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

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***Abstract*—*To best of the authors' knowledge, this is the first work that uses Kriging for early detection of seizure*. The threat of an epileptic seizure to the life of a patient is both social and physical. Seizure detection research has been developing over the years. Most efforts in the literature concentrate largely on accuracy and would often take computation to the cloud. However, there is a very short window between the onset of an epileptic seizure and a potentially fatal incidence that could lead to injury or loss of life. Hence, there is need for a more time-sensitive approach to seizure detection. Here, we propose a real time seizure detection model in an edge computing paradigm using signals collected through the electroencephalogram (EEG) from the brain of both healthy and epileptic patients. The fractal dimensions of the signals were taken after de-noising with the Discrete Wavelet Transform (DWT), and then classified using the Ordinary Kriging method which gives a training accuracy of 99.4% and a perfect sensitivity. The proposed model was validated with a hardware implementation using an edge computing device and the results show a comparable classification accuracy and a lower mean detection latency of 0.85 sec.**

***Index Terms*—Smart Healthcare, Seizure Detection, Epilepsy, Edge Computing, Kriging Method, EEG**

I. Introduction

A seizure is an eccentric activity of firing neurons in the central nervous system which results in the irregular functioning of the brain's circuitry. Approximately 10% of the world population will have at least one experience of seizure in their lifetime [1]. Not all seizures are epileptic. A seizure is said to be epileptic when it is unprovoked and recurrent [2]. Timely epileptic seizure detection is an important first step towards effectively managing the disorder and its attendant comorbidities. Real-time seizure detection will ensure that the subject receives the needed help as quickly as possible at the onset of a seizure crisis without the patient being restricted to a locked-in state. EEG signals are captured from the brain using portable devices while patients lead their normal lives, and are immediately analyzed for the presence of seizure.

Recent advances in the Internet of Things (IoT) and Artificial Intelligence (AI) technologies have increased the chances of success in this endeavor. As depicted in Fig. 1, real-time data processing is much more feasible at the edge of the IoT network which is closer to the user elements. For example, a smart wearable (Fig. 1, left) which senses the level of sweat and humidity during sleep in a smart home communicates to an edge device, such as a wrist watch (Fig. 1, center) which performs a computation to compare the measured values to some given threshold and decides if a cooling system is needed. Although the cloud (Fig. 1, right) has higher computational power, it takes a longer time to reach the cloud thereby causing an increased latency which may not be acceptable for a real-time application. Edge computing also enhances user mobility and location awareness [3].

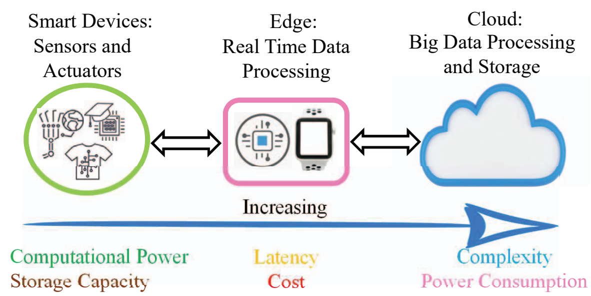


Fig. 1: Edge computing paradigm in a smart home.

The rest of the paper is organized as follows: Section II discusses related research works. Section III states the problem and novel contributions. Section IV presents the proposed edge computing paradigm for seizure detection. Section V is a presentation of the proposed real-time seizure detection model. Experimental validation of the proposed model and results are given in Section VI, while Section VII presents conclusions.

II. Related Research Work

Neuro-Detect was proposed in [4] as a consumer electronic device where a combination of discrete wavelet transforms and Hjorth parameters were used to preprocess the EEG signals and extract important features such as activity, mobility, complexity and standard deviation.

iSeiz was proposed as a real-time seizure detection system built on body motion sensors such as an accelerometer and a gyroscope to detect unusual movements of the body during the onset of a seizure [5]. In iSeiz, information from the wearable has to go through the iSeiz gateway to the cloud from where messages will then be sent to the concerned individuals. This may lead to a substantial delay in providing assistance to the suffering patient.

