

# Features selection by genetic algorithm optimization with k-nearest neighbour and learning ensemble to predict Parkinson disease

Nsiri Benayad<sup>1</sup>, Zayrit Soumaya<sup>1,2</sup>, Belhoussine Drissi Taoufiq<sup>2</sup>, Ammoumou Abdelkrim<sup>2</sup>

<sup>1</sup>Research Center STIS, M2CS, National Graduate School of Arts and Crafts of Rabat (ENSAM), Mohammed V University, Rabat, Morocco

<sup>2</sup>Laboratory Industrial Engineering, Information Processing, and Logistics (GITIL). Faculty of Science Ain Chock, University Hassan II, Casablanca, Morocco

## Article Info

### Article history:

Received May 2, 2021

Revised Jul 20, 2021

Accepted Aug 14, 2021

### Keywords:

Discrete wavelet transforms

Ensemble learning

Genetic algorithm

K-nearest neighbour

Mel frequency cepstral coefficient

Parkinson disease

Zero-crossing rate

## ABSTRACT

Among the several ways followed for detecting Parkinson's disease, there is the one based on the speech signal, which is a symptom of this disease. In this paper focusing on the signal analysis, a data of voice records has been used. In these records, the patients were asked to utter vowels "a", "o", and "u". Discrete wavelet transforms (DWT) applied to the speech signal to fetch the variable resolution that could hide the most important information about the patients. From the approximation  $a_3$  obtained by Daubechies wavelet at the scale 2 level 3, 21 features have been extracted: a linear predictive coding (LPC), energy, zero-crossing rate (ZCR), mel frequency cepstral coefficient (MFCC), and wavelet Shannon entropy. Then for the classification, the K-nearest neighbour (KNN) has been used. The KNN is a type of instance-based learning that can make a decision based on approximated local functions, besides the ensemble learning. However, through the learning process, the choice of the training features can have a significant impact on overall the process. So, here it stands out the role of the genetic algorithm (GA) to select the best training features that give the best accurate classification.

This is an open access article under the [CC BY-SA](https://creativecommons.org/licenses/by-sa/4.0/) license.



## Corresponding Author:

Nsiri Benayad

Research Center STIS, M2CS, Department of Applied Mathematics and Informatics National Graduate School of Arts and Crafts of Rabat (ENSAM), Mohammed V University, Rabat

Avenue de l'Armée Royale, Madinat Al Irfane 10100B.P. 6207 Rabat-Instituts Rabat, Morocco

Email: b.nsiri@um5r.ac.ma

## 1. INTRODUCTION

As a progressive degenerative neurological disease, Parkinson's disease affects the motor system. The Parkinson's disease is due to the lack of dopamine, and the death of cells in substantianigra by an unknown cause. This cause is likely to be due to environmental and genetic factors. Hence the Parkinson's disease causes serious damages to the vital function of many organs. Among them the larynx which becomes affected and causes abnormalities in speech signal [1]–[3]. Recently so much research recoured to speech processing in order to detect Parkinson's disease by employing the acoustical and decompositional features. The wavelet transform has been used to tackle the problem of constant resolution. In the paper, Drissi *et al.* [4] applied the different sorts of discrete wavelet transforms (DWT) on the speech signal to obtain the mel frequency cepstral coefficient (MFCC), then classified those coefficients by using the support vector machine (SVM).

In research [5], [6], authors used the Daubechies level 2 in the 3rd scale that gave the best results in [4] to extract the MFCC with two kernels of SVM Linear and radial basis function (RBF). Accuracy has been

obtained by the RBF kernel while in the article [7]. In 2020, Soumaya *et al.* [7] used the classifier K-nearest neighbour (KNN) instead. the predicting system has an accuracy of 98.68%. The features MFCC, linear predictive coding (LPC), energy, zero-crossing rate (ZCR), and Shannon entropy have been used in many speech signal studies, either for the detection of Parkinson's disease as in [8], [9] or either for recognition [10]. In the paper, Oung *et al.* [11] proposed a detection and a classification system of the Parkinson's disease centered on empirical wavelet transform (EWT) and empirical wavelet packet transform (EWPT). The aim of using EWT/EWPT was to decompose the signals from wearable motion and audio sensors. The three classifiers KNN, probabilistic neural network (PNN), and extreme learning machine (ELM) have been applied to analyze the performance of the algorithm. The accuracy of more than 90% has been obtained by EWT/EWPT-ELM based on signals from motion and audio sensors respectively.

