Ordinary-Kriging Based Real-Time Seizure Detection in an Edge Computing Paradigm

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Outline of The Talk

- Introduction
- Research Question & Novel Contributions
- Key Concepts of the Research
- Proposed Seizure Detection Model
- Experimental Results
- Conclusion & Future Research

What is Seizure?

- A seizure is an abnormal activity in the nervous system which alters the functioning of the brain and causes victims to lose consciousness and control.

Fig.1: A patient with seizure crisis

Why Seizure Detection?

- Timely epileptic seizure detection is an important first step towards effectively managing the seizure disorder.

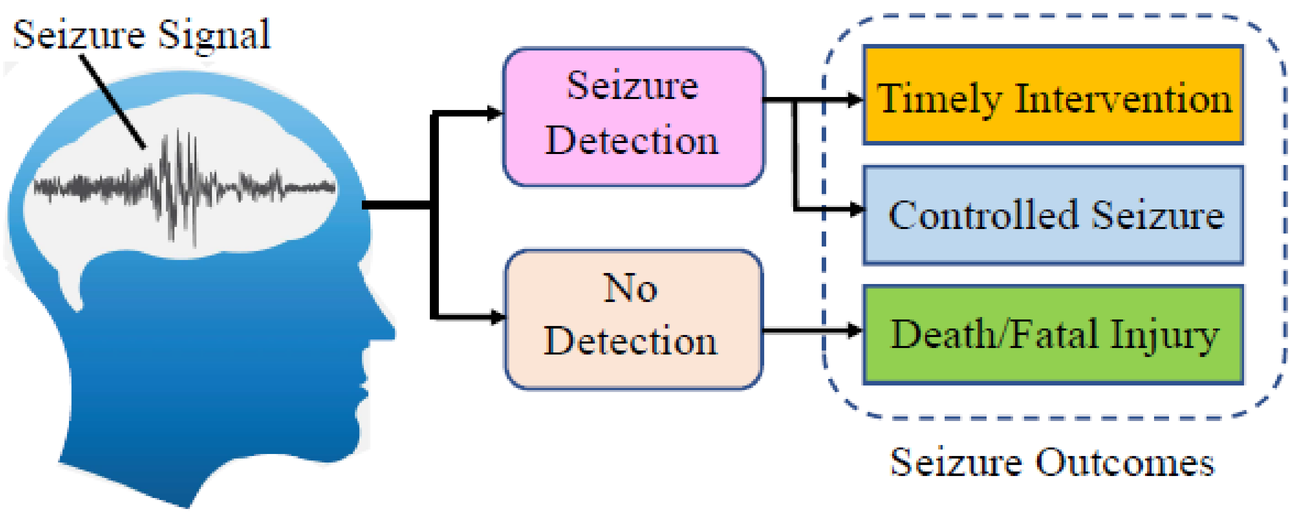


Fig.2: Seizure effects and benefits of seizure detection

Related Research in Seizure Detection

Published Works	Extracted Features	Classification Algorithm
Shoeb, et al. 2010	Spectral, temporal and spatial features.	Support Vector Machine (SVM)
Zandi, et al. 2012	Regularity, energy and combined seizure indices	Cummulative Sum (CUSUM) thresholding
Yoo, et al. 2013	Spectral and spatial features	Linear Support Vector Machine (LSVM)
Altaf, et al. 2015	Digital hysteresis	Linear Support Vector Machine (LSVM)
Vidyaratne, et al. 2017	Fractal dimension, spatial and temporal features.	Relevance Vector Machine (RVM)
Sayeed, et al. 2019	Hyper-synchronous pulses	Signal Rejection Algorithm (SRA)
Current Paper	Petrosian fractal dimension	Kriging Classifier

Table 1: Some related research work in the literature

Consumer Electronics for Seizure Detection

Source: https://spectrum.ieee.org/the-human-os/biomedical/diagnostics/this-seizuredetecting-smartwatch-could-save-your-life

Embrace2: Smartband which uses Machine learning to detect convulsive Seizures and notifies caregivers.

