SN Computer Science manuscript No.
(will be inserted by the editor)

Real-Time Automatic Seizure Detection using Ordinary Kriging Method in an Edge-IoMT Computing Paradigm

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Received:22 May 2020 /Accepted:date

Abstract Epilepsy is one of the leading neurological diseases in the world, affecting approximately 70 million of the world's population and often results in early mortality if not properly managed. The primary purpose of seizure detection is to reduce threat to life in the event of a seizure crisis. Previous efforts in the literature concentrate mostly on performance based on accuracy and other similar metrics. However, there is a short time lapse between the onset of a seizure attack and a potential injury that could claim the life of the patient. There is therefore the need for a more time-sensitive seizure detection model. We hereby propose a real-time seizure detection model in an edge computing paradigm using the Ordinary Kriging method, relying on the premise that the brain can be modeled as a three-dimensional spatial object, similar to a geographical panorama where Kriging excels. Fractal dimensional features were extracted from patients' electroencephalogram (EEG) signals and then classified using the proposed Ordinary Kriging model. The proposed model achieves a training accuracy of 99.4% and a perfect sensitivity, specificity, precision and testing accuracy. Hardware implementation in an edge computing environment results in a mean detection latency of 0.85 sec. *To the best of the authors' knowledge, this is the first work that uses the Kriging method for early detection of seizure.*

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Keywords Smart Home · Smart Healthcare · Internet-of-Medical-Things (IoMT) · Seizure Detection · Epilepsy · Edge Computing · Kriging Method · EEG

1 Introduction

Seizures are unpremeditated involuntary activities that often result into loss of consciousness and also cause the subject to be out of control. They are the outcomes of abnormal responses by firing neurons in the central nervous system due to the malfunctioning of the brain's circuitry. About 10% of the world's population will have at least one seizure experience during their lifetime [8]. A seizure is referred to as epilepsy when it is recurrent and unprovoked [42]. Epilepsy is among the top five neurological disorders and it affects roughly 70 million people worldwide [48]. A diagnosis of epilepsy is considered very sensitive due to the stigma attached to it and because there are other neurological conditions that mimic seizures but are actually not seizures [42]. Therefore, even the effect of a false positive diagnosis could be devastating, not to mention a truly positive one. A missed diagnosis is not helpful either. For a fully diagnosed epilepsy patient, especially the life-threatening Generalized Tonic-Clonic (GTC) type, adequate management is paramount until full remission is accomplished, if at all possible or for the entire life of the patient if not.

Timely detection of seizure is a very important first step in properly managing an epilepsy disorder. Real-time seizure detection ensures that the patient is afforded much needed attention as early as possible during a seizure onset. Real-time detection means detection anytime and anywhere, without constraining the patient to a limited space. EEG signals are collected continuously from the patients' brain while they lead their normal lives. The captured EEG signals are analyzed immediately for the presence of seizure. Current advances in Artificial Intelligence (AI) and Internet of Medical Things (IoMT) technologies have increased the chances of success in this effort.

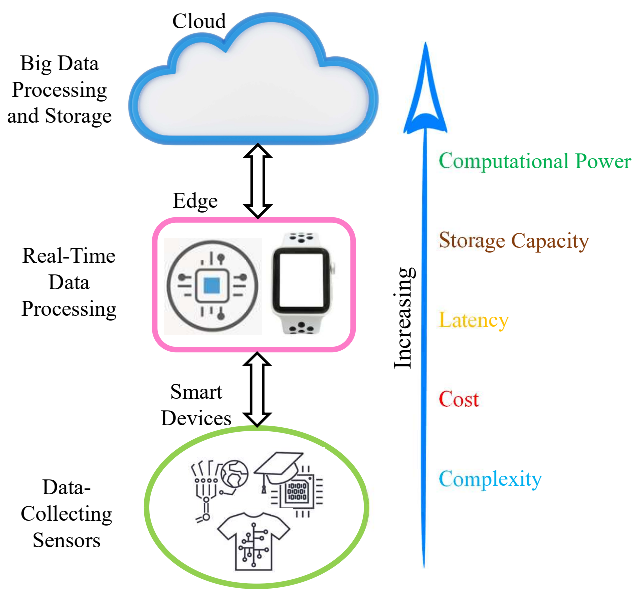


Fig. 1 Edge computing paradigm vs. cloud in a smart home environment

As shown in Fig. 1, data processing in real time is more realistic in the IoT network edge closer to the end users. For instance, a smart dress (Fig. 1, bottom) that senses humidity and sweat levels during sleep in a smart home conveys information to an edge device, a wrist watch in this case (Fig. 1, center), which handles the computation to compare the values with a given threshold and makes a decision on whether a cooling system is required or not. Even though the cloud has higher computational power and bigger storage capacity, the longer transmission time to the cloud causes an increase in latency. This is undesirable for real-time applications, especially when it involves a human life as in the case of epileptic seizure detection. Furthermore, Edge computing enhances location awareness and user mobility [32]. It is highly beneficial to process data at the edge since more data are now being generated at the edge of the network than ever due to the proliferation of sensing devices and mechanisms [39]. Reduced cost of deployment and portability are other advantages leading to the increasing popularity of the edge computing paradigm.

The remaining part of this paper has the following organization: Section 2 highlights prior related research works. Section 3 discusses the problem and novel contributions. Section 4 presents the proposed edge computing paradigm for seizure detection. Section 5 is a presentation of the proposed real-time seizure detection model. Experimental validation of the proposed model and results are presented in Section 6, while Section 7 states the conclusion and future direction of this research.

2 Related Research Work

An electronic circuit that detects a seizure when three spikes appear at the onset of the seizure was designed by Zapata-Ferrer et al. [53]. The circuit consists of an amplifier, a comparator, a filter and a differentiator. However, this design lacks any communication mechanisms for reaching out to care givers and it will only detect a seizure if it begins with three initial spikes, as determined by its EEG recordings. It therefore cannot handle more complex cases of epileptic seizures. This explains why machine learning and advanced signal processing concepts such as the Discrete Wavelet Transforms (DWT) are now widely used for seizure detection.

A seizure detection algorithm, employing the use of fractal dimensions (FD) and spectral energy extracted from Harmonic Wavelet Packet Transform (HWPT) as the main EEG features which were presented as input into a relevance vector machine (RVM) for an eventual classification of the EEG signals as ictal or otherwise, was proposed in [48]. The algorithm shows good performance but relied on the high computational power offered by a workstation. This means that cloud computational resources will be required for a real-time implementation of the algorithm on human subjects since it is not possible to connect a workstation directly to the EEG cap without compromising the mobility of the subject.

