Distributed Kriging-Bootstrapped DNN Model for Fast, Accurate Seizure Detection from EEG Signals

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Abstract—**The modeling of the brain as a three-dimensional spatial object, similar to a geographical landscape, has the paved way for the successful application of Kriging methods in solving the seizure detection problem with good performance but in cubic computational time complexity. The Deep Neural Network (DNN) has been widely used for seizure detection due to its effectiveness in classification tasks, although at the cost of a protracted training time. While Kriging exploits the spatial correlation between data locations, DNN relies on its capacity to learn intrinsic representations within the dataset from the basest unit parts. This paper presents a Distributed Kriging-Bootstrapped Deep Neural Network (DNN) model as a twofold solution for fast and accurate seizure detection using brain signals collected with the electroencephalogram (EEG) from healthy subjects and patients of epilepsy. The proposed model parallelizes the Kriging computation into different cores in a machine and then produces a strongly correlated, unified quasi-output data which serves as an input to the Deep Neural Network. Experimental results validate the proposed model as superior to conventional Kriging methods and DNN by training in 91% less time than the basic DNN and about three times as fast as the ordinary Kriging-Bootstrapped Deep Neural Network (DNN) model while maintaining good performance in terms of sensitivity, specificity and testing accuracy compared to other models and existing works.**

Index Terms—**Smart Healthcare, Edge AI, Distributed Machine Learning, Seizure Detection, Kriging Methods.**

I. Introduction

Epilepsy is a disease that transcends physical pain. Although the most prominent cause of death in epilepsy is injury sustained by patients in an unconscious state during their seizure crisis, depression suffered from social stigmatization can also lead to death or cause patients to take decisions that are harmful to their lives [1]. Fast and accurate seizure detection can improve the quality of life of epilepsy subjects and also contribute immensely towards the ultimate goal of eradicating the menace of epilepsy in the human race. While Kriging methods can be very accurate, the computational time requirement quickly escalates with increasing data due to their cubic time complexity. However, they are highly effective in realizing the correlation that exists in a set of data, and to what extent, irrespective of the data size. Deep Neural Networks (DNN) on the other hand, require huge amount of data to sufficiently learn the underlying representation within the dataset, which translates to a prolonged training time, for a quality classification performance. Consequently, a technical synergy of distributed Kriging across multiple cores or machines and the DNN as proposed in this paper, holds great potential for fast and accurate seizure detection. Fig. 1 schematically represents a distributed Kriging model which is achieved by parallelizing the computation across N different cores, hence reducing the Kriging time.

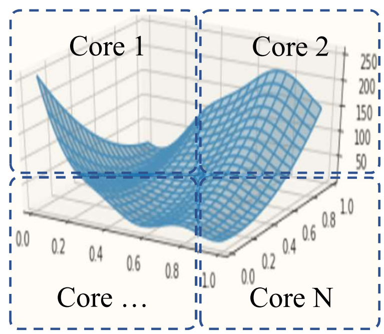


Fig. 1. Schematic representation of Distributed Kriging model

The remaining part of this paper has the following structure: Section II discusses related works in seizure detection. Section III presents the novel contributions of this paper. The proposed Distributed Kriging-Bootstrapped DNN model for real-time Seizure Detection is described in section IV. The computational analysis of the proposed model was presented in Section V while Section VI details the overall framework of the proposed model. Section VII is a discussion on the experimental validation of the proposed model. Conclusion and future works are presented in Section VIII.

II. Related Works in EEG-based Seizure Detection

The success of Kriging methods for seizure detection has been demonstrated in previous works by the authors of this paper [2, 3]. The Deep Neural Network (DNN) is also popular in the literature for EEG-based seizure detection [4, 5]. However, both methods become computationally expensive when the input data size scales high. A hierarchical seizure detection model which combines bootstrapped Kriging and DNN was proposed [6], exploiting their relative advantages in order to reduce the overall computational cost in time.