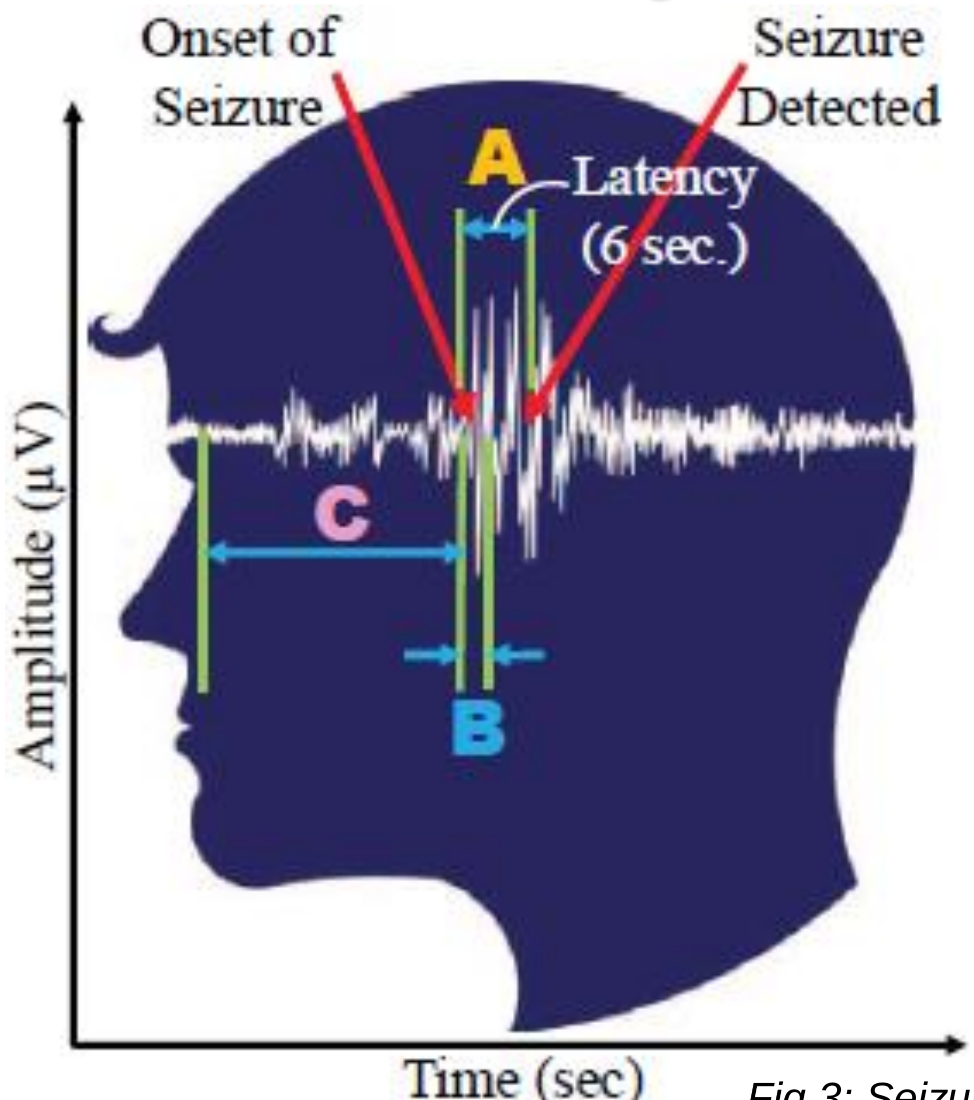
Source: https://www.empatica.com/embrace2/

Medical grade smart watch: It detects generalized clonic-tonic Seizures and notifies physicians.

What are the Drawbacks of Existing Works?

- High seizure detection latency.
- Models are complex and unrealistic for real time deployment in the Internet of Medical Things (IoMT).
- Lack of adequate intervention mechanism after detection.

Latency of Detection



A–Typical Latency (4 to 6s)
B–Early Detection (1 to 2s)
C– Prediction (>= 6s prior)

Fig.3: Seizure detection latencies

What Research Question Addressed in the Current Paper?

- Is it possible to run a seizure detection algorithm on the edge rather than the cloud, without significant compromise on accuracy?
- How can seizure detection be accomplished in real time?

Novel Contributions of the Current Paper

- A novel application of a soft thresholding Discrete Wavelet Transform (DWT) de-noising technique to remove noise in an epileptic seizure detection model.
- A novel achievement of an epileptic seizure detection latency of less than 1 second while maintaining a comparable accuracy with existing models and $O(1)$ time and space complexity for edge computation.

Edge Computing

- Realtime data processing is much more feasible at the edge of the IoT network which is closer to the user elements.

