Improving Cross-Patient Epilepsy Detection via EEG Decomposition into Canonical Brain Rhythms with Deep Learning

Jose Yauri, Elinar Carrillo-Riveros, Edith Guevara-Morote, Juan Carlos Carreño-Gamarra,
Karel Peralta-Sotomayor, Pelayo Quispe-Bautista
Dept. of Mathematics and Physics, Universidad Nacional de San Cristóbal de Huamanga, Ayacucho, Peru

***Abstract*—Epilepsy affects more than 50 million people worldwide, and almost 80% of them live in low-income countries with limited access to medical and public services. Beyond these challenges, epileptic patients also face other problems, such as stigma and social exclusion due the misunderstanding of epilepsy. Thus, epilepsy has become a major public health problem with a high social impact. Electroencephalography (EEG) remains the primary tool for diagnosing epilepsy; however, the traditional procedure of reviewing long EEG recordings is time-consuming, error-prone, and highly dependent on the neurologist's experience. Recent advances in deep learning (DL) have driven the development of new methods for automatic epilepsy detection. Despite these advances, most methods are not generalizable to all patients, limiting their clinical applicability in real-life cases. In this work, we present a cross-patient method capable of improving epilepsy detection by spectral decomposition of EEG signals into canonical brain rhythms. These spectral bands improve the signal significance and the model performance. The proposal was evaluated in a cross-patient validation scheme on the CHB-MIT dataset and proved superior performance using EEG signals from the interictal and ictal epilepsy stages. The model achieved of 100% of sensibility and specificity using the theta band, outperforming the state-of-the-art methods and offering a promising step towards real-world clinical implementation.**

***Keywords*—EEG signals; EEG signal decomposition; canonical brain rhythms; deep learning; convolutional neural network; transformer neural network**

I. Introduction

Epilepsy is a neurological disorder that is one of the most severe and affects the normal functioning of the brain [1]. Epilepsy is characterized by abnormal electrical activity in neurons that initiates seizures, which is the observable manifestation of this disease [2]. Seizures or convulsions consist of movements of the body, arms, and hands, and are often accompanied by loss of consciousness, fainting, and salivation [3]. The degree of seizures can vary, from subtle to strong manifestations. When seizures occur more than once in a day, the quality of life of patients deteriorates dramatically [4]. Furthermore, numerous epileptic patients experience social exclusion and stigmatization [5].

Epilepsy can affect anyone, regardless of age, gender, race, social status, or geographic location; it affects both children and adults [6]. Current research is centered on identifying the causes, medical treatments, and diagnosis of epilepsy since there is no definite cure [7]. The World Health Organization states that epilepsy affects over 50 million people worldwide, and most of them are living in poor or developing countries without access to medical services or treatments [8]. Because epilepsy strongly changes the lives of people, it has turned into a global public health problem with high social impact that deserves attention [9].

But not all seizures are epilepsy itself. Other diseases also cause seizures (e.g., Alzheimer's disease [10], stroke [11], diabetes [12]). Therefore, the goal of physicians and neurologists is to obtain a precise diagnosis of epilepsy to provide the best treatment [13]. Poor treatment of epilepsy could even worsen the disease [14].

Due to its low cost and non-invasive nature, the electroencephalogram (EEG) has become the standard method for diagnosing epilepsy [15]. EEG captures the electrical activity of neurons using electrodes placed on the scalp of the head [1]. In order to diagnose epilepsy, the physician visually observes the EEG signals to identify patterns of spikes, sharp, and slow waves that are characteristic of an epileptic seizure [16]. Although it may seem very simple, this work is visually-intense, time-consuming, and error-prone, depending on neurologist expertise [17]. So, it is crucial to have a proper diagnosis of epilepsy in order to provide an adequate treatment.

In the past two decades, there have been numerous research efforts conducted to create automatic tools for detecting epileptic seizures [18], [19], [20] and for predicting seizure episodes [21], [22], [23]. The majority of research studies rely either on machine learning (ML) or deep learning (DL) algorithms to detect seizure patterns in EEG signals. Among them, DL is one of the most popular due to its ability to model a more flexible feature space [24].

In spite of the recent progress, the classification of epileptic seizures still faced some challenging problems. Two main issues are addressed in this work:

- The majority of methods for developing a DL classifier to detect epileptic seizures commonly use raw EEG signals as input data. However, decomposing the EEG signal into major brain rhythms is more suitable for clinical diagnosis, as it enhances the interpretation of the signal [25]. Can classification performance be improved by the brain rhythms of EEGs?
- The majority of methods to detect epileptic seizures usually assess their model's performance at a cross-validation and intra-subject level. However, cross-patient assessment remains limited due to the difficulty

of achieving a good generalization model. Could it be feasible to create a population-level classifier by analyzing specific EEG brain rhythms/bands?

Therefore, the main contribution of this work is twofold:

- An approach that decomposes the raw EEG signal into the four main brain rhythms: theta (θ), alpha(α), beta(β), and gamma (γ) waves. A basic transformer neural network proposed in [26] is employed to objectively assess the performance caused by the decomposition of EEG signals .
- Two ways to evaluate the model's performance. First, a k-fold cross-validation level to determine how well the model works with the maximum number of raw data . Second, to determine how effectively the model works with the decomposed brain bands on a cross-patient assessment level.

The remainder of this study is organized as follows: Section II presents the fundamentals about epilepsy, as well as the related work. Section III exposes our proposal to detect epileptic seizures. Section IV shows the achieved results and provides a comparison against previous work. Lastly, Section V summarizes the findings of this study and the upcoming investigations.

