Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.

Journal Pre-proof

COVID-19 activity screening by a smart-data-driven multi-band voice analysis

Gabriel Silva, Patrícia Batista, Pedro Miguel Rodrigues

PII: S0892-1997(22)00360-5
DOI: https://doi.org/10.1016/j.jvoice.2022.11.008
Reference: YMVJ 3747

To appear in: *Journal of Voice*

Accepted date: 7 November 2022

Please cite this article as: Gabriel Silva, Patrícia Batista, Pedro Miguel Rodrigues, COVID-19 activity screening by a smart-data-driven multi-band voice analysis, *Journal of Voice* (2022), doi: https://doi.org/10.1016/j.jvoice.2022.11.008

This is a PDF file of an article that has undergone enhancements after acceptance, such as the addition of a cover page and metadata, and formatting for readability, but it is not yet the definitive version of record. This version will undergo additional copyediting, typesetting and review before it is published in its final form, but we are providing this version to give early visibility of the article. Please note that, during the production process, errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.

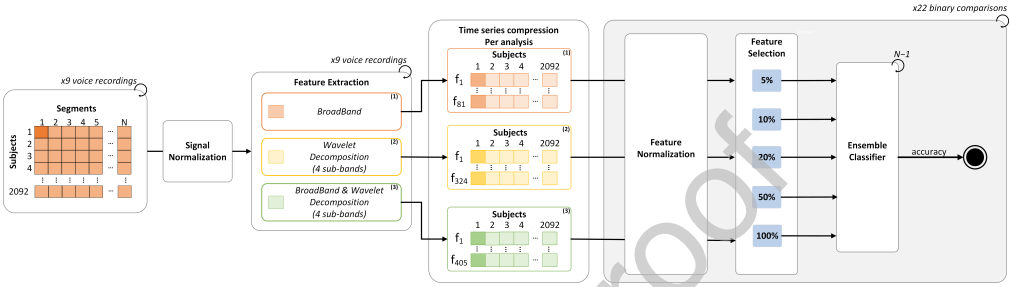
© 2022 The Authors. Published by Elsevier Inc. on behalf of The Voice Foundation.
This is an open access article under the CC BY-NC-ND license
(http://creativecommons.org/licenses/by-nc-nd/4.0/)

Journal Pre-proof

Graphical Abstract

COVID-19 activity screening by a smart-data-driven multi-band voice analysis

Gabriel Silva, Patrícia Batista, Pedro Miguel Rodrigues



Journal Pre-proof

Journal Pre-proof

COVID-19 activity screening by a smart-data-driven multi-band voice analysis

Gabriel Silva[a], Patrcia Batista[a,b], Pedro Miguel Rodrigues[a,*]

[a]*CBQFCentro de Biotecnologia e Qumica FinaLaboratrio Associado, Escola Superior de Biotecnologia, Universidade Catlica Portuguesa, Rua de Diogo Botelho, 1327, 4169-005 Porto, Portugal*

[b]*HNL/CEDHHuman Neurobehavioural Laboratory/Research Centre for Human Development, Universidade Catlica Portuguesa, Rua de Diogo Botelho, 1327, 4169-005 Porto, Portugal*

Abstract

COVID-19 is a disease caused by the new coronavirus SARS-COV-2 which can lead to severe respiratory infections. Since its first detection it caused more than six million worldwide deaths. COVID-19 diagnosis non-invasive and low-cost methods with faster and accurate results are still needed for a fast disease control. In this research, 3 different signal analyses have been applied (per broadband, per sub-bands and per broadband & sub-bands) to Cough, Breathing & Speech signals of Coswara dataset to extract non-linear patterns (Energy, Entropies, Correlation Dimension, Detrended Fluctuation Analysis, Lyapunov Exponent & Fractal Dimensions) for feeding a XGBoost classifier to discriminate COVID-19 activity on its different stages. Classification accuracies ranged between 83.33% and 98.46% have been achieved, surpassing the state-of-art methods in some comparisons. It should be empathized the 98.46% of accuracy reached on pair Healthy Controls vs all COVID-19 stages. The results shows that the method may be adequate for COVID-19 diagnosis screening assistance.

Keywords: COVID-19; Cough; Breathing; Speech signals; Non-linear patterns; Classification.

*Address correspondence and reprint requests to Pedro M. Rodrigues, PhD, Universidade Catlica Portuguesa, CBQF - Centro de Biotecnologia e Qumica Fina Laboratrio Associado, Escola Superior de Biotecnologia, Office EBI112, Rua Diogo Botelho 1327, 4169-005 Porto, Portugal

Email address: pmrodrigues@ucp.pt (Pedro Miguel Rodrigues)

Journal Pre-proof

1. Introduction

The COVID-19 pandemic provoked a vast negative impact on health, social and economic systems. Therefore, the development of methodologies to detect the virus has grown exponentially for controlling the pandemic. New diagnostic methods have been developed, such as reverse transcription-polymerase chain reaction (RT-PCR), serologic testing for immunoglobulins, and rapid diagnostic kits [1, 2, 3, 4, 5]. The RT-PCR is the most widely used method, but these tests are time-consuming, expensive, and invasive [1, 6]. So, new diagnostic methods with higher sensibility, non-invasive and low-cost are needed [1, 5].

Diagnostic methods through voice analysis seems like a solution. Nowadays, voice is considered an important digital biomarker for detection and monitoring the disease progress such as Parkinsons [7], Vocal Nodule [7], Alzheimers [8], Multiple Sclerosis [9], Asthma [10], Heart disease [11], and recent studies have reported that human audio analysis is found to be useful for COVID-19 detection [4, 12, 10]. It is known that Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) affects various parts of the body, with an emphasis on the respiratory system [13, 14, 15]. COVID-19 disease is characterized by infections of the respiratory tract, that affects not only the respiratory system but also the structure that is used for voice production [13]. So, symptoms such as coughing, altered breathing, voice, and speech have been reported.

Voice is a parameter related with the vocal cords characteristics and speech includes the speech speed and hesitation analyses. The voice production is conditioned by the respiratory process, being the sound generated when air is expelled from the lungs. Then the air passes through the larynx, where the vocal folds are in a vibrating position, occurring the phonation and resonating process [13]. Although voice modifications have been a less reported parameter, computed tomography scan data and human biopsies have shown that the virus affects the lungs, nasal tract, and vocal folds & tract [16]. So, voice changes in COVID-19 patients can be one of the sensitive symptoms detected at the beginning or in asymptomatic patients' case [16]. Other recent studies based on clinical trials, reported that voice perturbation can be considered as a COVID-19 manifestation [17, 14, 15]. Lechien and colleagues (2020, 2022) observed dysphonia and aphonia in COVID-19 patients [17, 14]. However, sometimes, the voices changes are very difficult to be accurately/efficiently distinguished by humans. So, computer technology has shown a potential to bridge this gap by allowing voice quantification [18]. In this way, the use of artificial intelligence through voice analysis has allowed the development of tools for virus diagnosis, prediction, and monitoring (see Table 1).

