An Investigation of Different Machine Learning Approaches for Epileptic Seizure Detection

Paulo Resque*, Alex Barros*, Denis Rosário*, and Eduardo Cerqueira*
* Federal University of Pará (UFPA), Belém – Brazil
Email: paulo.resque.souza@icen.ufpa.br, {alexbarros, denis, cerqueira}@ufpa.br

***Abstract*—Wearable devices increasing popularity provide convenient alternatives to healthcare services outside hospital premises. Wearables provide enhancements for automatic tools to assist physicians during patient diagnosis, treatment, and many other situations with limited costs and computing resources. In this context, in-device processing using machine learning algorithms can accelerate syndromes monitoring such as epilepsy detection and minimize risks of privacy disclosure due to extended data transmission to cloud servers. In this paper, we investigate the performance of five machine learning algorithms, *i.e.*, Support Vector Machine (SVM), Random Forest (RF), Naive Bayes (NB), K-Nearest Neighbor (KNN), and Neural Network (NN), in terms of accuracy to diagnose a syndrome and the computational cost to embed it in a wearable device. We tested the algorithms in the classification of an Electroencephalography (EEG) sampled dataset available at the UCI machine learning repository. From the results, we concluded that SVM and RF have good accuracy in identifying epileptic seizures from the EEG dataset. Additionally, only RF fulfills the low computational cost required to embed such applications in-device.**

***Index Terms*—Healthcare, eHealth, Wearable Devices, Machine Learning, Epilepsy Detection.**

I. INTRODUCTION

The enhancements in healthcare provide better medical therapies and life quality for individuals. As populations ages, patients with chronical diseases require frequent monitoring increasing the number of check-in at hospitals and clinics. In this scenario, wearable devices such as smartwatches, fitness tracker, smart glasses, and others, lead to a new healthcare era by allowing non-invasive diagnosis of vital and non-vital functions of the human body [1]. Wearable devices can sense, collect, and transmit physiological data continuously, where they are equipped with a radio to communicate with a gateway that sends the collected data across the Internet to a healthcare system (for processing and analysis) [2].

Patients with chronic conditions such as epilepsy require continuous monitoring. Therefore, epilepsy therapy could achieve better results with accurate information about the patient's vital signs. In this sense, wearable devices consisting of non-invasive body sensors, such as ECG (electrocardiography), EEG (electroencephalography), EMG (electromyography), accelerometer and others, could monitor the patients during diagnosis and treatment, sending physiological data to a hospital server. In this context, a relevant issue is to secure privacy and integrity during data transmission. According to Kraemer *et al.* [3], proceeding with the diagnostic in-device and transferring only the results to the cloud server enhances privacy. Additionally, some diagnosis and treatment, such as epilepsy detection, requires availability, reliability, low latency, and fast response time.

Wearable devices have the advantage to provide continuous monitoring outside the hospital with limited computing resources [2]. In this sense, in-device processing using machine learning algorithms can deliver such requirements by assisting the physician during diagnosis and treatment, such as epilepsy detection [4]. The field of machine learning applied to epilepsy detection is not new. Several algorithms were used to classify epilepsy based on EEG data, namely, NN (Neural Networks), RF (Random Forest), DT (Decision Tree), KNN (K-Nearest Neighbor), NB (Naive-Bayes), SVM (Support Vector Machine), and others. Nevertheless, wearable devices hold low computing, energy, and storage capabilities to execute the desired tasks. Hence, the payoff of computational complexity versus algorithm accuracy requires investigation.

Existing classification methods for epilepsy based on EEG data can perform in the frequency domain, time domain, or a combination of both [5]. Individually, time domain evaluates EEG based on the morphological and topological waveform characteristics, while frequency domain evaluates nonlinear waveform features. Hence, time domain analysis of EEG data provides the advantage of avoiding high complexity computations to convert voltage waveforms in its frequencies components, such as expected in wearable devices scenarios. Finally, to the best of our knowledge, these works do not focus on detecting epileptic seizures running directly in the wearable device.