II. Background

Since its invention, EEG has become the standard device for diagnosing epilepsy and investigating other brain disorders [1]. The neuronal electrical activity is recorded by the EEG through electrodes placed over the head. Thereby, EEG allows a real time investigation of what is happening in the brain due to the fact that each electrode registers data from a specific region of the head. As a result, the EEG produces a recording file that can be further analyzed by the neurologist [27]. Fig. 1 illustrates an EEG headset and its electrode placements over the head. The arrows indicate the EEG montage used during analysis.

Traditional epilepsy diagnosis involves human visual analysis of EEG registers, which is both time-consuming and susceptible to misdiagnosis. To overcome these issues, in the last years, many methods have been proposed for automatic detection of epilepsy [18], [19], [20]. Therefore, the goal of epileptic seizure detection is to classify EEG time windows as normal (non-seizure) or abnormal (seizure) through supervised binary classification.

To build a classifier, it is desirable to have a large amount of EEG data [24]. However, researchers select EEG data to reduce imbalance between seizures and non-seizures classes due to their strong unbalance. So, given a long-time EEG recording, investigators extract specific parts of the signal. These parts are taken from the stages of epilepsy that the patient experiences over time: the interictal, preictal, ictal, and postictal stages [1], [2].

The ictal stage refers to the patient's seizure episode, and the other stages are placed in relation to this stage over time. Fig. 2 shows the four phases of epilepsy in an long-time EEG recording. Note that the ictal stage lasts very short compared to other stages. Fig. 3 illustrates the ictal or seizure episode (red shaded), showing variability in the transition between episodes (green shaded).

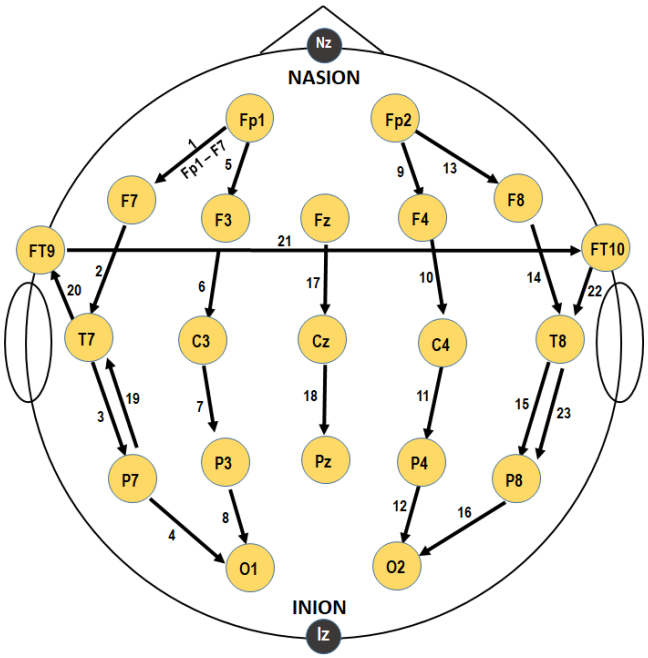

Fig. 1. An EEG device and its electrode placements according to the 10–20 system.

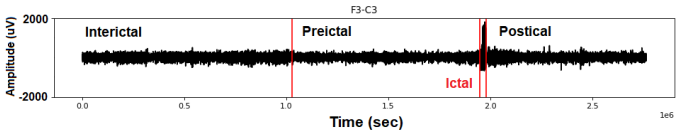

Fig. 2. Epilepsy phases in a long time EEG recording. For convenience, only a single channel is plotted.

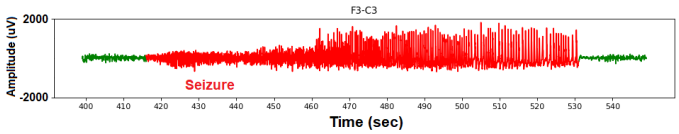

Fig. 3. An epilepsy seizure stage (red shaded). For convenience, only a single channel is plotted.

The interictal stage occurs a few hours before a seizure episode and the patient experiences a normal condition; the preictal stage occurs a few minutes preceding a seizure (e.g., 30 minutes); and the postictal stage occurs some minutes after a seizure (e.g., 5 minutes). However, it is worth mentioning that, yet there is no consensus about the duration of the interictal, preictal, and postictal stages due to the high variability of epilepsy symptoms between patients [28], [29], [30].

In order to construct their classification model for seizure detection, most researchers use signals from interictal and ictal stages as input data [31], [32], [33], [34], [35], and a few investigators use signals from preictal and ictal stages

[36], [37]. Regardless of the use of interictal versus ictal or preictal versus ictal sources to build the classification model, the authors have reported high accuracy results; however the lack of consensus on the signals used to train and test the model often prevents these results from being reproducible.

In order to examine how well models detect epilepsy using EEG signals, researchers have used various validation schemes to assess their generalizability and clinical relevance [38], [39]. One common approach is the k-fold cross-validation, that involves randomly partitioning an entire dataset composed of EEG recordings from multiple patients into training and testing subsets. The use of all available data for both training and testing in this method, typically results in highly optimistic performance results due to the possibility of EEG patterns of specific patients can be leaked between training and test folds. While this setup is useful for benchmarking algorithms in early development stages, it lacks the rigor needed to evaluate real-world deployment in clinical settings [26], [39].

Aiming to better approximate practical use cases, researchers also use two more realistic validation schemes: the intra-patient and cross-patient (or patient-independent) evaluation. In one hand, in the intra-patient mode [31], the model is both trained and tested exclusively on EEG data from the same individual. This approach produces a model that is tailored to the patient and can effectively capture their distinct seizure characteristics, but they are limited in scalability and do not generalize to new patients. Furthermore, as epilepsy symptoms can change over time even in the same patient, the model should be updated as well [40].

