Transfer Learning-based Seizure Detection on Multiple Channels of Paediatric EEGs

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***Abstract*— Epilepsy is a common neurological disease characterised by recurring seizures that affect up to 70 million people worldwide. During the first ten years of life, approximately one in every 150 children is diagnosed with epilepsy. EEG is an important tool for diagnosing seizures and other brain disorders. However, expert visual analysis of EEGs is time-consuming. In addition to reducing expert annotation time, the automatic seizure detection method is a powerful tool for assisting experts with the analysis of EEGs. Research on the automated detection of seizures in pediatric EEG has been limited. Deep learning algorithms are typically used in paediatric seizure detection methods; however, they are computationally expensive and take a long time to develop. This problem can be solved using transfer learning. In this study, we developed a transfer learning-based seizure detection method on multiple channels of paediatric EEGs. The publicly available CHB-MIT EEG dataset was used to build our method. The dataset was split into training (n=14), validation (n=4), and testing (n=6). Spectrograms generated from 10 s EEG signals with 5 s overlap were used as the input into three pre-trained transfer learning models (ResNet50, VGG16 and InceptionV3). We took care to separate the children into either the training or test set to ensure that the test set was independent. Based on the EEG test set, the method has 85.41% accuracy, 85.94% recall, and 85.49% precision. This method has the potential to assist researchers and clinicians in the automated analysis of seizures in paediatric EEGs.**

I. Introduction

Epilepsy is a common neurological disease characterized by recurrent seizures that affect an estimated 70 million people worldwide [8]. During the first ten years of life, approximately one in every 150 children is diagnosed with epilepsy [1]. Seizures in these children disturb their lives and can seriously damage the brain's development. Electroencephalography (EEG) is the most commonly used clinical tool to diagnose epilepsy [13]. Annotating seizure events in EEG recordings, however, requires time-consuming expert analyses [16]. Automated seizure detection methods are an effective tool for helping to reduce experts' annotation time. According to current research on automatic seizure detection methods, several methods have been established based on adult EEGs [2], [14]. However, research indicates that the adult-based seizure detection method may not be appropriate for paediatric since EEG changes with ageing [15], [17]. Therefore, it is necessary to develop seizure detection methods specifically for children.

Research on automatic seizure detection in pediatric EEG has been limited. The CHB-MIT Scalp EEG Database [10] is used by most paediatric seizure detection methods, and several deep learning methods have been developed to detect seizures in CHB-MIT EEGs [7], [11], [19], [23]. To obtain adequate performance, deep learning algorithms require a lot of training time and computational resources. However, these problems can be solved using transfer learning. Transfer learning can replace the last output layer of the previously trained model with fully connected layers and the output layer for seizure detection. By freezing the training weights of the pre-training network and training only the weights of the fully connected layers that are replaced, the required information can be obtained with a small computational cost [4].

To detect seizures in CHB-MIT EEGs, deep transfer convolutional neural networks based on VGG16, VGG19, and ResNet50 were presented in [22], with average accuracies of 97.75%, 98.26%, and 96.17%, respectively. However, these CHI-MIT EEG-based seizure detection methods divided their EEG dataset into epochs and trained and tested on epochs which may come from the EEG of the same person. As a result, there is a risk of overfitting, and the performance of the methods on patients not included in the training data is unknown.

In this study, we used transfer learning techniques that investigate multiple channels of paediatric EEGs (CHB-MIT, n=24) to detect seizures. We took care to separate the children into either the training or test set to ensure that the test set was independent, reducing the overfitting problem. Our method significantly increased the speed, reliability, and repeatability of seizure analysis in paediatric EEGs, which has the potential to be helpful in clinical research.

II. Materials and Methodology

A. CHB-MIT EEG Dataset

The CHB-MIT EEG recordings are provided by the Massachusetts Institute of Technology (MIT, USA), which is an open-source EEG database collected at the Children's Hospital Boston (https://physionet.org/content/chbmit/1.0.0/) [10]. The majority of CHB-MIT EEGs had eighteen channels, and these are channels FP1-F7, F7-T7, T7-P7, P7-O1, FP1-F3, F3-C3, C3-P3, P3-O1, FZ-CZ, CZ-PZ, FP2-F4, F4-C4, F4-P4, P4-O2, FP2-F8, F8-T8, T8-P8, and P8-O2. In the dataset, there were significantly fewer seizure events than non-seizure events. This would result in a class imbalance

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problem, making developing a machine learning algorithm difficult [17]. To address this, we used undersampling to balance the data set. We remove some non-seizure events so that the number of seizure and non-seizure events is similar. Table I shows the detail of the dataset.