Table 1: Sound-based COVID-19 diagnosis state-of-art methods

Reference	Dataset	Participants	Sound type	Features	Classifier	Accuracy
[1]	Coswara	N=1376 participants (127 COVID-patients (CP) and 1249 Healthy Controls (HC))	Cough, Breathing & Speech	Spectral Centroid, Spectral Bandwidth, Spectral Roll-off, Zero Crossing, Mel Frequency Cepstral coefficients (MFCC) & RMS Energy, Skewness, Kurtosis, Coefficient of variation, Stamdard Error of Mean	Deep Model Shallow classifiers	96.4% CP vs HC
[4]	Coswara	N=1103 participants (84 CP & 1019 H)C	Cough, Breathing & Speech	Geneva Minimalistic Acoustic Parameter Set (GeMaps), extended Geneva Minimalistic Acoustic Parameter Set (eGeMaps), ComParE feature set & Wavelet scattering transform	Multi-layer Perceptron (MLP)	88.52% CP vs HC
[5]	Coswara	N=210 participants (70 CP, 70 recovered negative COVID-19 patients (RP group) & 70 HC)	Cough & Speech	OpenSMILE features & INTERSPEECH2016 challenge features	Machine learning-based voice assessment (MLVA)	90.07% CP and HC & 92.81% CP vs RP & 92.81% RP vs HC
[15]	Not Coswara	N=116 participants (76 Pos-COVID-19 (PosC) patients & 40 HC)	Cough & Speech	Log-mel spectrograms	VGG19 Convolution neural network (CNN)	85% PosC vs HC
[19]	Not Coswara	N=54 participants (40 CP and 14 HC)	Cough & Speech	Computational Paralinguistics Challenge features and PRAAT and LIBROSA acoustic features	Deep Convolution Neural Network (dCNN)	83% CP vs HC
[20]	Coswara	N=1027 participants (77 CP & 950 HC)	Speech	Fundamental Frequency (F0), jitter, shimmer and Harmonic to Noise Ratio (HNR), MFCC, Spectral Centroid and Roll-off	VGG19 CNN	97% CP vs HC
[21]	Not Coswara	N=88 participants (29 positive COVID-19 & 59 HC)	Cough & Speech	80 Mel-scaled frequencies & 80 first derivatives	Support-vector Machines (SVM)	78% CP vs HC
[22]	Not Coswara	N=355 participants (62 positive COVID-19 & 293 HC)	Cough & Breathing	Mel spectrograms	ResNet CNN	84.6% CP vs HC
[23]	Coswara	N=2883 participants (539 positive COVID-19 & 2344 HC)	Cough	Mel spectrograms, MFCC & clinical features	Ensemble Deep Learning Model	77.1% CP vs HC
[24]	Coswara	N=3621 participants (2001 positive COVID-19 & 1620 HC)	Cough	Mel spectrograms, MFCC & RMS Energy & clinical features	ResNet-18 & Shallow classifiers	72% CP vs HC

Journal Pre-proof

Journal Pre-proof

Other technologies such as the Internet of Things, Big Data, and Blockchain also have been used to predict, detect, and control the virus [25]. So, Artificial Intelligence can play a significant role in the development of more effective and reliable, simple, non-invasive, faster, and less expensive diagnostic methods [26, 6, 20]. Thus, machine learning trained models and algorithms can be used for voice analysis in prognosis and scanning of SARS-COV-2 infection. So, new real-time algorithms based on voice analysis must be constructed in sense of being more reliably and sensitively to turn possible the distinguish between Healthy and pathological voice [26, 20]. To contribute for this development, the present research was designed to build a new COVID-19 screening activity machine learning tool based on Cough, Breathing & Speech analysis.

In terms of structure, this paper is organized in six main sections. In Section 2, the database is described. Thereafter, the methodology concerning the signal processing and the classification procedure is explained in section 3. The obtained results are detailed on Section 4 and its inherent discussion were covered in Section 5. Lastly, Section 6 makes remarks about conclusions.

2. Materials

The Coswara public database has been used on present work (released until 11 April 2022) [27]. The sound samples are collected via worldwide crowd-sourcing using the internet and also public available on Web [27]. Samples are labeled with 6 COVID-19 statuses (No respiratory illness exposed (nRE), Positive asymptomatic (PA), Positive moderate (PMo), Positive mild (PM), Recovered full (RF), and Respiratory illness not identified (RIn)) and 1 group of control (Healthy Controls - HC).

Every participant in the dataset has 9 different sound types with a sampling frequency (FS) of 44100Hz (Breathing-deep, Breathing-shallow, Cough-heavy, Cough-shallow, Counting-fast, Counting-normal, Vowel /a/, Vowel /e/, Vowel /o/), the data is described in detail here [27]. After removing items with either missing audio files or demographic data (therefore labels could not be retrieved), a total of 2092 participants were identified in the study, with an age range between 1 and 87 years, and more male participation, 70.4% (see Table 2).

The participants reported various locations, with the majority being from India (92.3%) and the United States (3.1%), however participants from Germany, Portugal, Finland, Thailand, South Africa, Australia, Oman, Spain, Canada, Switzerland, Sweden, France, United Kingdom, United Arab Emirates, Netherlands, China, Japan, Hungary, Turkey, Singapore, Saudi Arabia, Bahrain, Philippines,

Journal Pre-proof

Argentina, Indonesia, Italy, Romania, Bangladesh, Greece, Malaysia, Russia, Brazil, Pakistan, Sri Lanka, Belgium, Korea South, and Syria were also involved in the study.

The data obtained showed that the majority of the participants were Healthy Controls (55.9%), however 24.5% of the participants were infected with the virus, either with different symptoms or without symptoms (3.2%) (check Table 2 for more details).

Table 2: Socio-demographic and clinical characteristics

Continuous Measure	**Min**	**Max**	**Mean**	**SD**
Age	1	87	35.60	13.87
Categorical Measure			**%**	
Gender				
Female			29.6	
Male			70.4	
Country				
India			92.3	
USA			3.1	
Germany			0.5	
Other			4.1	
Clinical information				
Healthy Controls			55.9	
No respiratory illness exposed			8.8	
Positive asymptomatic			3.2	
Positive mild			15.4	
Positive moderate			5.9	
Recovered full			5.0	
Respiratory illness not identified			5.8	

Journal Pre-proof

3. Methods

The proposed methodology is divided into three main steps: (1) Preprocessing, (2) Signal Processing and Feature Extraction and (3) Classification. Figure 1 summarizes the methodology implementation steps.

