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RESEARCH ARTICLE

Transfer Learning for the Identification of Paediatric EEGs With Interictal Epileptiform Abnormalities

LAN WEI[1], JOHN C. MCHUGH[2], AND CATHERINE MOONEY[1]
[1]FutureNeuro SFI Research Centre, UCD School of Computer Science, University College Dublin, Dublin 4, D04 V1W8 Ireland
[2]Clinical Neurophysiology Department, Children's Health Ireland at Crumlin (CHI Crumlin), Crumlin, Dublin 4, D12 N512 Ireland

Corresponding author: Catherine Mooney (catherine.mooney@ucd.ie)

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ABSTRACT EEG is a test that helps in the clinical diagnosis of epilepsy. Epilepsy diagnosis is facilitated by establishing the presence of interictal epileptiform abnormalities on EEG, which predict an increased risk of seizure. The identification of interictal epileptiform discharges is a time-consuming task that requires highly-trained experts. A method to assist in the recognition of EEGs with epileptiform abnormalities was developed using transfer learning on multiple channels of paediatric EEGs, without the use of human annotations. The dataset included 350 children with normal EEGs and 597 children with interictal abnormalities, and it was divided into training data (n=452), validation data (n=112), and testing data (n=383). Spectrograms from each EEG signal channel were used as input for five pre-trained transfer learning models (Inception, ResNet, DenseNet, VGG16 and VGG19) and traditional feature-based machine learning methods were developed as a benchmark. A comparison was made between a transfer learning-based method and a traditional feature-based machine learning algorithm. The results revealed that the transfer learning-based method outperformed the feature-based machine learning methods, achieving an accuracy of 77%, an F1 score of 0.85, and a balanced accuracy of 77% on the test set. Our transfer learning-based method can identify interictal abnormalities without the need for feature estimation by domain experts or human annotations. This method can assist in the recognition of EEGs with epileptiform abnormalities in children thereby facilitating the clinical diagnosis of epilepsy.

INDEX TERMS Epilepsy, EEG, paediatric, transfer learning, machine learning.

I. INTRODUCTION

There is great optimism that the use of artificial intelligence (AI) in healthcare can greatly improve all aspects of the field, from diagnosis to treatment. AI is seen as a tool to support and enhance the work of health professionals. The application of machine learning on biomedical signals (e.g. ECG [1] and EEG [2]) and images (e.g. CT [3], MRI [4] and X-ray [5]) has facilitated medical diagnosis, prediction of potential diseases or events, and improvement of preventive care and treatment.

Unfortunately, there are many commonly encountered difficulties associated with the deployment of AI systems, such as "out-of-distribution generalization" [6]. When the distribution of a model's training data does not align with its performance distribution, the model may underperform. In addition, if the training data contains features that are

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misleadingly correlated with the outcomes the model is designed to predict, the model may rely on irrelevant features for making predictions. To mitigate these issues, creators of machine learning models should strive to match the training data distribution with the performance distribution as closely as possible. Clinicians using any machine learning model should be aware of its limitations and potential shortcomings stemming from its training distribution. Explainable Artificial Intelligence (XAI) offers a potential solution for certain issues. By providing a justification for the output generated by a system, XAI enables users to comprehend why it arrived at that particular conclusion. This interpretation can be contextualized within a specific framework, which makes machine learning models more acceptable and trustworthy for clinicians [7].

EEG is the most important test in the evaluation of patients with unprovoked seizures and epilepsy [8]. EEG recordings in individuals with epilepsy often reveal isolated abnormalities that occur between seizures but have a high association with epilepsy [9], [10]. These are referred to as interictal epileptiform discharges (IEDs), spikes or sharps [11]. IEDs are more frequent than seizures [11]. Most research to date has focused on seizure detection, whereas research on automated methods for identifying IEDs is limited, especially in children.

Most published IED detection methods [12], [13], [14], [15], [16] require EEGs to be divided into epochs which are labelled as having IEDs or not, which is a labour-intensive process. We are not aware of any research on automated methods to identify IEDs that do not rely on human annotations. Furthermore, the majority of IED detection methods have been developed using EEGs from adults or a mix of adults and children. Research has shown that EEGs change with age [17] making adult-based methods unsuitable for paediatric use. To the best of our knowledge, there is only one other paediatric-specific IED detection method [16]. In this study, we developed a transfer learning-based interictal EEG abnormality identification method on multiple channels of paediatric EEGs (350 normal EEGs; 597 EEGs with IEDs) without using human annotations. This approach could aid in identifying epileptiform abnormalities within children's EEGs, thereby supporting the clinical diagnosis of epilepsy.