On the other hand, the cross-patient mode [36], [30] is considered as an ideal evaluation setting. This approach uses data from one patient as the test set, while the model is trained on data from other patients. This scheme examines the generalizability of the model across individuals, which highlights its potential for clinical application in real-world. However, achieving high performance in this experimental setup remains challenging due to inter-patient variability in EEG patterns, making it a key focus of ongoing research [38], [39].

Ultimately, although DL approaches have achieved significant success in epilepsy detection using raw EEG signals, the exclusive reliance on unprocessed data may overlook clinically informative structures inherent in the signal. A notably underexplored yet promising alternative is the decomposition of EEG signals into canonical brain rhythms, such as thetaθ, alphaα, betaβ, and gammaγ bands, which are foundational to neurophysiological interpretation [1]. Moreover, from a clinical perspective, such decomposition aligns with well established diagnostic practices and facilitates the identification of abnormal frequency components associated with epileptic activity [2]. In addition, rhythm-based decomposition can enhance data quality by reducing noise and concentrating features that are more stable in the context of inter-patient variability [41].

In the context of DL, these frequency-specific components could serve as semantically enriched inputs, potentially improving both model generalization and interpretability. So, we hypothesize that selecting and integrating brain rhythm into the DL pipeline not only offers a biologically grounded data representation but also contributes to bridging the gap between computational learning strategies and clinical reasoning [42]. Therefore, it is expected to achieve an improvement in the effectiveness and the trustworthiness of diagnostic models to detect epilepsy.

This work studies the influence of brain rhythms on the performance of the model in the cross-patient evaluation scheme. In this way, although there have been many advances in epilepsy detection, the following literature revision is restricted to studies that have been experimented in cross-patient schemes that use preferably the largest public CHB-MIT EEG dataset [43]. Moreover, the basic assumption is that the extraction of spatial and temporal features is excellent and that the unbalanced nature of datasets is manageable. The studies of [38], [39] provide a deep insight into these problems.

The following are the most relevant works:

The first study to address universal generalization in cross-patient assessment scheme was presented by Hossain et al. [36]. The authors propose the EEG channel fusion in the first layer before proceeding to extract temporal features in the next layers. The model was trained by extracting data from the preictal and ictal EEG recordings, with a 2-second time window and an 80% overlap. The complete model consists of four CNN blocks (each block containing a convolution, an activation function, and a max-pooling). Evaluation in the CHB-MIT dataset, the models showed sensitivity of 90%, specificity of 91.65%, and accuracy of 98.05%. Despite the achieved high performance, the data selection process is unclear and the number of assessed seizures remains unknown.

Next, Liu et al. [44] also focused on detecting epilepsy in a cross-patient scheme. They propose a CNN-BiLSTM (Bidirectional Long Short Term Memory Network) model enhanced with a novel channel perturbation layer (CPL) during training, which randomizes EEG channel order to improve spatial generalization. First, EEG data is preprocessed using wavelet decomposition, focusing on clinically relevant brain rhythms (4–32 Hz). Evaluation in the CHB-MIT dataset, the models showed sensitivity of 86.5%, and AUC-ROC improvements from 77% to over 90% due to CPL. However, this study lacks interpretability analysis and offers limited insight into physiological relevance of learned features.

Then, Alqirshi et al. [45] proposed a cross-patient seizure detection method that utilizes graph convolutional networks (GCN) with the goal of overcoming the major limitations of conventional EEG analysis: the insufficient attention to inter-channel brain dynamics and reliance on patient-specific training. Hence, the GCN represents the EEG data as graph-structured input to capture spatial dependencies. Evaluated in a custom dataset from four unseen patients, the GCN-based approach achieved a sensitivity of 88.71%, precision of 91.32%, F1-score of 91.57%, and an accuracy of 91.70%. Although the method has reported high detection metrics, the dataset is too limited to prove that the model is highly generalizable. Moreover, it would benefit from a more transparent analysis of how specific graph features contribute to classification, and testing on larger data sets, such as the CHB-MIT database.

Next, Jana et al. [46] presented a channel selection strategy for EEG-based seizure prediction aimed at using only a single optimal channel in a cross-patient assessment. The authors propose a method that ranks each EEG channel based on

its average performance over five evaluation rounds using a CNN-LSTM1D model. The top-performing channel is then selected for prediction, and an ensemble learning framework (integrating CNN1D, DenseNet1D, and CNN-LSTM1D) is employed using majority voting. Evaluation in the CHB-MIT dataset, the model achieves a sensitivity of 94.25%, and a specificity of 92.94%. The study fails to explain why specific channels perform better than others, and assumes that a single channel cannot be generalized to all seizure types or patients with atypical EEG presentations. Furthermore, using ensembles increases complexity and could prevent real-time deployment even with a single-channel design.

Recently, Mohammadpoory et al. [47] proposed a method for epileptic seizure detection based on the weighted visibility graph (WVG). Features are extracted from both raw EEG signals and their decomposed sub-bands (delta to gamma) from the preictal and ictal EEG recordings. A combination of multiple feature selection techniques is used to select key features and evaluate them using five different classifiers. Next, a post-processing step is performed to improve detection accuracy and accurately identify seizure onset and offset. Evaluation in the CHB-MIT dataset, the model detected 163 out of 184 seizures, achieving a sensitivity of 92.31%, a specificity of 94.12%, and an accuracy of 94.02%. Despite the high performance, the main drawback is the complexity of feature engineering, which could hinder real-time applications and scaling over low-power clinical systems.

In summary, there are only a few studies focused on cross-patient or patient-independent settings. The high variability of epileptic seizures, even between the same patients, prevents achieving a generalizable model. It is worth mentioning that sub-bands as input data have only been explored by a small number of researchers, but those who have employed them have shown better results, such as the study of [47]. The main focus of this work is on EEG signal decomposition; we hypothesize it is the primary source of improvement for building a model that is highly generalizable at a cross-patient level.

