Detection of early Parkinson's disease with wavelet features using finger typing movements on a keyboard

Atemangoh Bruno Peachap^{1,2} · Daniel Tchiotsop² · Valérie Louis-Dorr³ · Didier Wolf³

Received: 17 April 2020 / Accepted: 31 August 2020 / Published online: 5 September 2020
© Springer Nature Switzerland AG 2020

Abstract

This study presents a new Parkinson's disease diagnosis technique based on wavelets extracted features and machine learning paradigms. The present-day diagnosis techniques suffer from low diagnosis accuracy and also require the patient to go to a medical facility, where the diagnosis is done by a specialist. In this work, we propose an automatic diagnosis method where by, all the patient has to do is to type some keys on their keyboard, and the algorithm will calculate the latency time, flight time and hold time of each key pressed, to make a diagnosis of Parkinson's disease. We use several wavelets to extract some features that are classified into Parkinson's disease or non-Parkinson's disease. The results are very encouraging and we obtain a classification accuracy of up to 100% in some of the cases, using a ten-fold cross-validation technique. Wavelets are a tool that can be used to complement and improve the detection of Parkinson's disease. These results will permit the amelioration of some state-of-the-art methods which use a similar technique to detect Parkinson's disease.

Keywords Parkinson's disease · Wavelets · Machine learning · Ten-fold cross-validation

1 Introduction

Parkinson's disease (PD) is a progressive neurological movement disease that is characterized by degenerative effects on mobility and muscle control [1]. It is the most common neurodegenerative disease after Alzheimer's disease affecting about 1% of persons aged 60 and above [2, 3]. There is presently no cure for Parkinson's disease and available medication just helps to manage the symptoms of the disease [4]. More so, the diagnosis of PD is done by trained specialists with a relatively high misdiagnosis rate and they use the Unified Parkinson's Disease Rating Scale (UPDRS) which is composed of four subscales used to evaluate specific motor tasks [5]. It has been modified and two more subscales added by the Movement Disorder Society-Sponsored Revision of the Unified Parkinson's

Disease Rating Scale (MDS-UPDRS). This is a comprehensive 50 question assessment of both motor and non-motor symptoms associated with Parkinson's used as a diagnostic tool. One of the problems relative to PD is that the frequency of diagnosis and follow up of the disease is limited due to the need for these trained specialists who have a mastery of these tools.

In recent years, many researchers have thought of techniques for diagnosing PD which do not entail trained specialists or a complex medical environment. In some studies, the authors use touch screen data from several users of smart phones in order to detect PD [6, 7]. Meanwhile in others, the authors use drawing movements as a biomarker to determine the motor impairments related to early PD symptoms [8]. Another technique is the detection of PD by finger typing on a usual keyboard [9, 10]. The

✉ Atemangoh Bruno Peachap, peachapbruno2013@gmail.com | ¹Unité de Recherche de Matière Condensée d'Electronique et de Traitement du Signal (UR-MACETS), Faculty of Science, University of Dschang, P.O. Box 69, Dschang, Cameroon. ²Unité de Recherche d'Automatique et d'Informatique Appliquée (LAIA), IUT-FV de Bandjoun, University of Dschang, P.O. Box 134, Bandjoun, Cameroon. ³Centre de Recherche en Automatique de Nancy (CRAN), UMR CNRS 7039, ENSEM, Université de Lorraine, Nancy, France.

idea is to measure the hold time of the keystrokes, which serve as data in a machine learning paradigm. The data is further analyzed, and features are extracted to compute using a machine learning algorithm the presence of PD or not. Several studies have been undertaken in this domain, yielding encouraging results.