Other than the Kriging methods and DNN, some models that have also been used for EEG-based seizure detection include κ-Nearest Neighbors (κ-NN) [7], Artificial Neural Network (ANN) [8], Naive Bayes classifier [7] and Support Vector Machines (SVM) [9]. This paper proposes a novel Distributed Kriging-Bootstrapped DNN Model for fast and accurate EEG-based seizure detection which eclipses the performance of the hierarchical Kriging-Bootstrapped DNN model proposed by the same authors of this work.

III. Novel Contributions of the Current Paper

A. Research Question

While the Kriging-Bootstrapped DNN seizure detection model [3] reduced the total training time by 75% compared to ordinary DNN, the major contributor to the reduction is the DNN, the Kriging time remains unchanged. Is it possible to achieve a further reduction in training time by distributing the Kriging computation across different cores without affecting the overall performance of the seizure detection model?

B. Proposed Solution

A Distributed Kriging-Bootstrapped DNN model for fast and accurate seizure detection from EEG signals is proposed in this paper. A Kriging model which is used as an input to the DNN is generated by parallel computation across different cores to improve the Kriging time and hence the overall training time of the hybrid model. Relevant simulation and experiments were carried out to validate the effectiveness of the proposed model with respect to other models.

C. The Novelty of the Proposed Solution

Our proposed distributed, hierarchical model improved the training time performance of basic DNN model by 91% and is also about three times faster than the baseline Kriging-Bootstrapped DNN model. Another novelty of this work is the achievement of a single-channel seizure detection model with a better performance than a 23-channel seizure detection model. A single-channel model is lightweight and more suitable for real time seizure detection. Furthermore, the proposed Distributed Kriging-Bootstrapped DNN seizure detection model in this paper achieved a mean seizure detection latency of 0.8s.

IV. A Novel Distributed Kriging-Bootstrapped DNN Model for Real-Time Seizure Detection

In this paper, we propose a distributed Kriging method in which the Kriging computation is parallelized across multiple cores in a machine. Fig. 2 is a schematic representation of our proposed Distributed Kriging-Bootstrapped DNN Model where the Kriging computation is split across four different cores in the machine. The outputs generated from the cores are then aggregated and presented as an input to the DNN model for final classification of the EEG signals as seizure or non-seizure. Since the Kriging time can be considerably reduced by distributing computation across multiple cores, why then is there need for an extra layer of DNN over the Distributed Kriging? The DNN is used as a wrapper model for the Distributed Kriging in this work for two major reasons. First, DNN is more tolerant to higher feature dimensions than Kriging. As feature dimension increases, Kriging becomes more complex and computationally expensive [10]. Second, every Kriging estimate involves the use of all the points in a dataset in calculating the weights specific to the particular estimate [11]. DNN on the other hand, generates generic weights in a single model for the classification of every unknown data point. For these reasons, it is therefore more advantageous to use Kriging under the hood to help speed up the DNN training while the final DNN model is used on the front end for real time detection of the seizure signals, hence exploiting the relative advantages of both models and eliminating there weaknesses to create a perfect synergy for a real-time seizure detection.

V. Computational Analysis of Distributed Kriging

The use of Kriging methods for seizure detection hinges on the fact that the brain shares some similarities with the Geographical Information System (GIS) map and can be modeled as such [12, 13]. Kriging has been successfully applied to the seizure detection problem [2, 3]. However, its cubic computational time complexity is a cause for concern when applied conventionally, especially as the data size and feature dimensions increase. A distributed deep network in which the training data is divided into subsets and trained on the same model in parallel across different machines to achieve faster training was proposed for large scale deep learning in [14]. The concept of spreading computation workload has also been used for Kriging methods as observed in [15] and [16], which proposed different ideas of Distributed Kriging for improving wireless communication analysis. This current work pioneers the use of Distributed Kriging for seizure detection application to the best awareness of the authors.