III. Our Approach

As stated in Section I, this work is an extension of the study of [26], which aimed to detect epilepsy in a k-fold cross-validation scheme. Different from the previous one, this work primarily concentrates on decomposing the EEG signal into canonical brain rhythms and aims to detect epilepsy in a cross-patient validation scheme, with minor changes during application.

Fig. 4 outlines a general pipeline for detecting epileptic seizures in EEG data using DL. First, a short description of the data acquisition is provided to collect a dataset of EEG signals. Then, the signal preprocessing is performed. Next, a neural classifier is trained in order to discriminate between non-seizure and seizure signals. Finally, the trained classifier is evaluated in cross-patient mode to evaluate its generalization capability.

A detailed description of each step of the pipeline is provided as follows:

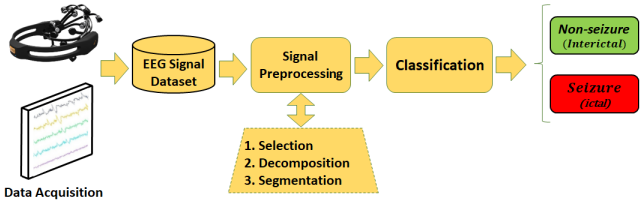

Fig. 4. The general pipeline for epileptic seizure detection.

A. EEG Dataset

The EEG dataset used in this study is derived from the CHB-MIT public dataset that contains more than 980 hours of EEG recordings and 198 seizures [43]. In extent, the dataset contains EEG registers from 23 pediatric patients, 3 to 22 age, with incurable epilepsy. Because another register of patient chb01 was obtained 1.5 years later, the chb21 register is considered a new patient's register.

EEG data was collected using EEGs of different numbers of electrodes, but registers of EEG of 23 channels at 256 Hz are the most common, which are organized in a longitudinal bipolar montage (see Fig. 1). Because the records are of long-term duration, as a result, the dataset is released in registers of one, two, or four hours long recordings. If the register contains at least one seizure, then it is named seizure records; otherwise, it is named non-seizure records. Each seizure register provides the start and end for each seizure episode as ground truth (GT).

The CHB-MIT dataset has been utilized extensively in numerous studies because it has a large amount of EEG recordings per patient and is openly accessible [48], [19]. On the other hand, there are other databases, but they are either small or privately accessible [49]. For instance, the Bonn EEG dataset contains sequences of 23.6 seconds long from a single EEG electrode, which are not suitable for training modern neural models. On the other hand, the EPILEPSIAE dataset is a large EEG database that contains continuous and long-term EEG recordings from 250 epileptic patients, but it is private.

B. Preprocessing

In this stage, four main activities are proposed: data selection, data decomposition, data segmentation, and data augmentation.

- Data selection aims to select and extract EEG registers to be used to train and test the model. In this work, we selected and extracted data from the interictal and ictal stages that best discriminate between non-seizure and seizure signals (see Fig. 2 to illustrate the selected data coming from). The use of interictal and ictal data to train classifiers is widely supported by previous studies [18], [38], [39].
  Therefore, the EEG signals come from EEG registers of 23 channels and contains a total of 181 seizures. The interictal data comes from signals two hours away of a seizure, whereas the ictal data comes from all seizures. Also, the data was downsampled to 128 Hz like in [26].
- Data decomposition aims to disassemble the raw EEG signal into four main brain rhythms: theta (θ: 4–8

Hz), alpha(α:8–12 Hz), beta(β:12–30 Hz), and gamma (γ:30–50 Hz) waves. Signal decomposition was performed via the Fast Fourier Transform (FFT). The delta (δ) The delta signal was excluded from this analysis due to its association with sleep [25].
The process of EEG signal decomposition is performed using the Fast Fourier Transform (FFT), with the goal of isolating and retaining the frequency components of a desired brain band [50]. Once the signal is isolated, it is possible to analyze the neural activity within the selected frequency band.

- Data segmentation aims to split the selected and decomposed EEG signals into small processable time windows. In accordance to the study [26], we use a time window of one second for non-seizure data, while seizure data has an 80% overlap to increase the amount of data.

C. Neural Network

To ensure an impartial evaluation of the proposed hypothesis and compare potential gains in model performance in the cross-patient evaluation scheme, we suggest reusing the model presented in [26]. Fig. 5 illustrated the reused neural architecture in this work.

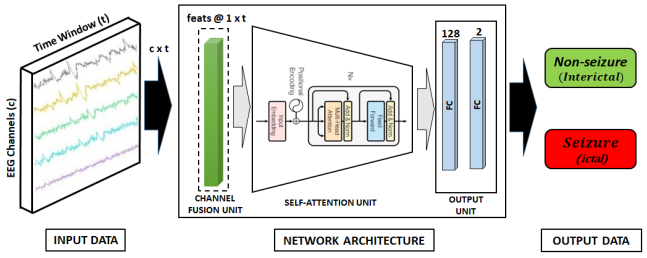

Fig. 5. The neural network architecture.

The proposed neural model has the main advantage of being a state-of-the-art (SoA) model for epilepsy detection in a k-fold cross-validation scheme and leverages the most recent advances in EEG channel fusion and attention mechanism.

D. Classification

After training, the model has the ability to discriminate between non-seizure and seizure signals. To determine the label class of input data, the final layer of the model calculates the probability distribution with the Softmax activation function [24].

E. Experimental Design

To determine the feasibility of the proposed brain rhythms decomposition into sub-bands to improve the model's ability to detect epileptic seizures in multiple patients, we use the leave-one-patient-out (LOPO) validation scheme [24].