TABLE I
TABLE SHOWING THE NUMBER AND DURATION OF SEIZURES AND NON-SEIZURES IN CHB-MIT EEG RECORDINGS USED IN THIS STUDY.

Data	N	Seiz No.	Non-seiz No.	Seiz D (s)	Non-seiz D (s)
Train & Val	18	8070	10020	40355	50105
Test	6	2000	1920	10005	9605

N: Number of patients; Seiz: Seizure; No.: Number; Non-seiz: None seizure; D: Duration;

B. Channel Selection

EEG recording is a highly complex process that necessitates alterations to the particular channel arrangement of each EEG or clinical site. Making the channel universal for all EEGs and offering a respectable level of performance is particularly advantageous [14]. We selected ten channels from different brain locations (See Figure 1). In order to obtain information for the left and right frontal lobes, channels FP1-F7, FP1-F3, FP2-F4, and FP2-F8 were selected. The information for the left and right central lobes is studied using channels F3-C3 and F4-C4, whereas C3-P3 and C4-P4 are used to obtain information for the left and right parietal lobes. EEG signals on channels P3-O1 and P4-O2 can get information for the left and right occipital lobes. As signals on channels T3-T5 and T4-T6 were not captured in the CHB-MIT dataset, these channels were excluded from this study.

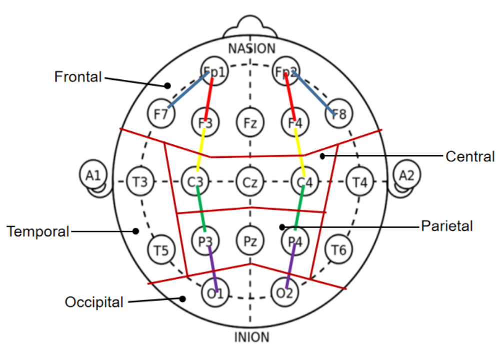

Fig. 1. Figure showing the selected channels in CHB-MIT EEGs. These channels are FP1-F7, FP1-F3, FP2-F4, FP2-F8, F3-C3, F4-C4, C3-P3, C4-P4, P3-O1, and P4-O2.

C. Data Pre-processing

EEG recordings from the CHI-MIT dataset were processed at the original sampling frequency of 256 Hz. To eliminate power line interference, each channel of the EEG recordings was filtered with a notch filter (60Hz). Signals in the band of interest were obtained using the Butterworth filter (infinite impulse response) (0.1-64 Hz). Fixed-duration epochs of 10 s with a 5 s overlap were used to segment the pre-processed EEG signal. The spectrogram was then generated using these EEG epochs, with each spectrogram corresponding to a seizure event or non-seizure event.

D. Method Development

The seizure detection methods in this study were built using three pre-trained transfer learning models: VGG16, ResNet50, and InceptionV3. These pre-trained models were employed as feature extractors by freezing the initial layers and taking the figure of size 256×256×3 as input. The final output layer was eliminated, adding two fully connected layers (Dense: 128 and 64), each followed by a rectified linear unit (ReLU) activation. Regularisation (L2: 0.05) was applied to improve generalisation ability and prevent overfitting [21]. The output layer has a sigmoid activation at the bottom for seizure detection. The training optimiser uses the Adam method [6], with a batch size of 64. The epoch is set to 100 for each of these three models. The architecture of the method is shown in Figure 2.

E. Post-processing

Research shows that not every channel's signal changes significantly when a seizure occurs [14]. Therefore, logistic regression was used to integrate the VGG16's predictions of each epoch (same time frame) from ten channels in the training set. (See Figure 2). The logistic regression model is then applied to the output of VGG16 on the ten channels of the test set. After applying the logistic regression model to multiple channels of EEGs, the final result for each spectrogram is classified as a seizure or non-seizure event.

III. RESULTS

A. Performance of transfer learning-based seizure detection methods

Table II shows that the VGG16 outperforms ResNet50 and InceptionV3 in terms of seizure detection on the validation set of CHB-MIT EEGs.

TABLE II
PERFORMANCE OF TRANSFER LEARNING MODELS FOR SEIZURE DETECTION ON THE VALIDATION SET.