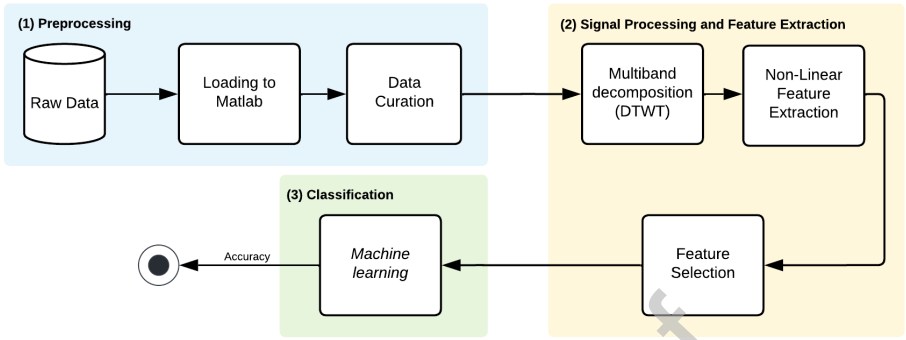


Figure 1: Methodology steps.

3.1. Preprocessing

The duration of each phoneme is always longer than 2 s, so, as recommended in [28], a stable and artifact-free with at least 2.2 s-long signal was guaranteed from each participant 9 different sound recording types.

All signals amplitude was normalized in the range $[-1, 1]$ to prevent the speaker-microphone distance from affecting the model.

At the end, the signals were then split into non-overlapping 20 ms-long segments using the Hamming window.

3.2. Signal Processing and feature extraction

This section describes the set of features extracted from each voice type sound recording.

3.2.1. Multiband Decomposition via Wavelet Transform

The discrete-time wavelet transform (DTWT) of a discrete-time finite-energy signal is its breakdown into a set of basis functions made from a finite number of prototype sequences and their time-shifted versions [29]. It is an optimal tool for time-frequency signal analysis because it not only allows us to change the signal domain from time to frequency, and vice versa, but it also allows us to localise the origin of frequency compounds in time [30, 31].

This structured expansion and its corresponding reconstruction are implemented by means of an octave-band critically decimated filter bank [32, 29]. Con-

Journal Pre-proof

Journal Pre-proof

sidering only the positive frequencies, the mth sub-band is confined to

$$W_k = \begin{cases} \left[0, \pi/2^S\right], & m = 0, \\ \left[\pi/2^{S-m+1}, \pi/2^{S-m}\right], & m = 1, 2, \ldots, S, \end{cases} \tag{1}$$

where S is the number of decomposition stages or levels, $S + 1$ is the number of sub-bands and π is the normalized angular frequency which is equivalent to half the sampling rate.

The DTWT uses an analysis scale function $\tilde{\phi}_1(n)$ and an analysis wavelet function $\tilde{\psi}_1(n)$ defined as

$$\tilde{\phi}_1(n) = h_{\mathrm{LP}}(n) \tag{2}$$

and

$$\tilde{\psi}_1(n) = h_{\mathrm{HP}}(n), \tag{3}$$

where $h_{\mathrm{LP}}(n)$ and $h_{\mathrm{HP}}(n)$ are the impulse responses of the half-band low-pass and high-pass analysis filters, respectively.

Defining the following recursion formulas

$$\tilde{\phi}_{i+1}(n) = \tilde{\phi}_i(n/2) * \tilde{\phi}_1(n), \tag{4}$$

$$\tilde{\psi}_{i+1}(n) = \tilde{\phi}_i(n) * \tilde{\psi}_1(n/2^i), \tag{5}$$

where the symbol $*$ denotes the convolution operator, the equivalent analysis filter of the mth sub-band is given by

$$h_m(n) = \begin{cases} \tilde{\phi}_S(n), & m = 0, \\ \tilde{\psi}_{S+1-m}(n), & m = 1, 2, \ldots, S. \end{cases} \tag{6}$$

The mth sub-band signal is given by

$$x_m(n) = \begin{cases} \sum_{k=-\infty}^{\infty} x(k) h_m(2^S n - k), & m = 0, \\ \sum_{k=-\infty}^{\infty} x(k) h_m(2^{S-m+1} n - k), & m = 1, 2, \ldots, S. \end{cases} \tag{7}$$

In this study, the DTWT was applied to each voice segment for sub-band decomposition up to the third level, i.e., S=3. The sub-band signals $x_m(n)$, $m = \{0, 1, 2, 3\}$, were resampled to the original sampling rate using the wavelet interpolation method [33]. The Wavelet decomposition tree is shown on Figure 2.

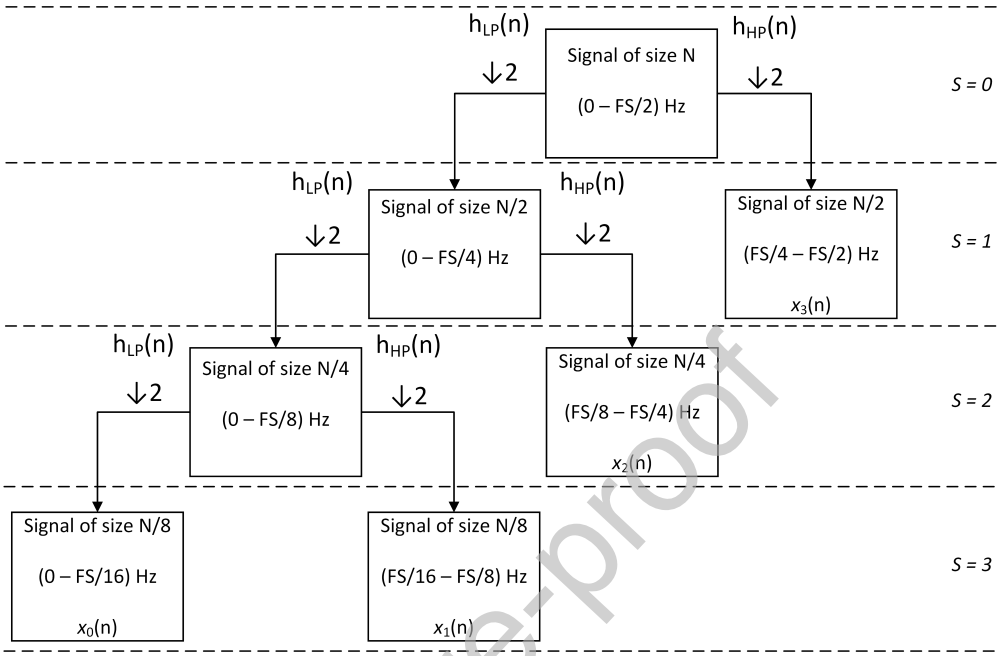


Figure 2: The discrete-time wavelet transform decomposition tree

3.2.2. Non-linear Analysis

Non-linear dynamic features characterize a complex system, according to non-linear dynamic theory. Non-linearity features are generally associated with entropy, exponents, and fractal dimensions parameters.