In LOPO, the model is trained on EEG data from all patients except one, and then tested on the held-out patient. This process is repeated for every patient to guarantee that their data acts as an independent test sample only once. Finally, LOPO offers a reliable estimation of the model's performance in real-world situations where the system needs to detect epileptic seizures in patients who have never had seizures before [47].

IV. Results and Discussion

In this work, we used the neural architecture presented in [26], which was implemented in the DL Framework PyTorch v.2.4 and Python v.3.9. The experimental platform consisted of a computer desktop Intel CPU I7-8550U, 16GB RAM, equipped with a GPU NVIDIA RTX 2070 with 8GB RAM. The model was trained from scratch with the following hyperparameters: the Adam optimizer, a weighted cross-entropy loss function to deal with unbalanced data samples, a batch size of 128, a learning rate of 0.0001, and 150 epochs for training the model.

The model performance was assessed using the LOPO validation scheme. Metrics such as sensitivity, specificity, precision, F1-Score, and accuracy are employed to display the results in the format mean average plus or minus the standard deviation.

Table I summarizes the achieved results in the CHB-MIT database. To highlight the difference between decomposition and non-decomposition, the non-decomposition (i.e., raw data) is also displayed in the first row of the table. The next rows of the table show the spectral signals that have been disaggregated (theta, alpha, beta, and gamma). The decomposition approach is proven to produce better results than the non-decomposition approach, particularly by utilizing only the theta spectral band (gray shaded row).

Table II shows the achieved results of the model only using the non-decomposed signal (or raw data) as input data. To gain an understanding of individual performance, each row of the table shows the performance of each patient. It is noticeable that there is variability in patients' performance.

Using the decomposed approach, the achieved by the model shown in Table III. In this situation, the input data is represented by the theta band. The table displays the performance of each patient in each row, and it is clear that the variability between patients' performance has decreased.

To compare the achieved results with the proposed approach and related work fairly, we selected the most recent methods of SoA that focus on cross-patient or patient-independent validation schemes (i.e., LOPO). Table IV summarizes the results reported by several SoA works. After analyzing the results, it is evident that our proposed method outperforms other studies by a significant margin. Only the studies of Jana et al. [46] and Mohammadpoory et al. [47] are among the most close to our reported results.

The following points are worth discussing:

First, although many methods have been proposed for detecting epileptic seizures, only a few are capable of generalizing to patient-independent scenarios, due to the challenges in capturing inter-patient variability and the high diversity of seizure patterns (see Table IV). However, the deployment of reliable and trustworthy seizure detection systems in clinical settings will not become a reality unless we continue to address cross-patient variability.

TABLE I. SUMMARY OF THE CLASSIFICATION EFFECTIVENESS OF THE PROPOSED METHOD IN THE LOPO EVALUATION SCHEME ON THE CHB-MIT DATABASE

Brain rhythm	Sensitivity	Specificity	Precision	F1-score	Accuracy
raw data	93.27±11	96.96±7.59	71.87±32.5	75.69±26.6	96.63±7.39
theta	100±0	100±0	100±0	100±0	100±0
alpha	99.98±0.09	100±0	100±0	99.99±0.04	100±0
Beta	99.91±0.26	100±0.01	99.94±0.31	99.92±0.19	100±0.01
Gamma	99.97±0.08	99.95±0.12	98.58±3.81	99.23±2.03	99.96±0.12

TABLE II. CLASSIFICATION RESULTS USING THE NON-DECOMPOSED EEG SIGNAL IN THE LOPO EVALUATION SCHEME ON THE CHB-MIT DATABASE

Patient	Sensitivity	Specificity	Precision	F1-score	Accuracy
chb01	94.12	99.96	98.81	96.41	99.76
chb02	98.26	95.52	23.02	37.31	95.55
chb03	96.52	99.96	98.73	97.61	99.85
chb04	98.94	98.44	62.96	76.95	98.45
chb05	98.03	98.81	78.48	87.17	98.78
chb06	92.16	98.97	37.11	52.91	98.92
chb07	95.38	63.33	5.55	10.48	64.04
chb08	100.00	99.56	95.83	97.87	99.60
chb09	100.00	92.50	20.35	33.82	92.64
chb10	99.33	99.42	84.25	91.17	99.42
chb11	97.15	99.98	99.75	98.43	99.81
chb12	51.97	99.94	99.23	68.21	94.15
chb13	97.95	98.22	81.78	89.14	98.20
chb14	70.41	99.06	50.00	58.48	98.68
chb15	88.40	99.79	98.55	93.20	98.24
chb16	97.10	99.63	58.77	73.22	99.61
chb17	92.49	92.58	22.47	36.16	92.58
chb18	85.80	99.99	99.63	92.20	99.64
chb19	88.56	99.94	96.31	92.27	99.73
chb20	99.66	99.99	99.66	99.66	99.98
chb21	99.50	99.96	97.54	98.51	99.95
chb22	98.04	99.96	97.56	97.80	99.93
chb23	100.00	92.10	27.16	42.72	92.33
chb24	98.63	99.35	91.47	94.92	99.30
	93.27±11	96.96±7.59	71.87±32.5	75.69±26.6	96.63±7.39