CHBMIT (validation)	Loss	Accuracy	Recall	Precision
ResNet50	0.6868	55.67	100.0	55.67
VGG16	0.5593	74.60	85.00	73.51
InceptionV3	0.6871	55.67	100.0	55.67

B. Post-processing using logistic regression for VGG16

Table III shows the performance of the VGG16 model for seizure detection on the training, validation and test set, as well as the performance after incorporating the post-processing method on the test set. After applying the post-processing method involving the results of multiple channels (using logistic regression), the accuracy, recall and precision on the test set increased by approximately 12%.

Table IV shows the performance of the seizure detection method (after post-processing) on the individual patients, with accuracy from 73.47% to 94.29% on the test set.

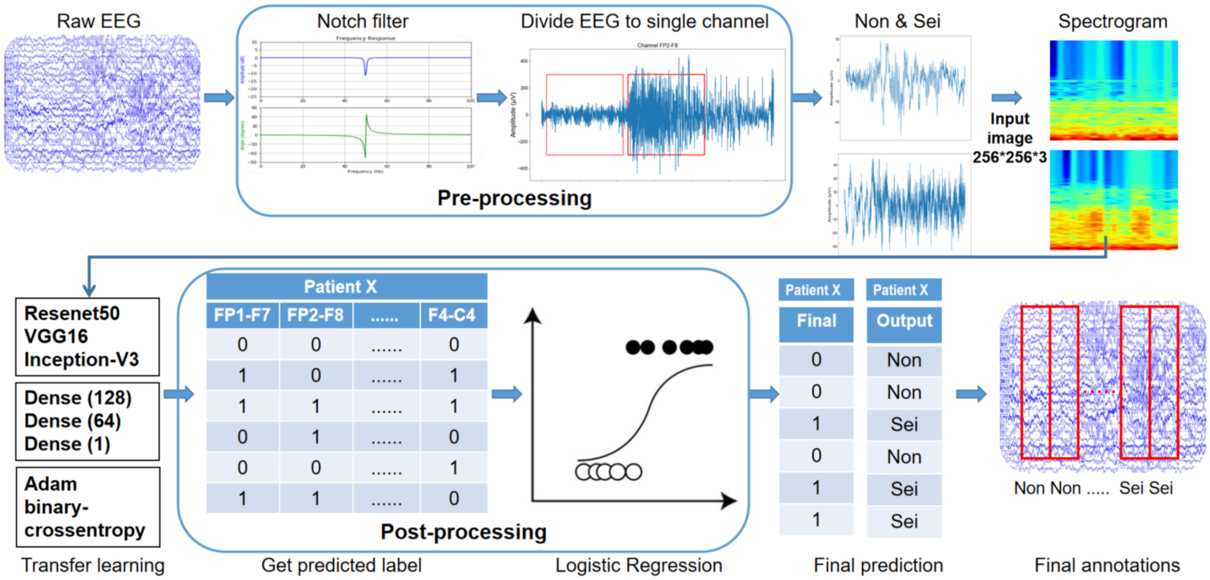

Fig. 2. An overview of the seizure detection method based on transfer learning. To remove powerline interference from EEGs, a 60 Hz notch filter was used, and then 10 s with 5 s overlap epochs were segmented on each channel (ten channels total), corresponding to seizure or non-seizure events. The spectrograms generated from the epochs were then fed into the pre-trained transfer learning models. To derive the final result, a logistic regression algorithm was used to post-process the outputs from multiple channels (10 channels) to classify the event as seizure or non-seizure (0 represents the non-seizure event; 1 represents the seizure event).

TABLE III

PERFORMANCE OF THE VGG16 MODEL FOR SEIZURE DETECTION ON THE TRAINING, VALIDATION AND TEST SET, AS WELL AS THE PERFORMANCE AFTER APPLYING THE POST-PROCESSING METHOD ON THE TEST SET.

CHBMIT	Loss	Accuracy	Recall	Precision
Train	0.4934	79.73	88.90	77.69
Validation	0.5593	74.60	85.00	73.51
Test	0.5852	73.78	80.73	70.20
Test (Post-processing)	-	85.41	85.94	85.49

TABLE IV

PERFORMANCE OF THE DEVELOPED METHOD (AFTER POST-PROCESSING) FOR SEIZURE DETECTION ON THE INDIVIDUAL PATIENTS.