A proposed consumer electronic device called Neuro-Detect [38], processes signals using the discrete wavelet transform before extracting Hjorth Parameters such as activity, mobility and complexity, as well as standard deviation from them. A Deep Neural Network was then used for eventual seizure detection. Although the Neuro-Detect reports good performance, the latency of detection is relatively high.

Marquez et al. [22] proposed a real-time detection system for epileptic seizures and called it iSeiz. It was built on body motion sensors such as an accelerometer and a gyroscope which would sense quirky movements of the body during the onset of a seizure. A low-cost, low-power wearable device with a microcontroller unit was used to collect three dimensional real-time motion measurement and temperature. iSeiz could potentially prove very effective in collecting data on the movement patterns of epilepsy patients towards a better understanding of the disorder. However, the seizure detection algorithm implemented by iSeiz depends on the setting of multiple thresholds which are determined by intuition rather than some established theoretical principles. Furthermore, caregivers and concerned family members will not be notified of the seizure onset directly from the wearable. In iSeiz, information from the wearable device has to go through the iSeiz gateway to the Amazon Web Services (AWS) cloud from where messages will be sent to the assigned caregivers. This may lead to a significant delay in getting help for the suffering subject.

A seizure detection and monitoring concept that is more comprehensive but similar to iSeiz was proposed in [47] with a wrist-wearable device comprising of an accelerometer and a heart rate monitor. The detection algorithm also relies on the unusual moving and jerking of the body during a seizure crisis but in this case, a Genetic Fuzzy Finite State Machine (GFFSM) was used rather than multiple thresholding. It uses a hybrid of Mobile Cloud Computing (MCC) and Cloud Computing (CC) for analytics and storage. While this addressed a wide variety of issues from the stand point of the Internet of Things (IoT), it is not clear how the system will handle certain legitimate but rare random movements of the body such as dancing or sporting activities. This is one of the reasons why EEG remains the most widely used data collection method for seizure detection research.

An EEG-based signal rejection algorithm was proposed for seizure detection in [37]. The proposed model was called eSeiz. Hyper-synchronous pulses were extracted from the EEG and compared with a predetermined threshold to recognize a seizure signal. However, the Ordinary Kriging and edge computing based seizure detection model proposed in this work surpasses the performance of eSeiz with respect to latency and sensitivity.

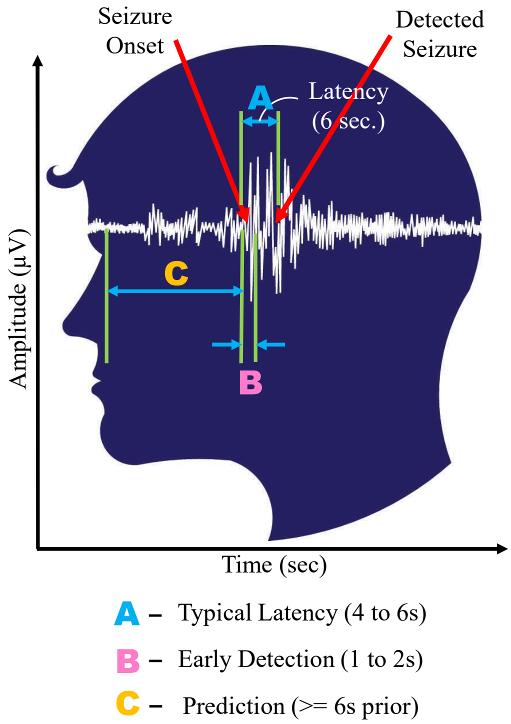


Fig. 2 Seizure detection latencies depicted on an EEG signal

3 Contributions of this Current Paper to the State-of-Art

3.1 Problem Definition

The literature presents many seizure detection models whose central focus is accuracy or similar metrics. Although this is important, the time required to rescue the patient in crisis is as important and probably more. A perfect accuracy is useless if the seizure patient cannot get help at the right time. This is what happens when seizure detection computation is done at the cloud because of its high computational complexity. Is it feasible for a seizure detection computation to run on the edge instead of the cloud, with little or no compromise in accuracy? How can a seizure onset be detected in real time? These research questions are thoroughly addressed in the following sections of this paper.

Fig. 2 shows the conventional seizure detection latency as depicted by region A, which ranges from 4 to 6 secs. This is often the outcome of cloud processing. However, early seizure detection indicated by region B with latency range within 1 to 2 secs can be accomplished in an edge computing paradigm. Region C refers to seizure prediction which takes place at least 6 secs before the onset of seizure. The objective of this work is to achieve early detection of seizure with as minimal latency as possible.

3.2 Proposed Solution of this Paper

An edge computing solution to the seizure detection problem using the Ordinary Kriging method on fractal dimensional features extracted from patients' EEG signals for a real-time seizure detection model is proposed in this paper. Edge processing of data improves the speed of seizure detection and also decreases the latency, hence reducing the risk of serious injury or death as often associated with epilepsy [8]. Further details of this concept are presented in subsequent sections of this paper.

Why Kriging? Kriging's primary application domain is geostatistical modeling and prediction of values at unknown locations, given some locations with known values. The modeling of the brain as a three-dimensional spatial object with multiple locations, similar to a geographical map is the main premise for the use of Kriging methods in epileptic seizure detection. The hippocampus which is situated in the brain consists of some cells which generate maps for recognition and navigation just like the typical Geographical Information System (GIS) map [24], [52]. This further strengthens the case for the use of Kriging in seizure detection. It is even noted in [4] that some of the EEG signals for seizure detection were collected from the hippocampus. Fig. 3 shows a conceptual modeling of the brain as a spatial map for seizure detection. The red circles represent locations of known seizure status while the green circles show otherwise. The dotted lines connecting the circles is a measure of the spatial correlation between the locations. Shorter lines signify higher correlation and vice versa. With this modeling, Kriging methods can be used to predict the seizure status at the unknown locations (green circles), given the appropriate dataset.