TABLE III. CLASSIFICATION RESULTS USING THE THETA BAND SIGNAL IN THE LOPO EVALUATION SCHEME ON THE CHB-MIT DATABASE

Patient	Sensitivity	Specificity	Precision	F1-score	Accuracy
chb01	100.00	100.00	100.00	100.00	100.00
chb02	100.00	100.00	100.00	100.00	100.00
chb03	100.00	100.00	100.00	100.00	100.00
chb04	100.00	100.00	100.00	100.00	100.00
chb05	100.00	100.00	100.00	100.00	100.00
chb06	100.00	100.00	100.00	100.00	100.00
chb07	100.00	100.00	100.00	100.00	100.00
chb08	100.00	100.00	100.00	100.00	100.00
chb09	100.00	100.00	100.00	100.00	100.00
chb10	100.00	100.00	100.00	100.00	100.00
chb11	100.00	100.00	100.00	100.00	100.00
chb12	100.00	100.00	100.00	100.00	100.00
chb13	100.00	100.00	100.00	100.00	100.00
chb14	100.00	100.00	100.00	100.00	100.00
chb15	100.00	100.00	100.00	100.00	100.00
chb16	100.00	100.00	100.00	100.00	100.00
chb17	100.00	100.00	100.00	100.00	100.00
chb18	100.00	100.00	100.00	100.00	100.00
chb19	100.00	100.00	100.00	100.00	100.00
chb20	100.00	100.00	100.00	100.00	100.00
chb21	100.00	100.00	100.00	100.00	100.00
chb22	100.00	100.00	100.00	100.00	100.00
chb23	100.00	100.00	100.00	100.00	100.00
chb24	100.00	100.00	100.00	100.00	100.00
	100±0	100±0	100±0	100±0	100±0

Second, with respect to the type of EEG input data, earlier studies primarily utilized raw signals [36], [45], whereas more recent approaches have begun to incorporate canonical brain rhythms. Hence, the studies of Liu et al. [44] and Mohammadpoory et al. [47] specifically perform EEG signal decomposition into main brain rhythms. But, while previous approaches attempted to combine features from multiple frequency bands using complex algorithms, this work evaluates each band individually, revealing that using isolated frequency bands as input data provides superior performance.

TABLE IV. COMPARISON OF THE PROPOSED METHOD AND RELATED WORK ON THE CHB-MIT DATABASE

Author	Method	Total seizures	Sensitivity	Specificity	Precision	F1-score	Accuraccy
Hossain et al. [36]	CNN	-	90.00	91.65	-	-	98.05
Liu et al. [44]	CNN-BiLSTM	-	86.50	-	-	-	-
Alqirshi et al. [45]	GCN	-	88.71	-	91.32	91.57	91.70
Jana et al. [46]	CNN-LSTM1D	-	94.25	92.94	-	-	-
Mohammadpoory et al. [47]	WVG-RF	163	92.31	94.12	-	-	94.02
This work (θ band)	CNN-Transformer	181	100.00	100.00	100.00	100.00	100.00

Third, the analysis of decomposed EEG signals is useful and intuitive from a clinical diagnostic perspective. For instance, neurologists and physicians are trained to recognize patterns within specific brain frequency bands and associate them with specific neurological conditions (e.g., delta band analysis to diagnose sleep disorders). Therefore, the analysis of canonical brain rhythms offers new opportunities to deepen our understanding of brain function, cognitive processes, and associated diseases [1], [42].

V. CONCLUSION

In this work, a new method to detect epileptic seizures in a cross-patient scenario has been presented. The method is based on the use of isolated frequency bands as input data to achieve superior model performance. This approach can be utilized to fuel any deep neural network, boosting its performance.

The feasibility of the proposed method was validated in the public CHB-MIT EEG dataset using the leave-one-patient-out (LOPO) evaluation scheme with 24 patients. We trained the well-established CNN-Transformer deep neural network proposed in [26], using individual EEG frequency bands (i.e., theta, alpha, beta, and gamma) as input data. Compared to using the raw EEG signal, our approach provides significantly superior performance. Furthermore, our approach outperforms several state-of-the-art methods and offers a promising step toward real-world clinical systems implementation.

For future work, it is necessary to conduct more research to enhance epileptic seizure recognition in clinical setting. First, the proposed method could be validated on other epilepsy datasets, such as the EPILEPSIAE database, to evaluate its generalizability and robustness across a population of patients. Second, instead of fixed band boundaries, some kind of adaptive decomposition may be feasible depending on the type of patient and his illness. Third, it is desirable to employ low-cost devices to implement and deploy the neural model, aiming to emulate clinical environments for epilepsy diagnosis in developing countries.

REFERENCES

[1] G. Cascino, J. I. Sirven, and W. O. Tatum, *Epilepsy*, 2nd ed. Wiley, 2021.

[2] V. S. Wasade and M. V. Spanaki, *Understanding Epilepsy: A Study Guide for the Boards*. Cambridge University Press, 2019.

[3] Mayo Clinic, "Epilepsy - Symptoms and Causes," 2025. [Online]. Available: https://www.mayoclinic.org/diseases-conditions/epilepsy/symptoms-causes/syc-20350093

[4] M. Tombini, G. Assenza, L. Quintiliani, L. Ricci, J. Lanzone, and V. Di Lazzaro, "Epilepsy and Quality of Life: What does Really Matter?" *Neurological Sciences*, vol. 42, no. 9, pp. 3757–3765, sep 2021. [Online]. Available: https://link.springer.com/article/10.1007/s10072-020-04990-6

[5] L. Hohmann, J. Berger, S. U. Kastell, and M. Holtkamp, "Perceived Epilepsy-related Stigma is Linked to the Socioeconomic Status of the Residence," *Frontiers in Public Health*, vol. 10, p. 952585, aug 2022.

[6] S. D. Howard, P.-A. Campbell, C. T. Montgomery, S. B. Tomlinson, D. I. Ojukwu, H. I. Chen, and M. H. Chin, "Effect of Race and Insurance Type on Access to, and Outcomes of, Epilepsy Surgery: A Literature Review," *World Neurosurgery*, vol. 178, pp. 202–212.e2, 2023.