In this paper, we investigate the most used machine learning algorithms, *i.e.*, SVM, RF, NB, KNN, and NN, to identify epilepsy seizures considering their applicability in a wearable devices context. Specifically, we analyze the accuracy of these algorithms to classify epilepsy in the time domain based on EEG (Electroencephalography) data. Additionally, we investigate their computational complexity, since the scenario requires a low complexity algorithm due to its constraints. Based on both analysis, we identified that SVM and RF methods could be used to identify epilepsy with high accuracy, *i.e.*, above 97% of correct epilepsy identification. However, only RF fulfills the low complexity requirement, *i.e.*, *O(n log n)*, such as expected for in-device processing. The main contributions of this paper are the following: i) analysis of different machine learning algorithms to classify epilepsy based on EEG data in the time domain; ii) computational complexity analysis of existing algorithms, and iii) applicability of machine learning algorithm on a wearable device in healthcare architecture.

The remainder of this paper is structured as follows. Section II outlines an overview of machine learning methods to classify epilepsy based on EEG dataset. Section III discuss the application scenario and methodology. Section IV discusses the machine learning performance and complexity analysis. Finally, Section V presents the concluding remarks and future works.

II. Related Work

Machine learning algorithms assist physiologists in the detection and diagnostic of epileptic seizures. In this sense, NN, SVM, DT, fuzzy logic, and others alternate the research attention. Polat and Günes [6] applied Welch FFT for feature extraction, Principal Component Analysis (PCA) for dimensioning reduction, and Artificial Immune Recognition System (AIRS) with Fuzzy resource allocation mechanism. Acharya *et al.* [7] investigated the application of convolutional NNs to review EEG recordings. Hosseini et al. [8] proposed a system composed of three tiers. In the first tier, an intracranial EEG (iEEG) sensor connected to a mobile device acquire data from the patient. In the second tier, a set of notebooks or home gateways perform feature extraction and classification. Finally, in the third tier, a cloud server stores the information for big data processing and decision making. The system filters the signal using Wavelet Transform (WT), reduces the dimensionality with Infinite Independent Component Analysis (I-ICA), and applies SVM for classification.

Cooman et al. [9] proposed an algorithm to detect Heart Rate Increase (HRI) based on ECG data to detect epilepsy. This approach considered ECG since it is easy to acquire compared to EEG for patients outside of the hospital facilities. This research combined the HRI algorithm for feature extraction with SVM for epilepsy classification. Vandercasteele et al. [10] compared the use of ECG and Photoplethysmography (PPG) sensors for epilepsy detection and correlated the results with the sensitivity of a hospital system. This approach focuses on the accuracy and convenience of using wearable devices as an alternative to hospital equipment for long periods.

The research works also alternate the feature selection between time and frequency domain. Polat and Günes [6] applied Fast Fourier Transform (FFT) to convert the EEG morphological features to the frequency domain. However, the transformation appended extra computational complexity to perform and demanded dimensionality reduction before classification. Acharya *et al.* [7] normalized the EEG signal with Z-score simplifying the feature extraction procedure. The normalization accelerates the neural network training procedure while its execution in the time domain reduced the computational complexity. Alternatively, Li *et al.* [11] proposed a time-frequency approach. Comparing the results from the related works, we conclude that the domain does not affect the algorithms classification accuracy, but working in the time domain provides less complex architectures.

The analysis of the related work exhibits high accuracy results. However, the research articles did not discuss the computational complexity nor the potential applicability of the proposed architectures in-device or edge. Moreover, the proposed architectures for epilepsy detection do not fulfill the low complexity requirements to be applicable in a wearable device context. Specifically, software for epilepsy detection running on the wearable device requires low-complex algorithm due to devices' limited processing, storage capacity, and battery lifetime. Additionally, architectures proposing data transmission to the cloud servers are subject to the security risks that need mitigation.