II. MATERIALS AND METHODS

A. SUBJECTS

Ethical approval was granted from the Medical Research Ethics Committee of Our Lady's Children's Hospital Crumlin, Dublin, Ireland (GEN/617/17). 350 children with normal EEGs and 597 children with epileptiform abnormalities were used in this study. The study included children with normal EEGs, ranging in age from 6 to 10 years old (with a median age of 8 years old). Additionally, children with epileptiform abnormalities were also included, comprising 287 cases of focal interictal EEG abnormalities (aged from 6 to 17 years old; median age: 9 years old) and 310 cases of generalised interictal EEG abnormalities (aged from 6 to 18 years old; median age: 11 years old). We created a balanced training dataset with 283 normal EEGs and 281 EEGs with epileptiform abnormalities. The remaining EEGs (normal = 67; epileptiform = 316) were used for testing. It is important to highlight that EEGs from normal children or those with focal or generalised epilepsy employed in this study have been labelled by an expert. However, the study did not annotate the specific IED events within these EEGs. The details of the dataset used in this study is shown in Table 1.

TABLE 1. Number and duration of EEG recordings used in this study.

	Normal	Interictal EEG abnormalities	Total
Train/Validation	283	281	564
Duration/file (mins)	66.12	69.97	68.03
Duration (hours)	311.85	327.70	639.55
Test	67	316	383
Duration/file (mins)	62.73	72.12	70.48
Duration (hours)	70.06	379.81	449.87

B. CHANNEL SELECTION

The EEG was recorded using the 10-20 system of electrode placement [18]. Nineteen channels were selected to obtain information from the different brain regions (Figure 1).

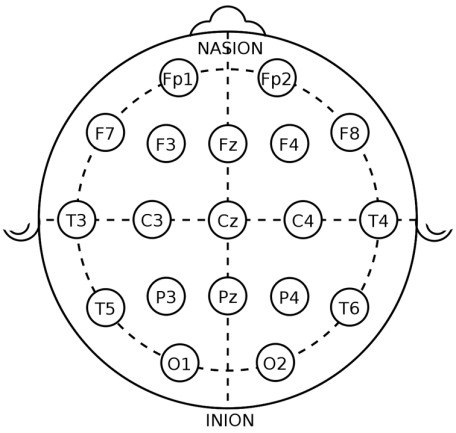

FIGURE 1. 10-20 system of electrode placement.

C. FEATURE-BASED MACHINE LEARNING METHODS

1) DATA PRE-PROCESSING

The CHI EEG dataset was sampled at different sampling frequencies of 200Hz, 256Hz, and 500Hz. Therefore, the EEG signal was resampled to 256Hz. Powerline interference was eliminated from the raw EEG signals using a 50 Hz notch filter, and DC offset was removed from the EEGs.

2) FEATURE ESTIMATION

Time and frequency domain features were estimated. To filter the signals, we employed Butterworth filters with a 6th-order

Infinite Impulse Response (IIR) design [19], for which the frequencies of interest mainly lie between 0-64 Hz. EEG frequencies are grouped into bands: delta frequencies are <4 Hz; theta is from 4 to 8 Hz; alpha is from 8 to 13 Hz; beta is 13 to 32 Hz; the gamma band is >32 Hz.

For each channel, 23 features were estimated from 5s epochs with 2.5s overlap. The mean, standard deviation, signal envelope, kurtosis, skewness, complexity, mobility, variance, and fractal dimension of preprocessed absolute amplitude were calculated in the time domain. In addition, wavelet decomposition was used to capture rhythm activities in delta, theta, alpha, beta, and gamma, and the relative and absolute band power of these rhythm activities was estimated. The absolute band power of EEG amplitude, Mel-frequency cepstral coefficients (MFCCs) [20], power spectral density (PSD), and amplitude modulation spectrogram (AM spectrogram) were also calculated as features. These features have been successfully used for brain event detection in EEGs in previous studies [21], [22], [23].

3) RANDOM FOREST ALGORITHM

We employed the random forest algorithm to develop an automated method for identifying interictal EEG abnormality in children. The implementation of the random forest classifier was done in a Python 3 environment, utilising the sklearn library [24]. Two parameters were optimised; n-estimators, the number of trees in the forest; and max depth, which is the maximum depth of the tree. These parameters (n-estimators and max-depth) were optimised based on the validation set's performance to improve the method for identifying interictal EEG abnormalities in EEG recordings. We did not have the specific start and end times of the epileptiform abnormalities in the EEG recordings. Therefore, we explored two random forest-based (RF) methods in this study.

a: RF 1 METHOD

We trained and tested the signal on 5s with 2.5s overlap epochs (23 features in each epoch) and used the final annotation (normal EEG: 0; epileptiform EEG: 1) to label each epoch. For instance, if a child had interictal EEG abnormalities, all their EEG epochs were labelled as 1; conversely, all epochs were labelled as 0 for children with normal EEGs. After that, we applied the random forest algorithm to these epochs. The majority vote of epochs was then used to determine the final diagnosis for each child. If more than 50% of the epochs in the EEG recordings were predicted as epileptiform EEG, the final annotation for that child was with epileptiform EEG and vice versa.

b: RF 2 METHOD

The mean value of each feature was calculated for the entire EEG recordings of each child to develop the random forest method. This means that each child had one value for each feature.