[7] H. Kumar, S. Debnath, and A. Sharma, "Can Epilepsy Be Cured? A Review," *Health Sciences Review*, vol. 5, p. 100062, dec 2022.

[8] World Health Organization, "Epilepsy," 2025. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/epilepsy

[9] Center for Disease Control and Prevention, "Epilepsy Is a Public Health Problem," 9 2025. [Online]. Available: https://www.cdc.gov/epilepsy/communications/infographics/cdc-epilepsy-text.htm

[10] J. Vöglein, I. Ricard, S. Noachtar, W. A. Kukull, M. Dieterich, J. Levin, and A. Danek, "Seizures in Alzheimer's Disease Are Highly Recurrent and Associated with a Poor Disease Course," *Journal of Neurology*, vol. 267, no. 10, p. 2941, 10 2020.

[11] J. Phan, M. Ramos, T. Soares, and M. S. Parmar, "Poststroke Seizure and Epilepsy: A Review of Incidence, Risk Factors, Diagnosis, Pathophysiology, and Pharmacological Therapies," *Oxidative Medicine and Cellular Longevity*, vol. 2022, no. 1, p. 7692215, jan 2022.

[12] A. Nangia, J. S. Saravanan, S. Hazra, V. Priya, R. Sudesh, S. S. Rana, and F. Ahmad, "Exploring the Clinical Connections Between Epilepsy and Diabetes Mellitus: Promising Therapeutic Strategies Utilizing Agmatine and Metformin," *Naunyn-Schmiedeberg's Archives of Pharmacology*, vol. 397, no. 12, pp. 9617–9632, 2024. [Online]. Available: https://doi.org/10.1007/s00210-024-03295-1

[13] U. Amin and S. R. Benbadis, "The Role of EEG in the Erroneous Diagnosis of Epilepsy," *Journal of Clinical Neurophysiology*, vol. 36, no. 4, pp. 294–297, 7 2019.

[14] W. Löscher and P. Klein, "The Pharmacology and Clinical Efficacy of Antiseizure Medications: From Bromide Salts to Cenobamate and Beyond," *CNS Drugs*, vol. 35, no. 9, pp. 935–963, 2021.

[15] M. Z. Koubeissi and N. J. Azar, *Epilepsy Board Review : A Comprehensive Guide*, 2017.

[16] N. M. Jadeja, *How to Read an EEG*. Cambridge university press, 2021.

[17] W. O. Tatum, "Mistaking EEG Changes for Epilepsy," in *Common Pitfalls in Epilepsy: Case-Based Learning*, D. Schmidt, W. O. Tatum, and S. Schachter, Eds. Cambridge: Cambridge University Press, 2018, ch. 2, p. 25–42.

[18] A. Shoeibi, M. Khodatars, N. Ghassemi, M. Jafari, P. Moridian, R. Alizadehsani, M. Panahiazar, F. Khozeimeh, A. Zare, H. Hosseini-Nejad, A. Khosravi, A. F. Atiya, D. Aminshahidi, S. Hussain, M. Rouhani, S. Nahavandi, and U. R. Acharya, "Epileptic Seizures Detection Using Deep Learning Techniques: A Review," *International Journal of Environmental Research and Public Health 2021, Vol. 18, Page 5780*, vol. 18, no. 11, p. 5780, 5 2021.

[19] S. Supriya, S. Siuly, H. Wang, and Y. Zhang, "Epilepsy Detection From EEG Using Complex Network Techniques: A Review," *IEEE Reviews in Biomedical Engineering*, vol. 16, pp. 292–306, 2023.

[20] A. Lucas, A. Revell, and K. A. Davis, "Artificial Intelligence in Epilepsy - Applications and Pathways to the Clinic," *Nature Reviews Neurology 2024 20:6*, vol. 20, no. 6, pp. 319–336, may 2024.

[21] R. Hussein, S. Lee, and R. Ward, "Multi-Channel Vision Transformer for Epileptic Seizure Prediction," *Biomedicines*, vol. 10, no. 7, p. 1551, 2022.

[22] Z. Altaf, M. A. Unar, S. Narejo, M. A. Zaki, and Naseer-u-Din, "Generalized Epileptic Seizure Prediction using Machine Learning Method," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 1, 2023.

[23] Z. Wang, X. Song, L. Chen, J. Nan, Y. Sun, M. Pang, K. Zhang, X. Liu, and D. Ming, "Research Progress of Epileptic Seizure Prediction Methods Based on EEG," *Cognitive Neurodynamics*, vol. 18, no. 5, pp. 2731–2750, 2024.

[24] C. M. Bishop and H. Bishop, *Deep Learning : Foundations and Concepts*. Springer, 2024.

[25] R. Sharma and H. K. Meena, "Emerging Trends in EEG Signal Processing: A Systematic Review," *SN Computer Science*, vol. 5, no. 4, pp. 1–14, apr 2024.

[26] J. Yauri, M. Lagos, H. Vega-Huerta, P. De-La-Cruz-VdV, G. L. E. Maquen-Niño, and E. Condor-Tinoco, "Detection of Epileptic Seizures Based-on Channel Fusion and Transformer Network in EEG Recordings," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 5, pp. 1067–1074, 2023. [Online]. Available: http://dx.doi.org/10.14569/IJACSA.2023.01405110

[27] L. Hu and Z. Zhang, *EEG Signal Processing and Feature Extraction*. Springer Singapore, 1 2019.

[28] A. Shoeb and J. Guttag, "Application of Machine Learning to Epileptic Seizure Detection," in *ICML'10: Proceedings of the 27th International Conference on International Conference on Machine Learning*, 2010, pp. 975–982.