III. Machine Learning Approaches and Applicability in Wearable Devices

Wearable devices are becoming popular with a market boost expected soon. According to the Ericsson Mobility Report [12], the market trends point out to 19% growth in the number o/f connected IoT devices reaching 20 billion up to 2023. In this scenario, systems designed to detect epileptic seizure outside the hospital facilities might benefit from the advances in the wearable devices. In this article, we analyze the applicability of machine learning algorithms in a wearable device context. The concept behind it is to secure user's privacy, using a machine learning algorithm to process vital signs in-device or fog. In this context, epilepsy detection running on the wearable device requires low-complex algorithm due to devices limited processing, storage capacity, and battery lifetime. In this section, we introduce the methodology used for the performance analysis, and also describe the classification results.

A. Application Scenario

We considered the epileptic seizure detection problem based on the EEG analysis on a wearable device context. Specifically, epilepsy is a brain syndrome with different disturbing causes characterized by an unprovoked predisposition to recurrent seizures. It affects the human neurobiological and cognitive functions with psychological and social consequences [8]. Clinical diagnostic strongly relies on the ambulatory EEG test to conclude if the patient has epilepsy [13]. Ambulatory EEG consists on a set of electrodes fixed on the patient's scalp at predefined positions, signal amplifiers, and computer software, which registers the brain's activity as a temporal series of the potential difference between each pair of electrodes.

After the diagnostic confirmation and therapy definition, it is required to monitor the patient condition and therapy effectiveness. In this context, wearable sensors can be used to collect and transmit EEG data to the wearable device that acts as a body gateway. We consider in-device data analysis using a lightweight machine learning method on a wearable device to enable fast response time, to detect an epileptic seizure, and to transmit only the analysis result. In this way, we evaluate the performance of five machine learning algorithms to classify epilepsy based on EEG data in the time domain. We consider this approach since time domain analysis of EEG data provides the advantage of avoiding high complexity task, such as expected in wearable devices.

B. Methodology

We considered the EEG dataset available at the UCI machine learning repository[1] to train and test different classification algorithms. The dataset contains five target classes denoted from 1 to 5, as shown in Table I. Each subset includes 100 single-channel EEG segments from healthy volunteers and epileptic patients, with 23.6 seconds duration. A specialist visually inspected and selected the samples to constitute the EEG segments. Recordings from healthy individuals considered standard electrode placement scheme positioned on the scalp with patients relaxed and awake. Intra-cranial electrodes implanted for pre-surgical evaluation registered EEG data from epileptic patients.

TABLE I: Target classes for ECG dataset classification.

Class	Description
1	Recording of EEG data during seizure activity
2	Recording of EEG data from tumor area
3	Recording of EEG data from healthy brain area
4	Recording of EEG data while patients had their eyes closed
5	Recording of EEG data while patients had their eyes open

The EEG registers a distinctive discharge during epileptic seizures, where the spike-and-wave pattern in the waveform generalizes most of the epileptic syndromes. In this context, a peak lasting from 20ms to 70ms or a sharp wave between 70ms and 200ms are strong waveforms characteristics during EEG visual inspection. Using a machine learning approach enhances physician survey capabilities. In this sense, we expect the classification models to detect the pattern of an epileptic seizure. We reduced the problem to binary classification, modifying the target from numerical to categorical. Therefore, seizure (class 1) and non-seizure (classes 2 to 5).

In this paper, we considered the configuration and simulation of the algorithms in R language release 1.1.456 using the implementations of the caret package version 6.0.80. In our customization, the R script read the CSV file downloaded from UCI machine learning repository and loaded it to a data frame. Additionally, we divided the available data into subsets for training, testing, and validation. The training procedure considered the application of cross-validation 20-fold and a grid of parameters. We computed the model's accuracy from a confusion matrix. Hence, we evaluate the performance and computational complexity of five machine learning algorithms, namely, SVM, RF, NB, KNN, and NN to classify epilepsy based on EEG data in the time domain.