The genetic algorithm (GA) has the main role to overcome the optimization problems. In the paper [9], [10] the genetic algorithm is applied for the purpose of selecting the convenient features to reach the most accurate prediction system. In the paper, Umar and Felemban [12] used the GA to execute cyber attacks as false data injection attacks (FDIA) in the power systems. As the case with the GA and the classifier KNN that has been used in the identification of COVID-19 [13]–[15], there are several methods utilized in the classification systems based on machine learning and dimension reduction [1], [16]–[22]. The gait followed in this paper is as follows: section 2.1 sheds light on the problem statement and the used material. Section 2.2 illustrates the hotlines followed in the proposed method. Section 3, provides the obtained results, and a discussion about them. Afterward, the last section concludes the topic of this paper.

## 2. RESEARCH METHOD

### 2.1. Problem statement and material

Data used in this paper have been collected by Sakar *et al.* [23], with the sound card of 16 bit in a desktop computer. Through a microphone standard with a sampling frequency of 44,100 Hz, the patients were asked to utter the vowels “a” “o”, and “u”. The collected records were made in stereo-channel mode then saved in WAV format. The data contains 34 voice records of “a” vowel, 30 of “o”, and 29 of “u”.

The diagnosis is the main and particular task in the trouble-shooting process. In this paper, the purpose is centered on the speech signal to build a classification system of Parkinson's disease. In this framework, it is worth mentioning two key issues; i) finding the best speech processing for extracting the features that hide the medical information of the patients, besides choosing the appropriate vowel for Parkinson's disease detection; and ii) selecting features to figure out the weighted ones by an optimization algorithm, and ensemble learning for classification. In the following section, the key details of our approach are explained.

### 2.2. Proposed method

The signal transformation, features extractions, features selections, and classification are the four main steps of the proposed method. This enhanced method seeks to detect Parkinson's disease based on speech signal processing. As it is depicted in Figure 1 the start was with the speech signal transformation with Daubechies db level 2 at the 3rd scale followed by the pre-emphasis applied on the a3 approximation. Then concatenate the 21 acoustical and decompositional features extracted. The GA is used as an optimization algorithm to select the features besides the classifier KNN.

The proposed method followed in this paper started by transforming the speech signal by using mathematical transformations. In this respect, although the effectiveness of the fourier transform (FT) and the short-time fourier transform (STFT), But the fixed resolution still have got some shortcomings. The adapted STFT which uses a single fixed window [5] gives a two-dimensional space of time and frequency map of the signal. With this resolution the best we can do is in a given time interval, target the spectral components that exist. Hence it can't give precisely the component spectral that exists at a given time. So they shifted to wavelet transforms (WT) that cover up the deficiency of the STFT, by the multi-resolution.

Before the formants frequencies and MFCC extraction, the transformed signal underwent a pre-processing. The first step of the pre-processing is the pre-emphasizing phase that is performed by a filter is as shown in (1). Then dividing the signal into frames that go through a hamming window that is given in (2) to minimize the discontinuities that occurred by the framing.

$$x(n) = a_3(n) - ka_3(n-1) \quad (1)$$

$$W_h(n) = 0,54 - 0,46\cos\left(\frac{2\pi n}{N-1}\right) \quad (2)$$

Concerning the acoustical features, the formant frequencies are extracted by the use of LPC presented in [9], which gives an accurate presentation of speech parameters. The square summation of each sample

represents the time domain energy of the signal. Whereas during a specific time period (a frame) the rate at which a signal changes its sign stands for the rate zero-crossings ZCR. Energy and ZCR are calculated by using (3) and (4), respectively.

$$E = \sum_{n=1}^N |x1(n)|^2 \quad (3)$$

$$ZCR = \frac{1}{N} \left[ \sum_{n=1}^{N-1} (x1(n+1) - x1(n)) \right] \quad (4)$$

With  $x1$  the windowed frame signal, and  $n = (1, 2, N)$  is the length of the windowed frame.