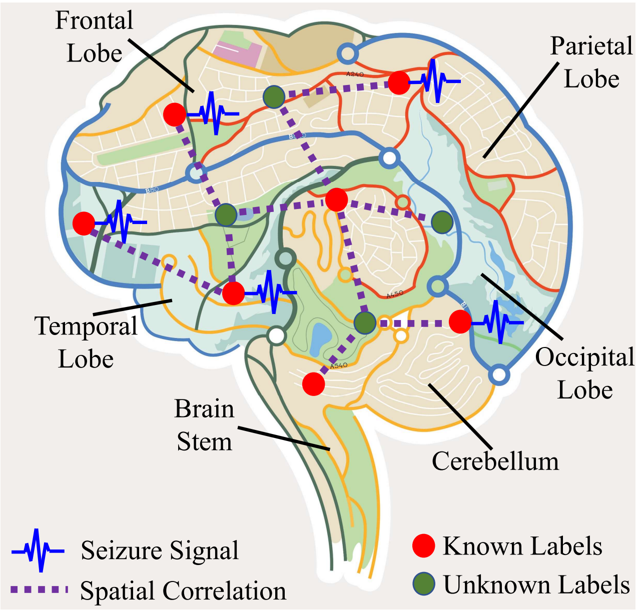


Fig. 3 A schematic picture of the brain as a spatial map

Kriging methods are very good with small datasets [9], unlike machine learning models such as the neural network which rely on large datasets for a good performance. Biomedical datasets, especially in the brain domain are very hard to come by due to stringent regulations regarding data collection from human or animal subjects. Hence, Kriging is useful on the available datasets with limited sizes. Kriging is also accompanied with an estimation of variance which measures the model's confidence in a certain prediction. This enhances the Kriging model's reliability even without using many hyperparameters [9]. Furthermore, Kriging is robust to unexpected events such as feature sets inconsistency or sudden reduction in quality of data [6]. Finally, the proposed Ordinary Kriging model's performance on seizure detection exceeds those of some machine learning models that were explored in this work.

3.3 Novelty of the Proposed Solution

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

1. A novel application of Ordinary Kriging method to the epileptic seizure detection problem with consistent performance across multiple datasets.
2. A unique synthesis of extracted feature (fractal dimensions) and classifier (Kriging method) that is suitable for edge computation relative to seizure detection.
3. A novel application of Discrete Wavelet Transform (DWT) soft thresholding for noise isolation in an epileptic seizure detection model.
4. Achievement of a mean seizure detection latency of 0.85 sec. without a compromise in accuracy and similar metrics when compared with previous models, as well as a constant $\mathcal{O}(1)$ complexity in time and space for edge computation.
5. A novel real-time edge-based hardware implementation of an efficient seizure detection algorithm.

4 Proposed Edge Computing Paradigm for Seizure Detection

A faster seizure detection can be achieved by bringing computation of the detection algorithm to the edge of the IoMT network, closer to the EEG signals from the seizure patient. Hence we propose a shift in paradigm from cloud seizure detection to edge seizure detection. Fig. 4 is a schematic representation of our proposed edge computing solution for seizure detection in real time.

The smart edge device directly collects the EEG signal from the brain for immediate processing, rather than traversing a long path to the cloud. There are three major functions performed by the edge hardware: It facilitates local processing of the EEG data in order to extract relevant features; it carries out real-time detection of seizure using the features extracted and finally, it triggers an alarm in the event of a seizure crisis. The seizure crisis alert is escalated to some assigned caregivers which may include some close acquaintances, a physician and an emergency response provider. Alert messages are directly initiated from the edge hardware, giving rise to faster communication of the patient's seizure status to the designated individuals. This is unlike iSeiz [47] in which messages are generated from the AWS cloud. The medical database in Fig. 4 is a means of continuous storage of EEG data streams from the patient, which can be useful for future patient-specific studies or further research on seizure detection and prediction as a whole. The edge-IoT epileptic seizure detector that was proposed in [34] only notified the physician, who is usually far away, about the subject's seizure state. However, a subject in a seizure crisis may need help immediately, if injury or death is to be prevented. Hence the reason for notifying other caregivers, including some who are mostly within the patient's vicinity such as relatives, in our proposed edge-computing-based seizure detection model.

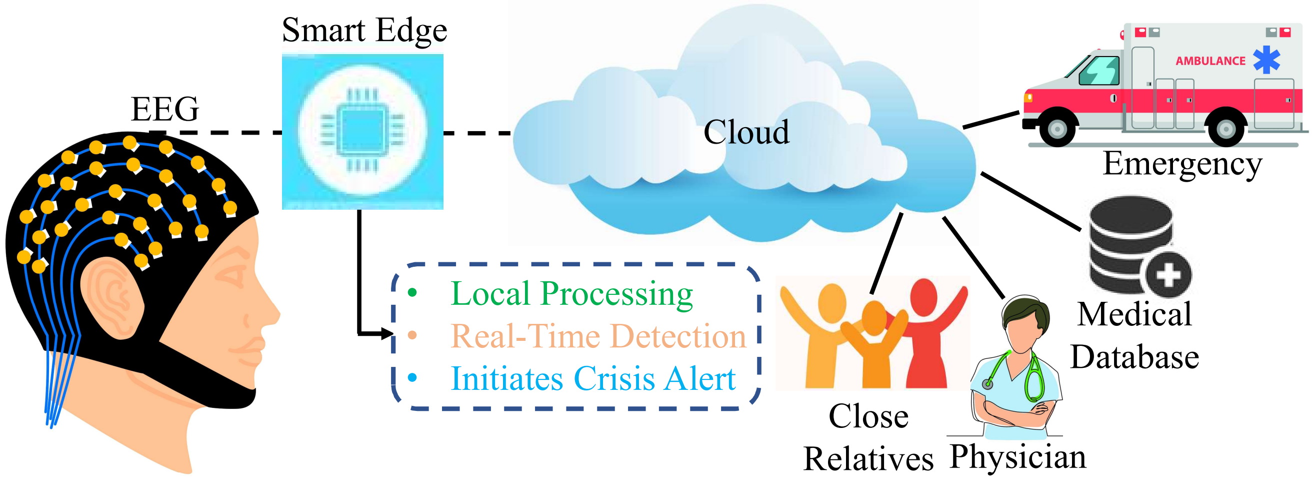


Fig. 4 Proposed edge computing model for early automatic seizure detection

5 The Proposed Real Time Seizure Detection Model

The real-time seizure detection model proposed in this paper is comprised of the input and output, as well as three major sections, as shown in Fig. 5. The three mid-sections of the model are signal de-noising, feature extraction and seizure state classification. All three mid-sections are executed on the smart edge shown in Fig. 4. The EEG signal collected from the patient is the input to the model while the output is the patient's seizure state. Fig. 6 shows a summarized flowchart of the proposed seizure detection model. A more comprehensive flow of the overall process is shown in Fig. 7.

