Krig-Detect: Exploring Alternative Kriging Methods for Real-Time Seizure Detection from EEG Signals

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***Abstract*—Epileptic seizures are dangerous. They render patients unconscious and can lead to death within seconds of onset. There is, therefore, the need for a very fast and accurate seizure detection mechanism. Kriging methods have been used extensively in geostatistics for spatial prediction and are known for very high accuracy. By modeling the brain as a spatial map, we demonstrate the effectiveness of Kriging Methods for efficient seizure detection in an edge computing paradigm. We explore three different types of Kriging - Simple Kriging, Ordinary Kriging and Universal Kriging. Results from various experiments with electroencephalogram (EEG) signals of both healthy and diseased patients show that all three Kriging methods have good performance in terms of accuracy, sensitivity and detection latency. However, Simple Kriging emerged as the slight favorite for seizure detection with a mean detection latency of 0.81 sec, an accuracy of 97.50%, a sensitivity of 94.74% and a perfect specificity. Simple Kriging is at least 5% better than Ordinary Kriging and Universal Kriging when evaluated at 68.2% confidence interval. The results obtained in this paper compare favorably with other seizure detection models in the literature.**

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

I. Introduction

Epilepsy is one of the most common neurological diseases, affecting more than 50 million people all over the world and does not discriminate based on age, race or gender [1]. People living with epilepsy experience a higher mortality rate than the general population [2]. Apart from the Sudden Unexpected Death in Epilepsy (SUDEP) which may or may not have a seizure relation [3], most other known causes of death in epilepsy such as fatal injury and drowning can be averted by an early and accurate detection of seizure, accompanied by prompt reaction from care givers. Accurate seizure detection is important because a few false alarms can dampen the urgency of care givers in the event of a real seizure crisis. Fig. 1 highlights the benefits of seizure detection and the consequences of none.

Kriging methods have been widely used in geostatistical applications for spatial predictions in an unknown space given some locations with known values of the quantity of interest. They use the Best Linear Unbiased Estimator (BLUE) and take advantage of the covariances among the data points to produce an estimate with the smallest possible error [4]. While

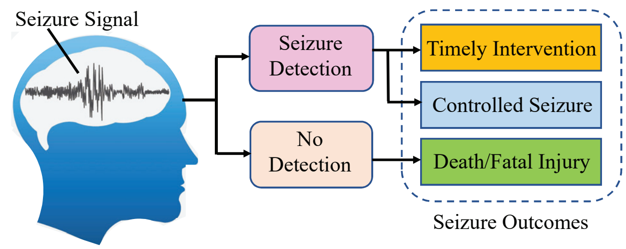


Fig. 1: Seizure effects and benefits of seizure detection.

Kriging improves performance in terms of accuracy, the other important aspect of this work is latency. Edge computing improves latency by bringing computations close to the source of the data to be processed, hence reducing the routing time that usually results from traversing the path from source to cloud.

The rest of this paper is organized as follows: Section II presents the motivation for proposing the use of Kriging in seizure detection. Section III highlights the novel contributions of this paper. Section IV is a review of related work. Our proposed edge computing paradigm for real-time seizure detection is described in section V. Section VI is a theoretical perspective on Kriging methods. Section VII discusses experiments and results while Section VIII states the conclusion and future works.

II. Why Kriging? - The brain envisioned as a spatial map suitable for spatial data processing

We envision the brain as a spatial map on which spatial data processing methods such as Kriging can be applied. The brain is a spatial multi-level and multi-scale entity with unceasing dynamic processes [5]. There are various similarities between brain mapping and geographical information system (GIS) mapping as evident from some GIS applications for pattern recognition of electronic medical records of the brain. Studies also show that the brain's hippocampus produces multiple maps (by the activity of some cells) which are used for recognition and navigation [6]. It was remarked in [7] that some of the EEG recordings collected from epilepsy patients were taken from the hippocampal region of the brain.