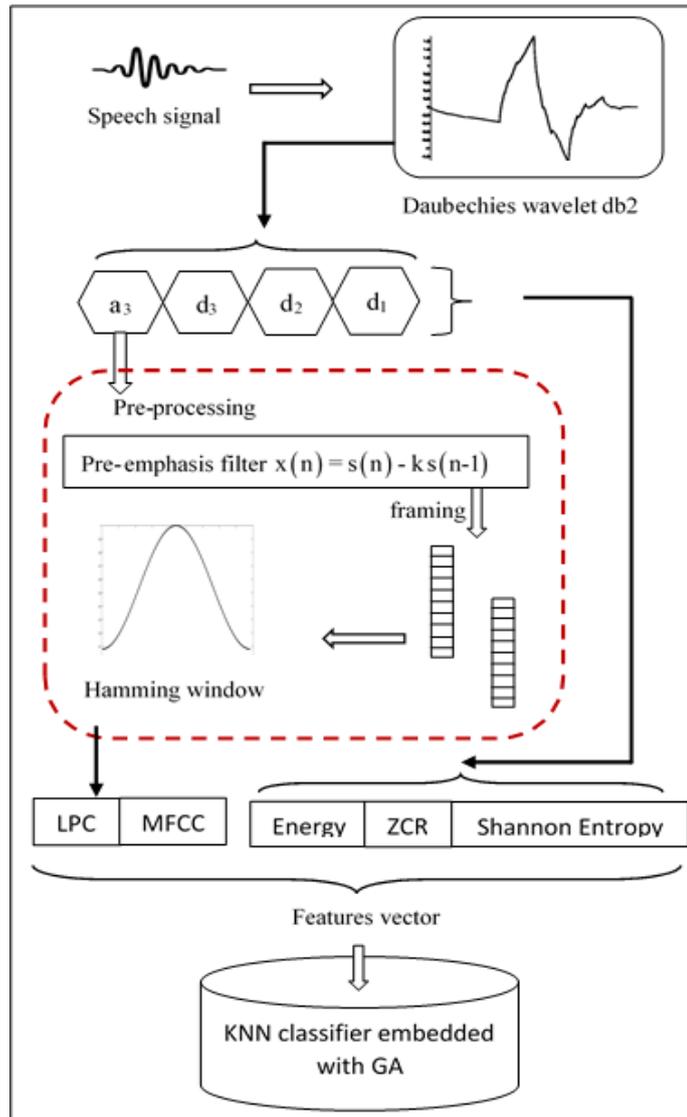


Figure 1. The flowchart explains the proposed predicting system

A set of 12 MFCC is extracted by relying on a cepstral analysis of the speech signal as it is depicted in Figure 2. First of all, the signal passed by a pre-processing as it is explained in Figure 1, then the FFT and the filtering by the filter bank. After that comes the cepstral analysis just before extracting the 12 MFCC coefficients. The reason for using a cepstral analysis in the log-spectral domain [23] is to cope with the problem of the convolution of the source through the vocal tract. This convolution became a product in the spectral domain. So we recourse to the log to separate this product by the cepstral analysis.

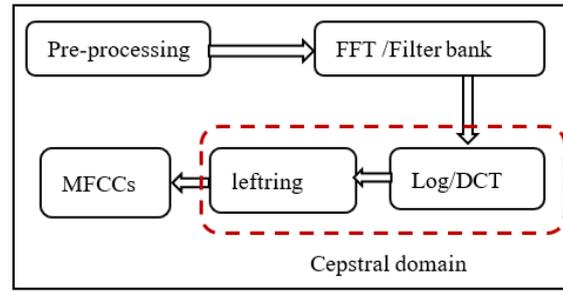


Figure 2. The MFCC extraction process

The decompositional features manifest in the Shannon entropy are calculated for the approximation a3, also for details d3, d2, and d1. The Shannon entropy is an important part of information theory, which describes the degree of confusion of a system. The more orderly the system is, the smaller the entropy is. Shannon entropy “H” is defined as (5):