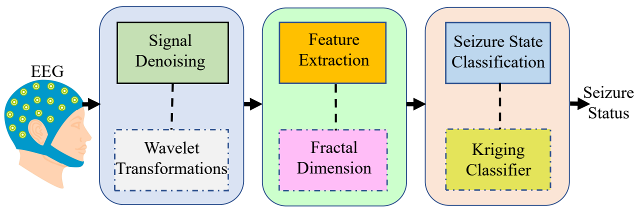


Fig. 5 Proposed real time seizure detection model

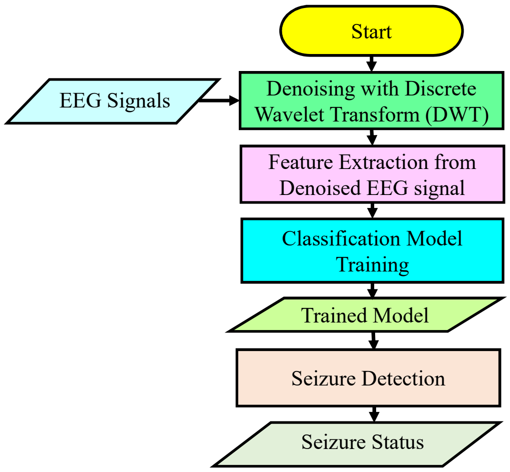


Fig. 6 Summarized flow process for the proposed seizure detection model

5.1 Signal De-noising

A noisy signal can have grave consequences, especially in applications involving human lives [16]. Although the EEG method is popular for seizure detection, it is also vulnerable to noise in the form of artifacts and physiological activities. It has been observed that Wavelet Transforms are the most effective EEG signal processing and de-noising method for seizure detection compared to Wiener filtering and Fourier Transforms [10]. Studies have also shown that Discrete Wavelet Transform (DWT) has better performance than the Continuous Wavelet Transform (CWT) in seizure detection tasks. However, a major limitation of wavelet analysis is the need to adopt a definite mother wavelet [2], [21] since there are at least a dozen mother wavelets with each having more than 5 orders. The fourth order Daubechies Wavelet (db4) has been identified as the most effective mother wavelet for feature extraction in EEG-based seizure detection. [10].

De-noising with wavelet transforms is achieved by first performing the wavelet decomposition of the signal followed by a thresholding operation on the decomposed coefficients. An inverse wavelet transform is then performed to recover a de-noised signal. Removing some frequency components in the decomposed signal with near-zero coefficients [15] is also a method that has been used in removing noise by reducing the dimension of the data. Both de-noising and dimension reduction were used together in [15], but not for seizure detection. In this paper, A five level DWT decompo-

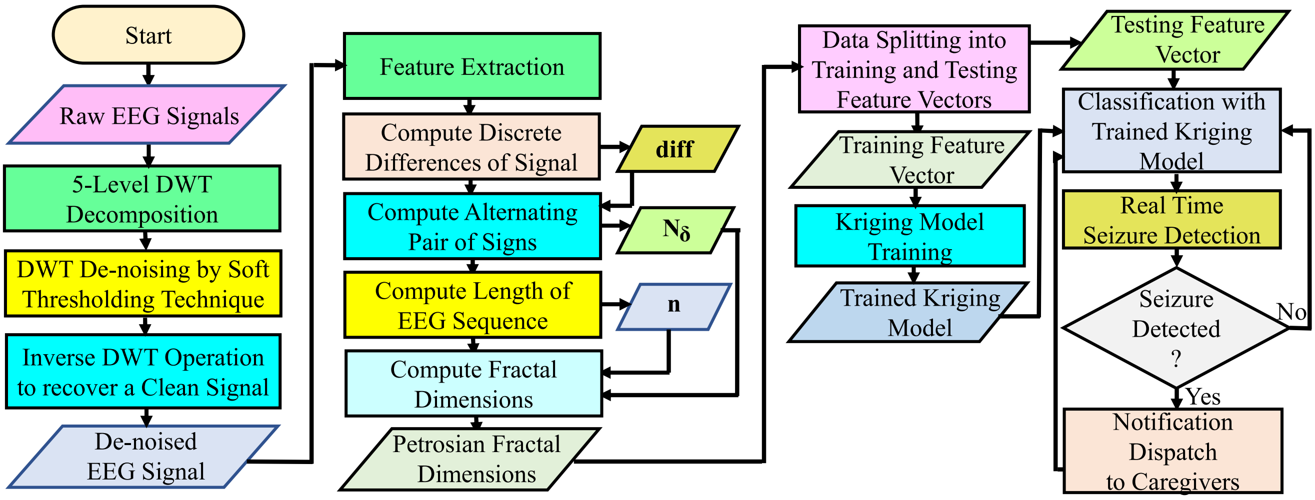


Fig. 7 Comprehensive flow process for the proposed seizure detection model

sition of the signal using the Daubechies Wavelet of order four (db4) was first performed before de-noising through soft-thresholding technique and inverse wavelet operation, respectively.

5.2 Feature Extraction

Even though Wavelet Transform coefficients can be used as features for seizure detection directly, there are other features which have been used. They include, but are not limited to, entropy, energy, variance, Hjorth parameters, fractal dimension and correlation [10], [36]. Moura et al. [25] conducted a study which compared 15 different features of EEG signals and concluded that none was significantly better than the other even though Maximum Fractal Length (MFL) marginally outperformed the others with a reduced error rate.

The use of Hjorth Parameters with Fisher ratio and band-pass filtering was demonstrated in [28] as a feature extraction method for EEG signals, but in this case, the application was geared towards Brain Computer Interface (BCI). The published results showed a much better performance in comparison to Short-Time Fourier Transform (STFT) method, while also stating that activity and mobility were more useful features than the third component of Hjorth Parameter which is complexity, because of their higher Fisher ratio. However, Najarian et al. [26] remarked that signal complexity is very effective for EEG data analysis because of the fact that healthy biomedical signals are usually more complex than unhealthy biomedical signals. Fractal Dimensions and Entropy are other signal complexity measures [26]. There are different fractal dimension algorithms [13] but Petrosian's Fractal Dimension algorithm has been selected for this work because of its fast computation of Fractal Dimensions [13], [31], a desirable quality for an edge computing application.

Petrosian's Fractal Dimension is given by the following formula [13], [31]:

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

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

This Fractal Dimension formula is directly applied on the recovered EEG signal through an inverse DWT operation after de-noising. The values obtained are then used as a final feature vector on which the Ordinary Kriging classifier is trained.

5.3 Seizure State Classification Algorithm

Various machine learning models have been used for seizure detection in existing works. Support Vector Machines (SVM) with radial basis function (RBF) kernel was used in [43]. It was used in conjunction with Linear Discriminant Analysis (LDA) for dimension reduction. Other machine learning algorithms which have also been used for seizure detection include the Naive Bayes classifier [34], κ Nearest Neighbor (κNN) classifier [36], [45], Artificial Neural Network (ANN) [27], [18], Relevance Vector Machine (RVM) [48], Decision Tree [49] and Deep Neural Network [7]. The emphasis in most of these cases is performance in terms of accuracy or related metrics and not suitability for edge computation. In this paper, we propose a novel application of Ordinary Kriging as a classifier for seizure detection.