D. SPECTROGRAM-BASED TRANSFER LEARNING METHOD

1) DATA PROCESSING

Butterworth filter (infinite impulse response) was used to obtain the band of interest in the CHI EEG recordings (0.1-64 Hz). Previous studies on identifying IEDs in EEGs primarily used time series plots [25], [26]. However, spectrograms offer a more comprehensive representation of the frequency content of EEG signals over time compared to time series plots [27]. Spectrograms facilitate the identification of frequency patterns and changes that may not be easily discernible in time series plots. Therefore, spectrograms were employed in this study for the identification of IEDs. We generated a spectrogram for each EEG channel, with each spectrogram corresponding to either the channel of a child with normal or epileptiform EEG.

2) PRE-TRAINED TRANSFER LEARNING MODELS

Five popular CNNs architectures were adept at building the interictal abnormality detection method as follows:

a: INCEPTIONV3

Inception is a deep convolutional neural network; a key characteristic of an inception network is that it uses an inception module in which convolution is performed on an input using three different filter sizes (1×1, 3×3 and 5×5) [28]. The outputs are concatenated and sent to the next inception module. 1×1 convolutions are used to reduce the computational cost dimension. More convolutions were added to further reduce the computational complexity and improve the accuracy of the model [29].

b: RESNET50

ResNet, short for Residual Networks, is a classic neural network used as a backbone for many computer vision tasks [30]. In ResNet, skip connection is used by residual blocks in their architecture so that training from a few layers is skipped and fed directly to the last layer or output. Therefore, if any layer reduces the performance of the architecture, regularisation will be applied to skip it. As a result, networks with a large number of layers can be trained without increasing the training error percentage. ResNet can help in tackling the vanishing gradient problem using identity mapping.

c: DENSENET

In a Dense Convolutional Network (DenseNet) [31], each layer is directly connected to the other and uses deep connections to reuse features. DenseNet layers are narrow and do not need to learn redundant feature maps. Each layer receives new input from the layer above it and sends its own feature map to the layer below it. These characteristics allow DenseNet to achieve better performance with fewer parameters and computational costs. In addition,

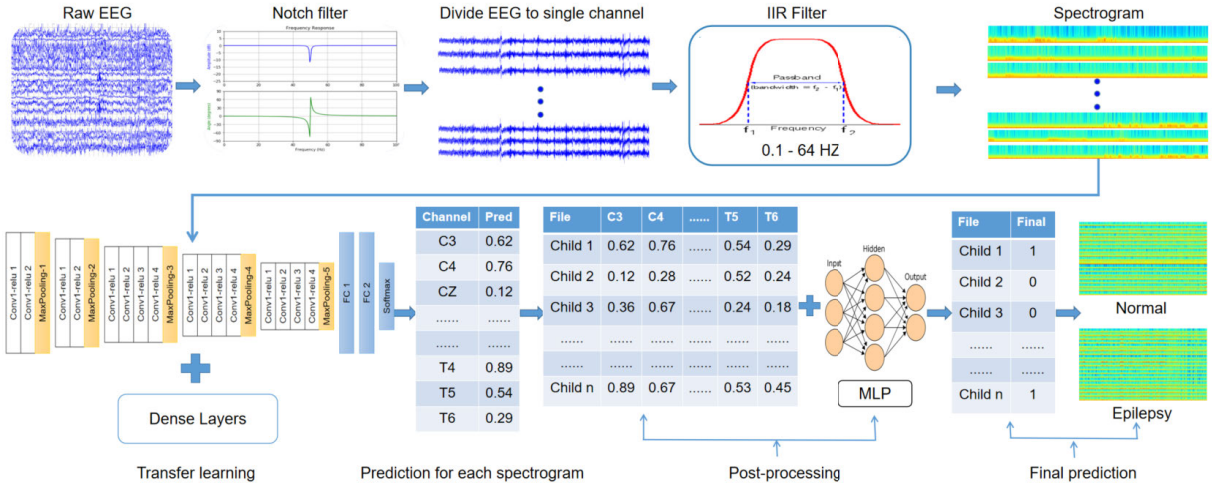

FIGURE 2. Overview of the transfer learning-based method for identifying interictal abnormalities in children. Powerline interference was removed by using a 50 Hz notch filter for EEGs. Butterworth filter (IIR: infinite impulse response) was used to obtain the signal in 0.1 - 64 Hz. The filtered signal on each channel was then converted into a spectrogram and fed to the VGG19 model. The post-processing method uses MLP on multiple channels (19 channels in total) to derive the final result, which defines whether the EEG belongs to the child with normal EEGs or abnormal epileptiform EEG (0 represents the child with normal EEGs; 1 represents the child with abnormal epileptiform EEGs).