$$H = \sum_{j=1}^N p_j \log_2(p_j) \quad (5)$$

For the features extraction phase, the last step is concatenating the acoustical features vector of  $1 \times 17$  size, and the decompositional features vector of  $1 \times 4$  size. Construct a vector of  $1 \times 21$  for every individual. Afterward, the selection of the features based on the KNN classifier embedded within the GA optimization. The GA is inspired by the nature of the genetic mechanism and biological evolution theory. The main objective of this algorithm is to find the optimal solution by simulating the process of natural evolution. It starts with generating randomly an initial population where each individual is supposed to be a solution, then we calculate the fitness function of how accurate the system is. Furthermore evolving generation over generation using the genetic strategies: crossover, mutation, and selection till the predetermined number of iterations.

Furthermore, in this study, the feature vector  $1 \times 21$  extracted from each patient is represented as a chromosome, and each feature of them is as a gene. Any gene of them takes a label of 1 or 0. Hence a new population is generated by focusing on the initial chromosome with the 1s while weeding out the 0 ones. The generated matrix is the input of the classification bloc. Therefore either the KNN classifier with the 10 fold cross-validation method has been used, or the ensemble learning by the KNN. If the system is more accurate that means the individual is the best solution. The KNN comes under the category of Lazy Learner approaches[15]. The KNN algorithm applied Euclidean distance to spot the K nearest neighbor of the testing samples [7].

$$d(v,u) = \sum_{i=1}^M \sqrt{v_i^2 - u_i^2} \quad (6)$$

The Euclidean distance  $d(v, u)$  between two points  $v$  and  $u$  are calculated using (9). Where  $M$  is the number of characteristics so that  $v = \{v_1, v_2, v_3 \dots v_M\}$  and  $y = \{u_1, u_2, u_3 \dots u_M\}$ . Intending to boost the performance of the KNN classifier, we use ensemble learning methods. This technique's basic concept is training multiple base learners like ensemble members. Their predictions combine into a single output that must have the best performance on average more than any other ensemble member with uncorrelated error on the target data sets. In this study, two classification systems are followed the first is the KNN with  $K=1$ , and the second is the KNN trained by the creation of a model by the random subspace method RSM [24]–[26].

Then by taking into account the fitness calculated by the classification phase the parents have been chosen among the current population by using the roulette wheel to create offspring. It is noteworthy to mention that the higher fitness chromosomes (individual) are usually more selected. The crossover and mutation intervened to produce a new offspring. The new offspring comes through the same process which is to calculate the accuracy of the probable solution and create other populations until reaching the iterations number predefined.

### 3. RESULTS AND DISCUSSION

Within the aforementioned framework, this paper sheds light on the selection of features in a predicting system of Parkinson's disease patients and aims at defining the suitable vowel to detect the PD. The experimental results are calculated by the predicting system executed by MATLAB 2018a installed in a laptop

with Intel\_CoreTM i5-6300U CPU (2.4 GHz, 4 CPUs) and 8 Go RAM, SSD.

Based on the hybrid method of time-frequency properties and SVM proposed in the [7] the speech signal has been transformed by the Daubechies db2 scale 3rd, level 2. The next step was the extraction of acoustical and decompositional features, after concatenating them the data matrix used in this paper is obtained. For selecting the best possible solution thus the genetic algorithm intervenes. In this study, we work with the records of each vowel alone “a” “o” “u”, the two by two, and then the overall as it is shown in Table 1.

For each combination, 50 attempts have been carried out, the algorithm has been run in each attempt. Starting from 1 iteration to 10 five attempts have been executed for each iteration. First, the data has been initialized randomly, afterward the offspring generated by the genetic algorithm used in the coming iterations. The classification step in order to calculate the fitness function has used classifier KNN, and the ensemble learning with KNN to differentiate between the healthy and the sick patients. Table 2 shows the results obtained by applying the method suggested in this paper.