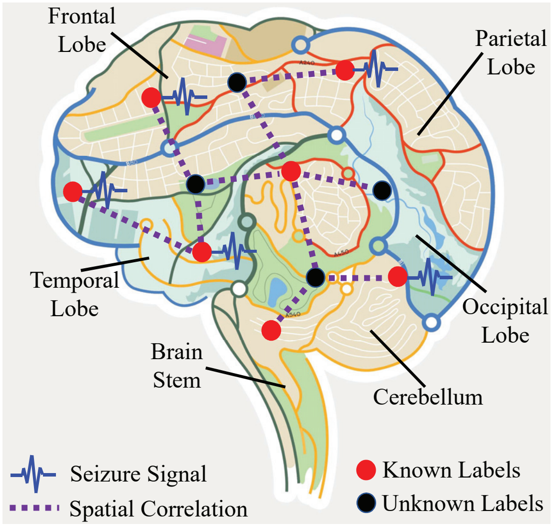


Fig. 2: Schematic representation of the brain as a spatial map.

Fig. 2 is a schematic representation of the brain map with labeled cortices which are analogous to geographical boundaries of the earth. Kriging [8] is a geo-statistical technique that is widely used to spatially predict processes or quantities in locations where they are not known, given other locations where they are known. The red and black circles in Fig. 2, respectively represent locations in the brain with known and unknown measures of the quantities or processes of interest while the dotted lines depict a measure of the spatial correlation among different locations. It has been observed that while seizures may begin from a specific region of the brain, they are not restricted and can be spatially distributed to the other parts of the brain [9]. Therefore, some of the locations with known values have seizure while some do not. Hence it might be possible to predict the actual locations of the brain that are affected by seizures. However, the specific focus of this work is to prove the effectiveness of Kriging methods for epileptic seizure detection.

III. Novel Contributions of the Current Paper

A. The Problem Addressed in the Current Paper

Based on the discussion in section II, is it possible to take advantage of the brain's spatial mapping characteristics in providing a better solution to the seizure detection problem? Furthermore, given the fact that the brain is like a spatial map, will Kriging methods which have been largely successful in geo-statistics be effective and efficient for seizure detection? If yes, which of the Kriging methods will produce the best performance in an edge computing paradigm? These are the research questions that are addressed in this paper.

B. The Challenges in Solving the Problem

Collecting a custom data-set that will fully explore Kriging and exploit its benefits in solving the seizure detection problem is a challenge due to the stringent regulations that are involved when collecting data from animals or human subjects. Most biomedical researchers are therefore left with the option of using public data-sets collected by some teaching hospitals [7]. Data collection from the brain is generally susceptible to noise as a result of artifacts but it is difficult to estimate the level of noise in public data-sets since the conditions of the environment in which they are collected are not known. Another challenge is the cubic time complexity of Kriging. This was however addressed in this work by not training the Kriging model on the edge device [10].

C. The Solution Proposed in the Current Paper

This paper proposes the use of the Kriging method as a worthy and effective solution to the problem of seizure detection in real-time with an edge computing paradigm based on the premise that the brain is analogous to a geographical map with contiguous locations that are cross-correlated. The main objective of this paper is to identify the most suitable Kriging method for real-time seizure detection with edge computing by comparing three different Kriging methods, namely Simple Kriging, Ordinary Kriging and Universal Kriging. Ordinary Kriging was used for real-time seizure detection in an edge computing paradigm in a previous work by the authors of this paper [10].

D. The Novelty of the Solution Proposed

Our conceptual analysis of the brain as a spatial map on which the Kriging methods can be applied with respect to a seizure detection problem is novel. To the best of the authors' knowledge, this is the first work where multiple Kriging methods have been used for real-time seizure detection in an edge computing paradigm. Our work reports an average detection latency of less than one second, which makes it suitable for real time applications. The accuracy, sensitivity and specificity of our proposed model are also comparable to those of other existing works.