DenseNet alleviates the vanishing-gradient problem, strengthens feature propagation, and encourages feature reuse.

d: VGG16 AND VGG19

VGG16 is a very deep convolutional neural network [32]. As a result of its good generalisation performance, VGG-16 can improve the classification accuracy by using its pre-trained model on the ImageNet dataset. VGG-16 commonly uses a small convolution kernel (3×3) to increase the depth of the network for better capacity. VGG-19 is another typical extended model that adds a fully connected layer and a pooling layer.

These pre-trained models are used as feature extractors by freezing the initial layers and using an input figure with a size of $256 \times 256 \times 3$. The final output layer is removed, and two fully connected layers (Dense: 128 and 64) are added to train the model, each followed by a rectified linear Unit (ReLU) activation. Regularization (L2: 0.05) is implemented to improve generalization and prevent overfitting. Sigmoid activation is at the bottom of the output layer for the detection of an abnormal epileptiform EEG. An Adam method [33] is used for the training optimiser, with a batch size of 64. The random seed was set to 42. The epoch is set to 100 for each of these five models. The early stopping technique [34] is applied to reduce overfitting with a patience value of 20.

3) POST-PROCESSING

Abnormal EEG activities are very often not evident on all recorded EEG channels; most EEG abnormalities are focal. To tackle this issue, a Multi-layer Perceptron classifier (MLP) is employed to combine the transfer learning model's (VGG19) predictions of each spectrogram (same time frame) from nineteen channels in the training set. The MLP model, trained using the VGG19 predictions, is then applied to the output of the transfer learning model on the nineteen channels of the test set, and the final result for each spectrogram would be classified as a child with normal EEG or child with abnormal epileptiform EEGs. The architecture of the method is shown in Figure 2.

4) EXPLAINABILITY (XAI)

Explainability of machine learning is particularly important in the healthcare sector [7]; the explanations can be used by domain experts to diagnose systematic errors and potential biases in the black box. To encourage the appropriate level of trust by clinicians in the machine learning method, SHapley Additive exPlanations (SHAP) is utilised to explain the predictions [35]. The SHAP plot is used in this study to show the importance of channels, which could help clinicians understand the prediction and assist them in identifying IEDs in children.

E. PERFORMANCE EVALUATION

The sensitivity, specificity, precision, accuracy, F1 score and balanced accuracy were used in estimating the performance of the transfer learning-based interictal epileptiform abnormality identification method.

$$Sensitivity = \frac{TP}{TP + FN} \tag{1}$$

$$Specificity = \frac{TN}{TN + FP} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

$$F1 = 2 * \frac{Sensitivity * Precision}{Sensitivity + Precision} \quad (5)$$

$$Balanced\ Accuracy = \frac{Sensitivity + Specificity}{2} \quad (6)$$

where:

- True Positives (TP): the number of children with interictal abnormalities predicted as children with interictal abnormalities
- False Positives (FP): the number of children with normal EEGs predicted as children with interictal abnormalities
- True Negatives (TN): the number of children with normal EEGs predicted as children with normal EEGs
- False Negatives (FN): the number of children with interictal abnormalities predicted as children with normal EEGs

III. RESULTS

A. RELATED WORK

Table 2 provides an overview of previous research on IED detection. However, the difference between datasets and evaluation methods makes a direct comparison between methods challenging.

TABLE 2. Previous work on IED automatic detection.

Ref	Subjects	Number	Sens (%)	Spec (%)	Prec (%)	Acc (%)
[25]	Adults	203	81.9	91.7	-	-
[36]	Children & Adults	241	60	99	-	-
[26]	Children	11	-	-	-	87
[37]	Children	11	-	-	-	96.1
[38]	Children	270	-	-	-	74.9
[39]	Children &Adults	24	96.9	-	97.0	-
[40]	Adults	12	-	-	-	93
[41]	Children & Adults	30	93.8	96.8	97.3	-
[16]	Children	19	77	-	-	-
[13]	Adults	545	80	-	-	-
[15]	Children & Adults	217	79	-	-	-

Sens: sensitivity; Spec: specificity; Prec: precision; Acc: accuracy;

B. FEATURE-BASED MACHINE LEARNING METHODS

Table 2 presents the performance of feature-based machine learning methods on the test set. The results indicate that RF 1 has high precision and specificity, both above 80%, but low sensitivity and accuracy, at 38% and 46%, respectively. RF 2 achieves a precision of 93% and a specificity of 92%, but its sensitivity and accuracy are only around 30%.