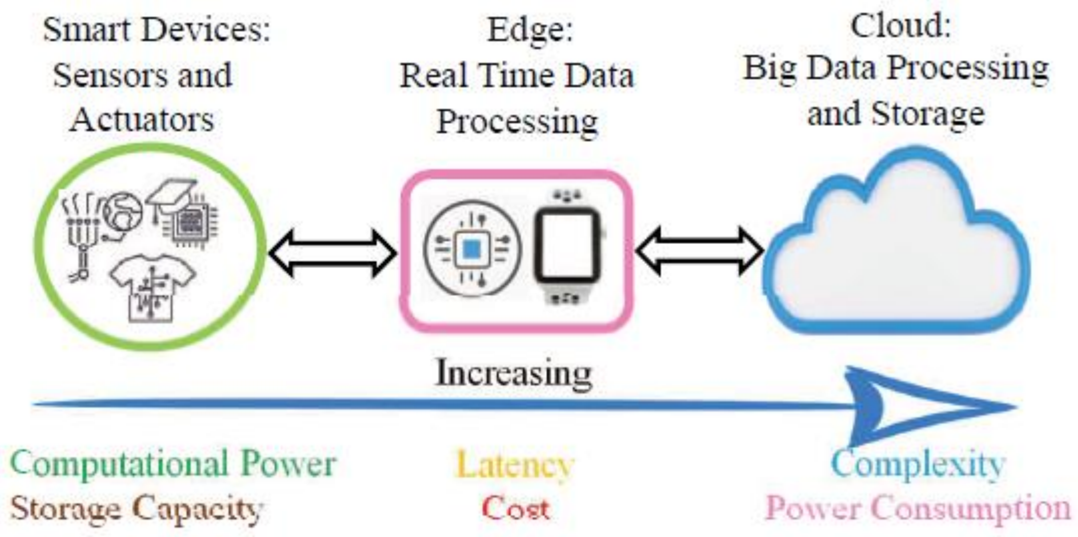


Fig.4: Edge computing paradigm in a smart home

Kriging

- Kriging was originally developed as a geo-statistical model for spatial prediction.
- It is a stochastic process that is governed by a mean value and the relative co-variances of known data points with respect to an unknown.
- The major types of Kriging are:

$$\left.\begin{array}{l}\text{Simple}\\ \text{Ordinary}\\ \text{Universal}\end{array}\right\}\ \text{Kriging}$$