*1) **Support Vector Machine (SVM)**:* It is a machine learning algorithm based on the notion of a kernel. The concept behind SVM is to construct a hyperplane to work as decision surface to separate patterns. In other words, the SVM algorithm extracts a small set from training data to work as support vector and compute the inner-product kernel between the support vector and the vector of the input data set.

[1] http://archive.ics.uci.edu/ml

*2) **Random Forest (RF)**:* Random Forest is a collection of Decision Trees trained with randomly selected data. Thus, the algorithm guarantees that each tree is slightly different from each other. Hence, each tree may return a distinct result for a given dataset. The RF algorithm classifies the data based on a voting system involving the results from the individual trees. Specifically, direct voting count how many trees classified a given feature under a particular class. Additionally, weighted voting returns the ratio of elements belonging to a given group.

Random Forest performs better than Decision Trees in two aspects, namely, overfitting and anomaly detection. During the RF training process, the outliers will be present in some of the trees but not in all of them, and thus the voting system guarantees the anomalies will be isolated. The voting system also minimizes the effect of overfitting concerning the individual decision tree. However, RF has problems to extrapolate data. Specifically, attribute values in the validation set must be within the value limits of the training set. Not trained or out-of-limit attributes may lead to unpredictable results when included in the validation set.

*3) **Naive-Bayes (NB)**:* Naive-Bayes is a probabilistic classification method based on the BAYES' rule. BAYES theorem definition derives from the conditional probabilistic theory [14]. It associates the occurrence probability of an effect A based on the certainty that an event B happened before (Eq. 1).

$$P(A|B) = \frac{P(A) * P(B|A)}{P(B)} \tag{1}$$

Where,

- $P(A|B)$, the conditional probability of B to occur knowing that A occurred.
- $P(A)$, the probability of the event A to occur
- $P(B|A)$, the conditional probability of A to occur knowing that B happened.
- $P(B)$, the probability of the event B to occur. This can be either known a priori or can be computed as $P(B) = \sum_A P(B|A) * P(A)$.

The algorithm initializes the probabilities for the outcome variables and adjusts it in each interaction based on what happened with the other variables in the dataset.

*4) **K-Nearest Neighbor (KNN)**:* It classifies data based on the distance, usually Euclidian distance, between a particular data point and its *k* neighbors. The KNN algorithm has a great heritage of possible applications, such as elderly fall detection, epilepsy seizures detection, and many others. KNN has the advantage of making no initial assumption about the data set because it merely groups the data points based in a neighborhood. However, the algorithm stores all training data, and only stops when all data is classified. Differently, from the other models discussed in this work, KNN does not require training.

*5) **Neural Networks (NN)**:* Neural Networks is a machine-learning method inspired in the behavior of natural neurons, capable of classifying linear and non-linear data. Multi-Layer Perceptron (MLP) is a network architecture with a variable number of artificial neurons arranged in one input layer, one or more hidden layers, and one output layer. MLP propagates a stimulus injected into the neurons on the input layer, through the connected neurons in the hidden layers, and reflecting in the results in the output layer. Training the MLP is commonly implemented with Back-Propagation algorithm, executing in two phases:

- forward phase: the algorithm fixes the weights of each neuron, injects the stimulus and propagates it to the output layer.
- backward phase: the algorithm calculates the error between the obtained and desired outputs, back-propagates the error in the network, and adjusts the neuron's weights in the way back.

The training process repeats the forward and backward phases for a certain number of interactions. In each round the algorithm focus on minimizing the error between the actual and the desired output. The training process stops when the error falls below a threshold, or the algorithm reaches the maximum number of interactions.