The partial derivative of the Kriging estimation variance (${\sigma^2}_{est.}$) with respect to the weights (λ_i) is given by:

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

where $i = 1, 2, 3, ..., n$, $\mathrm{C}(\mathbf{x}_i, \mathbf{x}_j)$ represents the Covariance between data locations at index i and index j, $\mathbf{x}_i$ and $\mathbf{x}_o$ are the known and unknown points respectively.

To estimate the weights that minimize the estimation variance, Eqn. 1 is set to zero and results in the following equation:

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

Refer to [2] for a full derivation of the Kriging equations in a previous work by the authors of this paper.

The matrix inverse calculation to calculate the unknown λ_j coefficients involves the computation of the determinant of the matrix and the matrix adjoint which is the transpose of its cofactor matrix. For example, if we assume that 3 known points are used to evaluate the function at one unknown point,

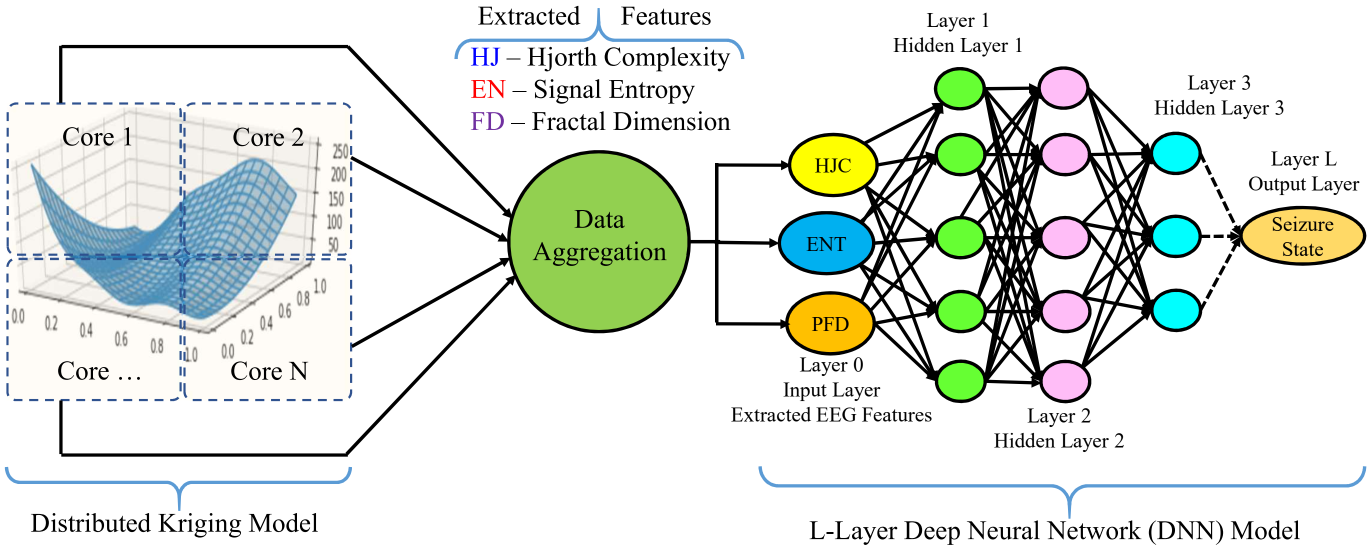


Fig. 2. Proposed Distributed Kriging-Bootstrapped DNN model for real-time seizure detection.

the system has order 3×3. The cofactor computation of a 3×3 matrix has 9 independent computations while its determinant has 3 independent computations. However, the processing unit of a computer naturally does all 12 computations sequentially. In this paper, all 12 computations are distributed across multiple processing cores. For example, the computations can be spread across 4 different cores at 3 computations per core, all running simultaneously, resulting in a faster overall computation.