In one of these studies, data were collected through software for the detection and classification of PD which consisted of 13 healthy controls and 18 PD sufferers for the first set as well as 30 healthy controls and 24 PD sufferers for the second set [11]. The authors devised a PD motor index that was used to determine the presence or not of PD. They used the hold time of each key to compute a 'neuroQwerty' index from which several features were devised aiming at classifying PD and non-PD patients with AUC results ranging from 0.61 to 0.81. A recent study was published in 2016 and showed that the results obtained with the data in the study in [11] can be achieved with a normal runtime keyboard [12]. The authors used the same method to confirm the 'neuroQWERTY' Approach in an Uncontrolled At-Home Situation of the participants. Within the same context, a similar study was carried out in Australia, with another database obtained through 'tappy' software installed in the computers of volunteers [13]. The database is more complex and can distinguish between PD patients who are on treatment and those who are not, PD patients with tremors or not, as well as non-PD patients. The authors used a feature extraction method and an ensemble of several classifiers which they obtained results of up to 98% classification accuracy.

Wavelets are a very important tool in the field of signal processing, and they are applied in several domains like medicine and engineering to perform tasks such as data compression, signal denoising, signal classification, etc. More so, they are popular due to the existence of algorithms that can compute wavelet coefficients fast such as the fast wavelet transform (FWT) algorithm [14, 15]. Many authors have devised several techniques to construct wavelets in the literature, which all started with the need to ameliorate the limits of the Fourier transform [16, 17]. Indeed, the Fourier transform is useful to analyze the frequency components of stationary signals, but when the signal is non-stationary (The frequency varies with time), the Fourier transform cannot tell at what time a particular frequency component occurs. This is a fundamental property that makes wavelets more performant in several signal processing tasks [18]. Wavelets have been widely used in the literature for the resolution of machine learning problems like the classification of electroencephalography (EEG), electrocardiograph (ECG) signals. Fundamentally, wavelets are digital filters that are used to extract distinctive features within a dataset. They are used alongside a machine learning paradigm like Artificial

neural networks (ANN), support vector machines (SVM), and K-nearest neighbor (K-NN) classifiers to improve the classification accuracy and the computation time of the classifiers [19, 20].

Our work is aimed at investigating the influence of wavelets extracted features of PD data on the classification accuracy of some machine learning paradigms. The objective is to ameliorate the detection accuracy of some existing techniques in the classification of PD and non-PD cases. The originality of this work is from the method, which is the use of wavelets for features extraction and four classification models with the tenfold cross validation technique. The results obtained are very encouraging and are destined to ameliorate the early detection of Parkinson's disease technique proposed by [13].

This paper is divided as follows. In section one, we introduce PD and some work done in the literature. Section two is a presentation of the materials and methods used in this work. In section three, we present the results obtained from this research and discuss them. We end this paper with a conclusion.

2 Materials and methods

This section gives a description of the materials and methods used in carrying out this research.

2.1 The database

The data used in this work is part of the data from [13] where it is shown that several features present in a keyboard typing task can be extracted, including the reaction speed, Jerkiness of motion, Variability of movement and signs of hand and finger tremors. The typing keystroke dynamics of participants with a computer keyboard were captured as they typed normally with the software 'Tappy'. Three main events are of interest here, the hold time (the time elapsed between a key down and a key up when a key is pressed and released), the latency (the time elapsed between the key down of one key to the key down of another key) and the flight time (the time elapsed between the release of a key and the pressing of the next key. It is also the difference between the latency time and the hold time). This study was carried out between July 2016 and March 2017 with the approval of the Human Research Ethics Committee (HREC) at Charles Sturt University, protocol number H17013 and the informed consent of all participants (between the ages of 50 and 80) as well as the anonymity of both participants and their data. Although the complete dataset comprised of 217 participants, only some were included in the analysis like those with more than 2000 keystrokes, and those not taking Levodopa

Table 1 Summary of the participant's data

Characteristic	All participants		Subset used in this study	
	Number	Percentage	Number	Percentage
<i>Disease status</i>				
PD	162	75	22	42.3
Non-PD	55	25	30	57.7
Total	217	100	52	100
<i>Gender</i>				
Male	116	53	28	53.8
Female	101	47	24	46.2
<i>PD tremors</i>				
Yes	97	60	12	54.5
No	65	40	10	45.5
<i>Severity</i>				
Mild	68	42	22	100
Medium	70	43		
Severe	24	15		
<i>Sidedness</i>				
Left	49	30	8	36.4
Right	60	37	9	40.9
None	53	33	5	22.7

medication, which could prevent the effect of the disease on the keystroke features. Table 1 below summarizes the data of the participants and their characteristics.