IV. Evaluation Metrics and Results

The machine learning evaluation metric expresses how good is the model in achieving its purpose comparing with chance. The standard metrics for binary classification problems using R caret package are Accuracy and Kappa. Specifically, Accuracy is the relation between the correct classified instances of the problem over the total number of instances, as expressed in Eq. 2.

$$Accuracy = \frac{CorrectlyClassifiedInstances}{AllInstances} \tag{2}$$

On the other hand, kappa complements the Accuracy interpretation normalizing the results with chance. In this sense, Kappa compares the observed accuracy with the expected accuracy if the classification results occurred by chance, as expressed in Eq. 3.

$$Kappa = \frac{ObservedAccuracy - ExpectedAccuracy}{1 - ExpectedAccuracy} \tag{3}$$

Figure 1 shows the Accuracy and Kappa results for five machine learning algorithms to classify epilepsy based on the EEG dataset. Examining the outcome, we observed that SVM and RF achieved the highest accuracy values turning into good candidates for applicability in a wearable device context. In the one hand, the SVM with radial kernel achieved 97.31% of accuracy. Additionally, the R script generated a model with 5.3MB, which makes it adjustable to any gateway, a Smartphone for instance. Nevertheless, training the SVM has *O*(n^3) complexity [15]. When the algorithm requires frequent updating to maximize accuracy, the computational complexity is challenging.

The RF model achieved an accuracy of 97.08% with 95% confidence interval. This result is statistically equal to the accuracy of SVM. However, RF is easy to implement and interpret, fast to train, and performs well for a small dataset. The implementation complexity increases in scenarios with high data volumes, but Choromanska and Langford [16] proposed an algorithm to training and retrieve information from the trees with *O(log k)* complexity. In this sense, RF constitutes a better candidate for applicability in a wearable device context compared with the SVM model. Additionally, the R script generated a model with 6.9MB, which fits such as Smartphone.

The NB model reached an accuracy of 95.98%, which is 1.67% above the lower accuracy limit and 1.10% below result achieved by RF. NB has the advantage of being simple to train and recover, where its computational complexity is equivalent to *O(mn)* with *m* equals to the number of features, and *n* equals to the number of instances, as presented by Ahmadi *et al.* [17]. However, for large dataset, such as the physiological streams, the dimensions for *m* and *n* are equals. In this sense, the complexity turns to quadratic.

The NN model achieved an accuracy of 93.53%, which is closer to the defined lower limit. The NN trained with the Backpropagation may converge to a local minimum, and thus the network will not achieve the optimum result. Therefore, the NN requires periodic training to enhance generalization capability when it starts lacking precision. In this context, the computational complexity to train the network is time-consuming for the application perspective. As discussed by Bilski *et al.* [18], training a neural network with an optimized algorithm such as Levenberg-Marquardt is equivalent to *O*(n^2) using parallel processing.

The KNN algorithm groups the nearest neighbors to the k initial centroids using a distance metric, *e.g.*, euclidian distance. The algorithm is space-consuming since it tries to accommodate all instances in the model to the memory physical limit [19]. For the analyzed dataset, our R script generated a model with 8.7MB, which occupies 64% more space usage than the SVM model. This characteristic turns to a problem when considering the limited resources for wearable applications. Additionally, for the analyzed dataset the KNN model did not achieve the minimum accuracy we defined.

Table II summarizes the results achieved in this work. We present the accuracy, computational complexity, and possible applicability in a wearable device context. The analysis considers A (for Applicable) or N/A (for Not Applicable). In this sense, SVM and RF present comparable outcomes. However, RF has lower computational complexity confronted with SVM. Hence, low computational complexity is an advantage in scenarios when the design requires continuous training to enhance accuracy. Thus, RF is a better choice for applications in a wearable context.