VI. The Proposed Fast and Accurate Real-Time Seizure Detection Model

Our proposed fast and accurate seizure detection model is shown in Fig. 3. The signal preparation block is where the EEG signal is cleaned up and the selected features shown in Fig. 2 are extracted. The extracted features are forwarded to two destinations, first to the seizure detection model block and then to the signal database block. The seizure detection model block consists of an already trained Distributed Kriging-Bootstrapped DNN Model running in an edge device. Once a seizure is detected, a crisis alarm is automatically escalated to the assigned caregivers who are always in close proximity to the patient, as well as the remote physicians in order to facilitate a fast seizure control.

The signal database which acts like a remote cloud storage also receives a feedback of the seizure status for each signal and maps it to the extracted feature for that specific signal which was already stored. When the stored patient data get to a predetermined threshold, they are forwarded to the data balancing block to prepare the data for training by tuning the positive and negative outcomes to a more balanced ratio. Next, the proposed distributed Kriging is performed on the balanced data to generate a well-correlated input for training the DNN in the next block. As soon as the DNN training and validation are done, the currently running model in the seizure detection

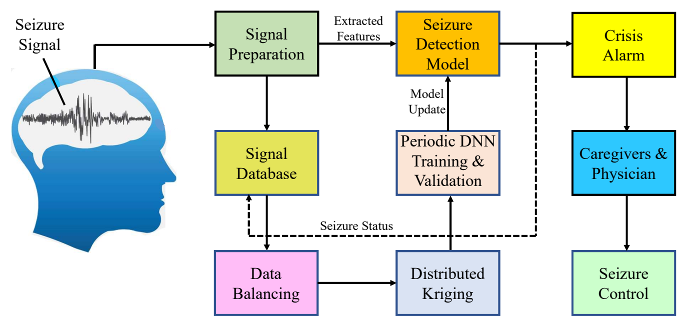


Fig. 3. Proposed fast and accurate seizure detection model.

model block is seamlessly updated with the new model. The process continuously repeats itself for as long as required.

VII. Experimental Validation of the Proposed Model

A. The Datasets and Features Extracted

Two different datasets were used to validate the proposed model in this paper. The two datasets, which are referred to as Dataset A [17] and Dataset B [18, 19] were independently collected in Germany and the United States at the University of Bonn's Department of Epileptology and Childrens Hospital Boston (CHB) respectively. Further description of the datasets follows shortly. While there are many features that can be extracted from EEG signals, the authors of this paper concentrated on three measures of signal complexity which are Fractal Dimension (FD), Singular Value Decomposition Entropy (EN) and Hjorth Complexity (HJ) due to their proven effectiveness in biomedical signal analysis [20].

1) Dataset A: This dataset was collected at the University of Bonn in Germany from 5 healthy subjects and 5 epileptic patients. They were classified into 5 different sets from A to E. Sets A and B are healthy signals from the healthy subjects.

while Sets C, D and E are signals from the patients, with set E being the only set with seizure signals. Sets C and D are inter-ictal signals, that is periods in between seizures. The signals were collected with a 128-channel EEG system and sampled at 173.61Hz. Each set consists of 100 EEG segments and each segment is 23.6s long and consists 4097 data points. The seizure signals were selected from all the channels manifesting ictal properties.

2) Dataset B: This dataset was collected at the Children Hospital Boston (CHB) in conjunction with the Massachusetts Institute of Technology (MIT). It is therefore referred to as the CHB-MIT Scalp EEG Database. The EEG signals were collected from 22 epileptic patients of CHB using a 23-channel EEG and sampled at 256Hz. The datasets are labeled according to the subjects as chb01 to chb23 (one of the subjects featured twice). The dataset consists of a total of 916 hours of EEG recordings across all 22 subjects. The EEG recordings are continuous for each subject. Unlike Dataset A, the readings for all 23 channels are available in this dataset. In this paper, datasets from 5 of the subjects were utilized. They include chb01, chb03, chb05, chb07 and chb09.