The use of a signal rejection algorithm for seizure detection using EEG was proposed in [6]. The approach called eSeiz, extracts hyper-synchronous pulses from the EEG as target feature and compares with a given threshold to determine the presence of seizure. However, the proposed Kriging [7] and edge computing based seizure detection model in this work outperforms the eSeiz in terms of both sensitivity and latency.

Several machine learning algorithms have been used for differentiating seizure signals from normal ones. Support Vector Machines (SVM) with radial basis function (RBF) kernels were used in [8]. Other machine learning algorithms which have also been used include κ-NN classifier [4], Artificial Neural Networks (ANN) [9], Decision Trees [10] and Deep Neural Networks [4]. The emphasis in most of these cases is performance in terms of accuracy and not suitability for edge computation. In this paper, we propose a novel application of Ordinary Kriging as a classifier for seizure detection.

III. Contributions of this Current Paper to the State-of-Art

A. Problem Definition

The literature is replete with seizure detection models whose focal point is accuracy. While this is important, the response time required to assist a subject in distress is equally as important, if not even more. A perfect accuracy score is of little value if the epilepsy patient cannot receive the needed help when due. This problem arises because most seizure detection computations are pushed to the cloud due to their heavy complexity. 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? These research questions are addressed in the different sections of this paper.

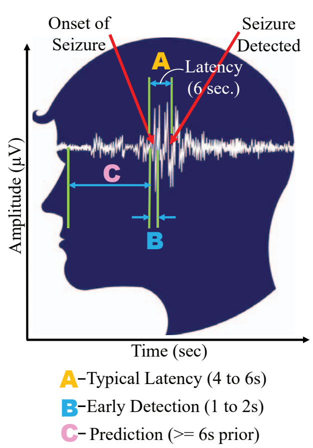


Fig. 2: Seizure detection latencies on an ictal EEG signal.

As shown in Fig. 2, the typical seizure detection latency indicated by region A ranges from 4 to around 6 secs. This is usually the result of cloud processing. However, early detection of seizures (region B) with a latency range of about 1 to 2 secs can be achieved with edge computation. Region C denotes seizure prediction which happens at least 6 secs prior to the onset of seizure. The goal of this work is to achieve early detection with as little latency as possible.

B. Proposed Solution of this Paper

This paper proposes an edge computing solution to the seizure detection problem with a real-time detection model using Ordinary Kriging and the fractal dimension as an efficient mix of a light classification algorithm and a simple feature that is fitted for edge computation. This makes seizure detection much quicker, with minimal latency thereby reducing the risk of death that is often associated with epilepsy.

Why Kriging? Whereas machine learning algorithms like artificial neural networks require large datasets for good performance, the Kriging method [7] performs very well even on a relatively small dataset [11]. This becomes very important given the fact that biomedical datasets are not quite ubiquitous as compared to other fields. Also, prediction from a Kriging model comes with a variance estimate which gives the level of confidence of the model in a given prediction. This makes the Kriging model very reliable without requiring the use of many hyperparameters [11].

C. Novelty of the Proposed Solution

The following are the novel contributions of this work to the state of the art in epileptic seizure detection research:

- A novel synthesis of a feature extraction method and a classification algorithm that is suitable for edge computation with respect to seizure detection, using the fractal dimensions of the EEG signals as a feature vector and Ordinary Kriging classifier.
- 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 $\mathcal{O}(1)$ time and space complexity for edge computation.

IV. Proposed Edge Computing Paradigm for Seizure Detection

By bringing the execution of the seizure detection algorithm to the edge, faster detection can be achieved. We propose a paradigm shift from seizure detection in the cloud to seizure detection on the edge. Fig. 3 shows a schematic architecture of our proposed edge computing paradigm for real-time seizure detection.