IV. Related Works in EEG based Seizure Detection

Seizure detection is a well-explored area in the literature. A good number of efforts concentrate largely on improving seizure detection performance using metrics such as accuracy, sensitivity and specificity with little or no emphasis on the computing paradigm utilized [11]–[13]. A few others recognized the importance of latency and included it in the metrics considered to measure the performance of their proposed seizure detection systems [14]. Machine learning algorithms such as Support Vector Machines (SVM) [11], κ-Nearest Neighbor (κ-NN) [15] and Artificial Neural Network (ANN) [12] are some of the most commonly used in previous works for classifying seizures from a pool of electroencephalogram (EEG) signals.

Apart from EEG-based seizure detection, other methods that are not so common have also been used. There are seizure detection systems which make use of accelerometers and gyroscopes in the form of wearable devices on the wrist or some other parts of the body to sense weird movements of the limbs and eccentric body vibration during epilepsy [16], [17]. One limitation of this method lies in accurately identifying the seizure movements from other non-epileptic random movements resulting from sports or dancing, to mention a few. The EEG method also has the advantage of taking the signals directly from the source of the seizure itself - the brain.

Although Faul et al. [9] proposed the use of Gaussian Process modeling otherwise known as Kriging for the detection of seizures in neonates, it was not in an edge computing environment, hence latency was not considered as a performance metric. It was however remarked that the detection time could be up to 15 seconds for a given computational power that was not stated. On the other hand, a previous work by the authors of this paper using Ordinary Kriging in an edge computing paradigm for seizure detection reported a mean detection latency of 0.85 second with very good accuracy and sensitivity [10].

V. A Novel Edge Computing Paradigm for Real-Time Seizure Detection

It is highly beneficial to process data at the edge since more data are now being generated at the edge of the Internet of Things (IoT) network than ever, due to the proliferation of sensing devices and mechanisms [18]. Reduced cost of deployment, portability and low latency are key advantages leading to the increasing popularity of the edge computing paradigm. These advantages are even more important when there is threat to life, as in the case of epileptic seizure. Seizure detection should be *affordable* since low income regions of the world are the most impacted, it should be *portable* so that patient's mobility is not confined to a limited environment, and it should have *low latency* in order to effectively reduce the threat to life during seizure crisis. These three elements, as well as accuracy, are reflected in our proposed edge computing paradigm for real-time seizure detection depicted in Fig. 3.

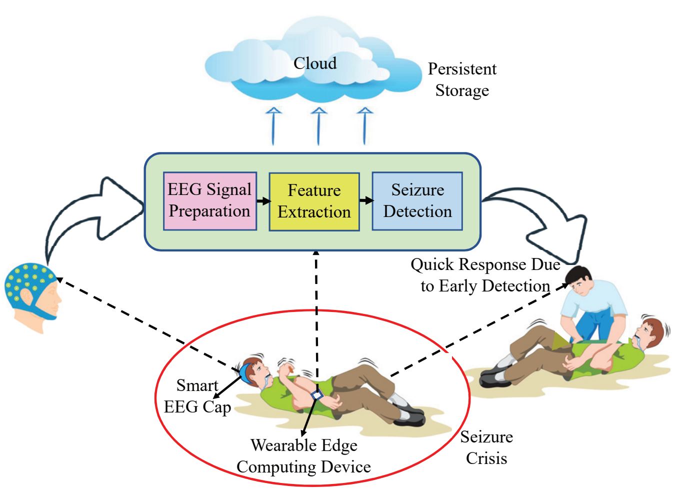


Fig. 3: Real-Time Seizure Detection for Rapid Response.

As shown in Fig. 3, the smart EEG cap and the wearable edge computing device attached to the suffering subject are portable devices that will not affect the mobility of patients in their daily lives, hence seizure can be detected anywhere and anytime without restriction. All signal processing of the EEG data leading up to seizure detection takes place in the wearable edge device that is very close to the subject, resulting in a fast seizure detection with low latency and a quick response to rescue the victim from injury or even death by the assigned care-givers. In this case, the cloud is only used as a means of persistent storage of data for later use by a physician or research scientists since it has a bigger capacity rather than its conventional use for computation. Adequate management of seizure crisis in this way is paramount until full remission is accomplished if at all possible, or for the entire life of the patient if not.

