarkers of posttraumatic epileptogenesis," *Epilepsia*, vol. 60, no. 11, pp. 2151–2162, 2019.

[8] J. A. Kim, E. J. Boyle, A. C. Wu, A. J. Cole, K. J. Staley, S. Zafar, S. S. Cash, and M. B. Westover, "Epileptiform activity in traumatic brain injury predicts posttraumatic epilepsy," *Annals of Neurology*, vol. 83, pp. 858–862, 2018.

[9] P. Vespa, M. Tubi, J. Claassen, M. Buitrago-Blanco, D. McArthur, A. G. Velazquez, B. Tu, M. Prins, and M. Nuwer, "Metabolic crisis occurs with seizures and periodic discharges after brain trauma," *Annals of Neurology*, vol. 79, pp. 579–590, 2016.

[10] P. Boonyakitanont, A. Lek-uthai, K. Chomtho, and J. Songsiri, "A review of feature extraction and performance evaluation in epileptic seizure detection using eeg," in *Biomedical Signal Processing and Control*, Mar. 2020, pp. 1746–8094.

[11] R. Vargas, A. Mosavi, and R. Ruiz, "Deep learning: A review," *Advanced Intelligent Systems*, pp. 1–11, 2017.

[12] G. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. van der Laak, and C. I. S. B. van Ginneken, "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60–88, 2017.

[13] L. Bellantuono, , L. Marzano, M. L. Rocca, D. Duncan, A. Lombardi, T. Maggipinto, A. Monaco, S. Tangaro, N. Amoroso, and R. Bellotti, "Predicting brain age with complex networks: From adolescence to adulthood," *NeuroImage*, vol. 225, p. 117458, 2021.

[14] B. Rim, N.-J. Sung, S. Min, and M. Hong, "Deep learning in physiological signal data: A survey," *Sensors*, vol. 20, p. 969, 2020.

[15] Y. M. Marghi, P. Gonzalez-Navarro, B. Azari, and D. Erdomu, "A parametric eeg signal model for bcis with rapid-trial sequences," in *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 2018, pp. 118–122.

[16] Y. Roy, H. Banville, I. Albuquerque, A. Gramfort, T. H. Falk, and J. Faubert, "Deep learning-based electroencephalography analysis: a systematic review," *Journal of Neural Engineering*, vol. 16, no. 051001, p. 37, 2019.

[17] R. Hussein, H. Palangi, R. K. Ward, and Z. J. Wang, "Optimized deep neural network architecture for robust detection of epileptic seizures using eeg signals," *Clinical Neurophysiology*, vol. 130, pp. 25–37, 2019.

[18] M. Zhou, C. Tian, R. Cao, B. Wang, Y. Niu, T. Hu, H. Guo, and J. Xiang, "Epileptic seizure detection based on eeg signals and cnn," *Frontiers in Neuroinformatics*, vol. 95, p. 95, 2018.

[19] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, "Deep convolutional neural network for the automated detection and diagnosis of seizure using eeg signals," *Computers in Biology and Medicine*, vol. 100, pp. 270–278, 2018.

[20] M. Hüsken and P. Stagge, "Recurrent neural networks for time series classification," *Neurocomputing*, vol. 50, pp. 223–235, 2003.

[21] H. Daoud and M. A. Bayoumi, "Efficient epileptic seizure prediction based on deep learning," in *IEEE Transactions on Biomedical Circuits and Systems*, vol. 13, Jul. 2019, pp. 804 – 813.

[22] C. M. Bishop, *Pattern recognition and machine learning*. springer, 2006.