An Accurate Epilepsy Diagnosis Approach Based on Fractal Dimension of Brain Rhythms and Chaos-Embedding

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***Abstract*—Epilepsy is a neurological disorder characterized by unpredictable seizures that can severely affect patients' quality of life. Diagnosis primarily relies on the analysis of the electroencephalogram (EEG), a complex, noisy, and nonstationary signal representing the summation of various brain rhythms (delta, theta, alpha, beta, and gamma). Since manual EEG analysis is difficult and time-consuming, automatic approaches are necessary to efficiently detect seizures and diagnose the disease. In this work, we propose a novel framework that integrates wavelets for brain rhythms estimation with *Chaos-Embedding* and the Higuchi fractal dimension to extract highly discriminative features. These features are then used in a robust representation space and classified using K-Nearest Neighbors is employed to differentiate between healthy patients, epileptic patients, and epileptic patients during seizures. Experimental results show that the proposed approach achieves near-perfect performance, outperforming existing methods and providing a promising tool for the automatic diagnosis of epilepsy based on brain rhythms.**

***Index Terms*—EEG, brain rhythms, epilepsy, Chaos-Embedding, Higuchi fractal dimension**

I. Introduction

Epilepsy is a serious neurological disorder that affects millions of people worldwide. Its seizures, often sudden and unpredictable, can have dramatic consequences on patients' daily lives. Early and accurate diagnosis is therefore essential to improve quality of life and optimize therapeutic management [1]. The electroencephalogram (EEG) is the most widely used medical examination for analyzing brain activity and detecting epileptic seizures [2]. However, EEGs are complex: they are noisy, chaotic [3] [4], and represent the summation of different brain rhythms (delta, theta, alpha, beta, and gamma) [5]. These characteristics make manual analysis time-consuming and necessitate innovative automated approaches to facilitate diagnosis. The development of automatic systems for the detection of epileptic seizures faces several significant challenges. One major difficulty is the variability of EEG activity, which complicates the identification of consistent seizure patterns. Additionally, EEG signals are inherently noisy and nonstationary, further hindering reliable detection. Another critical challenge lies in extracting relevant features that can effectively differentiate between various brain states. Finally, the complexity of many existing approaches often limits their practical applicability in clinical cases.

To overcome these challenges, our work aims to develop a reliable automatic approach for epilepsy diagnosis and seizure detection. The main objective is to propose a method capable of efficiently extracting relevant features from EEG signals and using them to distinguish between different patient states: healthy subjects, epileptic patients during seizure-free intervals, and epileptic patients during seizures. More specifically, our approach focuses on three main aspects. First, we utilize wavelets to decompose EEG signals, allowing us to identify and isolate the different brain rhythms: delta, theta, alpha, beta, and gamma. Second, based on this signal decomposition, we define robust feature spaces that effectively capture the distinctive characteristics of these rhythmic patterns, providing a meaningful representation of different patient states. Finally, by leveraging these carefully extracted features, we aim to achieve accurate and reliable classification results, ensuring that our system can distinguish between patient states with high precision and consistency. Numerous approaches have been proposed for the automatic detection of epileptic seizures from EEG signals.Among the various approaches used for EEG analysis, several complementary methods can be distinguished. Time domain approaches exploit simple statistical features, such as variance, entropy, or higher-order moments, to detect anomalies in the signal. Frequency-domain approaches, on the other hand, rely on *Fourier transform* (FFT) or wavelet transform analysis to extract rhythmic components (alpha, beta, theta, gamma, delta) and identify seizure related patterns. Some studies *Hilbert-Huang Transform* [6] [7] [8] propose hybrid and advanced methods, combining wavelet analysis with techniques from chaos theory, fractals, or machine learning to improve detection accuracy, for example, the use of fractal dimension or entropy has shown promising results in differentiating epileptic states. Finally, various classification techniques, including K-nearest neighbors (KNN), support vector machines (SVM), neural networks, and deep learning methods, have been extensively explored to classify the extracted features and detect seizures, with performance varying depending on the datasets and EEG signal quality [9].

Despite these efforts, the complexity and noise of EEG signals still make reliable and generalizable detection challenging.
Our approach uses wavelet decomposition for signal preprocessing and fractal dimensions for feature extraction. These two approaches have already been used in the literature, as previously mentioned, and we have already demonstrated their relevance in our previous work [10] [11].