B. Experimental Results with Analysis: Dataset A

Multiple experiments were carried out using our proposed Distributed Kriging-Bootstrapped DNN model on Dataset A. Set A (healthy) and Set E (ictal) of Dataset A were combined and shuffled together as a single dataset after extracting the earlier specified features. The combined dataset is then divided into training and testing sets in the ratio 4:1 before applying the proposed model in classifying the signals. Different training epochs were used during the experiment and the performance of our proposed Distributed Kriging-Bootstrapped DNN model was compared to the ordinary Kriging-Bootstrapped DNN model that was proposed in [6]. Comparisons were also made with bare Kriging and ordinary DNN in terms training time and accuracy. Table I shows the performance of the proposed Distributed Kriging-Bootstrapped DNN model with respect to training and testing accuracy, training epochs and training time. While there are other performance metrics such as sensitivity, specificity, precision and F1-score, most of which we have used in our previous works, the main goal of the paper is to establish the significant improvement in training time by the proposed model without compromise in performance. Besides, a perfect testing accuracy (Table I) will also result in a perfect score for all the unused metrics stated above.

TABLE I
DISTRIBUTED KRIGING-BOOTSTRAPPED DNN MODEL PERFORMANCE WITH 10,000 SAMPLES USING DATASET A.

Count	Training Accuracy	Testing Accuracy	Training Epochs	Training Time
1	99.14%	97.50%	500	12.80s
2	99.76%	100.00%	800	13.46s
3	99.84%	100.00%	1000	13.75s
4	99.92%	100.00%	1500	15.56s
5	99.92%	100.00%	10000	52.72s

Fig. 4 is a direct comparison between a baseline DNN model and the proposed Distributed Kriging-Bootstrapped DNN model. The baseline DNN took a much longer time to converge to a similar accuracy as the proposed model.

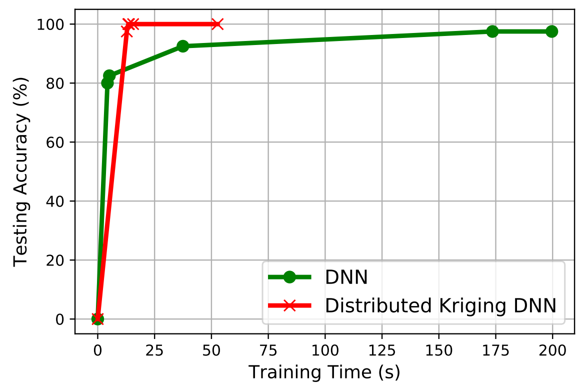


Fig. 4. Performance Comparison of Distributed Kriging- Bootstrapped DNN model with Basic DNN model in terms of training time.

Table II compares the proposed Distributed Kriging-Bootstrapped DNN model to the Kriging-Bootstrapped DNN model which was proposed in [6], Ordinary Kriging and a basic DNN model. It is observed the proposed Distributed Kriging-Bootstrapped DNN model trains in 91% less time than the basic DNN and also about three times faster than the baseline Kriging-Bootstrapped DNN model presented in [6].

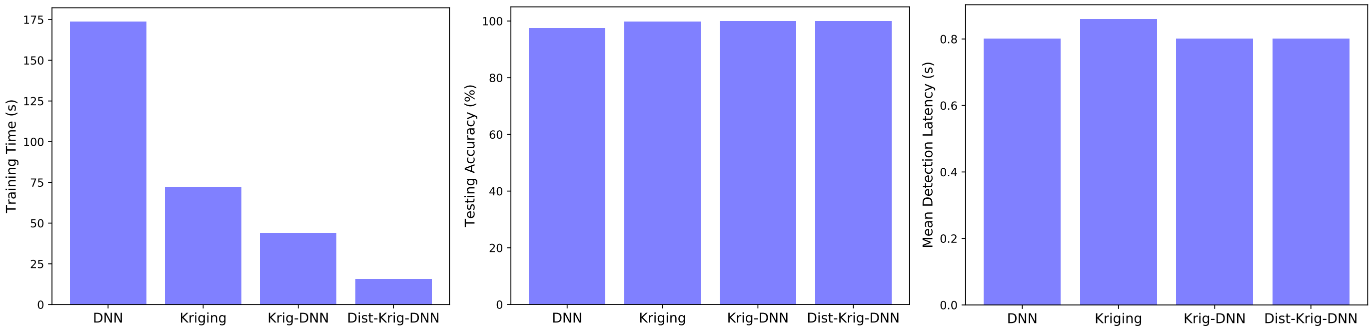
TABLE II
COMPARING BEST PERFORMANCES FOR ORDINARY KRIGING, BASIC DNN, KRIGING-BOOTSTRAPPED DNN AND DISTRIBUTED KRIGING-BOOTSTRAPPED DNN MODELS USING DATASET A.