VI. Kriging Methods - A Theoretical Perspective

Kriging was named after Daniel Krige, a foundational proponent of geo-statistical mining from South Africa [19]. Kriging relies on spatial continuity which is a measure of correlation between values over distance. This implies that values in closer locations are more correlated than those with larger separating distances. There are three important steps in the application of Kriging methods. First is the establishment of spatial continuity through the semi-variogram which is a function of the variations in values over distance, second is fitting a model to the generated semi-variogram and the final step is the actual estimation through the fitted model [20].

Fig. 4 highlights a cross-section of the different types of Kriging [19]. The top three Kringing types - Simple Kriging [21], Ordinary Kriging [10], and Universal Kriging [22] are the most commonly used and thus are the focus of this paper.

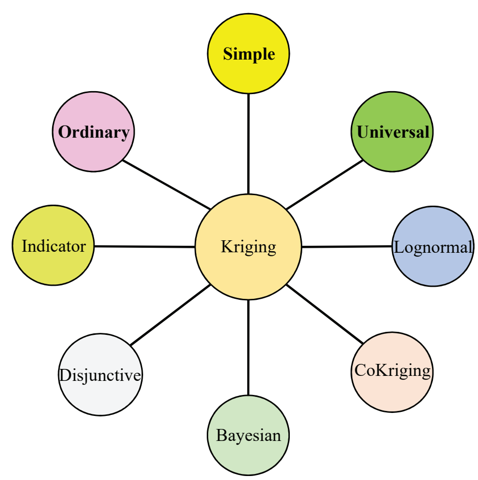


Fig. 4: The different types of Kriging methods.

A. The Semi-variogram

The semi-variogram is merely a scatter plot with each point representing the average variation among a group of location pairs with common distance known as the lag vector $\mathbf{h}$ [20]. The formula for generating the semi-variogram is given by:

$$\boldsymbol{\gamma}(\mathbf{h}) = \frac{1}{2\mathbf{N}(\mathbf{h})} \sum_{i=1}^{\mathbf{N}(\mathbf{h})} (\mathbf{Z}(\mathbf{x}_i) - \mathbf{Z}(\mathbf{x}_i + \mathbf{h}))^2, \tag{1}$$

where $\boldsymbol{\gamma}(\mathbf{h})$ represents the semi-variogram at the lag vector $\mathbf{h}$ between two points, $\mathbf{N}(\mathbf{h})$ is the number of lag vectors $\mathbf{h}$ considered for a single point on the semi-variogram plot and $\mathbf{Z}(\mathbf{x}_i)$ represents a Gaussian process over the observations $\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_i$ at different locations.

B. The Semi-variogram Model

The semi-variogram model simply fits a line or curve on the scatter plot represented by the semi-variogram. Fig. 5 shows the various types of semi-variogram models that are used in fitting the semi-variogram.

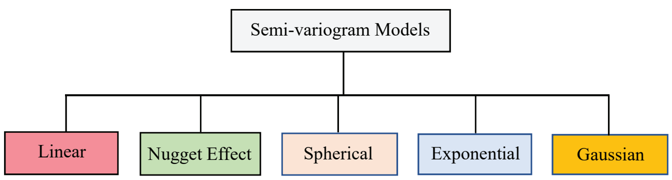


Fig. 5: Semi-variogram models.

The choice of semi-variogram model largely depends on the nature of the spatial relationship between the points on the semi-variogram [20]. It was remarked in [7] that EEG time-series recorded from normal and epileptic patients were congruent with Gaussian stochastic process. This further strengthens the case for Kriging (Gaussian Process Regression) in seizure detection and also positions the Gaussian model as the favored semi-variogram model. The Gaussian semi-variogram model is mathematically given by:

$$\boldsymbol{\gamma}(\mathbf{h}) = \begin{cases} C\left[1 - \exp\left(-\frac{\mathbf{h}^2}{a^2}\right)\right] & \mathbf{h} > 0 \\ 0 & \mathbf{h} = 0 \end{cases} \tag{2}$$

In the above expression, C is the sill (total variance contribution) and a is the range (distance on the horizontal axis corresponding to the sill).