The main novelty of this paper lies in two key contributions. *First*, we extend our previous work on fractal analysis of EEG signals by integrating wavelet decomposition with the Higuchi fractal dimension using dual parameters [11]. While our earlier study was based on temporal derivatives of raw EEG signals, the present work applies this approach to wavelet decomposed EEG signals, providing a more robust analysis of brain activity. *Second*, we use a *Chaos-Embedding* [12] strategy, originally proposed in our previous work, where we demonstrated that perturbing EEG signals with a chaotic signal improves the characterization of brain dynamics. We showed that healthy EEG signals tend to exhibit higher chaotic behavior, whereas pathological EEG signals display weaker chaos, with seizure activity moving toward more regular, but with increased artifacts. In addition, we previously observed that non-chaotic EEG signals are more sensitive to chaotic perturbations when measured using the Higuchi fractal dimension, while highly chaotic signals are less affected. In this work, we further exploit and validate this property in the context of wavelet based EEG analysis.

The paper is organized as follows. In the next section, we explain brain rhythms and their significance for medical analysis. We then present the database used and discuss the relevance of fractal dimension for EEG signal analysis. The following section describes our learning strategy and the methodological framework employed, with detailed explanations. Next, we present the experimental results, followed by a discussion. Finally, we conclude with the main findings and perspectives for future work.

II. Preliminary

A. Brain Rhythms

Brain rhythms play a very important role in EEG reading and analysis. Several techniques have been explored in the literature for their detection, including: *Wavelet analysis*, *filtering*, *Empirical Mode Decomposition*, *Hilbert-Huang Transform* [6] [7] [8]. The main brain signals identified are [13]:

- *Delta waves* (0.5–$4Hz$): associated with deep sleep and recovery.
- *Theta waves* (4–$8Hz$): linked to relaxation, meditation, and certain memory processes.
- *Alpha waves* (8–$13Hz$): appear when a person is calm but awake, often at rest with closed eyes.
- *Beta waves* (13–$30Hz$): associated with attention, concentration, and active mental activity.
- *Gamma waves* ($> 30Hz$): related to complex cognitive processing, learning, and memory.

B. Used Data

The University of Bonn EEG Dataset [14] is a widely used public database in epilepsy research. It contains EEG segments from different categories:
- A and B correspond to healthy subjects with eyes open and closed,
- C and D come from epileptic patients, including signals from both focal and non-focal areas,
- E contains recordings of subjects during a seizure. This dataset is particularly useful for machine learning and the development of seizure detection algorithms.

C. Fractal Features in Brain Analysis

The use of fractal dimensions for EEG characterization is particularly relevant, as the brain is a complex and chaotic system whose electrical activity exhibits nonlinear variations that are difficult to analyze using classical methods. EEG signals display self-similar patterns across different temporal scales, making the fractal approach ideal for quantifying their complexity. Among the most commonly used fractal dimensions are the Hausdorff dimension, Katz dimension, and Higuchi dimension, each offering a specific insight into the temporal dynamics of EEG [15]. The Higuchi dimension is particularly suited to non-stationary signals, while the Katz dimension is simple to compute and sensitive to fine variations.

III. Proposed approach

Our proposed approach is illustrated in Fig.1, which presents the following steps.

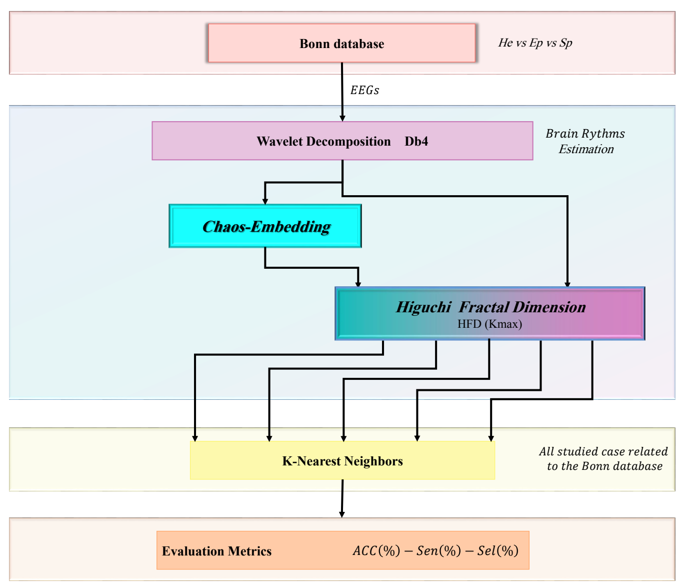

Fig. 1: Proposed approach

1) *Wavelet decomposition*: This approach is used in our work to identify the brain waves (delta, theta, alpha, beta, and gamma).
2) *Chaos-Embedding*: This method, presented in our previous work applied to EEG [12], is here applied to brain rhythms (delta, theta, alpha, beta, and gamma).