[29] S. M. Usman, S. Khalid, R. Akhtar, Z. Bortolotto, Z. Bashir, and H. Qiu, "Using Scalp EEG and Intracranial EEG Signals for Predicting Epileptic Seizures: Review of Available Methodologies," *Seizure*, vol. 71, pp. 258–269, 10 2019.

[30] J. Zhou, L. Liu, Y. Leng, Y. Yang, B. Gao, Z. Jiang, W. Nie, and Q. Yuan, "Both Cross-Patient and Patient-Specific Seizure Detection Based on Self-Organizing Fuzzy Logic," *International Journal of Neural Systems*, vol. 32, no. 6, 2022.

[31] 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. 12, p. 95, 12 2018.

[32] Y. Li, Z. Yu, Y. Chen, C. Yang, Y. Li, X. Allen Li, and B. Li, "Automatic Seizure Detection using Fully Convolutional Nested LSTM," *International Journal of Neural Systems*, vol. 30, no. 4, 2020.

[33] X. Wang, X. Wang, W. Liu, Z. Chang, T. Kärkkäinen, and F. Cong, "One Dimensional Convolutional Neural Networks for Seizure Onset Detection using Long-term Scalp and Intracranial EEG," *Neurocomputing*, vol. 459, pp. 212–222, 2021.

[34] A. Abdelhameed and M. Bayoumi, "A Deep Learning Approach for Automatic Seizure Detection in Children With Epilepsy," *Frontiers in Computational Neuroscience*, vol. 15, p. 29, 2021.

[35] C. Li, W. Zhou, G. Liu, Y. Zhang, M. Geng, Z. Liu, S. Wang, and W. Shang, "Seizure Onset Detection Using Empirical Mode Decomposition and Common Spatial Pattern," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 29, pp. 458–467, 2021.

[36] M. Shamim Hossain, S. U. Amin, M. Alsulaiman, and G. Muhammad, "Applying Deep Learning for Epilepsy Seizure Detection and Brain Mapping Visualization," *ACM Transactions on Multimedia Computing, Communications and Applications*, vol. 15, no. 1s, 2 2019.

[37] S. Chakrabarti, A. Swetapadma, and P. K. Pattnaik, "A Channel Independent Generalized Seizure Detection Method for Pediatric Epileptic Seizures," *Computer Methods and Programs in Biomedicine*, vol. 209, p. 106335, 9 2021.

[38] N. Fatma, P. Singh, and M. K. Siddiqui, "Survey on Epileptic Seizure Detection on Varied Machine Learning Algorithms," *https://doi.org/10.1142/S0219467825500135*, aug 2023.

[39] J. Xu, K. Yan, Z. Deng, Y. Yang, J. X. Liu, J. Wang, and S. Yuan, "EEG-based Epileptic Seizure Detection using Deep Learning Techniques: A Survey," *Neurocomputing*, vol. 610, p. 128644, dec 2024.

[40] G. M. Schroeder, P. J. Karoly, M. Maturana, M. Panagiotopoulou, P. N. Taylor, M. J. Cook, and Y. Wang, "Chronic Intracranial EEG Recordings and Interictal Spike Rate Reveal Multiscale Temporal Modulations in Seizure States," *Brain Communications*, vol. 5, no. 5, aug 2023.

[41] K. Lehnertz, T. Rings, and T. Bröhl, "Time in Brain: How Biological Rhythms Impact on EEG Signals and on EEG-Derived Brain Networks," *Frontiers in Network Physiology*, vol. 1, p. 755016, sep 2021.

[42] G. Buzsáki and M. Vöröslakos, "Brain Rhythms Have Come of Age," *Neuron*, vol. 111, no. 7, pp. 922–926, apr 2023.

[43] A. Shoeb and J. Guttag, "CHB-MIT Scalp EEG Database," 2010. [Online]. Available: https://physionet.org/content/chbmit/1.0.0/

[44] G. Liu, L. Tian, and W. Zhou, "Patient-Independent Seizure Detection Based on Channel-Perturbation Convolutional Neural Network and Bidirectional Long Short-Term Memory," *https://doi.org/10.1142/S0129065721500519*, vol. 32, no. 6, nov 2021.

[45] R. Alqirshi and S. B. Belhaouari, "EEG-Based Patient Independent Epileptic Seizure Detection Using GCN-BRF," in *Deep Learning Theory and Applications*, A. Fred, A. Hadjali, O. Gusikhin, and C. Sansone, Eds. Springer Nature Switzerland, 2024, pp. 351–366.

[46] R. Jana and I. Mukherjee, "Patient-Specific and Patient-Independent Seizure Prediction Using Ensemble Learning Technique," in *Lecture Notes in Networks and Systems*, vol. 1165. Springer, Singapore, 2025, pp. 41–52.

[47] Z. Mohammadpoory, M. Nasrolahzadeh, and S. A. Amiri, "Patient-independent Epileptic Seizure Detection using Weighted Visibility Graph Features and Wavelet Decomposition," *Multimedia Tools and Applications*, vol. 84, no. 6, pp. 3197–3221, feb 2025.

[48] A. A. Ein Shoka, M. M. Dessouky, A. El-Sayed, and E. E. D. Hemdan, "EEG Seizure Detection: Concepts, Techniques, Challenges, and Future Trends," *Multimedia Tools and Applications 2023 82:27*, vol. 82, no. 27, pp. 42 021–42 051, apr 2023.

[49] P. Handa, M. Mathur, and N. Goel, "EEG Datasets in Machine Learning Applications of Epilepsy Diagnosis and Seizure Detection," *SN Computer Science*, vol. 4, no. 5, pp. 1–11, sep 2023.

[50] S. Sanei and J. A. Chambers, *EEG Signal Processing and Machine Learning*, 2nd ed. Wiley, 2021.