For the distinction between the various classes, we use wavelets to extract some features from the signals.

2.2 The methodology

The part of the data set that respected the criteria enumerated in Sect. 2.1 was selected for analysis and classification. The three main properties of the date (Hold time, latency time and flight time) are those that are of interest to our study. Some participants had more data than was needed, so their data was divided into several parts, each part containing 8000 samples. The data in total is made up of 286 true PD samples and 203 false PD samples. We used the MATLAB R2016b software running on a 64 bits windows 10 operating system for the experiments.

2.2.1 Feature extraction

We used several wavelets (Daubechies, discrete Laguerre and biorthogonal) to extract features from the three data properties. Each data characteristic vector was decomposed at level 4 and for each level, we computed the maximum, minimum, mean, standard deviation, logarithmic entropy, Shannon entropy, and percentage power of the wavelet coefficients. For each data sample, we also

included a temporal feature, total variation as well as some spectral features like the standard deviation, mean and maximum of the fast Fourier transform of the sample. The features vector is made up of 35 wavelet features, one temporal feature and three spectral features for each data characteristic, making a total of 39×3 features. The choice of these features was geared towards achieving the best classification performances for most of the cases. (Table 2).

2.2.2 Classification

The 489×117 matrix which constitutes the features is used as input to several classifiers like the Pattern recognition artificial neural network (PR-ANN), the SVM, the K-NN and the Logistic regression classifiers. In order to avoid over fitting the data, we use the tenfold cross-validation technique. Here, the data is divided into 10 equal parts or folds, and for each iteration, 90% of the data is used for training and 10% for validation. This process is repeated 10 times, with each fold used as validation data in a rotatory manner. For each iteration, the performance of the classifier is calculated, and the final performance is the average of all the iterations [21].

One of the classifiers used is the SVM which is a supervised machine learning technique that is capable of solving linear and non-linear classification and regression problems [22]. In this work, we have used the quadratic kernel function for the SVM. The other classifier used is the artificial neural networks which emanate from the idea of emulating the human brain and they are capable of acquiring knowledge by learning and store it within the interneuron connections called weights. Although many types of Feed-forward architectures exist, multilayer perceptron and radial basis functions are the most popular architectures used by many researchers [23]. In our work, we have used the feed-forward back-propagation neural network with one hidden layer. The number of neurons in the hidden layer is chosen to be 80 with the aim to give the best possible results for the smallest number of neurons. The training function used is the scaled conjugate gradient function and the activation function used in this work is the 'tansig' function. The third classifier used is the K- nearest neighbor classification algorithm and it is a supervised machine learning model that classifies data based on the distances (feature similarity) between the

Table 2 Summary of the feature vectors

Features	Wavelets	Temporal	Spectral	Total
Hold time	35	1	3	39
Latency	35	1	3	39
Flight time	35	1	3	39

various data points [24]. The choice of K is crucial for the classification accuracy of the model so we computed 10 nearest neighbors as the most accurate number for K and we used the popular Euclidean distance metric. Finally, we have used the logistic regression algorithm also popularly used for data classification which is based on the probability of data to belong to a particular Class using a logistic function [25]. With logistic regression, we used a function called the Sigmoid function and also referred to as the logistic function which helps to limit the response between '0' and '1' [26].

3 Presentation of results

The results obtained from this work are presented in this section.