3) *Higuchi Fractal Dimension (HFDE)* : We rely on the Higuchi algorithm presented in [16], with $k_{\max}$ values adapted from our previous work [11].
4) *K-Nearest Neighbors (KNN)*: This classifier is used for its simplicity to evaluate the different feature spaces studied in this work.
   - HFDE6: HFDEs extracted for $k_{\max} = 6$
   - HFDE18: HFDEs extracted for $k_{\max} = 18$
   - HFDEC6: HFDEs extracted for $k_{\max} = 6$ after Chaos-Embedding
   - HFDEC18: HFDEs extracted for $k_{\max} = 18$ after Chaos-Embedding
   - All HFDEs: HFDEs extracted under different conditions.

   ◊ The classification model was validated through k-fold cross-validation for $k = 5$.
5) *Evaluation of our approach using different metrics*:
   - Accuracy (Acc) measures the overall classification performance,
   - Sensitivity (Sen) consists in correctly identifying positive cases,
   - Specificity (Spe) consists in correctly identifying negative cases, used to assess classifier performance.

IV. Results

A. Features space

For the different brain rhythms, we evaluate the feature space in the following figures[2,3,4,5,6]: $HFDE6$, presented in sub-figure (a); $HFDE18$, presented in sub-figure (b); $HFDEC6$, presented in sub-figure (c); and $HFDEC18$, presented in sub-figure (d).

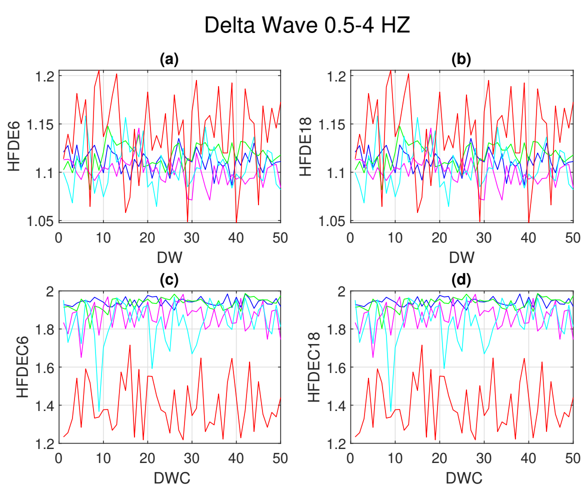

Fig. 2: Graphical evaluation of Chaos-Embedding impact on $HFDE$ of EEG-Delta rhythm (+ A, + B, ∗ C, ∗ D, □ E)

- *Delta waves*: Fig.2 shows that for both values of k_{max} the HFDE is not significant without *Chaos-Embedding*. However, when *Chaos-Embedding* is applied, the classification (D versus others) becomes more pronounced.
- *Theta waves*: Fig.3 shows that for different values of k_{max}, healthy subjects (class B) are separable from all other cases. This separability is further enhanced with *Chaos-Embedding*, which also allows the separation of class E (seizure) from the other classes.
- *Alpha waves*: Fig.4 highlights the relevance of this frequency band for detecting healthy subjects (class A), especially for the low value $k_{\max} = 6$.
- *Beta waves*: Fig.5 shows that this band becomes relevant only for $k_{\max} = 18$ and after the addition of *Chaos-Embedding*.
- *Gamma waves*: The addition of *Chaos-Embedding* does not provide a significant improvement for this band. This result is expected since Gamma waves correspond to the highest frequency range, where the effect of chaos is generally limited.

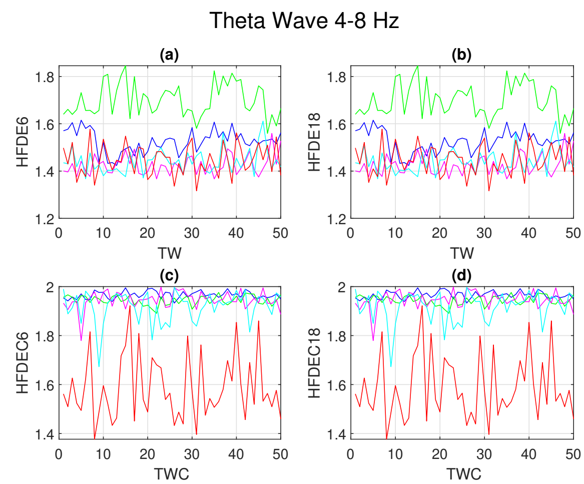

Fig. 3: Graphical evaluation of Chaos-Embedding impact on $HFDE$ of EEG-Theta rhythm (+ A, + B, ∗ C, ∗ D, □ E)