V. Conclusion and Future Works

In this paper, we investigated the accuracy and complexity of five machine learning models in a wearable device context. We considered the epileptic seizure detection problem in the time domain in a wearable application scenario. Hence, we minimized the architectural complexities associated with

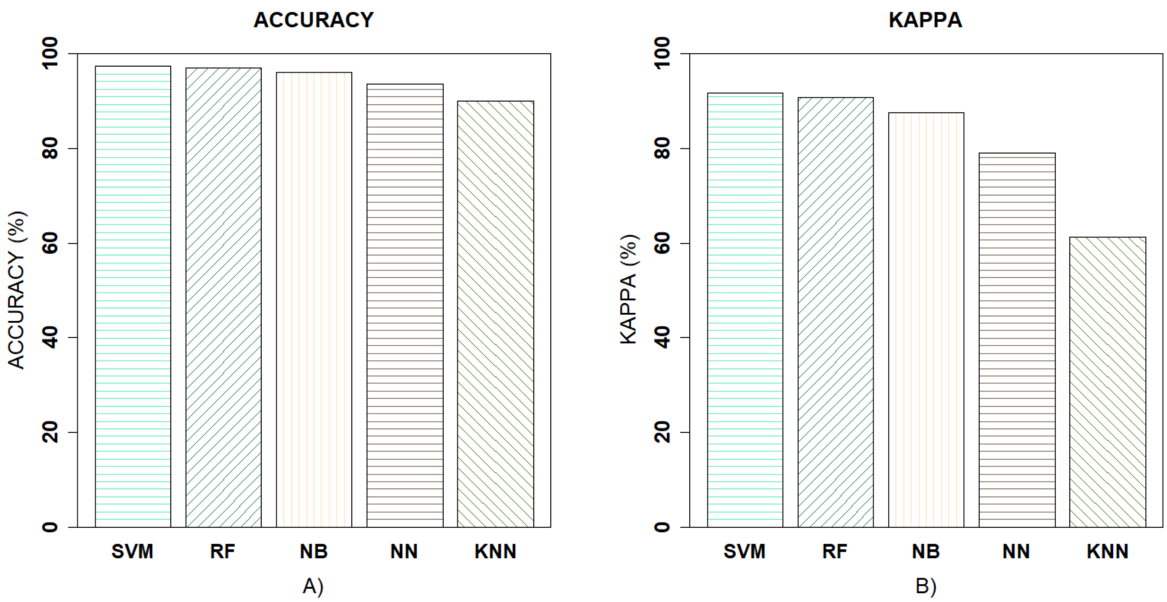

Fig. 1: Results from Tested Algorithms (**A**) Accuracy. (**B**) Kappa

TABLE II: Accuracy results and complexity for the verified models

Algorithm	Accuracy (%)	Computational Complexity	Applicability in Wearable
SVM	97.31	$O(n^3)$	N/A
RF	97.08	$O(n \log n)$	A
NB	95.98	$O(m\ n)$	N/A
NN	93.53	$O(n^2)$	N/A
KNN	90.01	space $O(n)$	N/A

feature transformation. According to the outcomes, we conclude that SVM and RF achieve good accuracy in classifying epilepsy in the time domain based on morphological EEG features. Additionally, RF produces acceptable computational complexity as expected for a wearable device application. Based on these conclusions, we move our investigations to an implementation level. We will focus our efforts on a test-bed to prove the concept and in investigating other potential application scenarios, *e.g.*, ECG.

Acknowledgments

We would like to acknowledge the financial support obtained from RNP-NSF for the project HealthSense: Assessing and Protecting Privacy in Wireless Wearable Sensor-generated Medical Data.

References

[1] M. Stoppa and A. Chiolerio, "Wearable Electronics and Smart Textiles: A Critical Review," *Sensors*, vol. 14, no. 7, pp. 11 957–11 992, 2014.

[2] S. Seneviratne, Y. Hu, T. Nguyen, G. Lan, S. Khalifa, K. Thilakarathna, M. Hassan, and A. Seneviratne, "A survey of wearable devices and challenges," *IEEE Communications Surveys & Tutorials*, 2017.

[3] F. A. Kraemer, A. E. Braten, N. Tamkittikhun, and D. Palma, "Fog computing in healthcare - a review and discussion," *IEEE Access*, vol. 5, pp. 9206–9222, 2017.

[4] M. Baig, H. GholamHosseini, A. Moqeem, F. Mirza, and M. Lindén, "A systematic review of wearable patient monitoring systems–current challenges and opportunities for clinical adoption," *Journal of medical systems*, vol. 41, no. 7, p. 115, 2017.