C. Kriging Estimate

This is the actual estimation of the unknown values at the locations of interest. Having established the trend through the fitted semi-variogram model, unknown values at given locations can be estimated from the fitted model. Kriging is also referred to as Best Linear Unbiased Estimator (BLUE) because it assigns weights to the link between two locations based on the auto-correlation between them. That is, higher weights are assigned to spatial links with stronger auto-correlation [10].

There are three fundamental types of Kriging based on the assumption about the global mean (μ_z) of the underlying Gaussian process $\mathbf{Z}(\mathbf{x})$. They are *Simple Kriging, Ordinary Kriging* and *Universal Kriging*. While *Simple Kriging* assumes a known and constant mean, *Ordinary Kriging* assumes a global mean that is constant but unknown. *Universal Kriging* on the other hand assumes a variable global mean [8]. Every other type of Kriging (Fig. 4) has one of the above mean assumptions together with some other assumptions.

The covariance $C(\mathbf{h})$ between two locations is obtained from the semi-variogram model as follows [4]:

$$C(\mathbf{h}) = C(0) - \boldsymbol{\gamma}(\mathbf{h}), \tag{3}$$

where $C(0)$ is the sill (variance of variable).

Now, by obtaining the covariance for every pair of known points using Eqn. (3) and multiplying by a given weight, we have the following system of equations:

$$\boldsymbol{\lambda}_{n\times 1}.\mathbf{C}_{n\times n} = \mathbf{c}_{n\times 1}, \tag{4}$$

where $\mathbf{C}_{n\times n}$ is a covariance matrix for all known pairs, $\mathbf{c}_{n\times 1}$ is a covariance vector of all the points relative to the unknown, $\boldsymbol{\lambda}_{n\times 1}$ is a vector of the weights and n is the number of points. Hence, we obtain the following expression:

$$\boldsymbol{\lambda}_{n\times 1} = (\mathbf{C}_{n\times n})^{-1}.\mathbf{c}_{n\times 1} \tag{5}$$

The final Kriging estimate $y(\mathbf{x}_o)$ is then obtained by multiplying the resulting weight vector in Eqn. (5) with the residual $\mathbf{R}(\mathbf{x}_i)$ as follows:

$$y(\mathbf{x}_o) = \sum_{i=1}^{n} \lambda_i \mathbf{R}(\mathbf{x}_i), \tag{6}$$

where

$$\mathbf{R}(\mathbf{x}_i) = \sum_{i=1}^{n} (Z(\mathbf{x}_i) - \mu_z) \tag{7}$$

VII. Experimental Results and Their Analysis

A. EEG Dataset and Extracted Features

The dataset [7] used for this work has been widely used for seizure detection research [11], [15]. It has five different sets (A - E) comprising ictal, interictal and healthy EEG segments. Sets A and E which are healthy and epileptic EEG signals respectively, are used in this work. Each set consists of 100 EEG segments sampled at 173.61 Hz.

To accurately model the seizure detection challenge as a Kriging problem, we extracted three different features from the EEG dataset. The features are Singular Value Decomposition (SVD) Entropy, Hjorth Complexity and Fractal Dimension. The first two features were modeled as the Kriging coordinates while the Fractal Dimension was modeled as the quantity to be estimated.

Fig. 6 which represents the 200 EEG segments as data points using the extracted features roughly depicts two categories by merely observing the colors of the data points except for a few outliers which could be due to some in the dataset. It also reveals that there is spatial continuity within the dataset. This shows that our modeling of the dataset using SVD Entropy, Hjorth Complexity and Fractal Dimension is a good candidate for Kriging methods.