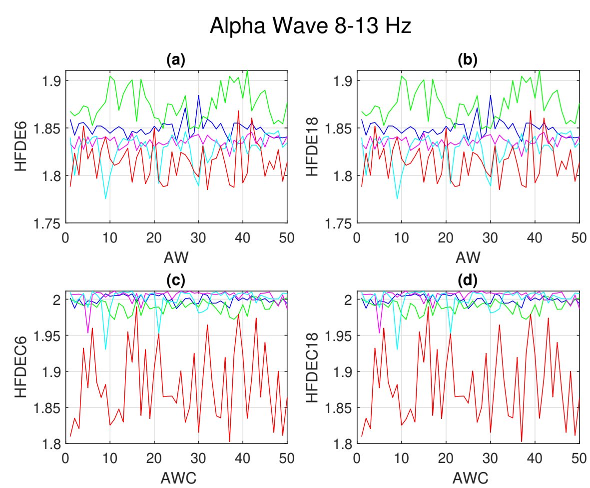

Fig. 4: Graphical evaluation of Chaos-Embedding impact on $HFDE$ of EEG-Alpha rhythm (+ A, + B, ∗ C, ∗ D, □ E)

Overall, the use of *Chaos-Embedding* and the dual parameterization of K_{max} improves the feature space for most fre-

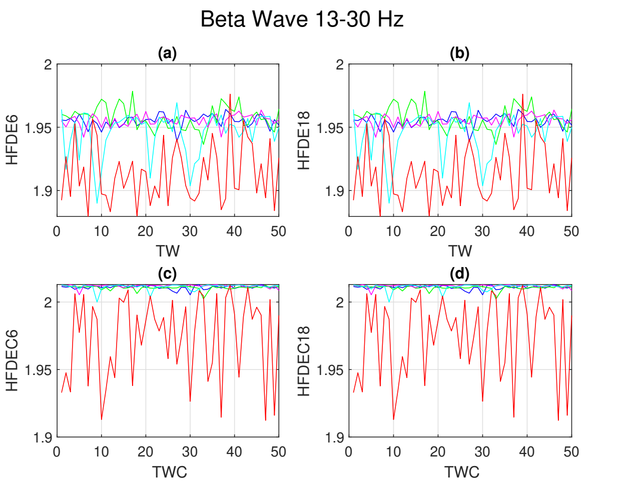

Fig. 5: Graphical evaluation of Chaos-Embedding impact on $HFDE$ of EEG-Beta rhythm ($+$ A, $+$ B, $*$ C, $*$ D, $\square$ E)

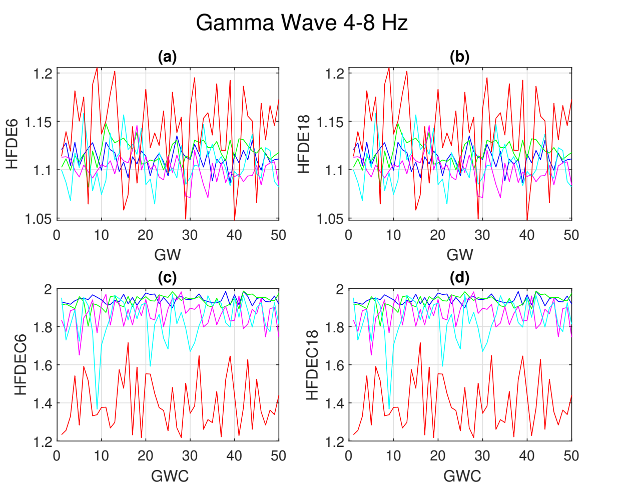

Fig. 6: Graphical evaluation of Chaos-Embedding impact on $HFDE$ of EEG-Gamma rhythm ($+$ A, $+$ B,$*$ C,$*$ D,$\square$ E)

quency bands, this is particularly evident for $K_{max} = 6$, where the feature spaces initially show poor separability, and in some cases no separation at all. The addition of *Chaos-Embedding* enables a clear separation between classes. However, for high-frequency bands (Beta and Gamma), the improvement remains limited. These feature spaces are then evaluated using a KNN classifier by computing three performance metrics.

B. Achieved Performance

In Fig.7, we present the performance results obtained for all possible cases related to the BONN dataset using our model, more detailed information are provided in the table presented in the appendix. The following observations can be made:

- For the feature space based on $k_{\max} = 6$, the HFDE without *Chaos-Embedding* is represented by light blue points, while brown points correspond to the results after *Chaos-Embedding*. It can be observed that the injection of chaos significantly improves the learning model performance.
- For the feature space based on $k_{\max} = 18$, the HFDE without *Chaos-Embedding* is represented by green points, and violet points correspond to the results after *Chaos-Embedding*. An improvement is still observed; however, it is less significant than that obtained for $k_{\max} = 6$.
- Finally, the use of all extracted features leads to excellent performance, highlighting the benefit of combining all features.