5.3.1 Kriging

Kriging was developed originally as a geo-statistical method for spatial modeling and prediction. However, its influence in other fields has been growing widely in the last few years [12]. It is a Gaussian process governed by mean and relative covariances of data locations with known values relative to data locations with unknown values [50], [20]. The specific assumption for Ordinary Kriging is that the mean is constant and unknown. Zaleshina et al. [52] compared the brain to a spatial map on which spatial data processing methods can be applied.

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 output, the input-output relationship based on Kriging is given by [20]:

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

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 can be formulated as [33]:

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

where $\mathbf{x}_i$ and $\mathbf{x}_o$ represent the known and unknown data points, 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 equation:

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

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:

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

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

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

where $\mathbb{E}\{.\}$ is the conventional symbol for representing expectation. By expanding eqn. 6 and substituting eqn. 5 into it, we have:

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

$\mathrm{C}(\mathbf{x}_i, \mathbf{x}_j)$ = 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.

Kriging works by finding the weights that minimize the estimation variance so as to produce the best linear unbiased estimator (BLUE) [33]. Hence, the partial derivative of eqn. 7 with respect to λ_i results in:

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

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:

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

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

5.3.2 Computational Complexity of Kriging

The main disadvantage of Kriging is its computational time complexity. The asymptotic time complexity of Kriging is $\mathcal{O}(n^3 d)$ [12], where n represents the number of samples and d stands for the feature dimension. However, this only applies to training. This means that real-time training of EEG data will be quite challenging in terms of the computational time required. In this work, training is not performed in real time; an already trained Ordinary Kriging model is ported to an edge device for the real-time seizure detection. After training, the time complexity for applying the Ordinary Kriging model to the test set is $\mathcal{O}(nd)$ [12] which is approximately linear for a small value of d. A single sample is passed to the model at a time and an output is generated, that is $n = 1$ for each detection task. Also, $d = 1$ in the proposed model since the DWT coefficients are re-combined into a single signal via inverse DWT operation after de-noising before extracting its fractal dimension feature. This means that the time complexity of the proposed edge-computing-based seizure detection model is $\mathcal{O}(1)$, which is a constant time complexity. The 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 on the edge hardware. It only receives the signal, processes it immediately and dispatches the output accordingly.

Employing Kriging methods for real time training with large data sets will present a difficult challenge. Efforts have been made to develop versions of Kriging with lower time complexity but this usually leads to some compromise in performance. Braham et al. [5] proposed the Fixed Rank Kriging (FRK) as a variant of Kriging with reduced time complexity for cellular network optimization but not without some compromise in performance.

6 Experimental Validation

6.1 Datasets

There are few datasets that can be used to develop a seizure detection model. Some are in the public domain, others are not. Two publicly available datasets have been used to validate the proposed model in this paper. The datasets are here referred to as Dataset A and Dataset B, respectively.

6.1.1 Dataset A

This dataset was originally collected from 5 healthy subjects and 5 epilepsy patients by the University of Bonn in Germany in the Epileptology department [4]. It consists of 5 different sets labeled as A to E. Sets A and B were collected from the 5 healthy subjects. Set A was collected with eyes opened while set B was with eyes closed. Sets C and D were collected in-between seizures (inter-ictal state) from the epilepsy patients while set E was recorded during seizure (ictal state).

Each set consists of 100 segments sampled at 173.61 Hz. The EEG signals were recorded using a 128-channel amplifier system based on the 10 - 20 international electrode system. Some examples of EEG segments from sets A, C and E, showing the healthy, inter-ictal and seizure states respectively are shown in Fig. 8.

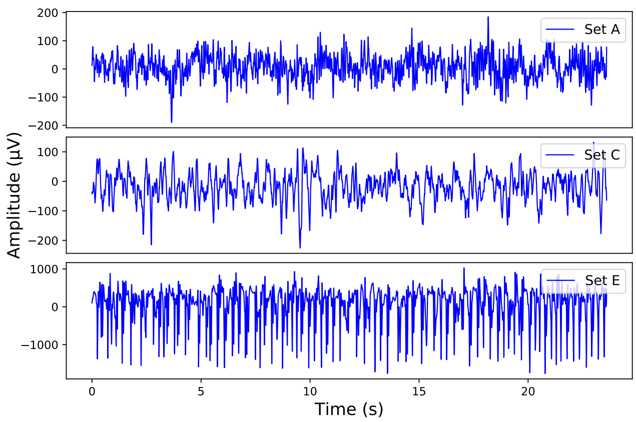


Fig. 8 EEG signals at healthy, inter-ictal and ictal states from Dataset A

6.1.2 Dataset B

This dataset was collected from 22 patients at the Children's Hospital Boston (CHB) in association with the Massachusetts Institute of Technology (MIT) [40], [14]. It is therefore popularly called the CHB-MIT Scalp EEG database. The patients were labeled as chb01 to chb23 (one patient recorded twice). Continuous EEG recordings were obtained from each patient at a sample rate of 256 Hz using a 23-channel EEG equipment.

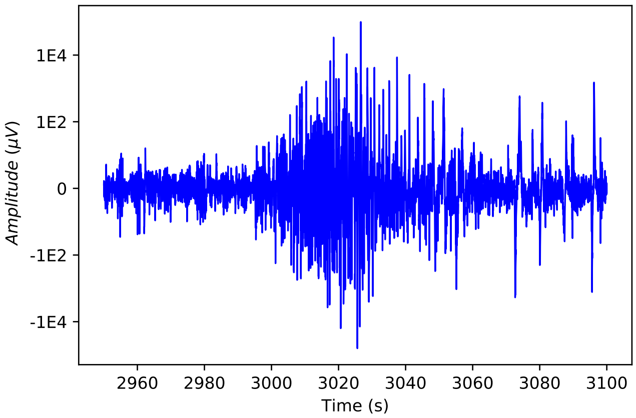


Fig. 9 Sample ictal EEG from patient chb01 in Dataset B

For the purpose of this work, the continuous EEG signals were divided into 10 seconds segments. EEG recordings of 5 of the 22 patients were used in this work. They are chb01, chb03, chb05, chb07 and chb09 with EEG record lengths of 40.65 hours, 38.00 hours, 39.00 hours, 65.05 hours and 67.93 hours respectively. These amount to a total of 250.53 hours of EEG recording. Fig. 9 shows a sample seizure EEG segment taken from the 14th channel of patient chb01's scalp EEG.

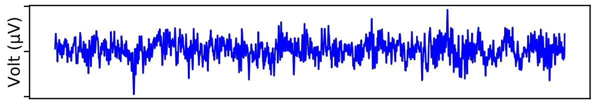
6.2 DWT De-noising

A DWT decomposition with the Daubechies Wavelet of the fourth order (db4) was employed for a 5-level disintegration of the EEG signals. There are two sets of coefficients at each level and they are called approximation coefficients (Ai) and detail coefficients (Di), i is the current decomposition level.