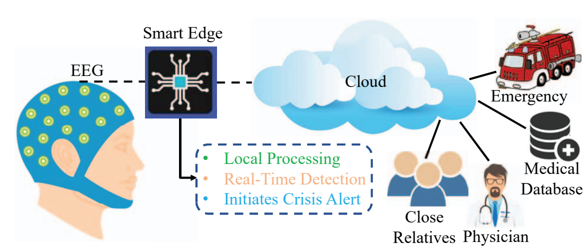


Fig. 3: Proposed edge computing model for seizure detection

The EEG signal is transmitted directly to the portable smart edge device. The three main functions of the edge hardware are as follows: It carries out local processing of the EEG signal to extract some specific features, it performs real-time seizure detection using the extracted features and it triggers a seizure crisis alarm in the event of a seizure. The generated seizure detection alert is disseminated to some designated caregivers which can include close relatives, the physician and an emergency service provider. Unlike the iSeiz [5] approach where messages are initiated from the cloud, messages here are initiated directly from the edge, enhancing faster communication of the seizure state of the patient to the concerned individuals. The medical database shown in Fig. 3 is used as a means of persistent storage of continuous EEG data from the subject for future use. Although an edge IoT seizure detector was proposed in [6], only the physician who is far away was notified of the patient's seizure status. However, a patient under a seizure attack needs immediate help to prevent injury or death. This explains the reason for notifying multiple care givers, including those who are in close proximity to the patient most of the time in our proposed edge computing seizure detection model.

V. The Proposed Real Time Seizure Detection Model

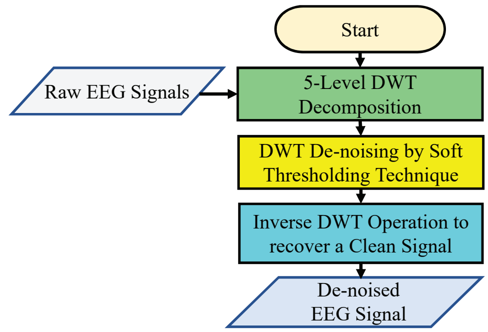
The proposed real-time seizure detection model in this paper consists of three major sections apart from the input and output. They are signal de-noising, feature extraction and seizure state classification. The input to the model is the EEG signal from the patient while the output is the actual seizure status of the patient. The process flows for the three phases of the proposed real-time seizure detection are shown in Fig. 4 and Fig. 5.

A. Signal De-noising

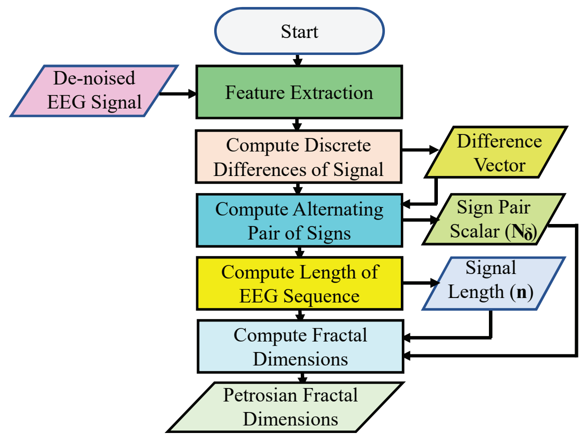
Despite the prevalence of EEG in seizure detection, it is also susceptible to noise as a result of motion artifacts and physiological activities, such as respiration. Wavelet Transforms have been identified as the most effective method of EEG signal pre-processing and de-noising for seizure detection as compared to other methods such as Fourier Transforms and Wiener filtering [12]. It was further observed that the Discrete Wavelet Transform (DWT) performs better than the Continuous Wavelet Transform (CWT). One major disadvantage of wavelet methods is having to select a specific mother wavelet [12] as there are over a dozen different mother wavelets. However, the Daubechies Wavelet of the fourth order (db4) has been identified in the literature as the most suitable mother wavelet for EEG-based seizure detection feature extraction having been noted for the best performance [12]. Wavelet de-noising is achieved by first performing a multi-level wavelet decomposition of the signal followed by a thresholding operation on the coefficients before an inverse wavelet transform to recover the de-noised signal.

B. Feature Extraction

While coefficients from Wavelet Transforms can be used directly as features for seizure detection, there exist other features which have also been used including energy, entropy, Hjorth parameters, variance, fractal dimension, and correlation [4, 12]. It is remarked in [13] that signal complexity is a very good feature for classifying EEG signals since healthy biomedical signals tend to be more complex than their unhealthy counterparts. Entropy and Fractal Dimensions are good



(a) EEG signal de-noising flow process



(b) Feature extraction flow process

Fig. 4: Real-time seizure detection flow process in segments.