$\Rightarrow$ The obtained results confirm the proposed hypothesis: the use of *Chaos-Embedding* combined with the double parameterization of the Higuchi Fractal Dimension is effective for differentiating brain states in patients by analyzing cerebral rhythms extracted through wavelet transforms. These findings highlight the relevance and potential of the proposed approach.

V. Discussion

The BONN database analyzed in this study is a widely used benchmark dataset. In [17] a fourth-order Daubechies wavelet was employed to extract different brain rhythms from the EEG signals. Each resulting sub-band was then analyzed using multifractal analysis based on Detrended Fluctuation Analysis (DFA). The extracted features were subsequently classified using a Support Vector Machine (SVM). The study focused on three subsets only (B, D, and E). The proposed approach achieved an accuracy of 99.6%, precision of 99.3%, recall of 99.3%, specificity of 99.7%, and an F-score of 99.3%. In [18] The study analyzed two EEG databases. For the Bonn database, the authors first applied a Butterworth band-pass filter. Subsequently, the dual-tree complex wavelet transform was used to decompose the EEG signals into different sub-bands. A wide range of features based on fractal and nonlinear theories were then extracted, including Higuchi, Katz, and Petrosian fractal dimensions, Hurst exponent, detrended fluctuation analysis (DFA), Sevcik fractal dimension, box-counting, multiresolution box-counting, Maragos–Sun method, multifractal DFA, and recurrence quantification analysis. Feature selection was performed using the minimum redundancy maximum relevance method to identify the most discriminative features. The selected features were classified using three different approaches: SVM, KNN, and a convolutional autoencoder. The authors investigated six different classification cases (A-E, B-E, C-E, D-E, ABCD-E, AB-CD-E) and evaluated performance using accuracy, sensitivity, specificity, and F1-score. The obtained results showed very high performance, with most metrics varying around 99%. Another approach based on spectral analysis was presented in [19]. In this study, the authors first filtered the raw EEG signals and segmented them into epochs. The power spectral density of each segment was then estimated using the Fast Fourier Transform based on Welch's method. From the resulting PSD, both periodic and aperiodic components were extracted. The feature set consisted of three parameters derived from the periodic component center frequency, power, and bandwidth