C. SPECTROGRAM-BASED TRANSFER LEARNING METHOD

1) TRANSFER LEARNING-BASED INTERICTAL EPILEPTIFORM ABNORMALITY IDENTIFICATION MODELS

Table 4 shows the performance of spectrogram-based transfer learning models on the training and validation set. The result shows that VGG 19 has the highest accuracy on the training and validation set, compared to Inception, ResNet, DenseNet and VGG16, with an accuracy of 80% and 77% on the training and validation set, respectively.

TABLE 3. Performance of feature-based machine learning methods on the test set.

	Sensitivity	Specificity	Precision	Accuracy
RF 1	38%	84%	91%	46%
RF 2	22%	92%	93%	34%

TABLE 4. Performance of spectrogram-based transfer learning models on the training and validation set.

Acc	Inception	ResNet	DenseNet	VGG16	VGG19
Train	65%	72%	66%	78%	80%
Val	63%	72%	66%	75%	77%

2) POST-PROCESSING USING MLP FOR VGG19

The performance of the transfer learning-based interictal epileptiform abnormality identification method on the training, validation and test sets is shown in Table 5. By employing the post-processing method using the MLP across multiple channels, the sensitivity and accuracy of the test set improved by approximately 20%, and the F1 score increased by around 0.15 as compared to the results obtained without post-processing.

3) EXPLAINABILITY (XAI)

Table 6 shows the rank of the channel importance in the training and test set (ranked in descending order of importance), which indicates that channel C3 is the most significant, while channel P4 is the least significant in most cases. The SHAP plot depicted in Figure 3 displays the

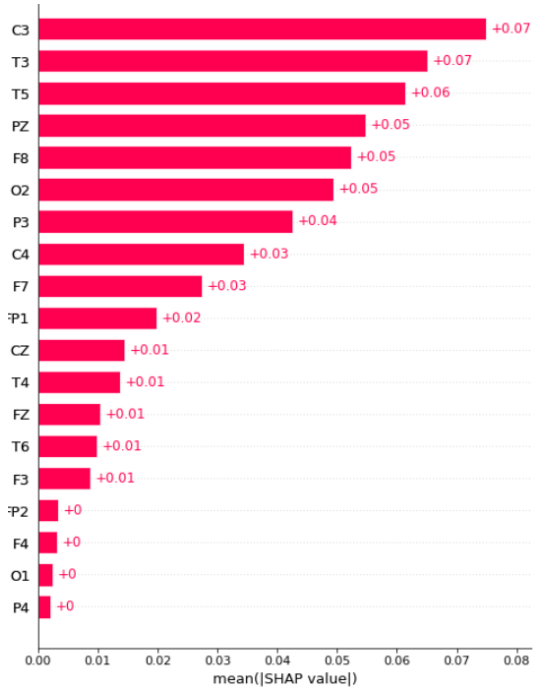

FIGURE 3. SHAP plot shows the rank of the important channels in the training dataset.

TABLE 5. Performance of the transfer learning-based interictal epileptiform abnormality identification method on training, validation and test set. Along with the application of the post-processing method using the MLP on the VGG19 model that involves multiple channels.

CHI	Sensitivity	Specificity	Precision	Accuracy	F1	Balanced accuracy
Train	76%	83%	82%	80%	0.79	79%
Validation	74%	81%	80%	77%	0.76	77%
Test	54%	79%	92%	59%	0.68	66%
Test (post)	77%	78%	94%	77%	0.85	77%

TABLE 6. The rank of channel importance in the training and test set (Train: The training set consists of EEG data used for training the model; Test All: The test set comprises a variety of EEG recordings, including normal EEGs, EEGs with focal interictal abnormalities, and EEGs with generalised interictal abnormalities; Test Normal: This subset of the test set exclusively contains normal EEG recordings; Test Focal: This subset of the test set includes EEG recordings with focal interictal abnormalities; Test Gen: This subset of the test set comprises EEG recordings with generalised interictal abnormalities).