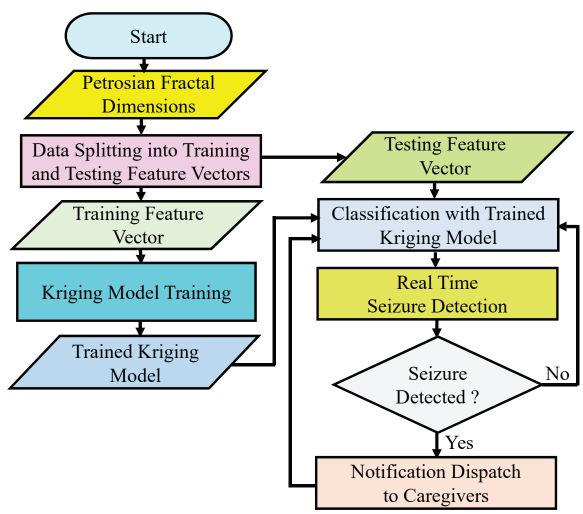


Fig. 5: Model training and seizure detection flow process

measures of signal complexity [13]. While there are different algorithms for fractal dimensions [14], Petrosian's Fractal Dimensions is used in this paper due to its fast computation [14], [15], which is desirable for an edge computing application such as this. The Petrosian's Fractal Dimension is given by the following expression [14, 15]:

$$FD_{\text{Petrosian}} = \frac{\ln(n)}{\ln(n) + \ln\left(\dfrac{n}{n + 0.4N_\delta}\right)}, \quad (1)$$

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.

C. Ordinary Kriging and its Computational Complexity

Kriging is a Gaussian or stochastic process that is governed by a mean value and the relative co-variances of known data points with respect to an unknown [7]. It was originally developed as a geo-statistical model for spatial prediction but is increasingly gaining relevance in other fields over the years [16–18]. The brain is envisioned as a spatial map on which spatial data processing methods can be applied [19].

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 [20]:

$$y(\mathbf{x}_i) = \mu + Z(\mathbf{x}_i), \quad (2)$$

where i is the data point index, μ is a mean constant and $Z(\mathbf{x}_i)$ is a Gaussian process of mean zero and σ^2 variance.

A linear estimator for an unknown is formulated as [20]:

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

where $\mathbf{x}_i$ and $\mathbf{x}_o$ represent the known data points and the unknown, respectively. λ_i represents the weights associated with each data point and μ_z represents the global mean. Eqn. 3 can be derived by simplifying the following residual:

$$y(\mathbf{x}_o) - \mu_z(\mathbf{x}_o) = \sum_{i=1}^{n} \lambda_i (Z(\mathbf{x}_i) - \mu_z(\mathbf{x}_i)). \quad (4)$$

The residual is defined as the difference between some value and a given reference. If we let $y = Z^*$ and represent a vector of residuals with $\mathbf{R}$, then Eqn. 4 can be reduced to:

$$\mathbf{R}^*(\mathbf{x}_o) = \sum_{i=1}^{n} \lambda_i \mathbf{R}(\mathbf{x}_i). \quad (5)$$

The estimation variance of Kriging's prediction is given by:

$$\sigma^2{}_{est.} = \mathbb{E}\{[\mathbf{R}^*(\mathbf{x}_o) - \mathbf{R}(\mathbf{x}_o)]^2\}. \quad (6)$$

$\mathbb{E}\{.\}$ is the expectation. By expanding eqn. 6 and substituting Eqn. 5 into it, we have:

$$\sigma^2{}_{est.} = \sum_{i=1}^{n}\sum_{j=1}^{n} \lambda_i \lambda_j \mathrm{C}(\mathbf{x}_i, \mathbf{x}_j) - 2\sum_{i=1}^{n} \lambda_i \mathrm{C}(\mathbf{x}_o, \mathbf{x}_i) + \mathrm{C}(0). \quad (7)$$

$\mathrm{C}(\mathbf{x}_i, \mathbf{x}_j)$ = Covariance between data points at indices i and j, $\mathrm{C}(\mathbf{x}_i, \mathbf{x}_o)$ = Covariance between each data point and the unknown, and $\mathrm{C}(0)$ = Variance.