3.1 Detection of PD using various wavelets

We have used several wavelets to extract features from the PD database, which serve various classifiers for the detection or not of PD. In Tables 3 and 4, we present the sensitivity, specificity, and classification accuracy results

Table 3 Classification accuracy for the various wavelets using PR-ANN and SVM classifiers for a tenfold cross-validation

Wavelets	PR-ANN SEN	Q-SVM SPE	PR-ANN ACC	Q-SVM SEN	PR-ANN SPE	Q-SVM ACC
<i>Discrete laquerre</i>						
dLag1	100	100	100	99.9	99.9	99.9
dLag2	99.8	99.9	99.9	99.3	99	99.2
dLag3	100	100	100	97.2	96.1	96.7
dLag4	99.3	99	99.2	99.6	99.5	99.6
dLag5	95.4	93.1	94.5	97.6	96.5	96.3
<i>Daubechies</i>						
db1	99.5	99.6	99.6	99	99	99
db2	99.9	99.9	99.9	99.6	99.8	99.8
db3	99.8	99.8	99.8	100	100	100
db4	99.8	99.7	99.8	99.6	99.9	99.8
db5	100	100	100	99.9	99.8	99.9
<i>Biorthogonal</i>						
Bior1.1	99.8	99.7	99.8	96.2	94.5	95.5
Bior1.3	100	100	100	99.8	99.6	99.8
Bior1.5	99.9	99.6	99.8	96.9	95.5	96.3
Bior2.2	95.8	94.1	95.1	97.9	97	97.5
Bior2.4	94.8	92.6	93.9	100	100	100
<i>Reverse biorthogonal</i>						
Rbio1.1	99.7	99.9	99.8	99.7	99.7	99.7
Rbio1.3	100	100	100	99.9	99.9	99.9
Rbio1.5	98	97	97.5	99	98.5	98.7
Rbio2.2	96.9	95.6	96.3	95.1	93.1	94.2
Rbio2.4	100	100	100	99.9	99.9	99.9
<i>Coiflets</i>						
Coif1	99.8	99.7	99.8	99.6	99.5	99.6
Coif2	96.8	95.6	96.3	99.3	99	99.2
Coif3	100	100	100	99.9	99.9	99.9
Coif4	99.9	99.9	99.9	95.8	94.1	95.1
Coif5	99.8	99.6	99.8	99.8	99.8	99.8
<i>Symlets</i>						
Sym2	100	100	100	99.7	99.5	99.6
Sym3	97	97	97	94.6	92.6	93.7
Sym4	99.9	99.7	99.8	99.9	99.8	99.9
Sym5	97.2	96.1	96.7	95.5	93.6	94.7
Sym6	98.3	97.5	98	99.8	99.7	99.8

Table 4 Classification accuracy for the various wavelets using KNN and Logistic regression classifiers and a tenfold cross-validation

Wavelets	KNN			Logistic Regression		
	SEN	SPE	ACC	SEN	SPE	ACC
<i>Discrete laguerre</i>						
dLag1	99.6	99.5	99.6	99	99	99
dLag2	98.6	98	98.4	97.2	96.1	96.7
dLag3	100	100	100	99.9	99.9	99.9
dLag4	99.9	99.8	99.7	99	98.5	98.6
dLag5	99.9	99.9	99.9	99.9	99.9	99.9
<i>Daubechies</i>						
db1	99.8	99.4	99.6	100	100	100
db2	99.9	99.7	99.9	99.9	99.7	99.8
db3	99.8	99.8	99.8	100	100	100
db4	99.9	99.9	99.9	99.8	99.6	99.7
db5	96.8	95.6	96.3	97.9	97	97.5
<i>Biorthogonal</i>						
Bior1.1	99.7	99.5	99.6	99.5	99.4	99.5
Bior1.3	98.6	98	98.4	99.8	99.5	99.7
Bior1.5	98	97	97.5	99.5	99.3	99.4
Bior2.2	99.9	99.9	99.9	100	100	100
Bior2.4	99.6	99.4	99.5	99.8	99.7	99.8
<i>Reverse biorthogonal</i>						
Rbio1.1	97.2	96	96.7	99.8	99.8	99.8
Rbio1.3	99.9	99.7	99.9	99.7	99.5	99.6
Rbio1.5	96.5	95.1	95.6	96.2	94.6	95.5
Rbio2.2	99.9	99.9	99.9	100	100	100
Rbio2.4	95.1	93.1	94.3	95.8	94.1	95.1
<i>Coiflets</i>						
Coif1	94.4	92.1	93.5	97.6	96.6	97.1
Coif2	99.8	99.5	99.7	99.9	99.7	99.8
Coif3	99.9	99.7	99.8	98.3	97.5	98
Coif4	100	100	100	99.9	99.9	99.9
Coif5	99.8	99.6	99.7	99.7	99.5	99.6
<i>Symlets</i>						
Sym2	99.3	99	99.2	99	98.5	98.6
Sym3	97.9	97	97.5	98	97	97.5
Sym4	99.7	99.5	99.6	99.6	99.5	99.6
Sym5	99.8	99.5	99.7	99.9	99.7	99.8
Sym6	97.6	96.6	97.1	99.3	99	99.2

obtained from these experiments using a tenfold cross validation-technique.