Table 1. The number of observations in each combination

Vowels	/a/	/o/	/u/	/a, o/	/a, u/	/o, u/	/a, o, u/
Observations	34	30	30	64	64	60	94

Table 2. Results obtained by using KNN and ensemble learning

Vowels	KNN	Ensemble learning
« a »	91.18%	91.18%
« o »	86.67%	86.67%
« u »	86.21%	82.76%
« a, o »	85.94%	87.5%
« a, u »	85.71%	87.3%
« o, u »	88.14%	86.44%
« a, o, u »	83.87%	84.95%

As presented in the Table 2, while using each vowel alone “a”, “o”, and “u” we obtain respectively the accuracy percentages 91.18%, 86.67%, and 86.21% with the method of KNN classifier. the same results are fulfilled when we use the ensemble learning of “a” and “o”, whereas the accuracy of the vowel “u” decreased. Concerning the combination of two vowels, the “a, u” and “a, o” gives almost the same accuracy with both of classification method. The accuracies were 87.3% and 87.5% with the ensemble learning technique and 85.71% and 85.94% with the KNN classifier. During the combination of “o, u” we reach an accuracy of 88.14% by the KNN classifier. The last combination that used the three vowels “a, o, u” the best accuracy that has been achieved was 84.95% by the ensemble learning technique. These results are depicted in the confusion matrix in the Figure 3.

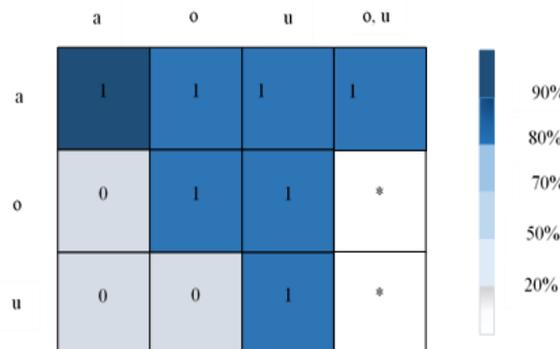


Figure 3. Confusion matrix

The previous percentages are achieved by the reduced features vector contain only 15 coefficients. the GA allowed to weed out the coefficient with the low fitness function and keep the others with the highest fitness. In our study, the phase of features selection by utilizing the GA reduced the features vector from 21 coefficient to 15 only. The reduced vector contains the F3 frequency formant, ZCR, 10 coefficients of MFCCs

which are (C1, C2, C5, C6, C7, C8, C9, C10, C11, C12), the last 3 Shannon entropy concerning the details  $d_1$ ,  $d_2$ , and  $d_3$ .

Taking into account the time of running the proposed algorithm, the KNN classifier was faster than the ensemble learning technique. So due to the obtained results, we can notice that the best results have been fulfilled by the vowel “a” with both of the classifications methods. Even for the other combination, the KNN was the best by giving 88.14% which is the second-best accuracy. Besides, the use of the genetic algorithm with wavelets increase the accuracy of the predicting system

In the paper, Benba *et al.* [27], they proposed a classification of Parkinson's disease by using 20 MFCCs with an SVM classifier and working with the same data used in this paper. The classification system gives an accuracy of 82.50% with the MLP kernel of SVM for the vowel “u” and the 77.50 % using the three vowels at once. In the present work, the proposed method intervenes in two phases. First at the signal processing by using the DWT to transform the speech signal. Then at the features selection phase, we recourse to the genetic algorithm which minimizes features and maximizes the accuracy. The best result was obtained with the vowel “a” 91.18% which is higher by 10.52% than the vowel “u” in the article [27] and 84.95% with the combination of the three vowels which is higher by 9.61%. Than while minimizing the length of features vector from 20 coefficient to 15 coefficients.

#### 4. CONCLUSION

The present study has been conducted to create a prediction system of Parkinson's disease based on speech signals (vowels). So, this paper we propose two methods. The first was the GA for feature selection embedded with the KNN classifier and the second was GA-KNN with ensemble learning. The speech signal used to validate the proposed methods is records of Parkinson's disease patients and healthy ones that utter the vowels “a”, “o”, and “u”.