[5] P. P. M. Shanir, K. A. Khan, Y. U. Khan, O. Farooq, and H. Adeli, "Automatic seizure detection based on morphological features using one-dimensional local binary pattern on long-term eeg," *Clinical EEG and Neuroscience*, 2017.

[6] K. Polat and S. GÃijnes, "Artificial immune recognition system with fuzzy resource allocation mechanism classifier, principal component analysis and fft method based new hybrid automated identification system for classification of eeg signals," *Expert Systems With Applications*, vol. 34, pp. 2039–2048, 2008.

[7] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, and H. Adeli, "Deep convolutional neural network for the automated detection and diagnosis of seizure using eeg signals," *Computers in Biology and Medicine*, vol. 100, pp. 270 – 278, 2018.

[8] M.-P. Hosseini, A. Hajisami, and D. Pompili, "Real-time epileptic seizure detection from eeg signals via random subspace ensemble learning," in *In Proceedings of IEEE International Conference on Autonomic Computing*. IEEE, 2016.

[9] T. De Cooman, C. Varon, B. Hunyadi, W. Van Paesschen, L. Lagae, and S. Van Huffel, "Online automated seizure detection in temporal lobe epilepsy patients using single-lead ecg," *International Journal of Neural Systems*, vol. 27, 2017.

[10] K. Vandecasteele, T. De Cooman, Y. Gu, E. Cleeren, K. Claes, W. V. Van Paesschen, S. V. Huffel, and B. Hunyadi, "Automated epileptic seizure detection based on wearable ecg and ppg in a hospital environment," *Sensors*, vol. 17, no. 10, 2017.

[11] Y. Li, X. Wang, M. Luo, K. Li, X. Yang, and Q. Guo, "Epileptic seizure classification of eegs using timeâĂŞfrequency analysis based multiscale radial basis functions," *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 2, pp. 386–397, March 2018.

[12] E. AB, "Ericsson mobility report," Available at https://www.ericsson.com/assets/local/mobility-report/documents/2017/ericsson-mobility-report-november-2017-central-and-eastern-europe.pdf (2019/04/19), 2017.

[13] W. Tatum, G. Rubboli, P. Kaplan, S. Mirsatari, K. Radhakrishnan, D. Gloss, L. Caboclo, F. Drislane, M. Koutroumanidis, D. Schomer *et al.*, "Clinical utility of eeg in diagnosing and monitoring epilepsy in adults," *Clinical Neurophysiology*, vol. 129, no. 5, pp. 1056–1082, 2018.

[14] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. MIT Press, 2016, http://www.deeplearningbook.org.

[15] A. Abdiansah and R. Wardoyo, "Time complexity analysis of support vector machines (svm) in libsvm," *International Journal of Computer Applications*, vol. 128, 2015.

[16] A. E. Choromanska and J. Langford, "Logarithmic time online multiclass prediction," in *Advances in Neural Information Processing Systems 28*, C. Cortes, N. D. Lawrence, D. D. Lee, M. Sugiyama, and R. Garnett, Eds. Curran Associates, Inc., 2015, pp. 55–63.

[17] H. Ahmadi and R. Bouallegue, "Comparative study of learning-based localization algorithms for wireless sensor networks: Support vector regression, neural network and na amp;x00ef;ve bayes," in *2015 International Wireless Communications and Mobile Computing Conference (IWCMC)*, Aug 2015, pp. 1554–1558.

[18] J. Bilski, J. Smoląg, and J. M. Żurada, *Parallel Approach to the Levenberg-Marquardt Learning Algorithm for Feedforward Neural Networks*. Springer International Publishing, 2015, pp. 3–14.

[19] A. Lodwich, F. Shafait, and T. M. Breuel, "Efficient estimation of k for the nearest neighbors class of methods," *CoRR*, vol. abs/1606.02617, 2016.