3.2 Receiver operating characteristics-area under the curve (ROC-AUC) for some of the cases.

For a two-class classification problem, the AUC of a ROC is a plot of the true positive rate versus the false positive rate. Some of the ROC-AUC characteristics are plotted in Fig. 1.

3.3 Discussion

We have used the first five members of the Laguerre wavelets alongside other benchmark wavelets like the Daubechies wavelets, biorthogonal wavelets, reverse biorthogonal wavelets, Coiflets, and Symlets to extract the wavelet features of the PD data. Our work is important because, not only do we propose a novel approach to the detection of PD, but the results obtained are as high or even higher than several other methods proposed in the literature. We therefore contribute to improve the classification accuracy in the detection of PD by machine learning. Most of the

Fig. 1 Some ROC-AUC results of Db 5 wavelet and PR-ANN classifier with a tenfold cross-validation

techniques used in this work have already been used in one form or the other. To the best of our knowledge, no author has associated all of these techniques the way we have. The novelty here is in that, we use wavelets to extract features associated with other temporal and spectral features which are sent to four machine learning algorithms for classification. The tenfold cross validation technique

used prevents over fitting the data thus the technique is more robust.

From the results presented in Tables 3 and 4 it can be seen that, the Laguerre wavelets perform the same, if not, they are better than some other wavelets. For this task, the Laguerre 1 and Laguerre 3 both have a 100% classification accuracy, while the minimum classification accuracy

Table 5 Overall classification performance classification results obtained for PD finger tapping methods using different approaches

Authors	Year	Methods	Accuracy (%)
Shimoyama et al. [9]	1990	Single key tapping	61
Taylor Tavares et al. [10]	2005	Alternating finger tapping	75
Giancardo et al. [11]	2016	The Neuro-QWERTY approach	81
Adams [13]	2017	Ensemble machine learning classification models	97–100
Teresa et al. [12]	2018	Validation of the Neuro-QWERTY approach	76–83
Our study	2020	Wavelets features and machine learning classifiers	93.5–100
		PR-ANN	93.9–100
		Q-SVM	93.7–100
		KNN	93.5–100
		LR	95.1–100

for the Laguerre family is the Laguerre 5 wavelet (94.5%). The Daubechies wavelets also performed well with 100% accuracy in almost all of them for the various classifiers. The minimum classification accuracy for The Daubechies wavelets is 95.6% using db5 with the KNN classifier. The biorthogonal wavelets also have a good performance with 100% classification accuracy for some of the classifiers and minimum classification accuracy of 93.9% with bior2.4. The reverse biorthogonal wavelets have a classification accuracy of 100% for rbio1.3 and rbio2.4, with a minimum classification accuracy of 94.2% for rbio2.2 with the Q-SVM classifier. With Coiflets, the coif3 and coif4 wavelets both have a 100% classification accuracy performance, meanwhile, the minimum performance stands at 93.5 for coif1 and the KNN classifier. Symlets have a maximum performance of 100% classification accuracy for sym2 and PR-ANN, while the minimum classification accuracy performance is 93.7 with Sym3 and Q-SVM classifier.

In Fig. 1, we present some ROC-AUC plots of the experiments conducted in Tables 3 and 4. We have observed that, for this two-class classification problem, the AUC of the ROC is proportional to the accuracy of classification. The results obtained in this research are compared to those obtained by other authors to perform a similar task, but using different techniques.