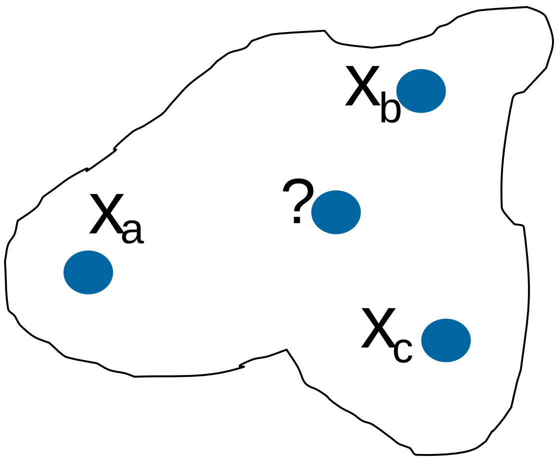


Fig.5: Kriging process schematic

Brain as a Spatial Image

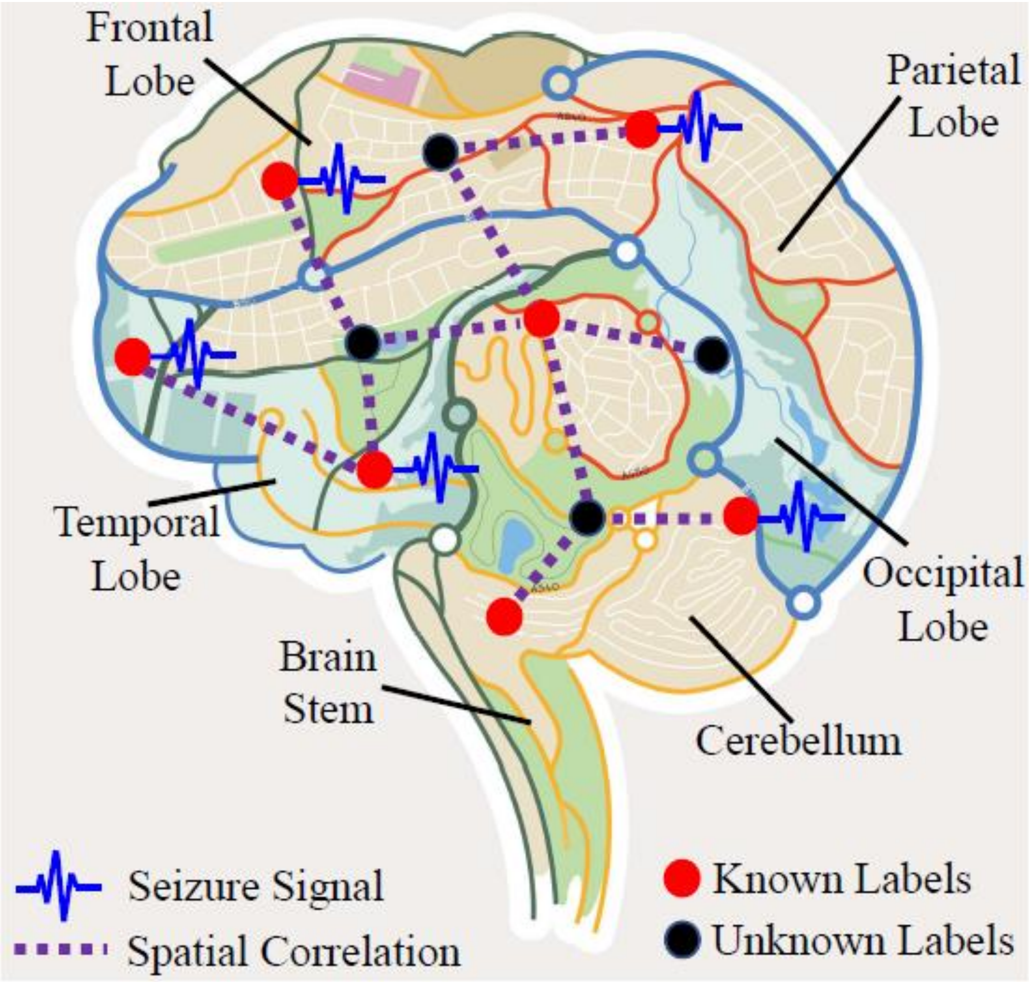


Fig.6: Schematic representation of the brain as a spatial map

Why Kriging?

- The brain can be modeled as a spatial map on which spatial data processing methods can be applied.
- Kriging method performs very well even on a relatively small dataset unlike machine learning algorithms. This is very important because of the difficulty in obtaining biomedical datasets.
- Kriging model comes with a variance estimate which gives the level of confidence of the model in a given prediction.
- Kriging model is very reliable without requiring the use of many hyperparameters.

Ordinary Kriging Estimates

- Given the following set of observations $\mathbf{x}_1$, $\mathbf{x}_2$, ..., $\mathbf{x}_n$ as inputs, and $y(\mathbf{x}_1)$, $y(\mathbf{x}_2)$, ..., $y(\mathbf{x}_n)$ as outputs, the input-output relationship based on Kriging is given by:

$$y(\mathbf{x}_i) = \mu + Z(\mathbf{x}_i), \qquad (1)$$

- *Where* i is the data point index, μ is a mean constant and $Z(\mathbf{x}_i)$ is a Gaussian process.
- The weights between the unknown and each of the known can be obtained by solving the following equation, where C(.) is covariance between two points:

$$\sum_{j=1}^{n} \lambda_j \mathrm{C}(\mathbf{x}_i, \mathbf{x}_i) = 2\mathrm{C}(\mathbf{x}_o, \mathbf{x}_i). \qquad (2)$$

- Hence, the final estimate can be obtained as:

$$y(\mathbf{x}_o) = \sum_{i=1}^{n} \lambda_i Z(\mathbf{x}_i) + (1 - \sum_{i=1}^{n} \lambda_i)\mu_z, \qquad (3)$$