First of all, the signal was transformed by the use of DWT Daubechies. After those 21 coefficients are extracted from the  $a_3$  approximation of each record and concatenated in the input matrix of the predicting system. In the optimization phase, the GA has been used to reduce the dimension of the features matrix. The KNN and ensemble learning have been employed to calculate the accuracy of each population generated by GA that stands for the fitness function. By the use of the classifier KNN, we obtain an accuracy of 91.18% as far as the vowel ‘a’ is concerned. So we conclude that the most appropriate vowel for the Parkinson's disease detection is the “a” and the KNN classifier that minimizes the programming and the time execution considerably.

#### REFERENCES

- [1] J. A. Logemann, H. B. Fisher, B. Boshes, and E. R. Blonsky, “Frequency and cooccurrence of vocal tract dysfunctions in the speech of a large sample of Parkinson patients,” *Journal of Speech and Hearing Disorders*, vol. 43, no. 1, pp. 47–57, Feb. 1978, doi: 10.1044/jshd.4301.47.
- [2] A. Ma, K. K. Lau, and D. Thyagarajan, “Voice changes in Parkinson’s disease: What are they telling us?,” *Journal of Clinical Neuroscience*, vol. 72, pp. 1–7, Feb. 2020, doi: 10.1016/j.jocn.2019.12.029.
- [3] C. Stewart *et al.*, “Speech dysfunction in early Parkinson’s disease,” *Movement Disorders*, vol. 10, no. 5, pp. 562–565, Sep. 1995, doi: 10.1002/mds.870100506.
- [4] T. B. Drissi, S. Zayrit, B. Nsiri, and A. Ammoumou, “Diagnosis of Parkinson’s disease based on wavelet transform and Mel frequency cepstral coefficients,” *International Journal of Advanced Computer Science and Applications*, vol. 10, no. 3, pp. 125–132, 2019, doi: 10.14569/IJACSA.2019.0100315.
- [5] Z. Soumaya, B. D. Taoufiq, B. Nsiri, and A. Abdelkrim, “Diagnosis of Parkinson disease using the wavelet transform and MFCC and SVM classifier,” *Proceedings of 2019 IEEE World Conference on Complex Systems, WCCS 2019*. IEEE, Apr. 2019, doi: 10.1109/ICoCS.2019.8930802.
- [6] S. Zayrit, T. Belhoussine Drissi, A. Ammoumou, and B. Nsiri, “Daubechies wavelet cepstral coefficients for parkinson’s disease detection,” *Complex Systems*, vol. 29, no. 3, pp. 729–739, Sep. 2020, doi: 10.25088/ComplexSystems.29.3.729.
- [7] Z. Soumaya, B. Taoufiq, N. Benayad, B. Achraf, and A. Ammoumou, “A hybrid method for the diagnosis and classifying Parkinson’s patients based on time-frequency domain properties and K-nearest neighbor,” *Journal of Medical Signals and Sensors*, vol. 10, no. 1, pp. 60–66, 2020, doi: 10.4103/jmss.JMSS\_61\_18.
- [8] J. R. Orozco-Arroyave, F. Hönig, J. D. Arias-Londoño, J. F. Vargas-Bonilla, and E. Nöth, “Spectral and cepstral analyses for Parkinson’s disease detection in Spanish vowels and words,” *Expert Systems*, vol. 32, no. 6, pp. 688–697, Mar. 2015, doi: 10.1111/exsy.12106.
- [9] Z. Soumaya, B. Drissi Taoufiq, N. Benayad, K. Yunus, and A. Abdelkrim, “The detection of Parkinson disease using the genetic algorithm and SVM classifier,” *Applied Acoustics*, vol. 171, Jan. 2021, Art. no. 107528, doi: 10.1016/j.apacoust.2020.107528.
- [10] Y. Korkmaz, A. Boyacı, and T. Tuncer, “Turkish vowel classification based on acoustical and decompositional features optimized by Genetic Algorithm,” *Applied Acoustics*, vol. 154, pp. 28–35, Nov. 2019, doi: 10.1016/j.apacoust.2019.04.027.
- [11] Q. W. Oung, H. Muthusamy, S. N. Basah, H. Lee, and V. Vijejan, “Empirical wavelet transform based features for classification of Parkinson’s disease severity,” *Journal of Medical Systems*, vol. 42, no. 2, Dec. 2018, doi: 10.1007/s10916-017-0877-2.
- [12] S. Umar and M. Felemban, “Rule-based detection of false data injections attacks against optimal power flow in power systems,” *Sensors*, vol. 21, no. 7, Apr. 2021, Art. no. 2478, doi: 10.3390/s21072478.
- [13] R. A. Nugroho, A. S. Nugraha, A. Al Rasyid, and F. W. Rahayu, “Improvement on KNN using genetic algorithm and combined feature extraction to identify COVID-19 sufferers based on CT scan image,” *Telkonnika (Telecommunication Computing*