Models	DNN	Ordinary Kriging	Kriging DNN	Distributed Kriging DNN
Tr. Data Size	10000	2000	10000	10000
Tr. Epochs	45000	NA	1500	1500
Learning Rate	0.00001	NA	0.001	0.001
Training Acc.	99.99%	100.00%	99.92%	99.92%
Testing Acc.	97.50%	99.78%	100.00%	100.00%
Training Time	173.57s	72.24s	43.83s	**15.56s**

It is also noted that while the ordinary Kriging model is about as accurate as the proposed model, it is highly computationally expensive as the size of data increases, reporting a training time that is about five times that of the proposed model with only 20% of the data size utilized by the other models evaluated. However, it must be said that the Kriging model thrives excellently on small amount of data.

Fig. 5(a) shows the downward spiral in training time across the different models that were evaluated in this work and how the proposed model in this paper eclipsed the training time performance of the other models by a significant margin.

The detection latencies of the different models were evaluated in an edge computing paradigm. This was achieved by porting the trained models into an edge device and then remotely streaming the EEG data into it for seizure detection. The mean detection latency was calculated over ten individual



(a) Improvement in training time by the proposed model

(b) Marginal improvement in testing accuracy by the proposed model

(c) Improvement in seizure detection latency by the proposed model

Fig. 5. Depicting the performance improvement of the proposed Distributed Kriging-Bootstrapped DNN model.

trials for each model. Evaluation results are presented in Table III and also shown as a bar plot in Fig. 5(c). It is observed that the mean detection latency of the proposed model is lower than that of the ordinary Kriging. However, the mean detection latencies for DNN, Kriging-Bootstrapped DNN and Distributed Kriging-Bootstrapped DNN models are all the same. This is because the same DNN architecture was maintained for the three models. The higher the complexity of the DNN architecture, the higher the detection latency. The deep learning architectural specification for this work is shown in Table IV. Overall, Fig. 5 shows the drastic improvement in training time without any compromise in the other performance metrics.

TABLE III
COMPARING MEAN DETECTION LATENCY OF MODELS IN AN EDGE COMPUTING PARADIGM.

Models	Detection Latency
DNN	0.80s
Ordinary Kriging	0.86s
Krig-DNN	0.80s
Dist-Krig-DNN	0.80s

TABLE IV
DNN ARCHITECTURAL SPECIFICATION

DNN Specifications	Values
No of Layers	4
Hidden Units	5, 5, 3
Hidden L. Activation	Rectified Linear Unit (ReLU)
Output L. Activation	Sigmoid Function
Initialization Method	Xavier Initialization [21]
Optimization Method	Adaptive Momentum [22]

C. *Experimental Results with Analysis: Dataset B*

A second dataset was employed to further validate the results produced by the proposed model with Dataset A. All 23 channels in Dataset B are often used in some previous works for seizure detection [9, 23] in order to achieve a good performance but this often comes with the training time as a trade-off. Here, we propose a single-channel seizure detection using our proposed Distributed Kriging-Bootstrapped DNN model with an even better performance than a 23-channel model in terms of accuracy and training time. After evaluating the dataset via series of plots, the 14th channel (F8 - T8) between the frontal lobe and the temporal lobe showed more consistency than other channels in reporting seizures and was therefore selected as the single channel used in this work. This is consistent with some literature which remarked that the temporal lobe epilepsy may be the most prevalent form of epilepsy [24]. Table V compares the performance of single and multiple channels with respect to our proposed model.