From Table 5, we can observe that the classification accuracy for PD detection using the finger tapping method has improved over the years. In our study, we have used several wavelets to extract features from a PD database and used these features alongside four machine learning models to discriminate between PD and non-PD data. Our study shows a CA of 93.5 to 100% depending on the wavelet and classifier used. This is better than the single key tapping method by Shimoyama et al. [9] (61%), or the alternating finger tapping by Taylor Tavares et al. [10] (75%), or the The Neuro—QWERTY approach by Giancardo et al. [11] (81%). Our results are similar to the Ensemble machine learning classification models method used by Adams [13] (97–100%). We have presented a novel approach to the

resolution of the problem, which has yielded a higher classification accuracy than most of the existing methods.

4 Conclusion

The objective of this research work is to classify Parkinson's disease signals gotten from keystrokes using wavelets features and machine learning paradigms. We have proposed a novel approach to detect PD from several wavelet and spectral features extracted from the data and classified these using four classification models with the tenfold cross-validation technique. The results obtained from the classification of PD using several benchmark wavelets are better than most state-of-the-art methods. We are reporting classification accuracies ranging between 93.5–100% with the tenfold cross-validation technique depending on the wavelet and the classifier used. This makes the process accurate, robust and prevents data over fitting. Although the method used in this work has already been used in one form or the other, to the best of our knowledge, no author has associated all of these techniques the way we have. These results are very important in the biomedical signal processing field because, the detection accuracy results of early PD and its diagnostic methods can be ameliorated with this method. More so, there is a limited need for medical experts who are supposed to have a mastery of the MDS-UPDRS in order to diagnose PD. The main limitations of this work rely in the small dataset dimension, and there are no details concerning the mean and std values of the UPDRS test for PD patients. We have simply classified the data into PD or non-PD. More so, there was no examination of cognitive abilities using MMSE test. The participants to the study are volunteers who based on their health history confirmed to be diagnosed of PD or not. In the future, we will write a web based program which will detect PD from wavelets extracted features of user typing data and artificial neural networks.

Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

1. Demaagd G, Philip A (2015) Parkinson's disease and its management: part 1: disease entity, risk factors, pathophysiology, clinical presentation, and diagnosis. *Pharm Therap* 40:504
2. Esmail S (2018) The diagnosis and management of Parkinson's disease. *Sch J Appl Sci Res* 1(9):13–19
3. De Lau M, Breteler M (2006) Epidemiology of Parkinson's disease. *Lancet Neurol* 5(6):525–535
4. Tarakad A, Jankovic J (2017) Diagnosis and management of Parkinson's disease. *Semin Neurol* 37(2):118–126
5. Martínez-Martín P, Gil-Nagel A, Gracia LM, Gómez JB, Martínez-Sarriés J, Bermejo F (1994) Unified Parkinson's disease rating scale characteristics and structure. The cooperative multicentric group. *Mov Disord* 9(1):76–83
6. Dimitrios I, Stelios H, Vasileios C, Sevasti B, Zoe K, Lisa K, Heinz R, Sofia D, José D, Dhaval T, Chaudhuri R, Kallol HL (2018) Motor impairment estimates via touchscreen typing dynamics toward Parkinson's disease detection from data harvested in-the-wild. *Front ICT* 5:28. <https://doi.org/10.3389/fict.2018.00028>
7. Iakovakis D, Hadjidimitriou S, Charisis V (2018) Touchscreen typing-pattern analysis for detecting fine motor skills decline in early-stage Parkinson's disease. *Sci Rep* 8:7663. <https://doi.org/10.1038/s41598-018-25999-0>
8. Gil-Martín M, Montero JM, San-Segundo R (2019) Parkinson's disease detection from drawing movements using convolutional neural networks. *Electronics* 8:907. <https://doi.org/10.3390/electronics8080907>
9. Shimoyama I, Ninchoji T, Uemura K (1990) The finger-tapping test. A quantitative analysis. *Arch Neurol* 47:681–684
10. Taylor Tavares A, Jefferis G, Koop M, Hill B, Hastie T, Heit G, Bronte-Stewart H (2005) Quantitative measurements of alternating finger tapping in Parkinson's disease correlate with UPDRS motor disability and reveal the improvement in fine motor control from medication and deep brain stimulation. *Mov Disord* 20:1286–1298
11. Giancardo L, Sánchez-Ferro A, Arroyo-Gallego T, Butterworth I, Mendoza CS, Montero P, Matarazzo M, Obeso JA, Gray ML, San José Estépar R (2016) Computer keyboard interaction as an indicator of early Parkinson's disease. *Sci Rep* 6:34468
12. Arroyo-Gallego T, Ledesma-Carbayo MJ, Butterworth I et al. (2018) Detecting motor impairment in early Parkinson's disease via natural typing interaction with keyboards: validation of the neuroQWERTY approach in an uncontrolled at-home setting. *J Med Internet Res* (<https://www.jmir.org>)
13. Adams WR (2017) High-accuracy detection of early Parkinson's Disease using multiple characteristics of finger movement while typing. *PLoS ONE* 12(11):e0188226. <https://doi.org/10.1371/journal.pone.0188226>
14. Workman MJ, Serov A, Halevi B, Atanassov P, Artyushkova K (2015) Application of the discrete wavelet transform to SEM and AFM micrographs for quantitative analysis of complex surfaces. *Langmuir* 31(17):4924–4933. <https://doi.org/10.1021/acs.langmuir.5b00292>
15. Sharma R, Pachori RB, Rajendra Acharya U (2015) An integrated index for the identification of focal electroencephalogram signals using discrete wavelet transform and entropy measures. *Entropy* 17(8):5218–5240. <https://doi.org/10.3390/e17085218>
16. Peachap AB, Tchiotsop D (2019) Epileptic seizures detection based on some new Laguerre polynomial wavelets, artificial neural networks and support vector machines. *Inf Med Unlocked* 16:100209. <https://doi.org/10.1016/j.imu.2019.100209>
17. Bruno Peachap A, Tchiotsop D (2018) Some New continuous wavelets based on laguerre polynomials applied in pattern detection of noisy signals. *Int J Adv Res Electr Electron Instrum Eng* 7(2)
18. M Misiti, Y Misiti, G Oppenheim, JM Poggi (2007) Wavelets and their applications. Printed and bound in Great Britain by Antony Rowe Ltd, Chippenham, Wiltshire. ISTE Ltd., pp 118–133
19. Miller AS, Blott BH, Hames TK (1992) Review of neural network applications in medical imaging and signal processing. *Med Biol Eng Comput* 30:449–464. <https://doi.org/10.1007/BF02457822>
20. Pereira T, Paiva JS, Correia C et al (2016) An automatic method for arterial pulse waveform recognition using KNN and SVM classifiers. *Med Biol Eng Comput* 54:1049–1059. <https://doi.org/10.1007/s11517-015-1393-5>
21. Colby E, Bair E (2013) Cross-validation for nonlinear mixed effects models. *J Pharmacokinet Pharmacodyn* 40:243–252. <https://doi.org/10.1007/s10928-013-9313-5>
22. Suykens JAK, Van Gestel T, De Brabanter J, De Moor B, Vandewalle J (2002) Least squares support vector machines. World Scientific, Singapore
23. Maier HR, Jain A, Dandy GC, Sudheer KP (2010) Methods used for the development of neural networks for the prediction of water resource variables in river systems: current status and future directions. *Environ Model Softw* 25:891–909
24. T Srivasava (2018) Introduction to k-nearest neighbors: a powerful machine learning algorithm (with implementation in Python & R). Anal Vidhya
25. Testi D, Cappello A, Chiari L et al (2011) Comparison of logistic and Bayesian classifiers for evaluating the risk of femoral neck fracture in osteoporotic patients. *Med Biol Eng Comput* 39:633–637. <https://doi.org/10.1007/BF02345434>
26. Pavan Kumar VV, Duffull SB (2011) Evaluation of graphical diagnostics for assessing goodness of fit of logistic regression models. *J Pharmacokinet Pharmacodyn* 38:205–222. <https://doi.org/10.1007/s10928-010-9189-6>

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.