The Kriging technique works by finding the weights that minimize the estimation variance in order to produce the best linear unbiased estimator (BLUE) [20]. Hence, the partial derivative of eqn. 7 with respect to λ_i results in:

$$\frac{\partial \sigma^2{}_{est.}}{\partial \lambda_i} = \sum_{j=1}^{n} \lambda_j \mathrm{C}(\mathbf{x}_i, \mathbf{x}_i) - 2\mathrm{C}(\mathbf{x}_o, \mathbf{x}_i), \quad (8)$$

where $i = 1, 2, 3, ..., n$. By setting Eqn. 8 to zero, we have a system of n equations and n unknown weights as follows:

$$\sum_{j=1}^{n} \lambda_j \mathrm{C}(\mathbf{x}_i, \mathbf{x}_i) = 2\mathrm{C}(\mathbf{x}_o, \mathbf{x}_i). \quad (9)$$

The weights can then finally be obtained by solving Eqn. 9.

The major limitation of Kriging is its time complexity. The asymptotic complexity in time for Kriging is $\mathcal{O}(n^3 d)$ [16], where n is the number of samples and d represents the feature dimension. However, this applies only to training. After training the Kriging classifier, the asymptotic time complexity for applying the model to the whole test set is given by $\mathcal{O}(nd)$ [16] which is approximately linear for a small d. In this work, our Kriging model is pre-trained on a workstation and then installed on an edge device for real time seizure detection in which a single sample is passed to the model at a time and a corresponding output is generated, that is $n = 1$ for each detection check. Also, $d = 1$ in the proposed model. This implies that the asymptotic time complexity of the proposed edge-based seizure detection model in this paper is $\mathcal{O}(1)$, which is a constant time complexity. The asymptotic space complexity of the proposed model is also $\mathcal{O}(1)$. This is because a single variable is repeatedly used for all the signals without storing it on the edge device. It just receives the signal, processes it in real time and dispatches the output accordingly.

VI. Experimental Validation of the Models

A. Dataset

The datasets used in this paper were originally collected from five healthy volunteers and five epilepsy patients by the University of Bonn in Germany [21].

Five different sets of data were collected as sets A, B, C, D and E. Sets A and B were collected non-invasively from the five healthy subjects in a relaxed but alert state with eyes opened and eyes closed for set A and set B, respectively. Sets C and D are intracranial EEGs collected during the period in-between seizures (inter-ictal state) from the epilepsy patients while set E is the only set collected during the actual seizure (ictal state). Each of the sets comprises 100 EEG segments. Fig. 6 shows some examples of EEG segments from sets A, C and D, representing the healthy, inter-ictal and ictal states, respectively.

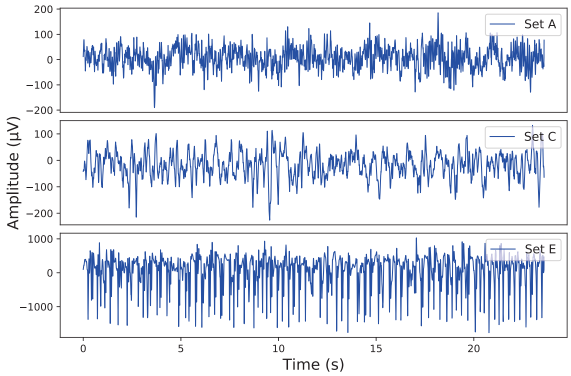


Fig. 6: EEG signals at healthy, inter-ictal and ictal states

B. DWT De-noising, Feature Vector and Model Training

The Daubechies Wavelet of order four (db4) was used for the discrete wavelet decomposition of the EEG signals into five different levels. At each level, there is a pair of approximation coefficients (Ai) and detail coefficients (Di), where i represents the present level of the decomposition. After decomposition, a soft thresholding technique is applied to each of the coefficients in order to remove noise. Afterwards, an inverse DWT operation is performed on the coefficients to produce a single de-noised EEG signal.

After de-noising, the fractal dimension feature is obtained for each EEG segment using Eqn. 1. Table I shows some of the values of the Petrosian fractal dimension (pfd) 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 [13]. Since fractal dimension is a measure of signal complexity [13], higher values of pfd are tantamount to higher complexity. Therefore, as observed from Table I, the values of pfd for Set E (ictal signals) are generally lower compared to Set A (healthy signals), confirming the superior complexity of Set A signals over those of Set E.