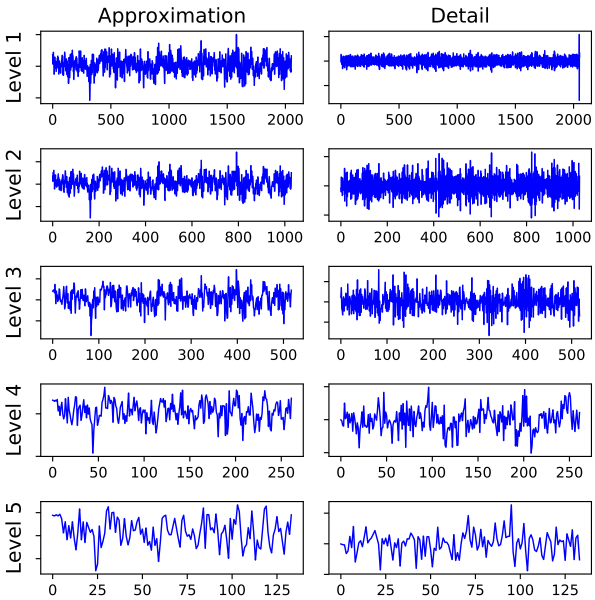
Fig. 10 shows the plot of the DWT coefficients after decomposition. The final output of the decomposition comprises the approximation coefficients of the fifth level (A5) and the detail coefficients of all five levels (D1 - D5) because the other approximation coefficients (A1 - A4) are not needed in reconstructing the signal.

Table 1 Frequency bands of DWT coefficients

Coefficients	Frequency (Hz)
D1	43.4 - 86.8
D2	21.7 - 43.4
D3	10.9 - 21.7
D4	5.4 - 10.9
D5	2.7 - 5.4
A5	0 - 2.7



(a) Sample EEG signal from Set A before decomposition



(b) 5-level approximation and detail coefficients after decomposition

Fig. 10 DWT coefficients of decomposed Set A EEG segment

The frequency representation of the output coefficients based on Nyquist's Theorem are shown in Table 1. After decomposition, DWT soft thresholding is performed on each of the coefficients to eliminate noise. An inverse DWT operation is then carried out to produce a single de-noised EEG signal from the coefficients. Fig. 11 shows a typical Set A signal before and after DWT de-noising. All DWT operations were carried out using PyWavelets which is a Python package for wavelet analysis [19].

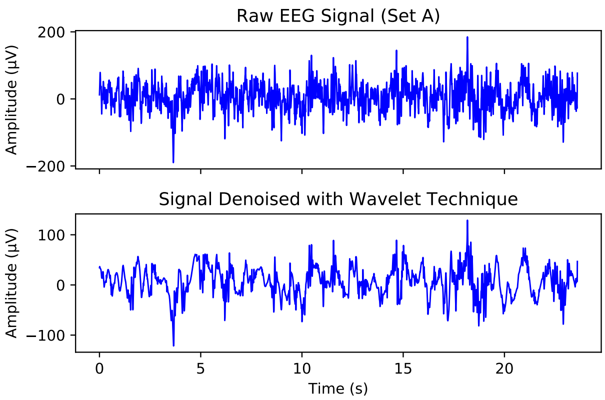


Fig. 11 DWT de-noising for a sample Set A EEG segment

6.3 Feature Vector and Model Training

After the de-noising operation, fractal dimension feature is extracted from each EEG segment using Eqn. 1. Table 2 shows some Petrosian fractal dimension (pfd) values for Sets A, C and E of Dataset A. Each set consists of 100 EEG segments but Table 2 only shows feature values of the first 10 EEG segments in each set. A sanity check confirms the effectiveness of pfd in detecting seizures given the assumption that healthy biological signals are more complex than unhealthy biological signals [26]. Fractal dimension being a signal complexity measure [26], means that higher pfd values signify higher complexity. Hence, as revealed in Table 2, pfd values for Set E (ictal signals) are generally lower than those of Set A (healthy signals). This confirms the superior complexity of Set A signals over those of Set E.

Table 2 Sample feature vectors for Dataset A

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
6	1.011934	1.006495	1.007439
7	1.011684	1.011061	1.007125
8	1.012391	1.013948	1.005456
9	1.013279	1.011542	1.007663
10	1.012977	1.009166	1.009619

The Ordinary Kriging model training for Dataset A has two categories. They are Category I (Set A against Set E), that is healthy signals versus ictal signals; as well as Category II (Set C against Set E), that is ictal versus inter-ictal signals. Table 3 records the training accuracy for both categories and compares the training accuracy of the Kriging model with other machine learning algorithms which were also tried on the same dataset. It is observed that the training accuracy for Set A versus Set E category is higher than that of Set C versus Set E. This shows that the complexity gap between Set A and Set E is higher than the complexity gap between Set C and Set E, hence the model could more easily classify Set A from Set E. However, in seizure situations, we are more interested in detecting the first onset of seizure than subsequent occurrences. Hence, Category I is more relevant for seizure detection than Category II. The bold characters in Table 3 therefore signify high relevance.

The training for Dataset B was first carried out patient by patient after which the data for all 5 patients considered in this work were combined as a single dataset for another training. Table 4 shows the training accuracy for each patient as well as for the combined dataset.

Table 3 Training accuracy for Dataset A

Classification Algorithm	**Healthy and ictal (Set A vs Set E)**	Interictal and ictal (Set C vs Set E)
Nave Bayes	98.75%	85.56%
LDA	98.00%	85.56%
κNN	99.40%	81.16%
Kriging	**99.40%**	86.85%

Table 4 Training accuracy for Dataset B

Patients	Training Accuracy
chb01	100.00%
chb03	100.00%
chb05	100.00%
chb07	100.00%
chb09	100.00%
Combined Data	99.70%

6.4 Kriging Classifier Testing

Before training the Oridinary Kriging Classifier for both Dataset A and Dataset B, the datasets were randomly divided into two according to the 80/20 rule [11]. That is, 80% of the dataset is used for training and 20% for testing.