Proposed Flow for Kriging based Fast Seizure Detection

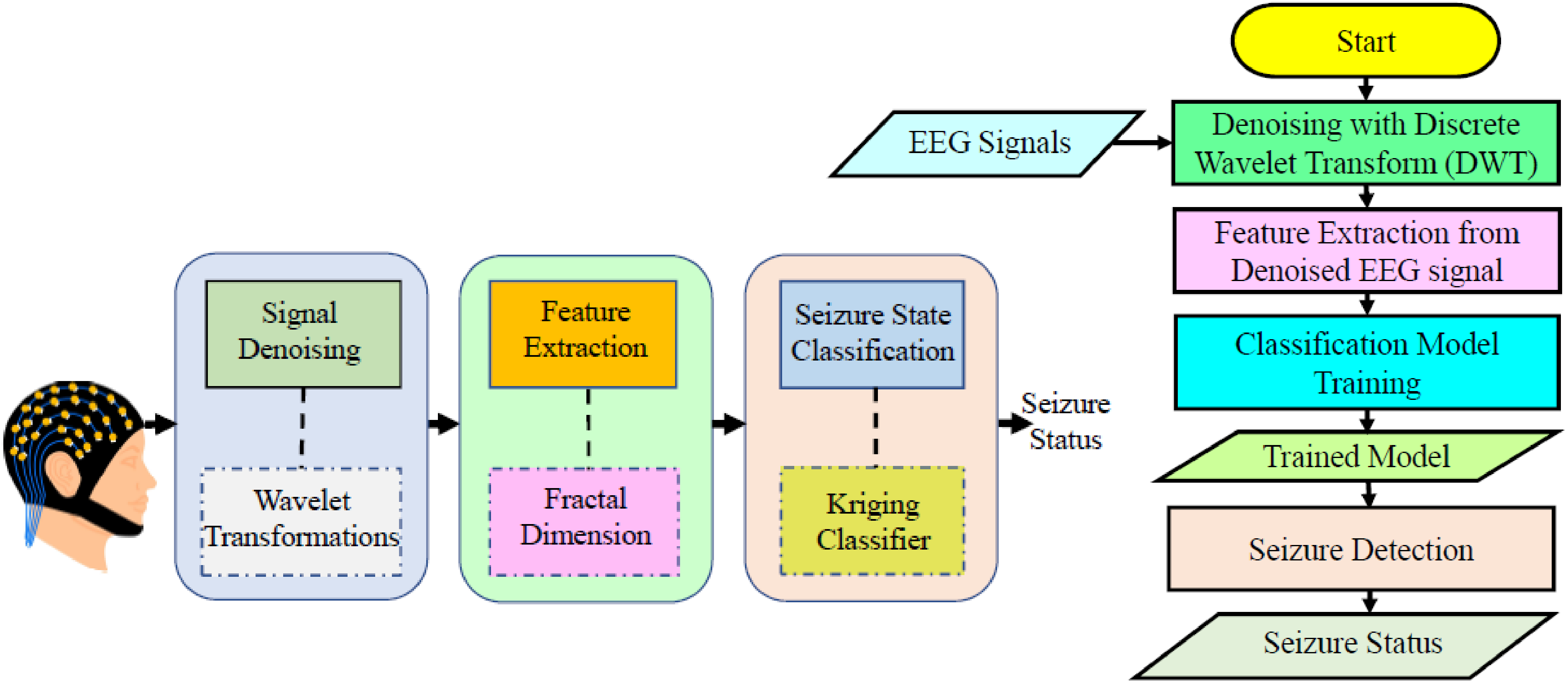


Fig.7: Overall flow process for the proposed Kriging fast seizure detection model

EEG Dataset

- The datasets used in this work were originally collected from five healthy volunteers and five epilepsy patients by the University of Bonn in Germany.