	Channel importance (ranked in descending order of importance)
Train	**C3**, T3, T5, PZ, F8, O2, P3, C4, F7, FP1, CZ, T4, FZ, T6, F3, FP2, F4, O1, **P4**
Test All	**C3**, T3, T5, F8, PZ, O2, P3, C4, F7, FP1, T4, CZ, T6, FZ, F3, F4, FP2, O1, **P4**
Test Normal	**C3**, T3, T5, PZ, O2, F8, P3, F7, C4, FP1, CZ, T4, T6, FZ, F3, FP2, F4, O1, **P4**
Test Focal	**T3**, C3, T5, F8, PZ, O2, P3, F7, C4, FP1, T4, CZ, T6, FZ, F3, F4, FP2, O1, **P4**
Test Gen	**C3**, T5, T3, F8, PZ, O2, P3, C4, F7, FP1, CZ, FZ, T4, T6, F3, F4, FP2, P4, **O1**

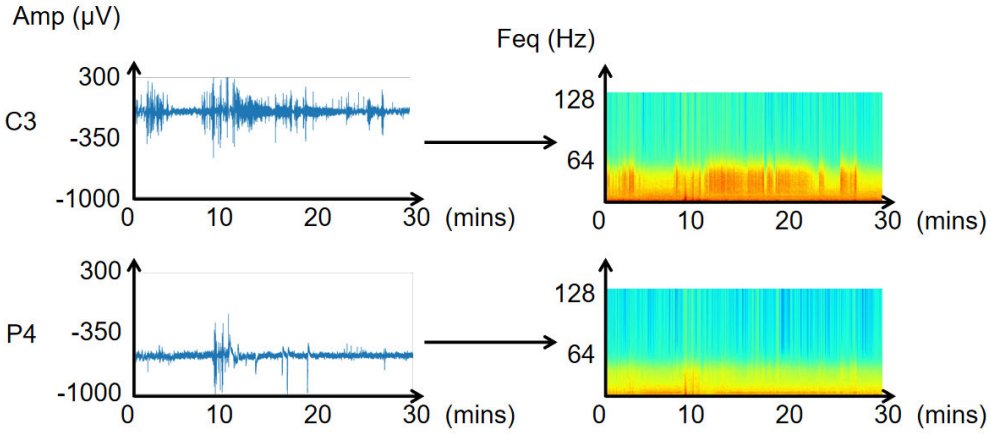

FIGURE 4. Example of EEG signal and spectrogram from a child with epileptiform abnormalities. Channel C3 is the most important channel, and channel P4 is the least important channel in this study.

channel importance in the training set. Figure 4 shows the EEG signal and spectrogram of the most and least important channels, demonstrating that channel C3 displays clear abnormal epileptiform activity, while channel P4's epileptiform activity is less evident.

IV. DISCUSSION

We investigated the use of feature-based machine learning algorithms in combination with random forest to identify IEDs in a paediatric population. The results (see Table 3) showed that while RF 1 had high specificity and precision, it had low sensitivity and accuracy, indicating a high number of false negatives (FN) and a low number of true positives (TP). This can be attributed to the fact that even abnormal EEGs consist of predominantly normal activities. Consequently, we labelled all events in each EEG as either normal or abnormal, without accurate times for the epileptiform abnormalities. This caused the random forest algorithm to predominantly learn normal events, thereby causing RF 1 to predict most events in the EEG as normal. As a result, the epochs were not labelled with specific start and end times of epileptiform abnormalities, making feature-based machine learning algorithms unsuitable. Therefore, accurate annotation of each epoch as normal or abnormal is necessary for feature-based machine learning algorithms to be effective.

The RF 2 approach resolves the annotation problem and computes the average value of each feature for each child's EEG, ensuring that no epoch is mislabeled. Based on the results shown in Table 3, specificity increased by about 10% compared to the RF 1 method. However, it is impossible to obtain the characteristics of the entire EEG accurately based on the mean value of each feature. Consequently, the performance was not satisfactory.

In order to address the challenges of identifying epileptiform abnormalities in paediatric EEGs, we proposed a spectrogram-based transfer learning model. Transfer learning can address this issue by adopting a well-trained network from one domain to another. To achieve this, convolutional layers are usually kept as general feature extractors, while only fully connected layers are retrained. As a result,

pre-trained networks require less data for fine-tuning. In this study, we employed five popular CNN architectures, Inception, ResNet, DenseNet, VGG16, and VGG19. Our findings indicate that VGG19 performed the best in terms of accuracy on the training and validation sets (Table 4). Previous work confirms that EEG abnormalities are not always evident in each EEG channel [42]. Thus, we utilised the MLP algorithm to combine the predictions of the VGG19 model across all 19 channels to obtain the final outcome. After post-processing, the sensitivity and accuracy of the test set increased by approximately 20%, and the F1 increased by around 0.17, as compared to the results obtained without post-processing (Table 5).