3.2.2.1 Energy

Energy is one of the most informative concepts in information theory, that has the ability to exploit multiple meaningful features from a non-stationary signal and it can be seen as the system's ability to accomplish work. In the case of a speech signal, such as the one used in this work, the energy describes the effort done by the speaker's lungs and vocal tract to make sound as a function of time [34, 35]. The energy of $x(n)$ is defined as

$$EN = \sum_{n=1}^{N} |x(n)|^2 \tag{8}$$

Journal Pre-proof

3.2.2.2 Entropy

Entropy is a measure that considers the amount of energy present in a complex system. Entropy features may also be used to quantify the information content that has been masked in a signal, modelling the unpredictability and irregularities of a pathological speech signal, as accurate as possible, within a certain signal's band [35]. The Shannon (SE), Logarithmic (LE) and Approximate (AE) entropies can be estimated as [36, 37, 38]

$$SE = -\sum_{n=1}^{N} |x(n)|^2 log[|x(n)|^2], \tag{9}$$

$$LE = \sum_{n=1}^{N} log[|x(n)|^2], \tag{10}$$

and

$$AE(m, r, N) = H^m(r) - H^{m+1}(r) \tag{11}$$

where N is the data length (suggested to be 1000 of the signal standard deviation), r is the similar tolerance (between 0.1 and 0.25) and m represents the embedding dimension (between 2 and 3). H is the Heaviside function that results from intermediate calculations [39].

3.2.2.3 Chaos theory

Chaos theory is a concept that is closely related to dynamic systems. Since a dynamic system lacks the properties of an equilibrium system for sure unpredictable disturbances can influence its behavior. As a result of these perturbations, the system travels from one state to another. The concept of phase space refers to the collection of all possible states that a dynamic system can experience over time.

There are two main exponents which provide a comprehensive framework of chaos [37, 40]. At each time instant, the state of a dynamic system characterized by m variables may be represented as a point in m-dimensional space.

The succession of states over time produces arcs called trajectories in this space, which is known as state or phase space. When these trajectories are tracked over extended periods of time, they can converge to a certain geometric shape, known as an attractor, regardless of the system's original settings.

- Correlation Dimension (D_2): It characterizes the distribution of the attractor points, reflecting the complexity of a dynamic system, and is estimated as

$$D_2 = \lim_{r \to 0} \frac{\log(C(r, M))}{\log(r)}, \tag{12}$$

where

$$C(r, M) = \frac{2}{M(M-1)} \sum_{i=1}^{M} \sum_{\substack{j=1 \\ j \neq i}}^{M} \Theta(r - \left\| \mathbf{x}_i - \mathbf{x}_j \right\|) \tag{13}$$

is the probability of the pair of points $\left\{ \mathbf{x}_i, \mathbf{x}_j \right\}$ on the attractor is separated by a distance less than or equal to r and Θ is the Heaviside function [41, 39].

- Lyapunov Exponent (L): It provides information of trajectories evolution over time [39], reflecting the stability of dynamic systems.

$$LE(x_0) = \lim_{n \to \infty} \frac{1}{n} \sum_{k=1}^{n} \ln |f'(x_k - 1)| \tag{14}$$

where f' is the iterator function f derivative [37].

- Detrended Fluctuation Analysis: It is a method that provides a feature for quantifying long-range correlations (self-similarity) of an apparently non-stationary time series [42]. From $x(n)$, the cumulative deviation series is calculated as follows

$$y(k) = \sum_{i=1}^{k} \left[x(i) - \overline{x} \right]. \tag{15}$$

Then, for each m-long segment of $y(k)$, a linear approximation denoted by $y_m(k)$ is estimated. The average fluctuation of the signal as a function of m is defined as

$$F(m) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} [y(k) - y_m(k)]^2}. \tag{16}$$

The slope of the best linear approximation of $\log[F(m)]$ as a function of $\log(m)$ is the scale exponent α that represents the correlation properties of the signal $x(n)$ [43].

Journal Pre-proof

3.2.2.4 Fractal Dimension

Self-similarity features of fractal structures allow for the description of both irregular processes and structures. Fractal geometry has been shown to be a beneficial strategy for identifying irregularities produced by various disorders in biomedical signals such as the voice [44]. In fact, monitoring the self-similarity of the speech enables for the clinical status of the patient to be assessed. Fractal dimension (FD) feature extraction such as the Higuchi fractal dimension is considered to be helpful in voice signal classification [40].

- Higuchi Exponent (D):

$$L(k)\alpha k^{-D} \tag{17}$$

  where k indicates the time interval, $L(k)$ is the length of the curve in the k time interval and D is the Higuchi Exponent [45].

- Katz Algorithm: According to Katz (1988) [46], the FD of a waveform $x(n)$ can be defined as

$$FD_k = \frac{log(L/a)}{log(d/a)} \tag{18}$$

  where L is the sum of the distances between the successive points of $x(n)$, a is the average distance between the successive points, and d is the greatest distance between $x(1)$ and the remaining points of $x(n)$.

3.2.3. Feature extraction process

For each study participant voice recording, 9 non-linear features (EN, SE, LE, AE, CD, L, α, D, FD_k) have been extracted from each 20 ms-long segments and their respective sub-bands computed by DTWT decomposition until level 3 using biorthogonal 3.1. As we are trying to find pathological patterns, most of times characterized as being time domain small signal oscillations imperceptible to human eye, the small size of Biorthogonal 3.1 filter (N = 4) helps to keep the quality of signal's information in time domain for each signal's sub-band, avoiding the lose of those pathological patterns along the DTWT analysis [47]. This Wavelet also proves to be a good choice for speech signal analysis in previous works [7, 48]. Treating the 9 extracted features of all segments as time series

Journal Pre-proof

distributions, mean statistic was used to compress them along time per sub-band and per broadband, reducing the problem dimensionality and, at the same time, ensuring that the number of metrics per subjects was equal for the classification task.

3.3. Feature selection and classification procedure

The study goal is to infer about the capacity of a XGBoost ensemble of machine learning model for evaluating the COVID-19 activity evolution along its different stages by voice analysis. The XGBoost classifier [49], that is a tree-based ensemble machine learning algorithm, has been used for the propose with the following optimized parameters: boosted trees to fit = 150, learning rate = 0.1, max. depth of the tree = 6, L2 regularization term = 1, and L1 regularization term = 0.

3 different modalities of binary comparison analyses have been studied: (1) per broadband (1 signal analysis resulting in a feature vector of 81 features per subject – 9 features $\times$ 9 voice recordings); (2) per sub-bands (4 signal analyses resulting in a feature vector with 324 features per subject – 9 features $\times$ 4 signal analysis $\times$ 9 voice recordings); and (3) per broadband and sub-bands (5 signal analyses resulting in a feature vector with 405 features per subject – 9 features $\times$ 5 signal analysis $\times$ 9 voice recordings). In each 22 binary comparisons, it was ensured that all datasets have been equally balanced for discrimination, for that, subgroups have been randomly selected from the main database previously defined on Table 2 taking in to account the lower maximum number of samples found individually in each group that form the study group pair. Thus, the group that has less number of samples in pair indicate the number of samples in both groups, respectively. Per analysis modality and binary comparison, the data have been normalized by z-score algorithm [50] and 5 different sets of features were selected by f-score algorithm [51], representing 5%, 10%, 20%, 50% and 100% of total of features, have been presented to the entries of the XGBoost ensemble machine learning model for discrimination. In all cases, to verify the generalization capacity of the classifier, a leave-one-out cross-validation procedure is used.