TABLE I: Sample feature vectors for sets A, C and E

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

The Ordinary Kriging model training is done in two categories, which are Category I (Set A versus Set E), that is detecting seizure from a pool of healthy signals and seizure signals; and Category II (Set C versus Set E), that is detecting an ictal signal from a stream of ictal and inter-ictal signals.

C. Kriging Classifier Testing

For each category of our proposed Kriging model (that is, Category I and Category II), there are a total of 200 EEG samples, with 100 samples of each class. The 200-sample dataset is randomly divided into two with 80% of the dataset used for training while 20% is used for testing.

TABLE II: Performance of the proposed kriging model on the testing set compared to other algorithms

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

The testing performance is a measure of how the model performs. It is an indication of how well the model fits the data with respect to unknown examples. The metrics used for scoring the testing performance are testing accuracy, sensitivity and precision. Table II shows the performance of the proposed model on the testing set with respect to other machine learning algorithms used on the same dataset.

D. Real Time Edge Seizure Detection Model Validation

As a representative edge device, a single-board computer (Raspberry Pi 3B+) with limited resources with WiFi and bluetooth connectivity has been used. It has a 1-GB Random Access Memory (RAM), 1.4 GHz 64-bit Quad-Core Arm Processor and a 32-GB microSD storage on which runs a lightweight version of the Linux operating system. Its small form factor of dimensions 85mm$\times$56mm$\times$17mm and weight of about 42g (1.48oz) compared to its computational power makes it very attractive as an edge device in many applications.

The trained Kriging model was ported to the Raspberry Pi through object serialization. The de-noising and feature selection algorithms were also run directly on the Raspberry Pi for each of the EEG segments to be processed. The validation setup consists of two major components, the server unit and the client unit. Using socket programming techniques, a stream of EEG segments was passed from the server unit to the client unit without any physical connection between them.

1) Server Unit: A conventional personal computer workstation is used as the server unit in this work. It mimics the brain of an epilepsy patient by ceaselessly transmitting EEG signals to the client unit for seizure detection. The server unit first initiates a connection to the Internet Protocol (IP) address of the client. Once connection is established, data transfer begins.

2) Client Unit: The Raspberry Pi which is the edge device serves as the client unit. It receives the EEG signals from the server unit and processes each EEG segment immediately in real time to determine the presence of an epileptic seizure. The mean seizure detection latency recorded in this work is 0.85 second. Table III compares the latency of the proposed model to some previous seizure detection systems.

VII. Conclusions

This paper presentes a novel real-time seizure detection model in an edge computing paradigm using the Ordinary Kriging method. As demonstrated here, it is important to bring seizure detection closer to the subject by running the algorithm on an edge device. The Ordinary Kriging method proved very effective in classifying the seizure signals with a

TABLE III: Comparing latency of the proposed edge seizure detection model with existing works in the literature.

Published Works	**Extracted Features**	**Classification Algorithm**	**Sensitivity**	**Latency**
Shoeb, et al. 2010 [22]	Spectral, temporal and spatial features.	Support Vector Machine (SVM)	96.00%	4.2 sec.
Zandi, et al. 2012 [23]	Regularity, energy & combined seizure indices	Cummulative Sum (CUSUM) thresholding	91.00%	9 sec.
Altaf, et al. 2015 [24]	Digital hysteresis	Linear Support Vector Machine (LSVM)	95.70%	1 sec.
Vidyaratne, et al. 2017 [25]	Fractal dimension, spatial/temporal features	Relevance Vector Machine (RVM)	96.00%	1.89 sec.
Sayeed, et al. 2019 [6]	Hyper-synchronous pulses	Signal Rejection Algorithm (SRA)	96.90%	3.6 sec.
Current Paper	Petrosian fractal dimension	Kriging Classifier	100.00%	**0.85 sec.**

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. We will consider different and bigger datasets in future research.

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 happens, and then injects drug or performs other control measures right after that [26]. We also intend to add security and privacy features to the overall system as it is IoMT enabled and always connected to Internet [27]. We will explore blockchain enabled system that will store the EEG data of individuals with security and privacy preserved and only authorized personnel have access to these. At the same tine only authorized personnel can program the drug-delivery system to release right amount of fluid.

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