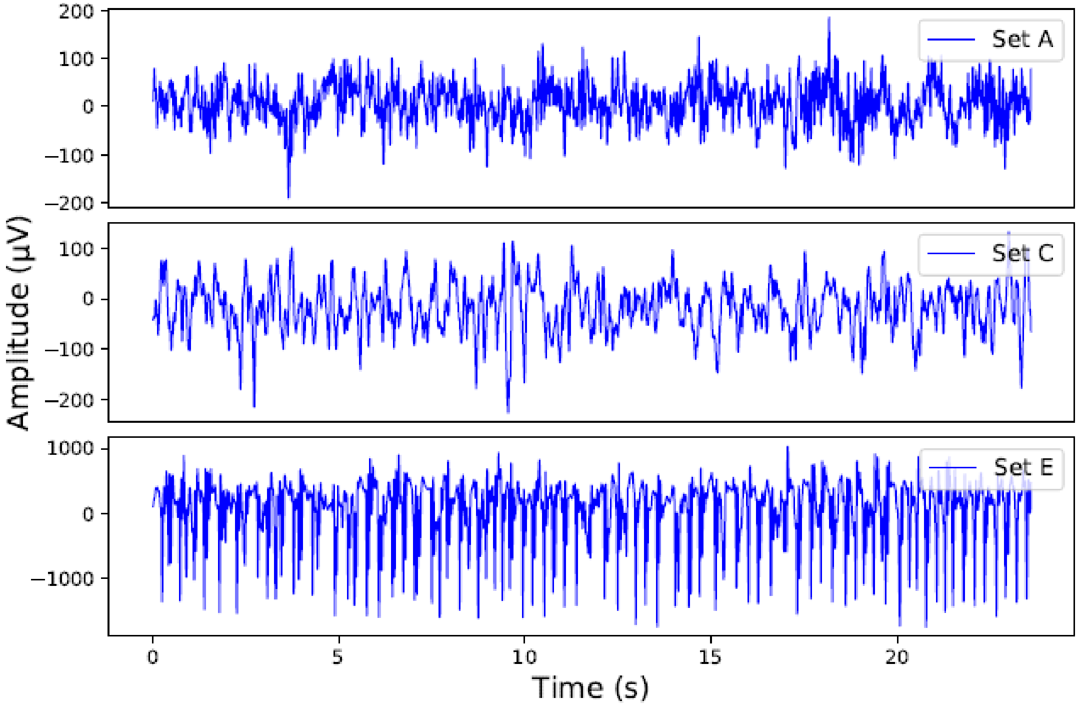


Fig.8: EEG datasets at healthy, inter-ictal and ictal states

EEG Signal Denoising

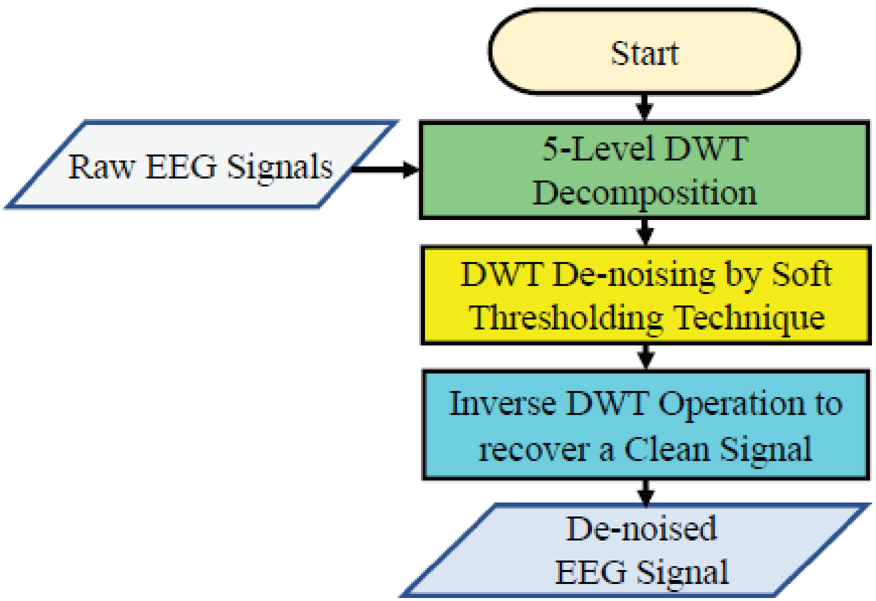


Fig.9a: EEG signal de-noising flow process

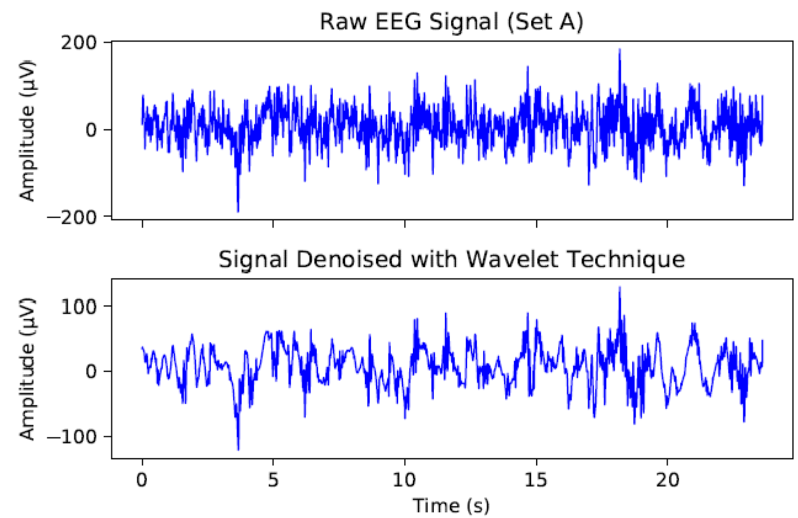


Fig.9b: DWT de-noising for an EEG segment

Features of EEG Signal

- Hjorth Parameters
- Signal Power
- Standard Deviation
- Fractal Dimension
- Maximum Fractal Length
- Signal Entropy
- Hurst Exponent
- Singular Value Decomposition Entropy
- Lyapunov Exponent

Feature Extraction

- The selected feature for this work is the Petrosian Fractal Dimension (pfd), which is given by:

$$FD_{\text{Petrosian}} = \frac{\ln(n)}{\ln(n) + \ln\left(\frac{n}{n + 0.4N_\delta}\right)}, \qquad (4)$$

where n is number of data points in the EEG sequence, or the length of the sequence, and N_δ represents the number of alternating pairs of signs in the inherent binary sequence.

Feature Extraction (contd.)