The testing performance is a measure of how well the model will perform when presented with data samples that are not within the training set. The metrics used for the testing performance in this paper are testing accuracy, sensitivity, precision, specificity and F1-score. The testing accuracy measures the number of accurate predictions relative to the total number of test samples. Sensitivity, which is otherwise known as recall or True Positive Rate (TPR) refers to the amount of positive cases within the test set that are correctly predicted while precision is a fractional measure of the number of positive predictions that are actually correct [11]. Specificity which is also referred to as the False Positive Rate (FPR) measures the rate of false alarms generated by the model and the F1-score is the harmonic mean of precision and sensitivity [11]. The mathematical expressions of the above metrics are given as follows:

$$\text{Accuracy} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N}, \tag{10}$$

$$\text{Sensitivity} = \frac{T_P}{T_P + F_N}, \tag{11}$$

$$\text{Precision} = \frac{T_P}{T_P + F_P}, \tag{12}$$

$$\text{Specificity} = \frac{T_N}{T_N + F_P}, \tag{13}$$

$$\text{F1-Score} = \frac{T_P}{T_P + \frac{F_P + F_N}{2}}. \tag{14}$$

In the above expressions, T_P, T_N, F_P and F_N represent True Positive, True Negative, False Positive and False Negative, respectively.

Table 5 shows the performance of the proposed Ordinary Kriging model on the testing set for Dataset A compared with some other machine learning models also used on Dataset A while Table 6 shows the performance of the proposed model on Dataset B. As observed in Table 6, the average performance of the patient-specific approach is better than that of the combined patients' data. This is further depicted in Fig. 12 which shows that the patient-specific performance surpasses the combined data performance in every metric department. Hence, we conclude that a patient-specific solution is a more viable option for epileptic seizure detection. The selection of 5 random patients, in accordance with standard randomized study protocols, enabled the comparison of a patient-specific approach with a combined data solution. Training the combined EEG data of 22 patients will be highly computationally expensive due to the training complexity. Most of the works where all 22 patients data were utilized only described the patient-specific approach, in which case training is done for each patient's data as seen in [41], [3], [1] and [46]. Furthermore, results obtained from the selected 5 patients is a true representation of the variation in performances from patient to patient when compared to other works where 22 patients have been used. Testing on the edge computing hardware indicates that the seizure detection latency is not dependent on the patient data utilized.

Table 7 compares the accuracy of our proposed model to some recent works in the literature that have also used Datasets A and B but without edge computing. The comparison shows that this work does not incur any compromise in accuracy compared to the referenced works in Table 7, despite the edge computing method and the improvement in latency.

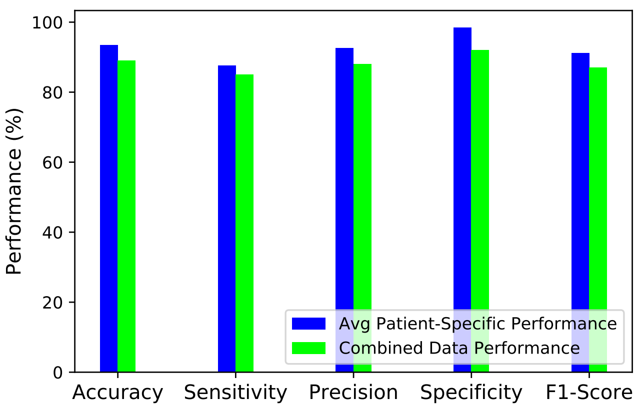


Fig. 12 Comparing patient-specific performance with combined data performance using Dataset B

Table 5 Performance of the proposed Ordinary Kriging model on the testing set of Dataset A compared to other algorithms

Dataset	Performance	Naive Bayes	kNN	LDA	**Kriging**
Healthy/Ictal (Set A vs Set E)	Accuracy	97.50%	100.00%	97.50%	**100.00%**
	Sensitivity	97.00%	100.00%	97.00%	**100.00%**
	Precision	98.00%	100.00%	98.00%	**100.00%**
Inter-ictal/Ictal (Set C vs Set E)	Accuracy	80.00%	75.00%	80.00%	82.50%
	Sensitivity	88.00%	76.00%	88.00%	94.00%
	Precision	71.00%	68.00%	71.00%	73.00%

Table 6 Performance of the proposed Ordinary Kriging model on the testing set of Dataset B

Patients	Accuracy	Sensitivity	Precision
chb01	94.47%	100.00%	88.00%
chb03	88.24%	67.00%	100.00%
chb05	100.00%	100.00%	100.00%
chb07	84.62%	71.00%	75.00%
chb09	100.00%	100.00%	100.00%
Average	93.47%	87.60%	92.60%
Combined Data	89.00%	85.00%	88.00%

6.5 Real Time Edge Seizure Detection Model Validation

A single-board computer (Raspberry Pi 3B+) with limited resources but having WiFi and bluetooth connectivity has been used as a representative edge device. 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 light version of the Linux operating system. It has a form factor whose dimensions are 85mm×56mm×17mm and a weight of approximately 1.48oz (42g). These are considerably small when compared to the computational power offered by the hardware. This makes it really appealing as an edge hardware in many applications. Its weight is approximately $\frac{1}{1500}$th part of the average human weight, hence constituting a body area network with a significantly low burden of weight. Fig. 13(a) shows the Raspberry Pi 3 model B+ used for this work.

The trained Ordinary Kriging model was ported to the Raspberry Pi via object serialization. The feature selection and de-noising algorithms were run directly on the Raspberry Pi for every EEG segment to be processed. The edge hardware validation setup has two major compartments. They are the server unit and the client unit. A stream of EEG segments was passed from the server unit to the client unit without any physical connection between them using the principles of socket programming.

6.5.1 Server Unit

A typical personal computer workstation has been used as a server unit in this work. It emulates the brain of an epileptic seizure patient by continually transmitting EEG signals to the client unit for seizure detection. The server unit first initiates connection to the Internet Protocol (IP) address of the client. Once connection is established, data transfer commences.

A set of EEG segments to be evaluated for the presence of seizure is hosted on the server and then streamed sequentially in real time to the client for further processing. Fig. 13(b) shows the output of the server unit after a successful connection to the client.

6.5.2 Client Unit

The edge device (The Raspberry Pi 3B+ in this case) serves as the client unit. It receives the EEG signals from the server unit and processes each EEG segment in real time to determine the presence of a seizure. It first performs the DWT de-noising operation and then extracts the fractal dimension feature before passing it to the serialized Ordinary Kriging model for seizure detection. There are two possible outputs on the client unit. They are ”0” which indicates ”No Seizure” and ”1” which stands for ”Seizure Detected”. Upon the detection of seizure, notifications are automatically forwarded to the assigned parties as shown in Fig. 4 in form of text messages and emails to facilitate a swift intervention. Fig. 13(c) displays the output of a running client unit.

The mean seizure detection latency in this work is **0.85 sec**. It is important to note that the reported mean seizure detection latency includes the pre-processing steps, feature extraction and Kriging prediction for a single EEG segment. Table 8 compares the seizure detection latency of the proposed model to those of some existing seizure detection models.