For a better understanding of the whole methodology Figure 3 presents a summary of the procedure.

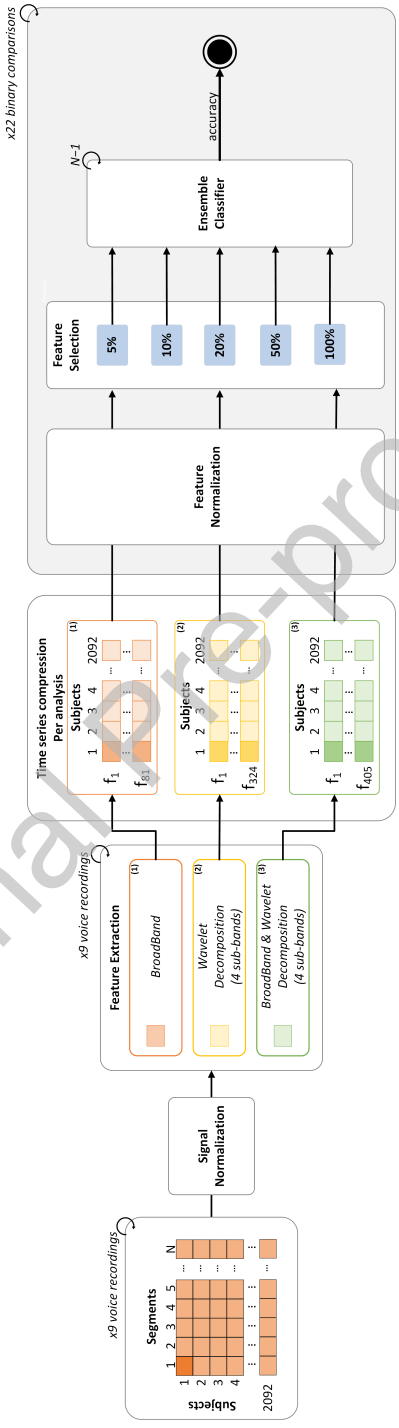


Figure 3: Methodology workflow.

Journal Pre-proof

Journal Pre-proof

4. Results

Classification accuracies for each pair of study groups, according to the procedure described in subsection 3.3, are presented in Table 3.

Table 3: Classification accuracy results for each pair of study groups.

Study pair comparison	# samples per group	Best analysis	% of features	Accuracy
Healthy Controls vs No respiratory illness exposed	181	2	10	96.69%
Healthy Controls vs Positive asymptomatic	65	3	20	96.92%
Healthy Controls vs Positive mild	318	2	10	98.11%
Healthy Controls vs Positive moderate	120	3	20	97.92%
Healthy Controls vs Recovered full	105	2	20	88.57%
Healthy Controls vs Respiratory illness not identified	120	2	20	97.92%
No respiratory illness exposed vs Positive asymptomatic	65	3	20	97.69%
No respiratory illness exposed vs Positive mild	181	1	10	98.90%
No respiratory illness exposed vs Positive moderate	120	3	10	97.50%
No respiratory illness exposed vs Recovered full	105	2	20	88.10%
No respiratory illness exposed vs Respiratory illness not identified	120	3	10	96.67%
Positive asymptomatic vs Positive mild	65	3	20	98.46%
Positive asymptomatic vs Positive moderate	65	3	20	97.69%
Positive asymptomatic vs Recovered full	65	3	20	86.15%
Positive asymptomatic vs Respiratory illness not identified	65	3	20	96.92%
Positive mild vs Positive moderate	120	3	10	86.67%
Positive mild vs Recovered full	105	2	20	87.62%
Positive mild vs Respiratory illness not identified	120	2	10	96.67%
Positive moderate vs Recovered full	105	1	20	83.33%
Positive moderate vs Respiratory illness not identified	120	3	10	97.92%
Recovered full vs Respiratory illness not identified	105	2	20	97.62%
Healthy Controls vs COVID-19 all stages	909	3	50	98.46%

Journal Pre-proof

5. Discussion

By analysing Table 3, some observations can be drawn about classification results between pairs of study groups. Accuracies higher than 83% were obtained for all pairs. Analysis 1 provided the best features set in 2 of 22 (9%) study pairs classifications, features from Analysis 2 have been used in 8 of 22 (36.5%) study pairs classifications and Analysis 3 brings the best features for 12 of 22 (54.5%)

Journal Pre-proof

study pairs classifications. All comparisons that involved the Recovery full group reached accuracies lower than 90%, meaning that even when the patients no longer carry the virus, it still has some impact on patients' health, the so called in the literature Long COVID-19 effect [52]. Besides that, all other comparisons reached higher accuracy rates than 90% except the pair Positive mild vs Positive moderate. The similarity between their symptoms and effects difficult the correct identification of those stages [53] and that reason can explain the obtained results.

Table 3 analysis also demonstrates the significance of Wavelet Transform decomposition, as 91% of the classifications with greater accuracy came either from analyses 2 or 3, in which wavelet information is employed entirely or in combination with metrics extracted from broadband, respectively. This finding helps us to argue the relevance of utilizing the Wavelet Transform for a signal multi-band analysis to extract metrics that can discriminate between several binary groups with higher efficiency and accuracy.

Regarding state-of-art methods showed on Table 1, it can be observed that most of the authors have focused mainly their research on Healthy Controls vs COVID-19 all stages. Particularly on that comparison, our algorithm outperforms the best reported accuracy on state-of-art methods that used the same dataset by 1% [20], showing in this way to be a good candidate for this kind of discrimination. As for the studies that didn't use the Coswara dataset, although comparisons must be done with some caution as different databases have been employed, our method outperformed the best result from those studies by 13% [15]. Regarding Positive - mild vs Recovered full our algorithm provided a slightly higher accuracy than the achieved in Suppakitjanusan *et. al.* study [15], 2% higher. About the other remaining 20 pairs, it can not be done a direct comparison as far as we know those discrimination's have been not reported on state-of-art works.

6. Conclusions

This study investigated the detection of COVID-19 by using multiband nonlinear parameters of Cough, Breathing & Speech. The detection was performed between pairs of study groups using 3 different modalities of signal analyses: (1) per broadband; (2) per sub-bands; and (3) per broadband and sub-bands. For each pair of study groups, a feature selection was carried out by f-score algorithm with different combinations, 5%, 10%, 20%, 50%, and 100% of the total features, and they were used as input for the XGBoost ensemble machine learning model for discrimination within a leave-one-out cross-validation pro-

Journal Pre-proof

cedure. The following classification accuracies have been obtained: 96.69% HC vs nRE, 98.11% HC vs PM, 97.92% HC vs RIn, 88.57% HC vs RF, 96.92% HC vs PA, 97.92% HC vs PMo, 97.50% nRE vs PM, 96.67% nRE vs RIn, 88.10% nRE vs RF, 97.69% nRE vs PA, 97.50% nRE vs PMo, 97.92% PM vs RIn, 83.33% PM vs RF, 98.46% PM vs PA, 86.67% PM vs PMo, 97.62% RIn vs RF, 96.62% RIn vs PA, 97.92% RIn vs PMo, 86.15% RF vs PA, 97.69% RF vs PMo, 97.69% PA vs PMo and 98.46% COVID-19 patients vs HC.