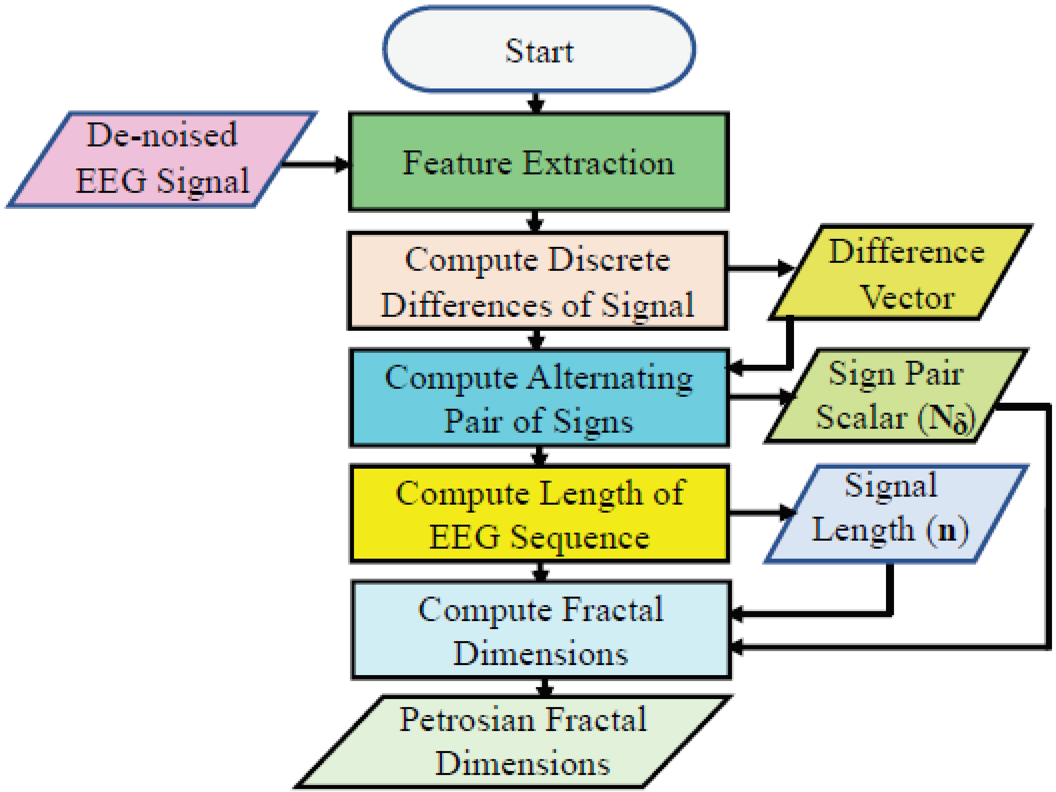


Fig.10: Feature extraction flow process

Kriging Model Training

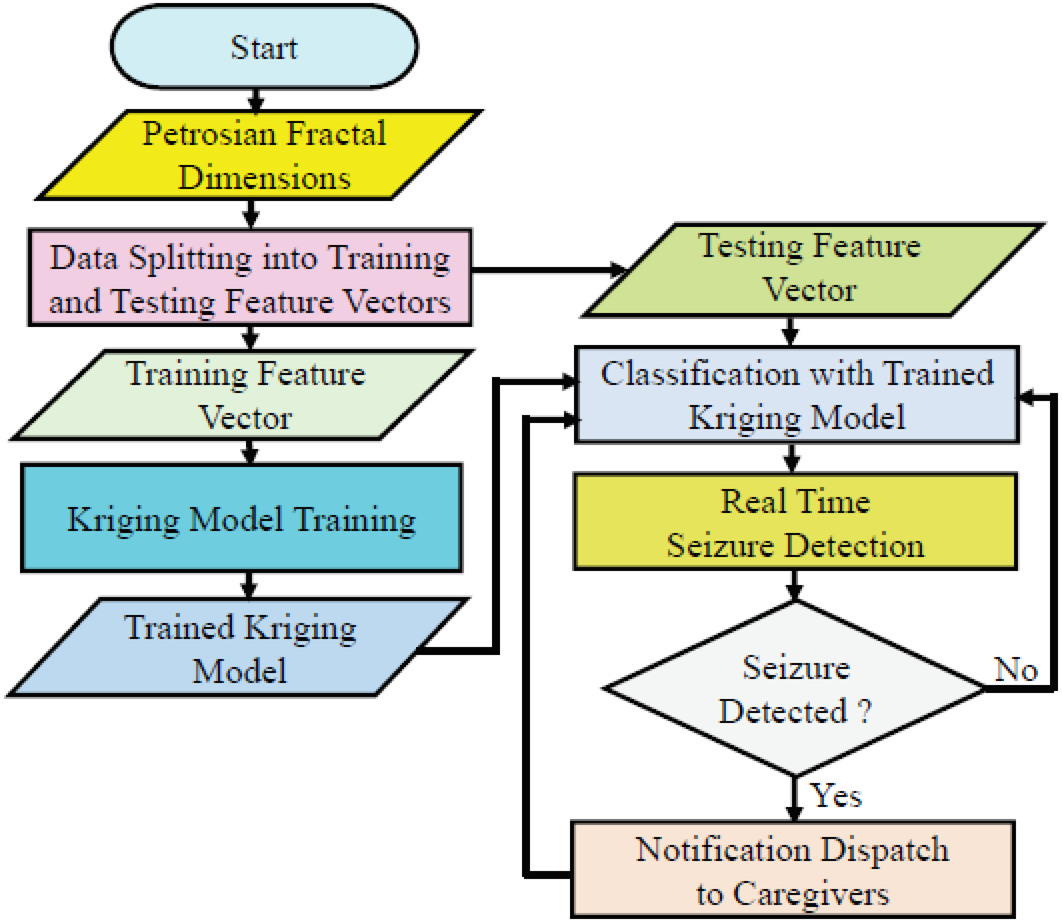


Fig.11: Ordinary Kriging model training and seizure detection flow process

Prototyping Framework

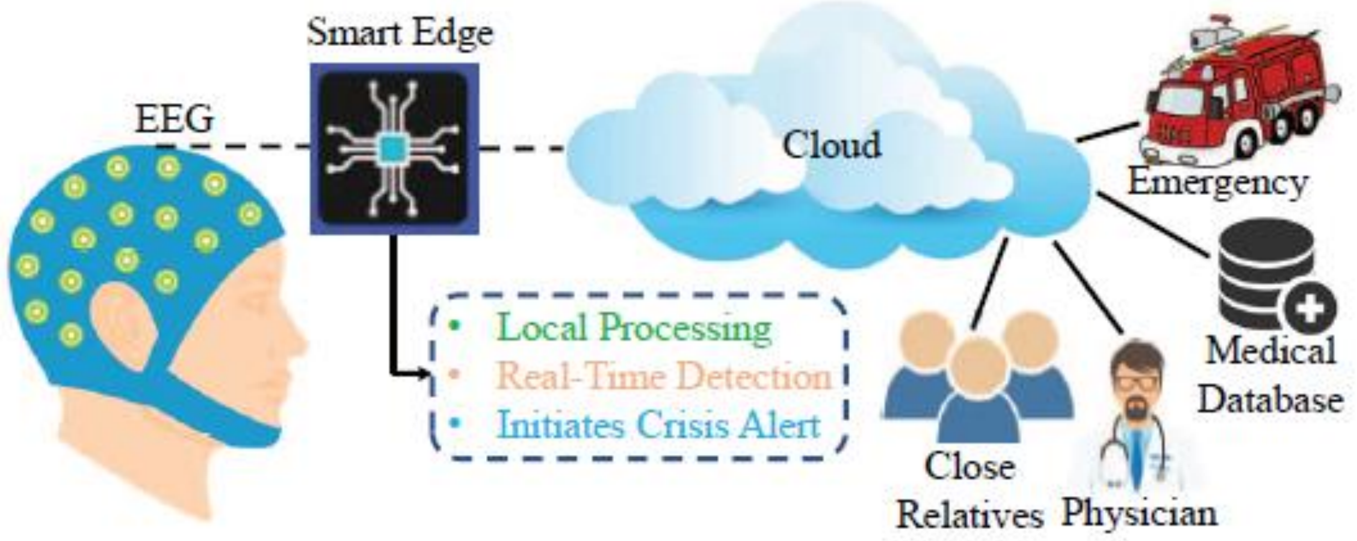


Fig.12: Proposed edge computing model for seizure detection

Experimental Results

Count	pfd_SetA	pfd_SetC	pfd_SetE
1	1.010204	1.008332	1.007853
2	1.010808	1.008588	1.008811
3	1.010182	1.010534	1.008522
4	1.015926	1.009299	1.007091
5	1.014859	1.011967	1.006821

Table 2: Sample feature vectors for sets A, C and E

- A simple sanity check confirms the effectiveness of pfd in detecting the onset of seizure based on the assumption that a healthy biological signal is often more complex than the unhealthy ones.

Experimental Results (contd.)

Dataset	Performance	Naive Bayes	kNN	Kriging
	Accuracy	97.50%	100.00%	**100.00%**
(Set A/Set E)	Sensitivity	97.00%	100.00%	**100.00%**
	Precision	98.00%	100.00%	**100.00%**
	Accuracy	85.00%	82.50%	87.50%
(Set C/Set E)	Sensitivity	85.00%	82.00%	88.00%
	Precision	89.00%	85.00%	88.00%

Table 3: Performance of the proposed kriging model on the testing set compared to other algorithms

- Table 3 shows the performance of the proposed model on the testing set with respect to other machine learning algorithms used on the same dataset.

Experimental Results (contd.)

Published Works	Extracted Features	Classification Algorithm	Sensitivity	Latency
Shoeb, et al. 2010	Spectral, temporal and spatial features.	Support Vector Machine (SVM)	96.00%	4.2 sec.
Zandi, et al. 2012	Regularity, energy & combined seizure indices	Cummulative Sum (CUSUM) thresholding	91.00%	9 sec.