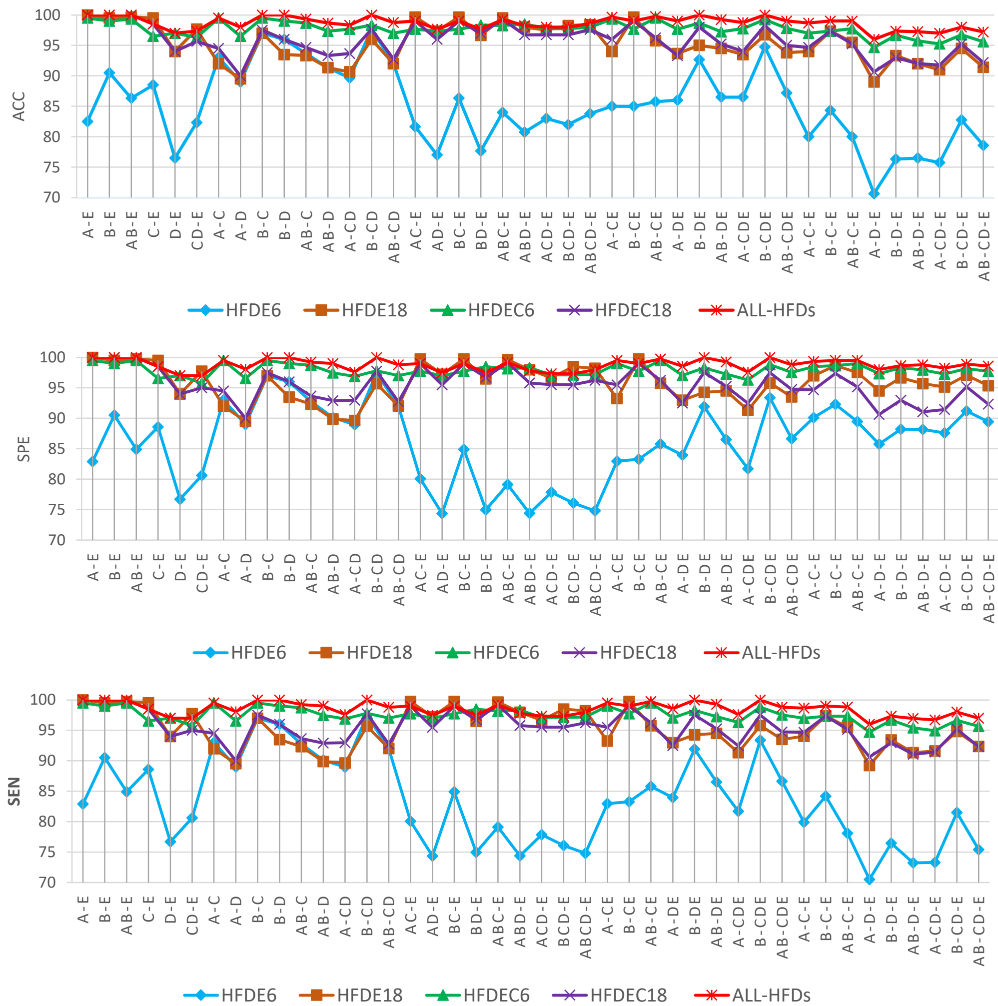

Fig. 7: Achieved Performance

of the highest spectral peak and two parameters from the aperiodic component, namely the offset and exponent. Finally, the extracted feature vectors were classified using SVM, KNN, Decision Tree, and Linear Discriminant Analysis classifiers. The evaluation metrics used in this study were [SEN-SPE-ACC]. The studied cases are : (A-E [100-100-100], B-E [100-100-100], C-E [100-99-99.5], AB-E [100-100-100], CD-E [97-99.5-98.7], AB-CDE [98-98-98], ABCD-E [95-99.25-98.4], A-D-E [97-98.5-98], AB-CD-E [94-100-98.8]). It is true that previous approaches lead to high performance, and that several other methods cited in [9] also lead to high performance. However, this work focuses on reducing methodological complexity while maintaining competitive accuracy.

- Work limitation

The two main novelties of this work lie in the injection of chaos into brain rhythms and in the dual use of k_{max} values, which lead to improved learning performance. However, these results require a deeper theoretical explanation as well as validation on other datasets in order to generalize the proposed approach. The chaotic behavior of brain waves, using methods from chaos theory such as the largest Lyapunov exponent, attractor reconstruction, and Poincaré sections,... will be studied in our future work.

VI. Conclusion

In this work, an automatic approach for epilepsy monitoring is presented, integrating *wavelets* for brain rhythm estimation with *Chaos-Embedding* and the Higuchi fractal dimension to characterize signal complexity. The proposed method extracts discriminative features that effectively distinguish between different patient states. Classification using *KNN* demonstrated very high performance, highlighting the robustness and reliability of our approach. These results underscore the potential of using advanced signal processing techniques and *chaos theory* to improve epilepsy diagnosis. In the future, this approach could be extended to larger databases and integrated into clinical systems for real-time patient monitoring.

VII. Appendix

Table 1 summarizes all the numerical values estimated to compute the performance metrics for all studied experiments.