There is limited research on automated methods for identifying interictal abnormalities. Thomas et al. [12] developed a classification system based on IEDs detection, which comprised pre-processing, waveform-level classification using a Convolutional Neural Network (CNN), and EEG-level classification using a support vector machine. The dataset was obtained from Massachusetts General Hospital (MGH), Boston, and was recorded using the International 10-20 electrode system, the age of the patients is not specified. Their approach involved analyzing 30-minute EEG recordings of 156 participants, which included 93 patients with epilepsy with annotated IEDs and 63 spike-free EEGs. The system achieved a mean 4-fold classification accuracy of 84% for classifying EEGs with and without IEDs.

In a follow-up study, Thomas et al. [13] trained and tested a CNN on a larger database from 545 subjects – 84 patients with epilepsy (43 males aged 35.2±27.2 years and 41 females aged 37.1±28.2 years) with annotated IEDs and 461 EEGs from people without epilepsy. Their system achieved a false detection rate of 0.2±0.1 per minute with 80% sensitivity on the MGH dataset. Furthermore, they evaluated their detector on two additional datasets: one from the Medical University of South Carolina with a range of ages from 0 to above 70 years, where the false detection rate at 80% sensitivity was 1.4 per minute, and another from the National University Hospital Singapore with 43 males (age 58.8±18.4 years) and 32 females (age 63.9±17.8 years), achieving an agreement accuracy of 81.4% with a clinical expert.

Lourenco et al. [15] built a VGG network to detect IEDs. EEG data from 217 patients between 4 and 72 years of age were used. The patients were randomly selected from the digital database of the Medisch Spectrum Twente in the Netherlands. The dataset analyzed in this study comprised interictal EEGs obtained from patients with either focal (50 patients) or generalised (49 patients) epilepsy, which contained IEDs. The dataset also included EEGs with non-epileptiform abnormalities (51 patients) and normal EEGs (67 patients). The method was trained on 2-second EEG epochs from patients with focal (39 patients) and generalised (40 patients) epilepsy, as well as 53 people without epilepsy. Their approach achieved a sensitivity of 79% on the independent test set.

Shoji et al. [16] developed a CNN for detecting both ictal and interictal epileptic abnormalities in children. The dataset used in this study was obtained from 19 patients at Juntendo University Nerima Hospital in Japan. The patients' ages ranged from 6 to 15 years old, and the dataset consisted of multiple measurements from each patient taken on different occasions. The highest sensitivity that their method achieved was 77%. Significantly, all 19 patients had generalised epilepsy. In contrast, our cohort of nearly 600 children had a mixture of focal and generalised epilepsy, which more accurately reflects the heterogeneity of a paediatric epilepsy population.

De et al. [25] conducted a study on unsupervised deep learning models, specifically Autoencoders and Variational Autoencoders, for detecting IEDs in adults. Their dataset consisted of 203 clinical EEGs, with 115 from patients diagnosed with epilepsy containing IEDs, and 88 normal EEGs. The best performance achieved a sensitivity of 81.9% and a specificity of 91.7%.

Zhang et al. [26] used a convolutional neural network framework for automatic IED detection in EEG analysis. They transformed the research topic into a 4-labels classification problem and validated the algorithm on long-term EEG recordings from 11 pediatric patients with epilepsy. The computational results demonstrated high classification accuracy, reaching up to 87%. Rao et al. [37] proposed a novel IED detection approach called ''IED Conformer'', which is based on Transformer architecture. By analyzing EEG data from 11 pediatric epilepsy patients, their approach achieved an IED detection accuracy of 96.11%.

Previous research (Table 2) has primarily relied on annotated epileptiform abnormalities, which is laborious. An automatic method that could identify epileptiform abnormalities without human annotations would be highly beneficial. To our knowledge, no existing research has explored automated epileptiform abnormality identification that does not require specific start and end times for epileptiform abnormalities. Our method addresses this gap and can identify epileptiform abnormalities based on multiple channel EEGs without annotations from clinicians. This method achieved sensitivity, specificity and accuracy above 77% on the independent test set, indicating good generalizability. Although our method's quantitative performance was inferior to that of previous methods [12], [13], [43], it was specifically developed and evaluated in the real-world setting of a diagnostic paediatric EEG laboratory, with a heterogenous patient case-mix. In addition, our method can recognize epileptiform abnormalities in children without the need for domain experts to estimate features and time-consuming human annotations. Moreover, in some work [12], [14], the epochs in the training and testing set may be from the same patient. This will result in overfitting, and the models may not generalise well. In our training and testing, we took care to separate the children into either the training or test set to ensure the independence of the test set and mitigate

overfitting. Furthermore, our method does not require a large amount of time and computational resources compared to most deep learning methods.