The results demonstrated that the combination of cough, breathing & speech signal multi-band analysis is adequate to detect COVID-19 activity. As voice recording systems are relatively inexpensive, non-invasive, mobile, and fast, this kind of solution can be widely spread and help in COVID-19 diagnosis screening at clinics and hospitals. As far as we could check this is the first attempt to distinguish between different COVID-19 stages by voice analysis. In future works, the results must be updated with a larger population to ensure generalization, an analysis of the most suitable wavelet family for each study group pairs may be performed, and it should be consider new methods for feature selection based on paraconsistency and paraconsistent feature engineering that have shown to be good candidates for the propose in other works [54, 55].

Journal Pre-proof

Acknowledgments

This work was supported by Fundaٰo para a Ciłncia e a Tecnologia (FCT), Portugal, through the project UIDB/50016/2020.

References

[1] M. Aly, K. H. Rahouma, S. M. Ramzy, Pay attention to the speech: COVID-19 diagnosis using machine learning and crowdsourced respiratory and speech recordings, Alexandria Engineering Journal 61 (5) (2022) 3487–3500, doi:10.1016/j.aej.2021.08.070.

[2] M. L. Bastos, G. Tavaziva, S. K. Abidi, J. R. Campbell, L.-P. Haraoui, J. C. Johnston, Z. Lan, S. Law, E. MacLean, A. Trajman, D. Menzies, A. Benedetti, F. A. Khan, Diagnostic accuracy of serological tests for covid-19: systematic review and meta-analysis, BMJ (2020) m2516doi: 10.1136/bmj.m2516.

[3] V. M. Corman, O. Landt, M. Kaiser, R. Molenkamp, A. Meijer, D. K. Chu, T. Bleicker, S. Brnink, J. Schneider, M. L. Schmidt, D. G. Mulders, B. L.

Journal Pre-proof

Haagmans, B. van der Veer, S. van den Brink, L. Wijsman, G. Goderski, J.-L. Romette, J. Ellis, M. Zambon, M. Peiris, H. Goossens, C. Reusken, M. P. Koopmans, C. Drosten, Detection of 2019 novel coronavirus (2019-nCoV) by real-time RT-PCR, Eurosurveillance 25 (3), doi:10.2807/1560-7917.es.2020.25.3.2000045.

[4] V. Despotovic, M. Ismael, M. Cornil, R. M. Call, G. Fagherazzi, Detection of COVID-19 from voice, cough and breathing patterns: Dataset and preliminary results, Computers in Biology and Medicine 138 (2021) 104944, doi:10.1016/j.compbiomed.2021.104944.

[5] C. Robotti, G. Costantini, G. Saggio, V. Cesarini, A. Calastri, E. Maiorano, D. Piloni, T. Perrone, U. Sabatini, V. V. Ferretti, I. Cassaniti, F. Baldanti, A. Gravina, A. Sakib, E. Alessi, F. Pietrantonio, M. Pascucci, D. Casali, Z. Zarezadeh, V. D. Zoppo, A. Pisani, M. Benazzo, Machine Learning-based Voice Assessment for the Detection of Positive and Recovered COVID-19 Patients, Journal of Voice doi:10.1016/j.jvoice.2021.11.004.

[6] A. Heidari, N. J. Navimipour, M. Unal, S. Toumaj, The COVID-19 epidemic analysis and diagnosis using deep learning: A systematic literature review and future directions, Computers in Biology and Medicine 141 (2022) 105141, doi:10.1016/j.compbiomed.2021.105141.

[7] M. Alves, G. Silva, B. C. Bispo, M. E. Dajer, P. M. Rodrigues, Voice Disorders Detection Through Multiband Cepstral Features of Sustained Vowel, Journal of Voice doi:10.1016/j.jvoice.2021.01.018.

[8] L. Toth, I. Hoffmann, G. Gosztolya, V. Vincze, G. Szatloczki, Z. Banreti, M. Pakaski, J. Kalman, A Speech Recognition-based Solution for the Automatic Detection of Mild Cognitive Impairment from Spontaneous Speech, Current Alzheimer Research 15 (2) (2018) 130–138, doi:10.2174/1567205014666171121114930.

[9] J. Rusz, B. Benova, H. Ruzickova, M. Novotny, T. Tykalova, J. Hlavnicka, T. Uher, M. Vaneckova, M. Andelova, K. Novotna, L. Kadrnozkova, D. Horakova, Characteristics of motor speech phenotypes in multiple sclerosis, Multiple Sclerosis and Related Disorders 19 (2018) 62–69, doi:10.1016/j.msard.2017.11.007.

Journal Pre-proof

Journal Pre-proof

[10] A. O. Popadina, A.-M. Salah, K. Jalal, Voice Analysis Framework for Asthma-COVID-19 Early Diagnosis and Prediction: AI-based Mobile Cloud Computing Application, in: 2021 IEEE Conference of Russian Young Researchers in Electrical and Electronic Engineering (ElConRus), IEEE, 1803–1807, doi:10.1109/elconrus51938.2021.9396367, 2021.

[11] M. Usman, M. Zubair, Z. Ahmad, M. Zaidi, T. Ijyas, M. Parayangat, M. Wajid, M. Shiblee, J. A. Ali, Heart Rate Detection and Classification from Speech Spectral Features Using Machine Learning, Archives of Acoustics 46 (2021) 41–53, doi:10.24425/AOA.2021.136559.

[12] K. K. Lella, A. Pja, Automatic diagnosis of COVID-19 disease using deep convolutional neural network with multi-feature channel from respiratory sound data: Cough, voice, and breath, Alexandria Engineering Journal 61 (2) (2022) 1319–1334, doi:10.1016/j.aej.2021.06.024.

[13] M. Asiaee, A. Vahedian-azimi, S. S. Atashi, A. Keramatfar, M. Nourbakhsh, Voice Quality Evaluation in Patients With COVID-19: An Acoustic Analysis, Journal of Voice doi:10.1016/j.jvoice.2020.09.024.