TABLE I: Achieved Performance

$U-SS$	HFDE6			HFDE18			HFDEC6			HFDEC18			All-HFDES		
	Acc	Spe	Sen	Acc	Spe	Sen	Acc	Spe	Sen	Acc	Spe	Sen	Acc	Spe	Sen
A-E	82.5	82.89	82.89	100	100	100	99.5	99.5	99.5	100	100	100	100	100	100
B-E	90.5	90.53	90.53	99.5	99.5	99.5	99	99.01	99.01	100	100	100	100	100	100
AB-E	86.33	84.91	84.91	99.66	99.75	99.75	99.33	99.5	99.5	100	100	100	100	100	100
C-E	88.5	88.59	88.59	99.5	99.5	99.5	96.5	96.54	96.54	98.5	98.5	98.5	98.5	98.5	98.5
D-E	76.5	76.71	76.71	94	94.01	94.01	97	97.01	97.01	94	94	94	97	97.01	97.01
CD-E	82.33	80.61	80.61	97.66	97.73	97.73	96.33	95.77	95.77	95.66	95.02	95.02	97.33	97	97
A-C	93	93.01	93.01	92	92	92	99.5	99.5	99.5	94.5	94.5	94.5	99.5	99.5	99.5
A-D	89	89.01	89.01	89.5	89.53	89.53	96.5	96.54	96.54	90	90	90	98	98.07	98.07
B-C	97	97	97	97	97	97	99.5	99.5	99.5	97.5	97.5	97.5	100	100	100
B-D	96	96.01	96.01	93.5	93.5	93.5	99	99	99	96	96.01	96.01	100	100	100
AB-C	93.66	92.78	92.78	93.33	92.33	92.33	98.66	98.74	98.74	94.66	93.66	93.66	99.33	99.25	99.25
AB-D	91.33	90.1	90.1	91.33	89.87	89.87	97.33	97.48	97.48	93.33	92.89	92.89	98.66	99.01	99.01
A-CD	89.66	88.95	88.95	90.66	89.65	89.65	97.66	96.88	96.88	93.66	92.96	92.96	98.33	97.61	97.61
B-CD	97.66	97.48	97.48	96	95.71	95.71	98.33	97.8	97.8	97.66	97.73	97.73	100	100	100
AB-CD	92	92.01	92.01	92	92.03	92.03	97	97.04	97.04	92.75	92.75	92.75	98.75	98.78	98.78
AC-E	81.66	80.09	80.09	99.66	99.75	99.75	97.66	97.73	97.73	99	98.99	98.99	99	98.99	98.99
AD-E	77	74.35	74.35	97.33	97.23	97.23	97.33	97	97	96	95.5	95.5	97.66	97.48	97.48
BC-E	86.33	84.91	84.91	99.66	99.75	99.75	97.66	97.73	97.73	99	98.99	98.99	99	98.99	98.99
BD-E	77.66	74.97	74.97	96.66	96.47	96.47	98.33	98.49	98.49	97	96.73	96.73	97.66	97.48	97.48
ABC-E	84	79.13	79.13	99.5	99.66	99.66	98.25	98.14	98.14	99.25	99.16	99.16	99.25	99.16	99.16
ABD-E	80.75	74.38	74.38	98	97.97	97.97	98.5	98.31	98.31	96.75	95.8	95.8	98.25	97.82	97.82
ACD-E	83	77.87	77.87	97.5	96.66	96.66	97.75	97.14	97.14	96.75	95.53	95.53	98	97.33	97.33
BCD-E	82	76.11	76.11	98.25	98.49	98.49	97.75	97.14	97.14	96.75	95.53	95.53	98	97.33	97.33
ABCD-E	83.8	74.8	74.8	98.4	98.21	98.21	98	97.21	97.21	97.6	96.24	96.24	98.6	97.98	97.98
A-CE	85	82.96	82.96	94	93.25	93.25	99.33	99.01	99.01	96	95.5	95.5	99.66	99.5	99.5
B-CE	85	83.26	83.26	99.66	99.75	99.75	97.66	97.73	97.73	99	98.99	98.99	99	98.99	98.99
AB-CE	85.75	85.79	85.79	95.75	95.75	95.75	99.5	99.5	99.5	96.24	96.25	96.25	99.75	99.75	99.75
A-DE	86	83.97	83.97	93.66	92.96	92.96	97.66	97.06	97.06	93.33	92.5	92.5	99	98.54	98.54
B-DE	92.66	91.92	91.92	95	94.28	94.28	98.66	98.27	98.27	98	97.53	97.53	100	100	100
AB-DE	86.5	86.51	86.51	94.5	94.5	94.5	97.24	97.26	97.26	95.24	95.25	95.25	99.25	99.26	99.26
A-CDE	86.5	81.7	81.7	93.5	91.33	91.33	97.75	96.32	96.32	94	92.48	92.48	98.75	97.61	97.61
B-CDE	94.75	93.38	93.38	96.75	95.8	95.8	99.25	98.84	98.84	98.25	97.51	97.51	100	100	100
AB-CDE	87.2	86.63	86.63	93.8	93.51	93.51	97.8	97.54	97.54	95	94.75	94.75	99	98.78	98.78
A-C-E	80	90.11	79.92	94	96.99	94.02	97	98.5	97	94.66	97.32	94.68	98.66	99.33	98.66
B-C-E	84.33	92.28	84.19	97.33	98.66	97.35	97.33	98.67	97.34	97.33	98.66	97.35	99	99.5	99
AB-C-E	80	89.47	78.1	95.5	97.54	95.53	97.75	99	97.33	95.25	97.49	95.14	99	99.5	98.83
A-D-E	70.66	85.76	70.52	88.99	94.49	89.24	94.66	97.33	94.7	90.66	95.34	90.63	96	98.02	96.01
B-D-E	76.33	88.2	76.48	93.33	96.66	93.4	96.66	98.33	96.68	93	96.5	92.97	97.33	98.66	97.34
AB-D-E	76.5	88.18	73.23	92	95.68	91.34	95.75	97.94	95.43	92	95.94	91.08	97.25	98.78	96.96
A-CD-E	75.75	87.59	73.31	90.99	95.15	91.61	95.24	97.26	94.94	91.75	95.33	91.45	97	98.24	96.72
B-CD-E	82.75	91.2	81.52	94.5	97.08	94.82	96.75	98.17	96.66	95.25	97.33	95.18	98	98.88	98
AB-CD-E	78.59	89.45	75.4	91.4	95.37	92.36	95.6	97.69	95.65	92.19	95.83	92.34	97.2	98.59	96.98

REFERENCES

[1] WHO, "Epilepsy." https://www.who.int/news-room/fact-sheets/detail/epilepsy, 7 February 2024. [Accessed 2025].