Previous studies on brain event detection in EEG recordings have addressed the concept of channel importance. Alotaiby et al. [44] developed a seizure detection method in EEGs and demonstrated that channel C3-C4 exhibited the best seizure detection performance compared to other single channels. Similarly, the work presented in [45] indicated that channels C3 and C4 yielded the most favourable results in EEG classification. Temko et al. [46] presented a seizure detection system based on SVM, where the utilization of a single channel C3-C4 achieved the maximum ROC (Receiver Operating Characteristic) in their EEG recordings. Furthermore, in the study conducted by Ellis et al. [47], a seizure detection method in EEGs highlighted that channels T8 and C3 were identified as the top two most important channels.

In this study, we also find that channel C3 is important in identifying epileptiform abnormalities in EEGs. The use of SHAP to evaluate channel importance is significant in the context of attributing plausible biological explanations to findings derived from AI models. In this regard, we are uncertain as to why the C3 channel was found to be important in our study. Central electrodes (C3, and C4) are involved in generalised epileptic discharges and in some focal discharges. It is possible that the relative importance of C3 may be attributable to an over-representation of left hemispheric focal epilepsies within the dataset. This possibility is supported by the relative SHAP importance of the T3 and T5 channels, which are adjacent to C3 and which may be particularly active in self-limiting epilepsy with centro-temporal spikes, for example [48]. The distribution of discharges and lateralization of the epilepsy was not included in the information provided to the algorithm. The importance of a central, left-sided channel may not generalize to other epilepsies and will need to be validated in further work in order to understand the biological significance of the finding.

A limitation of this study is the uncertainty regarding whether the method distinguishes EEGs with epileptiform abnormality based solely on interictal spike abnormality in the C3 channel or if other ''unseen'' measurements are involved. In future work, we aim to further explore explainable AI techniques to provide insights into the reasons behind the method's predictions and to build appropriate trust with clinicians. Additionally, we intend to integrate this method into a web server, enabling practical use for research purposes.

Another limitation is that the study focuses on identifying interictal epileptiform abnormalities in school-aged children and adolescents, aged 6 to 18 years old. We acknowledge the absence of a much younger age group in our analysis. In future research, we aim to address this limitation by expanding our dataset to encompass a wider age range, ensuring the applicability of our method across different age groups. Additionally, we will systematically evaluate how age influences interictal epileptiform abnormalities to enhance the comprehensiveness of our findings.

In this study, we have provided visualizations of the spectrogram of each EEG to aid clinicians in verifying epileptiform abnormalities in the frequency domain. Additionally, the importance of channels has been demonstrated using SHAP, which may assist clinicians in recognising EEGs with epileptiform abnormalities. It is important to note that certain events were EEG visible but not spectrographically visible [49], which could affect the method's performance. To enhance its effectiveness and suitability for clinical settings, we plan to integrate EEG signals and spectrograms into the method in future work.

V. CONCLUSION

In this study, a method for identifying epileptiform abnormalities on multiple channels of paediatric EEGs was developed using transfer learning with five popular CNN architectures (Inception, ResNet, DenseNet, VGG16, and VGG19). The CNNs were trained on the spectrogram of EEGs, with the convolutional layers being kept and frozen while the fully connected layers were updated for the new situation. The initial weights of the networks were taken from their previous training on the ImageNet dataset. Unlike traditional feature-based machine learning methods, our method does not require domain experts to extract features and can automatically identify epileptiform abnormalities. This method has the potential to enhance diagnostic accuracy, save clinicians time, and ultimately improve the quality of care for patients.

APPENDIX

Our code can be accessed at GitHub (https://github.com/LanWei0624/-identification-of-paediatric-EEGs-with-interictal-epileptiform-abnormalities)

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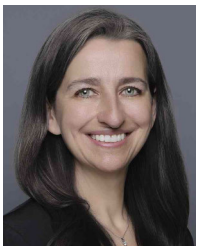
LAN WEI received the Ph.D. degree in computer science from University College Dublin, Ireland, in 2022. From 2022 to 2024, she was a Research Fellow with the School of Computer Science, University College Dublin. Her research interests include biomedical signal processing, EEG, and machine learning.

JOHN C. MCHUGH is a Consultant Clinical Neurophysiologist with the Children's Health Ireland (CHI) at Crumlin. He has extensive expertise in the electrodiagnosis of children with epilepsy.



CATHERINE MOONEY received the B.Sc. degree from Trinity College Dublin and the Ph.D. degree in computer science from University College Dublin, Ireland. She is an Associate Professor with the School of Computer Science, University College Dublin; and a VP for equality, diversity, and inclusion with the College of Science. She leads the Life Science Data Analytics Group (LiSDA). Her research focuses on using cutting-edge machine learning techniques, including deep learning, to develop biomarkers and clinical decision support systems.