TABLE V
COMPARING THE PERFORMANCES OF SINGLE AND MULTI-CHANNEL MODELS USING DATASET B.

Models	Channel Type	No of Channels	Training Accuracy	Testing Accuracy
Kriging	Single	1	68.00%	59.00%
Kriging	Multiple	23	99.70%	89.00%
Dist-Krig-DNN	Single	1	100.00%	98.53%

It is expected that 23 channels would contain more information than a single channel and produce better result. This holds true when a single-channel Kriging is compared to a multi-channel Kriging model - the multi-channel Kriging model is a clear winner as shown in Table V. However, our proposed Distributed Kriging-Bootstrapped DNN model excels on a single channel better than the multi-channel Kriging model as Table V reveals.

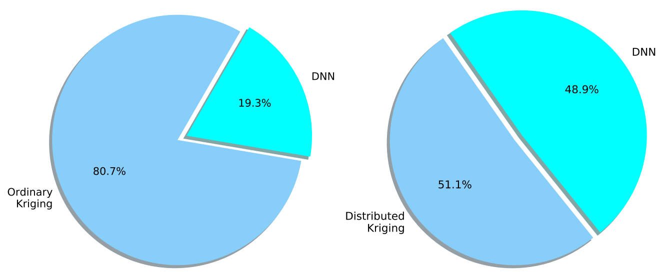
Table VI compares the best performances of a baseline DNN model with our proposed Distributed Kriging-Bootstrapped DNN model. The result shows that the training time of our proposed model is reduced by 83% compared to the baseline DNN and also trains in 20 times less training epochs. This corroborates the result obtained for Dataset A which is about 91% reduction in training time and 30 times less training epochs as shown in Table II.

Fig. 6 shows the comparison between the training time distribution of the Ordinary Kriging-Bootstrapped and the proposed Distributed Kriging-Bootstrapped DNN models. It is clear from Fig. 6(a) that Kriging occupies the larger chunk

TABLE VI
Comparing top performances for DNN and Distributed Kriging-Bootstrapped DNN models using Dataset B.

Models	Training Accuracy	Testing Accuracy	Training Epochs	Training Time
DNN	99.97%	98.53%	10000	42.03s
Dist-Krig-DNN	100.00%	98.53%	500	7.05s

of the total training time by a wide margin in the Kriging-Bootstrapped DNN model proposed in [6], with a ratio of about 4:1 for kriging against DNN. However, the Distributed Kriging-Bootstrapped DNN model proposed in this paper considerably reduced the training time ratio to about 1:1 (Fig. 6(b)) by parallelizing the Kriging computation across multiple cores. The DNN training time remains the same for both models.



(a) Training time distribution for Ordinary Kriging-Bootstrapped DNN model

(b) Training time distribution for Distributed Kriging-Bootstrapped DNN model

Fig. 6. Comparing training time distributions for Ordinary Kriging-Bootstrapped and the proposed Distributed Kriging-Bootstrapped DNN models.

VIII. Conclusions

This paper proposes a novel Distributed Kriging-Bootstrapped DNN model for a fast, accurate and seamless seizure detection from EEG signals. The emphasis in this work is to reduce training time without jeopardizing the performance of the system. This was achieved by parallelizing Kriging computation across multiple cores of a machine and then passing forward the now correlated aggregate output for a final training with a DNN. The proposed model reduces the training time by 91% compared to a baseline DNN without a compromise in performance and also trains about 3 times faster than the ordinary Kriging-Bootstrapped DNN model [6] previously proposed by the authors of this paper, with an achievement of a novel seizure detection latency of 0.8s.

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