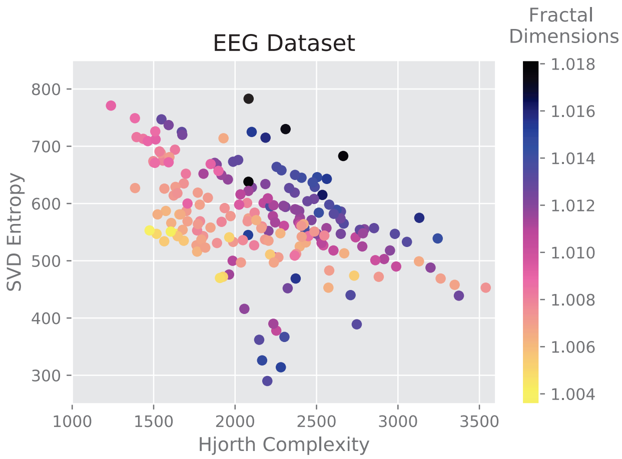


Fig. 6: Feature representation of EEG dataset using color map.

B. Training the Kriging Models

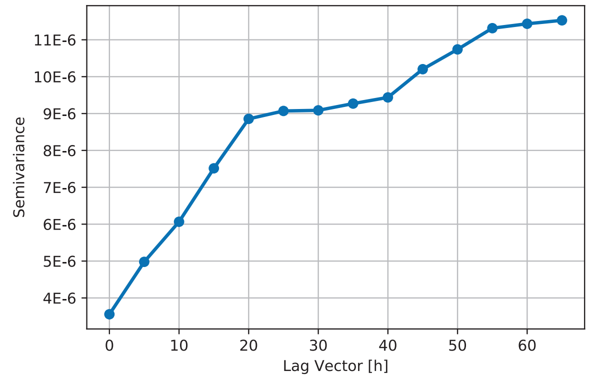
The dataset is divided randomly into training and testing sets using the recommended 80/20 rule [23], especially since the dataset is relatively small, as is the case for most biomedical datasets. The Kriging model training follows the process described in section VI. First we obtained the semi-variogram of the training set according to Eqn. (1) and then fitted the semi-variogram with the Gaussian semi-variogram model using Eqn. (2). Figs. 7a and 7b show the semi-variogram plot and the fitted semi-variogram plot of the training set respectively.

The covariance matrix that is used for generating the Kriging weights is obtained from the fitted semi-variogram. Finally, the Kriging estimates for the fractal dimensions are calculated by multiplying the weights with the residuals using Eqn. (6). During the Kriging estimation, the necessary assumptions stated in section VI are reflected in the calculation of the residuals to account for the specific type of Kriging. The resultant Kriging estimates are then mapped to one of two states - healthy or ictal which are represented by "0" and "1" respectively.

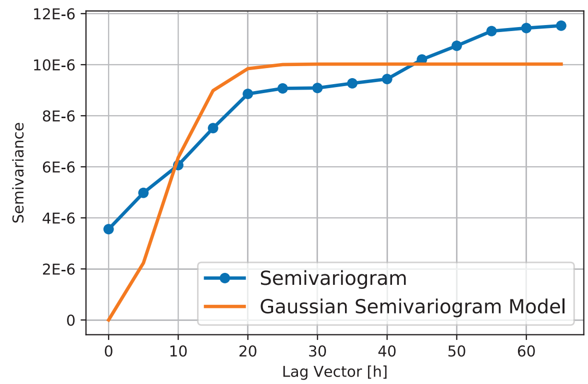
C. Performance Metrics for Edge Computing Paradigm based Seizure Detection

After obtaining the seizure states from the Kriging estimates, the performance of the three types of Kriging considered in this paper were evaluated and compared using metrics such as accuracy, sensitivity, specificity, F1-score and latency in an edge computing environment. The model training was done on a workstation because of the cubic time complexity of Kriging before porting the trained model to an edge device for further performance testing. Table I reveals the performance of the different types of Kriging.