[14] J. R. Lechien, C. M. Chiesa-Estomba, P. Cabaraux, Q. Mat, K. Huet, B. Harmegnies, M. Horoi, S. D. L. Bon, A. Rodriguez, D. Dequanter, S. Hans, L. Crevier-Buchman, B. Hochet, L. Distinguin, Y. Chekkoury-Idrissi, M. Circiu, F. E. Afia, M. R. Barillari, G. Cammaroto, N. Fakhry, J. Michel, T. Radulesco, D. Martiny, P. Lavigne, L. Jouffe, G. Descamps, F. Journe, E. M. Trecca, J. Hsieh, I. L. Delgado, C. Calvo-Henriquez, S. Vergez, M. Khalife, G. Molteni, G. Mannelli, G. Cantarella, M. Tucciarone, C. Souchay, P. Leich, T. Ayad, S. Saussez, Features of Mild-to-Moderate COVID-19 Patients With Dysphonia, Journal of Voice 36 (2) (2022) 249–255, doi:10.1016/j.jvoice.2020.05.012.

[15] P. Suppakitjanusant, S. Sungkanuparph, T. Wongsinin, S. Virapongsiri, N. Kasemkosin, L. Chailurkit, B. Ongphiphadhanakul, Identifying individuals with recent COVID-19 through voice classification using deep learning, Scientific Reports 11 (1), doi:10.1038/s41598-021-98742-x.

[16] S. Sondhi, A. Salhan, C. A. Santoso, M. Doucoure, D. M. Dharmawan, A. Sureka, B. N. Natasha, A. D. Danusaputro, N. S. Dowson, M. S. L. Yap, M. A. Hadiwidjaja, S. G. Veeraraghavan, A. Z. Hatta, C. Lee, R. A. Megantara, A. N. Wihardja, M. Sharma, E. L. Lardizabal, L. J.

Journal Pre-proof

Sondhi, R. Raina, S. Vashisth, R. Hedwig, Voice processing for COVID-19 scanning and prognostic indicator, Heliyon 7 (10) (2021) e08134, doi: 10.1016/j.heliyon.2021.e08134.

[17] J. R. Lechien, C. M. Chiesa-Estomba, S. Place, Y. V. Laethem, P. Cabaraux, Q. Mat, K. Huet, J. Plzak, M. Horoi, S. Hans, M. R. Barillari, G. Cammaroto, N. Fakhry, D. Martiny, T. Ayad, L. Jouffe, C. Hopkins, S. Saussez, S. Blecic, D. R. D. Siati, P. Leich, C. Souchay, C. Rossi, F. Journe, J. Hsieh, L. Ris, F. E. Afia, B. Harmegnies, L. Distinguin, Y. Chekkoury-Idrissi, M. Circiu, P. Lavigne, I. L. Delgado, C. Calvo-Henriquez, C. Falanga, F. Coppee, S. D. L. Bon, A. Rodriguez, D. Dequanter, J.-P. Cornelis, S. Vergez, L. Koenen, M. Giuditta, G. Molteni, M. Tucciarone, T. Radulesco, M. Khalife, A.-F. Fourneau, S. Cherifi, M. Manto, J. Michel, T. Radulesco, G. Molteni, M. Tucciarone, G. Mannelli, G. C. and, Clinical and epidemiological characteristics of 1420 European patients with mild-to-moderate coronavirus disease 2019, Journal of Internal Medicine 288 (3) (2020) 335–344, doi:10.1111/joim.13089.

[18] D. Shin, W. I. Cho, C. H. K. Park, S. J. Rhee, M. J. Kim, H. Lee, N. S. Kim, Y. M. Ahn, Detection of Minor and Major Depression through Voice as a Biomarker Using Machine Learning, Journal of Clinical Medicine 10 (14) (2021) 3046, doi:10.3390/jcm10143046.

[19] C. Shimon, G. Shafat, I. Dangoor, A. Ben-Shitrit, Artificial intelligence enabled preliminary diagnosis for COVID-19 from voice cues and questionnaires, The Journal of the Acoustical Society of America 149 (2) (2021) 1120–1124, doi:10.1121/10.0003434.

[20] L. Verde, G. D. Pietro, A. Ghoneim, M. Alrashoud, K. N. Al-Mutib, G. Sannino, Exploring the Use of Artificial Intelligence Techniques to Detect the Presence of Coronavirus Covid-19 Through Speech and Voice Analysis, IEEE Access 9 (2021) 65750–65757, doi:10.1109/access.2021.3075571.

[21] G. Pinkas, Y. Karny, A. Malachi, G. Barkai, G. Bachar, V. Aharonson, SARS-CoV-2 Detection From Voice, IEEE Open Journal of Engineering in Medicine and Biology 1 (2020) 268–274, doi:10.1109/ojemb.2020.3026468.

[22] H. Coppock, A. Gaskell, P. Tzirakis, A. Baird, L. Jones, B. W. Schuller, End-2-End COVID-19 Detection from Breath & Cough Audio, doi: 10.48550/ARXIV.2102.08359, 2021.

Journal Pre-proof

[23] G. Chaudhari, X. Jiang, A. Fakhry, A. Han, J. Xiao, S. Shen, A. Khanzada, Virufy: Global Applicability of Crowdsourced and Clinical Datasets for AI Detection of COVID-19 from Cough, doi:10.48550/ARXIV.2011.13320, 2020.

[24] P. Bagad, A. Dalmia, J. Doshi, A. Nagrani, P. Bhamare, A. Mahale, S. Rane, N. Agarwal, R. Panicker, Cough Against COVID: Evidence of COVID-19 Signature in Cough Sounds, doi:10.48550/ARXIV.2009.08790, 2020.

[25] O. Shahid, M. Nasajpour, S. Pouriyeh, R. M. Parizi, M. Han, M. Valero, F. Li, M. Aledhari, Q. Z. Sheng, Machine learning research towards combating COVID-19: Virus detection, spread prevention, and medical assistance, Journal of Biomedical Informatics 117 (2021) 103751, doi: 10.1016/j.jbi.2021.103751.

[26] S. Anand, V. Sharma, R. Pourush, S. Jaiswal, A comprehensive survey on the biomedical signal processing methods for the detection of COVID-19, Annals of Medicine and Surgery 76 (2022) 103519, doi: 10.1016/j.amsu.2022.103519.

[27] N. Sharma, P. Krishnan, R. Kumar, S. Ramoji, S. R. Chetupalli, N. R., P. K. Ghosh, S. Ganapathy, Coswara — A Database of Breathing, Cough, and Voice Sounds for COVID-19 Diagnosis, in: Interspeech 2020, ISCA, 4811–4815, doi:10.21437/interspeech.2020-2768, 2020.

[28] R. F. Coleman, Sources of variation in phonetograms, Journal of Voice 7 (1) (1993) 1–14, doi:10.1016/S0892-1997(05)80107-9.

[29] M. Vetterli, J. Kovačević, Wavelets and Subband Coding, Prentice Hall, Englewood Cliffs, New Jersey, 1995.

[30] R. C. Guido, F. Pedroso, A. Furlan, R. C. Contreras, L. G. Caobianco, J. S. Neto, CWT × DWT × DTWT × SDTWT: Clarifying terminologies and roles of different types of wavelet transforms, International Journal of Wavelets, Multiresolution and Information Processing 18 (06) (2020) 2030001, doi: 10.1142/s0219691320300017.