- Electronics and Control*), vol. 19, no. 5, pp. 1581–1587, Oct. 2021, doi: 10.12928/telkomnika.v19i5.18535.
- [14] H. M. Afify, A. Darwish, K. K. Mohammed, and A. E. Hassanien, “An automated CAD system of CT chest images for COVID-19 based on genetic algorithm and K-nearest neighbor classifier,” *Ingenierie des Systemes d’Information*, vol. 25, no. 5, pp. 589–594, Nov. 2020, doi: 10.18280/ISI.250505.
- [15] W. M. Shaban, A. H. Rabie, A. I. Saleh, and M. A. Abo-Elsoud, “A new COVID-19 patients detection strategy (CPDS) based on hybrid feature selection and enhanced KNN classifier,” *Knowledge-Based Systems*, vol. 205, Oct. 2020, Art. no. 106270, doi: 10.1016/j.knsys.2020.106270.
- [16] A. K. Singh, A. Kumar, M. Mahmud, M. S. Kaiser, and A. Kishore, “COVID-19 infection detection from chest X-Ray images using hybrid social group optimization and support vector classifier,” *Cognitive Computation*, Mar. 2021, doi: 10.1007/s12559-021-09848-3.
- [17] S. M. Al-Qaraawi and A. H. Al-Anbary, “Classification of EEG signals for facial expression and motor execution with deep learning,” *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 19, no. 5, pp. 1588–1593, Oct. 2021, doi: 10.12928/telkomnika.v19i5.19850.
- [18] M. A. Rasyidi, T. Baryyah, Y. I. Riskajaya, and A. D. Septyani, “Classification of handwritten javanese script using random forest algorithm,” *Bulletin of Electrical Engineering and Informatics*, vol. 10, no. 3, pp. 1308–1315, Jun. 2021, doi: 10.11591/eei.v10i3.3036.
- [19] R. Maulana, A. A. Baharin, and H. Fitriyah, “Classification of lung condition for early diagnosis of pneumonia and tuberculosis based on embedded system,” *Bulletin of Electrical Engineering and Informatics (BEEI)*, vol. 10, no. 3, pp. 1262–1270, Jun. 2021, doi: 10.11591/eei.v10i3.3033.
- [20] M. A. Marjan, M. R. Islam, M. P. Uddin, M. I. Afjal, and M. Al Mamun, “PCA-based dimensionality reduction for face recognition,” *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 19, no. 5, pp. 1622–1629, Oct. 2021, doi: 10.12928/telkomnika.v19i5.19566.
- [21] A. W. Sugiyarto, A. M. Abadi, and S. Sumarna, “Classification of heart disease based on PCG signal using convolutional neural network (CNN),” *Telkomnika (Telecommunication Computing Electronics and Control)*, vol. 19, no. 5, pp. 1697–1706, Oct. 2021, doi: 10.12928/telkomnika.v19i5.20486.
- [22] T. J. Wroge, Y. Özkanca, C. Demiroglu, D. Si, D. C. Atkins, and R. H. Ghomi, “Parkinson’s disease diagnosis using machine learning and voice,” *2018 IEEE Signal Processing in Medicine and Biology Symposium, SPMB 2018 - Proceedings*. IEEE, Dec. 2019, doi: 10.1109/SPMB.2018.8615607.
- [23] B. E. Sakar *et al.*, “Collection and analysis of a Parkinson speech dataset with multiple types of sound recordings,” *IEEE Journal of Biomedical and Health Informatics*, vol. 17, no. 4, pp. 828–834, Jul. 2013, doi: 10.1109/JBHI.2013.2245674.
- [24] Susan B. O’Sullivan and Edward W. Bezkor, *Parkinson’s Disease*, F. A. Davi. USA: Physical Rehabilitation, 5th ed. Philadelphia, 2007.
- [25] Y. Zhang, G. Cao, B. Wang, and X. Li, “A novel ensemble method for k-nearest neighbor,” *Pattern Recognition*, vol. 85, pp. 13–25, Jan. 2019, doi: 10.1016/j.patcog.2018.08.003.
- [26] J. Shin, “Random subspace ensemble learning for functional near-infrared spectroscopy brain-computer interfaces,” *Frontiers in Human Neuroscience*, vol. 14, Jul. 2020, doi: 10.3389/fnhum.2020.00236.
- [27] A. Benba, A. Jilbab, and A. Hammouch, “Analysis of multiple types of voice recordings in cepstral domain using MFCC for discriminating between patients with Parkinson’s disease and healthy people,” *International Journal of Speech Technology*, vol. 19, no. 3, pp. 449–456, Mar. 2016, doi: 10.1007/s10772-016-9338-4.