From the results shown in Table I, Simple Kriging and Ordinary Kriging maintained the same performance at 99.7% and 95.4% Confidence Intervals (CI). However, Simple Kriging performed better than Ordinary Kriging at 68.2% CI. Universal Kriging has the least performance across all the confidence intervals considered for the seizure detection task. This may be



(a) Semi-variogram of the EEG training set.



(b) Fitted semi-varigram using the Gaussian semivariogram model.

Fig. 7: Modeling of the semi-variogram for Kriging prediction.

TABLE I: Comparing Kriging performances for seizure detection at different confidence intervals (CI).

C. Int. (CI)	Kriging Models	Accuracy	Sensitivity	Specificity
99.7% CI	Simple Kriging	97.50%	94.74%	100.00%
	Ordinary Kriging	97.50%	94.74%	100.00%
	Universal Kriging	80.00%	89.47%	71.43%
95.4% CI	Simple Kriging	92.50%	94.74%	90.48%
	Ordinary Kriging	92.50%	94.74%	90.48%
	Universal Kriging	80.00%	89.47%	71.43%
68.2% CI	Simple Kriging	90.00%	89.47%	90.48%
	Ordinary Kriging	87.50%	84.21%	90.48%
	Universal Kriging	80.00%	89.47%	71.43%

due to the fact that Universal Kriging is slightly more complex than the other two Kriging methods and could not fit well to the limited size of the dataset.

Fig. 8 shows the histogram plot of the F1 scores based on the Kriging performances on the seizure detection. The figure further confirms the superiority of Simple Kriging method over the other Kriging types especially at 68.2% CI. Ordinary Kriging has the closest average F1 score to Simple Kriging while Universal Kriging has the least.

After training, the three Kriging models were ported to an edge device for a real time testing in an edge computing paradigm. Table II shows the performances of the models in terms of detection latency while running on the edge device. Simple Kriging again emerged here as the Kriging model with

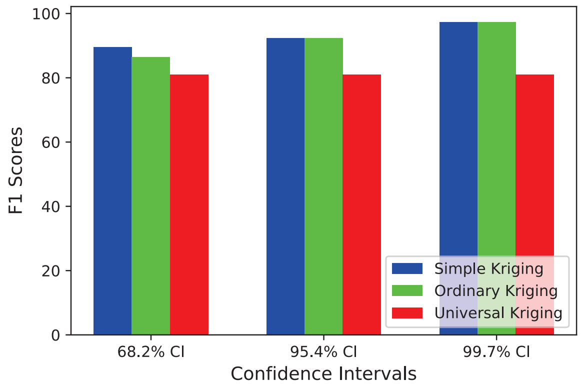


Fig. 8: Kriging performance comparison using F1-scores and confidence intervals.

the lowest mean detection latency of 0.81s while Universal Kriging has the longest latency of 16.25s. The mean detection latency was calculated over ten trials for each Kriging model.

TABLE II: Comparing mean detection latency of Kriging models in an edge computing paradigm.

Kriging Models	Detection Latency (in sec)
Simple Kriging	**0.81**
Ordinary Kriging	0.86
Universal Kriging	16.25

VIII. Conclusion and Future Work

The effectiveness of Kriging methods for real time seizure detection in edge computing paradigms was explored in this paper by modeling the brain as a three dimensional spatial entity, analogous to a geographical landscape on which Kriging methods excel. Three different Kriging methods were examined using various performance metrics for comparison. Simple Kriging emerged the winner with Ordinary Kriging coming very close to it while Universal Kriging had the worst performance by a wide margin.

A future work, the authors intend to work on a real-time hardware implementation of the idea presented in this paper and further explore the use of the Simple Kriging method for more efficient and timely seizure detection and prediction. We plan to integrate drug-delivery system along with the detector [24]. We also plan to explore integration of security features to the proposed medical device as it is IoMT enabled and can be part of large scale Internet-of-Everything (IoE) or healthcare Cyber-Physical Systems (H-CPS) [25], [26].

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