7 Conclusion and Future Work

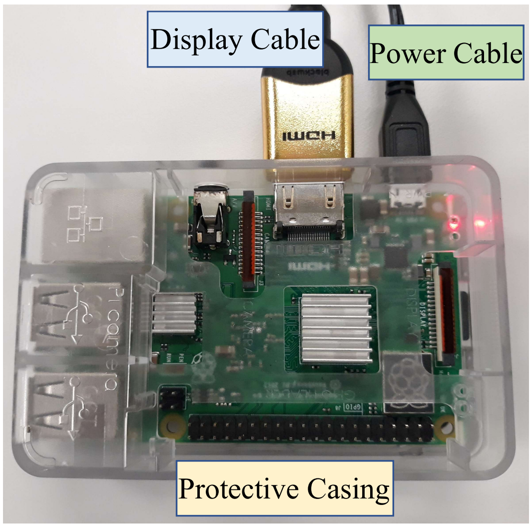
This paper presents a novel real-time epileptic seizure detection model in an edge computing paradigm using the Ordinary Kriging method. As demonstrated here, it is highly important to bring seizure detection closer to the patient by running the computation on an edge device. The proposed Ordinary Kriging method was very effective in classifying the seizure signals with a training accuracy of at least 99.4% and a perfect score of 100% for accuracy, sensitivity, precision, specificity and F1-score on the test set. The detection of seizure takes place in real time with a mean seizure detection latency of 0.85 second. We also proved that a patient-

Table 7 Comparing the proposed model with existing seizure detection systems

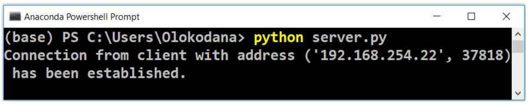
Referenced Work	Proposed Method	Dataset	Accuracy	Sensitivity	Edge Computing
Supriya et al. 2016 [45]	Weighted visibility graph (WVG) with SVM	Dataset A (Set A vs E)	99.50%	100.00%	No
Wen et al. 2017 [49]	Genetic Algorithm-Based Frequency-Domain Feature Search with kNN	Dataset A (Set A vs E)	99.50%	-	No
Daoud et al. 2018 [7]	Empirical Mode Decomposition (EMD) with Deep Neural Network (DNN)	Dataset A (Set A vs E)	100.00%	98.00%	No
Sayeed et al. 2019 [38]	DWT-based Hjorth Parameters with Deep Neural Network (DNN)	Dataset A (Set A vs E)	100.00%	96.90%	No
Park et al. 2018 [30]	Spatio-temporal Correlation and Convolutional Neural Network (CNN)	Dataset B	85.60%	80.60%	No
Ye Yuan et al. 2018 [51]	Wavelet Transform Context Fusion (WT-CtxFusion)	Dataset B	95.71%	98.65%	No
Olokodana et al. 2020 [Current Paper]	DWT-based fractal dimensions with Kriging model	Dataset A (Set A vs E)	100.00%	100.00%	Yes
Olokodana et al. 2020 [Current Paper]	DWT-based fractal dimensions with Kriging model	Dataset B	93.47%	87.60%	Yes

Table 8 Comparing latency of the proposed edge seizure detection model with existing works in the literature using Dataset B.

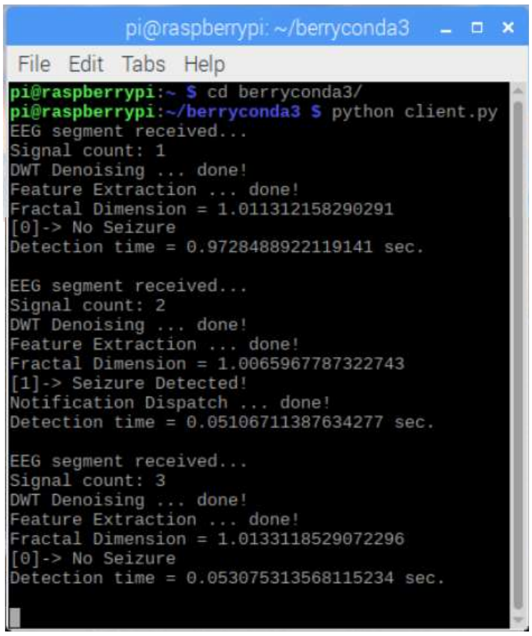
Published Works	Extracted Features	Classification Algorithm	Dataset	Latency
Shoeb, et al. 2010 [41]	Spectral, temporal and spatial features.	Support Vector Machine (SVM)	Dataset B	4.2 sec.
Park et al. 2018 [30]	Spatio-temporal Correlation	Convolutional Neural Network (CNN)	Dataset B	1.33 sec.
Khan, et al. 2012 [17]	Skewness, Kurtosis and Normalized Coefficient of Variation	Simple Linear Classifier	Dataset B	3.2 sec.
Ahammad, et al. 2014 [1]	Energy, Entropy, Std Deviation, Maximum, Minimum & Mean	Linear Classifier	Dataset B	1.76 sec.
Esbroeck, et al. 2015 [46]	Signal Energy of Channels	Multi-task learning based SVM	Dataset B	9.33 sec.
Altaf, et al. 2015 [3]	Digital hysteresis	Linear Support Vector Machine (LSVM)	Dataset B	1 sec.
Vidyaratne, et al. 2017 [48]	Fractal dimension, spatial and temporal features.	Relevance Vector Machine (RVM)	Dataset B	1.89 sec.
Sayeed, et al. 2019 [37]	Hyper-synchronous pulses	Signal Rejection Algorithm (SRA)	Dataset B	3.6 sec.
Supratak, et al. 2014 [44]	Unsupervised feature learning	Logistic Classifiers	Dataset B	3.36 sec.
Olokodana, et al. 2020 [Current Paper]	Petrosian fractal dimension	Kriging Classifier	Dataset B	**0.85 sec.**



(a) Edge device with Kriging Model



(b) Serve unit display interface



(c) Client unit display interface

Fig. 13 Real time edge seizure detection testing and validation

specific seizure detection solution will be more viable than a general model. The proposed model was validated using two widely accepted public datasets in the seizure detection research community.

In the future, we will investigate seizure prediction, which means having prior knowledge that seizure will occur before it actually does. Another future research is to have unified systems that detect seizure before it happens, and then inject drug or perform other control measures right after that [35]. We also intend to add security and privacy features to the overall system as it is IoMT-enabled and always connected to the Internet [23]. We will explore blockchain-enabled system that will store the EEG data of individual patients with security and privacy preserved, and only authorized personnel will have access. At the same tine, only authorized personnel can program the drug-delivery system to release the right amount of fluid. Other edge hardwares will also be explored in the future.

Acknowledgements This article is an extended version of our previous conference paper presented at [29].

Compliance with Ethical Standards

The authors declare that they have no conflict of interest and there was no human or animal testing or participation involved in this research. All data were obtained from public domain sources.

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