## BIOGRAPHIES OF AUTHORS



**Benayad Nsiri**    held MBI degree in computer sciences from Telecom Bretagne, in 2005, and Ph.D. degree in signal processing from Telecom Bretagne, in 2004. He received D.E.A (French equivalent of M.Sc. degree) in electronics from the Occidental Bretagne University, in 2000. Currently, he is a Full Professor in National Graduate School of Arts and Crafts of Rabat (ENSAM), Mohammed V University, Rabat, Morocco; a member in Research Center STIS, M2CS, Mohammed V University; and a member associate in Researcher, Industrial Engineering, data processing and logistic Laboratory, Hassan II University. He was a Professor in the Faculty of Sciences Ain Chock, Hassan II University. Benayad NSIRI has advised and co-advised more than 12 Ph.D. theses, contributed to more than 80 articles in regional and international conferences and journals. His research interests include but not restricted to computer science, telecommunication, signal and image processing, adaptive techniques, blind deconvolution, MCMC methods, seismic data and higher order statistics. He can be contacted at email: nsiri2000@yahoo.fr, b.nsiri@um5r.ac.ma.



**Zayrit Soumaya**    was born in Zaouiat Cheikh Beni Mellal, Morocco on July 18th, 1994. Received the Master degree in Electronics, Electrotechnics, Automatic, and Industrial Computing from Faculty of Science Ain Chok. University Hassan II -Casablanca, Morocco, in 2017 she is a research student in Research Laboratory in Industrial Engineering, Information Processing and Logistics (GITIL). Faculty of Science Ain Chok, University Hassan II -Casablanca, Morocco. Her interests are in speech processing for detecting people with neurological disorders. She can be contacted at email: zayritsoumaya@gmail.com.



**Belhoussine Drissi Taoufiq**    was born in Oujda, Morocco in 1978 received the Ph.D. degree in acoustics in 2009 at the university of le Havne (France) Since 2011 he has been an assistant professor at the sciences faculty of Ain chock university Hassan II, Casablanca. His scientific interest lies in the research of nondestructive testing and the signal treatment. He can be contacted at email: taoufiq\_belhoussine\_drissi@yahoo.fr.



**Abdelkrim Ammoumou**    received his Ph.D degree in Control and Signal Processing from Mohamed V University, Rabat, Morroco in 2002. Earlier, he received the DES degree in Control and Signal Processing from Mohamed V University, Rabat, Morroco in 1991. He is a professor of Process Control and computer science at EST, Hassan II University, Casablanca since 1991. He is also a responsible for the research team "modeling, simulation and control of production system". He can be contacted at email: ammoumou@hotmail.com.