[2] S. J. Smith, "Eeg in the diagnosis, classification, and management of patients with epilepsy," *Journal of Neurology, Neurosurgery & Psychiatry*, vol. 76, no. suppl 2, pp. ii2–ii7, 2005.

[3] C. A. Skarda and W. J. Freeman, "How brains make chaos in order to make sense of the world," *Behavioral and brain sciences*, vol. 10, no. 2, pp. 161–173, 1987.

[4] Z. Brari and S. Belghith, "An automated diagnosis of epilepsy using eeg derivation based on few features," in *2024 10th International Conference on Control, Decision and Information Technologies (CoDIT)*, pp. 2204–2209, IEEE, 2024.

[5] J. W. Britton, L. C. Frey, J. L. Hopp, P. Korb, M. Z. Koubeissi, W. E. Lievens, E. M. Pestana-Knight, and E. K. St Louis, "Electroencephalography (eeg): An introductory text and atlas of normal and abnormal findings in adults, children, and infants," 2016.

[6] M. Le Van Quyen, J. Foucher, J.-P. Lachaux, E. Rodriguez, A. Lutz, J. Martinerie, and F. J. Varela, "Comparison of hilbert transform and wavelet methods for the analysis of neuronal synchrony," *Journal of neuroscience methods*, vol. 111, no. 2, pp. 83–98, 2001.

[7] S. K. Khare, N. B. Gaikwad, and V. Bajaj, "Vhers: a novel variational mode decomposition and hilbert transform-based eeg rhythm separation for automatic adhd detection," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, pp. 1–10, 2022.

[8] S. Khoshnoud, M. A. Nazari, and M. Shamsi, "Functional brain dynamic analysis of adhd and control children using nonlinear dynamical features of eeg signals," *Journal of integrative neuroscience*, vol. 17, no. 1, pp. 17–30, 2018.

[9] M. K. Siddiqui, R. Morales-Menendez, X. Huang, and N. Hussain, "A review of epileptic seizure detection using machine learning classifiers," *Brain informatics*, vol. 7, no. 1, p. 5, 2020.

[10] Z. Brari, I. Bouzouita, and S. Belghith, "A comparative study of derivative-based and wavelet-based approaches for epilepsy eeg analysis," in *2024 IEEE 7th International Conference on Advanced Technologies, Signal and Image Processing (ATSIP)*, vol. 1, pp. 330–335, IEEE, 2024.

[11] Z. Brari and S. Belghith, "A novel machine learning model for the detection of epilepsy and epileptic seizures using electroencephalographic signals based on chaos and fractal theories," *Mathematical Problems in Engineering*, vol. 2021, no. 1, p. 2107113, 2021.

[12] Z. Brari and S. Belghith, "Chaos-embedding. i: An innovative approach to exploring chaos through higuchi's dimension with application to brain signals," *Chaos, Solitons & Fractals*, vol. 199, p. 116737, 2025.

[13] J. S. Kumar and P. Bhuvaneswari, "Analysis of electroencephalography (eeg) signals and its categorization–a study," *Procedia engineering*, vol. 38, pp. 2525–2536, 2012.

[14] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," *Physical Review E*, vol. 64, no. 6, p. 061907, 2001.

[15] S. Kesić and S. Z. Spasić, "Application of higuchi's fractal dimension from basic to clinical neurophysiology: A review," *Computer methods and programs in biomedicine*, vol. 133, pp. 55–70, 2016.

[16] T. Higuchi, "Approach to an irregular time series on the basis of the fractal theory," *Physica D: Nonlinear Phenomena*, vol. 31, no. 2, pp. 277–283, 1988.

[17] D. Sikdar, R. Roy, and M. Mahadevappa, "Epilepsy and seizure characterisation by multifractal analysis of eeg subbands," *Biomedical Signal Processing and Control*, vol. 41, pp. 264–270, 2018.

[18] A. Malekzadeh, A. Zare, M. Yaghoobi, and R. Alizadehsani, "Automatic diagnosis of epileptic seizures in eeg signals using fractal dimension features and convolutional autoencoder method," *Big Data and Cognitive Computing*, vol. 5, no. 4, p. 78, 2021.

[19] S. Liu, J. Wang, S. Li, and L. Cai, "Epileptic seizure detection and prediction in eegs using power spectra density parameterization," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 3884–3894, 2023.