[31] R. C. Guido, Wavelets behind the scenes: Practical aspects, insights, and perspectives, Physics Reports 985 (2022) 1–23, doi: 10.1016/j.physrep.2022.08.001.

Journal Pre-proof

[32] H. S. Malvar, Signal Processing with Lapped Transforms, Artech House, Norwood, Massachusetts, 1992.

[33] O. Rioul, M. Vetterli, Wavelets and signal processing, IEEE Signal Processing Magazine 8 (4) (1991) 14–38, doi:10.1109/79.91217.

[34] R. C. Guido, A tutorial on signal energy and its applications, Neurocomputing 179 (2016) 264–282, doi:10.1016/j.neucom.2015.12.012.

[35] A. Akbari, M. K. Arjmandi, An efficient voice pathology classification scheme based on applying multi-layer linear discriminant analysis to wavelet packet-based features, Biomedical Signal Processing and Control 10 (2014) 209–223, doi:10.1016/j.bspc.2013.11.002.

[36] L. Hu, Z. Zhang, EEG Signal Processing and Feature Extraction, Springer Singapore, doi:10.1007/978-981-13-9113-2, 2019.

[37] S. Sanei, J. Chambers, EEG Signal Processing, John Wiley & Sons Ltd,, doi:10.1002/9780470511923, 2007.

[38] N. Sairamya, M. Subathra, E. S. Suviseshamuthu, S. T. George, A new approach for automatic detection of focal EEG signals using wavelet packet decomposition and quad binary pattern method, Biomedical Signal Processing and Control 63 (2021) 102096, doi:10.1016/j.bspc.2020.102096.

[39] O. Faust, M. Bairy, Nonlinear analysis of physiological signals: A review, Journal of Mechanics in Medicine and Biology 12 (4), ISSN 0219-5194, doi:10.1142/S0219519412400155.

[40] T. D. Albertovich, R. I. Aleksandrovna, The Fractal Analysis of the Images and Signals in Medical Diagnostics, in: Fractal Analysis - Applications in Health Sciences and Social Sciences, InTech, 57–87, doi:10.5772/intechopen.68167, 2017.

[41] G. R. Bermdez, P. J. G. Laencina, Analysis of EEG signals using nonlinear dynamics and chaos - A review, Applied Mathematics & Information Sciences 9 (2015) 1–13, doi:10.12785/amis/090512.

[42] P. Gifani, H. R. Rabiee, M. Hashemi, P. Taslimi, M. Ghanbari, Optimal fractal-scaling analysis of human EEG dynamic for depth of anesthesia quantification, Journal of the Franklin Institute 344 (3-4) (2007) 212–229.

Journal Pre-proof

[43] J.-M. Lee, D.-J. Kim, I.-Y. Kim, K.-S. Park, S. I. Kim, Detrended fluctuation analysis of EEG in sleep apnea using MIT/BIH polysomnography data, Computers in biology and medicine 32 (1) (2002) 37–47.

[44] Z. Ali, I. Elamvazuthi, M. Alsulaiman, G. Muhammad, Detection of Voice Pathology using Fractal Dimension in a Multiresolution Analysis of Normal and Disordered Speech Signals, Journal of Medical Systems 40 (1), doi: 10.1007/s10916-015-0392-2.

[45] I. Wijayanto, R. Hartanto, H. A. Nugroho, Higuchi and Katz Fractal Dimension for Detecting Interictal and Ictal State in Electroencephalogram Signal, in: 2019 11th International Conference on Information Technology and Electrical Engineering (ICITEE), IEEE, 1–6, doi: 10.1109/iciteed.2019.8929940, 2019.

[46] M. J. Katz, Fractals and the analysis of waveforms, Computers in Biology and Medicine 18 (3) (1988) 145–156, doi:10.1016/0010-4825(88)90041-8.

[47] R. C. Guido, Effectively Interpreting Discrete Wavelet Transformed Signals [Lecture Notes], IEEE Signal Processing Magazine 34 (3) (2017) 89–100, doi:10.1109/msp.2017.2672759.

[48] M. Alves, G. Silva, B. Bispo, M. Dajer, P. Rodrigues, Detecção de Distúrbios Vocais através de Parâmetros Cepstrais Multibanda de Vogal Sustentada, in: Anais de XXXVIII Simpósio Brasileiro de Telecomunicações e Processamento de Sinais, Sociedade Brasileira de Telecomunicações, 1–5, doi: 10.14209/sbrt.2020.1570641723, 2020.

[49] T. Chen, C. Guestrin, XGBoost: A Scalable Tree Boosting System, in: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '16, Association for Computing Machinery, New York, NY, USA, ISBN 9781450342322, 785–794, doi: 10.1145/2939672.2939785, 2016.

[50] P. M. Rodrigues, B. C. Bispo, C. Garrett, D. Alves, J. P. Teixeira, D. Freitas, Lacsogram: A New EEG Tool to Diagnose Alzheimer's Disease, IEEE Journal of Biomedical and Health Informatics 25 (9) (2021) 3384–3395, doi: 10.1109/jbhi.2021.3069789.

Journal Pre-proof

[51] N. Sevani, I. Hermawan, W. Jatmiko, Feature Selection based on F-score for Enhancing CTG Data Classification, in: 2019 IEEE International Conference on Cybernetics and Computational Intelligence (CyberneticsCom), IEEE, 18–22, doi:10.1109/cyberneticscom.2019.8875656, 2019.

[52] A. Subramanian, K. Nirantharakumar, S. Hughes, P. Myles, T. Williams, K. M. Gokhale, T. Taverner, J. S. Chandan, K. Brown, N. Simms-Williams, A. D. Shah, M. Singh, F. Kidy, K. Okoth, R. Hotham, N. Bashir, N. Cockburn, S. I. Lee, G. M. Turner, G. V. Gkoutos, O. L. Aiyegbusi, C. McMullan, A. K. Denniston, E. Sapey, J. M. Lord, D. C. Wraith, E. Leggett, C. Iles, T. Marshall, M. J. Price, S. Marwaha, E. H. Davies, L. J. Jackson, K. L. Matthews, J. Camaradou, M. Calvert, S. Haroon, Symptoms and risk factors for long COVID in non-hospitalized adults, Nature Medicine doi: 10.1038/s41591-022-01909-w.

[53] B. Hu, H. Guo, P. Zhou, Z.-L. Shi, Characteristics of SARS-CoV-2 and COVID-19, Nature Reviews Microbiology 19 (3) (2020) 141–154, doi: 10.1038/s41579-020-00459-7.

[54] R. C. Guido, Paraconsistent Feature Engineering [Lecture Notes], IEEE Signal Processing Magazine 36 (1) (2019) 154–158, doi: 10.1109/msp.2018.2874549.

[55] F. S. Marcondes, D. Durães, F. Santos, J. J. Almeida, P. Novais, Neural Network Explainable AI Based on Paraconsistent Analysis: An Extension, Electronics 10 (21) (2021) 2660, doi:10.3390/electronics10212660.

Journal Pre-proof