Altaf, et al. 2015	Digital hysteresis	Linear Support Vector Machine (LSVM)	95.70%	1 sec.
Vidyaratne, et al. 2017	Fractal dimension, spatial/temporal features	Relevance Vector Machine (RVM)	96.00%	1.89 sec.
Sayeed, et al. 2019	Hyper-synchronous pulses	Signal Rejection Algorithm (SRA)	96.90%	3.6 sec.
Current Paper	Petrosian fractal dimension	Kriging Classifier	100.00%	**0.85 sec.**

Table 4: Comparing latency of the proposed edge seizure detection model with existing works in the literature

- The mean seizure detection latency of 0.85 second recorded in this work as shown in Table 4 is better than previous results in the literature.

Conclusion

- This paper presents a novel real-time seizure detection model in an edge computing paradigm using the Ordinary Kriging method.
- The Ordinary Kriging method proved very effective in classifying the seizure signals with a training accuracy of 99.4% and a perfect score of 100% for accuracy, sensitivity, precision and specificity on the test set.
- The detection of seizure onset takes place in real time with an average detection latency of 0.85 second which is better than previous models in the literature.

Future Work

- In future work, we will investigate seizure prediction, which means having prior knowledge that a seizure will occur before it actually does.
- Another future research is to have unified systems that detects seizure before it happens, and then injects drug or performs other control measures right after that.
- We also intend to add security and privacy features to the overall system as it is IoMT-enabled and always connected to Internet.

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Thank You !