Dataset	Patient	Accuracy	Recall	Precision
Train and validation set	CHB07	93.88	94.44	89.47
	CHB08	90.91	100.0	73.17
	CHB09	68.42	33.33	100.0
	CHB10	78.57	66.67	87.50
	CHB11	96.94	100.0	85.71
	CHB12	82.05	100.0	77.42
	CHB13	81.97	96.67	74.36
	CHB14	86.08	95.45	88.73
	CHB15	88.63	82.46	91.26
	CHB16	86.54	91.67	93.62
	CHB17	84.38	97.22	79.55
	CHB18	92.80	97.92	93.07
	CHB19	98.44	100.0	97.67
	CHB20	84.81	90.00	90.00
	CHB21	64.86	88.89	59.26
	CHB22	98.63	100.0	98.18
	CHB23	100.0	100.0	100.0
	CHB24	97.16	100.0	96.67
Test set	CHB01	92.94	100.0	87.50
	CHB02	94.29	94.44	94.44
	CHB03	77.50	83.33	76.09
	CHB04	84.09	88.89	76.19
	CHB05	89.29	73.33	95.65
	CHB06	73.47	78.57	89.19

IV. DISCUSSION

In this study, we present a transfer learning-based seizure detection method that can assist researchers in automatically analysing paediatric EEGs. Previous seizure detection methods require the application of domain knowledge to create feature extractors [9], which is a complicated and expensive process in terms of time, and expertise [18]. Transfer learning can solve these issues without requiring feature estimation.

Several deep learning-based seizure detection methods utilising CHI-MIT EEGs have been presented in [5], [7], [11], [12], [19], [23]. These methods achieved an accuracy of 67.2% to 77.6% and recall of 65.3% - 82.7% on patients 1, 6, 8, 9, 10, 18, and 22 of CHB-MIT EEGs (the performance for other patients is unknown, as these methods did not present the results for the other patients in their work). In the current work, we achieved a higher average accuracy (85.1%) and recall (82.4%) on these patients. Additionally, these CHI-MIT EEG-based seizure detection methods divided their EEG dataset into epochs and trained and tested on epochs that might originate from the same person's EEG. As a result, there is a risk of overfitting, and the performance of these methods on patients not included in the training data is unclear. We divided different children into the training or test set to verify that the test set was independent and to lessen the overfitting issue. Moreover, the deep learning method requires a lot of time and computational resources to achieve a satisfactory result. Therefore, transfer learning was used in this study to handle the aforementioned issues and reduce training time and computing costs while achieving higher performance.

Our transfer learning-based seizure detection method takes into account the output of the multiple channels, given that not every channel's signal changes noticeably when a seizure occurs [14]. Therefore, we post-processing the output of each channel. After applying the post-processing method on multiple channels, the accuracy, recall and precision improved by approximately 12% on the test set (See Table III).

The limitation of the current study is that certain patients had low recall and precision, with recall for CHB10 and CHB09 being 66.67% and 33.33%, and precision for CHB08 and CHB21 was 73.17% and 59.26%, respectively. It demonstrates that CHB05 and CHB09 contain high false negative (FN) events, and CHB08 and CHB21 contain high false positive (FP) events. One of the reasons is that we used the spectrogram to identify seizure events in EEG recordings. Some events were EEG visible but not spectrographically visible [20] (resulting in FN events), and artefacts may affect the prediction (leading to FP events). Therefore, some predictions contain high FN and FP events. However, seizure detection using a spectrogram can produce satisfactory results. By employing spectrograms as the input, our method achieved accuracy, recall, and precision of 85.41%, 85.94%, and 85.49% on the test set. In future work, we will incorporate the EEG signals and spectrograms to develop a seizure detection method that may reduce FN events. Additionally, since machine learning is a 'black box' method, we will incorporate Explainable Artificial Intelligence (XAI) [3] to help researchers understand why certain events are predicted to be seizures or non-seizures. XAI will gain the trust of researchers and assist them in analysing seizure events in pediatric EEGs.

V. Conclusions

In this study, we built a transfer learning-based seizure detection method on multiple channels of paediatric EEGs. We split the children into training or testing sets to ensure that the test sets are independent. In addition, our method uses pre-trained transfer learning models, which eliminates the need for extensive preprocessing and domain expertise while reducing time and computational resources. The method achieved accuracy, recall and precision above 85% on the test set, which has the potential to be useful in research by significantly improving the speed, reliability, and repeatability of seizure analysis in paediatric EEGs.

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